EVs and Renewable Energy: Paving the Way for Greener Electromobility Networks

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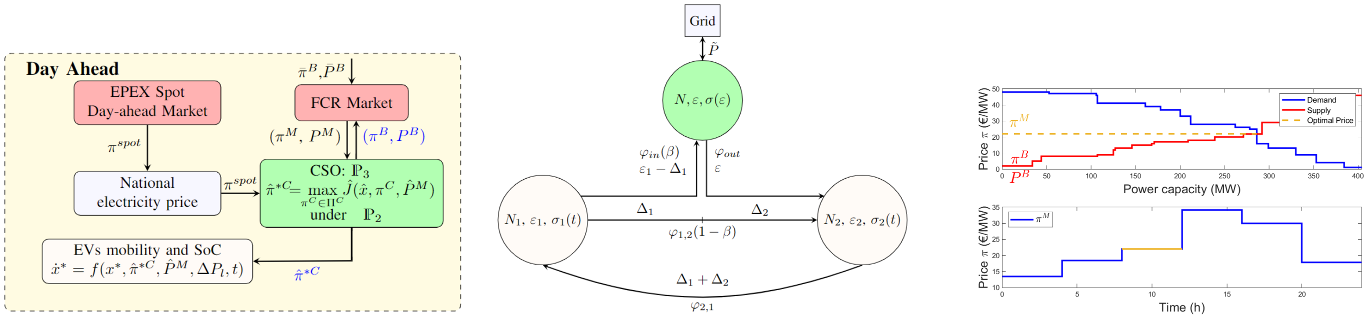
Summary. Electric vehicles (EVs) and the infrastructure of electric vehicle charging stations (EVCS) are emerging as essential components of sustainable energy systems. In this context, we introduce an innovative approach that utilizes aggregated EVCS to participate in the auxiliary market, thereby providing grid-balancing services. Our model continuously monitors changes in EV state-of-charge (SoC) across both time and space, taking into account various factors, including driver behavior, current SoC levels, and the associated charging/discharging costs and benefits. This approach will enable charging station operators (CSO), in collaboration with aggregators, actively engage in the frequency containment reserves (FCR) market. We introduce an optimization framework in conjunction with this EV model. For establishing pricing policies with the twin aims of maximizing profits for aggregators and charging station operators (CSOs), while also minimizing energy charging expenses for EV users. Our findings underscore the effectiveness of this pricing strategy in achieving these dual objectives, as demonstrated through realistic simulations integrating the EV mobility and the Electricity FCR market.

1 Introduction

The evolving landscape of transportation and energy systems is witnessing a significant transformation marked by the growing adoption of electrical vehicles (EVs) and the expansion of charging infrastructure towards sustainable transport (Razmjoo et al. 2022). Simultaneously, the global shift towards renewable energy sources poses challenges due to their intermittent generation, necessitating innovative energy storage solutions to address supply-demand imbalances (Clerjon and Perdu 2022).

In the realm of grid stability, electric vehicles equipped with Vehicle-to-Grid (V2G) technology and rapid response capabilities emerge as key players in grid management (Ravi and Aziz 2022). The Frequency Containment Reserves (FCR) market, operating with a response time of less than 30 seconds, emerges as a vital component in grid stability, providing a natural arena for electric vehicles to unlock their maximum potential (Codani, Petit, and Perez 2015). Recent emphasis has been placed on the role of electric vehicles in frequency regulation, with studies exploring vehicle aggregation through charging stations (Duan, Hu, and Song 2020) and individual advantages for EV users (Kolawole and Al-Anbagi 2019). Numerous papers explore the involvement of charging station aggregators with a fleet of vehicles in the European FCR market, some opting for V2G technology (Amamra and Marco 2019), while others manage their energy consumption in either an upward or downward direction (Duan, Hu, and Song 2020; Čičić, Gasnier, and Canudas-de-Wit 2023).

