Sizing and Profitability of Energy Storage for Prosumers in Madeira, Portugal

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Abstract—**This paper proposes a framework to select the best-suited battery for co-optimizing for peak demand shaving, energy arbitrage and increase self-sufficiency in the context of power network in Madeira, Portugal. Feed-in-tariff for electricity network in Madeira is zero, which implies consumers with excess production should locally consume the excess generation rather than wasting it. Further, the power network operator applies a peak power contract for consumers which imposes an upper bound on the peak power seen by the power grid interfaced by energy meter. We investigate the value of storage in Madeira, using four different types of prosumers, categorized based on the relationship between their inelastic load and renewable generation. We observe that the marginal increase in the value of storage deteriorates with increase in size and ramping capabilities. We propose the use of profit per cycle per unit of battery capacity and expected payback period as indices for selecting the best-suited storage parameters to ensure profitability. This mechanism takes into account the consumption and generation patterns, profit, storage degradation, and cycle and calendar life of the battery. We also propose the inclusion of a friction coefficient in the original co-optimization formulation to increase the value of storage by reducing the operational cycles and eliminate low returning transactions.**

I. Introduction

Renewable integration will increase opportunities for consumers in power networks for reducing their local cost of consumption [1]. Energy storage co-optimization is becoming popular with the possibility of doing more than one dedicated task without undermining the profit of storage by performing each task at a time. Authors in [2] show that co-optimizing profit leads to higher than doing one or few of tasks together.

In our prior work [3] we introduced power network rules in Madeira and show the profitability of a battery for a local prosumer. In this paper, we explore the dependencies of inelastic load and renewable generation size on the storage parameters and its profitability. Energy storage performing dedicated roles may not be profitable. Authors in [4], [5] show that batteries are not profitable if only used for energy arbitrage. Authors in [6] observe that the profit made by storage performing only arbitrage is sensitive to the ratio of selling and buying price of electricity. It is observed that as this ratio goes to zero, the value of storage increase for cases where the prosumer has inelastic consumption. Thus in the context of Madeira energy storage can help in increasing installed renewable generation as excess generation is not compensated and in this case, a battery can be used to locally increase self-sufficiency for the prosumer. It is noteworthy that the co-optimization of energy storage usage has been extensively researched due to the high cost of batteries. In Table I we list some of the works in this area. In this paper,

we use energy storage for performing energy arbitrage, increase self-sufficiency and facilitate peak demand shaving.

Authors in [7] observe that peak demand shaving for discharge period of more than an hour is not profitable. For Madeira the Peak Power Contracts (PPCs) are applied for the instantaneous power level in the time-scale of seconds, thus use of storage for peak shaving is reasonable. Authors in [8] propose battery cycle life optimization for prolonging the operational life of the storage. Authors in [9], [10] propose sizing of energy storage in context of a microgrid using mixed-integer programming. [9] consider microgrid reliability for sizing and [10] use storage devices for spinning reserves. Authors in [11] consider storage sizing in the context of wind power applications. In this paper, we provide a framework for identifying storage profitability battery for prosumers.

TABLE I
CO-OPTIMIZATION OF ENERGY STORAGE

Paper	Co-optimizing for
[12]	PV integration support, peak shaving, frequency regulation
[13], [14], [15]	Arbitrage and frequency regulation
[2], [16]	Peak shaving and frequency regulation
[17]	Arbitrage, congestion relief and curtailment reduction
[18]	Arbitrage with power factor correction.

Li-Ion battery life is measured in cycle and calendar life. In [19] the operational life of a battery is increased by matching calendar life degradation with the ageing degradation of the battery. Extending this idea and taking the depth-of-discharge (DoD) of the battery authors in [20] propose a way to measure the cycles of operation of the battery. It is highlighted that the nonlinear relationship between cycle life and DoD, [21], [8], encourages us to use this methodology to calculate storage returns per cycle. In this paper, we improve the factor *profit per cycles* proposed in [20] to make it independent of storage capacity. This new factor along with expected payback period of the battery can be used for identifying the expected break-even profit per cycle, thus by comparing these two scalars we can comment on the profitability of a battery.

