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A Limited-data-based Power and Energy Demand Profile Modelling of an Electric Vehicle Fleet Charging Station

Mobin Naderi, Erica Ballantyne, Maria Nunez Munoz, George Hind, David Stone, Dan Gladwin and Martin Foster.

University of Sheffield, Sheffield, UK
d.a.stone@sheffield.ac.uk

Abstract. The concept of off-grid electrification for electric vehicle (EV) fleets requires the supported of renewable energies and subsequently energy storage systems (ESSs) through a microgrid structure which is associated with modelling, analysis and design challenges. In this paper, a modelling method for off-grid EV fleet charging stations is proposed, which can generate different power and energy demand profiles required for long-term studies of corresponding microgrids, such as planning and sizing renewable energy sources (RESs) and energy storage systems. The modelling method is based on limited data, which is accessible from EV specification sheets. Some inputs to the model such as intervals of EV arrival time at the charging station, and the number of chargers required for each EV during a defined period, are assumed according to the fleet owner/manager requirements or current charging patterns if available. To model the random behavior of EVs such as real arrival times to the charging station, and the driver's preferred minimum EV battery state of charge (SOC) to decide charging again, probability distribution functions are used. The model is developed in MATLAB/Editor. Although the proposed modelling method is validated for a case study, where results show the potential of the method to appear important and useful power/energy profiles and corresponding analyses, it can be easily generalized to model any EV fleet because the input data to model is limited to specifications of EVs in the fleet and EV charge patterns, which both sources of inputs can be easily available.

Keywords: Electric Vehicle Fleet, Long-term Modelling, Microgrid Planning, Charger Availability.

1 Introduction

Electric vehicle (EV) fleets play an important role in national and international decarbonization plans in the transportation sector. In the UK, for fleet electrification, local authorities need to identify which vehicles are suitable for replacement with EVs, formulate a procurement strategy according to lifetime costs, install chargers, and implement supporting measures [1]. In addition, several research projects have been defined to investigate the technical and practical challenges of the installation of EV fleet charging stations to have a sustainable and reliable transition from the current situation to a 100% EV-based fleet. The Future Electric Vehicle Energy networks supporting Renewables (FEVER) project [2] is searching for possible solutions to facilitate off-grid EV

charging microgrid installation and operation, where renewable energy sources (RESs) and energy storage systems (ESSs) are used to provide green and reliable energy for EV charge points, including private EV fleet charging stations. To this end, it is necessary to estimate the demand for such off-grid microgrids, to find optimized sizes for energy resources and storage.
For fleet-specific charging infrastructure, NREL's EVI-X modelling suite offers modelling methods for EV charging infrastructure including both small and large EV fleets. These tools consider factors such as optimal charger placement, energy consumption, and integration with grid management systems, specifically for heavy-duty EV fleets [3]. Such fleet-specific modelling methods are vital for understanding the unique needs of large-scale EV deployments, helping optimize both economic and operational efficiency for commercial electric vehicle fleets. Some modelling tools of NREL's EVI-X modelling suite written in Python are available for public use.
Recent literature on EV fleet charging station modelling (see Table 1) has been done for several analysis, management, and optimization objectives, e.g. optimizing charging infrastructure to meet the growing demand for electric vehicles. One of the oldest papers details the development of a regional, discrete-time, agent-based model to investigate the management of a fleet of shared autonomous electric vehicles for city-range applications [4]. In [5], a stochastic modelling and analysis approach for public bus and taxi EV fleet charging stations is presented, focusing on operation and charging/swapping management methods, to maximize the charging station incomes. In [6], a four-step modelling method is proposed to model large-scale EV charging stations to find the long-term effect of charging station developments on the EV fleet development in EU urban areas. In [7], charging power and the corresponding energy requirements of EV fleets in commercial charging sites have been modelled to study future developments of EV fleets and predict required power and energy levels. Although EV charging stations are modelled in several works, as a power/energy load demand in autonomous microgrids, the charging station is generally modelled for EV visitors in a car park according to stochastics of visitors, e.g. number of EVs and visit duration [8]-[12]. A few works of literature exist investigating EV fleet charging station modelling for off-grid microgrid applications. In [13], a large-scale EV fleet including motorcycles, buses and cars has been modelled to minimize charging costs, maximize the renewable energy usage, and investigate the impact of the used EV charging strategy on the long-term planning of an off-grid microgrid. In [14], another large-scale EV fleet is modelled in detail using probabilistic models of EV specifications to study the performance of a self-optimizing fleet charging scheduling to cope with the effects of EV fleet charging on the efficiency of distribution grids. Due to the existence of several random behaviours in EV operation, probability functions are one of the basic tools in EV fleet modelling. In [15], there is another application of probability functions to evaluate the role of EV fleet batteries for smart energy storage in off-grid microgrids.

Table 1. Summary of key studies on EV fleet charging modelling.