Our work introduces an innovative approach utilizing aggregated electric vehicle charging stations for participation in the auxiliary markets, contributing to grid-balancing services. A significant departure from prior studies (Rodriguez-Vega et al. 2023; Mourgues, Rodriguez-Vega, and Canudas-de-Wit 2023; Niazi et al. 2021) lies in the introduction of a novel graph model, incorporating elements related to charging stations such as occupancy, average state of charge (SoC) of electric vehicles, and power exchange with the grid. Seamlessly integrated with an electric vehicle mobility model, our approach considers various allocation ratios based on the average SoC of vehicles near charging stations and the energy price, connecting with the frequency containment reserves market operation. Within this framework, we design pricing optimal strategies with the dual goals of maximizing profits for aggregators and charging station operators, while minimizing energy charging costs for EV users. Realistic simulations encompassing EV mobility and the Electricity FCR market validate the effectiveness of this pricing strategy in achieving these objectives.



(a) Overal Strategy (b) EVs mobility and SoC model (c) FCR market settlement

Figure 1: **(a).** Schematic representation of the whole systems operation. Decision variables are in blue **(b).** Tree-node model example used for illustration. Yellow circles represent origin/destination nodes, while green node symbolize the charging station. **(c).** (uper figure) FCR market price settlement process showing the demand, supply bits and the cleared market price. The lower curve show the FCR price evolution of FCR prices during a day in periods of 4 hrs

2 Methodology

Overal strategy Fig. 1a show an schematic representation of all the components including in this study. EPEX Spot determines spot prices π_{spot} in €/MW by constantly matching buyers' and sellers' orders based on their submitted bid and ask prices. The spot price used will be that of the day-ahead market, which is set one day before delivery for France. The Frequency Containment Reserve (FCR) , is a vital component of the ancillary service sector. This ancillary service is regulating grid frequency, safeguarding the stability of the power network. FCR is in the primary reserve category, characterized by its rapid response capability, acting in less than 30 seconds. Participation in the primary reserve market necessitates the ability to adjust power consumption, both upward and downward, ensuring a dynamic response to grid frequency fluctuations. Market resolution occurs on a day-ahead basis, segmented into six time blocks of four hours each. The CSO block represent the Charge station operators, or aggregators that wish to use the storage EVs capabilities for leveraging the "e-flexibility" from EVs, and enter into the FCR markets. For that the CSO, must submit available power quantity P^B in MW and minimum compensation price π^B in €/MW for every time block. Once the FCR market settles, it returns the approved power quantity P^M in MW and price π^M in €/MW. Simultaneously, the EPEX Spot market establishes electricity prices for the next day by country. In the Intraday phase, the CSO set the charge prices π^C in €/kWh , based on the spot and return price π^{spot}, π^M. When the CSO participates in FCR, it must be capable of both increasing and reducing its charging power. The CSO must also set price π^C in a way that ensures there is always enough vehicles available to meet the grid operator's demands. The optimal CSO strategy is determined through the utilization of a predictive model for Electric Vehicles (EVs) mobility and their State of Charge (SoC). This ensures that the optimization process quantifies the potential energy reserve of EVs. The three key phases involved in this process are briefly outlined below: the FCS market settlement process, the model for EVs mobility and SoC, and the optimization problem.

FCR market settlement process. The settlement of the FCR market is achieved by solving two LP problems. The first maximizes the amount of power exchanged while ensuring that the highest bid price remains lower than the lowest ask price. The second determining the buying/selling price for all participants in the FCR market, ensuring an equitable outcome for all. These two LP problems are including the whole optimization problem. Fig. 1c shows the market resolution process. All offers positioned before the intersection point of the demand curve and the supply curve are considered retained offers. The point where these two curves intersect also defines the price per MW. The figure also displays the evolution of the settled price in the FCR market for a day across the 6 time slots.

Mobility and SoC-Energy model The studied system, illustrated in Fig. 1b, consists of a single route connecting two nodes, featuring road links in both directions. Along this route, a public charging station is positioned on one of the roads. The flow of EVs traveling on this road is divided to access the charging station, based on factors such as the Evs' SoC and the prevailing charging/discharging prices. In the model used, vehicles present at the charging station are all connected to the grid. Their charge rate can be modulated by the Charge Station Operator to conform with the grid request operation. Once the EVs have completed their charging, the outflow from the charging station returns to the relevant node. Finally, and without of generality lost, EVs return to their origin node to complete the journey. Integration of all components lead to a model of a form (Details of the model can be found on Gasnier and Canudas-de-Wit 2024).

