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*Review*

# Review of Battery Energy Storage Systems Modeling in Microgrids with Renewables Considering Battery Degradation

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**Abstract:** The modeling of battery energy storage systems (BESS) remains poorly researched, especially in the case of taking into account the power loss due to degradation that occurs during operation in the power system with a large penetration of generation from renewables and stochastic load from electric vehicles (EV). Meanwhile, the lifetime varies considerably from the manufacturer's claim due to different operating conditions, and also depends on the level of renewable energy sources (RES) penetration, cyclic operation, temperature, discharge/charge rate, and depth of discharge. Choosing a simplistic approach to the degradation model can lead to unreliable conclusions in choosing the best management strategy and significant investment and operating costs. Most existing BESS models in stationary applications either assume zero degradation costs for storage or simplify battery life to a linear function of depth of discharge (DOD), which can lead to additional error in estimating the cost of BESS degradation. The complexity of constructing a lifetime model of BESS is due to the presence of nonlinear degradation of BESS at the beginning and at the end of the lifetime, as well as the difficulty in obtaining a large amount of experimental data that are close to the real-world operating conditions for the construction of most models. This article analyzes the features of BESS that are specific to their operation in microgrids in terms of the influence of the main stress factors on the degree of BESS degradation. This study also provides a review of existing models for assessing battery degradation.

**Keywords:** battery degradation; battery energy storage system; lithium ion battery; microgrid; renewable energy

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## 1. Introduction

To address the issues of instability that are caused by the intermittent nature of energy that is generated from renewables, one uses battery energy storage systems, which have response times in the range of milliseconds and are able to compensate in real-time for the high variability of the renewable resources [1]. As a result, the power output from renewable energy sources (RES) becomes more controllable, predictable, and less variable [2]. The integration of batteries for various levels of renewable energy penetration to increase the flexibility of energy systems was considered in [3]. The use of batteries significantly reduces the unsatisfied demand in the network, halves the number of renewable energy sources, and diminishes the $CO_2$ emission intensity. Due to their characteristics such as fast response, low self-discharge, long cycle, and calendar life, battery chemistry such as that of lithium-ion batteries can also contribute to primary frequency and voltage regulation as well as peak load reduction [4]. In addition, BESS can be used to increase electricity revenues for microgrid entities by charging energy during periods of low prices and discharging energy during periods of high prices [5]. There remains a poorly researched issue of modeling of BESS, especially when taking into account the loss of power due to degradation in the context of their operation in the power system with a large share of generation from renewable energy sources [6]. During the period of BESS operation, the capacity should be assessed during the entire service life of the battery storage. Hence, it is relevant to develop an accurate dynamic model for estimating the residual capacity and predicting the BESS degradation under microgrid conditions. Choosing a simplistic approach to the degradation model can lead to an unreliable conclusion on choosing the best management strategy [7]. Most existing models with a multi-period stochastic optimization problem (MSOP) either assume zero degradation costs for storage, or simplify battery lifetime to a linear function of depth of discharge (DOD), which can lead to additional error in estimating the degradation costs of the BESS [8].

To formulate the research problem, the Section 2 presents the main issues that are related to the power loss of batteries that is caused by their degradation and the possible management strategies to increase the service life of the battery. A review of the literature on the assessment of the optimal capacity of the battery is given with and without regard for the degree of the battery degradation. A conclusion is made about the need to factor in the power loss of the battery over time for planning and managing the energy system.

The Section 3 focuses on the main factors that affect the speed of the battery degradation where the emphasis is placed on batteries in stationary applications in combination with renewable energy sources and increasing stochastic load (electric vehicles). The most significant factors are identified for the batteries in stationary applications.

The Section 4 presents a critical analysis of the main models that are designed to project the battery service life and the speed of degradation. The conclusion is made on the most preferred model when it is used in stationary applications from the viewpoint of accuracy and computational complexity.

## 2. Research Problem Statement

Due to the fact that power delivery from the BESS is highly time-dependent, single-period optimization approaches such as optimal power flow fail to match the time-dependent characteristics that are needed to control and monitor the BESS in power systems [9]. Dynamic BESS scheduling is necessary to minimize the operating costs of the microgrid while satisfying the operational constraints of the distribution network [8]. Various studies in the literature address this issue by proposing methods for multi-period optimal power flow (MPOPF). Nevertheless, such approaches fail to solve the problem of battery degradation that causes a drop in BESS power [10]. Time domain analysis models and the contribution of BESS in the power system need to be considered with an accurate representation of available power throughout the operating time. Due to the stochastic nature of distributed generation and electric vehicles, the dynamic scheduling of BESS is essentially a multi-period stochastic optimization problem (MSOP). One way to solve an MSOP is to use scenario-based stochastic programming (SP) [8].

The issues of BESS operation and scheduling have been addressed by many researchers [11–14] but the development and evaluation of the optimal battery size to achieve a cost-effective system with minimal energy loss and minimal excessive energy storage investment outlays are still ongoing [15]. There are various models for finding the optimal power and energy capacity of storage units in distribution networks and for choosing their configuration strategy. The difficulty of BESS sizing and estimating the costs of such networks is related to the stochastic nature of renewable energy generation and abrupt load fluctuations [16]. At the same time, not enough research has been devoted to the issue of developing a model for optimal BESS sizing that would take into account the rate of battery storage degradation [17]. In some cases, the battery lifetime may differ considerably from the manufacturer's stated lifetime due to different conditions of battery operation. Depending on the objectives of using BESS in a microgrid, the degradation of the battery varies greatly and depends on the level of penetration of RES, cyclic operation, temperature, etc. [18]. Thus, the strategy for determining BESS capacity as well as the capital and operating costs can be improved by accurately estimating battery life and other operational information about the power system [19]. Consideration of the influence of various stress factors on the degradation of the battery allows one to develop a strategy to increase the lifetime. For example, the conventional method is to install more storage capacity than required to reduce the average depth of discharge (DOD) of the battery so as to maintain the operating cycle [20]. This also includes building up the BESS with the addition of new battery cells over time [21]. However, such an approach leads to technical difficulties in connecting new and old batteries. In addition, the rate of discharge current and temperature also significantly affect the amount of the available capacity of the battery storage and the rate of degradation [22]. The size and hence the cost of the energy storage also depends on the value of such reliability parameters as the loss of power supply probability (LPSP) that is required for a particular microgrid. This reliability parameter means the probability within a certain time frame when the generation will not be able to meet the demand [23]. This failure can be caused either by improperly designed distributed energy resources or by an instantaneous drop in renewable energy or by an increase in electricity demand [15,24]. Accordingly, it is necessary to design the capacity of the BESS so as to take into account its operating conditions in the network, which is a certain trade-off between the performance (available capacity and energy efficiency), reliability, and lifetime of the battery storage. In general, the optimal BESS sizing requires taking into account the various input quantities as shown in Table 1.

**Table 1.** Input quantities for optimal sizing of a battery in the microgrid [25,26].

| **Publication** | **Limitations of the Power Grid** | | | **Limitations of the BESS** | | | **Ref** |
|---|---|---|---|---|---|---|---|
| | Optimal Power Flow | Uncertainty | **Tariff-Based Energy Prices and Discount Rate** | Reliability | Degradation | **Cost per Unit of Capacity, Operation, and Maintenance** | |
| **1** | **2** | **3** | **5** | **6** | **7** | **8** | **9** |
| Shang Y., 2020 | ✓ | ✓ | | | | | [8] |
| Sufyan M., 2019 | ✓ | ✓ | | | | | [15] |
| Yang Y., 2013 | ✓ | | | | | | [19] |
| Narayan N., 2018 | ✓ | ✓ | | | | ✓ | [20] |
| Shin H., 2020 | ✓ | ✓ | | | | | [21] |
| Dulout J., 2017 | ✓ | ✓ | | | | | [22] |
| Lan H., 2015 | ✓ | ✓ | | | | | [27] |
| Carpinelli G., 2017 | | | ✓ | | | | [25] |
| Huo D., 2022 | | ✓ | | | | ✓ | [26] |
| Soltani N, 2020 | ✓ | ✓ | | | | ✓ | [28] |
| Yue M., 2015 | ✓ | ✓ | | | | | [29] |
| Bahramirad S., 2012 | | ✓ | | ✓ | | | [30] |
| Knap V., 2015 | ✓ | | | | | | [31] |
| Bhusal N., 2021 | ✓ | | | | | | [32] |
| Baloyi T., 2021 | | | | | | | [33] |
| Luo Y., 2014 | ✓ | | | ✓ | | | [34] |
| Astaneh M., 2018 | | | | ✓ | ✓ | | [35] |

**Table 1.** *Cont.*

| Publication | Limitations of the Power Grid | | | Limitations of the BESS | | Ref |
|---|---|---|---|---|---|---|
| Arabali A., 2014 | | ✓ | ✓ | | | [36] |
| Awad A., 2015 | ✓ | ✓ | ✓ | | | [37] |
| Zhang Y., 2017 | | ✓ | | | | [38] |
| Alsaidan I., 2017 | ✓ | ✓ | ✓ | ✓ | ✓ | [39] |
| Zhang Y., 2018 | | | | ✓ | | [40] |
| Fioriti D., 2022 | ✓ | | | ✓ | ✓ | [41] |
| Amini M., 2021 | ✓ | | | ✓ | ✓ | [42] |
| Tahir H., 2022 | ✓ | ✓ | | | ✓ | [43] |

