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# Review of the Remaining Useful Life Prognostics of Vehicle Lithium-Ion Batteries Using Data-Driven Methodologies

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**Abstract:** Lithium-ion batteries are the primary power source in electric vehicles, and the prognosis of their remaining useful life is vital for ensuring the safety, stability, and long lifetime of electric vehicles. Accurately establishing a mechanism model of a vehicle lithium-ion battery involves a complex electrochemical process. Remaining useful life (RUL) prognostics based on data-driven methods has become a focus of research. Current research on data-driven methodologies is summarized in this paper. By analyzing the problems of vehicle lithium-ion batteries in practical applications, the problems that need to be solved in the future are identified.

**Keywords:** data-driven; vehicle lithium-ion batteries; degradation modeling; remaining useful life (RUL)

## 1. Introduction

Electric vehicles have become a focus of global research owing to their energy savings and environmental friendliness [1]. However, power batteries restrict the development of electric vehicles (*i.e.*, the battery can cost as much as 30% of the total cost of the vehicle) [2]. Lithium-ion batteries are the ideal choice for electric vehicles due to their better performance, small volume, light weight, and low pollution [3]. However, the safety and reliability of lithium batteries are concerns for electric vehicle developers. When electric vehicles are used outdoors, poor pavement conditions, temperature, and load changes can cause performance degradation in lithium-ion batteries. Battery degradation may lead to leakage, insulation damage, and partial short-circuit. If the degradation is not detected timely, using the battery further will cause serious situations, such as a spontaneous combustion and explosions, especially if the current state of health has not been assessed in a timely fashion or the future state of health has not been estimated.

Three examples of serious degradation-related incidents are as follows. (1) A Zotye pure electric car made in China spontaneously combusted on 11 April 2011 [4]. (2) The U.S. National Highway Traffic Safety Administration (NHTSA) subjected a GM Volt to a side-impact crash test on 12 May 2011, during which the batteries suffered a great impact and degraded [5]. Three weeks later, the temperature of the Volt's lithium-ion battery pack increased sharply, causing spontaneous combustion. (3) A Tesla Model S made in Norway suddenly caught fire in 2014 when it was charging in the fast charging station [6].

To avoid such catastrophic incidents caused by the degradation of lithium-ion batteries and to predictively maintain the safety of vehicles, it is of great significance to carry out research on the RUL prognostics of lithium-ion batteries. With the rapid proliferation of lithium-ion battery applications, research based on data-driven methods (such as degradation model establishment, RUL prediction, and health states assessment) is summarized in this paper.

The remainder of this paper is organized as follows. Section 2 analyzes three methods based on data-driven RUL prediction, which are based on the artificial intelligence, filtering techniques and the stochastic degradation process, respectively. Section 3 describes the widespread challenges that lithium-ion batteries face in operation, such as the influence of time-varying environments, random variable currents, self-recharge characteristics, and different system configurations. Section 4 concludes this paper and provides future research directions.

## 2. Remaining Useful Life (RUL) Prognostics Methodologies

Remaining useful life (RUL) is defined as the time when equipment performance degrades to the failure threshold for the first time, or the first arrival time [7]. If the RUL can be predicted accurately, predictive maintenance of the equipment can be implemented. Preventive maintenance before degradation is helpful in reducing failure rates and maintenance costs. Therefore, RUL prognostics has become a focus of researchers globally. RUL prognostics methodologies can be divided into the mechanism analysis method and the data-driven method [8]. The degradation of lithium-ion batteries is a nonlinear and time-varying dynamic electrochemical process. Though mechanism analysis is clear in physical significance and concepts, it involves a lot of parameters and complex calculations for accurate modeling. In consequence, it is not suitable for real-time monitoring, which severely limits general applicability of the mechanism model. Instead, mechanism analysis is used more in theoretical research and battery designation than in practical engineering [9].

The data-driven method of modeling batteries does not require an accurate mechanism of the system. Data-driven methods use the battery state of health data, which can be measured through advanced sensor technology. These methods extract effective feature information and construct the degradation model to predict RUL. These methods are able to describe degradation-inherent relationships and trends based on data [10]. Therefore, data-driven methods have become the focus of RUL prediction in the world [11]. Data-driven RUL prediction methods can be divided into three groups based on the artificial intelligence filtering techniques and stochastic process degradation, respectively. Figure 1 shows the main RUL prognostics methodologies of vehicle lithium-ion batteries.

