# Statistical Analysis and Modeling of Plug-in Electric Vehicle Charging Demand in Distribution Systems

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***Abstract*—This paper establishes stochastic model of plug-in electric vehicle (PEV) charging and derives the probabilistic description of the electricity needs from EV charging for one charging station at any hour of a day. Three key variables are used to characterize the stochastic behavior of EV charging: starting time of charging, state of charge (SOC), and total number of charging EVs. The electricity needs of an EV charging station is a function of time, which can be depicted by the expectation of charging needs at a certain time of day. Numerical simulations are implemented to validate the proposed analysis approach and illustrate the impact of EVs' charging demand on the distribution systems.**

***Keywords—charging stations; plug-in electric vehicles; statistical analysis***

## NOMENCLATURE

| | |
|---|---|
| $d$ | Miles driven data |
| $PDF$ | Probability density function |
| $f(d)$ | PDF of miles driven value |
| $k$ | Shaping parameter of a Weibull distribution |
| $\lambda$ | Scaling parameter of a Weibull distribution |
| $\tau$ | Time index (continuously) for function $f_{ST}$ |
| $f_{ST}(\tau)$ | PDF of start time of charging value |
| $\alpha$ | Shaping parameter of a log-logistic distribution |
| $\beta$ | Scaling parameter of a log-logistic distribution |
| $\gamma$ | Location parameter of a log-logistic distribution |
| $SOC$ | State of Charge, , percentage left in the EV battery |
| $\mu$ | Percentage of distance driven in electric mode |
| $AER$ | All-electric range |
| $s$ | Index of SOC |
| $t$ | Time index (hour) |
| $r$ | Percentage of battery can be charged per hour |
| $\eta$ | EV charging efficiency |
| $i$ | EV index |
| $P_{EV}^{i,t,s}$ | EV charging power demand for EV i, with remaining SOC s, at time t |
| $SOC^{i,t,s}$ | Initial SOC before charging |
| $SOC^{f}$ | Final SOC after charging |
| $C_{cap}$ | Usable battery capacity |
| $P_{EV}^{t,s}$ | EV charging power demand for one charging station at time t |
| $N_{EV}^{t,s}$ | Total number of EVs in the target area |
| $\rho^{l}$ | Percentage of each type of vehicles (l) |
| $\psi$ | Population in the target area |
| $\delta$ | Average people amount per resident |
| $\varepsilon$ | Average number of EVs per resident |
| $\theta$ | EV penetration ratio |
| $n$ | Charger number |

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## I. INTRODUCTION

Electric Vehicles (EVs) are well-known as an alternative means of transportation due to the environmental advantages compared to the traditional gas-powered vehicles. Due to the relatively large amount of electricity that EVs consume, the charging of EVs can cause undesirable large peak demand, and therefore, has a tremendous impact on the distribution system, with uncontrolled and centralized charging [1]. The impact of EV penetration on distribution network are discussed at length in the literature [2-9]. To evaluate the impact of EVs and optimally coordinate their energy consumption, it is necessary to explore the EV characteristics, analyze charging/discharging profiles and establish typical models [10-11].

EVs pose challenges and introduce complexity in the analysis of the impact mainly because of the randomness of charging and driving behavior of EV owners. Battery characteristics, typical driving behaviors, and drivers' preferences are essential elements to be considered [12]. Thus, stochastic models need to be built to take into consideration the uncertainties in regard to the charging demand profiles, including charging locations, charging start time, capacity of battery, charging level, battery SOC while charging [1, 12-13]. Such studies allow for not only an estimation of the EV charging demand under different scenarios of EV market penetration, but also the potential to serve the power grid as a mobile energy storage [13-14].

