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► **To cite this version:**

Xuan-Linh Dang, Marc Petit, Paul Codani. Energy optimization in an eco-district with electric vehicles smart charging. PowerTech, 2015 IEEE Eindhoven , IEEE, Jun 2015, Eindhoven, Netherlands. 10.1109/PTC.2015.7232574 . hal-01266894

**HAL Id: hal-01266894**

**<https://hal-centralesupelec.archives-ouvertes.fr/hal-01266894>**

Submitted on 4 Feb 2016

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# Energy optimization in an Eco-district with Electric Vehicles smart charging

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**Abstract**—The energy modeling of an eco-district, composed of residential and commercial facilities, is proposed. First, an optimal strategy aiming at sizing the rated power of the substation transformer is introduced. Then, considering the introduction of photovoltaic (PV) panels and electric vehicles (EV) in the district, the new operating conditions of the transformer are detailed. In order to reduce (a) the peak power of the transformer and (b) the cumulative durations of the transformer overloading periods, an Energy Management System (EMS) is implemented. The latter uses the district EVs, which have Vehicle-to-grid (V2G) capabilities, as flexibility providing units. An economics layer is added in order to compute the electricity costs considering the French pricing. This approach is used to deduce the optimal contracted power with the local system operator. Results show a reduction of 70% in overloading durations, 71% in average overloading power, and 17% in electricity costs with the EMS.

**Index Terms**—Energy Management System; Micro-grid; Smart Charging; Vehicle-To-Grid;

## I. INTRODUCTION

Urbanization, population growth and climate change put increasing pressure on electricity consumption and CO<sub>2</sub> emission reductions. These challenges have fostered the development of Renewable Energy Sources (RES) (such as photovoltaic (PV) panels, wind turbines, etc.) in power systems. Their penetration rate has substantially increased during the last few years. In France, even though a slight decrease in growth rate was observed in 2013, the development of RES sources is expected to continue [1]. Similarly, plug-in Electric Vehicles (EV) appear as promising solutions to deal with the aforementioned issues. EV sales went up by 60% in Europe in 2014, and by around 20% in France for privately-owned EVs [2]. The expected trends in battery cost reduction and charging station deployment should strengthen the EV sales in the near future.

However, the increasing penetration of these two new units brings up concerns regarding their impacts on the electrical

This research is a part of the Energy Positive IT 2.0 project and benefit from the support of the Conseil General de l'Essonne

Paul Codani benefits from the support of the Chair "PSA Peugeot Citroen Automobile: Hybrid technologies and Economy of Electromobility", so-called Armand Peugeot Chair led by Ecole CentraleSupélec, ESSEC and sponsored by PEUGEOT CITROEN Automobile.

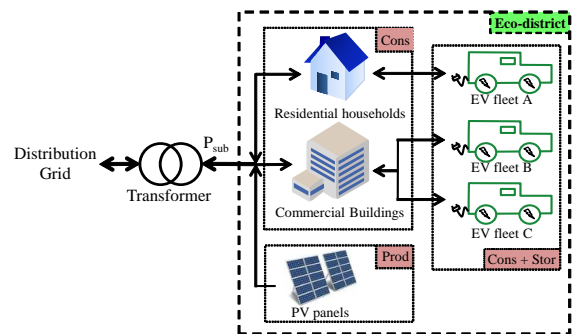


Fig. 1. System Overview

grid security. On one hand, RES are asynchronous and intermittent by nature, and distributed at the distribution level. They could trigger local congestion, frequency and voltage-related problems, as well as system wide balancing issues [3]–[5]. On the other hand, if not managed properly, the massive introduction of plug-in vehicles could jeopardize grid security [6]–[8].

In this paper, the authors focus on the electric and economics impacts induced by the introduction of PV and EVs in an eco-district, pictured in Fig. 1. As underlined in [9], very little research has been conducted on the coupling of microgrid energy management with Vehicle-to-grid (V2G) strategies.

This paper builds on [10]. In this previous work, the authors proposed an approach to determine the optimal rated power (in kVA) of the transformer when there was neither PV nor EV penetration. Then, considering the introduction of PV and EVs, the operating conditions of the transformer were characterized with and without the implementation of an Energy Management System using EVs as flexibility providing units.

