ISSN 2004-2965 Energy Proceedings, Vol. 20, 2021

International Conference on Applied Energy 2021
Nov. 29 - Dec. 5, 2021, Thailand/Virtual
Paper ID: 204

Integration of a Microgrid Laboratory Into an Aggregation Platform and Analysis of the Potential for Flexibility

Maite Etxandi-Santolaya[1*], Alba Colet-Subirachs[1], Mattia Barbero[2], Cristina Corchero[1,2,3]

[1] Catalonia Institute for Energy Research (IREC), Jardins de les Dones de Negre 1, 2, 08930, Sant Adrià de Besòs, Barcelona, Spain
(*corresponding autor: metxandi@irec.cat)

[2] Bamboo Energy, Jardins de les Dones de Negre 1, 2, 08930, Sant Adrià de Besòs, Barcelona, Spain

[3] Dept. Statistics and Operations Research, Universitat Politècnica de Catalunya - BarcelonaTech, Jordi Girona 1-3, 08034, Barcelona, Spain

ABSTRACT

The increase of Renewable Energy Sources (RES) has given momentum to demand-side flexibility, led by Demand Response (DR), to counteract the uncertainties of the new electricity system. Meanwhile, consumers, with the help of Demand Aggregators (DA), are becoming active participants by engaging in flexibility actions. As a tool for the experimental assessment of DR, this work integrates a microgrid laboratory with an aggregation platform. To test the environment created and analyse the impact of DR, two consumers have been defined using virtual, emulated and real elements: a residential user with a Heating Ventilation and Air Conditioning (HVAC) unit and a prosumer equipped with Photovoltaic (PV) panels and a second-life battery.

Keywords: Aggregation platform, demand-side flexibility, Demand Response, microgrid laboratory

NONMENCLATURE

Abbreviations	
DA	Demand Aggregator
DR	Demand Response
PV	Photovoltaic
IREC	Catalonia Institute for Energy Research
SCADA	Supervisory Control And Data Acquisition
EV	Electric Vehicle
RES	Renewable Energy Sources
SoC	State of Charge
KPI	Key Performance Indicator

1. INTRODUCTION

Demand Response (DR) can be a powerful tool to extract the existing demand-side flexibility and position customers at the centre of the electricity system, while providing services to grid operators [1]. With the help of the Internet of Things, demand, which has traditionally been perceived as relatively inelastic, can be controlled to balance the uncertainty and variability introduced by Renewable Energy Sources (RES) [2].

However, due to the complexity of participation and the technical requirements, such as the minimum bid size, single customers cannot enter flexibility markets [3]. In this context, the figure of the Demand Aggregator (DA) appears. DAs provide the necessary tools to aggregate the demand from several users and trade in flexibility markets [4]. Thanks to DAs, customers can actively participate in these markets to balance the electricity grid, reducing their bill and contributing towards a successful transition towards clean energy [5].

Rather than pure simulations, several projects have taken experimental approaches to analyse demand-side flexibility. Most of these experiments are field trials, and only a few take place in laboratories. Due to the difficulty of developing scenarios in real life, experiments in the laboratory offer a powerful tool before real-life implementations, especially considering the restrictions that are still present in many flexibility markets that limit the presence of DAs [3]. As an example of a laboratory work, Abrishambaf et al. [6] validated the performance of DR under aggregation in a community model using a real-time simulation and hardware-in-the-loop approach.

The Energy SmartLab is a microgrid laboratory located in the Catalonia Institute for Energy Research (IREC) [7]. The laboratory has both real storage elements and emulation cabinets for simulating a variety of assets. These elements are governed by a Supervisory Control and Data Acquisition (SCADA) system to develop software and hardware testing. In this way, scenarios that depend on phenomena that are uncontrollable in real life, like weather fluctuations, can be developed with real power flow [8]. By integrating the SmartLab with the Bamboo Energy aggregation platform [9], this project aims to build a tool for the experimental testing of demand-side flexibility by mimicking the interaction between a real-life user and a DA. The set-up is then validated by running two scenarios in which two consumer types are analysed.

2. METHODOLOGY

2.1 Laboratory set-up

This study uses two emulation cabinets, for emulating a Photovoltaic (PV) panel and a load, and the second-life Electric Vehicle (EV) battery from the SmartLab, along with a virtual Heating Ventilation and Air Conditioning (HVAC) unit. The electrical scheme of the laboratory configuration used can be seen in Fig 1 (left).

