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Spatial Markov chain model for electric vehicle charging in cities using geographical information system (GIS) data

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Abstract

In the recent years, the number of electric vehicles (EVs) on the road have been rapidly increasing. Charging this increasing number of EVs is expected to have an impact on the electricity grid especially if high charging powers and opportunistic charging are used. Several models have been proposed to quantify this impact. Multiple papers have observed that the charging stations are used by multiple users during the day. However, this observation was not assumed in any previous model. Moreover, none of the previous models relied on geospatial maps to extract information about the parking lots—where charging stations are installed—and the charging profiles of the potential users of these charging stations.

In this paper, a spatial Markov chain model is developed to model the charging load of EVs in cities. The model assumes three distinct charging profiles: Work, Home, and Other. Geospatial maps were used to estimate the charging profile, or mixture of profiles, of the charging stations based on the nearby building types.

A case study was made on the city of Uppsala, Sweden—a city with approximately 44,000 cars. The results of the case study indicated that the aggregate load of the EVs in the city reduced the charging impact. For example when using 22 kW chargers, the peak load in the city per EV was estimated to be 1.29 kW/car in case of spatio-temporally opportunistic charging, and 1.47 kW/car in case of residential only opportunistic charging. This is to say that the Swedish grid operators can expect that every EV in the city will increase the peak load by at most 1.47 kW due to aggregation; this is assuming that 22 kW chargers were used.

In addition, we showed that the minute-minute variability of the charging load in cities might cause some future challenges. In our case, up to 3% of the EVs in the city simultaneously started charging. This caused a one-minute-ramp in the charging load of 1.1 MW—if charging using 3.7 kW. Charging with higher powers will exacerbate these ramps, e.g., charging with 22 kW will cause sudden one-minute-increases as high as 6.7 MW in the charging load. Such a finding indicates that using high charging powers might cause high variability in the charging load of EVs in cities. This high variability might limit the synergy potentials between EVs and variable renewable energy sources (RES).

The proposed model can potentially be used along with RES models to estimate the spatio-temporal synergy potentials between the two technologies. Evaluating the synergy potentials might be of value to grid operators, policy makers, market traders, etc.

Keywords: Electric vehicles, Spatial electric vehicles charging model, Public charging infrastructure, Spatial load of electric vehicles.

1. Introduction

A rapid increase in the new registrations of electric vehicles (EVs) has been witnessed in the recent years [1]. In 2016, the growth rate of the publicly available charging has exceeded the growth rate of the EV stock, 72% compared with 60% [1]. The importance of estimating the impacts of charging EVs on the electricity grid increases with the increase in the EV penetration.

Multiple models for quantifying the EV charging load have been proposed in the literature. In [2], a non-

homogenous Markov chain model with three parking states and one driving state was proposed. In this study, the day was divided into 144 time steps, 10 minutes each. The authors assumed uncontrolled charging in two test locations a workplace and residential. For the workplace location, 100 EVs were simulated in a university network with 1,000 kVA transformer. The peak load increased from approximately 350 kVA to 650 kVA due to charging the EVs using 7.4 kW chargers. The authors noted that had it not been for the oversized transformer—1,000 kVA transformer supplying 350 kVA load—a transformer failure would have occurred. In the residential network, 17 households in a single phase distribution grid were simulated. The duration of the voltage bound violation reached 5 hours for the 100% EV penetration and 2.3 kW chargers.

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List of Abbreviations

<i>EV</i>	Electric vehicle.	<i>OSM</i>	OpenStreetMap.
<i>GIS</i>	Geographical information system.	<i>PV</i>	Photovoltaics.
<i>GPS</i>	Global positioning system.	<i>RES</i>	Renewable energy sources.
<i>KNN</i>	K-nearest neighbor.	<i>SOC</i>	State of charge.
<i>LiDAR</i>	Light detection and ranging.		

In [3], a Markov chain Monte Carlo model was developed. Three states were assumed: drive, park, and charge. Three different trip reasons were assumed: work, shopping and leisure. Based on their mobility patterns, the peak of weekend uncontrolled charging was later than that of weekday, 19:00–21:00 compared with 18:00–20:00. This observation highlights the influence of the mobility pattern of the studied country or city on the shape of charging load profile. A multiple driving states Markov model was presented in [4]. Each driving state representing a trip reason. This resulted in a model with 13 different states. Using a different approach, Rolink and Rehtanz [5] were able to eliminate the driving states from their model and still produce accurate results.

As regards the spatial EV models, Fraile-Ardanuy et al. [6] used global positioning system (GPS) data from taxi fleet to develop a spatial charging model for taxis. The authors assumed that every 30 minutes or longer stop could be used for charging the EV. The aim of the model was to spatially quantify the energy demand of the taxi fleet such that a fleet owner can plan the locations of charging stations.