The optimal size of the battery storage in the study [15] was determined, taking into account the depth of discharge to extend the life of the battery storage. This article discusses the firefly algorithm to achieve optimal scheduling that minimizes the overall cost of generation. A similar optimization algorithm is given in [27]. A numerical optimization method (particle swarm optimization) is used to find the correct placement and sizing of the BESS. However, the loss of storage capacity over time is not considered. The paper [8] presents a multi-period stochastic optimization model for the dynamic control of batteries in microgrids. The model aims to minimize the operating costs of the microgrid, taking into account the nonconvex degradation cost function of the BESS. The authors used one of the machine learning methods such as reinforcement learning as augmented by a Monte Carlo tree search and knowledge rules. The article [25] proposes a probabilistic method for optimal BESS sizing, based on the classical Monte Carlo approach as combined with an analytic formulation to estimate the total costs that are incurred by the end-user in implementing the BESS. The optimal size of the BESS is determined by the appropriate minimum average total cost. At the same time, battery degradation is represented only in terms of the number of life cycles to failure at 80% of the DoD discharge depth, without taking other stress factors into account. The determination of the optimal BESS capacity considering the RES-based generation and load forecasts was studied in [28], where they were presented as chance constraints. At the same time, the study did not take into account the prediction of BESS power loss as a result of degradation. The study [19] used a probabilistic approach to BESS sizing that was needed to compensate for the frequency variation that was caused by large solar energy penetration into the system by performing multiple simulations. In [30], a reliability metric that is known as the expected load curtailment was considered for optimal sizing of the BESS and mixed integer programming (MIP) was used to state the problem. The paper [31] presents a method of BESS sizing from the standpoint of power and energy intensity to ensure inertial response and primary frequency regulation in a power system with a large penetration of RES. The estimation of the rated power and energy capacity of the BESS is based on the characteristics that are associated with the frequency characteristic: the inertial constant and the power/frequency characteristic that measure the frequency characteristic in the grid immediately and during a shorter period of time following an imbalance of active power [44,45]. Thus, most power and energy capacity estimation models do not take into account battery aging predictions, meanwhile lifetime can vary significantly from the rated lifetime depending on the operating characteristics as well as idling conditions.

Battery degradation causes a decrease in the capacity and an increase in the internal resistance, which are commonly established as state of health (SOH) metrics for evaluating the remaining life of lithium-ion batteries (LIBs) [46]. In general, capacity fading is a relevant parameter for monitoring and evaluating BESS degradation. Nevertheless, one important parameter such as physical degradation must also be taken into account when studying the aging prediction. In addition to the decrease in capacity and power [47], it is necessary to monitor the degradation modes, which are characterized by insignificant aging at the initial stage of the battery storage life but may become noticeable by the end of its lifetime. Such degradation modes can be quantified by analyzing changes in the cell's voltage response and by such methods as incremental capacity and differential voltage [47]. Oftentimes, spent batteries are used in stationary applications after their use in electric vehicles, which requires a more accurate prediction of aging due to the more accelerated degradation of the second stage of life [48]. The inaccurate prediction of the residual capacity of the second stage of service life can lead to an emergency and failure of the entire BESS system.

From the planning point of view, information on the residual actual capacity allows one to determine the correct placement of the BESS based on an assessment of the electrical parameters of the system over a long period of time. Also, planning will be distorted after some time when the actual capacity is less than what is taken into account. From the point of view of operational management, the forecast of capacity fading makes it possible to replace the BESS cell in time and transfer it to perform other tasks that do not require high power output. In addition, the assessment of the actual capacity depends on the accuracy of the assessment of the degree of BESS charge, an incorrect assessment of which can lead to irreversible damage to the battery and the possible failure of the entire BESS. Therefore, it is very important for the safe operation of lithium-ion batteries to obtain data on the residual capacity.

Since BESS lifetime depends significantly on its charging and discharging behavior, its life-cycle degradation costs must be incorporated in the BESS model. The average lifetime of the BESS is more than ten years; however, lithium-ion batteries typically undergo a severe capacity fading throughout the entire planning period of a project. Therefore, BESS sizing, when performed without taking battery degradation into account, leads to inflated revenues and can seriously compromise reliability [21]. By incorporating the degradation costs of the BESS into grid optimization problems, significant cost reductions can be achieved in various ways, such as in grid planning and operation [49], as well as in the coordinated operation of the BESS and renewable energy sources [50]. An erroneous or overly optimistic prediction of capacity loss can lead to poor estimates of the capital and operating costs of the BESS. Therefore, in addition to electrical constraints, some ESS models use cost constraints [9,51]. For example, published research deals with the methods for estimating the cost of the power system that take into account BESS sizing, which depends on its operating conditions in the grid and the depreciation charges that are associated with the degradation of the battery. A time-dependent cost function that is based on the battery degradation model (BDM) is presented in [9]. The battery degradation model for optimal microgrid scheduling with two timescales [52] decomposes the long-term investment costs into short-term degradation costs based on the depth of discharge (DOD) and charge/discharge cycle life.

Power system planning and operation require more accurate forecasts of the stochastic nature of RES-based generation and load that take into account the impact of battery degradation on the system. At the same time, there are issues that are failed to be addressed adequately. They are the impact of the battery capacity fading as it depends on stochastic charging in microgrids with a large penetration of renewable energy as well as on stochastic discharge (in the case of connecting an active consumer or an increase in the load from electric vehicles), regulation of the energy market using BESS, etc. It is necessary to identify the main stress factors affecting the degree of degradation of the batteries thata re used in the microgrid, which is significantly different from their operating conditions in DC power systems [53]. The next section, based on existing studies, indicates the most important stress factors that influence the power losses of batteries in microgrids.

## 3. Consideration of Stress Factors in Modeling the Battery Degradation in Microgrids

Battery degradation manifests itself as a gradual decrease in the capacity, decreasing operating voltage, increasing internal resistance, and loss of energy, which occurs both during operation and during storage [54]. Degradation is divided into two components: calendar aging (it is strictly time-dependent and is associated with battery capacity fading while the battery is stored rather than used, and therefore, does not depend on charge/discharge cycles) and cycling aging (which depends on the BESS usage mode). Cycling aging plays a major role in cases where the operating time is relatively longer than the idle time, as in stand-alone solar power plants [20,55]. Factors affecting lifetime behavior include DOD, discharge/recharge rate (C-rate), temperature gradients, and cycling mode. In the case of non-regular battery use, as is the case with intermittent RES power generation, it is impossible to determine battery aging without taking into account the temporal dynamics of SOC and ESS temperature [9]. Furthermore, the higher cycling rate causes more polarization and Joule heating (further heating of the cell), which leads to more noticeable cell degradation [54].

Stress factors affecting the calendar lifetime also include the cell temperature (which is the most important factor), the state of charge (SoC), and the no-load voltage of the cell [46]. High SoC leads to high cell voltages, causing the greatest mechanical stresses on the materials and thus leading to a shortened battery life [7]. In addition, maintaining a high SoC while the battery is in standby leads to a greater loss of the cathode material, a thicker solid electrolyte interphase layer, and a greater anode resistance compared to a cell with a low SoC [56]. However, many of the BESS operating modes that are common to various WT applications require an idle SOC of 50% (i.e., the BESS is able to output or consume a large amount of energy at any given time) [57]. High temperatures cause a greater loss of calendar life (chemical degradation), while low temperatures and high current rates cause a greater loss of cycle life (mechanical degradation) [58].

The assessment of battery storage degradation presents a strong non-linear dependence on various aging factors. The effect of these stress factors on battery degradation, however, is not uniform, and some factors may have a disproportionately strong effect on degradation. A multi-factor experimental study [59] investigated the significance and ranking of the individual (main) and two-way interaction effects of all five stress factors (ambient temperature, discharge C-rate, charge C-rate C, DOD, and charge cut-off) that are necessary to compose a typical cyclic operation that is used in battery qualification tests. However, the stress-factor ranges in the experimental design were chosen with an emphasis on portable electronics. Accordingly, the ranking should be considered in the context of the stress-factor ranges that were chosen in the experimental design, since tighter levels of a minor charge rate factor could potentially trigger additional degradation mechanisms, such as lithium coating.

The most significant factors affecting capacity fading in [59] were temperature, discharge rate, and constant charge voltage as either their separate effects or those of their interaction. The study notes that the charge cut-off during the constant-voltage charging phase, an important parameter during battery charging that is underrepresented in the published research on batteries, was more dominant for battery degradation compared to the charge cut-off that was used during the constant-current charging phase. In [58], lifetime results showed that the capacity loss is strongly dependent on the rate, temperature, and depth of discharge (DOD).

