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Aware of the sunshine? Investigating the alignment of Electric Vehicle charging and solar photovoltaic generation in Australian households

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Abstract

The deployment of rooftop solar power generation and vehicle electrification is a synergistic technological advance with the potential to dramatically reduce carbon emissions associated with the transport sector. Many of the unanswered questions in this space hinge on human factors related to vehicle purchase decisions, preferences for housing attributes, travel demand, and charging behaviours. The system has developed sufficiently to allow observation of these behavioural responses in a population of early adopters. We aim to understand whether Electric Vehicle (EV) owners respond to variation in solar photovoltaic (PV) generation systems through their charging behaviour.

This study investigates the charging behaviour of EV owners in 129 Australian households with PV solar systems. The dataset contains generation and consumption data at 5-minute intervals over thirteen months (2022-2024). Using clustering methods, we identify seasonal trends in EV charging behaviour based on plug-in times and charging durations. Our findings show that 98% of households experienced at least one short-duration charging event where EVs were plugged in during PV generation hours and unplugged shortly after. This suggests a willingness among EV-PV users to charge when PV-generated energy is available.

This research highlights the way humans respond to contextual factors in their decision-making, and this responsiveness is crucial for policies aimed at optimising grid load reduction and enhancing the use of renewable energy. The insights from this study, moderated for the bias of working with a sample of early adopters of EV-PV integration, suggest that EV owners are responsive to taking advantage of dynamic charging conditions and can therefore contribute to sustainable grid management.

1. Introduction

In 2022, the transport sector produced 19% of Australia's carbon emissions and is projected to become the largest source of emissions by 2030 without significant intervention (Australian Government, 2024). Petrol-fuelled light vehicles contribute 60% of transport emissions (Australian Government, 2024). Fossil fuels accounted for 91% of transport energy consumption in Australia in 2021-2022 and Australian passenger cars use 40% more fuel than their European counterparts (Australian Government, 2023).

The introduction of EVs can help reduce greenhouse gas (GHG) emissions and meet global development goals (Bhatti *et al.*, 2016; Martin *et al.*, 2022; Khan *et al.*, 2024). Although the EV market in Australia remains relatively small, its development is crucial. EVs include both Plug-in Hybrid Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs). PHEVs combine an Internal Combustion Engine (ICE) with an electric motor and battery to operate either gas or

electric power and switch between the two sources. This enables the use of a smaller battery, which can typically be fully charged in 3-5 hours with a 230V charger. In contrast, BEVs are fully electric, relying solely on battery power. The same 230V charger would require 8-20 hours to fully charge a BEV, depending on its battery capacity.

However, the increased use of electric vehicles could impact the quality of the power distribution network, which has been largely developed to support forecasted household demand without the idiosyncrasies of EV charging. Negative effects include voltage imbalance, network congestion, and undesirable distortion (Hussain *et al.*, 2021; Sørensen *et al.*, 2023). Acute crises in the distribution systems are associated with energy utilisation peaks, including overloaded transformers and voltage instability, which affect the stability of the grid. The climbing demand for electricity to charge vehicles can also lead to an increase in GHG emissions, as the grid relies more heavily on fossil fuel energy sources to meet demand.

Since the environmental benefits of EVs are maximised when they are charged with renewable energy, it is desirable to harness renewable energy for EV charging. Australia has a unique renewable energy advantage with rich solar resources and widespread deployment of rooftop photovoltaic (PV) panels. Making use of this Australian Solar advantage to charge EVs from rooftop solar will further assist in eliminating the transport sector's dependence on fossil fuels.

PV systems can be categorised into two main types: PV-grid and PV-standalone fields (Youssef *et al.*, 2018). PV-grid systems generate energy from solar power and switch to grid power when solar is insufficient, whereas PV-standalone systems operate independently and store solar energy in batteries (Bhatti *et al.*, 2016). This research focuses on PV-grid systems, which are more commonly applied in domestic settings relevant to charging private vehicles.

In terms of the benefits of developing a PV-EV system, Longo, Yaïci and Foiadelli (2017) demonstrated that applying solar PV systems to charge electric vehicles can relieve pressure from the grid while effectively meeting the energy demands of EVs. There are two important concepts when describing the performance of PV systems: Self-consumption and self-sufficiency. Self-consumption measures the proportion of PV energy used within the household, calculated as total PV production minus exported energy, divided by total production. Self-sufficiency assesses the percentage of energy demand met by PV generation, calculated as total consumption minus imported energy, divided by the total consumption. The two concepts measure the efficiency and effectiveness of PV systems.

Over 30% of Australian households have solar panels (*Solar energy - Australian Renewable Energy Agency (ARENA)*, 2024). In 2024, 1.5% of the light-duty vehicle fleet was electric and the market share of sales is growing. The efficient integration of solar panels and EVs holds significant potential for reducing carbon dioxide emissions and improving air quality (Khan *et al.*, 2024). However, the optimal integration relies on EV owners responding to the availability of PV energy – considering when, where, and how long to charge – as this behaviour plays a key role in reducing emissions from EVs (Tang *et al.*, 2021).

This paper aims to investigate EV charging behaviours and whether household PV generation influences charging behaviours in Australia, providing insight into the self-sufficiency of the PV-EV system through clustering analysis.

