Quasi-Real-Time Management of Electric Vehicles Charging

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Abstract

This work presents a methodology to manage Electric Vehicles (EVs) charging in quasi-real-time, considering the participation of EV aggregators in electricity markets and the technical restrictions of the electricity grid components, controlled by the distribution system operator. Two methodologies are presented in this paper to manage EV charging, one to be used by the EV aggregators and the other by the Distribution System Operator (DSO). The methodology developed for the aggregator has as main objective the minimization of the deviation between the energy bought in the market and the energy consumed by EVs. The methodology developed for the DSO allows it to manage the grid and solve operational problems that may appear by controlling EVs charging. A method to generate a synthetic EV data set is used in this work, providing information about EV movement, including the periods when EVs are parked and their energy requirements. This data set is used afterwards to assess the performance of the algorithms developed to manage the EV charging in quasi-real-time.

Keywords: Aggregators; Distribution System Operators; Electric Vehicles; Electricity Markets; Load Management; Quasi-Real-Time Management.

1. Introduction

The foreseen deployment of Electric Vehicles (EVs) will considerably affect the way

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distribution grids will be managed and operated in the future. The extra amount of power they will demand from the grid will oblige Distribution System Operators (DSO) to understand the impacts resulting from EV connection to distribution grids. Several approaches to this problem have been presented in literature.

In [1][2], the authors analyzed the changes in the load diagrams of distribution networks for increasing penetration of EVs. Lopes et al., in [3][4], also studied the impacts of EVs on distribution grids. The innovation introduced by these authors was the evaluation of the EV charging impact on the grid technical constraints, like voltage and branches' congestion levels. Papadopoulos et al., in [5], also addressed the technical challenges related to the EVs integration in a Low Voltage (LV) grid. Clement et al., in [6][7], analyzed the Plug-in Hybrid EV (PHEV) impacts on energy losses and voltage deviations in distribution grids. Although the methodologies proposed in papers [1] to [7] revealed to be interesting approaches to evaluate EV impacts, they do not provide an adequate method to determine the optimal EV charging schedules in quasi-real-time.

It should be noted that for the purpose of this work, the term "quasi-real-time" is used in the sense of monitoring the grid and managing EVs in a short period of time, around 5 to 10 minutes (or even less, depending on the effectiveness of the communication infrastructure).

Several other works have been developed with the main purpose of determining the optimal (or near optimal) EV charging schedules, [8] to [11]. However, some of these approaches consume a lot of computation time, being unpractical for quasi-real-time applications. Additionally, the majority of these methods were designed focusing on a single specific goal, such as minimizing violations of the grid technical restrictions, peak load, energy losses, or violations of the EV owners' requests, among others.

It should be noted that the works [3][4][6][7], referred previously, also presented methods to determine optimal EV charging schedules, but they were designed focusing only on the optimization of the grid operating conditions. They do not take into account the eventual existence of energy retailers, like EV aggregators, [12], or the existence of electricity markets. This problem was tackled, in part, in [13], by Sanchez-Martin et al.. These authors presented a model to control EV battery charging in real-time, but the methodology proposed was developed only for EV parking facilities.

In [14], Deilami et al. also proposed a method for the EVs load management in real-time. It focuses on the minimization of the cost of producing the extra needed energy plus the energy losses, taking into account the voltage constraints. Yet, it does not consider the existence of aggregators, nor their economic interests, which are not interrelated with the optimization of the grid operating conditions.

This paper presents an innovative approach that uses a holistic methodology to manage EV charging in distribution grids in quasi-real-time, taking into account the concerns of all the players involved in the process: the technical restrictions of the grids (DSO concern), the periods during which EVs are parked (aggregators' concern), the EV owners' energy requests (EV owners' concern) and the operational requirements of electricity markets. The development of this work involved the creation of two expeditious methodologies to be used by aggregators and DSO to manage the EVs charging in quasi-real-time, which allow, respectively:

1. Minimizing the aggregators' penalties for the deviations between the energy they bought in the markets and the energy sold to EV owners (imbalance settlement), thus contributing to increase the aggregators' profit;
2. Solving technical problems related to voltages violating operational limits or overloading of branches that might appear in the grid.

In order to assess the performance of these methodologies, a synthetic EV data set was used. This dataset was created with an algorithm that uses a Markov chain to simulate the EV movement, as well as their power requirements.

In section 2 the framework required to enable the EVs charging management in quasi-real-time is described. A description of the methodologies developed to manage the EVs charging is provided in section 3. Section 4 describes the method used to generate the synthetic EV data set. The grid used as case study is described in section 5, together with the description of the studies performed. The main results obtained from the simulations are presented in section 6. Finally, the main conclusions are presented in section 7.

2. EVs Integration Framework

Moving from a "fit-and-forget" policy to an active EV charging management context implies the creation of a suitable technical/commercial framework capable of dealing with the technical aspects of electricity grids and the markets operation.

2.1 Control Structure to Manage EVs in Quasi-Real-Time

Under this new framework, when operating the grid in normal conditions, EVs will be managed by a new entity – the aggregator – whose main functionality will be grouping EVs, according to their owners' willingness, to exploit business opportunities in the markets [12]. If EVs entered the market individually, their visibility would be small and due to their stochastic behavior their participation in the market would be nearly impossible. Yet, if an aggregator exists, then the services potentially provided by EVs would be more significant and the confidence on its availability much higher.

Yet, even considering the EV aggregators' activities, a high degree of uncertainty will still exist related to when and where EVs will charge. Due to these uncertainties, and assuming that grids will evolve towards a decentralized generation paradigm, the existence of a grid monitoring structure, such as the one developed for micro-grids and multi-micro-grids, will be required [15]. This structure will be controlled by the DSO and should be capable of acting over EV charging in abnormal operating conditions, i.e. when the grid is being operated near its technical limits, or in emergency operating modes, e.g. islanded operation [15]. This system should follow a hierarchical structure, from a central Distribution Management System (DMS) down to specific EV controllers to be housed in EV charging points [8].