Reference	Study focus	Modelling methods	Key findings	Relevance to EV fleet charging modelling
[4]	Operations of shared autonomous electric vehicle (SAEV) fleets.	Simulation-based analysis using a discrete-time agent-based model.	The fleet size depends on charging infrastructure availability and vehicle range.	Provides insights into the impact of fleet size, charging times, and grid demand in EV fleet modelling.
[5]	Integration of charging stations and battery swapping stations for taxi and bus EV fleets.	Markov Stochastic modelling and validation using Monte Carlo simulations.	Operation and charging/swapping management methods maximize charging station income.	Provides insights into stochastic models for charging station design and operation.
[6]	Explore barriers to EV fleet deployment in EU urban areas.	Four-step analytical assessment model using discrete-time Markov chain.	he critical issue for developing charging infrastructure to support EV fleet growth is implementing civil works at the urban level.	Provides detailed steps to estimate the optimal size of minimum-cost charging infrastructure for passenger EVs in urban areas.
[7]	Influence of charging power on onboard EV chargers in commercial charging stations.	Model to forecast a number of PHEVs and BEVs and simulations of charging loads to create power profiles for each EV.	The study reveals that 77% of charging sessions have less than 5 minutes of idle time, a finding with practical implications for optimising charging station operations.	Provides realistic non-linear charging profiles, accounting for the reduced charging current as batteries become fully charged.
[8]	Smart charging of EVs with PV and vehicle-to-grid (V2G) technology.	Simulated real-time (RT) control algorithms and linear programming (LP).	The LP algorithm improves self-consumption outcomes compared to the RT algorithm and V2G technology.	Demonstrates how smart charging strategies can optimize grid interactions and support efficient fleet-level charging.
[9]	Relevance of EV load models for enhancing the accuracy of smart charging strategies.	Simulated models incorporating stochastics for visitor behaviour.	Load models improve the precision of smart charging strategies by better-predicting demand variability across different EV types.	Highlights the importance of accurate demand forecasting for optimizing EV fleet charging strategies.
[10]	Technical and economic modelling of an off-grid EV charging station microgrid.	Microgrid modelling and simulation using MATLAB and Simulink.	A new modified cost of energy (MCOE) is proposed, offering a more comprehensive decision-making characteristic compared to existing technical and economic metrics.	Provides a robust framework for the techno-economic optimization of EV fleet charging stations in off-grid settings.
[11]	Stand-alone microgrid for EV charging stations	Mixed-integer linear programming (MILP) formulation.	Increasing battery ESS capacity offers better reliability than expanding RES.	Highlights the cost-benefit trade-offs of battery ESS vs. RES in fleet microgrids.
[12]	Sensitivity analysis of an EV charging station microgrid for sizing RES and ESS assuming EV demand uncertainty.	Microgrid modelling and simulation using MATLAB and Simulink.	Microgrid module sizing based on the unmet energy needs of EVs provides an optimal solution for balancing technical and economic constraints.	Offers a detailed sensitivity analysis for fleet-level EV charging microgrids, guiding optimal storage and renewable energy system sizing.
[13]	Impact of EV charging strategies on minimizing the use of fossil-fuel generators in a microgrid.	Mathematical modelling using linear programming and HOMER Energy software.	EV charging strategies offer greater long-term benefits when compared to investing in new photovoltaic (PV) generation alone.	Demonstrates how tailored EV charging strategies can balance renewable generation with fleet charging demands.
[14]	self-optimizing fleet charging scheduling	K-means clustering and double-objective optimization	Model validation of optimal charging/discharging in large systems	Forecasts and validates fleet charging/discharging profile
[15]	EV storage technologies applied to domestic and commercial charging stations.	Markov Stochastic modelling and Monte Carlo simulations.	EVs' available capacity may not meet demand during outages in cases of long driving distances or incomplete charging.	Uses probability functions to evaluate the role of EV fleet batteries in supporting smart ESS in off-grid microgrids.

Fig. 1 shows an EV fleet charging station schematic in an off-grid microgrid including a possible range of EVs and chargers. The power/energy demand on the main feeder of chargers has a substantial role in design and planning of the off-grid microgrid especially when renewable energy resources are the main sources of energy.

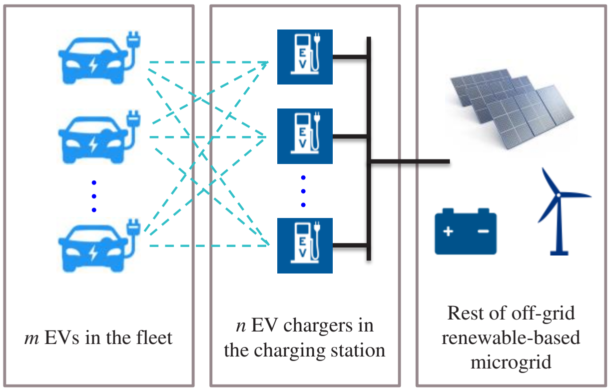


Fig. 1. EV fleet charging station schematic in an off-grid microgrid.

This paper aims to present a generalized five-step model to obtain the required power and energy profiles of an EV fleet, which is electrified in an off-grid renewable-based microgrid. The main contributions of this paper are listed below:

Simplicity: A limited-data-based modelling method is proposed, which requires an easily available set of EV specifications and a set of charging patterns, which can be estimated based on the fleet owner/manager requirements, instead of exact data such as fleet charging history, which is not available in most design cases.

Expandability: The five-step modelling method can be easily expanded by changing the model, number, and features of each EV in the fleet. The number and type of chargers as well as their chance to be used by EV drivers can also be varied.

Charger availability metric: One of the secondary outputs of the proposed model is to present an energy concept-based charger availability metric, which is suitable for optimizing the required number and type of chargers in the EV fleet charging station.

2 EV Fleet Charging Station Modelling

In the case of sizing and planning an off-grid microgrid solution to electrify an EV fleet charging station, finding an exact model of the fleet demand considering both instantaneous power and energy profiles is necessary. In fact, sizing/planning studies including required power and energy features are severely affected by the estimated demand.

Fig. 2 shows the proposed modelling method of an EV fleet charging station including five steps. Since it is assumed to have some limited data about the EVs in the fleet, which is not enough for a completely data-driven model, EV power profiles are modelled separately by a combination of the available data and suitable probability distribution functions at the first step. In the second step, the EV power profiles are shifted by different numbers of days to minimize the potential similarity between them possibly caused by the random numbers in the first step. The third step is to model the EV chargers according to the shifted EV power profiles. A type of charge event management is modelled in the fourth step, which is simple and suitable for fleet applications. The proposed modelling method can be considered without charge management if it is not used in the real operation of an EV fleet charging station. In this case, the fourth step should be bypassed, and the modelling process jumps from the third step to the fifth step, where the total power profile of the EV fleet charging station is obtained.

