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# A novel cycle counting perspective for energy management of grid integrated battery energy storage systems

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## Abstract

Battery energy storage systems (BESS) are essential for flexible and reliable grid performance as the number of renewable energy sources in grids rises. The operational life of the batteries in BESS should be taken into account for maximum cost savings, despite the fact that they are beneficial for economical grid operation. In this context, this paper present a new battery cycle counting perspective for energy management of grid-connected BESS. For this purpose battery's one full charge–discharge cycle characteristic is compared with the operating battery charge–discharge cycle every time step. This comparison was explained mathematically and graphically in detail. The results are compared with the rain flow counting method which is the most popular cycle counting algorithm. Consequently, this cycle counting approach successfully counts the battery charge/discharge cycles and it has shown that has an advantage for BESSs due to being specifically developed just for batteries.


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*Keywords:* Battery aging; BESS; Cycle counting; Energy management; Frequency ancillary service; SOC management

## 1. Introduction

BESS has recently drawn a great deal of attention in electricity grid applications due to its versatility, high energy density, and provide flexibility to the grid. As battery costs continue to decrease while performance and lifespan continue to increase, more grid applications have become available for BESS [1]. BESS responds almost instantly to grid demands, while also having a wide range of storage and power capacities [2]. BESS has benefits over traditional power generation sources such as faster response time, low self-discharge rate, storage size, energy efficiency, high charge/discharge rate capability and low maintenance requirements [3]. In grid size applications, BESS is used to reduce the fluctuations of the output power of renewable energies, in frequency regulation, as a spinning reserve, as a black start and to provide energy arbitrage. When used as a spinning reserve, the total

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production cost is reduced by using BESS instead of the spinning reserve in the electricity production system. For natural gas with the highest unit price, savings can be achieved by using batteries with a merit order effect [4]. BESS also helps frequency regulation with the framework of ancillary services. The main advantage of BESS in frequency regulation is the fast response time. It is also advantageous because it is easy to install and has a low operating cost. Numerous research has already developed different energy management control algorithms for optimum battery operation in the BESS applications such as frequency regulation ancillary service. Rule-based energy management control algorithms are commonly used for battery energy storage systems. PI-controlled [3], fuzzy logic method [5] and deep learning algorithms [6] were also applied for grid-tied BESS. One of the most important steps in these control algorithms is to use the battery efficiently during BESS operation and ensure that its life is used effectively. For this reason, observing and assessing battery life in BESS applications is vital. Although the goals and limitations of each application vary, they all share the fact that it is crucial to appropriately account for the operational costs of batteries. The degrading effects of repetitive charging and discharging are the principal source of battery operation costs [7]. End-of-life (EoL) is the term used to describe when a battery cell can no longer operate (generally 80% of original capacity) as intended due to capacity degradation that has exceeded a certain minimum level [8].

The absolute magnitude range of each particular SOC cycle, also known as "depth of discharge" DOD, is the main stress element for cyclic aging. Additionally, while they are not taken into account in this study, current, temperature, and terminal voltage also have an impact on cyclic damage. The widely used Rain flow technique is the most reliable method for identifying cycles from SOC trajectories. "Full" or "half" cycles may be among the identified cycles. An equal start and end SOC value for a battery charge and discharge cycle is referred to as a complete cycle. A single charging or discharging cycle is referred to as a half cycle. The differences and advantages of the proposed battery cycle counting algorithm compared to the rain flow algorithm;

- Since the signal information's peaks and valleys may be modeled using the traditional rain flow method, the load data is changed to data that only contains information on extreme points [9]. Rain flow method cannot be used with real-time data whereas the purposed method has the superiority of being applied to the real-time data second by second. It used the full charge and discharge cycles as a reference for comparing the SOC cycle graph. At the beginning of the purposed algorithm, the slope of SOC cycle is calculated and the method decided the battery's resting or charging/discharging status. In every time step cumulative SOC operation graph's area is calculated and when this area is equal to the full charge and discharge area, one full cycle is reached.
- Half-cycles are only counted in the rain flow method at the very end of the data. As a result, it is challenging to estimate the remaining usable life between the load points [9]. In this study, only the full charge and discharge cycles are used as a reference so a full cycle is calculated. Instead of estimating the total number of complete equivalent cycles at the conclusion of the data collection, this is done during the analysis. Thus, determining the usable life that still remains between the load points is straightforward.