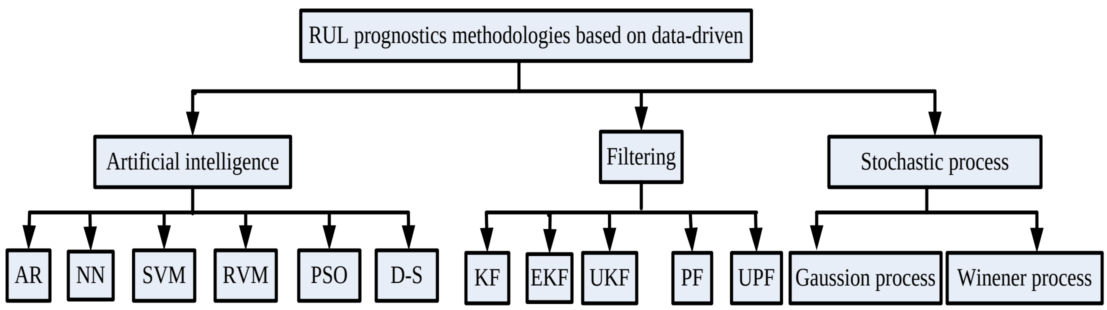


**Figure 1.** The main remaining useful life (RUL) prognostics methodologies of vehicle lithium-ion batteries.

Moreover, the advantages and disadvantages of these three kinds methods shows in Table 1.

**Table 1.** Comparison of RUL prognostics of vehicle lithium-ion batteries using data-driven methodologies.

| Methodology | Advantages | Disadvantages | Main Relevant References |
|---|---|---|---|
| Artificial intelligence | (a) Does not need a data model<br>(b) The algorithms are simple and feasible<br>(c) The algorithms are the best solution for non-linear systems | (a) The point estimated value of RUL<br>(b) Does not describe the uncertainty of measurement results | [12–33] |
| Filtering techniques | (a) Can be used in any form of state-space model<br>(b) best solution for non-linear, Gaussian, and non-Gaussian systems | (a) Needs data mode (state-space model)<br>(b) The point estimated value of RUL | [34–45] |
| Stochastic process | (a) Considers the time-dependence of the degradation process<br>(b) Describes the uncertainty of predictable results | (a) Higher calculation complexity<br>(b) Considers uncertain factors | [46–49] |

### 2.1. RUL Prognostics Methodologies Based on Artificial Intelligence

Methodologies based on artificial intelligence usually use the monitoring data to fit the variable degradation model and calculate the RUL by extrapolating the variables to the failure threshold. Methods such as the AutoRegressive (AR) model [12], neural network [13–18], support vector machine (SVM) [19–22], and relevance vector machine (RVM) [23–33] are used.

