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Travel Activity Based Stochastic Modelling of Load and Charging State of Electric Vehicles

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Abstract: The uptake of electric vehicles (EV) is increasing every year and will eventually replace the traditional transport system in the near future. This imminent increase is urging stakeholders to plan up-gradation in the electric power system infrastructure. However, for efficient planning to support an additional load, an accurate assessment of the electric vehicle load and power quality indices is required. Although several EV models to estimate the charging profile and additional electrical load are available, but they are not capable of providing a high-resolution evaluation of charging current, especially at a higher frequency. This paper presents a probabilistic approach capable of estimating the time-dependent charging and harmonic currents for the future EV load. The model is based on the detailed travel activities of the existing car owners reported in the travel survey. The probability distribution functions of departure time, distance, arrival time, and time span are calculated. The charging profiles are based on the measurements of several EVs.

Keywords: activity based modelling; EV charging current; EV load model; managed charging; SOC; unmanaged charging

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1. Introduction

The climate change and energy security concerns are pushing policy-making institutes towards setting strict targets towards reducing greenhouse gasses (GHG) emissions and dependency on fossil fuels. The transport sector consumes 58 % of the total oil, while 67% of fossil fuel is used to generate electricity [1]. Electric vehicles (EV) are promising an efficient replacement of the conventional transportation system. For a sustainable future with less dependency on fossil fuels and to meet the world's energy demand, the adoption of electric vehicles and renewable energy is essential. As EV's adoption is encouraged to meet energy security and climate-related targets, some challenges are also associated with their rapid integration. It would typically mean reinforcements to the existing grids to support the additional charging load. The EV charging is based on power electronic circuits that can compromise the network's sustainability by adding harmonic pollution. In planning such changes, the future load due to vehicle fleets would need to be known. A probabilistic EV usage model, based on the traffic surveys and the actual vehicle-driven data, can provide estimation of the EV charging load in the distribution grid.

Governments and automobile manufacturers are pushing towards developing efficient designs of electric vehicles. In 2017, electric vehicle's total stock increased to 3 million, including both battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). This number is expected to surge up to 13 million by 2020 and 130 million by 2030 [2,3]. This growth is anticipated because of the improved life cycle of EVs and a decrease in the prices. The payback time of EV is expected to reduce from currently 20 years to 5 years compared to internal combustion engine vehicles (ICEV) [4]. However, along with several advantages, this rampant growth of EVs will possess several challenges related to the grid capacity to support this additional load.

The integration of the EVs in the electricity distribution network is quite challenging as it requires additional infrastructure and investment. Because of the inadequate charging infrastructure, it is expected that the majority of the EVs owners will charge their vehicles at homes [4]. The impact of the EVs on the distribution network is widely discussed in the literature. The large residential distribution networks may not be sized for additional EV load added by the customers [5,6]. Therefore, the additional EV charging load is foreseen to affect the power system directly. The unmanaged charging will result in overloading of existing transformers, increase in the losses and power quality problems [7,8].

Despite the improved power electronics circuit, the EV charging load is mostly distorted with high total harmonic distortion up to the range of 60–70% [9]. The major problem of additional current drawn by the EV chargers is the increase of heating in transformers. The increased high-frequency harmonic current will result in losses because of nonuniform current distribution in the transformer winding. These harmonic currents also increase the losses in the cables. The current in the neutral conductor also increases [10,11].

To assess the impact of EV integration on the electric power system, and optimal planning of the investments, accurate forecasting of the EV ownership and usage is critical. Mathematical models of EV usage can provide a detailed insight into their impact on the power system grid operation, environment, and economics. The EV model provides charging profiles to estimate additional electricity load introduced by the EV charging in the distribution grid. The researchers have used different approaches to construct EV charging profiles [12]. In the first approach, simulation models of EV usage are made that are based on available data related to transportation patterns. In the second approach, real-time studies are carried out to understand the behavior of EV usage of individual customers [13]. While real-time studies require significant resources, the simulation models have a limited domain based on the type and amount of data. However, a hybrid approach, where the simulation model is based on the real-time EV usage and measurement along with transportation surveys, is more effective and flexible.

This paper proposes a mathematical model to determine EV's daily usage behavior based on the travel survey conducted in Finland. The commuter's daily routine from the travel survey is used, and a stochastic model has been developed to provide trip details and the state of charge (SOC) of the EVs. The utilization patterns will be based on the daily activities statistics to estimate each vehicle's state of charge upon home arrival. The charging load current patterns will be elaborated using recorded charging data of different vehicles used for the model. The Monte Carlo approach is used to determine the charging load curves of the EVs. The model will provide options to model charging load upon commute mode, type and length variance in the temporal space. With such variations, different models can be created to estimate charging load in different locations and conditions. The detailed state of charge statistics for different vehicles will also allow using the model for estimating the harmonic emissions, unbalancing, and overload conditions. Furthermore, this model can be used in both unmanaged and managed charging (peaks limiting) scenarios with small modifications for different motivators (price, availability, etc.). In the current paper, the scope will be limited to unmanaged and managed charging on weekdays, with the assumption that owners would charge their EVs as soon as they arrive home from the last travel activity. The paper's organization is as follows: Section 2 provides a brief overview of the existing methodologies used by the researcher to develop the EV models. The purpose methodology used in this study is described in Section 3. The results of the mathematical model are discussed in Section 4, while Section 5 presents the conclusion.