In this study, a new cycle counting approach specific to batteries used in grid-connected BESS applications is implemented. As an alternative approach to the rain flow cycle counting method, which is generally used as a mechanical stress analysis method, a life cycle analysis method based on the degradation that occurs as a result of charge/discharge specific to batteries has been developed. The SOC value, which is the formulation of the oxidation and reduction reactions occurring rapidly in the battery or the variation of the charge amount in the battery according to time, was used as the assessment criterion. The rest of the paper is organized as follows. Section 2 describes the SOC estimation, battery aging techniques, and cycle counting methods in the literature and explains the suggested cycle counting algorithm. Section 3 covers the case study for a 2 MW/1 MWh grid integrated BESS cycle counting. Section 4 sketches the simulation results and Section 5 concludes the paper and outlines future work.

## 2. Methods

### 2.1. SOC estimation

SOC is the remaining part of usable charge in a battery relative to its full capacity. In the literature, advanced methods are studied for battery state of charge estimation like adaptive estimation strategy [10], extended Kalman filter [11], LSTM neural network [12], convolutional neural network [13], enhanced Coulomb counting [14]. In this study, the Coulomb Counting method was used for SOC estimation which is the most common and basic method for charge estimation. Battery charge capacity can be expressed by battery current and time which is shown in Formula (1). Battery power output is related to battery power and voltage, formulated with Formula (2). Battery energy capacity also can be expressed by battery current and time which is shown in Formula (3). After rewriting the battery charge state, battery energy capacity and battery power equations SOC estimation formula was reached. In Formula (4), $Q_{batt}$ represents the battery's total capacity. Instead of the hour for time $SOC_n$ formula converted to second with 3600. SOC estimation is generalized for discrete time step and $SOC_0$ represent initial SOC condition of BESS.

$$Q_{batt} = I_{batt} * time \tag{1}$$

$$P_{batt} = I_{batt} * V_{batt} \tag{2}$$

$$E_{batt} = P_{batt} * time \tag{3}$$

$$SOC_n = SOC_0 + \frac{\int_{t_0}^{t_n} P_{batt}}{3600 * Q_{total}} \tag{4}$$

### 2.2. Battery aging techniques

Calendar life and cycle life are two common words used to describe battery life. A battery calendar life is the period of time to reach its end-of-life condition during which it may be kept idle or little used. The passivation layer on the negative electrodes is the main cause of battery calendar aging. The state of charge at which a battery is stored has an impact on the battery's calendar life. The battery chemistry will determine how SOC will affect calendar life. The battery's calendar life is also impacted by the storage temperature. The rate of a reaction rises with an increase in temperature. As a result, the battery will degrade at a faster pace due to unfavorable chemical reactions. Battery life is negatively impacted by higher temperatures. Battery management systems control the temperature for the dangerous side effects.

Cycle life is the number of full charge–discharge cycles a battery may go through before losing 80% of its initial capacity. The temperature at which a battery is operated has an impact on its cycle life. High operating temperatures reduce battery cycle life as well as shorten calendar life. Battery life is also impacted by how quickly it is charged and discharged. Faster charging decreases battery cycle life because it damages the battery's mechanical components and electrodes. Similar to faster charging rates, higher discharge rates also shorten battery life. The DoD, charging regime, dwell time at low and high SoC, and current ripple can also all have an impact on cycle life [15].

In the literature, studies on the aging effect of the battery continue in an interdisciplinary manner. While taking into consideration battery health and operating circumstances, a machine learning algorithm was used to estimate the remaining useful life (RUL) of lithium-ion batteries. Physics-informed long short-term memory (PI-LSTM) model combines a physics-based calendar and cycle aging (CCA) model [16]. Using the first 100 cycles of data, a convolutional neural network model was created to forecast the whole battery capacity fade curve. Discharge voltage-capacity curves were employed as an input in the study, and convolutional network layers were used to automate the feature extraction procedure [17]. A prediction technique that can use the data of the initial stage of partial cycle life tests as input and extrapolate to determine the remaining degradation trend. The proposed deep reinforcement learning-based approach is able to learn degradation patterns with various formulations and forecast long-term degradation trends, in contrast to existing methods [18]. A combination with broad learning system (BLS) algorithm and long short-term memory neural network (LSTM NN), a fusion neural network model was designed for predicting the battery capacity and remaining useful life [19]. A hybrid ensemble learning model (HEL) was applied to reach high-performance predictions while considering polarization recovery [20].

