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ORIGINAL PAPER

Monte Carlo simulation of electric vehicle loads respect to return home from work and impacts to the low voltage side of distribution network

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Abstract
Usage of electrical vehicles (EV) is increasing at high rate due to their great benefits to the community well-being. However, EVs have considerable impacts to electrical power networks and especially to the low voltage side of the distribution network. In order to determine the impacts of EVs accurately, uncertain behaviors of drivers were modeled using Monte Carlo simulations. This method is proven to be a robust tool for the evaluation of stochastic processes and getting deterministic results out of it. Furthermore, real-world traffic pattern data were used to model drivers' behaviors. Return home time of EVs was used as a charging start time, and average commute distance of drivers was used to determine the charging duration. Also, residential area was taken as a pilot network. Hourly basis transformer loading data were obtained and used to realistically reflect the base load of the pilot network. Load flow analysis was performed for non-EV and with-EVs scenarios. The results of the analysis were represented in a probabilistic approach. Violations of results were investigated according to power quality limits. Consequently, impacts of the EV charging load to the low voltage side of distribution network were analyzed in terms of voltage drops, transformers' loadings, power losses and voltage unbalance. This study showed that with a 50% penetration rate of EVs, the probability of voltage violation increases by approximately 25%.

Keywords Distribution network · Electrical vehicles · EV impacts · Load flow analysis · Monte Carlo simulation

1 Introduction

Uncertain gas prices and global warming are the main reasons for the electric vehicles (EV) becoming inevitable option against vehicles which contain internal consumption engine (ICE) [1]. Studies assert that EVs will take 86% of the vehicle sales by 2030 owing to the changing prices of oil and vehicles [2]. As the demand for EVs is increasing, more EV charging stations will be installed. Growing number of EV charging stations in the low voltage side will have an impact on the distribution network. If the EV charging stations will not integrate to the distribution network properly, future of EVs technology will not be reliable. When EV charging stations considered as loads, there will be changes in the distribution network parameters. In the literature, there were many studies that have been done to mitigate the future impacts of the EVs. Sortomme et al. [3] minimized the variations of loads, in order to obtain the minimum power losses and the maximum loading factor in their study. Kempton et al. [4] have forecasted that the system with insufficient energy storages will create an unbalanced in between demand and supply. Putrus et al. [5] examined impacts of the EVs, and they stated that the EVs have increased the peak load by 18%. Nyns et al. [6] investigated the EVs' charging load impacts to the 34 nodes IEEE test system. They stated that the grid components should be replaced. Gong et al. [7] investigated the impact of EVs to the distribution grid with the Monte Carlo method. The study showed that the life expectancy of transformer is calculated only as 6.7 years due to insulation degradation by the uncontrolled charging techniques. However, this might be increased to the 83.07 years by using the controlled charging techniques. Also, studies [8, 9] show that it decreased the reliability indices. Hadley et al. [10] predicted the unit price of the generation of electrical energy

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by taking the penetration levels of EVs as 25% and 60% of population for the 13 states of USA. Unit price of the electrical energy was increased about 200% of itself in some states. Scharrenberg et al. [11] determined probabilities of the EVs charging points, return home times and distance that traveled by Monte Carlo method for a distribution grid in Holland. Thereafter, EVs probabilities of the battery consumption and start time of the charging was calculated by Monte Carlo Simulation in the another study [12]. Studies show that when the percentage of the battery swapping technique has increased, peak load demand also decreased. Leuo et al. [13] compared the deterministic and stochastic load models with Monte Carlo Simulation in the IEEE 13 node test feeder. As a result of the study, stochastic load models are more efficient for the modeling the distribution network.

In this study, voltage profile and transformer loading changes were investigated by improved models in order to predict the impact of EVs to the low voltage side of the distribution network. The novelty of the paper is that real-world data were used to model the behaviors of drivers and electrical distribution network. Uncertain parameters are used as inputs in the modeling of EV charging loads. The impacts of EVs to the grid were investigated by Monte Carlo simulation which is an efficient way to analyze the stochastic events. Thereafter, a load flow analysis was done for the system in different penetration levels of EVs to forecast the impact in the future. Consequently, probabilities of voltage limit violations and transformer overloads were obtained for different penetration levels of EVs. Eventually, results of voltage drops violations were compared to the national electrical energy quality standard which is [14].