Ref. [7] employed a Markov chain traffic model to develop a spatio-temporal model for EV charging in urban areas. In the model, public, private and fast charging stations were included. The Markov chain states in this model represented road junctions unlike the previously mentioned Markov chain models. Moreover, the authors assumed that the charging stations were used by multiple consecutive users during the day.

Shun et al. [8] developed a trip chain Monte Carlo model. The model shared the concept of the parking states with the Markov chain model. In their study, the authors assumed 6 parking states, and charging could take place in only five states. Three charging scenarios were simulated. In the first scenario, uncontrolled charging throughout the city was assumed. In this scenario, the EVs were charged if the state of charge (SOC) was less than 50%. The second scenario was similar to the first, but residential charging was always preferred regardless of the SOC. In the third scenario, off-peak (from 22:00 to 06:00) residential charging was added to the second scenario. The results showed a difference in the peak load and peak time among the scenarios. The peak load was approximately 80 MW,

100 MW, and 120 MW for the first, second, and third scenarios, respectively. The charging energy demand on weekdays and weekends appeared similar—weekdays were higher by 1.6%–1.7%—which might be unlikely in a real scenario due to the different driving distances between weekday and weekend trips.

A similar approach was done in [9] where a Markov decision process was used to model the trip destinations. Three parking states were assumed: home, work, and other. Each charging station was assumed to belong to a unique parking state. A spatial network with area of 660 km² and an average daily driving distance of 50 km was studied. In total, 17 charging stations (7 homes, 6 workplaces, and 4 other) and 300,000 EVs with 3.3 kW charging power were studied.

In a recent study, Muratori [10] studied the impacts of uncontrolled charging on the residential demand. In his study, the load of 200 households and up to 348 EVs was modeled. Two charging powers 1.92 kW and 6.6 kW were compared. The author noted that the higher charging power induced higher peaks even though the number of simultaneously charging EVs was reduced. For example at 100% EV penetration, the number of simultaneously charging EVs was reduced by 55% while the peak increase per household increased by 70% when the 6.6 kW chargers were used instead of the 1.92 kW chargers. The impact of fast charging on the number of simultaneously charging EVs and the peak load can be influenced by 1) the rate and time of arrival of EVs to the station, 2) the energy demand of the arriving EVs. In the case study presented in [10], the number of simultaneously charged EVs was halved when tripling the charging power.

Neaimeh et al. [11] used a Monte Carlo model based on records from 19,000 charging events along with smart meter residential data to develop a spatio-temporal EV model. The authors noted that the energy efficiency of drivers varied by as much as 32% on the same route. This variation might be explained by the ambient temperature, as shown in [12]. The results showed that the urban networks are more resilient and can withstand up to 60% EV penetration compared with 15% for the rural network.

In a recent study, Mureddu et al. [13] studied the energy balance of renewable energy sources (RES) and EVs in the island of Sardinia, Italy. The authors investigated

the transmission grid power flow due to the unbalances which were induced by the charging the 700,000 EVs included in the study. The results indicated that the current RES could supply the charging load of EVs, however, not spatially. Li et al. [14] compared a deterministic and a stochastic spatial models for EV charging in Australia. In the deterministic model, the travel survey trips were directly used to estimate the charging load. On the other hand, the stochastic model relied on a k-nearest neighbor (KNN) algorithm to generate arrival and parking times of trips. The authors used geographical information system (GIS) data in their model, however, the resolution of the model was coarse—9 km × 9 km square grid.

In the literature, there seems to be a shift towards clustering the EV charging patterns into three categories Work, Home, and Other [2, 3, 9, 15]. Each category typically have a distinct load profile, where the category Work has an early morning peak representing charging at workplaces, schools, and universities. The category Home has a late afternoon peak representing charging at residential places. The category Other, however, has a flat profile which represent charging at shopping and leisure locations.

It is important to state that the shape of the load profile of the category differed among studies. For example in [9], the category Other had a flat profile with a late afternoon peak, while the category Work had a flat profile. In [15] on the other hand, the category Other’s charging had an early morning peak. Moreover, the authors showed that the category Home’s charging differed between rural and urban locations. Finally, Shun et al. [8] differentiated between shopping and leisure locations. This is to say that the shape of the load profile for the three categories depended on the travel patterns used in the study and on the assumptions behind which places belong to which category.

As noted by [9], the spatio-temporal modeling of EVs is still in development stage. Moreover, it has been demonstrated that the spatio-temporal aspect of the mobility of EVs reduced the severity of the impact on the grid [11], thereby exposing the importance of the spatio-temporal implementations in future models. From the previous literature review, the authors were able to identify three research gaps which are going to be complemented in this study:

1. Ref. [11, 16, 17] showed that the charging stations had a load which represented a mixture of charging profiles. In other words, the charging stations are used by multiple users during the day, and these users had different charging behaviors. For example in the university charging station studied in [16], some charging events occurred after 18:00. This can be presumed to be due to non-employees charging their EVs at the university. The authors, here, are not aware of any previous study that has modeled the mixture usage profiles for the charging stations.
2. The reliance on maps and light detection and ranging

(LiDAR) data is widely adopted in the RES potential studies—see [18]. However, for the EV load modeling, this is not the case. The authors are not aware of any previous paper that used GIS data to extract the locations of parking lots and cluster them according to the usage profile based on the types of the nearby buildings.

