CONTRIBUTION OF AN INTELLIGENT RECHARGE SYSTEM IN THE MASSIVE DEVELOPMENT OF ELECTRIC VEHICLES IN EUROPE

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1. Introduction

Transportation and electricity generation sectors are responsible of 23% and 40% of energy related CO_2 emissions respectevely. Road transport, including cars, motorcycles and buses, realise 16% of CO_2 emissions by their own. Concerning the power sector, coal power plants are the main emitters, responsible of 29% of CO_2 emissions. Europe, concerned and worried about the climate change, expects to reach the carbon neutrality by 2050.

To do so, EU defined specific targets for renewable energies (REn) deployment through the *Renewable Energy Directive*. This renewable energy target was updated to 40% in the new legislation package released on July 14th 2021 by the European Commission. By this date, it announced its new project to mitigate the climate change *Fit for 55*, and set the ambitious target of reducing 55% of the greenhouse gas emissions by 2030. A continuous and important evolution of particular vehicles, and of transportation in general was established as well. In this current legislation, the European Commission expects to ban the sales of new internal combustion engine cars by 2035, this means that even hybrid cars must be set apart from the roads, letting 100% of the particular vehicles market to alternative fuel systems. To achieve this goal within the expected term, by 2030 particular vehicles are expected to have reduced 55% of their CO_2 emissions.

The Vehicle Grid Integration (VGI) refers to the set of technologies, services and policies that create a link between transport with its electric vehicles (EV) and the power systems. This combination between transport and renewable energy supply is important because with a massive adoption of EV and with no control over the recharge, the power grid risks intermitent faillures when it will not be able to supply the required instantaneous power. A smart charge system becomes necessary.

Considering that the development of REn creates a flexibility requirement for the grid operation, the integration of EV in the power system is two-fold in the decarbonization goals: to reach the objective of getting a cleaner mobility and to assist adequacy and reliability in more renewable electricity mixes.

Nevertheless, a proper integration with a smart charging system requires synergy between the concerned parties including grid operators, governments, car makers and car owners as well as a good understanding of the main factors of the recharge system that could impact the power grid and that therefore are essential for the VGI e.g. the different chargers power or the charge behaviours. A technical and economic analysis of these components is the core of this paper.

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2. Methodology

In this context of the economic activity, different organizations estimate that there will be some millions of EV on the roads in a close future. The adoption of a significant EV fleet entails a new electric load during the recharge phases. We propose a decentralized algorithm that responds to the future concerns of an EV fleet and that improves the current electricity mix dynamics. The general concept is to create a virtual battery composed by the sum of a part of each EV battery. This cumulated capacity is managed in an optimal way, without aggregator which directly manages the EV charge. It will support the bulk power system for filling demand valleys through the smart charging and for shaving demand peaks through Vehicle-to-Grid (V2G).

We present the development and implementation of the VGI algorithm composed by a set of equations that respond to an optimal dynamic behaviour. Optimization is done over one week with the aim of taking into account the variations on the power system linked to regional behaviors (e.g. less consumption during weekend than during week days). The algorithm can receive and use different parameters as input signal e.g. electricity tariffs or CO_2 emissions. For our case study we use a residual demand signal that is calculated as the total electricity demand substracting photovoltaics and wind turbines electricity production. We consider conventional power plants generation and international flows are fixed. This choise is made since we find a close relation between residual demand with electricity market prices and CO_2 emissions. The algorithm output has two components: the state of the charge (SOC) that will be reached by the battery and a proportional factor that will regulate the amount of the appealed power at each time step.

Next, we implement the smart charging algorithm in a VGI simulator. This tool is able to reproduce the charging dynamics of an important EV fleet during one week in an hourly step. For the simulation we use real data from a national statistical survey in France. The objectif of the simulator is to understand the parameters that could have an important impact during the integration of EV in the power grid considering different car owners behaviors. Some of the parameters of the simulator are the chargers power, the chargers locations, charging thresholds (the SOC at which a car owner plugs its EV), etc.

The charge optimization is based on two references values, the energy reference and the charge reference as explained in the following equations.

