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Coordination of EV fleet charging with distributed generation to reduce constraints on distribution networks

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Abstract

Objectives for CO2 reduction as well as a more and more expensive gasoline have given a new breath to the plug-in vehicles (electric or hybrid). From an energetic point of view, the issue is then transferred from oil industry to the electrical power system sector. With this possible new demand, the question is then: will the power systems be able to accept the demand of several millions of vehicles, and how the power system control should be modified? Plug-in vehicles will be charge from the low voltage distribution network. Then their impact on the network is a critical issue to ensure the system security. The small storage devices brought by vehicles could be more a real opportunity than a constraint for distribution networks as vehicles could help reducing overload, voltage fluctuations observed with renewable sources. In this paper we present how plug-in vehicles charges can be managed to reduce the constraints on distribution networks. We propose controlled charging strategies to charge EVs when photovoltaic or wind generation feed power into the grid. Financial issues will also be discussed about sharing benefits between actors.

Keywords: plug-in vehicles, distribution networks, renewable energy

1 Introduction

The power system security depends of the balancing between generation and demand at each moment. A constant frequency is the indicator of the balancing. Beyond the real-time balancing requirement managed by the transmission system operators, it must be kept in mind that there are also voltage and congestion constraints that can affect the distribution networks – usually radial with a radial topology.

Distribution networks are at the center of the smart grids with several evolutions currently in progress: integration of distributed energy resources – wind, photovoltaic, combined heat power (CHP and µ-CHP) – and tomorrow new loads such as plug-in vehicles. With all these innovations the distribution operators (DSO) need to update their technical solutions to manage their networks, using more and more information and communication technologies to handle efficiently renewables and EV fleets.

Traditionally distribution networks that were radial with passive loads and power flows from the substation to the loads, are now subjected to bidirectional power flows that may impact the voltage profile, the protection plan, or generate congestions

Plug-in vehicles and renewables may have a real impact with possible peak power if all EV drivers plug their car to begin the charge immediately even if only a small charge is needed. As some distribution transformers may already be closed to

overloading, simultaneous EV connection could be a real problem for the transformers lifespan or management profile. Conversely with their batteries, plug-in vehicles can be seen as small storage systems distributed along the system. As the lack of storage devices is a weak point of the power system, these vehicles could be an opportunity that has been analyzed for several years [1-4] to help absorption of renewable decentralized generations.
But as time seems to be arrived for plug-in vehicles roll-out, many issues will have to be solved in the coming years. It worth noticing that the impact of plug-in vehicles will also depend on the Electric Vehicle Supply Equipment (EVSE) power, system which can be from 3 kW (single phase 230V and 16A) to 43 kW (three phases 400V and 63A) for AC systems.
If private EVSE for residential will mainly be 3 or 67kW (16 A or 32 A switchgear), public EVSE could be 11 kW, 22 kW or 43 kW. If we consider that in France a typical power for a low voltage distribution transformer is 400 – 630 or 1000 kVA with 100 customers, the simultaneous public or private charging decisions can be a real problem for the distribution networks.

In this paper, we present how plug-in vehicles charges can be managed to reduce the constraints on distribution networks subject to renewable generation. Our model proposes optimal charging strategies to EVs when photovoltaic or wind generation feed power into the grid. For simplicity reasons, we consider that PV and wind technologies have achieved the cost level of grid parity [5-8]. This hypothesis means that economic analysis would use the hourly French market pool prices for energy for PV and for wind generations even if in the later, grid parity will probably be effective later than in PV.
The section 2 describes the model used for this question, the section 3 presents the strategy for EVs charging following the PV or wind generation, and the section 4 gives simulation results. Financial issues will also be discussed about sharing benefits between actors.

2 Modelling

This section presents the different parts of the model built to analyse the coupling of EV charging with distributed renewable generations.
First, let us precise that our model is grounded on the French data for design of the distribution electrical system, on French data for car usages and on our solar panel in Supélec.

The distribution network is considered at the substation level. Only demand and generation connected to the network is taken into account: usual French electrical demand, EV demand, PV generation and wind generation. Nevertheless, neither voltage issues along feeders nor cables/lines overload are considered.

2.1 Distribution network

In France there are about 2500 substations to link the distribution networks (HTA level) to the transmission system (63 kV, 90 kV or 225 kV level). Considering a peak power of 100 GW, the mean peak power is 40 MW per substation, of course with a large spread because some substations only have a single 20 MVA transformer and others have three 36 MVA transformers. Regarding to the renewable distributed generation, 7500 MW of wind mills and 3500 MW of photovoltaic panels are connected to the distribution grid.

