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Battery Lifetime Analysis for Residential PV-Battery System used to Optimize the Self Consumption - A Danish Scenario

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***Abstract*—Residential photovoltaic (PV) systems with integrated battery energy storage (BES) are used to increase energy self-consumption, especially in countries with low feed-in tariffs and high electricity prices. In recent years, lithium-ion batteries have been established as common technology for this application. However, a major challenge is their performance degradation over time, which is influenced by how the BES is operated. In this work, the impact of the PV + BES system's Energy Management System (EMS) on the lifetime of the battery is investigated, by developing a performance model of the PV+BES system and analyzing the battery degradation under different operation scenarios, using a battery lifetime model. Simulation results show that the battery lifetime can be extended and a high self-consumption ratio achieved, by operating the EMS at different charging rates, depending on predicted future PV production based on weather forecast.**

***Index Terms*—Photovoltaics, Battery, Residential System, Battery Lifetime, Self Consumption**

I. Introduction

In 2017, the globally installed photovoltaic (PV) capacity was 402.5 GW, whereas Denmark accounted for only 910 MW, due to phased-out support policies and reduced feed-in tariffs [1]. However, Denmark has one of the highest household electricity prices in Europe, such that increasing the PV energy self-consumption is one of the main ways to offset cost of a PV installation and promote PV adoption in Denmark.

From a practical perspective, it is well known that most of the PV energy is produced during the day, whereas the household consumption is almost constant during day and night, with a slight increase during the morning and evening, depending on location and season. Therefore, households consume only about 30 % of the energy generated by the PV system [2], selling the rest to the grid operator for a low or no profit and buying electricity, when necessary at a high cost.

An attractive solution to increase the self-consumption in residential applications is the use of a BES in conjunction with the PV system [3]. However, battery cost and reduced lifetime are often limiting factors to such applications. Battery lifetime in particular is limited by the operating conditions of the BES. Therefore, the objective of this work is to understand the role of the EMS algorithm on battery lifetime in the context of improving energy self-consumption in a typical danish household scenario. To achieve this, we developed a performance model for a typical PV+BES system, in tandem with a battery lifetime model for a lithium-ion battery pack and a simple EMS for maximizing the energy self consumption. Using danish weather and residential load consumption data, we performed one-year simulations of the PV+BES system, with different EMS operating parameters, and determined the impact on the battery's lifetime. Last, we propose an improved EMS for maximizing self-consumption and battery lifetime, which takes into account one day ahead weather forecasts, to adjust the operating parameters of the EMS.

II. PV system model and energy flow control

A simplified diagram of a residential PV system with integrated battery energy storage is shown in Fig. 1, consisting of a PV array, PV inverter with integrated battery charge controller and a BES system. The power flow within the PV system is controlled by an EMS, that uses meter readings of household energy consumption, to increase the share of PV energy self-consumed, as well as to prolong the lifetime of the batteries.

A. PV system performance model

The PV array was modelled using the power-temperature coefficient model [4], that uses in-plane effective solar irra-

