

1

Introduction

1.1 Research Background and Significance

The global transition toward carbon neutrality has spurred rapid advancements in industries such as new energy vehicles, large-scale energy storage systems, and smart grids, all of which rely heavily on high-performance, safe, and long-lasting batteries [1]. Lithium-ion batteries (LIBs), renowned for their high energy density, long cycle life, and efficient rechargeability, have become indispensable for these applications [2]. As the demand for energy storage and electric vehicles (EVs) continues to surge, driven by both environmental concerns and technological progress, the battery industry faces unprecedented pressure to meet the growing need for reliable and efficient power sources [3].

However, despite the significant progress in battery technologies, several persistent challenges hinder the development and optimization of battery systems [4]. On the manufacturing side, the industry faces a fundamental mismatch between the increasing demand for batteries and the inconsistency in manufacturing processes. Battery production processes often struggle with issues such as low efficiency, high production costs, and challenges in predicting manufacturing capacity under nonstationary conditions, which can adversely affect both product quality and operational performance [5]. Achieving high manufacturing consistency and reliability is now one of the most pressing concerns in the battery manufacturing sector. Additionally, the increasing complexity of battery designs, such as those for EVs and large-scale energy storage, demands novel approaches to manufacturing, such as more precise grouping methods and optimized production forecasting [6].

From an operational perspective, ensuring the reliable performance of batteries, accurately predicting their remaining useful life (RUL), and estimating their state of charge (SOC) are critical challenges that have not been fully addressed by traditional methods [7]. These issues are further complicated by environmental variability, aging effects, and nonlinear degradation processes, which introduce significant uncertainty. Traditional state estimation methods, such as those based

on Kalman filtering, typically rely on assumptions of Gaussian noise and known system models, which are often incompatible with real-world applications where noise is unknown and time-varying. This mismatch between theoretical assumptions and practical realities underscores the need for more robust and adaptive estimation techniques capable of handling complex and uncertain battery systems.

To address these challenges, the integration of advanced filtering techniques and artificial intelligence (AI) strategies offers promising solutions [8]. Filtering methods, such as zonotopic filtering and particle filters (PFs), provide a solid framework for dealing with uncertainties and noise in battery data. These methods enable more accurate state estimation, particularly in scenarios where the underlying system exhibits nonlinearities and noise cannot be assumed to follow a Gaussian distribution. PFs, in particular, approximate the posterior probability distribution of the system state by using a set of random samples (“particles”), making them well-suited for complex and uncertain environments, such as those encountered in battery systems [9]. In addition to filtering techniques, AI strategies, including deep learning (DL) algorithms like long short-term memory (LSTM) networks and convolutional neural networks (CNNs), have been increasingly applied to battery systems for tasks such as forecasting manufacturing capacity, predicting RUL, and improving SOC estimation [4, 10]. These AI-driven approaches are adept at capturing nonlinear patterns and long-range dependencies in data, making them particularly effective for battery state estimation and performance prediction [11]. By combining the strengths of advanced filtering and AI techniques, this book aims to provide novel solutions to the key challenges faced by the battery industry, driving the transition from traditional manufacturing methods to “smart manufacturing” processes that are more efficient, reliable, and scalable.

The significance of this work lies not only in advancing the theoretical understanding of these techniques but also in providing practical insights that can be applied to real-world battery systems. Through the integration of cutting-edge filtering methods and AI strategies, this book offers a comprehensive approach to enhancing battery performance and optimizing manufacturing processes, which is crucial for meeting the increasing demand for high-quality, reliable batteries in the face of growing global energy needs. Ultimately, this research contributes to the long-term goal of creating smarter, more efficient battery systems that can support a sustainable future.

1.2 Battery Manufacturing

Battery manufacturing is a highly intricate process that encompasses the production of various components, including electrodes, separators, and electrolytes, which are subsequently assembled into functioning energy storage systems [5].

The complexity of this process is further heightened by the stringent requirements for uniformity, high performance, and safety, particularly in applications such as EVs and large-scale energy storage systems. As the demand for advanced batteries continues to rise, manufacturers face the challenge of maintaining high production standards while simultaneously increasing production capacity and reducing costs.