It is worth noting that the effects of stress factors on different lithium-ion battery storage systems will not be the same. Each commercially available battery has its own design, chemical composition, and set of additives, so it is necessary to repeat the testing procedure for each commercially available battery to develop a proper understanding of degradation and the subsequent aging prediction model [47]. For example, the life of some LFP battery cells depends only slightly on the C-rate when the current rates up to 4C are considered [57]. In terms of calendar aging, LFP cells have a lower degradation rate than lithium cobalt oxide (LCO) and lithium nickel manganese cobalt oxide (NCM)-cells under the same conditions, which can be explained away by the relatively low potential of LFP-cathodes [60]. Therefore, a lithium-ion battery (LIB) model that is based on a single reference may not be sufficient to present an overview of the degradation to which all LIB chemistry is subject [55].

A sufficient number of studies address the issue of analyzing the degree of influence of various stress factors on the battery degradation, both separately and as a result of their interaction. However, they are mainly based on experimental data of the batteries thata re used in the operating ranges of portable devices and electric vehicles. Creating models for predicting battery life in a microgrid is a challenging task, since the stress factors in a microgrid are stochastic in nature and are often interrelated and, therefore, require different testing procedures for battery storage performance under given conditions [44].

The definition of normal and critical operating conditions for electrochemical storage units as part of a microgrid is difficult to bring into the average range, due to the different functions that are performed in the microgrid and the stochastic generation and loading. The wide range of values of generated and consumed power determines the presence of ripple in the charging and discharging currents of the battery storage. Pulsed currents cause rapid degradation and shortening of battery storage life [53]. The effect of the depth of discharge on battery degradation at the grid scale has not been sufficiently studied. In contrast to the known dependency of the depth of discharge on the number of battery cycles, as derived from repeated regular cycles of charging and discharging to a certain range, BESSs in grids usually operate with irregular cycles [61]. For example, irregular cycles are caused by stochastic load and generation from RES; the use of BESS in frequency regulation (which entails shorter cycling times) and in price regulation in the energy market; and others. The power output of wind turbines is subject to a wide range of fluctuations, but daily power variations are smaller than in solar generation. In [21], the daily SoC profile for wind generation shows a variety of models with relatively smaller SoC changes compared to solar generation. The combination of BESS and solar generation shows higher degradation due to the large daily variation of solar generation. Thus, it is necessary to model battery degradation so as to capture the effects of irregular cycles and other stress factors.

In Table 2, work was carried out to study the degradation of BESS in power systems using RES.

**Table 2.** Models of battery storage degradation in power systems.

| Publication | Microgrid Application | Chemistry | Type of Aging | Model of Aging | Stress Factors | Ref |
|---|---|---|---|---|---|---|
| Shin H. (2020) | PV, WT power smoothing | LMO | Cycle and calendar | Degradation model proposed by Xu et al. [62] | DoD and SoC, C-rate, cycle count, T, total operation time | [21] |
| Dulout J. (2017) | PV power smoothing | LIB | Cycle and calendar | Lifetime model based on the concept of mechanical fatigue [63] | DOD | [22] |
| Olmos J. (2021) | Electric transport and power systems | LFP NMC | Cycle | Empirical cycling degradation model | DoD, C-rate, T, mSOC = 50% | [55] |
| Valentin Silvera Diaz (2021) | PV power smoothing | LFP | Cycle and calendar | Semi-empirical model | DoD, C-rate, T-calendar SOC-calendar | [64] |
| Vermeer W. (2020) | PV, EV, V2G | NMC | Cycle and calendar | Semi-empirical model based [54] | C-rate, T, ampere-hours processed | [65] |
| Lee M. et al. (2020) | PV power smoothing | LFP | Cycle | Cycle aging model | DOD | [66] |
| Sandelic M. (2018) | Secondary frequency regulation in a system with WT | LFP | Cycle and calendar | Lifetime model based [7] | T, SOC, C-rate | [67] |
| Wu Y. et al. (2022) | EV Charging station | LFP | Cycle | Modified Rainflow algorithm | T, DOD | [68] |
| Wang Y. (2016) | WT-ESS, participation in the energy market | LIB | Cycle | A linearized battery degradation model including battery degradation percentage constraints and degradation cost | DOD | [69] |
| Gräf D. (2022) | Grid frequency stabilization | NMC | Cycle | Semi-empirical model based [62] | T, C-rate | [70] |
| Scarabaggio P (2020) | V2G, frequency stabilization | LFP | Cycle | Degradation experimental model based [71] | DOD | [72] |

In [55], the authors examined the effect of different stress factors on the degradation rate based on data from two types of lithium-ion batteries (LFP and NMC). They analyzed the influence of various voltage factors on battery degradation (DoD, C-rate, T, mSOC). The authors found that the factors of temperature and depth of discharge have the greatest influence: their high values can reduce the lifetime down to 1000 full cycles. If low values such as 40% DOD and 25 °C are maintained, with a C-rate not exceeding 1C, the expected lifetime can be extended to 10,000 full cycles. The model was validated through a case study of electric transport and power system applications. At the level of the power system, two scenarios are considered: the use of RES as a frequency regulator and as smoothing of RES-based generation. The first case is characterized by a low level of discharge (20% DOD) but high currents (3C charge/discharge current), and the second case is characterized by a high depth of discharge (80% DOD) but low currents (0.5C charge/discharge current). The C-rate values are taken as average currents during operation. The mSOC stress factor remains unchanged, set at 50% due to the smallest effect for both types of LIB. There are two cases that are considered, those of winter and summer temperatures for southern Europe, 20 °C and 30 °C, respectively. When selecting the type of LIB technology for the applications under consideration, the NMC lifetime is the most appropriate chemical technology for high load and frequency response applications, while the LFP is the most appropriate chemical technology for the RES integration scenario. However, when the temperature rises to 30 °C, the LFP proves to be a better option. In this case, the NMC chemistry is the most suitable option for the vehicle.

The study [64] presents a comparative assessment of two models of BESS degradation, an event-oriented model that is based on Rainflow counting, which uses only the DoD cycle number curve, and a semi-empirical model in the PV smoothing application. The semi-empirical model showed the greatest degradation for all scenarios that were considered. The reason for the above is that it is supplemented by the stress factors of calendar battery aging (SOC, T), which is important in the case of using BESS for smoothing of photovoltaic batteries power. The model also incorporates cyclic aging factors: charge/discharge rate and an operating temperature of 25 °C.

Most degradation models ignore the external factors of battery aging assuming they are constant, with temperature being the dominant influence factor [73]. The paper [69] studies the distribution of energy storage capacity in distribution grids, taking into account the effect of ambient temperature. To describe the relationship, the effect of the temperature of the operating environment on the available capacity of the battery is described by the Arrhenius equation. In order to test the efficacy of the marginal aging costs of the BESS in the optimization model, different operating strategies were used under different seasons, taking into account the characteristics of traffic, traffic congestion, and ambient temperature, and those accounting for the marginal aging costs. In [70], the degradation process is modeled by a semi-empirical method including thermal stress factors and charge and discharge rates. The study analyzes a 7.2 MW/7.12 MWh electrical energy storage system operating in the frequency regulation market in Germany. As a result of the storage unit analysis, there is a large temperature difference between the individual battery units inside the battery container. The battery units that are located at the bottom are exposed to lower temperatures than those at the top (maximum average temperature 32 °C, minimum average temperature 23 °C). The authors note that the temperature gradients inside the battery containers are larger than expected and have a significant effect on the aging of lithium-ion batteries at the system level. In addition, the model is extended for various energy market applications, with long periods of high charge and discharge rate of 1C up to 1 h and an intraday market with volatile price spreads and, therefore, frequent and short periods (up to 0.25 h) of high charge rate up to 1C. Since the degradation of BESS differs by up to 0.97% between the highest and lowest observed average temperatures, the lifetime can be extended by 11 years.

The article [22] proposes a method for sizing of BESS integrated into a microgrid with renewable photovoltaic energy sources in order to minimize the cost of stored energy. The study presents a BESS model that describes performance and lifetime as a function of C-rate, cycle depth, and SOC level. However, the lifetime model does not take into account the effect of charge rate on battery degradation, or other parameters such as external temperature. The paper studies simple cycles but it is noted that complex cycles can be analyzed using this Rainflow method. Tracking and predicting lifetime can be improved by updating the rated power with a more detailed system analysis (e.g., using a seasonal power balance distribution). The effect of irregular battery cycles of different SOC levels on the rate of degradation was considered by the authors of [69], using the proposed linearized model for BESS participation in the energy market. The authors also plan to investigate the effect of different cycling modes in other power system applications on the BESS capacity fading rate, provision of regulation, and spinning reserves, which entails shorter BESS cycling times.

Analysis of the degradation of BESSs that are involved in the frequency regulation of the grid were considered in [65,67,71–76]. The paper [65] presents an algorithm for finding the optimal charging schedule based on projections of future supply and demand and taking into account battery degradation, as well as the reserve of primary frequency regulation. The authors apply a semi-empirical battery degradation model for both EVs (to estimate the operating costs of electric vehicles) and BESSs with a solar power plant. The model is based on 18,650 nickel-manganese-cobalt (NMC) cells. It takes into account temperature, current rate, and extra ampere hours, but the temperature is also taken as constant at 35 °C.

