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Monte Carlo Simulation for Assessing the Voltage Level and Losses with Photovoltaic and Electric Vehicle in Low Voltage Network

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Abstract. Livelab from Alliander is a program which started to measure electrical and power quality data in the Dutch distribution network since 2013. This paper presents a methodology to generate the residential load profiles by cumulative distribution function (CDF) based on Livelab measured data, then applying Monte Carlo simulation method, a statistic three phase Load Flow program is developed in order to investigate the voltage level and network losses (harmonic loss is considered) of a typical low voltage (LV) network with the consideration of variable loads and random locations. Then, the prospective impact to voltage level and losses due to the grid-connected photovoltaic power generation systems (PV) and electrical vehicles (EV) are discussed, Monte Carlo simulations are done with the different penetration rates of PV and EV, maximum capacity of grid-connected PVs and EVs can be estimated and the possible network losses are calculated.

Key words

Electric vehicle, load distribution, losses, LV network, photovoltaic, voltage level

1. Introduction

The distribution network's responsibility is to deliver the necessary electric power to each customer. Livelab of Alliander is a program that provide a living testing environment for its existing medium and low voltage networks, it supports this paper technically with the measured data of a LV network in the Netherlands. A typical low voltage grid is built in order to research on the voltage level and losses.

In order to analyze the LV network profoundly, a proper load modeling method is required with the consideration of rationality and accuracy. In this paper, the author proposes a method to generate the residential load power profiles based on Cumulative Distribution Function (CDF).

Traditionally, the electricity generation is centralized and transported to the loads in the distribution network, however, nowadays decentralized generation (DG) play a increasingly important role in the electricity production. Larger generation units like small wind farms are connected to medium voltage network while smaller generation units like photovoltaic power generation systems are connected to low voltage network. An increase of grid-connected PV systems will cause [1]:

- Voltage level rise and unbalance.
- Flicker and higher harmonic distortion.
- Change of network losses.

For the transition towards a cleaner energy future, there is a rapid increase of electric vehicles connected to the LV network recently. The Netherlands is among the country's with the highest EV market penetration in the world, with plug-in electric car registrations representing a 0.57% share of total new car registrations in the country during 2011 and 2012, ahead of other European countries with a larger car market, such as Germany, France, and the United Kingdom [2]. A high penetration level of EV can raise several technical problems on power systems such as mentioned in [3]:

- Changing the load profile of the network with an increase in peak demand (Overload).
- Voltage level decrease and unbalance.
- Increasing losses.
- Increasing harmonics on the network.

A larger load connected to the end of feeder can certainly cause bigger voltage drop and more network losses than that is near the substation, therefore based on the statistic analysis of the residential load power, a probabilistic three phase Load Flow program is developed by using Monte Carlo techniques in order to consider the variable load distribution and location influence, the program is used to investigate the voltage level and network losses of the LV network, the harmonic losses of cable and transformer are considered as well. For a future study, the load flow program runs with different penetration levels of PV and EV, the impacts to voltage level and network losses are presented.

2. Network Modeling

A typical LV network is consisted of 5 or 6 feeders with radial layouts, it can serve around 300 customers as each feeder has 50-60 customers [4]. In this paper, a network with 300 customers distributed in 5 feeders is built in MATLAB. A 400kVA transformer is used in the LV substation while each feeder has $4 \times 150mm^2$ aluminum conductors with XLPE insulation and is 500m long. 60 customers are assumed to distributed evenly on the feeder. A diagram of the network is shown in Fig. 1.

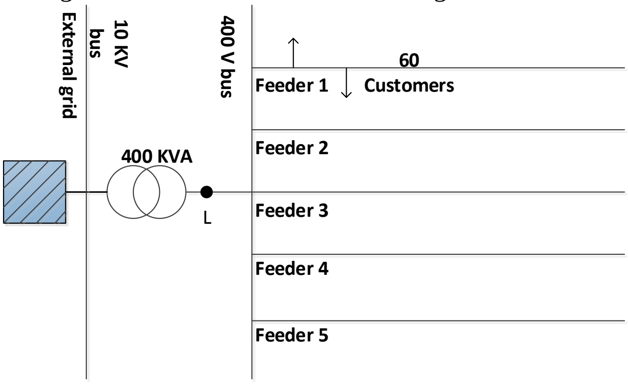


Fig. 1 LV network with household customers

3. Load Modeling

A. Available Data

1) Data from Livelab: A real residential LV network which has 383 customers was measured by Livelab in winter. At the low voltage side of transformer, the active power, the fundamental and harmonic current up to the 5th-order, the total distortion of current are available in 15-minute average. As the modeled network has 300 customers totally, the measured data should multiply by the ratio 300/383.

