

# Optimal battery sizing considering degradation for renewable energy integration

ISSN 1752-1416  
 Received on 26th June 2018  
 Revised 5th November 2018  
 Accepted on 11th December 2018  
 E-First on 17th January 2019  
 doi: 10.1049/iet-rpg.2018.5489  
 www.ietdl.org

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**Abstract:** The problem of sizing an electrochemical energy storage system for renewable energy integration is a complex task. There are several system input parameters that must be taken into account for a correct design. Among them, the ageing characteristic of the technology, the service that the system provides, i.e. the power profile that the system faces and the desired *C-rate* are considered. A simple solution for this problem is not available in the literature. This study presents a simple yet robust optimisation-based model for renewable energy integration. The model explicitly takes into account the intrinsic battery ageing process. The authors propose a formulation for the optimisation problem that can be written in terms of just one continuous variable, namely, the amount of energy that the battery is able to store (battery size); using the proposed procedure, solving the problem obtained is a relatively straightforward task. Results are first discussed using an illustrative example and later extended to two real case studies.

## 1 Introduction

With the success of wind and solar PV power plants worldwide, the potential benefits of energy storage for power variability smoothing and energy production time-shifting are becoming more important. Recent research has demonstrated that power variability increases with increasing levels of renewable generation [1, 2]. There is no fixed ceiling beyond which energy storage is indispensable. Rather, the point beyond which it is a viable option in the asset mix is a function of renewable penetration, geographic diversity and interconnection (or lack of), and the capacity of the system to absorb variability. On an empirical basis, some power systems seem to begin to show commercial deployment of storage beyond a level of roughly 10% of renewable penetration. As energy storage becomes more relevant for the grid, its development will benefit from taking a similarly well-structured approach.

The problem of sizing a battery is a complex task. Several input parameters must be taken into account for a correct design; for instance, the ageing behaviour of the technology, the service that the battery provides (the power profile that the battery faces) and the desired *C-rate*, among others.

Several authors have already addressed the problem of optimally sizing hybrid energy systems with different levels of detail and by using different optimisation techniques: Ru *et al.* [3] proposed a simple enumerative algorithm that sizes battery storage, however, average values are not the most reliable way of sizing a system that must ensure generation/consumption balance at all times.

The way of dealing with the sizing problem of an storage system mainly depends on its application. There is a sizable quantity of information for the best-known applications of these systems, for example, residential PV and battery systems in both grid-connected [4] and isolated applications [5], peak shaving [6] and increasing the renewable penetration in hybrid systems with PV and diesel generators [7].

In addition to the applications already discussed, other application that is attracting great interest in the technical community is the provision of ancillary services. In order to provide those services at minimum cost, batteries of optimal size must be used. Ancillary services usually include: load levelling, which consists in reducing large fluctuations in customer demand [8, 9]; frequency regulation, which tries to maintain the grid frequency within a specific range of the nominal frequency [10];

voltage regulation, that is, the ability of a system to provide near constant voltage over a wide range of load conditions [11]; PV and wind smoothing, whose objective is to reduce the variability of these energy sources [12–14] and so on.

Nevertheless, most of these studies do not include one of the most important contributions of this paper, battery degradation. This topic is widely analysed by diverse authors. In [15], the authors present a methodology used for accelerated lifetime testing of lithium-ion batteries, the results are used for the parameterisation of a performance-degradation lifetime model, while [16] introduces a lifetime model which estimates the decrease of energy capacity and power including the effects of temperature, state of charge profile and daily depth of discharge. Finally, in [17], the author develops a complex degradation model which includes the modelling of the electrical circuit and the calendar and thermal degradation, validating it with a lithium nickel cobalt aluminium oxide battery.

The complexity of these types of model is a very limiting factor to solve the battery storage sizing optimisation problem.

This work proposes an optimisation-based approach to find the optimal size of an electrical energy storage system given an expected battery profile.

The main contribution of this paper is the development of a simple yet robust electrochemical battery sizing methodology that explicitly considers battery degradation.

This paper is organised as follows. Section 2 provides the problem formulation considering battery ageing. In Section 3, a simple case study is proposed to highlight salient features of the proposed algorithm. A real-life case study is further analysed in Section 4. Finally, the conclusions close the paper.