This paper is structured so that the introduction is followed by the proposed methodology explained in Sect. 2, the modeling of the grid and results are given in Sect. 3, and the conclusions are summarized in Sect. 4.

2 Proposed method

In order to investigate the impact of EVs to the low voltage side of the distribution network, charging load profiles that form the extra load to the grid were obtained and modeled. While creating the EVs charging load profile, factors that affecting the load profile directly were taken into consideration. In this study, impact of EVs is analyzed with Monte Carlo simulation in order to predict the stochastic processes.

2.1 Modeling EVs charging load profile and driver's behavior

EVs charging profile is the load curve that depends on time, and it consists of information about connection of vehicles to the low voltage grid. It is depended on many uncertain parameters related with charging such as start–end time, duration, power consumption or connection phase. Furthermore, these parameters should be calculated as much as random due to the uncertain decisions of consumers. Nevertheless, some of the parameters were taken as fixed values in order to make simplifications in the charging load model. Parameters that are used as fixed or variable to create the charging load are shown in Table 1.

Table 1 Parameters that used for creating the EVs charging loads

Fixed parameters	Variable parameters
Number of EV	Start time of the charging
Battery consumption (kWh/km)	Charging duration
Charging power	Charging points and phases

"Battery consumption" and "charging power" were selected as 0.2 kWh/km 3.7 kW, respectively. Number of EVs was taken as a multi-state fixed parameter. Three states were created by differentiating the penetration levels of EVs by 10%, 30% and 50% for the "number of EV" parameter. Therefore, it can be stated that those three parameters are fixed in nature. To determine start time of the charging and charging duration for a specific EV, municipality transportation master plan study was used [15].

Charging load profile fully depends on the behavior of driver. Due to the fact that drivers in the residential areas usually travel for the purpose of going to the work, residents were considered that they traveled two times in a day. Therefore, EV's return time to home is taken as the start time of the charging owing to the residential area consumer behaviors. After the EVs are plugged in the charging stations, it is considered that battery will be fully charged until the next morning. In order to obtain the precise charging load profile, return time of the residents are received from the guideline of Istanbul Municipality Transportation Master Plan (IUAP) report [15]. In this report, probability density function of arrival times of vehicles is given in hourly time basis.

Additionally, duration of charging is another crucial parameter that affects the charging load profile. However, this parameter is fully related to the distance that EVs traveled. Therefore, duration of charging will be longer for the EVs that traveled more distance. With the aim of predicting the exact situation, daily average commute distance information is taken to calculate the state of charge in battery. Average distance that vehicles traveled was obtained from the Istanbul Municipality, and it was converted to a continuous probability function to be used an input parameter. Probability of the arrival times, average commute distance, charging point and phase connection are shown in Fig. 1.

"Charging connection points" and "connected phases" variables are created using uniform distribution probability density function. It means that connection probability of an

