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Optimal sizing of residential battery systems with multi-year dynamics and a novel rainflow-based model of storage degradation: An extensive Italian case study

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ABSTRACT

Residential battery storage to perform load shifting and demand side management has become of utmost importance to improve hosting capacity, increase renewable energy penetration and meet environmental targets, especially with energy community policies. As the lifetime of electrochemical batteries depends upon their scheduling and environmental conditions, the multi-year effects of operational strategies can affect the economics of the investment. However, rarely complete long-term simulations of the operation of storage systems are performed to assess the battery profitability including the operational effects of aging, and limited studies account for a large statistics of consumers. In this study, we propose a multi-year sizing methodology for residential applications, where the complete lifetime of batteries is simulated at 15-min time resolution till complete degradation using an improved non-linear non-convex degradation model; the photovoltaic plant aging is also considered. An extensive analysis on the economics and commercial size best suited for 399 real load profiles in Italy is proposed. Results suggest that the break-even price of the storage is about 400 €/kWh, which is lower than the average commercial price, and that, as reviewed, current market components may be unfit for consumers with low energy demand. Net Present Value (NPV) and Discounted PayBack Time (DPBT) can reach 500-1500 € and 8-11 years.

1. Introduction

1.1. Motivation

Energy investments are well known to be long-lasting, so their economic profitability must be assessed in a multi-year perspective. In this way, it becomes of primary interest to understand and properly model the aging mechanisms along the time of the system under consideration. Given the pressure for increasing the renewable penetration and meet environmental targets, the promotion of smart residential houses is of utmost importance, but their optimal sizing has rarely accounted for multi-year considerations, including the simulation of the battery degradation. In particular, degradation processes covering the battery, photovoltaic system and converter need to be carefully analysed, to correctly model how the system operation is affected over time. Among them, modelling the battery is one of the most complicated items.

Therefore, it is timely to address the optimal multi-year sizing of residential battery systems based on a detailed model of battery degradation model and realistic data to give a picture of the state-of-the art in the profitability of BESS systems for the Italian scene using 399 real load profiles. A detailed literature analysis to identify the most proper degradation models for all the system components has been performed and a modified version has been derived and implemented.

1.2. Battery degradation

The literature in battery modelling is very rich and long-lasting. While first studies regarding power systems focused on lead acid batteries [1], recent technology development lead to a variety of studies on different battery chemistries [2,3], among which lithium batteries represent the state-of-the-art for battery storage solutions in residential applications [4].

In the literature, studies related to battery degradation modelling span between theoretical and empirical approaches: in the former, the

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model is derived by known chemical dynamics and properties of the materials [5,6], while the latter approaches are based on correlations between stress and lifetime of the batteries [7,8]. Theoretical models involve a large number of parameters, which are often difficult to collect, and they are computationally more expensive [9], thus empirical or hybrid models may be more suitable for optimization purposes [10].

The main factors affecting the lifetime of batteries are: time, temperature, and the operating power profile (current and number of cycles) [11]. The different effects are often modelled as the combination of the so-called calendar life, referring to the aging effect involving time, and cycle life, related to the cyclical operating conditions of the battery. Among the simplest models rely on simple functional fitting (e.g. with a polynomial function) to capture the relationship between the capacity fading and the stress under consideration [9]. Other hybrid models, partially accounting for the chemical dynamics, are based on Arrhenius equation [12], which is widely used in chemistries to model velocity of chemical reactions, both for standard cyclical operation of the same cycle [13] and multiple operating conditions [14].

Given the significant complexity of modelling battery degradation, studies have often focused on a selected stress at a time, i.e. the Depth-of-Discharge (DoD) [7], the State-of-Charge (SoC) [15], or the temperature. However, battery ageing is a fatigue-like process where the repetitive application of the stress components affect the State-of-Health (SoH). Subsequently, models that consider multiple stresses have been introduced [9], also considering the cyclicities in production processes or meteorological conditions. Again, while initial studies have usually focused on the simple repetitive application of the same stress over time [7], methodologies for combining multiple stresses over time have been then developed [10,14,16]. Authors in [14] introduced an iterative formulation for the evaluation of the degradation effects. In [16], the authors proposed a degradation model based on a weighted sum of exponential functions, where the capacity fade is computed by combining N degradation events, based on the average SoC of the battery, the normalized standard deviation of SoC with respect to the average value, and the temperature. Furthermore, the empirical formulation described in [10] aims at capturing the effects of the repetitive stresses due to cycling, temperature effects and calendar life by means of equations: Arrhenius function, polynomial and exponential fitting. This modelling is able to capture a variety of different operating conditions and the cycling operation by means of the rainflow counting method, widely adopted in fatigue analysis [17] and introduced also for optimization techniques [10,18]. Moreover, the degradation model described in [10] is supported by quantitative data to replicate the methodology, therefore, has been used in this study.

1.3. PV and power converters degradation

Similarly to the batteries, the degradation of photovoltaic modules and power converters is generally related to technology, time, environmental conditions and the cycling operation of the devices [19–22].

When proper maintenance and operation of the system is in place, the degradation of photovoltaic modules is mainly linked to meteorological conditions [21,23] and weakly linked to the operation of the system. In particular, typical datasheets of PV systems usually guarantee a maximum yearly capacity fading, whose numeric values are aligned to the experimental studies by the National Renewable Energy Laboratory (NREL) of United States [24]. The findings of [24] showed that non-linearities occur in PV degradation, but they are difficult to model, tend to be mostly located in the early life and, thereafter, a linear trend can be a good approximation of the general ageing process, as also suggested by [21,23,25]. In this study, for simplicity and in agreement with data made available by producers, we considered a linear degradation of PV modules.

Similar ageing patterns occur also for power electronic degradation, as suggested in [22,23,26], however studies have traditionally focused on the identification of the time till failure, rather than on capacity or efficiency degradation. The experimental study in [23] proposed a methodology for assessing the lifetime of a power converter, overlooking its capacity degradation. Similarly, Sintamarean et al. [26] proposed a tool for the optimal reliability-oriented design of grid-connected PV inverters; no evidence on efficiency degradation of the power converter has been reported. Furthermore, in the empirical research activity discussed in [27] for a practical implementation of a solar inverter in Malaysia, the authors highlighted that in 3-years (2016–2019) no efficiency degradation has been noted for a variety of PV converters. A similar finding has independently been obtained in [28]. For these reasons, we preliminarly regarded efficiency degradation as a secondary effect for the power converter section, whereas the capacity fading of the PV modules is considered.

