Assessment of Battery Degradation Using Rainflow Cycle-Counting Algorithm: A Recent Advancement

Review Paper

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Abstract *– Battery based energy storage systems are increasingly popular in power systems as renewable energy continues to grow while ensuring the reliability of power supply. However, battery degradation is a significant issue that can impact power system operations and optimal scheduling strategies. Therefore, estimating the remaining life cycle or assessing the health of batteries due to the degradation process has become a new challenge and research focus in various engineering fields. This topic is relevant in the context of electric vehicles (EVs), where battery degradation caused by continuous and non-continuous operations (i.e., charging and discharging cycles). Degradation can limit the performance of batteries and occur throughout their lifespan whether they are in use or not. The degradation process is complex and influenced by usage and external conditions that are normally measured by state of health (SOH). Therefore, predicting the SOH of batteries is crucial in ensuring the safety, stability, and long-term viability of energy storage and EVs systems. This prediction requires a battery mechanism model that can be established from a complex electrochemical process. Alternatively, a rainflow cycle-counting algorithm (RCCA) has become popular among researchers for battery degradation estimation because of its simplicity. This paper presents a comprehensive review of the battery degradation estimation using RCCA to count the equivalent cycles of charging and discharging profiles.*

***Keywords**:* *Battery energy storage, Electric vehicles, Rainflow cycle-counting algorithm, State of health*

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1. INTRODUCTION

Renewable energy sources (RES) are one of the key solutions for global environmental pollution problems. However, renewable resources are intermittent, and their output heavily depends on weather conditions and local factors, thereby leading to new challenges especially in maintaining a good quality and reliable power supply [1]. In the last few years, the fluctuations in electricity generation from RES become a prominent issue among researchers and their main interest to solve. One effective solution is battery energy storage (BES) [2–5]. Currently, research on BES in power systems mainly covers the characteristics of system control [4], configuration modes [3], and mitigation actions [6, 7]. The operating cost due to degradation is a critical factor for the battery applications in power system. Therefore, extending the battery life cycle can significantly reduce maintenance and replacement costs [8]. The idea of using electric vehicles (EVs) as BES in the power system under the concept of vehicle-to-grid (V2G) was recognized as early as the last decade. The practicality of using EVs to provide ancillary services for power system including frequency regulation, base load fulfillment, peak shaving, and spinning reserve has been examined and tested, thereby leading to evaluations of the economic benefits when using different technologies such as battery, fuel cell, or hybrid plug-in vehicles [9].

EVs have attracted global attention due to their energy efficiency and environmentally friendly features. With the rapid advancement of technology, the use of batteries in the automotive sector has also become increasingly popular. As a result, the performance of rechargeable batteries presents a key concern for users. Furthermore, the cost of batteries contributes up to 30% in manufacturing of an EV, thereby limiting the development of EVs [10, 11]. Lithium-ion (Li-ion) batteries are preferrable for EVs as compared to other types due to their superiority in terms of performance, size, weight, and impact on environment [12]. However, the main concern of EV applications using Li-ion batteries are their safety and reliability. Poor road conditions, temperature changes, and load fluctuations can degrade the batteries performance when they are used outdoors. Apart from that, the performance degradation can be caused by insulation failure, current leakage and short circuits, and if not addressed appropriately and timely, can result in serious incidents, such as spontaneous combustions and explosions [12-15]. For that reason, monitoring the performance and estimating the degradation of batteries based on their state of health (SOH) are of great concern for EV users. Measuring the health or feature of batteries at their current state are required before estimating their SOH.

Three SOH estimation approaches are commonly used for Li-ion batteries, namely, the battery impedance method, ampere hour counting method, and cyclic method [16-18]. The cyclic method, which will be the main focus of this review, is based on a simple principle that does not require various measuring parameters [19]. However, this method requires high accuracy in monitoring the number of cycles. While previous studies on SOH primarily focused on impedance and capacity measurements, only few explored the life cycle of batteries. Furthermore, in-depth discussions on effective cycle criteria are limited due to the strong nonlinear characteristics of batteries, with most studies relying on impedance and capacity criteria [20]. Therefore, the limitations of the cyclic method in accurately estimating the number of cycles remain unsolved. This paper reviews the applications of the Rainflow cycle counting algorithm (RCCA), which is one of the cyclic methods used to establish degradation models, in assessing SOH. The main contributions of this paper as the following:

- A comprehensive review on RCCA to estimate an equivalent cycle for battery degradation assessment in electric vehicle and power system applications.
- The detailed calculations of the conventional and improved RCCA for better understanding on the equivalent cycle's computation for battery degradation assessment.

The remaining of this paper is organized as follows. Section 2 explains the concept of battery life cycle assessment. Section 3 discusses the applications of RCCA in power systems and electric vehicles. Section 4 outlines the improvements to RCCA. Section 5 draws a conclusion for this paper and provides a direction for future works.

2. BATTERY DEGRADATION ASSESSMENT

SOH is defined as a ratio between the maximum discharging capacity of the batteries and their nominal capacity. Given that the maximum discharge capacity is a characteristic of battery aging, SOH is used as an indicator of the degree of aging. A new battery without any degradation has an SOH of 100%. Fig. 1 depicts a general SOH curve over time to visualize the degradation based on the expression in (1).

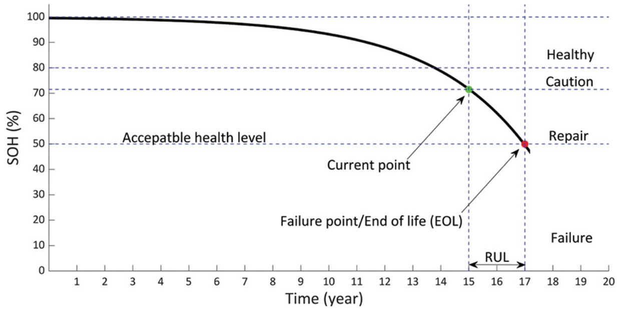

Fig. 1. A general SOH estimation curve [21]

$$SOH = \frac{Q_i}{Q_{max}} \times 100\% \quad (1)$$

where, Q_i refers as the battery capacity in Ampere-hour at i-th cycle, while Q_{max} is a new or fresh battery capacity in Ampere-hour. The degradation curve varies and depends on the battery type and characteristic. Furthermore, the battery can be replaced, or cautious action can be taken when the SOH reaches approximately 70%. Meanwhile, remaining useful life (RUL) is measured from the caution point (~70% SOH in the figure) until the SOH reaches the failure point or end of life [22]. A preventative or predictive maintenance procedure is useful to reduce battery failure rates and maintenance costs.

