Modelling Charging of Electric Vehicles Using Mixture of User Behaviours

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***Abstract*—With the rapid increase in the penetration level of electric vehicles (EVs), accurate modelling of the impacts of EVs on the electricity grid in cities is of important value to grid operators. In this paper, data from five charging stations (CSs) in Uppsala, Sweden are analysed. Then a spatial model is developed and validated using the previously analysed data. The results show that there is a big difference in the occupancy rate of stations. Some stations are more frequently used than others. Also, the energy charged in an average charging session is equivalent to driving for 27.7 km, which is 6% more than the daily driving distances in Uppsala. It is also shown that the load profile in some CSs is a mixture between two or more different load profile, for example residential and workplace profiles. The produced model can reflect the load of the charging stations when considering every CS to represent a mixture of different distinct charging profiles.**

I. Introduction

Electric vehicles (EVs) are quickly replacing the internal combustion engine vehicles (ICEVs). It is expected that there will be more than 10 million EVs on the road by 2020 compared with the 1.26 million in 2015 [1]. As a result of this increase several challenges concerning the charging infrastructure are expected to arise [2].

Few papers analysed data from CSs [3], for example [3]–[6]. The authors in [3] analysed data from three EV fleets in Germany. They used the data to develop a model for EV charging in which they compared three different charging scenarios. The analysis done in [4] showed that the charging frequency is higher in fast chargers compared with normal chargers. A non parametric Copula function along with Bayesian inference were used to develop the mobility patterns in [5]. The results were then validated using mobility data from a pilot EV demonstration trial. Data from eight CSs in Sweden were analysed in [6]. The authors noted that the charging frequency varies even between neighbouring stations.

In [7], a model for public fast and slow charging in Japan was developed. The model used Monte Carlo method with different states that indicated whether the vehicle is parked, driving or charging. The authors showed that the waiting time increases exponentially with the decrease of the number of fast chargers. A recent study showed that the charging behaviour have around 10% impact on the occupancy rate of charging stations (CSs) [8]. The authors then compared compared two different distributions for CSs: a uniformly distributed network, and distributed over both residential parking lots and petrol stations. The number of unused charging ports was shown to be higher in case of the uniformly distributed CSs network.

Markov models have been extensively used to describe travel patterns [9]–[14]. In [9], [10] a semi-Markov chain was developed to describe the traveling patterns. In [11] a hidden Markov chain model was developed. In [12] a Markov model with states representing different locations was used as basis for a controlled charging scheme, where an aggregator schedules charging of vehicles to minimise the power loss and ensuring that the grid voltage and power flow are within limits. An alternative method was presented in [13], where the states represented different trip purposes. Unlike the previous Markov models, the Markov chain states in [14] represented road junctions in a spatial network.

This paper complements the previous research gaps by analysing data from CSs in Sweden. In this paper, a spatial Markov chain model to generate a stochastic spatial load for EV charging in cities was developed and validated using the data from the Swedish CSs. Here, the authors explore the possibility of representing some CSs with several different charging profiles which, to the best of the authors' knowledge, was not done before.

A description of the used data in this paper is presented in Section II. The theoretical background for the modelling methods is presented in Section III. Section IV provides the results of the study, and conclusions are drawn in Section V.

II. Data

A. Charging stations data

Data from five CSs in Uppsala, Sweden were analysed in this paper. The data represented around 3000 charging sessions that took place from 30 June 2016 – 11 July 2017, though not all stations recorded data for the whole duration. For every charging session, the time plugged in, unplugging time, and the amount of charged energy were recorded. Table I presents a summary of the CSs. Charging frequency is defined as the number of charging sessions performed in the station per recorded day. This measure helps in identifying the more frequently occupied stations which depended on users' preferences. It can be seen from the table that there is a big variation between the charging frequency among the stations. Some stations with both high charging power and large number of charging ports are not as frequently occupied with their other stations with low

TABLE I
INFORMATION ABOUT THE CSS FROM WHICH THE VALIDATION DATA WERE OBTAINED.

Station	Charging power (kW)	Number of ports	Charging frequency
Station 1	3.7	8	7.3
Station 2	22	10	1
Station 3	22	4	0.6
Station 4	3.7	2	1.3
Station 5	22	2	3.2

charging power and small number of charging ports. It is also important to note that the charging frequency is not affected by the cost of charging, which is zero in all the stations in Uppsala. In Uppsala, drivers of EVs have only to pay the parking fee, similar to ICEVs, at the CSs and charging is done for free. Further studies are needed to determine the parameters that affect the charging frequency of CSs in Sweden.