3. The author in [10] showed that when tripling the charging power, the number of simultaneously charging EVs was halved. The aggregated load, nonetheless, was higher for the high charging power compared with the low one. More levels of charging powers, and different driving patterns so far have not been studied.

In this study, the authors attempt to contribute to the field of modeling the spatial opportunistic EV charging load in cities—similar to e.g., [5, 14, 15]. The attempt to fulfill the first and second research gaps was made by developing a novel EV charging model. Unlike the previous contributions, the model employs GIS data to extract the locations of parking lots and the charging profiles of the charging stations in these parking lots based on the nearby buildings types. This is expected to result in a mixture of usage profiles for the charging stations if different building types were close to the parking lot. In the case study, three charging powers were compared and a different driving pattern was used, thereby contributing to the third research gap.

The model developed here can be used along with RES models to quantify the spatio-temporal synergy potential between EVs and RES in cities. Studies with deterministic EV models, e.g., [19, 20], can be improved by employing the proposed model.

This paper is organized as follows. The methodology of the model is presented in Section 2. A method to fulfill the first and the second research gaps is provided in Section 2.2. In Section 3, a case study is presented, where the authors attempted to fulfill the third research gap by simulating various charging powers and a different driving pattern, namely the Swedish driving pattern. An analysis of the results of the case study is presented in Section 4. Conclusions are finally drawn in Section 5.

2. Method

2.1. Outline of the proposed model

The proposed model can be divided into three major components as shown in Figure 1. The first component, component A, extracts the parking lot data from maps and cluster them into types. This is presented in Section 2.2. The output of the first component is used by the second component, component B, where a non-homogeneous Markov chain is employed to spatially locate the EVs at every time step and calculate the charging load. This is described in Sections 2.3 and 2.4. In part C of the model, the results of the charging stations are spatially collected and allocated to their respective parking lots.

Figure 1: A layout of the spatial model developed in this paper.

2.2. Stations clustering

One of the main contributions of this study is the utilization of map data to spatially locate parking lots and extract their feature data. This model was designed so that it can be employed using open source data such as OpenStreetMap (OSM) data or other proprietary map data as long as it contains information about the shapes of the parking lots and the buildings—including the types of the buildings—in the studied area. OSM data were used before in [21, 22] for land use clustering.

This part of the model is supposed to extract the parking lots from the map data and to cluster these parking lots into types of usage behavior, Work, Home, and Other or mixture thereof. Buildings in a city can be categorized into workplaces, residential, and other buildings; each category correspond to a parking lot usage behavior. It is expected in a large city that the drivers of EVs will park near the visited locations [23, 24], especially if the parking fees are neglected [24]. Also different building categories might be

Figure 2: Imaginary map representing the buildings located within a randomly chosen buffer zone—the black solid line—from a parking lot. The buffer zone represents the maximum walking distance from the parking lot to the visited building. In this imaginary case, the buildings visited by users of this parking lot are workplaces and other, thereby the parking profile in this parking lot is a mixture between the Work and Other profiles, i.e., Work-Other. If no nearby buildings were found the parking lot is assumed to have an equal mixture of the three profiles: Work, Home, and Other.

located within the same walking distance from a parking lot.

In this model, the map data are used to cluster the buildings into one of the three categories, workplaces, residential, and other types. A buffer zone is assumed around the parking lots—obtained from the map data—representing the walking distance between the parking lot and the building visited by the EV driver. The buffer zone is estimated by specifying a buffer distance around a parking lot. The buffer distance—also called the air distance—was used before in parking models such as [25], and optimizing charging stations for taxis in [26]. In our model, the buildings within the buffer distance are considered to be visited by the drivers parking in this specific parking lot. Consequently, the parking profile in the parking lot is connected to the categories of the nearby building categories.

For example, Figure 2 depicts an imaginary parking lot surrounded by some buildings. After extracting the nearby buildings—the buildings intersecting the buffer zone—the parking lot is assumed to have the types of charging reflecting the categories of the nearby building categories. In our parking lot example depicted in Figure 2, the parking lot is assumed to be Work-Other parking lot. This means that this parking lot is used by visitors of both workplaces and other building categories, thereby making the overall parking profile in the parking lot a mixture of two distinct profiles.

