A STOCHASTIC MODEL TO SIMULATE ELECTRIC VEHICLES MOTION AND QUANTIFY THE ENERGY REQUIRED FROM THE GRID

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Abstract – The uncertainties related to when and where electric vehicles will charge in the future requires the development of stochastic based approaches to identify the corresponding load scenarios. This paper describes a tool based on Monte Carlo techniques to be used for distribution grid planning, providing a characterization of possible grid operation conditions, regarding voltage profiles, branch loading, grid peak power and energy losses. A medium voltage network based on real data is used to illustrate the application of the developed methodology.

Keywords: Driving Patterns, Electric Vehicles, Markov Model, Monte Carlo

1 INTRODUCTION

The foreseen rollout of Electric Vehicles (EV) will considerably affect the way distribution grids will be managed and operated. The extra amount of power they will demand from the grid will oblige system operators to understand the impacts resulting from EV connection into distribution networks. Several approaches to this problem have been pursued. Papers [1] and [2] present two strategies for assessing EV integration impacts. Paper [1] follows a deterministic strategy to locate EV along the network buses and, consequently, determine EV loads during an entire day. Conversely, paper [2] introduced a probabilistic method for determining EV load. Both options proved to be interesting approaches, though they were only able to reveal the effects of a possible scenario for a given period. Therefore, it is important to develop tools that allow exploring different scenarios in a coordinated way, which may result in both average scenarios and extreme case scenarios. Such tools can be used to enhance existing system operators planning techniques, allowing them to obtain additional knowledge on the impacts of a new type of load, so far unknown or negligible to the power systems, the EV battery charging. Given the fact that EV are mobile loads that may appear in almost any bus of a given electricity network, voltage profiles, lines loading, peak power and energy losses variations need to be properly evaluated for the planning exercise.

In this sense, a stochastic model using a Markov chain and a Monte Carlo method is proposed in this paper, in order to estimate the EV impacts along one year in a Medium Voltage (MV) network. The time horizon of one year was considered in order to evaluate EV impacts taking into account load seasonal variations. To locate EV and simulate their movement, the results of a region wide survey, [3], were used. However, different data regarding driving cycles could have been used for the same purpose, like, for instance, the ones published by the U.S. EPA [4].

2 MARKOV CHAIN TO SIMULATE ELECTRIC VEHICLES MOTION

2.1 Markov Chain Description

The EV movement in a one year period was simulated using a discrete-state, discrete-time Markov chain to define the states of all the EV at each time step of 30 minutes. It was assumed that, at every unit of time, one and only one event from a set of a finite number of events can occur to a given EV. Four event were considered: E_M, E_R, E_C and E_I, and are called event states. When the event E_k $(k = M, R, C, I)$ occurs, the EV passes into the state E_k. These four events correspond to an EV passing to the states "*in movement*", "*parked in a residential area*", "*parked in a commercial area*" and "*parked in an industrial area*".

Time terminology will be used, i.e. it is considered that one trial is performed at every unit of time. When the event E_k occurs at the moment t, it is represented by E_k^t. It is assumed that at the initial moment $t = 0$. Therefore, E_k^0 denotes that the initial state of an EV is E_k.

This method is classified as a discrete-time process, given that t is finite and can be enumerated. As the purpose of this work is to simulate EV movement along 365 days plus their initial state, 17521 time steps of ½ hour are considered. Thus, $t \in [0,17520]$.

One trial is performed initially to define every EV state when $t = 0$. In this trial, an EV may be in the state E_k with probability $P(E_k)$.

The conditional probability that at the moment t, for $t \in [1,17520]$, a given EV passes into the state E_k is denoted by $p_{j\to k}^t$ provided that after the trial $t-1$ it was in the state E_j $(j = M, R, C, I)$:

$$p_{j\to k}^t = P\left(E_k^t \middle| E_j^{t-1}\right) \tag{1}$$

As mentioned above, this sequence of trials forms a Markov chain, given that for any j and k and for any $t \in [1,17520]$, the equalities

$$p_{j\to k}^t = P\left(E_k^t \middle| E_j^{t-1}\right) = P\left(E_k^t \middle| E_j^{t-1} \cdot E_j^{t-2} \cdot \ldots \cdot E_j^1 \cdot E_j^0\right) \quad (2)$$

are arbitrarily satisfied for $E_j^{t-2}, \ldots, E_j^1 \cdot E_j^0$.