## 2 Problem formulation

In this work, we assume that the amount of energy exchanged between a battery and an external system is known (power profile); for instance, we know with certainty the amount of energy produced by a solar panel and we also know the energy demand of a household; the battery is connected to both systems, and may store the exceeding energy from the solar panels and it also may provide energy to the house when solar panels cannot provide it. In this context, we want to compute the optimal size that the battery must have so that it can provide the services demanded from it at a minimum cost. This minimum cost must include both the

acquisition cost and the degradation cost associated with the use that the battery will have.

## 2.1 Energy and power constraints

We assume the fixed load profile for the battery is defined by a chronological sequence of operations. During each operation, it is assumed that the power flow in the battery remains constant. Thus, the load profile is defined by two vectors, one for the values of power  $P_t$  for each operation, and the other for the time duration  $\Delta_t$ , for each  $t = 1, 2, \dots, |T|$ , in the chronological sequence of operations. A positive value of  $P_t$  corresponds to battery charging, and a negative value to battery discharging. Then, we can define

$$P_t = Pch_t - Pdis_t, \quad t \in T \quad (1)$$

$$Pch_t \geq 0, \quad t \in T \quad (2)$$

$$Pdis_t \geq 0, \quad t \in T \quad (3)$$

where  $Pch_t$  and  $Pdis_t$  are the charging and discharging powers at time  $t$ , directly obtained from the values of  $P_t$ .

If we call  $SoC_t$  the amount of energy stored in the battery at time  $t$ , and  $SoC_0$  the energy stored in the battery before the load profile begins [Note that parameter  $SoC_0$  can be arbitrarily chosen, because later on, only the differences in values of  $SoC_t$  will be considered.], the relation between  $SoC_t$  and the load profile is defined as follows:

$$SoC_t = SoC_0 + \sum_{t'=0}^{t'-1} \Delta_{t'} \cdot \left( \eta_{ch} \cdot Pch_{t'} - \frac{Pdis_{t'}}{\eta_{dis}} \right) \quad (4)$$

where  $\eta_{ch}$  and  $\eta_{dis}$  are the efficiencies of the charging and discharging operations.

A usual parameter when analysing batteries is the *depth of discharge* (DoD), defined as the percentage of the battery total capacity that is empty, or conversely, 100 minus the percentage of the battery that is charged,  $DoD = 100(1 - (SoC/BS))$ . Thus, when a battery is in a condition of 70% DoD we assume that the amount of energy stored in the battery equals 30% of its nominal capacity. Following advice from battery manufacturers, we consider a *maximum depth of discharge* ( $DoD_{max}$ ) parameter for the battery, as the highest DoD acceptable. Therefore, the size of the battery (BS) must verify the following equation in order to be able to perform the given load profile:

$$BS \geq \frac{100}{DoD_{max}} \cdot \left( \max_{t \in T} \{SoC_t\} - \min_{t \in T} \{SoC_t\} \right) \quad (5)$$

Also note that when sizing a battery, one must consider an additional constraint imposed by the technical limitations of the battery and the inverter; the instantaneous power exchanged by the battery must not exceed a certain value; this is usually specified in terms of the so-called maximum *C-rate*

$$C-rate_{max} \geq \frac{\max_{t \in T} \{|P_t|\}}{BS} \quad (6)$$

where  $C-rate_{max}$  is the predefined value imposed by the battery manufacturer or the inverter capability.

## 2.2 Battery ageing modelling

Ageing processes for batteries are a very important factor that must be taken into account when trying to optimally size a storage system.

On one hand, batteries deteriorate due to the amount of time elapsed since its construction, regardless of the use that the battery is made of. This process is usually condensed in a single number, the number of years until the battery becomes degraded and should not be used any longer, usually called *calendar life* [18, 19].

However, batteries also deteriorate due to other different reasons, including irreversibility of some chemical reactions and damage caused to them due to heat dissipation [20]. This deterioration, in general, is a non-linear process and depends on the depth of discharge, the number of cycles and the energy extracted from the battery in a given time period [21]. Regarding this second set of mechanisms of deterioration, manufacturers usually provide a non-linear relation between depth of discharge and the number of cycles to failure, for a given rate of discharge. In general, if a battery is used infrequently and operated at small *DoD*, the first degradation process described will dominate the ageing of the battery; conversely, if the battery is charged and discharged frequently and rapidly, the second process will dominate the ageing of the battery. In this paper, we implement a method to take into account both mechanisms involved in the ageing of batteries.