2. Overview of the Existing Models

The researchers have used various methodologies to model EV usage and their charging behavior, both in temporal and spatial dimensions. The various factors associated with the EV user behavior has made the EV modeling quite complicated. The climate and traffic conditions affect the EV user's behavior and alter the travel time and distance. Socioeconomic factors, market behavior such as electricity pricing, and policy decisions, including subsidies, influence the electric vehicles' user behavior and charging patterns.

The EV models usually exploit traffic surveys, vehicle ownership statistics, and parking data as a base to make a mathematical model that can provide qualitative and quantitative insights into EV usage and its environmental and economic impact [14]. The modeling approach depends on the research targets and the scope of the study. The models used to evaluate car ownership and annual driven distance are used to forecast the transportation demand and attribute that influence vehicle manufacturer and energy companies business. A similar model, based on a household travel survey (HTS), is used to predict vehicle ownership in Singapore [15]. These models can help the policymakers to estimate the growing demand for EVs but do not provide detailed insight into the vehicle's charging behavior and actual usage patterns.

The four-state approach has been widely discussing in the literature for transport modeling problems [16]. In the first step, the trips are generated in a region based on commuter's daily activities. Trip purpose defines the nature of the trip by indicating the starting and ending point. The trip's starting point is termed as the production end, while the ending point is called attractions. Most trips have their origin or destination as home. Trips are modeled on personal, household, or zonal level. Typically trips are originated from the household because of the activity demands associated with the dwellers. Therefore, the majority of the trips can be defined as home to work, home to others, and non-home based trips. The trip ends are combined geographically into full trip lengths by defining the second step's origin and destination. The general assumption is that most of the trips originated in a certain zone of a city will be attracted to the surrounding zones while some are attracted to the zones at a moderate distance. Only a few trips are destined for the far-off zones. The mode of travel is selected in the third step. A commuter can use a personal vehicle, shared vehicle, or public transport to fully or partially complete the trip. In the final step, the routes taken by the travelers are predicted. The four-state model lack to accommodate the activities affecting trip behavior. The travel activities affect the trip generation part only while the other states have less or no influence. A four-step transport model consists of trip generation, trip distribution, transportation mode, and route selection for travel activities is presented in [17]. The authors determined traffic flow, electricity demand, and the economic impact of EVs.

A better approach to model daily EV usage is to consider the daily travel activity of the commuters. The daily or weekly travel patterns provide a framework that can model EV usage based on the lifestyle of the users and their travel behavior. These activity-based modeling approaches can provide the user's charging behavior that may help to observe the effect of EV charging on the electric power network. The EV models based on the trip behavior can be divided into two categories; direct use of observed activity-travel schedules (DUOATS) and activity-based models (ABS) [12,16].

The DUOATS method uses external travel patterns previously developed for the existing cars to model EV usage and charging behavior. Various travel surveys conducted in different countries provide data related to the user's individual travel behavior. A web-based survey was used in California (US) to generate energy usage profiles of plug-in hybrid electric vehicles in [18]. The participants provide details of their travel using a car for one day. The information includes the number of trips, traveling time for each trip and the distance covered. Another study used the Monte Carlo approach to estimate the electricity demand of EVs using the US Household Travel Survey [19]. The arrival and departure times of vehicles on weekdays are converted in charging demand. A probabilistic approach has been used to determine the charging profiles using empirical cumulative distribution functions in [20]. The authors also used HTS data and employed queuing theory to estimate when a particular EV required charging. The EV charging impact of the Swiss distribution grid has been presented in [21]. The travel patterns were based on the mobility survey conducted in Switzerland. A large-scale EV charging model based on travel statistics in New Zealand used a multivariate probabilistic approach [22]. The authors report an increase in the peak electricity demand in the case of unmanaged EV charging. Although the DUOATS models based on the travel surveys provide reliable outcomes, most travel surveys are based on the conventional car owners and do not include specific details related to EVs, such as charging behavior.

The activity-based modeling (ABM) approach employs a collection of activities that may influence people's travel behavior. It enables to model the trips based on individual's activity patterns that can be affected by the behavioral preferences rather than individual trips. Several factors, including social and economic structures, influence travel behavior. The travel schedule is generated within the ABM model in comparison to DUOATS, which relies on external travel schedules. In [23], the household activity model is used to generate PHEV load profiles under an unmanaged charging scenario. The model relates the charging load of PHEV to the electricity consumption of other household appliances. Another activity-based modeling approach analyzed the vehicle-to-grid (V2G) impact on power flow of the distribution grid [24]. A dynamic ABM four-stage model has been developed based on the travel diaries and supporting data-set for household activities that can influence travel decisions [25]. This model is further used to simulate the electricity demand of EVs in Belgium [26]. Traffic survey data are used to generate probability density functions (PDF) of trip related parameters such as arrival time, departure time and distance to make EV usage patterns in [27–29]. These travel patterns are later compared with actual EV charging data to generate SOC and EV load profiles.

Transport simulation software can also simulate domestic activity-based travel behavior. A similar study used TRANSIMS to estimate the effect of PHEV penetration on electricity demand [30]. Another approach simulated traffic flow using multi-agent transport simulation (MAT-Sim), a software capable of simulating large-scale transport model. The MAT-Sim based model is used to generate EV penetration scenarios in Switzerland based on the trip and activities in [31]. The model lacks to take account of the driving range factor; therefore, suitable for PHEV only.

3. Methodology

Based on the overview of the existing models provided in the previous section, the ABM modeling approach is more flexible and can address the user activity and travel behavior interdependence with ease of aggregation because of its bottom-up approach. The electric power grid, planning, and perspective load estimations are expected to affect residential areas because of EV's home charging. Due to the expected charging upon home arrival at the end of the day by the majority of vehicle owners, it will be the most convenient option. The model here aims to simplify the load estimation limited only for residential grids.

