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Probabilistic Risk Assessment of Electric Vehicle Charging Load on Argentine Distribution Network

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Abstract

In this article, we propose a multivariate probabilistic model to analyze the impact of electric vehicle (EV) connection on low-voltage (LV) distribution networks. First, we analyze the distribution network behavior under unmanaged charging strategies, considering different EV penetration factors on the grid. We consider the distances traveled by EVs, EV arrival time, state of charge (SOC), and residential demand as statistical variables. We use a methodology that includes Monte-Carlo simulations. Then, we analyze the level of technical losses, node voltage, and power flows. The results show that leaving the charging process in the hands of the user produces unacceptable technical levels for the proper functioning of the grid. In this paper, we present two possible solutions to increase the level of EV penetration while meeting the technical requirements of the grid. The first is demand management, postponing the average start time of the charging process until late at night. This method depends on the demand curve, but our case study shows good results due to the low-load nature of the grids late at night. The second solution consists of modifying the load factor of the MV/LV transformer (and possibly the traditional radial grid design) to allow for greater EV insertion. This could be interesting in a context where grid design is being considered. Evaluating the results provides relevant information for Argentine distribution system operators (DSOs) and regulatory authorities before drafting efficient and well-founded regulations for the introduction of this technology.

Keywords: Electric vehicle charging; computational analysis of power systems; low-voltage power grids; adaptive grid.

Introduction

The number of electric vehicles is expected to increase significantly worldwide. This increase represents an environmental advantage due to their high efficiency and low or zero carbon emissions [1)-(6]). However, there are many questions about other possible effects. One of them is the uncontrolled connection of private EVs to LV networks. The connection of private EVs in Argentina is still in its infancy . [7] , [8] However, a Distribution System Operator (DSO) and a regulatory agency should have an estimate of the effects that such incorporation would have on low-voltage (LV) distribution networks. This information would allow for effective regulation. The impact on low-voltage distribution networks when a large number of EVs are connected simultaneously and randomly can be varied. Generally, the effects manifest as voltage drops, conductor overloads, increased losses, power quality issues, etc. Some works on the impact factors can be seen in [9)-(13] . These effects can be negative for the grid when the penetration of electric vehicles is high. Regarding the analysis methods, [14] presents a probabilistic methodology to evaluate the impact of EV charging and non-linear loads on power quality in low-voltage residential networks. The authors use stochastic models and perform a Monte Carlo simulation to obtain a probabilistic assessment of the power quality. In work [15,] the authors investigate the problems that EV charging causes to power quality in the electrical grid and how to mitigate it. In [16] , a literature review on the impacts of EV charging on residential networks is presented. In addition, a method is proposed to evaluate the impacts of EV loads on the grid voltage profile. Finally, a controlled charging algorithm is proposed to mitigate the effects. In [17,] the authors use statistical methods to find driving patterns that are then applied to studies . on the impact of unmanaged vehicle charging. The study evaluates the voltage profile and energy losses of the grid. In [18 cases] , an analytical model is developed to assess the reliability of smart grids. Monte Carlo simulation is used to validate the proposed reliability assessment method. In addition, the work studies the impact of different stochastic parameters on the grid.

In this article, we propose a multivariate probabilistic model for analyzing the impact of individual EVs on LV distribution networks. For this work, we consider the randomness of EV connection (residential charging), the randomness of EV charging times, and the statistical variation in residential demand.

1. The work is distinguished by:
2. 1. Use a probabilistic model where the input variables correspond to local patterns of the study region.
3. 2. Use a typical and widely used LV network in urban areas of Buenos Aires, Argentina.

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4. 3. Consider two strategies to improve grid performance: load control and grid modification. The latter is of great importance given the current modernization needs of Argentina's LV networks.

To develop these points, we first present the methodology used for analyzing electric vehicle charging in low-voltage distribution networks. Second, we present a case study using a typical distribution scheme in the province of Buenos Aires. Third, we present the results. Finally, the conclusions conclude the work.

Proposed Study

Obtaining a particular EV charging profile is not an easy task. It depends on several factors, including: the EV class, the battery capacity and state of charge, the penetration factor of EVs in the grid, the behavior and habits of drivers, and the type of charging required [19]-[26]. The introduction of human behavior is what makes the model difficult [22]. We can classify the behavior of private or residential drivers into two types: mobility behavior and charging behavior. The former depends on the distance traveled, vehicle type, driving mode, etc. It affects the arrival time and charging time. The latter depends on the charging frequency and, therefore, the charging location. It affects the charging points on the network. Based on the above, to study the impact of EVs on the LV grid, it is necessary to take into account:

1. i. Quantity of EVs in the charging process at each instant.
2. ii. Duration of the charging process.
3. iii. Link between EV and demand curve.
4. iv. Nodes affected by the load.

