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Health Prediction and Remaining Useful Life Estimation for Energy-Storage Systems

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Abstract

Purpose: The rechargeable batteries are their major element where the energy-storage systems are central to the modern power networks, electric transportation, and the portable electronic devices. The possibility to evaluate the battery condition and estimate the degradation with time is the key to the performance, reliability, and safety of these systems.

Materials and Methods: Two significant measures of such a purpose are the state of health (SOH), which is the present capacity or power capability compared to original specifications, and the remaining useful life (RUL), which is an approximation of operation life until the battery fulfills end-of-life conditions. SOH and RUL because predictability is necessary in order to manage the battery, preventive maintenance, and cost-efficient system operation. The degradation of batteries is dictated by complex electrochemical and mechanical mechanisms with dependence on the conditions of operation like temperature, rate of charge, depth of discharge and patterns of usage. These time-varying nonlinearities are very difficult to deal with through conventional estimation methods. In order to overcome these issues, a broad selection of prognostic techniques has been designed, which can be narrowed down into model-based, data-driven, and hybrid. Model-based approaches are based on physical and electrochemical models of battery behavior, providing interpretability but in most cases, these models are sensitive to the identification of accurate parameters. Machine learning and deep learning models are data-driven approaches that allow the establishment of complex degradation trends at high levels of predictive accuracy using past operational data. Hybrid frameworks strive to build the merits of the two paradigms by blending physical wisdom and data-driven flexibility.

Findings: When comparing previous research on the estimation of battery health and the remaining useful life, it becomes apparent that the performance trends are similar in various methodological types. Although, there is no universal method to be used in all of the operating conditions, the literature provides definite advantages and disadvantages related to model-based, data-driven, and hybrid prognostic methods.

Unique Contribution to Theory, Practice, and Policy: The article is a thorough piece of work that provides an evaluation of battery health prediction and RUL estimation approaches both in terms of their principles of operation, implementation strategies, and performance attributes.

Keywords: *Battery Health Prediction, Energy Storage Systems, Battery Life*

INTRODUCTION

Modern energy-storage systems are based on rechargeable batteries, most commonly lithium-ion (Li-ion) chemistries, which are used in portable electronics, electric vehicles and grid-scale applications. This is mainly because of their pleasant properties as they have high energy density, long cycle life, low self-discharge, and comparatively high efficiency compared to the old technologies like lead-acid and nickel-metal hydride batteries. These have facilitated quick electrification of transportation and introduction of intermittent renewable energy into power grids. Although these advantages exist, Li-ion batteries are characterized by a slow reduction in the performance of the batteries throughout their working life [1]. The prolonged life processes cause the irreversible reduction of capacity, internal resistance, and power capability, and the decrease of the useful life. The processes that lead to battery degradation are a sum of electrochemical, thermal, and mechanical processes, such as solid electrolyte interphase (SEI) growth, lithium plating, fatigue of electrode materials and decomposition of electrolyte [2]. Consequently, the nonlinearity and uncertainty of the operational behavior of batteries increases with age so proper prediction of battery condition is thus critical in terms of safe operation, maximum energy use and minimum costs associated with lifecycle. In other applications like electric vehicles and grid storage, unanticipated battery failure may lead to safety risk, system downtime and huge economic losses. Therefore, sound estimation of battery state of health (SOH) and remaining useful life (RUL) has become a fundamental need of advanced battery management conditions and energy-storage planning models. The State of Health (SOH) is a quantitative measure that shows the present position of a battery to its nominal or original position. It is typically characterized by the available capacity, internal resistance increase or power ability loss. SOH is normally expressed as a percentage with a fully healthy battery having a value of 100 and the degradation causes a reduction in the SOH value. Proper estimation of SOH will give understanding of how performance will be lost and help in decision making in an energy storage system [3].