It is important to stress that the aggregator should always take into account the EV owners' requests, which should provide information about the energy required and connection period via, for instance, the smart metering infrastructure [8]. The aggregator should have a hierarchical structure similar to the grid management architecture used by the DSO, as described in [15], to be capable of communicating and managing EV charging in quasi-real-time. Both technical and market layers will require an advanced communication infrastructure to enable information exchange between all the involved players.

2.2 Charging Levels Considered

There are several types of EV charging solutions being currently adopted, [16], which involve distinct power levels:

1. Level 1 – Around 3 kW that can be obtained through common domestic outlets;
2. Level 2 – 10-20 kW that can only be obtained through dedicated outlet/wiring;
3. Level 3 – More than 40 kW that can only be obtained through dedicated outlet and wiring and using a dedicated off-board charger for DC fast charging.

The charging type classified as slow refers to level 1, while the fast charging refers to level 3. Level 2 is an intermediate level. All the three levels were considered in this work, being assumed that slow charging corresponds to level 1 – LV connections, while fast charging includes level 2 and 3 – Medium Voltage (MV) connections.

Although not considered in this work, there are several studies suggesting that battery swapping can be an effective alternative to battery charging [17 – 22]. According to [23], swapping a battery can take less than 2 minutes while charging in a fast charging station can take up to 30 minutes. Nevertheless, this alternative also has some drawbacks, namely the capital expenditure of building the stations and having sufficient batteries in stock. Better Place filing for bankruptcy shows that this business model may be flawed [24]. Additionally, the need for standardization of battery dimensions, shape and chemistry across different manufacturers is another important issue for battery swapping that remains unsolved.

It should be noted, however, that battery swapping stations will need to absorb power from the grid for charging the batteries in stock. So from the grid point of view, a battery swapping station is not much different from a fast charging station – both are loads. For this reason, battery swapping stations could be easily integrated in the methodologies proposed in this paper, provided that the respective load diagram was available. As the batteries in stock do not have necessarily to be charged at a given time, swapping stations could even be modeled as flexible loads since the power they absorb from the grid can be controlled in order to cope with the needs of the DSO.

2.3 Charging Schemes Considered

Depending on the type of application, EV controllability may vary and, therefore, several control schemes may be adopted. In the solutions involving fast charging (level 2 or 3), a full charge might take less than 1 h [16]. Due to the urgent needs from the user of these types of services, especially level 3 clients, no controllability is envisaged. On the other hand, depending on the EV battery State-of-Charge (SOC) and capacity, full charge solutions involving level 1 might take up to 12 h [16]. In this charging alternative, it is assumed that EV owners can choose between three options: two passive or non-controlled (dumb charging and multiple tariff) and one active or controlled (smart charging), [8].

3. Quasi-Real-Time Management of EVs Charging

3.1 Aggregators´ Management

The main objective of the proposed methodology is to define which smart charging adherents should charge at each time step, in order to minimize the deviations between the energy bought in the market by the aggregators and the energy consumed by EVs. It should be stressed that it was assumed that the power charging rate for level 1, for smart charging adherents, could be controlled between 0 and 3 kW.

To achieve the intended objective, it is required to find a set of n load values, being n the number of smart charging adherents, which can be defined as optimal in the sense that they allow minimizing the deviations referred above.

This problem may be formulated as the optimization problem shown next.

$$min\left|EBA_t - TIEVL_t - \sum_{i=1}^{n} FEVL_t^i\right| \quad \textbf{(1)}$$

Subject to

$$0 \le SOCR_{td}^i - SOC_t^i \le \frac{\left(FEVL_t^i + \left(td-(t+1)\right)\times 3\right)\times\frac{1}{2}\times EV_{ce}}{EV_i^{bc}} \times 100 \quad \textbf{(2)}$$

$$0 \le FEVL_t^i \le 3 \quad \textbf{(3)}$$

$$0 \le SOCR_{td}^i \le 100 \quad \textbf{(4)}$$

$$0 \le SOC_t^i \le 100 \quad \textbf{(5)}$$

$$t + 1 \le td \quad \textbf{(6)}$$

where:

- i represents the "flexible EVs[1]" index;
- t represents the current time index;
- n is the nr. of "flexible EVs" under the aggregator control;
- $\mathrm{EBA_t}$ (Energy Bought by the Aggregator) represents the average power during ½ h, in kW, related with the energy bought in the day-ahead market by the aggregator for time period between *t* and *t+1;* $\mathrm{EBA_t(kW)} = \mathrm{energy\ bought}_{t\to t+1}\ (\mathrm{kWh})/{}^{1}/_{2}\,\mathrm{h}$;
- $\mathrm{TIEVL_t}$ (Total Inflexible EV Load) represents the "inflexible EVs[2]" load, in kW, in time step *t*;
- $\mathrm{FEVL_t^i}$ (Flexible EV Load) represents the power absorbed by "flexible EVs" i, in kW, in time step *t* (the *n* $\mathrm{FEVL_t^i}$ are the decision variables of the optimization problem; they can assume continuous values in the interval [0,3]);
- *td* represents the time step at which a given "flexible EV" will be disconnected from the grid by its owner;
- $\mathrm{SOC_t^i}$ (State-of-Charge) represents the EV *i* battery SOC, in percentage, in time step *t*;
- $\mathrm{SOCR_{td}^i}$ (State-of-Charge Requested) represents the battery SOC required by the owner of EV *i*, in percentage, in time step *td*;
- $\mathrm{EV_i^{bc}}$ represents the battery capacity, in kWh, of EV *i*;
- $\mathrm{EV_{ce}}$ represents the efficiency of the EVs charging process.