Battery life cycle assessment is an important step to determine cost over the reliability of battery-powered devices. Numerous life cycle models have been discussed in the literature, but they often require a compromise between precision and generality. Some models use a generalized equation which is derived from experimental data to evaluate the relationship between lifetime and relevant parameters such as depth of discharge (DOD). The relationship of battery degradation to its cycle life was also studied, and one of the significant factors that determine degradation is the number of cycles. Degradation is caused by irreversible physical and chemical changes within the battery, most commonly occurring during charging or discharging. The most visible sign of deterioration is a decrease in battery capacity after repeated charge and discharge cycles. However, the models tend to have low accuracy, and the relatively accurate models that account for the effect of aging in an equivalent circuit are usually specific to the battery being tested and are not generally applicable. A new estimation model of battery cycles taking into account capacity loss is proposed in [23]. This model can effectively explain the cycling behavior of batteries at different chemical compositions and able to make accurate battery life cycle assessment.

A reliable life cycle model is essential to accurately estimate the battery's SOH during operation and ensure demand is met. Motapon *et al.* [24] has developed a hardware testbed to evaluate the cycle-based aging process of a Li-ion battery and its impact on the battery's internal resistance and capacity. This model is based on fatigue theory and equivalent cycle counting that requires only limited data from battery data sheets and short-term cycle experiments to identify the relevant parameters. However, as batteries near end of life (EOL), they are prone to instability during charging or discharging and other problems such as overheating and excessive current. The temperature estimation method contains elements that could lead to errors in the battery SOH analysis, including errors in temperature measurement and in the predicted dynamic characteristics of temperature changes due to the state boundary. Kim *et al.* [25] introduced an effective approach to predict the life cycle of Li-ion batteries based on the entropy law and obtained promising results. Although temperature and time functions play an important role in the estimation, voltage and current are more responsive and effective in real-time battery state acquisition and processing. Adermann et la. [26] proposed a commuter cycling monitoring model to estimate the parameters of EV batteries. This model benefits from simple algorithms that work effectively with only a few measurements, enable real-time application on vehicle hardware, or outsource the assessment to a back end for advanced data gathering and processing. However, this model also requires a close relationship between the battery state of charge (SOC) and open circuit voltage (OCV) and assumes extensive knowledge of their relationship. This obstacle makes the application of this approach difficult because SOC is also influenced by other factors such as temperature.

An optimal scheduling strategy of renewable resources and BES in microgrid (MG) was used in [27] to minimize energy costs based on forecasted data of renewable energy generation, electricity prices and electricity demand. The most useful BES measurement in this case is to monitor the active power transferred back into the power grid. The costs due to battery life cycle were also taken into account and a recursive cost model was developed. Battery life cycle estimation is also crucial for designing solar home systems (SHS) and it requires experimental data to model the electrochemical processes of a battery at the cell level. Narayan *et al.* [28] developed a practical approach to estimate battery life cycle without having to perform experimental works or model the electrochemical processes in the battery. This method is based on battery data sheet provided by manufacturers. Therefore, it does not rely on technology-specific electrochemical processes where it can be used in other battery applications subjected to similar characteristics without affecting its accuracy. A summary of the discussed battery life cycle assessment approaches is presented in Table 1.

Table 1. Review of battery degradation assessment approaches

Research work	Highlight/Advantage	Limitation
[23]	Applicable for various chemistries	Temperature and current rates are fixed
[24]	Degradation model parameters are simplified	Limited to certain types of batteries
[25]	Model based on entropy law	Effect of temperature on degradation is not significant
[26]	Fast data collection and processing	SOC is derived from open circuit voltage only
[27]	Compatible with dynamic programming	An additional analytical approach is required
[28]	A dynamic capacity fading	Low C-rates are neglected

3. RAINFLOW CYCLE COUNTING ALGORITHM

RCCA was introduced by Matsuishi and Endo in 1950 to calculate a fatigue life and represent it in a load-time curve that enables the measurement of the actual stress history over several cycles of damage accumulation [29, 30]. RCCA uses SOC profiles to estimate battery life cycle. A SOC versus time graph is plotted and rotated 90 degrees clockwise where time axis is pointed vertically downward as depicted in Fig. 2.

In the figure, valleys are labeled with a, c, e, g, i, and k, while peaks are labeled with b, d, f, h, j, and l. The dropping rainflows at these peaks and valleys are denoted by DP and DV, respectively while, the rainflow between the peak and valley (i.e., on the rooftop) is denoted by RF. The following rules are observed in RCCA:

- A rainflow between a peak and valley (RF) starts at each peak or valley and stops at the opposite end point if there is no obstacle in between.

- A dropping rainflow is created after the RF reaches the end point. In this case, DP or DV is created after the RF reaches a peak or valley, respectively. New dropping rainflows are created at all valleys and peaks except those from the dropping rainflows at e and i.
- The dropping rainflow stops when the next dropping point is greater (i.e., smaller for valleys or higher for peaks) than or equal to the previous point just before the dropping is created. In this case, DP stops when the next valley is smaller than or equal to the previous valley or DV is stopped when the next peak is higher than or equal to the previous peak. For example, DP from peak b stops when the valley at c is smaller than the previous valley at a. Meanwhile, the DP from peak f continues when the valley at g is higher than that at e and keeps continuing when valley at i remains higher than that at e.
- The rainflow stops upon meeting another rainflow. In this case, the RF stops upon meeting the dropping rainflow (either DP or DV; for instance, at c', g', and j') and is replaced with the respective rainflow (i.e., DP or DV, respectively). This case also applies when the dropping rainflow meets an earlier dropping rainflow (for example, at f'), and the current dropping rainflow is replaced with the earlier dropping rainflow.

