Chapter 17
Performance Assessment of Distribution Network with Electric Vehicle Penetration

Riddhi Thorat and Praghnesh Bhatt

Abstract The adoption rate of electric vehicles (EVs) has been increased in recent times, as they are more environment friendly over the conventional internal combustion-based vehicles. Hence, upcoming years will foresee larger penetration of EVs in the distribution network (DN) which will lead to new challenges for distribution network operators (DNOs). Charging requirements for EVs depending upon travel behavior, significantly change the load pattern in DN. This paper presents different probability distribution functions (PDFs) to predict the uncertain travel behavior of EVs. The Monte Carlo simulation is used to simulate EV load demand considering important attributes of traveling patterns. The estimated load demand of EVs over different time durations of a day has been considered at different nodes of the standard 33-nodes radial distribution network. Time series power flow has been carried out to assess the impact of EVs integration on the performance of DN. Significant drops in voltage profile at all nodes and an increase in losses in DN are observed after the EV integration which guides the distribution network operator to take corrective actions.

Keywords Electric vehicle · Grid to vehicle (G2V) · Charging strategy · Voltage profile · Distribution network

1 Introduction

Recently, the problems such as global warming, greenhouse gases emissions, and depletion of fossil fuel reserves need utmost awareness for a sustainable and green future. The rise of harmful emissions in the environment is largely caused by the transportation sector. Therefore, electrification of the transport sector is seen as the

R. Thorat · P. Bhatt (✉)
Department of Electrical Engineering, School of Technology, Pandit Deendayal Energy Univerity, Gandinagar, Gujarat 382007, India
e-mail: praghnesh.bhatt@sot.pdpu.ac.in

R. Thorat
e-mail: Riddhi.tphd20@sot.pdpu.ac.in

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best possible alternative to solve these problems. However, the electrification of the transport sector by EV has been in existence for many years. But due to ease in availability of non-renewable fuel resources and simple operation of an internal combustion (IC) engine, EVs were put on hold [1, 2]. The Global market share of PEV is not vast due to its high costs [3]. However, with the support of government policies, PEV can be made cost competitive, which could result in large-scale adoption of it.

The charging of EVs greatly impacts the load pattern of the distribution network and subsequently affects its reserve capacity for carrying power through distribution lines. Uncoordinated charging of EVs in a fleet deteriorates power quality and increases energy losses, voltage deviations, and peak loading in the distribution network [4]. As a result, many charging strategies have been developed in the literature for effectively managing the EV load demand and minimizing its impact on the distribution system [5, 6]. Various recorded data needs to be analyzed in order to anticipate the impact on the grid. For example, by determining the state of charge (SOC) at the onset of charging, the profile of charging is accurately obtained. Due to fewer penetration of EVs into the grid, data are not easily available. This is a major drawback of such methods. So different methodologies are needed to be developed to estimate (forecast) the charging profiles of EVs at various time scales. Moreover, the charging needs of an EV are determined by random variables such as their daily distance traveled, mobility, arrival time, departure time, and various driving profiles of an EV owner. This implies that the energy of an EV cannot be determined by deterministic methodology but a stochastic approach must be adapted for the efficient operation of an EV. In [7–9], the effect of an EV on the distribution grid is analyzed, from which factors such as traveling patterns, battery characteristics, charging schedule, and EV penetration can be summarized to be playing a vital role.

The impact of the charging behaviors of electric vehicles (EVs) on the grid load is discussed [10]. The historical data of EVs traveling pattern in residential areas are analyzed and fitted in order to predict their probability distribution, so that the modeling of the traveling patterns of EVs can be done. Multi-objective charging strategy is adopted. Modeling of energy demand has been done and the Monte Carlo (MC) simulation process is designed in order to enhance the creditability of the model.

