Understanding the Role of Solar PV and Battery Energy Storage in a Snack Bar: A Case Study in Madeira Island

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***Abstract*—Industrial Kitchens (IKs) are spaces with very intensive electricity consumption. Nevertheless, unlike other sectors in industry and commerce, very little research has been carried out to understand the role of Renewable Energy Sources (RES) and Battery Energy Storage Systems (BESS) in improving the energy efficiency of such spaces. In this respect, this paper presents a year-long real-world assessment of employing the combination of solar PV and BESS in a small kitchen restaurant on Madeira Island. The results suggest that the PV-BESS can become profitable due to the high consumption levels observed in the restaurant, especially when energy arbitrage is also considered. The results also show that in the context of IKs it is essential to account for appliances with high power fluctuations when controlling the battery to avoid unintended grid feed-in.**

***Index Terms*—Industrial Kitchens, Snack Bar, Solar PV, BESS, Real-World.**

I. Introduction

Industrial Kitchens (IKs) are energy-intensive businesses, using between 5 and 7 times more energy per square meter than other commercial building spaces like office buildings and retail stores [1]. Still, despite the size and ubiquity of this industry, very little research exists related to understanding their consumption and devising energy efficiency strategies [2].

Overall, energy efficiency research in IKs can be divided into two bodies of work. The main body of work aims at developing standardized energy efficiency benchmark methodologies (e.g.,[3], [4], [5]). While all these works have proposed different Key Performance Indicators (KPIs) (e.g., kWh/turnover, kWh/seats) and comparison strategies (e.g., whole year vs. seasonal), there is a strong consensus regarding two points: first, the need to have a proper definition of the energy system to study, i.e., the activities to consider (e.g., cooking and cleaning), and the associated energy flows; second, the benefits of monitoring, since estimation tends to underestimate the size of this sector at large.

The second body of work aims at devising strategies to reduce and shape energy demand (e.g., [6], [7], [8]). In [6], the energy demand associated with food preparation and cooking activities were monitored in 14 restaurants in the UK to identify appliance usage patterns and quantify the energy consumption of those establishments. Besides confirming that consumption was much higher than reported in the literature, it is suggested that improved staff behavior would result in potential energy savings of around 70%. This corroborates with the conclusions from other works where it is argued that having the kitchen staff engaged in the sustainability process is of crucial importance [4], [9].

Surprisingly, despite being considered in the literature as one of the pillars for energy efficiency in IKs [4], research in the integration of Renewable Energy Sourcess (RESs) is very scarce, with only a few published works on the topic that spam different types of facilities: food trucks [10], mixed buildings with restaurants and residences [11], [12], [13], hotel restaurants [14], and snack bars [15].

This paper contributes to the ongoing body of work by presenting the results of a real-world case study that involved the deployment of three Lition-Ion Battery Energy Storage Systems (BESSs) in one snack bar with solar PV micro-production. More precisely, a combination of battery and inverter was installed in each phase of the electric installation. Control strategies were deployed to maximize self-consumption and enable energy arbitrage, i.e., storing energy from the grid when the prices are lower and discharging the battery when the prices are high.

The remaining of this paper is organized as follows. Section II presents related works. In Section III, the case study is presented, including an overview of the deployed technologies and the evaluation methodology. The year-long results are presented and discussed in Section IV. Finally, this paper concludes in Section V.

II. Related Works

In [10], the authors study the viability of installing Solar PV coupled storage in food trucks. Interestingly, the biggest challenge is sizing the system since this is highly coupled with the type and amount of food being served and how the chefs operate the kitchen, e.g., preparation and cooking times.

In [11], [12], [13], the authors present a series of studies aimed at understanding the cost-benefits of applying different combinations of solar PV, Battery, and thermal storage in a mixed building composed of apartments and a restaurant. Different dispatching algorithms are proposed based on the load to match (residential and restaurant alone vs. a combination of both). The latter shows the best cost-benefit trade-offs, especially when combining storage and thermal.

These results are aligned with the findings from [15], where it is shown that when compared to domestic solar PV coupled BESS installations, the payback time of a small restaurant (monthly consumption around 2MWh) would be at least four times faster. The main reason for this is that due to the high consumption throughout the day, it was always possible to fully charge the battery in the off-peak period and fully discharge it during the restaurant operation hours.