### 2.3. Cycle counting methods

Numerous efforts were made to build counting algorithms to offer information that could be compared with the material's fatigue strength due to the inherent difficulty of recognizing stress cycles in a real loading history [21]. From the stress cycle profile cycle counting algorithms extracted the information from the time of frequency domain analysis. To create a stress histogram, the time-domain approaches are mostly based on the use of traditional counting techniques. In addition to these traditional counting methods suggested in the literature (peak count, range count, range-mean count etc. [22,23]) rain flow counting algorithm, one of the time domain based stress analyses, is the most popular cycle counting method since formulated by Matsuishi and Endo [24]. For the fatigue study of structures subjected to cyclic loads, mechanical engineers have typically applied the rain flow counting approach. In recent years, rain flow counting algorithm is applied for estimating battery cycle life. Rain flow counting algorithm is currently used in international standards for stress cycle counting for fatigue analysis as the reference procedure (see ASTME E1049-85 [25]). The algorithm starts with the stress cycle rotated clockwise 90° direction, the SOC curve looks like a pagoda (a traditional tower) roof. The half-cycle for a particular raindrop is determined by tracking the drop's path down the roof by allowing a raindrop to begin at each peak and trough. Either a peak or a dip marks the beginning of each of the half cycles. The algorithm keeps track of how many complete cycles are experienced with each depth-of-discharge amplitude.

As mentioned in Section 3, the cycle life of the battery relies on different parameters, like temperature, charge and discharge profile, and depth of charge/discharge cycles. In this paper, only charge and discharge profiles according to the BESS energy management algorithm have been taken into account. SOC evolution often does not follow a regular cycle pattern since BESS operates according to the grid ancillary service operator's command. As a solution, SOC irregular pattern identified with cycle counting algorithms.

### 2.4. Suggested cycle counting algorithm

Battery degradation should be taken into account while determining the best BESS operation schedule. The battery's charge/discharge profile results in cell degradation and this subsequently decreases the battery capacity. From the BESS operation viewpoint, charge/discharge cycles and DoD have the most important effects on battery aging. A BESS has a number of charge and discharge cycles (cycle life), which is determined by counting the cycles until the battery capacity reduces to a predetermined level from the manufacturer. The battery must be changed when it reaches the maximum charge/discharge cycle and this level also depends on battery type and experimental conditions. Manufacturers provide DoD versus cycle number graph as well as cycle number of the battery which draw a profile for SOC management importance.

In this study, a novel approach for the cycle counting algorithm was developed and simulated for energy management of grid-integrated battery energy storage systems. Due to the rain flow counting algorithm developed for materials fatigue analysis and stress counting cycle, the purposed algorithm was considered for battery charge/discharge total cycle count. Owing to manufacturers testing the batteries' one full charge/discharge cycle at the production step, this full charge/discharge cycle area could be used for battery cycle counting. From this point of view, except for the other degradation effects (temperature, etc.), a healthy full charge/discharge cycle accounted for one full cycle. Subsequently, the area under one full cycle is calculated and it is used as the reference full cycle. In Fig. 1 the SOC value of a grid-connected BESS providing frequency ancillary service and the time graph shows the area under the curve in every discrete-time step. Since battery energy storage systems have to adjust the SOC value to 50% after their participation in the ancillary service specified in the grid criteria, the initial value of the SOC in the participation in the ancillary services is taken as 50% in this study. Label $A_1$ shows that the battery charge value did not change means that the battery keep its charge value and did not charge or discharge in other words battery resting according to the energy management control algorithm. In the next time step, the area under the curve is called $A_2$ and it continues with $A_3$, $A_4$, ... $A_\mathrm{n}$. The cumulative sum of these areas is calculated in every time step and when it would be equal to the one full charge/discharge area this can be counted as one full cycle. A flowchart for the procedure is in detail shown in Fig. 2.

