MONASH University

Title: **WP1.2 Technical modelling of electrification of transport profiles**

Document ID: Task 1: Literature review

Date: 30 November 2023

Prepared For: Centre for New Energy Technologies (C4NET)

Lead Researcher: Dr Hao Wang
Department of Data Science and IA
Monash University

Research Team: Ariel Liebman, Reza Razzaghi, Mahsa Salehi
Monash University
Mahdi Jalili, Kazi Hasan
RMIT

Contact: Dr Hao Wang
Hao.Wang2@monash.edu

Table of Contents

Executive summary

As part of the Enhanced System Planning (ESP) project, a pioneering initiative in the realm of energy infrastructure planning, Work Package 1.2 (WP 1.2) focuses on the cutting-edge technical modelling of electric vehicle (EV) charging patterns. This research is pivotal in sculpting future scenarios of EV charging demand, particularly in the post-2030 era. This project's cornerstone lies in the development of high-resolution, multi-parametric models of EV charging load profiles, which are integral to various ESP work packages.

The literature review conducted as part of this project bifurcates into two principal areas: EV charging detection and disaggregation from meter data to extract real-world charging behaviours and EV charging profile modelling to produce close to real future EV charging demand, particularly where the majority of vehicle charging is likely to occur, ie at home. This not only aids in assessing the impact of EV charging but also underpins infrastructure planning in other ESP work packages. This report thus collates and presents insights from the literature review on existing studies, algorithms, and tools worldwide for extracting EV charging profiles from meter data and modelling EV charging demand, taking into account a range of input variables.

In the realm of EV charging detection and disaggregation, this report delves into the methodologies for disaggregating EV charging loads from the overall electricity consumption of customers. The challenge here lies in differentiating EV charging from other appliance loads, like air conditioning and water heaters, which often present similar load patterns in meter data. Additionally, the variance in customers' consumption habits can lead to diverse EV charging behaviours embedded in the meter data, introducing additional complexity. To address these challenges, we explore a spectrum of approaches in the literature, encompassing rule-based, machine learning, and deep learning techniques, to effectively identify and separate EV charging activities within the non-intrusive load monitoring (NILM) framework. Several critical factors, such as data sampling rate and ground-truth labels of EV charging, are also reviewed. The output of the EV charging detection and disaggregation will provide useful insights into real-world EV charging behaviours, such as charging time, duration, and demand, of various customers across different locations (zip codes), thus facilitating the EV load profile modelling task.

Advancing to the EV charging load profile modelling built upon the above extracted EV charging behaviours, we review and outline the multi-parametric modelling methods for EV charging load profiles. We scrutinise and discuss the pipeline of modelling EV charging load profile, including the input parameters, methodologies for building probabilistic models, diversity profiles of EV behaviours, and the output load profiles. Critical inputs such as charging location, time, duration, and charging amount, are considered. The modelling methodologies play a vital role in generating realistic and varied EV charging profiles, and the diverse profiles make the output more realistic, all together contributing to the understanding of future EV charging demand and planning for the evolving needs of the grid.

Last but not least, the final part of the report synthesises the findings from the literature review and proposes a comprehensive framework for EV charging extraction from meter data and EV load profile modelling. Two distinct methodologies are proposed to extract EV charging loads from meter data in Victoria. The first method capitalises on globally available knowledge, utilising publicly accessible meter data and EV charging data to train machine learning models. These models are subsequently applied to the meter data from Victoria to identify EV charging. The second method adopts a more direct approach, focusing specifically on Victoria's meter data. It involves modelling meter data excluding EV charging, thereby enabling the identification of additional, separate EV charging profiles within the meter data. As for modelling EV charging load profiles, we propose to incorporate EV charging behaviours informed by the meter data and refine the Gaussian Mixture Model (GMM) to model realistic EV charging profiles in different scenarios, such as different zip codes, day of week, and season. The proposed framework is expected to provide reliable EV charging load data for other ESP work packages focused on network infrastructure planning.

1 Background

The global landscape of transportation is undergoing a transformative shift towards electric vehicles (EVs), a trend that is rapidly gaining momentum across continents. This shift is propelled by a growing awareness of environmental concerns, advancements in EV technology, and supportive governmental policies [1], [2]. As a result, the demand for EVs is soaring worldwide, leading to an increasing need for robust EV charging infrastructure. In Australia, and particularly in the state of Victoria, this global trend is echoed with a rise in EV adoption [1]. This surge in electric mobility is significantly impacting the nation's energy infrastructure. The escalating demand for EV charging not only poses new challenges in terms of energy supply and grid stability but also opens up opportunities for strengthening the existing energy infrastructure. As more Australians opt for EVs, the ensuing demand for efficient and accessible charging options becomes a pivotal concern, requiring strategic foresight and planning to integrate this new wave of energy consumption seamlessly into the current grid framework.

In this context, the Enhanced System Planning (ESP) project emerges as a strategic initiative, specifically tailored to address the evolving landscape of EV integration within Victoria's energy infrastructure. The ESP project encompasses a broad spectrum of research areas, each focusing on different aspects of energy system adaptation and optimisation in the face of increasing EV penetration. Within this comprehensive framework, Work Package 1.2 (WP 1.2) holds a pivotal role. It is dedicated to the in-depth analysis and modelling of EV charging load profiles, a key component in understanding and managing the implications of EV adoption on the energy grid. By providing detailed insights into EV charging behaviours and demands, WP 1.2 aids in shaping a more accurate and efficient framework for energy planning. Its findings are expected to produce realistic EV charging data and offer valuable guidance for infrastructure development, policy-making, and energy distribution strategies, thereby reinforcing the overall objectives of the ESP project.

A profound emphasis is placed on comprehending the nuances of EV charging behaviours in WP 1.2. Grasping the intricacies of how, when, and where EV charging occurs allows for a more tailored and effective approach to integrating these new demand patterns into the energy grid. However, achieving this level of understanding is complex, given the variability in EV charging behaviours influenced by numerous factors including regional preferences and customer habits across days of week. To address this complexity, WP 1.2 prioritises a thorough literature review of existing studies focusing on the modelling of EV charging profiles. This review is essential to gather and synthesise global insights and methodologies, which can then be adapted and applied to the specific context of Victoria.

A significant gap in the current energy landscape of Victoria is the lack of direct residential EV charging data, an obstacle that WP 1.2 of the ESP project aims to overcome. This gap presents a major challenge in accurately assessing the EV charging demands within the state. To circumvent this, the project adopts an alternative approach – utilising general meter data to extrapolate EV charging information. However, this indirect method introduces additional complexities. Meter data encompasses a wide array of household energy consumption patterns, making the isolation of specific EV charging activities a formidable task. Given these challenges, it becomes imperative for WP 1.2 to conduct an extensive review of relevant literature that explores methodologies for effective extraction of EV charging data from general meter readings. This review is vital in uncovering and adapting advanced techniques and models that have been successfully implemented in other regions or contexts. By scrutinising various approaches – from sophisticated machine learning algorithms to nuanced statistical methods – WP 1.2 aims to develop a framework capable of accurately discerning EV charging patterns from the meter data. This endeavour is not only crucial for filling the data gap in Victoria but also sets the stage for more informed planning and policy development in the context of a rapidly evolving EV landscape.