The Remaining Useful Life (RUL) is the estimated time or the number of operational cycles that a battery can operate before it reaches an established end-of-life that has been specified. A required capacity limit is often set by the end of-life which is often taken as 80% of the rated capacity after which the battery may not perform or be safe. RUL estimation is essential in the maintenance scheduling, evaluation of warranty, planned replacements and reduction of risk in safety-critical applications. The mathematical formulation for it can be defined as: Let a battery be characterized by a health indicator *H(t)*, which represents a measurable or estimated degradation metric such as capacity, internal resistance, or state of health (SOH). For most lithium-ion battery applications, SOH is defined in terms of remaining capacity:

$$SOH(t) = \frac{C(t)}{C_0} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

Where:

- $C(t)$ is the available capacity at time or cycle t,
- C_0 is the rated (initial) capacity of the battery.

The process of battery degradation is not an easy one. On the contrary, it is a combination of a number of interacting mechanisms that are highly dependent on the manner of battery use and the environment in which the battery functions. The temperature, charge and discharge rate, depth of discharge and the environmental conditions are all important factors. To make it worse, variations in usage patterns and minute differences injected during manufacturing are also sources of additional uncertainty. All these complicate the process of estimating the state of health (SOH) and the useful life (RUL) of a battery with great certainty, particularly in more realistic scenarios where operating conditions keep varying. In most cases, traditional battery management systems use simple methods, such as coulomb counting, open-circuit voltage, or simple rule-based thresholds. These techniques are simple to use and need little computations but they fail to capture the nonlinear behavior of degradation of the battery and they tend to get errors as long as the load changes or the temperature changes [4]. With increasing demands of modern energy-storage systems being more reliable and have a longer service life, more comprehensive prognostic methods are required to be able to address uncertainty, nonlinearity, and various data better to provide reliable and accurate predictions of battery health.

Energy storage systems (ESS) play a critical role in modern power grids, electric vehicles, and renewable energy integration; however, accurately predicting system health and estimating remaining useful life (RUL) remain challenging due to degradation complexity, operational variability, and uncertainty in usage conditions. Existing approaches often focus on either health estimation or RUL prediction in isolation, rely on simplified aging assumptions, or lack robustness across different operating profiles and battery chemistries. Moreover, there is limited consolidation of data-driven and physics-informed techniques that can support reliable, real-world decision-making. This study aims to address these gaps by systematically analyzing health prediction and RUL estimation methods for energy storage systems, highlighting their strengths, limitations, and practical applicability. The outcomes of this research primarily benefit battery manufacturers, energy system operators, electric vehicle developers, and researchers by enabling improved condition monitoring, predictive maintenance, and lifecycle management of energy storage assets.

LITERATURE REVIEW

Physics and Degradation Mechanisms

The aging of batteries is caused by a combination of various processes such as solid electrochemical interface (SEI) and active lithium depletion, microstructure alterations of the electrode, and electrolyte decomposition. These processes decrease capacity and augment internal opposition with the course of time. The prognostics models need to understand these mechanisms. The early development of physics of degradation was done by foundational work on mathematical models of capacity fade [5].

Model-Based Methods

The prognostic process models provide an estimate of battery health using physical and electrochemical understanding of the degradation reactions. These techniques are normally based on mathematical models of battery behavior that are developed based on either equivalent circle models (ECM), electrochemical models, or state-space equations. Model-based approaches allow a systematic monitoring of battery degradation and remaining useful life (RUL) through the connection of measurable quantities (voltage, current, temperature, and others) to internal states [6].

Some of the most popular techniques in this category are kalman filtering frameworks. Different versions that include the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) [7], and Particle Filter (PF) were widely used to estimate the internal battery states, such as state of charge (SOC) and state of health (SOH). Whereas EKF is based on local linearization, UKF and PF are more robust to highly nonlinear battery dynamics, since uncertainty propagation is done by deterministic sampling or Monte Carlo representations. These methods have been shown to exhibit high levels of estimation in the dynamic operating conditions, such as variable loads and changes in temperature.