1.4. Multi-year optimization methods

Traditional optimization methodologies have usually focused on the identification of the optimal sizing of a system by using representative year profiles [29], sometimes modelled by means of representative days [30]. However, energy systems change over time: demand may grow and the generation assets age, thus affecting the economics of the investments [31].

Multi-year planning is a well-known topic for generation plans in large power systems [32,33], but assets degradation has often been overlooked as of secondary importance, also considering that traditional power plants may be less subject to operational degradation especially when adequate maintenance is implemented. On the other hand, despite capacity fading of renewable sources, converters and batteries has higher dynamics; it has often been neglected in microgrid or residential planning [34]. Conversely, in this study, which is focused on battery storage for residential application, the use of accurate battery system modelling is a must-have.

Multi-year optimization is a tough problem whose computational requirements are significant, often exceeding hours for 10-year problems [31,35], because of the large number of variables and constraints. Moreover, when complex non-linear constraints and objective functions are in place, the complexity can grow even further and traditional mathematical programming, i.e. Mixed-Integer Linear Programming, may be difficult to apply, unless optimization tolerances are increased significantly, even beyond 5–10% [36]. This is the reason why heuristic approaches, able to simulate the actual system operation and non-linear system behavior, have been proposed [31], or sometimes the main long-term period is decomposed in multi-steps [37]; yet full methodologies, accounting for uncertainties in the demand [31] or not [35], better capture the long-term economics of renewable investments. In particular, in [31], the authors quantified that multi-year optimization algorithms can reduce by 25–50% the initial investment costs (CAPEX) and even by 16-20% the Net Present Cost of the investment; assets degradation can play an additional 6% forecasting error costs when not considered in the optimization process. The findings are also quantitatively aligned to the results in [37], although the paper focused on country-wide system optimization. Acknowledging these needs, commercial tools have been proposed to address multi-year methodologies [38], yet significant improvements are required.

Recently, multi-year dynamics have been proposed also for residential applications [18,39–41], but often in a limited way. Authors in [40] used a simple model based on calendar life and energy throughput, whereas in [18] a more complex algorithm based on rainflow counting has been considered; however, the operational effects due to the degradation have not been properly taken into account with long-term simulations, as the degradation model has been considered to estimate the lifetime of the battery, and PV degradation was neglected. Moreover, typical residential users can only choose the optimal system according to a number of commercial options, which depend on the specific user. In traditional studies, the modularity of the commercial options is only limited and a specific load profile is considered. In this study, instead, we aim to develop a methodology for the selection of the best component, out of a list, for 399 household in the Italian context.

1.5. Main contributions

According to the proposed literature analysis and to the authors' best knowledge, the main contributions of this paper are listed below:

1. Development of a methodology for the selection of the battery energy storage system most suited for a residential application out of a number of commercial options, including the simulation of the operational effects of battery and PV degradation and the detailed analyses with two objective functions: Net Present Value (NPV) and Discounted PayBack Time (DPBT).
2. Improvement of the degradation model introduced in [10], to better detail the calendar and cycling aging of the battery.
3. Estimation of the household BESS needs for the Italian market, by considering a large Italian case study, based on 399 load profiles collected from different regions of Italy, to represent a realistic overview of the Italian domestic consumption patterns.

1.6. Organization

In Section 2, the proposed methodology including assets degradation is described. The case study is discussed in Section 3 and in Section 4 the results are reported. Finally, conclusions are drawn.

2. Sizing methodology

2.1. Optimization procedure

The procedure used to identify the optimal size of the storage to be installed for a residential user is depicted in Fig. 1.

The main goal of the formulation is identifying the BESS that maximizes the profitability of the investment until it ages, chosen among a pre-defined set of commercially available BESS. Given the non-linearities in the converter and in the battery degradation dynamics, which also lead to non-homogeneous life of the components spanning several years, the proposed iterative approach described in Fig. 1 is regarded as a suitable option for the analysis [18,31]. The approach is based on a three-loop nested methodology: in the most inner loop (Time step loop), the simulation of the BESS operation is performed at 15-min resolution, in the mid loop (Simulation period loop) the degradation effects of the BESS are iteratively estimated by a rainflow algorithm, and finally in the external loop (BESS configuration loop) multiple BESS configurations are tested to select the most profitable one. The profitability, evaluated in terms of Net Present Value and Discounted PayBack Time, is based on simulations of the battery operation including degradation until the End Of Life (EOL) of the battery is reached.

It is worth noticing that the execution of each rainflow algorithm in the simulation period loop is relatively computationally expensive. As a compromise between optimality and computational requirements, the proposed methodology performs the rainflow algorithm only every a given pre-defined period (i.e. 3 months), rather than at any time step of the simulation, and within each period it is assumed that no degradation occurs. Since the degradation is a slow process, this approximation has limited economic and operational effects but enables reducing computational time.

The iterative algorithm stops when the actual battery capacity falls below a given threshold (β^{EOL}) the capacity of the brand-new BESS ($B_c^{B,N}$).

Although the proposed approach is based on estimating the BESS profitability for all the investment options of the users, in practical applications, the number of design options for domestic BESS are relatively limited. Therefore, the computational requirements do not rise significantly.