This Markov Chain is periodically stationary, or cyclostationary [5], as the transition probabilities are periodically repeated. The period of this cycle is one week and will be represented by τ. As time steps of ½ hour are being considered, $\tau = 7 \times 48 = 336$. To fulfill one complete year (365 days), τ will have to be repeated ≈ 52.14 times (52 weekly cycles plus one day).

$$p_{j\to k}^t = p_{j\to k}^{t+\tau} \quad (3)$$

One transition matrix can be created with the transition probabilities $p_{j\to k}^t = p_{j\to k}^{t+\tau}$ for each moment t, where $t \in [1{,}17520]$. This matrix is denoted by M_t and, given the cyclostationary properties of this Markov chain, it will be periodically repeated every τ time steps, in accordance with equation (4):

$$M_t = M_{t+\tau} \quad (4)$$

For a given moment t, the transition matrix assumes the following form:

$$M_t = \begin{bmatrix} p_{M\to M}^t & p_{M\to R}^t & p_{M\to C}^t & p_{M\to I}^t \\ p_{R\to M}^t & p_{R\to R}^t & p_{R\to C}^t & p_{R\to I}^t \\ p_{C\to M}^t & p_{C\to R}^t & p_{C\to C}^t & p_{C\to I}^t \\ p_{I\to M}^t & p_{I\to R}^t & p_{I\to C}^t & p_{I\to I}^t \end{bmatrix} \quad (5)$$

All the elements $p_{j\to k}$ of the matrix, being probabilities, are non-negative.

Supposing that an EV is in the state E_j, the event where, as a result of one trial, the EV remains in the state E_j or passes to any of the states E_k, where $j \neq k$, is the sure event. Since the events E_k are mutually exclusive, for $k = M, R, C, I$, the following equation holds:

$$P\left[\sum_k E_k^t \middle| E_j^{t-1}\right] = \sum_k p_{j\to k}^t = 1 \quad (6)$$

Thus, the sum of the terms in each row of the matrix M_t equals one. However, the sum of the terms in a column might be different from one.

Figure 1 presents an overview of the Markov chain developed for this study.

2.2 *Initial State and State Transitions Probabilities*

As mentioned previously, the Markov chain developed is cyclostationary and the period of one complete cycle, t, is one week. This cycle is, in fact, a composition of two sub-cycles with the duration of one day: one for the week days (repeated five times in a row) and other for the weekend days (repeated twice consecutively). Therefore, to have the Markov chain completely characterized, it is only needed to define the initial state probabilities, $P(E_k^t)$ for $t = 0$, and the state transition probabilities, $p_{j\to k}^t = P\left(E_k^t \middle| E_j^{t-1}\right)$ for $t \in [1{,}48]$, of these two sub-cycles and then repeat them to compose the full weekly cycle. The required probabilities were determined by analyzing the results of a statistical study, whose main goal was the characterization of the common traffic patterns in a region in the north of Portugal, covering the city of Porto and other smaller surrounding cities [3]. The values obtained from this study for the initial state probabilities ($t = 0$) were 0.89 for "*parked in a residential area*", 0.04 for "*parked in a commercial area*", 0.02 for "*parked in an industrial area*" and 0.05 for "*in movement*". Regarding the state transition probabilities, the values obtained for the week day sub-cycle, weekend day sub-cycle and full weekly cycle are presented in Figures 2, 3 and 4, respectively.

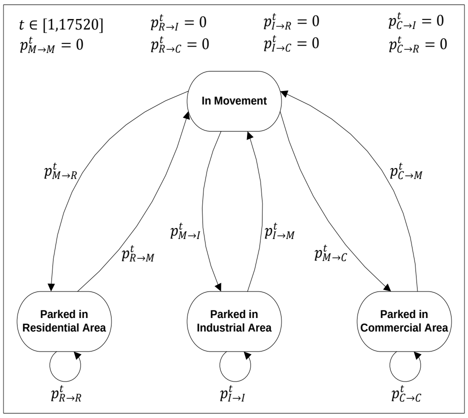

Figure 1: Discrete-state and discrete-time Markov chain.