In our proposed model, direct data input from the national traffic survey (NTS) is used to categorize the car owner's travel patterns into different categories.The probability distribution for arrival and departure times of each travel activity is defined. A trip of the chain is used to evaluate the distance traveled and the time at which the outgoing and the incoming trip took place. The charging decision depends on the SOC of the EV that is calculated based on the distance traveled by the vehicle during different trips. The charging would occur when the vehicle reaches home and does not have enough SOC for the next trip.

The NTS is carried out in Finland every six years [32]. The survey collects one-year travel data, including all days and seasons, from 30,000 people aged six and above. The survey provides details about the mobility of Finnish people, including the reasons for the trips, modes of transportation, and differences in mobility between population groups. In order to understand the background of mobility, participants have been asked for different background information. The background information has been used to determine, for example, the respondent's age, gender, the form of residence, household members, use and ownership of a passenger car, driving license management, employment and earnings. As complementary data, regional characteristics related to the location of homes, workplaces, schools/kindergartens, study places, second homes, and destinations, as well as information on how the journey would have been folded by public transport or passenger car. Table 1 shows the daily indicators for domestic trips.

Table 1. Daily indicators for domestic travel [32].

Domestic Travel Indicator	Average Value per Day
Number of domestic trips per person	2.89
Travel expense per person	41.4 (euros)
Total journey time per person	65.5 (min)
The average distance of a trip	14.3 (km)
Average travel time per km	22.7 (min)

3.1. Travel Activities

The daily trips are categorized based on the activities responsible for the trip's need. The majority of the trips are related to work or education and shopping. The other activities include business-related trips, leisure activities, and visits or vacation trips. Table 2 shows the number of trips and distance traveled for all trip purposes.

The data shows that the travel activities from Monday to Friday are very similar. The work and school trips dominate these days. All other trips also follow a similar pattern. The visits have a lower share in the first five days of the week. The work and school trips drop significantly over the weekend; however, both visits and leisure trips have increased on weekends. The shopping trip frequency is almost the same for all days of the week except Sunday. The frequency of business trips is also on the higher end during weekdays. The travel activity data provides an excellent base to model the EV trips by assuming that the travel pattern would remain the same for the Evs.

Table 2. Weekly travel information for different trips [32].

Day	Work	School	Business	Shopping	Visits	Leisure	All
			Number of trips				
Monday	0.64	0.27	0.13	1.02	0.04	0.69	2.79
Tuesday	0.62	0.26	0.14	1.14	0.03	0.71	2.9
Wednesday	0.65	0.29	0.16	1.12	0.03	0.75	3.01
Thursday	0.65	0.27	0.13	1.09	0.03	0.64	2.8
Friday	0.54	0.25	0.11	1.11	0.04	0.68	2.72
Saturday	0.13	0.01	0.03	1.03	0.05	0.88	2.13
Sunday	0.12	0	0.02	0.58	0.06	0.81	1.59
Average	**0.48**	**0.19**	**0.11**	**1.01**	**0.04**	**0.74**	**2.56**
			Distance traveled for each trip (km)				
Monday	15.8	7.74	34.04	6.87	40.48	11.18	116.11
Tuesday	16.73	6.04	33.94	6.6	49.11	11.94	124.36
Wednesday	14.92	6.29	36.77	6.87	38.56	9.6	113
Thursday	17.53	7.82	37.55	6.34	57.17	11.84	138.25
Friday	15.28	7.54	58.2	8.3	80.08	19.12	188.52
Saturday	16.55	25.16	53.21	7.99	48.22	19.48	170.59
Sunday	13.13	69.81	95.58	9.03	65.46	16.56	269.56
Average	**15.98**	**7.27**	**41.39**	**7.3**	**55.14**	**14.43**	**141.52**

3.2. Departure Times

We have defined three travel activities based on the six travel activities mentioned in Table 2. The details of these activities are provided below.

- "Work and school" (WS), is described as the most likely routine trip. The departure and arrival times of these trips will have only slight dispersion, and this will be carried out for all weekdays practically with no exceptions. The trip length will also have rather a low variance for a particular vehicle.
- "Shopping and business" (SB) is also a routine trip; however, the dispersion of the likeliness of such a trip will be greater. Furthermore, the average trip length will vary to a greater extent. There could also be several trips of the same type on the same day.
- "Leisure and vacation" (LV) has the most variance included. It means both variance in trip length as well as trip probability and start-time variance. These trips also tend to be one of the longest ones.

The average trip lengths for each travel activity are also available from the traffic survey. The data for the trips distance have been presented in Table 2. For the WS activity, it is assumed that the driver of the vehicle will be participating in vocational or university-level studies. This means a longer trip to the location rather than to the local school. The SB include two activities; shopping and business trips. It is assumed that private business trips are similar to work-related business trips, for example, visiting a specialized shop at a longer distance. The probability of a long trip is low, and it will be tied together with the distribution of the shopping activities (expected at a shorter distance) length and probability. Similar is valid for the VL activities; however, these activities are less probable than the SB. The departure times for each activity are available in the NTS survey. Figure 1a shows the departure time for each travel activity on a weekday. The data is converted into WS, SB, and LV activities, as shown in Figure 1b.