2.2 Electricity demand profile

The daily demand profiles at the substation are based on the demand curves published by the French TSO. A scale factor (1/2500) is applied to convert a daily curve at the substation level. Two example of demand profiles are given in Fig. 1.

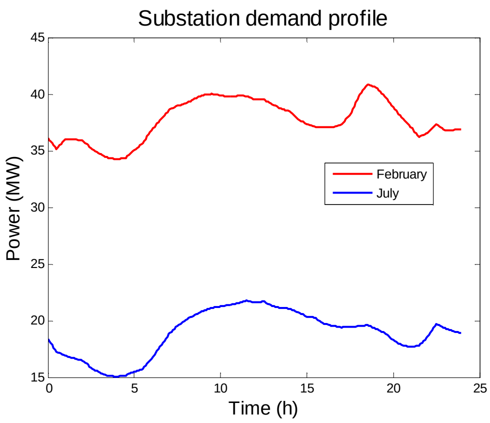

Figure 1: two demand profiles at the substation level during a week day.

2.3 EV fleet

An EV fleet must be modelled to indicate when the EVs are connected to the grid and consequently available for charging. We propose a repartition function of vehicle trips from [9] taking into account only daily trips less than 60km, which represents about 80% of actual French trips. Moreover, we only consider particular EVs for travel between home and work. EV business fleets

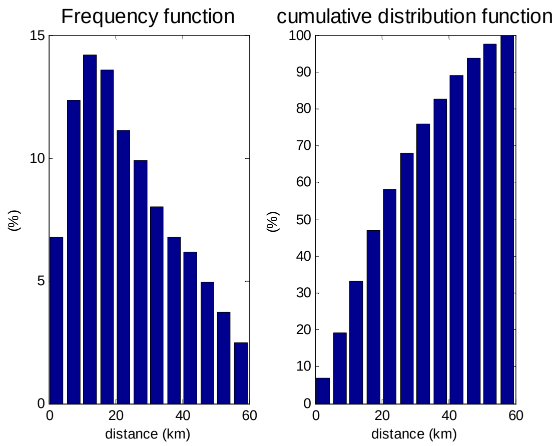

Figure 2: Frequency and cumulative distribution functions for EV daily trips

are not considered owing to their commercial use. For the sake of simplicity, all EVs are considered to have a 24kWh battery, and to use a 3kW (230V-16A) or a 7 kW (230V-32A) plug.

We consider distributions for travel durations, with the hypothesis that people stay at work all day. Each day is then characterized by four instants (t0, …, t3) which correspond to EV connection to and disconnection from the grid. In the morning, the EV is unplugged (t_0) before leaving, and the EV is then plugged in (t_1) after arriving at work. At the end of day, the EV is unplugged (t_2) before leaving work to return home. Finally the EV is plugged in at home (t3). Our reference is the instant t_1 = 8.30 in the morning with a 20min standard deviation and a Gaussian distribution. Then t_0, t_2, and t_3 are calculated with:

$$
\begin{aligned}
t_0 &= t_1 - trip\ duration - \Delta t_{10\,\min} \\
t_2 &= t_1 + \Delta t_{work} + \Delta t_{30\,\min} \\
t_3 &= t_2 + trip\ duration + \Delta t_{30\,\min} + \Delta t_{10\,\min}
\end{aligned}
\tag{1}
$$

$\Delta t_{10\ min}$ and $\Delta t_{30\ min}$ are stochastic delays (uniform distribution) that are introduced to respectively consider that the EV is disconnected a couple of minutes before leaving (or connected some minutes after arriving), and that time is spent in the evening for shopping before coming home. Δt_{work} is the daily duration spent at work (typically nine hours)

The trip duration is calculated from the mean speed that has been supposed to depend on the trip length (Table 1), and a uniform distribution inside a +/-20% range is considered. Energy consumption also depends on the trip length.

We suppose that small urban trips require more energy per km. For a 24 kWh battery automakers often give autonomy of 150km. To base our calculations on a more realistic usage, autonomy between 90 and 120km is considered. A uniform distribution (+/-20%) is considered around the mean values.

