Stochastic Modeling of Vehicle Arrival for the UK's First Electric Vehicle Charging Forecourt

F. M. Aboshady[1], Ioana Pisica[2] and Colin J. Axon[3]

[1] Institute of Energy Futures, Brunel University, London, UK. Fathy.Aboshady@brunel.ac.uk
[2] Dept. of Electronic and Computer Engineering, Brunel University, London, UK. Ioana.Pisica@brunel.ac.uk
[3] Dept. of Mechanical and Aerospace Engineering, Brunel University, London, UK. Colin.Axon@brunel.ac.uk

***Abstract*—Increased attention is paid to reducing the greenhouse gases resulting from combustion processes either from energy generation stations or the transportation sector. Countries are setting rules and targets to govern this issue and electrification of transportation is spreading. One of the motivations for people use electric vehicles may be the availability of rapid charging stations which function similarly to the conventional fuel stations (forecourts). The UK's first solar EV charging forecourt is being built and commissioned with a 5 MW on-site battery to store energy from a solar farm and to enable arbitrage for grid services. To enable optimum site operation, predicting the arrival of electric vehicles at different times of the day and hence the load demand, determines the availability of the battery for bulk power supply or fast-frequency response to the grid. This paper presents the outline of a stochastic model for the electric vehicle arrival and charging at the site using the concept of vehicle population-types. The model considers the stochastic nature of different parameters controlling the charging process e.g. the charging start time and the state of charge (SoC) at start of the charging session.**

***Keywords*—electric vehicle; electric forecourt; EV charging station; EV charging infrastructure; stochastic model**

I. Introduction

Transport accounts for 28% of UK greenhouse gas (GHG) emissions [1]. Liquid fuels (fossil and renewable) have been shown to be unlikely to meet GHG reduction targets, even in the near-term [2] yet transportation is considered one of the hardest sectors to decarbonize. The barriers hindering the take-up of electric vehicles (EVs) include: high initial costs, limited charging facilities, limited driving range, and long battery recharge times [3],not the least of which is access to charging infrastructure [4].

The UK Government has committed the nation to become net-zero carbon by 2050 [5], and introduced a target year of 2035 to cease sales of new gasoline and diesel automobiles [6]. In the UK in 2019 there were 32,884,320 registered passenger vehicles [7] of which 0.7% were EVs (battery EV (BEV) and plug-in hybrid EV (PHEV)). EV sale rate is increasing in the UK where the 2019 sales share of EVs was 3.2% compared to 0.2% in 2013 [8].

Currently, the principal options for charging are at home, on-street, or a car park (work or retail). In the UK there are 19,167 public charging devices providing 33,301 connectors [9]. Of these public chargers, 75% of the chargers have charging rate less than or equal to 22 kW and only 3% are ultra-rapid chargers (100 kW or more) [9]. Charging at home is limited to 3-5 kW and requires a suitable off-street space. For those living in apartment blocks or other high-density housing this is problematic.

Uncontrolled charging of EVs either at home or public places may lead to significant increases in demand on the electric grid e.g. increasing load during the peak periods of the day [10]. Accordingly, forecasting and modelling EV charging demand is important for power system planning and operation. Su *et al* [11] formulated a stochastic model estimating the effect of EVs charging on the distribution system. They considered different charging scenarios and showed uncontrolled domestic charging to be the worst-case scenario. Probabilistic modelling using the Copula method [12] was used to find the joint probability of home arrival time, daily travelled distance and home departure time. Markov chain modelling was implemented to investigate when and where the EV will be recharged [13]. Using deep learning methods Kara *et al* [14] provided super-short-term forecasting of EV charging. The method predicts the EV charging profile with one-minute resolution and uses real data with one-minute resolution for training, validation and testing. The concept of smart (controlled) charging was introduced to avoid problems associated with the uncontrolled charging [15].