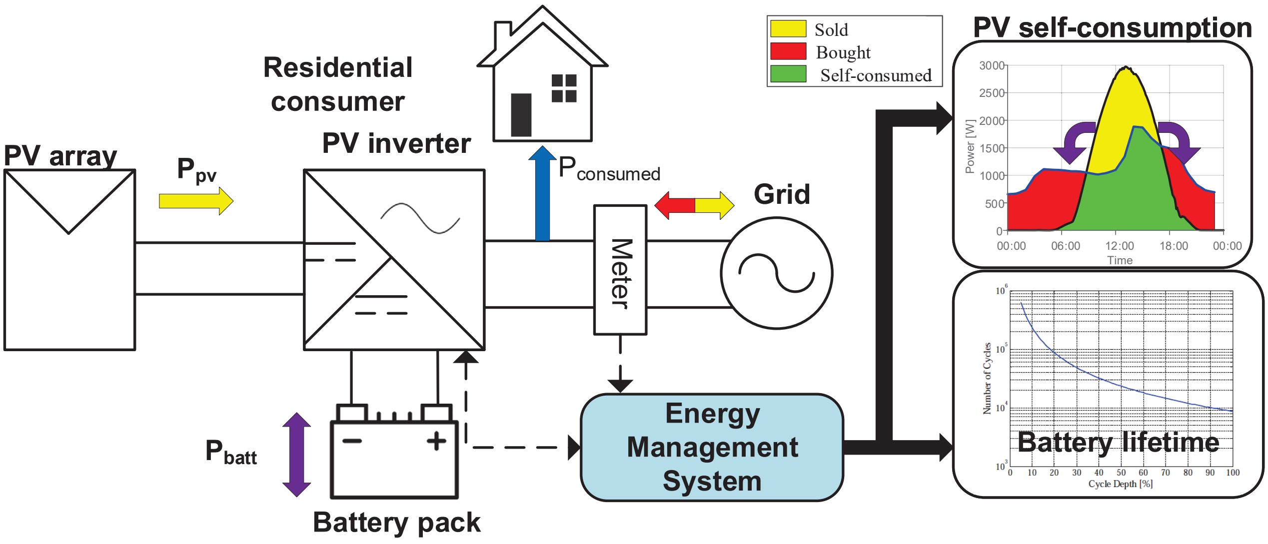

Fig. 1. Overview of the residential PV system with integrated energy storage, operating to maximize PV energy self-consumption and battery lifetime.

diance and solar cell temperature to estimate the maximum power output of a PV panel.

The output power of a PV panel is determined by the ratio between actual effective solar irradiance G_e and the solar irradiance under Standard Test Conditions (STC) (25°C and $1000\,W/m^2$). This ratio gives the proportion of the rated peak power of the panel's $P_{mp,\,STC}$, that can be produced depending on the effective solar irradiance.

The effect of the temperature on the PV performance is considered with a temperature coefficient γ_{mp} and the difference between actual cell temperature T_c and temperature at standard test conditions T_{STC} (25°C). However, if solar cell temperature T_c measurements are not available, these can be estimated from ambient temperature, solar irradiance and wind speed measurements, using the Sandia model [2], as was done in this work.

To get the power of a whole PV array, the power of one module has to be multiplied by the number of panels in series N_s and strings in parallel N_p. The power output of a PV array at maximum power point is calculated by:

$$P_{mp,\,array} = N_s \cdot N_p \cdot \frac{G_e}{G_{STC}} \cdot P_{mp,\,STC} \cdot [1 + \gamma_{mp}(T_c - T_{STC})] \quad (1)$$

The main advantage of this PV performance model is that it can be parametrized from solar panel datasheet parameters.

The PV inverter is modelled using a simple efficiency model, given in (2). In this model, only the peak efficiency of the inverter η_{peak} is considered and the output of the inverter is limited to its maximum output power P_{max}, emulating the inverter clipping under high irradiance conditions.

$$P_{pv} = \begin{cases} \eta_{peak} \cdot P_{mp,\,array} & \text{if } \eta_{peak} \cdot P_{mp,\,array} \leq P_{max} \\ P_{max} & \text{if } \eta_{peak} \cdot P_{mp,\,array} > P_{max} \end{cases} \quad (2)$$

B. Battery performance model

The battery energy storage system was modelled based on the Equivalent Electric Circuit (EEC) model, [5], which provides a good trade off between model accuracy and reduced complexity, which is necessary for long period system performance simulations, as is the case in this work.

The model, described in detail in [6], estimates the battery SOC over time based on the Coulomb counting method (Ah counting) [7]. By integration of the battery current I_{bat} over time, the amount of charge that was exchanged by the battery can be calculated. That, divided by the battery's capacity C, leads to the change in SOC over the relevant time period. With knowledge of the battery's initial state of charge SOC_i the actual state of charge in dependence on time follows to:

$$SOC(t) = SOC_i \pm \frac{1}{C}\int_0^t I_{bat}\, dt \quad (3)$$

$$C(Ah) = \int_0^t I\, dt \quad (4)$$

This model takes into account only the SOC behaviour of the battery system, because the focus of this work is not mainly on detailed battery modelling, but on the overall optimization and development of the EMS for optimizing the trade-off between the SCR and the lifetime of the battery.

C. Battery lifetime model

Lifetime is an important parameter during battery long-term operation as it effects both economic and technical calculations. The battery lifetime is influenced by both idling and cycling operation, as well as operation temperature [8].