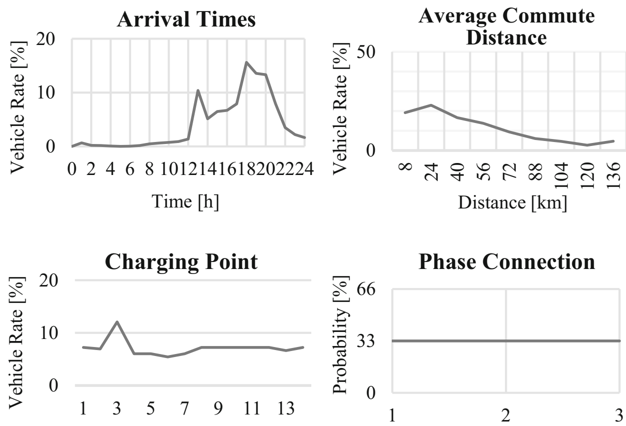

Fig. 1 Probability density functions of the random variables

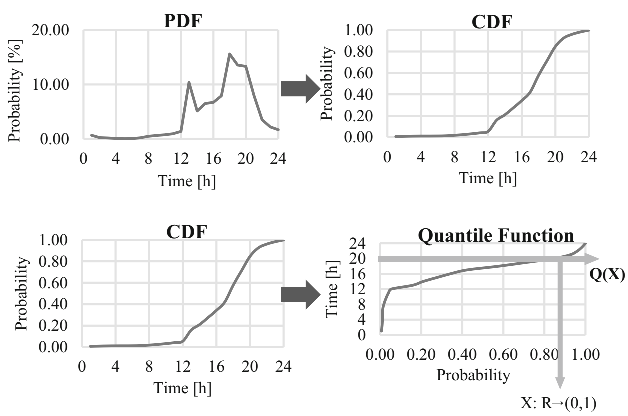

Fig. 2 Calculation process of the start time of the EVs charging

EV to any phase of grid is equal (Phase 1, Phase 2 or Phase 3). This approach is also valid for the connection point.

To produce stochastic outputs from these probability density functions, quantile function conversion technique was used. This process is visually summarized in below depiction (Fig. 2).

Process that is defined above was implemented in order to determine the random variables of parameters. Steps of this process are explained below. This was implemented to charging start time of EVs and the distance traveled by them.

- Probability density function is converted to the cumulative distribution function.
- Inverse of cumulative distribution function is taken which is the quantile function.
- A data set is created using uniform distribution density function. In this data set, number of data points is equal to the number of electric vehicles.
- Value of these random numbers is taken as parameter of the related quantity.

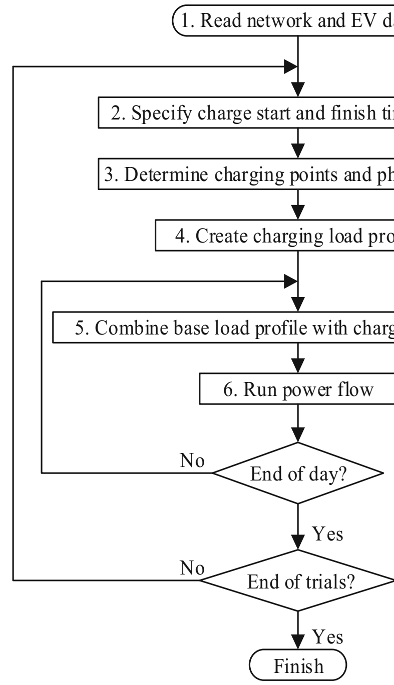

Fig. 3 Flowchart of the Monte Carlo simulation

2.2 Monte Carlo simulation and load flow analysis

In order to reflect mobile nature of the charging load and obtain more accurate results, stochastic modeling technique which includes uncertain parameters of EV charging was used. Monte Carlo simulation is the method that creates a set of random sampling and repeats the simulation in large number of times. Probabilities of events can be calculated in a deterministic system. Consequently, Monte Carlo simulation is a well-suited method for investigating uncertain events like the impacts of EV charging load on distribution network.

Outputs of Monte Carlo simulation were taken as input parameters for load flow analysis. Main purposes of the load flow analysis are (i) obtaining the power loss of the lines, (ii) calculating equipment loadings in terms of ampacity and (iii) calculating voltage magnitudes and angles on busbars and terminals. One of the many power flow techniques is the Forward–Backward Sweep. It is a widely used method for distribution systems having high *R*/*X* ratios. Applicability of this technique and mathematical expressions can be found in [16]. Load flow analysis was performed for non-EV and with EVs scenarios. Charging load profile of EVs was created with the stochastic process and base load profile was gathered from a field study. Total number of 1000 different charging load profile was created with a resolution of 1 min. Aggregated load profiles were used in load flow studies. Flowchart of the Monte Carlo simulation is shown in Fig. 3.

To perform this process, based on the process of the Monte Carlo Simulation in Fig. 2, an algorithm was created in MAT-

LAB. This algorithm consists of one main function and the two assisting functions. The main function was used to take inputs from users and cooperates the assisting functions to create the results. Accordingly, one of the assisting functions calculates the EVs arrival times, average commute distance, charging points and phases in the stochastic process. Furthermore, the other one calculates the load flow with the method of forward–backward sweeping method. In the MATLAB module, there are user inputs that are needed to perform the study which are; the number of EVs, number of trials, charging power, time intervals and battery consumption in this algorithm. Number of EVs is the percentage of the population that uses an electric car. This number was used to create different scenarios. Number of trials determines the how many times load flow will be calculated with the random variables. Also, time interval input is needed for determining the how many equal parts a day will be divided. Additionally, probability density functions are the inputs for the assisting function that creates the random variables for stochastic processes. At last, base load profile and the line impedances are the inputs for the other assisting function. Basically, these inputs were accessed via an excel file which has the data on low voltage side of the distribution grid.