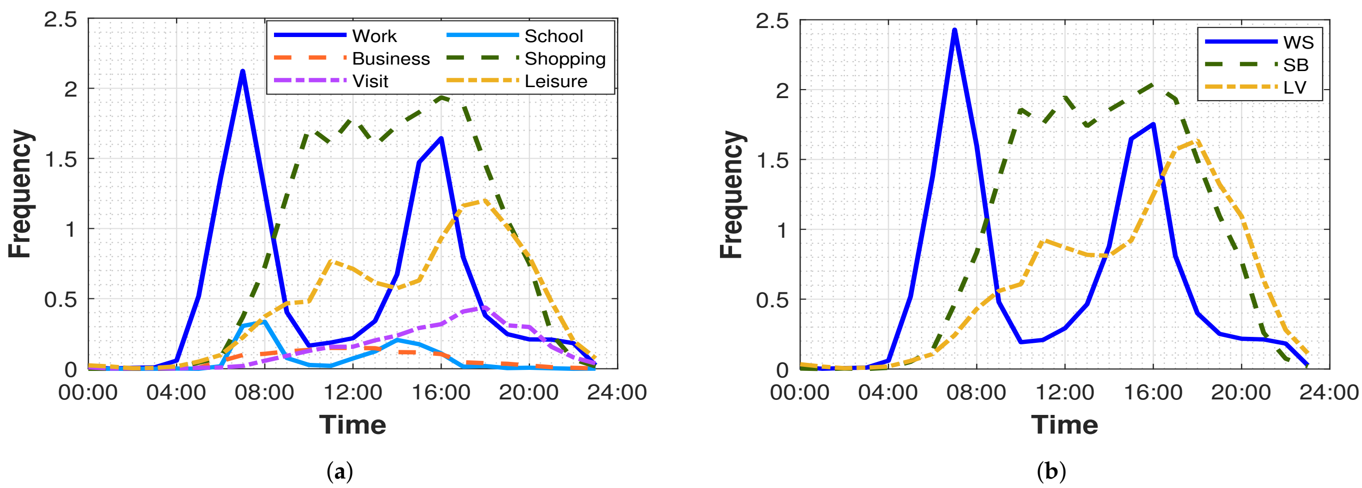


Figure 1. Frequency of departure per hour (**a**) Data from NTS survey (**b**) Data used in the model.

The distribution of the departure times from Figure 1b shows trips cannot distinguish as outgoing or incoming trips for each travel activity. For EV modeling, both incoming and outgoing trips are essential to estimate charging profiles. The time resolution of the initial data is also low, with a 1-h resolution. Therefore, the data interpolation is used to improve the resolution.

3.3. Incoming Trip Estimation

The estimation of an incoming trip to home is critical to model EV charging profiles. The vehicle charging will be initiated once the vehicle returns home and does not have a sufficient battery charge for the next trip. However, the travel activity information does not provide details about the outgoing and incoming trips. Two distinctive peaks are visible in the WS departure frequency shown in Figure 1b. By assuming a low number of night-shifts workforce, the morning peak will likely indicate the outgoing trips to work, and the evening peak represents the incoming trips from work to home. This assumption will provide us separate distributions for incoming and outgoing WS trips. The evening incoming trips have more spread over a longer time span than the morning outgoing rate. The t location-scale distribution is used to define both incoming and outgoing WS trips separately, as shown in Figure 2. This distribution helps to model data that have a normal distribution with heavier tails. The PDF of the t-location-scale distribution can be calculated by using Equation (1).

$$f(x,v,\sigma,\mu) = \frac{\Gamma\frac{(v+1)}{2}}{\sigma\sqrt{v\pi}\times\Gamma(\frac{v}{2})} \times [\frac{v(\frac{x-\mu}{\sigma})^2}{v}]^{-(\frac{v+1}{2})} \quad (1)$$

Here v is the shape parameter and σ defines the scale. μ determine the location of the PDF and Γ is the gamma function. As the v approaches towards positive infinity the $f(x,v,\sigma,\mu)$ tends towards the normal distribution. The smaller values of v results in a heavier tail.