In order to better characterise these ageing mechanisms, some definitions and equations are presented next. We define a battery discharging cycle as the process of extracting energy from a battery, each cycle  $c$  can comprise several consecutive time periods  $t$  of the load profile, and it is characterised by: (i) the total amount of energy extracted from the battery  $D_c$ , in kWh and (ii) the total cycle duration  $\Delta_c$ , in hours. For the remainder of the paper we contend that the ageing of a battery can be captured by modelling only its 'discharging' operations; we argue that this assumption is sensible for several reasons, it is known in the industry that discharging operations tend to be more damaging to batteries than charging operations [22], also, in the long term, battery SoC is a variable that moves around an average, and hence for every discharging operation there must be a similar charging operation, otherwise the battery will be depleted and no more discharging will take place. Note that, though we only characterise the ageing of the battery using parameters related to the discharging processes, the amount of ageing computed by our method considers both the ageing related to discharging and to charging.

With the previous definitions, the depth of discharge for a specific cycle can be defined as

$$DoD_c = 100 \cdot \frac{D_c}{BS} \quad (7)$$

Also, the rate for the discharging cycle  $c$ , usually called *C-rate* and noted here as  $C-rate_c$ , can be computed as

$$C-rate_c = \frac{P_c}{BS} = \frac{D_c}{\Delta_c \cdot BS} \quad (8)$$

where  $P_c$  is the average value of the power discharged over discharge process 'c'.

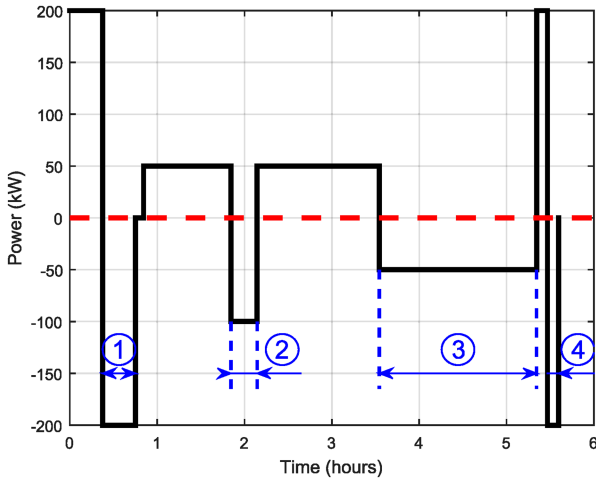
With the above definition, a cycle characterised by  $C-rate_c = 1$  is a cycle that will deplete the battery completely in 1 h; a cycle performed at  $C-rate_c = 3$  will deplete the battery three times faster, and hence, the battery will be depleted in 1/3 of an hour.

The first ageing mechanism described above can be measured simply using the following equation:

$$FoL_c^{CAL} = \frac{2 \cdot \Delta_c}{24 \cdot 365 \cdot CalendarLife} \quad (9)$$

where  $FoL_c^{CAL}$  is the fraction of the battery life that is consumed in discharge process 'c' due to CalendarLife consumption. Note that the 2 in the numerator of (9) is introduced to take into account not only the discharging cycle but also the charging cycle, estimating a similar duration.

Regarding the second ageing mechanism, battery manufacturers usually provide information of battery ageing as a graph or set of graphs relating the cycles to failure to the dimensionless parameters depth of discharge and the *C-rate*. As our input data are the battery load profile, we need to relate the unknown battery size BS with the information given by the battery manufacturers in order to take into account the battery ageing. We can do that by approximating the data in the manufacturers graphs by a suitable



**Fig. 1** Battery load profile

function,  $F$ . This function uses as arguments the values of DoD and  $C$ -rate, and gives as a result the number of cycles to failure, CtF. The link to the unknown BS is implicit in the definition of DoD and  $C$ -rate as they are functions of the BS and the load profile. Thus, for a given specific discharge cycle  $c$ , the number of times that this cycle can be repeated until failure can be computed as

$$CtF_c = F(DoD_c, C-rate_c) \quad (10)$$

Recall that, in general, function  $F$  is non-linear and in most occasions, an algebraic form is not available, instead, most of the time this information must be obtained from a graph or set of graphs provided by the manufacturers.

For the purposes of this work, we have found that a suitable analytic expression for this function can be obtained with the following general form:

$$CtF_c = \frac{k_1 \cdot DoD_c^{-k_2}}{C-rate_c^{k_3}} \quad (11)$$

where parameters  $k_1$ ,  $k_2$  and  $k_3$  must be obtained from the ageing curves mentioned above.