2. Review of past approaches

Understanding household EV charging behaviour is essential to optimise energy demand for PV systems and ensure efficient grid management. Flammini *et al.* (2019) proposed a Beta Mixture Model to analyse EV charging behaviours. While it focuses on averages and distributions which provide high-level insights, it overlooks group-specific behaviours. This statistical analysis is effective for datasets with limited behaviour diversity. However, EV users

make different charging decisions based on their heuristic choices and modelling each EV user is unrealistic due to the large population size (Wen, MacKenzie and Keith, 2016). To address uncertainties in user behaviours during charging sessions, Gaussian-based Kernel Density Estimation (GKDE) has been developed (Wang *et al.*, 2017). However, due to the optimal bandwidth selection which has the probability of overestimation, Khaki *et al.* (2018) proposed Diffusion-Matrix Kernel Density Estimation (DKDE) which refines bandwidth selection for better user behaviour modelling. Other methods, such as Markov Decision Process (MDP) and Queuing Theory (QT) have also been used to account for the uncertainty of the behaviours (Wang and Infield, 2018). While these approaches predict the uncertainty in users' charging behaviours effectively, they lack integration of user behaviour patterns and do not categorise charging behaviours with distinct features.

Clustering, particularly K-means clustering, is more suitable for classifying charging behaviours into distinct groups. K-means is a distance-based clustering method that iteratively recalculates centroids using Euclidean distance until cluster centroids stabilise. It categorises user behaviour patterns without requiring repeated analysis of historical datasets to assess demand. Crozier, Apostolopoulou and McCulloch (2018) utilised clustering analysis of travel survey data from the UK to identify EV charging patterns. One of the findings was that peak charging demand varied between areas and more data is needed for further analysis. Zhu *et al.* (2023) performed a multidimensional K-means clustering analysis on user characteristics such as average charging power, average charging duration and power consumption time, identifying five user categories. Märtz *et al.* (2022) developed K-means clustering to identify the charging patterns based on the empirical dataset of real-world charging data. Our study further employed K-means clustering but with empirical real-world data on PV generation and home EV charging. The approach allows for a deeper understanding of EV charging choices in the context of available rooftop solar, addresses gaps in prior research and enables a better understanding of the synergistic integration of EVs and PVs. It manages to find a balance between the high-level insights provided by averages while also steering clear of the unrealistic nature of modelling each EV user. By finding and comparing the average behavioural characteristics of different clusters, the frequencies of different common behaviours could be explored and assessed.

Several studies have conducted various methods to estimate household PV generation to match the EV charging demand (Table 1). Munkhammar *et al.* (2015) estimated a PV generation combined model for photovoltaic power production on tilted planes based on the location, while the study simulated EV demand with a Markov-chain model to assess the synchronisation between household PV output and EV demand. Their study shows that the PV generation and consumption by EVs do not match. Martin *et al.* (2022) combined real EV charging data with simulated PV output based on regional solar data. The research reveals that only 15% of the vehicles' energy demand is met by household-generated solar (Martin *et al.*, 2022). However, these studies overlook the fact that EV charging behaviours might vary between users with and without PV systems (Deng and Newton, 2017). Our paper provides valuable insights into a real-world dataset that fills in the blank, addressing a significant gap in the literature by analysing actual household PV generation and clustering the EV charging behaviour among those households to evaluate whether energy demand is adequately met and whether EV owners are willing/able to respond to the availability of PV energy (Table 1). The research is focused on the Australian context, whereas the aforementioned studies are based on international cases.

Table 1: Comparison of PV and EV Data Sources and Methodologies in Related Studies

Case Study & Data Geo Location	PV Data	EV Data	PV Methodology	EV Methodology
Munkhammar et al. (2015), City of Westminster, London	Estimated	Simulated	Location-based production model	Markov-chain for demand
Longo, Yaïci and Foiadelli (2017), Ottawa, Canada	Estimated	Simulated	Mathematical model for PV sizing and orientation optimization	Deterministic load profile based on EV use
Martin *et al.* (2022), Switzerland	Simulated	Real	Regional solar data simulation	Statistics Modelling
Current Study, Australia	Real	Real	Statistics modelling	K-means clustering of EV charging behaviour

3. Dataset

The research utilises a dataset encompassing data from 129 households with both solar panels and EVs across Australia. The data is provided by Solar Analytics, a firm that makes PV system monitoring software. The data spans from 2022 to 2024, including the key variables of overall energy consumption, EV charging consumption and PV generation at 5-minute intervals for each household. These variables are sufficient to capture energy usage patterns contextualised by site attributes (postcode, maximum generation rate, maximum charging rate, total consumption) and timestamp (time of day, day of week, season).

Table 2: Description of columns in the dataset

Column Name	Description
site_id	Site Identifier
post_code	Postcode
t_stamp	Timestamp (site local time)
pv_gen_wh	PV Generation
load_total_wh	Total Household Consumption
Load_ev_wh	Electric Vehicle Charger Consumption

