Loads scheduling for energy community Demand Response on Smart Grids

Mariam Sangaré [1,2,a] Michael Poss[1] Eric Bourreau[1] Amaury Pachurka[2]
University of Montpelier [a]
LIRMM, Team MAORE [1]
Beoga [2]
(msangare michael.poss eric.bourreau)@lirmm.fr amaury.pachurka@beoga.fr

1 Introduction

The energy transition is a means to meet the objectives set by the Paris Agreement [3]. Faced with the challenges of the energy transition, many innovative companies are emerging and propose continuous technological progress. This paper focuses on optimizing collective self-consumption in an energy community composed of various members: households and public premises (stadium). Each member can produce, consume, exchange, sell (within the community or on the grid) and/or store photovoltaic energy. The considered community remains connected to the public grid and uses it. This study aims finally to provide optimal planning of the controllable loads for each member in the planning horizon. Moreover, it gives a plan of energy exchanges and a management scheme for electricity storage units installed in the community.

2 Loads scheduling

We consider a collective self-consumption community composed of n members. Each member can have production and storage equipment. In addition, each member performs a set of tasks with electrical devices. These tasks are detailed as follows. The objective is to schedule the tasks to minimize the use of the grid. According to [1], controllable loads are those with flexible and programmable operation. The controllable loads are grouped into two categories: type A and B loads, which reorganization over time allows increasing the community's energy efficiency.

- ⋄ **Type A loads**: these are related to tasks whose execution allows to regulate the temperature of certain environments to ensure human comfort. As an example of such tasks, we have heating and water heaters. In practice, an individual regulates the temperature of a room to reach a comfort zone temperature and then maintains this zone until a certain time of the day.
- ⋄ **Type B loads**: these relate to tasks that must be done within some given time windows and with fixed periodic levels of electrical consumption. They are generated by the use of appliances such as washing machines, dryers, and electric vehicles. For each corresponding task, the user will indicate the different time windows where she could execute the task and indicate the periodic consumption levels in each time window.
- ⋄ **Type C loads** these are loads that must be executed without delay after the request and necessarily with the required levels of electrical consumption. As type C-tasks, we can mention lighting, cooking, television. For each member, we estimate the periodic accumulation of the consumption of those tasks in the planning horizon.

The proposed solution consists of determining the starting period and the periodic consumption levels to be used for each type A task and also choosing the best schedules to operate the type B tasks while respecting the community's operating constraints.

3 Resolution method

In a first step, we developed a mixed-integer linear programming (MILP) model inspired by the model proposed in [2]. However, the MILP is not efficient for large problem instances. We then developed a heuristic based on column generation algorithm. That heuristic allows us to generate only the schedules likely to improve the restricted master problem (RMP) instead of explicitly generating them all. We begin this resolution approach by generating some feasible schedules to get the dual values by solving the RMP. Then, we solve a pricing problem at each iteration to get the potentially improving plans (with a negative reduced cost). Next, we add these columns to the RPM and solve it. We repeat this process until no improving solution is returned or until the maximum iteration is reached. Finally, we solve the RMP with integrality constraints to get the result of the heuristic.

4 Results

The used instances are built with data from the BEOGA's Smart Lou Quila demonstrator located in Cailar in the Guard. Smart Lou Quila is composed of seven members. The other instances are built by duplicating those members. The planning horizon is consists of a day sliced into 48 periods. The MILP's solving time is `time_limit`=5600s, the column generation's pricing problem has a maximum time `time_limit`=200s, and the maximum number of GC iterations is `maxIter`=10 for each instance. Finally, the RMP with integrality constraints has a `time_limit`=3600s. The results are reported in Table 1 where $|N|$ denotes the number of members in the community. obj and obj_{GC} represent respectively the sum of the electricity extracted from the main grid during the planning horizon returned by the MILP and the column generation. Output " *** " means that no feasible solution has been found after the `time_limit`. We notice that the MILP approach is more efficient for the small instances while the column generation is more efficient for the large ones.

	MILP's solutions			Column generation solutions	
$\|N\|$	obj	Gap	CPU	obj_{GC}	CPU
7	111.38kWh	0.08%	5605.4	112.00kWh	110.44
28	481.68kWh	0.2%	5601.66	482.59kWh	1311.08
56	974.89kWh	0.4%	5601.78	976.87kWh	1035.71
112	***	***	***	1964.57kWh	1882.25
224	***	***	***	3904.91kWh	1162.68

Table 1: Comparison between the solutions of the two approaches.

References

[1] Raffaele Carli et al. "Energy scheduling of a smart microgrid with shared photovoltaic panels and storage: The case of the Ballen marina in Samsø". In: *Energy* 198 (2020).

[2] Anjos F. Miguel et al. "Load Scheduling for Residential Demand Response on Smart Grids". In: *VAME 2017 - Variational Analysis and Applications for Modelling of Energy Exchange*. Perpignan, France, May 2017.

[3] United Nations. *The Paris Agreement*. URL: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement. (accessed: 02.11.2021).