The first variable to consider is the daily distance traveled by the vehicle. As expected, each vehicle has different distances traveled, driving modes, and experiences different traffic congestion. For an initial estimate, we use a normal probability function with mean and deviation taken from a group of users in the province of Buenos Aires. The distance (in kilometers) traveled in a daily trip by EVs (di) and the connection time (start of charging) (tp, i) are determined by normal probability functions represented in equation (1) and equation (2).

$$f_{(d_i)} = \frac{1}{\sigma_{d,i} \cdot \sqrt{2\pi}} e\left[-\frac{(d_i - \mu_d)^2}{2\sigma^2}\right] \quad () \; 1$$

$$f_{(t_{p,i})} = \frac{1}{\sigma_{p,i} \cdot \sqrt{2\pi}} e\left[-\frac{(t_{p,i} - \mu_p)^2}{2\sigma^2}\right] \quad () \; 2$$

Where:

μ: mean value

σ: standard deviation (σ > 0)

We consider that the kilometers traveled take into account all the factors existing in a trip (type of road traveled, driver's driving style and stops at traffic lights). For more detailed efficiency studies (based on traffic statistics), traffic jams and other factors that affect energy consumption during the trip could be considered [22), (27), (28).] In this work, and to study the impact of charging power on the grid, we consider a random variable that allows quantifying the battery status at the time of charging. The time of arrival at the final destination is taken as a reference for connecting the EV. This parameter is characteristic of each city, town or neighborhood, depending on the habits of its inhabitants.

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The state of charge (SOC) for the i th EV is given by equation (3):

$$E_{0,i} = E_{\max} - c \cdot d_i \quad (3)$$

Where: E $_{0/}$: SOC, E $_{max}$: maximum battery capacity, c: consumption per km, di: km traveled.

For our case we consider that the initial SOC, equation (4), is between,

We assume that the day starts with a fully charged battery. Some authors consider a maximum SOC of 0.95 to account for battery self-discharge. Considering a Mode 1 charge, slow residential at constant power, [29], [30]. The charging time of each vehicle (t_C ,i) will be given by equation (5).

Where: t_{Ci} : charging time, rj $_C$: charging process efficiency, P_{EV} : constant EV charging power.

Based on observations and customs, we estimate the mean arrival time to be 7 pm for a group of residential users in the Buenos Aires province suburbs. In these estimates, we use an average distance traveled by residential users of 40 km on weekdays. Furthermore, we take the arrival time to be the EV charging start time for uncontrolled EV charging. To illustrate the methodology, we show the distance traveled (Figure 1), arrival time (Figure 2), and state of charge (Figure 3) for a group of private EVs.

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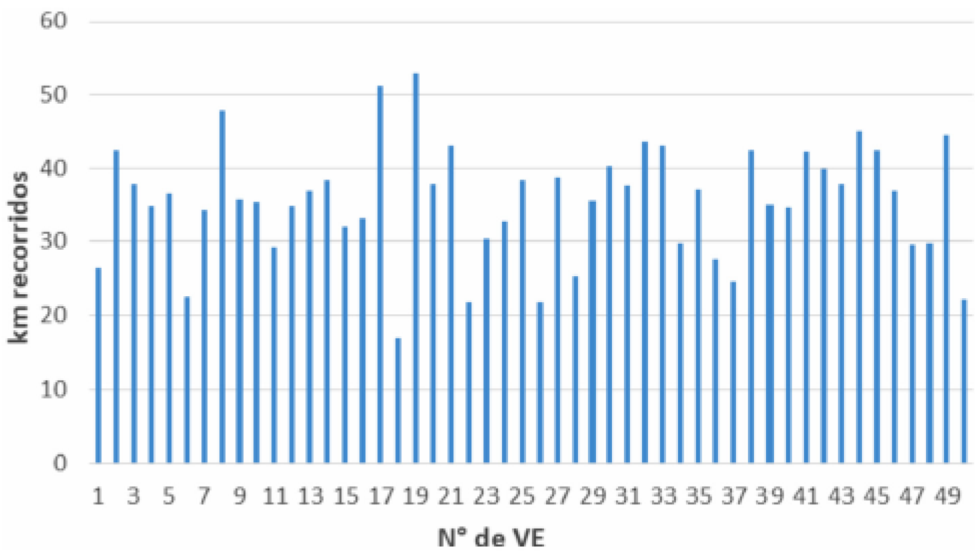

Figure 1 Distance traveled by each VE.

