A Novel Aggregation Framework for the Efficient Integration of Distributed Energy Resources in the Smart Grid

Extended Abstract

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ABSTRACT

In this paper, we put forward a novel DER aggregation framework, encompassing a multiagent architecture and various types of mechanisms for the effective management and efficient integration of DERs in the Grid. One critical component of our architecture is the Local Flexibility Estimators (LFEs) agents, which are key for offloading the Aggregator from serious or resource-intensive responsibilities—such as addressing privacy concerns and predicting the accuracy of DER statements regarding their offered demand response services. The proposed aggregation framework allows the formation of efficient LFE cooperatives. Our experiments verify its effectiveness for incorporating heterogeneous DERs into the Grid in an efficient manner—showing that the use of appropriate mechanisms results in higher payments for participating LFEs.

KEYWORDS

Flexibility Aggregators; Smart Grid; Mechanism Design; Distributed Energy Resources

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1 INTRODUCTION

The emerging Smart Grid, with its bidirectional electricity and information flow, is envisaged to deliver electrical power in very resourceful ways, to efficiently optimize the performance of intermittent assets [1] and successfully exploit all the Distributed Energy Resources (DERs) that are continuously emerging [9, 15]. DERs are the various electricity supply or demand assets that are spread across the Grid; and which, however small, when combined, can enhance the Grid's ability to seamlessly provide power, even if it largely originates from intermittent renewable energy sources.

Furthermore, recent developments regarding environmental policies and the emergence of a multitude of (distributed) energy markets, have turned the attention of the electricity stakeholders to research on DERs' flexibility [11]. The notion of *flexibility* corresponds to the DERs' ability to either offer produced/stored energy or consumption reduction services to the Grid to promote its stability [18]. There is much work on estimating the flexibility of DER assets [8, 23]; while the use of *aggregators* [6, 13, 14] is one of the most important mechanisms that were created to utilize the flexibility of the DERs in the Smart Grid.

An *aggregator* is a mediator between DERs and the energy markets [6], with the mission to trade the flexibility obtained from the DERs by participating in the markets on behalf of the DERs' owners [13]. Generally, aggregators offer stability guarantees to the Grid by offering flexible loads. Currently, the existing legal frameworks of many countries, especially in the EU and USA, have been updated to allow the existence of such aggregator mechanisms [2, 20].

In this paper, we employ ideas from mechanism design and cooperative game theory to outline a novel aggregator framework for the efficient integration of DERs in the Grid. Our framework provides an aggregation architecture, shown in Fig. 1, along with mechanisms for its effective and efficient operation and manages to increase the flexibility offered to the Grid and the profits of participating agents.

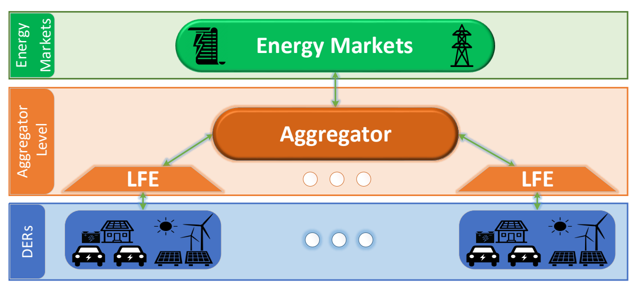

Figure 1: Component diagram of the proposed framework.

2 THE DER AGGREGATION FRAMEWORK

In our multiagent [22] architecture, we introduce the so-called *Local Flexibility Estimators (LFEs)* that allow us to address some severe aggregator issues, such as privacy concerns and evaluation of the DERs' flexibility accuracy. LFEs essentially serve as DER coalition managers, coordinating their members' market activities. Given this, we focus on creating efficient LFE cooperatives intending to increase the profits of every stakeholder. To achieve this, we have populated our framework with various selection mechanisms—some of which are *scoring rules* [7], and some are (deep) *reinforcement learning (RL)* [19] techniques. Therefore, an Aggregator agent can then use these selection mechanisms to decide which LFEs to include in its (flexibility) offers to the day-ahead markets.

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In practice, LFEs are end-nodes that only have to publish to the Aggregator limited information with respect to their flexibility and availability. Other works try to preserve the privacy of DERs by introducing new communication protocols and algorithms [5, 21]. We propose a new all-in-one framework that can, on top of all other benefits, contribute to the privacy concerns that arise when information flows from DERs toward the Aggregator. In our case, DERs with common interests could form an LFE and participate as a multipurpose flexibility provider in any Aggregator, hiding their details from the (potentially non-trusted) Aggregator.

The total communication complexity of the proposed framework unavoidably increases compared to a traditional aggregator [6]. However, since LFEs are *local* entities (e.g., managing the assets of a single company or local energy community), the added communication load with their DERs is expected to be minimal. Overall, incorporating LFEs within an Aggregator agent allows us to generalize and scale up, since an Aggregator can serve more DERs by just adding LFEs to take up some of its optimization burden. Therefore, offloading some of the optimization complexity to a lower level (that of LFEs) could mean more accurate and scalable outcomes in terms of flexibility provided to the Grid.