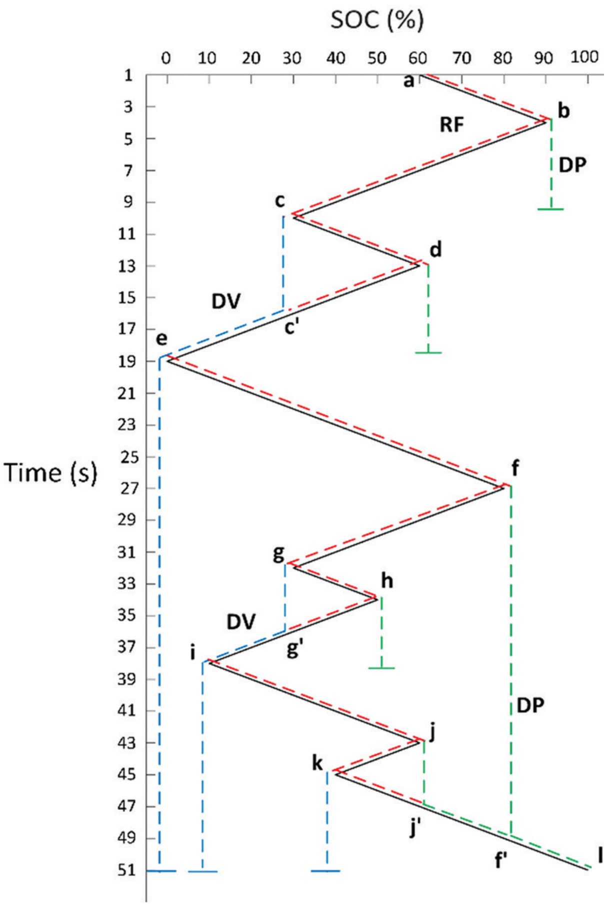

Fig. 2. A rotated curve of SOC over time

A half cycle is counted whenever the RF stops, and a full cycle is counted when the RF meets the DP or DV while considering a starting point from where DP or DV is created. Fig. 2 shows 3 full cycles for c-d-c', g-h-g', and j-k-j' and 5 half cycles for a-b, b-c, e-f, f-g, and i-j. Therefore, a total of 5.5 cycles is counted, and their amplitudes are recorded for further analysis. Applications of RCCA for battery life cycle assessment can be divided into power systems and EVs as will be discussed in the following subsections.

3.1. APPLICATIONS IN POWER SYSTEMS

A large-scale BES is normally used in power systems to improve their operation. Muenzel *et al.* [31] developed a battery life cycle prediction technique that focuses on the operational optimization of battery management. This technique considers multiple changing cycling parameters of Li-ion battery cells. Five operating factors are considered in four separate models, including charge and discharge currents, maximum and minimum operating cycle limits, and temperature. The models were then calibrated using experimental battery data. RCCA and discretization technique were used to incorporate dynamic factors into the battery cycle profiles and to solve the optimal battery operation problem. Xu *et al.* [32] introduced a semi-empirical degradation model to make assessment on the battery cell degradation from its charging and discharging profiles. This model can be applied for various types of Li-ion batteries by tuning the model based on manufacturer's data. The incorporation of RCCA allows the model to determine stress cycles from irregular charging and discharging operations. Shi *et al.* [33] established a convex RCCA degradation cost with respect to BES charging and discharging operations. The degradation model can be easily incorporated into a sub-gradient of the optimization algorithm due to its convexity. Shi *et al.* [34] later proposed an optimal control of BES to maximize profit under a "pay-for-performance" scheme where a payment is made when the BES operation complies with the utility company instructions. The degradation cost was also considered by using the convex RCCA as discussed in the previous work.

Assessing the economics of using batteries to reduce peak demand and price arbitrage is becoming attention among researchers and energy suppliers. Schneider *et al.* [35] developed an approach to minimize investment and operational costs by determining appropriate battery technology and size, and scheduling the battery operation, respectively. RCCA has been integrated into a multitasking optimization platform for battery selection and shipping. The results of a simulation study conducted by a Swiss power provider showed that battery integration can make economic sense if its capacity and drive units are carefully selected, highlighting the importance of battery size selection. Rosewater *et al.* [36] presented an advanced optimal control method to maximize the benefits of battery integration. The SOC, temperature and SOH of Li-ion battery cells are modeled in a predictive controller that allows battery operation scheduling, air conditioning and forced air convection, optimizing energy consumption and reducing electricity bills. RCCA was also used to develop the SOH model that produces a linear relationship between battery usage and degradation. Singh *et al.* [37] proposed Mixed Number Linear Programming (MILP) to optimize the operation of home appliances and manage energy from distributed energy resources (DERs) and the power grid based on price-based pricing and usage hours. An energy management system and a load planning system were developed, integrated into a house. Data were analyzed using RCCA to assess the decline in performance of residential BESs through EOL.

The financial benefits of BES are usually estimated based on the profits gained from system operations by utilizing batteries, but this approach ignores the fact that battery operations reduce the battery lifetime itself. Foggo *et al.* [38] developed a framework for BES valuation that co-optimizes with a realistic degradation model to maximize profits and mitigate battery degradation at the same time. RCCA was used to calculate equivalent cycles from SOC profiles that gives the battery degradation. Lee *et al.* [39] proposed a new battery degradation cost formula for optimal BES operation planning. The RCCA-based mining cost was formulated as piecewise linearity using an auxiliary SOC. Therefore, the optimal scheduling of BES together with the battery life cycle characteristic can be modelled as a MILP problem and solved using a gradient-based solver. As a result, an optimal scheduling BES operation can be determined quickly. Soleimani *et al.* [40] presented an active distribution network (ADN) that uses an energy storage system (ESS) within their constraints to optimize battery lifespan and minimize the operating cost. They found that BES is operated at a lower rate if the battery lifespan is taken into account, thus underutilizing the battery capacity. In their later work, Soleimani *et al.* [41] proposed a method for BES scheduling in ADN to minimize operating costs and reduce the impacts on BES lifespan. This method uses a linearized and convex AC-OPF model for a quick and accurate calculation. A two-stage stochastic optimization approach and K-means clustering were also used to address the uncertainties in different case scenarios where the battery degradation was determined using RCCA.

