



# Optimal Electric Vehicle Fleet Charging Management with a Frequency Regulation Service

Yassir Dahmane, Raphaël Chenouard, Malek Ghanes, Mario Alvarado Ruiz

## ► To cite this version:

Yassir Dahmane, Raphaël Chenouard, Malek Ghanes, Mario Alvarado Ruiz. Optimal Electric Vehicle Fleet Charging Management with a Frequency Regulation Service. World Electric Vehicle Journal, 2023, 14 (6), pp.152. 10.3390/wevj14060152 . hal-04123606

**HAL Id: hal-04123606**

**<https://hal.science/hal-04123606>**

Submitted on 9 Jun 2023

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# Optimal Electric Vehicle Fleet Charging Management With Frequency Regulation Service

Yassir Dahmane <sup>1,†</sup>, Raphaël Chenouard <sup>1,\*</sup> , Malek Ghanes <sup>1</sup>  and Mario Alvarado Ruiz <sup>2</sup>

<sup>1</sup> Nantes Université, École Centrale Nantes, CNRS, LS2N, UMR 6004; raphael.chenouard@ls2n.fr, malek.ghanes@ls2n.fr

<sup>2</sup> Renault Group Technocentre Guyancourt; mario.alvarado-ruiz@renault.com

\* Correspondence: raphael.chenouard@ls2n.fr

† Current address: Envision Digital; yassir.dahmane@envision-digital.com

**Abstract:** Electric vehicles are able to provide immediate power through the vehicle-to-grid function and adjust their charging power level when in grid-to-vehicle mode. This allows them to provide ancillary services such as frequency control. Their batteries differ from conventional energy storage systems in that the owner's energy requirement constraint must be met when vehicles participate in a frequency control system. An optimization problem has been defined considering both owner satisfaction and frequency control performance. The main contribution of the proposed paper, compared to the literature, are (1) to keep the total available energy stored in the batteries connected to a charging station in an optimal region that favors the frequency regulation capability of the station and the proposed QoS and (2) to consider the optimal region bounded by the efficiency thresholds of the charger to allow for maximum regulation power. The problem is expressed as a multicriteria optimization problem with time-dependent references. The paper presents an energy management strategy for frequency control, describes a concept of optimal time-dependent state of charge for electric vehicle charging demands, and considers the power dependence of the electric vehicle charger efficiency. Finally, simulation results are presented using Matlab/Simulink to prove the effectiveness of the proposed algorithm.

**Keywords:** electric vehicles, smart charging, frequency regulation, maximum regulation power

**Citation:** Dahmane, Y.; Chenouard, R.; Ghanes, M.; Alvarado Ruiz, M. Optimal Electric Vehicle Fleet Charging Management With Frequency Regulation Service. *World Electr. Veh. J.* **2023**, *1*, 0. <https://doi.org/>

Received:

Revised:

Accepted:

Published:

**Copyright:** © 2023 by the authors. Submitted to *World Electr. Veh. J.* for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

Electric vehicles (EVs) can help improve the quality of the power grid by participating in ancillary services such as valley filling, reactive power compensation, voltage drop, and frequency regulation. The massive integration of vehicle-to-grid (V2G) functionality into the EVs' charger will make EVs flexible connected energy resources. In addition, the fast response of EVs and the high power density of lithium batteries make EVs suitable for frequency regulation [1], [2], [3].

The problem of charging EVs with a frequency control service has been the subject of several researches. EV charging problem, considering frequency regulation using control theory has been for example addressed in [4–11]. Others, such as [1,12–16] use the optimization approach to find the optimal charging power. Other methods based on fuzzy logic, deep reinforcement learning and priority model, have been used in [17–20].

To solve the problem of frequency-controlled EV charging, several considerations must be taken into account. The objective of keeping the operational capacity limit in the optimal region - where the up-regulation power is maximum and the down-regulation power is maximum - is considered in [14,16], whereas [13,15] did not consider this aspect. Furthermore, [14,15] considers a constant value for the upward power control as well as for the downward power control of the EV. Therefore, it does not take into account the dependence of the regulation capacity on the up and down state of charge of the battery (SoC). In addition, addressing the expectations of EV owners' is a major challenge in this

area. In [13,14,16,21], user satisfaction was taken into account, while this point was totally ignored in [22,23]. Ignoring this aspect could discourage the EVs' owner from participating in ancillary services.

Many studies consider a large number of EVs participating in ancillary services. In [14], the study was conducted with a large number of EVs equal to 100,000, while [1] assumes the use of 1,000 EVs in the simulation and [6] sets the total number of EVs involved in the simulation of the frequency control algorithm to 500. The focus of this paper is to investigate the feasibility of providing frequency control service with a small number of EVs. Therefore, in all simulations, the maximum number of EVs is 20. In addition, [14,16] uses an assigned symmetric disturbance signal that simplifies the problem of achieving the SoC objective and the maintaining problem of the control capacity. Moreover, [6] and [14] consider an equally likely distribution of the number of EVs in each SoC category (low, medium and high).

Most research using the [14,16] optimization approach sets a strict equality constraint in their optimization models. Equalities are harder to satisfy exactly and are not compatible with all solvers. One modeling trick is to reformulate each equality as two inequalities, but this increases the number of constraints and thus the size of the problem [24]. Accordingly, only inequality constraints are used in the proposed optimization model.