2) The Second Data Source: 190 single household customers' load profiles are collected by another research project in Electrical Energy System group of Eindhoven University of Technology, the Netherlands, the data include each customer's one week power consumption in every 15-minute both in summer and winter.

B. Generation of Residential Load Profiles based on Cumulative Distribution Function

To apply a proper probability distribution provides one possibility to model the loads on one feeder in each time interval. The previous research has shown that the power of customers on one feeder is good-fitting a Gamma distribution in New Zealand and Italy [5]–[7]. In [5], the author used Gamma distributions to generate residential load profiles, the disadvantages of this method are the parameters of Gamma distribution are estimated by the polynomial fitting of mean and deviation values which will decrease the accuracy and it cannot describe the time-relevant characteristic of a single residential load profile. Therefore in this section, the method to generate the exact number of load values in one time interval based on the CDF (Cumulative Distribution Function) is given.

1) Create CDF based on the real measured data.
2) Use $U_Y(0,1)$, which is a uniform distribution between 0 and 1, to generate necessary number of random values and lookup into CDF from Step 1, read the values on the abscissa.

Fig. 2 shows two CDFs' curves, the blue line is the CDF based on the measured data in summer and the red line is the CDF coming from 100 values, it is clear that they have a good matching. The aggregated power at the beginning point of each feeder is available from Livelab, in another word, the mean value of each customer's load can be got, this mean value is definitely different from that of second data source which is used to derive the CDF. Fig. 3 shows that two CDFs which have same shape but different mean value. The transfer is completed by multiplying the ratio between the Livelab average value and the original average value.

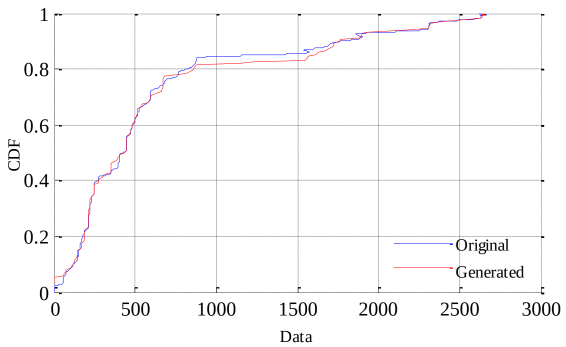


Fig. 2 100 customers CDF example

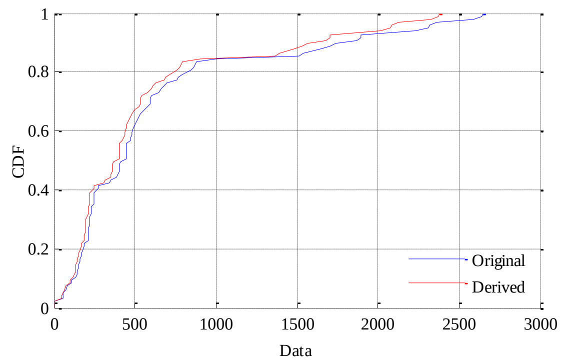


Fig. 3 Two CDFs with different mean value

E_i, the daily energy consumption value, where i indicates the house number, is determined from the measured data P_{ik}, where k is the sequence number of time intervals.

$$\mathrm{E_i} = \sum_{k=1}^{N_t} \mathrm{P_{ik}} \tag{1}$$

where $\mathrm{N_t}$ is the total number of time intervals in one day, for instance, there are 96 for 15-minute. In the next step, $\mathrm{L_{ik}}$ is defined as

$$\mathrm{L_{ik}} = \frac{\mathrm{P_{ik}}}{\mathrm{E_i}} \tag{2}$$

Then, the power of each customer at every time interval can be calculated as

$$\mathrm{P_{ik}} = \mathrm{E_i}\frac{\mathrm{P_{ik}}}{\mathrm{E_i}} = \mathrm{E_i} \cdot \mathrm{L_{ik}} \tag{3}$$

As mentioned above, in [5] the author uses two Gamma distributions to generate the values of E_i and L_{ik}, the disadvantages are the distributions are difficult to define accurately and the generated random values of L_{ik} are not related to time. Therefore, the method using two CDFs is applied in this paper. Based on the second data source, the Cumulative Distribution Function of E_i can be got, in Fig. 4, the blue line shows the CDF from the second data source while the red line gets the connection with the Livelab data.