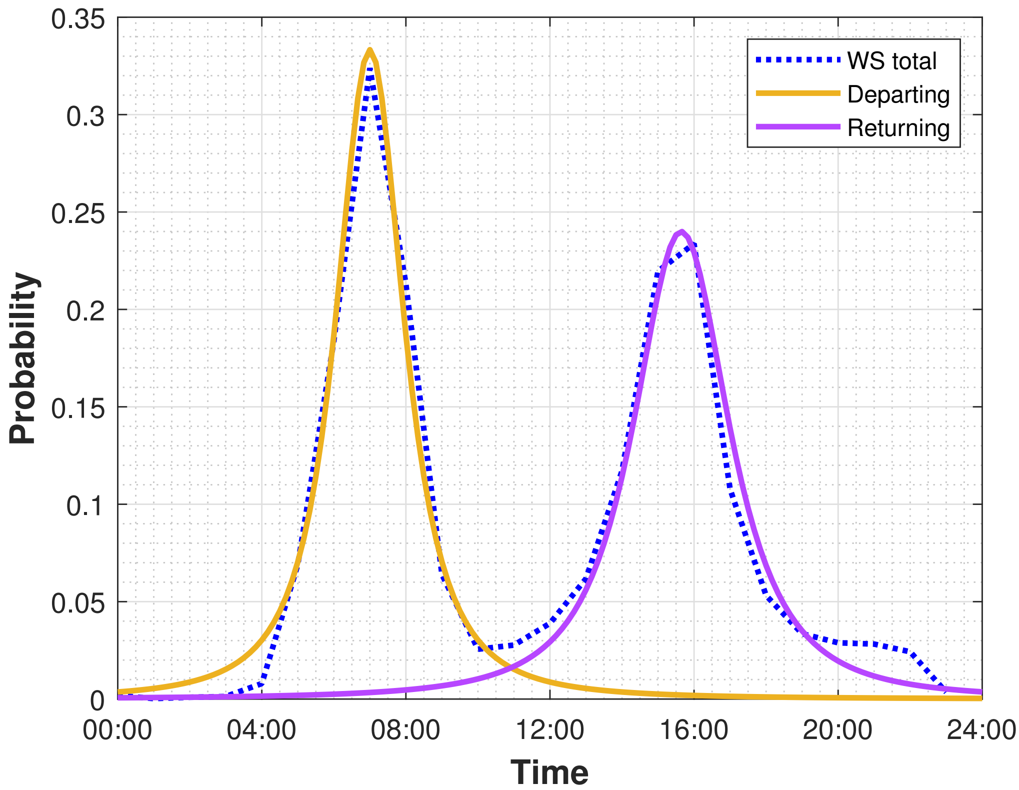


Figure 2. Probability plots of outgoing and incoming trip for WS travel activity.

The LV activity distribution in Figure 1b also shows twin peaks; however, the relation is not straightforward. The higher evening activity in the LV trip frequency is likely due to the vehicle owner's leisure activities after work. The average time at a leisure activity (after the arrival to the place and before the departure from the place) has been observed as 3 h. The duration for the LV activities is calculated using Poisson distribution, as shown in Equation (2).

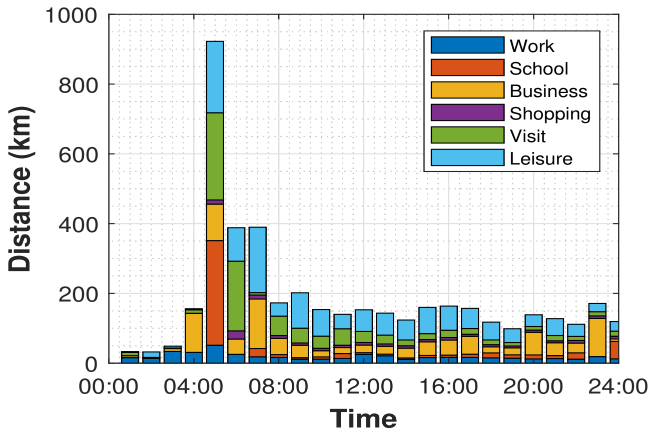
$$f(x|\lambda) = \frac{\lambda^x}{x!}e^{-\lambda} \quad (2)$$

The λ in Equation (2) shows the variance of the distribution. The detail of the travel distance for different trip activities is also available from the NTS survey. Figure 3a shows the average distance traveled in kilometers at a different time of the day for various travel activities mentioned in the NTS survey. This data is converted into WS, SB, and VH travel activities used in this model, and the average distance traveled for each activity at a different time of the day is shown in Figure 3b. For each trip, the distance is calculated using Poisson and log-normal distribution defined for the trip distance. Equation (3) represents the log-normal distribution's probability density function, where μ represents the mean and variance is indicated by σ.

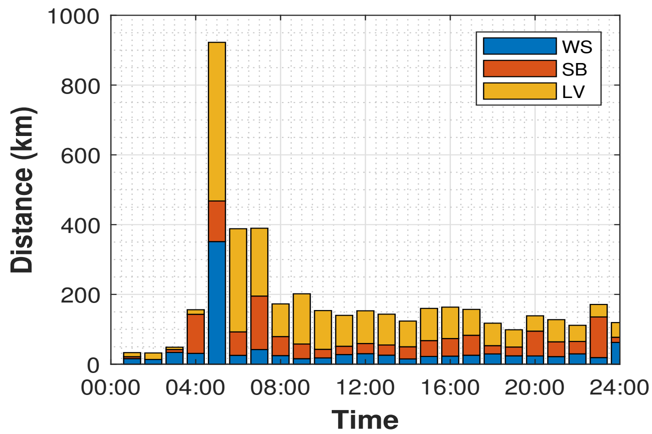
$$f(x, \sigma, \mu) = \frac{1}{x\sigma\sqrt{2\pi}} exp(-\frac{(ln(x) - \mu)^2}{2\sigma^2}) \tag{3}$$

3.4. Electric Vehicle Characteristics

Another challenging task is to define the electric vehicle mix. Although new EV models are introduced in the market by the major auto manufacturer, EV adoption is still low. The performance evaluation data of these EVs is also not readily available. Therefore, it is a complex task to select the EVs for developing a model in the perspective of future vehicles, and results can be highly inaccurate. However, most of the daily routines likely remain the same; the travel distances would be identical, and vehicle utilization would remain the same. As the energy distribution would be similar in the future; therefore, the charging power limits and current drawn by the EV's is expected to be in the same range. Therefore it could be assumed that the vehicle charging would remain to follow identical patterns as of today.



(a)



(b)

Figure 3. Trip distance frequency per hour for different travel activities (**a**) From NTS survey (**b**) Data used in the model.

In this study, the vehicle mix is created by assuming an equal share of each electric vehicle in the network. Seven different vehicle types are selected, including three Plug-in hybrid vehicles (PHEV) with relatively long electrical driving distance. The EVs are selected based on the ease of market availability. The different parameters of the Evs used in this model are described in Table 3.

Table 3. Type and electrical parameters of the EVs used in the model.