Then, the amount of life consumed due to the second mechanism can be obtained as the inverse of the  $CtF_c$

$$FoL_c^{OP} = \frac{1}{CtF_c} \quad (12)$$

Also, note that (12) is very interesting, as it effectively computes the fraction of the battery that is used when the battery undergoes a certain cycle. It is also remarkable that this calculation is only dependent on the DoD and the  $C$ -rate values of the discharging process; note that the value of BS is implicitly needed to calculate DoD. To illustrate the importance of this result, consider that a certain battery only performs two cycles during one day of operation, also assume that the manufacturer informs us that if the battery only performs cycles of the first type, the battery will be able to perform 3000 such cycles and if the battery only performs cycles of the second type, it will be able to perform 2000 cycles. What (12) tells us is that when the battery performs one of each type of cycle every day, the daily fraction of life consumed is

$$FoL = FoL_1 + FoL_2 = \frac{1}{3000} + \frac{1}{2000} = 0.000833 \quad (13)$$

This implies that the battery will be able to work for 1200 days.

Taking into account both mechanisms described, we can now compute the fraction of life consumed when performing cycle ' $c$ ',  $FoL_c$ , as the maximum of the two values provided in (9) and (12)

$$FoL_c = \max \{ FoL_c^{OP}, FoL_c^{CAL} \} \quad (14)$$

Consequently, the total fraction of life consumed during the whole time horizon, FoL, can be obtained by adding the respective fractions of life consumed over each discharging cycle

$$FoL = \sum_{c \in \Omega} FoL_c \quad (15)$$

where  $\Omega$  is the set of all discharge cycles in the profile under study.

### 2.3 Battery optimal sizing

Given a fixed load profile, a precise non-linear problem that includes ageing modelling can be stated. The objective function for the problem is

$$\min_{BS} \{ BS \cdot UBC \cdot FoL(BS) \} \quad (16)$$

where BS is the battery size, usually expressed in kWh; UBC is the acquisition cost of a battery, expressed in \$/kWh and FoL is the fraction of the life of the battery that is consumed due to the specific operation that the battery must perform. Note that in (16) the objective is to minimise the cost incurred during the specific proposed operation of the battery; also note that, in general, the solution to this problem is not to select the smallest possible battery size, because the same operation may cause bigger damage to smaller batteries than to bigger batteries, and hence, an intermediate value might be optimal. For the sake of simplicity, we assume for this work that the cost of the battery, UBC, comprises all direct and indirect costs, including the electronic components needed to operate the battery. Note that there is only one explicit optimisation variable in this problem, namely, BS. Also note that this is a non-linear objective function. For the sake of simplicity, in this work the effect of the temperature on the operation of the batteries is not considered directly.

It is relevant to point out that in (16) UBC is a constant and its specific value does not affect the optimal value of BS.

The problem constraints are all linear: (5) and (6). These linear constraints can be understood as imposing lower bounds for the optimal size BS, and can be easily incorporated into the problem as only one limit to variable BS previously computed.

In order to solve (16), and using the results from Section 2.2, we can rewrite the third term in the objective function as follows:

$$\begin{aligned} FoL(BS) &= \sum_{c \in \Omega} \left( \max \{ FoL_c^{OP}, FoL_c^{CAL} \} \right) \\ &= \sum_{c \in \Omega} \left( \max \left\{ \frac{C-rate_c^{k_3}}{k_1 \cdot DoD_c^{-k_2}}, \frac{2 \cdot \Delta_c}{24 \cdot 365 \cdot CL} \right\} \right) \\ &= \sum_{c \in \Omega} \left( \max \left\{ \frac{(D_c / (\Delta_c \cdot BS))^{k_3}}{k_1 \cdot (D_c / BS)^{-k_2}}, \frac{2 \cdot \Delta_c}{24 \cdot 365 \cdot CL} \right\} \right) \end{aligned} \quad (17)$$

Note that in the above expression, there is only one variable, BS and the rest of the values are either constants or parameters. Finally, the optimisation problem comprises (16), and constraints (5), (6) and (17).