Studies of the BESS capacity fading in a system with a large penetration of RES (about 30%) are covered in [67] with respect to secondary frequency regulation. However, it should be noted that the optimal lifetime was not studied. The main focus was to investigate how BESSs of different sizes degrade over time under the same grid conditions. Studies of optimal SOC idling, recharging strategy, SOC limits, and other relevant parameters are suggested as future work. According to the charging profile, the cycling and idle time of the battery in the power grid with a large penetration of WPP is determined. To determine cyclic aging performance the authors use the following parameters: average SOC, DOD, number of cycles (obtained with the Rainflow cycle counting algorithm). The SOC and temperature constant of 25 °C are used as parameters for calendar aging.

The paper [71] analyzes the effect of the discharge depth on BESS degradation in any frequency regulation period under real operating conditions, with the current rate and temperature assumed to be constant in the study. The model shows that the design lifetime is reduced to 8.6 years, instead of the rated lifetime of 15 years.

The V2G concept, which presupposes the ability to use electric vehicle battery power as a power system service for power rebalancing and frequency stabilization of the main grid, is becoming more promising due to the high growth rate of the number of electric vehicles. At the same time, most V2G models aim to optimize the use of as much storage capacity as possible without taking into account the degradation of electric vehicle batteries [77,78]. However, the simplified EV charging/discharging mode approach is not economically feasible due to the impact of the extra V2G cycles on battery life [47]. To select a charging management strategy that reduces battery degradation, it is necessary to develop accurate models for predicting battery aging and analyzing the causes of battery degradation. Strategies to minimize the degradation of electric vehicle drives as part of the V2G operation to stabilize the frequency of the power grid are considered in the paper [72]. The paper compares the profits that are obtained by participating in the regulation of the grid frequency and the costs resulting from the degradation of the battery. The influence of the depth of discharge on the battery degradation process at irregular cycles is considered.

The HOMER software is widely used for microgrid modeling, including BESS modeling. In [79], the authors evaluate BESS lifetime prediction using the HOMER software, in which lifetime is estimated by tracking the amount of energy flowing through the storage unit. This does away with the need to consider the depth of various charge-discharge cycles. At that, it is assumed that the properties of the batteries remain unchanged throughout their lifetime and are not affected by external factors such as temperature, etc. SimSES (Simulation of Stationary Energy Storage Systems) software is used to simulate BESS, including an open-source degradation model module. This model assesses the decrease in capacity and performance under various stress factors. The calculated residual capacity is transferred to other modules to continue calculations until the end of the period assessed. A semi-empirical model is built into SimSES to account for the effects of discharge rate, operating temperature, depth of discharge, self-discharge, and calendar aging on the degradation rate [64].

Thus, the aging rates vary for various profiles of the battery use in microgrids for almost all stress factors, of which depth of discharge and temperature remain the most significant. Many studies, however, consider the depth of discharge as simple cycles, do not take into account the stochastic charge/discharge, and overlook the temperature or use it as an unchanged parameter that is equal to the operating temperature. At the same time, according to [70], batteries inside container blocks have large temperature gradients, which cause a significant impact on their degradation. In addition, it must be borne in mind that for each type of lithium-ion battery, the degree of various stress factors will have a different effect, and the cross-dependence of the factors should also be taken into account.

## 4. Survey of Battery Degradation Models

To develop a lifetime model, it is required to obtain experimental data by testing batteries under various conditions, as close as possible to the conditions in which the battery will be used, namely the cyclic nature of operation, downtime, the effects of various stress factors both individually and as a result of their interaction. Basically, tests are performed under laboratory conditions to analyze the degradation response of the battery to different operating conditions [80]. Based on the test data that are obtained, predictive models of battery degradation are built. The simple form of the battery degradation model is the empirical correlation of the observed values such as a capacity, internal resistance and time function, the number of cycles, various aging factors (the depth of cycles, temperature, discharge/charge). Polynomial and exponential power laws, logarithmic, and trigonometric functions [81] are usually used as empirical models. As mentioned earlier, the aging model is based on two conditions leading to various losses of capacity: due to calendar aging and due to cyclic aging [82]. The process of calendar aging, depending on the temperature and degree of charge, is usually described by the empirical law of aging as follows:

$$Q_{loss}^{cal} = B_{cal}(SOC)\exp\left(-\frac{Ea_{cal}}{RT}\right)t^{z_{cal}}$$

where, $B_{cal}$ is a pre -exponential coefficient depending on SOC, expressed in $-\frac{Ah}{S^{z_{cal}}}$, $Ea_{cal}$ is the activation energy that is expressed in J mol$^{-1}$, which describes the dependence of the calendar aging on the temperature expressed in K, and $z_{cal}$ is a dimensionless constant that is equal to about 0.5, given the phenomenon of capacity losses that are associated with the growth of solid electrolyte interphase and diffusion constraints [82].

For cyclic aging, a similar approach is used. In this study, the loss of capacity due to aging depends on the two main factors: current and temperature:

$$Q_{loss}^{cyc} = B_{cyc}\exp\left(\frac{-Ea_{cyc} + \alpha|I|}{RT}\right)Ah^{z_{cyc}}$$

In this expression, $B_{cyc}$ is a pre-exponential coefficient, expressed in $Ah^{1-z_{cyc}}$, which depends on current; $Ea_{cyc}$ is the activation energy for aging cycle expressed in J mole$^{-1}$; $z_{cyc}$ is the exponent that is equal to 0.5. $Ah$ stands for Ah throughput, i.e., the value of charge that is transferred to the cell.

The published research generally distinguishes between four basic models of battery life, as shown in Table 3. This is an electrochemical model [83–86] that is based on physical and chemical laws and describes complex mechanisms representing the most important state variables at any point in the cell and at any time [64]. These models analyze basic degradation processes, such as solid electrolyte interphase interaction and lithium coating, allowing one to determine the loss of lithium concentration and active materials [61]. Such models have high accuracy, but at the same time are of high computational complexity, which makes it impossible to apply them in practice. They can be employed only under laboratory conditions for detailed analysis of chemical and physical processes of the battery under the influence of various factors. Electrochemical models, used mainly to optimize the physical aspects of battery design, characterize the fundamental mechanisms of energy production and relate battery design parameters to macroscopic (e.g., battery voltage and current) and microscopic (e.g., concentration distribution) information. However, they are complex and time-consuming because they involve a system of differential equations of the spatial part with variable time. The solution to the above requires daytime modeling time, complex numerical algorithms, and battery-specific information that is difficult to obtain because of the confidential nature of the technology.

Circuit-based models represent the equivalent electrical circuit of a battery consisting of electrical elements such as resistors, capacitors, voltage, and current sources [64]. But the equivalent circuit representation is the most popular because it describes electrochemical processes using a simple electrical circuit. ECMs are a trade-off between computational simplicity and accuracy. In particular, the model that is augmented with a parallel RC circuit can reproduce the effects of battery polarization describing the dynamic characteristics, and the more elements of RC circuits are in the circuit, the more accurate it is, but the complexity of resolution increases. The purpose of the model is to update the actual battery capacity to get an accurate value of the battery charge. Typically, ECM is used in a degradation model to obtain a lifetime analysis [87]. For example, degradation characteristics such as ohmic resistance and polarization resistance, extracted from the Thevenin's model, are approximately linearly related to battery capacity degradation; the increase in resistance increases as the capacitance fades. Further, these parameters are used as input data to create a degradation model that is based on the extreme learning machine (ELM) in [88]. Since the ECM parameters depend on many factors such as SOC, temperature, and discharge rate, the batteries are tested under different operating conditions. However, obtaining experimental data is a time-consuming and very costly process, so it becomes relevant to use virtual physical models or digital twins that are capable of the accurate simulation of the dynamics and behavior of the real-world environment and that can synthesize additional datasets, to evaluate the effectiveness of optimization approaches [89].

The dependency of ECM parameters on the electrochemical properties of the battery was examined in [90] using a pseudo-two-dimensional (P2D) model. The virtual P2D model simulates changes in electrochemical properties and then the ECM parameters are determined.

The relationship between the parameters of RC models and SOC and temperature is presented in the published research [91–94]. In [95], the authors conducted several tests of the battery at different temperatures (15 °C to 45 °C) and SOH of the battery. In the study, a thorough assessment was made of the variation of the battery model parameters that was caused by different operating conditions. The results represent the dependency of the internal resistance on temperature. The behavior of the parameters is characterized by a higher resistance at low temperatures and a decrease as higher temperatures are reached. The resistance values are higher for the old battery cell than the values corresponding to the initial lifetime of the cell. The sensitivity of the capacity to temperature using temperature-dependent correction coefficients has also been discussed in [96,97]. These extracted parameters can be used to build degradation models that are based on machine learning.

Since the SOC changes as the battery is charged and discharged, the SOC is considered in the studies [97] as another state of the system, added to the fragment of the equivalent circuit to model it. Such a circuit is an isolated circuit with a controlled current source that simulates the capacity of the battery. In the above, the total battery capacity is calculated with a correction factor to account for the temperature dependency of the battery capacity and a correction factor to simulate the aging process (this is the number of charge-discharge cycles). The resistance element also simulates the self-discharge of the battery. In the study, the authors extracted battery parameters from four LGHG2 (3Ah) units that were connected in series at different discharge currents and SoC values to account for the dynamic effects of capacity fading rate to predict run time, state of charge tracking, and I-V characteristics.