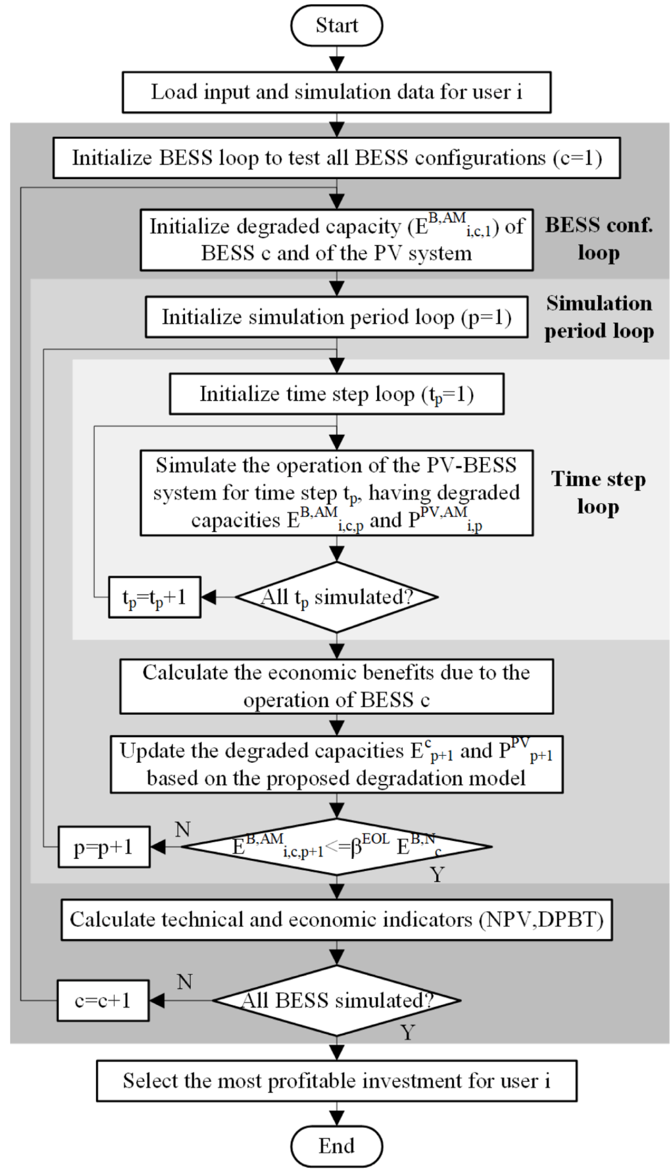


Fig. 1. Flowchart of the simulation model for each user I.

2.2. Objectives

In the proposed study we consider two main objective functions that are widely used in the power systems literature: maximizing Net Present Value (NPV) and minimizing Discounted PayBack Time (DPBT). The mathematical formulation of NPV for a user i and a specific battery system c is reported in (2), where $CAPEX_{i,c}$ represents the investment costs for the battery system and $DCF_{i,c,t}$ represents the discounted cash flows. $DCF_{i,c,t}$ is defined in (1) where $\pi_t^{M,V-}$ is the variable component of the electricity tariff related to buying electricity from the public market, $\pi_t^{M,V+}$ represents the electricity price applied when the user sells electricity to the public market, $P_t^{B+/-}$ represents the avoided energy flows with the public grid due to the BESS. $T_{i,c}(P_t^{B+/-})$ is the expected lifetime of the BESS, dependent on its operation, d represents the discount rate and Δ is the time step resolution. The rational of this formulation is that, when renewable production exceeds demand, the energy that would be normally sold to the grid is stored in the battery ($P_t^{B-} > 0$); therefore, avoided profits occur that penalize the return of the investment. However, the same electricity stored in the BESS can later be used to supply the load ($P_t^{B+} > 0$), that, without the storage, would be met by withdrawing energy from the grid at a higher cost; this generates avoided costs that increase cash flows. y_t is the year corresponding to time step t. DPBT is instead defined in (3), as the period $\widehat{y}$ in years where the sum of the discounted cash flows equals to the investment costs.

$$DCF_{i,c,t} = \Delta \frac{\pi_t^{M,V-} P_{i,c,t}^{B+} - \pi_t^{M,V+} P_{i,c,t}^{B-}}{(1+d)^{y_t}} \tag{1}$$

$$NPV_{i,c} = -CAPEX_{i,c} + \sum_{t=1}^{T_{i,c}\left(P_{i,c,t}^{B+/-}\right)} DCF_{i,c,t} \tag{2}$$

$$DPBT_{i,c} = \widehat{y} : CAPEX_{i,c} = \sum_{t=1}^{T(\widehat{y})} DCF_{i,c,t} \tag{3}$$

It is worth noticing that the methodology accounts for the non-linear degradation of the battery that affects the lifetime of the project ($T_{i,c}(P_{i,c,t}^{B+/-})$) and its operation, which has been usually neglected in the literature.

2.3. Main constraints

The electricity balance of the residential user is guaranteed with (4), where $P_{i,t}^{PV}$ is the renewable production at every time step, $P_{i,c,t}^{L}$ is the load demand, and $P_{i,c,t}^{P+/-}$ represents the power exchanged with the public grid.

$$P_{i,t}^{PV} + P_{i,c,t}^{B+} - P_{i,c,t}^{B-} - P_{i,c,t}^{L} = P_{i,c,t}^{P+} - P_{i,c,t}^{P-} \tag{4}$$

The battery balance is guaranteed with (5), where $E_{i,c,t}^{B}$ represents the energy stored in the battery, and $\eta^B(P^B)$ is the non-linear model of the efficiency of the battery, as specified in (6). The maximum power dispatch of the aggregator is modelled using (7), where $P_c^{B,max}$ is the maximum power of the BESS system, which also accounts for the both the converter capacity and the maximum nominal C-rate; no converter degradation has been modelled in agreement with the literature [27]. Finally, the maximum and minimum energy capacity in the storage are accounted for with (8), where $E_{i,c,p_t}^{B,AM}$ represents the actual maximum capacity of the storage corresponding to the time step t and $SoC^{max/min}$ are the maximum and minimum State-of-Charge of the battery. It is worth noticing that the value of $E_{i,c,p}^{B,AM}$, for the simulation period p_t corresponding to time step t, is calculated according to the model and procedure described in the following subsections.

$$E_{i,c,t}^{B} = E_{i,c,t-1}^{B} + \Delta P_{i,c,t}^{B-} \eta^B\left(P_{i,c,t}^{B-}\right) - \Delta \frac{P_{i,c,t}^{B+}}{\eta^B\left(P_{i,c,t}^{B+}\right)} \tag{5}$$

$$\eta^B\left(P_{i,c,t}^{B}\right) = 1 - \frac{a}{\frac{P^B}{P_c^{B,max}}} - b - c\frac{P^B}{P_c^{B,max}} \tag{6}$$

$$P_{i,c,t}^{B+/-} \le P_c^{B,max} \tag{7}$$

$$E_{i,c,p_t}^{B,AM} SoC^{min} \le E_{i,c,t}^{B} \le E_{i,c,p_t}^{B,AM} SoC^{max} \tag{8}$$