A primary concern in battery production is ensuring the uniformity of the cells. Variations in materials and manufacturing processes, such as discrepancies in electrode coating thickness, separator porosity, or electrolyte composition, can lead to significant differences in battery performance, cycle life, and safety. Such variations can also compromise the long-term reliability of the batteries, making precise quality control essential throughout the entire manufacturing process. Traditional methods of ensuring uniformity often rely on manual inspection and empirical techniques, which are not only time-consuming but can also be prone to error. As a result, there is an increasing interest in automating the manufacturing process and applying more advanced techniques such as machine learning (ML) and AI to achieve greater precision and consistency in production.

Another major challenge in battery manufacturing is predicting and optimizing production capacity, particularly when the manufacturing environment is subject to variability. The production process is often nonstationary, meaning that the data generated during production, such as temperature, pressure, and voltage, can fluctuate over time due to factors like equipment aging, material degradation, and environmental conditions. This variability complicates the task of forecasting production efficiency and capacity. Traditional methods of capacity prediction are ill-equipped to handle such fluctuations, leading to inefficiencies in production scheduling and resource allocation. To address these issues, recent studies have explored the use of data-driven models, such as those incorporating trend filtering segmentation under fuzzy information granulation, which can adapt to changes in the production environment and provide more accurate predictions [6]. These models allow for dynamic adjustments in response to variations in the production process, thus enabling more reliable capacity forecasting.

Furthermore, the grouping of battery cells based on their characteristics, such as voltage, capacity, and internal resistance, is a critical step in ensuring the optimal performance of battery packs. Poorly matched cells can result in imbalanced charge/discharge cycles, reduced capacity, and increased risk of thermal runaway or other safety hazards. While traditional grouping methods typically involve manual sorting and empirical rules, these approaches are time-consuming and often ineffective. Recently, AI-based algorithms, such as genetic algorithms and active equalization methods based on clustering analysis, have been proposed to automate the cell grouping process [12]. These methods improve the accuracy

and efficiency of grouping by using optimization techniques to identify the best match between cells, thus enhancing the overall performance and longevity of the battery pack.

In addition to these technical challenges, battery manufacturers also face increasing pressure to meet both environmental and economic goals. As the demand for EVs and renewable energy systems grows, manufacturers must adopt cost-effective production methods that do not compromise quality or performance [3]. This is especially critical in a highly competitive global battery market, where cost reduction and environmental sustainability are key priorities. The integration of advanced technologies such as AI-driven optimization, robotics, and automated quality control systems is enabling manufacturers to improve efficiency, reduce energy consumption, and minimize waste generation during production. These innovations contribute to the environmental sustainability of the industry while simultaneously enhancing the economic feasibility of battery manufacturing.

In conclusion, battery manufacturing remains a complex and evolving field, with significant challenges related to production consistency, capacity forecasting, and performance optimization. The application of advanced filtering techniques, AI-driven models, and automation presents promising solutions to these challenges, enabling manufacturers to meet the growing demand for high-performance batteries. The future of battery manufacturing will likely see the continued adoption of smart manufacturing techniques that leverage real-time data, AI, and automation to optimize production efficiency and quality.

1.3 Battery Operating Status Analysis

The analysis of battery operating status plays a crucial role in ensuring the safe and efficient operation of battery-powered systems, particularly in applications such as EVs, renewable energy storage, and portable electronic devices. The primary goal of battery status analysis is to estimate key parameters, such as the SOC, state-of-health (SOH), and RUL, which are essential for monitoring the battery's performance and predicting potential failures [2]. These parameters are influenced by various factors, including operational conditions, aging effects, and environmental influences, making their accurate estimation a challenging task.

One of the most critical parameters in battery operating status analysis is the SOC, which indicates the remaining energy in the battery and is essential for efficient operation. Accurate SOC estimation ensures that the battery operates within safe limits, preventing overcharging or deep discharging, both of which can significantly reduce the battery's lifespan. However, SOC estimation is complicated by the nonlinear behavior of batteries, which are influenced by factors

such as temperature, charge/discharge rates, and internal resistance. Traditional SOC estimation techniques, including the open-circuit voltage (OCV) method and coulomb counting, are often insufficient in dynamic environments where the battery's behavior changes due to aging or external conditions.