### 3 Illustrative case study

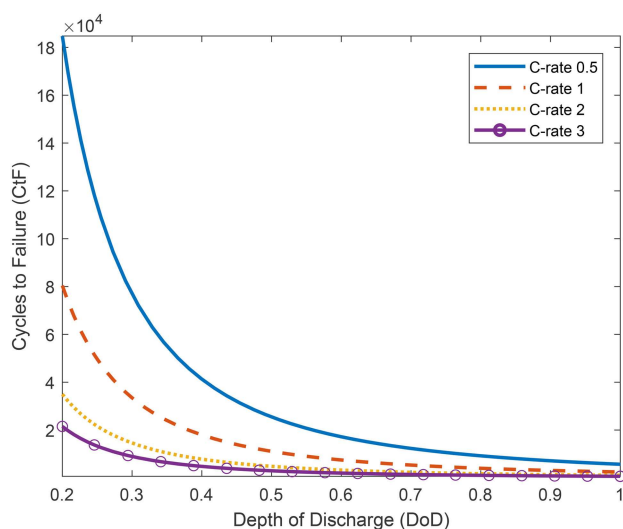
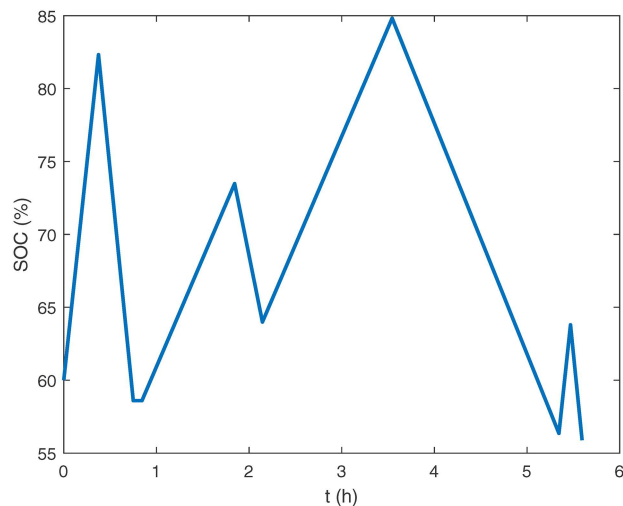
In this section, the proposed methodology is applied to a simple illustrative case. For this case, we assume  $DoD_{max} = 80\%$ ,  $C-rate_{max} = 3$  and  $LifeTime = 15$  years. The rest of the input data are the load profile and the cycle to failure function.

The load profile and discharge cycles are depicted in Fig. 1. It comprises four discharge cycles, each one defined by the energy discharged,  $D_c$ , and the discharge time,  $\Delta_c$ , whose numerical values are listed in Table 1. The energy discharged allows us to compute the depth of discharge for each cycle, while the discharge time is used to calculate the  $C$ -rate.

As previously stated, both variables impact the maximum number of cycles allowed for the battery (cycles to failure). Fig. 2 presents a typical ageing curve for lithium batteries, which shows

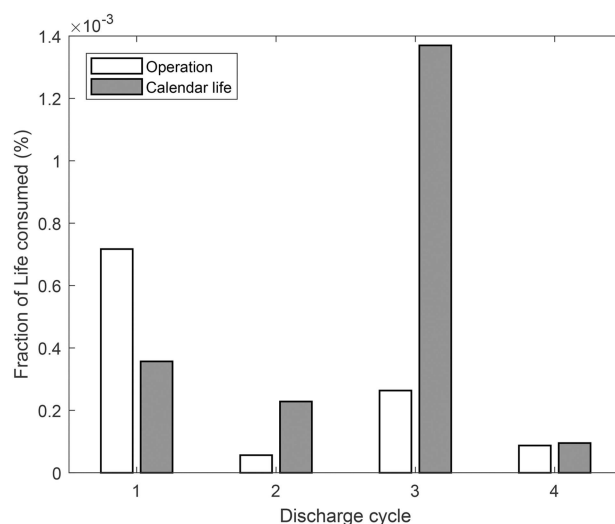
**Table 1** Battery load profile and discharge cycles

$t$	$P_t$ , kW	$\Delta_t$ , h	$c$	$D_c$ , kWh	$\Delta_c$ , h
1	200	0.375	1	75.0	0.375
2	-200	0.375	2	30.0	0.300
3	0	0.094	3	90.0	1.800
4	50	1.000	4	25.0	0.125
5	-100	0.300	—	—	—
6	50	1.400	—	—	—
7	-50	1.800	—	—	—
8	200	0.125	—	—	—
9	-200	0.125	—	—	—

**Fig. 2** Cycles to failure (CtF) versus depth of discharge (DoD), for different C-rate values**Fig. 3** Battery SoC in the illustrative case

the number of cycles to failure depending on the depth of discharge and the C-rate. These curves are different for other technologies, and also different batteries based on the same technology may present different behaviours [23, 24]. For example, the relative capacity of a battery decreases more with the number of cycles in a LCO type than in a LCO-NMC type battery.