Different EV scenarios and charging management approaches are considered to analyze the impact of EVs on distribution systems grid in [11], and the effect of charging strategies on load profile pattern is described [12]. Voltage deviation and abrupt change in various aspects of grid parameters are seen when EVs are integrated into the actual test system. In this paper, the implementation of integration of an EV is done in 33 bus distribution systems. Every node is assigned with EV and the voltage profile of the system is obtained. Obtained results of the voltage profile are compared by using two scenarios of before and after integration of EV into the grid for various charging strategies. Grid system losses are also compared, and thus, the effect of EV on the grid can be analyzed.

This paper is organized as follows: The statistical modeling of travel behavior is analyzed in Sect. 2. Section 3 deals with the formulation of charging strategies. The Monte Carlo simulation is used to calculate the solution of the model with random variables in Sect. 4. In Sect. 5, test system and simulation results are discussed followed by conclusions and future work at the end of the paper.

2 Probability Distribution Functions (PDFs) to Model EV Traveling Behavior

Traveling behavior of EVs owners obtained from traffic survey data [14] is represented in Fig. 1. It can be noticed that traveling periods of EVs are mainly distributed over 06:00 to 09:00 and 16:00 to 19:00 and forms morning peak and evening peak, respectively. On the other hand, approximately 40% of EVs parking time is distributed between 18:00 and 21:00 where EVs owners may charge their vehicles. If these EVs are charged without any guidance, then the electric grid would be impacted by large-scale EV charging load during this parking period. With the growing demand for EVs in near future, the grid would face heavy power demand or even lead to failure of the power grid. Hence, it is very important to analyze the impact of large-scale EVs charging on the performance of the electric grid.

Electrical power requirement from the grid for EV charging at the particular time period depends mainly on (i) battery characteristic, (ii) EV numbers, (iii) charging piles, and (iv) travel behavior of EVs owners. The first three factors are assumed to be known variables and listed in Appendix I. The factor describing travel behavior is completely uncertain; therefore, different PDFs are used to model the travel behavior of EVs.

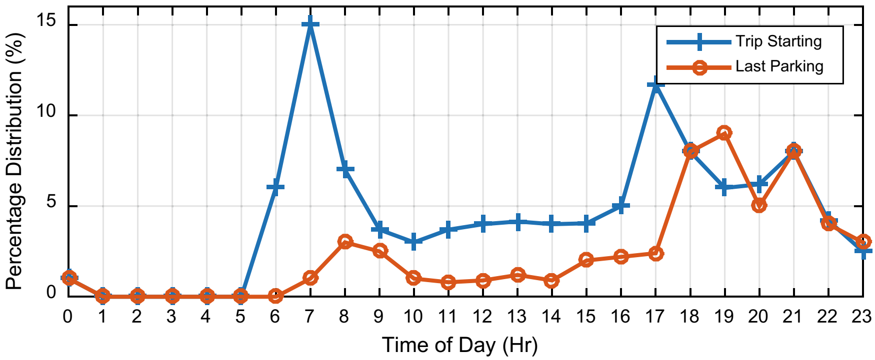

Fig. 1 Traveling behavior of EVs—Beijing [13]

2.1 PDF to Model Different Traveling Variables

The major traveling variables to model EVs traveling behaviors are based on (i) daily travel frequency, (ii) daily driving mileage per trip, (iii) duration per trip, (iv) arrival time per trip, and (v) departure time per trip. To derive PDF for these traveling variables, from the data obtained from GPS installed on private EVs and listed in Table 1, PDFs are obtained for these traveling variables as given in Table 2 [10]. The scale and shape parameters as well as expected mean and variance for the obtained PDFs are listed in Table 3. Scale and shape parameters for PDFs are estimated through maximum likelihood estimation. K-S, F-test, and T-test are used to ensure a 95% of accuracy level of generated data. The comparison between the fitted curve of traveling variables and actual data is shown in Fig. 2.

