Queuing Analysis Based PEV Load Modeling And Impact Of Electric Vehicle Charging On The Power Grid

Nikhil Dhende[1], Dr. R.N.Awale[2]
[1, 2] VJTI, H.R.Mahajani Road, Matunga Mumbai 400019,India

Abstract- *Electric vehicles are becoming an alternative to Vehicles powered by an internal combustion engine. This leads to environmental benefits, but these PEVs represent new challenges facing the power grid. Therefore, the power grid must be prepared for these challenges.*

This paper present 24-hour charging load profile of plug-in Electric vehicle (PEV) using Queuing analysis. PEV has varying arrival rates over the day. PEV charging depend on customer convenience during peak hour and unlike charging prices. Main contribution of paper is to model PEV service time by considering Vehicle size, battery,

Keywords- Queuing Analysis, Plug in electric vehicle, Battery charging behavior, distribution system

NOMENCLATURE

Sets and Indices

i, j Index for buses
k Index for time
l Set of SOC intervals *l . {1, 2, 3,4}*
N Total number of buses in the system
n Set of all possible options of simultaneous charging of PEVs, for a given N0
n {0, 1, 2, 3, …, N0}
s Index for stochastic scenario
y Index for PEV class

Parameters

C_{Bat} *Total PEV battery capacity, kWh*
DD *Daily driven miles by PEV, mile*
DD_{Max} *Maximum driving distance until PEV battery is fully discharged, mile*
EC *Daily recharge energy, kWh*
EM *Energy consumption of PEV battery per mile driven, kWh/mile*
I *Charging current, A*
Imax *Charging current level, A*

M1/M2/N0 *Queuing model, M1 denotes PEV arrival rate (Minute) / M2 denotes PEV charging time (Minute) / N0 is the number of PEVs being charged simultaneously at a given hour*

N_{Cap} *Maximum number of PEVs that can be charged simultaneously at the station*

P(n) *Probability of n*
μ *Mean service time, minute*
λ *Mean of inter-arrival time, minute*
ρ *Occupation rate of PEV at charging station*

I. INTRODUCTION

Because of environmental concerns associated with vehicles driven by Internal Combustion Engine, there is rapid growth of EVs in the market. EVs play a significant role in reducing of air pollution and emission of greenhouse gases. Demand for Energy has been rapidly increasing which imposes a large burden on existing energy resources.

Electrical vehicle technology is growing rapidly this will cause burden on system peak demand and thus over loading distribution feeders.

Coordinated charging should be implemented to avoid peak load, losses, voltage drop, Transformer ageing. While uncoordinated charging of 10% penetration can cause unacceptable variation.

Charging demand of PEV is affected by different factors such as the number of PEV being charged simultaneously, their charging level, battery capacity and charging duration.

Monte Carlo simulation (MCS) is used to generate virtual trip distance of different vehicles and formulate annual energy consumption model

The Model Predictive Control (MPC) has applied to various operation and control problem of smart grid to consider effect of uncertainties. In a prediction based real time charging method has been proposed that consider effect of future penetrating vehicle into the grid.

Most of the work on PEV charging demand modeling that use queuing analysis, consider the arrival rates as a poison process, which have a constant arrival rate. Only a few have arrival as a non-homogeneous process.

It should be noted during process of Fast charging, the charging power typically starts at high rate and drops as per the battery State of Charge (SOC) approaches full capacity,

As per the battery charging behavior (BCB) of PEV this affect charging time and need to be considered in load model, the main objective of this paper are:

- Estimate number of vehicle on the road and construct PEV arrival rate profile at charging station and also considering the charging price.
- Using the arrival rate profile, the service time of PEV using BCB's develop to determine 24 hour charging demand profile at charging station.
- The arrival of customer has been modeled as continuous and random process considering two different arrival patterns ,customer convenience and charging price
- The queuing model proposed in this paper consider for the first time, a detailed representation of BCB of PEVs.

II. MATHEMATICAL MODEL

A. PEV Queuing Model

Estimation of total charging power of PEVs. The PEV customers are considered to be served using M1/M2/N0 at a PEV charging station, where M1 denotes the arrival rate which varies from hour to hour of the day and is modeled as,M2 denote the service time includes the waiting time and the charging time. The service time is modeled considering the PEV BCB. Poisson process is a continuous process that counts the number of arrivals in a given time interval where the time between each pair of consecutive arrivals has an exponential distribution with (mean of inter-arrival time) λ and each of these inter-arrival times are assumed to be independent of other inter-arrival times. It is useful for modeling arrival thatoccur independently from each other. Since the arrival of PEVs at the charging station is a continuous-time stochasticprocess. In accordance to M1/M2/N0 queuing analysis the probability of the number of PEVs charging simultaneously at an hour is modeled as a discrete distribution, as follows

$$p_k[n] = \frac{(N_0\rho)^n}{n!} P_k(0) \qquad n=1, 2, 3\ldots.N_0 \qquad (1)$$

Where

$$p_{k_{(0)}} = \sum_{m=0}^{N_0-1}\left[\frac{(N_0\,\rho)^m}{m!} + \frac{(N_0\rho)^{N_0}}{N_0!}\frac{1}{(1-\rho)}\right]^{-1} \qquad (2)$$