Finally one or more charging stations are created for each parking lot depending on the nearby building categories. Each charging station is assumed to have an area which is proportional to the nearby building footprint areas belonging to each category. In case there were no nearby buildings the parking lot was equally divided into the three parking categories, i.e. three equally sized stations were created. Each charging station is assumed to

have a number of charging ports representing the number of parking places in the station. An area per car is assumed to determine the number of parking places per square meter parking lot area.

The reason for creating multiple charging stations for each parking lot is that it enables careful analysis of different types of charging, for example Home only or Work only charging. Moreover, this enables accurate estimation of the load for the different charging profiles. In the end of the simulation, the results of the several charging stations are then summed to calculate the load for every parking lot, as depicted in part C in Figure 1.

2.3. Markov chain model

In this section, a mathematical representation of a general Markov process is provided. Reviewing Ref. [27, 28] is encouraged, if more deep details about Markov chains are sought. A Markov chain is a stochastic process that follows the Markov property, which entails that the conditional probability of the next state depends only on the current state. A stochastic process $\{X_t\}_{t=0}^{\infty}$ is a Markov chain in an M-state-space $S = \{1, 2, \dots, M\}$ if,

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

where p_{ij} is the transition probability for transitioning from state i to state j , where i & $j \in S$, and $\sum_{j=1}^M p_{ij} = 1$, for all i . The previous Markov chain, in Equation 1, is a homogeneous Markov chain since the conditional probability of the next state is independent of the time t , and it can be represented by a transition matrix:

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

When calibrating the model with data, it can be shown that the optimal estimate of the transition probability using the maximum likelihood estimate is

$$p_{ij} = \frac{N_{ij}}{\sum_{j=1}^M N_{ij}}, \quad (3)$$

where N_{ij} is the number of observed transitions from state i to state j [27].

The method of estimating the future state given the transition matrix T , as was also used in Widén et al. [29], is presented in Algorithm 1. In this algorithm, the authors presented the procedure for a four states Markov process, i.e., $M = 4$, but the algorithm can be implemented for other processes with a different number of states.

A non-homogeneous Markov chain is a Markov chain whose transition matrix is time dependent. In practical traffic modeling, the transition matrix probabilities vary

Algorithm 1: Estimating the states for an example Markov process with four states, $M = 4$.

Data: The transition matrix T

Initialize $X_1 = i$;

for $t = 2 : \infty$ **do**

 Generate uniform random number U in $[0, 1]$;

if $0 \leq U < p_{i1}$ **then**

$X_t = 1$;

else if $p_{i1} \leq U < p_{i1} + p_{i2}$ **then**

$X_t = 2$;

else if $p_{i1} + p_{i2} \leq U < p_{i1} + p_{i2} + p_{i3}$ **then**

$X_t = 3$;

else if $p_{i1} + p_{i2} + p_{i3} \leq U$ **then**

$X_t = 4$;

end

during the day due to the hourly change in traveling patterns between the different states [7, 30]. For example, the probability of departing home at midnight is not equal to the same departing probability at midday. Moreover, the transition matrix depends on the day of the week. Weekend travel patterns are not similar to weekday patterns. As a result, the transition matrix defined in Equation 2 was made time dependent: $T(\delta) = ((p_{ij}(\delta)))_{M \times M}$ where δ is a variable that varied based on the minute of the day and whether the day was a normal working day or a weekend. Thus in total there were 2,880 transition matrices 1,440 minutes a day $\times$ 2 days (a weekday and a weekend). Algorithm 1 was adapted to calculate the states given the time dependent transition matrices as described in part B step I in Figure 1.

2.4. Spatial load

The spatial clustering of the model provided a set of stations with various types: Home, Work, and Other. Each type of station is considered to be represented by one state S of the Markov chain, i.e., $S = \{\text{Work, Home, Other}\}$ and $M = 3$. When an EV transitions from one state to another state at a specific time step, the model randomly assigns the EV to a location in the city that belonged to the new state, see part B step II in Figure 1. If no transition between states takes place, the EV is assumed to remain in its location, i.e., EVs change locations in the city when they change the state. The authors here, following [5], decided to eliminate the driving state from the Markov chain for simplicity reasons. The EVs instead switch between parking states with zero driving time. This assumption is expected not to have an adverse effect on the results, since in Sweden the average car trip takes 44 ± 2 minutes (95% confidence interval) [31]. This trip duration is shorter than the hourly meter used by the grid operators in Sweden. Thus, the error due to eliminating the driving state is estimated to be 44 extra minutes of connection to the charger in the previous station in the end of every charging session.

As defined by Grahn et al. [32], the depleted capacity E (kWh) of the battery of vehicle n at time t is given by

$$E_t^n = \begin{cases} E_{t-1}^n + C^\psi \times \Delta t & \text{if charging at station } \psi, \\ E_{t-1}^n - \eta \times D & \text{if driving,} \\ E_{t-1}^n & \text{else,} \end{cases} \quad (4)$$

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 . The electricity consumption η (kWh/km) is the AC electrical energy needed to drive one kilometer. In this paper, the driving is assumed to be instantaneous, $\Delta t = 0$, when a change of state occur, and the distance D was sampled from the measured trip distance between the two states.