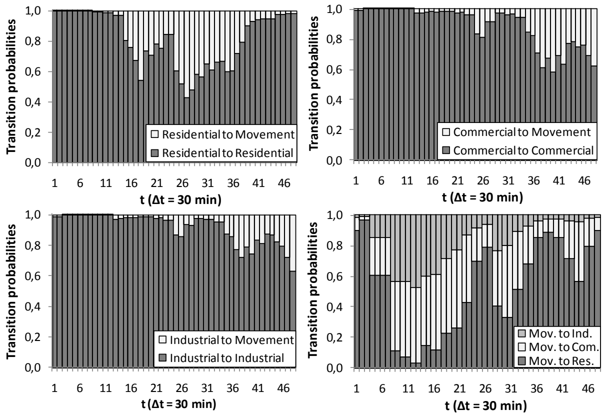

Figure 2: EV state transition probabilities: week day.

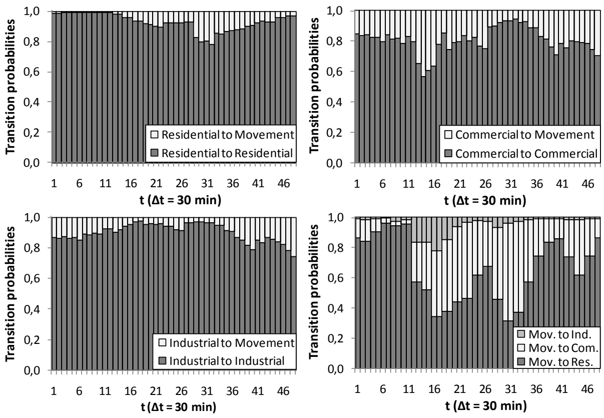

Figure 3: EV state transition probabilities: weekend day.

2.3 *Buses Allocation Probabilities for Parked EV*

After defining the EV states for each time step, it is required to determine the probabilities of EV in "*parked*" states and to allocate them to the network buses. If an EV is in the state "*in movement*", there is no need to define its location. However, if it is in a "*parked*" state and connected to the grid for charging purposes, it is crucial to know the EV location to allocate its load to a specific network bus.

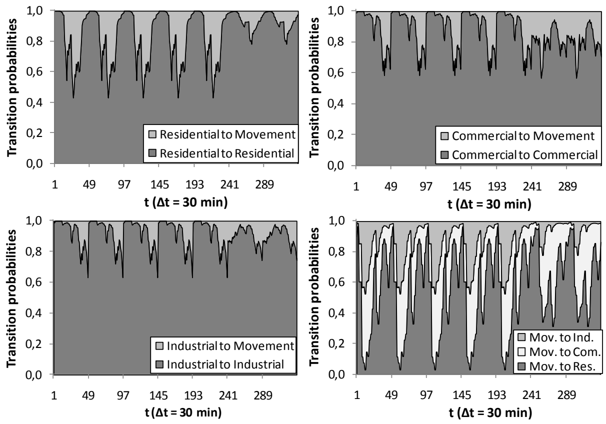

Figure 4: EV state transition probabilities: full weekly cycle (Monday to Sunday).

The procedure adopted to solve this issue is to consider the real nature of the loads connected to each network bus. Thus, for the network under study, all the existing loads need to be classified as industrial, commercial or residential loads. After, using equations (7) to (9), it is calculated the probability of an EV be located at a specific bus. For instance, if an EV is "*parked in a residential area*" at time instant t, a bus location will be drawn and assigned to it, according to a probability distribution proportional to the residential load installed in each bus. The same happens for the "*parked in a commercial/industrial area*" states.

$$P^R(Bus\ b) = \frac{Load^R_{Bus\ b}}{\sum Load^R} \qquad (7)$$

$$P^C(Bus\ b) = \frac{Load^C_{Bus\ b}}{\sum Load^C} \qquad (8)$$

$$P^I(Bus\ b) = \frac{Load^I_{Bus\ b}}{\sum Load^I} \qquad (9)$$

where:

- $P^{R/C/I}(Bus\ b)$ – probability of an EV be located in bus b, if "*parked in a residential / commercial / industrial area*";
- $Load^{R/C/I}_{Bus\ k}$ – residential / commercial / industrial load installed in bus b;
- $\sum Load^{R/C/I}$ – network total residential / commercial / industrial load.