$$\dot{x}(t) = f(x(t), \pi^C, P_k^M, \Delta P_l, t) \tag{1}$$

where $\Delta P(t) \in [-P^M, P^M]$ is a random variable describing the real-time power requested by the TSO to the CSO, and representing the mismatch between power supply and load demand due to the renewable energy sources (RES) uncertainly production. Solving (1) isn't a straightforward due to non-causal components stemming from P_k^M, and the random nature of ΔP_l. Nevertheless, solving (1) is equivalent to solve the following optimization problem. $\mathbb{P}_1$: Given ΔP_l, solve $\forall k \in \mathbb{Z}_k$: $P_k^M = \max_{\lambda_k \geq 0} \lambda_k$, under: $i)$: $\dot{x}(t) = f(x(t), \pi^C, \lambda_k, \Delta P_l, t)$, $ii) 0 \leq \lambda_k \leq \min_{\tau \in \mathbb{I}_k} \left\{ \frac{P_{CS} N(\tau)}{2} \right\}$.

Optimal energy-price strategy The CSO has two different sources of revenue. The first is the earnings from selling energy to EVs, given by $\int_0^t \pi^C \tilde{P}$, while the second source is the earnings from selling capacity in the FCR market, which is calculated as $\sum_{k=1}^6 \pi_k^M P_k^M$ for each 4-hour block k. Therefore, the function J calculates the total earnings for the full day, $J(x, \pi^C, P^M, \pi^M) = \int_0^T \pi^C \tilde{P} dt + \sum_{k=1}^6 \pi_k^M P_k^M$. The ideal optimization problem aims to find the values of π^C that maximize the earnings given by the function J under the systems dynamics (1), or equivalent under the solution of problem $\mathbb{P}_1$: $\pi^{*C} = \max_{\pi^C} J(x, \pi^C, P^M, \pi^M), \text{under}\, \mathbb{P}_1$. The optimization is solvable only if the following information is available: 1) the results of the FCR market settlement (i.e. P^M and π^M), and 2) the grid's regulation demand ΔP_l. However, π^M becomes known only after the market clears and cannot be predicted in advance. Additionally, real-time knowledge of ΔP_l is not available. For the optimization be feasible,the problem $\mathbb{P}_1$ is modified through the incorporation of bounds on $\Delta P_l \leq P^M$, i.e. $\mathbb{P}_2$: $\hat{P}_k^M = \max_{\lambda_k \geq 0} \lambda_k$, under: $\dot{\hat{x}}(t) = f(\hat{x}(t), \pi^C, \lambda_k, \Delta \hat{P}_l, t)$, $0 \leq \lambda_k \leq \min_{\tau \in \mathbb{I}_k} \left\{ \frac{P_{CS} \hat{N}(\tau)}{2} \right\}$, $\Delta \hat{P}_l \leq \lambda_k$, $\Delta \hat{P}_l \geq -\lambda_k$. And introducing computable upper bound on J; $\hat{J}(\hat{x}, \pi^C, \hat{P}^M) = \int_0^T \pi^C P_{CS} \hat{N} dt + \pi_{max}^M \sum_{k=1}^6 \hat{P}_k^M$, where $\hat{N}$, and $\hat{P}_k^M$ are obtained from Problem $\mathbb{P}_2$. The final optimal energy-price strategy is now defined as:

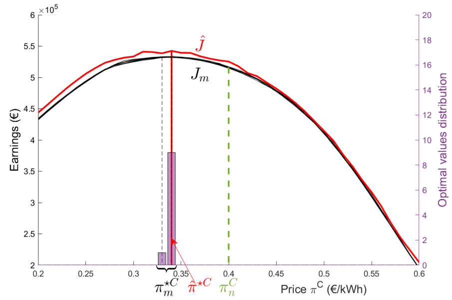
Main result. *The computable optimal energy-price strategy consist in solving the optimal problem:* $\mathbb{P}_3$*: For all* $k \in \mathbb{Z}_k$, $l \in \mathbb{Z}_l$ *solve:* $\hat{\pi}^{*C} = \max_{\pi^C \in \Pi^C} \hat{J}(\hat{x}, \pi^C, \hat{P}^M)$ *under* $\mathbb{P}_2$