Calendar aging of a battery means it is losing capacity just by idling at a SOC level or another. Thus the primary factors linked to calendar aging are the battery idling time, and the SOC level it is idling at [8].

The calendar aging of the capacity of Li-Ion batteries can be estimated by (5), as derived in [9].

$$C_{\text{fade}} = 0.1723 \cdot e^{0.007388 \cdot \text{SOC}} \cdot t^{0.8} \tag{5}$$

Here, the capacity fade C_{fade} depends on the SOC and the idling time t. SOC represents the average SOC level during storage, t represents the time, expressed in months, during which the battery is not being used. The coefficients are obtained via laboratory measurements [9].

Cycling aging, which causes degradation of the battery capacity, is dependent on the number of charge/discharge cycles, as well as the depth of these cycles [10]. This aging process can be modelled starting from the battery SOC profile for a period of time. Thereafter, a rainflow counting algorithm is used to count the number of cycles and their corresponding depth [10]. Next, these are used in conjunction with the battery's lifetime curve (obtained experimentally or provided by the manufacturers) as inputs to the Palmgren Miner's rule [11] to calculate the accumulated degradation of the battery capacity.

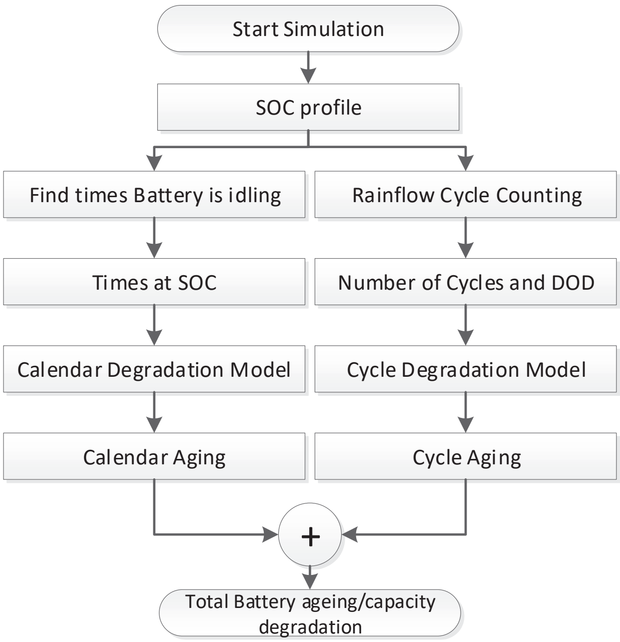

Fig. 2. Steps for modelling the battery energy capacity degradation due to power cycling and calendar ageing.

The steps for modelling the calendar and cycling aging are summarized in Fig. 2. Here, the SOC time profile of the battery, obtained from simulation, is the input. The degradation due to calendar and cycle aging are summed up to get the total capacity degradation of the battery.

D. Energy management system

The EMS controls the charging of the battery storage from the PV array generated power, and the discharging of the battery, when necessary, with the objective of increasing the overall PV energy self-consumption in the household.

In this regard, we implemented a simple EMS according to the flowchart in Fig. 3, which is based on the real time power consumed by the household (the measurements are taken directly from the energy meter), the battery SOC, and the actual output power produced by the PV plant.

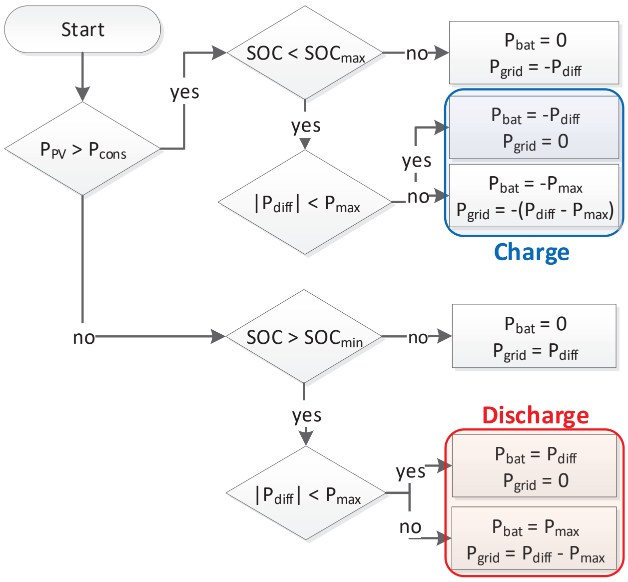

Fig. 3. Flowchart of the basic EMS strategy used as a standard case for the simulations.