In [14], the authors build on month-long deployments of waste generation, water, and electricity consumption monitoring in three IKs to draw some challenges and future research directions. Noticeably, the authors identified two potential roles of BESS: in performing energy arbitrage and phase balancing.

Finally, in [16], the authors studied the possibility of conducting hour-ahead forecasts of aggregated and disaggregated (i.e., at appliance level) electricity consumption in one IK. It was concluded that the stable working routines made it possible to forecast the aggregated demand with a Normalized Mean Absolute Error (NMAE) between 6% and 7%. This is an interesting result since accurate forecasts are crucial to properly controlling assets such as PV and BESS.

In summary, although the literature on this topic is short, there is a consensus on the potential of introducing PV and BESS in IKs, mainly concerning economic benefits. Nevertheless, the results presented in this survey are based on simulations, which tend to result in over-optimistic estimates since real-world constraints are not considered. The present paper contributes to attenuating this research gap by presenting the results of a real-world case study on deploying PV and BESS in a restaurant kitchen.

III. Materials and Methods

The IK considered in this work is part of a family-owned and operated snack bar. This snack bar serves primarily light meals and only a small number of daily lunches. It operates seven days a week, from early morning to late evening. It contains several single-phase (e.g., several fridges, freezers, and one microwave) and three-phase (e.g., professional coffee machine and deep-fryer) loads.

The snack bar has a three-phase power installation with a contracted power of 20.7 kVA. It also has 4.95 kWp of solar PV installed, also in a three-phase setup. The electricity tariff in place is a time-of-use use of two periods (2-TOU): 0.0982€ in the off-peak period (X to Y), and 0.1894€ during the peak period (from ZZ to AA) [17].

One battery/inverter pair of 8.6kWh / 3kWp was installed in each phase, for a total capacity of 25.8kWh and nominal power of 9 kW. The control of the BESS is performed remotely, with one new set-point every two minutes. An overview of the entire system is given fig. 1. A brief description of the main components is provided next.

A. Production and Consumption Data

The electricity consumption and solar PV production were monitored using a custom-created monitoring system. The system comprised two Carlo Gavazzi smart meters (EM111, EM112, and EM340) and a Raspberry PI micro-computer that acted as a gateway, pulling measurements from the smart meters and uploading them to a cloud-based Energy Management System (EMS). The electricity consumption and solar PV production data are measured at the granularity of 1Hz, but only 1-minute averages are uploaded to the EMS [18].

B. Battery Energy Storage System

As mentioned, one battery/inverter pair was installed in each phase. The BESS consists of the following components:

- Interconnected battery cells make up the battery system, with a total nominal capacity of 8.6 kWh;
- The Battery Protection Unit (BPU) – a set of switching and current sensing devices controlled by the underlying Battery Management System (BMS);
- The BMS - responsible for battery safety, control of BPU, monitoring, and diagnostic of the BESS;
- The inverter – a bidirectional power converter DC/AC. Single-phase inverters with a 3 kW nominal capacity;
- A site controller – a local controller responsible for inverter control and its safe connection and disconnection, collecting all relevant data and transferring them to the Energy Management System (EMS) (e.g., State of Charge (SOC)) and receiving control signals from the remote control system (e.g., active power setpoints) using cloud-to-cloud communication protocols.

C. BESS Control

1) Remote Control Service: The energy storage systems are controlled remotely through services that reside in a dedicated cloud from the system provider (BESS Cloud in Figure 1). More precisely, two control modes are available: 1) single actions and 2) multiple actions.

In the single-action mode, only one setpoint can be sent at a time. This setpoint remains active until another one is sent or the battery reaches the minimum or maximum SOC. In contrast, in the multiple action mode, several setpoints are sent simultaneously. In this mode, the BESS controller will apply the setpoints ordered by timestamp and keep the last setpoint active until either a new command is sent or the BESS cannot fulfill the request (i.e., the minimum or maximum SOC are reached).