In the control theory, the perturbation is distributed uniformly among the EVs. In the case of a small disturbance and a high number of controlled EVs, each EV with small power fluctuations will participate in frequency regulation to maintain the SoC without considering the poor efficiency of the charger in low power regions. However, according to [22], the charger is designed to operate more efficiently closer to the maximum power levels. In the same context, [13] and [22] study the effect of charger efficiency on the tracking accuracy of the spurious signal and assume that without considering the dependence of charger efficiency on power, the tracking error increases.

**Charger efficiency constraint :** To our best knowledge, none of the existing work takes into account the dependence of charger efficiency on power. Almost all studies assume a constant charger efficiency in the range  $[0.8, 1]$ . Some of them do not use a discharge efficiency or assume a perfect charger with unit efficiency.

In EV charging management, the available energy provides information about the accumulation of energy to charge the EV. So the energy gives a kind of future energy usage possibilities, such as the maximum charging and discharging rates and the energy remaining to reach full capacity or full discharge. However, energy cannot convey long-term knowledge about the state of the EV or its history, but it does provide short-term information. Combining two heterogeneous physical quantities, such as energy and power, in the same objective function provides a global vision of the charging management of the EV fleet in both the long and short term, its past, present, and future. This model allows solving the optimization planning problem as a moment problem. Thus, the scheduling problem, whose solution is hard in terms of computational time and memory consumption, will be replaced by an instantaneous dispatching problem whose solution is simple and fast. The added value in this model allows us to reduce the execution time, thus we can tackle real-time problems such as frequency regulation for coordinated charging of electric vehicles, and reduce the time step as much as the desired accuracy.

The main contribution of this paper compared to the previous investigated literature, is to propose an optimal EV Fleet charging management that takes into account the power dependence of charger efficiency and extend our previous work [20], which is significantly improved, to the case of bidirectional charging. In details, the contributions highlighting the proposed strategy are to:

- Maximize the regulatory reserve by using an EV charging algorithm based on preventive actions, replacing the planning problem with one on the fly.
- Avoid the use of hard constraints, reducing the number of decision variables and the number of constraints to reduce computation time and memory usage.

- Take into account the efficiency of the charger and its dependence on power and therefore maximizing charging efficiency. 90
- Take into account the SoC and temperature dependence of regulation capacity and keeping the total regulation capacity in the optimal zone. 91
- Control the bi-directional charging of EVs (V2G), taking into account both the power demand of the grid operator and the satisfaction of the SoC target of the EVs' users. 92

The paper remaining is structured as follows: the optimization problem modeling is the subject of Section II. The simulation results of the control strategy are presented in Section III. Finally, Section IV discusses the paper conclusion and the future work. 93

## 2. Optimization Problem Modeling 99

In this paper, we formulate the EV charging problem as a power dispatch problem considering two distinct cases: 100

- Case 1 (namely P1): the standard power dispatch problem with frequency disturbance. In this context, the main goal is to charge EVs but the idea is to keep a regulation capability up and down, i.e. to keep EVs in an optimal region to be able to better face the second case. 101
- Case 2 (namely P2): the frequency regulation problem with a power request from or to the power grid. Then, the main goal becomes to answer this power demand emerging from the power grid, while trying to consider EVs charging expectations. 102

In P1, the problem is expressed as a general quadratic optimization problem where the objective function aggregates two criteria: 103

$$F_1 = w_1 C_1^2 + w_2 C_2^2 \quad (1) \quad 104$$

The criterion  $C_1$  computes the sum of gaps between an energy target and the energy in EV batteries at each time step. This target is determined by considering the optimal region to get the best regulation capability (up and down) as depicted on Fig. 1. 105

$$C_1 = (E_{i-1} + \sum_{j=1}^{N_{EV}} P_i^j \Delta t) - E_i^{ref} \quad (2) \quad 106$$

Where  $E_i$  is calculated by the given equation (3): 107

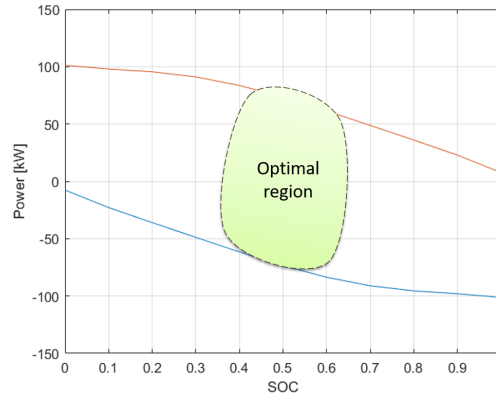
$$E_i = \sum_{j=1}^{N_{EV}} SoC_i^j \cdot E_{batt}^j \cdot SoH^j \quad (3) \quad 108$$

$E_i^{ref}$  is tracked to maintain the regulation capacity at the maximal value and is computed (considering Fig. 1 optimal region) as follows: 109