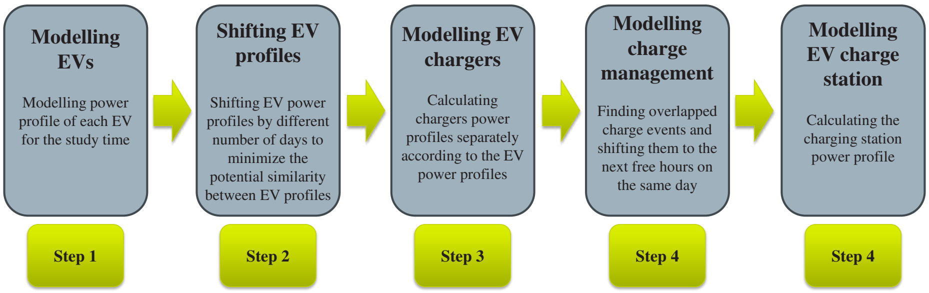


Fig. 2. The proposed five-step modelling method of an EV fleet charging station

2.1 Step 1: Modelling Separated EV Power Profiles

Figure 3 shows a schematic of the EV power demand profile modelling at the first step. This method is applied to all EVs one by one and separately for any number of days required in studies. As mentioned, this method needs some EV features, which can be easily available for an existing fleet or can be estimated for a new fleet. They include battery capacity (kWh), annual mileage (miles), and driving efficiency (mile/kWh). Three different periods are assumed in a charging-discharging cycle of an EV power profile model including the EV charging period, full driving days without charging, and driving hours before the next charging on the same day of the next charging. The charging-discharging cycles, including these three periods, repeat several times with different patterns based on EV charging requirements. In the EV charging period, the power value is the same as the rated power of the charger assigned, $P_{charger}^{rated}$, but the length of this period, $\Delta t_1(h)$, is calculated according to the required energy to fully charge the EV, $E_{last-driving-days}$ using (1). This energy is calculated according to the number of last driving days in which there has not been any other charging event, before $\Delta t_1(h)$.

$$\Delta t_1(h) = \frac{E_{last-driving-days}(kWh)}{P_{charger}^{rated}(kW)}, \tag{1}$$

where $E_{last-driving-days}$ is the total energy consumed during the last driving period, which can be obtained by multiplying the daily average of EV energy consumption by the number of last driving days. The daily average of EV energy consumption can be calculated by dividing the annual mileage by the driving efficiency of the EV. On the other hand, the number of last driving days can be calculated as follows:

$$last\ driving\ days = \left\lfloor \frac{\left(1-\left(\frac{Driver's\ preferred\ minimum\ SOC\ (\%)}{100}\right)\right)\times EV\ battery\ capacity\ (kWh)}{Daily\ average\ of\ EV\ energy\ consumption\ (kWh)} \right\rfloor \tag{2}$$

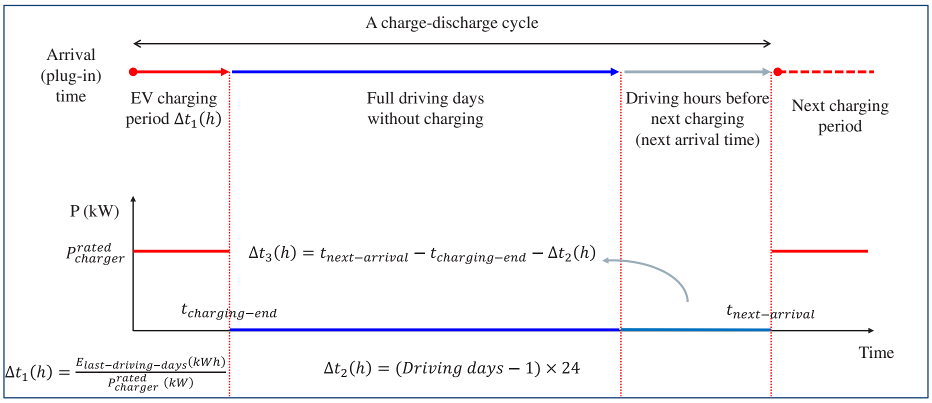


Fig. 3. Power profile modelling of an EV of the fleet.

where $[.]$ represents the floor function, and driver's preferred minimum state of charge (SOC) can be randomly selected in a reasonable range, e.g. 20 % - 50 %, using a uniform probability distribution function. For example, if an EV has a daily average consumption of 5 kWh/day and the EV battery capacity is 50 kWh, driving days before charging are obtained as a random integer number among 5-8 days for the above-mentioned typical range.

During the other two periods, the power value is zero. The length of the second period, i.e. full days without charging, $\Delta t_2(h)$, is calculated in (3) according to the number of driving days in each charging-discharging cycle, which can be obtained from (2) the same as last driving days. A lower driver's preferred minimum SOC leads to more driving days for an EV before the next charging event. The length of the third period is calculated according to the next arrival time of the EV to be connected to the charger and the current charging end time as presented in (4).

$$\Delta t_2(h) = (Driving\ days - 1) \times 24. \tag{3}$$

$$\Delta t_3(h) = t_{next-arrival}(h) - t_{charging-end}(h) - \Delta t_2(h). \tag{4}$$

where $t_{next-arrival}$ and $t_{charging-end}$ are shown in Fig. 3. Arrival time at each charge/discharge cycle should be modelled considering EV fleet work patterns and charger type, which is different from one case to another. For example, for a university EV fleet, each EV can arrive at the station randomly between 8 am – 8 pm to be charged using the fast chargers or between 5 pm – 8 pm to be charged using low-power standard chargers.

Assuming a reasonable value for the EV charging power is necessary at this step. Therefore, a part of charger modelling should be done in Step 1. Each EV at each arrival time to be charged can be connected to each one of the EV chargers, i.e. the driver does not know which charger is empty and assumes at least one of them is free. The charger is selected using a chance vector, e.g. [7 7 50 50 50]. The chance of each charger being used for EV charging increases by adding a greater number of its rated power in the chance vector. The chance vector should be determined reasonably according to the real number of chargers in the fleet charging station (in the example above, 2 x 7kW and 3 x 50kW chargers). Note that EV charger availability is considered in Step 3 of the proposed modelling method, where the charger power profile is modelled. Finally, the output of Step 1 is a set of separate EV power profiles fully satisfying the charge/discharge pattern of EVs for a long period, i.e. required days for a study period, which is usually used in long-term sizing and planning studies.