Further, battery prices are falling with more research in this domain, which will promote increased usage of batteries in power networks. Historically, the cost of battery fell by 85% from 2010 to 2018, reaching an average price of $176/kWh. The price of an average Li-Ion battery pack is projected to be around $94/kWh by 2024 and $62/kWh by 2030 [22].

The key contributions of this paper are:
● *Index for measuring the profitability of Li-Ion battery*: Taking into account storage parameters and profit, we propose using *profit per cycle per unit capacity* and expected payback period as

the factors for selecting storage parameters ensuring profitability. These factors take into account battery degradation, profit, cycle and calendar life of the battery. For calculating operational cycles we use algorithm `DoDofVector` proposed in [20].

• *Numerical evaluation*: Based on consumer load and renewable generation consumer are categorized into four categories. Using these four categories of prosumers we use the data collected for June 2019 and apply time-of-use (ToU) rates and Peak Power Contract (PPC) improvement to identify the marginal value of storage. We observe that a smaller sized and ramping capability storage is profitable in all four categories.

• *Observations*: Using data and numerical results we make the following observations which can be generally of interest:

- The marginal value of storage reduces with increase in size and ramping capability.
- Under zero-feed-in tariff, a higher average net-load significantly improves the profit prosumer can make.

This paper is organized as follows. In Section II we introduce the Madeira data collection initiative under H2020 project SMILE. In Section III we provide the system description, battery model and we summarize the co-optimization formulation proposed in [3] and extend this formulation for controlling cycles of operation for increasing the operational life of the battery. In Section IV we present an algorithm for identifying the profitability of a battery. In Section V we present the numerical results. Section VI concludes the paper.

II. CONTEXT AND DATA COLLECTION IN MADEIRA

In the Madeira archipelago, since 2014, prosumers are not allowed to inject the excess energy to the local grid. This imposition is owing to the isolated nature of the Madeira electric grid that is very sensitive to variations in the energy produced by RES. Yet, while this technical restriction helps to maintain grid stability, it is also leading to a stagnation in the number of prosumers. For example, as of this writing, there are only 49 solar PV prosumers registered in Madeira island (an average of about 0.6 kWp installed capacity), in a universe of 270,000 residents [3], [23]. Inclusion of energy storage along with oversizing renewables at consumer end have the potential to increase renewable installations in the island.

The development of better control strategies for battery energy storage is one of the goals of the H2020 SMILE, https://www.h2020smile.eu, Project, an European Union co-funded project. Under the scope of this project, PV production (PV) and power consumption ($Load$) measurements were taken from 14 prosumers in the island [24], [25]. The monitored prosumers are categorized into four categories, based on their inelastic load and PV generation: (C1) PV generation slightly more than the inelastic load leading to some waste of excess generation, (C2) consumer actively managing the load to match the instantaneous PV generation thus reducing the production wastage, (C3) PV generation is comparable to the magnitude of inelastic load with significantly higher average net-load compared to other cases considered and (C4) PV generation is significantly more than the inelastic load leading to significant amount of energy wastage.

For this paper, one prosumer was selected from each category. The PPC, installed solar PV capacity, and the monthly totals of each prosumer for June 2019 are presented in Table II.

In Table II, PV_{Loads} is the amount of solar PV production that is consumed directly by the loads, PV_{Grid} is the amount of solar PV production injected into the grid (hereby considered wasted production since there is no feed-in tariff), $Grid_{Loads}$ is the amount of power from the grid that is consumed by the loads, and $Savings$ is the amount of saving due to the installation of the solar PV (assuming a fixed cost of 0.16 Euro per kWh).