Table 1 Variables for EV traveling pattern analysis [10]

Total distance	Distance per trip	Travel duration	Duration per trip	Travel times
35.4 km	15.5 km	1.51 h	0.63 h	2.29

Table 2 Probability distribution functions to model traveling behavior [10]

Daily travel frequency, F_d	$f(x\|\alpha,\beta) = 1/(\beta^{\alpha}\Gamma(\alpha))x^{(\alpha-1)(e^{((-((x)/\beta))}}, \Gamma(\alpha) = \int_0^{\infty} t^{(\alpha-1)}e^{(-t)}dt$	(1)
Daily driving mileage per trip, M_d	$(x\|\beta,\alpha) = \frac{1}{2\pi}\left\{exp\frac{-\left(\frac{\sqrt{x}}{\beta}-\frac{\sqrt{\beta}}{x}\right)^2}{2\alpha^2}\right\}.\left\{\frac{\left(\frac{\sqrt{x}}{\beta}+\frac{\sqrt{\beta}}{x}\right)}{2\alpha x}\right\}$	(2)
Duration per trip, T_d	$f(x\|\alpha,\beta) = 1/(\beta^{\alpha}\Gamma(\alpha))x^{(\alpha-1)(e^{((-((x)/\beta))}}, \Gamma(\alpha) = \int_0^{\infty} t^{(\alpha-1)}e^{(-t)}dt$	(3)
Departure time per trip (AM), D_t^{am}	$f_{D_t^{am}}(x\|\mu,\beta,\alpha) = \frac{\Gamma\left(\frac{\alpha+1}{2}\right)}{\beta\sqrt{\alpha\pi}\Gamma\left(\frac{\alpha}{2}\right)}\left[\frac{\alpha+\left(\frac{x-\mu}{\beta}\right)^2}{\alpha}\right]^{-\left(\frac{\alpha+1}{2}\right)}$	(4)
Departure time per trip (PM), D_t^{pm}	$F_{D_t^{pm}} = \frac{1}{\sigma\sqrt{2\pi}}e^{-(t-\mu)^2/2(\sigma)^2}$	(5)

Table 3 Parameters of Probability distribution functions [10]

Traveling variables	Shape parameter (α)	Scale parameter (β)	Expected mean (μ)	Variance (σ)
Daily travel frequency, F_d	3.71	0.64	2.39	1.24
Daily driving mileage per trip, M_d	0.97	10.57	15.52	15.09
Duration per trip, T_d	1.87	18.35	34.4	25.12
Departure time per trip (AM), D_t^{am}	2.16	1.08	18.36	1.08
Departure time per trip (PM), D_t^{pm}	–	–	18.2	2.84

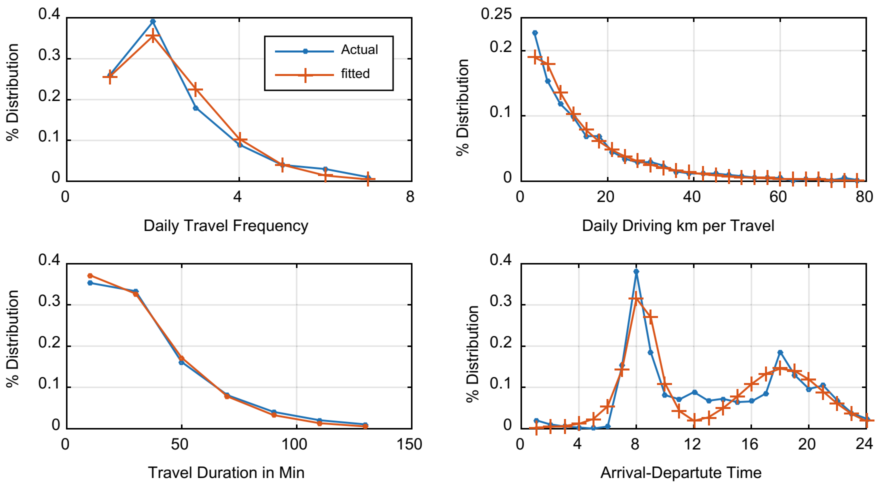

Fig. 2 The distribution of various traveling variables

3 Charging Strategies for Electric Vehicle

In this paper, the impact of three different EV charging strategies on the performance of RDN is addressed. Selection of charging strategy would play the different roles to reduce EV charging load requirement and to encourage EV users to charge their vehicles at the time of lower tariff. The general flowchart for charging strategy is shown in Fig. 3.

