A review on prognostics approaches for remaining useful life of lithium-ion battery

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Abstract. Lithium-ion (Li-ion) battery is a core component for various industrial systems, including satellite, spacecraft and electric vehicle, etc. The mechanism of performance degradation and remaining useful life (RUL) estimation correlate closely to the operating state and reliability of the aforementioned systems. Furthermore, RUL prediction of Li-ion battery is crucial for the operation scheduling, spare parts management and maintenance decision for such kinds of systems. In recent years, performance degradation prognostics and RUL estimation approaches have become a focus of the research concerning with Li-ion battery. This paper summarizes the approaches used in Li-ion battery RUL estimation. Three categories are classified accordingly, i.e. model-based approach, data-based approach and hybrid approach. The key issues and future trends for battery RUL estimation are also discussed.

1. Introduction
With the significant advantages, such as high energy density, high galvanic potential, wide temperature range, no memory effect and long service life, lithium-ion (Li-ion) battery has been widely used in industrial areas, including communication, aviation and vehicle [1]. However, the performance of battery will deteriorate with time gradually, and failure will occur from time to time when the performance exceeds a given threshold. It will lead to a reduction in system’s performance, and result in increased cost and even catastrophic failures [2]. By now, various studies have been carried out on performance degradation and remaining useful life (RUL) estimation of Li-ion battery.

RUL is usually defined as the time from the present health state to failure. RUL estimation tries to use previous and current performance to predict system’s future state. In addition, reliable forecast information can provide alarm before failures occur, thus timely repair and maintenance schedule can be made in advance to prevent performance degradation, malfunction or even catastrophic failures [3]. As for Li-ion battery, RUL can be defined as the number of cycles remaining until the battery’s capacity falls below a predetermined threshold [4].

Generally, the approaches for RUL estimation are divided into model-based approach and data-driven approach [3]. However, some novel estimation approaches belong to neither of them. Therefore, in this study we classify the prediction methods into three categories, i.e. model-based approach, data-driven approach and hybrid approach.

2. Model-based approach
Model-based approach is to establish physical model of equipment’s life cycle, including load condition and failure mechanism. Therefore, it is necessary to study system’s failure mechanism, build a right model, select appropriate parameters which can reflect system characteristics, revise and adjust
the prediction model in time.

According to [5] and our findings, model-based prediction methods of Li-ion battery can be classified into physical-based model, equivalent circuit model and filtering approach. In some literatures, filtering approach is also grouped into data-driven method [6]. In this study, three types of model-based approaches are considered:

- Physical-based model: describe and model the battery physical performance evolution.
- Equivalent circuit model: use equivalent circuit model to simulate the operation process.
- Filtering approach: provide a sequential estimation to the system states.

2.1. Physical-based model

Physical-based model seeks to quantify the factors that influence battery’s performance, and obtains the description of performance evolution. However, considering that several factors may interact with each other to impact the degradation of the performance, it is not easy to make a reliable and precise model to simulate battery system. Thus, this approach usually focuses on the specific physical and chemical phenomena occurring during the utilizations [5].

Phenomenological model is extensively used in performance prediction. It can provide dynamic description of battery cell, while it does not involve in the electrodes materials. Christensen, et al [7,8] linked the capacity decay with side reactions and resistance increase, they also developed a model to represent the solid electrolyte interphase (SEI) which causes a significant increase in impedance. Safari, et al [9] introduced a phenomenological model to estimate the health state of a Li-ion cell and assessed the impact on battery performance caused by capacity loss and the increase of SEI.

In some phenomenological models, the intrinsic properties related to electrode and electrolyte materials cannot be precisely involved and considered. In order to further understand the phenomena appearing during degenerative process at a nanoscale level and with a higher prediction accuracy, some models have adopted atomic and molecular methods. By using a multi-interface superlattice method and calculated through density functional theory (DFT), Dalverny, et al [10] investigated the interface electrochemistry in conversion reactions. Tasaki, et al [11] linked the capacity fade and lithium salts dissolution. In addition, molecular dynamic is also an effective way to understand the degradation mechanism.