Deterministic models are developed based on average and worst case peak load in some studies, but the required information for system operation is often not available. In addition, an enormous difference between deterministic and stochastic analysis is observed in [12]. Among stochastic modeling methods, lots of studies use Monte Carlo approach to simulate the randomness [15-17]. Paper [18] assume probability models to predict the EV charging load under different charging scenarios. In some papers [1, 11-12, 19], the EV parameters are derived from actual survey data and measurements, such as National Household Travel Survey

(NHTS) and Electric Power Research Institute (EPRI) report [20]. In this paper, the survey data from NHTS [21] is utilized to simulate the EV characteristics. This data source provides abundant real information including vehicle types, daily trip departure times, last trip arrival time, miles driven per day, driving behavior at weekdays and weekends, and etc. Paper [11] describes the type of data from NHTS 2009 in detail.

Two main places to recharge the EV batteries are either at home or public parking with charging locations [1]. Due to the long waiting time for the charging to complete, it is very possible that the EV owners will leave the vehicles at the charging station close by their work place on their way to work. Thus, in this paper, the target lies on public charging stations close by the working area and the estimated electricity consumption is for one target charging station.

In short, this paper is an integration and improvement of the existing approaches. It utilizes the actual survey data from NHTS to build the statistical model of each key variable for each EV. Different types of vehicles, battery capacities, percentages of market shares for each type, levels of EV penetration are considered.

The rest of the paper is organized as follows: the framework of the proposed analysis is described in Section II; Section III describes the methodologies and formulates the relations of the variables; case studies are implemented in Section IV; and contributions of this paper are outlined in Section V.

## II. Framework

In order to generate EV charging schedules and model the charging need for each charging station at each time point, three random variables to build the stochastic model are studied:

- Starting time of charging
- SOC
- Total number of charging EVs

The EV charging load of a single EV charging station is determined by the stochastic distribution considering the starting time of charging, SOC, as well as AER (range of distance of a fully charged EV), battery technology, charging level, and the amount of energy required to recharge [16]. The relation of the related variables are shown in Fig. 1. The starting charging time is determined by drivers' behavior and the battery capacity of the vehicles. The remaining SOC in the battery when arriving at the charging place relates to the miles driven, the capacity fading of the battery, and customers' driving behavior. The number of charging EVs in total is determined by market penetration of EVs in that target area. It also depends on the charging start time, the remaining SOC and how fast the charging is. Moreover, the output of the estimated electricity consumption of EV charging can be used for centralized feedback control in order to reduce the charging impact on power distribution systems.

Fig. 2 shows the flowchart of the proposed statistical analysis. The first step is to consider the above details on EV charging characteristics. After developing statistical descriptions of each random variable, the uncertainties of the variables are integrated and the joint stochastic model is obtained. Based on the stochastic model, the time-variant EV charging demand is estimated with an input of the EV penetration.