The UK's first Solar Electric Forecourt demonstrator project aims to design, deliver and operate an integrated, utility-scale site located in Braintree, Essex consisting of 24 ultra-rapid charging points (of various power ratings from 90 kW to 350 kW) with charging times of less than 30 minutes, in addition to other lower-rated chargers. Charging will be via a 5 MWh on-site battery energy storage system (BESS) coupled to a solar farm. The objectives of the demonstrator include balancing EV charging and the provision of grid services, and demonstrating the economic, social and environmental benefits of ultra-rapid public EV charging hubs. Furthermore, such electric forecourts may help mitigating the burden on the distribution system as the EVs charge from the BESS not through direct connection to the main electric grid.

The aim of this paper is to introduce a model to mimic EV arrival rates at the site. This will model is designed to serve two purposes: 1) to help predict likely site use in the next 24 hour period for planning the BESS strategy for providing grid services, and 2) to learn about patterns of use to assist in developing the second and subsequent sites.

II. Model Design and Methods

The aim of the model is to understand how the energy demand from vehicle charging through the day may vary. The variation is driven by factors such as time of the day, daily distance travelled , and battery capacity of the EV. The predicted EV arrival is used to estimate the power and energy withdrawn from the BESS during the day. Firstly, the EV arrival model is explained, then, the site operation to charge EVs is described.

Neither a deterministic nor system dynamics approaches are appropriate, we need to introduce stochastic variation in most parameters in some way to mimic the uncertainty demonstrated in the real-world data. At present, the site is in the early stages of operation and experience of the parameters is being gained daily. Accordingly, the stochastic nature of the parameters is initially modeled based on information available from literature and the transport sector data. The code is written in Matlab (version 2016b).

To match the half-hourly settlement periods each day consists of 48 slots. When EVs arrive at the site they start charging unless no suitable charging point is free, in which case they queue in the waiting area. Each EV's SoC is checked every two minutes until reaching the required energy target.

We model the EV fleet as three principal populations 1) those who live in the catchment postcodes, 2) those who work at the adjacent business park but live outside of the catchment area, and 3) opportunistic charging by passing traffic with no direct connection with the area. It is expected that EV drivers from outside the site catchment area will show a different behaviour (charging requirement) compared to people working/living close to the site. Each population is modelled independently and the total number of EV arriving is the sum of all populations.

A. Local Populations

Generally, the resident and work populations show different behaviors, although there is likely to be a small subset of those who live and work locally. This is most clear during the weekends when it is not expected that EVs from the work population will charge. The work population will be determined once the site is operational and the local live/work populations can be deconvoluted i.e. those who work at the business park but commute from non-local postcodes.

The common models for EVs in the market and their relative share are given by [8]. These databases are updated as the market changes. EVs owned by postcode can be obtained from Department of transport records [7]. Basic technical information such as full electrical range, charging rate, and battery capacity of EVs were obtained from [16].

Modeling the total local population (N_{max}) starts by estimating the total number of EVs needing to charge (N_{ev}) and therefore most likely to arriving during the day (next 48 half-hour periods). The flowchart in Fig. 1 shows the two steps to model the local population. Modeling the local population relies on monitoring the current SoC for each EV. By exploiting the distribution for distance travelled per day with vehicle battery capacity we can determine the likely state of charge. Assuming the SoC decreases linearly with the distance travelled, the current SoC is calculated by

$$SoC_c = SoC_f - (d/D_m) \times 100\% \quad (1)$$

where SoC_c and SoC_f are the current and final SoC respectively, and d and D_m are the total travelled distance and total electrical range for the EV respectively.

If the current SoC for an EV is below a threshold level that would risk the driver being unable to make many additional journeys, then this EV potentially needs recharging. The tracking and checking for the SoC is applied to all EVs in the resident population, giving the number potential EVs needing to charge on a certain day, N_{ev} in Fig. 1. The threshold level for SoC is initially assumed 50% in this paper which can be easily adjusted to better reflect the actual real data collected from running the site.