2.2 Step 2: Shifting EV Power Profiles

Although arrival time on the day of charging is random, the driver's preferred minimum SOC and charger selection for each EV are assumed as random variables, the overall charge/discharge cycle repetition patterns of different EVs may have a level of similarity, especially for two or more EVs of the same model. Shifting EV power profiles by different numbers of days can minimize the potential similarity between different EV profiles. Assuming m complete days as the $shifting\ step$ for power profile of all EVs, one can write:

$$\begin{aligned}
&\boldsymbol{EV_1\ profile\ duration}: from\ Day_1\ to\ (Day_1 + Study\ days),\\
&\boldsymbol{EV_2\ profile\ duration}: from\ Day_{m+1}\ to\ (Day_{m+1} +\ Study\ days),\\
&\vdots\\
&\boldsymbol{EV_n\ profile\ duration}: from\ Day_{(n-1)*m+1}\ to\ (Day_{(n-1)*m+1}\\
&\qquad + Study\ days).
\end{aligned} \tag{5}$$

Therefore, the duration of all EV profiles equals to $Study\ days$. However, each EV profile starts and ends on a different day from other EVs. To this end, enough days need to be added to the $Study\ days$ to satisfy the idea of the shifting. Therefore, the total simulated days equal $Study\ days$ plus $Excess\ days$, which can be obtained as follows:

$$Excess\ days\ =\ Shifting\ step\ \times\ (Number\ of\ all\ fleet\ EVs\ - 1). \tag{6}$$

2.3 Step 3: Modelling EV Charger Power Profiles

Although shifted EV power profiles have been obtained assuming the number and the type of chargers available at the fleet charging station, an exact model of chargers is still not available. EVs are assumed to be allowed to connect to any charger, but generally, the number of chargers is lower than the number of EVs, which causes simultaneous use of a charger by two or more EVs according to the modelling method presented in Step 1. To eliminate such an unreal operation of chargers, the availability of chargers should be modelled at this step.

The goal is to maximize the usage time of chargers to charge the maximum feasible number of EVs at each sample time, remembering that the EV power profiles have been

obtained as time series with a resolution of sample time, e.g. one minute. To find the power value at each sample time of the power profile of each charger, the idea is to check all EV power profiles at the same sample time. The first found power value equal to the charger rated power is the power value of the charger at that sample time. If there is more than one power value from other EVs and there are not more EV chargers of the same power value available at that sample time, all remaining power values should be considered as unmet EV power demand due to charger unavailability. When there is no power value from none of EV power profiles as the same power as the charger rated power, the charger is free at that sample time. Two *while* loops in MATLAB can manage this process to calculate the power value of all chargers at all sample times. Therefore, the power profile of EV chargers can be obtained considering their availability.
As an example, assume a fleet including four EVs, two 7 kW standard chargers and one 50 kW rapid charger, where we have the EV power values for three samples, t_1 to t_3. The left-hand matrix shows the EVs power matrix by merging EV power profiles and the right-hand matrix is the obtained chargers power profiles in a merged matrix form.

Table 2. Obtaining chargers power values/profiles according to available EV power values/profiles.

EVs power matrix	Chargers power matrix
$\begin{array}{c} \\ EV1 \\ EV2 \\ EV3 \\ EV4 \end{array}\begin{array}{c} \begin{array}{ccc} t1 & t2 & t3 \end{array} \\ \begin{bmatrix} 7 & 50 & 50 \\ 7 & 7 & 50 \\ 50 & 0 & 0 \\ 7 & 0 & 7 \end{bmatrix} \end{array}$	$\begin{array}{c} \\ Ch1-7kW \\ Ch2-7kW \\ Ch3-50kW \end{array}\begin{array}{c} \begin{array}{ccc} t1 & t2 & t3 \end{array} \\ \begin{bmatrix} 7 & 7 & 7 \\ 7 & 0 & 0 \\ 50 & 50 & 50 \end{bmatrix} \end{array}$

2.4. Step 4: Modelling Charge Event Management

There are two reasons for the lack of fully satisfying EV charge profiles by chargers: 1) real unavailability of chargers due to their being a lower number of chargers than EVs, and the fact that the number of drivers who may arrive at the charging station at the same period, can be greater than the number of available chargers, and 2) an unreal availability, which is possible at Step 1 of the modelling due to mis-selection of an occupied charger by EVs arriving at the same time when there is another free charger. This is due to the asynchronous modelling of power profiles of EVs and chargers. Note that synchronous modelling requires EV SOC modelling, which causes some difficulties in the modelling process. Both reasons can be recognized in modelled EV power profiles through an overlap among two or more than two charge events, and then it can be resolved by modelling a type of charge event management. Fig. 4 shows the idea of charge event management. In Fig. 4(a), the two charge events on a charger power profile have an overlap. At this step, all such charge overlaps on the corresponding charger power profile can be recognized. One of the charge events remains in its period and others are shifted to the next free hours of the same day, which are allowed for an EV arrival. This is shown in Fig. 4(b). In a real case, this charge event management can be achieved using a simple smartphone application. An enhanced charger power profile can be achieved, which is longer than the case where there is no charge event management. This also results in a higher availability of chargers and satisfying a higher level of EV power profiles.

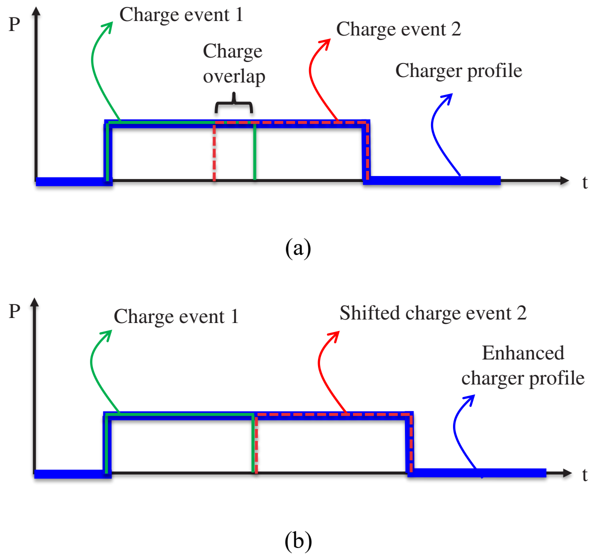


Fig. 4. A typical EV charger profile: (a) before, and (b) after charge event management.