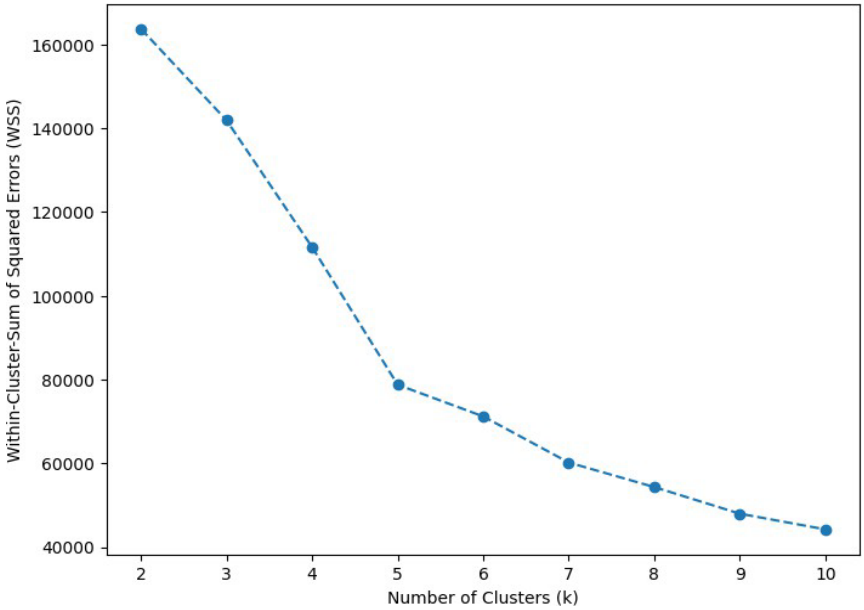
The data reveals that there are three household charging levels widely used in Australia. Level 1 charging ranges from 1.8 kW to 3.7 kW and is supplied from 230V AC. Level 2 charging includes two types: single-phase charging at approximately 7kW from 230V, and three-phase charging at around 22 kW from 400VAC. Level 3 or fast charging ranges from 25 kW up to 350 kW, but is rarely used for domestic settings due to its high cost. In our dataset, 58% of the sites use Level 2 chargers, and 42% of the sites use Level 1. Any negative values of energy generation and consumption were treated as noise and recoded to 0. These steps ensured that a clean and reliable dataset was produced for further analysis. Filtered data took the form of 5-minute readings for each household. Generation amount and the charging amount maximums were then taken across 3 data reading intervals to smooth data into 15-minute points, aiming to reduce the noise. Charging events were extracted between plug-in and plug-out times to produce each household's daily charging profile.

4. Methodology

4.1. Clustering

To observe patterns in charging behaviours, unsupervised learning was employed to identify commonalities in the charging events. This approach involves grouping a set of data points into clusters based on shared features, without the use of predefined labels. It involves grouping a set of data points into clusters based on their features, without predefined labels. We focus on K-means clustering in this paper using a set of features describing the household's charging events. For K-means, the mean position of the points is the centroid of each cluster. Each point belongs to the closest centroid. The elbow method is used to check the best selection of K (Bholowalia, 2014). K represents the number of clusters used to partition the data, and each K has a corresponding number of Within-Cluster-Sum of Squared Errors (WSS), illustrated in Figure 1. As Figure 1 shows, the elbow occurs where there are 5 clusters, and the corresponding clustering results are presented.

Figure 1: Elbow method for selecting the best number of clusters in the charging behaviour



This study focuses on charging events and patterns within EV charging behaviour. The features generated to represent these patterns include plug-in time, plug-out time, charging duration, the amount of energy charged, and the percentage of the battery charged. The following sections describe the data processing steps undertaken to identify these features.

4.1.1. Plug-in time, plug-out time and charging duration

Plug-in time was classified as any reading for a household EV energy consumption that exceeded 1.8 kW. This value was obtained from the lower bound of Level 1 charging. Similarly, the plug-out time was identified as the time when the EV energy consumption dropped back below 1.8 kW, indicating the end of a charging session. Charging duration was defined as the time between the plug-in and plug-out. Once a site experienced a plug-out, it was reset and set as eligible for a new plug-in time to be recorded. These plug-in and plug-out times were found across every day for every site under analysis. The details of the detection algorithm can be found in the appendix named 'Define plug-in and plug-out time and establish charging events'.

Plug-in time is an important measure of charging behaviour because it demonstrates a user's intent to charge (Gschwendtner, Knoeri and Stephan, 2023). Plug-out time can represent a user's awareness of PV generation or activity-based constraints on charging. Charging duration can capture the user's inclination toward opportunistic, full or top-up charging.

4.1.2. Charging amount and percentage of the battery charged

The charging amount for each session was calculated based on the accumulated EV consumption between each plug-in and plug-out. Like duration, this measure captures the type of charging, but it controls for the fact that households with higher charging levels can complete charging faster.

Any behavioural insights into charging should be interpreted in the context of the battery's State of Charge (SoC) (Märtz *et al.*, 2022) and the user's travel plans. However, neither of these is available in this dataset. To estimate the percentage of the battery charged, we assume that the maximum observed charging amount at each site represents that household's battery capacity and we calculate how much of the capacity was replenished in each charging event. However, this approach has limitations. The maximum observed charging amount may not accurately represent the full actual battery capacity for every EV if the vehicle is not charged from empty at home during the data collection period. More specifically, the percent-charged feature differs from the true state of charge, as the initial battery level at the start of each charging session is unknown. Despite these limitations, this study explores charging behaviour by using attributes of charging events as features to identify clusters of charging habits.

4.1.3. EV is covered by PV in each cluster

In order to understand whether EV owners respond to the availability of solar energy in their charging choices, it is necessary to understand how much of each charging event's energy was supplied by PV. We create a feature called PV coverage which captures this. In this context, we ignore any non-EV household consumption occurring at the same time and focus on whether the PV was supplying enough energy to charge the battery in each interval, *e*, belonging to charging event E. The PV coverage, *C*, ranges from 0 to 100% and is expressed in Eq. 1.

$$C = 100\% \times \sum_{e \in E} \frac{\min(EV_e, PV_e)}{EV_e} \quad \text{(Eq.1)}$$

A log transform was applied to *C* to compare different PV utilisation groups within a single plot. The transformation standardises the scale across groups, making it easier to compare the groups in seasons and between weekdays and weekends.

4.2. Seasonal and weekend analysis

Acknowledging the influence of the broader context around activity patterns and seasons, we compute features based on the timestamp of a charging event. To further observe how PV is utilised across seasons and between weekdays and weekends for households with EVs, binary variables were constructed based on the day of the week and the month of the year. Following a standard Australian calendar, weekends were defined as Saturdays and Sundays, whilst seasons were defined as Summer (December, January, February), Autumn (March, April, May), Winter (June, July, August) and Spring (September, October, November).