ρ is occupation rate of PEV charging station

$$\rho = \frac{1/\lambda_k}{N_0\frac{1}{\mu_k}} \qquad (3)$$

B. *PEV Battery Charging Behavior (BCB) Model*

The charging service time is affected by different factors, such as the charging level, battery capacity, battery SOC, and PEV BCB. One of the main objectives of PEV customers is to have fast charging at a charging station i.e., minimum service time. In order to achieve this, the BCB of each class of PEVs are considered; for example, the battery of a typical Compact PEV during fast charging attains an SOC of 50% in 10 minutes, 75% in 15 minutes, beyond which there is a drop in charging rate, as shown in Fig.1. Considering a maximum required SOC for the PEVs to be 85%, it can be noted from Fig.1 that this is attained in 22 minutes, for Compact PEVs, and therefore, the service time depends on the BCB of the PEV class.

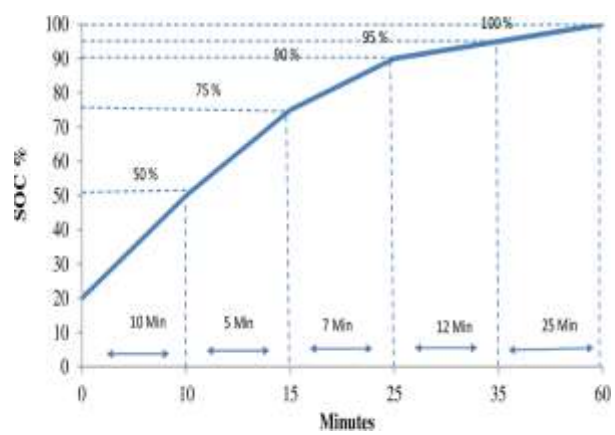


Fig.1: Typical BCB of a Compact PEV during fast charging

The SOC of battery can be obtained as follows:

$$SOC_y = 1 - \frac{E_{C_Y}}{C_{bat_y}} \quad \text{........y} \qquad (4)$$

and Following condition are imposed, from above BCB of PEV in fig 1

$$SOC_y = \begin{cases} 0.2 & \text{if } soc \leq 0.2 \\ SOC_y & \text{if } 0.2 < soc \leq 0.85 \\ 0.85 & \text{if } soc > 0.85 \end{cases} \qquad (5)$$

Once the SOC of a PEV is known, the required charging time of PEV, given by T, is obtained from BCB using following relation

T= (Max time to set SOC)-(SOC-lowest SOC)*slope(6)

$$I_{k,y} = \min\left(\frac{E_{c_y}}{VT_k}, I_{max}\right) \qquad (7)$$

Where I_{max} and V are dependent on the charging level and hence fixed

Ecy is daily recharge energy of PEV

$$E_{c_y} = \begin{cases} Cbat & if \quad DDy \geq DDmax \\ EMy\, DDy & if \quad DDy < DDmax \end{cases} \qquad (8)$$

E_{My} is the energy consumption by a PEV class Y, per mile
DD_{Max} Maximum driving distance is calculated as

$$DD_{Max_y} = \frac{C_{bat_y}}{E_{M_y}} \qquad (9)$$

Therefore, the total charging power for *N0* number of PEVs being charged simultaneously at time *k* is given as follows:

$$Pch_{i,k} = \sum_{m=1}^{N_0} I_{m,k,y} V \qquad (10)$$

The total expected PEV charging demand at time *k* for all possible values *N0*

$$E[Pch_{i,k}] = \sum_{N_0}^{N_{cap}} P_k(N_o) Pch_{i,k} \qquad (11)$$

III. CASE STUDY

A. Distribution System and Mobility Data

The analysis reported in this paper is carried out considering the IEEE 69-bus radial distribution system, whose single line- diagram is given in Fig 2. The distribution system is supplied through the substation at bus-1. It is assumed that PEV charging station is located at bus-59. In this paper, Level-3 charging is considered since high power level charging is preferred at PEV charging stations, and thus IMax= 63 amps and V = 400 volts.

Distribution systems are generally balanced by using various load balancing schemes, and hence can be represented by single phase equivalents. The unbalanced nature of distribution system is more prevalent at the end-user level (residential customer level) but since this work considers a PEV charging station load model, it is assumed to be connected at 12.66 kV feeder level and at this voltage level, the loads are assumed to be balanced three-phase.