To quantify the performance of the EMS to maximize the PV self-consumption, we use two metrics: i) the self-consumption ratio (SCR) defined in (6), where $E_{\text{self-consumed}}$ is the amount of energy consumed either directly from the PV or from the battery storage. E_{consumed} is the total energy consumed by the household; ii) the total energy self-consumed E_{sc} during the useful lifetime $T_{lifetime}$ of the battery, relative to the yearly energy consumption of the household $E_{\text{yearly-consumed}}$, as in (7):

$$\text{SCR} = \frac{E_{\text{self-consumed}}}{E_{\text{consumed}}} \tag{6}$$

$$E_{\text{sc}} = E_{\text{yearly-consumed}} \cdot SCR \cdot T_{\text{life}} \tag{7}$$

To simplify comparison between EMS operation cases, we normalize the E_{sc} parameter to a baseline scenario, described in the next section.

III. Simulation and Results

A. Sizing of the PV system and battery energy storage

The majority of Danish PV installations are rated at either between 3 - 4 kWp or 6 kWp - 7 kWp [12]. Therefore the PV system modelled in this work was sized to 6.4 kWp, corresponding to 20 multicrystaline-Silicon solar panels [13] rated at 320 Wp each. Moreover, the solar inverter was modelled after a commercial 7.5 kWp SMA inverter [14], having a peak efficiency of 97 %.

The sizing of the battery energy storage was made based on a survey of PV + battery energy systems installed in the city of Aalborg, Denmark and surrounding areas, using information available from [15]. We found that typical residential PV systems with battery energy storage in Northern Denmark, have a PV to battery size ration of approximately 1:1 [15].

In addition the the battery storage size and performance parameters, which are available in the datasheet of the battery pack, battery lifetime data is also necessary. Therefore, starting for a known Li-Ion based battery [16], we had previously studied and obtained lifetime measurements and models [10], we designed a 5.94 kWh BES, consisting of 720 Li-Ion cells, each with a capacity of 2.5 Ah and cell voltage of 3.3 V.

B. Danish solar generation and residential consumption profile

To reproduce a typical danish solar generation profile, we used a one year solar irradiance dataset measured in the city of Aalborg. The data was acquired with a one-minute sampling time, using a reference cell, mounted with a 45 °tilt, south orientation.

To characterize typical danish residential household consumption, we obtained a one year dataset of energy meter readings, from the local grid operator. Similar energy consumption profiles were described previously in [17]. Fig. 4 shows the PV generation for a 6 kWp PV system, as well as the consumption for a typical danish summer fay.

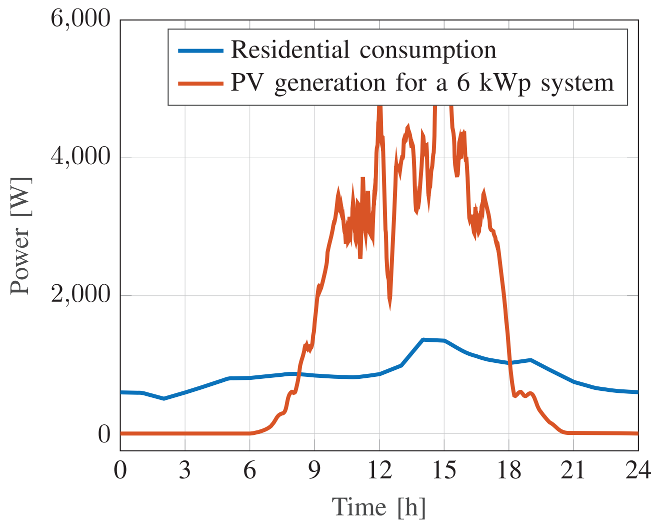

Fig. 4. Solar power generation for a 6 kWp PV system and residential consumption profile during a typical summer day.

C. Simulation scenarios

The simulation process is divided into four different cases summarized in Table I.