Figure 2 Arrival time at home for each VE.

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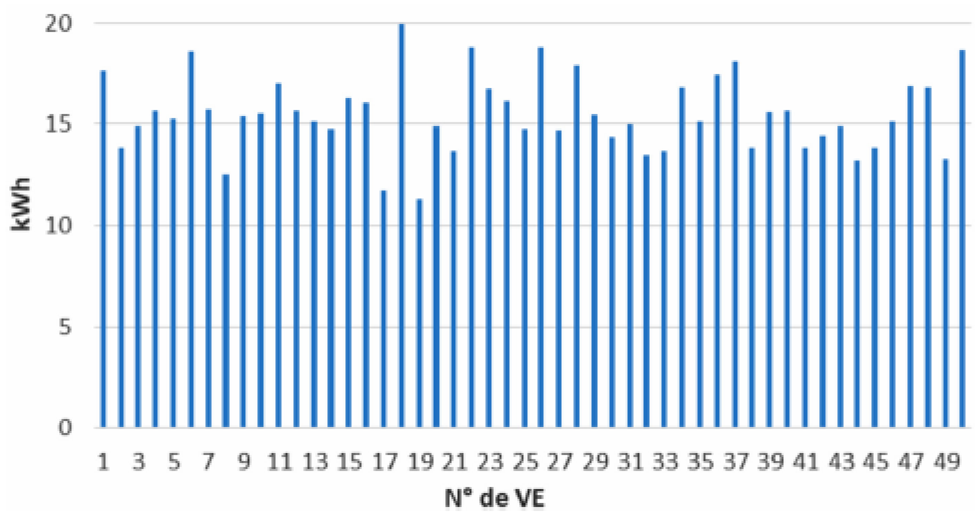

Figure 3 State of charge for each EV.

The battery characteristics, SOC, and charging mode [31] determine the charging time of each electric vehicle. This is also determined by a statistical variable. Not all EVs are connected to the grid simultaneously. The connection time is random for each EV (depending on the SOC). This means that, every hour, new vehicles connect, others remain connected, and others disconnect with a full charge (in this work, we assume that EVs always complete their charge). With all these elements, we determine the nodes occupied by EVs in the process of charging at any given time. This effect can be visualized in Figure 4 , which shows the EVs connected for each hour for an unmanaged charging strategy.

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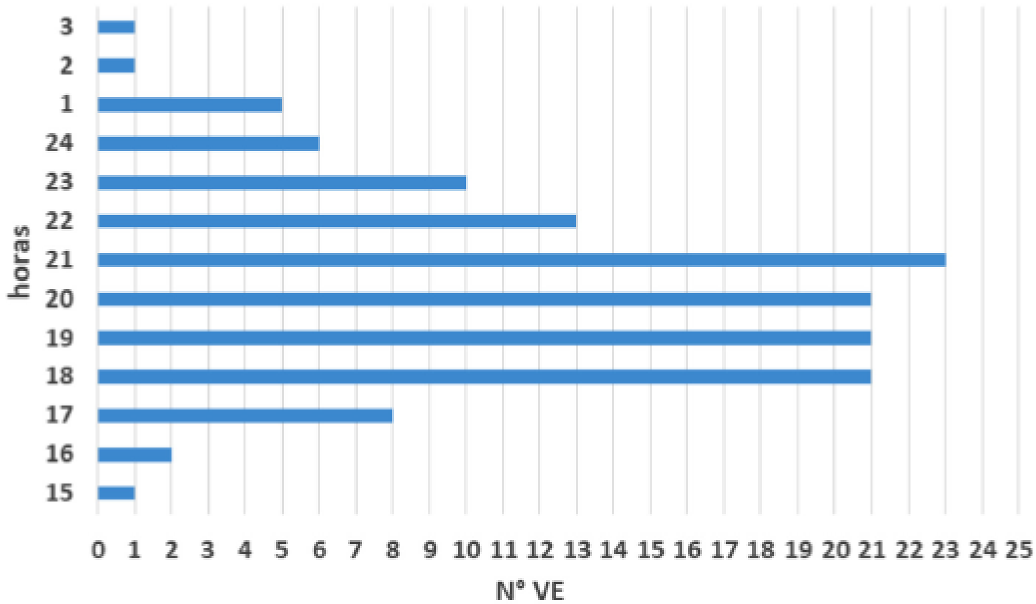

Figure 4 Total number of EVs being charged.

