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Integration of Electric Vehicles into the Power Distribution Network with a Modified Capacity Allocation Mechanism

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Abstract: The growing penetration of electric vehicles (EVs) represents an operational challenge to system operators, mainly at the distribution level by introducing congestion and voltage drop problems. To solve these potential problems, a two-level coordination approach is proposed in this study. An aggregation entity, i.e., an EV virtual power plant (EV-VPP), is used to facilitate the interaction between the distribution system operator (DSO) and EV owners considering the decentralized electricity market structure. In level I, to prevent the line congestion and voltage drop problems, the EV-VPP internally respects the line and voltage constraints when making optimal charging schedules. In level II, to avoid power transformer congestion problems, this paper investigates three different coordination mechanisms, or power transformer capacity allocation mechanisms, between the DSO and the EV-VPPs, considering the case of EVs charging and discharging. The three mechanisms include: (1) a market-based approach; (2) a pro-rata approach; and (3) a newly-proposed constrained market-based approach. A case study considering a 37-bus distribution network and high penetration of electric vehicles is presented to demonstrate the effectiveness of the proposed coordination mechanism, comparing with the existing ones.

Keywords: coordination mechanisms; electric vehicles; network-constrained operation; virtual power plants

1. Introduction

The growing availability of electric and plug-in hybrid electric vehicles (both denoted as EVs in this paper) offered by the most significant car manufactures implies a high penetration of EVs in the near future. Worldwide, more than 300,000 EVs were sold in 2014 [1]. According to [2], EV sales approximately doubled each year since 2010 in Europe. In 2014, around 65,000 EVs were sold in Europe.

However, the integration of EVs in the distribution network may create new challenges to the distribution system operator (DSO), such as congestion situations in the network and in the HV/MV (high voltage/medium voltage) power transformers [3,4]. In addition to electric vehicles, the increasing number of other emerging resources, such as heat pumps, brings more complexity to distribution systems as well. Over the last few years, intelligent EV charge management methods have been proposed in the academic and industrial fields to handle these potential problems, instead of new network investments. In general, a business entity capable of responding to the EV's and DSO's requirements is necessary in nearly all of the proposals. Several terms have been proposed and used concerning the entity including "virtual power plants", "virtual power players", "aggregators", or "fleet operators". These proposed entities have the purpose of coordinating the charge and the discharge processes of the EVs with the goal of optimizing the operation costs and, at the same time, avoiding network problems. In the present paper, the acronym EV-VPP (electric vehicle virtual power plant) is used.

In this study, a two-level coordination approach is proposed to integrate electric vehicles into the power distribution system, with focus on coordination mechanisms used in level II. In level I, to prevent the line congestions and voltage drop problems, the EV-VPP internally respects the line and voltage constraints when making the optimal charging schedules. In level II, to avoid power transformer congestion problems, three different coordination mechanisms of managing the HV/MV power transformer congestion between the DSO and the EV-VPP entities are studied and compared. The three coordination mechanisms include a market-based negotiation mechanism which is previously reported in [5], a pro-rata mechanism [6], and a proposed constrained market-based mechanism which is an evolution of the market-based strategy proposed in [5], taking into account different power transformers limits.

The rest of the paper is organized as follows: the related work is presented in Section 2; Section 3 presents the system architecture; Section 4 shows the proposed methodology for the power transformers' capacity management; Section 5 presents the case study considering a 37-bus distribution network; and, finally the conclusions are presented in Section 6.

2. Related Work

In this section, the related work that aims to help the DSO resolve the potential problems caused by a growing number of electric vehicles is introduced. In Section 2.1, the related work in the academic field is described that focus on reviewing coordination methods, optimization techniques, etc. Section 2.2 describes the related concept, demonstration projects, or start-up firms that focus on market architecture, information flow between the market actors, etc.

2.1. Research in Academic Field

To resolve the challenges, an EV-VPP is proposed to manage the EV charging operation [7]. Typically, two types of methods [8] are used for coordinating the charging schedule of EVs between the DSO and the EV-VPPs; namely, the centralized and the market-based approaches.

In the centralized approach, the DSO defines and sends technical constraints or allocated capacity to EV-VPP agents who use these constraints, defined by the DSO, in their scheduling problem. López et al. [9] proposed a congestion management algorithm based on technical constraints, namely power distribution factors, that determines the amount of energy for a specific EV in order to solve the congestion problem. In [10], a scheduling problem involving EV owners, EV-VPPs, and a DSO is analyzed. The approach requires a complex interaction between the DSO and the EV-VPPs, on each interaction, the EV-VPP obtains a specific grid constraint from the DSO and adds it to the EV charging cost minimization problem. The interaction stops when the grid congestion and voltage problems are solved. The principle of the centralized capacity allocation is similar to the pro-rata approach that was proposed to share the transmission loss [6].

Instead, the market-based approach [5,11,12] is applied to address the congestion problem caused by EVs. In [5], the power transformer congestion is prevented from using the market-based approach. In this approach, the DSO iteratively sends a congestion price to the EV-VPP who will respond to the congestion price with an updated charging schedule, the DSO updates the congestion price until convergence. In [11], the methods aim to achieve valley filling by iteratively altering the price information to the EV owners. The EV owners respond to the price sent out by the DSO and resubmit their charging schedule to the DSO. After certain iterations, the methods [11] reach a flat power profile. A similar approach is also reported in [12] where the method is implemented in a decentralized way. The EV owners take the responsibility of constructing the charging schedules, while the charging location manager or EV-VPP deals with the network congestion issues. By exchanging limited information, the method assures that all vehicles can follow their planned trajectories and that power constraints on each car park are always met. Compared to [11], the study [12] removed the assumption on homogeneity, such as allowing varied states-of-charge of EV batteries, maximum charge rates, etc.

However, both type of methods have drawbacks; the introduced market-based approach, in general, brings high congestion prices. As indicated in [13], it might bring oscillations if congestion prices are not properly defined, while the centralized approach leads power transformers loaded to full capacity. Note that distribution transformers are generally not recommended for continuous overloading, even though overloading for a short duration cannot be avoided. In case of overloading, the additional loss generates more heat, which effects the burning of winding insulation, causing reduced lifetime and ultimate failure of the transformer [14]. To overcome these drawbacks, this paper proposes an integrated mechanism that can reduce the congestion prices, as well as improve the power transformer operational condition. Additionally, this study also solves the voltage problem, as well at the first level, which is not the case in previous studies [5,9–13].

Before elaborating on this mechanism, the following section introduces the actors proposed in some new market architecture proposals, which provides important context for this study.

2.2. Solutions from Industrial Field and Demonstration Projects

2.2.1. The Flexibility Clearing House Concept Developed in the Danish Smart Grid Project

FLECH (flexibility clear house) is a platform developed in the Danish smart grid project iPower for trading ancillary services between DSOs and VPPs who manage aggregated distributed energy resources (DERs) [15]. It is designed to facilitate the interactions between DSOs and VPPs across multiple stages from the auctioning of the flexibility contracts to the final settlement. In the FLECH vision, five types of services for load management and two types of services for voltage management are identified. An auction-based method is used in FLECH to find the service balance between DSOs and VPPs, which falls into a market-based approach. In FLECH, the DSO identifies needs and tenders the services to FLECH, which will be announced by FLECH to all VPPs registered in the area. The VPPs bid into the FLECH regarding the flexibility. After gate closure their bids are forwarded to the DSO, which evaluates the offers and decides which bids to accept.

2.2.2. The Universal Smart Energy Framework Developed in the Netherlands

USEF (universal smart energy framework) [16] is a framework developed by the USEF foundation that aims to use the demand-side flexibility to address the problems at different levels, such as the localized peak load issue in distribution network and the system-wide balancing problem. Similar to FLECH, USEF's operation scheme distinguishes four phases: plan, validate, operate, and settle. The service agreements between VPPs and system operators are made in the plan and validate phase using a market-based control mechanism. In the validation phase, the DSO determines whether the forecasted energy demand and supply of VPP can be safely distributed without limitations. If the prognosis predicts congestion, the DSO may procure flexibility from the VPP to resolve it. It is noted in [16] that multiple iterations between the plan and validation phase might be needed and these iterations continue until all the forecasted energy can be safely distributed without limitations.

