BIDDING BEHAVIOR OF NAIVE VS. LEARNING AGENTS IN THE BALANCING ENERGY MARKET UNDER REGULATORY CHANGE

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Overview

Supply and demand in the power system must remain balanced at all times. Most European transmission system operators (TSOs) procure balancing services in a market-based way, through a two-stage process by first reserving the necessary balancing capacity and then activating balancing energy when actual system deviations occur. Yet, market-based procurement is not necessarily synonymous with efficient procurement. Due to strict technical requirements, the current number of eligible balancing service providers (BSPs) is limited. As a result, balancing markets are highly concentrated, which opens up room for opportunistic behaviour and market inefficiencies. The EU regulation establishing a guideline on electricity balancing (GL EB) attempts to tackle the existing inefficiencies by defining the main features of the design of European balancing markets [1]. Among these markets, the balancing energy (BE) market is expected to be decoupled from the balancing capacity market, i.e. the balancing energy bids would be submitted in a separate auction close to real time.

In order to analyze and study the behavior of market players under this new setup, in this work, we simulate a standalone BE market with the help of an agent-based model (ABM). To this end, we implement naive and intelligent agents and compare their relative performances. For the former, simple bidding rules are implemented; for the intelligent agent, we consider a fitted Q-iteration algorithm, i.e. a class of reinforcement learning algorithms, to identify their optimal bids. Then, we investigate the potential efficiency gains from the introduction of a BE market as compared to a joint market for balancing capacity and energy. Finally, we analyse how the bidding behaviour, profits of BSPs, and market outcome change in the face of this regulatory transformation.

Balancing markets have in some form been modelled using ABM (e.g. [2]), but the procurement of balancing energy was either disregarded or considered together with capacity reservation. This paper represents the first attempt to model a standalone BE market that takes the results of the balancing capacity market into account.

Methods

ABM has proven to be a useful tool for addressing market design questions that otherwise cannot be solved by other approaches such as optimization or game theory(e.g. [3]). In particular, optimization models cannot address the issue of strategic behaviour due to their intrinsic assumptions of perfect competition and foresight. Similarly, game theoretical approaches, while useful for identifying optimal strategies of market actors, lack flexibility in integrating multiple agents and are unable to reflect their heterogeneity. ABM does not only include all these features, but also makes it possible to replicate the repeated nature of balancing auctions in which agents learn from their experience.

Under current market rules, only actors who are successful in the balancing capacity market can take part in the BE market [4]. Empirical evidence from European balancing markets shows that for those balancing products for which both balancing capacity and balancing energy is awarded, balancing capacity prices are very low [5]. Therefore they can be considered as exogenous for the current discussion.

For our study, as a first step, the main mechanisms of the BE market are implemented in a simulation framework. For the case of having balancing capacity and energy being procured in a joint auction, both bids are submitted simultaneously. As a result, the same balancing energy bids are used throughout the entire reservation period (bid lock-in) and the market clearing price depends on the actual system imbalance volume alone. Conversely, in case of a standalone BE market, BSPs can submit different balancing energy bids for different time periods. As a second step, we compare the two market environments with learning and simplified "naïve" agents and then trace the effect of their bidding strategies on the market outcome.

The key characteristics of the BE market are modeled in a way to approximate the actual balancing market design implemented in multiple European countries. In particular, each iteration clears the BE market clearing with a 15-minute frequency and all actors submit BE bids equal to the required minimum bid size of 5MW. The actors decide on the bid prices individually based on their marginal costs or prior experience (see types of agents below).

To simulate the bidding behaviour of BSPs, we consider three types of agents:

1) Naive agents that bid their true marginal costs as it would be expected from the classical economic theory under perfect competition;

2) Naive agents that bid according to a predefined simplified rule (reduce bid if not awarded in the previous round, keep the bid unchanged if awarded in the previous round);

3) Intelligent agents that, using a reinforcement learning (RL) algorithm called fitted Q-iteration [6], learn the optimal behavior when submitting market bids to maximize their profit. In detail, as any RL algorithm, the method considers that the agent and the BE market can be modeled via a Markov decision process, i.e. the agent modeled by a state x is controlled with a discrete set of actions $A = \{a1, ..., aN\}$, and transitions from one state to the other based on a probabilistic distribution. In addition, when transitioning, the agent receives a reward based on a different distribution. During the training, the RL agent learns an optimal policy that outputs, for each state x, the optimal action a^* so that it maximizes the expected value of the cumulative sum rewards. After each round, the agents' information about their respective profits is updated.

Results

Upward regulation when a BSP is expected to increase generation and downward regulation when generation must be reduced are typically procured in two separate auctions. Since the cost structures of the bidders in the two markets are different due to the nature of these balancing products, their bidding strategies will also be different.

The bidding behaviour of the market participants of 3 types is therefore analysed with the help of two case studies:

1) BE market for upward regulation where BE is procured either jointly or independently from the balancing capacity market;

2) BE market for downward regulation where BE is procured either jointly or independently from the balancing capacity market.

Preliminary results indicate that if a standalone BE market is introduced, this is likely to produce lower bid prices in the BE market for upward regulation and negative bid prices in the BE market for downward regulation. In turn, the costs appear to be at least partially shifted to the balancing capacity market due to a higher risk of not being activated.

On the other hand, the contrasting of the results for three different agent types indicates that bids of learning agents can deviate – at times significantly – from those of naive true-cost bidders and depend on the time of the day. This implies that the proposed change does not eliminate the problem of potential market power entirely and additional characteristics of balancing market design need yet to be adjusted.

Conclusions

The issue of an efficient balancing market design has gained importance both due to the ongoing market harmonization efforts and due to the increasing shares of volatile renewables in European power systems. The results from this study are meant to inform policymakers and glean insight into potential development of bidding strategies in the balancing market given the upcoming regulatory change.

This analysis allows to estimate the effect of the planned change in the market design and to anticipate potential issues linked to the introduction of a standalone balancing energy market. Finally, the presented approach has a methodological value, which will be further exploited in the future work to integrate intertemporal constraints and to apply ABM to more complex cases with interrelated markets.

References

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