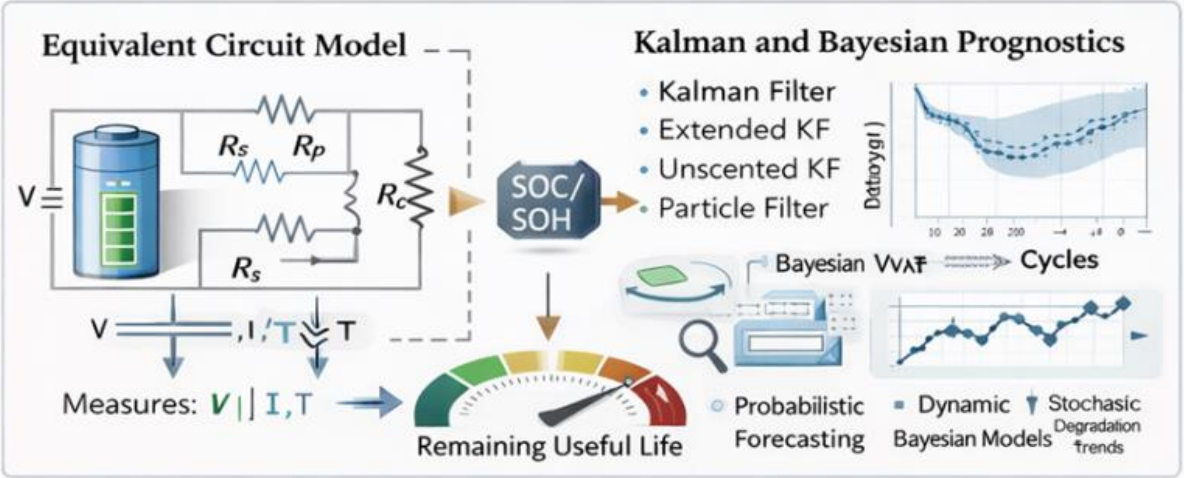

Figure 1: Kalman and Bayesian Prognostics for Battery Life

The Bayesian and probabilistic prognostic techniques are further extensions of model-based estimation, which explicitly characterizes the degradation behavior uncertainty. The prediction of battery RUL has been developed using grey models, Bayesian filtering methods and central difference particle filters that model stochastic degradation trends and measurement noise [8]. These techniques can give probabilistic health indications, which are especially useful in risk conscious decision making in safety-critical systems. Although model-based methods are interpretable and highly grounded on physical aspects, they have significant weaknesses. These parameters are identified accurately and their model fidelity matters significantly in their operation that can be different in the various battery chemistries, aging conditions and in their usage profiles. Moreover, the models might not be able to capture complex and nonlinear degradation processes experienced in different real-life working conditions, which has led to the adoption of data-driven and hybrid models in the recent past.

Data-Driven Techniques

The recent years have seen data-driven prognostic methods gaining substantial popularity because of the development of machine learning algorithms and the increased availability of large-scale battery aging data. Data-driven techniques, in contrast to model-based ones, do not need explicit knowledge of electrochemical processes. They are instead instructed on the patterns of degradation directly on historic measurements and are therefore especially appealing to complex battery systems that may work under varied and uncertain environments.

Statistical Models and Regression

Initial applications of data-driven methods were based on regression and statistical modeling to determine the condition between measurable battery measurements and health outcomes like state of health (SOH) and remaining useful life (RUL). Informative features that are extracted using voltage, current, and capacity trajectories have been obtained through the use of linear and regularized regression methods, and ridge regression and lasso regression [9]. Such characteristics are usually characterized by features of voltage curves, peak of incremental capacities and statistical characteristics of charge discharge profiles. These models are computationally inexpensive and fairly straightforward to interpret, and thus can be used in embedded or low resource applications. Their low representational ability, however, limits their capability to model very nonlinear degradation behavior, especially when different load profiles and environmental conditions are used [10].