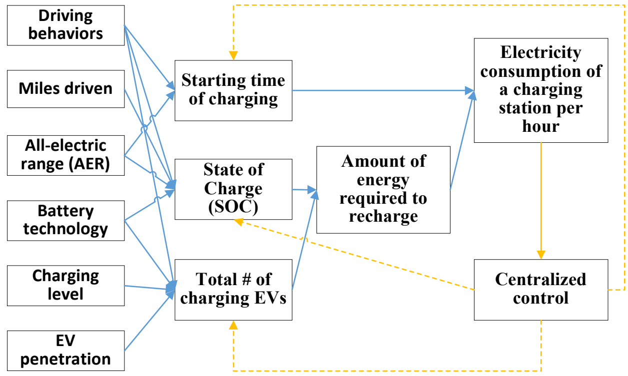


Fig. 1. Relation of the EV variables

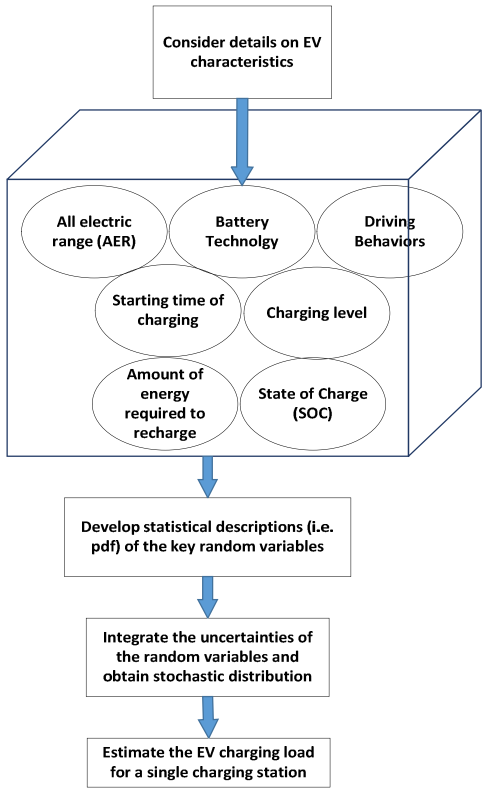


Fig. 2. Flowchart of the Statistical Analysis

## III. Mathematical Methodology

### *A. Characterization of Charging Behavior*

- Behavior of Miles Driven

Miles driven data can be obtained from survey results of NHTS [21]. As shown in Fig. 3 with miles driven as x axis and probability as y axis, the miles driven data best fits Weibull distribution, with shaping parameter $k = 1.5311$, and scaling parameter $\lambda = 35.044$.

$$f(d;\lambda,k) = \frac{k}{\lambda}\left(\frac{d}{\lambda}\right)^{k-1} e^{-\left(\frac{d}{\lambda}\right)^k}, \quad d \geq 0 \qquad (1)$$
$$= 0 \qquad , \quad d < 0$$

Numerical integral is utilized over an interval of 5 miles to calculate the probabilities using the above equation. The curve fitting result is shown in red line, while the probabilities are shown in blue bars.

- Behavior of Start Time of Charging

If daily arrival time to work place is used to estimate the charging start time, the daily travel data can be obtained from survey results of NHTS. As shown in Fig. 4, with hour of a day as x axis and probability as y axis, the start time of charging data best fits log-logistic distribution, with shaping parameter $\alpha = 8.5$, scaling parameter $\beta = 6.8$, and location parameter $\gamma = 0.65$.

$$f_{\mathrm{ST}}(\tau;\alpha,\beta,\gamma) = \frac{\alpha}{\beta}\left(\frac{\frac{\tau}{0.93}-\gamma}{\beta}\right)^{\alpha-1}\left[1+\left(\frac{\frac{\tau}{0.93}-\gamma}{\beta}\right)^{\alpha}\right]^{-2} \qquad (2)$$

Numerical integral is utilized over an interval of 1 hour to calculate the probabilities using the above equation. The curve fitting result is shown in red line, while the probabilities are shown in blue bars.

In our work, the charging station provides two options for the connected EVs, charging and discharging. In addition, discharging bonus is provided as incentives to attract EVs to be charged at work place, rather than at home. Thus, the arrival time to work place and the daily miles driven data are used.

When NHTS survey data is used to estimate charging start time, it means, uncoordinated charging scenarios are considered. As shown in Fig.1, to intelligently control the EV charging consumption, the EV charging start time can be coordinated.

- Behavior of State of Charge (SOC)

$$\mathrm{SOC} = g = \left(1-\frac{\mu d}{AER}\right)\times 100\%, \text{ if } d \leq AER \qquad (3)$$
$$= 0 \qquad , \text{ if } d > AER$$

For $d > AER$, the SOC is zero, indicating 0% left in the battery. In this case, it will force the drivers to charge immediately, in other words effecting the start time of charging variable. AER indicates the maximum miles that percentage of distance driven in electric mode. In (3), it is assumed that the battery is fully charged before the driving. Actually, since the electricity demand for the trip is what we really considered, the SOC after the miles driven can be adjusted by substituting 1 to different initial SOC values. In other words, it is not required to fully charge the battery, but sufficient for the trip. Charging can also be completed after the driving to supplement the consumed part. Zero SOC does not mean that the battery will be consumed completely once, but that if the vehicle is going to be driven d miles, at least the whole battery capacity need to be charged in that day. Since our target is one charging station near work place, we will not consider the extra charge needed. Thus, for the trips exceeding $AER$, it is believed that the customers wish to charge the vehicles to the maximum as possible for the long trips.