3 MARKOV CHAIN MONTE CARLO SIMULATION

3.1 Monte Carlo Sampling

The flowchart of the Markov chain Monte Carlo algorithm developed in this work is presented in Figure 5.

The first step of the sampling process is to make the initial characterization of all the EV.

The EV battery capacity, charging power, energy consumption and initial battery State-of-Charge (SoC) are defined according to truncated Gaussian probability density functions, whose average, standard deviation, maximum and minimum values allowed are presented in Table 1.

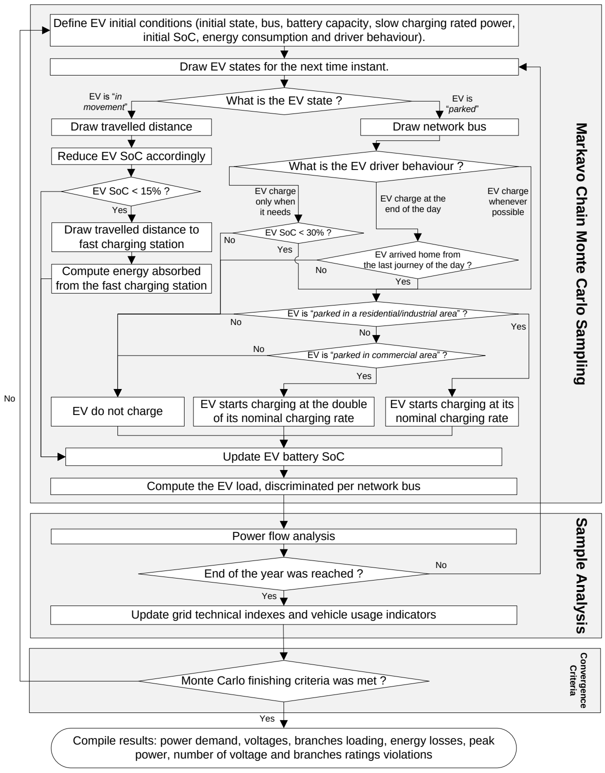

Figure 5: Markov chain Monte Carlo algorithm flowchart.

	Average	Standard deviation	Maximum value allowed	Minimum value allowed
Battery capacity (kWh)	24.73	17.19	85.00	5.00
Slow charging rated power (kW)	3.54	1.48	10.00	2.00
Energy consumption (kWh/km)	0.18	0.12	0.85	0.09
Initial battery SoC (%)	75.00	25.00	95.00	25.00

Table 1: Gaussian distributions for EV characterization.

While the initial battery SoC values were assumed for the purpose of this work, the values for battery capacity, slow charging rated power and energy consumption were obtained from the information made available by the manufacturers of 42 different EV. In [6]-[9] are presented some of the Internet sites from where EV characteristics were obtained for this study. The maximum and minimum values allowed, presented in Table 1, were used to confine the values drawn for each EV within realistic boundaries.

As mentioned previously, a given driver behavior was also assigned initially to each EV. The different behaviors considered in this study were defined according with the findings of a survey made within the framework of the MERGE project [10]. The results revealed that there are four major types of behaviors regarding EV charging, as presented in Table 2.

For the purpose of this work, regarding the behaviors modeling and simulation, there was no relevant differences between the drivers that "charge at the end of the day" and those who "charge whenever is convenient and they have time". Therefore, the EV to which one of these drivers' behaviors was assigned, were assumed to behave equally along the simulations.

	Percentage of the responses
EV charge at the end of the day	33%
EV charge only when it needs	23%
EV charge whenever possible	20%
EV charge whenever is convenient and the driver has time	24%

Table 2: Drivers' behaviors considered.

For the drivers who charge their EV only when it needs, it was assumed that the minimum battery SoC that triggers the need for charging was 30%.

The second step of the sampling process was to simulate EV movement along one year. To start with, the EV states for each time instant were defined according with the Markov chain described in section 2.1 and with the probabilities presented in section 2.2. After, for each time instant, a bus location was attributed to parked EV, as explained in section 2.3. For the EV in movement, a procedure was developed to account their energy consumption and the respective reduction in the battery SoC. First a Gaussian probability density function was used to draw the travelled distances for all the EV in movement. Therefore, if an EV was in movement in time instant t and its battery SoC went below a predefined threshold (assumed to be 15%) in time instant $t+1$, it was considered that the EV would make a short detour to a fast charging station for recharging purposes. The travelled distance during the detour was obtained using also a Gaussian probability density function, whose parameters are presented in Table 3.