2.2.3. Fenix Project

The FENIX (Flexible Electricity Network to Integrate the eXpected energy evolution) project [17] proposes different roles for virtual power plants that were divided according to technical and economic aspects. This division leads to different players namely the technical VPP (TVPP) and the commercial VPP (CVPP) [17,18]. The TVPP should use the DER information "in conjunction with detailed network information e.g. topology, network constraints etc., to characterize the contribution of the distribution network (and associated generation and loads) at the point of connection to the transmission system". The CVPP intends to negotiate the energy/capacity available in the DER units in the markets that enable them to become visible by market operators. The CVPP can represent several TVPPs in the electricity markets. After the market clearing, the CVPPs send the results to the TVPPs. The TVPPs should optimize the power flows on their network, taking into account the market results and the new forecast data for generation and consumption and the new incident events. In case of congestion in its network, the TVPP should reschedule their aggregated DER and inform the system operator concerning the situation. The system operator is responsible for the system balance and for the coordination between the TVPPs and other generators to avoid critical situations [19].

By reviewing the latest congestion management strategies developed in European smart grid projects that involves both academies and industries [16–19], it is summarized that VPP is an important actor to achieve the massive rollout of distributed energy resources, although the role and functions of the VPP might differ a bit in each solution. Another observation is that the detailed coordination mechanisms between the DSO and VPP needs further investigation, which will be addressed in Section 4.

3. System Architecture for Integrating Distributed Energy Resources

The proposed system architecture is shown in Figure 1 that considers a two-level control to integrate distributed energy resources, with focus on electric vehicles. The DSO is the entity responsible for the coordination between the EV-VPPs assuring the function of the distribution network in their operational limits. The DSO can also assure the technical management of parts of the distribution network. The EV-VPP aggregates the DERs with the goal of optimizing the joint schedule of these resources, as well as ensuring the security of the thermal limits of lines and the bus voltage inside its operational area. In the lower layer, the DER players (mainly EVs in this study) are responsible for the management of their resources according to the contracts established with the EV-VPPs. Note that the role of the EV-VPPs assumed here share the similar functionality with the TVPP studied in the Fenix project. Furthermore, the role of the EV-VPP assumed here is in line of the European Commission vision for the VPP framework [20]. In [21], it is mentioned that the VPPs can aggregate several resources and microgrids in a hierarchical control scheme. However, VPPs should coordinate their operation actions with power system operators in any case, such as the DSO in this study. This means that the methodologies studied in this paper can be used by other type of aggregators which manage other types of resources, like the distributed generators or the energy storage systems.

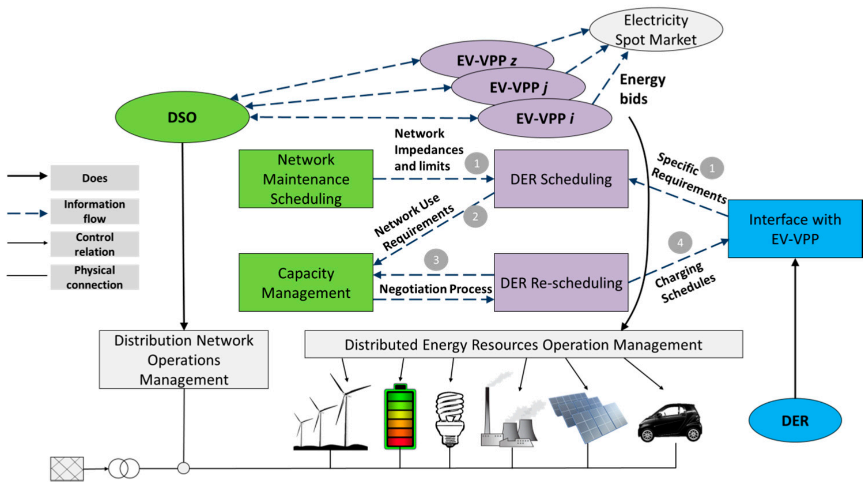

Figure 1. Illustration of the control system with hierarchical architecture for future power distribution network management.

3.1. Operation of the Distributed System Operator

The distribution network normally has the capacity of accommodating all of the connected loads considering the consumption evolution over the next couple of years. To prevent expected congestions, the DSO provides information regarding the network characteristics, namely the impedance matrix and the technical limits of each line and each bus to all EV-VPPs in EV-VPPs' corresponding area. Note that, in this study, there is only one EV-VPP per distribution grid feeder. The network topology does not change every day. However, the DSO can have some maintenance activities scheduled during the day, or can change the network thermal limits according the weather conditions. EV-VPPs use this information to schedule the EVs charge/discharge.

After the EV-VPPs obtain their schedules at level I and communicate the results to the DSO, the DSO should evaluate the use of the HV/MV power transformers in all periods. If the amount of energy required by the EV-VPP is higher than the power transformer capacity, the DSO should adopt a coordination mechanism to mitigate the congestion at level II. The coordination mechanisms are described in Section 4.

3.2. Operation of the EV-VPP

The EV-VPP coordinates the charge and discharge processes of the aggregated electric vehicles. The main goal is to charge during the periods with low energy prices and to discharge energy in periods of high-energy prices. Meanwhile, each EV-VPP considers the technical constraints of the network inside the corresponding distribution network area in the optimization problem, namely thermal limits of lines and bus voltage limits to avoid technical violations inside the medium voltage distribution network. Regarding consumers' other demands, a passive consumer behavior is considered (fixed demand). The energy resources scheduling optimization formulation for each EV-VPP in level I is presented as follows:

$$\min Z = \sum_{t=1}^{T} \left(\begin{array}{l} \sum\limits_{V2G=1}^{N_{V2G}} P_{Ch(V2G,t)} \times \left(c_{Market(t)} + c_{Cong(t)} \right) + \\ \sum\limits_{V2G=1}^{N_{V2G}} P_{Dch(V2G,t)} \times c_{Dch(t)} + \sum\limits_{l=1}^{N_l} P_{NSD(l,t)} \times Penal_{NSD(l,t)} \end{array} \right) \tag{1}$$

Subject to

$$\begin{array}{l} P^i_{SP(t)} + \sum\limits_{V2G=1}^{N^i_{V2G}} \left(P^i_{Dch(V2G,t)} - P^i_{Ch(V2G,t)} \right) - \sum\limits_{l=1}^{N^i_l} \left(P^i_{Load(l,t)} - P^i_{NSD(l,t)} \right) = \\ G_{ii} V^2_{i(t)} + V_{i(t)} \sum\limits_{j \in L^i} V_{j(t)} \left(G_{ij} \cos\theta_{ij(t)} + B_{ij} \sin\theta_{ij(t)} \right) \\ \forall t \in \{1, ..., T\};\ \forall i \in \{1, ..., N_B\};\ \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)} \end{array} \tag{2}$$

$$\begin{array}{l} Q^i_{CAP(t)} - \sum\limits_{l=1}^{N^i_l} \left(Q^i_{Load(l,t)} - Q^i_{NSD(l,t)} \right) = \\ V_{i(t)} \sum\limits_{j \in L^i} V_{j(t)} \left(G_{ij} \sin\theta_{ij(t)} - B_{ij} \cos\theta_{ij(t)} \right) - B_{ii} V^2_{i(t)} \\ \forall t \in \{1, ..., T\};\ \forall i \in \{1, ..., N_B\};\ \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)} \end{array} \tag{3}$$

$$\begin{array}{l} \left| \overline{V_{i(t)}} \times \left[Y_{ij} \times \overline{V_{ij(t)}} + Y_{sh\_i} \times \overline{V_{i(t)}} \right]^* \right| \leq S^{max}_{Lk} \\ \left| \overline{V_{j(t)}} \times \left[Y_{ij} \times \overline{V_{ji(t)}} + Y_{sh\_j} \times \overline{V_{j(t)}} \right]^* \right| \leq S^{max}_{Lk} \\ \forall t \in \{1, ..., T\};\ \forall i, j \in \{1, ..., N_B\};\ i \neq j;\ \forall k \in \{1, ..., N_K\} \\ \overline{V_{ij(t)}} = \overline{V_{i(t)}} - \overline{V_{j(t)}} \end{array} \tag{4}$$