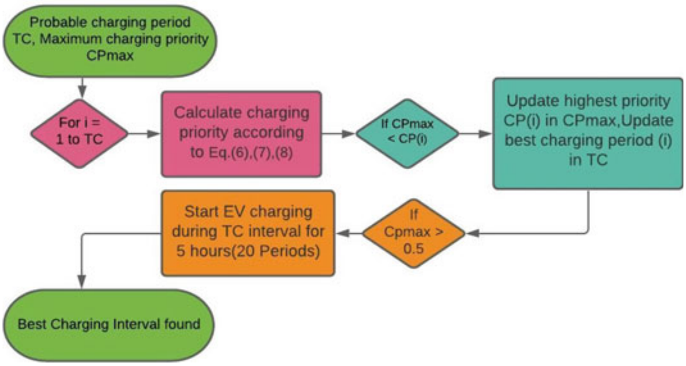

Fig. 3 Flowchart for charging procedure

3.1 Random Charging Strategy

In this charging strategy, charging of a single or large fleet of EVs occurs in an uncoordinated manner without considering any scheduled plan. It can also be called as "plug-and-play" type of charging or "Direct" charging. Whenever the EV is plugged in, the charging starts immediately. When EV gets charged up to desired SOC or when EV is disconnected, charging stops.

$$\text{Charging}_{\text{priority}} = R, \quad R \in [0, 1] \tag{6}$$

In (6), R is a random number that follows a uniform distribution. When $SoC_{\text{min}} \leq SoC_{\text{current}}$ and $Charging_{\text{priority}} > 0.5$, EV will start charging. This random or uncoordinated EV charging strategy imposes negative impacts on the distribution network as it increases the loading randomly.

3.2 Tariff Guided Charging Strategy

Tariff schemes can be divided into static pricing and dynamic pricing. In dynamic pricing or tariff guided schemes, electricity prices at different periods of the day vary with the load variations, availability of power, and time of use. In static pricing schemes, electricity prices remain constant throughout the day and do not vary with load demand. In this work, tariff guided scheme is adopted as per (7). The electricity price during different time periods of the day is listed in Table 4 [14].

$$Charging_{priority} = \left(1.5 - \frac{\tilde{C}_{period}}{\tilde{C}_{day}}\right) \tag{7}$$

Table 4 Time-of-use electricity prices per day (unit Yuan/kWh)

Hours	0–7	7–9	9–11	11–14	14–16	16–19	19–21	21–23	23–24
Price	0.23	0.61	0.92	0.61	0.92	0.61	0.92	0.61	0.23

where $\tilde{C}_{period}$ is the average charging price for a certain period and $\tilde{C}_{\text{day}}$ is the average charging cost of one day. When $SoC_{\min} \leq SoC_{\text{current}}$ and $Charging_{\text{priority}} > 0.5$ in (7), EV charging starts with the lowest tariff rate during the parking period. The probability of charging priority to be higher than 0.5 increases if $\tilde{C}_{\text{period}}$ is smaller as compared to $\tilde{C}_{\text{day}}$.

Tariff guided scheme shifts the peak load toward off-peak periods and encourage EV users to charge their vehicle during off-peak periods where electricity prices are lower. This charging scheme can improve the performance of the grid by smartly managing the charging load of EVs and also reduce the charging cost. However, tariff guided charging scheme results in a sharp peak for a short duration during night hours and may cause some adverse situations in DN.