In fact, the SOC also depends on the driving pattern of the driver and other factors, so it is a nonlinear function of many other uncertain factors. Since the purpose of the paper is to build a general model for EV charging demand, linear relationship is utilized at this stage. More accurate relation function can be considered in future research.

Given the distribution of *d*, and the relationship between *s* and *d*, we may derive the distribution of *s*.

$$f_{\mathrm{S}}(s) = \frac{AER}{\mu}\frac{k}{\lambda}\left(\frac{AER(1-s)}{\mu\lambda}\right)^{k-1} e^{-\left(\frac{AER(1-s)}{\mu\lambda}\right)^k}, \; s < 1 \qquad (4)$$

We may plot the probabilities of SOC, shown in Fig. 5, which is calculated using numerical integral over an interval of 10%.

### *B. Joint Probability of SOC*

Based on the charging level, SOC is assumed to increase r per hour. Therefore, if we consider the charging demand at time t, the EVs that start to charge at time t-1 with initial SOC of s-r, has the same impact for time t+1 as that start to charge at time t with initial SOC of s.

Therefore, the probability that SOC takes the value s at time t is:

$$p(s,t) = \sum\nolimits_{j=1}^{t} p_{ST}(j)\, p_S\left(s - r(t-j)\right) \qquad (5)$$

Where $p(\cdot)$ denotes the discretized probability, as compared to $f(\cdot)$, which is a continuous distribution function.

If we consider a given time *t*, all the possibilities of $p(s,t)$ at time t should add up to one.

$$p(:,t) = \sum\nolimits_{S}\sum\nolimits_{j=1}^{t} p_{ST}(j)\, p_S\left(s - r(t-j)\right) \qquad (6)$$

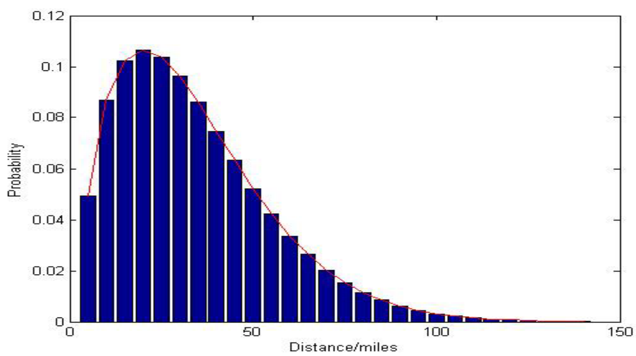


Fig. 3. Miles Drive Data and Probability Distribution

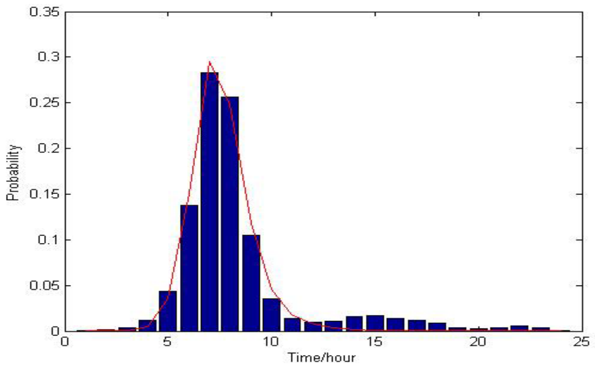


Fig. 4. Start time of Charging Data and Probability Distribution

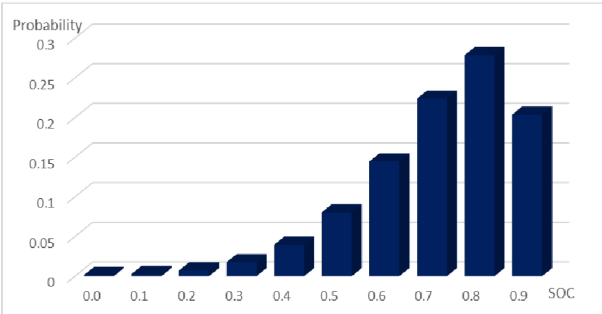


Fig. 5. Probability Distribution of SOC

However, the right side of the above equation do not equal to 1. It is noticed that the deficiency is due to the neglect of $s=1$. Thus, we need to consider the situation when no charging is required. In this case,

$$p(1,t)=1-\sum_{s=0}^{0.9}\sum_{j=1}^{t}p_{ST}(j)\,p_S\big(s-r(t-j)\big) \quad \text{, if } s=1 \tag{7}$$