Equation (2) is used to assure that the EVs battery SOC, required by the EV owners at the moment of disconnection, is always possible to attain when considering a maximum

[1] "Flexible EV" are the EV whose owners have adhered to the smart charging scheme.
[2] "Inflexible EV" are the EV whose owners adhered to the dumb charging or multiple tariff schemes.

charging rate of 3 kW. The condition implemented in Equation (3) assures that only charging rates between [0,3] kW will be attributed to “flexible EVs”, as it was assumed that a “flexible EV” is a smart charging adherent that is charging either in a residential or industrial area at level 1. Equations (4) and (5) are used to guarantee that the required EV battery SOC and EV battery SOC in the time step t are always within the interval [0,100]%. Equation (6) assures that the time of disconnection always takes place after time step $t+1$.

The objective of this optimization problem is then to minimize the sum of the absolute value of the deviations[3]. It is a linear optimization problem, which is suitable for quasi-real-time applications since it is very fast to solve and does not require any type of forecasted data. It is only needed to know, for the current time step (t), the energy bought by the aggregators, the power consumed by the “inflexible EVs”, the moment of disconnection of the “flexible EVs” that are plugged-in and the energy required by their owners during the connection period. At this stage grid restrictions are not limiting EV charging, since the problem is being dealt only taking into account the market operation.

3.2 DSO Management

After defining which “flexible EVs” should charge and its charging rate at each time step, the grid operating conditions should be analyzed to detect eventual technical problems that may occur. If operational restrictions are violated, the DSO needs to define the amount of load that is required to decrease in order to bring voltages and ratings of branches back to the allowable limits and to define which of the “flexible EVs” should decrease their charging rates in order to achieve the desired load reduction.

[3] There are two types of deviations: positive and negative. In this work, it is assumed that positive deviations are referred to the situations where the energy bough by the aggregators in the market is higher than the EV consumption, whereas negative deviations are referred to the opposite situation.

An effective procedure to tackle these problems was developed for this purpose, which is capable of tackling simultaneously multiple low voltage and lines overloading problems, whether these problems occur in separate feeders or in the same feeder of a given network. Despite only providing near-optimal results, it allows a rapid identification of solutions to solve technical problems in the network (by changing EVs load) with very satisfactory results. This approach is based on a heuristic that comprises two stages:

A. On the first stage all the load data is gathered and, having knowledge of the grid topology and characteristics, a power flow is run to evaluate its operating conditions. Then, a list of problematic buses is identified and these buses are sequentially analyzed. A bus is flagged as problematic if it has a voltage value below V^{min} or if it is located in the upstream end of a branch with a rating above S^{max}. For each problematic bus, the feeder that contains the bus under analysis is selected and the amount of load that is required to decrease in each of the feeder's buses is calculated. This calculation is performed iteratively, by decreasing in fixed value steps, in this case assumed to be 10%, the existing EV load in each of the buses in a feeder. Yet, it should be noted that a different load step decrease can be adopted.

B. On the second stage, the "flexible EVs" that should reduce their charging rates are selected, in order to decrease the amount of power calculated in the first stage. As this methodology was developed for MV and LV networks, considering three-phase balanced operation, the loads resulting from the EV batteries charging were modeled as three-phase balanced loads. Thus, all the "flexible EVs" charging downstream to a feeder that contains problematic buses are eligible to reduce their charging rates. Yet, only "flexible EVs" that are capable of effectively contributing to solve the grid problems identified before may be selected (this depends on their location in the grid).

It should be noted that in a first phase this heuristic process only reduces the charging rates of "flexible EVs", always taking into consideration their owners' requests in what regards the battery SOC required in the moment they will disconnect from the grid. Nevertheless, when low voltage and branch overloading problems are so severe that the emergency operating state is triggered, this heuristic reduces the charging rates of all the EVs located in the problematic areas of the grid, disregarding if they are "flexible EVs" or "inflexible EVs", in order to avoid jeopardizing global system security.

For MV grid studies, the EVs charging at level 1 are assumed to be connected to one of the LV grids that are downstream the MV grid. Yet, as in this simulation the MV grids were modeled up to the MV/LV substation, the loads of the EVs that are connected to a given LV grid are grouped and represented as a single load in the respective MV bus of the substation. When charging at levels 2 or 3, EVs are assumed to be directly connected to the MV grid and thus their load will be allocated to the respective MV bus.

The implementation of this heuristic is illustrated in **Figure 1**. After processing the load data and running a power flow, the buses 31 and 45 are flagged as "problematic buses" and feeder 4 and 5 are flagged as "problematic feeders" (**Figure 1**). The total load that is required to decrease is then calculated (first stage), by simulating that the EVs load in the buses that belong to feeders 4 and 5 is decreased by 10%. After, a power flow is run to verify if the low voltage and lines overloading problems were solved. If so, the total amount of load that is required to decrease in the buses that belong to feeders 4 and 5 is computed. If not, the EVs load in the buses that belong to feeders 4 and 5 continues to be iteratively decreased in steps of 10%, until feasible operating conditions are attained.

After calculating the amount of power that is required to decrease in the buses of the problematic feeders, it is defined which "flexible EVs" should decrease their charging rates to achieve the desired load reduction (second stage). In order to avoid interfering repeatedly with the same EVs charging in buses 31 and 45, as branches overloading and voltages under the allowed limits are problems that usually appear recurrently in the same locations of the grid, all the "flexible EVs" charging in the "problematic feeders" are considered to be eligible to decrease their charging rates in order to solve the network problems. Thus, all the "flexible EVs" charging downstream feeders 4 and 5 are considered to be eligible to decrease their charging rates.

Figure 1: Illustration of the approach used to solve grid technical problems.

The two problems referred above (low voltage and lines overloading) could have been solved using an Optimal Power Flow (OPF)-like method for distribution networks. However, as the resolution of this type of problems is usually very time-consuming, [26], the expeditious approach presented in this section was chosen over the OPF-like option since the latter is rather impractical for quasi-real-time applications, [27].

4. Generation of the Synthetic EV Data Set

The first step to generate the EV data set was to characterize all the EVs assumed to be enclosed in a MV grid used as case study (further details are provided in section 5).

Then, the movement of the EV fleet was simulated for one week according to common traffic patterns (data from a region in the north of Portugal [28] was used). Having the EVs movement defined, their power requirements were computed and the data obtained was used in the case study of section 5.