3.3 Slack Period Charging Strategy

In this scheme, EV starts charging when it comes to a parking lot. This type of charging scheme ensures the success of traveling plan if the EV starts charging immediately after the arrival and when idle or slack time is greater than that of charging time.

$$\text{Charging}_{\text{priority}} = \left(1.5 - \frac{T_{\text{charge}}}{T_{\text{parking}}}\right) \tag{8}$$

where T_{charge} is the estimated time interval needed by EV to fully charge its battery and T_{parking} is parking time intervals. When $SoC_{\min} \leq SoC_{\text{current}}$ and $\text{Charging}_{\text{priority}} > 0.5$ in (8), EV charging starts. The probability of charging priority to be higher than 0.5 increases when EV starts charging immediately after its arrival.

4 Monte Carlo Simulation for EV Charging Model

The Monte Carlo simulation is used to simulate and form the model of the probability of different outcomes in a process that cannot easily be predicted due to the involvement of random variables. The impact of uncertainty in prediction and forecasting models can be understood from this technique. MC simulation has statistical convergence where the deviation of the fitted model converges to a certain threshold value.

Based on MC random sampling simulation, the charging capacity model of EV is predicted. The battery charging capacity is calculated for each day which is divided into 96 intervals of 15 min each. The total charging capacity (TCC) of EV for pth time interval [10] is described as

$$TCC_p = \frac{1}{D}\sum_{d=1}^{D}\left(\sum_{q=1}^{N} tcc_{pq}(d)\right) \tag{9}$$

where $tcc_{pq}(d)$ represents the charging capacity of the qth EV in the pth time slot on the dth workday, N *gives* the total number of EVs receiving power from the grid in the pth time period, and D is the total number of days. Considering the condition that the battery is always 100% charged before driving, the starting time of the EVs battery charging can be depicted as follows

$$\Delta Tq = \frac{Q_{cq}}{W_c} = \frac{\left(1 - SOC_{ini,q}\right)Cap * Vol}{W_c},\ t_q \in \left(T_{0q}, T_{1q} - \Delta T_q\right) \tag{10}$$

where

T_{0q} and T_{1q}	start and end slack status of qth EV.
ΔT_q	maximum continuous charging duration.
Q_{cq}	charging capacity of EV.
$SOC_{ini,q}$	initial state of charge of the qth EV.
t_q	starting of charging moment.

MC sampling technique adopts a condition for convergence which is expressed as follows

$$\alpha_p = \frac{\sqrt{V_p}(y)}{y_p} = \frac{\sigma_p(y)}{y_p} \tag{11}$$

where α_p is the coefficient of variance of the system at the pth moment and V_p, y_p, and σ_p are the variance, expectation, and standard deviation, respectively. The variance coefficient α_p is set to less than 0.5% when MC simulation is repeated several times.

Firstly, the daily driving/traveling duration, frequency of travel, and mileage of EV are determined by modeling users' travel behavior, while the charging time period of EV is dependent on the traveling situation, characteristics of the battery or SOC, and the selected charging strategy. After the EV driving/charging period is determined, the total driving mileage, power consumed from the grid, and required EV charging power can be calculated for 96 time intervals per day. Finally, load modeling of an EV for a complete whole day is simulated by MC simulation and totalcharged power drawn by EV from grid is obtained and then it is integrated into 33-nodes RDN.