The Department for Transport's National Travel Survey (NTS) is used to develop a distribution for the daily travelled distance [17]. A dataset of 100,783 trips is used to build the distribution which is found to be lognormal (Fig. 2 with a mean and standard deviation of 1.9 and 1.1 respectively. Therefore, the average travelled per day is 12 km with a standard deviation of 14 km.

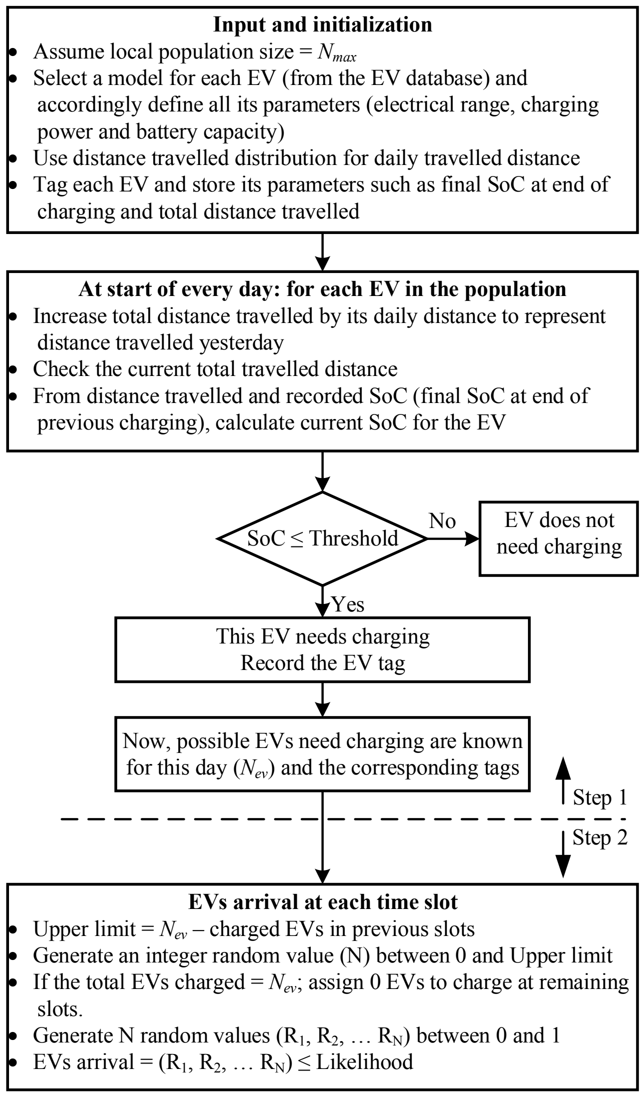

Fig. 1. Local population model flowsheet.

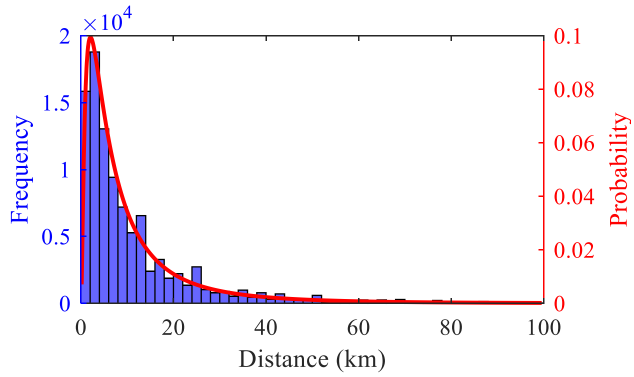

Fig. 2. Modelled distribution (red line) of daily travelled distance. Data source: [17].