For L_{ik}, in each time interval, the CDF of L_{ik} can be calculated in order to give the percent of energy consumption in the particular period. Fig. 5 shows the two CDFs at 02:00 and 20:00. Obviously, L_{ik} at peak load time is mostly more than that at low load time. Therefore, E_i's CDF and L_{ik}'s CDF at each time interval can be calculated and the reasonable load profiles of one day can be generated.

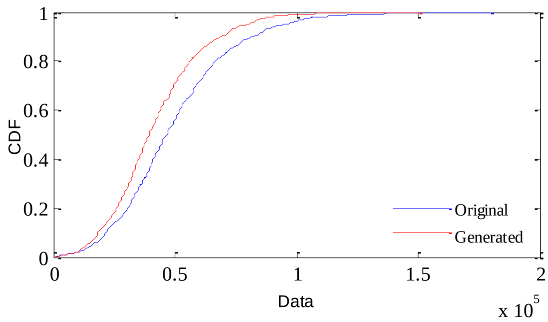


Fig. 4 Two CDFs of energy consumption (E_i)

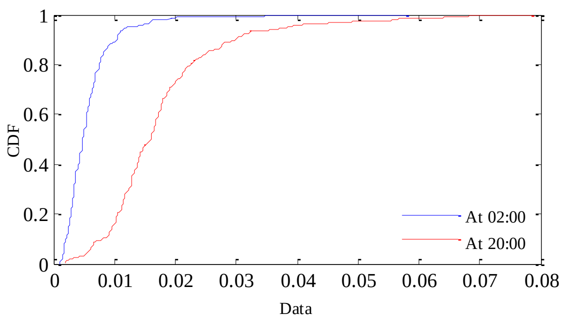


Fig. 5 CDFs of L_{ik} at two different time

4. Photovoltaic System and Electric Vehicle Modeling

A. Photovoltaic System Modeling

Photovoltaic systems are assumed to connect to the LV network. To simplify the problem, only one type of PV system with peak generation of 2.5kW and smooth generation curve is considered to be installed by the customer (Fig. 6). The maximum allowed PV capacity which can be installed evenly on a LV cable depends on the thermal cable capacity and the allowed voltage rise across the cable. The calculation formula is given in [8]. Table I shows the calculated PV capacity, the load at 12 : 00 (the peak generation time), the maximum limits of cable and transformer for one feeder. It shows that the maximum capacity of PV can be connected to the feeder is $24.1 + 80.0 = 104.1$kW, in another words, 70% of customers can have PV systems, otherwise the transformer will overload.

Table I. - Determination of PV capacity

Calculated PV capacity	Load	Cable limit	Transformer limit
190.0kW	24.1kW	186.3kW	80.0kW

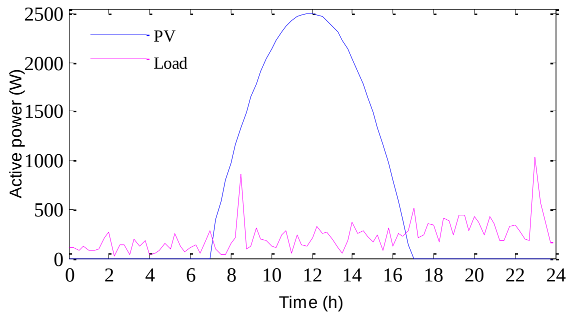


Fig. 6 The generation curves of PV and load

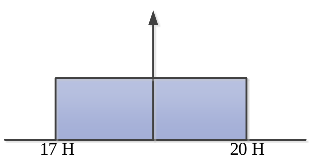
B. Electric Vehicles Modeling

It is unreasonable to connect fast charging to the residential LV network directly as the charging power is around 20kW which can cause severe problems (Overloading and voltage drop), so slow charging is considered here (3kW, 25kWh). Stochastic process is used to describe the charging state and the worst case is considered with the premise that the charging time mostly meets the peak load time (20:00). It is assumed that the process of electric vehicle recharging is determined by two random variables:

- The charging start time
- The initial state of EV battery at the charging start time

The charging start time is considered as a uniform distribution (Fig. 7) between 17:00 to 20:00 while the charging time is related to the initial state of battery, which is a random variable described by another uniform distribution (Fig. 8), the battery level before charging is considered between 20% and 80%. Fig. 9 shows one example when the charging start time is 18:00 and the initial state of battery is 50%.