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

$$P_t^\psi = C^\psi \times m_t^\psi, \quad (5)$$

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

The authors defined a metric, the normalized power $\tilde{P}_t$, to measure the load of each car in the city in (kW/car). The metric is defined as the load per number of cars in the simulation—or EVs in the city. This metric was evaluated for the total load in the city and for the different charging profiles, i.e., Work, Home, and Other, and was estimated according to

$$\tilde{P}_t = \frac{1}{n_{EV}} \sum_{\psi \in n_{st}} P_t^\psi, \quad (6)$$

where n_{EV} is the number of EVs in the city and n_{st} is the set of charging stations belonging to one charging profile, Work for example, or all the stations in the city. This metric measured the expected charging load per EV in the city with different charging powers. The peak value of $\tilde{P}_t$ (kW/car) is named the peak of the normalized power (PNP).

3. Case study

In this paper, Uppsala—a medium sized city in Sweden with approximately 220,000 inhabitants—was selected for a case study where various charging powers and various penetration levels for EVs were simulated. Table 1 presents the assumed parameters used in the case study.

The map of the city is presented in Figure 3. The buildings were obtained from the Swedish land survey maps [33]. The map of the parking lots was obtained from OSM [34], since they were not provided in [33]. It is important to state that the model can solely rely on OSM maps in case of unavailability of official maps. The authors assumed that workplaces included buildings categorized by the Swedish land survey to belong to the industries, schools, universities, hospitals, government related buildings, and unspecified workplace buildings. Other buildings were assumed to be the buildings that the Swedish land

Parameter	Simulated values
Penetration level (%)	25, 50, 75, 100
Charging power (kW)	3.7, 6.9, 22
Charging location	Everywhere, Home only
Buffer distance (m)	100
Area per car (m ²)	28
η (kWh/km)	0.25
Time resolution (min)	1

Table 1: Simulated parameters.

survey categorized to be sports and cultural related buildings along with the unspecified buildings.

In Uppsala there were 44,192 personal cars in 2016 according to [35]. In this study, the authors simulated the future scenarios of 25%, 50%, 75%, and 100% penetration levels of EVs. In addition, the authors relied on the Swedish travel survey [36] to model the mobility of EVs in the city. Data from this travel survey were used to estimate the transition matrices following the same methodology presented before in [32] and by sampling 12,000 trips—equal the number of recorded trips on the weekday, see [32] for a detailed description of this methodology.

In Uppsala, 3.7 kW and 22 kW chargers are used in the majority—79%—of the charging ports [37]. In addition, the authors here simulated the 6.9 kW charging power following Ref. [32]. This power was included as an intermediate power for two reasons: to better see the impact of the two extremes, and to see the effects of the change of the charging power on the peak load in the city, see research gap number 3 in Section 1.

As regards the locations in which the EVs can charge two possibilities were simulated representing two possible future scenarios. In the first opportunistic charging was enabled in all locations in the city, following [4, 14]. In other words, the EVs can charge whenever they are parked regardless of their location. The second possibility assumes that the vehicles are only allowed to charge at residential locations, thereby representing the future scenario of exclusive residential charging in cities, following [3, 10, 32]. Home charging is preferred among EV owners and the lack thereof is one of the barriers to the purchase of EVs [38, 39].

A reasonable buffer distance is equal to the acceptable walking distance from the parking lot to the destination building which is dependent on such factors as type of users, age of users, reason of trip, frequency of trip, weather condition, walking environment, security concerns, etc [40, 41]. In the survey made in [42], the maximum walking distance for work related trips was 50 m and 100 m for weekday work and shopping, respectively. On the weekends, the maximum walking distance became 500 m for shopping related trips. In another survey [43], the majority of respondents—who had dedicated parking location—either parked in their yard or within less than

Figure 3: A spatial map for the city of Uppsala.

100 m from their residence. Smith and Butcher [40] proposed that the maximum acceptable walking distance of the ideal design of an outdoor uncovered parking lot should be less than 400 ft.—approximately 122 m—neglecting the climate. In this paper, the authors considered a 100 m buffer distance to be a reasonable assumption. A sensitivity analysis of this assumed value is presented in Section 4.5.

Similar to the buffer distance, there was no universal estimate for the area of parking lot per car since it depends on many parameters such as the parking lot design standards in the country, the number and direction of driving lanes in the parking lot, the landscape of the parking lot, etc. In the parking lot design examples provided in [44], the examples had an area per car which ranged from 28–49 m²/car. It was assumed in this case study that the area per car to be 28 m²/car. This value resulted in the largest number of parking places which best matched the number of cars currently registered in the city of Uppsala.