A simplified overview of the requests is shown in Table I. In ideal circumstances (e.g., no network or data failure), the

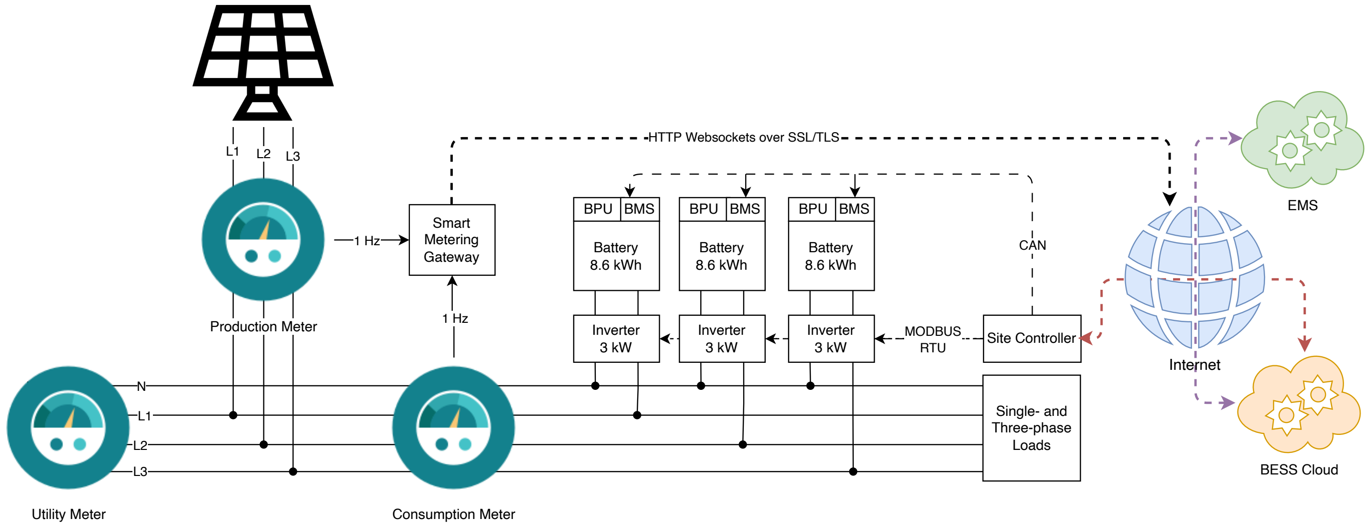

Fig. 1. Overview of the deployed technologies and their interactions.

TABLE I
SINGLE VS. MULTIPLE ACTIONS MODE: EXAMPLE OF SEQUENCE OF COMMANDS SENT TO THE BESS CLOUD

ID	Single Action	Multiple Actions
1	06-11-2019 12:00 |1 kW	06-11-2019 12:00 |1 kW 06-11-2019 12:05 |0 kW
2	06-11-2019 12:01 |2 kW	06-11-2019 12:01 |2 kW 06-11-2019 12:06 |0 kW
3	06-11-2019 12:10 |3 kW	06-11-2019 12:10 |3 kW 06-11-2019 12:15 |0 kW

two modes will produce the same results, i.e., the battery will charge 1kW between 12:00 and 12:01 and 2kW between 12:01 and 12:02. However, in case of failure, the modes will have different outputs. For example, if at 12:01 it is not possible to send the command (e.g., due to network error) in the single-action mode, the battery will continue to charge at 1kW until the minimum or maximum SOC is reached. In contrast, using the multiple actions mode, the battery would go to the idle mode after five minutes in response to the 0kW setpoint sent last.

Considering the real-world nature of this deployment, it was decided to use the multi-action strategy, where each calculated setpoint is followed by a reset setpoint (0kW). Furthermore, it was decided that a new control action would be sent every two minutes to avoid potential bottlenecks in the BESS cloud.

2) Control Algorithm: Considering the small capacity of the PV installation concerning the installed power (less than 20%) and the fact that a 2-TOU tariff is available, it was decided to use a hybrid control strategy. This control strategy uses the Greedy strategy during peak hours, i.e., from 9 AM to 11 PM, aiming at maximizing self-consumption. During the off-peak hours, 11 PM to 9 AM, the battery is charged to a pre-calculated SOC and cannot discharge until the peak period starts.

The greedy control algorithm is a standard operation strategy in self-consumption scenarios. It works by determining the residual load (i.e., the difference between production and consumption) and actuating the battery accordingly. I.e., storing excess production until the upper SOC limit is reached or supplying the excess demand from the battery until the lower SOC is reached.

The amount of pre-charge depends on the battery's capacity and the electricity demand during peak periods. It is calculated using Equation (1), rounded to the next multiple of 5. P_{G_L}(PH) is the average consumption from the grid during the peak hours (PH), and BNC is the nominal battery capacity in kWh.

$$SoC_{PC} = \min\left(\frac{P_{G\_L}(PH) - P_{PV\_G}}{BNC} + SOC_{min}, SOC_{max}\right) \tag{1}$$

For this concrete case, the pre-charge was set to 80% of the battery's nominal capacity. The minimum and maximum SOC values were set to 20% and 90%, respectively.