The PV production is formulated in (9) accounting for the specific production rate p_t^{PV}, due to environmental and meteorological condition, and the actual degraded capacity of the PV system $P_{i,p_t}^{PV,AM}$, where p_t is the simulation period corresponding to time step t, similarly to the battery system.

$$P_{i,t}^{PV} = p_t^{PV} P_{i,p_t}^{PV,AM} \tag{9}$$

2.4. Battery aging model

The degraded capacity of the battery is calculated at the end of each simulation period p with Eq. (10), where ξ_{i,p_t} represents the degradation with respect to the brand-new battery for user i at the end of period p_t and $E_i^{B,N}$ is the capacity of the brand-new battery. ξ_{i,p_t} is calculated using the model reported in (11)–(14), which is a modified version of the one in [10], where $f_{p_t}^{d}$ represents the quantity combining the degradation effects due to the cycling operation ($f_r^{d,cyc}$) and of the calendar life ($f_s^{d,cal}$) of the battery [10]. α^{sei} and β^{sei} are parameters to model the initial degradation due to the solid-electrolyte interphase; R_{p_t} represents the sets of cycles calculated with the rainflow algorithm in the time period till p_t, and S_{p_t} represents the set of SoC intervals over to calculate the degradation due to the calendar life. Function $S^\delta(\delta)$ models the capacity fading component due to the Depth-of-Discharge (DoD), $S^\sigma(\sigma)$ describes the effect of the SoC, S^T captures the effects of temperature, and S^t denotes the effects due to time, as denoted in (15)–(18); k^T, k^t, k^σ, and $k^{\delta 1/\delta 2/\delta 3}$ are experimental parameters, T_{ref}^{B} is the reference battery temperature (25°C) and σ_{ref} is the reference SoC (50%). In particular, as denoted in (12), the effects due to cycling operation are decomposed by each operating cycle r the battery is subject to, calculated by the rainflow algorithm [17] that returns a series of average SoC (σ_r) and DoD (δ_r) describing the cycling operation of the battery. Eq. (13) describes the degradation quantity for a cycle r. In the case of the calendar life, as denoted in (12) and (14), the proposed formulation improves the model described in [10] by introducing the term $f_s^{d,cal}$ that is specialized in different SoC intervals (S), so to account for the specific duration along which the battery stays and the corresponding non-linearities. For every SoC section s, the algorithm calculates the time period Δ_s the battery has spent within the pre-defined SoC bounds and the corresponding average SoC $\overline{\sigma}^s$ performed in the time domain ($\overline{\sigma}^s$ is not the average value of the bounds).

$$E_{i,p_t}^{B,AM} = \left(1 - \xi_{i,p_t-1}\right) E_i^{B,N} \tag{10}$$

$$\xi_{i,p_t} = 1 - \alpha^{sei} e^{-\beta^{sei} f_{i,p_t}^{d}} - \left(1 - \alpha^{sei}\right) e^{-f_{i,p_t}^{d}} \tag{11}$$

$$f_{i,p_t}^{d} = \sum_{r \in R_{p_t}} f_r^{d,cyc} + \sum_{s \in S_{p_t}} f_s^{d,cal} \tag{12}$$

$$f_r^{d,cyc} = S^\delta(\delta_r) S^\sigma(\sigma_r) S^T\left(T_r^B\right) \tag{13}$$

$$f_s^{d,cal} = S^\sigma(\overline{\sigma}^s) S^t(\Delta_s) S^T\left(T_s^B\right) \tag{14}$$

$$S^T\left(T^B\right) = e^{k^T\left(T^B - T_{ref}^B\right)\frac{T_{ref}^B}{T^B}} \tag{15}$$

$$S^\sigma(\sigma) = e^{k_\sigma\left(\sigma - \sigma_{ref}\right)} \tag{16}$$

$$S^t(\Delta) = k^t \Delta \tag{17}$$

$$S^\delta(\delta) = \left(k^{\delta 1} \delta^{k^{\delta 2}} + k^{\delta 3}\right)^{-1} \tag{18}$$

2.5. PV degradation model

The degraded capacity of the PV system is modelled using (19), accounting for a linear degradation rate of the modules [23]. The PV capacity for every simulation period p is modelled with a linear degradation rate ($\alpha^{PV,deg}$) with respect to the time elapsed since the initial installation of the PV system t_p. $P_i^{PV,N}$ is the non-degraded capacity of the PV system.

$$P_{i,p}^{PV,AM} = P_i^{PV,N}\left(1 - \alpha^{PV,deg} t_p\right) \tag{19}$$

3. Case study

3.1. Description

In this case study, we investigate the benefits of adding a battery storage system for a number of residential grid-connected application with a pre-installed PV system in Italy with NPV and DPBT objective functions. Given the system configuration shown in Fig. 2, we consider two main cases:

1. OnlyPV: it is the base case where each user is equiped with a PV system only.
2. PV+Batt: each user is equiped with the same PV as base case and an ESS, whose size is chosen among available commercial types at minimum cost using the procedure described in Section 2.

3.2. Load consumption and PV production

In order to provide generalized results for Italian residential users, an extensive measurement campaign was carried out on hundreds of houses over one year at 15-min time resolution and 399 real load profiles have been collected, spanning between 0.9 MWh/y and 9.6 MWh/y, as shown in Fig. 3. The data are a realistic sample of the Italian household consumption as they map the entire Italian territory: 198 households are located in the North, 78 in the Center, 94 in the South, and 29 in Sicily and Sardinia. Fig. 4 shows the average daily consumption pattern over a year, and the corresponding 5th, 50th and 95th percentiles for all users under consideration. We considered that each user has a pre-installed PV system whose total yearly production corresponds to a given share of the annual demand. A sensitivity analysis on this parameter (80%, 100% and 120%) has been performed. Since the PV production changes over a year due to many aspects (e.g. season, temperature, weather), the analysis considers an yearly PV production profile measured in Milan in 2018 on a real 4-kW PV plant. A PV aging rate of 0.8%/y has been taken into account [42].

The simulations of the household energy system are performed considering the entire multi-year simulations at 15-min time resolution, including the seasonalities of the demand and the PV production.