The algorithm starts with the specified battery's one charge/discharge SOC cycle area calculation. The battery power output that electricity grid operators request as ancillary service and estimated SOC profile depending on the energy management algorithm are analyzed. For each interval, the slope of the SOC curve is calculated for determining the battery condition. If the slope is equal to zero which means battery resting and is the slope smaller or greater than zero which means battery discharging and charging, respectively. When the battery is not resting, the area under the curve was calculated and cumulative results were compared with one full charge and discharge cycle area value. If the region corresponds to the whole charge/discharge cycle area, one cycle is considered to have occurred. In Fig. 2, a detailed discharge area is shown as $A_2$. In this instance, calculating the triangle area is used to compute it with Formula (5).

$$A_n = \frac{(SOC_n - SOC_{n-1})\,(\Delta t)}{2} \tag{5}$$

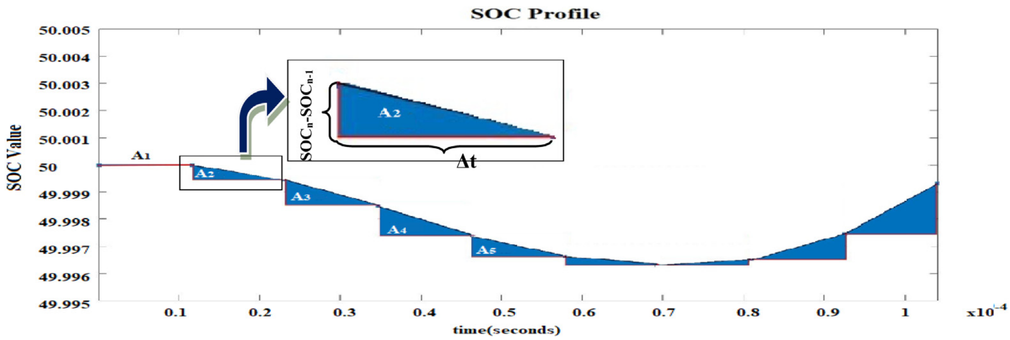


**Fig. 1.** Grid-connected BESS SOC profile for area under curve at discrete time step.

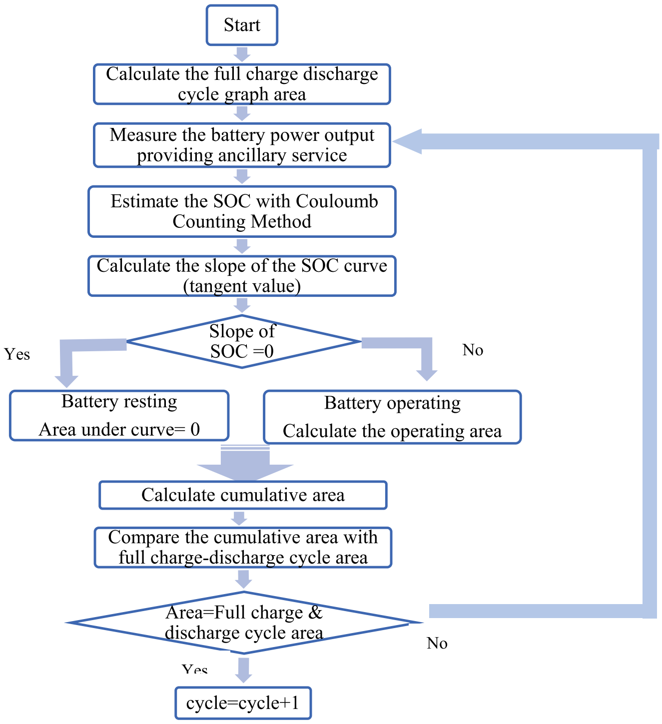


**Fig. 2.** Flowchart of purposed cycle counting algorithm.

### *2.5. Aging analysis for purposed algorithm*

One of the most important factors for the aging effect is temperature. In this study, an algorithm has been developed on the assumption that the temperature is measured with the help of sensors and the appropriate control is provided by the battery management system (BMS). The calendar life is also not included, only the cycle life is studied. Aging analysis can be roughly done by comparing the amount of complete charge–discharge cycles given in the battery catalog with the number of cycles counted according to the algorithm. According to the conclusion to be drawn from that method, life estimations can be made, excluding the failure condition of the batteries. In addition, feedback control can be created and charge control can be provided according to the effect of energy management on the cycle life. Thus, besides the grid parameters (such as frequency and reactive power), a control parameter is created from the battery perspective for energy management.