High depths of discharge and C-rates produce greater wear by operating the battery, reducing the number of cycles to failure. Under these assumptions, and according to (11), the following equation has been introduced in the algorithm in order to model the degradation of the battery due to the operation. This equation is based on the curves of Fig. 2

**Fig. 4** Fraction of life consumed by operation and calendar life in the illustrative case (best viewed in colour online)

$$CtF_c = \frac{2480.5 \cdot DoD_c^{-2.1615}}{C-rate_c^{1.2}} \quad (18)$$

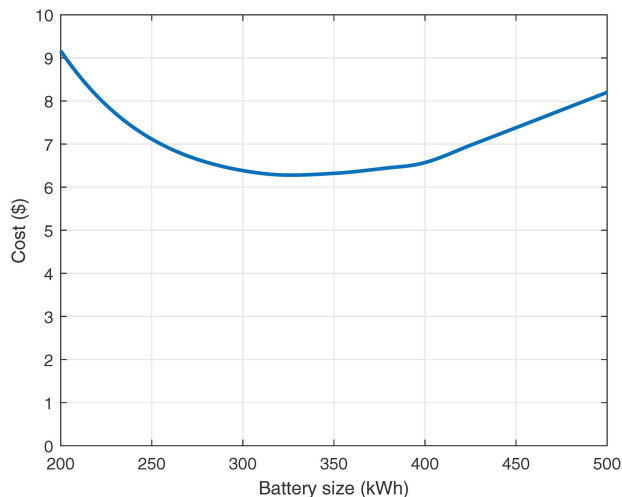
We now can run the algorithm and find the optimal solution. Once the optimal solution is attained, we can check that the solution is within the bounds for DOD and C-rate<sub>max</sub>. In this case, the values obtained for the DoD are {23.7%, 9.5%, 28.5%, 7.9%}, all of them below the upper bound of 80% for all discharge cycles. We can also check the values of C-rate, which are {0.61, 0.31, 0.15, 0.61}, all of them below the limit of 3. Fig. 3 shows the evolution of the state of charge of the battery.

Finally, we analyse the battery ageing, which is affected by the operational degradation and the life time. Fig. 4 presents both simultaneously for each discharge cycle; the blue bars indicate the former and the orange bars the latter. Although the DoD is not high, the first discharge cycle is dominated by the operational degradation due to the relatively high C-rate. On the other hand, the rest of discharge cycles are dominated by the degradation due to calendar life. The second and the fourth are in this circumstance because of the reduced DoD, while the third one works at a very low C-rate.

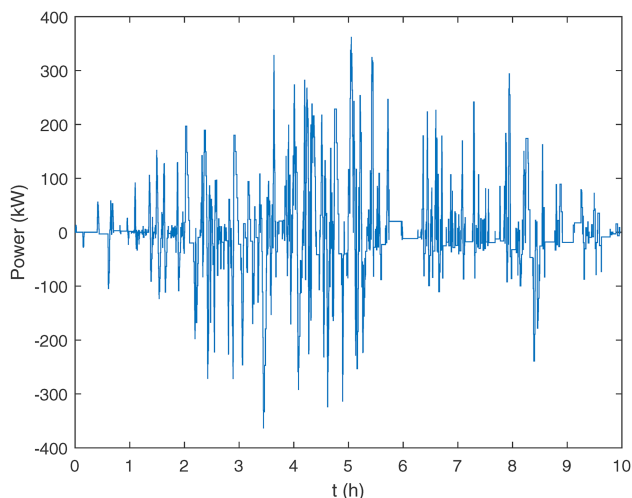
Fig. 5 presents the total costs for different battery sizes; note that, in this case, the battery size (BS) that minimises the cost of performing the given load cycle is BS = 326 kWh. Operating a battery of these characteristics with the profile of the illustrative case and a market price of 800 \$/kWh has a total cost of \$6.28. If this profile represents the daily operation of the battery, then that cost value will be the daily cost of operation of the system.