4.1 Characterization of the EV Fleet

Each EV was initially characterized in terms of battery capacity, charging power, energy consumption and battery SOC in the beginning of the simulation ($t=0$). These values were defined according to truncated Gaussian probability density functions, whose average, standard deviation, maximum and minimum values are shown in **Table 1**. The maximum and minimum values of the functions were introduced in order to avoid unrealistic values for these variables when making the draw for each EV.

While the initial battery SOC values were assumed for the purpose of this work, the remaining values were gathered from the information made available by 42 different EV manufacturers. It was assumed that the efficiency of the charging process was 90%.

Table 1: Truncated Gaussian Distributions for EVs Characterization.

A driver behavior was also assigned to each EV. The behaviors considered in this paper were obtained from a survey made within the framework of the MERGE project [16]. The results revealed that there are three major types of behaviors regarding EV charging: EV charge at the end of the day (57%), EV charge only when it needs (23%) and EV charge whenever possible (20%). For the drivers who charge their EVs only when it needs, it was assumed that the battery SOC that triggers the need for charging was 40%.

4.2 Simulation of the EVs Movement

The movement of the EVs during a week was simulated using a discrete-state, discrete-time Markov chain, as described in [29], to define the states of all the EVs for each time step (in this case with a duration of 30 minutes). It was assumed that, at every unit of time, each EV can be in one of the following states: in movement or parked in residential/commercial/industrial area. After defining the EV states, a network bus location was attributed to parked EVs, according to a probability distribution proportional to the load installed in each bus. For the EVs in movement, a procedure was developed to account their energy consumption and the respective reduction in the battery SOC, as defined in [29].

At each time instant, the battery SOC is updated according to the energy spent in travelling or absorbed from the grid. It was assumed that EVs parked in residential/industrial areas charge at 3 kW (level 1), EVs parked in commercial areas charge at 12 kW (level 2) and the charging power in fast charging stations is 40 kW (level 3). When an EV is parked, the decision to plug it in for charging, or not, is made considering its driver behavior and its current SOC.

4.3 Output Data

The methodology described in sections 4.1 and 4.2 allows obtaining, for the period of one week, the following data: the periods during which EVs are plugged-in and available to charge, the network bus to which EVs are plugged-in, the EVs power absorbed in each 30 min interval, the EVs battery SOC evolution and the EVs travelled distances.

5. Case Study

The single line diagram of the MV grid from a rural area (15 kV) used as test case in this research can be found in [31]. It is composed by residential, industrial and commercial areas, thus allowing tracking each EV while commuting to and from work and to and from leisure activities. The power factor assumed for the conventional load is 0.96, whereas the specified voltage in the feeding point is 1.05 p.u..

There is a total of 7035 conventional cars enclosed in the geographical area covered by this grid and it was assumed that only one fast charging station exists, located in a robust area of the grid (bus 231), not prone to technical limit violations.

In order to perform the simulations, a typical weekly load diagram for this network was used. This diagram, depicted in **Figure 2**, was obtained by aggregating the load diagrams of the different types of consumers within the network. The network has 309 buses, from which 115 have loads connected. The peak load of this network is 7.3 MW (without EVs consumption) and the energy consumption during a typical week is 789 MWh.

Figure 2: Load diagram of a typical week (the pie chart shows the energy consumption per sector).

Regarding the studies performed, three simulations were run, considering all EVs as: smart charging adherents (to evaluate the performance of the approach developed for the EVs charging management performed by the aggregators), dumb chargers, and multiple tariff[4] adherents (to evaluate the performance of the approach developed for the EVs charging management performed by the DSO). For these studies, an EV integration level of 25% was considered (meaning that 1759 EVs were considered to exist in this area). In each simulation two situations are evaluated: the presence and absence of the grid monitoring performed by the DSO. While in the former the DSO might reduce EV load to avoid the violation of the grid components' technical limits, in the latter it is assumed that the DSO never interferes with EV charging. These two situations were evaluated for comparison purposes, with the objective of analyzing the influence that the DSO might have over the EVs charging.

6. Results

6.1 Mobility Patterns

The journeys distribution during a week and a weekend day for the dumb charging, multiple tariff (22h – 8h) and smart charging scenarios are presented in **Figure 3**. As it can be observed, the curves for the three charging strategies follow the same trend. This is, in fact, an expected result, as the same assumptions were used to simulate the EVs movement in all the scenarios addressed (the discrete-time, discrete-state Markov chain

[4] The lower electricity price period assumed was that of the dual tariff policy currently implemented in Portugal: 22h to 8h. More information can be found in: http://www.edpsu.pt/pt/particulares/tarifasehorarios/ (in Portuguese).

described previously). During the week day, three peaks are clearly noticeable in the figure, two most likely related with household – work commuting (around 8h and 18h), and the third, slightly after noon, probably related with people leaving their working places to have lunch somewhere else. In the weekend days, probably due to the absence of the household – work commuting, the journeys are more distributed during the day.

Figure 3: Journeys distribution for the dumb charging, multiple tariff and smart charging scenarios.

In order to provide some insights about the locations where the EVs stay parked during the day, the number of EVs parked in residential, commercial and industrial areas is presented in **Figure 4**. In what regards residential areas, as expected, there is a large number of EVs parked during the night period, both on the week and on the weekend days. During the day, the number of EVs parked in these areas is considerably lower during the week than during the weekend, probably due to the fact of most of the people not working during the weekend. The results are quite different for commercial and industrial areas, where the number of EVs parked reaches the highest values during the day, both on week and weekend days. Nevertheless, while the number of EVs parked in commercial areas reaches almost the same maximum value during all the days of the week, the number of EVs parked in industrial areas is considerably lower during the weekend than during the week.

Figure 4: Nr. of EVs in movement and parked in the smart charging scenario.