Recent advances in battery state estimation have seen significant improvements through robust filtering strategies. While Kalman filters (KFs) provide recursive state estimation from noisy measurements, their assumption of linear state-measurement relationships often proves inadequate for strongly nonlinear battery dynamics. More flexible approaches like particle filtering approximate the posterior probability distribution using random samples ("particles") [9]. Beyond probabilistic methods, set-membership filtering employing zonotopes—convex polytopes efficiently representing multidimensional uncertainty sets—has demonstrated particular strength in estimating SOC under unknown but bounded (UBB) and time-varying noise conditions. Zonotopic filtering models state uncertainty through a center vector and generator matrix, using linear mappings and Minkowski sums for prediction and update steps without requiring specific noise distributions. This framework not only provides point estimates but also computes guaranteed state bounds, offering a computationally efficient and robust solution for battery management systems (BMSs) operating under significant uncertainty.

Alongside SOC, SOH is another essential parameter that reflects the overall condition of a battery. SOH is typically determined by factors such as internal resistance, capacity fade, and voltage response, which change as the battery ages. Accurate SOH estimation is vital for understanding the degradation of a battery over time, as it helps predict when the battery will no longer perform at optimal levels. Conventional methods of SOH estimation often rely on empirical models or simplified battery aging models, which may fail to capture the complex degradation processes occurring in real-world applications.

To overcome these limitations, more advanced techniques have been proposed, combining both model-based and data-driven approaches. DL methods have demonstrated the ability to estimate lithium-ion battery SOH without additional degradation experiments [10]. Hybrid DL methods have also been developed for the estimation of the SOH of LIBs, showing improved accuracy and robustness [4]. Battery degradation prognosis and health management based on grey iterative modeling provides another innovative approach to SOH estimation [13]. These hybrid methods, which combine model-based and data-driven approaches, have proven effective in improving SOH estimation by leveraging the strengths of both techniques.

Finally, predicting the RUL of a battery is another critical aspect of battery operating status analysis. RUL prediction is important for determining when a battery will no longer be able to perform its intended function, thus enabling

timely maintenance or replacement. RUL prediction is particularly challenging due to the complex and nonlinear nature of battery aging, which is influenced by numerous factors such as charge/discharge cycles, temperature, and operating stresses. Traditional RUL prediction models often fall short of capturing the time-varying nature of the battery degradation process.

Recent advancements have significantly improved the accuracy of RUL prediction. Techniques such as particle filtering and neural networks, especially LSTM networks, have demonstrated exceptional performance in predicting RUL. Survival analysis combined with ML has emerged as a powerful framework for predicting Li-ion battery RUL [11]. These models are capable of learning complex temporal dependencies and nonlinear patterns in the battery data, which is essential for predicting the RUL accurately. By training these models on large datasets, they can effectively predict the remaining lifespan of a battery based on historical data and operational conditions.

In conclusion, battery operating status analysis is fundamental for ensuring the efficient and safe operation of battery systems across a wide range of applications. The accurate estimation of SOC, SOH, and RUL is crucial for optimizing battery performance, enhancing safety, and extending the battery's lifespan. The integration of advanced methods, such as particle filtering, ML algorithms, and hybrid techniques, provides robust solutions to the challenges of battery status analysis. These methods not only improve the accuracy of status estimation but also enable more effective monitoring and management of battery systems in real-world environments.

1.4 Principle of Filter Design Methods

Filter design methods are essential tools for addressing the challenges of state estimation, particularly in systems characterized by uncertainty and noise. In battery systems, these methods are crucial for accurately estimating parameters such as SOC, SOH, and RUL, which are often affected by various disturbances and uncertainties, including measurement noise, model inaccuracies, and environmental factors. A filter is an algorithm that processes a sequence of noisy observations to estimate the state of a dynamic system. The objective of filter design is to reduce the uncertainty in the system's state estimation by using mathematical models that describe the system's dynamics and measurement process.

The design of effective filters for battery systems involves several fundamental principles that stem from various fields, including linear and nonlinear systems, estimation theory, and statistical inference. These principles are broadly categorized into linear filters, nonlinear filters, and robust filters, each offering different advantages and applicable scenarios.