The penetration of DERs has created challenges in distribution network to maintain its operation within the statutory limits. Tang *et al.* [42] proposed a Lagrangian-relaxation-based algorithm that solves an optimal BES scheduling in distribution networks with DERs by incorporating an RCCA-based degradation model and using Copula theory to capture the uncertainties of DERs. This algorithm allows the incorporation of more scenarios into the BES scheduling framework and effectively captures the uncertainties of DERs. Chawla *et al.* [43] examined the major applications of energy storage in utilities as well as the requirements and challenges faced by BESs. RCCA was used to estimate the battery degradation under dynamic duty cycles, assuming that duty cycles are known in advance and that battery degradation in microcycles is independent of macrocycles. This work illustrates the trade-off between the initial investment cost of BESs (i.e, battery sizing) and the battery life cycle degradation cost. Abdulla *et al.* [44] introduced a stochastic dynamic programming approach that optimizes ESS performance over a shorter time horizon by leveraging available forecasts and a multifactor battery degradation model that takes operational influences into account. This approach aims to maximize the battery life cycle based on information from the forecasted data and operational impacts on battery degradation. This degradation model uses a dynamic RCCA that uses the time-history of discharge profiles to determine the equivalent degradation cycles.

Photovoltaic (PV) energy production fluctuates due to high intermittent in the solar radiation intensity caused by moving clouds. An ESS equipped with a ramp-rate (RR) control can be used to mitigate the fluctuations of PV output. Martins *et al.* [45] conducted a comprehensive analysis of PV power balancing techniques using ESS through RR control scheme and ensure SOC at the end of the day is remain as the start. ESS capacity requirements were quantified using RCCA from operation profile and DOD analysis. A grid-connected PV system aims to generate power according to the hourly production bids in the electricity market to avoid penalties. Beltran *et al.* [46] analyzed the aging of six different battery chemistries, including Li-ion, Sodium-sulfur, Nickel-cadmium, Nickel-metal hydride, Lead-acid, and Lead-gel, in a large-scale grid-connected PV system that participating in the electricity market. A systematic annual analysis was performed using RCCA to determine the number of cycles experienced by BES. In this case, BES was used to ensure that the energy input from PV meets the market demand. Alam *et al.* [47] elucidated the influence of PV variability on the ESS life cycle using RCCA. A realistic concept of life cycle degradation was derived from data from a real PV system in Australia. Hossain *et al.* [48] implemented a preventative energy management scheme that taking into account the battery degradation costs to accurately represent the actual cost of ownership. The management scheme considers the operation cost of battery from charging/discharging profiles and then, uses particle swarm optimization and RCCA to minimize the cost.

As RES become more widespread, the need for fast and reliable support services increases. Ochoa-Eguilegor *et al.* [49] analyzed ESS's participation in dynamic storage and continuous intra-day auctions in the UK. A battery SOC management strategy was developed, and the battery life cycle was estimated using an aging model based on RCCA and Wöhler curves. Furthermore, a techno-economic analysis was carried out to demonstrate the technical feasibility and reliable operation of the BES. Karmiris *et al.* [50] evaluated different control methods for BES in renewable power smoothing applications. The effectiveness of each control algorithm in terms of renewable smoothing and battery stress was analyzed, and the battery stress and life cycle were estimated using RCCA. A good renewable smoothing strategy can negatively impact the battery life cycle. Bouakkaz *et al.* [51] proposed a strategy for maximizing battery life cycle by managing the battery operations. This strategy minimizes the number of battery cycles per day by scheduling adjustable loads and controlling the charging and discharging processes. The optimization problem was solved using particle swarm optimization, and RCCA was used to calculate the number of battery cycles. Dragicevic *et al.* [52] proposed a technique to minimize the energy consumption of an autonomous remote installation based on robust mixed-number linear programming. This model identifies the optimal combination of renewable energy and ESS, considering the service life of the telecommunications system and the attractiveness of different battery technologies. This technique shows flexibility in solution accuracy and computational load, and RCCA was applied to account for the DOD-related cycles.

Lee *et al.* [53] presented an optimal scheduling framework for BES in MG to address the uncertainties in RES and load demand. This framework minimizes BES service life degradation and ensures economic viability of MG operations. Monte Carlo simulation and K-means clustering algorithm were used to deal with the uncertainties, while RCCA was used to process the BES charging/discharging profiles. In isolated MGs, the integration of RES, diesel generators and storage batteries are necessary to minimize fuel consumption and ensure continuous power supply. Boqtob *et al.* [54] investigated the optimal power distribution for MG engines and used RCCA to count charge/discharge cycles and quantify battery degradation. Li-ion batteries are widely used for real-time power balancing to ensure the economic operations in islanded MGs. With respect to battery degradation, Lyu *et al.* [55] proposed a novel degradation model for Li-ion batteries in islanded MGs that considers real-time management using RCCA and an online auction system. This model was formulated as a mixed integer non-linear programming (MINLP) and used weighted model predictive control to address uncertainties in the look ahead window.