Prediction models based on AR only need battery degradation data and can predict the RUL of the battery. The method is simple and easy to be realized. However, vehicle lithium-ion batteries are influenced by many factors, including temperature, discharge current, and so on, which has led to a decline in accuracy. The neural network is often adopted to estimate the nonlinear degradation process due to its superior nonlinear approximation ability. The lithium battery degradation process is a strongly nonlinear process, so neural networks can be a good fit in this process. Min [16] used a neural network to fit the relationship between open voltage, resistance, and discharge capacity at different depths of discharge (DOD). Min [16] also proposed a fast battery capacity prediction method to assess the feasibility application of an artificial neural network in the lithium-ion battery discharge mass rapid prediction. However, the degradation process of lithium batteries is dynamic. In order to reflect the dynamic characteristics of the system, the dynamic recurrent neural network (El-man network) is optimal for describing the system. Wu [17] proposed a method based on a modified Elman neural network to predict the lithium-ion battery remaining capacity and analyzed the relationship among the varying characteristics, internal resistance, and open-circuit voltage. It can be concluded that the network is not only a local generalization but also equipped with better dynamic performance and approximation capability. The network can effectively reduce the total prediction error. Given that the working state of the battery might change with the change course, Liu *et al.* [18] adopted an adaptive recurrent neural network aimed at using lithium battery impedance spectroscopy data to predict the RUL of lithium batteries. The method can be satisfied with the forecast results. However, compared with the SVM, the neural network requires a large amount of training data and is prone to fall into a local minimum. Therefore, many scholars use the SVM to estimate the RUL. Wang [19] devised an iterative multi-step linear prognostics model based on the SVM. It used the energy efficiency and working temperature as input parameters and estimated the RUL of lithium-ion batteries at room temperature. Dong *et al.* [20] mathematically modeled the relationship among the battery cycle times, the capacity, and the internal resistance. They combined the SVM with the particle filter (PF) to achieve a parameter estimation and predict the RUL. Klass *et al.* [21] used several groups of battery degradation data at constant temperature to construct the vehicle battery degradation model based on the SVM and estimate the battery state of health (SOH). Nuhic *et al.* [22] used the SVM to study the battery capacity degradation to estimate the RUL. The SVM is a linear learning machine in high dimensional feature space. Compared with the linear model, it not only increases the complexity of computation, but also avoids the curse of dimensionality to a certain extent. However, the SVM has to choose the appropriate kernel function and only provides the point estimate values of the RUL. It is hard to reflect the uncertainty of estimation. RVM based on the Bayesian framework reduces the computation of the kernel function [23]. The number of the association vectors of RVM is less than SVM, which has better generalization performance and can acquire point estimation and interval estimation. Zhang *et al.* [24] introduced the advantages of RVM and regarded it as one of the main potential methods for lithium-ion battery RUL estimation. Hu *et al.* [25] presented a sparse Bayesian learning method for Li-ion battery capacity estimation and trained an RVM regression model. The performance of the method is verified by 10 years of data. Xing *et al.* [26] proposed a naive Bayes (NB) model for the RUL prediction of batteries under different operating conditions. The results show that prediction performance surpasses that of SVM. Wang *et al.* [27] obtained the relevance vectors from the degradation of battery capacity and the number of cycles. The method is based on the RVM and uses the experiment data of multiple constant current discharge under constant temperature and constant load. They constructed an empirical degradation model using three parameters to estimate RUL, but their models lack the ability of dynamic updating. Therefore, Liu *et al.* [28] proposed an enhanced optimized RVM algorithm, which improved the ability of dynamic model updating and improved the prognostics accuracy of the lithium-ion battery RUL with the same data. Widodo *et al.* [29] predicted the RUL of the battery using the RVM algorithm and found that the long-term prediction performance is poor and not suitable for direct RUL prediction. In order to solve this problem, Zhou *et al.* [30] presented a novel dynamic gray RVM algorithm to achieve a lithium-ion battery RUL prediction. The result indicates that the multi-step prediction precision with fewer sample sizes could be improved. At the same time, in order to reduce the influence of noise on the prediction, Miao *et al.* [31] put forward a fault detection system based on a wavelet transform and hidden Markov model (HMM) modulus maximum distribution. This algorithm was validated by experimental data sets that achieved the classification of the two device statuses (normal and failure). However, the model cannot be directly used to predict the RUL and has certain limitations. Thus, Yuan *et al.* [32] proposed a training algorithm (Baum-Welch algorithm) based on an improved particle swarm optimization (MPSO)-amended hidden semi-Markov model (HSMM) to produce the RUL reliability function and the system failure rate, and finally acquire the RUL distribution of the equipment. Given that RUL prediction accuracy of the training algorithm is not high and applicability is not perfect, Zhang *et al.* [33] reduced noises in characteristic signals using wavelet decomposition and estimated the battery RUL, which was based on NASA's lithium-ion battery data and used the RVM degradation model. The prediction methods based on RVM are the main methods for lithium-ion battery RUL estimation. However, the training time increases rapidly with the increase of the training sample. Other methods are also used in the parameter identification of the model. Tseng *et al.* [34] constructed three kinds of regression models based on the statistical data (N order polynomial regression model [35], bivariate polynomial regression model, and the index regression model), and introduced the particle swarm optimization (PSO) algorithm to optimize the model parameters. Simulations indicate that the regression models using discharged voltage and internal resistance as aging parameters can more accurately build a state of health profile than those using cycle numbers. He *et al.* [36] proposed a double-index lithium battery degradation model and used the Dempster–Shafer theory (DST) to initialize the model parameters and the Bayesian Monte Carlo (BMC) method to update the model parameters, which are used to predict the battery RUL. Hu *et al.* [37] put forward a nonlinear kernel regression model of lithium battery degradation, obtained degradation parameters through the K-nearest neighbor, and used PSO to optimize the weight of the K-nearest neighbor regression model. Chen *et al.* [38] developed a quantitative approach for the battery RUL prediction based on an adaptive bathtub-shaped function and used the artificial fish swarm algorithm method to optimize the parameter model. This prognostic model can capture the dynamic behaviors of the battery capacity.