With these assumptions, a single line-to-neutral equivalent circuit for the feeder has been used, and a three phase distribution system is represented by a single-phase equivalent.

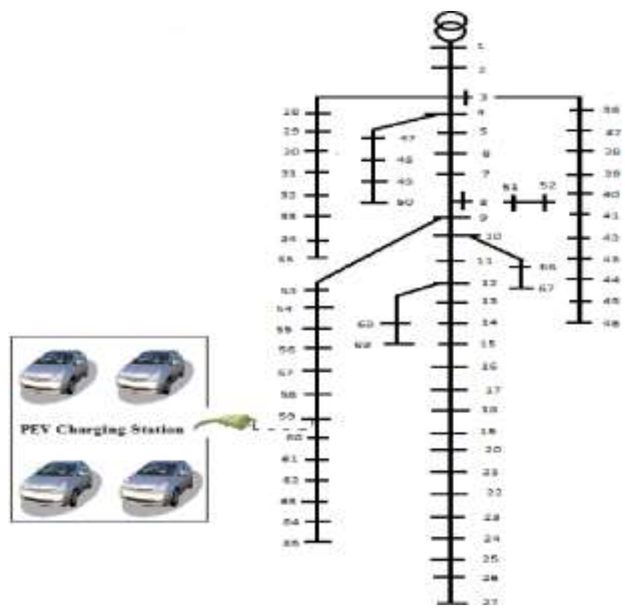
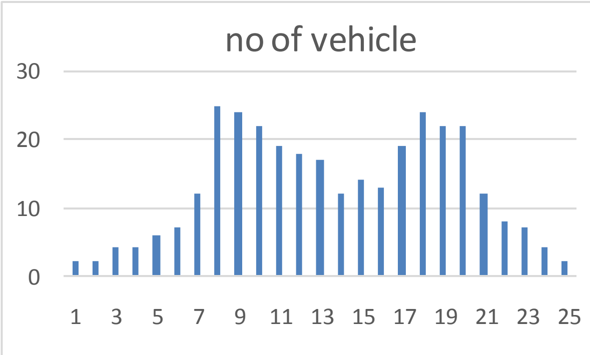


Fig 2: 69-Bus radial distribution system

Waterloo Region TTS data and Ontario, Canada, TOU winter tariff rates are used in order to obtain realistic results. Survey conducted every five years in the region. In this work the 2011 TTS for Waterloo Region is used which considers of 43,165 unique trips. Fig. 3 presents the winter TOU rates of Ontario over a day. The distribution of vehicles on the road over a 24 hour period is calculated using the same TTS data and shown in Fig. 3.



Hours

Fig.3: Distribution of vehicles on the road and Ontario winter TOU

B. Modeling Daily Driven Miles and PEV Arrival Rate,M1

Fig 4 shows the distribution of daily miles driven on all vehicle driving days based on the TTS data. So, the daily driven miles by the PEVs DD_y, is modeled as a lognormal distribution in this work, and is given by:

$$DD_y = e^{(\mu_M + \sigma_M f)} \quad (12)$$

where $\mu_M$and $\sigma_M$are the mean and the variance of the lognormal distribution, respectively.

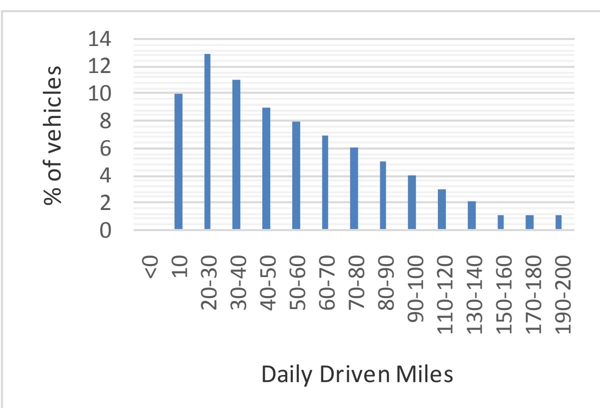


Fig.4: Distribution of daily driven distance per vehicle as per TTS

In this paper, four classes of PEVs are considered-

Compact, *Economy*, *Mid-Size*, and *Light Truck/SUV*, to present a realistic picture of the PEV charging station load. The queuing algorithm is initiated by randomly generating *N0*. The PEV arrival rate *M1* depends on the hour ofday and customer behavior pattern. Under a rational behavior assumption, two *M1*profiles are modeled as follows:

- Scenario-1: considers that the PEV arrival rate depends on customer convenience, *i.e.*, the number of vehicles on the road. When the number of vehicles on the road is high the arrival rate is high, irrespective of the price or Local distribution company operational constraints. In this paper, using TTS data, a relationship between vehicles on the road and PEV arrival rate at the charging station is assumed. As shown in Fig.5, if the percent of vehicles on the road is up to 4%, at any hour, a uniformly distributed PEV arrival in the range of 1 to 4 PEVs/hour is assumed, and similarly 5 to 11 PEVs are assumed to arrive if 4-7% of vehicles are on the road, and so on. For example, at hour 7, about 7% of the vehicles are on the road (see Fig.3) and consequently, 5 to 11 PEVs may arrive for charging (as per Fig.5), on the other hand, at hour 17 , 9.3% of the vehicles are on the road, and it is assumed that 12 to 17 PEVs may arrive for charging.
- Scenario-2: considers that the PEV arrival rate depends on the charging price, *i.e.*, more PEVs will charge when the price is low, and *vice versa*. In this scenario a relationship between Ontario's winter TOU price and PEV arrival rate at the charging station is assumed. As shown in Fig.7, if the charging price ranges between 7.5 and 11.2 cents, at any hour, a uniformly distributed PEV arrival in the range of 5 to 11 PEVs/hour is assumed, and similarly 12 to 17 PEVs are assumed to arrive if the charging price is in the range of 11.2 to 13.5 cents. For example, at hour 6, the charging price is 13.5 cents (*see Fig.3*) and consequently, only 1 to 4 PEVs may arrive for charging (*as per Fig.6*).

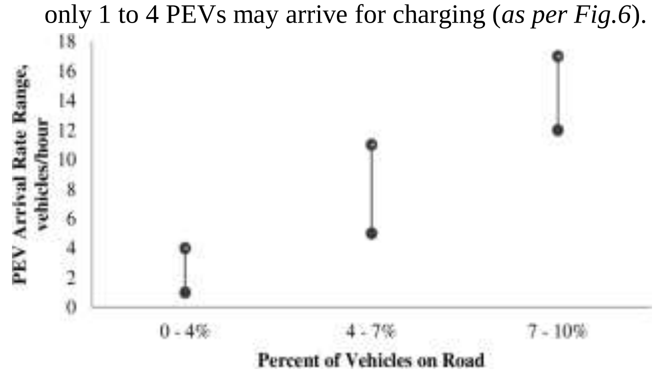


Fig.5: Relationship between vehicles on road and arrival rate of PEVs

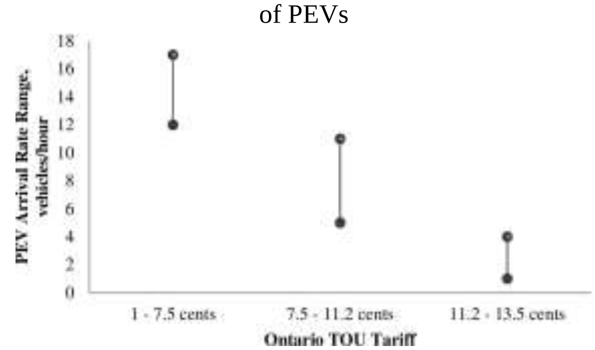


Fig.6: Relationship between TOU tariff and arrival rate of PEVs

Arrival rates modeled in this paper are based on assumption of number of vehicle on the road, charging price, and how PEV's arrive for charging at charging station. Such assumptions are necessary in order to understand the impact of PEV charging on the distribution grid but, need be validated with realistic data from ground level surveys.

As per Scenario-2, the arrival rate would be high at night since the PEV charging price is low at these hours. However, considering charging during night is low, because of customer inconvenience, the arrival rate is modified appropriately, as shown in Fig. 7, where the removed arrival data of early hours are indicated. Also to be noted that since home charging has been ignored in this work, there will be no effect on the early morning arrival rates. The two arrival rate profiles, as discussed above, are modeled as non-homogeneous Poisson processes with mean λkwhich is the time dependent number of expected car arrivals at a charging station throughout the day.

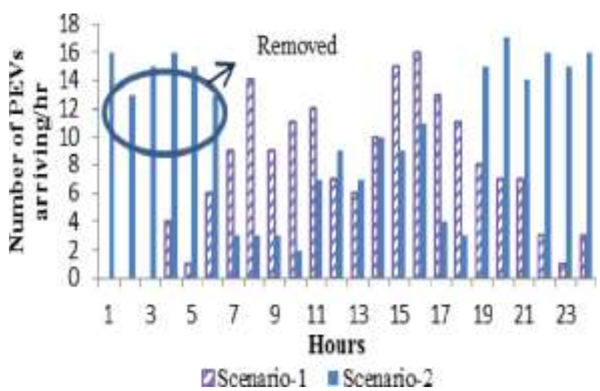


Fig.7: Number of PEVs arriving per hour at the charging station (Arrival rate)

C. Simulation of the Queuing Process

Arrival rate scenario is selected, for every value of *N0*, the following steps are repeated:

- Assume PEV class are commonly distributed over the sample set N_0 , PEV class are randomly selected from among four different classes
- The battery capacity for each PEV class is uniformly distributed between their upper and lower limits.
- Calculate battery SOC for each PEV from its daily recharge energy, which depends on different factors such as the daily driven miles, and battery capacity.
- Determine the time required for charging for each PEV, using the BCB.
- Determine the total charging power arising at the charging station, for the total *N0*PEVs using .