*C. Collective Behavior of EVs*

For each EV i, with remaining battery level s, at certain time t, the charging demand needed is formulated as

$$\begin{aligned}\eta En_{EV}^{i,t,s} &= \left(SOC^f - SOC^{i,t,s}\right)C_{cap}, \text{ if } SOC^f - SOC^{i,t,s} < r\\ &= r\times C_{cap} \qquad\qquad \text{, if } SOC^f - SOC^{i,t,s} \geq r\end{aligned} \tag{8}$$

Where $\eta$ is a constant number for charging efficiency, $SOC^f$ is a constant number in this study (in the case of controlled charging, $SOC^f$ is not constant), $SOC^{i,t,s}$ is a random variable, and $C_{cap}$ is the usable battery capacity that depends on the type of vehicles (l, see Table I) and corresponding AER.

$$C_{cap}^{l} = ECM^{l}\times AER \tag{9}$$

where ECM is the estimated electrical energy consumption per mile proposed by Pacific Northwest National Laboratory (PNNL) [22].

The collective behavior of $N_{EV}^{t,s}$ EVs charging at the same charging station can be characterized as:

$$\begin{aligned}\eta En_{EV}^{t,s} &= \eta\sum_{i=1}^{N_{EV}^{t,s}} En_{EV}^{i,t,s}\\ &= \sum_{l=1}^{4}\sum_{i=1}^{\rho^l\times N_{EV}^{t,s}}\left(\min(r, SOC^f - SOC^{i,t,s})\right)C_{cap}^{l}\end{aligned} \tag{10}$$

Thus, the original problem can be simplified as: given the joint probabilistic distribution of $p(s,t)$, find the expected value of $En_{EV}^{t,s}$, for each hour.

*D. Expected Value of Initial SOC for one EV*

Based on statistic theory, the expected value of $SOC^{i,t,s}$ can be formulated as:

$$E(s)=\sum_{s=0}^{1} sp(s,t) \tag{11}$$

Where

$$p(1,t)=1-\sum_{s=0}^{0.9}\sum_{j=1}^{t}p_{ST}(j)\,p_S\big(s-r(t-j)\big) \quad \text{, if } s=1 \tag{7}$$

$$p(s,t)=\sum_{j=1}^{t}p_{ST}(j)\,p_S\big(s-r(t-j)\big) \quad \text{, if } s\neq 1 \tag{12}$$

*E. Expected Value of Electricity Consumption for one Charging Station*

Taking the expectation for both sides of Eq. (10), we have

$$\begin{aligned}E\left(En_{EV}^{t,s}\right) &= \sum_{l=1}^{4}\frac{C_{cap}^{l}}{\eta}\left(\sum_{i=1}^{\rho^l N_{EV}^{t,s}} E\big(\min(r,1-s)\big)\right)\\ &= \sum_{l=1}^{4}\frac{C_{cap}^{l}}{\eta}\rho^l N_{EV}^{t,s}\left(E\big(\min(r,1-s)\big)\right)\end{aligned} \tag{13}$$

Where

$$N_{EV}^{t,s} = \frac{\psi}{\delta}\times\varepsilon\times\theta \tag{14}$$

The total amount of charging EVs is a random variable. However, if we regard each EV as a stochastic target, there will be one more redundancy if the number of charging EVs is considered as an individual random variable. Therefore, we only need to consider the total amount of EVs in the target area, which is $N_{EV}^{t,s}$, and market shares for each vehicle type.