At each time step, EVs are randomly distributed across the residential network nodes with a uniform distribution. The number of active vehicles in the network defines an EV penetration factor, equation (6).

$$F_{EV} = \frac{N_{EV}}{n} \quad (6)$$

Where: F_{EV} : EV penetration factor, N_{EV} : number of EVs, n: users.

The EV demand at each node is added to the existing residential demand, determining the total load of the node at the time corresponding to equation (7) [32], [33] .

() 7

The total demand per node is used to solve for a power flow in a given network by the Monte Carlo method [34]-[37] . In this way, technical parameters (losses, voltages,

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etc.) are obtained to evaluate the behavior of the LV electrical network. Figure 5 shows the proposed methodology to study the impact of private electric vehicles on LV networks. The process is iterated using the Monte Carlo method.

Case Study

Loading patterns

We propose three possible scenarios in addition to the base case (scenario without VE).

1. 1. Connection at the time of arrival at home (charging process not managed).
2. 2. Connection postponed until late at night (managed charging process).
3. 3. Connection at the time of arrival at home, but with a modified network (modified network).

In the first, unmanaged scenario, each user begins the charging process upon arrival at home. We propose a normal distribution with an average arrival time of 7 p.m. for suburban areas of the province of Buenos Aires. We expect this to be the most adverse condition, as this time is close to peak demand. We consider an electric vehicle penetration rate of 30% to 50%.

The second scenario represents managed demand. To achieve this, we postpone connection time until late at night, when other demands are lower. We assume an EV penetration rate of 30%.

Figure 5 Proposed methodology for studying the impact of EVs on BT networks.

The third scenario represents unmanaged demand, but with a modified network. We use a radial LV network similar to the first scenario with a smaller number of

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users, maintaining the original radius. This results in a lower transformer load factor under peak demand conditions. In this last case, we consider an electric vehicle penetration factor of 30%.

For EVs, we consider a 24 kWh battery with a fuel consumption of 0.24 kWh/km and a total charging time of 8 hours. We use a constant power charge of 3 kW. Table 1 shows the parameters used in the density functions.

Table 1 Parameters used in the density functions.

Parámetro	Distribución	μ	σ
Distancia recorrida (km)	Normal	40	8
Hora conexión, no gestionada (hs)	Normal	19	2
Hora conexión, gestionada (hs)	Normal	2	2
Hora conexión, red modificada (hs)	Normal	19	2

LV distribution networks and residential demand

In our case, we consider an urban overhead radial network. The power grid is fed by a 500 kVA MV/LV transformer with a 90% load factor under peak demand conditions.

The transformer supplies 310 users through 4 outputs. Residential consumption is statistically modeled using a normal probability density function (8) , equation (28), (38), (39).

$$f_{(r_n)} = \frac{1}{\sigma_{r,n} \cdot \sqrt{2\pi}} e^{\left[-\frac{(r_n - \mu_{r,n})^2}{2\sigma_{r,n}^2}\right]} \quad () \; 8$$

Where: u $_{rn}$: average demand of each user, σ $_{κη}$: standard deviation of the demand for each user.

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For the purposes of the statistical model, we considered similar consumption characteristics for all users. Figure 6 shows the studied network, and Figure 7 shows the demand curve for residential users. Residential demand was selected, peaking at 8 p.m.

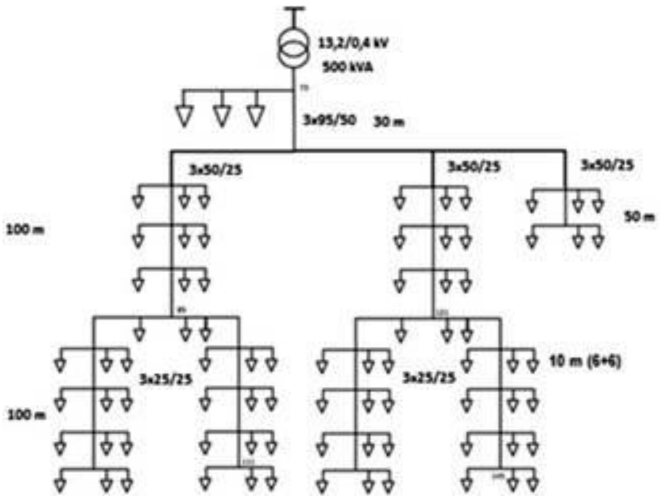

Figure 6 BT radial network model.