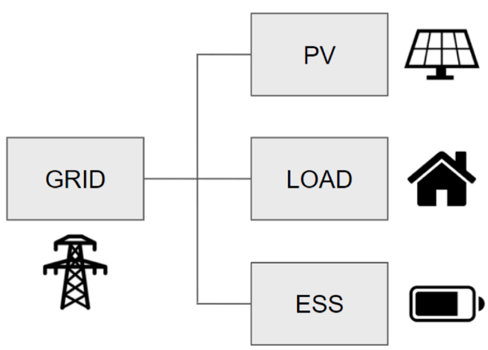


Fig. 2. Case study scheme: ESS for residential applications.

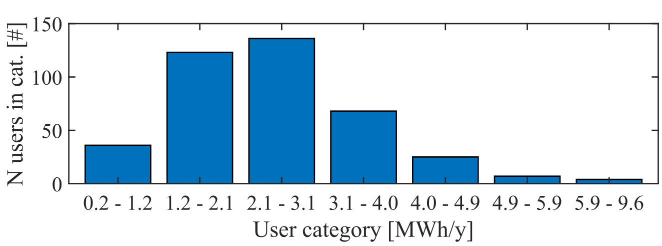


Fig. 3. Number of users per consumption class.

3.3. ESS characteristics

Based on a market analysis focused on the main manufacturers of residential BESS, listed in Table 1, we normalized the different configurations with 12 BESS discrete capacities spanning from 1 to 12 kWh. Although this methodology can accommodate custom BESS technology, each one with a specific price, peak power and energy capacity, in this study we performed a sensitivity analysis on the specific BESS price (200, 300 and 400 €/kWh), so to facilitate the comparison between multiple assets and cost configurations. The considered price range is typically lower than the present market price (spanning from 400 to 2200 €/kWh, according to authors' market review and internal sources); our values are assumed to include future costs reductions, incentives applied by governments, discounts by companies, and economies of scale for collective procurement. The BESS is assumed to have 3kW-power capacity and the battery is supposed to have a maximum C-rate of 1. The degradation parameters, derived from [10], are reported in Table 2.

3.4. Converter model

The efficiency curve of the power converter has been tailored the real behavior of a ESS converter for residential application (SMA SBS2.5-

Table 1
List of commercial ESSs for residential application.

Manufacturer	ABB	Tesla	SOLAX	SMA + LG	VARTA
Energy [kWh]	4–12	13.5	3–12	3.3–13	3–13
Power [kW]	3–5	5	3–7.5	2.5–8	1.6–4

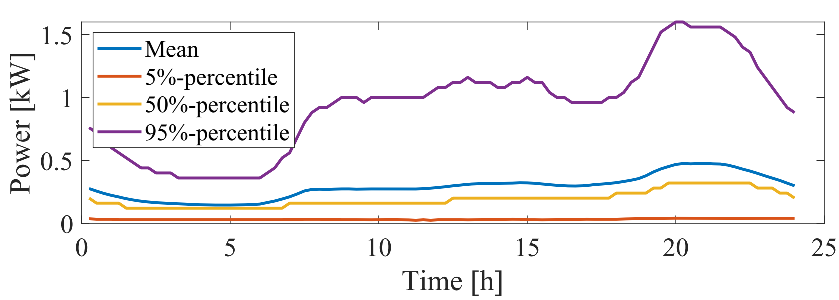


Fig. 4. Average and statistical properties of the daily consumption pattern of all 399 users.

Table 2
Parameters of the BESS degradation model.

Symbol	Value	Symbol	Value	Symbol	Value
α^{sei}	5.75E-2 [-]	β^{sei}	121 [-]	$k^{\delta 1}$	1.4E5 [-]
$k^{\delta 2}$	-5.01E-1 [-]	$k^{\delta 3}$	-1.23E5	k^{σ}	1.03 [-]
σ^{ref}	0.5 [-]	k^{T}	6.93E-2 [-]	T^{B}_{ref}	25 [°C]
k^{t}	4.14E-10 [s^{-1}]				

1VL-10 [43]). With respect to (6), the numeric values of the converter parameters are: $a = 0.0068$ [-], $b = 0.0148$ [-] and $c = 0.0150$ [-].

3.5. Electricity tariff

The market tariffs are chosen according to the Italian standard values [44]. In particular, the variable energy cost for purchasing energy ($\pi^{M,V-}$) is 16 c€/kWh and the selling price ($\pi^{M,V+}$) is 5 c€/kWh.

It is worth noticing that in this study we considered the future case where the Italian policy ”Scambio sul posto” (economic Net Metering) will become obsolete [44]. This policy, introduced in 2007, is aimed to support renewable sources by granting also to the production that exceeds the local load a price corresponding to the purchase tariff; in this way, the entire production, not only the part self-consumed, counts for the avoided purchase price and the grid behaves as a ”virtual battery”. Since this subsidy takes out any kind of physical storage, it has not been considered in this future-oriented study.

The discount rate is 2%.

4. Results

The main results of the case study are shown in Figs. 5–11. First, we discuss the differences in economic results obtained when selecting the battery by optimizing NPV or DPBT, based on Fig. 5; then, the technical results of the sensitivity analysis are better detailed and finally the disaggregated analyses by user type are reported. The sensitivity analysis over the size of the PV system is not reported, as we considered for the sake of brevity only the case where the panels are sized to produce the same energy as the load, since the results of the other tested cases (80% and 120%) where similar or slightly sub-optimal, typically within 2–5% on average.

Each user optimization, testing all 12 battery configurations, typically requires between 10 and 60 seconds to compute performed on a 16-Gb RAM 6-core 2.2-GHz computer, which is regarded as an acceptable time interval for practical operations.

4.1. Effect of the objective function

Fig. 5 reports NPV, DPBT and the optimal size of the BESS for the considered objective functions: pictures on the left refer to the configurations that maximize NPV, whose corresponding DPBT is calculated, while images on the right are obtained by minimizing DPBT, then NPV is calculated.