The control strategy is executed inside the EMS that resides in the cloud. In very simplified terms, the system works as follows:

1) Every 2 minutes, the next setpoints to be sent to the inverter are calculated in the EMS for each phase. For this calculation, the inputs are the most recent consumption, production, and BESS measurements (e.g., SOC).
2) The calculated setpoints are sent to the BESS cloud using the multiple actions web service. The BESS cloud places the requests on a buffer ordered by timestamp.
3) The BESS cloud sends the commands to the battery site controller and waits for a response.
4) The battery site controller performs the requested action and returns an acknowledgment to the BESS cloud.
5) The BESS cloud forwards the battery site controller response to the EMS.
6) Back to step 1.

D. Evaluation Methodology

The evaluation is made on top of the data collected from the real-world deployment for 12 consecutive months - between March 2020 and February 2021. For this analysis, the data were aggregated by month and season to enable a more granular analysis of the results. By analyzing the results per season, it is possible to understand the effects of weather changes on the usage of the BESS. The assessment is performed based on the following KPIs:

- Degree of self-supply before and after the BESS installation (%): Measures the percentage of PV generation used for self-supply. This is the same as Self-Consumption (SC), the term used in this paper.
- On-site energy ratio before and after the BESS installation (%): Measures the relationship between the energy supplied from the PV and the total demand. This is the same as Self-Sufficiency (SS), the term used in this paper.
- Monetary Savings before and after the BESS installation (Euros): Measures the saving in Euros from owning just a PV or a PV + BESS, considering the rates in place during the deployment.
- Number of battery cycles: An estimate of the number of cycles performed by the battery. It provides a good indication of the degree of usage of a BESS. For the calculation method, one cycle is a full charge and discharge cycle at 70% Depth of Discharge (DoD).
- Available data: refers to the ratio between the available consumption and PV production data and what was expected. This is an indicator of Advanced Metering Infrastructure (AMI) stability.
- BESS uptime: refers to the ratio between the available data points and what was expected from the BESS. This indicates the stability of the cloud-2-cloud infrastructure for storage control.

IV. Results and Discussion

The obtained results for each phase are shown in Figure 2.

The first observation refers to the technical infrastructure (AMI and BESS). As can be observed by the high data availability (around 99%), the AMI was very stable for the entire period. Regarding the BESS, the average uptime is slightly lower, around 90%. The exceptions are the months of December 2022 and February 2021, when issues were experienced with the system installed in phase 3. This indicates that in some instants, the setpoint could not be computed and sent to the BESS cloud, hence leaving the BESS in standby mode. Hence, reducing the potential profitability of the PV-BESS system.

Regarding the SC and SS, it can be observed that the three phases have very high SC and low SS. This, and the calculated pre-charge of 80%, are clear indicators that this restaurant would heavily benefit from upgrading the PV installation for double the installed capacity.

It is also possible to observe that, unlike the domestic systems, which see an increase in demand during the Holidays (e.g.,[17]), the snack bar presents a very stable consumption throughout the year. Nevertheless, a decrease in the SS rates is observed in Winter, primarily due to the sun-hours reduction. This effect can be observed in Figure 3, which shows the energy flows and SOC during one week in August (Figure 3a) and another in December (Figure 3b).

It is also possible to observe a decrease in consumption in April and May due to the Covid-19 lockdowns, leading to a decrease in the SC rate. This is especially visible in Phases 1 and 3, where equipment such as the coffee machine and the deep-fryer is installed.

Concerning the savings, in the current scenario, the highest share arrives from the arbitrage operation, which would cover an average of 26% of the total demand with energy acquired at a lower price (Phase 1: 20.3%, Phase 2: 31.7%, Phase 3: 25.5%). However, it is also possible to observe that in phase 3, the monetary savings are much lower than in the other phases, despite having similar levels of SC and pre-charge.

After further exploration, it was concluded that this happens due to the very fast power fluctuations caused by the coffee machine since it requires a constant boiler temperature. This effect can be easily observed in Figure 4, where L3.P represents the load on phase 3, where L3.P means the demand on phase 3. Other less pronounced fluctuations can also be observed in Phase 1 (L1.P), mainly caused by the refrigeration units.