Machine Learning and Neural Network

In order to overcome the shortcomings of the simple regression models, more sophisticated machine learning methods have been extensively used. Treatment of nonlinear correlations between measurable battery variables and degradation trends Support vector regression (SVR), random forests, gradient boosting and ensemble learning methods have been shown to perform well under degradation prediction. These methods can access more complicated feature interactions and have better generalization than linear models do. The methods based on neural networks have also contributed to data-driven battery prognostics, as they allow automatic features learning [11]. General regression model The SOH or RUL (or any other battery health indicator) may be modeled as a response to extracted features x (voltage, current, temperature, capacity measurements, etc.):

$$\hat{y} = f(\mathbf{x}; \theta) + \epsilon \qquad \ldots\ldots(2)$$

Where y is the forecasted SOH or RUL, f is the regression model (linear or nonlinear), θ is model parameters and ε is the error residual. Recurrent neural networks (RNNs), in general, and Long Short-Term Memory (LSTM) models, in particular, are particularly suitable to battery degradation modeling since they allow modeling temporal dependencies in charge cycles and discharge cycles. The LSTM-based models have demonstrated strong performance in predicting SOH and RUL through learning of long-term trend of degradation using sequential data despite the presence of noise and variability in the operation. Recently, Convolutional Neural Networks (CNNs) with recurrent layers as hybrid deep learning architectures have also been studied. CNNs improve the extraction of features through the detection of local patterns and correlations of battery signals whereas RNNs learn their dynamics. These hybrid models have been found to have better predictive performance and strong performance, especially in long-horizon RUL estimation in complex operating conditions. Although they are highly performing, data-driven approaches demand large volumes of high-quality data and can be associated with low interpretability [12]. Consequently, recent studies give more attention to hybrid and physics-informed learning models to integrate the flexibility of data-driven models and the understandability of physical knowledge.

Hybrid and Fusion Models

The vision of hybrid prognostic methods is to have the benefit of both worlds: clear physical insight into processes provided by physics-based models and the ability of data-driven methods to be flexible and learn. These hybrid models can be implemented by combining methods, like particle filters and neural networks, or a combination of several methods of modeling to deliver more precise and credible forecasts. They in particular are useful in managing issues such as sensor noise, changes in operating conditions, and other uncertainties that tend to negatively affect the behavior of purely physics-based or purely data-driven models.

Despite significant progress in health prediction and remaining useful life estimation for energy storage systems, several research gaps persist. Many existing studies evaluate prediction models using limited datasets or controlled experimental conditions, raising concerns regarding generalizability under real-world operating environments. Additionally, the impact of operating factors such as temperature variations, charge-discharge patterns, and aging heterogeneity on model robustness is not consistently addressed. There is also a lack of unified frameworks that effectively integrate data-driven, machine learning, and physics-based approaches for long-term health prognosis. These gaps give rise to key research questions, including: How can health and RUL prediction models be made robust across varying operational conditions? What combinations of modeling techniques best balance prediction accuracy, interpretability, and computational efficiency? And how can uncertainty in degradation behavior be systematically incorporated into ESS prognostics? Addressing these questions is essential for advancing reliable and scalable ESS health management solutions.

MATERIALS AND METHODS

Battery Remaining Useful Life (RUL) and State of Health (SOH) prediction demands a systematic architecture that involves data collection, feature mining, model development and forecasting. An effective methodology will ensure that the models are able to reflect the underlying degradation dynamics and variability in operating conditions, and give credible predictions that can be used in practice.

Data Collection

The quality of predicting battery health starts with strong and quality datasets. The battery datasets can be acquired in the controlled laboratory experiments using the method of repeated charge discharge cycles of individual cells (or battery packs) with specified environmental and load conditions. These controlled tests make it possible to monitor voltage, current, temperature, and capacity changes over time with an exact amount of accuracy to serve as a ground truth to estimating the SOH and RUL.