Basically, simplified performance-based models that are based on mathematical equations, such as empirical models, are used to predict battery capacity fading in stationary energy storage systems. Models that are based on modern algorithms, such as machine learning, are also growing in popularity. Performance models predict capacity fading over the entire lifetime, but their accuracy depends on the quality and quantity of the dataset under study and the choice of modeling methodology [80].

Empirical models describe by means of mathematical equations the relationship between battery capacity and cycles, without considering electrochemical processes. Semi-empirical models (SEM) [21,62,65,70–72] are based on the value of the transferred charge multiplied by a weighted linear or nonlinear coefficient that is derived from the results of long-term tests or accelerated tests [64,80]. The model can be built based on a wide range of input values that are responsible for both cycling and calendar aging. In contrast to empirical models, SEM incorporates electrochemical principles in the battery capacity degradation model [98]. The efficacy of the model is verified on the basis of real-world profiles by comparing the simulated capacity with actual measurements. However, the accuracy of the model depends on the quality of the generated data, going beyond which leads to a decrease in the accuracy of the model.

Black box models, such as data-driven models, do not require knowledge of battery chemistry; learning is based on available historical data. However, such models are still computationally quite complex due to the need for a large training sample size to achieve high accuracy. Data-driven methods include Support Vector Machines (SVM) [99], Neural Networks (NN) [100–102], and Gaussian/Bayesian Process Regression (GPR) [100,103]. A comparison of [98] machine learning-based prediction models showed that GPR and SVM are more efficient compared to RF (random forest), GBRT (gradient boosting regression tree), and NN. As the models are relatively simple, they can be built based on small samples, unlike NN, which showed worse prediction results, due to the use of large amounts of data to train the network. A serious limitation of such models is the large amount of experimental data that are required to build a data-driven model. The availability of data is now increasing due to the development of the Internet of Things technology. However, when building ML models, it is necessary to obtain experimental data that are close to the real-world operating profile, taking into account the cyclic nature of operation and the interrelation of various stress factors, as well as training data on rare events/conditions, such as the battery failures. Carrying out such tests in the laboratory requires a significant amount of funding and time. Therefore, the use of the digital twin approach allows one to simulate the variables of operating conditions in the real-world in the form of a virtual physical system. Such a system will provide enough data to improve ML models. The paper [104] uses a digital twin of the battery to describe the relationship between cell voltage and cell state of charge (SOC). The actual battery capacity can be obtained by almost completely discharging this digital model. The digital twin implements real-world scenarios with a physical and controlled models. The physical model is built on the basis of physical rules and the data-driven models (DDMs) are based on a large array of real-world data. Together, the models aim to accurately simulate real-world scenarios and synthesize additional datasets, i.e., a transition from physical to a digital model is carried out using descriptive artificial intelligence/machine learning [104]. The potential capabilities of digital twins as output parameters of the model given in [105] include the identification of stress factors and the determination of their impact on the parameters of the model to evaluate the battery degradation indices, the choice of the optimal charging strategy based on the updated model integrated with data on charging, and the control of thermal conditions. The digital model is also flexible since it can download various degradation algorithms and suit various types of batteries [106].

Event-oriented models are quite common due to their simplicity, since they are based only on the curve of the relationship between the number of cycles and the depth of discharge. The Rainflow model is based on an event-oriented aging model. The method allows one to analyze complex cycles in applications such as PV power smoothing [64] or frequency regulation in the power grid with WT [67]. In contrast to the traditional Rainflow algorithm of converting the charging and discharging process into several half-cycles and full cycles, free of the influence of other external factors, the authors of [68] proposed a modified Rainflow algorithm that also takes into account the ambient temperature and SOC of the battery under real-world operating conditions. Since this algorithm is responsible only for the cycling aging of the battery, it can be applied together with the method of counting the calendar aging [67].

**Table 3.** Advantages and disadvantages of lifetime models [64,80,98,107].

| Lifetime Model | Advantages | Disadvantages | Input Parameters and Stress Factors |
|---|---|---|---|
| **Physicochemical model** | High accuracy | High complexity and duration of the computational process. Requires extensive information about chemical and physical interactions | C-rate, DoD, SOC, Power, Ah-throughput |
| **Event-oriented aging model** | Low computational complexity | Takes into account only the lifetime stress factor, which is the depth of discharge. Low accuracy. | DOD |
| **Semi-empirical model** | Represents a trade-off between computational complexity and accuracy | Prediction accuracy with unknown profiles depends on the quality of the generated dataset; it is limited by the operating conditions of the data under study, beyond which the prediction accuracy decreases. It is difficult to accurately predict battery life at the early stages of degradation | T, DoD, SoC, C-rate, Ah-throughput, the number of cycles, $T_{calendar}$, DoD, $SoC_{calendar,}$ storage duration, Internal resistance. |
| **Data-driven model** | Ability to describe the complex process of battery degradation without the need for an in-depth study of the mechanism. Ability to predict battery life at the early stages of degradation. Accounts for the non-linear degradation of the capacity. High accuracy | The difficulty is in the availability of large amounts of data; model accuracy is directly dependent on the quantity and quality of data | T, DoD, SoC, C-rate, internal resistance, capacity |

Nowadays, semi-empirical models remain widespread to evaluate degradation in a microgrid because they have relatively high accuracy and do not require a large learning sample compared to data-driven models. Nevertheless, the use of data-driven models helped increase the accuracy of predicting the residual capacity of the batteries as it factors in the non-linear nature of degradation, especially for batteries of the second service life. A limiting factor for the use of such models, as noted by many researchers, is an insufficient sample size for the complete modeling of various scenarios. The development of the digital battery model and its use together with the model of battery degradation will considerably expand the use of DDM.

## 5. Conclusions

Most of the optimization problems of power systems with ESSs do not take into account degradation, which renders their use non-viable. Determining the power and energy capacity of ESSs without considering battery degradation can lead to inflated revenues and drastically reduce reliability. The use of accurate models that take into account battery aging factors show that the predicted degradation rate is several times [70,108] higher than that which is stated by the manufacturers in stationary systems of use, such as RES-based power systems, EV2G. Aging prediction models allow one to develop a strategy for operating batteries in such applications, thus reducing the strain on them through a variety of approaches.

The difficulty in assessing the actual capacity and forecasting the service life of the battery is due to the non -linear nature of degradation, which is especially true in the second service cycle that is characterized by an accelerated process of degradation, and cross-dependence of aging factors. In addition, stress factors have different effects for various types of lithium-ion batteries. All this complicates the construction of an accurate model of battery degradation for the microgrid application. Most of the existing models use a simplified approach of cycling of the battery, however, due to the stochastic generation and load, the batteries can be prone to high rates of degradation that are caused by frequent charging cycles. In the energy systems with a large share of renewables, the batteries are subject to deep discharge, and in the case of frequency regulation, they are prone to high impulse currents and frequent short cycles. Many models of aging apply temperature as an unchanged aging factor, however, this factor has a strong effect on the degradation of the battery in stationary systems, along with the depth of the charge.

The estimation of the BESS service life relies basically on the performance-degradation models, such as semi-empirical models. However, the accuracy of such models largely depends on the quality and quantity of data that are used for their construction. The data-driven models are more promising in terms of accuracy, however, their use is complicated by a large size of training sample. In addition, the difficulty in obtaining extended data covering various operating scenarios, including those using different types of electrochemical batteries, contributes to the decrease in the performance of these models. However, independent tests in the laboratory require significant funds and time. Therefore, the use of virtual models such as a pseudo-two-dimensional (P2D) model and digital twin allows simulating variable operating conditions of real-world batteries in the form of a virtual physical system and provides sufficient data to improve DDM.

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## References

1. Saez-de-Ibarra, A.; Martinez-Laserna, E.; Stroe, D.; Swierczynski, M.; Rodríguez, P. Sizing study of second life Li-ion batteries for enhancing renewable energy grid integration. *IEEE Trans. Ind. Appl.* **2016**, *52*, 4999–5008. [CrossRef]
2. Rasmussen, C.N. Energy storage for improvement of wind power characteristics. In Proceedings of the 2011 IEEE Trondheim PowerTech, Trondheim, Norway, 19–23 June 2011; pp. 1–8. [CrossRef]
3. Zantye, M.S.; Gandhi, A.; Wang, Y.; Vudata, S.P.; Bhattacharyya, D.; Hasan, M.F. Optimal design and integration of decentralized electrochemical energy storage with renewables and fossil plants. *Energy Environ. Sci.* **2022**. [CrossRef]
4. Pinson, P.; Papaefthymiou, G.; Klockl, B.; Verboomen, J. Dynamic sizing of energy storage for hedging wind power forecast uncertainty. In Proceedings of the 2009 IEEE Power & Energy Society General Meeting, Calgary, AB, Canada, 26–30 July 2009; pp. 1–8. [CrossRef]
5. Lombardi, P.; Styczynski, Z.; Sokolnikova, T.; Suslov, K. Use of energy storage in Isolated Micro Grids. In Proceedings of the 2014 Power Systems Computation Conference, Wroclaw, Poland, 18–22 August 2014. [CrossRef]
6. Perez, A.; Moreno, R.; Moreira, R.; Orchard, M.; Strbac, G. Effect of battery degradation on multi-service portfolios of energy storage. *IEEE Trans. Sustain. Energy* **2016**, *7*, 1718–1729. [CrossRef]