The results shown in Fig. 5 highlight that the profitability of adding a battery energy system in actual residential applications exists, however the break-even cost of the BESS is around 400 €/kWh, yet dependent on BESS price and EOL. However, it is worth noticing that current BESS market prices for residential application are generally higher (see Section 3.3), which suggests that incentives at domestic level are still

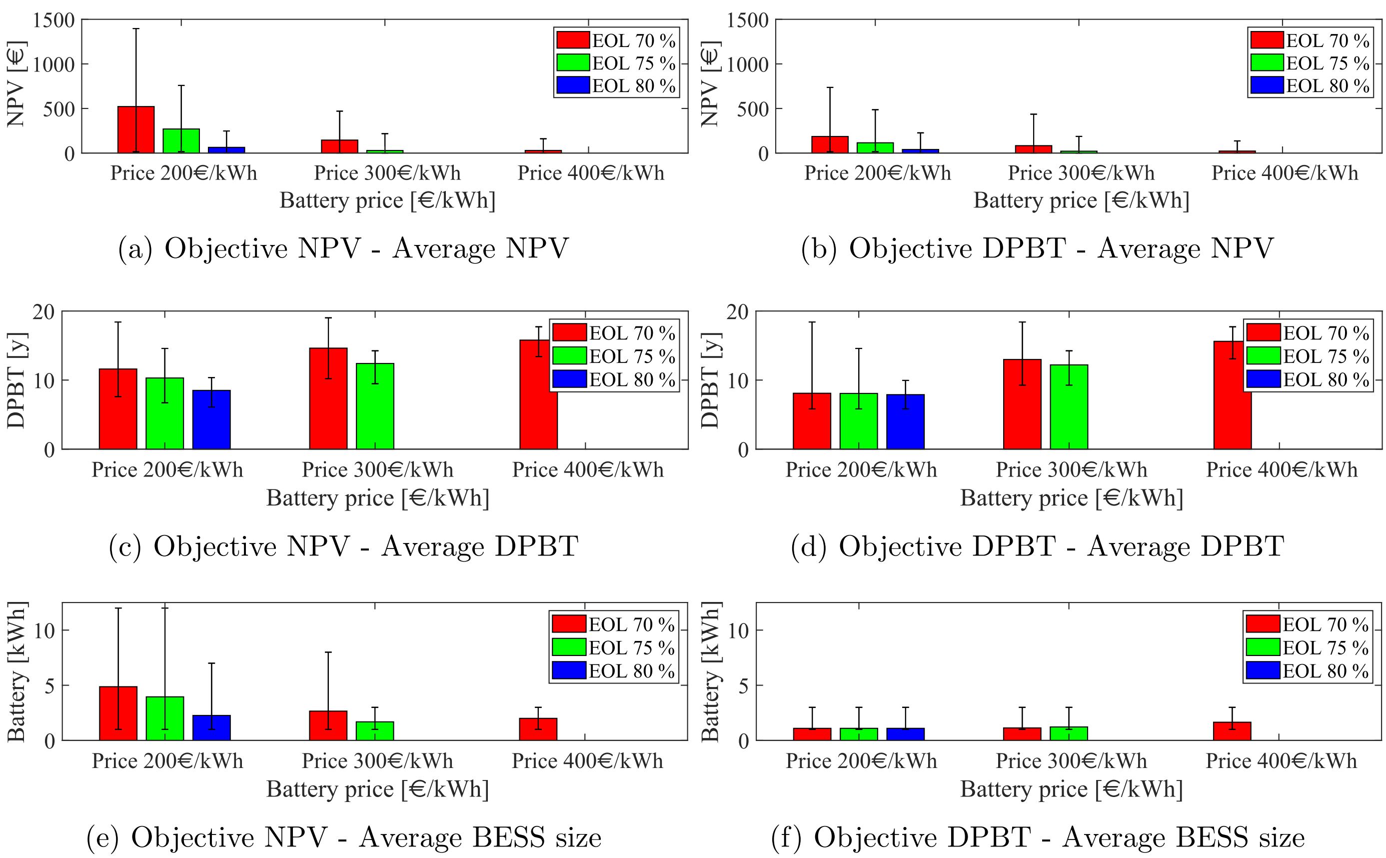


Fig. 5. Values of the objective functions and optimal BESS sizing; error bars denote maximum and minimum values.

required, or significant economies of scale through collective procurement, given current load consumption patterns, contract conditions and market prices. However, given the current trend in decreasing prices and the expected increase in the use of domestic BESS solutions, the affordability of these devices can increase significantly.

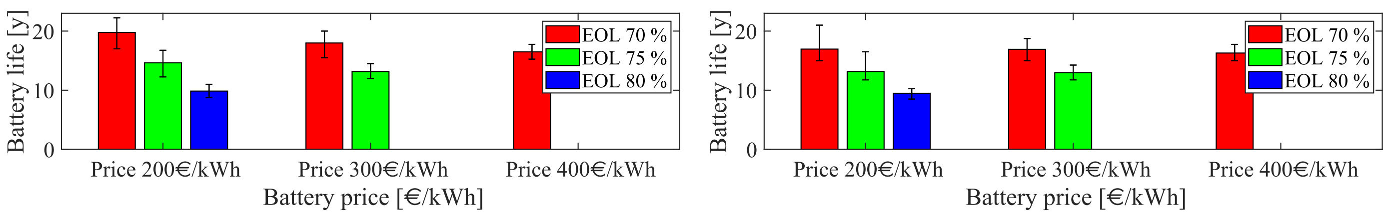
According to Fig. 5a, NPV can exceed 500-1000 € in some configurations where NPV is maximized, while the corresponding DPBT is on average 12 years, as shown in Fig. 5b. Contrarily, when the optimization is performed using DPBT, this reduces to around 8 years on average (Fig. 5d), and the corresponding NPV shown in Fig. 5b is significantly lower than in Fig. 5a.

The main reason lays in the optimal sizing of the BESS, which is completely different when NPV or DPBT are optimized, as shown in Fig. 5e and f, respectively. In the DPBT case, generally the optimal sizing of the storage is around 1 kWh, since this capacity leads to a significant marginal improvement in the profits even if it does not correspond to maximizing NPV. On the contrary, when NPV is maximized, the optimal size of the BESS is generally 3–5 kWh on average, which leads to both higher NPV and DPBT.