Most of the studies also use publicly available datasets in addition to the experimental data, which can be used to benchmark and validate the models. The most notable ones are NASA Prognostics Data Repository which offers Li-ion battery cycling data with environmental and operational data, and the CALCE battery dataset, which offers longitudinal degradation data of various chemistries and applications. Such datasets in general cover high-resolution data of electrical parameters and thermal conditions which are crucial in detecting minute trends of degradation leading to performance loss. Another benefit of using such datasets is that they enable researchers to test the model generalization to other battery chemistries and operating profiles, which is one of the key challenges of practical battery prognostics.

Feature Engineering

Once data is collected, the next step is feature extraction, which transforms raw measurements into meaningful indicators of battery health. Features can be broadly categorized into time-domain**,** frequency-domain, and statistical metrics, all of which provide complementary insights into the degradation process.

- Time-domain features contain methods like incremental capacity analysis (ICA) and differential voltage analysis (DVA), that measure changes in the charge/discharge curves that are highly related to capacity fade. Such approaches are able to observe small changes in plateaus or heights in voltage prior to any observable serious degeneration in the crude measurements.
- Statistical features are the calculation of the mean, standard deviation, skewness, and kurtosis of voltage, current and temperature signals. These indicators are useful to capture variability, noise and trends which can be attributed to battery aging. As an example, the terminal voltage discharge is getting larger and larger, and this might be indicative of increasing internal resistance.
- In itself, physics-informed features are more and more popular in hybrid modeling, in which the measurable quantities are converted depending on the known electrochemical processes. These can be normalized capacity loss, resistance growth trends or cycle

energy efficiency. These characteristics make the models more interpretable and enable them to take into account basic insights of battery chemistry.

The feature engineering is important, since it directly determines the predictive accuracy of data-driven models [13]. The features are carefully filtered and preprocessed into the features like noise cancelling, missing data, and normalization to assure that the models can learn meaningful patterns and not spurious correlations.

Model Training

With features extracted, the next step is to train predictive models that map these features to SOH and, subsequently, forecast RUL. Models can be data-driven**,** physics-based**,** or hybrid**,** each with distinct advantages:

- Data-driven models apply machine learning models like support vector regression (SVR), random forests and gradient boosting, or deep learning models like Long Short-Term Memory (LSTM) networks, which are well-suited to modeling temporal relationships in sequence data.
- Physics-based models use equivalent circuit models (ECMs) or electrochemical state-space models to have a predictive model of internal states, which are interpretable and allow prediction to be based on physical laws.
- The hybrid models are a combination of both and include examples such as physics-informed features as an input to deep learning models.

Training is done with caution when it comes to the hyperparameter tuning, cross-validation and testing on different validation sets to prevent overfitting. Practically, k-fold cross-validation or rolling-window validation is usually used to make sure that the model can be well generalized to various operational conditions. Root Mean Squared error (RMSE) and Mean Absolute error (MAE) and correlation to observed degradation trajectories are usually used to measure model performance. This is aimed at developing a model that is able to not only predict SOH at a particular time but also the trend of degradation, which is fundamental to effective RUL prediction.

RUL Estimation

After training, the model is used to predict the Remaining Useful Life. RUL estimation can be performed using several approaches:

- Multi-step forecasting**:** Models like LSTMs are sequence based and they are used to predict future values of SOH across a series of cycles. RUL can be estimated by making extrapolations of these predictions until a pre-determined end-of-life limit is attained [14].
- Probabilistic forecasting: Bayesian models, Gaussian Process Regression (GPR), or particle filters have the ability to not only produce point estimates, but also uncertainty bands. This plays a critical role to make decisions with risk awareness in applications such as electric vehicles or in energy storage on a grid scale.
- Health-state classification and transition modeling: There are frameworks in which battery health is discrete (e.g., is in state H1, H2, or H3) and the transition probability is used to predict how long it will take the battery to reach a critical state. This method is especially applicable in cases where the nonlinearity induced by operational variability or in cases where precision SOH estimation is difficult.