In this paper, we go a step further and propose the following novel contributions:

- an economics analysis of the electricity costs of the eco-district, considering the French price scale fixing;
- a method to optimally choose the contracted power of the transformer with respect to the associated costs;

- a sensitivity analysis on the EV penetration rate in the district.

The authors would like to draw the reader’s attention on the fact that we will distinguish two characteristic powers for the substation transformer:

- the rated power  $P_{rated}$ , which is a physical feature of the transformer. This power is used in the energy analysis of the transformer operating conditions.
- the contracted power  $P_c$ , which has no physical meaning; it is the power that has been contracted between the eco-district energy operator and the system operator (SO). This power is used for the economics considerations, as peak power values are evaluated by the SO with respect to this value.

The paper is organized as follows. The system description is recalled in section II. The transformer sizing method, and the EMS description are then provided in section III. In section IV, the electricity French pricing scales for ecodistrict-type units are explained. Finally, section V and VI provide respectively the results and the conclusion.

## II. ECO-DISTRICT ENERGY SYSTEMS DESCRIPTION

### A. Residential consumption modeling

The residential consumption model is based on the study of Ian and Murray [11], in which a stochastic model is proposed to simulate the habitants behaviors. More specifically, the duration of electricity use in households is highly dependent on the timing of the occupants activities. Thus, the use of electric appliances, lighting, heating and domestic hot water within a residential household are also taken into in the model.

### B. Commercial building modeling

A load model is built to simulate the electric consumption of the commercial building, taking into account the difference between working days and weekend; and typical load shape.

From commercial building data, it is observed that most buildings have a base load during the night time. In the early morning, the buildings electric demand increases for cooling/warming depending on the outdoor air temperature. This will trigger a short-lived load spike called morning start-up. Later, as people come to work in the building, the electricity consumption increases with the arrival of occupants. Its value varies daily, seasonally and yearly. After working time, the power consumption reduces quite significantly, due to the fact that electric appliances are successively turned off.

### C. Electric Vehicle fleet modeling

All EVs are assumed to be full-electric vehicles. They have a 22kWh battery with a state of charge (SOC) in the range [20%, 90%]. These values are based on the optimal operation range of the battery. The EV fleet is shared into three different sub-fleets:

- EV fleet A: people living in the eco-district. These EV are typically plugged-in during the night, and leave in the morning to go to work and come back at late afternoon;

- EV fleet B: people working in the eco-district. These EVs typically arrive in the morning in the eco-district, and leave in the late afternoon. They charge at work during the day;
- EV fleet C: a company fleet, for instance belonging to the mail services. These EVs are typically used from early morning to noon for the first-round deliveries, and from the early afternoon to the middle of the afternoon for the second-round deliveries.

Several driver behaviors are considered. First, the drivers of fleet B are divided into two categories: (a) the fleet of drivers having an ordinary behavior, that is charging at home during the night and participating in the EMS during the day; and (b) the fleet of drivers who aim at charging the most as they can at work, thus charging only the required energy for their morning trip during the night at home, and not participating in the EMS during the day.

Then, range anxiety is taken into account for all the drivers: when they inform their EV controller with their future driving needs (see section III-B2), we assume that they overestimate their future trip distances and that they always provide the EV controller with their yearly maximum distance traveled.

Based on [12], the Electric Vehicle Supply Equipment (EVSE) powers are distributed according to table I. Home charging is mainly done at low power, while working charging stations are more equally distributed (although fast charging is still marginal). Finally, the company fleet has 22kW EVSEs only.

TABLE I  
EVSE REPARTITIONS

EVSE power plug	Fleet A	Fleet B	Fleet C
Slow (a) - 3kW	93%	35%	0%
Slow (b) - 7kW	7%	34%	0%
Intermediate charging - 22kW	0%	29%	100%
Fast charging - 43kW	0%	2%	0%

The EV fleets model is dynamic and stochastic. EV fleets average distance trip ( $D$ ), departure time ( $T_d$ ), daily number trips ( $N$ ) and seasonal energy consumption ( $E$ ) are obtained from PSA internal data and from the CROME project results and from French government agencies [13], [14] as described in TABLE II. Then, trips distances and departure times are distributed according to Gaussian distributions with mean ( $\mu$ ) and standard deviations ( $\sigma$ ) values provided in TABLE II.