Table I
SIMULATION STUDY CASES EVALUATING THE DIFFERENT EMS OPERATING PARAMETERS

	Battery capacity	SOC range	C-rate
Baseline	100 %	0 - 100 %	1 C
Case α	10, 50, 100, 200 %	0 - 100 %	1 C
Case β	100 %	Variable	1 C
Case γ	100 %	0 - 100 %	1, 0.5, 0.25, 0.125 C

In study case α, we evaluate the influence of the battery capacity on both the SCR and the battery lifetime. From the simulation results shown in Fig. 5 we observe that for an increase of the size of the battery, both the SCR and the lifetime increase, this occurs because the BES is less exploited and therefore the degradation per year decreases.

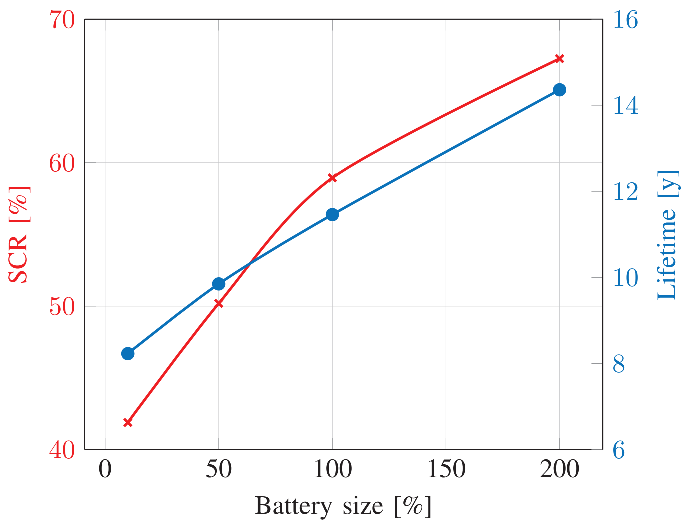

Fig. 5. Behaviour of SCR (red) and lifetime (blue) for different battery capacities

In the second case, we investigate the influence of battery SOC charging and discharging limits on SCR and on battery lifetime. In this case the size of the battery and C-rate are kept fixed, while eight different charging/discharging boundaries of SOC are evaluated: 0 - 100 %, 5 - 95 %, 10 - 90 %, 20 - 80 %, 30 - 70 %, 0 - 60 %, 0 - 70 %, and 0 - 80 %.

From Fig. 6, one can observe that the SCR is always reduced compared to the baseline case. The battery lifetime gets increased if the upper SOC limit is reduced. For increased lower SOC limits the lifetime decreases, as the calender aging is increasing due to the big impact of an higher average SOC.

The E_{sc} parameter, defined in (7) gives a greater overview of the situation, since an E_{sc} value smaller than 1 implies, that there is no improvement in the total amount of self-consumed energy by the system during its lifetime, therefore changing the SOC charge/discharge boundaries is not advantageous.

The last scenario evaluates the impact of different charging and discharging C-rates on the SCR and battery lifetime, as indicated in Table I. From Table II we can see that the battery lifetime increases, as the C-rate is lower. On the other hand, as