2.4 Step 5: Modelling EV Fleet Charging Station Power Profile

Whether applying Step 4 or not, inputs to Step 5 consist of charger power profiles, i.e. $P_{ch,j}(t), j = 1, \dots, Number\ of\ chargers$. The EV fleet charging station power profile, $P_{station}(t)$, can be modelled by adding all the charger power profiles as follows:

$$P_{station}(t) = \sum_{j=1}^{No.\ chargers} P_{ch,j}(t). \tag{7}$$

Please note that (t) shows that the power profile is a time series obtained as a function of the sample time variable, t.

3 Analytical Metrics

A list of metrics required for validating and analysing the EV fleet charging station demand model are provided below.

Power profile in a period: This is the primary output of the proposed modelling method, which can be obtained for each EV, each charger, and finally the EV fleet charging station. It includes two important features, EV charge (or charger usage) periods and the corresponding power amount, which can be shown for $i'th$ EV as $P_{ev,i}(t)$ and for $j'th$ charger as $P_{ch,j}(t)$. The power profiles should be used in sample-based simulations for sizing and planning studies. They also can be provided for a shorter period to validate the model by checking modelled features like arrival time, power value, and charge duration length.

Average daily power profile: Analysing a daily average of annual/monthly power profiles make it easier to validate their features. The daily average of the EV fleet charging station power profile, $P_{station,davg}(t)$, can be calculated as follows:

$$P_{station,davg}(t) = \frac{\sum_{n=1}^{No.\ days} P_{station}(t)}{No.\ days}. \quad (8)$$

Annual Profile of Daily Energy Demand: This is suitable for finding the daily energy demand of the EV fleet and its variation in the long term. To calculate this metric, firstly the power profile of the EV fleet charging station should be separated for all days of the period in which the power profile is obtained. Then, the daily energy of $N'th$ day can be found as follows:

$$E_{station,N} = \sum_{t=1}^{No.\ samples} P_{station,N}(t) \times sample\ length. \quad (9)$$

To calculate $E_{station,m}$ in kWh, $P_{station,N}(t)$ should be in kW and $sample\ length$ should be in h.

Annual/monthly Energy Demand: These are so beneficial to compare with annual/monthly renewable energy generation in a normal microgrid sizing/planning problem. To calculate them, total daily energy values for all days of a month/year should be calculated using (8) and then added together as follows:

$$E_{station,period} = \sum_{n=1}^{No.\ days} E_{station,n}, \quad (10)$$

where $E_{station,n}$ is the daily energy demand in $n'th$ day, and $E_{station,period}$ is the total energy demand for a period including several days.

Charger Availability: This metric can show the availability of chargers for EVs in the fleet charging station. It can be calculated according to the total energy delivered to the EV fleet by all chargers and total energy demand required for charging the fleet as follows:

$$Charger\ availability\ (\%) = \frac{Chargers\ delivered\ energy\ to\ EV\ fleet\ (kWh)}{Total\ EV\ fleet\ required\ energy\ (kWh)} \times 100. \quad (11)$$

It can be used as the main validation metric for the proposed modelling method for the EV fleet because of the asynchronous modelling of EVs and chargers power profiles and its subsequent potential lack of availability mentioned in Section 2.4.

4 Case Study and Results

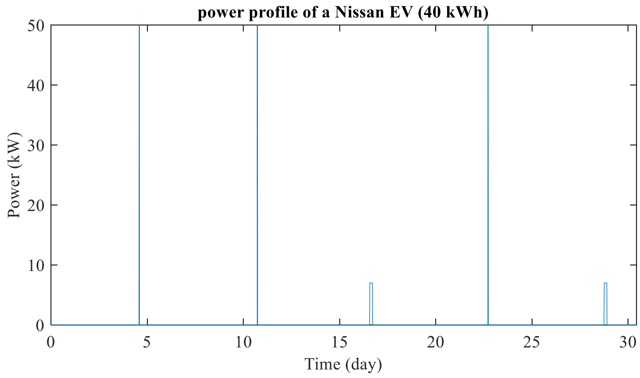
Table 3 shows the number, model, and required specifications of the EVs existing in the studied fleet, which is a real EV fleet belonging to a hospital in the UK. Chargers are selected from two types including 7-kW ac and 50-kW dc chargers. In the base case scenario, two 7-kW chargers and one 50-kW charger are assumed. Arrival times of EVs to the charging station are presented in the last column of Table 3, which are different according to the charger type. The driver's preferred minimum SOC is a random value between 20 % and 50 %.

Table 3. The EV model, number, specification, and assumptions in the studied fleet.

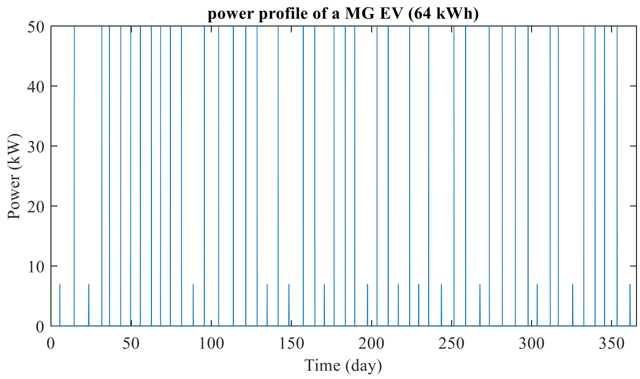
<table>
<tr><th>No. of Vehi-cles</th><th>Vehicle</th><th>Battery Size (kWh)</th><th>Annual Mileage (miles)</th><th>EV driving Efficiency (mile/kWh)</th><th>Arrival time to charging station (h)</th></tr>
<tr><td>6</td><td>MG4 150KW Trophy EV long Range 64 kWh</td><td>64</td><td>6000-9000</td><td>3.5</td><td rowspan="9">8 am – 8 pm us-ing 50 kW charger
or
5 pm – 8 pm us-ing 7 kW charger (Randomly)</td></tr>
<tr><td>3</td><td>Renault Master Advance e-Tech 52 kWh LM35 L3H2 FWD Ambulance</td><td>52</td><td>5000</td><td>4</td></tr>
<tr><td rowspan="5">5</td><td rowspan="5">Renault Kangoo L1 E-Tech ML19 90 kW Advance</td><td rowspan="5">44</td><td>1100</td><td>4</td></tr>
<tr><td>3300</td><td>4</td></tr>
<tr><td>5100</td><td>4</td></tr>
<tr><td>10600</td><td>4</td></tr>
<tr><td>12800</td><td>4</td></tr>
<tr><td>1</td><td>Vauxhall e-Combo Cargo L2 2300 100 KW Dynamic 50 KWh Hi Van (11KWCH)</td><td>50</td><td>6000</td><td>4</td></tr>
<tr><td>1</td><td>Nissan Leaf 100 KW N-Connecta 40 KWh</td><td>40</td><td>5000</td><td>4</td></tr>
</table>