With this model, the mean time when the EV is disconnected to the grid is 1h 35min per day with a 20min standard deviation. Then, if each EV can be connected to an EVSE when it is parked at work, the EV is available at least 21h per day. Fig. 3 represents the probability for EV connection to the grid availability (either for charging or frequency regulation) during the day. Our model shows a probability that drops to less than 50% and 30% respectively during morning and evening trips.

Table 1: Trip intervals, mean speed and mean energy consumption

Trip intervals (km)	0-5	5-15	15-25	25-40	40-55	55-60
Speed (km/h) +/-20%	20	30	40	50	60	70
Consumption (km for 24kWh battery)	90	90	90	105	120	120

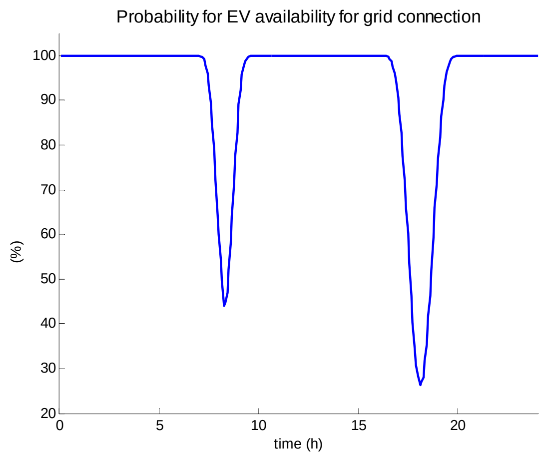

Figure 3: Probability for an EV to be connected to the grid during the day

2.4 Photovoltaic generation

The photovoltaic generation profile is based on measurements (time step 30 seconds done with a single PV panel located on the roof of Supelec (25 km south of Paris). We also use data about the number of sunny hours per month in the area [10]. As the weather is considered sunny if the direct sun power is greater than 120W/m², and

considering the generation characteristic of a SunPower module [11], the 120 W/m² threshold corresponds to a 15 W/m² electrical generation.
Due to some data collection shortcomings during the 2010-2012 years, we have decided to manage our rough solar data by creating a PV generation profile for all days of a normalized year. The method is described in Fig. 4. For each month there is a credit of sunny hours (H_0). Then a first sunny day is randomly chosen, and the associated PV profile is also randomly chosen amongst the registered profiles of this month. The chosen profile brings a certain amount of sunny hours. The remaining number of sunny hours to complete is $H_1 = H_0 - h_1$. If H_1 is positive, another sunny day is randomly chosen. The process is gone on until the sunny hours credit is over.

As the total installed power in France is 3500 MW (peak), and considering a 150W peak per square meter, the PV panel surface is around 10000 m² per HV/MV substation. Of course there are disparities between geographical areas, with more PV panels in the south-east, and less in the north.
Finally, this model has been used to calculate the load factor of the PV panels. A 10% value is found which is in agreement with usual values in France.

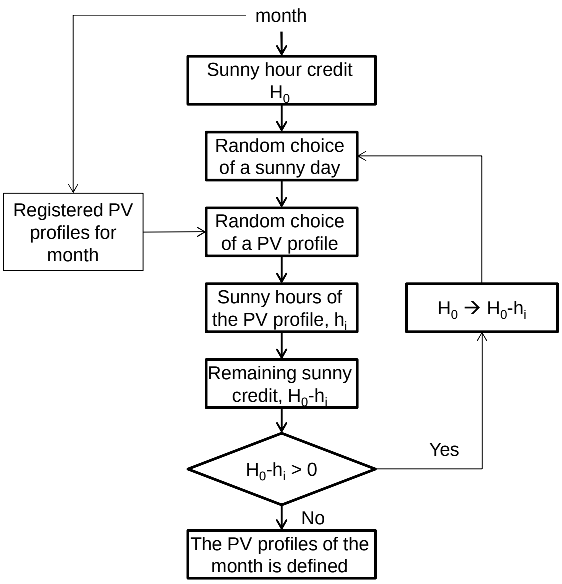

Figure 4: flow chart to define the monthly PV profiles

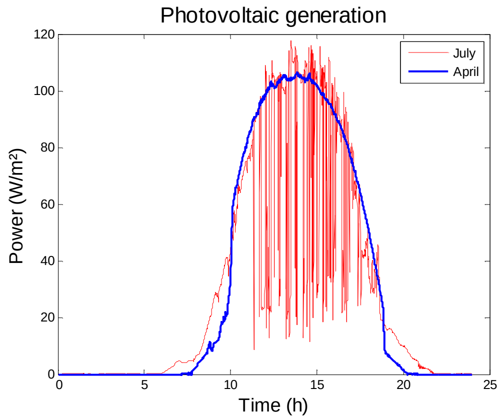

Figure 5: Example of two photovoltaic profiles (W/m²), for one day of April and one day of July.