7. Schmalstieg, J.; Käbitz, S.; Ecker, M.; Sauer, D.U. A Holistic Aging Model for Li(NiMnCo)O2 Based 18650 Lithium-Ion Batteries. *J. Power Sources* **2014**, *257*, 325–334. [CrossRef]
8. Shang, Y.; Wu, W.; Guo, J.; Ma, Z.; Sheng, W.; Lv, Z. Chenran Fu Stochastic dispatch of energy storage in microgrids: An augmented reinforcement learning approach. *Appl. Energy* **2020**, *261*, 114423. [CrossRef]
9. Korjani, S.; Mureddu, M.; Facchini, A.; Damiano, A. Aging cost optimization for planning and management of energy storage systems. *Energies* **2017**, *10*, 1916. [CrossRef]
10. Suslov, K.; Shushpanov, I.; Buryanina, N.; Ilyushin, P. Flexible power distribution networks: New opportunities and applications. In Proceedings of the 9th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS), Prague, Czech Republic, 2–4 May 2020; pp. 57–64. [CrossRef]
11. Gu, B.; Mao, C.; Liu, B.; Wang, D.; Fan, H.; Zhu, J.; Sang, Z. Optimal Charge/Discharge Scheduling for Batteries in Energy Router-based Microgrids of Prosumers via Peer-to-Peer Trading. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1315–1328. [CrossRef]
12. Tobajas, J.; Garcia-Torres, F.; Roncero-Sánchez, P.; Vázquez, J.; Bellatreche, L.; Nieto, E. Resilience-oriented schedule of microgrids with hybrid energy storage system using model predictive control. *Appl. Energy* **2022**, *306*, 118092. [CrossRef]
13. Gupta, S.; Maulik, A.; Das, D.; Singh, A. Coordinated stochastic optimal energy management of grid-connected microgrids considering demand response, plug-in hybrid electric vehicles, and smart transformers. *Renew. Sustain. Energy Rev.* **2021**, *155*, 111861. [CrossRef]
14. Ilyushin, P.V.; Sukhanov, O.A. The Structure of Emergency-Management Systems of Distribution Networks in Large Cities. *Russ. Electr. Eng.* **2014**, *85*, 133–137. [CrossRef]
15. Sufyan, M.; Abd, R.N.; Tan, C.; Muhammad, M.; Sheikh Raihan, S.R. Optimal sizing and energy scheduling of isolated microgrid considering the battery lifetime degradation. *PLoS ONE* **2019**, *14*, e0211642. [CrossRef]
16. Suslov, K.V. A microgrid concept for isolated territories of Russia. In Proceedings of the IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), Berlin, Germany, 14–17 October 2012; pp. 1–5. [CrossRef]
17. Jing, Y.; Wang, H.; Hu, Y.; Li, C. A Grid-Connected Microgrid Model and Optimal Scheduling Strategy Based on Hybrid Energy Storage System and Demand-Side Response. *Energies* **2022**, *15*, 1060. [CrossRef]
18. Andrenacci, N.; Vellucci, F.; Sglavo, V. The Battery Life Estimation of a Battery under Different Stress Conditions. *Batteries* **2021**, *7*, 88. [CrossRef]
19. Yang, Y.; Li, H.; Aichhorn, A.; Zheng, J.; Greenleaf, M. Sizing strategy of distributed battery storage system with high penetration of photovoltaic for voltage regulation and peak load shaving. *IEEE Trans. Smart Grid* **2013**, *5*, 982–991. [CrossRef]
20. Narayan, N.; Papakosta, T.; Vega-Garita, V.; Qin, Z.; Popovic-Gerber, J.; Bauer, P.; Zeman, M. Estimating battery lifetimes in Solar Home System design using a practical modelling methodology. *Appl. Energy* **2018**, *228*, 1629–1639. [CrossRef]
21. Shin, H.; Hur, J. Optimal energy storage sizing with battery augmentation for renewable-plus-storage power plants. *IEEE Access* **2020**, *8*, 187730–187743. [CrossRef]
22. Dulout, J.; Jammes, B.; Alonso, C.; Anvari-Moghaddam, A.; Luna, A.; Guerrero, J.M. Optimal sizing of a lithium battery energy storage system for grid-connected photovoltaic systems. In Proceedings of the 2017 IEEE Second International Conference on DC Microgrids (ICDCM), Nuremburg, Germany, 27–29 June 2017; pp. 582–587. [CrossRef]
23. Shushpanov, I.; Suslov, K.; Ilyushin, P.; Sidorov, D. Towards the flexible distribution networks design using the reliability performance metric. *Energies* **2021**, *14*, 6193. [CrossRef]
24. Ilyushin, P.V. Emergency and post-emergency control in the formation of micro-grids. *E3S Web Conf.* **2017**, *25*, 02002. [CrossRef]
25. Carpinelli, G.; Mottola, F.; Proto, D. Addressing technology uncertainties in battery energy storage sizing procedures. *Int. J. Emerg. Electr. Power Syst.* **2017**, *18*, 2. [CrossRef]
26. Huo, D.; Santos, M.; Sarantakos, I.; Resch, M.; Wade, N.; Greenwood, D. A reliability-aware chance-constrained battery sizing method for island microgrid. *Energy* **2022**, *251*, 123978. [CrossRef]
27. Lan, H.; Wen, S.; Fu, Q.; Yu, D.C.; Zhang, L. Modeling analysis and improvement of power loss in microgrid. *Math. Probl. Eng.* **2015**, *2015*, 493560. [CrossRef]
28. Soltani, N.Y.; Nasiri, A. Chance-constrained optimization of energy storage capacity for microgrids. *IEEE Trans. Smart Grid* **2020**, *11*, 2760–2770. [CrossRef]
29. Yue, M.; Wang, X. Grid inertial response-based probabilistic determination of energy storage system capacity under high solar penetration. *IEEE Trans. Sustain. Energy* **2015**, *6*, 1039–1049. [CrossRef]
30. Bahramirad, S.; Reder, W.; Khodaei, A. Reliability-constrained optimal sizing of energy storage system in a microgrid. *IEEE Trans. Smart Grid* **2012**, *3*, 2056–2062. [CrossRef]
31. Knap, V.; Chaudhary, S.K.; Stroe, D.I.; Swierczynski, M.; Craciun, B.I.; Teodorescu, R. Sizing of an energy storage system for grid inertial response and primary frequency reserve. *IEEE Trans. Power Syst.* **2015**, *31*, 3447–3456. [CrossRef]
32. Bhusal, N.; Gautam, M.; Benidris, M.; Louis, S.J. Optimal sizing and siting of multi-purpose utility-scale shared energy storage systems. In Proceedings of the 2020 52nd North American Power Symposium (NAPS), Tempe, AZ, USA, 11–13 April 2021; pp. 1–6. [CrossRef]
33. Baloyi, T.; Chowdhury, S. Sizing and Selection of Battery Energy Storage System for Time of Use Arbitrage in a Commercial Building in South Africa. In Proceedings of the 2021 IEEE PES/IAS PowerAfrica, Nairobi, Kenya, 23–27 August 2021; pp. 1–5.
34. Luo, Y.; Shi, L.; Tu, G. Optimal sizing and control strategy of isolated grid with wind power and energy storage system. *Energy Convers. Manag.* **2014**, *80*, 407–415. [CrossRef]