Now, ranking and selecting LFEs is a key concern: LFEs with unreliable (low-accuracy predictions regarding their) flexibility estimations can trade with the Grid directly, but should not participate in the Aggregator's flexibility offers, since they can damage its profits and overall reputation. The Aggregator is thus able to calculate the total energy flexibility it can offer by selecting which LFEs will participate in the upcoming flexibility trades, using various scoring and ranking mechanisms. Moreover, the Aggregator is responsible for splitting the profits back to the LFEs, based on their contribution and appropriate scoring mechanisms that may also take into account the accuracy of LFE flexibility predictions.

3 MECHANISMS AND EVALUATION

We conducted a systematic experimental evaluation using data from the PowerTAC [10] simulator in various experimental scenarios to test the different aspects of our framework. To this end, we created and compared five different methods, each of which combines different LFE selection and pricing mechanisms (distributing the Aggregator's profits to the LFEs):

The first method uses the *Simple Selection mechanism* to decide which LFEs to participate in the aggregator. This scoring mechanism uses the Mean Absolute Error of each LFE's flexibility prediction. In detail, the aggregator calculates the average *score* of LFE_i over a time period w of past trading cycles, and then selects LFE_i if that score exceeds a threshold τ. Also, we use the (simple) *Prediction Accuracy* pricing mechanism [3], for this method since we assume that LFEs in this setting are able only to provide point estimates regarding their anticipated delivered flexibility.

In the rest of our methods, we make use of the *Continuous Ranked Probability Score (CRPS) pricing mechanism* [7, 16, 17], assuming that LFE agents are now able to provide distributions over their prediction error. Given these, *CRPS* provides incentives for truthful and reliable LFE predictions, as it postulates that agents should be rewarded according to both the actual flexibility they delivered and the accuracy of their probabilistic predictions.

Our second method employs the so-called *DQN Selection* we put forward. Specifically, we use the celebrated Q-Networks (DQN) [12] RL algorithm, using two different reward functions. We formulate the aggregator's decision-making problem as a decision process, aiming to find the action with the highest Q-value—corresponding to the long-term utility of selecting a set of LFEs at a time step.

The third method uses *CRPS* as a selection mechanism also. Specifically, we calculate the average CRPS score of a time period w and check if the final average score is higher than a specific threshold. Higher (normalized to $[0, 1]$) CRPS values represent LFEs with higher prediction accuracy, while lower CRPS values correspond to less accurate LFEs; and our *CRPS Selection* picks LFEs whose CRPS scores exceed a threshold for inclusion in the Aggregator.

In the fourth method, every LFE interacts *directly* with the energy markets using the *CRPS Pricing* mechanism. This serves actually as a baseline method, corresponding to how the LFEs would have performed if they had never participated in our framework. In the last method, all LFEs participate in the Aggregator without selection criteria. This mirrors the current state-of-the-art aggregation scenario, in which an aggregator incorporates all available resources.

Results and concluding remarks. Our aggregator framework contributes to the smooth DERs' integration into the Grid since *(a)* it allows smaller DERs to participate in the Smart Grid markets; *(b)* it selects which LFEs to participate in the energy transactions, increasing the expected accuracy of the promised offers, thus indirectly aiding the Grid's stability; and *(c)* as verified via our experiments, the use of certain designed selection and pricing mechanisms leads to higher payments for LFEs that the aggregator manages.

In some detail, the use of the truthfulness-incentivizing *CRPS Selection* mechanism rewards effectively LFEs that have reliable flexibility estimates and results to the highest aggregator-to-LFEs payments for those LFEs, compared to those achieved with other selection mechanisms; or compared to assets' earnings in "baseline settings" when they either participate in a "traditional" aggregator that manages all available DERs or when they trade directly with the Grid. Also, using the *CRPS Selection* mechanism, and regardless of the LFEs' prediction accuracy, our framework results in increased profits for every LFE, compared to those potentially accrued via participation in functional commercial flexibility aggregators paid via pricing mechanism in use in the current Smart Grid [4].

The *Simple Selection* mechanism we propose ranks as a close second to CRPS. However, this mechanism is easier for non-specialists to comprehend. This result implies a trade-off between using a highly efficient yet complex scoring rule vs. a slightly less efficient yet easy-to-understand selection mechanism, since using the latter can motivate the participation of small DERs (e.g., corresponding to small and medium-sized enterprises or private homes).

Finally, the *DQN Selection* mechanisms were better than the aforementioned baseline settings only for certain settings in which DER accuracy does not fluctuate dynamically over time. Additionally, low-accuracy LFEs prefer to participate in larger LFE cooperatives so the team can balance out their errors.

Overall, our results demonstrate the effectiveness of our framework. Future work includes studying scenarios that allow LFEs to replace inefficient DER assets; and enhancing our framework with the ability to include multiple competing aggregators.

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