# STOCHASTIC ELECTRIC VEHICLE LOAD MODELING FOR HV/MV SUBSTATION CONSTRAINT ASSESSMENT

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## *ABSTRACT*

*This paper presents an innovative method that allows assessing Electric Vehicle (EV) load impact on HV/MV substation over multi-year horizons. Especially, this uses a multi-dimensional model to predict as closely as possible, under certain assumptions, the future electric demand of a large number of EVs.*

## INTRODUCTION

Climate Plan launched by French Government in July 2017 is part of a European drive to combat climate change, and by 2040 it is planned to end sales of petrol and diesel vehicles. France commitment is to reach 1,000 000 of EVs including 400 000 PHEV in circulation within the next 4 years [1] [2]. These actions are clear proof that the number of EVs will be dramatically increased in future years.

ENEDIS carries out at each regional level an electrical distribution system master plan project based on mid-term to long-term electricity power demand projections to determine both appropriate investments decisions at the distribution level as well as the optimal reinforcement and location for the new HV/MV substations. However, the integration of EVs development projections calls for the development of new innovative approaches. Several studies have shown that new tools are needed to assess the EV impact on the electric distribution network and to identify the most suitable planning solutions to allow the effective integration of EV and boost electric mobility [3] [4].

In this work, an innovative method addressing this issue and helping to design an improved probabilistic model considering high EV penetration level is proposed. For each substation in the studied area, the model estimates the number of EVs in different categories: personal cars, corporate vehicles, car-sharing etc. It is assumed that vehicles assigned to a given substation are always charged by this substation, whether at home, in the street or at work. The model adds up the individual probabilistic load curve of each vehicle to estimate the global consumption due to EVs. The results could be used to review and assess the need for reinforcement at primary substation level.

For this purpose, the probabilistic approach combines other parameters such as: battery capacity, travel distance, plug-in time and arriving charging power rate by considering unmanaged charging schemes as a baseline scenario [5]. In addition, the proposed model is extended by considering the decision-making process of an EV user for daily charging. Based on human expertise and common sense, a Fuzzy Logic inference system is applied to simulate the EV charging decision.

This method is well adapted to model human reasoning's imprecision's and doubts [6]. Based on these models, a Monte Carlo (MC) simulation method is finally performed to estimate the daily load power generated by EVs fleet by simulating the random behaviour.

The proposed model is depicted in Figure 1. It shows the different factors that influence the charging load of EVs fleet. This approach is built by considering Ile-de-France (IdF) region data hypothesis. The given results should help ENEDIS to assess EVs integration impact on HV/MV substations over 10-30 year scenarios and to give a decision support system to design the electrical distribution system master plan project.

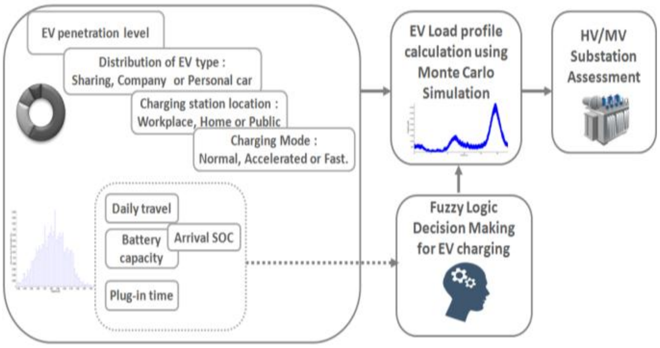

Figure 1: Flow diagram of the proposed approach.

## STOCHASTIC MODELLING APPROACH OF ELECTRIC VEHICLES LOAD CHARGING

To help understanding the problematic of EVs charging from the electric grid point of view, and even proposing solutions for load peak reduction, the proposed study aims to identify EVs charging pattern over a period of 24h through stochastic modeling. The model is precisely studied by including a combination of different factors that influence EVs charging demand behavior (Figure 1). All the corresponding features of the EVs load model, mentioned above, are discussed in details in the following parts.