4.1 Model Validation Through Power Profiles at Different Steps

In this section, model validation is done by checking different modelled features of the EV fleet using power profiles at different steps of the proposed modelling method. Fig. 5 Shows two power profiles typically of two EV models as a validation for Step 1. Fig. 5(a) shows a monthly power profile for the Nissan EV shown in the last row of Table 3. It shows five charge events including two occurrences of using a 7-kW charger and three of using the 50-kW rapid charger. 7-kW charge events take a longer time than the 50-kW charge events. Charge event days are 4, 10, 16, 22 and 28, which have been calculated randomly according to the driver's desired minimum SOC and the EV battery size, i.e. 40 kWh using (2). Fig. 5(b) shows an annual power profile of an MG EV introduced in the first row of Table 3. This profile includes 52 charge events, where a higher portion is done by the 50-kW charger. The chance charger selection has been selected differently for the Nissan and MG power profiles. In the Nissan power profile, the chance of selecting 7-kW and 50-kW is assumed the same, however, the chance of selecting the 50-kW charger is assumed as twice the chance of selecting a 7-kW charger in the MG power profile. Therefore, the MG power profile model has a greater tendency to select the 50-kW charger. The hour resolution of the charge events cannot be validated according to such relatively long power profiles shown in Fig. 5. This can be proved using the average daily power profile, which is obtained for the total demand of EV fleet charging station when Step 5 is validated at the end of this section.



(a)



(b)

Fig. 5. Modelling validation for Step 1: (a) monthly power profile of a Nissan EV (40 kWh), and (b) Annual power profile of an MG EV (64 kWh).

To validate Step 2 of the proposed EV fleet modelling method, Fig. 6 shows the shifted and unshifted power profiles of two MG EVs. In this validation, all three chargers are assumed to be available from 8 am to 8 pm to make a more challenging scenario in terms of charge event distribution. Firstly, both the shifted and unshifted power profiles show two different power profiles for two EVs in the same model, which shows a suitable diversity of modelled charging patterns even for two of the same EV types. On the other hand, the shifted power profiles show a slightly more distributed power profile, which results in a lower similarity of EV power profiles. Such a greater level of distribution has a considerable effect on the validity of the model assuming a greater number of EVs in the fleet for a longer period.

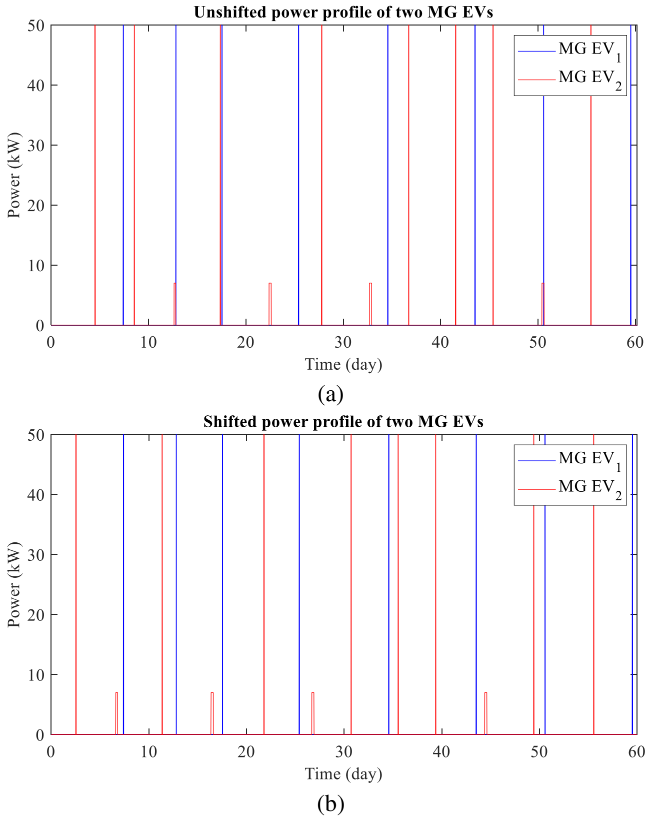


Fig. 6. Modelling validation of Step 2: (a) unshifted, and (b) Shifted power profile of two MG EVs in two months.

Fig. 7 shows the monthly power profiles of the two 7-kW and 50-kW chargers, which are calculated in Step 3 from the 16 EV power profiles and assuming the charger availability. As shown in the last column of Table 3, the arrival times of 7-kW and 50-kW chargers are 5 pm – 8 pm and 8 am – 8 pm, respectively. Therefore, a low ratio of overlapping between 7-kW and 50-kW charge events can be seen. Since the chance of selecting the 50-kW rapid charger is assumed two times the chance of selecting one of the two 7-W chargers at Step 1, the higher usage of the 50-kW charger is seen. Longer charge durations for 7-kW charge events can also be seen because of the lower rated power of the 7-kW chargers.

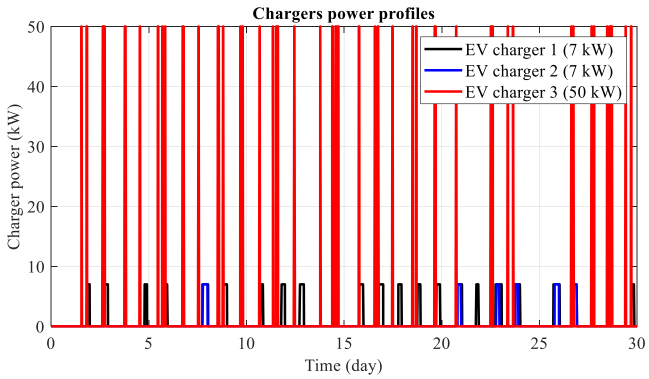


Fig. 7. Modelling validation of Step 3: EV chargers power profiles.