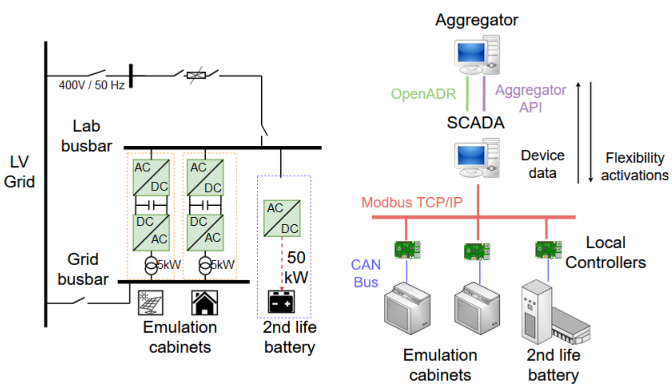

Fig 1. Electrical (left) and communication (right) scheme of the configuration used in the SmartLab

The emulation is performed via hardware. Each cabinet is composed of two AC/DC converters in back-to-back configuration allowing a bidirectional power flow that follows the desired path. This way, the emulation cabinets can behave as generating or consuming nodes.

The second-life battery, shown in Fig 2, belonged to a Renault Kangoo EV with 23 kWh of capacity. After its service in the vehicle, the battery is now used as a static storage system to study second-life applications [10].

Fig 2. Laboratory second-life battery

Since the laboratory only allows emulating electrical behaviours, a virtual HVAC model has been defined, consisting of a thermal zone model and a control model. The thermal zone model is an RC model that simulates the indoor temperature of the building [11]. The control model defines the power that the HVAC supplies to achieve the desired temperature, defined by a thermostat setpoint.

The aggregator acts as the highest level of control, on top of the SCADA, as shown in the communication scheme of Fig 1 (right). Two methods have been used to communicate with the aggregator: their own API and the OpenADR protocol [12]. The flexibility activations received are translated into commands by the SCADA and sent to the Local Controllers of the cabinets and the second-life battery via Modbus TCP/IP.

2.2 Scenario definition

For each of the two scenarios, two sub cases were developed. 1) A base case where the user consumes electricity as usual and 2) the aggregator case, where the DA has the ability to influence the consumption. Each case considers a duration of three consecutive days.

2.2.1 Residential scenario

The first scenario represents a customer that owns a controllable 1.5 kW HVAC unit and an uncontrollable load. Both summer and winter tests have been developed for this scenario. In the base case, the HVAC assures the thermal comfort defined by the user. In the aggregator case, the DA can overwrite the temperature setpoint, within the limits fixed by the users [-2 °C; +2 °C]. A change in the setpoint can directly modify the consumption of the HVAC to solve grid constraints [13].

2.2.2 Prosumer scenario

For this scenario, the prosumer owns a 4 kW PV panel coupled with a second-life battery and a load. This scenario uses two emulation cabinets (PV and load), and a portion of the second-life battery (5 kWh). In the base case, the battery follows a basic self-consumption control [14] with the addition of security grid charges after the battery remains in minimum State of Charge (SoC) for a specific time. This avoids having the battery in low values of SoC for too long, which can accelerate the degradation. In the aggregator case, the battery setpoints can be overwritten. When constraints appear on the grid, the battery can be discharged to reduce the electricity consumption, or even act as a generator and inject electricity into the grid. The charging strategy can also be controlled to absorb power whenever there is a surplus of generation [10].

2.3 Key Performance Indicators (KPIs)

Key Performance Indicators (KPIs) obtained from literature [15] and from the aggregator have been used to analyse the scenarios.

1. Energy consumption change: change in the consumption from the grid for the entire test.
2. Energy cost change: change in the electricity cost during the entire test, considering a two-period tariff and a selling price for the prosumer scenario.
3. Load reduction: change in the power consumed during the events defined by the aggregator.
4. Rebound effect: measure of the rebound effect, that is, the additional energy consumed following a flexibility activation [16]. This KPI compares the energy consumed during the hour after an event is finished between the base and aggregator cases.
5. Reliability index: measure of whether the user has successfully received the activation.
6. Thermal comfort level (only for the residential): measure of the thermal discomfort, defined as the amount of intervals that the indoor temperature exceeds the comfort of the users (19ºC to 24ºC) during events and rebound periods.
7. Self-consumption factor change (only for the prosumer): change in the self-consumption factor between the aggregator case and the base case, defined as the percentage of load that has been covered by the PV system, directly from it or from the battery.

3. RESULTS AND DISCUSSION

3.1 Residential scenario

In both summer and winter scenarios 5 events were received, as shown in Fig 3, with a duration of 30 minutes or 1 hour and modifying the temperature setpoint by -1.5ºC or -2ºC. Most of the flexibility activations impacted the HVAC consumption by reducing the power output.