The future of smart grids highly depends on large battery storage. As the use of batteries in energy markets continues to increase, the need for an optimal bidding strategy becomes increasingly important. Batteries can increase profitability through a rapid regulation service based on their performance. However, frequent charge/discharge cycles can shorten battery life, especially with quick setup services. He *et al.* [56] developed an auction model that takes battery life cycle into account for profit maximization in the energy market bidding. This model determines optimal bids in energy, reserve trading and day-ahead regulatory markets and uses an online distributed calculation method to decrease its complexity. The model offers battery storage investors a valuable tool to make decisions about tenders and operating programs and to assess economic feasibility. Correa-Florez *et al.* [57] proposed a stochastic approach for home energy management systems (HEMS) that considers BESs, PV resources and electric water heaters in daily operation framework. A swarm optimizer minimizes operating costs by considering the purchase of energy from the wholesale market and the corresponding cost of battery aging. This approach takes into account uncertainties in PV production and charging and is a valuable tool for optimizing HEMS operations. The cost of cyclic battery aging was considered using a memory disaggregation algorithm based on Lagrangian relaxation and RCCA. This approach can handle complex switching behavior and reduces the search space in optimization problem. Therefore, the decomposition strategy is supplemented by a competitive swarm optimizer.

Rapid charge/discharge operation in off-grid wind energy systems and high discharge currents during motor start-up and other high-load scenarios can reduce the battery life cycle. Li *et al.* [58] attempted to solve this issue by integrating superconducting magnetic energy storage into conventional batteries to minimize short-term power cycling and high discharge currents. The wind power was incorporated with ESS, load fluctuations and wind turbulence to demonstrate system performance. A battery life model was also used to estimate the improvement in battery life due to the reduction of charge/discharge cycles and discharge rate, while RCCA was used to isolate irregular charge cycles and discharges experienced by the battery within the simulation period. Pan *et al.* [59] integrated cyber-physical systems (CPS) into the control framework of hybrid energy storage system (HESS) and used multi-objective optimization to solve the problem. The performance of HESS can be significantly improved by incorporating physical models and real-time data through CPS. The multi-objective optimization control scheme was developed for the HESS battery supercapacitor that considers component characteristics, reduces power consumption and maintains SOC within the required limits. RCCA was used to predict battery life and quantify the benefits of using HESS as part of the control plan.

Open cycle gas turbines (OCGTs) are often used to provide fast-frequency regulation in maintaining the system frequency within the required limits. However, these OCGTs are expensive. As an alternative, frequency regulation can be provided using ESS due to its quick response capability. Lian *et al.* [60] proposed a suitable size of OCGTs and ESSs to provide frequency regulation in response to load fluctuations. RCCA was used to determine the battery life cycle, and to accurately determine the cost savings from ESS specifically for frequency regulation, hence highlighting the advantages of ESS over OCGTs. Loew *et al.* [61] implemented a cycle identification system using RCCA in model predictive controller for Li-ion batteries to accurately estimates the revenue of ESS by considering the cost of aging. Anand *et al.* [62] improved the large-scale integration of wind energy into the power grid. An economical nonlinear model predictive controller (ENMPC) was developed to operate a wind turbine and a battery as a hybrid system to supply energy to the grid. ENMPC calculates the revenue from electricity generation considering the costs associated with mechanical fatigue damage to the wind turbine tower and the cyclical loss of Li-ion battery capacity. An online parametric RCCA was implemented to determine the cyclical loss.

Traditional energy generation facilities have exhibited a marked dependence on hydrocarbon resources to meet the increasing energy requirements prompted by accelerated demographic expansion and an array of technological advancements. Obaro *et al.* [63] modelled an optimal energy framework and power management strategy for an off-grid distributed energy system (DES). The management strategy is co-optimized with various energy generation modalities as a fundamental objective to guarantee reliable and cost-effective power delivery to electrical loads, whilst conforming to a defined set of operational system requirements. Furthermore, the MINLP optimization methodology is applied to improve the generation efficiency of power systems that are interconnected with diverse energy sources and variable electrical demands. Considering the recurrent cycling behavior of batteries within the DES, the RCCA is implemented to calculate the cumulative number of cycles.

The cost function of Li-ion battery within the electricity market necessitates an optimal equilibrium between the maximization of revenue derived from energy arbitrage and the minimization of capacity degradation resulting from operational usage. The optimal equilibrium can be attained by integrating the stresses associated with DOD and thermal conditions of the battery into the optimal economic dispatch framework. A series of physics-based sufficient conditions have been formulated to effectively manage the non-analytical nature of RCCA, while simultaneously accounting for temperature variations at the cell level. The suggested stress-conscious optimal battery dispatch (SC-OBD) paradigm is executed within the framework of a battery operating in both day-ahead and real-time balancing market environments. Furthermore, Singh *et al.* [64] introduced a predictive control-based framework model to address the unpredictability of real-time electricity pricing and the need to guarantee adherence to agreements made in the day-ahead market. Table 2 summarizes the applications of RCCA for battery degradation assessment in power systems.

Table 2. RCCA applications in power systems

Research work	Highlight/Advantage	Limitation
[31]	Multiple changing cycling parameters are considered	A fixed operating temperature
[32]	Adaptable degradation model to various Li-ion batteries	Extreme conditions (i.e, low SOC, over-voltage, etc.) are not considered
[33]	A convex degradation model	Underestimate the actual degradation effects
[34]	An online model for market bidding	Uncertainties of loads are not considered
[35]	An optimal sizing of battery for investment	A calendar aging is neglected
[36]	A linear degradation relationship with battery usage	A specific usage behavior (air-conditioning)
[37]	A smart residential energy management system	Open loop battery capacity assessment
[38]	An improved battery lifetime framework	A pre-determined set of battery actions
[39]	A piecewise linear degradation cost	High computational cost
[40]	Battery utilization in power grid ancillary services	A specific type of batteries
[41]	A linear and convex AC-OPF model	High C-rates are neglected
[42]	A correlation between degradation cost and DER uncertainties	The potential voltage instability of DERs is underestimated
[43]	Battery degradation accounted in micro cycle	Internal battery resistance is neglected
[44]	A multi-factor battery degradation model	A time value-of-money is not accounted
[45]	Constraints on RR and SOC endpoint are included	Battery capacitance is neglected
[46]	Various battery chemistries for a large-scale PV	Operating temperature is fixed
[47]	A realistic life cycle degradation for PV plant	Low DOD is not considered
[48]	An optimal energy management for PV and ESS system	High computational time
[49]	Wöhler curves are integrated for aging evaluation	Variation of DODs is not considered
[50]	Various battery stress conditions including low DOD	Variation of C-rates is neglected
[51]	Optimal scheduling of shiftable loads and battery operation	Intermittent of resources and loads is not considered
[52]	Lifespan of the telecommunications facility is considered	Time consuming due to integer variables
[53]	A Monte Carlo simulation is used to consider uncertainties	Applicability to real system is not tested
[54]	Battery degradation in optimal energy dispatch framework	Tested on a specific type of batteries
[55]	Energy market bidding during an islanded operation	Irregular life cycle profiles
[56]	A fast market bidding decision for battery owners	Appropriate size of battery is not identified
[57]	Lagrangian relaxation is used for model simplification	Limited for planning perspective
[58]	Integrated with superconducting magnetic energy storage	Effect on different temperature is ignored
[59]	Actual field data is considered using CPS platform	Multiple units require additional scheduling framework

