Frequency Containment Reserve and Imbalance participation: a Battery-Integrated Reinforcement Learning Strategy

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ABSTRACT

With the increasing integration of renewable energy sources (RES), the electrical grid is facing an amplified uncertainty in the energy supply. Transmission System Operators (TSOs) are offering remuneration in exchange for energy exchanges that reduce system imbalances. Helping stabilize the grid frequency is hence an economically viable endeavor, but it requires strategies that can properly manage stochasticities. To tackle this, we analyze the participation of grid-scale batteries in Frequency Containment Reserve (FCR) using a Reinforcement Learning (RL) control strategy. Acting in a multi-market scenario, the RL agent learns to effectively leverage imbalance prices for a high-quality energy recovery strategy. We trained the agent to maximize the imbalance settlement profit while ensuring conforming participation in the FCR service. The agent is also trained to keep the battery yearly cycles below a planned value. In our simulations, we demonstrated the efficacy of RL when dealing with different FCR participation magnitudes, obtaining an average improvement of +9% in profit compared to a rule-based controller baseline.

CCS CONCEPTS

• **Computing methodologies → Intelligent agents**; *Multi-agent systems*; • **Hardware →** *Batteries*; • **Theory of computation →** *Reinforcement learning*; *Multi-agent learning*.

KEYWORDS

Reinforcement Learning, Grid Frequency Regulation, Battery

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1 INTRODUCTION

As the global electrification process advances to curb CO2 emissions, the electrical grid is undergoing an increasing amount of stress to ensure a functional energy transmission. The growing reliance on renewable energy sources (RES) significantly amplifies uncertainties in the energy supply, posing a considerable obstacle to preserving a consistent balance in the grid's frequency [6]. To tackle this, Transmissions System Operators (TSOs) offer remuneration to Balance Responsible Parties (BRPs) for reacting to frequency deviations by keeping (and restoring) the grid balance. We specifically focus on Frequency Containment Reserve (FCR) participation, which requires the fastest response to the frequency deviations.

Given the short reaction time required, batteries are a neat solution for this service participation [2]. However, their finite energy storage might impede them from correctly reacting to the frequency deviations. Because of this, TSOs require an Energy Management Strategy (EMS) from BRPs with finite energy storage [4]. The EMS has to define a strategy to keep the battery's State of Charge (SoC) between operational bounds by using external energy sources. Using the Imbalance settlement mechanism as part of the EMS can be a valuable choice [3]. The Imbalance settlement mechanism is a fee TSOs use to deter energy deviations that disrupt the grid balance. Specifically, dynamic prices based on the grid's system imbalance are applied to energy exchanges that differ from the nominated values declared by BRPs. This mechanism enables a real-time energy exchange that allows the battery to efficiently satisfy the bounds imposed by the EMS.

However, to efficiently exploit this mechanism by buying (selling) energy during low (high) price slots is not a straightforward task, and requires an appropriate control technique [1]. A high-quality policy should effectively regulate the participation in the imbalance settlement by addressing substantial stochasticity originating from frequency deviations and imbalance prices, which are hard to forecast for long horizons. Reinforcement Learning (RL) is a well-established data-driven control technique that has been shown to effectively manage stochasticities [7]. Thus, we used an RL algorithm to control the imbalance participation while providing FCR.

In our experiments, we showed the advantages of smartly incorporating Imbalance participation in the FCR EMS, and we evaluated the results of the RL algorithm in comparison with a standard rule-based controller (RBC).

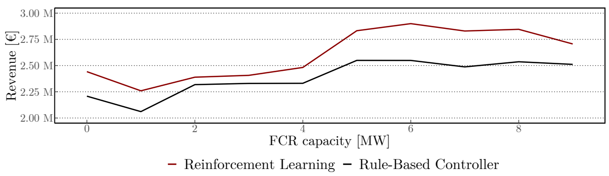

Figure 1: Comparison between the RBC and the RL agent. The RL agent consistently obtains higher imbalance revenues.