The second step estimates the number of EVs arriving during each 48 slot, requiring a plug-in time distribution [18, 19]. for starting the charging. This distribution is used to give a relative weighting to different time slots of the day (likelihood for each time slot is used). Firstly, an integer (N) is randomly generated between 0 and N_{ev}. This is the number of trials the EV arrival routine is run at this time slot. Accordingly, the number of EVs turning up will be between 0 and N. For each trial, the decision that an EV will charge or not is defined by comparing a randomly generated value (uniform distribution between 0 and 1) with the likelihood of the plug-in distribution at this time slot. If the random value is less than or equal to the likelihood, then this trial is counted as an EV that will charge during this time slot. N_{ev} recursively decreases accounting for EVs charged during the previous slots of the day.

Initially, statistics on local authority rapid plug-in vehicle charge points in England in 2017 [20] are used to develop the plug-in time distribution. The plug-in time distribution can be easily modified in the algorithm to reflect the actual behavior of the EVs when more operational data is available. The rapid charge points in this dataset are chargers of 22 kW or more and are used as a reference as the chargers adopted in the project are of high power. The EV charging datasets combine 108,746 charging events recorded for 237 rapid chargers located in 27 local authorities, of which 697 were recorded in Essex. The frequency of charging events was affected more by the time of the day than the day of the week. Accordingly, the same plug-in time distribution is used for different days of the week. The number of events by time of the day for Essex county is shown in Fig. 3. The data for Essex is used to build the plug-in time distribution which is found to be normal distribution. The peak plug-in time for the distribution is 13:40 pm.

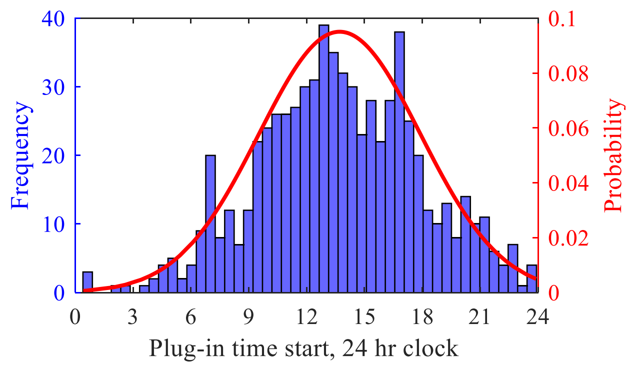

Fig. 3. Modelled plug-in start time distribution (red line) in Essex (local population). Data source: [20].

B. Passing Traffic

The passing traffic population is undertaking medium and long distance journeys using the main roads (A12, A120 and A131) nearby the site. These journeys may or may not end in Essex, but are using the forecourt as part of their journey plan. This population is a direct function of the vehicle flow-rate along the main roads. A step in the modeling is to pick a model for the EV coming to charge. For this purpose, the relative share of EVs is used to set the probability for each EV model.

The total daily number of vehicles passing along the roads of interest is known [21], but not the temporal distribution. Fig. 4 shows the normalized average motor vehicle traffic distribution by time of day and day of week for all roads in Great Britain in 2018 [21]. The weekdays are similar with bimodal peaks in the morning and late afternoon. On the other hand, the weekends have a single peak in the early afternoon. This information is used to build two traffic flow probability distributions; one for weekdays and one for weekends.

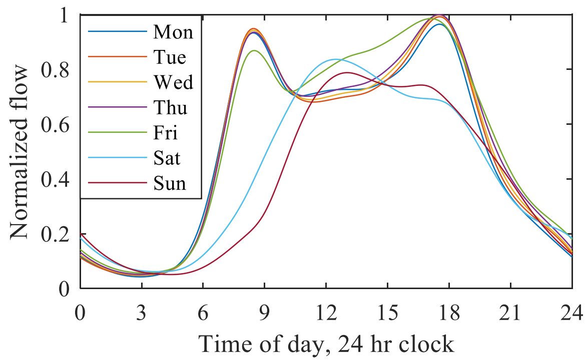

Fig. 4. Traffic flow distribution. Data source: [21].