Target SOC at the end of the chargin period :

$$\mathcal{E}_T = \sum \overline{y_t} - y_t \mid t = tr + 1$$

Power reference :

$$min \;\; \mathcal{J}_{x,y,z,t} = \sum_{1}^{T} \left| \overline{y_t} - z_t \right|^2 = \sum_{1}^{T} \left| \overline{y_t} - (y_t + P_t) \right|^2$$

$$s_{n,0} = b \qquad s_{n,T} = \mathcal{E} \cdot B_n \qquad p_{n,0} = 0$$

$$s_{n,t} = s_{n,t-1} + p_{n,t} \cdot u_{n,t} - c_{n,t}$$

$$p_{n,t} = Q_{n,t} \cdot (\mathcal{E}_T - s_{n,t}) \cdot \frac{x_t}{\sum_0^T x_t - \sum_0^t x_t}$$

$$\dot{s}_{n,t} = p_{n,t}$$

With,

$$s_{n,0} = b \qquad s_{n,T} = \mathcal{E} \cdot B_n \qquad p_{n,0} = 0$$

$$s_{n,t} = s_{n,t-1} + p_{n,t} \cdot u_{n,t} - c_{n,t}$$

$$p_{n,t} = Q_{n,t} \cdot (\mathcal{E}_T - s_{n,t}) \cdot \frac{x_t}{\sum_0^T x_t - \sum_0^t x_t}$$

$$\dot{s}_{n,t} = p_{n,t}$$

The charge power p follows the control variable $\boldsymbol{x}$

3. Empirical results

The simulation of a real vehicle fleet applying a smart charging algorithm is a powerful tool to understand the main EV challenges. Such simulation is useful for all stakeholders: grid operators, governments, car makers and academics. A first outcome is the technical one. We consider that smart charging for balancing the power grid is done through low power chargers (home and work chargers mainly). We calculate the real driving consumptions and therefore, the real electricity supply requirements for each day of the week. We use a typical labouring week. Through the simulation we can estimate the impact of different proportions between chargers power, the impact of using or not the EV as work transport and we can consider the fact of preparing a long trip for the next day for example.

A second outcome is the economic one. For estimating the surplus related to VGI we consider two different income sources. The first one is the distribution grid deferral. An intelligent and controlled EV charge could contribute to reduce the investment requirements since the existent grid would be used in an optimal way. Through VGI the distribution system operator (DSO) can supply the EV fleet electricity demand while keeping the appealed powers into ranges that do not need or that need just a small reinforcement. Our next income source estimation is the recharge cost. In this analysis we do not consider taxes neither the grid related costs. We use spot market prices to calculate the real cost of the EV fleet recharge.

For this purpose, we used a French national survey from 2008 to constitute a trips schedule for around 10000 cars representatives of the total fleet. The trips schedule represents one repetitive week in hourly steps. We take into account departure / arrival time, travel motivation (work, etc.) and traveled distance.

The following plu-in batteries are considered :

- If the battery is under a certain SOC, the EV charges at any time of the day at maximal power. Over this value, the minimal SOC at which the EV is plugged is parameterized.
- The EV is plugged only at home or at work (if it disposes of a charging point at work place)
- If the EV is commuter, it privileges the charge at work place and it charges at home only when a long trip is intended

- If the EV is not commuter, it does not plug during the day except under the acceptance of an advised plug behavior given by the TSO / DSO

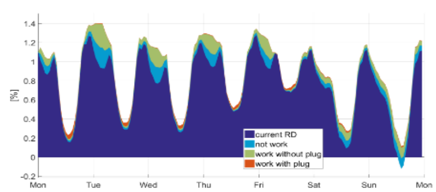
Then, we apply this optimization of EV charging to France and Germany wgo are two leading countries for the passengers cars (Table 1). The simulation results applying the smart EV charge algorithm and changing some parameters at each time. The empirical results point out the importance of this charging optimization both for France (figure 1) and Germany (figure 2).

Table 1 – Passenger car fleet in Europe

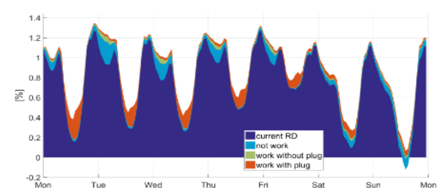
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Germany	42.3	42.9	43.4	43.8	44.4	45	45.8	46.4	47.1	47.7
Italy	36.7	37.1	37	36.9	37	37.3	37.8	37.9	39	39.5
France	31.6	31.7	32.1	32.8	32.5	32.3	32	32	32	32.4
U.K.	28.4	28.4	28.7	29.6	30.1	30.2	30.8	31.2	31.5	32.5
Spain	22.1	22.2	22.2	22	22	22.3	22.8	23.5	24	24.5
Poland	17.2	18.1	18.7	19.3	20	20.7	21.6	22.5	23.4	24.3

Unit : million, Source : Eurostat

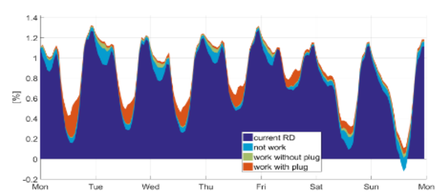
Figure 1 – EV charging in France



(a) With 15% of available charging points at work.