In the forthcoming sections of this report, we will delve into an extensive literature review, dissecting two pivotal topics central to WP 1.2's research agenda. The first area of focus will be on existing methodologies for EV charging detection and disaggregation. This exploration will encompass a range of studies and techniques that have been employed worldwide to identify and isolate EV charging activities from general meter data. Following this, the second area of our literature review will concentrate on the modelling of EV charging profiles. Here, we will scrutinise approaches used globally to model and simulate EV charging load profiles, considering diverse factors such as charging times, durations, rates, and regional specificities. In addition to these comprehensive literature reviews, we will also introduce our proposed methodologies. These methodologies are designed to address the specific challenges and nuances of extracting and modelling EV charging data in Victoria. This report aims to provide the readers with a clear roadmap of our research direction, methodologies, and anticipated contributions to the broader ESP project.

2 EV Charging Detection and Disaggregation

2.1 Review of datasets

As explained above, because of the lack of direct EV charging data in Victoria, we take an alternative approach to studying meter data to extract EV charging information. We first review the available datasets worldwide containing both meter data and EV charging data.

Table 1. The summary of available datasets.

Dataset	Including EV	Sampling frequency	Duration	Unit	Country
REDD	No	3 Sec	3-19 days	6 houses	USA
REFIT	No	8 Sec	3 years	20 houses	UK
UK-DALE	No	1 Sec – 6 Sec	3 years	5 houses	UK
ECO	Yes	1 Sec	8 Months	6 houses	Switzerland
COOLL	No	100 kHz	6s	42 appliances	France
Pecan Street	Yes	1 min	2 Years	44 houses	USA
PLAID	No	30 kHz	5s	60 houses	USA

According to [3] and [4], several dimensions characterise the reviewed dataset.

- Sampling rate: Different appliances exhibit unique power consumption patterns, necessitating varied sampling rates for effective feature extraction. For instance, a lower sampling rate may suffice for single-state appliances to minimise costs, while multi-state and continuously variable appliances require higher sampling rates to capture transient features accurately.
- Time scale: Data collection must also account for different time scales, ensuring that the temporal aspects of power consumption are adequately represented.
- Data coverage: The granularity of the dataset is pivotal. For example, the REDD dataset primarily focuses on residential energy usage, making it suitable for predicting overall energy consumption and analysing consumption patterns at a household level. In contrast, the COOLL dataset, which concentrates on individual appliances, may not be as effective for analysing patterns in a specific family setting.
- Regional Variations: Recognising that usage habits can vary significantly between regions and countries is essential. Applying the same analytical methods to datasets

from different areas might yield varying results or patterns due to these differences in usage habits.

These considerations are fundamental in developing robust methods for EV charging data extraction and analysis, accommodating the unique challenges presented by diverse customer energy consumption behaviours.

2.2 The pipeline of EV disaggregation and detection and literature review

The task of EV charging detection and disaggregation form a crucial component of the Non-Intrusive Load Monitoring (NILM) process. NILM involves breaking down a customers' total electricity consumption into specific usages by individual appliances, using data obtained from the residential smart meter. This process is conducted without the need for individual appliance monitoring, relying instead on the aggregate meter data. Figure 1 shows the pipeline for this task, encompassing several key stages, starting with the collection of input data from smart meters. This data is then processed through sophisticated models designed to identify and separate the electricity consumption of EV charging. The final stage involves analysing the results to accurately attribute portions of the total energy usage to EV charging load. This comprehensive approach allows for a deeper understanding of EV charging.

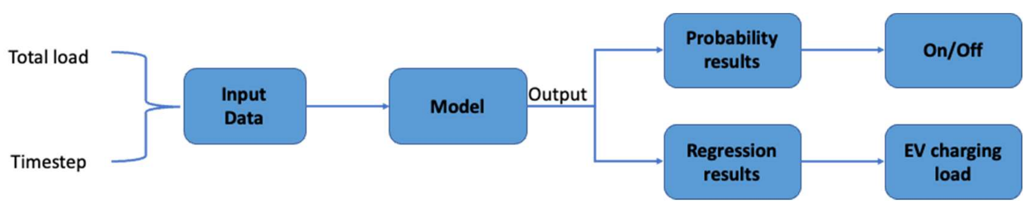

Fig. 1. The pipeline of EV charging detection and disaggregation.

Building on our exploration of the intricate process of EV charging detection and disaggregation, we have conducted a thorough literature review to deepen our understanding and refine our methodologies. This review has culminated in the identification and analysis of a range of key papers in the field, each contributing valuable insights into various aspects of NILM and EV charging data analysis. The results of this literature review are compiled in the following table, which presents a curated list of these studies, offering a clear view of the existing knowledge landscape and guiding our approach in this complex domain.

Table 2 The related works in the literature review on EV charging detection and disaggregation methods.

Ref.	Approach	Sampling rate	Require labelled EV data
[5]	Rule-based approach	N.A.	No
[6]	Rule-based approach	1/60 Hz	No
[7]	Rule-based approach	1/60 Hz	No
[8]	Machine learning approach	1/60 Hz	Yes
[9]	Machine learning approach	10 Minutes	Yes
[10]	Deep learning approach	1/60 Hz	Yes
[11]	Deep learning approach	NA	Yes
[12]	Deep learning approach	NA	No
[13]	Deep learning approach	NA	Yes

2.2.1 Rule-based approach

Rule-based methods in EV charging analysis involve the creation of algorithms that leverage distinct patterns and characteristics of electrical signals to differentiate between various appliances. These methods primarily depend on unique features within the electrical signals, like specific power usage patterns, voltage fluctuations, and current waveforms that are typically associated with certain appliances.

In [5], an unsupervised rule-based approach is introduced. This method utilises only the total load data from smart meters to estimate EV charging rates and durations for residences. The process begins with the identification and removal of air conditioning (AC) loads from the aggregated load profile, given their similarity in magnitude to EV charging loads. Figure 2 illustrates the comparison between AC load and EV load over time. Following this, statistical methods are employed to establish regular (non-EV) daily load profiles, aiding in the identification of residences with EVs. The approach then detects charging periods by comparing load variations between adjacent time points against a predefined threshold. This method not only identifies charging periods but also determines charging rates by adjusting the threshold to minimise the false positive rate (FPR).