Figure 7 Individual demand curve.

The network parameters are shown in Table 2 .

Table 2 Network parameters.

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Conductor	Características	r (Ω/km)	x (Ω/km)
3x95/50	Al- XLPE	0,372	0,1
3x50/25	Al- XLPE	0,743	0,1
3x25/25	Al- XLPE	1,39	0,1
6+6	Cu-XLPE	5,61	0,06

Results

Power in transformers

Below, we present the results obtained in the three proposed scenarios. Figure 8 shows the average apparent power flow through the MV/LV transformer for the tested scenarios. In the unmanaged case, with EV penetration of 30% and 50%, the power flow values through the transformer exceed technical limits. However, as shown in Table 3 , the strategy is effective for penetration factors below 10%. According to technical studies, Argentina expects not to exceed 2% of the EV penetration factor by 2030 [40] . In such a situation, the studied charging strategy would be adequate.

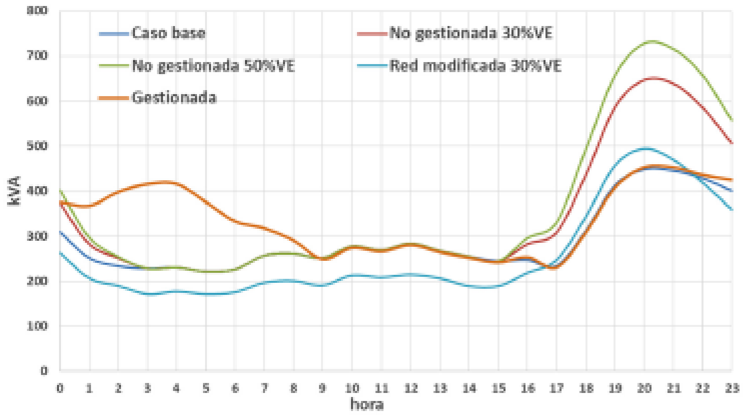

Figure 8 Power flow in the MT/LV transformer.

Table 3 Unmanaged transformation power.

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Factor de penetración de VE (%)	Potencia de transformación (kVA)
3	476
6	493
10	516
15	541
20	564
30	576
50	648

Regarding managed EV charging, and for the proposed penetration factor, the transformer power limits are not exceeded. Figure 8 shows that part of the demand is shifted to off-peak hours, which improves the shape of the load curve. We can also see that the penetration factor is very appropriate for the proposed grid. In this case, a fixed statistical charging schedule has been chosen. An alternative is to create a sliding time window that centers the probability density function according to the battery charge level. Considering that the vehicle should be fully charged at, for example, 7 a.m., in this case, the load curve will be smoother at night. For the modified residential grid scenario, it is possible to meet the transformer's technical limits for an EV penetration level of 30 percent.

Energy losses

Energy losses are those that arise during grid operation. These are related to the Joule effect in cables and any other conductive material carrying current. Figure 9 shows the average energy losses for each time interval considered in the different scenarios. Losses increase as EV penetration increases. In the case of unmanaged EV charging, losses far exceed those typical for the base case.

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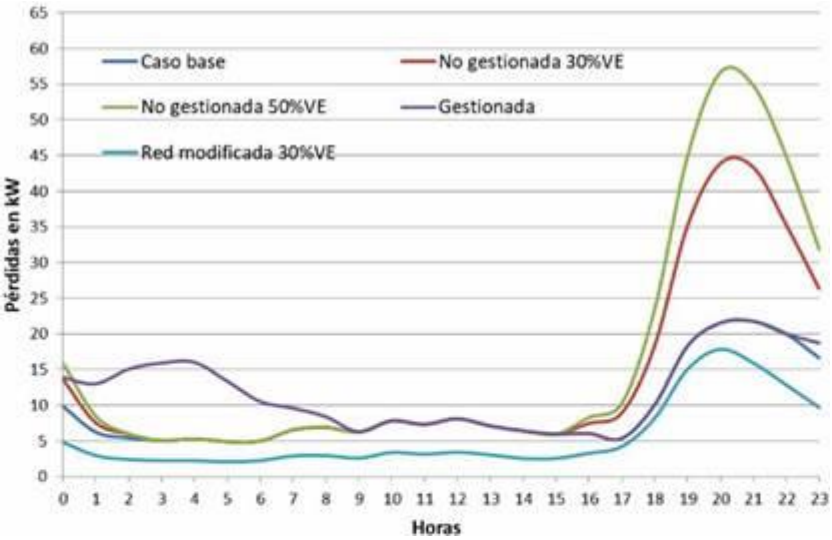