$$V^i_{Min} \leq V_{i(t)} \leq V^i_{Max} \tag{5}$$

$$P_{SP(t)} \leq P_{Max\_Alloc(t)} \tag{6}$$

$$Q_{CAP(t)} \leq Q_{Max} \tag{7}$$

$$E_{Stored(V2G,t)} = E_{Stored(V2G,t-1)} - E_{Trip(V2G,t)} + \eta_{c(V2G)} \times P_{Ch(V2G,t)} - \frac{1}{\eta_{dc(V2G)}} \times P_{Dch(V2G,t)} \tag{8}$$

$$E_{BatMin(V2G,t)} \leq E_{Stored(V2G,t)} \leq E_{BatMax(V2G,t)} \tag{9}$$

$$P_{Ch(V2G,t)} \leq P_{Max(V2G,t)} \times X_{Ch(V2G,t)} \tag{10}$$

$$P_{Dch(V2G,t)} \leq P_{Max(V2G,t)} \times X_{Dch(V2G,t)} \tag{11}$$

$$X_{Ch(V2G,t)} + X_{Dch(V2G,t)} \leq 1 \tag{12}$$

In order to minimize the EVs operation cost (Equation (1)), the EV-VPPs consider the price of the energy supplied by external suppliers, i.e., the day-ahead market prices $\left(c_{Market(t)}\right)$ and the congestion prices $\left(c_{Cong(t)}\right)$ defined by the DSO to be multiplied by the scheduled charge power of EVs $\left(P_{Ch(V2G,\ t)}\right)$. In [22], an optimization formulation considering other type of DERs is presented that can replace the proposed one. Regarding the scheduled EVs discharge power defined by $P_{Dch(V2G,t\ )}$, the EV-VPPs will establish contracts with the EVs' owners in order to define the remuneration of this service of providing power to the grid. To the EV-VPP, the use of EVs' discharge represents a cost $\left(c_{Dch(t)}\right)$ and this cost should be higher than the EV's batteries' degradation cost. For example, the degradation cost can be obtained using the methods proposed in [23]. Considering the example presented in [24] for a lithium iron phosphate battery (LiFePO4), the degradation factor (V2GDeg) is -2.71×10^{-5}; the replacement cost for a 16 kWh battery pack is around \$5000 USD, leading to a degradation cost of 0.042 \$/kWh. To increase the robustness of the solution, the objective function includes a penalization factor $\left(Penal_{NSD(l,\ t)}\right)$ to the non-supplied demand $\left(P_{NSD(l,t)}\right)$. This penalization factor is necessary to deal with situations when the consumers' demand (not considering the electric vehicles) is higher than the power transformers capacity.

The problem constraints take into account an AC power flow model [25] for determining the active (Equation (2)) and reactive (Equation (3)) power that flows in each line of the distribution network, the power losses, and the voltage magnitude and angle in each bus. Equation (2) establishes an equality constraint between the active power that is injected in bus i and the active power generation minus the active power demand in the same bus. The active power generation is the sum of the active power supplied by the external suppliers $\left(P^i_{SP(t)}\right)$, and of the active power discharge from EVs $\left(P^i_{Dch(V2G,\ t)}\right)$. The active power demand is determined by the sum of the consumers' active load consumption $\left(P^i_{Load(l,\ t)}\right)$ and the EV's battery charging $\left(P^i_{Ch(V2G,\ t)}\right)$. The reactive power equality (Equation (3)) considers the reactive power injected and consumed in bus i. The capacitor banks are scheduled to supply the reactive power generation $\left(Q^i_{CAP(t)}\right)$ to match the reactive power of consumers $\left(Q^i_{Load(l,\ t)}\right)$. Moreover, the power flow is lower or equal to the line thermal limit defined by Equation (4). This method avoids possible congestion problems regarding this issue. Finally, the voltage magnitude in each bus $\left(V_{i(t)}\right)$ is under upper and lower bounds, as formulated by Equation (5).

The power supplied by the external suppliers to each EV-VPP depends of the established contracts, but also on the power transformer capacity. The proposed methodology assumes that the EV-VPPs can participate in the electricity markets and buy all of the required energy. Concerning the power transformer use, the DSO should inform the EV-VPPs about the capacity allocated $\left(P_{Max\_Alloc(t)}\right)$ to each one. This capacity depends on the capacity management mechanism described in Section 4 and can be different in each period. Thus, the constraint in Equation (6) defines that the power supplied by the external suppliers to each EV-VPP $\left(P_{SP(t)}\right)$ must be lower or equal to the capacity allocated $\left(P_{Max\_Alloc(t)}\right)$. The reactive power generation $\left(Q_{CAP(t)}\right)$ is limited by the capacitor bank capacity (Q_{Max}) connected at the medium-voltage side of the substation Equation (7).

Regarding the EVs, the energy stored in the batteries at each period is included as an equality constraint in Equation (8). The hourly balance of batteries considers the initial status $\left(E_{Stored(V2G,t-1)}\right)$ and the energy required to the travels during period t $\left(E_{Trip(V2G,t)}\right)$. The EV owner [26] can send this trip consumption to the EV-VPP, or it can be obtained by using a forecast tool [27] to predict the EV owner's behavior. The charging $\left(\eta_{c(V2G)}\right)$ and discharging $\left(\eta_{dc(V2G)}\right)$ efficiency of the battery are also considered.

The energy stored in the battery requires a maximum $\left(E_{BatMax(V2G,\,t)}\right)$ and minimum limit $\left(E_{BatMin(V2G,\,t)}\right)$ of energy in all optimization periods (Equation (9)). The EV-VPP and the EV users need to use an adequate communication system to exchange information about the minimum energy stored in the battery and in which period that energy must be guaranteed [28]. Moreover, the charge/discharge rates are limited by their own maximum limits in Equations (10) and (11), respectively. Finally, the constraint in Equation (12), with two binary variables, is included to avoid that charge $\left(X_{Ch(V2G,\,t)}\right)$ and discharge $\left(X_{Dch(V2G,\,t)}\right)$ happens in the same period. The present methodology is developed for the MV distribution network and a balanced three-phase system is assumed. The decision variables of this optimization problem in Equations (1)–(12) are the charge and discharge power of EVs ($P_{Ch(V2G,\,t)}$ and $P_{Dch(V2G,t)}$) and the power supplied by external suppliers ($P_{SP(t)}$).

After solving the optimization problem, the EVs charge and discharge scheduling of each EV-VPP should be informed to the DSO. If a HV/MV power transformer congestion situation occurs in some periods, the DSO should define a congestion price $\left(c_{Cong(t)}\right)$ or a new power supply limit $\left(P_{Max\_Alloc(t)}\right)$ to the EV-VPP at level II. In this case, the EV-VPP should re-execute the optimization algorithm considering the new information provided by the DSO. This sequence can be executed more than one iteration until all of the congestion situations are solved. When all of the congestion situations are solved, the EV-VPP should communicate the final scheduling to the EVs.

3.3. Operation of EV Owner

In the proposed approach, the EVs owner should define the requirements regarding the expected use of energy for daily trips. The EV's owner should also provide the periods and the locations where the EVs will be connected during the day. In order to avoid inconveniences of range anxiety caused by the low energy in the EV's batteries, the users can impose some minimum limits in some periods of the day. Normally, these values should be higher than a minimum defined by the batteries' manufacturers to avoid fast degradation [24]. Concerning the possibility of discharging energy, the EVs owner should consider predefined contracts with the EV-VPP allowing the discharge through an established reward. Note that an automatic controller or agent could facilitate the operation of the EV owner. Then, the EV owner's trip requirement is represented by the parameter $E_{Trip(V2G,t)}$ in constraint Equation (8).