Three more charts are presented below, showing the power absorbed by EVs in level 1, 2 and 3 charging facilities in the dumb charging, multiple tariff (22h – 8h) and smart charging scenarios. In the dumb charging scenario, **Figure 5**, the EVs tend to charge at level 1 mostly at the end of the day, which is the time period when people arrive home from work. The amount of power requested by the EVs during these periods would provoke some violations of the voltage limits of several network nodes and, in order to avoid them, the DSO would have to curtail part of the EVs load (dotted blue line).

When the system enters in the emergency operating state, the DSO tries to solve the problems detected only by curtailing load from EVs charging at level 1. Then, if this measure is not enough, the DSO might also curtail load from EVs charging at level 2 (in commercial areas) and at level 3 (in fast charging stations). However, it should be stressed that in the present case, only load from EVs charging at level 1 was curtailed.

Regarding charging at level 2, as expected, the power absorbed by EVs follows the trend of the number of EVs parked in commercial areas, as it can be observed in **Figure 4**.

In the multiple tariff scenario, **Figure 6**, the EVs only charge in level 1 and 2 charging facilities between 22h and 8h, which is the period when the energy prices are assumed to be lower. For this reason, there are a high number of EVs connecting to the grid for charging at 22h and the amount of power requested provokes the violation of the technical limits of several network components. In order to avoid them, as it happened in the dumb charging scenario, the DSO would have to curtail part of the EVs load (dotted blue line).

The results obtained in the smart charging scenario, **Figure 7**, are very similar to those obtained with the dumb charging, namely in what concerns level 2 and 3 power consumption. The only relevant differences are related with the power consumption at level 1, where it is clear a shift of the EVs consumption from the 19h – 24h period to the 2h – 7h period.

Figure 5: Power consumption by EVs in the dumb charging scenario.

Figure 6: Power consumption by EVs in the multiple tariff (22h – 8h) scenario.

Figure 7: Power consumption by EVs in the smart charging scenario.

6.2 Changes in Load Diagrams

Figure 8, **Figure 9** and **Figure 10** show the load diagrams changes for the scenarios simulated, assuming an EV integration of 25%.

As shown in **Figure 8**, with the dumb charging, the EVs tend to charge mostly at the end of the day. The amount of power requested by the EVs causes a very large increase in the peak load, leading to the violation of the technical limits of several grid components. In order to avoid these violations, the DSO would have to override the aggregators' control signals and reduce 25.7 MWh of the energy demanded by EVs during the week (black areas in **Figure 8**). The load reduction is calculated according to the heuristic described in section 3.2[5].

Figure 9 shows the changes in the load diagram for the multiple tariff case. The EVs only charge at level 1 (slow charging) between 22h and 8h, which is the period of time when the energy prices are lower. For this reason, there is a high number of EVs connecting to the grid for charging at 22h and the amount of power requested leads to the violation of the technical limits of several network components. In order to avoid these violations, the DSO would have to reduce 21.1 MWh of the energy demanded by EVs during the week (black areas in **Figure 9**). Again, this value was obtained using the heuristic described in section 3.2. The remaining EVs load that appears outside the period 22h – 8h, is due to EVs charging at level 2 (commercial areas) and at level 3 (fast charging station).

In what regards smart charging, the existence of aggregators was assumed; these are responsible for the EVs charging management in normal operating conditions. Seeking to maximize their profit, the aggregators will try to buy energy in the markets in the periods when its price is lower and manage the "flexible EVs" charging accordingly. For illustration purposes, it was assumed that the energy bought by the aggregators corresponds to the "valley filling" curve represented by the black line in **Figure 10**. The

[5] This heuristic was coded in Python programming language, whereas the power flows were run in the PSS/E software.

“valley filling” curve was obtained in two steps. First, a simulation was run considering all EVs as dumb charging adherents in order to quantify the average amount of load required by EVs during one typical week. Then the total amount of EVs load obtained was distributed through the week in a way that minimizes the sum of the square of the total load in the grid, in each time interval of ½ hour.

On the following day, if deviations between the energy bought by the aggregators (“valley filling” curve) and the energy consumed by EVs are registered, the aggregators will be penalized in the imbalance settlement. Thus, the maximization of the aggregators profit cannot disregard the minimization of the referred deviations. The light grey area in **Figure 10**, referred to as aggregators’ smart charging, shows the results obtained with the “flexible EV” charging management performed by the aggregators. The “flexible EV” charging management was performed according to the optimization problem described in section 3.1[6]. As no technical violations were detected with the smart charging, no EV load reduction was requested by the DSO, meaning that the DSO does not interfere with the aggregators’ profit in this case.

Figure 8: Load diagram in the dumb charging scenario.

Figure 9: Load diagram in the multiple tariff (22h – 8h) scenario.

Figure 10: Load diagram in the smart charging scenario.

6.3 Deviations from the Energy Bought by the Aggregators

The deviations between the energy bought in the markets by the aggregators (black line) and the energy effectively consumed by the EVs (grey line), in the aggregators’ smart charging, are shown in **Figure 11** (dashed black line). When the energy bought by the aggregators is higher than the EVs consumption, it means that no further “flexible EVs” are available for charging and thus the aggregator will have an energy surplus that

[6] This linear optimization problem was solved using the simplex method available in the LINGO 13.0 software. More information can be found in: http://www.lindo.com/index.php?option=com_content&view=article&id=2&Itemid=10

should be sold in the intraday market. Conversely, when the EVs consumption is higher than the energy bought, it means that the availability restrictions imposed by some of the “flexible EVs” exhausted the possibility of the aggregator to postpone further their charging. Thus they will start charging immediately. In these situations the aggregator will have an energy deficit that can be compensated by buying extra energy in the intraday market. It should be noted that these deviations would be greatly reduced if adequate forecasting techniques were used to determine “flexible EV” availability.

Figure 11: Deviations between the energy bought in the markets and the energy consumed by EVs.