Last, the capacity of a charging station may be limited due to the charging limitation of the specific distribution feeder j where the charging station is located, e.g. limited EV market penetration, limited charger number n. Thus, the constraints are as follows,

$$En_{EV,j}^{t,s}/t \leq P_{\max}^{j} \tag{15}$$

$$\theta \leq \theta_{\max}^{j} \tag{16}$$

$$n \leq n_{\max}^{j} \tag{17}$$

Where $P_{\max}^{j}$ is determined by the capacity of the specific feeder; $\theta_{\max}^{j}$ and $n_{\max}^{j}$ are also affected by how the EV charging can be coordinated. In factor, since the maximum charging rate for each charger is fixed in a charging station, $n_{\max}^{j}$ is decided by $P_{\max}^{j}$ . Thus, as long as (17) is satisfied, all the three constraints are satisfied. If the simulation result at t shows that it requires more than $n_{\max}^{j}$ chargers, i.e. $n > n_{\max}^{j}$, the $En_{EV,j}^{t,s}$ at t should be adjusted to $En_{EV,j}^{t,s} = P_{\max}^{j} * t$ .

## IV. CASE STUDY

Available data are survey results of daily travel data and mile driven data, which can be obtain from NHTS. The probability distributions of SOC and Start time of charging are derived by curving fitting the probability distributions of given data and survey results, and then discretized in acceptable resolutions. Output data should be the electricity demand from EV charging for one charging station at each hour.

Based on experiences, $\eta = 83.33\%$, $SOC_f = 100\%$ . The value of ECM and market shares for each vehicle type are shown in Table I [11, 21]. Since the charging rate is assumed to be 7.2 kW/h, the SOC is assumed to increase 20% per hour. The interval of index t is assumed to be an hour. Thus, $r = 0.2$ and the estimated value will be electricity demand within the hour. The target area is assumed to have a population of 5000 with 50% EV penetration. Through MATLAB simulation, the expected value of $SOC_{i,t,s}$ can be calculated, shown in Table II and demonstrated in Fig. 6.

Substituting Eq. (13) with actual values, we have

$$E\left(En_{EV}^{t,s}\right) = N_{EV}^{t,s}\left(E\left(\min(r,1-s)\right)\right)\sum_{l=1}^{4}\frac{ECM^{l}\times AER^{l}\times\rho^{l}}{0.8333} \quad (18)$$

Final results of electricity consumption for a charging station are shown in Table III and demonstrated in Fig. 7.

The expected number of charging EVs are calculated based on the expectation of the electricity consumption, as shown in Fig. 8. If the limitation of the charger number is 200 as an example, the expected number of charging EVs and electricity consumption need to be adjusted accordingly, as shown in Fig. 7 and 8.

By adjusting the value of parameters used in the algorithm, the expected results can be obtained for different cases. EV schedules can be assumed for each case study by making it match the expected EV consumption results, if a general assumption or forecast of EV charging scenarios is needed. Further studies of how to use the results will be investigated.

TABLE I. EXPECTATION OF SOC

| Vehicle type (l) | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| | **Compact sedan** | **Mid-size sedan** | **Mid-size SUV** | **Full-size SUV** |
| ECM (kWh/mile) | 0.26 | 0.3 | 0.38 | 0.46 |
| Percentage (%) | 51.48% | 10.35% | 23% | 15.17% |
| Battery capacity (kWh) for PHEV100 | 26 | 30 | 38 | 46 |

TABLE II. EXPECTATION OF SOC

| Hours(h) | Expectation | Hours(h) | Expectation |
|---|---|---|---|
| 1 | 0.999620118 | 13 | 0.993885068 |
| 2 | 0.999568834 | 14 | 0.993211351 |
| 3 | 0.998827898 | 15 | 0.99375874 |
| 4 | 0.996104875 | 16 | 0.994597666 |
| 5 | 0.98612041 | 17 | 0.995748641 |
| 6 | 0.95551344 | 18 | 0.99756828 |
| 7 | 0.902823004 | 19 | 0.998570485 |
| 8 | 0.892104147 | 20 | 0.998523125 |
| 9 | 0.934065576 | 21 | 0.997780209 |
| 10 | 0.970407273 | 22 | 0.998235568 |
| 11 | 0.988209595 | 23 | 0.999197851 |
| 12 | 0.994138224 | 24 | 0.993885068 |