	Average	Standard deviation	Maximum value allowed	Minimum value allowed
Travelled distance in common journeys (km)	9.01	4.51	27.03	0.90
Travelled distance to fast charging station (km)	4.51	2.25	13.52	0.45

Table 3: Gaussian distributions for travelled distances.

The fast charging was assumed to be made during 15 minutes with a power of 40 kW [11].

The average of the Gaussian distribution used to characterize the travelled distance in common journeys was obtained by dividing the average daily mileage in Portugal (35 km) [12] by the average number of journeys per day (3.88 journeys) [3]. The standard deviation was assumed to be 50% of the average.

The values of the Gaussian function for the travelled distance to the fast charging station, were obtained by assuming that they were 50% of those used in the travelled distance in common journeys distribution.

At each time instant, the EV battery SoC is updated according with the energy spent travelling or accordingly with the energy absorbed in slow charging mode or in fast charging stations. It was assumed that EV "*parked in a residential area*" and "*parked in an industrial area*" charge at their nominal charging rate while "*parked in a commercial area*" EV have the capability of charging at the double of their nominal charging rate.

With this procedure it is possible to fully characterize the EV power consumption and, together with the definition of the conventional load of the network under consideration, it is possible to compute the total amount of power required from the network, discriminated per bus and per time instant.

3.2 Sample Analysis

The evaluation of the samples is made by running a power flow for each time instant, using the *PSS/E* software, to gather information regarding voltage profiles, power flows in branches and energy losses.

During the simulation, the average, maximum and minimum power demand and voltage value is recorded for each bus of the system under study. A similar procedure is adopted for the power flows in the network branches. The day where the highest peak load occurs is also recorded, in order to provide an idea of the worst situation that might occur when a percentage of conventional vehicles are replaced by EV.

In order to keep track of the most problematic buses and branches within the grid, the number of out of limit voltages and lines overloading occurrences are recorded along the simulations. According with [13], voltages must be kept with the interval 0.90 – 1.10 p.u. during 95% of the time, in a weekly basis. It was considered in this work that a voltage violation occurs when the values are outside the referred interval.

3.3 Convergence Criteria

To terminate the Monte Carlo process, two criteria are used: number of iterations and the variances of the aggregated network load of each one of the 17520 time instants. The latter means that one variance value is computed for the total network load per time instant t, $t \in [1{,}17520]$. The process is set to perform 200 iterations (200 years) and check, in the end, if the variation of all the 17520 variances in the last 5 iterations is lower than $1e^{-3}$. If at least one of the 17520 variances did not meet this convergence criterion, the process is kept running more iterations until all the variances variations are lower than the predefined value.

4 CASE STUDY

The selected case study to test the developed Markov chain Monte Carlo algorithm was the distribution network from the Flores Island, from the Azores archipelago. The network is presented in Figure 6. It is a very robust 15 kV Medium Voltage (MV) grid, which encloses 44 branches and 45 buses. From these, only buses 1, 19, 28 and 43 do not have any loads connected. The network load diagram, for the week that contains the annual peak load, is presented in Figure 8 (power demand without EV curve). The total energy demand for the selected year is 11.87 GWh and the peak load is 2.70 MW. The typical average power factor (ratio between active and apparent power) in this island is 0.77.

Two scenarios of EV integration were simulated: 25% and 50% of the light vehicles fleet replaced by EV, corresponding to a total of 571 and 1142 EV, respectively.

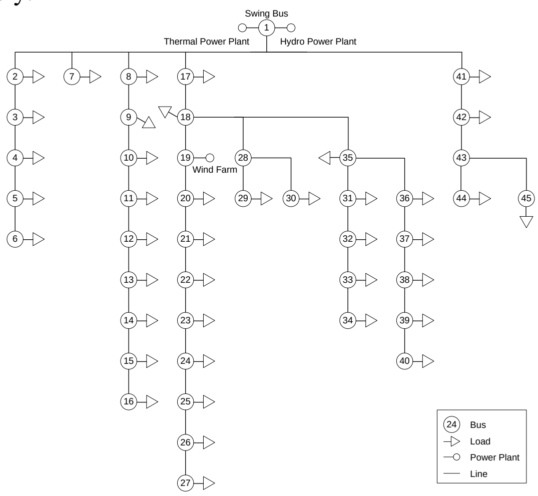

Figure 6: Flores Island network (15 kV).