[60]	A cost saving of ESS for frequency regulation	Huge deviation between actual and projection loads
[61]	A moving horizon of cyclic aging based on MPC	Not tested on real-life battery storage
[62]	Non-linear characteristics of degradation are considered	Micro cyclic damage is not considered
[63]	A modular multi-energy sources to improved power reliability	Micro cycling operation is neglected
[64]	A stress-aware optimal battery system dispatcher	Low DOD C-rates are neglected

3.2. APPLICATIONS IN EVS

EVs primarily rely on batteries for operation, necessitating an effective management system to enhance their performance. Muenzel *et al.* [31] developed a battery life cycle prediction technique that focuses on the operational optimization of battery management. The life cycle discussions presented in the previous subsection are mainly based on the planning perspective, which uses a large time interval spanning 15-60 minutes. However, the battery charging and discharging profiles for EVs have a much shorter time interval that depends on the driver's action to accelerate (discharging) or decelerate the vehicle through regenerative braking (charging). In 2010, the Racing Green Endurance project designed and built the world's largest EV with a range of over 514 km [65]. Operational data of battery usage from the Racing Green Endurance project was used to develop a new battery degradation model. This model uses the RCCA method to produce highly reliable and accurate predictions of capacity and power losses in vehicle traction batteries. Li *et al.* [66] introduced a CPS-based electric vehicle platform to collect and store battery consumption data in the cloud, which can be used for battery degradation assessment. Support vector regression algorithm and RCCA were used to develop a battery degradation model and study the dynamic characteristics of the batteries. In their subsequent work, Li *et al.* [67] used RCCA with a deep learning algorithm to estimate the aging of EV's batteries. The RCCA-based approach effectively extracts the aging history of the battery and provides an aging index to evaluate the degradation.

EVs are becoming popular for public transportation because of target to reduce greenhouse gas emissions. Bai *et al.* [68] proposed a hierarchical optimization of energy management strategies using HESS to reduce the impact of battery aging in plug-in hybrid electric buses. This strategy includes a power limit management module that controls the flow rate of the supercapacitor and battery by redistributing power between them to drive the motor. A simple but effective battery life cycle model based on RCCA was used to quantify the rate of degradation in a battery performance control strategy. In another work [69], a low profit margin was identified as the main challenge in managing a fleet of EVs. A control strategy was proposed for managing a fleet of EVs in terms of charging and discharging for grid ancillary services. This strategy minimizes the operational cost by simultaneously determining the wear of batteries in EVs and assigning suitable routes for the ancillary services. The wear of battery was calculated using RCCA and the integral of the wear density function. Sandelic *et al.* [70] proposed an incremental degradation cost using RCCA to allow for a real-time evaluation of the true cost of battery operation while considering the degradation effects in a specific time interval.

An aggregator can achieve frequency regulation by controlling its generation and demand to cater the fluctuations in the electricity market due to increasing contributions from RESs. Vatandoust *et al.* [71] studied the participation of an aggregator to manage a fleet of EVs and ESS operations in a day-ahead energy market regulation framework. The fleet of EVs and ESSs provide unidirectional (charging) and bidirectional (charging and discharging) regulations, respectively. Risk-free mixed-integer stochastic linear programming was then applied to plan aggregator participation, and RCCA-based linear degradation was formulated to account for the expected degradation costs incurred by EVs participation. The degradation cost is a key concern for EV owners that discourages their participation in vehicle-to-grid (V2G) services for regulation purposes. Li *et al.* [72] proposed a novel anti-aging V2G active battery planning approach, which quantified battery degradation using RCCA during V2G services. The V2G scheduling problem is modelled as a multi-stage optimization problem that aims to minimize battery degradation and load fluctuations in the power grid.

In contemporary discourse, the implementation of sophisticated charging paradigms and management frameworks that encompass vehicle-to-everything (V2X) functionalities is essential to alleviate the increasing ubiquity of battery electric buses (BEBs) in urban settings. Nevertheless, the integration of these advanced functionalities into charging systems may have repercussions on the longevity of the charging infrastructure. This phenomenon remains unexplored, despite its significance for operators of BEBs. Verbrugge *et al.* [73] developed a thorough evaluation of reliability to investigate the consequences of intelligent and bidirectional (V2X) charging on the longevity of silicon carbide-based high-power off-board charging infrastructure employed for battery electric buses (BEBs) within a depot environment designated for overnight charging. The thermal stress is converted into a quantifiable metric of failure cycles and cumulative damage through the utilization of RCCA, a life cycle prediction model for damage accumulation. Ultimately, a Monte Carlo simulation along with a Weibull probability distribution fitting is utilized to determine the reliability of the system.

An essential improvement in the accessibility of rapid-charging infrastructure is crucial for the effective shift towards EVs. Nevertheless, the process of charging a battery pack at increased C-rate has detrimental effects on SOH, thereby expediting its deterioration. Pelosi *et al.* [74] proposed a strategic battery management, which considers the diurnal operational patterns of a Li-ion battery utilized in EVs, anchored in a defined driving cycle that includes charging phases occurring when DOD attains 90%. Through the dynamic modeling of the EV's battery system, the progression of the state of charge is determined for a range of charging C-rates, with meticulous attention given to both discharging and charging profiles. RCCA was employed to examine the SOC profiles, thereby determining the DOD for each individual cycle, which subsequently informs the practical applications on the experimental testing apparatus. The above applications of RCCA for assessing battery degradation in EVs can be summarized in Table 3.