### 2.2. RUL Prognostics Methodologies Based on Filtering Techniques

The methods of RUL prediction based on filtering techniques have also been studied. Wang *et al.* [39] proposed a state estimation method of lithium-ion batteries based on Kalman filtering (KF), but the method did not consider the influence of actual road conditions. Besides, the KF algorithm aims at linear Gauss, and its accuracy is not high when it comes to the strong nonlinear degradation process of the lithium-ion battery. Given that the extended Kalman filter (EKF) can better deal with the nonlinear Gauss problem, Sepasi *et al.* [40] presented an inline SOH and SOC estimation method for Li-ion battery packs, which used the coulomb counting method to calculate SOC and an extended Kalman filter (EKF) technique to estimate SOH. The advantages of algorithm are less estimation error and fast response time. However, the EKF is a nonlinear part for the first-order Taylor expansion, which ignores the high order, so the errors become larger. Unscented Kalman filter (UKF) is similar to the EKF, which uses Gauss distribution to approximate state distribution to only a few data points called Sigma. Through the nonlinear model, the mean and variance can be accurate to the nonlinear term of second-order Taylor expansion, so the accuracy of nonlinear filtering is higher. Thus, He *et al.* [41] not only built a joint coulomb counting method and battery voltage model but also introduced the UKF to adjust model parameters, estimated the battery status, and predicted the RUL, which was better than the EKF. Zheng *et al.* [42] built a nonlinear time series prediction model to predict the battery life and adopted the UKF to predict residual. The accuracy of estimation was obviously higher than the EKF. In order to improve prediction accuracy, PF based on the Bayesian filter and the Monte Carlo method has also been used in RUL prediction in recent years and achieves the prediction values of posterior probability density through the update of time and measurement. Yu *et al.* [43] constructed a state-space model based on logistic regression and PF to predict RUL with NASA's lithium battery degradation experiment data. Miao *et al.* [44] used a PF algorithm to calculate RUL based on the statistical data of lithium-ion battery life and compared it with the calculation method in the EKF. The results show that the PF shows more accuracy and can predict the actual failure time better than the EKF. Xing *et al.* [45] proposed a model fused with an empirical exponential and a polynomial regression model to describe the battery's degradation trend. Model parameters are adjusted by the PF method. Dalal *et al.* [50] proposed a methodology for the prediction of RUL using the PF framework. Walker *et al.*'s [51] research has found that PF is more accurate than the method (nonlinear least squares and an unscented Kalman filter (UKF)) for predicting RUL. Daniel *et al.* [52] presented the implementation of a PF prognostic framework that uses statistical characterization to estimate the state of charge of a battery. The results show that the proposed framework can prognosticate the discharge time in terms of conditional expectations. Wang *et al.* [53] proposed a spherical cubature particle filter (SCPF) to solve the degradation state-space model of lithium-ion batteries. The analytical results show that it is more effective compared to the existing PF-based prognostic method. At the same time, Miao *et al.* [54] proposed a battery RUL prediction algorithm based on the UKF, and the result shows that it is better than the PF. These algorithms based on artificial intelligence or filtering techniques contribute to the improvement of prediction accuracy. The experimental result shows that these approaches can efficiently estimate the RUL of lithium batteries. However, in the actual operation process, this is not the case. Temperature and currents are time-varying. The methods mentioned above mainly consider discharging at a constant temperature and current. A time-varying temperature and a random variable current have only partly been considered in the actual process of lithium battery operation, and the predicted results are inconsistent with the actual results. At the same time, the prediction result is the RUL point estimation or the average estimate, which cannot provide the prediction probability density analytic function form and does not easily guide later maintenance.

### 2.3. RUL Prognostics Methodologies Based on the Stochastic Degradation Process

RUL prediction based on stochastic process degradation is degraded by a stochastic model on the performance degradation data modeling, and then infers and predicts the distribution of the RUL, making it easy to quantify the uncertainty of prediction results. Given that the lithium battery degradation process is essentially an uncertain stochastic process, many scholars have proposed stochastic process models (such as Gaussian process, Wiener process, *etc.*) to predict the RUL of lithium-ion batteries. The Gaussian process is based on the statistical learning theory and adapts well to high dimensions, small samples, and nonlinear and other complex problems. Its generalization ability is also strong. Goebel *et al.* [55] put forward a Gaussian process model to assess battery capacity degradation. Liu *et al.* [46] constructed a battery data Gaussian process. They not only adopted the Gaussian process regression (GPR) method to give the uncertain interval of the RUL prediction and build the method system of lithium-ion battery online RUL prediction, but also set a RUL prediction verification and assessment experiment through NASA lithium battery validation data. However, none of the above experiments has fully explored the degradation model. Therefore, Li *et al.* [47] built a mixed Gaussian battery degradation model through the data of charging and discharging at room temperature and a constant current, and used PF for model parameter identification, rather than assuming a particular state-space capacity degradation model, which can better predict battery SOH. The experiments and comparative analysis of the method can be obtained with high efficiency. He *et al.* [48] put forward the multi-scale Gaussian process modeling method in wavelet analysis, which was based on the degradation data of lithium batteries in constant-current discharge to predict the RUL. Tang *et al.* [49] proposed a RUL prediction method based on measure errors of the Wiener process, which can better predict the battery RUL.