3 Creating network model and its analysis

A residential area was chosen as the pilot network for EV impact analysis. Impedance data and loading of the distribution transformer were obtained during a field study. In the analysis, "Base Model" represents a scenario where no EVs are connected to the network. Only hourly basis transformer loading data which do not contain charging loads were used for base model analysis. In addition, three scenarios were created for EV impact analysis for different penetration levels. The results of the scenarios were compared with power quality limit values for the purpose of determining the possibility of violations of the evaluated outputs. Evaluated outputs were classified as; voltage drops, voltage unbalance, transformer loading.

3.1 Modeling of residential area

Electrical network parameters of the pilot area and hourly averaged load profile of the MV/LV distribution transformer were obtained from a field study. This is important, because realistic effects of EV charging stations can only be actualized using the real data. In the chosen residential area, there is one distribution transformer which has 14 LV feeders. It supplies power to 15 blocks that has 662 residential customers. It is assumed that each household owns one vehicle. This indicates that total number of vehicles in pilot area is also 662.

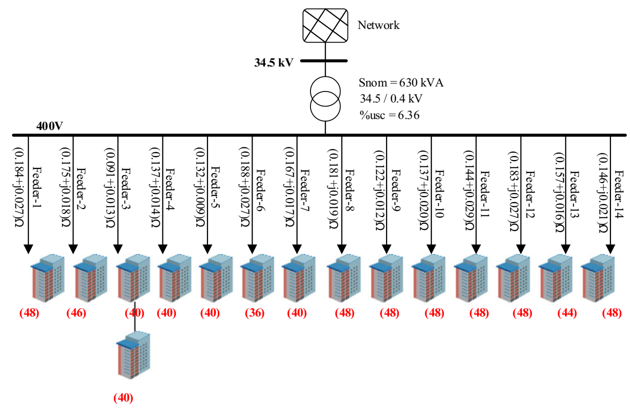

Fig. 4 One-line diagram of the residential area

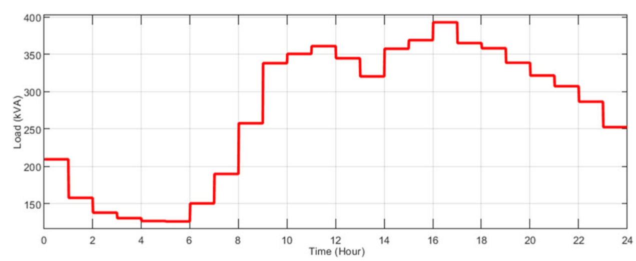

Fig. 5 Transformer loading data

One-line diagram of the residential is shown in Fig. 4. There are totally 15 blocks and 13 of them connected from a dedicated feeder and two blocks are feed through a common LV line. Additionally, number of the households in the blocks is depicted in red brackets. Also, line impedances of each feeder are shown in Fig. 4. Loading data of the distribution transformer that supplies energy to the residential area were received from the automatic meter reading system which is shown in Fig. 5. As we have only the 24-h load profile of the distribution transformer and not having any consumption data of individual feeders, a top-down load allocation technique was applied.

Total transformer load is distributed to each feeder in a way that feeders having a higher number of households will demand more power from the transformer.

3.2 Results of implementation

In this study, simulations were performed for different penetration levels of EVs. Furthermore, voltage drop, voltage unbalance and transformer limit violations were evaluated, and the results were examined based on the national standard [14]. First scenario was conducted for base load without any EVs. Thereafter, analyses were performed with the additional charging loads that EVs created. Number of EVs was assumed to be 10%, 30% and 50% of total 662 vehicles. Monte Carlo algorithms and forward–backward sweep