As mentioned in section 2.3, all the network loads were classified as industrial, commercial or residential. As examples, the 400 kW load installed at bus 25 is 35% commercial and 65% residential, while at bus 10 there is a load of 315 kW, 100% industrial. After, using equations (7) to (9), it was calculated the probability of an EV be located at a specific bus. The allocation probabilities of each bus, for "parked" EV, are presented in Figure 7.

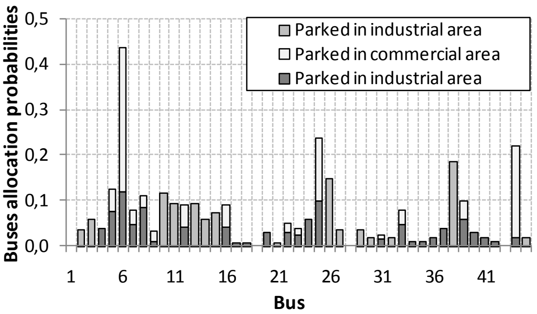

Figure 7: Buses allocation probabilities for "*parked*" EV.

5 RESULTS

5.1 Power Demand

Figure 8 shows the power demand for the week containing the yearly peak load for both EV integration scenarios studied (25% and 50%), as well as for the grid in its initial conditions, where no EV were considered.

With 25% of EV, the peak hour consumption increases 21%, from 2.7 to 3.3 MW, whereas with 50% of EV it increases 44%, from 2.7 to 3.9 MW. The yearly energy demand increases from 11.9 GWh to 13.7 GWh, with 25% of EV, and to 18.8 GWh, with 50% of EV.

5.2 Voltage Profiles

In order to assess the worst voltage conditions that these levels of EV integration might lead to, the highest peak load scenarios registered along the 200 iterations were analyzed, and the corresponding voltage values were plotted in Figure 9.

The extra power demanded by EV provokes a significant voltage drop along the grid, namely during the periods when the demand is higher, that, as Figure 9 shows, violate by far the lower limit of 0.90 p.u..

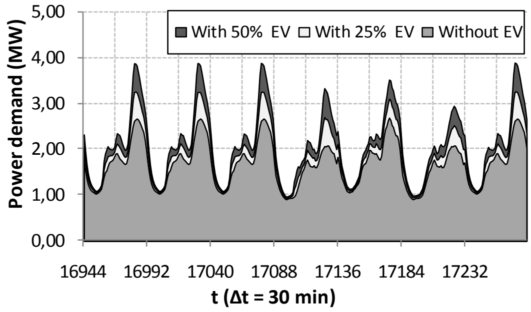

Figure 8: Power demand along a cycle (Monday to Sunday).

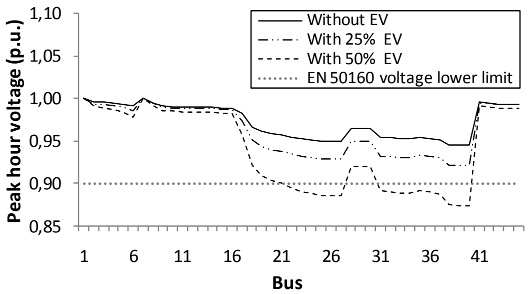

Figure 9: Network voltage profiles for the highest peak load.

The network voltage profile in the scenario without EV is also presented in Figure 9, for comparison purposes, as well as the reference voltage level stipulated by EN 50160 [13].

While an EV integration of 25% does not decrease voltages to problematic values, 50% of EV integration lead voltages to considerably low values, which in 37% buses are below the 0.90 p.u. threshold.

As mentioned in section 3.2, all the voltage and lines loading limit violations were recorded along the simulation, in order to keep track of the most problematic areas of the network. As this network is exceptionally robust, despite the increase in the network power flows, no lines loading above the limit were registered. Given that the EV integration only increases consumption, only voltages decrease will occur and so, as it is obvious, no voltages above the higher limit were recorded.