Ultimately, such fast fluctuations and the relatively slow rate of setpoint updates (every two minutes) imply that during several instants, energy from the battery is injected into the grid, significantly reducing the savings due to the energy arbitrage operation. This effect can be easily observed in Figure 5, which summarizes the energy flows to and from the BESS. More precisely, the graph shows that in phase 3, 550 kWh are injected from the BESS into the grid. This corresponds to roughly 30% of the total energy stored in the battery. This result shows that more frequent setpoint updates are required for consumers with such appliances (ideally, under one minute). Alternatively, an edge device can keep track of grid feed-ins due to battery discharge and adjust the setpoints in real time.

Finally, from Figure 4, it is also possible to observe some unbalance across the three phases. Ultimately, such unbalance can cause three-phase motors and other three-phase loads to experience poor performance or premature failure. As such, and in line with what was suggested in [14], there is room for using storage to reduce this unbalance. However, this would also require a more frequent update of the inverter setpoints to avoid unnecessary BESS charge and discharge operations.

V. Conclusion

This paper presented a real-world case study to understand the role of solar PV and BESS in a snack bar. The studied system comprises 4.95kWp of solar PV and one 8.6kWh/3kW BESS in each phase.

Analysis of year-long results of the real-world operation revealed that due to the small size of the PV installation

Year	Season	Month	Available Data (%)	PV (kWh)	Load (kWh)	PV Only					PV + BESS									
						SC (kWh)	To Grid (kWh)	SC	SS	Savings (€)	SC (kWh)	To Grid (kWh)	SC	SS	OPE (kWh)	OPE	Estimated Cycles	Uptime	Savings (€)	
																			BESS	Total
2020	Spring	Mar	99.98%	172.40	986.10	132.02	40.39	76.6%	13.4%	31.20	152.02	38.43	88.2%	15.4%	159.00	16.1%	31.3	95.7%	12.60	43.81
		Apr	99.97%	182.41	684.98	116.97	65.44	64.1%	17.1%	26.58	144.18	49.02	79.0%	21.0%	101.43	14.8%	22.5	87.4%	10.72	37.30
		May	99.98%	222.46	593.69	149.67	72.79	67.3%	25.2%	34.98	178.97	56.28	80.4%	30.1%	74.19	12.5%	18.3	78.1%	8.92	43.90
			99.98%	**577.3**	**2264.8**	**398.7**	**178.6**	**69.3%**	**18.6%**	**92.76**	**475.2**	**143.7**	**82.6%**	**22.2%**	**334.62**	**14.5%**	**72.1**	**87.1%**	**32.24**	**125.01**
	Summer	Jun	99.90%	198.76	923.86	163.95	34.81	82.5%	17.7%	37.16	175.37	38.02	88.2%	19.0%	113.80	12.3%	22.3	69.0%	9.02	46.19
		Jul	100.00%	257.11	928.91	212.58	44.53	82.7%	22.9%	49.70	230.51	45.45	89.7%	24.8%	156.49	16.8%	30.5	94.5%	11.96	61.66
		Aug	99.92%	210.29	827.09	158.69	51.60	75.5%	19.2%	37.51	183.54	49.06	87.3%	22.2%	147.70	17.9%	29.8	98.9%	10.75	48.25
			99.94%	**666.2**	**2679.9**	**535.2**	**130.9**	**80.2%**	**19.9%**	**124.37**	**589.4**	**132.5**	**88.4%**	**22.0%**	**418.00**	**15.7%**	**82.7**	**87.5%**	**31.73**	**156.10**
	Autum	Sep	99.89%	170.73	674.27	112.96	57.77	66.2%	16.8%	25.69	146.30	51.85	85.7%	21.7%	150.57	22.3%	32.1	99.0%	11.87	37.57
		Oct	99.98%	148.62	724.09	95.97	52.66	64.6%	13.3%	22.83	123.96	56.37	83.4%	17.1%	157.84	21.8%	32.4	97.8%	10.36	33.21
		Nov	99.97%	124.32	763.36	76.90	47.42	61.9%	10.1%	17.38	101.62	55.66	81.7%	13.3%	167.44	21.9%	33.2	98.9%	9.18	26.58
			99.95%	**443.7**	**2161.7**	**285.8**	**157.9**	**64.2%**	**13.4%**	**65.90**	**371.9**	**163.9**	**83.6%**	**17.4%**	**475.85**	**22.0%**	**97.7**	**98.6%**	**31.41**	**97.36**
	Winter	Dec	99.97%	113.39	761.41	71.96	41.43	63.5%	9.5%	16.91	85.39	65.78	75.3%	11.2%	109.27	14.4%	28.9	90.3%	6.67	23.58
2021		Jan	99.98%	100.44	835.59	66.84	33.60	66.5%	8.0%	15.61	75.56	61.86	75.2%	9.0%	110.44	13.2%	29.5	94.3%	6.18	21.79
		Feb	99.82%	168.77	740.05	100.77	67.99	59.7%	13.6%	20.53	128.41	81.95	76.1%	17.4%	120.84	16.3%	31.9	93.6%	8.32	28.86
			99.92%	**382.6**	**2337.0**	**239.6**	**143.0**	**63.2%**	**10.4%**	**53.05**	**289.4**	**209.6**	**75.5%**	**12.5%**	**340.55**	**14.6%**	**90.3**	**92.7%**	**21.17**	**74.23**
Grant Total			**99.95%**	**2069.7**	**9443.4**	**1459.3**	**610.4**	**70.5%**	**15.5%**	**336.08**	**1725.8**	**649.7**	**83.4%**	**18.3%**	**1569.02**	**16.7%**	**342.8**	**91.5%**	**116.55**	**452.70**