1.4.1 Linear Filters

Linear filters are among the most commonly used and simplest types of filters in state estimation. They assume that the system and measurement models are linear, and that the noise affecting the system is Gaussian. The KF is the most widely used linear filter and is optimal in the sense that it minimizes the mean square error of the state estimate, given the assumptions of Gaussian noise and linearity. In the KF, the system's state is updated iteratively using both the previous state estimate and the new measurements, and it provides an estimate of the state along with a covariance matrix that quantifies the uncertainty in the estimate.

The extended Kalman filter (EKF) is an extension of the KF that deals with systems exhibiting nonlinear behavior. It linearizes the system's nonlinear dynamics around the current estimate, enabling the use of KF principles for nonlinear systems. However, EKF has limitations in handling highly nonlinear systems, as it may introduce errors in the linearization process.

1.4.2 Nonlinear Filters

While linear filters work well for systems with linear dynamics and Gaussian noise, they are often inadequate for handling nonlinear systems, which are common in battery modeling due to the complex electrochemical processes involved. PF, also known as sequential Monte Carlo (SMC) methods, represent a class of filters that do not require linearity assumptions. PFs represent the system's state with a set of random samples, or "particles," each of which has a weight based on its likelihood. The filter updates the particles over time according to the system's dynamics and measurement model, and the state estimate is obtained by calculating the weighted average of the particles.

PFs are particularly well-suited for battery systems, as they can handle the nonlinearities and uncertainties associated with battery dynamics, such as temperature effects, varying charge/discharge rates, and aging processes [9]. Furthermore, PFs can be used to estimate complex battery parameters, such as SOC and SOH, in real-time under uncertain operating conditions. Novel approaches such as particle flow filter frameworks with grey models have been developed to further enhance the performance of PFs for RUL prediction [14].

1.4.3 Robust Filters

Robust filters are designed to address the limitations of traditional filters when the noise characteristics are unknown or highly uncertain. In battery systems, noise can often be non-Gaussian and time-varying, making traditional filtering methods less effective. Zonotopic filtering, a robust filtering technique, uses geometric structures called zonotopes to represent uncertainty in the system's state.

Zonotopes are convex polytopes that provide a way to represent sets of possible states and measurement errors, making them useful for handling uncertainty in both the state and measurement models. This method is particularly advantageous when dealing with non-Gaussian noise and systems with bounded uncertainty, as it can efficiently estimate the state while taking into account the shape of the uncertainty set.

Zonotopic filters can be combined with other estimation techniques, such as Kalman filtering or particle filtering, to form hybrid filters that are both robust and efficient. These hybrid methods can be tailored to the specific needs of battery systems, where noise is often unknown and time-varying. Moreover, zonotopic filtering can be used in conjunction with particle swarm optimization (PSO) to further improve the robustness of the filter by adapting the filter's parameters in response to changes in the system's behavior.

1.4.4 The Integration of Filters with AI

The integration of traditional filter design methods with AI techniques is an emerging trend in the estimation of battery operating states. AI methods, such as DL and reinforcement learning (RL), are particularly suited for handling the large amounts of data generated by battery systems. By combining AI with filtering techniques, it is possible to improve the accuracy and robustness of state estimation, particularly in complex systems where the dynamics are not well understood or difficult to model.

For example, LSTM networks, a type of recurrent neural network, have been used to improve the estimation of SOC and SOH by learning the temporal dependencies in the battery data. Similarly, domain-adapted frameworks such as HybridoNet-Adapt combine DL with filtering techniques to enhance the accuracy of RUL prediction across different operating conditions [15]. RL techniques can be used to optimize filter parameters and adapt the filter's behavior in real-time based on the changing operating conditions of the battery system. By leveraging the strengths of both filtering and AI methods, it is possible to achieve more accurate and adaptive state estimation in battery systems.

Reviews of Bayesian-filtering-based techniques in RUL prediction for LIBs provide comprehensive insights into the integration of filtering methods with AI strategies [16]. These approaches demonstrate how the combination of traditional filtering principles with modern AI techniques can address the complex challenges of battery state estimation.

In conclusion, the design of effective filters for battery systems requires an understanding of both traditional estimation techniques and modern approaches that address the complexities of battery behavior. Linear, nonlinear, and robust filters each offer unique advantages depending on the nature of the system and the

type of noise present. The integration of filtering methods with AI techniques further enhances the capability to accurately estimate key battery parameters, providing a comprehensive solution to the challenges of battery operating status analysis.