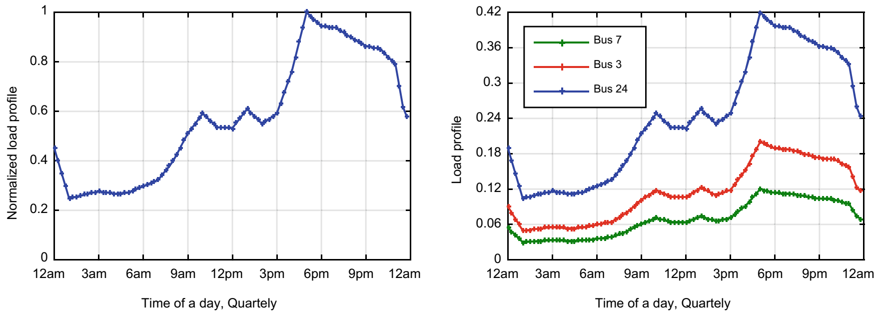

Fig. 4 Active and reactive power load profile for RDN

5 Simulation Results and Discussion

5.1 Test System

To analyze the impact of EV charging on the performance of distribution networks, standard 33-nodes radial distribution network is used from [15]. The test system consists of different feeders with active and reactive power loads connected at different nodes [15]. The total active and reactive power load for the test system is 3.72 MW and 2.7 MVAR, respectively. The normalized active and reactive power load profile in RDN is shown in Fig. 4. Active and reactive power loads given in [15] have been varied as per the normalized load profile, and sample active power load variations for Bus 3, Bus 7, and Bus 24 are shown in Fig. 4.

5.2 EV Load Variation

In this simulation study, EVs are randomly distributed to the all-load nodes of RDN in a range from 1 to 100 EVs. Three types of charging strategies discussed in Sect. 3 are adopted to charge EVs. The charging requirement of EVs at a specific period depends mainly on (i) battery characteristics of EVs, (ii) capacity of charging piles, (iii) number of EVs, and (iv) traveling behavior of EV owners. The parameters used in the simulation for EVs load are given in Appendix I. It is assumed that charging infrastructure is available at each node of RDN. The EV load demands at each node of RDN at different periods throughout the day are shown in Fig. 5 for different charging strategies. In this analysis, a day is divided into 96 slots, each slot of 15 min. Based on the charging strategy and number of EVs distributed on the load nodes, the system has experienced EV load in addition to the base load. Figure 6 represents the aggregate load demand of RDN during each slot of a day. The impact of EVs load has been analyzed for standard test systems by adopting the Time Series Power Flow method [16].

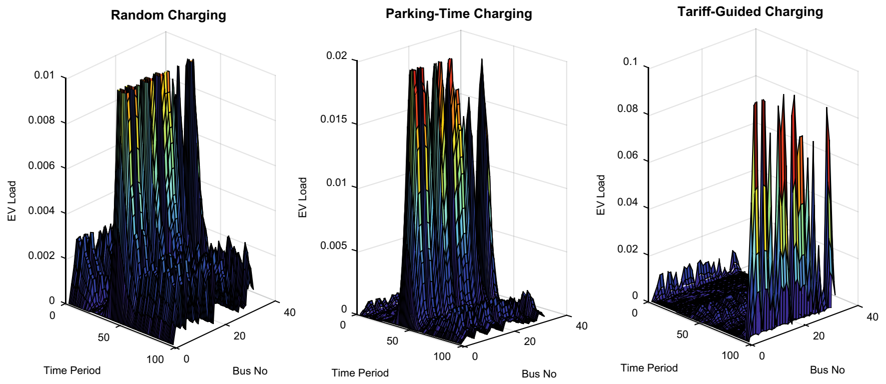

Fig. 5 Load profile at different nodes of RDN during a day for different charging strategies

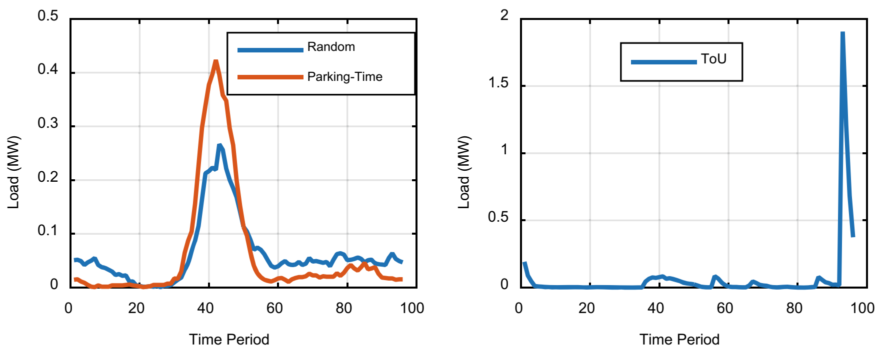

Fig. 6 Aggregate load demand of RDN during a day for different charging strategies