### D. PV production data

The photovoltaic generation data has been measured in the area of Paris over one full year.

## III. TRANSFORMER SIZING AND EMS CHARACTERIZATION

### A. Transformer sizing

Only the residential and commercial consumptions are considered when sizing the rated power of the transformer,

TABLE II  
EV FLEET TRIP CHARACTERISTICS

Parameters	Fleet A		Fleet B		Fleet C	
	$\mu$	$\sigma$	$\mu$	$\sigma$	$\mu$	$\sigma$
D (km)	22	4.5	22	4.5	50	10
					30	
$T_d$ (h)	8	2	8	2	7	0.5
	18		18		14	
N	2					
E (kWh/km)	Winter: $c_w = 0.18$ // Summer: $c_s = 0.13$					

$P_{rated}$ . With respect to thermal limitations provided by a transformer manufacturer [15], we design an algorithm which will determine the optimal rated power of the transformer, while still allowing some overloading occurrences. The final choice for the transformer depends on the typical rated power proposed by the manufacturers. In the present case  $S_{rated} = 315$  kVA is chosen, with a 0.8 power factor, then  $P_{rated} = 252$  kW. The transformer operating conditions after the sizing are presented in Fig. 2. More details on the sizing algorithm can be found in [10].

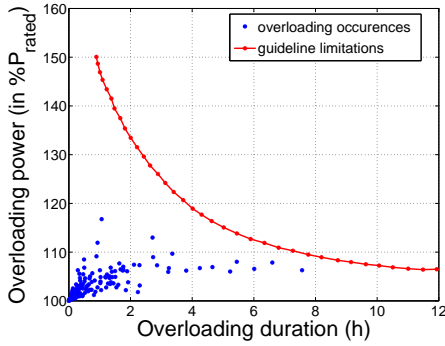


Fig. 2. Operating conditions of the transformer (no EV & no PV)

## B. EMS description

1) *District Energy Management System*: At each time interval, the power flow,  $P_{flow}(t)$ , between the micro-grid and the distribution grid (excluding the available EVs for the EMS) is calculated as following:

$$P_{flow}(t) = P_{PV}(t) - (P_{resi}(t) + P_{com}(t) + P_{EV\_nonEMS}(t)) \quad (1)$$

where  $P_{EV\_nonEMS}(t)$  denotes the consumption of EVs that are not available for the EMS most of the time, because they need to charge at full power for transportation needs. Then, based on the power flexibility that the EVs can provide (see (4)), the EMS calculates the power  $P_{EV\_EMS}(t)$  that has to be supplied by the available EV fleets. It depends on the current balance between supply and demand in the district as shown in Fig. 3. The mathematical formulation is described by (2):

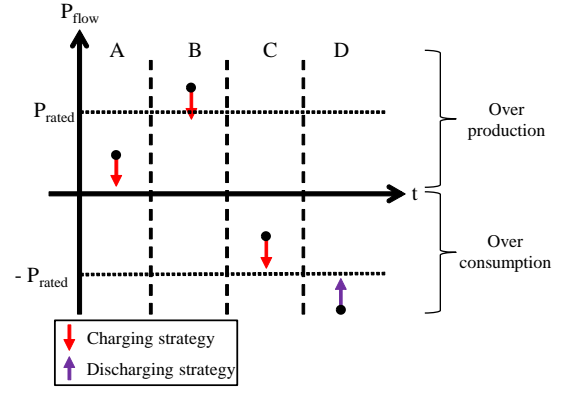


Fig. 3. Energy Management System strategy in the district

$$P_{EV\_EMS}(t) = \begin{cases} \max(P_{charg}(t), -P_{flow}(t) - P_{rated}), & \text{cases A or B} \\ \max(P_{charg}(t), |P_{flow}(t)| - P_{rated}), & \text{case C} \\ \min(P_{disch}(t), |P_{flow}(t)| - P_{rated}), & \text{case D} \end{cases} \quad (2)$$

where  $P_{charg}(t)$  and  $P_{disch}(t)$  denote respectively the charging and discharging power flexibilities that can be provided by the EVs.