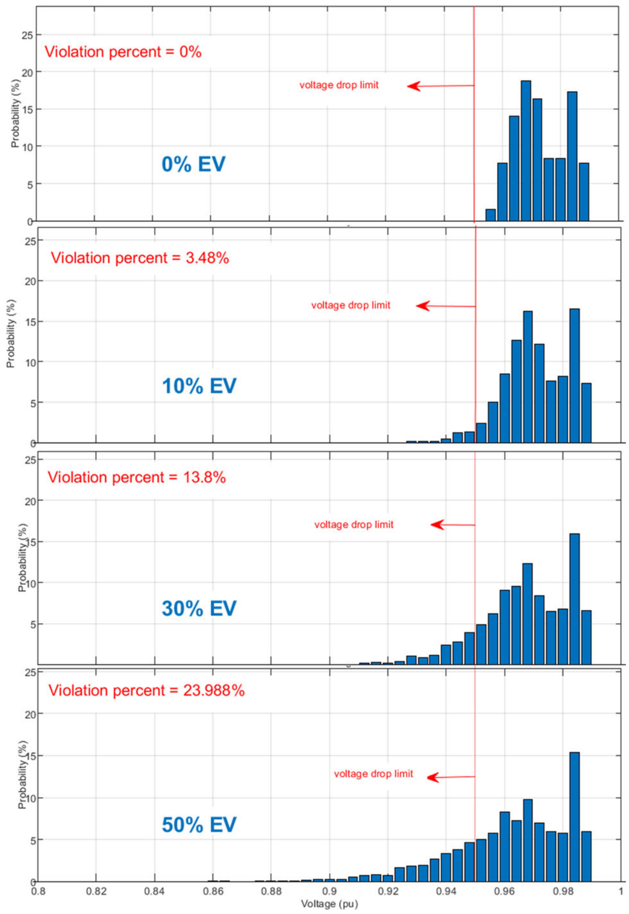

Fig. 6 Probabilities of the voltage in p.u. at the transformer

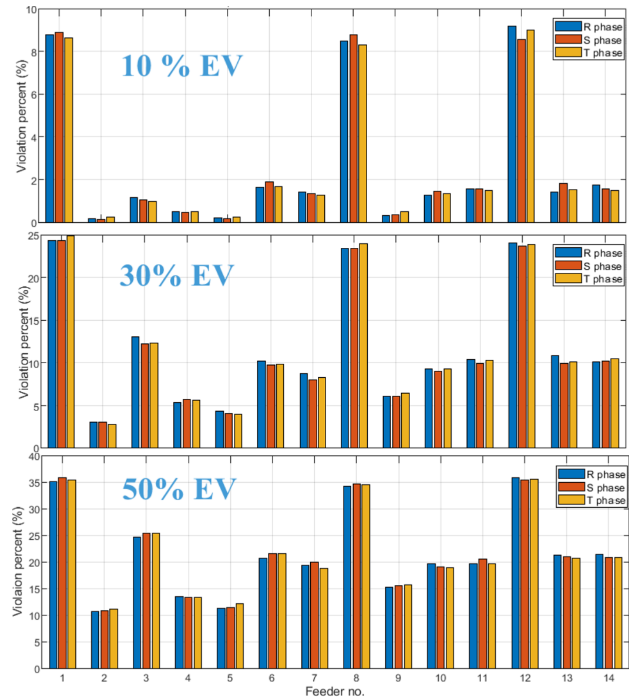

Fig. 7 Percent of the voltage drop violations in feeders

load flow method were developed in MATLAB environment. Also, simulations were performed, and depictions were obtained using the same tool. The tests were executed by sequentially running the code blocks on a dual processor of an Intel Core 5 with 2.5 GHz and 4 GB of RAM. For each scenario, execution of code blocks lasted 9.75 s. The time interval of the load profile data is 60 min. However, analyses were performed with per minute resolution as the charging load profiles were created in 1-min basis. Number of trials was taken as 1000 for all the simulations.

In Fig. 6, voltage magnitudes in per unit (p.u.) are shown for 4 different cases. The red line represents the lower limit value of voltage violation threshold which is defined as 0.95 p.u. This limit value was obtained from the national power quality standard [14]. It can be said that probability of violations is increasing with the growing number of EVs. The voltage violation probabilities exceed 13% with 30% EV penetration and approach to 25% violation risk in case of 50% EV penetration level.