Section 4.4 provides a comparison between the charger availability of some charging station structures, which can be used as a validation for Step 4. Assuming a charge management strategy as described in Step 4 results in a 98.6 % charger availability, Fig. 8 shows the total power profile of the EV fleet charging station by adding the three power profiles of the two 7-kW and the 50-kW chargers. In most charge events, only one 7-kW or one 50-kW charger is required. Only 5 charge events show the case of using more than one charger with a resulting operating power of 57 kW and 64 kW. Most charge events show the operation of only the 50-kW rapid charger or only one of the 7-kW chargers. Instantaneous use of both 7-kW chargers can also be seen in a few charge events.

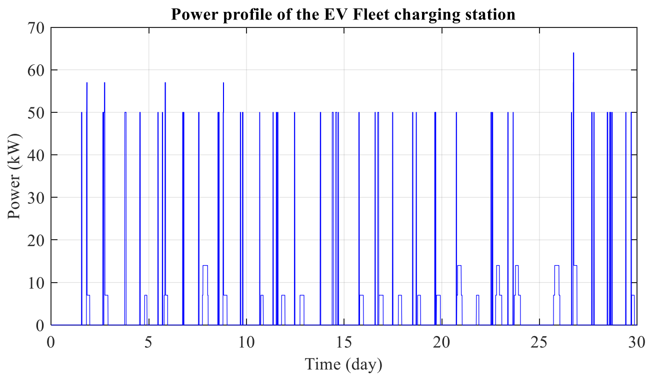


Fig. 8. Modelling validation of Step 5: the power profile of the EV fleet charging station.

Fig. 9 shows an average daily profile of total EV fleet charging station power demand without charge event management, which is obtained from the modelled power profiles for five separate years. This average daily profile is suitable to validate hour-resolution features of the proposed model, e.g. arrival time to charging station. There is no charge event starting sooner than 8 am, which is matched with the arrival time to the charging station selected as shown in Table 3. Peak power can be seen in all daily average profiles around 8 pm, and a tail of charge in the early morning hours, which are due to EV fleet night charging by 7-kW chargers.

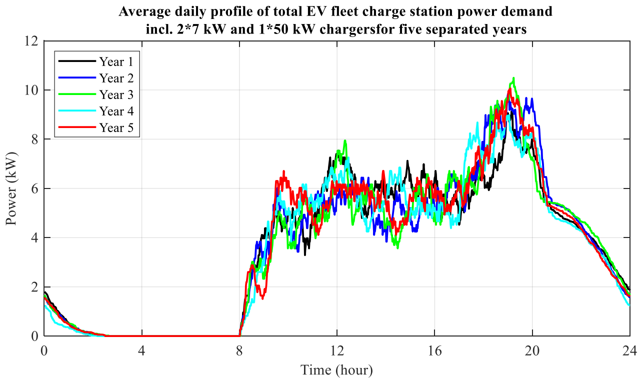


Fig. 9. Modelling validation for hour-resolution modelled features in the five-step model: average daily profile of total EV fleet charging station power demand without charge event management.

4.2 Energy Demand Analysis

After performing the five steps of the general proposed modelling method for the EV fleet charging station and validating power profiles as the main output of the modelling method, the total energy demand of the EV fleet charging station can be studied as another important metric in sizing and planning studies. Fig. 10 shows the annual profile of the daily energy demand of the studied EV fleet charging station introduced at the beginning of Section 4 and Table 3. This is affected by all requirements for 16 EVs in the fleet and considering the availability of the three chargers in the charging station. In twelve days, the energy demand is zero, i.e. the charging station is not used at all. The peak demand is 223 kWh/day, and the annual average of the EV fleet's daily energy demand is around 89 kWh/day. One can simply find the annual energy demand by multiplying 365 by the annual average of the energy demand, which is approximately 32.5 MWh/year. These values of energy demand need to be compared with corresponding available energy values in an off-grid microgrid to find technically acceptable sizes of renewable energy generation.

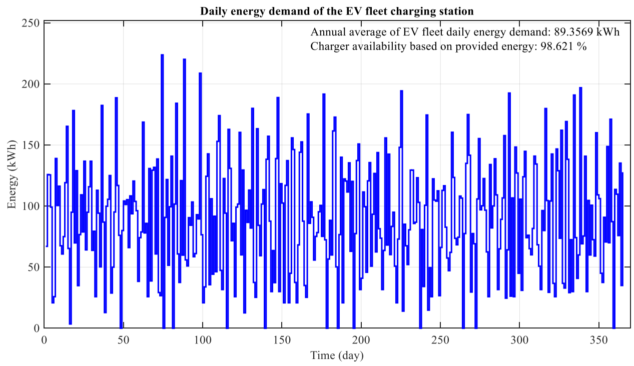


Fig. 10. Annual profile of daily energy demand of the EV fleet charging station.

4.3 Charger Availability for Different Number of Chargers

The charger availability could not be 100 % using two 7-kW and one 50-kW charger in the base case scenario, even applying the charge management method from Step 4. If the charge management is not used, the charger availability is 94.2 %. There may be still two main reasons for this low availability of chargers including lack of enough chargers and short available time to use 7-kW chargers, i.e. 5 pm – 8 pm. To study the impact of these two reasons on charger availability, different numbers of 7-kW and 50-kW chargers are assumed in the studied EV fleet charging station without any charge management. Fig. 11 shows a comparison of charger availability assuming two dispersion levels of 7-kW chargers usage period, i.e. a low dispersion level (5 pm – 8 pm) and a high dispersion level (8 am – 8 pm) for a longer period of ten years. Generally, the higher dispersion level leads to a higher charger availability for different numbers of chargers. Increasing the number of chargers, whether 7-kW or 50-kW, results in an increase in charger availability. Taking the charger availability changes into account, both results show the reasonability and reliability of the proposed modelling method. However, cost affordability should also be considered for finalizing the decision-making about the suitable number of chargers for the studied charging station. For example, using two 7-kW and one 50-kW charger can achieve around 94% - 97 % charger availability without any special management activities and time scheduling, which can be a cost-effective choice in comparison with the combinations including higher number of chargers. Such a low unavailability, i.e. 3-6 %, can be covered by assuming a simple charge management as explained in Step 4 of the proposed modelling method.