## Electric Vehicle development

During the last decades, the French EV market has, registered a total of more than 170 thousand of EVs. Considering this evolution and French regulation, ENEDIS has defined several scenarios to estimate the development of EVs. In this context, the expected EV deployment in IdF region could exceed 3 million EVs in 2035. In addition, we supposed that the EV market will be composed mainly of personal EV, with also corporate and EV car-sharing. These scenarios were developed taking into account several parameters such as: household purchasing power, ecological awareness, the effect of energy regulation changes, the development of EV charging infrastructures and the cost of EV. For all French cities an EV penetration level has been deduced, based on the characteristics of each of them. In order to determine the total number of EVs connected to each HV/MV substation two parameters are considered: ($\alpha$) the Low Voltage (LV) customer's density and ($\beta$) the sum of MV customers subscribed power. They are respectively used to spread the personal EV and corporate EV/car-sharing fleet. The calculation principle is given in equation 1.

$$N_{EV\ substation\ i} = N_{EV\ tot} \times \frac{\alpha_i}{\gamma} \qquad (1)$$

Where $\alpha_i$ is the LV customer's density supplied by the substation $i$, $\gamma$ represents the total number of LV customer's in the city *and* $N_{EV\ tot}$ is the total number of EVs in the same city.

Below (Table 1) is an example of how you would distribute 5,000 EVs on different HV/MV susbtations which power a city of 18,600 LV customers.

Table 1: Illustration of the distribution of 5,000 EVs on two HV/MV substations.

| Number of LV customers | MV feeder | HV/MV substation | Estimated personal EV number |
|---|---|---|---|
| 4600 | A | 1 | **1237** |
| 3000 | B | 2 | **806** |
| 6000 | C | 2 | **1613** |
| 3500 | D | 2 | **941** |
| 1500 | E | 1 | **403** |

## Power charging rate and charging location scenarios

In France, currently three charging patterns are mainly proposed: normal, accelerated and fast charging infrastructure. The table 2 below shows different types of charging infrastructure.

Domestic chargers (1 phase, AC) usually start with 3.7 kW and can be even up to 7.4 kW. This is the cost effective and the most convenient home-based charging method, but also the slowest solution (around 5-10 hours for an EV to be fully charged). However in commercial areas and public charging station, accelerated charging mode is generally used and is a bit faster with for example 22 kW as a power rate. Fast charging pattern can in some cases be used as an emergency charging in unexpected situations. It can be also applied to EV with relatively short parking time and for irregular travelling habits (long distance travel) or for owners who cannot charge at home or at work. This mode uses both AC and DC outlet standard. The charging power exceeds 40 kW and it is expected to reach 350 kW in the future. As more than 90% of EV charging is carried out at residential and workplace charging station, we consider only AC charging standard with 22 kW as a maximum charging power.

Table 2: Different charging mode for EV/PHEV.

| Charging mode | Power | Potential location of charging station |
|---|---|---|
| **Normal** | 3.7 – 7.4 kW single phase (230 V - 16/32 A) | Home, workplace |
| **Accelerated** | 11 – 22 kW three phase ( 400 V – 16/32 A) | Workplace, public |
| **Fast** | 43 kW three phase (400 V – 64 A)<br>≥ 50 kW DC | Public, commercial areas, airports, highway, etc. |

Concerning the classification of EV categories, 3 classes are defined: private cars, corporate vehicles and EV car-sharing. Moreover, this distribution considers geographic type's area: rural, suburban, urban and dense urban area. The underlying assumptions were deducted from the national data assessment of charging infrastructure deployment.

Taking into account the optimists forecasts for EV market growth in the years to come, the owning of an EV will become more commonplace even for those drivers without the possibility to have a private charging point. Therefore, charging at public and workplace station is likely to increase to face the lack of access for home charging. This situation is expected to happen more frequently in urban than rural area.

## EV battery performance

Characteristics of the battery are a very important factor for the charging load of EV. Based on EV market data analysis [7], Lithium-ion battery outfits the majority of EVs / PHEVs, and that, thanks to its good performance in terms of energy and power density. The Figure 2 gives an overview of EV fleet market share composition by considering the autonomy (km), the battery capacity (kWh) and the market share for each EV.

As we can see in Figure 2, EV saw rapid growth energy efficiency improvements compared with previous generation. The theoretical average value of battery consumption of an EV is estimated at 0.11 kWh/km. In order to model more closely the energy transferred to EV battery when plugged-in for recharging, the model involves two criteria: the charging efficiency ~ 90% [8] and the EV performance under actual operating conditions ~ 70% [7]. Therefore, the adjusted value is set at 0.18 kWh/km. It can be noted as the EV coefficient of performance ($C_P$).