4.2. Technical results

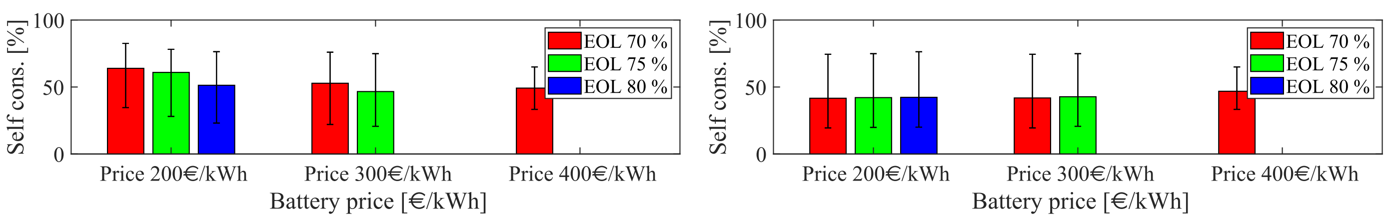
The profitability of the investment is strictly dependent on battery lifetime. When EOL of the battery is 80% the nominal capacity, the battery lasts about 10 years and the portion of users that receive benefits from BESS is still high, but their NPV is very limited, as shown in Fig. 6. On the other side, when EOL is 70%, NPV can reach 500 € on average, and up to 1500 € for most energy-intensive, when NPV is maximized. NPV and DPBT shown in Fig. 5 reflect this behavior, however the battery lifetime is generally lower in the DPBT case, as battery is subject to more frequent and deeper cycling.

Economic benefits are mainly related to the self-consumption that increases from about 30% in the OnlyPV case without BESS, up to 47-64% on average when NPV is maximized, and up to about 80% in some cases (Fig. 7a). When DPBT is minimized (Fig. 7b), instead, self-consumption is no higher than 48% on average, as the BESS is sized with a lower capacity.



(a) Objective NPV (b) Objective DPBT

Fig. 6. Average battery lifetime.



(a) Objective NPV (b) Objective DPBT

Fig. 7. Average self-consumption rate.

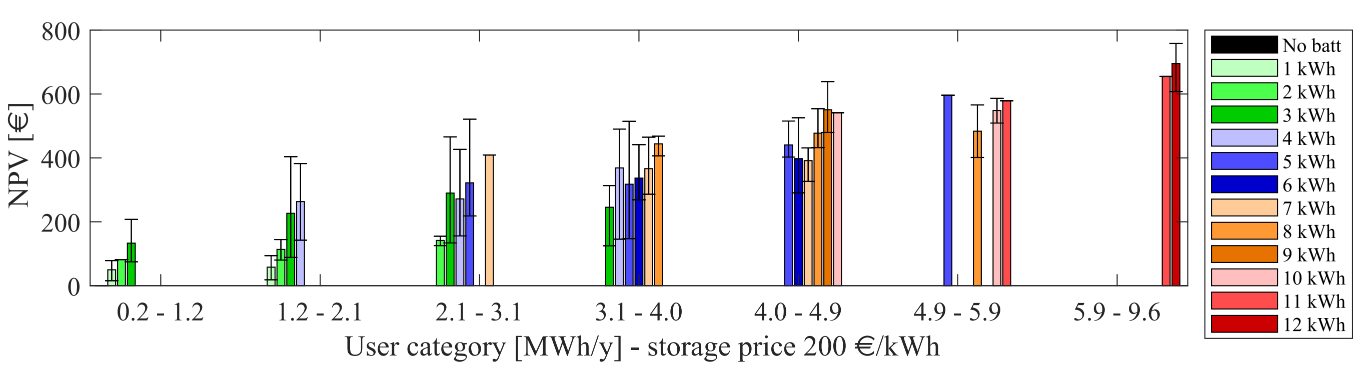


Fig. 8. NPV by user class and battery price, with 75% EOL and 200-€/kWh BESS; error bars denote maximum and minimum values.

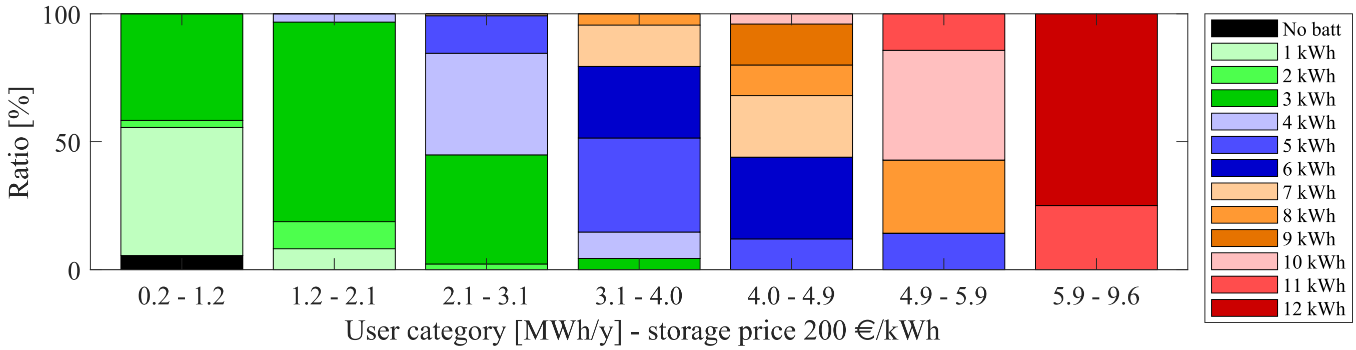


Fig. 9. Optimal battery size by user class and battery price, with 75% EOL and 200€/kWh-BESS; error bars denote maximum and minimum values.

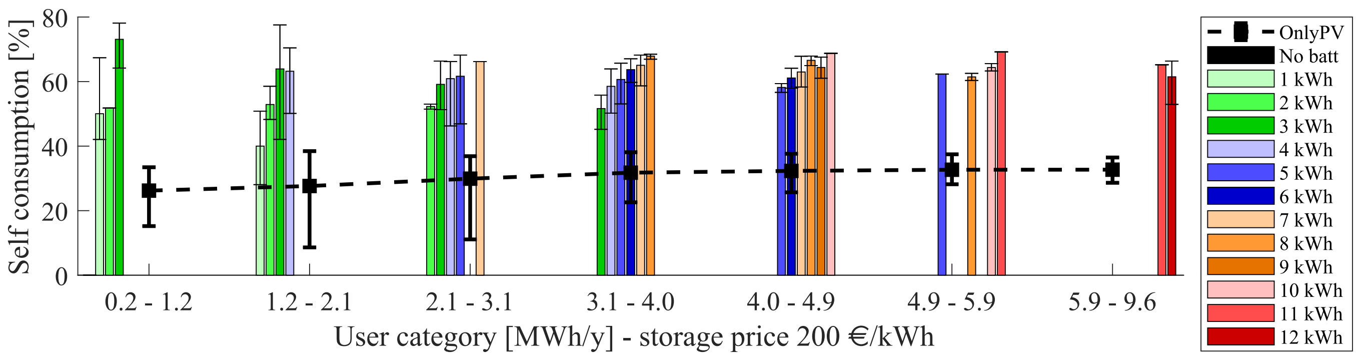


Fig. 10. Self-consumption rate by user class and battery price, with 75% EOL and 200-€/kWh BESS; error bars denote maximum and minimum values.