The recorded data were used to generate a charging load for every CS. The load was further used to validate the developed spatial model.

B. Swedish mobility data

In this study we used data from the 2005–2006 Swedish travel survey [15]. This survey contained data regarding trips departure and arrival time, departure and arrival locations, trip distances, and reasons for trips. In this paper, the trips were grouped and categorised based on the arrival and departure locations. In total, three categories were formed: Work, Home, and Other [9]. Category "Work" contained locations like workplaces, schools, and universities. Residential locations were grouped in the "Home" category. Finally, the rest of the locations were considered to belong to the "Other" category. The "Other" category represents trips with shopping and leisure reasons. Data about trips between every two categories were grouped together to form six combinations of data.

Every location category was expected to represent a charging profile as presented in [9]. Workplace charging, taking place at the "Work" locations, is expected to have an early morning load profile mostly on weekdays. Residential charging, taking place at the "Home" locations, was expected to be a late afternoon or early evening charging load profile. The category of "Other" locations represented the charging profile of public parking lots which was expected to be a flat midday to late afternoon load profile.

III. METHODS

The model could be divided into three major building blocks. The first building block estimated the probabilities of performing trips, and it is presented in Section III-A. Section III-B describes the second building block which distributed the vehicles on a spatial network. Finally, the third building block estimated the charging load and it is presented in Section III-C.

A. Markov chain

A Markov chain is a stochastic process $\{X_t\}_{t=0}^{\infty}$ where the probability of the next state only depends on the probability of the current state [16], [17]:

$$P(X_{t+1} = j | X_t = i, ..., X_1, X_0) = P(X_{t+1} = j | X_t = i) \\ = p_{ij}, \quad (1)$$

where p_{ij} is the probability to transition from state i to state j. Both $i, j \in S = \{1, 2, 3, ..., M\}$, a state space with M states. The probabilities of transition from states can be presented as the transition matrix T:

$$T = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1M} \\ p_{21} & p_{22} & \cdots & p_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ p_{M1} & p_{M2} & \cdots & p_{MM} \end{pmatrix}. \quad (2)$$

Homogeneous Markov processes are Markov processes where the transition probabilities are not time dependent like the probabilities described in (1), (2) [17]. Non-homogeneous Markov processes are, conversely, Markov processes with a time dependent transition probabilities.

In this paper, a non-homogeneous Markov process with three parking states was used. The parking states represented the locations described in Section II-B. As a results, the state space S became $S = \{\text{Home, Work, Other}\}$. The time dependent transition matrix $T(\delta) = ((p_{ij}(\delta)))_{M\times M}$ replaced the homogeneous transition matrix in (2), where δ represented the time of the transition. The variable δ varied according to every minute in the day and wether the day is a weekday or a weekend. In total, there were 1440×2 transition matrices (minutes $\times$ days). Each transition matrix was estimated using the arrival statistics from the travel survey in a similar method to what was previously described in [13].

The decision to eliminate the driving states from the transition matrix was done for simplification reasons in [9], [10]. Similarly, in this paper the driving states were eliminated. This entails that vehicles alternate between parking states instantaneously in no driving time. In Sweden, the average car trip takes 44 ± 2 minutes (95% confidence interval) [18], which is shorter than the hourly meter used by the grid operators in Sweden. As a result, the error due to the elimination of the driving state, approximately 44 minutes of extra time connected to the charger at the end of every charging session, was assumed to have a small impact on the results of the model.

B. Spatial distribution of the EVs

The simulation assumed that the initial condition for the location of all vehicles in the beginning of the simulation was home, i.e., all vehicles were initially parked at home. Then for every vehicle, the Markov chain was used to determine the location state S of the vehicle at each time step. In case there was a change in the state S at time t, meaning $X_t \neq X_{t-1}$, the vehicle was randomly assigned to a parking lot in the city that belonged to the same location state S of the current time step X_t. This location of the vehicle was not changed until the vehicle changed its state S at a future time step.

At every transition of states S, which in turn changed locations in the city, the driving distance was randomly sampled from the traveling distances between similar states obtained from the travel survey [15].