Finally, the method selected is based on the need of the application, the data available and acceptable trade-off between precision, computing complexity and readability. An effective methodology can be used to guarantee reliability and actionability of RUL predictions in order to provide effective maintenance planning, replacement planning, and risk reduction in practical energy-storage systems.

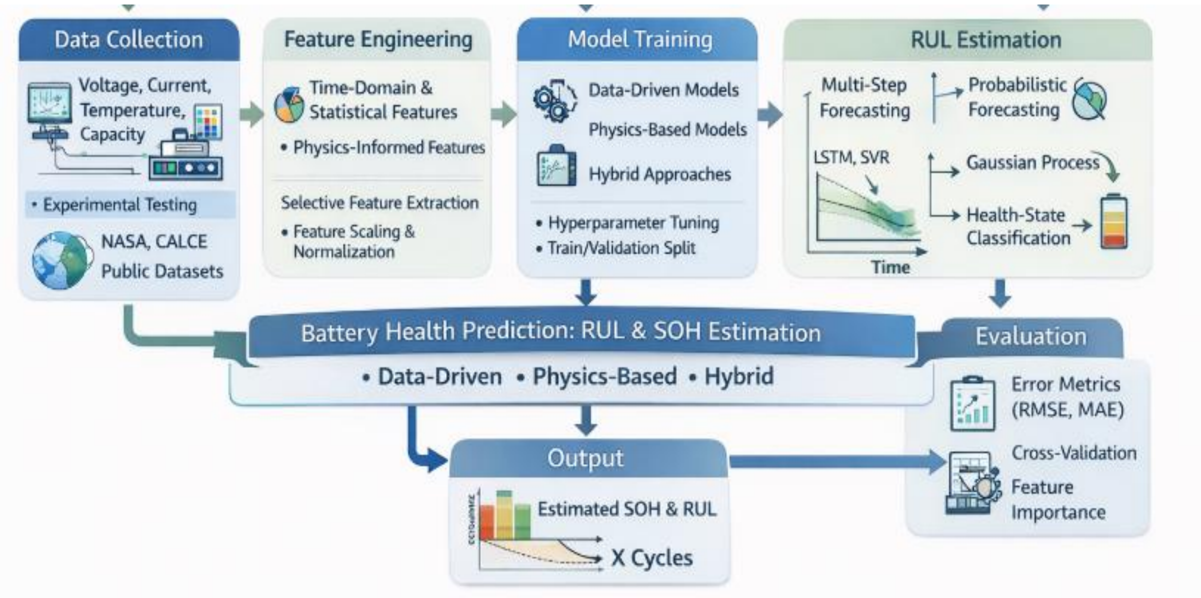

Figure 2: Battery Health Prediction: Rul & Soh Estimation

FINDINGS

When comparing previous research on the estimation of battery health and the remaining useful life, it becomes apparent that the performance trends are similar in various methodological types. Although, there is no universal method to be used in all of the operating conditions, the literature provides definite advantages and disadvantages related to model-based, data-driven, and hybrid prognostic methods. These observations have been summarized and discussed as follows in the subsections that follow.

Model-Based Prognostics

Prognostic approaches that use electrochemical models or equivalent circuit models are appreciated to have a high degree of physical interpretability and stability. Explicitly modeling degradation processes including solid electrolyte interphase growth, lithium plating or internal resistance increase, these methods give some understanding on the underlying aging processes of batteries. This openness makes them especially appealing to safety critical applications, in which it is as crucial to know what causes degradation as it is to know how it will evolve. Nonetheless, literature findings show that model-based methods tend to be inaccurate when operating in real-world conditions [15]. Temperature variability, load dynamics, charging dynamics and manufacturing irregularities have nonlinearities that are hard to represent with constant model parameters. Moreover, the proper calibration of such models often involves a close understanding of the chemistry of battery and large amounts of experimental data, which is not always available. Subsequently, although model-based approaches are particularly accurate in the short term and stable behavior, their long-term predictions of RUL can be spoiled by operational uncertainty and sensor noise.