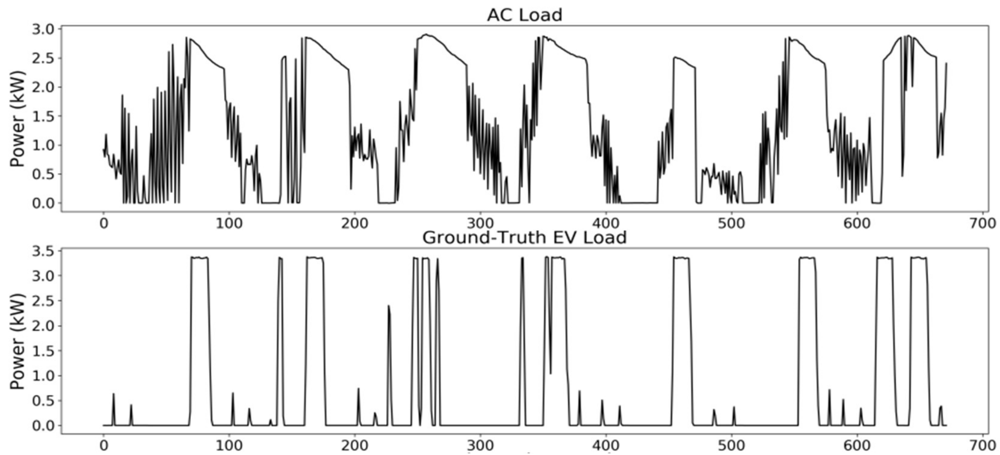

Fig. 2. AC load Versus EV load (x-axis unit: Hour) [5].

A similar idea that removes power curve spikes of AC power signatures can be found in [6]. This approach, differing from [5], initially filters out rough estimates of EV charging by setting a threshold. It then refines these estimates by subtracting the AC charging load, thereby isolating the final EV charging load.

Additionally, a sliding window approach was employed for extracting features from the active power profile [7]. Unlike [5] which identifies EV charging states using adjacent time points, this method employs a sliding window to iteratively calculate the mean of the power consumption curve and its variation. The identification of charging events is then achieved by comparing these mean values against a set threshold, incorporating the context information within a period of aggregated load. This approach offers a nuanced way to discern EV charging amidst other household electricity consumption.

2.2.2 Machine learning approach

In the realm of EV charging disaggregation, the application of machine learning approaches follows a structured pipeline, enhancing the accuracy and efficiency of the process. This pipeline generally encompasses several key stages.

1. Data Pre-processing: This initial step involves cleaning the data, such as removing outliers, to ensure that the subsequent analysis is based on accurate and relevant information.
2. Feature Engineering: Techniques like normalisation, Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) are employed to prepare and optimise the data for machine learning algorithms. This stage is crucial for extracting meaningful patterns from the data.
3. Algorithm Selection and Training: A variety of machine learning algorithms, including Support Vector Machine, Decision Tree, Random Forest, K-Nearest Neighbours, and Naïve Bayes, are considered. The chosen algorithm is then trained on historical data to learn and fit decision models.
4. Model Evaluation and Tuning: The performance of the model is rigorously evaluated and fine-tuned to achieve optimal disaggregation results.
5. Model Deployment: Once fine-tuned, the model is deployed for future EV charging disaggregation tasks, applying its learned patterns to new data sets.

Unlike rule-based methods, which depend on manually setting rules and thresholds, machine learning approaches adaptively learn from historical data. They minimise the discrepancy between predicted values and actual ground-truth data through iterative learning, enabling direct disaggregation of EV charging loads from aggregated data.

For example, in one study [8], a mean value was derived from a sliding window covering five samples to assess the occurrence of EV charging events. The k-nearest neighbours (KNN) algorithm was then applied for classification, achieving F-Scores between 83% and 86% in various test scenarios for EV charging events at a 1/60 Hz sampling rate. Another work [9] introduced a non-intrusive load monitoring (NILM) method tailored for low sampling rate scenarios (every 10 minutes). This method incorporated a supervised machine learning pipeline, where PCA was employed for dimensionality reduction to eliminate redundant information. Subsequently, the Random Forest (RF) algorithm was used to identify the presence of EV charging, leveraging the principal component parameters generated by PCA.

2.2.3 Deep learning approach

Deep learning-based NILM (Non-Intrusive Load Monitoring) methods utilize neural networks to autonomously learn and discern patterns in electrical signals. These approaches typically involve training a neural network with electrical consumption data, where the input is the aggregate power signal of the entire building, and the output is the disaggregated power usage of individual appliances. The network is trained to map the input signal to specific appliances, recognizing distinct patterns and features within the data. In these methods, load disaggregation tasks are often approached as time series regression problems.

A notable development in EV charging identification is presented in [10], which integrates a denoise autoencoder (DAE) with convolutional neural networks (CNN) for EV charging disaggregation. This study addresses the challenge of differentiating EV charging waveforms from similar patterns produced by air conditioners (AC). The CNN acts as a feature extractor, isolating potential EV-related features from the input signals. The DAE is then used to filter out 'noise', which in this context refers to other appliance loads, thereby reconstructing the EV load from the total consumption.

While CNN and DAE are effective in feature extraction, they have limitations in handling time-series data. To address this, the work in [11], introduced a deep generative model (DGM), employing a convolutional neural network within a Markov process to capture the probabilistic distribution of time-series data. This approach differs from traditional hidden Markov models, as the DGM contains one more layer named representation layer, which has the same node with HMM but without directed paths from EV charging states to total load consumptions. DGM utilises a convolutional neural network and the input variable of total load to estimate the likelihood distributions of representation variables. Following the acquisition of the likelihood distributions for representation variables, it is used to estimate the posterior distribution, thereby obtaining the results for the EV charging state.

In the work [12], challenges related to limited labelled data and varying load profile distributions are tackled through a semi-supervised deep learning approach. The model consists of two sets of convolutional neural networks with shared parameters. During the training phase, labelled data from the source domain and unlabelled data from the target domain are simultaneously input into the two sets of neural networks and output two sets of features that are relevant to their respective domains. Before the final output layer produces results, the difference in features between the source and target domains is computed using Maximum Mean Discrepancy (MMD). This allows the model to learn invariant representations across different domains and minimise the distance between the distributions of the source and target domains in a higher-dimensional space.

An innovative approach in [13] combines deep learning with intuitive filtering to identify EV charging states. This method employs convolutional layers and stacked bidirectional long short-term memory networks to process time-series information and generate initial outputs. These outputs from the DNN model will be smoothed using a filtering process. It uses a stack to record charging events and sets "ON" states based on a threshold. The window size and threshold are tailored for each customer, informed by statistical features or domain knowledge. The filter parameters, including window size and threshold, are set by a transfer learning framework, leveraging labelled training data. This ensures adaptability and customization for different customers.

3 EV Charging Load Profile Modelling

While power systems are inherently designed to accommodate uncertain load conditions, the escalating load due to EV charging presents significant challenges to grid reliability and stability. The variability in EV charging is characterised by four key aspects: the charging location, the timing of charge, the duration of charging sessions, and the amount of electricity consumed during charging. These factors introduce uncertainties that can be effectively modelled as input parameters in EV charging profile modelling. Such parameters are typically derived from raw data sources, such as travel and charging records obtained from travel surveys or extensive databases. Probabilistic methods are employed to capture the diversity (i.e., distribution) of these input parameters. These methods, combined with sampling-based simulations, are used to create diverse profiles of EV charging. The workflow of this modelling process is illustrated in Fig. 3.