2.5 Wind generation

The wind generation profile is based on a one year wind data measured in the north of France (with a 30 minutes time step), and on a windmill steady-state characteristics (cut-in, rated and cut-off wind speeds): $v_{cut\text{-}in} = 3.5$ m/s, $v_{rated} = 13$ m/s and $v_{cut\text{-}off} = 25$ m/s.
The frequency function and cumulative distribution function for the wind speed are given in Fig. 6. For each day, we randomly choose a 24h continuous wind sequence and the electric power is calculated from the power-wind curve.

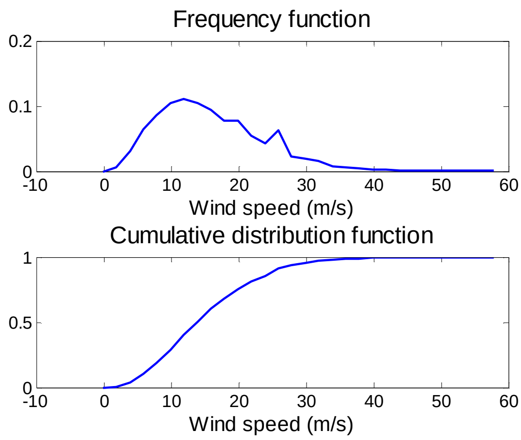

Figure 6: frequency function and cumulative distribution function for the wind speed data used in the simulations.

3 Strategies for EV charging

The model presented in the section 2 is used to test various EV charging strategies. In the first strategy EVs are only charged during the night from 1 am to reduce the risk of power overload in the substation. The second strategy proposes to charge EV when PV panels generate electricity.

In all cases, we consider week days with trips between home and work. The battery energy level is given by its state-of-charge (SOC). It is known that battery charging at constant current (maximum power) is limited to a SOC less than 90 or 80%. Beyond this limit the battery is charging at constant voltage, thus charging power is decreasing. As we have not introduced a model of the constant voltage charging, the SOC will be limited to 90%, and the maximum charging power will be equal to the EVSE power (3 or 7 kW).

The three key instants are t_0, t_1, t_2 and t_3 (see definition in section 2.3). The battery targeted SOC at t_0 is called SOC_init_am, and it is called SOC_init_pm at t_2.

3.1 Non controlled charging

In this strategy EVs are mainly charged at rated power during the night after 1 pm, and they can be charged during the day if $SOC(t_1)$ is less than the targeted SOC_init_pm. In that case EVs are charged immediately after the connection at work.

3.2 Synchronisation with PV generation

For this strategy, we consider an aggregator managing a fleet of private EV that are connected to the grid at work time when PV is possibly generating. The aim of the the aggregator is to maximize the green charging of EV. In order to manage this goal, the aggregator has to forecast the PV generation and to send a charging profile to each EV. The profile is built as following:

1) PV generation forecast P_{PV} in the area of the distribution network is required. In the present study the forecast curve is a mean profile with a one-hour time step based on the measured PV curve.
2) PV profile available for each EV, P_{PV_EV} is then given by equation (2).

$$P_{PV\_EV} = P_{PV} / N_{EV} \tag{2}$$

The PV profile available is sent to each EV and is used by the BMS (battery management system):

3) The BMS updates the profile to take the maximum plug power, P_{max}, into account (3):

$$P_{PV\_EV} = \max\left(P_{PV} / N_{EV}\ ;\ P_{\max}\right) \tag{3}$$

4) When the EV is connected at work (instant t_1), the BMS calculates the energy required by the battery (4), and the energy available from PV panels (5):

$$W_{bat} = \left(SOC\_init\_pm - SOC(t_1)\right) * W_{\max} \tag{4}$$

$W_{\max}$: *battery capacity*

$$W_{PV\_EV} = \int_{day} P_{PV\_EV}\, dt \tag{5}$$

5) The BMS calculates the charging profile used between t_1 and t_2 (6):

$$\begin{aligned} &if \quad W_{PV\_EV} < W_{bat} \\ &then \;\; P_{EV\_charge} = P_{PV\_EV} \\ &else \;\; P_{EV\_charge} = P_{PV\_EV} \frac{W_{bat}}{W_{PV\_EV}} \end{aligned} \tag{6}$$

Presently the SOC_init_pm value may not be reach if $W_{PV\_EV} < W_{bat}$. That is why the SOC value at time t_2 will be analysed.