35. Astaneh, M.; Roshandel, R.; Dufo-López, R.; Bernal-Agustín, J.L. A novel framework for optimization of size and control strategy of lithium-ion battery based off-grid renewable energy systems. *Energy Convers. Manag.* **2018**, *175*, 99–111. [CrossRef]
36. Arabali, A.; Ghofrani, M.; Etezadi-Amoli, M.; Fadali, M.S. Stochastic performance assessment and sizing for a hybrid power system of Solar/Wind/Energy Storage. *IEEE Trans. Sustain. Energy* **2014**, *5*, 2. [CrossRef]
37. Awad, A.S.; El-Fouly, T.H.; Salama, M.M. Optimal ESS allocation for benefit maximization in distribution networks. *IEEE Trans. Smart Grid* **2015**, *8*, 1668–1678. [CrossRef]
38. Zhang, Y.; Lundblad, A.; Campana, P.E.; Benavente, F.; Yan, J. Battery sizing and rule-based operation of grid-connected photovoltaic-battery system: A case study in Sweden. *Energy Convers. Manag.* **2017**, *133*, 249–263. [CrossRef]
39. Alsaidan, I.; Khodaei, A.; Gao, W. A comprehensive battery energy storage optimal sizing model for microgrid applications. *IEEE Trans. Power Syst.* **2017**, *33*, 3968–3980. [CrossRef]
40. Zhang, Y.J.A.; Zhao, C.; Tang, W.; Low, S.H. Profit-maximizing planning and control of battery energy storage systems for primary frequency control. *IEEE Trans. Smart Grid* **2018**, *9*, 712–723. [CrossRef]
41. Fioriti, D.; Pellegrino, L.; Lutzemberger, G.; Micolano, E.; Poli, D. Optimal sizing of residential battery systems with multi-year dynamics and a novel rainflow-based model of storage degradation: An extensive Italian case study. *Electr. Power Syst. Res.* **2022**, *203*, 107675. [CrossRef]
42. Amini, M.; Khorsandi, A.; Vahidi, B.; Hosseinian, S.H.; Malakmahmoudi, A. Optimal sizing of battery energy storage in a microgrid considering capacity degradation and replacement year. *Electr. Power Syst. Res.* **2021**, *195*, 107170. [CrossRef]
43. Tahir, H.; Park, D.H.; Park, S.S.; Kim, R.Y. Optimal ESS size calculation for ramp rate control of grid-connected microgrid based on the selection of accurate representative days. *Int. J. Electr. Power Energy Syst.* **2022**, *139*, 108000. [CrossRef]
44. Ilyushin, P.V.; Pazderin, A.V. Requirements for power stations islanding automation an influence of power grid parameters and loads. In Proceedings of the International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), Moscow, Russia, 15–18 May 2018. [CrossRef]
45. Eroshenko, S.A.; Ilyushin, P.V. Features of implementing multi-parameter islanding protection in power districts with distrib-uted generation units. In Proceedings of the 2018 IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga, Latvia, 12–13 November 2018. [CrossRef]
46. Ecker, M.; Nieto, N.; Käbitz, S.; Schmalstieg, J.; Blanke, H.; Warnecke, A.; Sauer, D.U. Calendar and cycle life study of Li (NiMnCo) $O_2$-based 18650 lithium-ion batteries. *J. Power Sources* **2014**, *248*, 839–851. [CrossRef]
47. Uddin, K.; Dubarry, M.; Glick, M.B. The viability of vehicle-to-grid operations from a battery technology and policy perspective. *Energy Policy* **2018**, *113*, 342–347. [CrossRef]
48. Faessler, B. Stationary, second use battery energy storage systems and their applications: A research review. *Energies* **2021**, *14*, 2335. [CrossRef]
49. Yang, Y.; Lian, C.; Ma, C.; Zhang, Y. Research on energy storage optimization for large-scale PV power stations under given long-distance delivery mode. *Energies* **2019**, *13*, 27. [CrossRef]
50. Gonçalo, C.; Brouhard, T.; DeForest, N.; Wang, D.; Heleno, M.; Kotzur, L. Battery aging in multi-energy microgrid design using mixed integer linear programming. *Appl. Energy* **2018**, *231*, 1059–1069. [CrossRef]
51. Lee, J.O.; Kim, Y.S.; Kim, T.H.; Moon, S.I. Novel droop control of battery energy storage systems based on battery degradation cost in islanded DC microgrids. *IEEE Access* **2020**, *8*, 119337–119345. [CrossRef]
52. Ju, C.; Wang, P.; Goel, L.; Xu, Y. A two-layer energy management system for microgrids with hybrid energy storage considering degradation costs. *IEEE Trans. Smart Grid* **2017**, *9*, 6047–6057. [CrossRef]
53. Obukhov, S.G.; Plotnikov, I.A.; Masolov, V.G. A Study of Battery Storage Operating Life in Isolated Power Systems with Renewable Energy Sources. *Ipolytech J.* **2021**, *25*, 463–477. [CrossRef]
54. Wang, L.; Qiu, J.; Wang, X.; Chen, L.; Cao, G.; Wang, J.; He, X. Insights for understanding multiscale degradation of $LiFePO_4$ cathodes. *eScience* **2022**, *2*, 125–137. [CrossRef]
55. Olmos, J.; Gandiaga, I.; Saez-de-Ibarra, A.; Larrea, X.; Nieva, T.; Aizpuru, I. Modelling the cycling degradation of Li-ion batteries: Chemistry influenced stress factors. *J. Energy Storage* **2021**, *40*, 102765. [CrossRef]
56. Alipour, M.; Ziebert, C.; Conte, F.V.; Kizilel, R. A Review on Temperature-Dependent Electrochemical Properties, Aging, and Performance of Lithium-Ion Cells. *Batteries* **2020**, *6*, 35. [CrossRef]
57. Stroe, D.I.; Świerczyński, M.; Stan, A.I.; Teodorescu, R.; Andreasen, S.J. Accelerated lifetime testing methodology for lifetime estimation of lithium-ion batteries used in augmented wind power plants. *IEEE Trans. Ind. Appl.* **2014**, *50*, 4006–4017. [CrossRef]
58. Wang, J.; Purewal, J.; Liu, P.; Hicks-Garner, J.; Soukazian, S.; Sherman, E.; Sorenson, A.; Vu, L.; Tataria, H.; Verbrugge, M.W. Degradation of lithium ion batteries employing graphite negatives and nickel–cobalt–manganese oxide+ spinel manganese oxide positives: Part 1, aging mechanisms and life estimation. *J. Power Sources* **2014**, *269*, 937–948. [CrossRef]
59. Saxena, S.; Roman, D.; Robu, V.; Flynn, D.; Pecht, M. Battery stress factor ranking for accelerated degradation test planning using machine learning. *Energies* **2021**, *14*, 723. [CrossRef]
60. Dubarry, M.; Qin, N.; Brooker, P. Calendar aging of commercial Li-ion cells of different chemistries—A review. *Curr. Opin. Electrochem.* **2018**, *9*, 106–113. [CrossRef]
61. He, W.; Pecht, M.; Flynn, D.; Dinmohammadi, F. A physics-based electrochemical model for lithium-ion battery state-of-charge estimation solved by an optimised projection-based method and moving-window filtering. *Energies* **2018**, *11*, 2120. [CrossRef]

