A distributed scheduling method for demand response in energy communities with distributed generation and storage

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1 Introduction

In [2], we have developed heuristics for load scheduling in energy communities. This work assumes a centralized decision maker assigns optimal decision to the community members. Besides the computational issue, this management approach faces the social acceptance issue. We have, therefore, started as in [1] to study how to efficiently decentralize this decision process. Instead of dictating schedules, the centralized authority (Community Coordinator, CC) would merely provide some incentives to demand a response from the members to achieve a given objective, knowing the members do not directly interact.

1.1 Description

We consider a community of N members with different asset possession characteristics, as presented in Figure 1. Producers can store and exchange their energy surplus with other members through the coordinator or the primary grid. No additional links exist between members; CC is the intermediary between members, disseminating information. The members remain connected to the main grid and collect energy when needed. We aim to provide a decentralized model that incentivizes the consumption of the local generation in the community as much as possible.

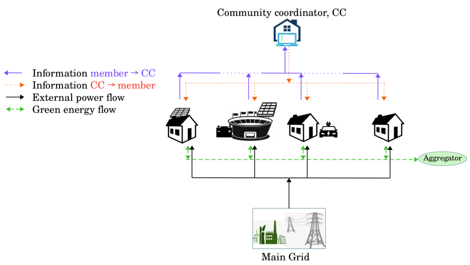

Figure 1: Community's presentation.

2 Allocation keys

As there are no direct links between the members, each member determines their local schedules and sends information about energy needs and availability to the CC. The latter determines the allocation keys (the maximum periodic amount of energy each member can draw from the community) and sends them to members, who adjust their decisions according to this information to maximize their gain. The notion of allocation key is used in practice to share the economic gain among community members at the end of a given period. We adapt this notion to ensure the proactive management of the community. We calculate the allocation keys in different ways:

- Key **K1**: It is a calculation method based on the total periodic energy consumption and availability. This iterative method allows fair energy allocation among members.

- Key **K2**: consists of determining the candidates for the energy reception and then sharing (uniformly) the power between these members, and iteratively update the allocation according to members reactions. A candidate is a member who does not inject energy.
- Key **K3**: is a combination of **K1** and **K2**.
- Keys **K4** and **K5** respectively share energy in prorate to consumption and investment in generation and/or storage tools.

3 Experimental Results

We conduct experiments on some realistic instances built with data collected from Smart Lou Quila over one month sliced into 30 minutes. We use the MILP in [2] to solve the scheduling problem of each member with `time_limit` $= 50s$ per member. And compare the solutions for the a priori and a posteriori management. Table 1 presents the solutions, where column `obj` is the total amount of power collected from the main grid. Column `Available` is the total amount of energy that can be shared in the planning horizon, and `Loss` is the share of `Available` that goes to the main grid.

	A posteriori			A priori		
Key	`obj` kWh	`Available` kWh	`Loss` kWh	`obj` kWh	`Available` kWh	`Loss` kWh
K1	4240.87	846.11	409.52	4153.15	714.77	303.78
K2	**4194.44**	846.11	**363.83**	**4063.07**	714.77	**205.14**
K3	4209.16	846.11	380.75	4133.72	714.77	285.91
K4	4198.4	846.11	367.22	4079.30	714.77	225.87
K5	4369.30	846.11	538.13	4234.52	714.77	378.83

Table 1: Key comparison.

We notice that key **K2** returns the best solution in the a priori and a posteriori management. Further, we compare the solutions of the centralized and distributed approaches. We report the amount of energy collected from the main grid for each approach in Table 2. The column **gap** presents the gap between distributed and centralized solutions.

Horizon	Centralized optimal value kWh	Distributed solution kWh	**gap** %
August 2021	3867.88	4063.07	5.04
February 2023	7422.74	7433.97	0.15
August 2023	7159.68	7196.06	0.51
September 2023	6781.69	6803.74	0.32

Table 2: Solutions' quality.

The average gap between the centralized and decentralized solutions is 1.51% for the experiments carried out.

4 Conclusion

We have proposed an efficient management process where members build their schedules according to incentives sent by the centralized authority. That management process is easily implementable; it will be even easier in a community where everything is smart.

References

[1] Cheng Lyu, Youwei Jia, and Zhao Xu. Fully decentralized peer-to-peer energy sharing framework for smart buildings with local battery system and aggregated electric vehicles. *Applied Energy*, 299:117243, 2021.

[2] Mariam Sangaré, Eric Bourreau, Bernard Fortz, Amaury Pachurka, and Michael Poss. Loads scheduling for demand response in energy communities. *Computers & Operations Research*, 160:106358, 2023.