Table II shows the calculated EV capacity, the load at 20 : 00 (the peak generation time), the maximum limits of cable and transformer for one feeder. It shows that the maximum capacity of EV can be connected to the feeder is $80.0 - 44.3 = 35.7$kW which means 20% of customers can have electric vehicles, otherwise the transformer will overload.



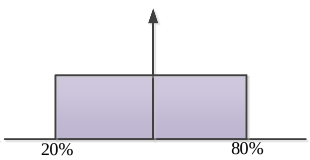


Fig. 7 Distribution of charging start time

Fig. 8 Distribution of the initial battery state

Table II. - Determination of EV capacity

Calculated EV capacity	Load	Cable limit	Transformer limit
72.4kW	44.3kW	186.3kW	80.0kW

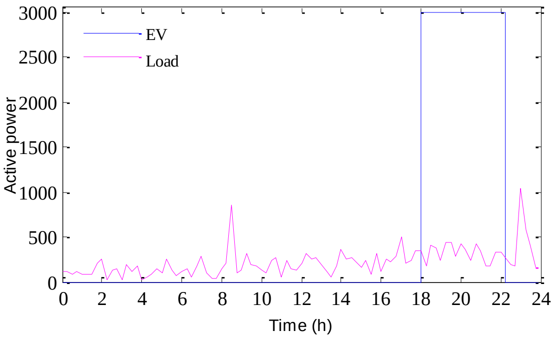


Fig. 9 The EV and residential load curves

5. Simulation Tool

Monte Carlo simulation is applied with the consideration of variable load profiles and random location of PV and EV. The simulation tool is expected to bring several advantages.

- The consideration of diverse residential and EV load profiles for different customers.
- The consideration of location occasionlity of loads, PV and EV.
- An ability to include the harmonic and neutral losses.

Fig. 10 shows the description of simulation tool. For investigating the voltage level, an indicator is defined in advance that the voltage should be stay in the range of 0.95pu to 1.05pu which take account of the possible MV network voltage change.

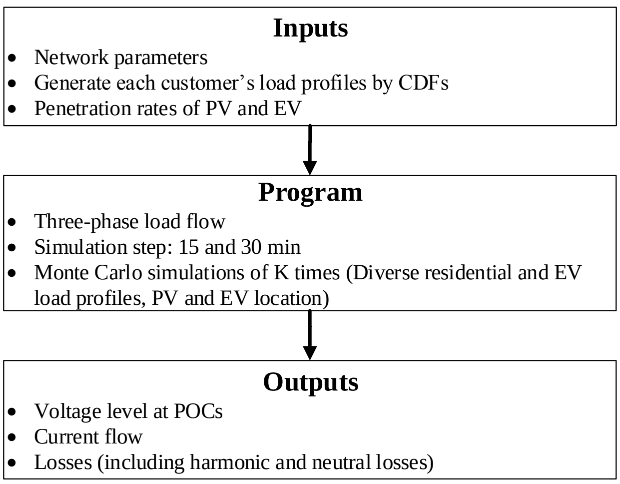


Fig. 10 The description of simulation tool

6. Results

For the voltage level, the simulations have been done with PV and EV respectively and for the network losses, the simulations are carried out of current situation, with PV, EV and both of them respectively.

A. Voltage Level

For PV, the simulation starts from the penetration rate of 70% based on the previous calculation, Fig. 11 has shown the voltage level of feeder in one day, the highest voltage level usually happens at the end POC of feeder . Then 1000 times Monte Carlo simulations are carried out, Fig. 12 shows the 1000 possible voltage levels of end POC in 24h.

Obviously, the voltage levels cannot always under the limit (1.05pu) in all 1000 situations. Therefore, the Monte Carlo simulations are carried out with different penetration level of PV. Fig. 13 shows the possibility of the maximum voltage level exceeds 1.05pu when different amount of PV systems are connected to random POCs of the network. The safe level of penetration rate of PV is 60% according to the figure. With different penetration rates of electric vehicles, Fig. 14 is drawn and the safe penetration level of EV is around 12%.