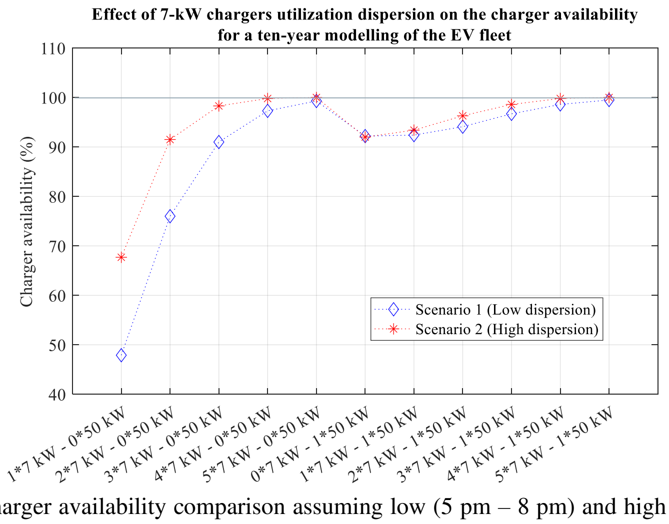


Fig. 11. Charger availability comparison assuming low (5 pm – 8 pm) and high (8 am – 8 pm) dispersion of charge events of the 7 kW chargers.

4.4 Charge Management Effect on Charger Availability

Assuming the high dispersion level for both 7-kW and 50-kW chargers, another charger availability comparison for different numbers of chargers is considered in Fig. 12 with and without charge event management to investigate the effect of the charge management on the proposed model of the EV fleet charging station. Considering the charge event management, most combinations of several chargers can have approximately 100 % charger availability. Three 7-kW chargers provide the lowest rated power of 21 kW to satisfy 100 % charger availability. One 50-kW charger, a combination of one 7-kW charger and one 50-kW charger, and a combination of two 7-kW chargers and one 50-kW charger are the next cheapest and lowest rated power structures for the studied EV fleet charging station, respectively.

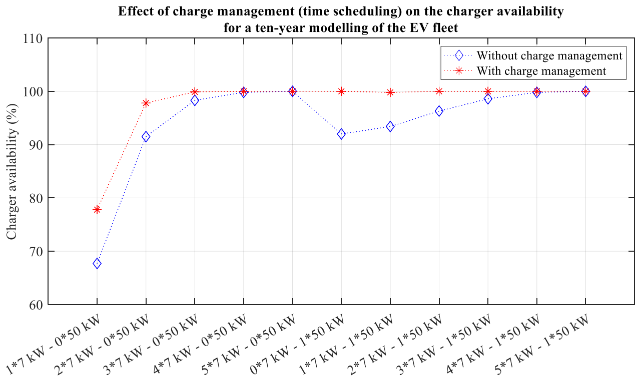


Fig. 12. Charger availability comparison with and without charge event management (Step 4 in the proposed five-step modelling method).

4.5 Decision-making for Chargers' number

Another technical comparison between different structures of the charging station assuming different numbers of chargers can be done using daily power profiles. Fig. 13 shows the average daily profile of the total EV fleet charging station power demand for different numbers of chargers, i.e. More 7 kW chargers lead to more distributed daily charge profiles and shifted into the night because of longer charge durations of 7 kW chargers and required shifting process in Step 4 to improve the charger availability. A design including two 7 kW and one 50 kW has both advantages of a distributed profile because of using 7-kW chargers, and available fast charging when required due to employing a 50-kW charger. The goal of this paper is not to present a comprehensive method for decision-making about selecting the number of chargers for an EV fleet charging station, where more technical and economical inputs are required. Therefore, according to just the technical analysis provided for this case study, using two 7-kW ac chargers and one 50-kW dc rapid charger can be one of the reasonable choices.

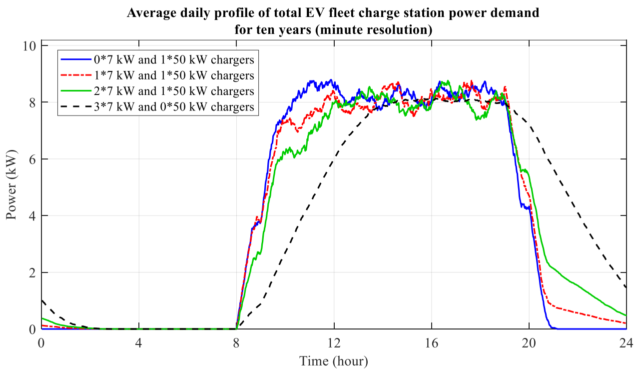


Fig. 13. Average daily profile of total EV fleet charging station power demand for different number of chargers ($\leq \mathbf{3}$).

5 Conclusion

A generalized model of an EV fleet charging station is proposed, which requires minimum input data and employs reasonable random variables to mimic the random behaviours of an EV charging station. Each step of the proposed model is validated by showing corresponding results including different power and energy profiles. The primary output of the model is the power profile of the EV fleet charging station, which can be obtained for any period. This can be used in long-term studies, e.g. planning/sizing of microgrids electrifying the EV fleet load demand, where optimized sizes of the main modules, e.g. renewable resources and energy storage systems, are calculated. The secondary outputs of the model are energy profiles and values, e.g. daily average of required energy for the EV fleet. These values are beneficial to be compared with available renewable energies in off-grid microgrids to analyse energy requirements. Another output of the model is the energy-based charger availability metric, which is used to find the appropriate number and model of chargers to be installed in the charging station. This metric helps to avoid over/under-estimation of chargers' number of rated power. For the studied fleet including 16 EVs, results show that different combinations of 7-kW and 50-kW chargers can satisfy a 100 % availability. However, the structure including two 7-kW and one 50-kW has the advantages of a distributed daily power profile as well as available fast charging. Generalizing the proposed method for modelling large-scale EV fleets and adding more features, e.g. assuming different charging patterns for weekday and weekend for commercial company fleets, can be done in future work.

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