The performance degradation of battery is dynamic and non-linear. Due to the complexity of electrochemical system, it is difficult to monitor a battery’s internal state in real time, thus an exact physical model is not so easy to obtain. Furthermore, accurate estimation requires a variety of parameters and complex calculations due to the various uncertain factors. Therefore, although physical-based method has significant achievements in mechanism analysis, technically it is unavailable for industrial applications at present.

2.2. Equivalent circuit model

Equivalent circuit model is widely adopted to simulate battery’s running process and estimate parameters in models [5]. This method requires large and diverse data set.

Yoshida, et al [12] investigated the mechanism of capacity fade with experimental data from Li-ion cells on satellite, and build a prediction model to fit the capacity decay data. Later, they improved the previous estimation model where the SEI growth blocking mechanism was taken into account [13]. The result shows that the improved model can fit long-term capacity decay data better. Andre, et al [14] proposed a structured neural network (SNN) algorithm to describe the mathematical function of battery. The SNN is achieved through the mathematical description of the electrical equivalent circuit model.

2.3. Filtering approach

Filtering approach is one of the most common-used methods in RUL estimation. Usually, the calculation of filtering approach includes two steps, i.e. prediction and correction.

Kalman filter (KF) is a recursive filter especially for time-varying linear systems. It estimates the
state of a process by combining the past measurement estimation errors into new measurement errors so as to estimate the future errors. Wang, et al [15] presented a battery state estimation method based on KF. Considering that the extended Kalman filter (EKF) can deal with nonlinear Gauss problem better, Xu, et al [16] adopted expectation maximization (EM) and EKF to estimate the parameters o in the model and update the states. Given that the unscented Kalman filter (UKF) has higher precision than EKF, He, et al [17] proposed a joint coulomb counting method, where UKF is used to adjust parameters, estimate health states and predict RUL of the battery.

Particle filter (PF) is based on Monte Carlo method with sequential importance sampling technique. The core idea of PF is to express the distribution by extracting random state particles from a posteriori probability. Yu, et al [18] integrated PF and logistic regression to predict RUL of Li-ion battery with the degradation experiment data. Wang, et al [19] constructed a state-space model to assess the capacity degradation, and then presented a spherical cubature particle filter to solve the state-space. The analysis result shows that this algorithm is more effective than the other PF-based prediction approaches.

Model-based method can reflect physicochemical characteristics of the battery to some extent. However, due to the complex reaction mechanism as well as the calculation, model-based method is not usually used to estimate the RUL of Li-ion battery alone, some other methods are mixed together to improve the prediction performance.

3. Data-driven approach

Data-driven approach extracts effective feature information to form system’s operational data obtained by advanced sensor technology, and then constructs a degradation model to predict RUL. Thus, accurate descriptions of the system mechanism are not essential for it. In other words, it describes the degradation-inherent relationship and the trend based on data. Generally, data-driven approach includes two categories, i.e. artificial intelligence (AI) technique and life expectancy model [6,20].

3.1. Artificial intelligence

AI method uses monitoring data to fit a degradation model, and estimate RUL through extrapolating the characteristics variables. AI approach mainly includes neural network (NN), support vector machine (SVM) and relevance vector machine (RVM). Table 1 gives a comparison for the three kinds of AI methods.

| Item               | NN                                                                 | SVM                                                                 | RVM                                                                 |
|--------------------|--------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|
| Principle          | A non-linear and self-adaptive information processing system formed | A supervised learning model in high dimensional feature space.       | Based on Bayesian framework                                          |
| Advantage           | 1. Non-linear approximation ability                               | 1. Avoid the curse of dimensionality to a certain extent              | 1. Effectively avoid over-fit or less-fit                           |
|                     | 2. High robustness and strong fault-tolerant capacity              | 2. Require less training data than NN                                 | 2. Better generalization performance                                 |
|                     | 3. Strong capacity of synthetically processing information         | 3. Effectively avoid a local minimum                                  | 3. Acquire point estimation and interval estimation                  |
|                     |                                                                    | 4. High precision, and convergence                                   | 4. Support uncertainty representation                                |
|                     |                                                                    |                                                                      | 5. Do not need many parameters                                       |
Disadvantage

1. Require lots of data
2. Network structure is complex
3. Training may lead to over-fitting and high computation
4. Computational complexity is large
5. Lack of uncertainty representation

1. Require lots of data
2. Kernel function must satisfy Mercer conditions
3. Parameters selection lack of guidance and hard to determined,
4. Lack of uncertainty representation
5. Computational complexity is large
6. Lack of uncertainty representation

1. Require lots of data
2. Parameters selection lack of guidance and hard to determined
3. Poor long-term prediction capability
4. Low stability

Wu, et al [21] used modified Elman network to predict the remaining capacity, and analysed the relationship among varying characteristics, internal resistance and open-circuit voltage.