To create a distribution of types of EV in the passing traffic population, the EV share in the market (BEV and PHEV) is used to scale the average daily flow to represent EV daily flow on the roads of interest. The licensed cars statistics in the UK at the end of 2019 are used where the BEV and the PHEV represent 0.3% and 0.4% respectively [7].

Therefore, from the daily flow, the percentage of long journeys needs to be extracted. Car journeys longer than 25 miles (40 km) are assumed to form the passing traffic population. The long journeys are found to be approximately 7% of all trips from the NTS dataset [17]. Therefore, the traffic flow distribution, average daily flow, EV share and percentage of long journeys can be used to estimate the EV arrival at different time slots of the day.

For a certain slot, the EV decision to charge is defined by comparing a randomly generated value between 0 and 1 with a threshold level. If the random value is less than or equal to the threshold level, then the EV will charge at the site at this time slot. At this initial stage of the model design, a threshold level of 0.5 (50%) is used to give equal opportunity to charge or not.

The likely initial SoC of the EV was estimated from the travelled distance for the local population. On the other hand, the passing traffic population requires a distribution for the initial SoC. The distribution of the initial SoC is assumed in this study until a real operating data is collected from the site. The initial SoC distribution is shown in Fig. 5.

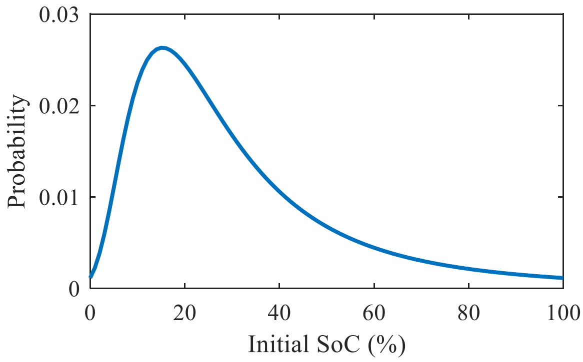

Fig. 5. Initial state of charge distribution.

C. EV Charging

For the 48 slots the flowchart (Fig. 6) illustrates the process of charging sessions at the site, aiming to estimate the power demand from the BESS. Once the total number of EVs that will be charging is estimated from all the populations, the EV model and the corresponding parameters e.g. rated charging power and battery capacity is selected from the EV database [16]. Monitoring the EV charging status is carried out every Δt time step (2 minutes).

The energy required is defined from initial SoC, final SoC and the battery capacity. Initial SoC is defined either by estimation for the local population or the distribution for the passing traffic. For the final SoC, data from literature is used to build a distribution (Fig. 7) for the final SoC [22]. The final SoC is close to full charge, however, leaving a portion of the battery capacity to charge through regenerative braking may be required. Therefore, the distribution shows a high probability for high SoC but gets lower when approaching the full capacity (100%).

For every time step Δt, the total charged energy for each EV is calculated using (2). The EV charging power is assumed constant during the short time period Δt. The charged energy is compared with the required energy to decide ending the charging session. Also, a stop request by the EV user can terminate the charging and this has been given a probability of 1%. When the time slot is over, any EVs arriving for the next time slot is determined and this process is repeated for the whole day,

$$E_{t+\Delta t} = E_t + P_{ch} \times \Delta t \times \eta_c \tag{2}$$

where E is the energy, P_{ch} is the charging power during the interval Δt, and η_c is the battery charging efficiency.

III. Results and Discussion

The model remains under development, but the current version has been implemented with a (real) local (residential) population size of 50 EVs. Typical EV arrival patterns for two different days for the residential and passing traffic populations are shown in **Error! Reference source not found.**. Table I displays the total daily EV arrival for 7 days. The charging power drawn from the BESS at different time steps is shown in **Error! Reference source not found.** for two typical days. EV arrival is more likely during the daytime (8am to 6pm) which follows the plug-in time and traffic flow distributions. The arrival rate is low, but this is dependent on the fleet sizes, daily travelled distance and vehicle electrical range. The total charging power is used to estimate the energy delivered by the BESS. Accordingly, the SoC, number of discharging/charging cycles and the degradation rate for the BESS (major asset) can be estimated and considered for the optimal operation of the charging forecourt.