#### 4 Case study

The proposed methodology is now tested in two typical applications in order to find the optimal electrical storage size. Specifically, the storage system is sized for a case of a 500 kWp PV power plant and for an 800 kW wind generator.



**Fig. 5** Cost depending on BS in the illustrative case



**Fig. 6** Battery power profile for the first case study

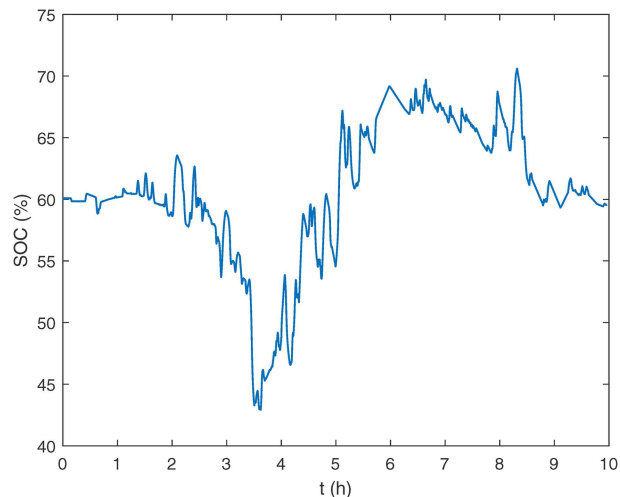
#### 4.1 First case study: PV plant

The power supplied by a photovoltaic plant is subject to weather variability. The case study analyses a storage system whose function is to smooth short-term power fluctuations that would otherwise negatively affect the quality and reliability of the electricity supply. This type of systems is a requisite in new grid-codes. For instance, the Puerto Rico Power Authority's regulation imposes some restrictions to the ramp rate of PV plants, establishing a maximum variation of 10%/min of the plant's nominal power [25].

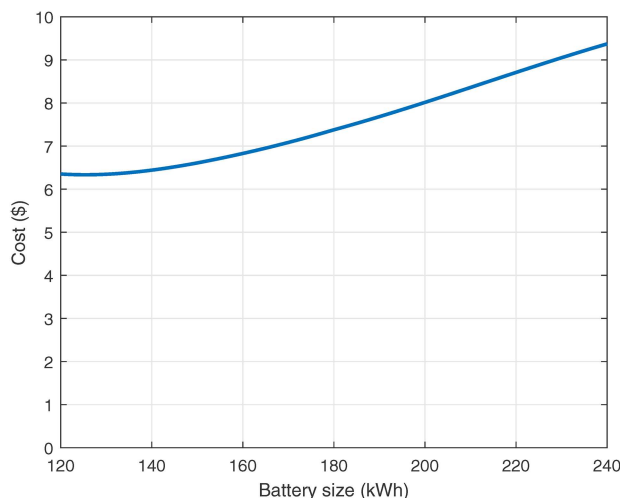
Several battery power profiles have been tested to verify the proposed algorithm. The profile shown in Fig. 6 has been selected to perform the study case, it represents one day of operation for the PV plant. This profile is a typical case of solar photovoltaic output that needs smoothing, because it presents a large number of short duration power peaks.

The algorithm computes a solution in which the SoC and the DoD are always within the imposed limits. The evolution of the battery state of charge is presented in Fig. 7. The SoC reaches a maximum value of 75.4% and a minimum value of 35.3%. The largest DoD of this profile with the computed battery is 5.2%, while the maximum *C-rate* is 2.9, a value very close to the imposed limit.

The value of battery size (BS) that minimises the ageing cost of performing the given load profile is  $BS = 125$  kWh. Operating this battery under these conditions and with a market price of 800 \$/kWh has a cost of \$6.34. Fig. 8 presents the evolution of the cost for different values of battery size; in this figure, values of BS below 120 kWh are not presented as these values are infeasible for



**Fig. 7** State of charge for the battery sized in the first case study



**Fig. 8** Cost depending on BS in the first case study

the problem; hence, we can conclude for this case that the optimal battery size is near the minimal feasible battery size.

This solution shows that the optimal size is not the minimum size that satisfies the DoD and *C-rate* constraints, and hence ageing is a key factor that must be taken into account in this process. Note that, for the same load profile, ageing has a smaller impact in larger batteries, as the values of DoD and *C-rate* are smaller, thus increasing the life of the battery without excessive costs.