Following are the parameters used in this paper to simulate the queuing process of PEVs charging at a charging station:

- PARAMETERS FOR SIMULATION OF QUEUING MODEL

<table>
<tr><td colspan="2">ITR_{Max}</td><td colspan="4">2000</td></tr>
<tr><td colspan="2">Ncap</td><td colspan="4">17</td></tr>
<tr><td colspan="2">λ_k</td><td colspan="4">Non-homogeneous Poisson Process</td></tr>
<tr><td colspan="2">μ_k</td><td colspan="4">Non-homogeneous Poisson Process including BCB and SOC</td></tr>
<tr><td rowspan="3">PEV</td><td>Class</td><td>Compact</td><td>Economy</td><td>Mid-size</td><td>SUV</td></tr>
<tr><td>C_{Bat}, KWH</td><td>8 - 12</td><td>10 - 14</td><td>14 – 18</td><td>19 – 23</td></tr>
<tr><td>E_M, KWH/mile</td><td>0.2 – 0.3</td><td>0.25 – 0.35</td><td>0.35- 0.45</td><td>0.48 – 0.58</td></tr>
<tr><td></td><td>DD, miles</td><td colspan="4">Lognormal Distribution
μ_M=40 miles, σ_M= 20 mile</td></tr>
</table>

IV. RESULTS AND DISCUSSIONS

A. PEV Charging Load Using Queuing Analysis

In this section the effect of PEV charging on the distribution system performance is examined. Queuing analysis is used to model the 24-hour PEV charging demand at the charging station. The objective is to determine the optimal distribution system operation considering PEV charging demand while minimizing the system losses. The probability distribution of *N0* is obtained from (1) and shown in Fig.9 which is used as an input to the M1/M2/N0queuing model. Different NCapvalues are examined within the proposed queuing model and it is noted that when NCapis high, the probability of simultaneously charging of NCapnumber of PEVs, *i.e.*, P (NCap) is very low, as seen from Fig.9. Because of this low probability, there is insignificant impact on the total expected charging demand for high values of NCap. By various trial runs it is noted that beyond NCap=*17*, the effect on expected charging demand does not change significantly and hence, NCap=*17* was chosen for the paper.

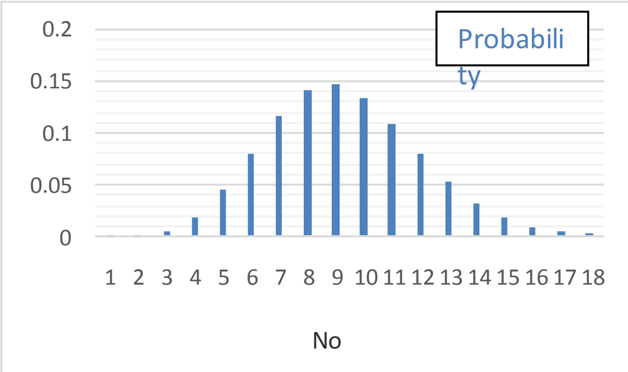


Fig.8 : Probability distribution of *N0* as input to *M1/M2/N0* queuing model

It is noted from Fig.10 that the expected PEV charging demand is low for low arrival rates (*M1 = 40, i.e., a PEV arriving every 40 minutes*) and. As the arrival rate increases, *i.e., M1 = 25 (a PEV arriving every 25 minutes)*, and then for *M1 = 10*, the expected PEV charging demand increases and the distribution pattern becomes a standard normal distribution with a high mean value of *N0*.

The expected charging demand of PEVs at a specific hour can be obtained, as shown. It is seen that when the arrival rate is high, the expected load is high, and the discrete distribution pattern of the PEV charging demand as a function of *N0* is normally distributed.