6) When the driver is back home at evening, the energy required to reach the SOC_init_am value is delivered to the battery with two possible strategies:
   i. EVs are charged from 1 am at maximum power P_{max}. Then a peak power will be seen on the demand curve.
   ii. The aggregator built a charging profile to fulfil the deep of demand in the middle of the night. First each EV sends its energy need, W_{EV_night}, to the aggregator who computes the energy need of its fleet, W_{fleet_night}. The aggregator also needs a forecast of the demand curve at the substation level. Then he computes the load profile P_{fleet_night} for its fleet, and sends it to all EVs. Finally, each EV BMS deduces its own charging profile from equations (7):

$$\begin{aligned} &W_{EV\_night} = \left(SOC\_init\_am - SOC(t_3)\right) * W_{\max} \\ &P_{EV\_night} = \max\left(P_{fleet\_night} * \frac{W_{EV\_night}}{W_{fleet\_night}}\ ;\ P_{\max}\right) \end{aligned} \tag{7}$$

3.3 Synchronisation with wind generation

The method is the same as for PV generation. The aggregator uses the profile of wind generation forecast, P_{wind}, and sends the profile P_{wind_EV} to each EV

$$P_{wind\_EV} = \max\left(P_{wind}/\,N_{EV}\,;P_{\max}\right) \tag{8}$$

Then, the BMS calculate the day charging profile between t_1 and t_2-1h ,

$$\begin{aligned}
& W_{bat}^{day} = \left(SOC_init_pm - SOC(t_1)\right) * W_{\max} \\
& W_{wind_EV} = \int_{t_1}^{t_2-1H} P_{wind_EV}\,dt \\
& if \quad W_{wind_EV} < W_{bat}^{day} \\
& then \quad P_{EV_charge} = P_{wind_EV} \\
& else \quad P_{EV_charge} = P_{wind_EV} \frac{W_{bat}^{day}}{W_{wind_EV}}
\end{aligned} \tag{9}$$

And the night charging profile between t_3 and t_0-1h

$$\begin{aligned}
& W_{bat}^{night} = \left(SOC_init_am - SOC(t_3)\right) * W_{\max} \\
& W_{wind_EV} = \int_{t_3}^{t_0-1H} P_{wind_EV}\,dt \\
& if \quad W_{wind_EV} < W_{bat}^{night} \\
& then \quad P_{EV_charge} = P_{wind_EV} \\
& else \quad P_{EV_charge} = P_{wind_EV} \frac{W_{bat}^{night}}{W_{wind_EV}}
\end{aligned} \tag{10}$$

The last hour before departure is available for a charge at full power the SOC_init_am value has not been reached.

4 Simulation results

In the base case, the simulations have been run for a fleet of 500 EVs, 16 500 m² of PV panels, and 7 kW EVSE. The simulation time step is 5 min.

4.1 Non controlled charging

The mean daily energy consumed by the fleet is 3.2 MWh (6 kWh per EV). In the example of Fig.7, the targeted SOC at t_0 is equal to 0.9. Vehicles begin to charge simultaneously at 1 am. Even if the peak power due to EV (19 MW) is lower than the peak value of the demand (22 MW), the network operator may rather charge

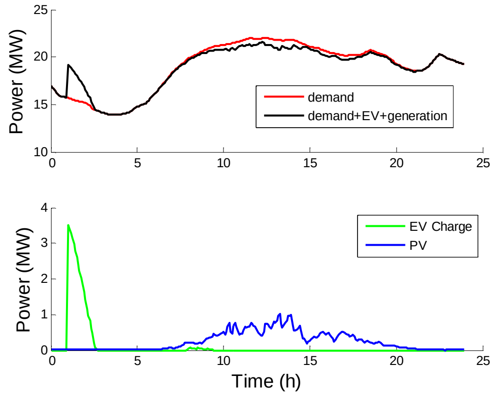

Figure 7: load profile at the substation (top), EV charging profile and PV generation (bottom) for a day of June

EVs when distributed sources feed-in energy (to prevent voltage troubles).