4. Capacity Management Coordination Mechanisms between DSO and EV-VPP

At level II, the DSO can adopt different mechanisms to manage the congestion of the HV/MV power transformer. Three different coordination mechanisms are investigated in this study, namely, (1) the market-based negotiation method; (2) the power transformer pro-rata use limit; and (3) the constrained market-based (CMB) control mechanisms using congestion prices and power transformer use limits. Figure 2 presents a detailed flowchart of the implemented process for the 'capacity management' block in Figure 1. In the first step, each EV-VPP does the scheduling considering the congestion price as zero and the power transformer capacity as their maximum value. Each EV-VPP sends their power demand requirements to the DSO. In this stage, the DSO should evaluate the power transformer's use and verify the congestion conditions. In the case of a congestion situation, the DSO should determine the congestion price or the power transformer limits for each EV-VPP according the adopted mechanism.

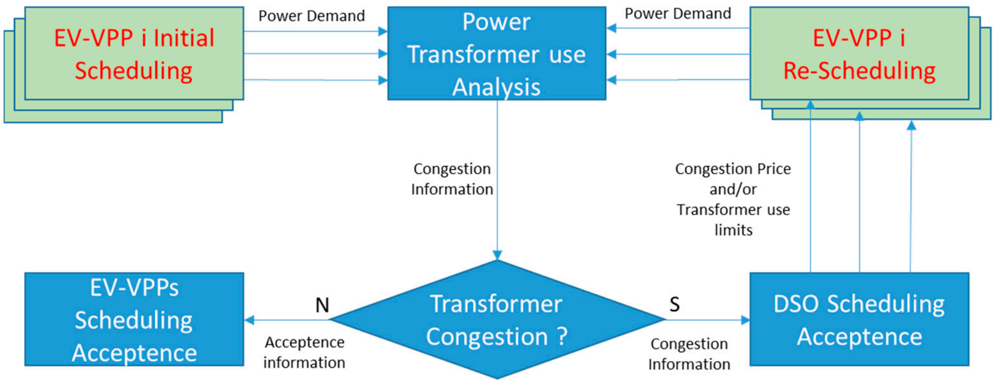

Figure 2. Flowchart of HV/MV power transformer congestion management.

Comparing the three mechanisms, it is possible to say that with the pro-rata mechanism no economical parameter is included. A power limitation is imposed to all EV-VPPs independently of their flexibility to change their initial scheduling (represented by variable $P_{SP\_original(VPP,t)}$). In the constrained market-based mechanism, the DSO imposes some limits in the power use to each EV-VPP, but also introduces a price-signal, like in the market-based mechanism. The main advantage of this mechanism is that it relies on the imposed power limits that are less strict than the pro-rata mechanism and the price signals are lower than the market-based mechanism. This mechanism can be seen as a middle-term (or compromise) solution between the other two mechanisms. This means that the EV-VPP has more flexibility to change its initial scheduling compared to the pro-rata mechanism and, consequently, will be penalized less due to the smaller price signals introduced by the constrained market-based mechanism.

4.1. Market-Based Mechanism

The market-based mechanism is a paradigm for controlling complex systems with conflicting resources [29]. It includes the features found in a market, such as decentralized decision-making and interacting agents. Normally, two-way communication is required. For this study, it means that the DSO will interact with the EV-VPP to exchange the power requirements (EV-VPP sends information about the power demand to the DSO) and price information (DSO sends the price to alter the power schedule of the EV-VPPs).

To formulate such a coordination mechanism, different approaches can be applied to find the equilibrium, such as the uniform price auction mechanism or the shadow price-based penalizing mechanism. In this study, the shadow price-based penalizing mechanism proposed in [5] is applied to solve the power transformer capacity allocation problem. Firstly, a quadratic cost function, Equation (13), is constructed for the EV-VPP to characterize the cost of deviating from the original power schedules:

$$c_{Cong(t)} = u_{(VPP,t)} \times \left(P_{SP\_new(VPP,t)} - P_{SP\_original(VPP,t)}\right)^2 \tag{13}$$

where, $P_{SP\_original(VPP,t)}$ and $P_{SP\_new(VPP,t)}$ are the initial and new power supplied by external suppliers to each EV-VPP, respectively. $u_{(VPP,t)}$ corresponds to the cost coefficient associated with the power difference between the initial and new power scheduling.

The objective is to minimize the cost Equation (14) of all of the EV-VPPs, as well as respect the constraint from the DSO:

$$\min \mathrm{W} = \sum_{VPP=1}^{N_{VPP}} \sum_{t=1}^{T} u_{(VPP,t)} \times \left(P_{SP\_new(VPP,t)} - P_{SP\_original(VPP,t)} \right)^2 \tag{14}$$

subject to:

$$\sum_{VPP=1}^{N_{VPP}} P_{SP\_new(VPP,t)} \leq P_{Transf} \tag{15}$$

where, P_{Transf} corresponds to power transformer capacity.

This is a convex optimization problem, which can be solved by introducing Lagrange multipliers, or shadow prices $\Lambda_{(t)} \in R^T$. The above optimization problem is transferred into a Lagrange-based problem:

$$\begin{aligned} \mathrm{L} = \sum_{VPP=1}^{N_{VPP}} \sum_{t=1}^{T} u_{(VPP,t)} \times \left(P_{SP\_new(VPP,t)} - P_{SP\_original(VPP,t)} \right)^2 \\ + \Lambda_{(t)} \times \left(\sum_{VPP=1}^{N_{VPP}} P_{SP\_new(VPP,t)} - P_{Transf} \right) \end{aligned} \tag{16}$$

To solve the optimization problem, this study uses a numerically iterative method, which also emulates the market negotiation behavior of the DSO and the EV-VPPs:

Step 1: DSO defines a value for $\Lambda_{(t)}$, e.g., $\Lambda^{*\omega}_{(t)}$ in the first step. Given the known $\Lambda^{*\omega}_{(t)}$, the problem L is decomposable for each EV-VPP.

Step 2: A new optimal charging schedule $P^*_{SP\_new(VPP,t)}$ of each EV-VPP is calculated by solving the following optimization problem, with the given $\Lambda^{*\omega}_{(t)}$:

$$\min u_{vpp,t} \left(P_{SP\_new(VPP,t)} - P_{SP\_original(VPP,t)} \right)^2 + \Lambda^{*\omega}_{(t)} \times P_{SP\_new(VPP,t)} \tag{17}$$

Step 3: After receiving the new schedules from EV-VPPs, DSO updates the shadow price to change the charging schedule of EV-VPPs and the updating method is presented in the following formula:

$$\Lambda^{*\omega+1}_{(t)} = \Lambda^{*\omega}_{(t)} + \alpha_\omega \left(\sum_{VPP=1}^{N_{VPP}} P^*_{SP\_new(VPP,t)} - P_{Transf} \right) \tag{18}$$

Step 4: Repeating the process in step 2 and step 3, the price is defined as the new congestion price when it converges. The new congestion price $\mathrm{c}_{\mathrm{Cong(t)}}$ will be reused by the EV-VPP in Equations (1)–(12) to reschedule the EVs' energy plan.

The decision variable of this market-based mechanism is the new power supplied by external suppliers, which is represented by $P_{SP\_new(VPP,t)}$.

4.2. HV/MV Power Transformer Pro-Rata Mechanism

In this mechanism, the DSO imposes limits to the HV/MV power transformers which defines the maximum active power that each EV-VPP can use. A pro-rata approach [6] (or proportionate allocation) assigns an amount of a fraction, according to its share of the whole. In the initial scheduling, the EV-VPP agents assume that it is possible to use all of the power capacity available in the power transformer. After receiving the initial scheduling from all EV-VPP agents, the DSO agent analyses if a congestion situation occurs in some period. If there is no congestion, the DSO accepts the EV-VPP agent scheduling. In the case of congestion, the DSO should impose HV/MV power transformer use limits for each EV-VPP $\left(P_{Max\_Alloc(VPP,t)}\right)$ considering the initial power requirements for each EV-VPP $\left(P_{SP\_original(VPP,t)}\right)$:

$$P_{Max\_Alloc(VPP,t)} = P_{SP\_original(VPP,t)} \times \frac{P_{Transf}}{\sum\limits_{VPP=1}^{N_{VPP}} P_{SP\_original(VPP,t)}} \tag{19}$$

The new capacity $P_{Max\_Alloc(VPP,\,t)}$ will be reused by the EV-VPP in Equations (1)–(12) to reschedule the EVs' energy plan.