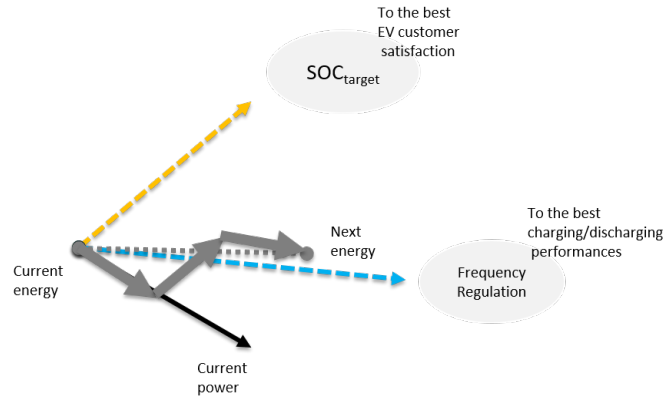
$$E_i^{ref} = \sum_{j=1}^{N_{EV}} SoC_i^{ref} \cdot E_{batt}^j \cdot SoH^j \quad (4) \quad 110$$

As shown by the example of Fig. 1, the best tradeoff between charging and discharging capability is at SoC 0.5 with a maximal charging power of 80kW and a discharging power of -80kW. The optimal region is defined between a SoC of 0.4 and a SoC of 0.6, where both charging and discharging powers stay high. In these conditions, EVs can be managed in a flexible way to: 1. charge their batteries, 2. answer a power demand from or to the grid. To give a priority to the charging of EVs, the optimal SoC ( $SoC_i^{ref}$ ) may be set over 0.5. In our benchmark, we set  $SoC_i^{ref}$  to 0.6. 111

At the global EV fleet level, the global strategy has to consider various subtleties to deal with conflicting objectives, so that the SoC of EVs is maximized at the end of the day. The total available energy stays in an optimal region and get the best response for a frequency regulation demand as illustrated on Fig. 2. 112



**Figure 1.** Optimal capability region for charging or discharging lithium-ion batteries, depending on their SoC.



**Figure 2.** An illustration of two conflicting objectives

A frequency deviation is unpredictable as well as its duration, when considering a planning horizon of a day. Then, the EV fleet must be able, at any moment, to face any disturbances in the power grid, but taking into account two opposing criteria for each EV:

- To charge its battery in order to get a high SoC to meet the EV owner needs ( $>0.7$ ).
- To keep the SoC within an optimal range to improve the capability of the fleet to answer a frequency control request ( $>0.4$  and  $<0.6$ ).

This strategy allows a better power management of the EV fleet charging and a quick response to the power request in case of a frequency deviation.

Then, the purpose of the criterion  $C_2$  is to keep the EV charging, so the total power approaches to  $P_i^{ref}$ , thus the total available energy stored in the EVs increases gradually to the maximal capacity of the EVs' battery by the end of the day (cf. Fig. 3). The strategy of increasing the EVs' SoC at the end of the day is fully justified because of high power demand during the peak period between 6 PM and 10 PM. Thus, the necessity to discharge EVs for power grid's relief.

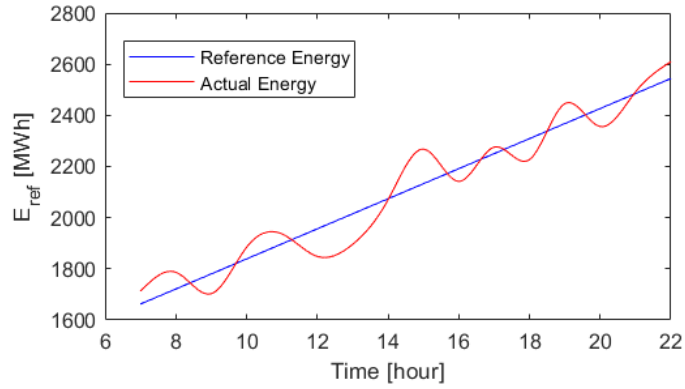
$$C_2 = \left( \sum_{j=1}^{N_{EV}} P_i^j \right) - P_i^{ref} \quad (5)$$

The  $P_i^{ref}$  is defined as the average power that must be used to reach  $E^{saturation}$  at the end of the day, with a total station opening time of  $t_{op}$  hours. The detailed expression of  $P_i^{ref}$  is given in the following equations:

$$E^{saturation} = \sum_{j=1}^{N_{EV}} SoC^{limit} \cdot E_{batt}^j \cdot SoH^j \quad (6)$$

$$E_i^{remain} = E^{saturation} - E_i \quad (7)$$

$$P_i^{ref} = \frac{E_i^{remain}}{t_{op}} \quad (8)$$



**Figure 3.** Example of a reference energy and actual energy in the scope of a day.

P1 aims to prepare the EV fleet to respond to any power request by keeping the average SoC of the EV fleet into the optimal region and charging the EVs with higher priority. However, the main goal of P2 is to minimize the error between the requested power and the used charging power, and to maximize the charging efficiency of the fleet.

When there is a power request, P2 is activated and the optimization problem is expressed as a multi-criteria minimization:

$$F_2 = w_3 C_3^2 + w_4 C_4 \quad (9)$$

The purpose of the criterion  $C_3$  is to offer the best answer to the power request by minimizing the tracking error, i.e.  $P - P^{request}$ .

$$C_3 = \left( \sum_{j=1}^{N_{EV}} P_i^j \right) - P_i^{request} \quad (10)$$

The criterion  $C_4$  take into account the chargers' efficiency, to minimize the losses related to this component.

$$C_4 = \sum_{j=1}^{N_{EV}} P_i^j (1 - \eta(P_i^j)) \quad (11)$$

P1 and P2 have a different objective function, but they are subjected to the same set of constraints relating to physical limits or operational constraints.