Fig. 1 shows the relationship between PV and inelastic load for the selected prosumers. U2, U3, and U12 are domestic prosumers. U8 is a commercial prosumer, a small family restaurant.
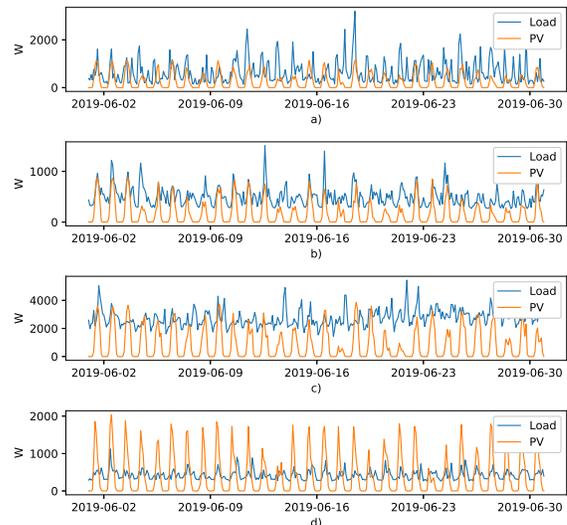

Fig. 1. PV and inelastic load for 4 types of prosumers C1, C2, C3 and C4

TABLE II
INDICES OF LOAD AND GENERATION FOR U2, U3, U8, U12 FOR JUNE 2019

Case	UPAC ID	Contracted Power (kVA)	Installed PV (kWp)	PV (kWh)	Load (kWh)	PV_{Load} (kWh)
C1	U2	6.9	1.5	180	459	121
C2	U3	5.75	1	120	360	113
C3	U8	20.7	3.92	610	1969	531
C4	U12	6.9	3	305	306	145

Case	UPAC ID	PV_{Grid} (kWh)	$Grid_{Load}$ (kWh)	Savings (Euros)	Average PV (W)	Average Load (W)
C1	U2	59.64	338	19.30	251	637
C2	U3	6.85	247	21.19	168	501
C3	U8	78.53	1438	85.09	848	2736
C4	U12	160	162	26.37	424	426

III. SYSTEM MODEL AND STORAGE CO-OPTIMIZATION

In this section, we present the system and battery model and the summarize the co-optimization formulation developed in [3]. We extend this formulation for limiting storage cycles of operation using a friction coefficient.

A. System and Battery Model

We consider operation over a total duration T, divided into N steps indexed by $\{1, ..., N\}$. The duration of each step is denoted as h. Hence, $T = hN$. At time instant i, the information available is the end user consumption d_i, the renewable generation r_i and the storage energy output s_i. The load without storage is denoted as $z_i = d_i - r_i$. The load seen by grid is denoted as $L_i = d_i - r_i + s_i$.

Battery Model: The efficiency of charging and discharging is denoted by $\eta_{ch}, \eta_{dis} \in (0,1]$, respectively. The change in energy level of the battery is denoted as $x_i = h\delta_i$, where δ_i denotes storage ramp rate at time instant i, such that $\delta_i \in [\delta_{\min}, \delta_{\max}], \forall i$. The energy output of storage in the ith instant is given by $s_i = \frac{[x_i]^+}{\eta_{ch}} - \eta_{dis}[x_i]^-$, where $[x]^+ = \max(0, x)$ and $[x]^- = -\min(0, x)$. The ramping constraint induce limits on s_i given by

$$s_i \in [\delta_{\min} h \eta_{dis}, \delta_{\max} h/\eta_{ch}], \quad \forall i. \tag{1}$$

The energy stored in the battery is denoted as b_i, defined as $b_i = b_{i-1} + x_i$. Battery capacity constraint is given as

$$b_i \in [b_{\min}, b_{\max}], \quad \forall i. \tag{2}$$

where $b_{\min}$ and $b_{\max}$ are minimum and maximum permissible battery charge levels respectively. We use xC-yC notation to represent the relationship between ramp rate and battery capacity. xC-yC implies battery takes 1/x hours to charge and 1/y hours to discharge completely.

B. Cost of the battery with inverter

The cost of inverter depends on the rated apparent power output capability. Based on cost of 6 kW SMA Sunny Boy 2.0, the cost per kW of inverter is 100 euros/kWh [26]. The cost of Li-Ion battery is assumed to have two components: (a) capacity cost and (b) ramping capability cost, similar to [27]. The cost of battery (with inverter) for per kWh in euros is given as

$$\text{Battery Cost} = 300 + 0.25 \max(x, y)100 \quad \text{per kWh}, \tag{3}$$

where x, y denotes the charging and discharging rates as described in the battery model xC-yC.