4.3. Constrained Market-Based Negotiation Mechanism

In this mechanism, the DSO imposes limits on the use of the HV/MV power transformers and imposes congestion prices at the same time. The method can be seen as a combination of the previous described strategies. However, some variations have been introduced to both methods. The main goal is to overcome the drawbacks of the previous methods, meaning that the constrained market-based negotiation mechanism has smaller congestion prices than the market-based mechanism and is more flexible than the pro-rata mechanism because it imposes more relaxed limits on the power transformer use for each EV-VPP in terms of power transformer limits. Each EV-VPP has different price sensitivity according to the demand flexibility, which is related to the number of electric vehicles. With the proposed mechanism, in the first step, a power transformer use limit $\left(P_{Max\_Aloc(VPP,t)}\right)$ is determined for each EV-VPP according to Equation (20):

$$P_{Max\_Alloc(VPP,t)} = \frac{P_{SP\_original(VPP,t)}}{\omega} \times \left((\omega - 1) + \frac{P_{Transf}}{\sum\limits_{VPP=1}^{N_{VPP}} P_{SP\_original(VPP,t)}}\right), \forall \omega \geq 1 \tag{20}$$

The main difference with respect to the pro-rata mechanism is the introduction of the ω parameter. This parameter allows defining different limits in the power transformer use. If $\omega = 1$, the power transformer use limitations are the same of pro-rata mechanism defined in Equation (19). However, if $\omega > 1$, less strict power limitations are imposed to the EV-VPPs, representing more flexibility for each EV-VPP. When $\omega = \infty$, no power limitation is imposed to the EV-VPPs. Figure 3 presents the impact of ω in the proposed mechanism.

In fact, the DSO expects, like in the market-based approach, that the EV-VPPs change their scheduling not only because of the power limits, but also because of the increasing congestion prices. In a simple comparison, the market-based mechanism only uses the congestion price to solve the congestion problem, in the pro-rata mechanism, a fixed power limit is imposed to solve the congestion problem, while in the proposed mechanism, an integration of the congestion price and power limit is used.

In the second step, a congestion price $\left(c_{Cong(t)}\right)$ is determined using a similar approach as the one described in Section 4.1. The main difference is introduced in Equations (15) and (16) with the inclusion of the value determined in Equation (20). In this sense, in the proposed method, Equations (15) and (16) should be replaced by Equations (21) and (22), respectively. Considering that $\left(\sum_{VPP=1}^{N_{VPP}} P_{Max\_Alloc(VPP,t)}\right)$ is higher than the P_{Transf}, the resulted congestion cost will be lower.

$$\sum_{VPP=1}^{N_{VPP}} P_{SP\_new(VPP,t)} \leq \sum_{VPP=1}^{N_{VPP}} P_{Max\_Alloc(VPP,t)} \tag{21}$$

$$\mathrm{L} = \sum_{VPP=1}^{N_{VPP}} \sum_{t=1}^{T} u_{(VPP,t)} \times \left(P_{SP\_new(VPP,t)} - P_{SP\_original(VPP,t)}\right)^2 + \Lambda_{(t)} \times \left(\sum_{VPP=1}^{N_{VPP}} P_{SP\_new(VPP,t)} - \sum_{VPP=1}^{N_{VPP}} P_{Max\_Alloc(VPP,t)}\right) \tag{22}$$

Like the market-based mechanism, the decision variable of this proposed mechanism is $P_{SP\_new(VPP,t)}$.

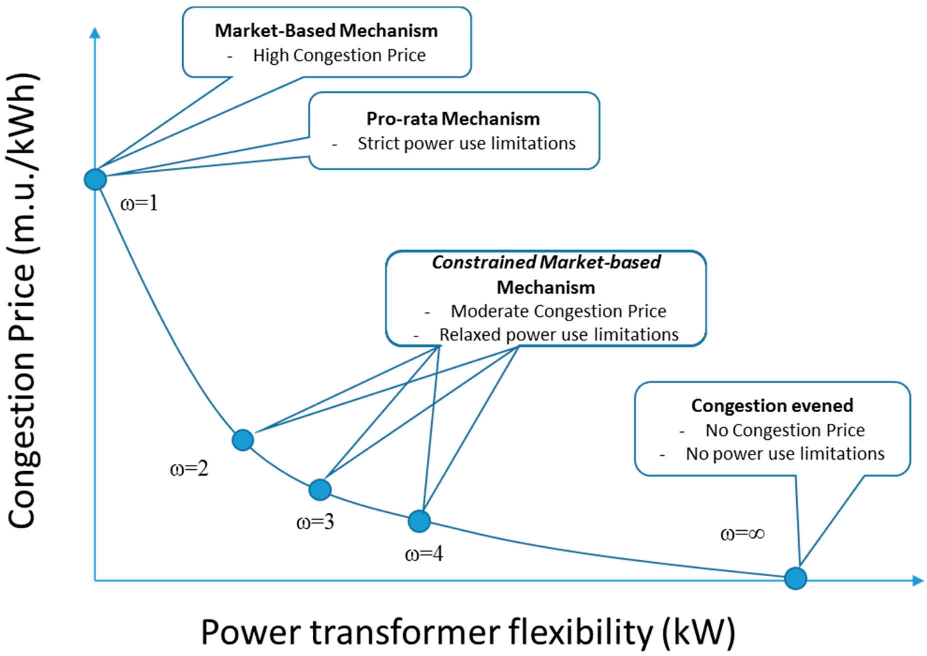

Figure 3. Impact of ω in the proposed constrained market-based mechanism.

5. Simulation Results

This section presents a case study considering the distribution network presented in [30] and shown in Figure 4. The distribution network is composed by 37 buses, connected to the high-voltage network through two 10 MVA power transformers. The distribution network supplies energy to 1908 consumers: 1850 domestic consumers (DM), two industries (Ind), 50 commerce-oriented stores (Co), and six service buildings (SB) [31]. Regarding EVs, a penetration of around 50% of the total number of vehicles is assumed, i.e., 1053 EVs. Table 1 shows the number of EVs and the number of each type of consumer for every EV-VPP. The EVs' characteristics were determined based on the characteristics of some real models and driving patterns presented in [32]. The study assumes that all of the reactive power is supplied by the capacitor banks that are connected to the secondary side of the power transformers. It is also assumed that four EV-VPPs manage the EVs in different parts of the distribution network, and the total power transfer capacity is 19 MW in all periods.

The spot market price was taken from the Nordpool Spot market, of which the lower price period of one day may result in peaks that increase the probability of congestion violations. In the initial scheduling, the information concerning the power transformer use or congestion price is provided by the DSO, each EV-VPP uses the forecast load demand, and the network characteristics determined by the DSO for making schedules for next day.

The optimization problem at level I has been solved using the general algebraic modeling system (GAMS) software [33]. GAMS has different solvers to solve this mixed-integer non-linear programming (MINLP) optimization problem and the DICOPT solver was selected [34]. This solver separates the mixed-integer programming (MIP) and non-linear programming (NLP) parts of the optimization problem. The CPLEX and CONOPT solvers are used to solve MIP and NLP, respectively. The DICOPT solver uses the "outer approximation", "equality relaxation", or "augmented penalty" to coordinate the solutions obtain in each part of the optimization problems (MIP and NLP). This is done by creating relaxed problems for the CPLEX and CONOPT to solve, and then the relaxed problems are decreased until the stopping criteria are reached. Therefore, DICOPT is an iterative process that only stops when the MIP and NLP solvers obtain solutions with a difference less than a pre-defined error (by default this is 0.01%). DICOPT does not guarantee a global optimum solution, because MINLP problems have non-convexities (e.g., non-convex constraints) resulting in local optima. At level II, the optimization problem is solved using CVX, a package for specifying and solving convex programs [35].