The amount of power used to charge or discharge a battery is bounded as defined in (12):

$$\begin{aligned} P_i^j &\leq C_i^j \\ P_i^j &\geq D_i^j \end{aligned} \quad (12)$$

The definition of  $C_i^j$  and  $D_i^j$  is given by the following equations :

$$\begin{aligned} C_i^j &= s_i^j \cdot \alpha_i^{j,ub} \cdot P_i^{j,max+} \\ D_i^j &= s_i^j \cdot \alpha_i^{j,lb} \cdot P_i^{j,max-} \end{aligned} \quad (13)$$

$$\begin{aligned} P_i^{j,max+} &= \min(P_{chpt+}^j, P_{Charger+}^j, P_{i,Bat+}^j) \\ P_i^{j,max-} &= \max(P_{chpt-}^j, P_{Charger-}^j, P_{i,Bat-}^j) \end{aligned} \quad (14)$$

$s_i^j$ ,  $\alpha_i^{j,ub}$ , and  $\alpha_i^{j,lb}$  are defined in the equations (15), (16), and (17) as follows:

$$s_i^j = \begin{cases} 1, & \text{plugged-in} \\ 0, & \text{plugged-out} \end{cases} \quad (15)$$

$$\alpha_i^{j,ub} = \begin{cases} 1, & SoC_i^j < 0.9 \\ 0, & SoC_i^j \geq 0.9 \end{cases} \quad (16)$$

$$\alpha_i^{j,lb} = \begin{cases} 1, & SoC_i^j \geq 0.2 \\ 0, & SoC_i^j < 0.2 \end{cases} \quad (17)$$

To avoid the overloading of the transformers, a maximal power limits the sum of power that is dispatched to EVs for each time slot:

$$\sum_{j=1}^{N_{EV}} P_i^j \leq P_{total} \quad (18)$$

The SoC of EVs is dynamically evaluated through the following equations:

In charging mode:  $P_i^j \geq 0$

$$SoC_{i+1}^j = SoC_i^j + \frac{\eta(P_i^j)P_i^j \cdot \Delta t}{E_{batt}^j \cdot SoH^j} \quad (19)$$

In discharging mode:  $P_i^j < 0$

$$SoC_{i+1}^j = SoC_i^j + \frac{(P_i^j / \eta(P_i^j)) \cdot \Delta t}{E_{batt}^j \cdot SoH^j}$$

For the sake of simplicity, the joule heat generation is considered as evenly distributed. As a consequence, the temperature in battery cells is considered well distributed too. Then, the estimation of the temperature uses the first order equation:

$$T_{i+1}^j = T_i^j + \frac{1}{m^j C_p^j} (P_{joule,i}^j + P_{convective,i}^j) \quad (20)$$

To compute the joule power, a linear approximation is used:

$$P_{joule,i}^j = k^j \times P_i^j \quad \forall i, \forall j \quad (21)$$

The Newton law is applied for computation of the convective power:

$$P_{convective,i}^j = \frac{T_i^j - T_i^{out}}{R_{th\_out}^j} \quad i = 1, \dots, N \quad (22)$$

The presented results were obtained with MATLAB optimization toolbox using *fmincon* with an Intel Core i7 CPU @ 2.70GHz.

### 3. Simulations and results

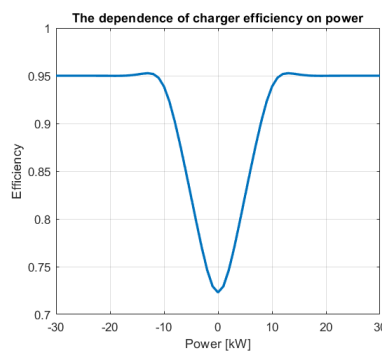
The parameters used for the simulations are summarized in Table 1. The default full rate power for the charging stations is 22 kW.

**Table 1.** EV parameters used for simulations

Parameters	Value
Sampling time	5min
Maximum number of EVs	20
Battery capacity	60kWh
Starting SoC	[0.1, 0.6]
Desired SoC	[0.3, 0.9]
Maximum/minimum SoC	0.9/0.2

### 3.1. Impacts of the charger efficiency

The charger efficiency can have a significant impact on the amount of energy put in batteries. Approximating the efficiency with a constant value may lead to low accuracy in results, as shown in Fig. 4, with variations from 0.72 to 0.96 percent. Fixed arrival and departure times (see Table 2) with a constant number of EVs is used to focus on the tracking error relating to the proposed strategy.