C. Load estimation

The driving distance led to an instantaneous discharge of energy from the battery of the EV according to the AC consumption rate $\eta = 0.15$ kWh/km in summer and 0.25 kWh/km in winter, as shown in [19] and by assuming AC/DC conversion efficiency of 0.9 [20]. Winter months are defined as the months from December to March. In this model, there was no assumption regarding the battery capacity of the EVs. Instead, all EVs were assumed to have enough battery capacities to satisfy their planned trips, possibly in a near future scenario. As a result, only energy depletion was estimated, i.e., discharged energy of EVs were used instead of the state of charge in this paper. The discharged energy E (kWh) of the battery for vehicle n at time t is given by:

$$E_t^n = \begin{cases} E_{t-1}^n + C^\psi \times \Delta t & \text{if charging,} \\ E_{t-1}^n - \eta \times D & \text{if driving,} \\ E_{t-1}^n & \text{else,} \end{cases} \tag{3}$$

where C^ψ is the charging power (kW) of the station ψ, D is the distance (km) driven by the vehicle during the duration Δt [21]. The discharged energy $E_t^n \leq 0$ kWh was equal to zero when the EV had charged all the discharged energy consumed for all the prior trips.

Finally, the charging load P (kW) of each station ψ at time t is

$$P_t^\psi = C^\psi \times N_t^\psi, \tag{4}$$

where N_t^ψ is the number of charging vehicles in station ψ at time t.

IV. Results

The results of the analysis of the data from the CSs is presented in Section IV-A followed by the model results in Section IV-B.

A. Charging stations' data

The amount of energy consumed in the charging sessions in all the CSs is presented in a histogram in Fig. 1(a). The average energy consumed is 5 kWh, and 95% of the charging sessions consumed less than 16.9 kWh. Only two charging sessions consumed around 70 kWh. Estimating the equivalent driving distance for the charged energy, depicted in Fig. 1(b), showed that the average equivalent distance is 27.7 km. This distance is 1.7 km more than the average daily driving distance in large cities, like Uppsala, in Sweden [18]. It is, nonetheless, not clear wether the EV drivers charge once per day or once per multiple driving days. In case of the former, it can be concluded that the EV drivers and ICEV drivers have similar driving patterns, which is similar to the conclusion of a recent study [22]. On the other hand, if EVs charge once per multiple driving days, further studies using GPS tracking of vehicles are needed to estimate the daily driving distance.

The load of an average day of the stations is compared in Fig. 2. First, the load profile varied among the stations. Some stations have a more flat load profile, e.g., stations 1 and 4. The rest of the stations had one or multiple peaks in their load of the average day. The flat load profile can be attributed to a station that belongs to the "Other" location state, which in turn has a load profile that correspond to the public charging profile. It can also be noted that the load of each station varies with the occupancy of the station. Some stations with high charging power and a large number of charging ports are less frequently occupied compared with other stations with low charging power and small number of charging ports. More preferred stations have higher load compared to the less preferred counterparts regardless of the charging power of the ports in the CS. Further studies need to explore the criteria that influence the occupancy of the stations in Sweden.

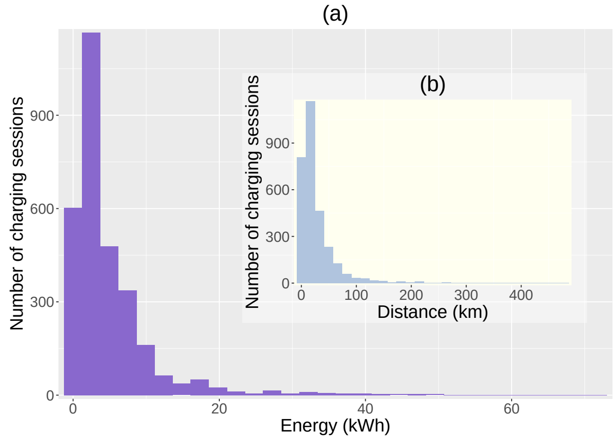

Fig. 1. Plot (a) presents a histogram of the amount of energy charged per charging session. Plot (b) presents the equivalent driving distance for the charged energy assuming the AC consumption rate η defined in Section III-C.