5. Result

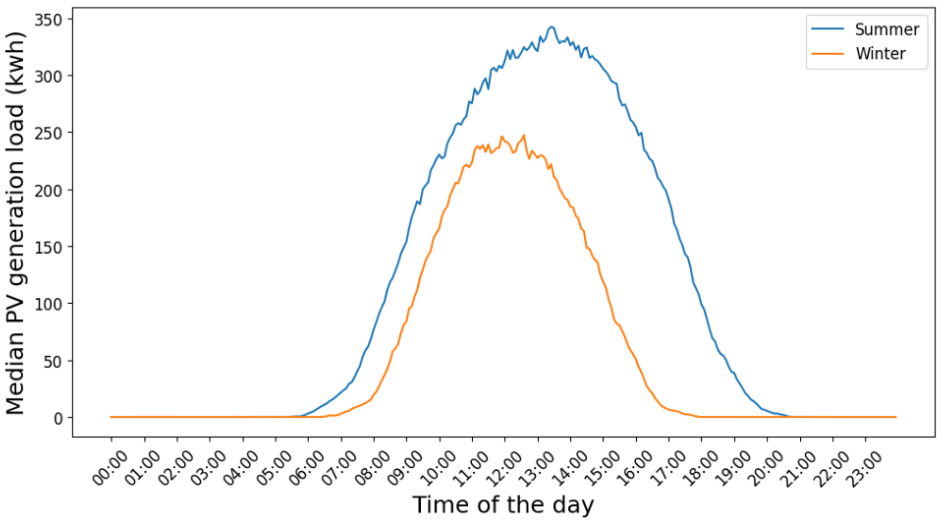
PV generation varies significantly with the seasons, with higher production in summer and lower output in winter as shown in Figure 2. The summer curve is both wider and higher than the winter curve representing better availability of sunlight, while the peak PV generation time in summer is around 1 hour later than that in winter. Despite this, overall household EV usage is not synchronised with PV generation. 36% of the charging events occurred when PV generation was insufficient to meet real-time EV consumption, whilst 21.6% were simply because the event occurred outside daylight hours. A detailed analysis was conducted to better understand the relationship between PV availability and EV charging behaviour. The following sections present insights into users' charging patterns, including clustering results,

along with calculated coverage values. Additionally, charging level, state, season, weekday and weekend variations are analysed in greater detail.

To have a greater understanding of users' charging behaviour in households, a t-test was conducted to examine seasonal differences in charging duration. The results indicate that users in summer charge for longer durations (mean = 1.75 hours) compared to those in winter (mean = 1.55 hours) with a statistically significant difference (t=5.45, p-value=5.343-08).

These observed behavioural patterns suggest the presence of distinct user groups. To explore this further, the following paragraphs will present the clustering results, classifying the charging behaviours.

Figure 2: Median of PV generation (kWh) across 24 hours by season



The k-means clustering results identify 5 distinct clusters (k = 5). The percentage and the median values for each cluster are summarised in Table 4.1. Cluster 0 and Cluster 4 contain 74% of the charging sessions, while Cluster 1, Cluster 2 and Cluster 3 make up 17%, 8% and 1% respectively. Short charging durations (median of 0.75 hours) in Cluster 0 and Cluster 4 suggest a pattern that most people in these two clusters tend to charge briefly during the daytime. Cluster 3, comprising 1% of the sessions, has a large solar panel capacity and experiences the longest duration, with a median of 15 hours. Meanwhile, Cluster 1 and Cluster 2 show moderate charging duration with median times of 3.75 hours in Cluster 1 in the afternoon and 4.25 hours in Cluster 2 at night. The charging amount is used to classify the charging events into different charging levels. Above all, Table 3 shows the median values of all features related to charging behaviour within clusters. Interestingly, for Cluster 3 which has the largest median charging duration of 15 hours, the median battery charged was only 20%. This suggests that a larger battery and slower charger were present in this cluster, compared to Clusters 1 and 2, which had 40% and 38% battery charged, respectively, within a shorter charging duration of approximately 4 hours. The median amount of battery charged in Cluster 0 and Cluster 4 is 6% and 5%, which suggests these are quick top-up charges.