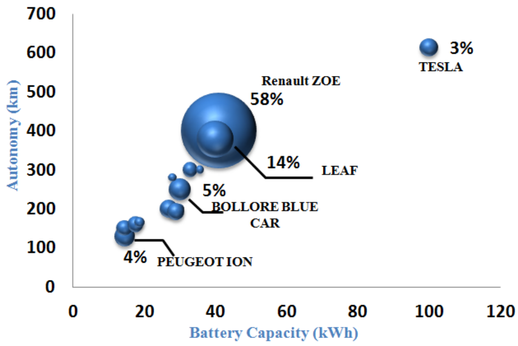

Figure 2: French EV market data analysis.

## Arrival charging time

Modelling arrival time of an EV user at charging station was inspired from daily traffic behaviour of the transportation given in [9]. Therefore, based on the traffic habits analysis of IdF region, during the working days, we note that the traffic values peaks are observed respectively at 8h30 and 18h30 (Figure 3). To estimate home and workplace plug-in time, a proper delay is considered (e.g. 45 minutes). It corresponds to an average home-office commuting time in IdF region [10]. Then, it was concluded that the majority of French people in IdF region arrive at their office around 9h15 and return home usually at 19h15. To generate the set of arrival time for the vehicles, a normal probability distribution is considered [Equation 2]. As a standard deviation value, we used respectively 45 minutes and 1 hour for office and home plug-in time.

$$f(x,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (2)$$

Where μ and σ are respectively the average and the standard deviation of the random variable (x).

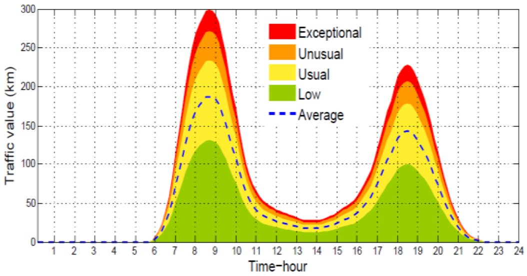

Figure 3: An example of daily traffic evolution on weekday in IdF region [7].

With regard to EV plug-in time at public and car-sharing station, the model proposed below was inspired from data analysis of EVs load profiles of public charging stations. The diagram (Figure 4) shows the plug in time probability density function (PDF) at home and at workplace.

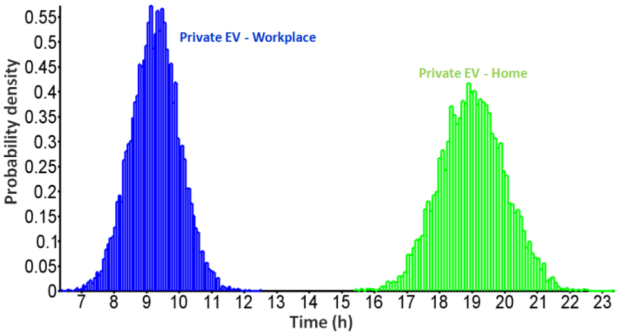

Figure 4: Plug-in time histogram for different charging locations.

## Daily Travel Distance

The aim of this part is to find the best-fitted representative PDF for daily travel distance. Based on INSEE (French National Institute for Statistical and Economic Studies) and DRIEA (Paris Region Urban and Environmental Agency) statistics data, the daily distance performed by car users is about 30 km. Moreover, as the diagram representation given by INSEE [10] is a non symmetrical shape around the peaks, normal distribution could not be chosen, while a PDF with shape parameter could be more adaptable. Gamma distribution function with $k$-$\theta$ parameter is more convenient (Equation 3). The distribution function is depicted in Figure 5.

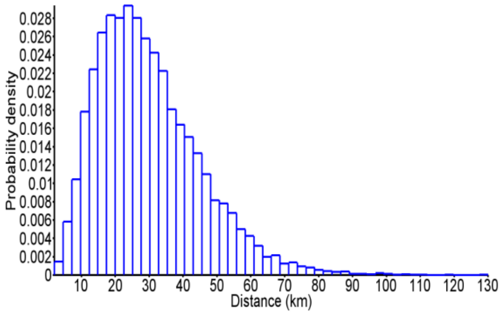

Figure 5: Daily travel distance histogram.

$$f(x;k,\theta) = A \times \frac{x^{k-1}e^{-\frac{x}{\theta}}}{T(k)\theta^k} \qquad (3)$$

T denotes the Euler Gamma function, $k$ and $\theta$ are strictly positive and set respectively at 5 and 4, and $A$ is an adaptive coefficient fixed at 37.4 to fit the mean value to 30 km.