In total, there were 49,919, 27,293, 8,728 Home, Work, and Other parking places, respectively. This resulted in a 1.94 parking place per vehicle in the city, which is close to the 2.2 estimated for the USA in [45]. The 49,919 Home parking places are divided into 19,929 parking places in publicly accessible parking lots and 29,990 parking places in villas—2 assumed parking places per villa. All the previously mentioned parking places were assumed to have charging ports. The authors assumed that there were enough parking places in every location, for example Other, to satisfy park all the simulated vehicles, thus new parking lots were added without charging. The reason for this is to prevent errors if they arise in the case of more EVs parking in a certain parking type than the number of places allow. Say, for example, 9,000 EVs need to park in the clustered 8,728 Other parking places.

The electricity consumption η , following [46], is assumed to be 0.25 kWh/km to represent winter driving. A detailed evaluation for the impacts of temperature on η can be found in [47, 48]. In this study the depleted capacity E of EVs is assumed to always be less than or equal to 0 where it is zero when the battery is fully charged. All vehicles are assumed to have sufficient battery capacity to perform their planned trips until charging, thus, the exact battery capacity of each vehicle is irrelevant in the study. This assumption is considered to be realistic given that Jakobsson et al. [49] showed that, in Germany and Sweden, an EV with 400 km range could satisfy around 80% of the daily needs of the drivers and around 15% of the drivers will have to adapt their driving once per month. The sampled trip distance D was assumed to not exceed 200 km, i.e. trips with larger distance than 200 km were excluded from this study. These trips, 0.44% of the recorded trips, were considered to require fast highway chargers and will not charge in the conventional parking lots in the city.

Figure 4: Load profile of an average day for the 25% penetration level case charging opportunistically everywhere, subplot (a). Subplot (b) presents a violin plot of the normalized power P_t for every charging power.

Figure 5: Load profile of an average day for the 100% penetration level case charging opportunistically everywhere, subplot (a). Subplot (b) presents a violin plot of the normalized power P_t for every charging power.

4. Results

The results of the penetration level and the charging power on the total load in the city is presented in Section 4.1. The load of the three charging types is presented in Section 4.2. Section 4.3 presents the measured peak power at different time resolutions. Finally, the spatial load in the city is presented in Section 4.4.

4.1. Total load in the city

The total load from the simulations of 25% and 100% penetration levels are presented in Figures 4 to 7, where everywhere charging load profiles are presented in Figures 4 and 5 and Home only charging in Figures 6 and 7.

For the everywhere charging case, the load of an average day seems to have two peaks representing the early morning Work charging and the late afternoon Home charging. Unlike in [10], the PNP in the city did not change as the penetration level changed, instead it increased as the charging power increased. This increase, however, was smaller than the increase in the charging power—both measured in percentage. Moreover, as shown in the violin plots the probability of having extreme peak powers

Figure 6: Load profile of an average day for the 25% penetration level case charging only at Home, subplot (a). Subplot (b) presents a violin plot of the normalized power $\bar{P}_t$ for every charging power.

Figure 7: Load profile of an average day for 100% penetration level case charging only at Home, subplot (a). Subplot (b) presents a violin plot of the normalized power $\bar{P}_t$ for every charging power.

Figure 8: The number of arriving trips recorded in each minute in the hour obtained from the travel survey.

Figure 9: Histogram of the estimated—from the load profile—minute-minute changes in the number of simultaneously charging EVs for the simulation of the 3.7 kW 25% penetration level. A positive value means that the number of simultaneously charging EVs in the city increased from one minute to the next. A negative value means that the number of simultaneously charging EVs in the city decreased from one minute to the next.

became less frequent as the charging power increased. For example in the 25% penetration case, the 95th percentile of the load was at 83.37% and 53.6% of the peak load value for the charging powers 3.7 kW and 22 kW respectively.

For the Home charging case, the load of an average day peaked higher than that of the everywhere charging case. This was expected since everywhere charging reduced the charging requirements at Home and the range anxiety [50, 51], which in turn changed the shape of the load profile.

In Figures 4 to 7, abrupt changes in the charging power was conspicuous on minute basis. These changes echoed the changes in the number of simultaneously charging EVs in the city as it increased when new EVs started charging, and as it decreased when already charging EVs finished charging. One important factor which impacted these power spikes was traced back to the data obtained from the travel survey. As shown in Figure 8, the vast majority—91%—of the recorded trips by the survey respondents arrived sharply on a 5 minute basis. In fact, 25.4% of the recorded trips arrived either on the hour or on the half hour—minutes 0 and 30. Consequently, sudden increases in the number of charging EVs occurred on 5 minute intervals as new EVs arrived to their new locations.

On the other hand, the time at which an EV would finish charging depended on the amount of energy needed and the charging power, and no patterns were observed for these two parameters. As a result, the decreases in the charging power in the city was not as abrupt as the increases.