Table 3: Descriptions of the median values of each feature in each cluster

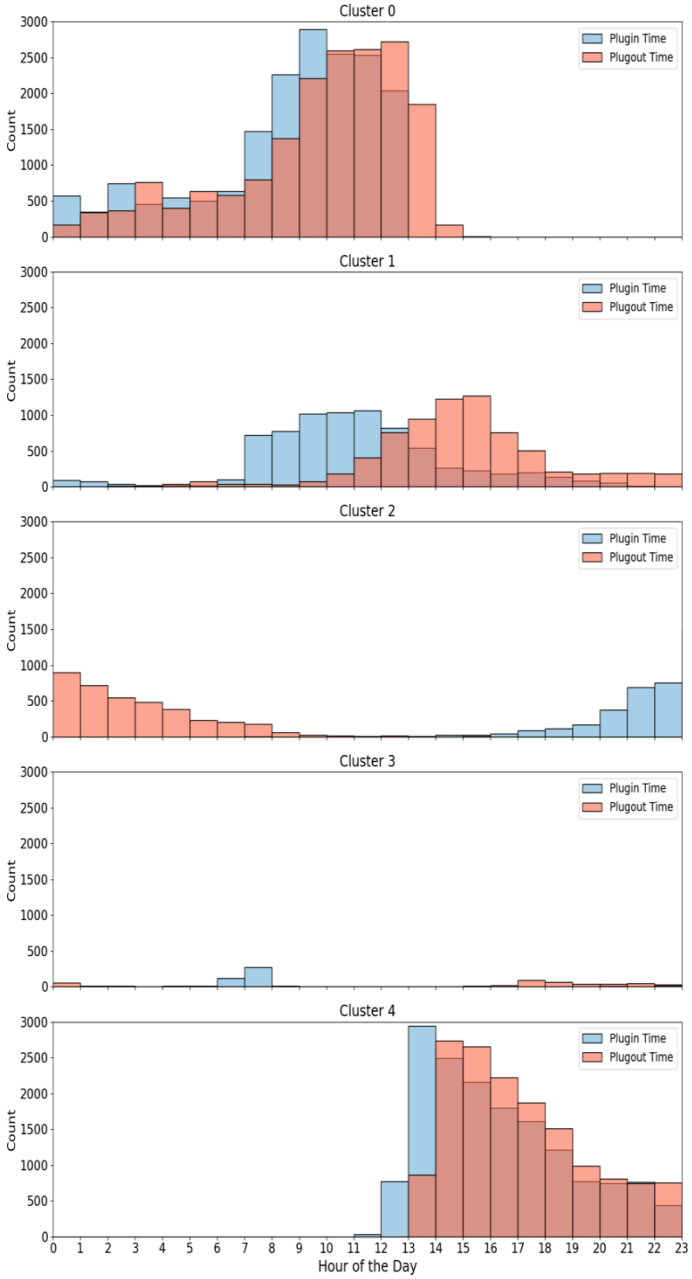
Cluster	% of observations	Plug In	Plug Out	Duration (h)	Amount (kWh)	Battery Charge %
0	39	09:00	10:00	0.75	2.48	6
1	17	10:00	14:00	3.75	18.22	40
2	8	22:00	02:00	4.25	20.86	38
3	1	07:00	17:00	15	129.61	20
4	35	15:00	16:00	0.75	2.24	5

Clusters plug-in and plug-out times are visualised in Figure 3. The 5 clusters show different behaviour patterns for the charging sessions in plug-in and plug-out hours:

- **Cluster 0** (39%): The majority of plug-in and plug-out events happen **overnight** and **morning**, with fewer in the **noon** and **evening** periods. This suggests that Cluster 0 primarily consists of quick top-up charges (0.75 hours) in the morning, slightly reliant on daytime PV generation.
- **Cluster 1** (17%): Has charging and disconnection events across **morning** and **noon**, with a median charging duration (3.75 hours). Cluster 1 events occur when PV generation is highest making them super PV aware.
- **Cluster 2** (8%): Shows a distinct pattern of **overnight** plug-in and plug-out with median charging duration (4.25 hours), suggesting that these users typically charge during the night when grid energy costs tend to be lower with no reliance on PV generation.
- **Cluster 3** (1%): This cluster is small representing the all-day chargers. With plug-in times in the **morning** and plug-out in the **afternoon/evening**, these events are long (median charging duration of 15 hours) and demonstrate some awareness of PV availability.
- **Cluster 4** (35%): Primarily charges and unplugs during the **afternoon/evening** period, which is symmetrical to Cluster 0 with a median charging duration (0.75 hours) as well. Like Cluster 0, these charging events are top-up charges that are used when the car and owner are both at home at the end of the day. They are slightly reliant on daytime PV generation but more reliant on grid energy than Cluster 0.

All households in the sample have charging events in Cluster 1, suggesting that this cluster captures a universal behaviour across the dataset—when activity patterns and weather make it possible, EV+PV owners do make use of PV in their EV charging. For Cluster 0, 97% of households have at least one charging session that falls within this category and Cluster 4 also takes the majority, at 98% of the households. These common behaviours match the expectation that EV owners prefer to charge their cars during daylight hours but typically tend to do so at the start or end of the day since the car is often away from home during peak PV generation hours. Cluster 2 includes 79% of households, and these events should be responsive to time-of-day energy pricing. In contrast, Cluster 3 is much rarer, with only 2% of households exhibiting this category. Above all, this is expected as most EV owners are likely to use their car at some point during the day.

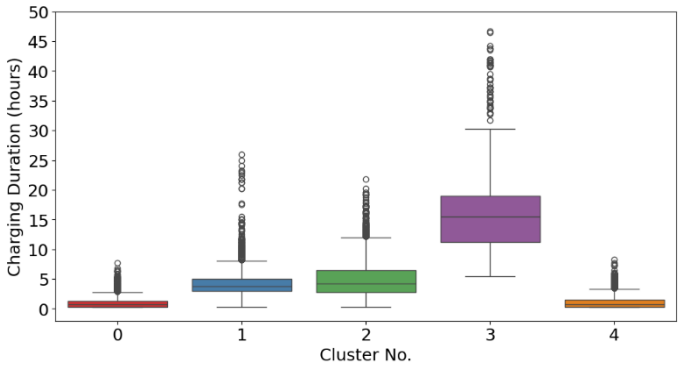
Figure 3: Clustering results in plug-in and plug-out time



The box plot in Figure 4 shows the distribution of charging duration across different clusters. Cluster 0 and Cluster 4, with the shortest durations, have low variability in charging duration from 0.5 to 2 hours. In contrast, Cluster 1 and Cluster 2 have more variable charging durations with medians between 4 and 6 hours. While Cluster 1 has more spread-out outliers, extending up to 26 hours, Cluster 2 shows a narrower spread up to 22 hours. Cluster 3 has the longest charging duration, with a median of 15 hours and several events exceeding 45 hours.