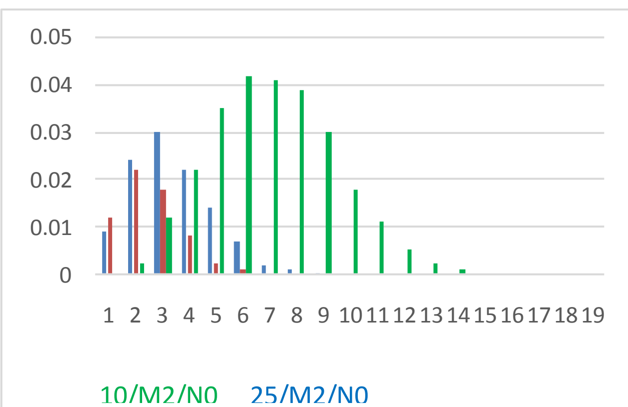


Fig.9: Expected PEV charging demand for some typical arrival rates

For example, at hour-8 the PEV arrival rate is high for Scenario-1 (Fig.10) while at hour-22 it is high for Scenario-2 (Fig.11), and the discrete distribution patterns are accordingly normally distributed at these hours, for the respective scenarios. When PEV charging takes place at hour 10 (Fig.12), which is not the most convenient hour and neither the cheapest hour for customers to charge their vehicles, both scenarios have almost similar distributions.

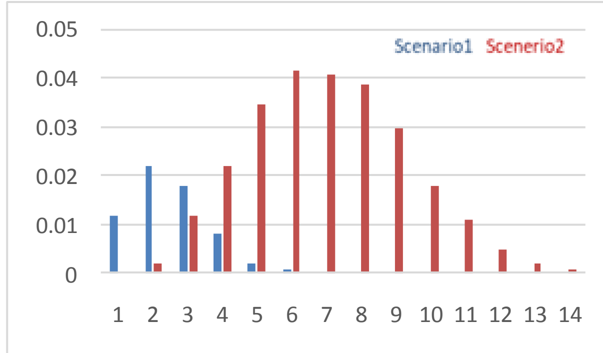


Fig.10: Expected PEV charging demand at hour-08 for different *N0*

The overall expected PEV charging demand obtained for both Scenarios, presented in Fig.13, shows that the PEV charging demand increases in both scenarios as compared to the Base Case. In Scenario-1 the charging demand appears during the peak price hours since these hours are more convenient for customers, while in Scenario-2 the increase is significant during off-peak price hours. It is also noted that as *N0* increases, the expected charging demand will gradually merge with the Base Case load profile as the probability of a large *N0* is low.

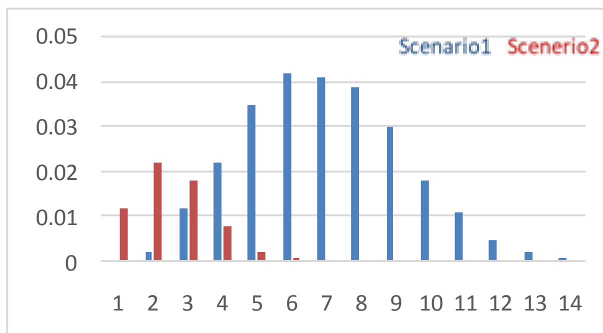


Fig.11: Expected PEV charging demand at hour-22 for different *N0*

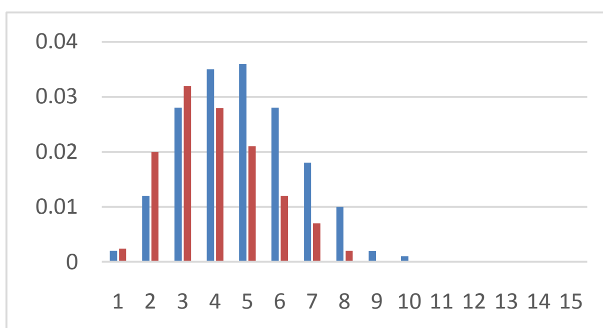


Fig.12: Expected PEV charging demand at hour-10 for different *N0*

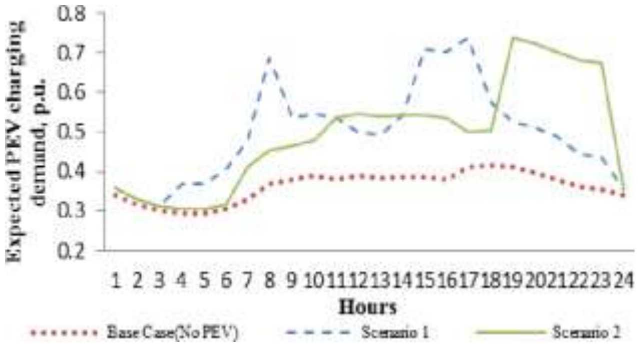


Fig.13: Total PEV expected charging demand for all queuing model

B. Impact of BCB on Service Time and chargingdemand

Since minimizing the charging time and wait time for PEVs at the charging station is one of the main objectives, the PEV charging time (*i.e.*, the service time) is modeled considering the BCB. In queuing analysis based approaches, charging time is typically modeled using exponential distributions with upper and lower limits randomly assigned to each PEV. It is seen that from Fig.14 that when BCB is considered, all the PEVs are served within the hour they arrive at the station, there is no overflow across the hour, and there is no waiting time.