Wang [22] devised an iterative and multi-step linear SVM model using energy efficiency and working temperature as input and estimated the RUL at room temperature.

Liu, et al [1] used an online training strategy in RVM to improve the ability of dynamic model updating and enhance prediction ability.

Andre, et al [14] proposed a SNN algorithm with prior knowledge to describe the mathematical function of battery voltage, current and resistance with the equivalent circuit.

Dong, et al [23] modelled the relationship among the battery cycle times, capacity, and internal resistance. They combined SVM with PF to achieve parameters estimation and predict the RUL.

Zhang, et al [24] used wavelet decomposition to reduce noise, and RVM improved by differential evolution algorithm is used to estimate battery’s RUL based on the denoised data.

3.2. Life expectancy model

Life expectancy model determines RUL of individual component based on the expected deterioration risk under known operating conditions. It can also be divided into two types, i.e., stochastic model and statistical model [20].

3.2.1. Stochastic model. Stochastic model is used to characterize the performance degradation process, and infer the distribution of the RUL. Given that the degradation process of Li-ion battery is essentially an uncertain stochastic process, various stochastic process models have been proposed, including Gaussian process (GP), Wiener process (WP), hidden Markov model (HMM).

Liu, et al [25] adopted Gaussian process regression (GPR) to obtain the uncertain interval of RUL prediction results, and built a model to predict RUL of the battery online. However, by now this method has not been fully explored. Li, et al [2] constructed an improved Gaussian degradation model by monitoring data in different battery conditions, and PF was used for the parameters identification. Tang, et al [26] presented a WP-based method with measurement error, which has higher accuracy of battery RUL prediction than the simple WP-based method. Si, et al [27] presented a WP model with recursive filter algorithm, both the recursive filter and EM algorithm were used to update drift coefficient and re-estimate unknown parameters in time. Pattipati, et al [28] applied the HMM model into SVM to represent the uncertainty of prognostic.

According to these studies, stochastic model can describe the degradation process of Li-ion battery. However, some dynamic factors have not been taken into consideration, such as time-varying environment, random varying current, self-recharge characteristics [6].

3.2.2. Statistical model. Statistical model predicts the damage initiation and progression according to
the previous inspection results on similar machines. This method does not need knowledge on the ageing mechanism, while it requires a large number of effective data set. Among them, autoregressive (AR), autoregressive and moving average (ARMA), autoregressive integrated moving average (ARIMA) models are widely used for the modeling and prediction of the time series data.

Long, et al [29] adopted AR model to track battery’s capacity degradation process, particle swarm optimization (PSO) algorithm and a new error criterion were used to decide the order of AR model. Liu, et al [3] used an optimized nonlinear degradation AR model and regularized PF to estimate the RUL. Saha, et al [30] adopted an ARIMA algorithm to model battery internal parameters and its capacity. Besides, they compared the prediction ability of several data-driven methods on Li-ion battery, including ARIMA, RVM, EKF and PF.

Furthermore, some data-driven prognostics approaches have not been covered in this paper, for example grey model, Markov chains, similarity matching. In summary, data-driven approach considers only the features of data, and establishes prediction model based on historical and monitoring data. Thus, the adaptability and robustness are always the challenges for the application of this kind of method. In some situations, the sensitivity of parameters setting is another major concern. Among the various data-driven prognostic methods, the methods supporting uncertainty representation and management are hot issues for battery applications.

4. Hybrid approach

Hybrid approach is proposed via combining two or more model-based or data-driven methods to strengthen their advantages, overcome their limitations and thus improve the prediction performance. Generally, there are two categories of hybrid approach, one is the fusion method containing both model-based and data-driven methods, the other one integrates different data-driven methods [4]. Here we focus mainly on the first category.