C. Co-optimization formulation

The power network in Madeira impose time-of-use (ToU) electricity prices for consumption, applies peak power restriction and imposes zero feed-in-tariff. The ToU price considered is shown in Fig. 2. The PPC contracts have 8 levels: 3.45, 4.6, 5.75, 6.9, 10.35, 13.8, 17.25 and 20.7 kVA for LV prosumers with per day cost as 0.1643, 0.2132, 0.2590, 0.3080, 0.4532, 0.5981, 0.7436 and 0.8892 respectively. The detailed consumer contracts in Madeira are summarized in [3]. The co-optimization formulation is developed in [3] and given as

$$(P_{opt}) \quad \underset{s_i}{\text{minimize}} \quad \sum_{i=1}^{N} p_{\text{elec}}(i)\theta_i(s_i)h \tag{4a}$$

subject to

$$\text{Ramping constraint, } Eq.\ 1 \quad , \tag{4b}$$

$$\text{Capacity constraint, } Eq.\ 2, \tag{4c}$$

$$\text{Self-sufficiency, } \theta_i(s_i) \geq 0, \tag{4d}$$

$$\text{Arbitrage, } \theta_i(s_i) \geq [z_i + s_i], \tag{4e}$$

$$\text{Peak shaving, } [z_i + s_i]/h \leq P_{\max}^{set} \tag{4f}$$

where $\theta_i(s_i) = \max(0, z_i + s_i)$. The peak power threshold, $P_{\max}^{set}$, is selected close to the power level $(P_{\max} + \delta_{\min})$, subject to $P_{\max}^{set} \geq (P_{\max} + \delta_{\min})$. $P_{\max}^{set}$ is selected by the electricity consumer as a PPC contract with the utility in Madeira. Note that this formulation prioritizes self-consumption over arbitrage.

D. Co-optimization with control of cycles

Note that the formulations discussed previously do not consider battery life that is affected by charge-discharge cycles. Battery manufacturers measure the life of a battery using two indices: cycle life and calendar life. Cycle life denotes the number of cycles a battery can operate at a certain depth-of-discharge before reaching its end-of-life or EoL (EoL is reached when battery capacity reduces to 80% of its initial rated capacity in Wh). Similarly, calendar life denotes the maximum probable age that the battery can be operational before reaching EoL. Following our prior work [20], we define a friction function for the active power to model the degradation due to cycles of operation as $P_{\text{fric}}^i = \frac{[P_B^i]^+}{\eta_{\text{fric}}} - [P_B^i]^-\eta_{\text{fric}}$. In the original formulation (P_{opt}) the constraint Eq. 4e is modified as $\theta_i \geq [z_i + P_{\text{fric}}^i]$. The friction coefficient takes a value from 1 to 0. η_{fric} needs to be tuned so as the operational life is increased by matching calendar and cycle degradation [20]. If the battery is not over operating then η_{fric} is set to 1. For cases where the battery is over-performing, the low returning transactions is eliminated by decreasing value of η_{fric}.

IV. Energy storage profitability

We propose a mechanism for ensuring storage profitability considering battery cycle and calendar life, thus in effect considering battery degradation. Algorithm `BatteryProfitability` provides the steps to identify storage profitability. For more than one battery is profitable, in such a case it will depend on the prosumer on whether they prioritize payback period or the returns per cycle.