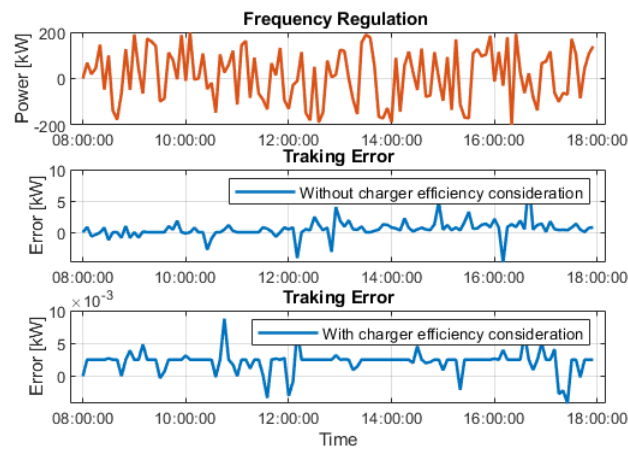
**Figure 4.** EV charger efficiency**Table 2.** Simulation parameters of EVs in 3.1

Parameters	
Arrival times	8h
Departure times	18h

The Fig. 5 shows the results obtained on a scenario with frequency regulation between 8:00 to 18:00. In this case, P2 is used and multiple charging and discharging decisions are applied, thus increasing the energy transfers between the power grid and the EVs. Using an efficiency as a function of power (see Fig. 4), the tracking error is much smaller compared to a fixed efficiency (around the kilowatt). In the first case with a constant efficiency, the tracking error is at the order of magnitude of kW compared to the varying efficiency scenario where it falls down to the order of magnitude of W.

### 3.2. Impacts of the number of EVs

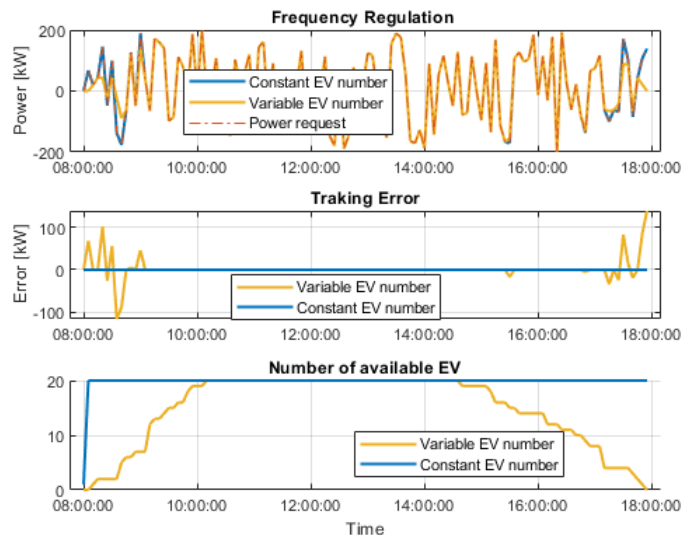
Fig. 6 shows the comparison of two scenarios for the same power request with parameters summarized in Table 3. In the first case (blue line), the number of EVs is constant, whereas in a more realistic second case (yellow line), it varies with all arrivals between 8:00 to 10:00 and departures between 15:00 and 18:00. In the first case, tracking errors are low whereas in the second case, it becomes more significant as the number of EVs is low. This is due to the low regulation capacity when fewer EVs are available at the charging station. As shown on Fig. 6 the tracking error is close to zero when the number of EVs is greater than ten. Then, EVs offer a high regulation reserve. In such scenario, the charging station cannot ensure regulation request with a low number of EVs and another energy storage solution should be considered to compensate the lack of EVs in some periods of the day.



**Figure 5.** Frequency regulation (FR) Signal, and impact of charger efficiency response error

**Table 3.** Simulation parameters of EVs in 3.2

Parameters	
Arrival times	$\mathcal{N}(9, 0.5)$
Departure times	$\mathcal{N}(17, 0.5)$



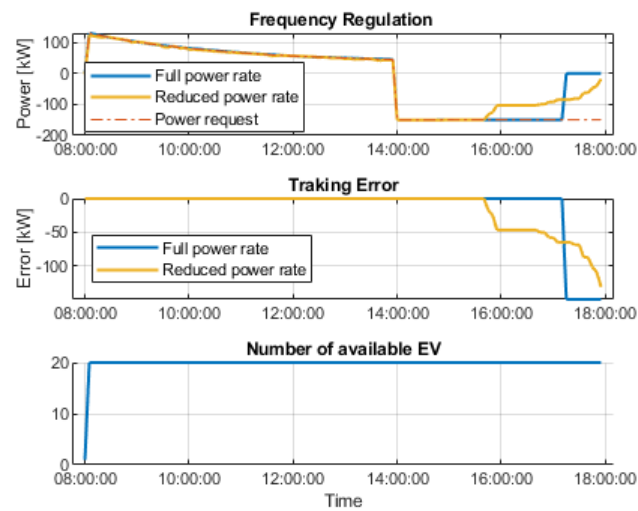
**Figure 6.** FR Signal, response error, and EV availability

### 3.3. Impact of long frequency drops and maximum charging rate

A power plant shutdown or failure may lead to high frequency drops for a long period. This critical situation may lead to a black-out on the power network. The simulation detailed in this subsection shows how EVs can play a crucial role to support the power grid. Two scenarios are investigated with a fixed number of available EVs. The first one considers a full power rate of 22kW, whereas in the second scenario, each EV selects a random maximal power rate from [3.2, 7.4, 11, 22]. In the charging station, the charging points have the following ratios: [30%, 30%, 20%, 20%] respectively.