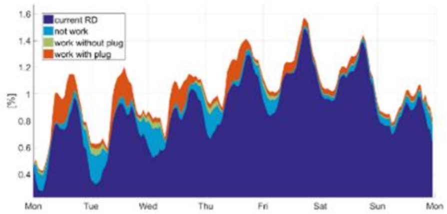


(b) With 80% of available charging points at work.

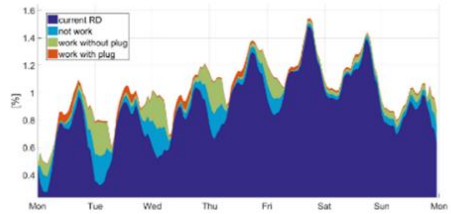


(c) With 70% of advised charge acceptance.

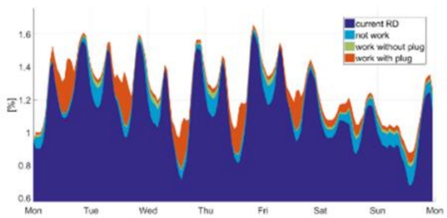
Figure 2 – EV charging in Germany



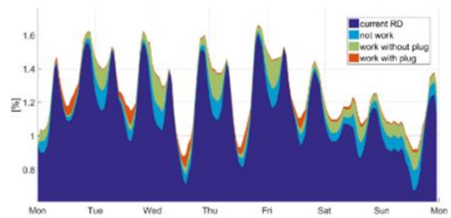
(a) With 85% of available charging points at work in winter.



(b) With 25% of available charging points at work in winter.



(c) With 85% of available charging points at work in summer.

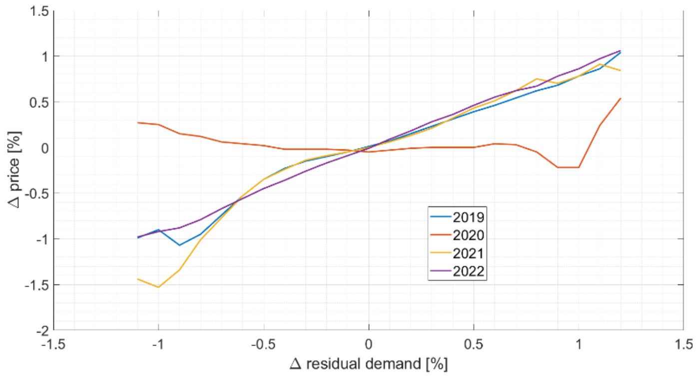


(d) With 25% of available charging points at work in summer.

This charging optimization has an impact on the electricity market. When analyzing data from 2019 to 2022 we found a close relationship between the residual demand and the day-ahead market prices as pointed out in figure 3: variation of electricity prices strongly correlated to the variations of the residuals demand. We run a polynomial regression model which explay the day-ahead price P[elec] by the electricity transaction [elec] to confirm the price-quantity relationship on the electricity market:

$$
\begin{array}{lllll}
P[elec] = & -7.48 & +2.92\times 10^{-3}[elec] & -7.94\times 10^{-8}[elec]^2 & +9.26\times 10^{-13}[elec]^3 \\
 & (98.02E-2) & (1.42E-4) & (5.89E-09) & (6.46E-14) \\
R^2 = 0.969 & & & & \\
n = 144 & & & &
\end{array}
$$

Figure 3 - Relationship of variations in wholesale electricity price with respect to variations on residual demand



If EV charge changes the residual demand curve, the day-ahead market price changes as well. This is why optimization is done using the residual demand curve as reference signal instead of using a price signal.

Finally, we compare the mean price of EV charge which fall down from 57 €/Mwh with a natutal charge to 43 € with an optimal charge.

4. Conclusion

In this paper, we study the impact of EV charging optimization with a large number of Electric Vehicles. We develop an optimization algorithm which aims to simulate the Electric charging behaviour over several days with a large personal vehicle fleet. We apply it tho France and Germany.

When a fleet of some millions of electric vehicles are on the roads, their charge will have an impact on the power grid. If no action is taken over the charge, this impact might be negative. Higher power peaks will be attended, appealing a more expensive and more pollutant production mix. While, if a smart charge is applied, the EV batteries capacity could contribute to the power grid flexibility and limit power and price peaks.

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