In Fig. 7, voltage drop violations were evaluated for all phases of feeders. Number of voltage drop violations is considerably higher in the transformer feeders of 1, 8 and 12 than the others. The reason for this issue is that those lines have higher impedances due to low cross section and high cable lengths. Feeder 3 has the greatest power demand compared to others because it supplies energy to the two different blocks. However, length of the line is shorter, and thus line impedances are much lower. Therefore, magnitude of voltage drop violation is low for the Feeder 3.

Probability of exceeding the nominal power of the distribution transformer is shown in Fig. 8. Loading of the transformer is calculated for the minimum, average and maximum loading values of the 1000 trials by per minute. It can be seen from the figure that the transformer overloading probability is 8.5% for the scenario in which 50% of residents use an electric car. In addition, overloading risk might be neglected for 10% and 30% EV penetration scenarios, as the violation probabilities are near to zero. Although overloading probabilities seem to be considerable low in general, majority of these violations are aggregated at the peak times. For this reason, it could be a crucial problem for the distribution grid operators especially in the cases where EV penetration level approaches to 50%.

Loading of the distribution transformer in hourly basis is shown in Fig. 9. When all the results are examined, the loading of the transformer is higher at the times when EVs are returning to homes. The peak load is experienced at the time between 16:00 and 21:00.

Moreover, maximum simultaneity was calculated by dividing the maximum number of EVs charging at the same time to the total number of EVs. In addition to, total power

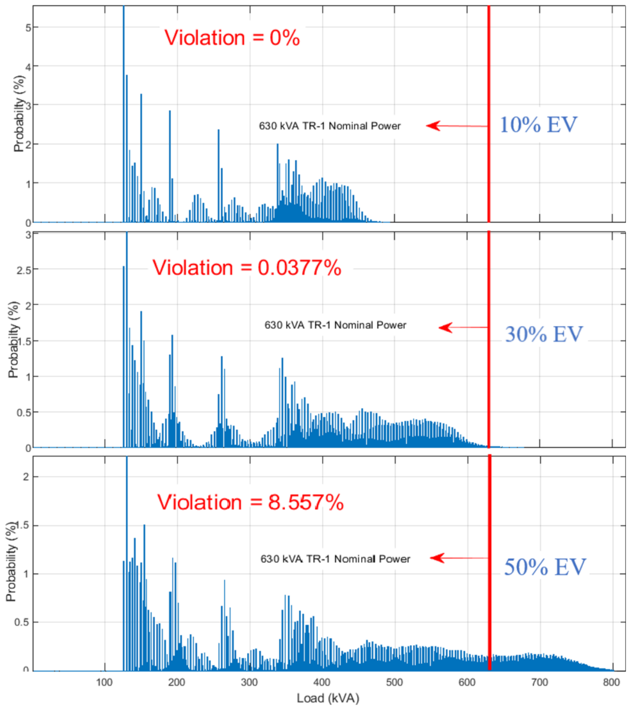

Fig. 8 Probability density of the distribution transformer

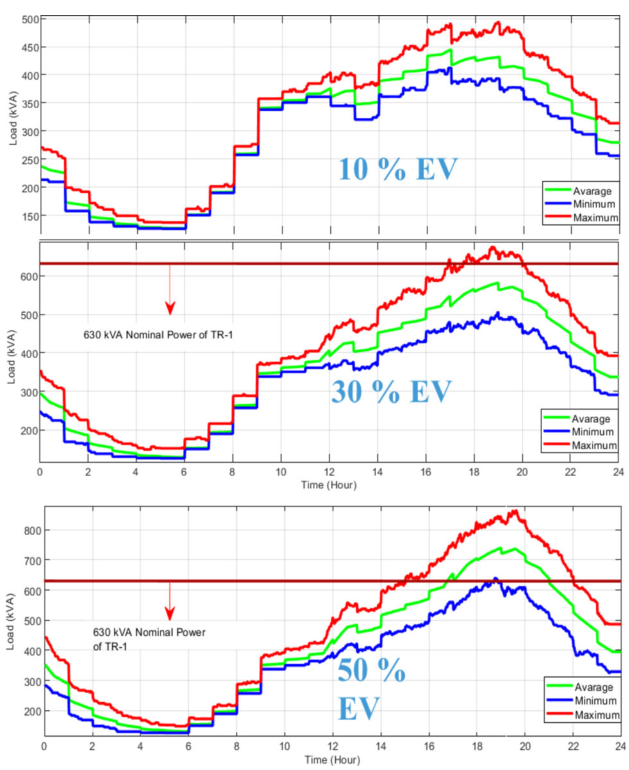

Fig. 9 Loading of the distribution transformer in hourly basis

losses of the lines are calculated for minimum, average and maximum values in the analyses. The results are shown in Table 2.