On the basis of the probability distribution model of the EV traveling pattern and three types of charging strategies, the EVs operation procedure through MC simulation gives indices like estimated peak load, the average load of grid, and average to peak ratio (APR) as shown in Table 5. It can be observed from Table 5 that there is a huge difference in peak value and APR with different charging strategies. The maximum peak value is observed in tariff guided scheme due to the generation of another peak for a short duration during night hours.

Table 5 Daily EV charging load prediction for different strategies (W)

Charging strategy	Average value	Peak value	Average to peak ratio (APR)
Random	7591.1	31,375	0.2419
Tariff guided	7447.9	279,500	0.0266
Parking	7526.0	49,875	0.1509

5.3 Impact of EV Load on RDN

In order to evaluate the impact of EV on the voltage profile of RDN, base case power flow analysis is carried out before integrating any EVs in RDN. The voltage profile at different nodes in RDN during different time slots of the day is shown in Fig. 7 for base case analysis. It can be seen that the voltage profile of tail nodes of RDN has resulted in comparatively low value as expected. The changes in voltage profile with the integration of EVs at different nodes are also depicted in Fig. 7 for different charging strategies. As it can be seen from Figs. 5 and 6, the RDN has experienced greater EV load during 35–55 time slots of the day when randomness or parking time charging strategies are adopted. Hence, the bus voltage profiles are affected more during these time slots, and a dip in the bus voltage profile can be easily observed in Fig. 7 due to these EV load demands. On the other hand, the tariff for EV charging at night is fairly low; hence, EV owners prefer to charge their vehicle during night hours. The peak load demand can be observed during the last few slots of a day when a tariff-guiding charging strategy is adopted. Due to the peak demand of EV charging during night hours, voltage profiles are reduced to a greater extent for all tail-end nodes as shown in Fig. 7. Similarly, active and reactive power loss variations in RDN without and with EVs are shown in Fig. 8, where changes in losses with different charging strategies are clearly observed.

In the simulation studies, the EV loads are calculated with reference to only 100 EV; hence, impacts of EV integration on voltage profile and losses are not

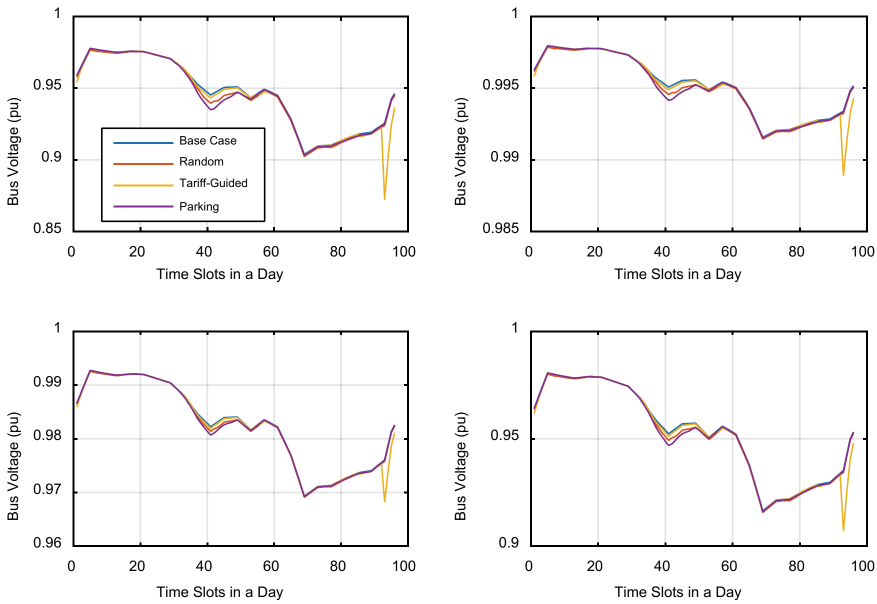

Fig. 7 Voltage profile at tail-end nodes 18,22,33,25 (clockwise) for different charging strategies