The objective of this EV power management is to maximize EVs charging power during the off-peak periods (cases A, B and C in Fig. 3) either from the PV (case A, B) or from the distribution grid (case C); and to minimize the discharging energy from available EVs when the demand has reached the peak load or when the generation is too low to supply to the total demand (case D in Fig. 3). Finally, the net power flow at the substation level is given by (3):

$$P_{sub}(t) = P_{flow}(t) + P_{EV\_EMS}(t) \quad (3)$$

2) *EV fleet smart charging regime*: Once the required power from the available EVs  $P_{EV\_EMS}(t)$  has been determined by the EMS, it must be dispatched among those vehicles. If EV charging is ordered, we choose to first charge the EVs that have the biggest difference (in absolute value) between their current SOC and their required energy for next trip ( $SOC_{req}^i(t_d)$ ). On the contrary, we consecutively discharge the EVs that have the highest SOC.

To respect the future driving needs, each EV is able to decide for each moment whether to participate in the EMS or to charge quickly for transportation. Therefore, individual EVs provide the EMS with their available charging powers over the next timeframe as described by (4):

$$P_{charg}^i(t) = -\min(P_{EVSE}^i, \frac{SOC_{max}^i - SOC^i(t)}{\Delta t})$$

$$P_{disch}^i(t) = \min(P_{EVSE}^i, \frac{SOC^i(t) - SOC_{req}^i(t + \Delta t)}{\Delta t}) \quad (4)$$

Where  $P_{charg}^i(t)$  and  $P_{disch}^i(t)$  are respectively the available charging and discharging powers of  $i^{\text{th}}$  EV for the next time interval,  $P_{EVSE}^i$  is the EVSE power;  $SOC^i(t)$ ,  $SOC_{max}^i$ ,  $SOC_{req}^i(t)$  denote respectively the current, the maximum and the required state of charge for the  $i^{\text{th}}$  EV.

It is noticeable that we assume EVs to have a good estimation of their future trip distances and departure times. This could be achieved in practice by either implementing a machine learning algorithm, the EV controller being able to estimate future driving needs depending on the previous ones, or by having the EV user directly informing the EV controller with its future driving needs (through, for instance, a smartphone application).

#### IV. ECONOMICS CONSIDERATIONS

We consider the French electricity price scale fixing to compute the electricity costs in the eco-district. All the details on the French pricing are provided in [16]. Considering the value of the transformer rated power ( $P_{rated} = 252kW$ , see section III-A), the district is connected at the medium voltage level (so-called HTA level in France). The cost structure is twofold:

- an energy component  $C_E$  which is related to the electricity consumption/production (kWh)
- a capacity component  $C_P$  which is related to the contracted power  $C_P$  (kW)

These different costs are all dependent on the season and time during which the energy exchanges occur. We subscribe to a pricing structure with five different temporal classes; they are described in TABLE III. We also provide the power and energy coefficients that will be used in the power and energy components calculation.

TABLE III  
TEMPORAL CLASSES CONSIDERED FOR ELECTRICITY PRICING [16]

Class number	Corresponding period of time	Power coeff $k_i$	Energy coeff $d_i$ (c€/kWh)
1	critical peak	100%	2.98
2	on-peak winter	92%	2.56
3	off-peak winter	55%	1.53
4	on-peak summer	40%	1.30
5	off-peak summer	12%	0.87

For each temporal class  $i$ , a contracted power  $P_{c_i}$  has to be chosen, while still abiding by the constraint expressed in equation (5):

$$\forall i \in \{1; 4\}, P_{c_i} \leq P_{c_{i+1}} \quad (5)$$

It is noticeable that we do not take into account the metering and customer management costs, which are other components included in the cost structure but would not be impacted by the energy management strategy.

#### A. Capacity component calculation

The capacity component  $C_P$  is itself divided into two sub-components: the yearly capacity subscription cost  $C_{sub}$ , and the monthly overloading costs  $C_{over}$ . Both components are computed according to equation (6):

$$C_{sub} = a_2 \times \left( k_1 \times P_{c_1} + \sum_{i=2}^5 k_i \times (P_{c_i} - P_{c_{i-1}}) \right) \quad (6)$$

$$C_{over} = 0.15 \times k_i \times a_2 \times \sqrt{\sum \Delta P^2}$$

with the constant  $a_2 = 9.24$  (€/kW/year),  $P_{c_{1 \rightarrow 5}}$  and  $k_{1 \rightarrow 5}$  respectively the contracted powers and power coefficients for the various temporal classes, and  $\Delta P$  the difference between the substation power and the contracted one (only when the substation power exceeds the contracted one).