Figure 9 Losses in the BT network.

By managing the charging start time, technical losses are reduced to values compatible with a network with these characteristics. A planned restructuring or design of the LV residential network results in improved system performance. A sliding charging time strategy would flatten the network's loss curve at night. Figure 10 shows the energy losses over a day for each scenario. We can see again that a managed charging process improves network performance. As in the previous cases, a well-thought-out network design improves its performance in the face of EV penetration.

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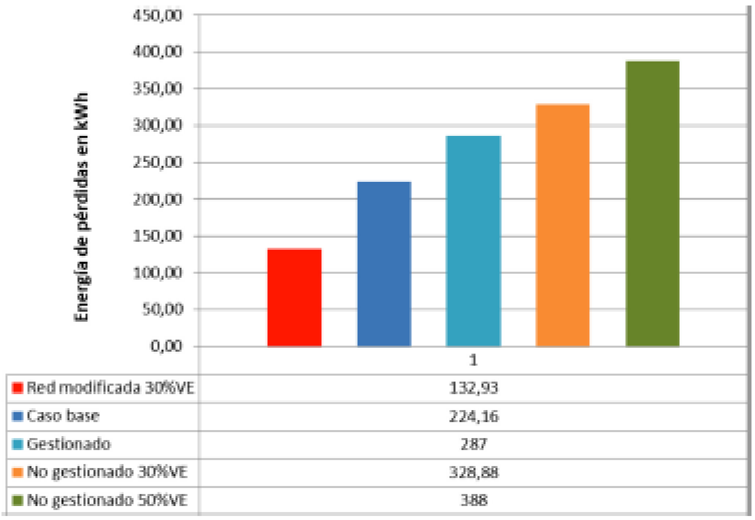

Figure 10 Losses in the BT network.

Voltage drop

Radial distribution networks have the disadvantage that the voltage value drops as the distance from the transformer increases. An increase in demand exacerbates the problem, leading to node voltage values that fail to comply with technical standards. This situation can worsen with EV connections. In this case, node voltage must be monitored to avoid voltage instability in the network. Figure 11 shows the minimum voltage at the farthest node for each scenario.

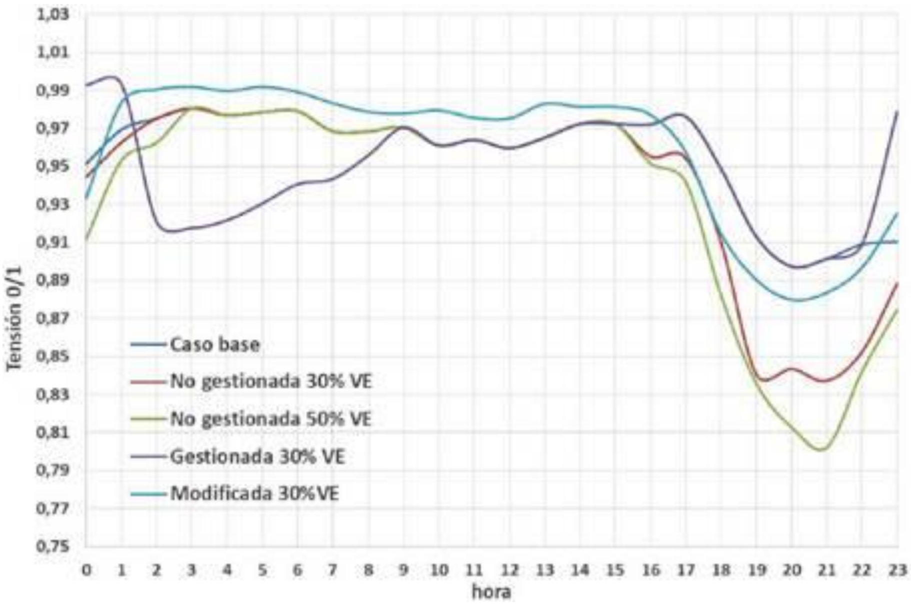

Figure 11 Minimum voltage at the farthest node for each scenario.