As shown on Fig. 7, EVs are charged until 14:00, where a high frequency drop occurs. In both scenarios, the power request cannot be met until the end, but in both case the support is offered for most of the duration.

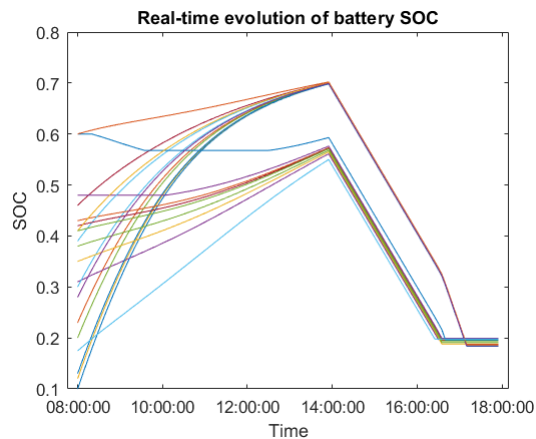
The SoC evolution of EVs is illustrated in Fig. 8 for the first scenario and in Fig. 9 for the second one. We can see that the constraints for the minimal SoC threshold are active at



**Figure 7.** FR Signal, response error, and EV availability

the end of the two scenarios and the tracking errors increase from this moment, since no more energy can be taken from EVs.

In the first scenario and before some EVs reached the minimal SoC threshold, the discharge rate is homogeneously divided over all EVs. After that event, the slopes of the remaining EVs change, i.e., it goes up to the maximal discharge power rate but only for a short period after which all EVs reach the minimal SoC of 0.2. In the second scenario, the maximal discharging power constraint act to limit the discharging rate. Some EVs are no more able to supply the grid around 15:45 and the tracking error becomes sensitive sooner than in the first scenario. However, the supply of the grid is provided until the end, even if it is for a small amount and the decrease in the grid support is smoother.

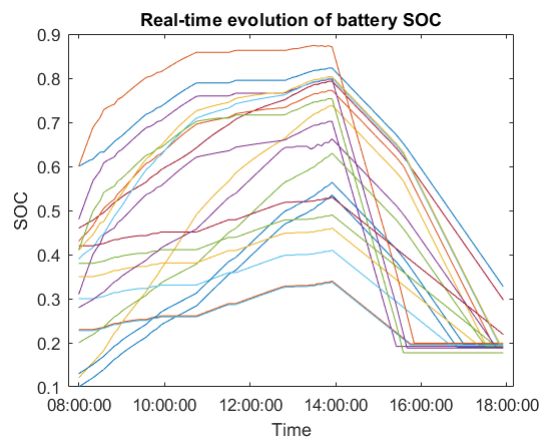


**Figure 8.** The SoC evolution of every EV in the charging station for full power rate 22kW

### 3.4. Discussions about EV usage in the frequency regulation market

Previous results show the good behavior of fleets of EVs to participate in the frequency regulation even with a relatively low number of EVs if a relevant charging strategy maintains their SoC in an optimal region. The ancillary services market is mainly divided into a primary reserve and a secondary reserve, which require different condition to satisfy. These conditions are in general specific to each country, but the most common conditions are presented in the Table 4.

From the previous results and Table 4, the participation to the primary reserve can be ensured by EVs. However, a station should better contain a limited number of charging



**Figure 9.** The SoC evolution of each EV in the charging station for reduced power rate

points, but with a high charging rate to be able to attain the minimum limit of 1MW. The uncertainties about the availability of EVs (arrival and departure times) and their number are not the main issue, since the major constraint is the minimum contracted reserve. The duration of the primary reserve activation is 15 minutes. Since EVs charge for a longer period, the charging station can easily interrupt the charging to satisfy the primary reserve requirements and resume the charging afterward. This short interruption may not significantly reduce the satisfaction of EV owners to get the expected SoC when leaving at the departure time. In the case of a V2G support, the action may retribute owners while compensating the extra cycling of the battery.

**Table 4.** General condition of primary and secondary reserve [25]

	Primary reserve	Secondary reserve
Dynamic of activation	50% within 15s and 100% of the reserve enabled within 30s	100% of the reserve activated within 5min
Duration of activation	maximum of 15 minutes	unlimited during the duration of the contract
Minimum power	1MW	5MW
Power direction	Negative AND Positive	Negative OR Positive

The case of secondary reserve participation requires a greater capacity than for the primary reserve, mainly because of the longer activation time. Then, it is better to consider charging stations with a high number of charging points, high attendance rates with long periods of EVs availability. Depending on the spatial organization of the power network, small charging stations close enough can be grouped on the same aggregator to build a virtual station that meet the requirements for the secondary reserve participation. In this context, the mix of slow and fast charging points is not an issue, as demonstrated by our results.

#### 4. Conclusion

This work addresses the possibility of using EVs for ancillary services relating to frequency regulation. This paper describes a strategy to manage EVs to be able to participate in a frequency regulation as well as to meet EVs owner expectations. This strategy is implemented as two optimization problems. The first one addresses the normal situation without any frequency deviation and tries to enforce a maximum power availability. A SoC target (0.6%) for regulation is defined for EVs, so that EVs in this region can better answer any kind of frequency regulation. This criterion is combined with the SoC target defined

by EVs owners to satisfy both criteria at the same time. The second optimization problem is used when a frequency regulation request occurs. In this scenario, the objective is also composed of two criteria to minimize at the same time the tracking error with the power request and the losses relating to charger efficiencies.