The results presented in section V-B showing the optimal contracted power result from an optimization algorithm, which minimizes the total capacity costs  $C_P$  while abiding by constraint (5).

#### B. Energy component calculation

The energy cost component  $C_E$  is computed according to equation (7):

$$C_E = \sum_{i=1}^5 d_i \times E_i \quad (7)$$

with  $d_{1 \rightarrow 5}$  the energy coefficients (see TABLE III) and  $E_i$  the net energy exchanged during temporal class  $i$ . It is noticeable that we assume grid parity in the energy cost calculation, i.e. energy is sold at the same price as it is bought.

#### C. Capacity costs optimization

We formulate an optimization problem, which objective function is the total capacity costs  $C_P$ :

$$\min_{P_{c_{1 \rightarrow 5}}} C_P \quad (8)$$

The problem is subject to the constraint expressed in equation (5). The power and energy flows between the district and the grid are given as parameters; they are computed for the baseline scenario, once with the EMS implemented and once without.

### V. RESULTS AND DISCUSSIONS

#### A. Baseline simulation scenario

The baseline scenario is the following. We consider that 800 people are living in the eco-district, and that 1000 persons are working there. Then, it is assumed that 20% of the living people and 10% of the working people own an electric vehicle (fleets A and B). Additionally, the surface area of the PV panels is supposed to be 3000 m<sup>2</sup> and there are 10 electric vehicles in the company fleet (the fleet C). The total number of EVs per fleet is provided in TABLE VII.

## B. Economics results

The results from the optimization problem described in section IV-C are shown in TABLE IV.

TABLE IV  
OPTIMAL CONTRACTED POWERS

$P_{c_i}$ (kW)	$P_{c_1}$	$P_{c_2}$	$P_{c_3}$	$P_{c_4}$	$P_{c_5}$
Non EMS	406	406	406	406	406
EMS	288	288	310	310	310

Without any EMS, the transformer peak powers occur during the critical peak tariff periods. As a consequence, and because of constraint (5), all the contracted power values are set by the critical peak contracted power ( $P_{c_1}$ ). On the other hand, thanks to the EMS, it is possible to have lower high-tariff contracted powers than low-tariff contracted powers. Moreover, the absolute values of the contracted powers are significantly reduced. These results have an impact on the electricity costs as shown in TABLE V.

TABLE V  
ENERGY COSTS FOR BOTH SCENARIOS

Scenario	Capacity costs $C_P$	Energy costs $C_E$	Total Electricity costs
Non EMS (k€)	4.01	15.5	19.51
EMS (k€)	3.04	13.5	16.14
Gains (%)	24	13	17

As the contracted power values are much lower with the EMS, the capacity costs are reduced by 24%. Overall, the savings in electricity payment are reduced by 17%.

## C. Transformer overloading

1) *Baseline scenario*: We analyze the transformer operating conditions under the baseline scenario, with and without the EMS. Fig. 4 shows the monotonically decreasing maximal daily substation power (in absolute value) without EV and with EV (with and without EMS). It is noticeable that the EMS allows a 25% reduction of the substation peak power in comparison with the unmanaged charging scenario.

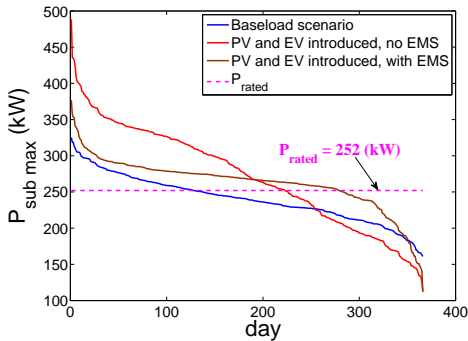


Fig. 4. Daily maximal substation power during the whole year with the different scenarios