Data-Driven Models

Machine learning and deep learning methods have demonstrated good predictive accuracy on a vast selection of benchmark datasets, and are data-driven. Support vector machines, random forests, and neural networks are models of degradation that are directly trained using historical data directly, without directly assuming any model of electrochemical behavior. Recurrent neural networks in particular long short-term memory (LSTM) networks are one of these that have been extensively documented to deliver low forecast errors in SOH estimation, as well as in long-horizon RUL forecasting [16].

Empirical findings of various studies show that the LSTM-based models are efficient in the ability to extract the temporal dependencies and nonlinear trends of degradation of battery aging data. These models are particularly effective in cases where high quality and large datasets are also present and operating conditions are within the range of conditions during training. However, there is no limitation of data-driven models. They may perform poorly on invisible operating regimes and their inability to be physically interpreted is an issue of concern in terms of trust and explainability especially in safety-critical energy storage systems.

Hybrid Approaches

Hybrid prognostic models, where physics-based models are combined with data-driven learning, are always found to be more robust and adaptive than nonspecialized ones in comparative studies. The interpretability and constraint analysis of physical models, as well as the flexibility of machine learning methods, can be combined to make hybrid methods better suited to deal with noisy measurements and variable operating conditions. An example would be the use of physics-informed features during neural network training, or the use of data-driven corrections to account for errors in modeling in conventional degradation models. According to the reported results, hybrid methods tend to deliver better results than purely model-based or purely data-driven methods, especially in those cases where only partial data information is available, sensor uncertainty arises, or the usage pattern is highly dynamical. Even though these approaches bring with them a certain level of added complexity and computation costs, the tradeoff between accuracy, robustness, and interpretability they achieve is highly appropriate in the context of real-world battery management. In turn, hybrid prognostics are also becoming considered as a viable way to compromise in an attempt to achieve reliable SOH and RUL prediction in contemporary energy-storage systems.

Table 1: Comparative Analysis of Battery SOH and RUL Prediction Approaches

Aspect	Model-Based Prognostics	Data-Driven Models	Hybrid Approaches
Core principle	Relies on physics-based or electrochemical models to represent battery degradation mechanisms	Learns degradation patterns directly from historical data using machine learning algorithms	Integrates physical models with data-driven learning to leverage strengths of both
Interpretability	High; model parameters and outputs have clear physical meaning	Low to moderate; often treated as black-box models	Moderate to high; physical constraints improve interpretability
Prediction accuracy	Reliable for short-term prediction under known conditions	High accuracy, especially for long-term RUL forecasting	Generally high and more stable across varying conditions
Robustness to Noise & Variability	Limited; sensitive to parameter uncertainty and modeling assumptions	Sensitive to unseen operating conditions and data quality	Strong; better handling of noisy and non-stationary data
Data requirement	Low to moderate; requires domain knowledge and calibration data	High; performance improves with large, diverse datasets	Moderate; benefits from both historical data and physical insight
Computational complexity	Low to moderate	High, especially for deep learning models	Moderate to high due to model integration
Generalization ability	Limited across different battery types or usage profiles	Often poor without retraining	Improved generalization due to physical constraints
Suitability for Real-World Applications	Suitable for safety analysis and controlled environments	Suitable for data-rich systems with stable operating regimes	Highly suitable for practical battery management systems
Typical use cases	Early-stage design, fault diagnosis, safety assessment	Long-term RUL forecasting, condition monitoring	Online health monitoring, adaptive battery management

Discussion

The comparative review of battery health prediction systems indicates a substantial advancement and a current shortcoming of SOH estimation and RUL forecasting. Although sophisticated modeling methods have enhanced the accuracy and strength of prediction, there are still a number of technical and practical problems that render their extensive application not feasible to real-life energy-storage systems. This section talks about such challenges, the practical implications of better prognostic capabilities and where future research might go without the need to go further.