Several simulations are presented to highlight the impact of the charger efficiency, the number of available EVs and the duration of the frequency regulation request. Most existing works focus on a high number of EVs, but we show in this paper, that even with as low as 20 EVs a good behavior can be observed, in most cases. Then, the paper discusses on the position of EVs charging stations for the primary and secondary reserve participation.

**Author Contributions:** Conceptualization, Y. Dahmane and M. Ghanes and R.Chenouard; methodology, Y. Dahmane and R. Chenouard.; software, Y. Dahmane; validation, Y. Dahmane and M. Ghanes and M. Alvarado Ruiz; writing—original draft preparation, Y. Dahmane; writing—review and editing, R. Chenouard and M. Ghanes; visualization, Y. Dahmane; supervision, M. Ghanes and M. Alvarado Ruiz; All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the chair between Renault Group and Ecole Centrale de Nantes about performances of electric vehicles propulsion.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

$w_1, w_2, w_3, w_4$	Weighting factors
$E_i$	Total available energy stored in the EVs
$N_{EV}$	Number of EVs
$P_i^j$	Charging power of the $j$ -th EV at the time $i$
$\Delta t$	Sampling time
$E_i^{ref}$	Energy reference at the time $i$
$SoC_i^j$	State of charge of the $j$ -th EV in the time step $i$
$E_{batt}^j$	Battery capacity of the $j$ -th EV
$SoH^j$	State of health of the $j$ -th EV' battery
$SoC_i^{ref}$	SoC reference at the time $i$
$P_i^{ref}$	Power reference at the time $i$
$E^{saturation}$	Energy threshold of the charging station
$SoC^{limit}$	Maximum SoC limit
$E_i^{remain}$	Remaining energy before reaching
$E^{saturation}$	at the time $i$
$t_{op}$	Station opening hours
$P_i^{request}$	Power request at the time $i$
$\eta$	Charger efficiency
$C_i^j, D_i^j$	Power upper/lower bound of the $j$ -th EV during the time step $i$
$s_i^j$	State of the $j$ -th EV at the time $i$
$\alpha_i^{j,ub}, \alpha_i^{j,lb}$	Binary variables depending on the SoC of the $j$ -th EV at the time $i$
$P_i^{j,max+}, P_i^{j,max-}$	Maximal authorized charging/discharging rate for $j$ -th EV at time step $i$
$P_{chpt+}^j, P_{chpt-}^j$	Maximum charging/discharging power of the charging point of $j$ -th EV
$P_{charger+}^j, P_{charger-}^j$	Maximum power of $j$ -th charger in charging or discharging mode
$P_{Bat+,i}^j, P_{Bat-,i}^j$	Maximum accepted/delivered battery's power of $j$ -th EV at time $i$ depending on the SoC and the battery's temperature
$P_{total}$	Maximum transformer power of the charging station
$m^j$	Mass of the $j$ -th EV battery
$C_p^j$	Specific heat coefficient of the $j$ -th EV battery
$T_i^j$	Temperature of the $j$ -th EV battery at the time $i$
$P_{joule,i}^j$	Power dissipated by joule effect of the $j$ -th EV battery at the time $i$
$P_{convective,i}^j$	Power heat transfer between the battery and the outside of $j$ -th EV battery at time $i$
$k^j$	Thermal factor depending on the thermal inertia of the $j$ -th EV battery
$T_i^{out}$	Outside temperature in the time $i$
$R_{th\_out}^j$	Heat convection coefficient between the $j$ -th EV battery and the outside

## References

- Amamra, S.A.; Marco, J. Vehicle-to-Grid Aggregator to Support Power Grid and Reduce Electric Vehicle Charging Cost. *IEEE Access* **2019**, *7*, 178528–178538.
- Tchagang, A.; Yoo, Y. V2B/V2G on Energy Cost and Battery Degradation under Different Driving Scenarios, Peak Shaving, and Frequency Regulations. *World Electric Vehicle Journal* **2020**, *11*. <https://doi.org/10.3390/wevj11010014>.
- Calearo, L.; Marinelli, M. Profitability of frequency regulation by electric vehicles in Denmark and Japan considering battery degradation costs. *World Electric Vehicle Journal* **2020**, *11*, 48.
- Liu, H.; Hu, Z.; Song, Y.; Lin, J. Decentralized vehicle-to-grid control for primary frequency regulation considering charging demands. *IEEE Transactions on Power Systems* **2013**, *28*, 3480–3489.
- Xu, X.; Zhang, C.; Gu, L. Decentralized primary frequency regulation control strategy for vehicle-to-grid. In Proceedings of the 2016 3rd International Conference on Systems and Informatics (ICSAI). IEEE, 2016, pp. 217–222.
- Liu, H.; Qi, J.; Wang, J.; Li, P.; Li, C.; Wei, H. EV dispatch control for supplementary frequency regulation considering the expectation of EV owners. *IEEE Transactions on Smart Grid* **2018**, *9*, 3763–3772.
- Izadkhast, S.; Garcia-Gonzalez, P.; Frías, P. An aggregate model of plug-in electric vehicles for primary frequency control. *IEEE Transactions on Power Systems* **2015**, *30*, 1475–1482.