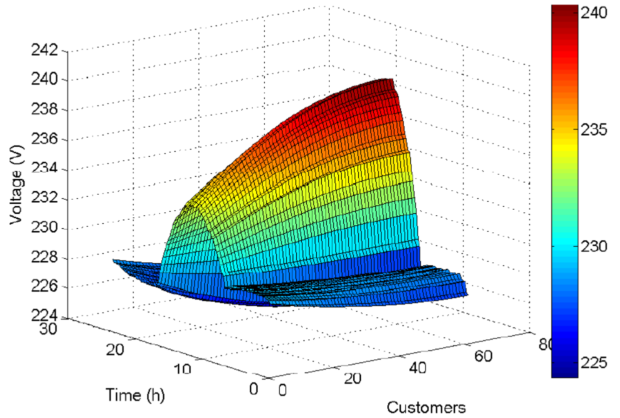


Fig. 11 The voltage level of feeder in one day

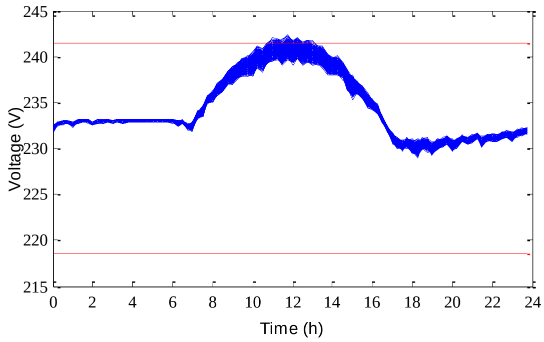


Fig. 12 The voltage level of feeder in one day (Penetration rate is **70**%)

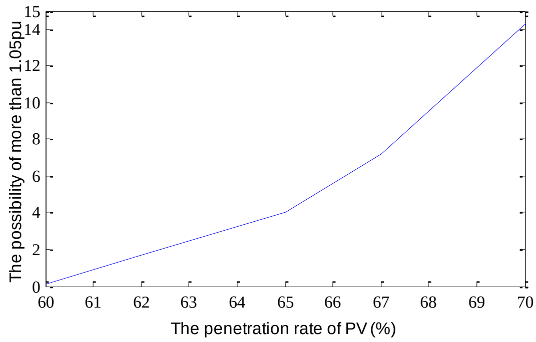


Fig. 13 The possibility of more than 1.05pu with PV

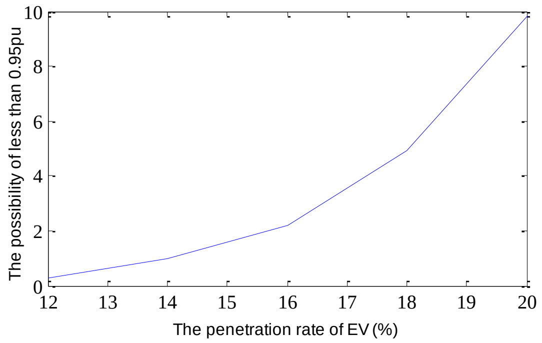


Fig. 14 The possibility of less than 0.95pu with EV

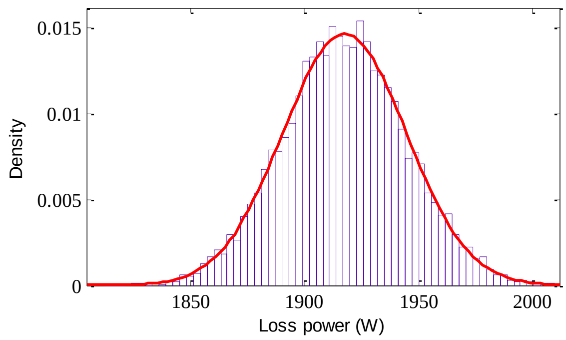


Fig. 15 The current network losses range

B. Network Losses

Several scenarios are also carried out by the Monte Carlo simulation tool:

- The current fundamental losses and total losses with harmonic.
- The losses with different penetration rates of PV or EV respectively.
- The losses with a certain penetration rate of PV and different penetration rates of EV.
- With shifting of the charging time of EV, the losses of third situation.

All losses of each penetration rate is obtained by averaging results of 1000 times Monte Carlo simulations.

The harmonic effect of hysteresis loss in transformer is presented in [9] and that of eddy current loss is discussed in [10]. The current network losses are shown in Table III by 1000 times Monte Carlo simulations. Loss1 is the daily average fundamental losses and Loss2 includes harmonic losses, P is the daily average consuming power of the whole grid. Fig. 15 shows the range of possible network losses.