Table 2 Results of the analyses

		Base	10%	30%	50%
Voltage (pu)	Min.	0.9571	0.881	0.8098	0.7669
	Avg.	0.9752	0.9731	0.9688	0.9643
	Max.	0.9898	0.9898	0.9898	0.9898
TR (kVA)	Min.	126.3	126.3	126.3	126.3
	Avg.	272.9	299.2	352.5	407.6
	Max.	392.8	495.2	677.6	866.1
TR loading (%)	Min.	20	20	20	20
	Avg.	43.3	47.4	55.9	64.7
	Max.	62.3	78.6	107.55	137.4
Voltage violation probabilities (%)		0	3.48	13.805	23.988
TR overloading probabilities (%)		0	0	0.0377	8.557
Balance violation probabilities (%)		0	0	0.0152	0.1573
EVs simultaneously (%)		–	56.06	41.41	39.27
Power losses (kWh)		189.76	242.12	367.46	526.83

The results shows that power losses are increasing with the growing number of EVs as expected. Technical losses were nearly tripled in the 50% EV penetration scenario compared to base case. This issue should also be monitored by distribution network operators and market regulatory authorities. Minimum, average and maximum values are given for voltage magnitudes at end nodes and transformer loading. The results indicate that voltage level may decrease to 0.76 p.u. level which can easily cause malfunction of end-user equipment. This risk emerges for 50% EV penetration scenario. In the same scenario, it can also be observed that there is possibility of 137% loading of the distribution transformer. As the distribution transformers are generally designed to withstand 120% overloading in steady state, this issue might be problematic if the damage curve of equipment is violated.

4 Conclusions

In this study, impacts of the EV charging stations to the low voltage side of the distribution grid were investigated. There are many uncertain parameters in EV charging load phenomena due to dynamic nature of drivers' behavior. Therefore, Monte Carlo simulation was used to make accurate predictions. Start and end time of the charging, distance that EVs traveled, connected phase and connection points are the random variables that were used in the stochastic processes for the modeling.

Like as most scientific researchers did, simplifying assumptions have been made for modeling due to lack of information about real distribution networks. As result of this simplification, difference between real and modeled system results is an expected result. In this study, dynamic EV charging stations were not used for modeling due to there is not any data regarding the charging stations in the residential distribution networks.

Load flow analysis was performed using Forward–Backward Sweeping method which is developed in MATLAB. One limitation of the study is that forward–backward calculation method is generally not much effective in large-scaled electrical grids with high loads.

The results of the simulations showed that when 10% of residents have an EV, loading of distribution transformer did reach to its rated apparent power even though the voltage drop violation probability is uncritical. On the other hand, simulation results for 30% and 50% EV penetration scenarios showed that voltage drop violations may reach to critical values especially in the evening times. Besides, average transformer loading does exceed the nominal power of transformer for 50% of EV population. Transformer capacity should be upgraded before half of conventional vehicles are replaced with EVs for this case study. Nevertheless, considering the fact that 30% and 50% penetration EV levels are expected to be actualized approximately in 20–30 years, equipment should have been already renewed in distribution networks. As a result, this situation will not affect the increasing costs. Moreover, simultaneity factor has been evaluated. This data can be used for to determine the number of the charging stations depending on the number of residents. Also, there will be an increase in the technical losses. In order to mitigate the need for the new equipment and reduce the line power losses, distribution operator should find state-of-art solutions. Additionally, there might be different paying options such as real-time schedules in order to reduce the peak loads at the nighttimes. Likewise, with the communications systems, EV drivers could be directed to another charging point which is supplied from a transformer with less loading ratios. Finally, controlled charging techniques could be used. Charging will be controlled from operator to regulate the demands.

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