Parameter	EV 1	EV 2	EV 3	EV 4	EV 5	EV 6	EV 7
Type	PHEV	PHEV	PHEV	BEV	BEV	BEV	BEV
Electric-motor power (kW)	111	51	60	80	40	16	16
Charging current RMS (A)	14.9	12.7	9.7	10.3	10.3	13	13
Battery capacity (kWh)	17.1	10.3	8.8	24	16	16	16
Electric range (km)	61	53	54	117	127	127	127

The EV charging would vary based on the different charging patterns; current ramp-up, constant current range, and ramp-down at the end of the charge. Therefore charging current depends on the state of charge (SOC) of the EV. Figure 4 shows the SOC of the EVs used in charging profile modeling in this study. EV 6 and 7, although from different car manufacturers, shows a similar SOC curve as they employed similar specifications for the battery and electric motor.

Energy used by a vehicle for a driven range is assumed to be 180 Wh/km. This assumption is applied after considering the EV manufacturer's data and future vehicles are expected to provide a similar range as the motor and drives are already quite efficient. The variance in energy consumption also depends on the climate conditions, terrain, and region but is not considered in this study. The SOC of an EV is estimated after its arrival at home. For the next trip assigned by the generated travel activity, the SOC is analyzed. If the EV battery SOC drops below the required level for the next trip, the EV will go under the charging state. The EV SOC will be checked before any trip for their estimated range; in case there is not enough energy in the battery for completing the trip, the vehicle will be assumed not to take the trip.

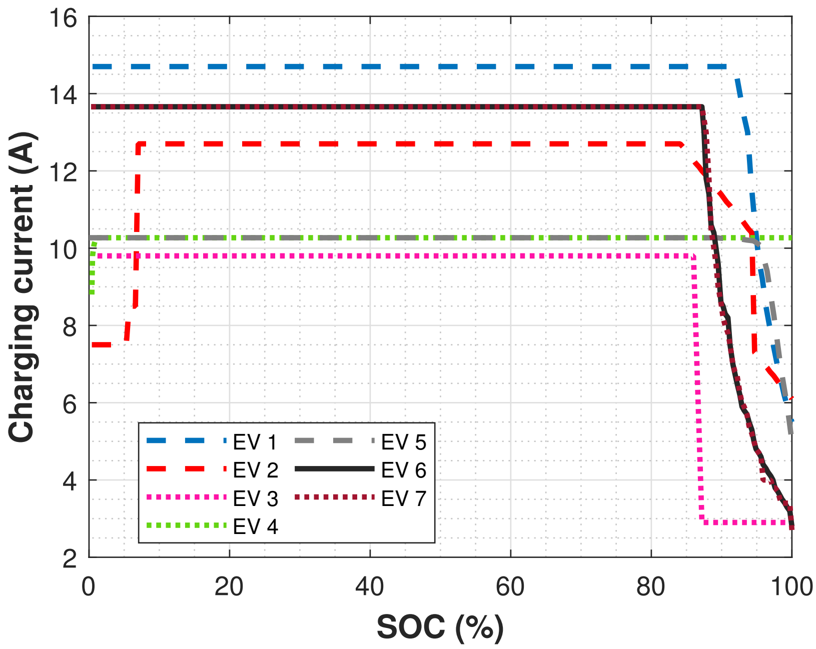


Figure 4. Charging current levels during charging span of 0–100% of the full charge.

3.5. Daily Routine Estimation

The vehicle owners are categorized based on age group and gender in the NTS survey. This data is used to evaluate the number of people going for daily WS travel activity. The remaining vehicle owners are assumed to be on vacation, to be retired, or engaged in other travel activities. For estimating the daily routines for the selected population of vehicles, an array of random seed numbers are assigned to each of the vehicles. In the first step, the permanent routine parameters are created. These routine parameters are used in the later stages for the specification of the daily action. The permanent routine parameters are used to generate the vehicle schedule for each simulated day. The vehicle will be assumed to leave home following the similar outgoing time distribution assigned for each travel activity. If the travel activity is WS, then returning from work will take place during the time following the WS incoming distribution. The other activities after the daily routine will be estimated for each day based on the probabilities of the SB and WS actions. A total of ten different vehicle states are used to describe the vehicle activity. The first state is termed as the home state, while for each type of activity (WS, SB, VL) there will be three states—outgoing, at activity and, incoming state. The vehicle's utilization will be calculated when the vehicle is in outgoing or incoming states for a trip activity. The incoming state is assumed to always end at home. When the vehicle returns home, the SOC will be dropped because of the trip's energy consumed. The SOC is determined based on distance travel during the trip obtained in Section 3.3. The amount of charge left in the EV battery will determine whether the vehicle can leave to other activity or required charging before the next trip. If the next trip is scheduled for the next day, then the vehicle will be charged until full SOC. The EV load for the given number of EVs is estimated using the Monte Carlo approach. The steps during each iteration are as follows.

- Step 1: Determine the probability of outgoing and incoming for WS travel activity;
- Step 2: Probability of SB or VL travel activity after WS is complete;
- Step 3: Distance traveled for all WS, SB, and VL activities;
- Step 4: Duration for all WS, SB, and VL activities;
- Step 5: EV utilization and the SOC after each trip;
- Step 6: SOC tolerance level, when owner always charges the vehicle;
- Step 7: Probability of the owner to charge after every incoming trip.

The flow chart of the algorithm is shown in Figure 5. During each day, the trip activity is determined for each trip. The departure time, distance, average speed, and trip duration is determined based on each parameter's probability distribution. At the end of each trip, SOC is calculated, and the battery charging decision is made. Another VH or SB trip could also take place if the departure time is less than 22:00, and SOC is enough to support the trip. Any given number of EVs can be simulated for the required number of days.