Conversely to high voltage problems, voltages below the lower limit occurred very often in some buses, in the scenario with 50% of EV, as denoted in Figure 10.

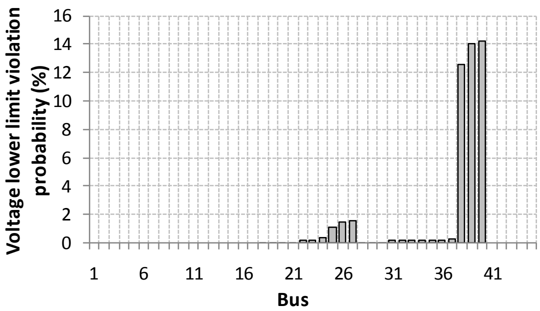

Figure 10: Voltage lower limit violation probability for the scenario with 50% of EV.

The probabilities presented in this figure were obtained using equation (10):

$$P^{Bus\ k}_{Voltage\ violation} = \frac{Voltage\ violations^{Bus\ k}}{Nr.iterations \times 17520} \times 100 \quad (10)$$

For the scenario with 25% of EV, only a negligible number of violations were record. There were only some problems in buses 38, 39 and 40. The probability of having in these buses voltages below 0.93 p.u. is lower than 1%.

In what regards the scenario of 50% EV integration, the probability of having voltages below the imposed limit is rather significant in some network buses. The highest probabilities appear again for buses 38, 39 and 40, reaching values around 13%.

5.3 Branches loading

Even though this is not the most critical aspect of this network, since the highest branch loading is 71% for the peak hour in the scenario with 50% of EV, branches loading is also an issue that deserves special attention. In fact, in other networks with different characteristics, the branch loading can be the limiting factor to high integration levels of EV.

Figure 11, 12 and 13 provide an overall idea of the impact provoked by EV in the network lines loading, for the peak load demand. Figure 11 is referred to the peak load of the scenario without EV, while Figure 13 and Figure 14 are referred to the peak loads of the scenarios with 25% and 50% of EV, respectively. The color grading between light green and dark red stands for increasing line loading values, ranging from 0 to 100%.

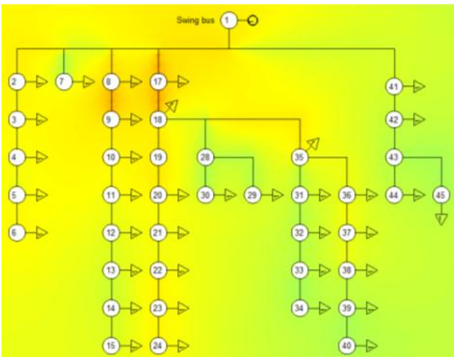

Figure 11: Lines loading for the peak load without EV.

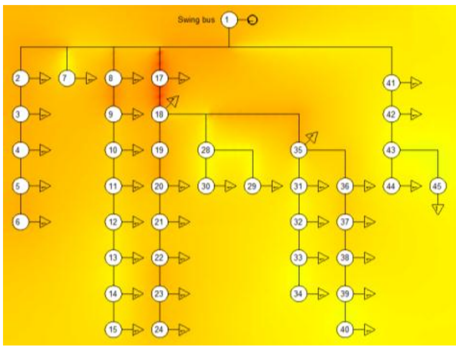

Figure 12: Lines loading for the peak load with 25% EV.

As expected, the line loadings increase with the number of EV in the network, being the most problematic branches those located in the beginning of the heavily loaded feeders.

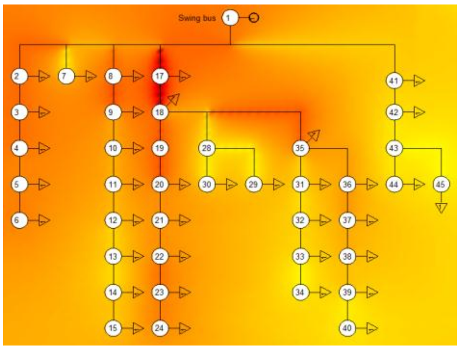

Figure 13: Lines loading for the peak load with 50% EV.

5.4 Energy Losses

In Figure 14, it is depicted the average value of the yearly energy losses, obtained along all the iterations performed.