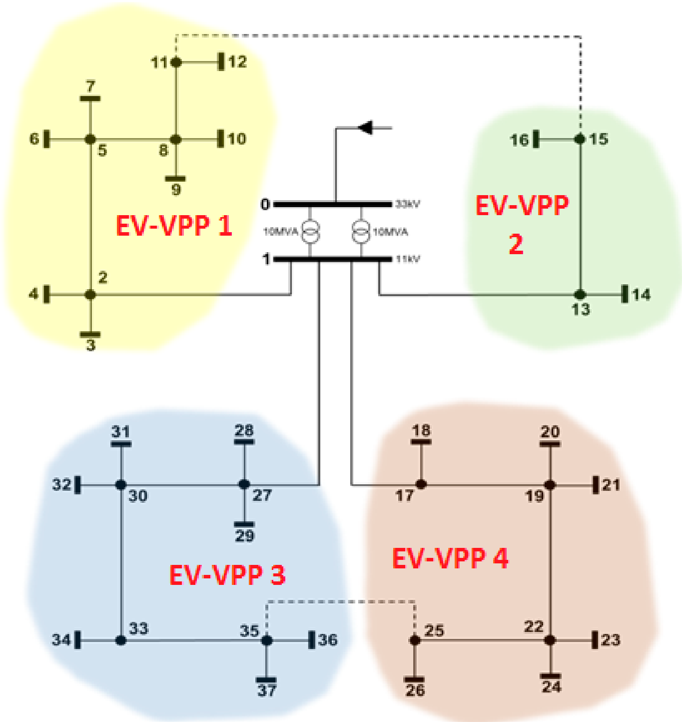

Figure 4. 37 bus distribution network (adapted from [31], with permission from IEEE Transactions on Power Systems, 1991).

Table 1. Number of consumers and electric vehicles.

VPPs	Driving Pattern					Electric Vehicles
	DM	Ind	SB	Co	Total	
EV-VPP 1	630		2	20	652	326
EV-VPP 2		2			2	100
EV-VPP 3	620		2	10	632	316
EV-VPP 4	600		2	20	622	311
Total	1850	2	6	50	1908	1053

Figure 5a shows the aggregated power schedule of EV-VPPs and Figure 5b shows the EVs charge scheduling after the first scheduling process. The graphics show the scheduling for one day (96 periods of 15 min). In Figure 5a, it is also possible to see the market prices (line blue) and the power transformer capacity (line green).

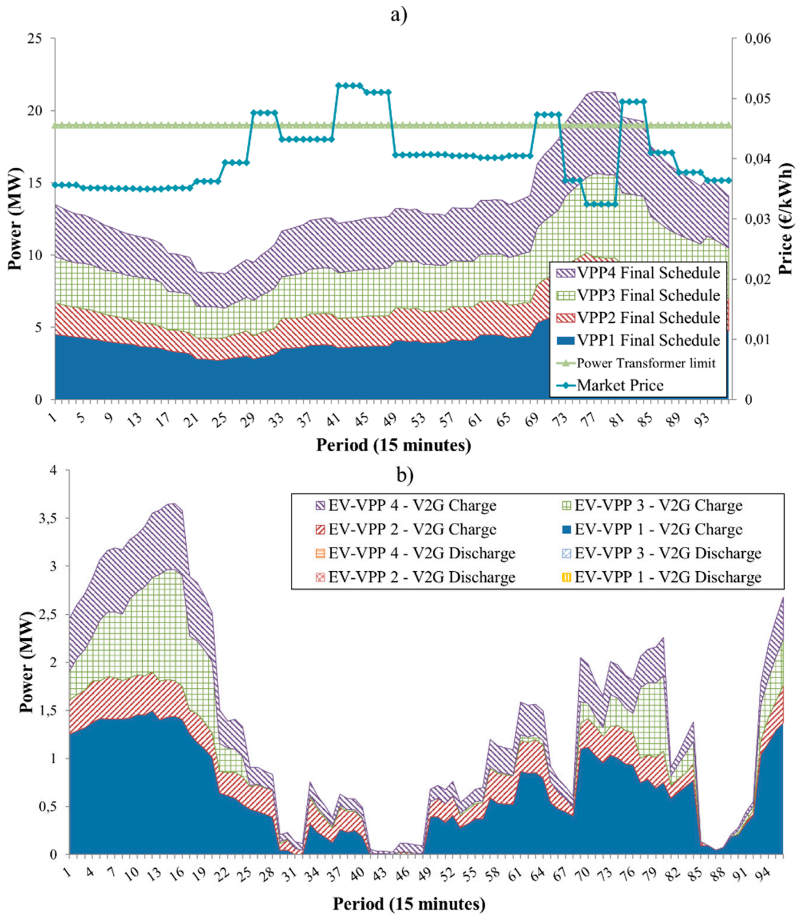

Figure 5. Initial scheduling: (**a**) total demand schedule by EV-VPP; and (**b**) EVs schedule by EV-VPP.

As seen in Figure 5, the EV-VPPs attempt to schedule the greatest part of the EV charges to periods with a lower energy price. In some cases, like in EV-VPP2, it is necessary to schedule the EVs charge during the day due to the intensive EV use. The initial scheduling causes the congestion of the HV/MV power transformer between periods 73 and 80 (periods of 15 min). This situation is, partly, caused by the intensive charging level of EVs, which reaches more than 3 MW due to the lower prices in those periods.

The three mechanisms presented in Section 4 to avoid the congestion situations are tested and the results are presented in Figure 6 (market-based mechanism), Figure 7 (pro-rata mechanism), and Figure 8 (constrained market-based mechanism). The results indicate that, in the present case study, the congestion can be effectively solved after three information exchanges (or iterations) between the DSO and the EV-VPPs in all of the mechanisms.

Analyzing Figures 6–8, all negotiation mechanisms can be adopted for solving the congestion problem in all time periods, since it is shown in Figures 6a, 7a and 8a that the sum of the four EV-VPPs' schedules is lower than the power transformer capacity indicated by the green line. However, the strategies have very different impacts on the final scheduling of each EV-VPP. In the market-based approach (Figure 6), the congestion price is very high (around 0.25 €/kWh) leading to a re-scheduling of the EVs charge to other periods, but also the discharge in the periods initially with congestion. The discharge is intensively used in the congestion periods, because the discharge price is lower than the defined congestion price. In the DSO perspective, the power transformer congestion was solved but the excessive response of the EV-VPPs caused large fluctuations in power demand and a new unexpected 'off-peak' period in the initially congested periods, which is because of the excessive discharge of EVs in the congested periods.