6.4 Battery SOC Evolution

In order to exemplify the battery SOC evolution of a smart charging adherent, **Figure 12** describes how the battery SOC is influenced by the charging management performed by the aggregator and by the DSO. **Figure 12** shows three situations: when the EV charging is not controlled, i.e. when the EV behaves as a dumb charging adherent (black line), when the EV charging is only controlled by the aggregator, in normal operating conditions, according to the market negotiations (black dashed line) and when the EV charging is controlled by the DSO under emergency operating conditions. As it can be observed, in the first situation, the EV charging starts immediately after the EV is plugged-in, while in the other situations the charging is postponed according to the needs of the aggregator or the restrictions the DSO has to deal with.

Figure 12: EV battery SOC evolution of a smart charging adherent.

6.5 Voltage Profiles

The highest peak load registered in the iterations performed for each scenario was analyzed, and the corresponding voltage values were plotted in **Figure 13**.

The data presented in **Figure 13** refers to the voltage profile of one feeder (buses downstream bus 107) during one day (the day selected was Wednesday). The top left figure refers to the scenario without EVs, the top right figure to the aggregators' smart charging, the center left figure to the dumb charging without DSO monitoring, the center right figure to the dumb charging with DSO monitoring, the lower left figure to the multiple tariff without DSO monitoring and the lower right figure to the multiple tariff with DSO monitoring.

The extra power demanded by EVs causes a significant voltage drop in this feeder, namely during the periods when the demand is higher, that, as **Figure 13** shows, violate by far the lower limit of 0.90 p.u. (voltage level stipulated by EN 50160 [29]) in the dumb charging (center left) and multiple tariff (lower left). These are the violations that trigger the emergency operating state and that obliges the DSO to reduce some of the EVs load. After running the DSO management algorithm and reducing the EVs load required, the voltages obtained for the dumb charging (center right) and multiple tariff (lower right) do not violate the lower limit specified. The voltage drop is greatly reduced in the aggregators' smart charging (top right), where no violations were detected.

Figure 13: Voltages downstream bus 107.

7. Conclusions

The integration of EVs in distribution networks is expected to impact the management and operation of distribution grids. In order to avoid large capital expenditures in network reinforcements, methods to manage the EVs charging will be required. In this sense, two methodologies were presented in this paper to manage EVs charging in quasi-real-time, one to be used by the EV aggregators and the other by the DSO.

The approach developed for the aggregator proved to be an efficient method to minimize the deviation between the energy bought in the market and the energy consumed by EVs. Even so, some deviations were recorded in the case study analyzed, which would oblige the aggregator to buy or sell the extra energy in the intraday market in order to avoid high penalizations in the imbalance settlement. Nonetheless, as referred previously, these deviations would probably be greatly reduced if adequate forecasting techniques were used to determine the “flexible EVs” availability.

The approach developed for the DSO also proved to be very efficient, since it allowed the performance of the grid monitoring and the management of EVs in order to solve all the voltage problems detected (see **Figure 13**). It should be mentioned that no branch overload was detected in this network, not even in the scenarios with EVs.

Both methodologies are suitable for quasi-real-time applications since they are capable of defining optimal (in the case of the aggregator management presented in section 3.1) or near-optimal (in the case of the DSO management presented in section 3.2) EV charging schedules in a very short period of time. The time needed to run the algorithms in a 3.16 GHz Intel Core 2 Duo CPU with 4.00 GB RAM, for this case (grid with 309 buses and 1759 EVs), was always lower than one minute for the 336 time steps.

For the DSO, the algorithm presented in section 3.2 can be used as a tool to detect the grid components that are subject to the more demanding operating conditions and that might need to be upgraded, to perform the grid monitoring and evaluate its operating conditions and manage the EVs charging in quasi-real-time to mitigate voltage or line overloading problems. For aggregators, the algorithm of section 3.1 can also be very helpful, as it allows defining the optimal bids for the day-ahead markets and managing the EVs charging in quasi-real-time with the purpose of minimizing the deviations between the energy bought in the market and the energy consumed by EVs (when the system is in the normal operating state).

It should be noted that the Markov chain proposed for simulating EV travelling patterns and energy requirement also proved to be efficient in performing a realistic evaluation of the commuting patterns and impacts that may result from the integration of EVs in distribution networks. It is important to notice that the model can be used for both plug-in hybrid and full electric vehicles, as it allows specifying a wide range of characteristics for each vehicle that is considered in the simulation. The proposed tool uses a stochastic method to simulate the EV movement, allowing exploring different scenarios in a coordinated way. This methodology grants the possibility of obtaining detailed knowledge on EV individual daily routes, as well as other global indicators such as the electricity grid impacts provoked by the EV battery charging. It also allows creating prospective EV uptake scenarios, which can be used to plan the future of the transportation sector and of the power distribution systems. Additionally, the accurate quantification of the EV fleet mobility patterns and energy needs can also be used to evaluate the global fleet energy requirements, environmental impacts and recharging infrastructure needs.

Regarding future work, the integration of the V2G mode of operation in the methodology developed for the EV aggregators and the impact that the network management performed by the DSO might have on the aggregators' profit will be addressed.

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Figure Captions

Figure 1: Illustration of the approach used to solve grid technical problems.

Figure 2: Load diagram of a typical week (the pie chart shows the energy consumption per sector).

Figure 3: Journeys distribution for the dumb charging, multiple tariff and smart charging scenarios.

Figure 4: Nr. of EVs in movement and parked in the smart charging scenario.

Figure 5: Power consumption by EVs in the dumb charging scenario.

Figure 6: Power consumption by EVs in the multiple tariff (22h – 8h) scenario.

Figure 7: Power consumption by EVs in the smart charging scenario.

Figure 8: Load diagram in the dumb charging scenario.

Figure 9: Load diagram in the multiple tariff (22h – 8h) scenario.