Based on the above studies, stochastic process modeling can better characterize the lithium battery degradation processes, and the results illustrate that these methods can predict the RUL of lithium-ion batteries. However, none of these studies has considered the self-recharge characteristics of lithium-ion batteries, which mainly aimed at the prediction of lithium battery RUL in situations where the temperature is fixed and the discharge current is constant. These studies have not involved the widespread problems of lithium-ion batteries in operation, such as the influence of a time-varying environment, a random varying current, self-recharge characteristics, and system configuration.

## 3. Problem Analysis

Through the above review, it is not difficult to find that lithium battery RUL prediction based on data-driven methods has made great progress in recent years. However, there is still a lack of theoretical research and need for further study. Accordingly, several problems with RUL prediction for lithium-ion batteries used in electric cars will be specifically analyzed as follows:

(1) Degradation modeling and RUL prediction methods for vehicle lithium-ion batteries with time-varying ambient temperature

Among all the environmental factors, the temperature has a great influence on the performance of the lithium battery. The lithium battery degradation rate is greatly influenced by the ambient environmental temperature [56–59]. The lithium battery may burn as the car starts in a below-freezing environment and as battery capacity rapidly fades under high-temperature conditions [60]. However, electric vehicles work outdoors, and its lithium-ion batteries were often influenced by time-varying ambient temperature. Firstly, the temperature is different between day and night, or among four seasons. Secondly, the lithium battery in the charging and discharging process generated a lot of heat, which causes the lithium battery environment temperature to change, and the difference is very big. The existing methods of degradation modeling and the prediction of RUL are mostly based on the laboratory temperature, and the ambient temperature stress level is constant. These studies [58,61] considered the ambient temperature changes. However, they only aimed at several groups of constant temperature and assumed that a working environment temperature will remain constant. These studies ignored the variability of subsequent working environment temperature. All of these factors resulted in limitations of the RUL algorithm. Therefore, degradation modeling research and RUL prediction methods for lithium-ion batteries with time-varying ambient temperature problem are of important theoretical significance and practical value. Taking into account that the time-varying temperature, we can adopt a multi-state continuous-time Markov model process to describe a transition temperature. Considering time-varying temperature affects the rate of degradation, we can construct a class of degradation models influenced by varying random ambient temperature.

(2) Degradation modeling and RUL prediction methods for vehicle lithium-ion batteries with a random variable current

According to the vehicle behavior, the vehicle acceleration and deceleration process has randomness [4], which produces the lithium battery output current corresponding random changes. The degradation rate is different when the battery discharges at a different current [5]. For example, Li *et al.* [62] tested a capacity fade of 18,650-type lithium-ion batteries cycled with different discharges and found that at 2C discharge rate, the capacity decays were 18.8% of the initial capacity after 300 cycles. And at 1C and 0.5 discharge rate, the capacity decays were only 14.2% and 10.5%, respectively. The reason is that the surface thickness of anode particles and the number of lithium-ions changes with different discharge. Now, existing research on lithium battery degradation modeling and RUL is aimed at fixed loads that build a relationship model of cycles and degradation through the constant current discharge to predict the RUL. Although studies [38,48,49,51] have considered several groups of lithium battery RUL prediction problems under different constant discharge currents, they did not consider the random variation of the current under actual operation process. Random-variable current affects battery degradation rate, which results in the fact that lithium battery degradation function is a nonlinear time-varying function influenced by random effects. Therefore, random-variable current RUL prediction is an enormous challenge [59]. Searching for current rules and the RUL influence becomes the key to this problem. According to a survey, research on random-variable current realistic effects of degradation on the lithium battery has not yet been a concern. To address this problem, we consider the corresponding laws between random-variable current and speed changes, and we can also use the vehicle speed variation to characterize the random-variable current process. Thus, a class of degradation models can be established that are affected by a random-variable current.

(3) Degradation modeling and RUL prediction methods for vehicle lithium-ion batteries considering self-recharge characteristics

The work principle of lithium battery refers to the theory of charge and discharge. As the battery are charged, the battery cathode generates lithium ions. Then, lithium ions will pass through the electrolyte to the cathode carbon microporous layer. The more the lithium-ion is embedded, the higher the capacity. When the battery discharges, lithium ions in the cathode carbon layer prolapse will go back to the cathode.