Fig. 16 shows the average losses vary with the percentage of customers with PV. It shows that the losses reach the minimum point when the penetration of PV system is around 18%. When less than 34% of customers have PVs, the network losses are less than the situation without PV. Fig. 17 shows the average losses vary with the percentage of customers with EV. It is clear that the losses increase when the penetration of EV is more and a linear function $y = 56.78x + 1912$ can be used to describe the relation between penetration rates of EV and losses definitely.

Table III. - The Current Network Losses

Item	Grid (P=124.78kW)			Transformer
Loss1 / Time	Mean	Minimum	Maximum	Mean
15-minute	1917W	1808W	2009W	821W
30-minure	1904W	1810W	2011W	820W
Loss2 / Time	Mean	Minimum	Maximum	Mean
15-minute	1962W	1851W	2053W	857W
30-minure	1949W	1853W	2056W	856W

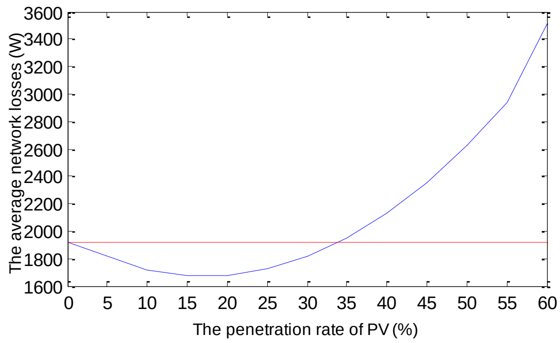


Fig. 16 The losses with different penetration rates of PV

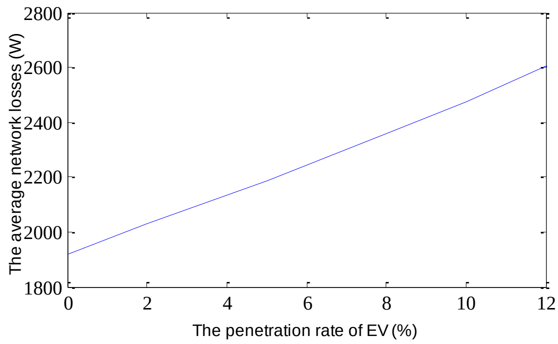


Fig. 17 The losses with different penetration rates of EV

With 60% of customers have PV systems, the losses are calculated with different penetration rates of EV. The average values are shown in Fig. 18. Then shift the charging start time to 8h to 10h in the morning, the network is more energy saving.

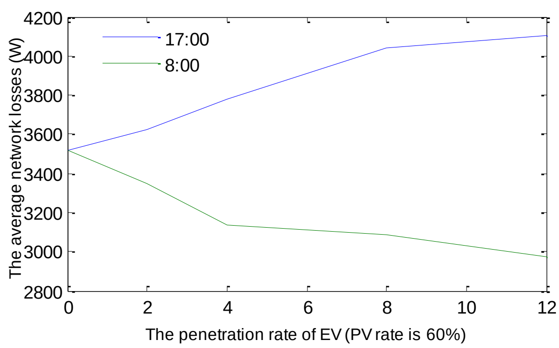


Fig. 18 The losses with different penetration rates of EV (PV rate is **60**%)

7. Conclusion

A typical LV network is modeled in order to analyse with the measured data of Livelab Alliander.

Based on the two data sources, it is found that generating residential load values during one period by CDF is feasible and effective. The single customer's load profile can be generated by two CDFs which can overcome the disadvantages of using a particular probability distribution (eg. Gamma).

Monte Carlo simulation is applied to discuss the voltage level and losses. An indicator of 0.95pu to 1.05pu is set to observe the voltage level, the possibilities of more than 1.05pu and less than 0.95pu are obtained with different penetration rates of PV and EV by 1000 times Monte Carlo simulations, then the safe level of connected PV is 60% and that of EV is 12%.

Currently, the percentage of fundamental losses to distribution power is about 1.53%, with the harmonic, the percentage increases 2.3% relatively, which is mainly because of transformer. For transformer, harmonic effect of no load loss dominates. With the consideration of variable load profiles and random locations, the average losses change around 10%. When less than 34% customers have PV, the losses are less than the situation without PV, then the losses increase dramatically by the rise of penetration level. For the EV, more connection leads to more losses and a linear function could describe the relation between penetration rates of EV and losses exactly. To shift the charging time of EV shows an obvious advantage on the energy saving aspect, a more convincing algorithm for smart charging of EV with DG is necessary for improving the network efficiency.

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