In order to verify that the *C-rate* is a key limiting factor in battery sizing, we run a similar case study with a maximum battery *C-rate* of 2. As expected, the solution obtained is different. Remember that in the original solution, the result was not affected by the *C-rate* because the maximum value obtained was lower than 3; however, the value was higher than 2 and, as a consequence, the optimal sizing must be different to comply with this more strict constraint. The new solution for this case study is a battery with a capacity of  $BS = 182$  kWh and a total cost of 7.35\$, up from the previous 6.34. Moreover, this more constrained value of *C-rate* will very likely imply that a cheaper battery can be purchased; so, we run the algorithm again assuming a lower price of 700 \$/kWh for the battery and now a smaller cost of \$6.42 is obtained.

#### 4.2 Second case study: wind generator

In order to further illustrate the proposed algorithm, we have simulated a different system, featuring an 800kW wind generator. The power profile that the battery must deal with is presented in Fig. 9 and was obtained from real wind data readily available for a location in southern Spain. The evolution of the state of charge for the battery is shown in Fig. 10. We have selected a maximum *C-rate* of 3 for this application, obtaining an optimal battery size of

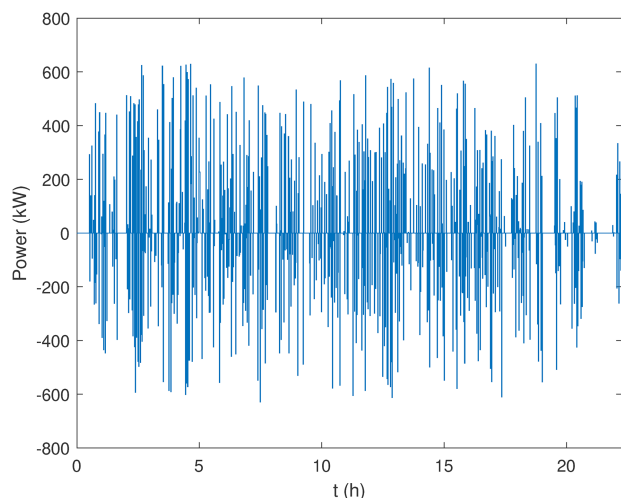


Fig. 9 Battery power profile for the second case study

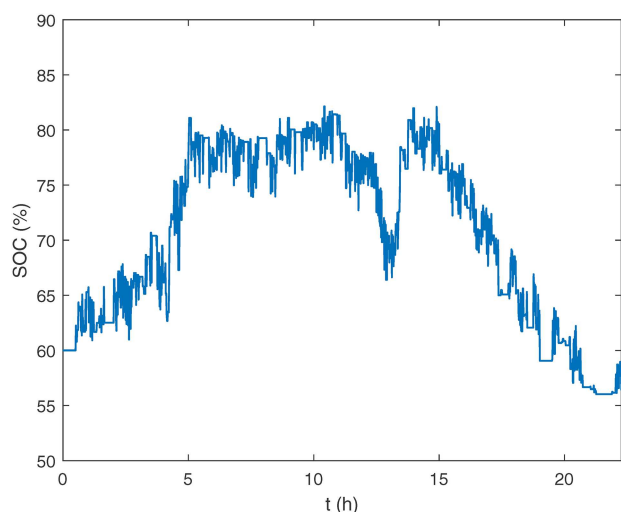


Fig. 10 Battery state of charge for the second case study

209.77 kWh, and, in turn, a daily battery cost of \$24.43. Note that for higher values of the maximum  $C$ -rate, smaller batteries can be achieved, but these batteries would be more expensive.

## 5 Conclusions

In the general context of renewable energy integration, the sizing of batteries is an important decision that must be taken carefully; we propose a simple yet robust method to optimally size a battery for real applications; this method incorporates the main ageing processes that appear in real batteries. This model takes the form of an optimisation problem that features a non-linear objective function and two simple constraints. Moreover, the proposed model as we have presented it, only contains one variable, and hence, finding the solution is rather easy. It should be noted that the procedure is neither technology nor application specific and can be applied to many different types of batteries in many different applications.

We have tested our method in an illustrative case study and in two realistic case studies, obtaining satisfactory solutions in all cases.

The model has many applications in the area of energy storage systems design, helping size of the batteries for a number of different settings, both large (wind and solar farms) and small (households, small isolated electric systems).

## 6 Acknowledgments

This work has been partially funded by project ENE2016-80638-R granted by Ministerio de Economía y Competitividad of the Government of Spain.

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