Challenges

Nevertheless, battery prognostics is a complicated and developing field of research even when significant progress is achieved in the field of modeling and data analytics. The limitation of measurement is a basic issue. There are many critical internal battery conditions including lithium inventory loss, electrode degradation or internal resistance increase, which cannot be directly measured during normal operation [17]. They instead have to be observed using external cues like voltage, current and temperature which are normally noisy and are affected by environmental and operational variability. Incorrect sensor measurements, sampling constraints and communication delays also make it hard to estimate SOH in real-time especially in large or distributed energy-storage systems. Lack of data and variation is also one of the significant limitations. Good quality degradation data with long operational life, different application pattern, and different environmental conditions are scarce. The majority of publicly available data sets are gathered in the controlled laboratory conditions and might not reflect the real life behavior completely. Such inability to have a variety of data may result in biased models that may work well on benchmark data but fail when used in real-life situations. Another problem that persists is model generalization. Models that have been trained on a given battery chemistry, form factor or usage profile are frequently unable to extrapolate to other systems. The differences in manufacturing, operating conditions and user operation bring along divergences which are hard to encompass in one predictive model. This is a specific challenge to approaches based on data, where it depends strongly on the statistical characteristics of training data, and can tend to become invalid as conditions not seen during training are encountered.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The problem of a complex and interdisciplinary nature proposes to predict the health and useful life of a battery necessitating a combination of the understanding of electrochemical principles, statistical modeling with machine learning methods. Advances in data-driven approaches especially deep neural networks with the ability to model nonlinear and temporal patterns of degradation have achieved significant gains in the accuracy of prognostic across a spectrum of benchmark studies. Simultaneously, physics-based models remain significant with respect to being interpretable and offering physically meaningful restrictions to facilitate safe and reliable operation.

Frameworks that involve a combination of both physical intuition and data-guided flexibility are known as hybrid prognostic frameworks, and they have developed into one of the most promising paths. These methods bring out a trade-off between accuracy, robustness, and explainability and are therefore suitable to be applied in practice within battery management systems under varying and uncertain conditions. Nonetheless, issues of data availability, generalization of models and real-time implementation remain.

Further attempts of standardized datasets and real world validation and adaptive online prognostic methods are likely to increase the reliability and utility of SOH and RUL estimation. With energy-storage systems becoming an even larger part of transportation and power infrastructure, effective battery health predictive analytics will be essential in enhancing safety, improving asset durability, and finding sustainable energy solutions.

Recommendations

Irrespective of these obstacles, the correct SOH and RUL estimation has significant practical value in various areas of use. In electric cars, predictive maintenance, limited failures, and informed reuse of battery or second-life choices can be made because of reliable predictions of RUL. Enhanced safety is also enabled with the aid of better health estimation as defective degradation patterns are identified early. In the energy storage systems of the grid scale, prognostics is crucial in scheduling, load balancing and managing the assets efficiently. By predicting trends in degradation, the operators are able to readjust the operations strategy in order to increase battery life, minimize the replacement costs, and enhance the overall reliability of the system [18]. More accurate health predictions, in turn, can be used to improve the value of warranty policies and lifecycle costs of manufacturers and operators, which will enhance the economic justification of energy-storage technologies.

Future Directions

Future studies need to be dedicated towards establishing more general and adaptive prognostic models. Techniques of transfer learning and domain adaptation provide promising opportunities to use the experience of one battery system in another and minimise data needs and enhance the resistance of models to cross-chemistry and cross-application. It is also necessary to continue working on hybrid models. The incorporation of physical restrictions and electrochemical knowledge into data-driven models can enhance interpretability, stability, and the lack of dependence on big data. These models are more appropriate to manage noisy measurements and variability of operation used in the real-life application. Lastly, more focus is to be put on online and adaptive prognostics as models are updated with the latest data. Uncertainty-conscious prediction schemes and real-time learning systems will be essential in the implementation in battery management systems, where constant health awareness and decision-making at various points in the battery life cycle are required.

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