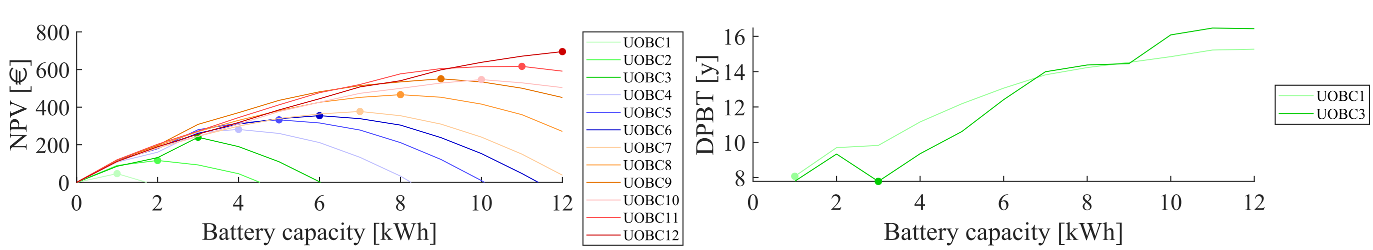
4.3. Disaggregated data

When looking at the results disaggregated by user category, as in Figs. 8–10 for the case at 75% EOL and BESS price 200 €/kWh, it is possible to highlight how the demand capacity affects the technical parameters and the economics of the investment. Fig. 8 highlights that NPV increases with demand requirements but, interestingly, a 200-€/kWh BESS storage is profitable for most users even with demand below 2 MWh/y. Similar results can be found also at a BESS price of 300 €/kWh, but the profitability is lower. In particular, as shown in Fig. 9, the optimal BESS size of each user category usually corresponds to a specific BESS capacity with little variations (usually within ± 1 kWh and sometimes ± 2 kWh). However, the commercial battery sizes available on the market tend to have a larger resolution, so they may not accommodate the specific needs of small consumers, at current electric demand. This suggests that there are possible market opportunities for BESS to accommodate needs for low-demand consumers. The increased profitability of BESS is justified by an increased self-consumption rate up to about 80%, as shown in Fig. 10 and the final share is generally invariant with the user category. In particular, the users with the lowest energy demand increase their self-consumption rate from 24% to about 50–80%, which is an increase higher than in other categories, because they have a lower fraction of activities located in daily hours.

The disaggregated value of the battery lifetime shows that in all applications the battery tends to reach EOL after around 15 years, depending on the specific user profile and demand category. This value is in agreement with the literature and is in agreement with the calculated DPBT that is around 10 years, with variations of 1-3 years. Given the flat behavior, the plots have not been included.

4.4. Profitability by battery capacity

To further clarify the effect of different battery capacities on the objective function, Fig. 11 shows the average profitability (NPV and DPBT) of the BESS for all the tested battery capacities (1kWh to 12kWh) by selected classes of Users by Optimal Battery Capacity (UOBC), each one



(a) Objective NPV (b) Objective DPBT

Fig. 11. Average profitability (y-axis) by battery capacity (x-axis) and Users by Optimal Battery Capacity (UOBC) categories (legend) with 75% EOL and 200€/kWh BESS, where each group UOBCX selects users whose optimal battery capacity is X and the dot specifies the maximum profitability by group.

gathering consumers with the same optimal battery capacity. For example, UOBC3 corresponds to all users whose optimal battery capacity is 3kWh, according to Fig. 9. In particular, as shown in Fig. 11a, the peak value of each UOBC curve corresponds to the expected optimal battery capacity for each UOBC category, e.g. 3kWh for the UOBC3 curve, and that other battery capacities tend to be sub-optimal. This confirms that our approach successfully selects the optimal battery capacity that maximize NPV for each user among the tested configurations. The same also applies for the DBPT objective function, as shown in Fig. 11b. Note that in Fig. 11b only UOBC1 and UOBC3 are reported because all users install a 1-kWh or a 3-kWh batteries only, as shown in Fig. 9.

5. Conclusions

This study proposes a novel methodology for sizing battery energy storage systems for residential applications, using detailed multi-year simulations of the entire lifetime of the battery including an improved degradation model that accounts for battery operation, temperature and calendar life. The novel methodology is applied for the case of 399 Italian households in different regions (North, Center, South and islands) and the results give a broad picture for the BESS needs for Italian residential users. Sensitivity analysis over the battery prices, end of life and size of the PV system, also accounting for a brief review of the market.

The proposed analysis suggests that BESS can be cost-effective solutions for increasing self-consumption by about 30% to even beyond 80% in some cases, over the entire lifetime of the BESS, considering not only BESS but also PV degradation. The increased self-consumption rate enables consumers to economize on the purchase of electricity and leads to a NPV even up to 500-1500 € when NPV is optimized, depending on the BESS cost, but high DPBT (around 10 years, on average). However, when DPBT is minimized, its value can decrease to 8 years. Furthermore, the results suggested that 400 €/kWh represents the break-even price for residential BESS, given the current consumer demand and contractual subscription. Therefore, the break-even cost for the BESS tends to be still below current market prices, which suggests that cost reductions, economies of scale for collective procurement and incentives are still required. However, the current decreasing trend of battery costs and the expected uptake in the market for domestic BESS can reduce the need for incentives.

This work can lay the basis for further studies in the multi-year sizing of residential systems with battery degradation and can give insights to developers and policy makers on current market needs for domestic systems.

CRediT authorship contribution statement

Davide Fioriti: Conceptualization, Methodology, Software, Formal analysis, Validation, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Luigi Pellegrino:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Giovanni Lutzemberger:** Conceptualization, Writing – review & editing, Supervision, Project administration. **Enrica Micolano:** Conceptualization, Writing – review & editing, Supervision. **Davide Poli:** Validation, Writing – review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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