A summary of the charging levels and state locations present in each cluster is shown below in Figure 5 and Figure 6. For charging levels in Figure 5, Cluster 4 contains the highest proportion of Level 1 chargers, whereas Cluster 1 and Cluster 2 have a significant share of Level 2 three-phase chargers. Cluster 3, in contrast, has the highest percentage of higher-level chargers, including Level 2 three-phase chargers.

Figure 4: Charging duration distribution by clusters



For state location distributions in Figure 6, Cluster 3 is all in South Australia, which has the lowest number of households but the highest proportion of higher-level chargers. This cluster also contains the largest energy charging consumption, indicating high demand in this region. New South Wales accounts for over 40% of the total charging events across all clusters except Cluster 3, representing the widely distributed charging activities in the state. The remaining states (QLD, VIC, TAS, WA, ACT) all distribute equally, with only a few charging events located in NT.

Figure 5: Charging Level distribution across clusters

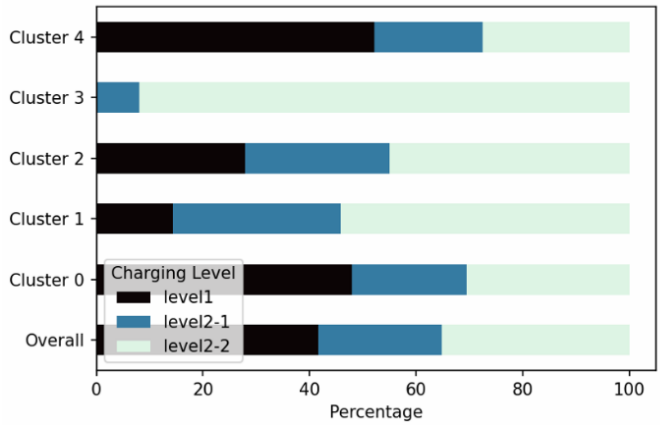
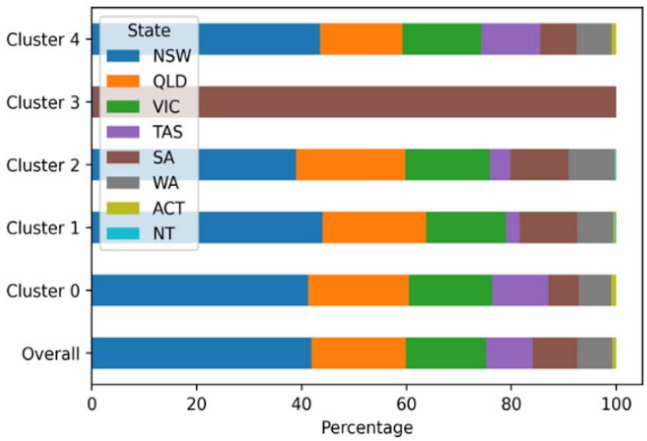


Figure 6: States distribution across clusters



Additionally, the percentage of PV coverage presents a detailed representation of how much EV energy demand is covered by actual PV generation. For 37% of charging events, the EV charging amount was fully covered by PV generation.

Figure 7 shows that Clusters 0, 1 and 4 have PV coverage above 50% for the majority of

charging events, indicating that PV can partially fulfil the demand from users while the remaining depends on the grid load. Cluster 2 stands out with 99% of events occurring when there is insufficient PV for charging, indicating low PV awareness in this group of events. Cluster 3, with the longest charging duration, also shows the highest PV reliance, with over 90% of charging events being mostly covered by PV.

Figure 7: Proportion of PV coverage over 50%

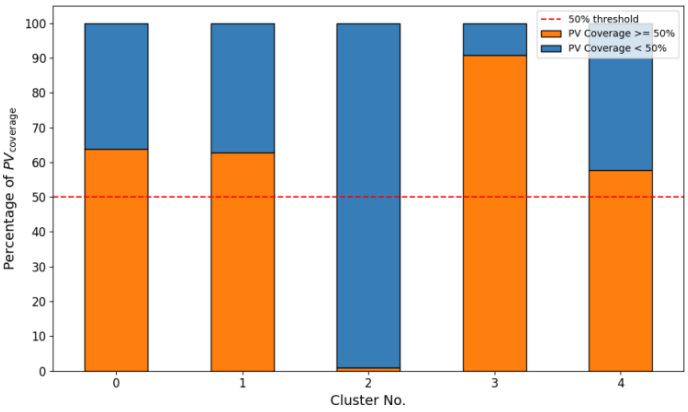
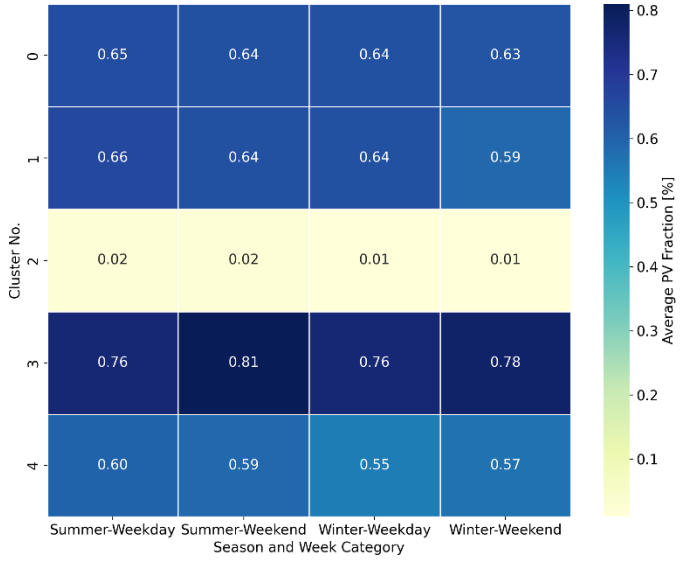