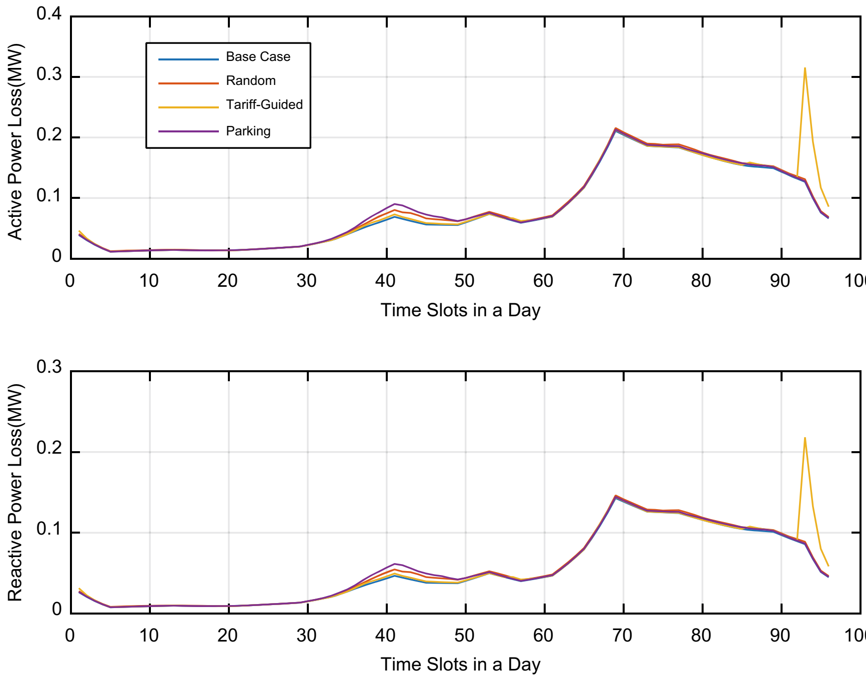

Fig. 8 The variation in active and reactive losses for different charging strategies

significant. But the obtained results clearly reveal that the choice of charging strategy has a direct impact on the performance of RDN. The voltage profile of load nodes will definitely result in a lower value with the increased penetration of EVs.

Hence, careful planning of RDN and decision on EV charging strategies need to be devised by Distribution Network Operator (DNO) to allow further penetration of EV in the distribution network. The variation of real and reactive power losses in RDN for the base case is also depicted in Fig. 8.

6 Conclusion

This paper investigates the impact of EV integration on voltage profile and losses of standard 33-nodes radial distribution network. The probability distribution function of different variables which represents the travel behavior of EV is formulated to model EV loads during different time intervals of the day. Three charging strategies are adopted to analyze the contribution of EV charging load throughout the day. The charging requirement of EVs for different charging intervals for each charging strategy has been formulated using the Monte Carlo simulation. The penetration of EV in RDN has different impacts on voltage profile and losses for each strategy.

The charging requirement of EVs from the grid results in a lower voltage profile and increased power losses as compared to the base case performance of RDN. The formulation of a multi-objective charging strategy is required to overcome the detrimental impact of EV penetration in RDN.

Appendix I

Number of EVs	100
Battery capacity	100 Ah
Voltage	230 V
Charging efficiency	75%
Energy consumption per kilometer	0.125 KW/h/km
Full charge duration	5 h
Constant power from the grid	15 KW

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