## EV user behavioural modelling

In this part, behavioural laws are studied to model the decision-making process of an EV user for daily charging habits. This parameter is essential to estimate as closely as possible the future peak power amplitude. In order to determine the probability of EV charging, a Fuzzy Logic inference system is applied to simulate the EV charging decision. This method is well adapted to model human reasoning's imprecision's and doubts [6]. It is supposed that the EV autonomy, arrival battery $SOC_{EV}$ (state of charge) and the daily travel distance ($D_d$) are the key factors that influence the drivers' charging decision. Therefore, the proposed model is supposed to be the same for all EV users. For instance, a high EV autonomy ($A_{EV}$) with small daily travel distances ($D_d$) could provide a user the ability to recharge his EV once every two or three days. Moreover, a sufficient battery $SOC_{EV}$ is also considered as a prerequisite of an EV user to make the next trip without plug-in his EV. Otherwise, the probability ($\rho_C$) of EV charging is supposed to be more significant.

Table 3: Fuzzy rules for EV charging probability.

| D | $A_{EV}$ | $SOC_{EV}$ | $\rho_C$ |
|---|---|---|---|
| S | S | L | H |
| S | M | M | ML |
| S | L | H | L |
| M | S | L | H |
| M | M | M | ML |
| M | H | H | L |
| H | S | M | MH |
| H | M | M | MH |
| H | H | H | ML |

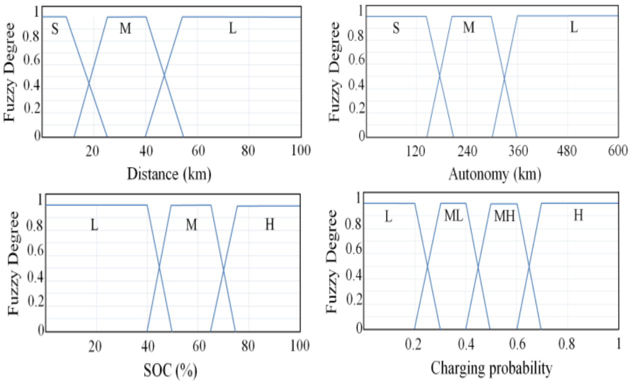

Figure 6: Inputs and output Membership Function.

Inputs ($A_{EV}$, $D_d$ and $SOC_{EV}$) and output ($\rho$) variable are set using membership functions (MF). Linguistic rules are also defined to ensure the transitions between different states. For this purpose, the battery $SOC_{EV}$ value is resolved into linguistic fuzzy sets described as: Low (L), Medium (M) and High (H). In the same way, $A_{EV}$ can be considered as Small (S), Medium (M) and Long (L). Likewise, $D_d$ uses the same MF as $A_{EV}$. Finally, the output variable $\rho_C$ is fuzzified as Low (L), Medium Low (ML), Medium High (MH), and High (H). Figure 6 shows the inputs and output MF. Trapezoids MFs are used to represent different fuzzy sets and their shapes are empirically designed. Table 3 gives an example of some fuzzy rules with AND operator among 27 possible ones. In defuzzication step, center of gravity method is applied. Therefore, the Figure 7 represents the fuzzy logic surface and gives the charging probability values as a function of $SOC_{EV}$ and $A_{EV}$ inputs values. It shows how the response rule changes with different states.

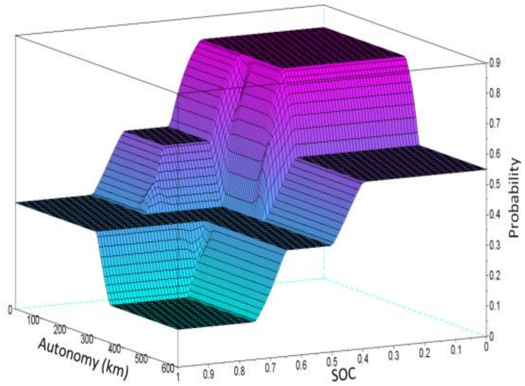

Figure 7: Fuzzy logic response surface.