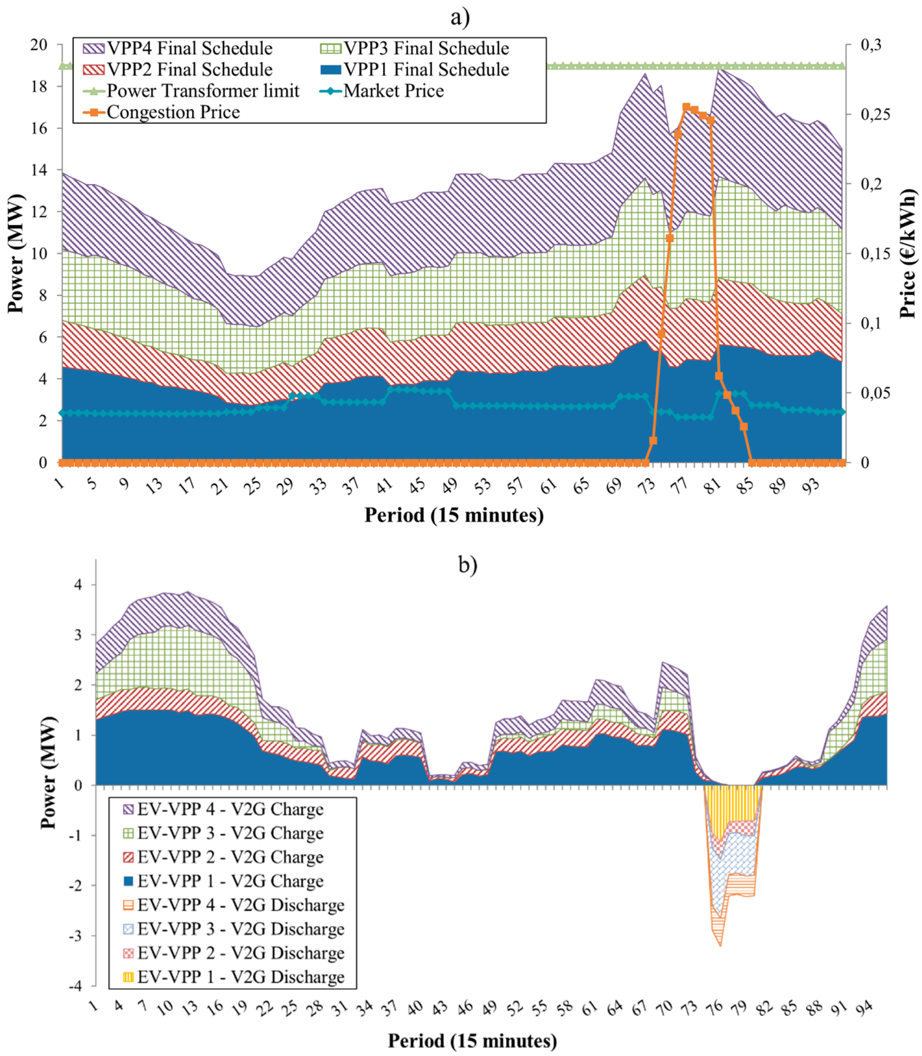

Figure 6. Market-based strategy: (**a**) total demand schedule by EV-VPP; and (**b**) EV's schedule by EV-VPP.

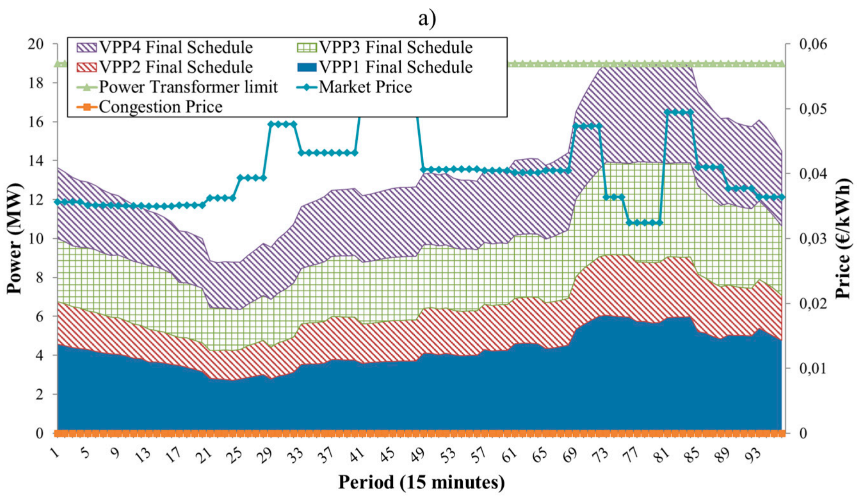

Figure 7. *Cont.*

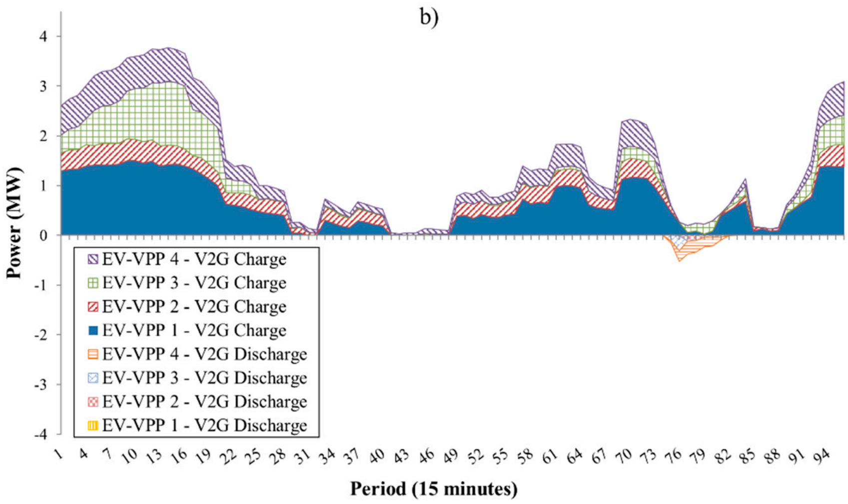

Figure 7. Pro-rata strategy: (**a**) total demand schedule by EV-VPP; (**b**) EV's schedule by EV-VPP.

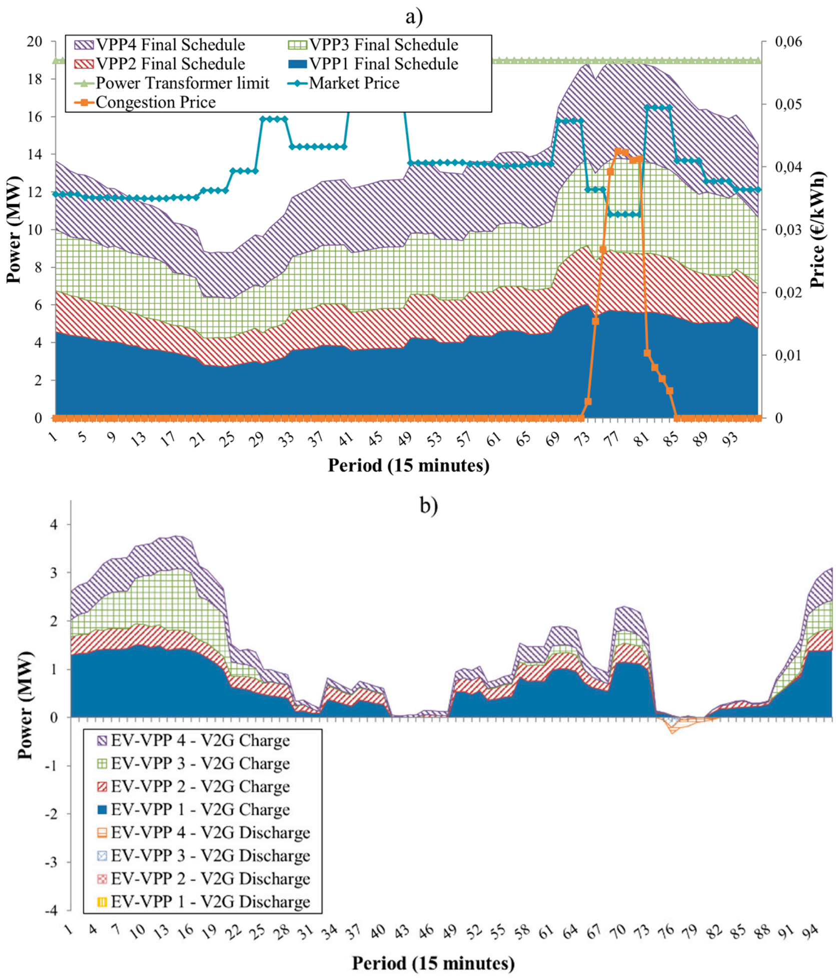

Figure 8. Constrained market-based strategy: (**a**) total demand schedule by EV-VPP; and (**b**) EV's schedule by EV-VPP.

Concerning the use of pro-rata strategy (Figure 7), the power transformers are used at their maximum capacity during the initially congested periods. This situation has a particular impact in EV-VPPs 3 and 4 because of their lower demand flexibility in the congested periods. To guarantee the new power supply limits imposed by DSO when using the pro-rata mechanism, EV-VPPs should use the EVs' discharge to supply all consumers' demands, increasing their operation costs. From the DSO perspective, this mechanism allows a constant demand profile during the initially congested periods.