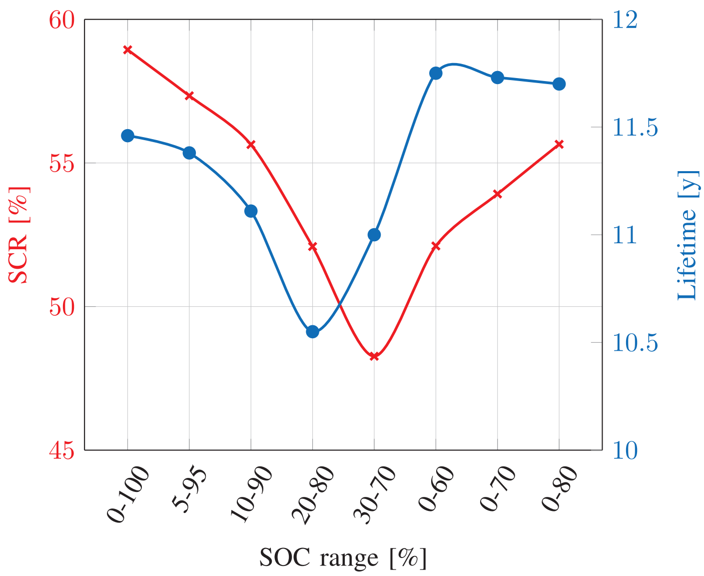

Fig. 6. Behaviour of SCR (red) and lifetime (blue) for different SOC ranges

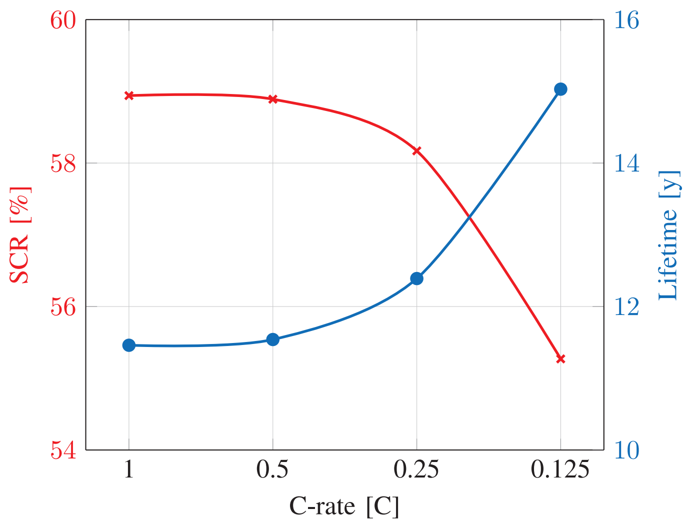

Fig. 7. Behaviour of SCR (blue) and lifetime (red) for different C-rate

expected the SCR decreases in all the scenarios. Fig. 7 shows the pattern of the SCR and the lifetime of the different C-rates. If we evaluate the E_{sc} for this scenario, we observe that E_{sc} increases as the C-rate decreases. This result implies that there has been an improvement for what concerns the total amount of energy self-consumed by the system, therefore changing the C-rate seems to be effective for increasing battery lifetime and keeping high SCR.

IV. Improved EMS based on one day ahead weather forecast

As shown in the previous sections, decreasing the battery charge / discharge rate can potentially increase battery lifetime, while maintaining a high self consumption ratio. Therefore we propose an EMS strategy that adjusts the battery

Table II
SIMULATION RESULTS OF SCR, LIFETIME AND E_{SC} FOR DIFFERENT C-RATES

C-rate	1 C	0.5 C	0.25 C	0.125 C
SCR	58.94 %	58.89 %	58.17 %	55.27 %
Lifetime (y)	11.46	11.54	12.39	15.03
Aging	2.98 % - 5.75 %	2.97 % - 5.69 %	2.87 % - 5.20 %	2.48 % - 4.18 %
Δ SCR abs.	-	- 0.05 %	- 0.77 %	- 3.67 %
Δ Lifetime (y)	-	+ 0.08	+ 0.93	+ 3.57
E_{sc}	1	1.0061	1.0670	1.2299

charge / discharge C-rate based on one-day ahead weather forecasts, illustrated in Fig. 8. Such forecasts can be obtained in real-time form by most online meteorological services.

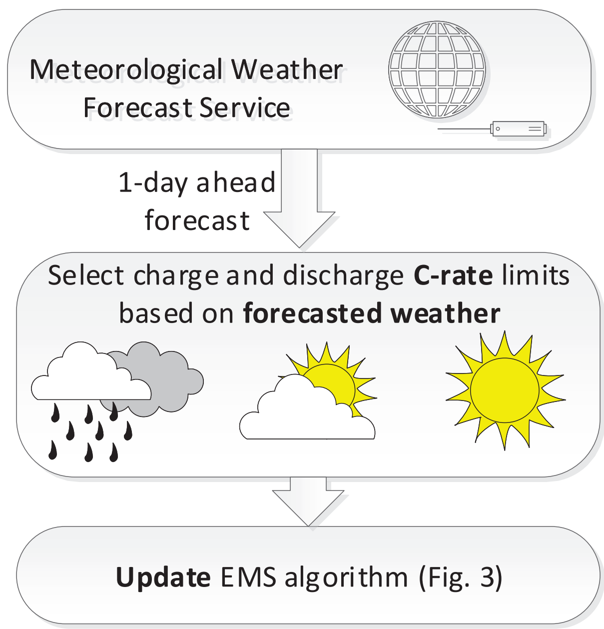

Fig. 8. Flowchart of weather forecast based EMS

For the purpose of simulation, we used an ideal forecast, derived from one year of local irradiance measurements, grouped intro three weather categories based on the averaged daily (24-hour) irradiance G_{avg}, as shown in Table III.