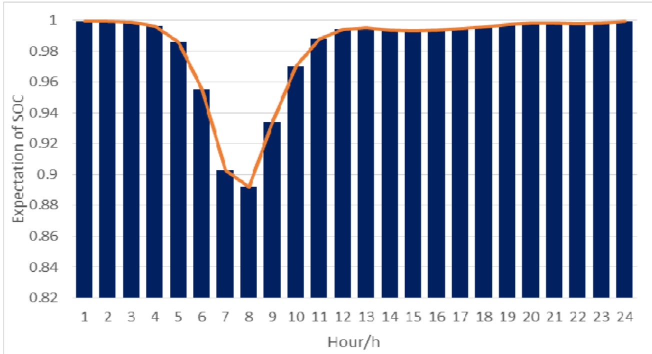


Fig. 6. Expectation of SOC at time t (1-24h)

TABLE III. ELECTRICITY CONSUMPTION OF A CHARGING STATION

| Hours (h) | Expectation (kWh) | Hours (h) | Expectation (kWh) |
|---|---|---|---|
| 1 | 13.33316916 | 13 | 159.6805307 |
| 2 | 13.89383688 | 14 | 195.9353062 |
| 3 | 36.4158834 | 15 | 219.386913 |
| 4 | 120.4460023 | 16 | 204.465763 |
| 5 | 428.5495602 | 17 | 177.8155963 |
| 6 | 1376.845181 | 18 | 141.0527576 |
| 7 | 3040.768944 | 19 | 83.37086034 |
| 8 | 3488.105237 | 20 | 48.82979993 |
| 9 | 2245.234638 | 21 | 47.91638331 |
| 10 | 1047.928805 | 22 | 70.50275645 |
| 11 | 424.2160016 | 23 | 58.49847578 |
| 12 | 203.7457454 | 24 | 28.36626053 |

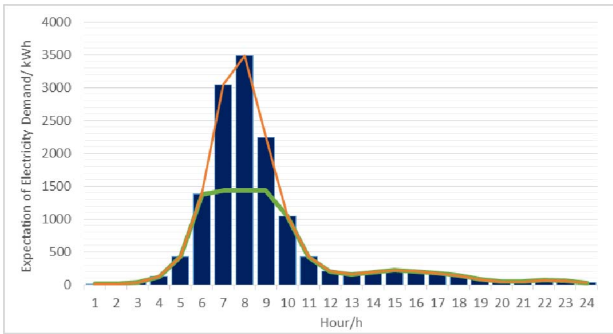


Fig. 7. Expectation of electricity demand at time t (1-24h)

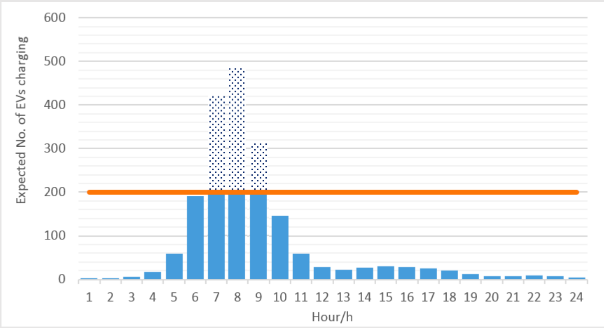


Fig. 8. Expected number of charging EVs at time t (1-24h)

## V. Conclusion

The contributions of this work are as follows:

- The EV driving and charging characteristics are analyzed using the real statistical data. Battery technology, charging level, EV penetration, AER, daily trip miles, starting time of charging, and SOC are taken into consideration;
- The statistical descriptions (pdf) of the key variables are developed. The continuous functions are discretized to simulate the probability distribution;
- The uncertainties of the random variables are integrated and interconnected;
- Numerical experiments are implemented to verify the proposed analysis and illustrate the electricity demand that EVs contribute to the distribution systems.

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