4.2 Synchronisation with PV generation

The strategy presented in section 3.2 has been analysed with a main goal: what is the ratio of green charging? It depends on SOC targets (at t_0 and t_2), EV number, and PV surface.

4.2.1 Day charging profile with PV

First, let us verify that the day charging profile follows the PV generation (Fig. 8). In this case the SOC_init_am and SOC_init_pm are respectively equal to 0.7 and 0.9 to privilege the day charging when sun is shining. It can be seen that day charging matches with the hourly mean value of PV generation.

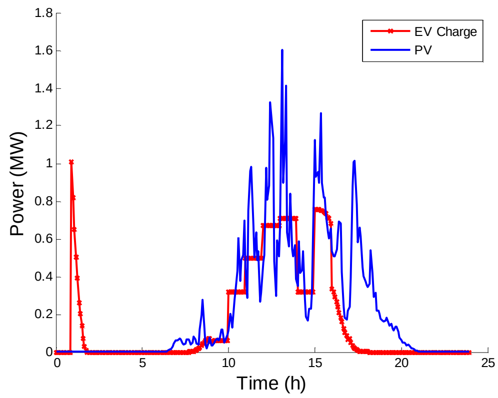

Figure 8: EV charging profile and PV generation

EV charging drops to zero at 5 pm, and a one MW peak is observed at night to charge EVs that come back home with a SOC lower than SOC_init_am.
back home with a SOC lower than SOC_init_am.

4.2.2 SOC at t_0 and t_2

In our strategy, the day charging is only done with PV sources. Then if there is no sun, the SOC_init_pm value will not be reached at t_2. In Fig. 9, we give the cumulative distribution function of SOC(t_2) and SOC(t_0) after one day trip. SOC(t_2) varies between 0.4 and 0.9; 50% of the values are greater than 0.87. The lowest values correspond to cloudy days when EV charging is low at work (it is confirmed with simulations where PV generation is forced to zero). SOC(t_0) is mainly distributed (65%) between 0.7 and 0.75. Values greater than 0.75 are those of EVs that have a SOC greater than 0.8 at t_2.

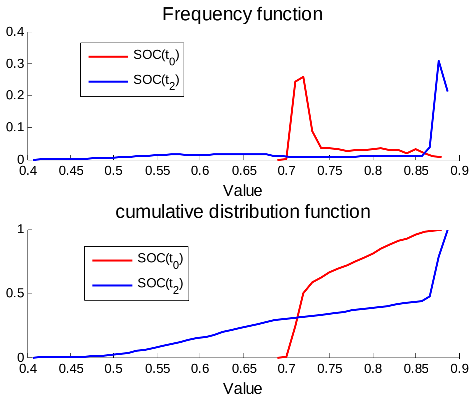

Figure 9: frequency functions and cumulative distribution functions for SOC(t_0) and SOC(t_2). 500 EVs and 195 days. SOC_init_am = 0.7 and SOC_init_pm=0.9

4.2.3 Rate of charge from PV

As our strategy aims at increasing the green charging from PV, let us look at the rate of charge from PV for all the fleet. This rate is define by (11)

$$\frac{\int_{day}\left(\sum_{all\ EV} P_{EV\_charge}\right) - P_{PV}\left(if\ P_{PV} < \sum_{all\ EV} P_{EV\_charge}\right)dt}{\int_{day}\left(\sum_{all\ EV} P_{EV\_charge}\right)dt} \quad (11)$$

In the case presented previously, this rate is equal to 62%. An analysis per season gives 43% in winter, 65% in spring, 73% in summer, and 65% in autumn.

4.2.4 Power profiles

Here we show the profiles for a cloudy day and a sunny day. In the first case, EVs are charged at night during the deep of demand. The peak seen in Fig. 7 has been deleted.