The status of lithium batteries used in vehicles can be divided into charge, discharge, and standing. The battery circulates between discharge and standing after every charging. When standing, due to the diffusion effect, the ion concentration tends to balance and the voltage rises, which will improve the battery life. We called it the restoration phenomenon self-recharge. The vehicle lithium-ion batteries are generally an intermittent discharge, as shown in Figure 2. Obviously, the intermittent discharge can improve battery life. For an intermittent discharge, when passing a pulse current, the battery relaxes for a period of time; thereby, the active material recovery in the diffusion process and the consumption increases, which improves battery performance. Because the car is in motion and standing most of the time, lithium battery self-recharge is a common phenomenon. Moreover, self-recharge strength will affect the RUL of lithium-ion batteries with the change of battery charge and discharge time [63]. These studies [13–55] about RUL of lithium battery are carried out in a continuous discharge mode, without considering the phenomenon of actual intermittent discharge process. Therefore, it is difficult to describe the dynamic performance of lithium batteries in actual operation. The gap between the theoretical predictions and the actual results is larger. Therefore, RUL prediction methods for vehicle lithium-ion batteries considering self-recharge characteristics are a problem worthy of theoretical research. Furthermore, it is urgent that the automotive lithium battery RUL prediction in practice is solved. Self-recharge is the inherent electrochemical characteristics of a lithium battery. The degree of self-recharge is different, and its independent distribution is a random variable. The degree of self-recharge caused by the accumulation of the effect, that is, the self-healing, can be superimposed. Therefore, the change rule of lithium battery self-healing can be described by a non-homogeneous Poisson process, and the influence on the degradation for lithium battery life can be considered a compound Poisson process description. We may use the compound Poisson process to describe the self-recharge generation based on real-time monitoring battery degradation data, and construct an automotive lithium battery degradation model that is influenced by the self-recharge phenomenon.

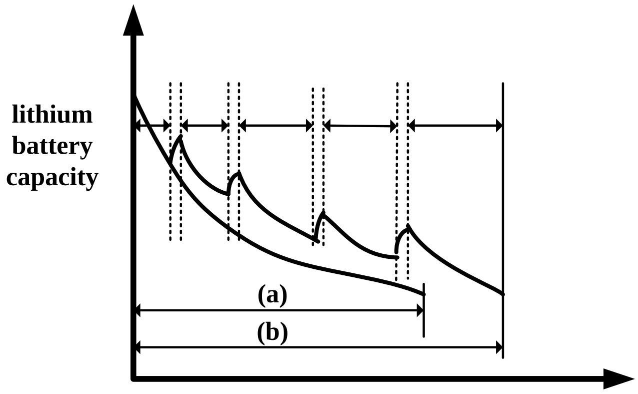


**Figure 2.** Lithium battery capacity changing with discharge process. (**a**) Continuous discharge; (**b**) intermittent discharge.

(4) Denoising of random signals for vehicle lithium-ion batteries considering the system configuration of the cars

Under different system configuration environments, vibration signals from the device contain different information, which contains a lot of harmful component features (*i.e.*, noise). These features influence the research results of lithium-ion battery degradation [31]. Therefore, in order to reduce vehicle production losses and to reduce fatal faults, we should conduct in-depth research on the issue of noise cancellation random signal from different devices, which can improve the purity of the extracted lithium-ion battery vibration signal. This is now one of the most important areas of concern and research.

The key issues for the analysis of RUL prediction for lithium batteries is time-varying ambient temperature, random-variable current, self-healing features, different system configurations, and denoising of random signals. All of these issues involve many uncertain factors, such as the changes of environment temperature, the current random variation, vehicle status, the car's own system configuration features, denoising of random signals, and so on. The uncertainty factors are bound to make a significant impact on the car with the battery RUL prediction accuracy, and these uncertainties have become a top priority for automotive lithium battery RUL prediction research [64].

## 4. Conclusions

The growing use of electric cars makes the RUL prediction of lithium-ion batteries more imminent, but the greatest challenge is the uncertainties. Safe and reliable operation of the vehicle battery is directly related to the reliable operation of the car. In this paper, RUL prediction methods based on data-driven methodologies for lithium-ion batteries were reviewed. First, the existing RUL prediction methods were introduced by category; then, the four critical issues were analyzed, which included a time-varying environment temperature effect, a random-variable current, self-healing characteristics, and a different system configuration. With the RUL prediction of lithium batteries, the above problems can affect the automotive lithium-ion performance, the life, and thereby the entire vehicle system.

In addition, these four problems are mainly aimed at the RUL prediction of the battery under the condition of uncertainty. Therefore, in view of these issues mentioned in this paper, further exploration in these aspects is still needed.