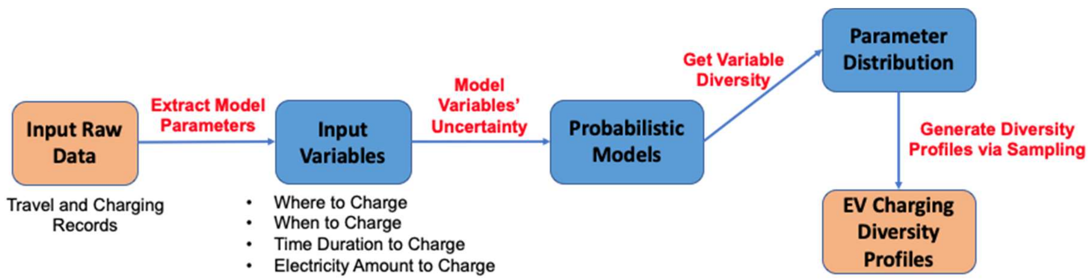

Fig. 3. The general pipeline of EV charging profile modelling.

To offer a comprehensive understanding of this modelling pipeline, we have structured this section in a sequential manner. Section 3.1 delves into the definitions of the input parameters, laying the groundwork for the subsequent analysis. This is followed by Section 3.2, where we explore various methodologies employed to construct probabilistic models, aimed at determining the distributions of these input parameters. Finally, Section 3.3 discusses the generation of EV charging profiles using the estimated probabilistic distributions, detailing how these models translate into practical charging scenarios.

3.1 Input parameters of charging profile modelling

The key input parameters in EV charging profile modelling, also referred to as random variables, comprise four main aspects: charging locations (such as residential or workplace charging), start time of charging, duration of charging, and the amount of electricity consumed during charging. The first two parameters are intricately linked to the travel behaviours of EV drivers, encompassing aspects like commuting patterns, preferred charging locations, and arrival times of EVs. Conversely, the latter two parameters focus on the charging habits of drivers, including factors such as parking duration, the state of charge (SoC) of EVs upon parking, charger speeds, queuing times for charging services, and the individual charging decisions made by drivers, which are often unpredictable.

Various studies have explored one or more of these input parameters. For instance, research [14] based its analysis on the premise that charging typically occurs once daily, post-travel, with the assumption that each EV achieves a full charge during this session. This study concentrated on travel behaviours, segmented into four categories: urban weekdays, urban weekends, rural weekdays, and rural weekends. Data from the 2009 National Household Travel Survey, involving 150,147 households and 294,408 light-duty vehicles, was used, assuming these vehicles were replaced by EVs.

Similarly, the research [15] employed empirical probability density distributions to model the uncertainty surrounding the start time of EV charging. Other studies [16], [17], [18] have used extensive survey data to derive probability density functions (PDFs) of vehicle usage, assuming EV charging commences upon the vehicle's arrival at home. Notably, these surveys primarily involved conventional vehicle users, not EV drivers, leading to an assumption that EV usage mirrors that of traditional vehicles. However, this assumption may not hold true in the rapidly evolving global EV landscape. These approaches, which primarily consider when and where to charge, often overestimate peak load due to their neglect of diverse charging behaviours and the lack of detailed information on EV drivers' travel patterns, a limitation also present in the Victorian customer meter dataset.

In addition to modelling the input travelling parameters, extensive research has also focused on the uncertainty of input charging parameters, e.g., charging duration and charging electricity consumption. For example, the work [19] used a large-scale database of field-recorded driving cycles stamped with parking times and locations to predict the realistic driving habits of drivers in an urban setting. The study [20] extended the previous work by introducing travel distance from home. One primary challenge during modelling the input charging parameters in our project lies in the lack of extensive EV charging data to accurately estimate charging behaviours, as the EV charging is not recorded separately. Additionally, the accuracy of EV charging profiles can be compromised by the limited scope of input charging parameters, as seen in studies like [20], which only considers three parameters. Expanding the range of parameters could potentially enhance the precision of these profiles, but this approach necessitates access to more comprehensive data to establish these additional parameters with confidence.

While previous studies tend to separately consider input travelling and charging parameters, several works have systematically integrated both travel and charging parameters in their modelling. Research [21] considered both residential and workplace charging and the commuting between these locations, including uncertainties in charging duration and power. The study [22] focused on understanding the unpredictability of EV arrivals at public charging stations, monitored through queuing times and charging levels.

Table 3 provides a summary of these input parameters, detailing their definitions and applications in both travel (where and when to charge) and charging aspects (such as charging duration).

Table 3. The summary of input parameters included in the literature.

Ref.	Traveling Parameters	Charging Parameters
[14]	The parking time of EVs, i.e., exact hour on weekday or weekend. The parking area of EVs, i.e., urban or rural areas	Not specified. Only assuming fixed charging behaviours
[15]	EV start charging time	Not specified. Only assuming fixed charging behaviours
[16], [17], [18]	EV start charging time	Not specified. Only assuming fixed charging behaviours
[19]	EV parking locations, i.e., residences and workplaces	EV parking durations EV charging speed, i.e., level 1 and level 2 chargers
[20]	EV parking locations, i.e., residences and workplaces Travel distance from home	EV parking durations
[21]	EV parking locations, i.e., residences and workplaces	EV charging durations
[23], [22]	EV start charging time	EV charging durations EV charging speed

3.2 Probabilistic modelling of input parameters

Incorporating the defined input travel and charging parameters (as discussed in the previous section), probabilistic models are frequently employed to capture the inherent uncertainties of these parameters, treating them as random variables.

For instance, the work [14] directly estimated the probability of input charging parameters, such as the likelihood of EVs parking in urban or rural areas on weekdays and weekends. This was done by using the frequency of these parking scenarios in the dataset as a proxy for the probability of EV parking occurrences, with the results illustrated in Fig. 4.

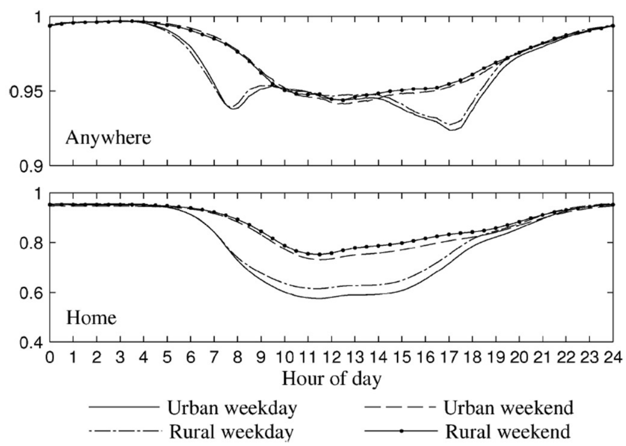

Fig. 4. Probability of an EV to be parked anywhere or at home in four charging locations on a daily basis [14].