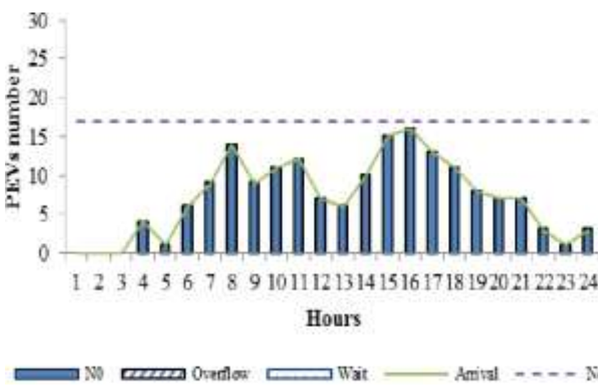


Fig.14: PEVs charging overflow, waiting: considering BCB

when BCB is not considered, all the EVs will be allotted with full charging time i.e 60 minutes which results in overflow. These service overflows will be transferred to the next hour, which may lead to waiting times if the total number of PEVs to be served, exceeds *NCap*. The effect of considering the BCB on the PEV demand profile is quite noticeable, when the BCB model is not considered the charging demand is higher at certain hours because of the waiting.

In order to introduce a service overflow and waiting time for PEVs when considering BCB of the PEVs, it is now assumed that the arrival rate is greater than the station capacity, *i.e.*, λ *>NCap*. The service overflow and PEVs waiting are significantly increased when BCB is not considered. It is also noted that the average waiting time is significantly reduced when BCB is considered as compared to the case without BCB (Fig. 15) which is in line with the preferences of customers for fast charging. Finally, Fig.16 shows the effect of BCB on total charging demand when the arrival rate is more than e station capacity. Comparing this profile with Fig.18, it is noted that the charging demand is significantly affected by the BCB, and also when λ >NCap.