Figure 8: Average PV coverage by cluster and week category



Furthermore, weekdays and weekends show a mild relationship with charging behaviour, reflecting the role that activity patterns play. Figure 8 illustrates the average coverage among clusters for different seasons (Summer and Winter) and day-of-week categories (Weekday and Weekend). Across all clusters, coverage tends to decrease in winter compared to summer, regardless of whether it is a weekday or a weekend. Clusters 0 and 1 unexpectedly show lower coverage during the weekend. Cluster 4 shows a distinct drop in coverage during summer weekends but rises during winter weekends. Cluster 2 remains consistent over all days of the week and across all seasons. This aligns with the fact that Cluster 2 is overnight charging, which is not affected by PV generation. Cluster 3 demonstrates an increase in coverage during weekends for both seasons, which indicates those users' willingness to charge EVs during weekends. However, all the increases or drops are relatively small, which indicates a weak relation between the day-of-week categories and clusters.

6. Conclusion and discussion

Household EV charging behaviour shows a higher frequency of plug-in events during winter compared to summer. Since the study takes place in an Australian climate, this is likely not due to the reduced battery efficiency in low temperatures. Rather, the less frequent and longer durations in summer suggest that users might be snatching at brief opportunities for sunlight in winter months. This behaviour indicates a certain level of awareness among users in using solar energy for EV charging, suggesting strong potential for further development in promoting PV self-consumption and EV-PV synergy.

Clustering analysis further supports this observation. By clustering charging behaviour based on attributes of the charging events, it becomes clear how much of the current demand can be met by existing PV capacity. The result shows that almost all households experienced at least one quick burst charging event. EVs were plugged in either the morning or the afternoon during PV generation time and unplugged shortly after. This suggests an awareness of the benefits of using PV energy to charge their EVs. Helmus, Lees and van den Hoed (2020) highlighted that charging behaviour is often driven more by opportunity than necessity. Availability of locally generated PV energy is one component of this opportunity, offering people the chance to charge their EVs for “free”. This opportunity needs to align with the households’ activities in such a way that the vehicle is at home and not already fully charged.

Accordingly, the dominant pattern of short plug-in and plug-out time in Cluster 0 and Cluster 4 (collectively 74% of the charging events) reflects a willingness among certain groups to charge when they get a chance. This finding aligns with Märtz *et al.* (2022) who found that a large number of opportunity-based charges occur during the day. Furthermore, Cluster 0, Cluster 2 and Cluster 4 are observed in at least 79% of the sampled households, further supporting Märtz *et al.* (2022)’s conclusion that multiple types of opportunity-based charges are employed by each household. Building on Märtz *et al.* (2022), our study provides deeper insight into the shared groups. Specifically, half of the households switching between clusters primarily use Level 1 chargers, followed by Level 2 single-phase chargers. This finding indicates that households with lower-level chargers tend to charge frequently and when the opportunity arises.

Interestingly, households in South Australia were found to have the highest proportion of higher-level chargers, reflecting a larger energy demand requirement. The households are also located in regions that experience the longest solar exposure compared to the other states. This fits with South Australia’s more aggressive renewable energy strategies, which have increased residents’ awareness of their region’s solar advantages and motivated them to actively maximise PV energy utilisation for EV charging.

Additionally, only 37% of the EV charging amount was fully covered by PV generation, indicating an opportunity to improve the integration of PV generation and EV charging, consistent with the findings by Munkhammar, Grahn and Widén (2013). On the other hand, 92% of the charging events (i.e. total charging events excluding the events in Cluster 2) occur during periods when the PV generation is sufficient to power at least half of the charging energy demand for at least half of the charging duration. Martin *et al.* (2022) estimated that only 15% of PV would be used for EV charging. Although in this study PV shows higher self-sufficiency, a great amount of PV energy remains unmatched by EV demand, consistent with Munkhammar *et al.* (2015) who observed that while EVs can enhance PV utilisation, the impact is still limited by the intermittent and mismatched nature of PV generation and EV charging needs. The widespread use of quick opportunistic charges, with 97% of households having a charging event in Cluster 0 and 98% in Cluster 4 suggests that almost all the households have a willingness to plug and unplug during daylight hours to utilise PV generation when the opportunity arises. When PV cannot fully fulfil energy demand due to limited daytime and fluctuating generation, many households charge overnight (Cluster 2) to fulfil part of the demand.

Large fleets of EV charging are sometimes portrayed as an additional burden on the grid (Chandra, Singh and Samuel, 2024). During the daytime, PV energy can relieve part of the

load, and during nighttime the load on the grid is generally not high. 8% of the charging events in this study are overnight charging, accounting for more than 20% of battery charging assuming that home charging is the primary source for energy replenishment. To further address demand on the grid, government policies could incentivise the implementation of household battery storage to capture excess PV energy. Given the high cost of individual battery systems, Community-Scale Battery (CSB) systems present a viable alternative for sharing and storing solar power on a larger scale (Javadi, 2024). Alternatively, using EV batteries to feed the grid (vehicle-to-grid) would be suitable for the vehicles that experience charging events >20 hours since they are not being driven and are connected to power. The increasing capacity and decreasing cost of batteries indicate that EVs will not overburden existing power infrastructure.

However, time-varying load on the grid may pose a problem. 74% of charging events were short with low variability in duration, ranging from 0.5 to 2 hours. This suggests that charging sessions are primarily used for short trips or top-ups. Frequent short-term plug-in and plug-out behaviour can cause sudden spikes in energy demand, leading to bursts of charging that may further stress the grid during peak hours (Hussain *et al.*, 2021). Smart charging strategies can reduce the burden on the user to align their activity patterns with PV generation in order to fully use their PV by shifting the load earlier and later. Goli and Shireen (2014) and Fattori, Anglani and Muliere (2014) introduced smart charging stations to increase PV utilisation, mitigating the impact on peak loads. Subsequent research has shown that smart charging enhances self-consumption and self-sufficiency, improving the synergy between PV generation and EV charging (Martin *et al.*, 2022). The wide adoption of smart charging could help households rely more on PV energy for charging, reducing grid dependency and maximising PV utilisation during the daytime.