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## References

1. Hu, J.; Morais, H.; Sousa, T.; Lind, M. Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects. *Renew. Sustain. Energy Rev.* **2016**, *56*, 1207–1226. [CrossRef]
2. Fotouhi, A.; Auger, D.J.; Propp, K.; Longo, S.; Wild, M. A review on electric vehicle battery modeling: From Lithium-ion toward Lithium–Sulphur. *Renew. Sustain. Energy Rev.* **2016**, *56*, 1008–1021. [CrossRef]
3. Jaguemont, J.; Boulon, L.; Dubé, Y. A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures. *Appl. Energy* **2016**, *164*, 99–114. [CrossRef]
4. Battery Defect Is the Biggest Hidden Trouble of Pure Electric Vehicles. Available online: http://finance.sina.com.cn/roll/20150429/113022073040.shtml (accessed on 29 April 2015).
5. Self ignition electric vehicle. Available online: http://www.diandong.com/news/201508312701.shtml (accessed on 31 August 2015).
6. Tesla Model S Catches Fire at Supercharger Station in Norway. Available online: http://blog.caranddriver.com/tesla-model-s-catches-fire-at-supercharger-station-in-norway (accessed on 4 January 2016).
7. Escobar, L.A.; Meeker, W.Q.; Luis, A.; William, E.; Meeker, Q. A review of accelerated test models. *Stat. Sci.* **2006**, *21*, 552–577. [CrossRef]
8. Chen, C.; Pecht, M. Prognostics of Lithium-Ion Batteries Using Model Based and Data-Driven Methods. In Proceedings of the 2012 Prognostics & System Health Management Conference, Beijing, China, 23–25 May 2012.
9. Lin, C.; Tang, A.; Wang, W. A review of SOH estimation methods in Lithium-ion batteries for electric vehicle applications. *Energy Proc.* **2015**, *75*, 1920–1925. [CrossRef]
10. Liu, D.; Luo, Y.; Liu, J.; Peng, Y.; Guo, L.; Pecht, M. Lithium-ion battery remaining useful life estimation based on fusion nonlinear degradation AR model and RPF algorithm. *Neural Comput. Appl.* **2013**, *25*, 557–572. [CrossRef]
11. Si, X.S.; Wang, W.; Hu, C.H.; Zhou, D.H. Remaining useful life estimation-A review on the statistical data driven approaches. *Eur. J. Oper. Res.* **2011**, *213*, 1–14. [CrossRef]
12. Long, B.; Xian, W.; Jiang, L.; Liu, Z. An improved autoregressive model by particle swarm optimization for prognostics of lithium-ion batteries. *Microelectr. Reliab.* **2013**, *53*, 821–831. [CrossRef]
13. Eddahech, A.; Briat, O.; Bertrand, N.; Delétage, J.Y.; Vinassa, J.M. Behavior and state-of-health monitoring of Li-ion batteries using impedance spectroscopy and recurrent neural networks. *Int. J. Electr. Power Energy Syst.* **2012**, *42*, 487–494. [CrossRef]
14. Kim, J.; Lee, S.; Cho, B.H. Complementary cooperation algorithm based on DEKF combined with pattern recognition for SOC/Capacity estimation and SOH prediction. *IEEE Trans. Power Electr.* **2012**, *27*, 436–451. [CrossRef]
15. Bai, G.; Wang, P.; Hu, C.; Pecht, M. A generic model-free approach for lithium-ion battery health management. *Appl. Energy* **2014**, *135*, 247–260. [CrossRef]
16. Min, W. Lithium battery remaining capacity prediction method. *Rural. Electr.* **2008**, *7*, 15–16.
17. Wu, Z.Y.; Cao, L.-H.; Chao, T.; Li, T.; Zeng, L.-B.; Hu, B. Research of Modified Elman Neural Network in the Lithium-ion Battery Capacity Prediction Method. *J. Southwest Univ. Sci. Technol.* **2012**, *27*, 65–69.
18. Liu, J.; Saxena, A.; Goebel, K. An adaptive recurrent neural network for remaining useful life prediction of lithimion batteries. In Proceedings of the Annual Conference of Prognostics and Health Management Society, Portland, OR, USA, 10–16 October 2010; pp. 1–9.