1.5 Artificial Intelligence Strategy

AI has become a key strategy in advancing the capabilities of battery systems, particularly in the fields of manufacturing, state estimation, and predictive maintenance [8]. The rapid development of AI techniques, including ML and DL, has introduced powerful tools for improving battery performance, enhancing the accuracy of SOC and SOH estimations, and optimizing the design and operation of battery systems.

In battery manufacturing, AI techniques are employed to optimize production processes, improve consistency, and predict manufacturing capacity. ML models can process large volumes of sensor data from production lines, identifying patterns that are not immediately apparent to human operators. These models are capable of making real-time adjustments to the manufacturing process, ensuring that production goals are met while maintaining high quality and efficiency. For instance, AI models based on supervised learning techniques, such as regression analysis and classification, can predict production outcomes based on input parameters, thus enhancing control over the manufacturing environment and reducing waste.

For modern battery systems, AI has become an indispensable tool for state estimation. Inferring the SOC, SOH, and RUL requires capturing strongly nonlinear and time-varying behaviors that conventional modeling approaches struggle to represent accurately. DL algorithms, particularly LSTM networks, are capable of learning temporal dependencies in battery data and can be trained to predict battery performance under various operating conditions [10]. PatchFormer, a novel patch-based transformer, has been developed for accurate RUL prediction of LIBs, demonstrating the potential of advanced AI architectures in this domain [13]. These models are capable of handling large amounts of data generated by battery systems and provide real-time updates of the state estimation, significantly improving the accuracy of predictions compared to traditional methods.

Furthermore, AI strategies enable predictive maintenance by providing advanced capabilities for forecasting battery degradation and predicting failure points. By analyzing historical data on battery performance, AI models can identify early signs of deterioration and predict when maintenance or replacement will be required. Survival analysis with ML has emerged as a particularly powerful approach for predicting Li-ion battery RUL [11]. This is particularly valuable in applications where battery failure can result in significant operational downtime or safety concerns, such as in EVs or renewable energy storage systems.

Another application of AI in battery systems is in the optimization of BMSs. AI techniques, including RL, can optimize the charging and discharging cycles of batteries to maximize their efficiency and lifespan. By continuously learning from the battery's behavior, RL algorithms can adapt to changes in the battery's operating conditions and adjust the control strategy accordingly. This leads to improved battery utilization and extended operational life, especially in systems with multiple batteries connected in series or parallel.

Large language models are also being explored for battery prognostics, opening up new possibilities for AI applications in battery health management. The integration of stress-informed transfer learning approaches enables accelerated battery life evaluation across diverse operating conditions and cell mechanisms, further expanding the capabilities of AI in battery systems.

In conclusion, AI has proven to be an invaluable strategy in improving the performance, reliability, and efficiency of battery systems. Through its application in manufacturing, state estimation, predictive maintenance, and optimization, AI provides the necessary tools to address the challenges posed by modern battery systems. As AI techniques continue to evolve, their integration into battery management and manufacturing systems will undoubtedly play a key role in driving the future of energy storage technologies.

1.6 Outlines

Although some progress has been made in the theory, methodology, and application of filtering techniques in battery systems, there is still much to be done. This book builds on the existing research, focusing on improving current methods and integrating them with emerging technologies. The content of this book highlights the continued development and application of state-of-the-art filtering methods in battery manufacturing, operating status analysis, and fault diagnosis.

The overall layout of the book, including its principal contents and their order, is summarized as follows: In Chapter 2, we present methods for optimizing battery manufacturing processes and predicting manufacturing capacity using data-driven models. Chapter 3 focuses on advanced state estimation techniques for battery systems, including methods for forecasting battery health and performance under various operational conditions. In Chapter 4, we explore the integration of advanced filtering methods with AI techniques for battery state estimation, emphasizing their effectiveness in nonstationary environments. In Chapter 5, we introduce advanced SOC estimation techniques using set-membership filtering methods and optimization strategies. These methods address the challenges of accurately estimating battery state under bounded uncertainties. Chapter 6 introduces methods for predicting the RUL of batteries, integrating

advanced filtering strategies with AI to enhance the accuracy and reliability of RUL predictions. Finally, in Chapter 7, we summarize the research presented in this book and outline the future directions for the development of battery systems, focusing on the role of filtering techniques and AI in advancing battery technologies.