According to [31] and our study, hybrid approach combining model-based and data-driven methods for battery RUL prediction can be divided into four types.

- Use data-driven method to infer/compensate the physical model. It is acceptable to displace or compensate the complicated physical model by data-driven model when the degradation model is tedious to obtain or the system state cannot be measured directly. In [32], a NN model was developed to estimate the battery’s state of charge, and then UKF was used to reduce the errors and improve the prediction accuracy.

- Use data-driven method to estimate future measurements for model-based method. The predicted measurements from data-driven method can be regarded as new measurements in model-based method when lack of measurements during long-term prediction. Wang, et al [33] adopted a data-driven predictor to predict battery’s future measurements, and these predicted measurements are incorporated into PF to update the prediction model parameters.

- Use data-driven method to estimate/adjust the parameters of physical-based method. Data-driven method describes the degradation-inherent relationship and trend based on data, and uses it to estimate the parameters in the model. In [34], RVM was used to obtain the most representative relevant vectors and to determine the parameters of the capacity degradation model.

- Use filtering approach to estimate/adjust the parameters of data-driven method. Filtering is often used to reduce noise in data and estimate the parameters of the model. In [35], PF approach was adopted to adjust the parameters of a fused regression model online in order to track the degradation trend of the battery.

In the future, the ensemble learning can be used for the fusion and integration of different data-driven prognostic methods. The fusion of online algorithm and uncertainty may be one key issue in hybrid approach for battery’s RUL estimation.

5. Conclusions

Various RUL prediction methods for Li-ion battery are explored in this paper, and their characteristics
are also discussed and compared. Figure 1 gives a summary.

![Figure 1](image)

**Figure 1.** Prediction methods for RUL of Li-ion battery.

As we know that each kind of method has its own advantages and disadvantages. Table 2 lists the pros and cons of proposed methods.

**Table 2.** Comparison of the proposed methods.

| Categories               | Advantages                                      | Disadvantages                                                                 | References       |
|--------------------------|------------------------------------------------|-------------------------------------------------------------------------------|------------------|
| Physical model           | 1. Give the details of degradation              | 1. Require detailed knowledge of system                                        | [7-11]           |
|                          | 2. Provide confidence limits                    | 2. The prediction accuracy is affected by experimental conditions             |                  |
|                          | 3. More accurate estimation                     | 3. Not suitable for practical application                                       |                  |
| Filtering approach       | 1. Suitable for any form of state-space model   | 1. Need data mode                                                             | [15-19]          |
|                          | 2. Suitable for nonlinear, systems              | 2. Point estimation                                                           |                  |
|                          |                                                  | 3. (PF)Initialization process complicated                                     |                  |
| Artificial intelligence  | 1. No data model required                       | 1. Point estimation                                                           | [1,14,21-24]     |
|                          | 2. Simple and feasible calculation              | 2. Lack the uncertainty of prediction results                                 |                  |
|                          | 3. Suitable for nonlinear systems               | 3. Need large amount of data is needed                                         |                  |
| Life expectancy model    | 1. Consider the time-dependence of degradation  | 1. Complex calculation                                                        | [25-30]          |
|                          | process                                         | 2. Consider uncertain factors                                                 |                  |
| Hybrid approach          | 1. Combine the merits of different methods      | 1. Huge calculation                                                           | [31-35]          |
|                          | 2. Effective, accurate and stable               |                                                                              |                  |

For Li-ion battery, the key issues during RUL prediction include time-varying environment, random-variable current, self-healing feature, etc. [6]. Various uncertain factors caused by these issues have a significant impact on the accuracy of the prediction. The uncertainty has become a hotspot in the Li-ion battery RUL prediction research.

In the future, RUL estimation approaches for Li-ion battery can combine monitoring with prognostics techniques. The following aspects can be considered:

- RUL estimation under dynamic operating conditions.
- Fusion and integrated methods for Li-ion battery health status assessment.
- Related issues on battery pack.
- Integrated prognostic framework involving state monitoring, anomaly detection, intelligent diagnostics and prognostics.

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