Additionally, a line of work, such as [19] and [20] utilized fuzzy-logic-based algorithms to deduce the probability of EV charging. This method factors in the battery's state of charge (SoC) and the driver's parking duration, emulating an EV driver's charging decision-making process. The fuzzy rules applied in this charging inference system are detailed in Table 4. The probabilities derived from this fuzzy-logic inference, delineating differences in charging patterns between residential and workplace environments, are depicted in Table 4. The probabilities derived from this fuzzy-logic inference, delineating differences in charging patterns between residential and workplace environments, are depicted in Fig. 5.

Table 4 The fuzzy rules of the charging inference system [19].

SoC Level	Parking Time Length	Probability of Charging
Low	Short	Medium Low
Low	Average	Medium High
Low	Long	High
Medium	Short	Medium Low
Medium	Average	Medium
Medium	Long	Medium High
High	Short	Low
High	Average	Medium Low
High	Long	Medium

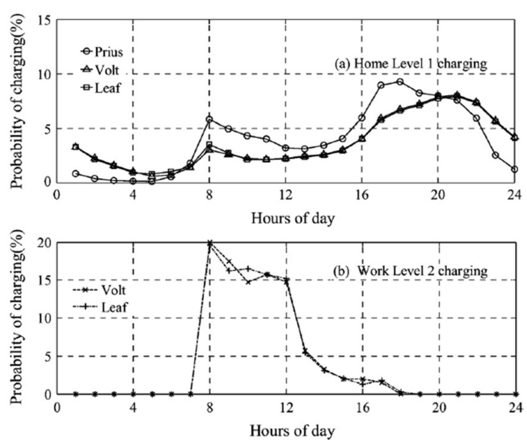

Fig. 5. Probability of charging at home and workplace using fuzzy-logic inference [19].

Beyond direct probability estimation and fuzzy-logic inferences, the Gaussian Mixture Model (GMM) has gained traction for modelling parameter uncertainties. The GMM assumes each input parameter follows a Gaussian distribution, with each distribution estimated from the dataset. For example, [24] leveraged the GMM model and set three parameters (including charging power, battery capacity, and electricity consumption) in the GMM model, aiming to calculate the charging probability of an EV for any minute of a day for distinct charging power and any interval of battery capacity and electricity consumption. Specifically, the normal distributions of the battery capacity and electricity consumption are determined from the data of the German Aerospace Centre. Moreover, [25] also modelled the uncertainties of four input parameters, including the number of charging events per day, start charging time, initial/final SoC, and the percentage of EVs charging on the same day. The fitted GMM models based on historical EV charging data in the UK are shown in Fig. 6.

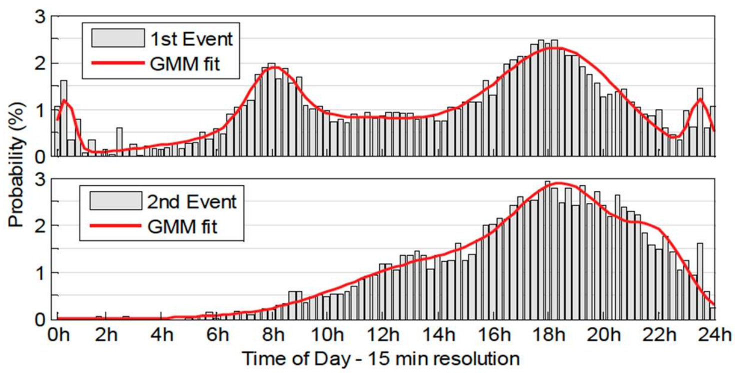

Fig. 6. Histograms of the start charging time per event – Weekday. 1st Event and 2nd Event represent the first and second EV charging within one day, respectively [25].

In addition to the GMM model, the work [21] conceptualised EV charging as a semi-Markov decision process, whose workflow is shown in Fig. 7. They calculated charging probabilities, as well as the transition probabilities (e.g., the probability of travelling from home to workplace for EV charging) in residential and workplace areas based on a German traffic study, namely Mobility in Germany 2008. Such a formulated semi-Markov decision process, with estimated charging and transition probabilities, is capable of generating synthetic EV charging data for charging profile analysis.

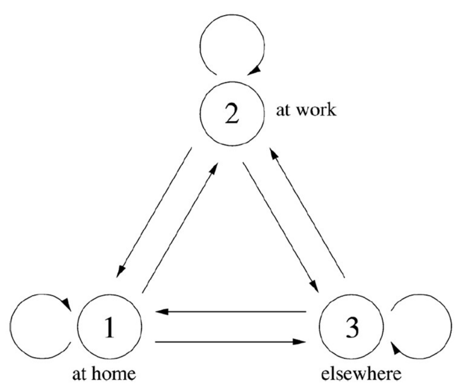

Fig. 7. State transition of semi-Markov Process [21].

Furthermore, [22] and [23] characterised the input travelling behaviours using the Poisson process. A random variable, referred to as the arrival rate of EVs, describes the uncertain travelling behaviours. The value of the arrival rate is often obtained based on traditional vehicle traffic monitoring techniques [26], assuming a certain penetration level of EVs. Once the Poisson process is formulated, it can generate synthetic EV travelling data, preparing for EV charging profile generation. For the modelling of input charging parameters, they introduced the queuing theory, modelling the charging station as a service centre with multiple servers (i.e., chargers), and EVs are modelled as customers in the service centre. These two studies are better suited to public charging or workplace charging, since the availability of chargers is a limiting factor.

The above methods modelling input parameters tend to be computationally expensive, since vehicle data recorded in travel surveys are often high-dimensional, where the timings and distances of a potentially large number of journeys are recorded. Instead of directly deriving certain distributions of both travelling behaviours and charging behaviours, several studies have adopted clustering algorithms to group raw data, thereby simplifying the dimension to a single parameter. For example, in [27], the feature vector included vehicle-day (e.g., Monday, Tuesday, and etc.) and the time durations (including the beginning and end travel time) of vehicle trips. They divided EV drivers into various clusters based on average EV velocity profile (inferred using the distance and length of the journeys completed) on a daily basis, as shown in Fig. 8. The probability distributions of each cluster occurring on each weekday are also shown in Fig. 9.

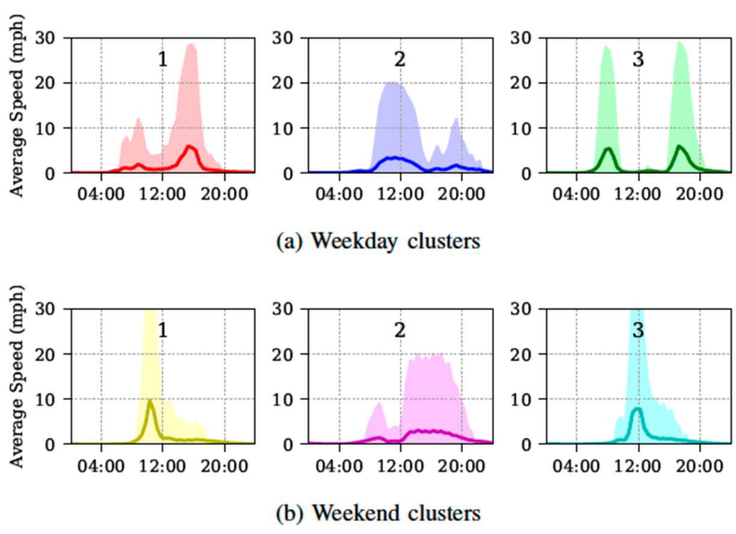

Fig. 8. The average speed profiles of EVs in each cluster. The lines show the mean values, and the shaded areas cover the 90% confidence interval [27].