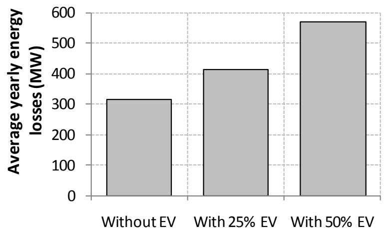

Figure 14: Average yearly energy losses.

The daily energy losses grow 30% from the scenario without EV to the one with 25% of EV and 80% to the one with 50% of EV. As expected, these values prove that energy losses do not follow linearly the load demand increase. Thus, for higher EV integration levels, where the network would be operated near its technical limits, losses are likely to be a rather important issue for the system operator. Therefore, in such circumstances, the system operator should look for efficient mechanisms to manage EV charging somehow, in order to mitigate this problem.

5.5 Monte Carlo Convergence and Sample Variance

As mentioned in section 3.3, the Markov chain Monte Carlo algorithm ends when two criteria are met: when 200 iterations are performed and when the variations of the 17520 variances in the last 5 iterations are lower than 1×10^{-3}. The variances variation is calculated using equation (11):

$$\Delta Variance = \left| Variance^t_h - Variance^t_{h-5} \right| < 1 \times 10^{-3} \quad (11)$$

where $Variance^i_h$ represents the variance of the network load at time instant t, $t \in [1,17520]$, in the h^{th} iteration.

For all the scenarios simulated, the variances variation criterion was met before the algorithm reach iteration 200. As an example, Figure 15 shows the evolution of the variance with the highest variation rate of the scenario with 50% of EV integration. As it is shown, the variation rate after iteration 100 is very low, indicating that the algorithm reached the convergence criteria.

When iteration 200 was reached in the simulation of the scenario with 25% of EV, the variance with the highest $\Delta Variance$ converged to 3.3×10^{-5}. For the scenario with 50% of EV, the variance with the highest $\Delta Variance$ converged to 6.9×10^{-5}. The higher value registered in this scenario indicates that the samples generated have a lower precision when compared with the samples of the scenario with 25% of EV. In simpler terms, these findings show that, as expected, the uncertainty in the network load estimation is larger in the scenario with a higher number of EV.

Figure 15: Evolution of the variance with the highest variation rate of the scenario with 50% of EV integration.

6 CONCLUSIONS

By analyzing the results obtained for the case study addressed in this work, it might be concluded that the network under study is very robust, being therefore capable of integrating a large number of EV without the occurrence of line loading and voltage limits violations. With 25% of EV only a small number of voltage lower limit violations were recorded along the 200 years simulated. However, in the scenario with 50% of EV the number of violations registered was greatly increased. These results show that while the network resists to a 25% replacement of the conventional vehicles fleet by EV, it is impossible to proceed to a 50% replacement rate without making investments in network reinforcements or by adopting smart charging solutions [1], in order to tackle the low voltage problems identified.

Important findings were also made regarding the energy losses. Their value grows 30% from the scenario without EV to the one with 25% of EV and 80% to the one with 50% of EV. These values show that, for higher EV integration levels, losses are likely to become a very important issue for the system operator. Therefore, in such circumstances, the system operator should look for efficient mechanisms to manage EV charging, like smart charging, in order to avoid wasting large amounts of money in the energy distribution process and in network reinforcements.

The simulation platform developed in this work proved to be very efficient in performing a realistic evaluation of the impacts that result from a massive integration of EV in distribution networks. Besides the evaluation of the steady state operating conditions of the grid, it also allows identifying the most critical operation scenarios and the network components that are subjected to more demanding conditions and that might need to be upgraded.

ACKNOWLEDGMENT

This work was supported in part by Fundação para a Ciência e Tecnologia under Grants SFRH/BD/48491/2008 and SFRH/BD/47973/2008 and within the framework of the Project Green Island with the Reference MIT-PT/SES-GI/0008/2008, by Fundo de Apoio à Inovação (Ministério da Economia, da Inovação e do Desenvolvimento), within the framework of the Project REIVE-Redes Eléctricas Inteligentes com Veículos Eléctricos, and by the European Union within the framework of the European Project MERGE-Mobile Energy Resources in Grids of Electricity, Contract 241399 (7th Framework Programme).

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