It is noticeable that the events happening early in the summer mornings (events 1 and 4) had a much lower power reduction than the rest. Since the HVAC is off most of the night the indoor temperature increases, requiring the HVAC to turn on at high powers early in the morning. For this reason, even if the setpoint is modified, the HVAC still needs to provide large amounts of cooling.

A similar behaviour can be seen in the 4th event during the winter case. However, in this winter test, two of the activations received did not have any effect on the HVAC for different reasons. During the 1st event the

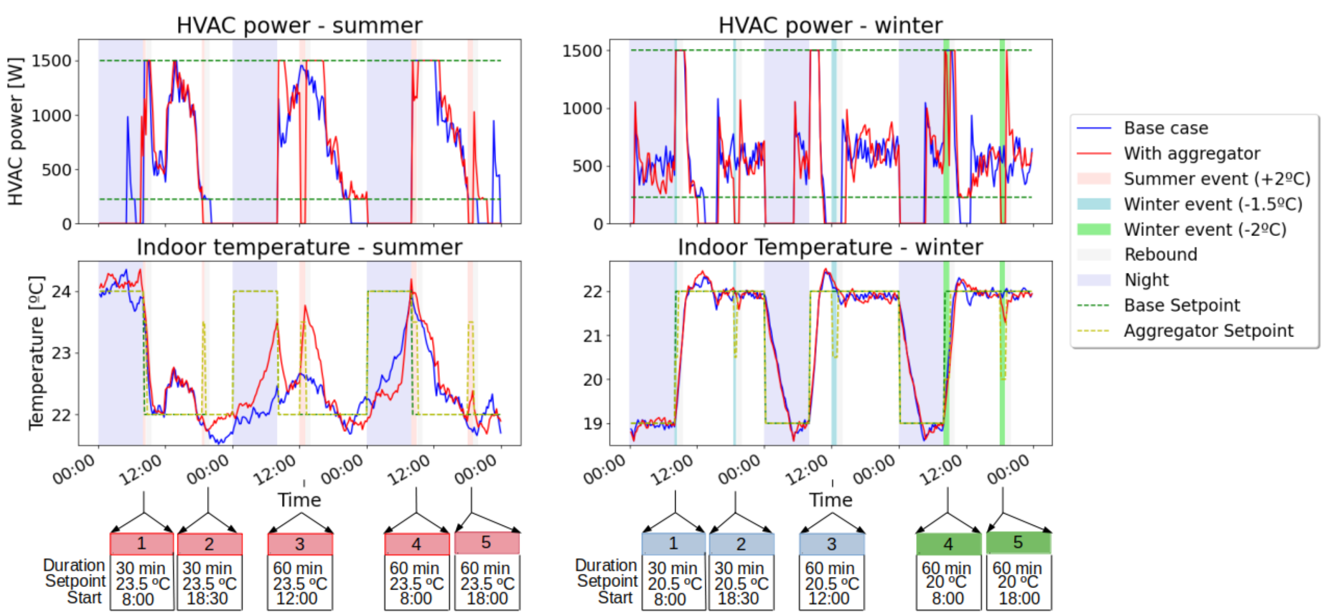

Fig 3. Residential scenario results: HVAC power and indoor temperature for summer (left) and winter (right)

HVAC still needed to turn on at maximum power, as in the base case, because the difference between the setpoint received and the indoor temperature was too high. For the 3rd event, the HVAC was already turned off in the base case and therefore, could not provide flexibility. These two behaviours were caused by an incorrect activation received from the aggregator.

For both scenarios we can see that the indoor temperatures were only slightly affected, and managed to return to the base setpoints a short time after the events. This is especially noticeable for the winter, as the temperatures were barely modified. The differences in the indoor temperature outside of the events are caused by a stochastic factor included in the thermal model.

3.2 Prosumer scenario

Fig 4 shows the results of the prosumer scenario. On top, the power balance of the system, with energy consumptions on the positive direction and generations in the negative one. Due to the laboratory conditions, the battery required a minimum setpoint of 1500 W. The highest consumption from the grid took place during the security grid charges of the battery.

For two of the events (1st and 2nd), the aggregator detected the start of the security charges and postponed them until the event was over. The 3rd event, imposed a discharge on the battery for 30 minutes.

Besides modifying the energy consumed during the events, controlling the battery also had longer term effects. For example, since the battery charge was postponed due to the 2nd event, the discharge that occurred in the base case right after the 2nd event was also postponed. In this case, we see that it took place in the morning of the 3rd day, where the battery in the aggregator case had a higher SoC than in the base case.