Overall, this study identifies behavioural patterns using clustering, which offers valuable insights into diverse charging behaviour. Additionally, the use of actual household-level PV generation and EV charging data provides a realistic picture of PV utilisation patterns, making the findings more applicable to real-world scenarios and relevant for developing actionable solutions.

7. Limitations and future work

This study treats the household as a single unit and considers the maximum observed capacity as the household's total charging capacity, without accounting for the travel demand of the household, the energy pricing of the household's provider, the number of EVs or the specific conditions of each EV within the household. This approach may reduce the accuracy of the estimated charging percentage, as households with multiple EVs could lead to a lower charging percentage per vehicle than what is reflected in the analysis.

Future work will expand the analysis by incorporating the total household load, which has not been explored in this paper. This will provide a more detailed view of how PV energy is applied across overall household consumption and assess whether there is potential to implement the battery storage system and further develop smart charging technology to meet household energy demand, further maximising PV generation usage. Additionally, demographic factors, such as travel demand and actual remaining battery percentage, could be included to explore more granular charging patterns. Additional practical applications can result from dataset analysis including calculating optimum solar battery sizes for households based on their consumption and generation load profiles, simulating future grid loads based on neighbourhood postcodes, and simulating different time-of-use tariff structures to optimise renewable energy usage.

8. References

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9. Appendix
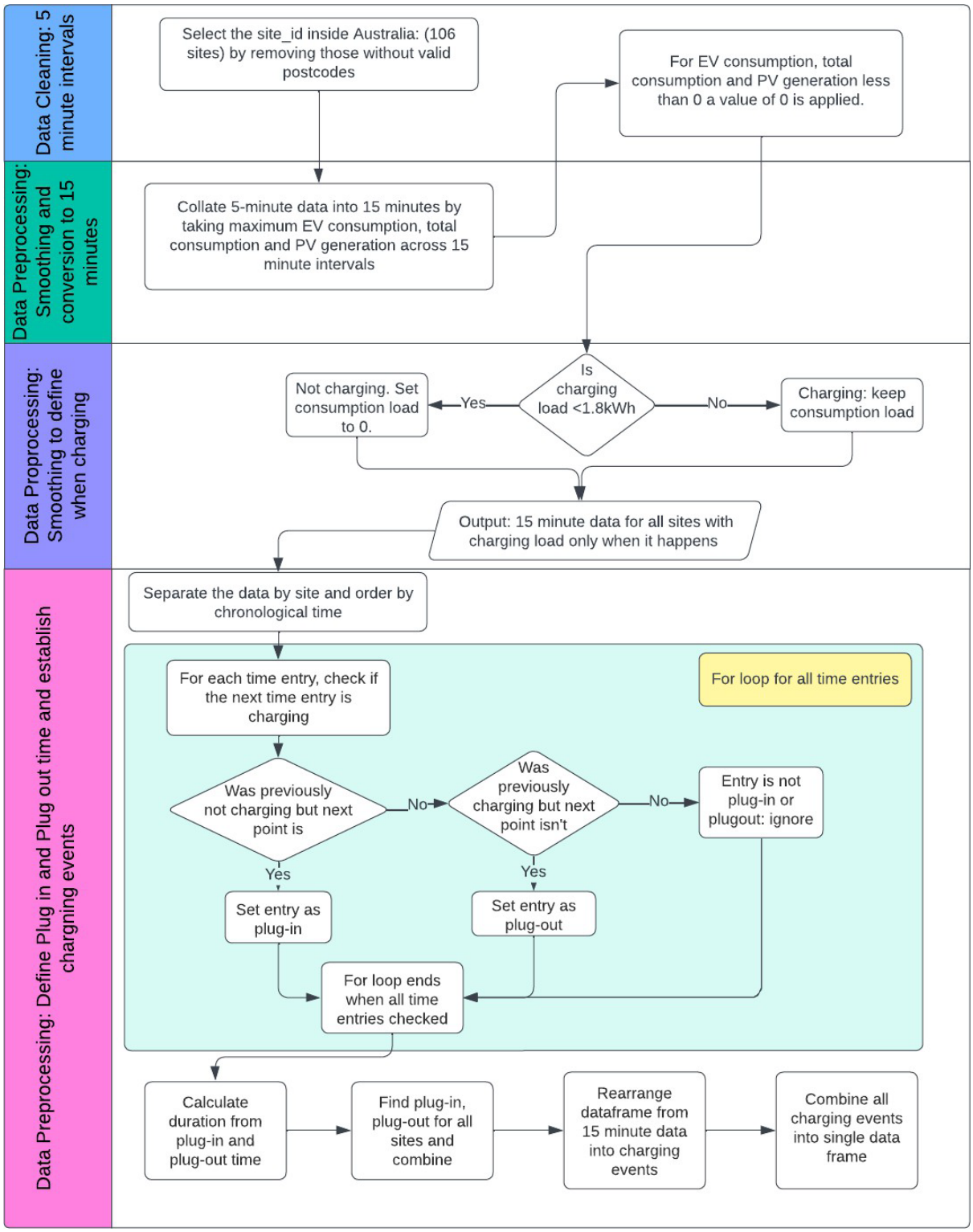
Figure 9: Define plug-in and plug-out time and establish charging events