In Argentina, it is common practice to consider 0.9 pu as the allowable voltage limit at nodes in overhead networks such as the one used in this study . [41] The unmanaged EV charging scenario results in unacceptable voltage drops. However, if the penetration factors are less than 10%, then the technical criteria are met. Managed EV charging appears to be the best solution for this limit in this case study.

The modified network is an interesting case. This network meets other requirements, but presents voltage dip problems at the most distant node. This occurs because the transformer load factor was reduced by limiting the number of users, but the original radius of the LV network remained unchanged. Below, we show the cumulative probabilities of voltage dip at the most distant node during the statistically maximum demand time. Figure 12 , Figure 13 , and Figure 14 show the

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cumulative probability, for the studied network, that the voltage value at the most distant node will be below a certain value with a EV penetration of 30%.

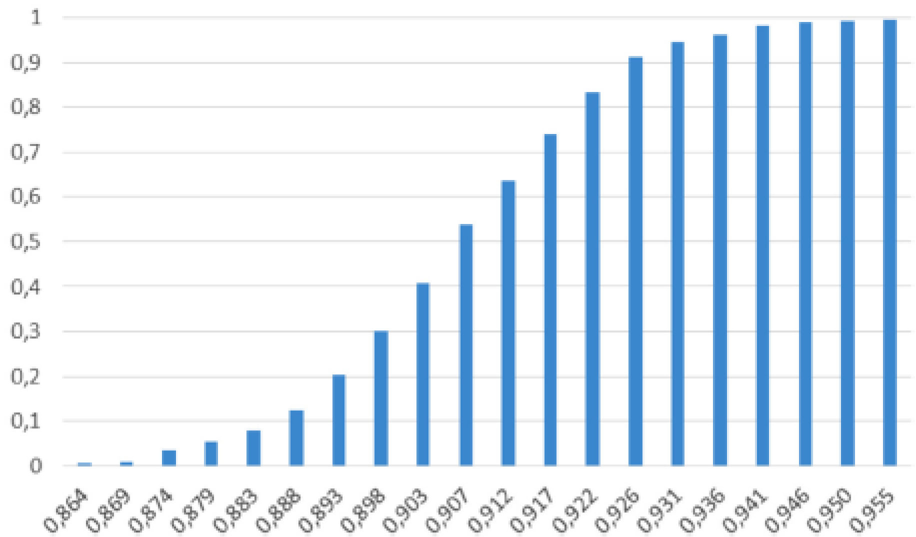

Figure 12 Cumulative probability of voltage drop for the unmanaged charging process.

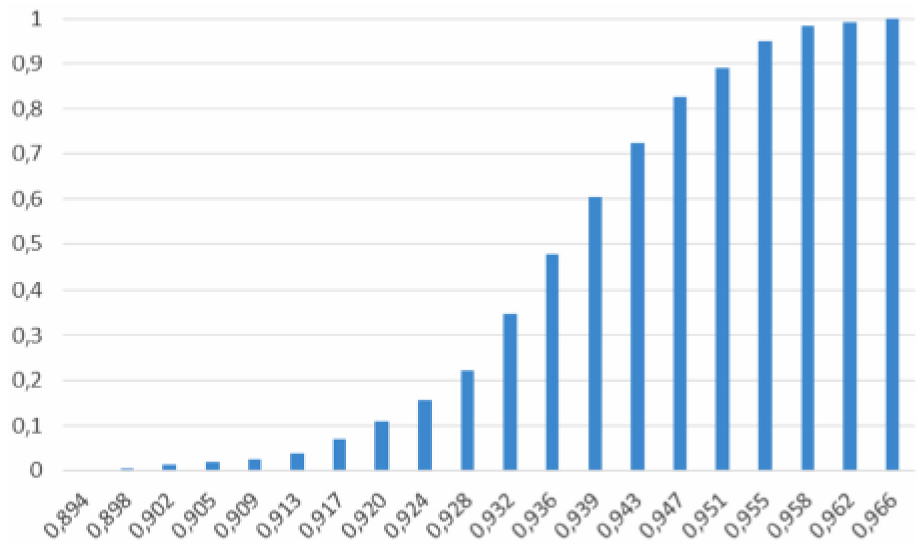

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Figure 13 Cumulative probability of voltage drop for the managed charging process.