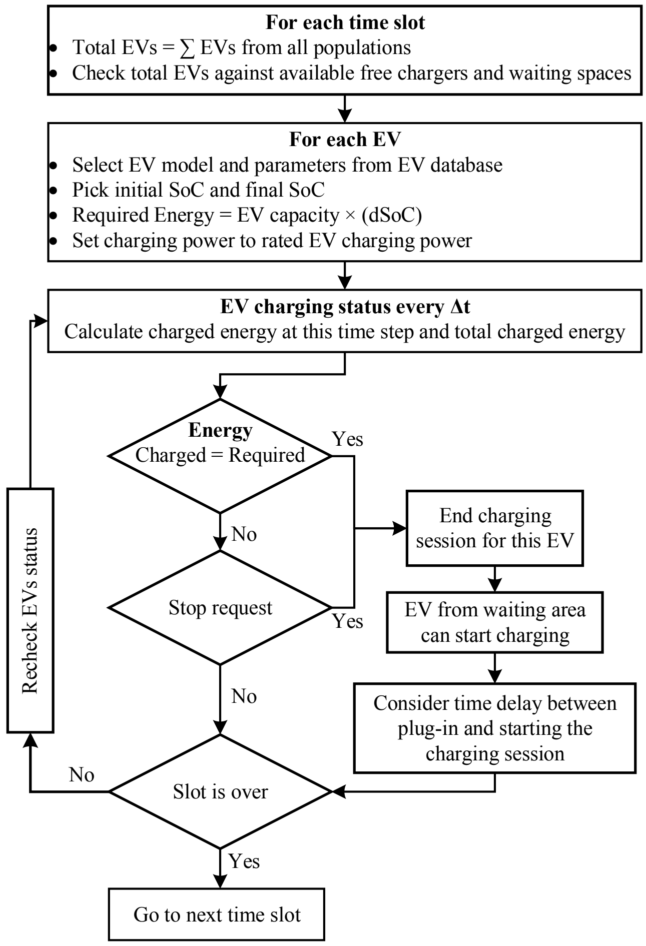

Fig. 6. Charging session operation.

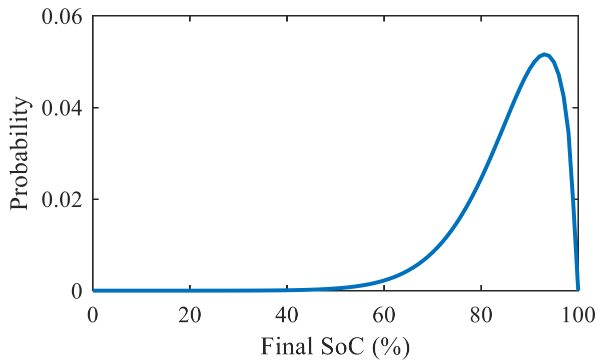

Fig. 7. Modelled final state of charge distribution. Data source: [22].

TABLE I. Total EV Arrival for 7 Days

Day	1	2	3	4	5	6	7
EV arrival	23	35	35	28	27	19	31

IV. Conclusions and Further Work

Home and on-street charging cannot deliver fast charging times, so super-fast EV charging forecourts are expected to spread across many countries in the next decade to help meet the growth in high-capacity (long range) EVs. Electric forecourts with BESS can provide other services to the power grid e.g. bulk power delivery or fast frequency support during peak load periods. This paper outlines a stochastic model to predict EV arrival for charging, aiding the optimal running of the forecourt. The model accounts for the stochastic nature of many parameters affecting the arrival rate e.g. plug-in start time, daily travelled distance and vehicle SoC. Steps to implement the proposed model have been discussed with defining important parameters and the corresponding possible sources. The model has been implemented using Matlab and sample of the results has been presented. Work is on-going to fully understand the effect of different populations and their characteristic parameters. Operational data from the site will enhance the model design. Detailed statistical analysis for different parameters affecting the arrival rate is to be considered in future work.