Algorithm 1 `BatteryProfitability`

Inputs: $\eta_{\text{ch}}, \eta_{\text{dis}}, \delta_{\max}, \delta_{\min}, b_{\max}, b_{\min}, b_0, h, N, T, i = 0$
1: Calculate total storage profit, G_T, by solving P_{opt} over the instants, N_{total}, based on load, price and renewable generation,
2: Calculate equivalent 100% DoD cycles denoted as N_{cyc}^{100} using `DoDofVector` proposed in [20],
3: Calculate $G_{cyc} = G_T/(N_{cyc}^{100}\ b_{\text{rated}})$,
4: Calculate $P_{cyc} = G_{cyc} - C_{cyc}$, where C_{cyc} is the per cycle (100%) cost of the battery,
5: Calculate the Expected Payback Period (ExPB) in years $= (B_{cost}N_{total})/(G_T N_{year})$, where B_{cost} denotes the battery cost and N_{year} denotes number of samples in a year,
6: Battery is profitable if $P_{cyc} > 0$ and ExPB $<$ Calendar life of the battery.

V. Numerical Results

For the numerical simulations we use the battery parameters listed in Table III. The characteristics of the four prosumers are described in Figure 1 and Table II. Simulations are performed for the month of June 2019.

The performance indices used for evaluation are:
• *Arbitrage and self-sufficiency gains* (G_{arb});
• *Peak shaving gains* (G_{PD}): difference between nominal PPC and the new PPC contract after adding storage;
• *Total gains* (G_T): is the sum of G_{arb} and G_{PD},
• *Gains per cycle* (G_{cyc}): In prior work [20] we develop a mechanism to measure the number of cycles of operation based on DoD of energy storage operational cycles.
• *Profit per cycle* (P_{cyc}): is the profit battery owner makes

per cycle compared to the per cycle cost of the battery (C_{cyc}); $P_{cyc} = G_{cyc} - C_{cyc}$;
- *Expected payback period* (ExPB): is the linear extrapolation of the payback period compared to G_T. ExPB $= C_{bat}/G_T$
- *Self-sufficiency* (SS): calculated using the total energy consumed, PV generation and storage output,
- *Wasted energy*: The surplus production is wasted energy is measured in kWh.

We consider the battery cycle life equals 4000 cycles at 100% DoD. Using this description the euros per cycle per rated battery capacity for different ramping batteries are listed in Table IV. Considering the calendar life equals 7 years, the battery should perform ≈ 47.6 cycles per month in order to last 7 years and make more than the values listen in Table IV to be profitable.

TABLE III
BATTERY PARAMETERS

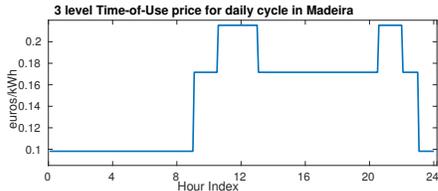| b_{min}, b_{max}, b_0	10%, 100%, 50% of b_{rated}
b_{rated}	1, 2, 5 kWh
$\eta_{ch} = \eta_{dis}$	0.95
$\delta_{max} = -\delta_{min}$	0.25 b_{rated} W for 0.25C-0.25C, b_{rated} W for 1C-1C, 2b_{rated} W for 2C-2C

Fig. 2.   Time-of-use (ToU) electricity prices

TABLE IV
STORAGE PROFITABILITY WITH DIFFERENT RAMPING PER KWH

Battery Model	Inverter Cost/kWh	Battery Cost/kWh	Battery Cost (C_{bat}/kWh)	euros/cycle/b_{rated} (C_{cyc})
0.25C-0.25C	25	400	425	0.1062
1C-1C	100	600	700	0.1750
2C-2C	200	700	900	0.2250

A. Co-Optimization and storage profitability

The co-optimization results for each prosumer are presented in Tables V, VI, VII and VIII. U2, U3, U8 and U12 belong to categories C1, C2, C3 and C4, respectively.