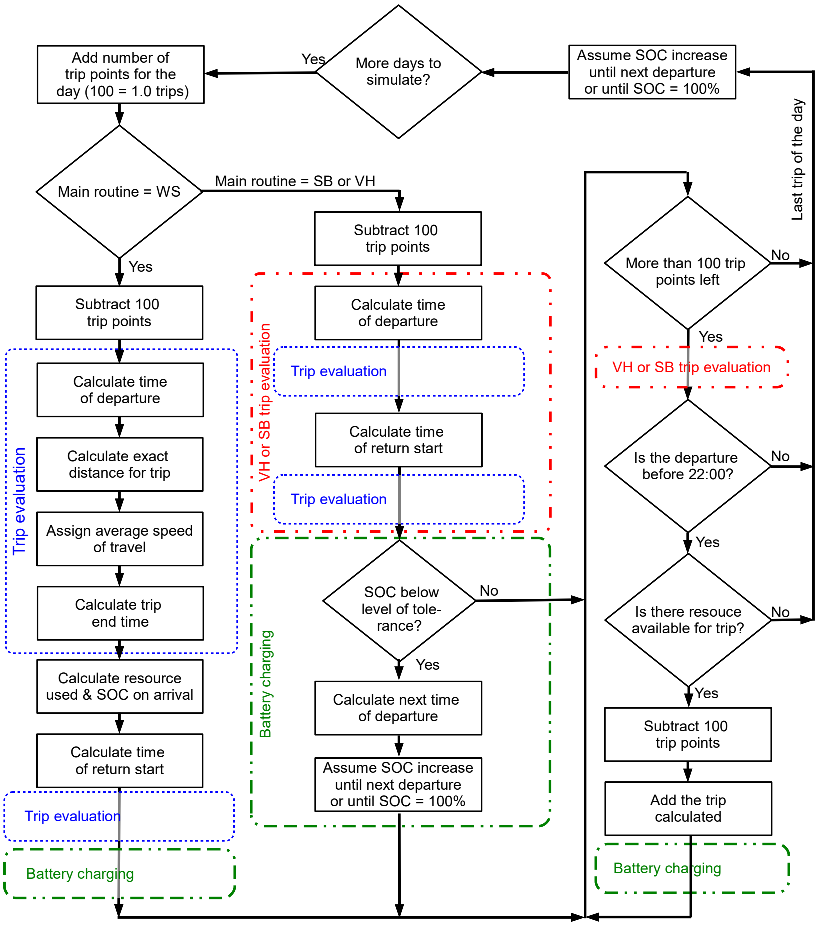
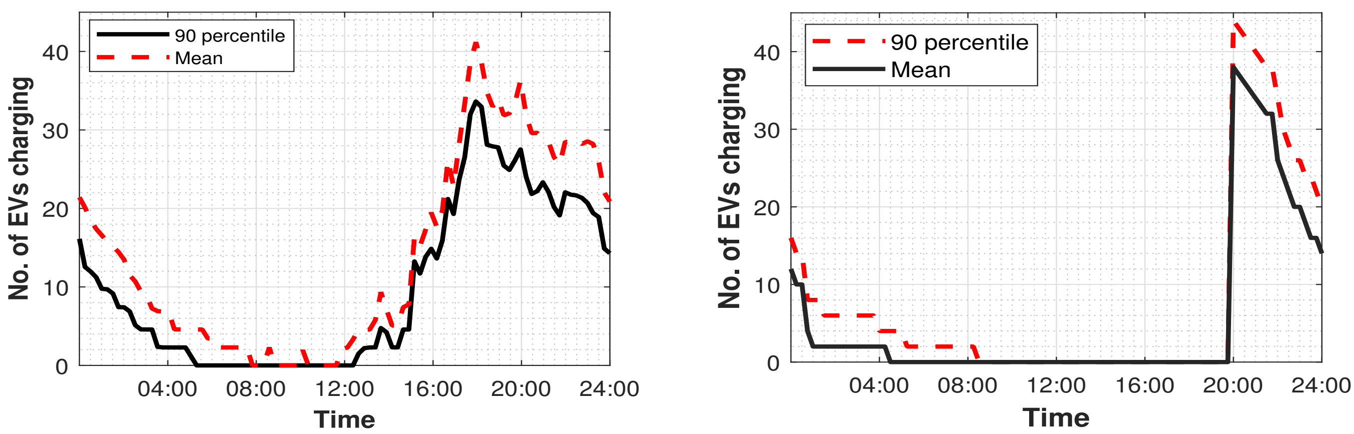


Figure 5. Algorithm of the EV charging profile model.

4. Results and Discussion

The EV model can be used to estimate the load and charging profiles for the required number of EVs and days. To evaluate the outcome of the model, the Monte Carlo approach is used to simulate usage of 50 EVs for 100 days. For each day, vehicle's daily schedule is estimated. The vehicle's daily schedule will provide the vehicle's battery SOC information, including the SOC after arrival at home. Based on the SOC, the respective charging current value is specified for each vehicle, and charging power is calculated for the time instance. Using the charging power, the SOC is calculated for the next time-step until the completion of the charging (SOC = 100%). The total charging current will be the sum of charging currents of all vehicles at any given time.