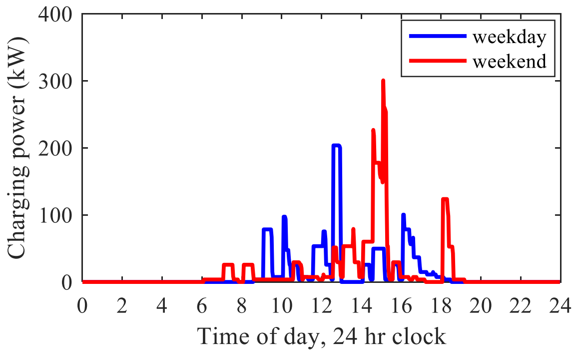

Fig. 8. Total charging power for typical weekday and weekend.

ACKNOWLEDGMENT

We gratefully acknowledgment financial support for this project from the UK Research Council (UKRI) through Innovate UK under grant No. TS/T006471/1. We thank our consortium partners GRIDSERVE, Upside Energy, and Essex County Council for constructive feedback on this work.

REFERENCES

[1] Committee on Climate Change, "Reducing UK emissions: 2019 Progress Report to Parliament," ed: London, UK, 2019.

[2] J. D. K. Bishop, C. J. Axon, M. Tran, D. Bonilla, D. Banister, and M. D. McCulloch, "Identifying the fuels and energy conversion technologies necessary to meet European passenger car emissions legislation to 2020," *Fuel,* vol. 99, pp. 88-105, 2012.

[3] S. Bubeck, J. Tomaschek, and U. Fahl, "Perspectives of electric mobility: Total cost of ownership of electric vehicles in Germany," *Transport Policy,* vol. 50, pp. 63-77, 2016.

[4] E. Azadfar, V. Sreeram, and D. Harries, "The investigation of the major factors influencing plug-in electric vehicle driving patterns and charging behaviour," *Renewable and Sustainable Energy Reviews,* vol. 42, pp. 1065-1076, 2015.

[5] HM Government, "Climate Change Act 2008 (2050 Target Amendment) (No. SI 2019 No. 1056)," ed: London, UK, 2019.

[6] Department for Transport, " The Road to ZeroNext steps towards cleaner road transport and delivering our Industrial Strategy," ed: London, UK, 2018.

[7] Department for Transport. "Statistics and data about the number of licensed vehicles." https://www.gov.uk/government/collections/vehicles-statistics (accessed 6/8/2020.

[8] EV-volumes. "Global xEV sales tracker." https://evboosters.com/ev-treasury-room-ev-volumes/ (accessed 6/8/2020.

[9] Zap-Map. "EV Charging Stats 2020." https://www.zap-map.com/statistics/ (accessed 6/8/2020.

[10] J. Su, T. T. Lie, and R. Zamora, "Modelling of large-scale electric vehicles charging demand: A New Zealand case study," *Electric Power Systems Research,* vol. 167, pp. 171-182, 2019, doi: 10.1016/j.epsr.2018.10.030.

[11] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of Load Demand Due to EV Battery Charging in Distribution Systems," *IEEE Transactions on Power Systems,* vol. 26, no. 2, pp. 802-810, 2011, doi: 10.1109/tpwrs.2010.2057456.

[12] N. H. Tehrani and P. Wang, "Probabilistic estimation of plug-in electric vehicles charging load profile," *Electric Power Systems Research,* vol. 124, pp. 133-143, 2015, doi: 10.1016/j.epsr.2015.03.010.