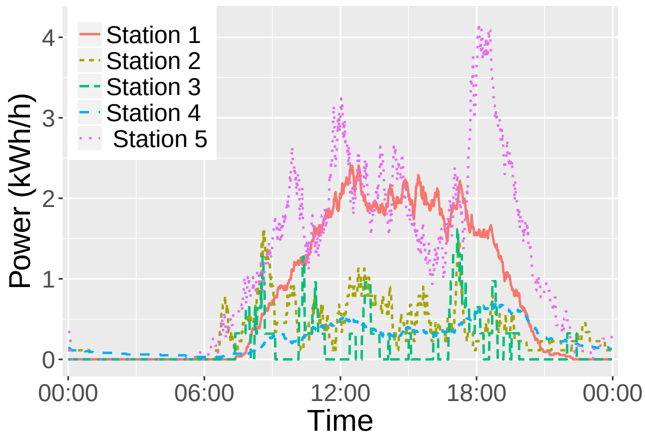

Fig. 2. The load of an average day of all CSs.

B. Model results

The model was used to generate the load of the validated CSs as shown in Fig. 3. Each station was simulated solely in a spatial network. This choice was made to aleviate the effect of the preference of the stations. In this simulation each station was modelled as a mixture of load profiles. The mixture of profiles for every station is presented in Table II. The choice of the mixture of profiles was made based on visual inspection of the modelled load and the actual load, i.e., through comparing Fig. 3 and Fig. 2. We can see that the model could represent the daily load of stations 1 and 4. However, the model could not represent the charging profile of Station 5, a station with only two charging ports, using two charging profiles. This station could better

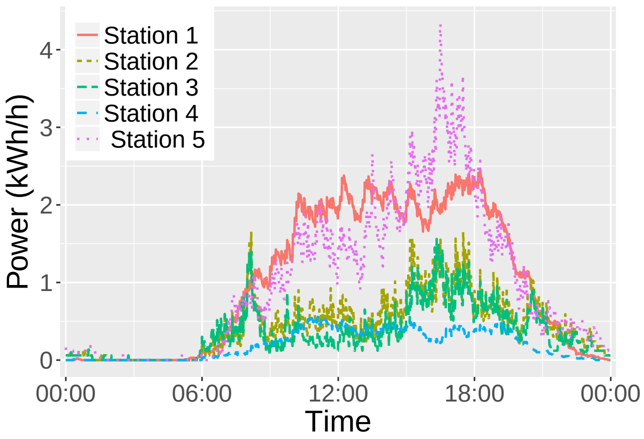

Fig. 3. The load of CSs as generated by the model.

TABLE II
THE MIXTURES OF CHARGING PROFILES THAT BEST REPRESENTED EACH STATION.

Station	Number of ports		
	Workplace	Residential	Public
Station 1	–	–	8
Station 2	1	7	2
Station 3	1	2	1
Station 4	–	–	2
Station 5	–	1	1

be represented by three charging profiles. On the other hand, stations, 2 and 3 had the lowest charging frequency and the model could not reflect this low, almost zero during most of the day, occupancy. In station 2, on average a charging event takes place at once every 10 days for each charging port. Each port in station 3 has on average one vehicle connected roughly once every week.

In a larger spatial network with higher EV penetration the differences in the charging frequency between station might be small. Moreover, fewer CSs might have very low charging frequency. This would result in a more predictable charging load. In this case the spatial model developed here could accurately reflect the load profiles.

V. Conclusion

This paper analysed the load measured from five CSs in Uppsala, Sweden. The analysis revealed that the mean recorded energy consumed during a charging session is 5 kWh. Moreover, it was estimated that the mean equivalent driving distance per charging session is 27.7 km. Some CSs had several daily peaks. These stations could better be modelled as a mixture of different load profiles, i.e., these stations are occupied by different EVs during the day periods. A clear difference in the charging frequency between stations were noticed. This difference indicated an uneven preference of EV owners towards CSs.

A spatial Markov chain model was developed in this paper. The load from the CSs were used to validate the model. The model was used to generate the load for each station. Some stations were simulated as a mixture of different load profiles. The results showed that the model could represent the frequently occupied stations better than the seldom occupied ones.

Further research could explore a method to incorporate the user preferences in the spatial occupancy of the CSs. Moreover, research is needed to estimate the criteria of preference of EV owners.

The developed model could be further used to generate EV charging data for grid studies as well as planning.

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