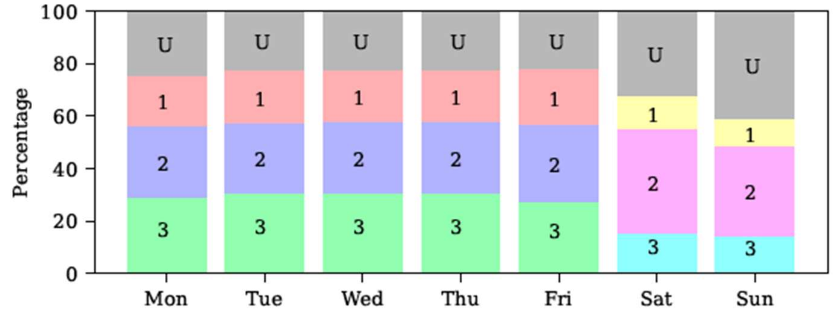

Fig. 9. The percentage of each cluster occurring on each weekday [27].

Additionally, the work [28] applied a hand-crafted hierarchical clustering to identify the distinct charging patterns in residential and workplace charging, as shown in Fig. 10.

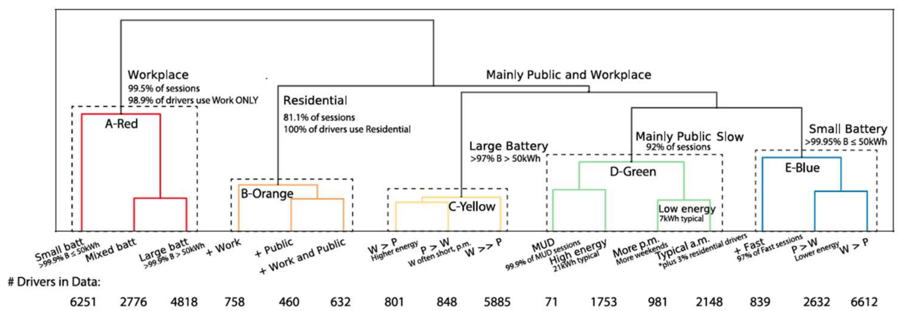

Fig. 10. The result of the hierarchical clustering with 16 clusters [28].

Table 5 summarises the various modelling approaches for input travel and charging parameters.

Table 5. The summary of modelling approaches of input travelling and charging parameters.

Ref	Modelling Approach
[14]	Estimated probabilities based on event frequency in large databases
[19], [20]	Fuzzy-logic algorithm to infer charging probabilities under various scenarios
[24], [25]	GMM model. Each input parameter follows a certain Gaussian distribution to be fitted through historical data
[21]	Semi-Markov decision process. Consider both home and workplace charging
[22], [23]	Poisson process to model input travelling parameters, i.e., EV arrivals. Queuing theory to model input charging parameters, e.g., waiting and charging time
[27], [28]	Use clustering algorithms to first categorise the input travelling parameters into clusters. Then GMM-based method to model input charging parameters.

3.3 EV charging load profile generation

Having established the probabilistic distributions of input parameters in Section 3.2, the generation of EV charging profiles becomes a more straightforward process, primarily facilitated through sampling techniques. The Monte-Carlo simulation is a widely adopted approach in this domain. In essence, each EV's charging profile is artificially generated based on the distributions of various input parameters, such as arrival time, charging duration, and charging speed. This process is repeated to create numerous profiles, which, when aggregated, reflect the overall EV charging profile for a specific scenario, like those in the Victorian customer meter dataset.

To illustrate this, we reference the work shown in [28], where EV drivers are categorised into 16 distinct clusters based on unique driving behaviours. This categorization is depicted in Fig. 12. The study aggregates the EV charging load profiles from five different types of charging stations: residential level 2, multi-unit dwelling level 2, workplace level 2, public level 2, and public fast charging. The aggregation of these diverse charging profiles results in a comprehensive representation of the overall EV charging landscape. This method not only captures the variability in charging behaviours but also provides insights into the aggregate impact of EV charging on the energy grid under various scenarios.

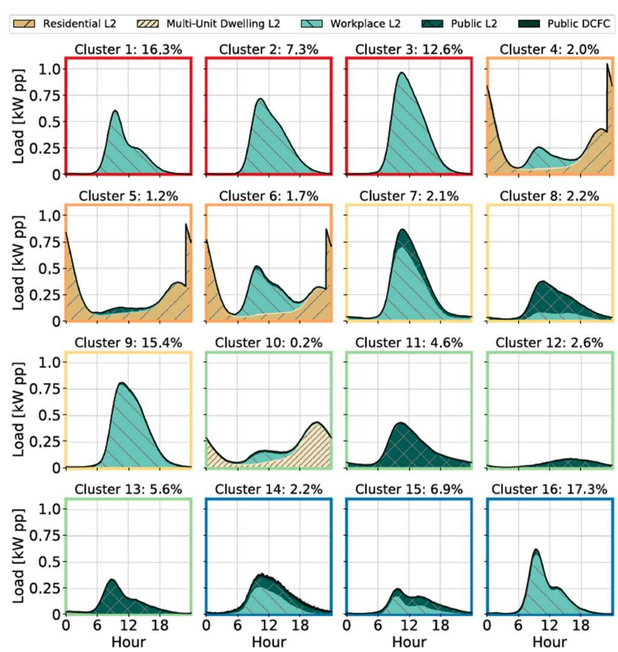

Fig. 12. The typical weekday load profile for each driver group [28].

4 Final insights and overview of proposed modelling framework

4.1 Proposed framework of EV charging detection and disaggregation

Given the constraints of the meter data, where EV charging data and charging rates are not directly available, conventional supervised learning approaches in literature are insufficient for our purposes. To bridge this gap, we have identified two alternative approaches tailored to the specifics of our project.

4.1.1 Domain adaptation supervised learning approach

The first approach addresses the absence of historical EV charging load data in residential records, which limits the applicability of common deep learning methods. However, we can leverage open-source datasets, such as the Pecan Street dataset, that include residential EV charging load data. A deep learning model like Seq2Seq can be pre-trained using this open-source data. This pre-trained model can then undergo domain adaptation with the Victorian customer meter data for effective transfer learning. The steps for this approach are as follows, also illustrated in Fig. 13.

1. Select data from the open-source dataset that closely resembles Victorian customer data in terms of total consumption and sampling rate.
2. Pre-train an EV disaggregation deep learning model (e.g., Seq2Seq, BERT) using the selected data.
3. Apply domain adaptation techniques (e.g., Maximum Mean Discrepancy) to fine-tune the model.
4. Execute EV charging disaggregation on Victorian customer meter data.