62. Xu, B.; Oudalov, A.; Ulbig, A.; Andersson, G.; Kirschen, D.S. Modeling of lithium-ion battery degradation for cell life assessment. *IEEE Trans. Smart Grid* **2016**, *9*, 1131–1140. [CrossRef]
63. Sauer, D.U.; Wenzl, H. Comparison of different approaches for lifetime prediction of electrochemical systems—Using lead-acid batteries as example. *J. Power Sources* **2008**, *176*, 534–546. [CrossRef]
64. Diaz, V.S.; Cantane, D.A.; Santos, A.Q.O.; Ando Junior, O.H. Comparative analysis of degradation assessment of battery energy storage systems in PV smoothing application. *Energies* **2021**, *14*, 3600. [CrossRef]
65. Vermeer, W.; Chandra Mouli, G.R.; Bauer, P. Real-time building smart charging system based on PV forecast and Li-Ion battery degradation. *Energies* **2020**, *13*, 3415. [CrossRef]
66. Lee, M.; Park, J.; Na, S.I.; Choi, H.S.; Bu, B.S.; Kim, J. An analysis of battery degradation in the integrated energy storage system with solar photovoltaic generation. *Electronics* **2020**, *9*, 701. [CrossRef]
67. Sandelic, M.; Stroe, D.I.; Iov, F. Battery storage-based frequency containment reserves in large wind penetrated scenarios: A practical approach to sizing. *Energies* **2018**, *11*, 3065. [CrossRef]
68. Wu, Y.; Xu, T.; Meng, H.; Wei, W.; Cai, S.; Guo, L. Energy storage capacity allocation for distribution grid applications considering the influence of ambient temperature. *IET Energy Syst. Integr.* **2022**, *4*, 143–156. [CrossRef]
69. Wang, Y.; Zhou, Z.; Botterud, A.; Zhang, K.; Ding, Q. Stochastic coordinated operation of wind and battery energy storage system considering battery degradation. *J. Mod. Power Syst. Clean Energy* **2016**, *4*, 581–592. [CrossRef]
70. Gräf, D.; Marschewski, J.; Ibing, L.; Huckebrink, D.; Fiebrandt, M.; Hanau, G.; Bertsch, V. What drives capacity degradation in utility-scale battery energy storage systems? The impact of operating strategy and temperature in different grid applications. *J. Energy Storage* **2022**, *47*, 103533. [CrossRef]
71. Yan, G.; Liu, D.; Li, J.; Mu, G. A cost accounting method of the Li-ion battery energy storage system for frequency regulation considering the effect of life degradation. *Prot. Control. Mod. Power Syst.* **2018**, *3*, 4. [CrossRef]
72. Scarabaggio, P.; Carli, R.; Cavone, G.; Dotoli, M. Smart control strategies for primary frequency regulation through electric vehicles: A battery degradation perspective. *Energies* **2020**, *13*, 4586. [CrossRef]
73. Haidl, P.; Buchroithner, A.; Schweighofer, B.; Bader, M.; Wegleiter, H. Lifetime analysis of energy storage systems for sustainable transportation. *Sustainability* **2019**, *11*, 6731. [CrossRef]
74. Baure, G.; Dubarry, M. Durability and reliability of EV batteries under electric utility grid operations: Impact of frequency regulation usage on cell degradation. *Energies* **2020**, *13*, 2494. [CrossRef]
75. Świerczyński, M.; Stroe, D.I.; Lærke, R.; Stan, A.I.; Kjær, P.C.; Teodorescu, R.; Kær, S.K. Field experience from Li-ion BESS delivering primary frequency regulation in the Danish energy market. *Ecs Trans.* **2014**, *61*, 1. [CrossRef]
76. Stroe, D.I.; Knap, V.; Swierczynski, M.; Stroe, A.I.; Teodorescu, R. Operation of a grid-connected lithium-ion battery energy storage system for primary frequency regulation: A battery lifetime perspective. *IEEE Trans. Ind. Appl.* **2016**, *53*, 430–438. [CrossRef]
77. Peng, C.; Zou, J.; Lian, L.; Li, L. An optimal dispatching strategy for V2G aggregator participating in supplementary frequency regulation considering EV driving demand and aggregator's benefits. *Appl. Energy* **2017**, *190*, 591–599. [CrossRef]
78. Dik, A.; Omer, S.; Boukhanouf, R. Electric Vehicles: V2G for Rapid, Safe, and Green EV Penetration. *Energies* **2022**, *15*, 803. [CrossRef]
79. Lambert, T.; Gilman, P.; Lilienthal, P. Micropower system modeling with HOMER. *Integr. Altern. Sources Energy* **2006**, *1*, 379–385. [CrossRef]
80. Hosen, M.S.; Jaguemont, J.; Van Mierlo, J.; Berecibar, M. Battery lifetime prediction and performance assessment of different modeling approaches. *Iscience* **2021**, *24*, 102060. [CrossRef]
81. Jin, X.; Vora, A.P.; Hoshing, V.; Saha, T.; Shaver, G.M.; Wasynczuk, O.; Varigonda, S. Comparison of Li-ion battery degradation models for system design and control algorithm development. In Proceedings of the 2017 American Control Conference (ACC), Seattle, WA, USA, 24–26 May 2017; pp. 74–79. [CrossRef]
82. Petit, M.; Prada, E.; Sauvant-Moynot, V. Development of an empirical aging model for Li-ion batteries and application to assess the impact of Vehicle-to-Grid strategies on battery lifetime. *Appl. Energy* **2016**, *172*, 398–407. [CrossRef]
83. Li, J.; Landers, R.G.; Park, J. A comprehensive single-particle-degradation model for battery state-of-health prediction. *J. Power Sources* **2020**, *456*, 227950. [CrossRef]
84. Wang, J.; Liu, P.; Hicks-Garner, J.; Sherman, E.; Soukiazian, S.; Verbrugge, M.; Tataria, H.; Musser, J.; Finamore, P. Cycle-life model for graphite-LiFePO4 cells. *J. Power Sources* **2011**, *196*, 3942–3948. [CrossRef]
85. Dong, G.; Wei, J. A physics-based aging model for lithium-ion battery with coupled chemical/mechanical degradation mechanisms. *Electrochim. Acta* **2021**, *395*, 139133. [CrossRef]
86. Wang, D.; Zhang, Q.; Huang, H.; Yang, B.; Dong, H.; Zhang, J. An electrochemical–thermal model of lithium-ion battery and state of health estimation. *J. Energy Storage* **2022**, *47*, 103528. [CrossRef]
87. Gailani, A.; Al-Greer, M.; Short, M.; Crosbie, T. Degradation cost analysis of li-ion batteries in the capacity market with different degradation models. *Electronics* **2020**, *9*, 90. [CrossRef]
88. Chen, L.; Wang, H.; Liu, B.; Wang, Y.; Ding, Y.; Pan, H. Battery state-of-health estimation based on a metabolic extreme learning machine combining degradation state model and error compensation. *Energy* **2021**, *215*, 119078. [CrossRef]
89. Lv, C.; Zhou, X.; Zhong, L.; Yan, C.; Srinivasan, M.; Seh, Z.W.; Liu, C.; Pan, H.; Li, S.; Wen, Y.; et al. Machine learning: An advanced platform for materials development and state prediction in lithium-ion batteries. *Adv. Mater.* **2022**, *34*, 2101474. [CrossRef]

90. Barzacchi, L.; Lagnoni, M.; Di Rienzo, R.; Bertei, A.; Baronti, F. Enabling early detection of lithium-ion battery degradation by linking electrochemical properties to equivalent circuit model parameters. *J. Energy Storage* **2022**, *50*, 104213. [CrossRef]
91. Dişçi, F.N.; El-Kahlout, Y.; Balıkçı, A. Li-ion battery modeling and SOC estimation using extended Kalman filter. In Proceedings of the 10th International Conference on Electrical and Electronics Engineering (ELECO), Bursa, Turkey, 30 November–2 December 2017; pp. 166–169.
92. Diab, Y.; Auger, F.; Schaeffer, E.; Wahbeh, M. Estimating lithium-ion battery state of charge and parameters using a continuous-discrete extended kalman filter. *Energies* **2017**, *10*, 1075. [CrossRef]
93. Khandorin, M.M.; Bukreev, V.G. Method to estimate the available capacity of a lithium-ion battery when the battery temperature changes. *TUSUR Rep.* **2017**, *20*, 2. [CrossRef]
94. Xia, B.; Zhang, Z.; Lao, Z.; Wang, W.; Sun, W.; Lai, Y.; Wang, M. Strong tracking of a h-infinity filter in lithium-ion battery state of charge estimation. *Energies* **2018**, *11*, 1481. [CrossRef]
95. Nikolian, A.; Firouz, Y.; Gopalakrishnan, R.; Timmermans, J.M.; Omar, N.; Van den Bossche, P.; Van Mierlo, J. Lithium ion batteries—Development of advanced electrical equivalent circuit models for nickel manganese cobalt lithium-ion. *Energies* **2016**, *9*, 360. [CrossRef]
96. Patel, D.D.; Sharma, S.; Salameh, Z.M. Electric vehicle grade lithium polymer battery model using PSCAD. In Proceedings of the 2014 IEEE PES General Meeting | Conference & Exposition, National Harbor, MD, USA, 27–31 July 2014. [CrossRef]
97. El Mejdoubi, A.; Oukaour, A.; Chaoui, H.; Gualous, H.; Sabor, J.; Slamani, Y. State-of-Charge and State-of-Health Lithium-Ion Batteries' Diagnosis According to Surface Temperature Variation. *IEEE Trans. Ind. Electron.* **2016**, *63*, 2391–2402. [CrossRef]
98. Fei, Z.; Yang, F.; Tsui, K.L.; Li, L.; Zhang, Z. Early prediction of battery lifetime via a machine learning based framework. *Energy* **2021**, *225*, 120205. [CrossRef]
99. Zhang, Y.; Liu, Y.; Wang, J.; Zhang, T. State-of-health estimation for lithium-ion batteries by combining model-based incremental capacity analysis with support vector regression. *Energy* **2022**, *239*, 121986. [CrossRef]
100. Li, X.; Yuan, C.; Li, X.; Wang, Z. State of health estimation for Li-Ion battery using incremental capacity analysis and Gaussian process regression. *Energy* **2020**, *190*, 116467. [CrossRef]
101. Crocioni, G.; Pau, D.; Gruosso, G. Li-Ion Batteries Releasable Capacity Estimation with Neural Networks on Intelligent IoT Micro-controllers. In Proceedings of the 20th Mediterranean Electrotechnical Conference (MELECON), Palermo, Italy, 16–18 June 2020; pp. 153–158. [CrossRef]
102. Chemali, E.; Kollmeyer, P.J.; Preindl, M.; Fahmy, Y.; Emadi, A. A Convolutional Neural Network Approach for Estimation of Li-Ion Battery State of Health from Charge Profiles. *Energies* **2022**, *15*, 1185. [CrossRef]
103. Lyu, Z.; Wang, G.; Tan, C. A novel Bayesian multivariate linear regression model for online state-of-health estimation of Lithium-ion battery using multiple health indicators. *Microelectron. Reliab.* **2022**, *131*, 114500. [CrossRef]
104. Qu, X.; Song, Y.; Liu, D.; Cui, X.; Peng, Y. Lithium-ion battery performance degradation evaluation in dynamic operating conditions based on a digital twin model. *Microelectron. Reliab.* **2020**, *114*, 113857. [CrossRef]
105. Singh, S.; Weeber, M.; Birke, K.P. Implementation of Battery Digital Twin: Approach, Functionalities and Benefits. *Batteries* **2021**, *7*, 78. [CrossRef]
106. Xu, Z.; Xu, J.; Guo, Z.; Wang, H.; Sun, Z.; Mei, X. Design and optimization of a novel microchannel battery thermal management system based on digital twin. *Energies* **2022**, *15*, 1421. [CrossRef]
107. Wang, S.; Guo, D.; Han, X.; Lu, L.; Sun, K.; Li, W.; UweSauer, D.; Ouyang, M. Impact of battery degradation models on energy management of a grid-connected DC microgrid. *Energy* **2020**, *207*, 118228. [CrossRef]
108. Zeynali, S.; Rostami, N.; Ahmadian, A.; Elkamel, A. Stochastic energy management of an electricity retailer with a novel plug-in electric vehicle-based demand response program and energy storage system: A linearized battery degradation cost model. *Sustain. Cities Soc.* **2021**, *74*, 103154. [CrossRef]