The evaluation of the real benefits need to be done using the true cost function J, by replacing the computed optimal price $\hat{\pi}^{*C}$ and $\hat{P}^M$ obtained from $\mathbb{P}_3$, in the ground true equation (1), i.e. $\dot{x}^*(t) = f(x^*(t), \hat{\pi}^{*C}, \hat{P}^M, \Delta P_l, t)$ and finally using this ground true solution to evaluate the effective utility benefits $J(x^*, \pi^{*C}, \hat{P}^M, \pi^M)$. This value will depends on the particular sequence ΔP_l resulting from the day profile difference between power demand and power production variability.

3 Results–simulation scenarios

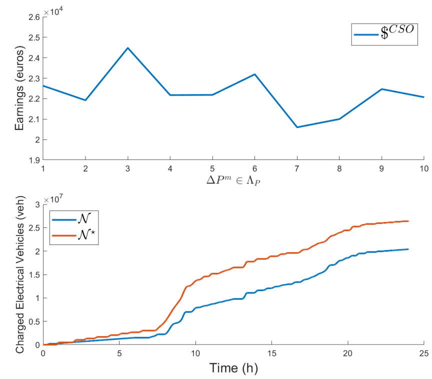
The first Scenario shown in Figure 2a evaluates the distant to optimally. From this figure we can observe that the optimization problem is indeed convex. We can also see that the upper bound $\hat{J}$ of the approximated problem results in a tied bound for J, and provides optimal prices closed to the true optimal ones. Finally, note that the electricity price to be sell to the EVs user, is with this optimisation strategy, substantially lower than the one of the "nominal" (without enter to the FCR market) electricity price $\pi_n^C = 0.4$€. $\hat{\pi}^{*C}$ is 15% lower than π_n^C.

Figure 2b shown the profits evaluation incurred by the CSO due to its participation to the FCR market. Consider the previous realization set Λ_P for ΔP_l. Assume that the CSO sell electricity at nominal price $\pi_n^C = 0.4$€ without participating to the FCR market. The CSO revenues is: $J_n = \int_0^T \pi_n^C \tilde{P}_n dt$ where $\tilde{P}_n$ results from solving problem $\mathbb{P}_1$ with $\pi^C = \pi_n^C$. However, when the CSO enter to the market, the CSO optimal revenues are: $J^* = \int_0^T \hat{\pi}^{*C} \tilde{P}^* dt + \sum_{k=1}^6 \pi_k^M \hat{P}_k^M$ where $\hat{\pi}^{*C}$ comes from solving problem $\mathbb{P}_3$, and $\tilde{P}^*(x^*)$ from solving



(a) Distant to optimally

Figure 2: Simulation scenarios.



(b) FCR market profit evaluation

the ground true system, with the optimal value $\hat{\pi}^{*C}$. Benefits (Figure 2a) for the CSO are then computed: $\$^{CSO} = J^* - J_n$. An EV is considered charged when it leaves the charging station. We compute the number of EVs served (charged) at the CS during a 24hr day period, $\mathcal{N}, \mathcal{N}^*$ for nominal price π_n^C, and optimal price $\hat{\pi}^{*C}$, respectively. Figure 2b shows the respective benefits as a function of the different realizations. The average profit increase for the CSO $\$_k^{CSO}$ is $22,700$€, with 1,476.80€ coming from the sale of capacity on the FCR market. The rest of the profit increase is attributed to a higher influx of EVs due to the more attractive pricing illustrated by the comparison of $\mathcal{N}$ and $\mathcal{N}^*$.

4 Conclusions

In this study, we introduce an approach to integrate Charging Station Operators (CSOs) into the Frequency Containment Reserves (FCR) market. Our framework includes a mobility model, CS aggregators/operators, and FCR market operations. Anticipating the FCR market settlement price is a challenge; nevertheless, our research introduces a strategic bidding approach and an energy pricing strategy for CSOs. Our findings highlight that CSOs' active involvement in the FCR market not only boosts their revenue but also reduces charging expenses for Electric Vehicle (EV) users. Future research could extend the framework by incorporating competition dynamics among multiple charging stations.

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