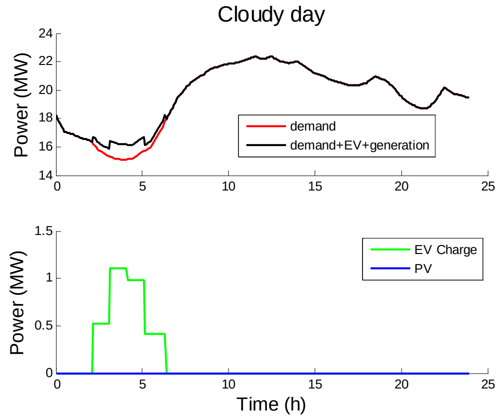

Figure 10: profiles for a cloudy day. EV are only charged at night

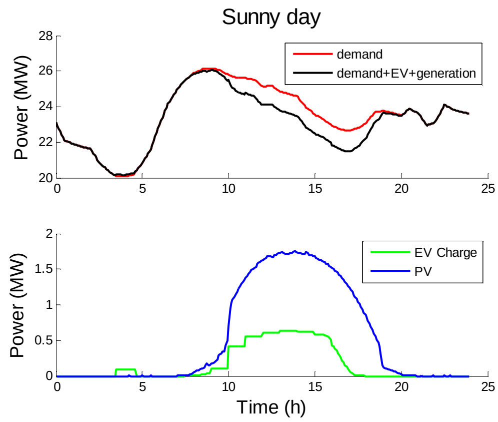

Figure 11: profiles for a sunny day.

For a very sunny day (Fig. 11) EVs are mainly charged between 10 am and 5 pm if SOC_init_pm is chosen greater than SOC_init_am. Here, SOC_init_am and SOC_init_pm are respectively equal to 0.7 and 0.9, thus the energy needs are very small at night. It can be noticed that in Fig. 11, only a part of the PV energy is used for EV charging. On a yearly base, 40% of the PV generation is used for EV charging.

4.3 Parametric analysis

First, we analyse the influence of EV number, and PV panels' surface (Fig. 12). It confirms that the rate of charge from PV decreases when EVs number increases, and when PV surface decreases. Second, we analyse the influence of SOC_init_am and SOC_init_pm, on the rate of charge from PV (Fig.13). These SOC values are in the range [0.5; 0.9]. It can be seen that for low values of SOC_init_am, a saturation is observed for the

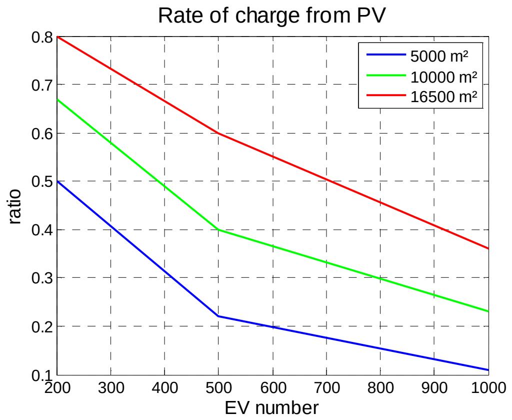

Figure 12: rate of charge from PV versus EV number for three PV surfaces. SOC_init_am = 0.7 and SOC_init_pm = 0.9

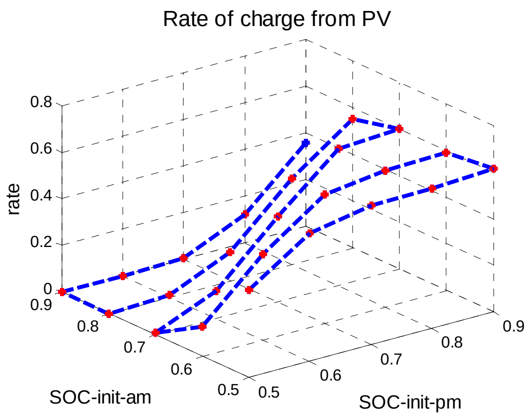

Figure 13: rate of charge from PV as function of SOC_init_am and SOC_init_pm. 500 EVs and 16500 m²

rate of charge from PV. The saturation level depends on the sun irradiation and PV surface. Then to maximize the green charging from PV, and to secure the driver with a high enough SOC value at t_0, an optimal choice could be circa SOC_init_am = 0.75 and SOC_init_pm = 0.9.

5 Conclusion

In the present paper, we have proposed strategies to maximize the green charging of EVs with either PV or wind generation. Results have been presented in case of PV generation. It is possible for an aggregator to propose green charging of its EVs fleet if he matches the charging profile with PV forecast. Rate of green charging can be as high as 60-70%, but it depends on the fleet size and on the PV panels' size. Nevertheless the optimal green charging can be reached if the drivers accept to live their home in the morning with a battery that is not fully charged. In order to reduce this uncertainty, a mix PV/wind energy content is relevant.

Finally, the charging strategy has been proposed in the context of distribution network, which means that EV and renewable sources have to be located in the same area. Nevertheless, the strategy can be applied to an aggregator that operates a fleet in France and that sells renewable energy to producers located everywhere in France. He would just have to match the generation forecast of the producers.

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