8. Liu, H.; Huang, K.; Yang, Y.; Wei, H.; Ma, S. Real-time vehicle-to-grid control for frequency regulation with high frequency regulating signal. *Protection and Control of Modern Power Systems* **2018**, *3*, 13. 293
9. Iqbal, S.; Habib, S.; Khan, N.H.; Ali, M.; Aurangzeb, M.; Ahmed, E.M. Electric Vehicles Aggregation for Frequency Control of Microgrid under Various Operation Conditions Using an Optimal Coordinated Strategy. *Sustainability* **2022**, *14*, 3108. 294
10. Sahu, P.C.; Prusty, R.C.; Panda, S. Frequency regulation of an electric vehicle-operated micro-grid under WOA-tuned fuzzy cascade controller. *International Journal of Ambient Energy* **2022**, *43*, 2900–2911. <https://doi.org/10.1080/01430750.2020.1783358>. 295
11. Hajiakbari Fini, M.; Golshan, M.E.H.; Martí, J.R. Coordinated Participation of Electric Vehicles and Generating Units in Primary Frequency Control in the Presence of Renewables. *IEEE Transactions on Transportation Electrification* **2023**, *9*, 130–141. <https://doi.org/10.1109/TTE.2022.3185547>. 296
12. Yao, E.; Wong, V.W.; Schober, R. Robust frequency regulation capacity scheduling algorithm for electric vehicles. *IEEE Transactions on Smart Grid* **2016**, *8*, 984–997. 297
13. Wenzel, G.; Negrete-Pincetic, M.; Olivares, D.E.; MacDonald, J.; Callaway, D.S. Real-time charging strategies for an electric vehicle aggregator to provide ancillary services. *IEEE Transactions on Smart Grid* **2018**, *9*, 5141–5151. 298
14. Liu, H.; Huang, K.; Wang, N.; Qi, J.; Wu, Q.; Ma, S.; Li, C. Optimal dispatch for participation of electric vehicles in frequency regulation based on area control error and area regulation requirement. *Applied energy* **2019**, *240*, 46–55. 299
15. Kaur, K.; Kumar, N.; Singh, M. Coordinated power control of electric vehicles for grid frequency support: MILP-based hierarchical control design. *IEEE Transactions on Smart Grid* **2019**, *10*, 3364–3373. 300
16. Kaur, K.; Singh, M.; Kumar, N. Multiobjective optimization for frequency support using electric vehicles: An aggregator-based hierarchical control mechanism. *IEEE Systems Journal* **2019**, *13*, 771–782. 301
17. Jeong, H.; Jeong, M.; Lee, S. Vehicle-To-Grid Based Frequency Regulation Method In An Isolated Microgrid Considering Charging Requests Of Electric Vehicles. In Proceedings of the 2019 International Conference and Exhibition on Electricity Distribution (CIRED). AIM, 2019, pp. 1–5. 302
18. Wang, M.; Mu, Y.; Li, F.; Jia, H.; Li, X.; Shi, Q.; Jiang, T. State Space Model of Aggregated Electric Vehicles for Frequency Regulation. *IEEE Transactions on Smart Grid* **2019**. 303
19. Khooban, M.H.; Gheisarnajad, M. A Novel Deep Reinforcement Learning Controller Based Type-II Fuzzy System: Frequency Regulation in Microgrids. *IEEE Transactions on Emerging Topics in Computational Intelligence* **2020**. 304
20. Dahmane, Y.; Ghanes, M.; Chenouard, R.; Alvarado-Ruiz, M. Coordinated Charging of Large Electric Vehicle Fleet in a Charging Station With Limited Transformer Power. In Proceedings of the 2020 4th IEEE Conference on Control Technology and Applications (IEEE CCTA), 2020, pp. 1–6. 305
21. Dahmane, Y.; Ghanes, M.; Chenouard, R.; Alvarado-Ruiz, M. Decentralized Control of Electric Vehicle Smart Charging for Cost Minimization Considering Temperature and Battery Health. In Proceedings of the 2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), 2019, pp. 1–6. <https://doi.org/10.1109/SmartGridComm.2019.8909796>. 306
22. Ziras, C.; Zecchino, A.; Marinelli, M. Response accuracy and tracking errors with decentralized control of commercial v2g chargers. In Proceedings of the 2018 Power Systems Computation Conference (PSCC). IEEE, 2018, pp. 1–7. 307
23. Ye, X.; Ji, T.; Li, M.; Wu, Q. Optimal control strategy for plug-in electric vehicles based on reinforcement learning in distribution networks. In Proceedings of the 2018 International Conference on Power System Technology (POWERCON). IEEE, 2018, pp. 1706–1711. 308
24. Yao, E.; Wong, V.W.S.; Schober, R. Robust Frequency Regulation Capacity Scheduling Algorithm for Electric Vehicles. *IEEE Transactions on Smart Grid* **2017**, *8*, 984–997. 309
25. Maxime, Z.; Sebastian, B.; Dago, C.; Alexis, G.; Edward, B. Flexibility within the electrical systems through demand side response: Introduction to balancing products and markets in Germany, France, and the UK. Technical Report number, European Commission, 2017. 310

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content. 311