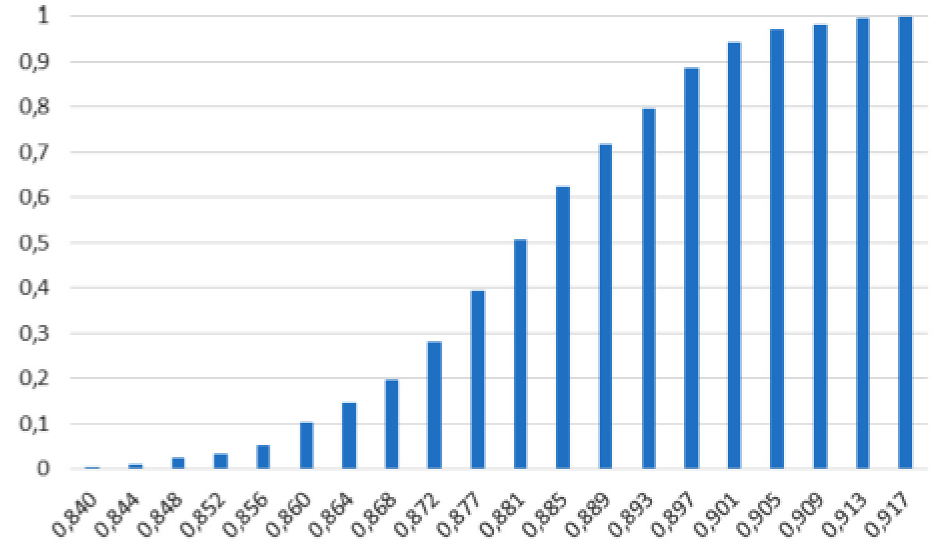

Figure 14 Cumulative probability of voltage drop for the modified network.

For unmanaged loads (Figure 12), there is a 40% probability that the voltage value at the farthest node will be below the 0.9 pu limit. We also found that the cumulative probability of exceeding the limits is 25% for the EV penetration factor of 20%, and only 2% for the EV penetration factor of 6%.

For managed charging, there is a nearly 1.2% chance of exceeding the voltage drop limit.

In the case of a modified network, the probability of exceeding the limits is approximately 95%.

Conclusions

In this article, we propose a statistical methodology to study the impact of EV connection on residential networks in LV. We consider slow EV charging at constant power, with random connection points, charging times, and connection times. The resulting EV demand is added to the statistical residential demand at the corresponding connection points. The results show that leaving the charging start time in the hands of users has a negative impact on the system. An EV penetration factor greater than 6% results in exceeding technical limits during peak hours. While this penetration factor is admittedly low, we must consider that Argentina is not expecting a significant growth rate for EV penetration. Official data estimate growth of 1.5% to 2% by 2030. Therefore, our results are appropriate because they show the technical limits of the network and allow for accurate estimates of the timing of network investments.

However, there will always be some networks with a penetration factor higher than our maximum estimate. In such cases, we propose two different solutions. The first is demand management, which postpones the average charging start time until late at night. This way, there is no overlap between peak hours and the charging process time. This method shows good results because networks are underloaded late at night. With this method, EV connection times (mean and deviation) must be controlled. Large deviations can cause unacceptable voltage drops. Furthermore, delays in connection times can result in insufficient time to complete battery charging. Based on this, a sliding time methodology based on battery charge is proposed. This methodology would allow the average connection time to be centered on the remaining charging time (ensuring vehicle availability before, for example, 7 a.m.).

Second, a network with radial characteristics like the original is proposed, but with a smaller number of customers. This frees up the transformer's load factor and allows for increased EV penetration. While this may yield good results for low penetrations (less than 30%), a larger number of vehicles would result in a very low load factor on the transformer. This modification, however, leads to unacceptable voltage levels, which is resolved by shortening the network radius. We believe that load transfer during peak demand times outweighs other methodologies and is even more effective when these times vary dynamically (a topic under development). Evaluating the results of EV penetration is relevant information for Argentine DSOs and regulatory authorities prior to developing efficient and solidly based regulations for the introduction of this technology.

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