TABLE V
(C1) U2: PV GENERATION SLIGHTLY MORE THAN INELASTIC LOAD

Case	G_{PD} Euro	G_T Euro	P_{cyc}	Cycles	ExPB (years)	SS (%)	Waste (kWh)
Load + PV	-	-	-	-	-	26.82	57.4
1 kWh Battery							
0.25C-0.25C	0	10.13	**0.1675**	37.01	**3.50**	31.91	30.12
1C-1C	1.39	13.79	**0.0867**	52.70	**4.23**	33.56	18.59
2C-2C	2.85	15.48	**0.0536**	55.56	**4.84**	33.69	15.39
2 kWh Battery							
0.25C-0.25C	1.39	15.83	**0.0798**	42.53	**4.47**	34.96	12.97
1C-1C	2.85	19.26	**0.0355**	45.75	**6.06**	35.85	5.15
2C-2C	2.85	19.33	-0.016	46.24	7.76	35.88	3.96
5 kWh Battery							
0.25C-0.25C	1.39	22.46	0.0288	33.27	7.88	36.38	0.39
1C-1C	2.85	24.67	-0.0295	33.91	11.82	36.29	0.19
2C-2C	2.85	24.67	-0.0795	33.91	15.20	36.29	0.18

The best-suited battery is selected based on: (P1) profit per cycle per unit capacity, (P2) cycles of operation and (P3) expected payback period.

The best-suited battery for U2, U3, U8 and U12 are marked in bold in Tables V, VI, VII, and VIII respectively. For battery installation to make sense the value of P_{cyc} should be positive and ExPB should be lower than 7 years (i.e. the calendar life of battery). For prosumer U2 5 batteries satisfy the feasibility

criteria. However, the best-suited battery will vary with preference. For instance if payback period is priority the U2 should select 1 kWh 0.25C-0.25C battery. Note that the marginal value of storage decreases with increase in ramping capability and charge capacity. Thus if P_{cyc} is used to select the battery then slowest ramping battery with smallest capacity will be selected.

The self-sufficiency increases with increase in battery capacity and ramping capability thus the wasted excess generation decreases.

TABLE VI
(C2) U3: ACTIVE LOAD MANAGEMENT TO REDUCE EXCESS GENERATION

Case	G_{PD} Euro	G_T Euro	P_{cyc}	Cycles	ExPB (years)	SS (%)	Waste (kWh)
Load + PV	-	-	-	-	-	32.71	2.72
1 kWh Battery							
0.25C-0.25C	0	7.57	**0.1715**	27.26	**4.68**	32.73	0.01
1C-1C	0	8.13	**0.0197**	41.76	7.18	32.53	0
2C-2C	0	8.14	-0.0318	42.13	9.21	32.52	0
2 kWh Battery							
0.25C-0.25C	0	9.74	**0.0791**	26.28	7.27	32.09	0
1C-1C	0	10.07	**0.0065**	27.74	11.59	32.04	0
2C-2C	0	10.07	-0.0436	27.76	14.90	32.04	0
5 kWh Battery							
0.25C-0.25C	0	13.92	0.0189	22.25	12.72	30.66	0
1C-1C	0	14.02	-0.05	22.43	20.80	30.64	0
2C-2C	0	14.02	-0.1	22.43	26.75	30.64	0

TABLE VII
(C3) U8: COMPARABLE GENERATION AND LOAD WITH AVERAGE LOAD HIGHER THEN C1,C2 AND C4

Case	G_{PD} Euro	G_T Euro	P_{cyc}	Cycles	ExPB (years)	SS (%)	Waste (kWh)
Load +PV	-	-	-	-	-	28.02	58.14
1 kWh Battery							
0.25C-0.25C	0	35.62	**0.8589**	36.91	**0.99**	28.71	40.68
1C-1C	0	39.42	**0.4543**	62.64	**1.48**	29.42	22.69
2C-2C	0	40.02	**0.3765**	66.53	**1.87**	29.57	17.88
2 kWh Battery							
0.25C-0.25C	0	40.04	**0.2941**	50.01	**1.77**	29.21	27.27
1C-1C	0	44.36	**0.1842**	61.75	**2.63**	29.79	10.73
2C-2C	4.31	48.70	**0.1774**	60.51	**3.08**	29.79	9.09
5 kWh Battery							
0.25C-0.25C	0	50.44	**0.1117**	46.30	**3.51**	29.90	4.80
1C-1C	4.31	58.64	**0.1106**	41.06	**4.97**	29.80	1.54
2C-2C	4.31	58.65	**0.0598**	41.18	**6.39**	29.80	1.36