Table 3. RCCA applications in EVs

Research work	Highlight/Advantage	Limitation
[65]	Long-range empirical EV data	A specific battery type
[66]	An online SVR-based assessment	Inadequate data for verification purposes
[67]	A deep learning-based assessment	A fixed temperature and specific type of battery
[68]	An integrated with super-capacitor for electric buses	Maintenance cost is not considered
[69]	EVs scheduling for grid ancillary services	The wear function is not validated on actual batteries
[70]	An incremental degradation cost of EVs	A calendar aging is neglected
[71]	EVs participation in the electricity market regulation	Framework is mainly based on linear approximations
[72]	Minimize degradation during V2G services	Prediction errors of battery capacity fade are neglected
[73]	Silicon carbide (SiC)-based high-power off-board charging	Not tested on real-life battery storage
[74]	Capacity degradation tailored with high C-rates	Low C-rates are neglected

4. IMPROVEMENT AND FUTURE WORKS

Despite its wide usage in cycle counting, RCCA has a non-closed form that hinders its use in optimization. As a result, recent studies have explored ways to improve RCCA. For instance, Huang *et al.* [75] proposed an accurate life cycle prediction for Li-ion batteries. The charge and discharge profiles are usually faced with interference from noise, which is not addressed properly in the traditional ampere hour approach. The unscented Kalman filter algorithm addresses this issue and provides a highly accurate SOC for SOH prediction. Li-ion batteries also have a strong non-linearity characteristic that leads to many small cycles counted in traditional RCCA. An improved RCCA was then introduced by adding intermediate judgement to reduce its sensitivity to data peaks. A linear damage criterion was then used together with the improved RCCA to accurately predict the remaining life of a battery without the need to measure process parameters. In a later study, Huang *et al.* [76] improved RCCA by combining this approach with the autoregressive integrated moving average (ARIMA) model to predict the SOH of a Li-ion battery. Experiments were conducted under dynamic stress tests and cycle conditions to validate the performance of the SOH prediction model using a confidence interval as the acceptable error range. The combined RCCA and ARIMA show promising results in predicting the SOH of batteries.

BES duty cycle counting in frequency control is hard due to irregular charging and discharging caused by fluctuations in grid frequency. The traditional RCCA is based on extreme points (peaks and valleys) and only starts counting at the end of data, hence it is inapplicable to determine the RUL in between load points, especially in real-time applications. Gundogdu *et al.* [77] modified the RCCA to develop a rapid/fast battery cycle counting method that estimates an equivalent number of completed cycles that can be used to calculate RUL in microcycles. Unlike traditional RCCA, the proposed method can calculate half a cycle when the SOC of each battery charge and discharge independently reaches the maximum value of 100% and one full equivalent cycle can be achieved as single battery charge and discharge cycles are recorded. Furthermore, the number of complete equivalent cycles can also be estimated during the process continuously rather than waiting for the data collection to end. This method was applied to 1 MWh BES at 2 MW maximum operating power to mitigate the frequency fluctuation problem. The lack of a comprehensive mathematical formulation for the RCCA have represented the one of primary barriers to the widespread implementation of the cycle-based degradation framework. Diao *et al.* [78] proposed a meticulous analytical formulation of the sub-gradients pertaining to the cycle-based aging cost function to facilitate the effective resolution of the optimal operational dilemma irrespective of a mathematical representation for the RCCA. The sub-gradient projection algorithm is introduced to determine the theoretical optimal operation in particular circumstances where the constraints governing battery operations may be alleviated.

An example application for the improved RCCA is also provided in this review for further understanding. Fig. 3 depicts a flowchart of the improved RCCA used for real-time applications.

The same notations presented in the previous section are used in the figure. A flag is used to indicate the condition wherein RF meets DV or DP where (1 if true, and 0 if false). The direction of rainflow is important in determining whether the next edge is a peak or valley. Therefore, $DirVP$ is used to indicate a flow from valley to peak ($DirVP$ = 1) or, from peak to valley ($DirVP$ = 0). In a casual event as mentioned in the first rule in the rainflow cycle counting algorithm section, an amplitude (Amp) of the half cycle is calculated as:

$$Amp = P - V \tag{2}$$

In the event where RF meets DP or DV (flag = 1), Amp is recorded using the following expression:

$$Amp = \begin{cases} DP - V, & \text{if } DirVP = 1 \\ P - DV, & \text{otherwise} \end{cases} \tag{3}$$

The equivalent number of cycles can then be updated using the recorded Amp at each time step in as follows:

$$Cycle(t) = Cycle(t-1) + 0.5\left(\frac{Amp}{100}\right) \quad (4)$$

Fig. 4 shows the total number of equivalent cycles in respect to SOC at each time step using the improved RCCA algorithm. The SOC curve in Fig. 4(a) is based on data as in Fig. 2. The total number of equivalent cycles at the end of the data can be observed at approximately 2.1 cycles as shown in Fig. 4(b). The equivalent cycle is much smaller than that obtained by the traditional RCCA at 5.5 cycles as discussed earlier.

The equivalent cycle plot in Fig. 4(b) resembles a staircase due to the cycle cannot be updated until the SOC reaches peaks or valleys. A plateau at the end of the equivalent cycle plot is caused by the failure to locate a peak or valley. The limitations of equivalent cycle counting should be addressed in the future works to ensure a smooth and accurate representation of the battery degradation process.