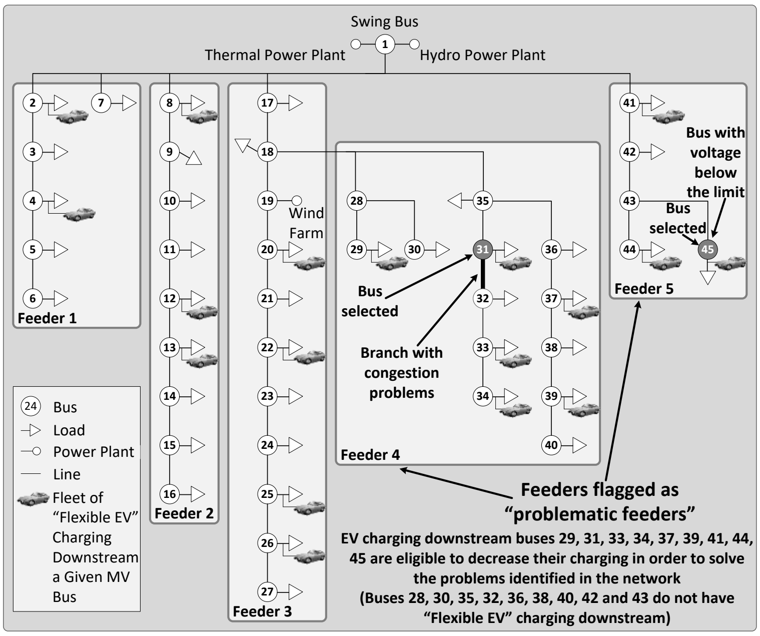
Figure 10: Load diagram in the smart charging scenario.

Figure 11: Deviations between the energy bought in the markets and the energy consumed by the EVs.

Figure 12: EV battery SOC evolution of a smart charging adherent.

Figure 13: Voltages downstream bus 107.

Figures



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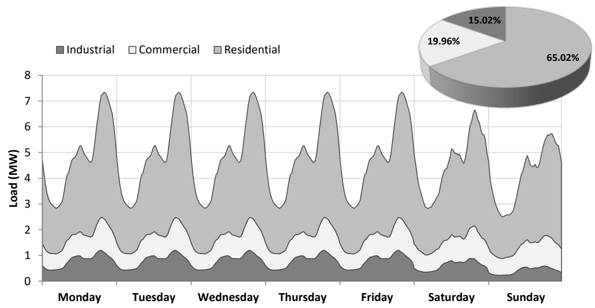


Figure 2: Load diagram of a typical week (the pie chart shows the energy consumption per sector).

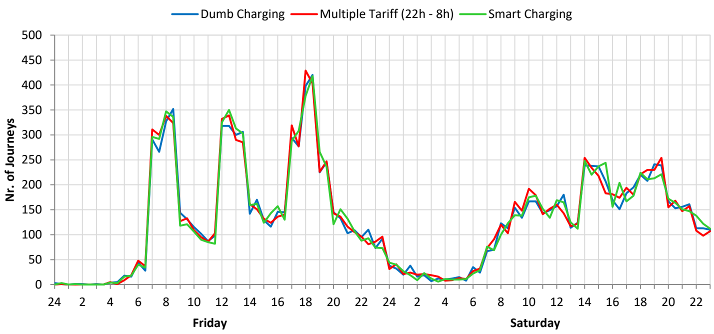


Figure 14: Journeys distribution for the dumb charging, multiple tariff and smart charging scenarios.

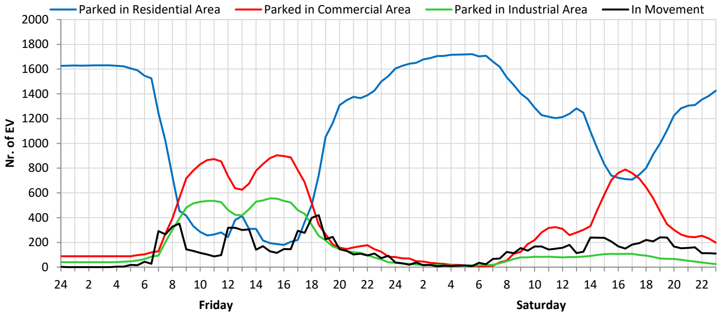


Figure 15: Nr. of EVs in movement and parked in the smart charging scenario.

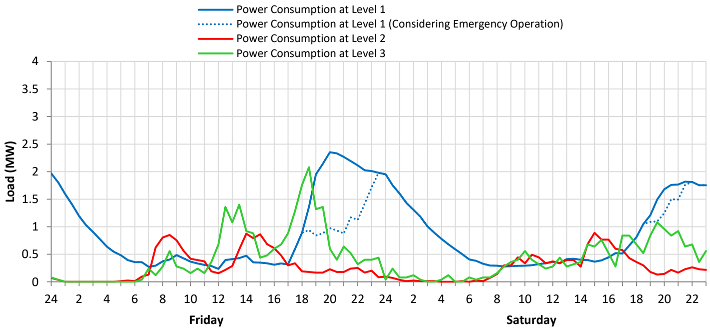


Figure 16: Power consumption by EVs in the dumb charging scenario.

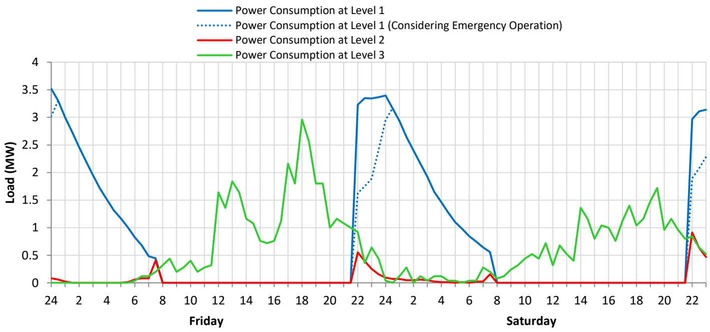
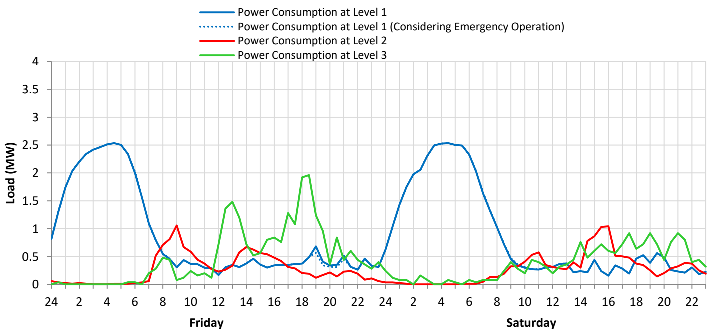


Figure 17: Power consumption by EVs in the multiple tariff (22h – 8h) scenario.