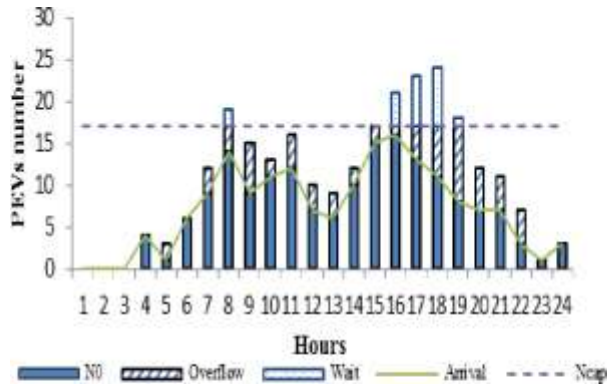


Fig.15: PEVs charging overflow: waiting not considering BCB

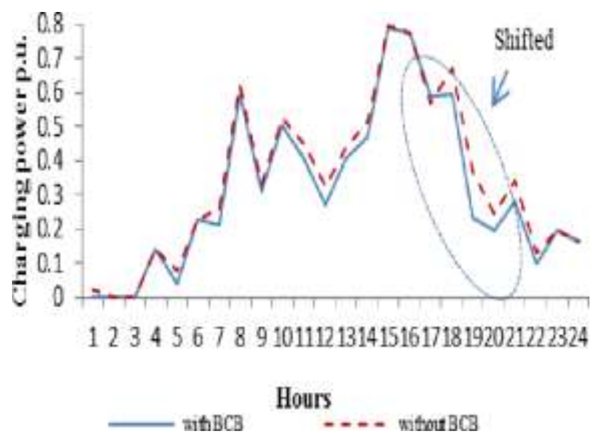


Fig.16: Effect of BCB on total charging demand

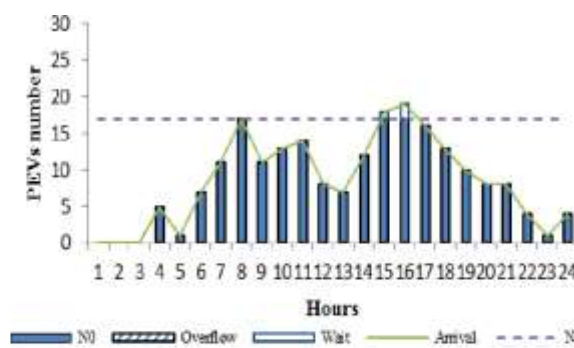


Fig.17: PEVs charging, overflow, waiting: considering BCB, λ >NCap

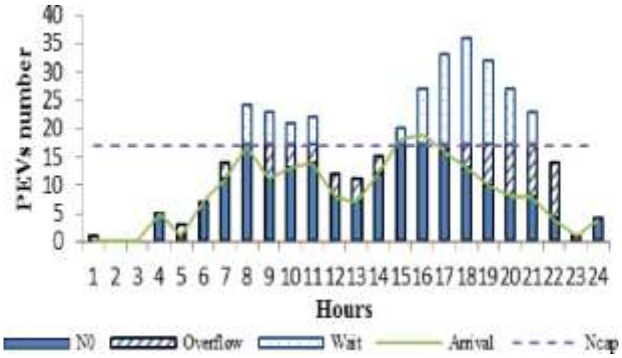


Fig.18: PEVs charging, overflow, waiting: not considering BCB, λ >NCap

C. Impact of PEV Charging on Distribution System

The Base Case is the case when no PEVs are present in the system. Analyses are then carried out to examine the impact of PEV charging loads considering:

Uncontrolled operation of distribution system- in this case power flow analysis is carried out to examine the impact of PEV charging loads appearing on the distribution feeder while the LDC takes no operational and control actions to manage the system voltages.

V. CONCLUSIONS

In this paper, a queuing analysis based methodology for modeling the 24-hour charging demand of PEVs at a charging station was presented. Four different PEV classes with their appropriate parameters that determined the charging behavior were taken into consideration. The proposed queuing model considered the arrival of PEVs as a non-homogeneous Poisson process with different arrival rates at different times of the day and the PEV BCB was also considered. Different arrival rate patterns were considered for different groups of customers- one based on customer convenience and the other based on PEV charging price which were estimated from Waterloo Region TTS data and Ontario TOU rates respectively. A novel feature of the proposed PEV charging load model was that a piece-wise linear function of the SOC was used to represent the BCB of PEVs, and hence determine the charging time which then integrated with the *M1/M2/N0* queuing model. PEV SOC and BCB were found to be a sufficient method in order to determine appropriate PEV charging time. The developed load model of PEVs was then incorporated in deterministic and stochastic analysis frameworks of the distribution system, to study their impact on the distribution system, and examine how the LDC can accommodate PEV charging loads while maintaining the system constraints.

REFERENCES

[1] O. Hafez and K. Bhattacharya, "Modeling of PEV charging load using queuing analysis and its impact on distribution system operation," *2015 IEEE Power & Energy Society General Meeting*, Denver, CO, 2015, pp. 1-5.

[2] H. Ramadan, A. Ali and C. Farkas, "Assessment of plug-in electric vehicles charging impacts on residential low voltage distribution grid in Hungary," *2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG)*, Istanbul, 2018, pp. 105-109.

[3] S. Deb, K. Kalita and P. Mahanta, "Review of impact of electric vehicle charging station on the power grid," *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*, Kollam, 2017, pp. 1-6.

[4] A. Dubey and S. Santoso, "Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations," in *IEEE Access*, vol. 3, pp. 1871-1893, 2015.

[5] M. F. Shaaban, Y. M. Atwa, and E. F. El-Saadany, "PEVs modeling and impacts mitigation in distribution networks," *IEEE Transactions on Power Systems, vol. 28, no. 2, May 2013.*

[6] S. Deb, K. Kalita and P. Mahanta, "Impact of electric vehicle charging stations on reliability of distribution network," *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*, Kollam, 2017, pp. 1-6.

[7] The 2011 Transportation Tomorrow Survey [Online]. Available: http://www.dmg.utoronto.ca/reports/ttsreports.html.

[8] Ontario hydro Time of use pricing rates [Online]. Available: http://www.ontario-hydro.com/index.php?page=current_rates.

[9] G. T. Heydt, "The impact of electric vehicle deployment on load management strategies," *IEEE Transactions on Power Apparatus and Systems, vol. 1, no. 144, pp. 1253–1259, May 1983.*

[10] C. Canizares, J. Nathwani, K. Bhattacharya, M. Fowler, M. Kazerani, R. Fraser, I. Rowlands, H. Gabbar, "Towards an Ontario action plan for plug-in-electric vehicles (PEVs)," Waterloo Institute for Sustainable Energy, University of Waterloo, May 17, 2010.

[11] J. C. Gomez and M. M. Morcos, "Impact of EV battery chargers on the power quality of distribution systems," in *IEEE Transactions on Power Delivery*, vol. 18, no. 3, pp. 975-981, July 2003

[12] L. Bremermann, M. Matos, J. Peças Lopes, M. Rosa, "Electric vehicle models for evaluating the security of

supply," *Electric Power Systems Research, vol.111, pp.32-39, Fevereiro, 2014.*

[13] D. Wu, D. C. Aliprantis, and K. Gkritza, "Electric energy and power consumption by light-duty plug-in electric vehicles," *IEEE Transactions on Power Systems, vol. 26, no. 2, pp. 738-746, May 2011*