For example, in the simulation of 25% penetration level with 3.7 kW, presented in Figure 4, the estimated minute-minute changes in the number of simultaneously charging EVs is presented in Figure 9. A positive value means the number of simultaneously charging EVs increased from one minute to the next, while a negative value means that the number of simultaneously charging EVs decreased from one minute to the next. The minute-minute increase in the

Figure 10: Load profile of an average day for the 25% penetration level case charging with 3.7 kW in the different locations, subplot (a). Subplot (b) presents a violin plot of the the normalized power $\bar{P}_t$ for every charging type.

number of simultaneously charging EVs never exceeded 306 EVs, or 3% of the EVs in the simulation. This number of EVs, nonetheless, increased the load by 1.1 MW, and as the charging power increases the impact of these relatively small minute-minute changes in the number of charging EVs is expected to become more severe. The authors are not aware of any previous analysis of the impacts of this phenomenon on the system components such as transformers. However, in the field of RES this phenomenon was studied extensively, see for example [52, 53]. This might be because the minute load was rarely presented in the previous EV model contributions. Accurate evaluations of this phenomena are needed since some contributions proposed alleviating the impacts of RES variability by using EVs [54], such a proposal might be challenging to achieve if the load of EVs was also highly variable. This is left for future studies to investigate.

It is important to state that evaluating the accuracy of the travel survey is beyond the scope of this study. Instead it is left for future work. The respondents to the travel survey might have approximated their arrival time, in such a case randomizing the arrival time within 5 minutes might be a reasonable approximation. Moreover, the same phenomenon was observed in the results of the 2009 national household travel survey [55], used before in for example [56, 57], where 76.5% of the recorded arrival times were sharply on a 5 minute basis. Hence, the authors decided not to attempt to repair the published survey data and instead study the effects of the time resolution on the peak power in Section 4.3.

4.2. Load of different types of charging

Figures 10 to 12 depict the load of an average day for the different types of charging for the three charging powers, 25% penetration level and everywhere charging. The PNP of the Home charging was higher than that of the Work charging, but as the charging power increased, this relation was inverted, possibly because of the travel patterns.

Figure 11: Load profile of an average day for the 25% penetration level case charging with 6.9 kW in the different locations, subplot (a). Subplot (b) presents a violin plot of the the normalized power $\bar{P}_t$ for every charging type.

Figure 12: Load profile of an average day for the 25% penetration level case charging with 22 kW in the different locations, subplot (a). Subplot (b) presents a violin plot of the the normalized power $\bar{P}_t$ for every charging type.

The PNP for all the simulations are presented in Tables 2 and 3. As shown in Table 2, the PNP depended on the type of charging and on the charging power, and similar to the normalized power of the load, increasing the charging power did not proportionally increase the PNP with the same rate.

As shown in Table 3, while the PNP in the city, for the case presented in Figure 4 was 0.69 kW/car, 0.85 kW/car, 1.29 kW/car for the three different charging powers, this increased to 0.83 kW/car, 1.08 kW/car, 1.47 kW for Home only charging with the same charging powers. Thus, Home charging required higher normalized power when compared with the everywhere charging.

4.3. Time resolution

As described before, the minute load in the city had high variability especially for the higher charging power. However, such high variability would not have been observed if the results were presented in a coarser time resolution. Some publications, for example [2, 3, 6], used coarser time resolutions—more than 10 min—in their analyses. The reason for this might be that many papers focus on the voltage magnitude variations which is measured on several minutes basis, for example 10 minutes in [58]. However, some countries impose stricter regulations, for example the 1 minute variations adopted by Norway [59].

As shown in Table 4, as the time resolution coarsened the PNP decreased. This was, nonetheless as expected, more conspicuous as the charging power increased. For example, changing the time resolution from minute to 5 minutes reduced the observed PNP power by 3%, 5%, 22% for the 3.7 kW, 6.9 kW, and 22 kW, respectively.

4.4. Spatial load

The spatial load for the 100% penetration level case with 6.9 kW in the city of Uppsala is presented in Figures 13 and 14 at 09:00 and 18:00, respectively. The spatial load is expected to have a significant role in evaluating the performance of the grid or when combined with spatial RES potentials such as photovoltaics (PV).

A full analysis of the impacts of the spatial load on the city of Uppsala is left for future studies where combinations with, possibly, grid studies, RES potential, and customers' load are interesting aspects to analyze.

4.5. Sensitivity analysis of the buffer distance

The authors, here, aim to perform a sensitivity analysis for the assumption of 100 m buffer distance, thus the buffer distance was once changed to 50 m and another to 150 m.

Changing the buffer distance changed the buildings that are located within a walking distance and visited by the drivers who use a parking lot. Consequently, the stations created for every parking lot were changed. The authors simulated the 25% penetration with 3.7 kW charging everywhere case. For the 50 m buffer distance, the PNP

in every location was 0.54 kW/car, 0.45 kW/car, and 0.16 kW/car for Home Work and Other, respectively.