(a) Phase 1

Year	Season	Month	Available Data (%)	PV (kWh)	Load (kWh)	PV Only					PV + BESS									
						SC (kWh)	To Grid (kWh)	SC	SS	Savings (€)	SC (kWh)	To Grid (kWh)	SC	SS	OPE (kWh)	OPE (%)	Estimated Cycles	Uptime	Savings (€)	
																			BESS	Total
2020	Spring	Mar	99.98%	167.77	614.96	124.52	43.25	74.2%	20.2%	29.24	151.05	27.18	90.0%	24.6%	141.86	23.1%	29.3	95.7%	14.22	43.46
		Apr	99.97%	178.43	557.00	120.92	57.51	67.8%	21.7%	27.37	144.74	41.93	81.1%	26.0%	100.27	18.0%	21.7	87.2%	10.64	38.02
		May	99.98%	218.06	441.56	145.09	72.97	66.5%	32.9%	33.69	174.26	48.18	79.9%	39.5%	44.96	10.2%	13.2	78.2%	8.92	42.62
			99.98%	**564.3**	**1613.5**	**390.5**	**173.7**	**69.5%**	**24.9%**	**90.30**	**470.0**	**117.3**	**83.7%**	**30.0%**	**287.09**	**17.1%**	**64.2**	**87.0%**	**33.78**	**124.10**
	Summer	Jun	99.90%	193.79	498.41	143.66	50.13	74.1%	28.8%	32.45	167.75	31.37	86.6%	33.7%	63.25	12.7%	15.7	69.1%	9.63	42.08
		Jul	100.00%	251.80	526.85	185.63	66.17	73.7%	35.2%	43.25	226.04	31.32	89.8%	42.9%	67.60	12.8%	18.7	94.5%	11.87	55.12
		Aug	99.92%	206.00	548.42	158.07	47.93	76.7%	28.8%	37.23	186.06	26.97	90.3%	33.9%	112.86	20.6%	24.3	98.9%	12.60	49.83
			99.94%	**651.6**	**1573.7**	**487.4**	**164.2**	**74.9%**	**31.0%**	**112.93**	**579.8**	**89.6**	**88.9%**	**36.8%**	**243.71**	**15.4%**	**58.7**	**87.5%**	**34.10**	**147.03**
	Autum	Sep	99.89%	165.69	539.65	126.32	39.37	76.2%	23.4%	28.62	149.80	23.04	90.4%	27.8%	116.21	21.5%	24.4	88.6%	12.14	40.76
		Oct	99.98%	144.41	501.05	103.07	41.34	71.4%	20.6%	24.34	128.30	28.00	88.8%	25.6%	136.73	27.3%	28.3	99.0%	13.48	37.83
		Nov	99.97%	120.14	474.09	82.91	37.23	69.0%	17.5%	18.59	105.86	28.95	88.1%	22.3%	143.16	30.2%	28.2	99.1%	9.73	28.33
			99.95%	**430.2**	**1514.8**	**312.3**	**117.9**	**72.2%**	**20.5%**	**71.55**	**384.0**	**80.0**	**89.1%**	**25.2%**	**396.11**	**26.3%**	**80.8**	**95.6%**	**35.35**	**106.92**
	Winter	Dec	99.97%	110.36	443.17	73.98	36.38	67.0%	16.7%	17.24	93.98	30.92	85.2%	21.2%	116.69	26.3%	24.0	90.3%	10.53	27.77
2021		Jan	99.98%	98.47	425.18	66.96	31.51	68.0%	15.7%	15.27	85.42	28.43	86.7%	20.1%	131.10	30.8%	25.9	94.3%	10.34	25.62
		Feb	99.82%	166.90	447.93	99.21	67.69	59.4%	22.1%	20.01	135.79	45.36	81.4%	30.3%	94.47	21.1%	22.7	88.6%	10.38	30.40
			99.92%	**375.7**	**1316.3**	**240.2**	**135.6**	**64.8%**	**18.2%**	**52.52**	**315.2**	**104.7**	**84.4%**	**23.9%**	**342.25**	**26.1%**	**72.6**	**91.0%**	**31.25**	**83.79**
Grant Total			**99.95%**	**2021.8**	**6018.3**	**1430.3**	**591.5**	**70.7%**	**23.8%**	**327.30**	**1749.0**	**391.6**	**86.5%**	**29.1%**	**1269.16**	**21.2%**	**276.3**	**90.3%**	**134.48**	**461.84**