## 3. Case study: A 2 MW/1 MWh grid-integrated BESS cycle counting

A case study was performed by Gundogdu, B., et al. (2017) with a 2 MW/1 MWh grid-integrated BESS to provide EFR service was analyzed the Li-ion battery aging [26]. According to created rule-based energy management control algorithm before, the effectiveness of the algorithm was analyzed with a battery cycle life approach. Rain flow counting algorithm was tested for how the BESS was affected by irregular charge/discharge profile and occasionally outside of the optimum SOC limits inasmuch as the unbalanced grid frequency level. Simulation results of the 2 MW/1 MWh BESS one-day SOC profile and rain flow counting algorithm histogram profile were shown in Fig. 3. The histogram results show the amount of the SOC changes in a discrete time period, which gives information about the rate at which the battery degrades. For enhancing the battery's condition of health and cycle life, the SOC level should be approximately 50%, according to the literature. It can be seen that the SOC profile with cycle average change between 0%–60%, and at the same time number of cycles in that SOC range is shown and nearly 600 cycles counted for 40% and 60% SOC levels.

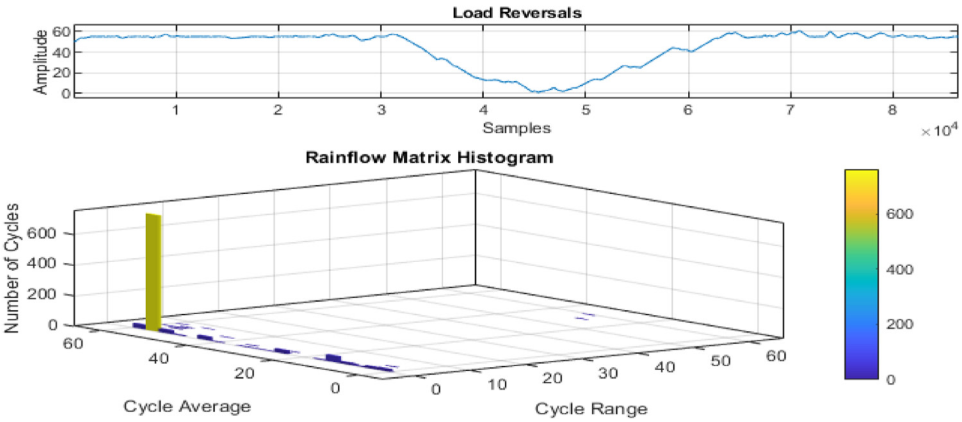


**Fig. 3.** 1 day (21st Oct 2015) battery SOC data obtained from energy management algorithm and rain flow counting algorithm histogram.

## 4. Simulation results

In this section, MATLAB simulation results for the purposed cycle counting algorithm were shown in Fig. 4 for 24 hour and Fig. 5. and Fig. 6 for one month period. After obtaining the SOC profile from the BESS energy management controller developed, the cycle counter started to operate. For one day and one-month cycle counting results are analyzed with the help of SOC versus time graph and 38 total cycle counted for one month period. In Fig. 3, the SOC sharply drops, reaching 0%, and stays there for about 30 min due to the grid frequency demands at that time. As the grid frequency stabilizes, the algorithm charges the battery when it is permissible (frequency in DB) and returns the battery SOC to within the specified band of 45%–55%. As shown in Fig. 3, this is because of the SOC reaching 0% and therefore there is no power available for delivery to the grid. This non-conformance would cause a small penalty in Service Performance Measurement (SPM); hence, it is necessary to improve the algorithm to minimize such occurrences. The battery's SOC would decrease to 0% as a result of this algorithm's inability to handle the extended 15-min grid frequency occurrences, which would result in a service performance penalty fee. In order to increase the availability of the BESS, it is necessary to stop any grid frequency response activity after an extended 15-min frequency event, as allowed by the grid frequency response service specifications [27].

## 5. Conclusion

As an alternative to cycle counting methods used in the literature, in this study a novel battery cycle counting method is developed for grid-connected BESS energy management. The suggested cycle counting algorithm counts all of the BESS's cycles throughout the duration of a specified period of time. The rain flow counting algorithm is mostly used for stress cycle counting for fatigue analysis in material science. Battery manufacturers provide cycle life with full charge/discharge cycle numbers in datasheets. Based on this, an algorithm is developed specifically for