When the buffer distance was increased to 150 m the values changed to 0.52 kW/car, 0.33 kW/car, and 0.16 kW/car, respectively. The difference between the sensitivity analysis results and the results previously mentioned in Table 2 was at most 0.13 kW/car for the Work stations when the buffer distance was 150 m.

The authors presented before that there is no consensus regarding a reasonable walking distance between the parking lots and the nearby buildings. Thus, there is a difficulty in obtaining a universally valid value for the buffer distance to use in the model.

5. Conclusion

In this paper, the authors complemented previous spatial electric vehicle (EV) charging models by introducing spatial maps to extract and cluster the types of stations from parking lots and nearby buildings. The novelty of the proposed model concerns the assumption that some parking lots will be used by different users representing a mixture of charging profiles—as it was shown before in previous studies [11, 16, 17]. The authors also used a Markov chain model to simulate the spatio-temporal mobility of cars in the city.

A case study was made on the city of Uppsala in Sweden, with up to approximately 44,000 EVs simulated. Multiple charging powers were also compared. Similar to [10], the authors here observed an increase in the total load of the city when the charging power increased. However, the authors showed that this percentage increase was dependent on the time resolution of the results. As the time resolutions increases the impacts of high charging power on the total load decreased, see Table 4.

The authors also noticed that the higher the charging power the higher the variability in the charging load of the EVs in the city. Even if a small number of suddenly connected EVs in the city—in our case it was at most less than 3% of the EVs in the city—this induced 1.1 MW of charging load if charging with 3.7 kW and would induce 6.7 MW if charging with 22 kW. Such abrupt fluctuations in the EV charging load might hinder the usage of EVs to balance the variability of the renewable energy sources (RES). Controlled charging, nonetheless, might have a potential to counteract these fluctuations.

The authors defined the normalized power as the load in the city per unit car measured in kW/car. This value depended on the charging power and on whether the EVs were allowed to charge in all the locations in the city or in only the Home locations. The peak of the normalized power was—in the case study—at most 1.47 kW/car when charging using 22 kW at Home only.

The model developed in this paper can be employed along with the electricity consumption load in order to perform grid studies aiming to investigate the impacts of

Penetration level %	Home			Work			Other		
	3.7 kW	6.9 kW	22 kW	3.7 kW	6.9 kW	22 kW	3.7 kW	6.9 kW	22 kW
25	0.52	0.61	0.92	0.46	0.63	1.11	0.16	0.22	0.36
50	0.52	0.60	0.88	0.45	0.61	1.05	0.16	0.21	0.35
75	0.52	0.60	0.88	0.45	0.62	1.04	0.16	0.20	0.34
100	0.51	0.60	0.87	0.44	0.62	1.04	0.15	0.21	0.33

Table 2: The PNP (kW/car) for everywhere charging as a function of the charging power.

Figure 13: Spatial load for the 100% penetration level everywhere charging case with 6.9 kW charging power at 09:00 at a randomly chosen weekday. Note that the load of the 14,995 villas was not plotted here in order to improve presentability. For the same reason, this figure was cropped to the city center—where most of the parking lots are located, and that it does not present the complete results of the simulation.

Figure 14: Spatial load for the 100% penetration level everywhere charging case with 6.9 kW charging power at 18:00 at a randomly chosen weekday. Note that the load of the 14,995 villas was not plotted here in order to improve presentability. For the same reason, this figure was cropped to the city center—where most of the parking lots are located, and that it does not present the complete results of the simulation.

Penetration level %	Home		
	3.7 kW	6.9 kW	22 kW
25	0.83	1.08	1.47
50	0.83	1.06	1.42
75	0.84	1.06	1.44
100	0.84	1.07	1.43

Table 3: The PNP (kW/car) for Home only charging as a function of the charging power.

Charging power (kW)	Time resolution (minute)					
	1	5	10	15	30	60
3.7	0.69	0.67	0.66	0.66	0.65	0.65
6.9	0.84	0.8	0.79	0.78	0.76	0.72
22	1.28	1.0	0.94	0.88	0.84	0.78

Table 4: The PNP (kW/car) in the city as a function of time resolution for the 25% penetration level everywhere charging case. The one minute time resolution results were presented before in Figure 4.

the spatial load of EVs on the grid components and power quality. The model can also be employed along with RES studies to evaluate the self consumption and spatial closeness between the RES and EV charging loads in the city.

Future studies might complement the proposed model with smart charging strategies to, for example, reduce the local charging peaks in the grid, or improve the RES utilization, or reduce the charging costs. Employing the knowledge regarding the parking profiles—obtained from the geographical information system (GIS) maps—can be beneficial in optimizing the locations of charging stations in cities. This is, however, left for future works.

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