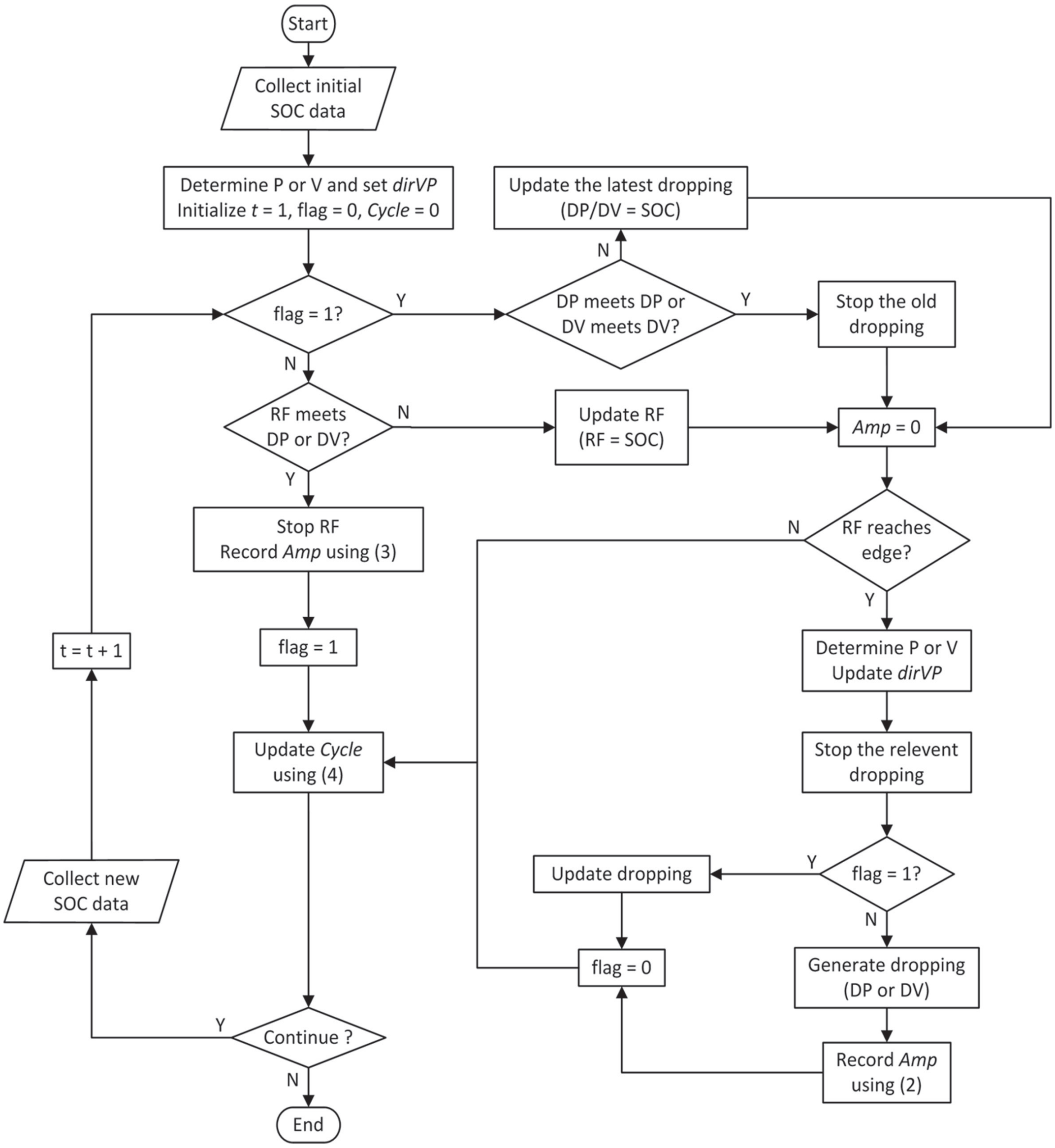

Fig. 3. Flowchart of the modified RCCA

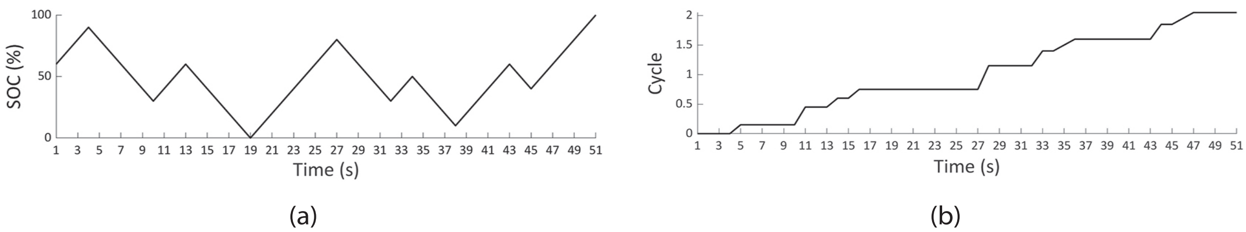

Fig. 4. Equivalent cycle counting using the improved RCCA algorithm

5. CONCLUSIONS

This paper discusses a comprehensive overview of the applications of RCCA in battery degradation assessment. The relevant literature on the topic is reviewed by highlighting the advantages and limitations of each approach. The significance of RCCA in analyzing and interpreting the battery life cycle is emphasized, and other popular counting algorithms for predicting battery degradation in EVs and power grid applications are reviewed. In addition, improvement of RCCA for battery degradation assessment in the respective applications is reviewed and compared with the conventional approach. A comparison between the conventional and improved RCCA on an exemplar SOC data shows a significant low equivalent cycle at 2.1 cycles for the improved RCCA as compared to the compared to the conventional RCCA at 5.5 cycles. Furthermore, the equivalent life cycle can be updated in each time step using the improved RCCA rather than at SOC peaks or valleys in the conventional RCCA. The obtained equivalent cycle using RCCA can also be used to evaluate the aging process of other electronic equipment. However, RCCA has several limitations, including its sensitivity to test conditions such as negligible fluctuations in current and temperature. Despite these limitations, RCCA, together with open-source mechanisms and cloud data sharing, offers the opportunity to reform battery health assessment. This review serves as a useful reference for the design and operation of battery health diagnosis and prediction systems and provides guidance for future work on battery degradation assessment.

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