In the proposed constrained market-based mechanism (Figure 8), the congestion price is substantially lower than in the market-based mechanism, leading to a more balanced (or compromised) variation of the EVs' charge scheduling. The power transformer constraints were solved after three negotiation iterations. EVs' discharge are not used in EV-VPP 1 due to the imposed supply limits that are, in fact, higher than the power transformer capacity, allowing a relaxation of the constraints. On the other hand, EV-VPP2, EV-VPP3, and EV-VPP4 are more sensitive to the price due to the higher energy requirements of their EVs. For the DSO, this mechanism leads to a relaxation of the power transformers near their limit, improving the global operation efficiency. Table 2 shows the EVs' operation costs (Op.cost.) by each EV-VPP and the variation in percentage concerning the initial scheduling.

Table 2. Result comparison of the three mechanisms.

VPPs	Initial Scheduling	Market-Based Mechanism		*Pro-rata* Mechanism		Constrained Market-Based Mechanism (CMB (ω = 1.2))	
	Op. Cost (€)	**Op. Cost (€)**	**Var (%)**	**Op. Cost (€)**	**Var (%)**	**Op. Cost (€)**	**Var (%)**
EV-VPP 1	402.10	625.22	55.49	402.73	0.16	442.62	10.08
EV-VPP 2	212.37	339.83	60.02	213.50	0.53	234.85	10.58
EV-VPP 3	324.16	516.86	59.45	325.66	0.46	359.58	10.93
EV-VPP 4	346.96	560.05	61.42	350.58	1.04	385.21	11.02

In Table 2, it is possible to see that the market-based mechanism significantly increases the EVs' operation costs for all VPPs because of the increase of the charging costs, but also because of the payments with the discharged energy. The pro-rata mechanism presents less variation in terms of operation cost for each VPP. The constrained market-based mechanism imposes less EV-discharge showing the higher flexibility of this method. However, the EV-VPPs have more costs since the congestion price is applied to all of the power consumption. Note, the choice of the parameter ω influences the operation cost of EV VPPs, and the following table (Table 3) shows the difference when ω varies.

Table 3. Result comparison of EV VPPs' cost under different ω.

VPPs	CMB (ω = 1.2)		CMB (ω = 1.5)		CMB (ω = 2)		CMB (ω = 3)		CMB (ω = 5)	
	(€)	**%**	**(€)**	**%**	**(€)**	**%**	**(€)**	**%**	**(€)**	**%**
EV-VPP 1	442.62	10.08	484.17	20.41	520.65	29.48	556.07	38.29	583.96	45.23
EV-VPP 2	234.85	10.58	257.79	21.39	278.34	31.07	299.03	40.81	315.41	48.51
EV-VPP 3	359.58	10.93	395.48	22	427.92	32.01	458.2	41.35	481.95	48.67
EV-VPP 4	385.21	11.02	422.96	21.9	457.1	31.74	491.64	41.7	519.04	49.06

In addition to these main findings, note that the pro-rata mechanism requires less communication between the DSO and the EV-VPPs compared to the other two mechanisms, since the market-based mechanism and constrained market-based mechanism need to negotiate several times to reach the congestion price. However, the (constrained) market-based mechanisms allow the power transformer capacity allocations via an economic method, which may truly reflect the needs of the EV users. This leads us to the future work on defining a proper EV VPP cost function to characterize the cost of deviating from the original power schedules. Note that, furthermore, even the constrained market-based mechanism increases the operation cost of EV VPP, however, it solves the grid congestion problem which otherwise needs to be solved by upgrading the grid. The grid upgrading implies a cost that will also be distributed to the EV VPPs. In this study, we do not compare the cost differences since that requires a long-term perspective study. Summarizing the advantages for each player, it is possible to mention that, for the DSO, all of the mechanisms could avoid the network investments. For the EV-VPPs, the introduction of price signals will increase their costs. However, when the pro-rata mechanism is used, the EV-VPP can be forced to shed some loads or not deliver energy to charge EVs, with consequences to the EVs' owners. From the EVs' owner's perspectives, the pro-rata mechanism can be the worst mechanism due to the possibility of not delivering the required energy during trips. This situation it is also possible in the constrained market-based mechanism but with less probability due to the relaxed limits imposed by this mechanism.

6. Conclusions and Discussion

The growing use of EVs introduces new constraints to power system operation and management. One of the most important impacts are the congestion situations created by high EV charge demands during specific periods of the day. In a competitive environment, the system operators should assure equal opportunities for all network users supplying energy in every period for all resources. However, this is impossible without high investments to reinforce the network capacity, or without a coordination of the network use.

This paper proposes and compares three different coordination mechanisms for negotiation between the DSO and the aggregators' EV-VPPs (electric vehicles virtual power plant), considering the possibility of EV charge and discharge. The three different mechanisms include: (1) the market-based approach; (2) the pro-rata mechanism; and (3) the constrained market-based approach. The constrained market-based mechanism uses the market-based principles, but considers different power transformer capacities. The main advantage of this mechanism is the fairness, since it is fairer than the market-based strategy, which leads to lower congestion prices. In addition, compared to the pro-rata mechanism, the constrained market-based mechanism imposes more relaxed power consumption limits. This aspect is important to the EV-VPPs with smaller flexibility to change their initial scheduling. Additionally, the pro-rata mechanism the power transformer will be used under their nominal capacity during the original congestion periods while, in the constrained market-based mechanism, the power transformer capacity is used at an average of 95% of their capacity, allowing some capacity to respond to uncertainties. Taking into account the obtained results, it is possible to conclude that the proposed constrained market-based mechanism has advantages to the DSO and to the aggregators, resulting in a balanced solution concerned with solving the congestion problem.

In future work, the authors intend to develop the methodology to include other distributed energy resources, especially considering photovoltaic (PV) generation. To include PV generation in the study, it is suggested that two types of setup could be used, considering the PV connection scheme in reality: (1) PV would benefit more if the produced electricity is sold out to system; (2) there is no price difference between selling electricity to the system or use it locally. These two different setups will influence the schedule of PV and EVs in the study.

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Nomenclature

A. Parameters

α_ω	Step used to determine the shadow price
η_c	Grid-to-Vehicle efficiency [0–1]
η_d	Vehicle-to-Grid efficiency [0–1]
Λ	Shadow price or Lagrange multiplier
ω	Constrained market-based negotiation parameter
B	Imaginary part in admittance matrix [pu]

c	Cost in period t [m.u./kWh]
E	Stored energy in the battery of vehicle at the end of period t [kWh]
$E_{Initial}$	Energy stored in the battery of vehicle at the beginning of period 1 [kWh]
E_{Trip}	Energy consumption in the battery during a trip that occurs in period t [kWh]
G	Real part in admittance matrix [pu]
L^i	Set of lines connected to bus i
N	Total number of resources
$Penal$	Penalization factor
S_L^{max}	Maximum power flow (or thermal limit) in a specific line [pu]
T	Total number of periods
u	Cost coefficient used in the coordination mechanisms between DSO and EV-VPP
$\overline{V}$	Complex amplitude of voltage [pu]
Y	Series admittance of line that connects two buses [pu]
Y_{sh}	Shunt admittance of line that connects two buses [pu]
Z	Operation cost regarding EV-VPP [m.u.]

B. Variables

θ	Voltage angle
P	Active power [pu]
Q	Reactive power [pu]
S	Apparent power [pu]
V	Voltage magnitude [pu]
X	Binary variable [0,1]

C. Indices

B	Bus
$BatMax$	Battery energy capacity
$BatMin$	Minimum stored energy to be guaranteed at the end of period t
CAP	Shunt capacitor
Ch	Charge process
$Cong$	Congestion
Dch	Discharge process
i , j	Bus i and Bus j
k	Line
$load$, l	Load
$Market$	Day-ahead market
Max	Upper bound limit
Max_Alloc	Maximum limit allocated
Min	Lower bound limit
NSD	Non-supplied demand
SP	External supplier
SP_new	New power supplied by external suppliers
$SP\_original$	Initial power supplied by external suppliers
$Stored$	Stored energy in the battery of the vehicle
$Transf$	Power transformer
$V2G$	Electric vehicle
VPP	EV-VPP

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