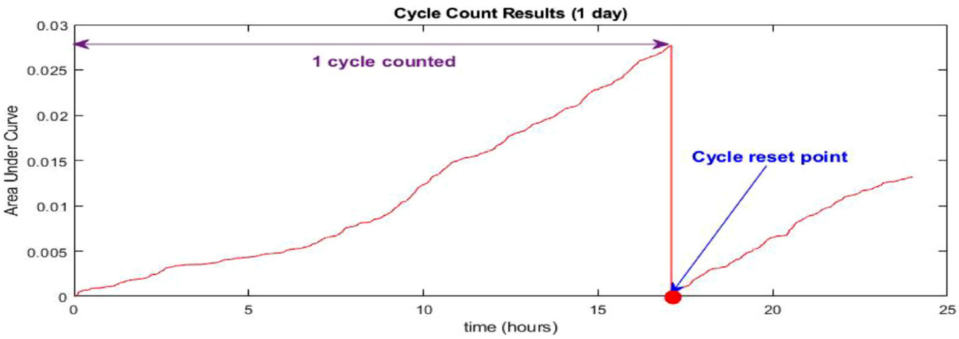


**Fig. 4.** 1 day 2 MW/1 MWh BESS cycle data according to purposed cycle counting algorithm.

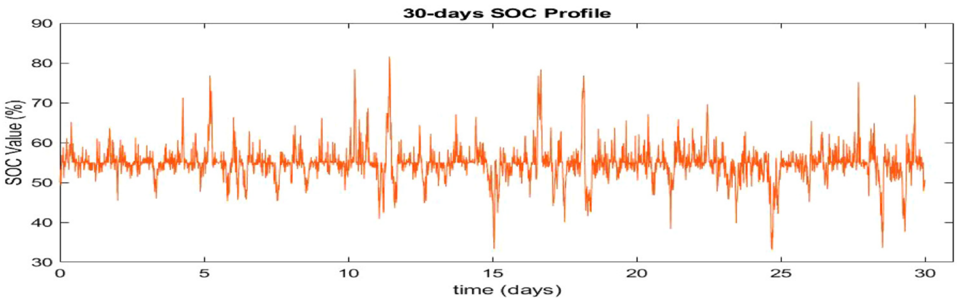


**Fig. 5.** 1-month SOC profile of 2 MW/1 MWh BESS which provides the frequency response service.

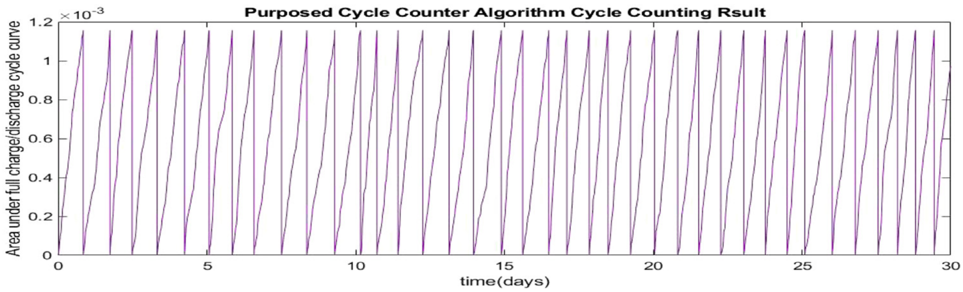


**Fig. 6.** 1-month 2 MW/1 MWh BESS cycle counting result according to the purposed algorithm.

batteries used in various grid-size BESS applications. A case study is simulated with 2 MW/1 MWh BESS energy management controller's SOC profile which is used for input data in the purposed algorithm. A full charge/discharge SOC curve area was used as a reference for one battery SOC cycle and the cumulative sum for every discrete time step area of the operating BESS SOC profile was compared with one full cycle (SOC curve area). Inasmuch as the SOC profile of the BESS which is attending the frequency ancillary service is changing so fast due to the grid frequency variability caused by the imbalance of supply and demand of the electricity, it is hard to predict and count the cycle life. Every time step is critical since battery cycle life changes for every unique SOC value. The findings of the analysis indicate that the suggested cycle counting approach counts 38 total full charge/discharge cycles for a 2 MW/1 MWh BESS which is providing frequency response ancillary service within a one-month period. The results were compared with the traditional rain flow stress cycle method using the same SOC values for the input data. The SOC level-time graph was subjected to the rain flow counting technique, and the resulting matrix histogram was displayed. In the SOC graph, each axis provides details regarding the counting cycle. Due to the fact that the rain flow method analyzes the amount of variation between values instead of performing a complete charge–discharge counting at each time step, the consequent cycles are counted at around 600 for SOC levels of 40 and 60 percent. In this study from a different perspective, a comparison is held with the battery full charge/discharge cycle for grid-tied BESS providing frequency ancillary service and case study results prove the algorithm counts the cycle effectively. In future studies, the temperature, depth of discharge or terminal voltage effects could be added to the algorithm with the cost function.

## 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.

## Data availability

The authors do not have permission to share data.

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