(b) Phase 2

Year	Season	Month	Available Data (%)	PV (kWh)	Load (kWh)	PV Only					PV + BESS									
						SC (kWh)	To Grid (kWh)	SC	SS	Savings (€)	SC (kWh)	To Grid (kWh)	SC	SS	OPE (kWh)	OPE	Estimated Cycles	Uptime	Savings (€)	
																			BESS	Total
2020	Spring	Mar	99.98%	149.63	688.60	98.08	51.55	65.5%	14.2%	21.34	110.40	83.33	73.8%	16.0%	146.97	21.3%	24.4	100.0%	1.98	23.32
		Apr	99.97%	168.01	585.38	97.41	70.60	58.0%	16.6%	22.98	123.09	98.16	73.3%	21.0%	106.93	18.3%	29.9	95.6%	2.87	25.85
		May	99.98%	177.44	470.17	99.32	78.13	56.0%	21.1%	22.54	125.89	103.41	70.9%	26.8%	93.19	19.8%	23.2	87.3%	0.62	23.15
			99.98%	**495.1**	**1744.2**	**294.8**	**200.3**	**59.8%**	**17.3%**	**66.86**	**359.4**	**284.9**	**72.7%**	**21.3%**	**347.09**	**19.9%**	**77.5**	**94.3%**	**5.47**	**72.32**
	Summer	Jun	99.90%	218.55	548.47	127.89	90.67	58.5%	23.3%	29.81	157.96	104.56	72.3%	28.8%	101.80	18.6%	21.6	78.1%	2.08	31.90
		Jul	100.00%	194.42	630.62	121.56	72.86	62.5%	19.3%	27.48	141.83	97.73	72.9%	22.5%	116.33	18.4%	21.7	69.0%	1.66	29.15
		Aug	99.92%	251.90	627.96	144.76	107.14	57.5%	23.1%	33.78	184.73	120.91	73.3%	29.4%	148.06	23.6%	27.2	94.4%	2.79	36.57
			99.94%	**664.9**	**1807.1**	**394.2**	**270.7**	**59.5%**	**21.9%**	**91.07**	**484.5**	**323.2**	**72.9%**	**26.9%**	**366.19**	**20.3%**	**70.4**	**80.5%**	**6.53**	**97.62**
	Autum	Sep	99.89%	206.42	642.27	121.57	84.86	58.9%	18.9%	28.83	150.83	114.11	73.1%	23.5%	165.50	25.8%	30.5	98.9%	1.85	30.69
		Oct	99.98%	166.70	653.04	100.69	66.01	60.4%	15.4%	22.88	124.81	102.52	74.9%	19.1%	129.97	19.9%	33.1	99.0%	2.76	25.64
		Nov	99.97%	137.30	673.74	88.60	48.70	64.5%	13.2%	21.00	105.48	78.74	76.8%	15.7%	124.50	18.5%	25.6	75.2%	1.03	22.04
			99.95%	**510.4**	**1969.0**	**310.9**	**199.6**	**61.3%**	**15.8%**	**72.71**	**381.1**	**295.4**	**74.9%**	**19.4%**	**419.97**	**21.3%**	**89.2**	**91.1%**	**5.64**	**78.37**
	Winter	Dec	99.97%	112.83	671.73	77.96	34.87	69.1%	11.6%	17.59	86.62	63.98	76.8%	12.9%	147.47	22.0%	22.9	70.2%	0.96	18.55
2021		Jan	99.98%	109.02	664.91	75.45	33.57	69.2%	11.3%	17.78	79.99	66.36	73.4%	12.0%	118.15	17.8%	26.7	90.2%	4.82	22.59
		Feb	99.82%	98.05	614.87	71.19	26.87	72.6%	11.6%	16.58	73.82	52.23	75.3%	12.0%	120.70	19.6%	20.9	69.2%	3.79	20.36
			99.92%	**319.9**	**1951.5**	**224.6**	**95.3**	**70.3%**	**11.5%**	**51.95**	**240.4**	**182.6**	**75.1%**	**12.3%**	**386.32**	**19.8%**	**70.5**	**76.5%**	**9.57**	**61.50**
Grant Total			**99.95%**	**1990.3**	**7471.8**	**1224.5**	**765.8**	**61.5%**	**16.4%**	**282.59**	**1465.4**	**1086.1**	**73.6%**	**19.6%**	**1519.58**	**20.3%**	**307.6**	**85.6%**	**27.21**	**309.81**