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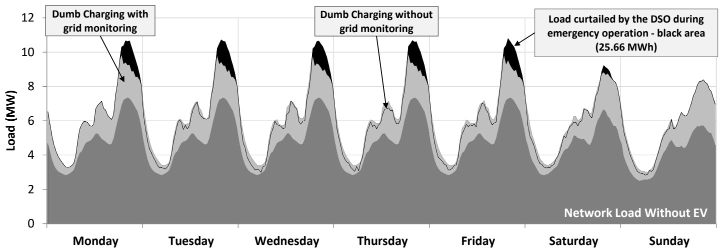

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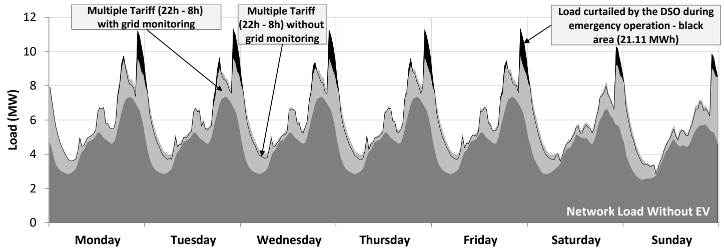
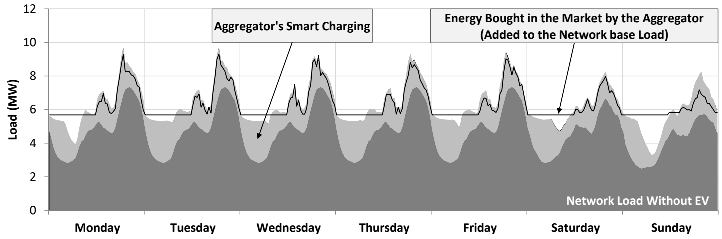


Figure 9: Load diagram in the multiple tariff (22h – 8h) scenario.



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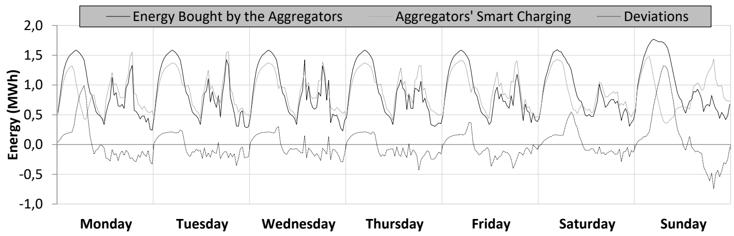

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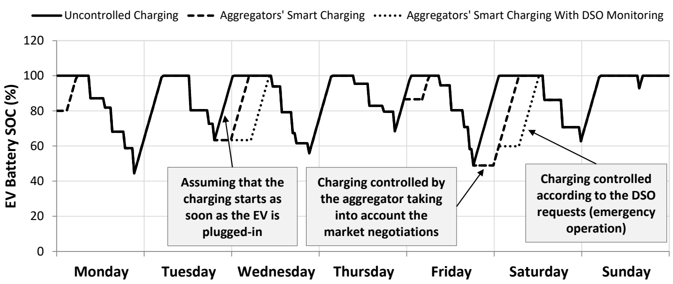

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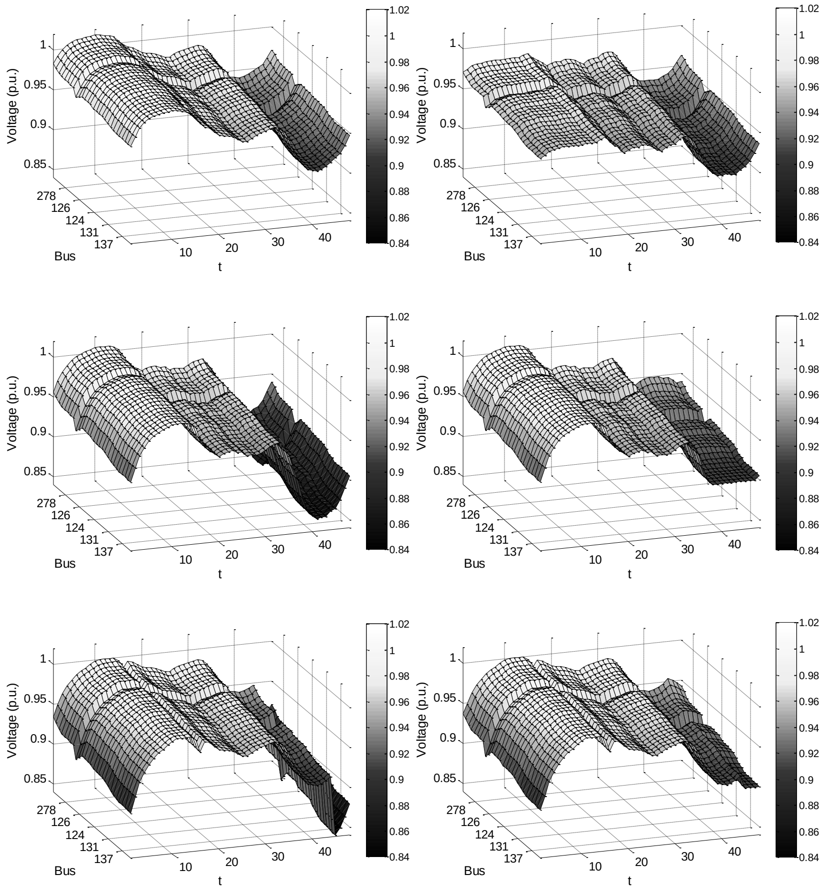

Figure 13: Voltages downstream bus 107.