The model is capable of evaluating the EV load under two charging scenarios. In the first case, an unmanaged charging approach is used where the EV owner can charge the vehicle at any time during the day. Figure 6a shows the EV load for the unmanaged charging scenario. The red dotted line shows the 90th percentile value for the number of vehicles undercharging at a given time, while the black line shows the mean value. The EV load starts appearing around 12:00 and increases exponentially to the maximum value of the charging load. The maximum charging load is around 18:00, as most people came back from the daily routine activities and charged their vehicle. The mean and 90th percentile value of the maximum load is 34 and 42, respectively. The EV load starts decreasing after 18:00 to almost half at 24:00, where the mean and 90th percentile values of the charging vehicle are 14 and 22, respectively. Both mean and 90th percentile values of the charging load are less than ten after 3:00, and the load curve continues to decrease and reaches the minimum value between 06:00 and 08:00.



(**a**) (**b**)

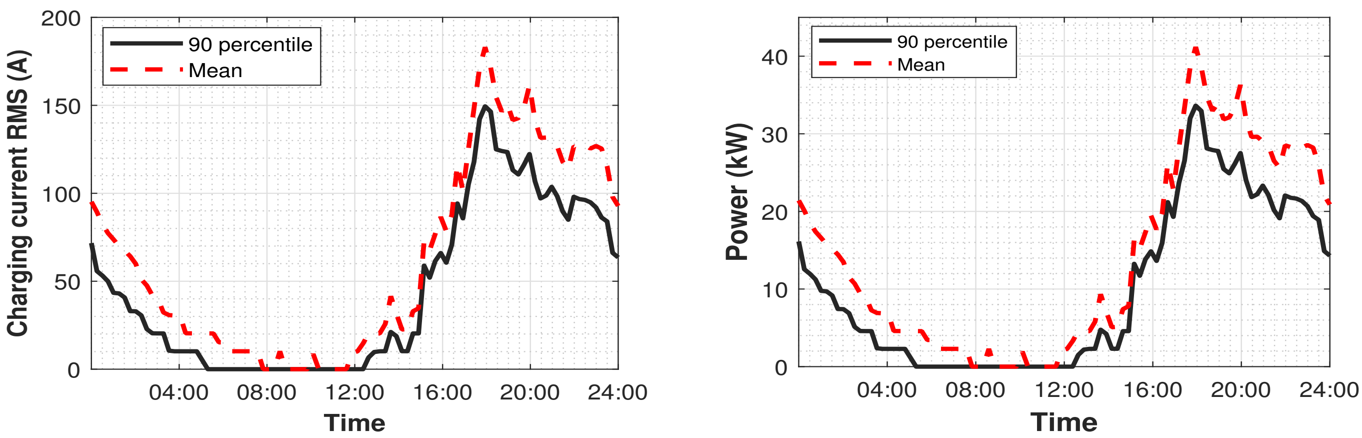
Figure 6. EVs load curve for (**a**) Unmanaged charging (**b**) Managed charging.

For the managed charging scenario, the EV owners are forced to charge from 20:00 onwards, and the load curve is shown in Figure 6b. As expected, the maximum load is more in comparison to the unmanaged charging scenario. The mean and 90th percentile charging load is decreased from their maximum value of 38 and 44 to 14 and 22 EV charging at 24:00. The load curve continues to decrease until it reaches a minimum value between 04:00 and 08:00.

The model provides a fast and optimized way to find the expected load curves of EVs under managed (time-driven) and unmanaged charging scenarios. These load curves provide the base to estimate additional current drawn by the electric vehicles during charging in the distribution grid. The estimation is critical for the network operators to plan additional investment to improve the network capacity that can handle EV charging. Additionally, the current harmonic emission by this additional charging load can also be estimated. As a test case, we have estimated the RMS current drawn by the EV charging using the load curves estimated by the model for the unmanaged charging scenario.

The EVs are measured at 230 V sinewave using power quality analyzer. The detail of the measurement setup is provided in [33,34]. The charging current at different SOC is assigned to the EVs and aggregated to find the total current drawn by the EV load at any given time during a particular day. The power consumed by the EV load is also calculated. Figure 7 shows the mean and 90th percentile values of charging current and power for unmanaged charging of 50 vehicles for 100 days.

The results show that the range of current drawn by EV charging could reach 183A in a distribution grid where 50 EV are present and employ home charging. It means an additional 42 kW power is required in the peak hours during the evening. The model can provide results for any given number of EVs under different charging scenarios. The model's EV power consumption estimations follow EV load estimated in [22,27–29]. Particularly, the peak load values and peak load time period, and the load curve form follow nearly identical trends. However, the proposed model provides better flexibility and a simple approach with fewer variables. The results also validate the applicability of the NTS travel survey effectiveness in comparison to the other travel surveys used in various studies to model EV usage patterns.



(**a**) (**b**)

Figure 7. For unmanaged charging scenario (**a**) EVs charging current (**b**) EVs power consumption.

5. Conclusions

A travel activity-based EV model is presented in this paper based on the National Travel Survey results conducted in Finland. The model provides a simpler and flexible approach and can handle various EVs and travel activities. The travel activity data is used to define three different travel activities during the weekdays. The probability distribution function of the distance traveled, travel time, departure, and arrival time for incoming and outgoing trips are calculated based on the survey data. The EV model is capable of providing the charging load under managed and unmanaged charging scenarios. The model can be also be used to evaluate the load and power quality aspects, including current harmonics and power factor, for the EV integration in the balanced or unbalanced distribution network. Although, at the moment, the scope is limited to home charging of the EVs, however, the model can easily be extended to include charging stations. The model is flexible enough to integrate future models of EVs, including BEV and PHEV.

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