(c) Phase 3

Fig. 2. Year-long real-world results per phase using the hybrid control strategy.

concerning the installed power, the effects of the BESS in increasing SC rates were minor (an average increase of 18%). In contrast, the energy arbitrage resulted in significant savings by moving power demand to off-peak hours. Ultimately, these results suggest that the solar PV installation is under-dimensioned for the power consumption levels in this restaurant.

Regarding the obtained savings, it is important to stress that they are slightly under-evaluated since the BESS was not operational 100% of the time. Likewise, in phase 3, the latencies introduced by the cloud-to-cloud communications when updating the inverter setpoints resulted in sub-optimal control and a considerable reduction in the overall savings. However, this technical issue can be fixed by increasing the rate at which the control setpoints are updated.

Finally, it is important to remark on the simplicity of the control strategy that does not consider future variations in load demand and PV production. Hence, developing and evaluating forecasting-based control strategies is an essential future work direction, especially considering the results from [16] that indicate that good accuracies can be obtained for load demand forecasting in IKs.

ACKNOLEDGMENT

This work has received funding from H2020 under grant agreement No 731249 and FCT under the project EXPL/CCI-COM/1234/2021. Lucas Pereira has received funding from the FCT under grants CEECIND/01179/2017 and UIDB/50009/2020. This work reflects only the author's view.

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(a) August

(b) December

Fig. 3. Energy flows and battery SOC for one week in August (top) and another in December (bottom).

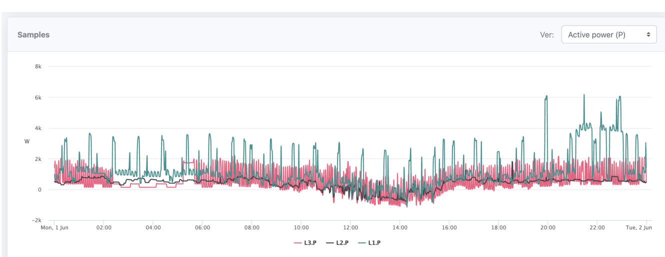

Fig. 4. One day of minute averages of active power for the three phases

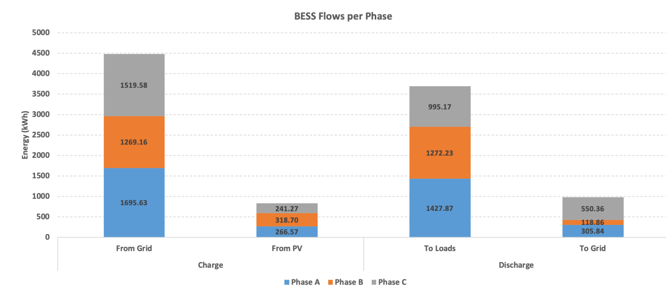

Fig. 5. Overview of BESS energy flows per phase.

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