Table III
DIVISION OF THE DAYS ACCORDING TO THE AVERAGE IRRADIANCE OF THE DAY.

Type of day	Average irradiance	Days
Sunny	$G_{avg} \geq 210\, W/m^2$	108
Partially cloudy	$70\, W/m^2 \leq G_{avg} < 210\, W/m^2$	130
Cloudy	$G_{avg} < 70\, W/m^2$	127

Afterwards, depending on the forecasted weather, different C-rates are used to charge and discharge the battery. To exemplify the operation of the method, we evaluated three sets of charge / discharge C-rates, listed in Table IV as *EMS A*, *EMS B*, and *EMS C*.

Table IV
DIFFERENT C-RATES USED BY THE EMS STRATEGIES ACCORDING TO WEATHER CATEGORY

Category	EMS A		EMS B		EMS C	
	Chrg.	Dscrg.	Chrg.	Dscrg.	Chrg.	Dscrg.
Sunny	0.125 C	0.5 C	0.125 C	1 C	0.1 C	1 C
Mixed	0.25 C	0.5 C	0.5 C	1 C	0.3 C	1 C
Cloudy	1 C	0.5 C	1 C	1 C	1 C	1 C

Simulations are performed for the three weather-based EMS parametrization scenarios and compared with the *baseline EMS*, presented in the previous sections. The results presented in Table V show, that *EMS A*, *EMS B* and *EMS C* cause a decrease in SCR, compared to the *baseline* case. On the other hand, the lifetime of the battery is increasing in all three weather-based EMS scenarios. Moreover, the highest lifetime is reached with *EMS C*, which also has the lowest SCR. The increased lifetime of the *EMS A*, *EMS B* and *EMS C* cases is mainly due to the decrease of the battery degradation caused by calendar aging.

In all the cases the weather forecast based EMS have increased the lifetime of the battery while they decreased the SCR. If we evaluate the E_{sc} for the different cases, which factors both the SCR and lifetime of the battery, we can observe an improvement of up to 20% compared to the baseline case. These improvements depend on the accuracy of the weather forecast, which was not in the scope of this work. Furthermore, the results could be improved by introducing a wider range of weather categories with more adjusting C-rates.

When adapting the C-rates of the applied EMS, for practical implementations of such system it should be verified that the minimum charging current needed at the battery's actual SOC is exceeded.

Table V
COMPARISON BETWEEN THE DIFFERENT WEATHER FORECAST BASED EMS

EMS	Baseline	EMS A	EMS B	EMS C
SCR %	58.94 %	58.33 %	58.81 %	58.05 %
Lifetime (y)	11.46	13.64	13.04	14.02
Cycle Aging	2.98 %	2.91 %	2.97 %	2.97 %
Calendar Aging	5.75 %	4.42 %	4.70 %	4.26 %
Total Degradation	8.73 %	7.33 %	7.67 %	7.23 %
Δ SCR abs.	-	- 0.61 %	- 0.13 %	- 0.89 %
Δ Lifetime (y)	-	+ 2.18	+ 1.58	+ 2.56
Δ Lifetime (%)	-	+ 19.02 %	+ 13.79 %	+ 22.34 %
E_{sc}	1	1.1779	1.1354	1.2049

V. CONCLUSIONS

The results show that by lowering the charge / discharge C-rates, it is possible to increase the battery lifetime of a BES, while simultaneously maintaining a high SCR. The total energy self consumption over the useful lifetime of the BES can be increased as well. Based on these results, we proposed an EMS that additionally adapts the C-rates according to the type of the next day's weather, depending on one-day ahead weather forecast information. Thereby, the decrease in SCR can be minimized compared to constantly decreased C-rates, while the battery lifetime is still increased. This trade-off leads to a decent increase in self-consumed energy over the useful lifetime of the BES and can help to improve the system's financial viability.

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