3.3 KPI discussion

Table 1 presents the KPIs defined in Section 2.3:

	KPI	Residential		Prosumer
		Summer	Winter	
1	Energy consumption change	+2.0%	-2.6%	-0.2%
2	Energy cost change	+5.3%	-4.0%	0%
3	Load reduction	-32.5%	-28.1%	-50.7%
4	Rebound effect	+12.9%	+15.8%	+17.8%
5	Reliability index	100%	100%	100%
6	Thermal comfort level	0%	0%	-
7	Self-consumption change	-	-	+0.4%

Table 1. Resulting KPIs

KPI 1 shows that the DA did not necessarily reduce the overall consumption. In fact, in some cases like the summer residential one, it increased. This is explained by the fact that the goal of the aggregator is to solve constraints, not to reduce the overall consumption. Similarly, as reflected in KPI 2, the cost did not always decrease, highlighting the importance of incentives for customer engagement. KPI 3 proves that the activations sent by the aggregator were successful, since the loads during the events were reduced up to 50%. However, as explained in Section 3.2, some of the events did not provide any flexibility to the system. KPI 4 shows, that the rebound effect ranged from + 12 to + 18%. The 100% in KPI 5 means that the connection with the aggregator was stable during the entire test. KPI 6 shows that indoor temperatures did not go out of the comfort range in any

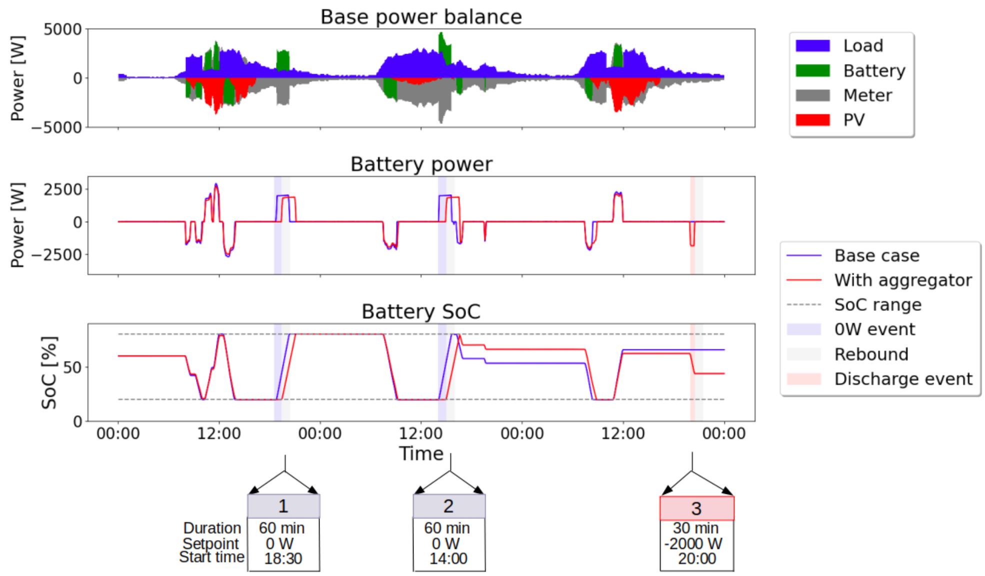

Fig 4. Prosumer scenario results: power balance and battery power and SoC

moment during the events or rebound periods. Finally, KPI 7 shows that the prosumer's self-consumption factor was slightly improved, as a consequence of the discharge imposed in the last activation.

4. CONCLUSIONS

The work developed in IREC's SmartLab has created a set-up for the experimental testing of demand-side flexibility. The laboratory SCADA has been integrated with the Bamboo Energy aggregation platform in order to communicate with the aggregator and receive flexibility activations for different laboratory assets.

The scenarios developed have enabled the experimental assessment of the flexibility potential of two customer types: a residential one and a prosumer. Both a HVAC unit and a second-life battery from a self-consumption system have proved to be reliable assets for DR purposes. By modifying the thermostat setpoint, the aggregator reduced the consumption of the HVAC during the events, while maintaining the temperature inside the thermal comfort of the user. Regarding the battery, both the charging and discharging were controlled by the aggregator to modify the energy consumed or injected into the grid. After developing the scenarios, the importance of defining adequate economic incentives was brought to light, as the total cost of electricity did not decrease in all cases.

Based on this work, further testing is expected in the laboratory to define new scenarios and contribute to increasing the knowledge on the experimental assessment of demand-side flexibility. Such work would allow stakeholders to understand the impact of DR on users and consequently help the aggregators to improve strategies for the real-life dispatch of DR assets.

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