## MONTE CARLO SIMULATION

Taking into account the multi-dimensional problem with complex factors, this paper employs Monte Carlo simulation (MC) to model and analyze the charging load of EVs [5]. The simulation uses bottom up approach and is performed by considering an N days charging pattern. N is defined large enough to allow convergence of the algorithm calculation. First, the algorithm chooses the type of each EV in the fleet based on the market contribution portion. This provides battery capacity and autonomy. Secondly, according to the geographic type's area, the algorithm assigns for each EV the category to which it belongs (private car, corporate vehicle and car-sharing) and the charging power (3.7, 7.4 or 22 kW). The selection is random but related to the probability for each variable. At next step, the arrival $SOC_{EV}$ is estimated using equation 4. Afterwards, the charging period ($T_c$) is calculated from arrival time variable and the required charging time (Equation 5). This depends on daily travel distance and charging power. Finally, the $\rho_C(A_{EV}, D_d, SOC_{EV})$ function value decides if the EV will be considered in the simulation step or not. Once the charging load of one EV is determined, the operation is repeated through MC simulation to get the cumulative load of large scale EV. The algorithm uses 5 minutes as a sample time.

$$SOC_{EV}^{i} = SOC_{EV}^{i-1} - \frac{D_d^i}{B_C^i} \times C_p^i \quad (4)$$

$$T_{EV}^{i} = \frac{B_C^i \times SOC_{EV}^i}{P_C^i} \quad (5)$$

Where $B_c$ is the battery capacity and $P_c$ corresponds to the charging power.

The Figure 8 provides an example of a probabilistic simulation scenario (N=500) with 1000 EV in dense urban area. First, it can be seen that the expected EV charging load could takes many forms with different peaks power rate, which shows the interest of MC simulation. Then, by analyzing the load behavior two peaks power can be observed in the morning and evening when EVs users are arriving at workplace or at home area. Likewise, it can be noted here that the charging at residential area is relatively high than at workplace or at public area.

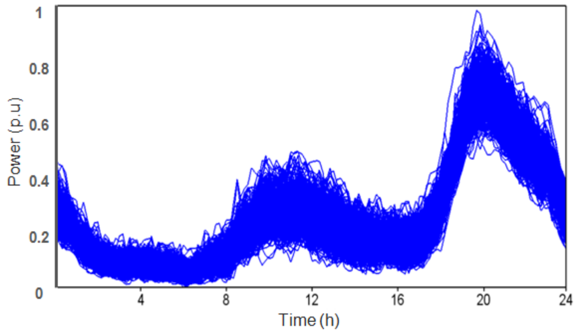

Figure 8: Cumulative EV power demand at dense urban area.

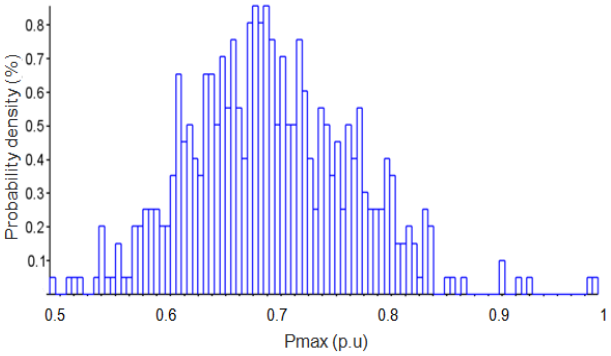

Figure 9: Maximal power distrbution histogram.

In addition, Figure 9 gives a statistical comparison of different peaks values observed at each simulation. It shows the occurrence of extremes values and all possible situations. In this way, MC simulation provides a much more comprehensive view of how EVs load profile may behave in future. Therefore, the assessment of the potential EV impact on HV/MV substation can be achieved by fixing a certain risk level.

Further simulations and analysis of different cases can be performed to show for each geographical type's, the evolution of the ratio p.u or kW/EV depending on the EV fleet size at a given risk level. This conclusion can be considered as a simplified tool to model and assess the EVs impact on HV/MV substation.

## CONCLUSION

This paper presents a generic approach based on stochastic modeling that allows assessing the impact of various EV deployment scenarios on HV/MV substation. Further work will focus on the integration of other aspects of electric mobility such as electric buses [11].

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