[13] A. Ul-Haq, C. Cecati, and E. El-Saadany, "Probabilistic modeling of electric vehicle charging pattern in a residential distribution network," *Electric Power Systems Research,* vol. 157, pp. 126-133, 2018, doi: 10.1016/j.epsr.2017.12.005.

[14] J. Zhu *et al.*, "Electric Vehicle Charging Load Forecasting: A Comparative Study of Deep Learning Approaches," *Energies,* vol. 12, no. 14, 2019, doi: 10.3390/en12142692.

[15] E. C. Kara, J. S. Macdonald, D. Black, M. Bérges, G. Hug, and S. Kiliccote, "Estimating the benefits of electric vehicle smart charging at non-residential locations: A data-driven approach," *Applied Energy,* vol. 155, pp. 515-525, 2015, doi: 10.1016/j.apenergy.2015.05.072.

[16] EV Database. "Electric Vehicle Database." https://ev-database.uk/cheatsheet (accessed 6/8/2020.

[17] Department for Transport. "Statistics and data about the National Travel Survey." https://www.gov.uk/government/collections/national-travel-survey-statistics (accessed 6/8/2020.

[18] M. G. Flammini, G. Prettico, A. Julea, G. Fulli, A. Mazza, and G. Chicco, "Statistical characterisation of the real transaction data gathered from electric vehicle charging stations," *Electric Power Systems Research,* vol. 166, pp. 136-150, 2019, doi: 10.1016/j.epsr.2018.09.022.

[19] E. Xydas, C. Marmaras, L. M. Cipcigan, N. Jenkins, S. Carroll, and M. Barker, "A data-driven approach for characterising the charging demand of electric vehicles: A UK case study," *Applied Energy,* vol. 162, pp. 763-771, 2016, doi: 10.1016/j.apenergy.2015.10.151.

[20] Department for Transport. "Experimental statistics on observed charging patterns for local authority rapid chargepoints in England in 2017." https://www.gov.uk/government/statistics/electric-chargepoint-analysis-2017-local-authority-rapids (accessed 6/8/2020.

[21] Department for Transport. "Road traffic statistics." https://roadtraffic.dft.gov.uk (accessed 6/8/2020.

[22] J. Schäuble, T. Kaschub, A. Ensslen, P. Jochem, and W. Fichtner, "Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany," *Journal of Cleaner Production,* vol. 150, pp. 253-266, 2017, doi: 10.1016/j.jclepro.2017.02.150.

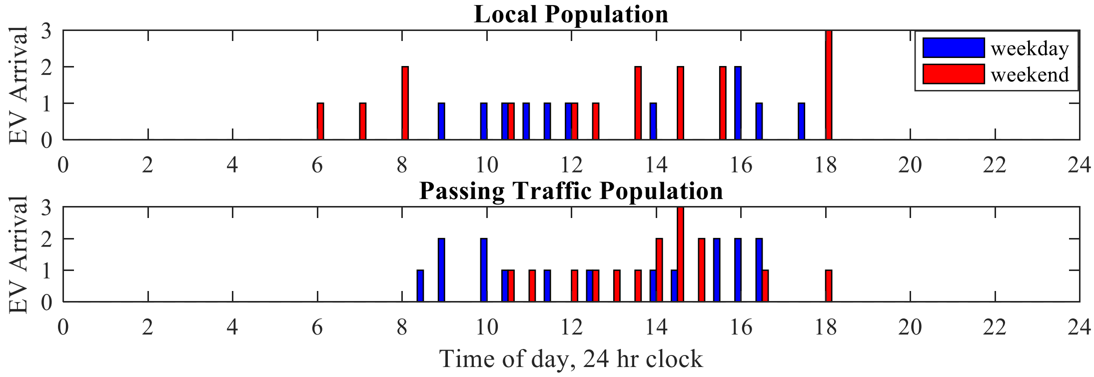

Fig. 9. EV arrival by time of the day.