TABLE VIII
(C4) U12: PV GENERATION SIGNIFICANTLY MORE THAN INELASTIC LOAD

Case	G_{PD} Euro	G_T Euro	P_{cyc}	Cycles	ExPB (years)	SS (%)	Waste (kWh)
Load + PV	-	-	-	-	-	47.84	158.1
1 kWh Battery							
0.25C-0.25C	0	8.57	**0.1922**	28.69	**4.13**	56.91	126.13
1C-1C	0	9.49	**0.1107**	33.22	**6.15**	57.72	115.66
2C-2C	0	9.56	0.0739	35.55	7.85	57.84	106.63
2 kWh Battery							
0.25C-0.25C	0	13.41	**0.0566**	41.19	**5.28**	65.00	97.50
1C-1C	0	13.84	0.0214	35.23	8.43	65.77	81.94
2C-2C	0	13.86	-0.0116	32.47	10.82	65.80	70.04
5 kWh Battery							
0.25C-0.25C	0	18.28	-0.007	36.85	9.69	74.90	53.58
1C-1C	0	18.71	-0.0758	37.72	15.59	75.66	31.16
2C-2C	0	18.70	-0.1257	37.66	20.05	75.65	27.41

B. Friction Coefficient

The friction coefficient can help in reducing the cycles of operation for cases where the battery is performing more number of cycles compared to the value which matches the calendar life degradation. For equalizing cycle and calendar life degradation of the battery, it should perform ≈ 47.6 cycles in 1 month (considering 4000 as cycle life at 100% DoD and 7 years as calendar life). From Tables V, VI, VII, and VIII it is clear that

inclusion of friction coefficient for limiting cycles of operation is only relevant for 1 and 2 kWh batteries for U8 and 1 kWh battery for U2, as for these case the battery is operating more number of cycles than the optimal value of 47.6 cycles in a month (marked in red). Table IX compares the tuned friction coefficients for batteries which performed more cycles than expected. Note that friction coefficient can only reduce cycles of operation, therefore it is only applicable when the battery is over-performing. Inclusion of η_{fric} for over-performing batteries increases P_{cyc}, however, also increases ExPB.

TABLE IX
FRICTION COEFFICIENT.

Battery Model	η_{fric}	Profit euros	P_{cyc}	SS (%)	Waste (kWh)	Cycles	ExPB yrs.
For prosumer U2							
1kWh,1C-1C	0.796	12.85	0.0962	32.45	25.70	47.38	4.54
1kWh,2C-2C	0.797	14.45	0.0796	32.53	24.99	47.44	5.19
For prosumer U8							
1kWh,1C-1C	0.796	38.17	0.6805	29.33	26.82	44.62	1.53
1kWh,2C-2C	0.796	38.50	0.5829	29.37	25.16	47.65	1.95
2kWh,1C-1C	0.9398	43.98	0.3143	29.67	13.71	52.29	1.61
2kWh,1C-1C	0.9397	43.47	0.3286	29.73	14.34	43.17	2.68
2kWh,2C-2C	0.9397	47.85	0.3228	29.76	12.91	43.68	3.13

VI. CONCLUSION

The profitability of investment in storage is a crucial factor for deciding future investment in batteries. In this paper, we co-optimize storage in the context of power network norms in Madeira. The batteries are used for performing energy arbitrage, increasing self-sufficiency and peak demand reduction.

The proposed formulation prioritizes self-sufficiency over energy arbitrage, thus minimizing the excess production at the prosumer end. Four types of prosumers are selected based on the different relationship between inelastic load and renewable generation to identify the value of storage.

It is observed that the marginal value of installing battery decreases with storage size and ramping capability. We observe that value of storage for an average net-load comparable to storage ramping rate leads to profits several folds higher than for otherwise. Faster ramping batteries perform much more number of cycles which deteriorates the profit made per 100% DoD cycles per unit of storage capacity making such batteries financially unviable.

We propose the inclusion of friction coefficient which reduces the cycles of operation by eliminating storage operations for low returning transactions thus increasing the profit per cycle per unit of storage capacity and makes such batteries more profitable, however, it increases the payback period.

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