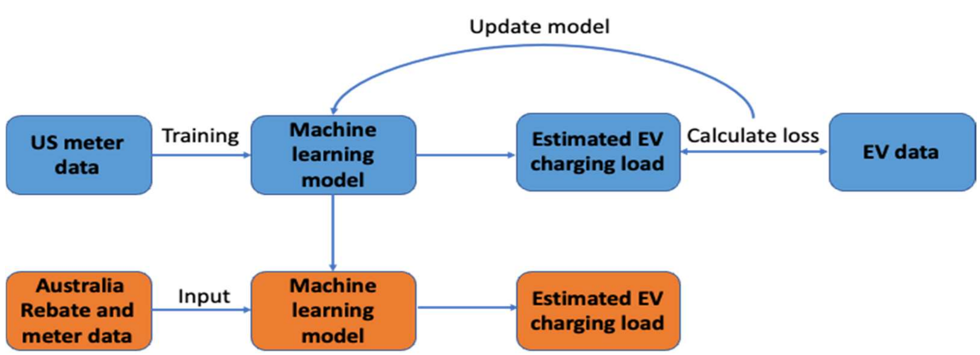

Fig. 13. The pipeline of Domain adaptation Supervised learning approach.

4.1.2 Semi-supervised learning approach

The second approach exploits the availability of historical meter data from customers both before and after the receipt of EV rebate in the Victorian customer meter dataset. By using the data from periods prior to EV charging installation, we can train a model to forecast total load consumption, assuming no EV charging presence. This model can then be used to estimate EV charging data by comparing it against meter records after EV charging installation. The steps for this method are summarised as follows and in Fig. 14.

1. Identify residences that were not EV users during a certain period.
2. Train a forecasting model to predict their future total load usage (excluding EV charging).
3. Select time periods when the residences identified in step 1 become EV users.
4. Utilize the forecasting model to predict total consumption for these residences in a hypothetical scenario without EV charging.
5. Calculate the difference between the model's estimated total load and actual meter records to get an initial estimate of EV charging.
6. Conduct statistical tests on the estimated EV charging from step 5 to filter out outliers and refine the estimated EV charging data.

These innovative pipelines enable us to overcome the challenges posed by the lack of direct EV charging data in the Victorian customer meter dataset, offering a feasible path to accurate EV load disaggregation and analysis.

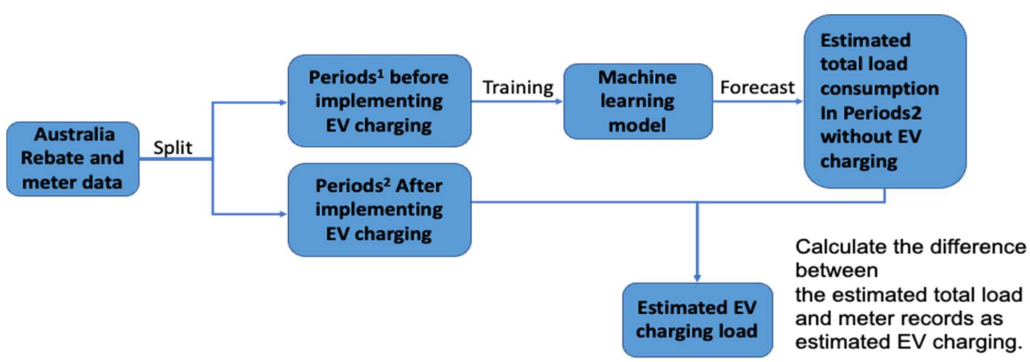

Fig. 14. The pipeline of the semi-supervised learning approach.

4.2 Proposed framework of EV load profile modelling

Leveraging the disaggregated historical EV charging profiles from the Victorian customer meter dataset, we gain valuable insights into various input parameters, as defined in Section 3.1. These include EV charging durations and consumption levels. Utilising these available parameters, we can calculate the charging profile for an individual EV. However, with the increasing adoption of EVs in road transport, it's imperative to capture the diverse charging behaviours across the EV population. To achieve this, we apply probabilistic models, like the Gaussian Mixture Model (GMM), based on the methodologies discussed in Section 3.2. We assume that all input parameters conform to specific Gaussian distributions, which are determined using the disaggregated EV charging data. This approach allows us to encapsulate the diversity of parameters across different scenarios, such as zip codes, weather conditions, days of the week, and seasonal variations.

With the GMM model tailored to these diverse scenarios, the Monte-Carlo sampling technique, as detailed in Section 3.3, enables the generation of individual EV charging profiles. These profiles are then aggregated to form a comprehensive view of the overall diversity in EV charging behaviours. The steps of our proposed EV charging profile modelling process, illustrated in Fig. 15, are as follows.

1. Extract relevant charging and travelling variables from raw input data.
2. Fit Gaussian distributions for each parameter using historical data, considering specific conditions like zip code and weather.
3. Develop the GMM model by integrating the distributions of each parameter.
4. Employ Monte-Carlo simulation to create individual EV charging profiles.
5. Aggregate these individual profiles to construct the overarching EV charging profile.

This pipeline not only facilitates an accurate representation of current EV charging trends but also provides a scalable framework for predicting future EV charging behaviours under various scenarios.

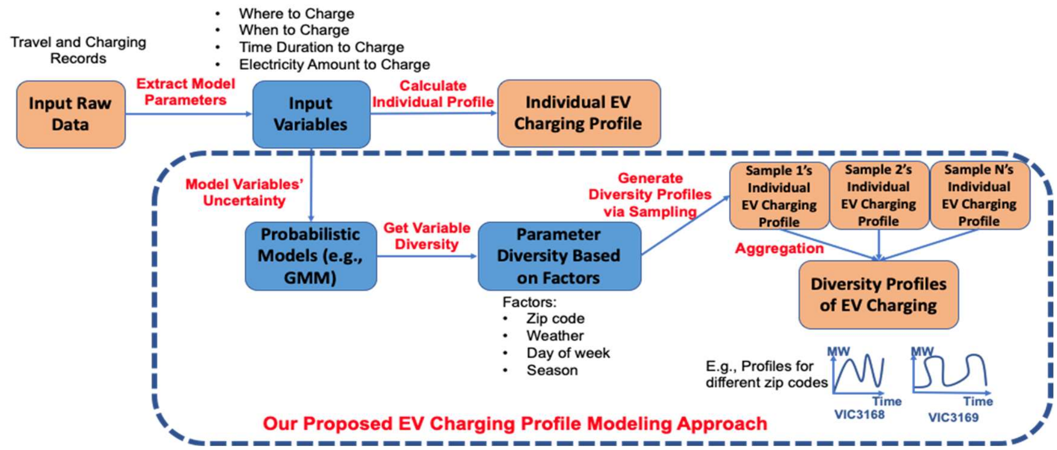

Fig. 15. The pipeline of proposed EV charging profile modelling.