Table VI details the comparison of the energy efficiency with and without EMS, in terms of absolute maximal daily substation power ( $P_{max\_global}$ ), exceeded exchanged energy ( $E_{ex}$ ), cumulative overloading durations and average substation power ( $P_{sub\_ave}$ ) during the overloading periods. The energy  $E_{ex}$  is determined by (9) when the substation power is overloaded:

$$E_{ex} = \sum_{i=1}^n \left( \int_{t_j}^{t_k} (|P_{sub}^i(t)| - P_{rated}) dt \right), \quad (9)$$

with  $|P_{sub}^i(t)| > P_{rated}$

TABLE VI  
RESULTS: SCENARIO COMPARISON

Items	$P_{max\_global}$ (kW)	$E_{ex}$ (MWh)	Duration (h)	$P_{sub\_ave}$ (kW)
Non EMS	488	21.2	613	35
EMS	376	2.0	186	11
Improvement ratio (%)	23	90	70	71

Results show a drastic improvement in the transformer operating conditions with the implementation of the EMS, with a reduction of 70% in the cumulative overloading durations, and a reduction of 90% in the energy exchanged during overloading periods.

2) *EV penetration rate: sensitivity analysis*: Finally, we aim at conducting a sensitivity analysis on the EV penetration rate, and assessing the impact of the latter on the transformer operating conditions. This analysis could provide insights on the ability of the EMS to accept more or less EV charging periods, depending on the EV sales' evolution. We consider three scenarios in terms of EV numbers in each fleet. They are summarized in TABLE VII.

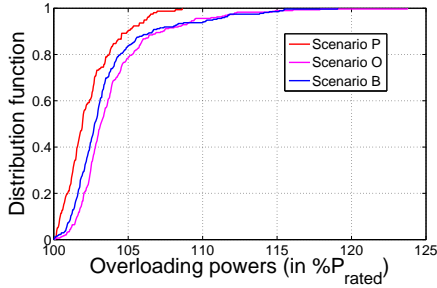
TABLE VII  
SENSITIVITY ANALYSIS; NUMBER OF EVS PER FLEET

Scenario	EV Fleet A	EV Fleet B	EV Fleet C
Pessimistic Scenario (P)	80	50	5
Baseline Scenario (A)	160	100	10
Optimistic Scenario (O)	240	150	15

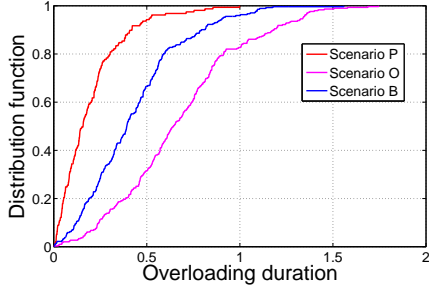
Fig. 5a and 5b show respectively the distribution function of the overloading average powers and overloading durations.

The EMS performs well in terms of overloading average powers. The EV penetration rate only has a small impact on this parameter. On the other side, the impacts on the overloading durations is more significant. As indications, the transformer rated power that would be required, if there was no EMS, are provided in TABLE VIII (with the EMS, in the main scenario, there is no need to change the rated power ( $P_{rated} = 252kW$ )).

These results could be used in future work to compute savings in investment costs.



(a) Overloading power



(b) Overloading durations

Fig. 5. Operating conditions of the transformer during overloading occurrences, with respect to the limitations provided in [15]

TABLE VIII  
TRANSFORMER RATED POWER THAT WOULD BE REQUIRED WITHOUT EMS

Scenario	Apparent power $S_{rated}$ (kVA)	Active power $P_{rated}$ (kW)
Pessimistic Scenario (P)	400	320
Baseline Scenario (A)	500	400
Optimistic Scenario (O)	630	504

## VI. CONCLUSION

In this paper, the energy modeling of an eco-district is presented. First, only residential and commercial consumptions are considered, and an optimal sizing for the substation transformer is determined. Then, PV panels and EVs are introduced in the district. In order to limit the impacts both in terms of transformer operating conditions and electricity costs, and Energy Management System is proposed. Results show a reduction of 70% in overloading durations, 71% in average overloading power, and 17% in electricity costs with the EMS.

Overall, yearly electricity savings amount to 3370€(TABLE V), considering 270 flexible EVs (baseline scenario A). Thus,

a direct remuneration of the EV end users does not appear as a very suitable business model, as drivers would only earn 12€/year. Policy recommendations, such as changes in electricity pricing, driven by the environmental gains of this solution could foster the developments of such EMS. In a next work, the impact of single phase 7kW chargers in residential parkings will be analysed because there seems to be a consensus for installing them. Their cost is barely more expensive than a 3 kW charge.

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