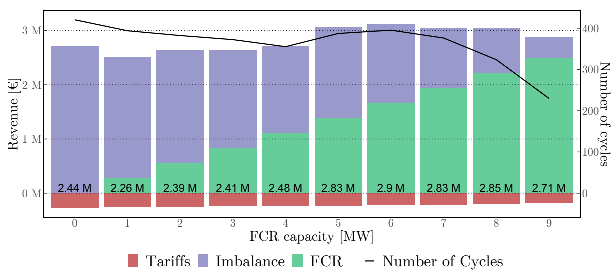

Figure 2: Distribution of revenues made by the battery when the RL agent is used. The sum of each column is numerically shown at the bottom.

2 METHODOLOGY AND EXPERIMENTS

We modeled a battery with a capacity of 10MW / 20MWh, and a constant efficiency of 90%. To simulate the FCR participation, we used historical data covering the frequency deviations in Europe with a granularity of one second. We simulated the battery participation by making it follow the frequency deviations as described by the Belgian TSO's FCR note design [4]. The participation is obtained through price-taking bids in a pay-as-cleared mechanism, using the other historical bids in Belgium to determine the marginal price. For each experiment, the volume submitted in every bid is fixed.

The Imbalance participation is simulated using historical data of Belgian Imbalance prices. The agent makes decisions on a minute basis by using an input composed of the time of the year, the current battery SoC, an estimation of the imbalance price, and the battery cycles consumed in the last 24 hours. When the SoC gets too close to the energy boundaries required by the FCR participation, a backup controller restores the battery's SoC balance using the imbalance participation. The imbalance power capacity reserved consists of the remaining battery capacity after the FCR reservation.

The RL agent is trained to maximize the revenue from the imbalance participation while keeping the battery's number of yearly cycles lower than a planned value (specifically, we soft-constrained the agent to 420 yearly cycles). We used a Soft Actor Critic (SAC) [5] algorithm with a discrete action space containing 3 actions (charge, discharge, and idle) for the battery participation in the imbalance settlement. We also considered a bang-bang RBC with tuned parameters to benchmark the RL agent.

Through our experiments, we aim to assess the RL agent's capability to devise optimal strategies for both imbalance and FCR participation, effectively managing the considerable stochastic nature of these environments. We hence performed a line search by varying over the battery power capacity reserved to FCR, starting from 0MW (i.e., no FCR involved), up to 9MW (i.e., the maximum amount of capacity allowed for the battery to participate in FCR). We then performed the simulations for a whole year of evaluation (2022), using the overall revenue (i.e., the sum of the FCR remuneration, the imbalance profit, and the grid tariffs costs) as a metric.

3 RESULTS

In Fig. 1, we show the comparison between the total revenues of the RL agent and the ones obtained by the Bang-Bang controller. We can observe a substantial and consistent increase in profit (average improvement of +9%, up to +14% when 6MW are reserved to FCR). This shows that the RL agent can obtain high revenues in the multi-market participation. In Fig. 2 we show the revenue distribution of the RL agent. We observe that the number of yearly cycles in each experiment stayed below the battery constraint value, suggesting that the cycles-constraint was correctly infused in the RL agent. Moreover, in all our experiments we observed no violations of the FCR energy constraints, demonstrating the robustness of the method even for high imbalance capacities. Finally, regarding the overall revenue, we can observe a peak around the FCR capacities of 5, 6, 7, and 8 MW. This demonstrates the benefits of having a balanced participation in FCR and imbalance to optimize the value of the battery.

Overall, we can observe that the RL agent can (i) obtain high quality EMS policies, and (ii) properly address the stochasticities of the problem.

4 CONCLUSIONS AND FUTURE WORKS

In this work, we demonstrated the efficacy of RL techniques when providing an EMS for a battery participating in FCR using the imbalance settlement. Although preliminary, we believe these results signify the initial phase of effectively deploying RL techniques for multiple ancillary services participation. Following this, further studies will investigate a more advanced bidding strategy to further increase the battery revenue by setting FCR prices and volumes based on the expected imbalance profit. Another research direction includes enhancing the RL agent by integrating a distributional prediction to explicitly manage the risk attitude of the imbalance participation.

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