References

[1] N. Thompson, “State of Electric Vehicles Report 2023,” Electric Vehicle Council - Increasing the uptake of EVs in Australia, Jul. 31, 2023. https://electricvehiclecouncil.com.au/reports/soevs-report-2023/ (accessed Nov. 29, 2023).

[2] N. V. Emodi, S. Dwyer, K. Nagrath, and J. Alabi, “Electromobility in Australia: Tariff design structure and consumer preferences for mobile distributed energy storage,” Sustain. Sci. Pract. Policy, vol. 14, no. 11, p. 6631, May 2022.

[3] R. Gopinath, M. Kumar, C. Prakash Chandra Joshua, and K. Srinivas, “Energy management using non-intrusive load monitoring techniques – State-of-the-art and future research directions,” Sustain. Cities Soc., vol. 62, no. 102411, p. 102411, Nov. 2020.

[4] M. Pullinger et al., “The IDEAL household energy dataset, electricity, gas, contextual sensor data and survey data for 255 UK homes,” Sci Data, vol. 8, no. 1, p. 146, May 2021.

[5] K. Pu and Y. Zhao, “Behind-the-meter disaggregation of residential electric vehicle charging load,” in 2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), IEEE, Oct. 2022. doi: 10.1109/smartgridcomm52983.2022.9961024.

[6] Z. Zhang et al., “Training-free non-intrusive load monitoring of electric vehicle charging with low sampling rate,” in IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society, IEEE, Oct. 2014. doi: 10.1109/iecon.2014.7049328.

[7] A. U. Rehman, T. T. Lie, B. Valles, and S. R. Tito, “Low complexity event detection algorithm for non-intrusive load monitoring systems,” in 2018 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), IEEE, May 2018. doi: 10.1109/isgt-asia.2018.8467919.

[8] A. U. Rehman, T. Tjing Lie, B. Valles, and S. R. Tito, “Low complexity non-intrusive load disaggregation of air conditioning unit and electric vehicle charging,” in 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), IEEE, May 2019. doi: 10.1109/isgt-asia.2019.8881113.

[9] A. F. Moreno Jaramillo, D. M. Laverty, J. M. del Rincon, J. Hastings, and D. J. Morrow, “Supervised non-intrusive load monitoring algorithm for electric vehicle identification,” in 2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), IEEE, May 2020. doi: 10.1109/i2mtc43012.2020.9128529.

[10] S. Wang, L. Du, J. Ye, and D. Zhao, “Robust identification of EV charging profiles,” in 2018 IEEE Transportation Electrification Conference and Expo (ITEC), IEEE, Jun. 2018. doi: 10.1109/itec.2018.8450086.

[11] S. Wang, L. Du, J. Ye, and D. Zhao, “A deep generative model for non-intrusive identification of EV charging profiles,” IEEE Trans. Smart Grid, vol. 11, no. 6, pp. 4916–4927, Nov. 2020.

[12] S. Wang, L. Du, and Q. Zhou, “A semi-supervised deep transfer learning architecture for energy disaggregation,” in 2019 IEEE Power & Energy Society General Meeting (PESGM), IEEE, Aug. 2019. doi: 10.1109/pesgm40551.2019.8973556.

[13] X. Wang, G. Tang, Y. Wang, S. Keshav, and Y. Zhang, “EVSense,” in Proceedings of the Thirteenth ACM International Conference on Future Energy Systems, New York, NY, USA: ACM, Jun. 2022. doi: 10.1145/3538637.3538860.

[14] D. Wu, D. C. Aliprantis, and K. Gkritza, “Electric energy and power consumption by light-duty plug-in electric vehicles,” IEEE Trans. Power Syst., vol. 26, no. 2, pp. 738–746, May 2011.

[15] R.-C. Leou, C.-L. Su, and C.-N. Lu, “Stochastic analyses of electric vehicle charging impacts on distribution network,” IEEE Trans. Power Syst., vol. 29, no. 3, pp. 1055–1063, May 2014.

[16] S. Huang and D. Infield, “The impact of domestic Plug-in Hybrid Electric Vehicles on power distribution system loads,” in 2010 International Conference on Power System Technology, IEEE, Oct. 2010. doi: 10.1109/powercon.2010.5666513.

[17] Z. Darabi and M. Ferdowsi, “Aggregated impact of plug-in hybrid electric vehicles on electricity demand profile,” IEEE Trans. Sustain. Energy, vol. 2, no. 4, pp. 501–508, Oct. 2011.

[18] G. Hilton, M. Kiaee, T. Bryden, B. Dimitrov, A. Cruden, and A. Mortimer, “A stochastic method for prediction of the power demand at high rate EV chargers,” IEEE Trans. Transp. Electrif., pp. 1–1, 2018.

[19] S. Shahidinejad, S. Filizadeh, and E. Bibeau, “Profile of charging load on the grid due to plug-in vehicles,” IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 135–141, Mar. 2012.

[20] N. Ghiasnezhad Omran and S. Filizadeh, “Location-based forecasting of vehicular charging load on the distribution system,” IEEE Trans. Smart Grid, vol. 5, no. 2, pp. 632–641, Mar. 2014.

[21] J. Rolink and C. Rehtanz, “Large-scale modeling of grid-connected electric vehicles,” IEEE Trans. Power Delivery, vol. 28, no. 2, pp. 894–902, Apr. 2013.

[22] H. Liang, I. Sharma, W. Zhuang, and K. Bhattacharya, “Plug-in electric vehicle charging demand estimation based on queueing network analysis,” in 2014 IEEE PES General Meeting | Conference & Exposition, IEEE, Jul. 2014. doi: 10.1109/pesgm.2014.6939530.

[23] M. Alizadeh, A. Scaglione, J. Davies, and K. S. Kurani, “A scalable stochastic model for the electricity demand of electric and plug-in hybrid vehicles,” IEEE Trans. Smart Grid, vol. 5, no. 2, pp. 848–860, Mar. 2014.

[24] M. Godde, T. Findeisen, T. Sowa, and P. H. Nguyen, “Modelling the charging probability of electric vehicles as a gaussian mixture model for a convolution based power flow analysis,” in 2015 IEEE Eindhoven PowerTech, IEEE, Jun. 2015. doi: 10.1109/ptc.2015.7232376.

[25] J. Quiros-Tortos, A. N.- Espinosa, L. F. Ochoa, and T. Butler, “Statistical representation of EV charging: Real data analysis and applications,” in 2018 Power Systems Computation Conference (PSCC), IEEE, Jun. 2018. doi: 10.23919/pscc.2018.8442988.

[26] “Website.” https://www.researchgate.net/publication/254424803_Road_Traffic_Data_Collection_Methods_and_Applications

[27] C. Crozier, T. Morstyn, and M. McCulloch, “A stochastic model for uncontrolled charging of electric vehicles using cluster analysis,” 2019, doi: 10.48550/ARXIV.1907.09458.

[28] S. Powell, G. V. Cezar, and R. Rajagopal, “Scalable probabilistic estimates of electric vehicle charging given observed driver behavior,” Appl. Energy, vol. 309, no. 118382, p. 118382, Mar. 2022.