19. Wang, S.; Zhao, L.-L.; Su, X.-H.; Ma, P.-J. Prognostics of Lithium-Ion batteries based on battery performance analysis and flexible support vector regression. *Energies* **2014**, *7*, 6492–6508. [CrossRef]
20. Dong, H.-C.H.; Jin, X.-N.; Lou, Y.-B. Lithium-ion battery state of health monitoring and remaining useful life prediction based on support vector regression-particle filter. *J. Power Sources* **2014**, *271*, 114–123. [CrossRef]
21. Klass, V.; Behm, M.; Lindbergh, G. A support vector machine-based state-of-health estimation method for lithium-ion batteries under electric vehicle operation. *J. Power Sources* **2014**, *270*, 262–272. [CrossRef]
22. Nuhic, A.; Terzimehic, T.; Soczka-Guth, T.; Buchholz, M.; Dietmayer, K. Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods. *J. Power Sources* **2013**, *239*, 680–688. [CrossRef]
23. Chen, X.-Z.; Yu, J.-S.; Tang, D.-Y.; Wang, Y.-X. Probabilistc Residual life prediction for lithium-ion batteries based on Bayesian LS-SVR. *Atca Aeronaut. Astron. Sin.* **2013**, *34*, 2219–2229.
24. Zhang, J.; Lee, J. A review on prognostics and health monitoring of Li-ion battery. *J. Power Sources* **2011**, *196*, 6007–6014. [CrossRef]
25. Hu, C.; Jain, G.; Schmidt, C.; Strief, C.; Sullivan, M. Online estimation of lithium-ion battery capacity using sparse Bayesian learning. *J. Power Sources* **2015**, *289*, 105–113. [CrossRef]
26. Ng, S.S.Y.; Xing, Y.; Tsui, K.L. A naive Bayes model for robust remaining useful life prediction of lithium-ion battery. *Appl. Energy* **2014**, *118*, 114–123. [CrossRef]
27. Wang, D.; Miao, Q.; Pecht, M. Prognostics of lithium-ion batteries based on relevance vectors and a conditional three-parameter capacity degradation model. *J. Power Sources* **2013**, *239*, 253–264. [CrossRef]
28. Liu, D.-T.; Zhou, J.-B.; Liao, H.-T. A health indicator extraction and optimization framework for lithium-ion battery degradation modeling and prognostics. *IEEE Trans. Syst. Man Cybern. Syst.* **2015**, *45*, 915–928.
29. Widodo, A.; Shim, M.C.; Caesarendra, W.; Yang, B.S. Intelligent prognostics for battery health monitoring based on sample entropy. *Expert Syst. Appl.* **2011**, *38*, 11763–11769. [CrossRef]
30. Zhou, J.; Ma, Y.; Peng, Y.; Peng, X. Remaining Useful Life Estimation with Dynamic Grey Relevance Vector Machine for Lithium-ion Battery. *Int. J. Adv. Comput. Technol.* **2013**, *5*, 460–469.
31. Miao, Q.; Viliam, M. Condition monitoring of rotating machinery hidden markov models. *Acta Aeronaut. Astron. Sin.* **2005**, *26*, 641–646.
32. Yuan, Y.; Zhuo, D.-F. Application of Hidden Semi—Markov Model in Prediction of Residual Life. *Comput. Technol. Dev.* **2014**, *24*, 184–191.
33. Zhang, C.-L.; He, Y.-G.; Yuan, L.-F. Prognostics of lithium-Ion batteries based on wavelet denoising and DE-RVM. *Comput. Intell. Neurosci.* **2015**, *2015*, 1–8. [CrossRef] [PubMed]
34. Tseng, K.-H.; Liang, J.-W.; Chang, W.-C. Regression models using fully discharged voltage and internal resistance for state of health estimation of Lithium-Ion batteries. *Energies* **2015**, *8*, 2889–2907. [CrossRef]
35. Orchard, M.E.; Hevia-Koch, P.; Zhang, B.; Tang, L. Risk measures for particle-filtering-based state-of-charge prognosis in Lithium-Ion batteries. *IEEE Trans. Ind. Electr.* **2013**, *60*, 5260–5269. [CrossRef]
36. He, W.; Williard, N.; Osterman, M.; Pecht, M. Prognostics of lithium-ion batteries based on Dempster-Shafer theory and the Bayesian Monte Carlo method. *J. Power Sources* **2011**, *196*, 10314–10321. [CrossRef]
37. Chao, H.; Gaurav, J.; Zhang, P.-Q. Data-driven method based on particle swarm optimization and k-nearest neighbor regression for estimating capacity of lithium-ion battery. *Appl. Energy* **2014**, *129*, 49–55.
38. Chen, Y.; Miao, Q.; Zheng, B.; Wu, S.; Pecht, M. Quantitative Analysis of Lithium-Ion Battery Capacity Prediction via Adaptive Bathtub-Shaped Function. *Energies* **2013**, *6*, 3082–3096. [CrossRef]
39. Wang, S.; Shang, L.; Li, Z.; Deng, H.; Ma, Y. Lithium-ion battery security guaranteeing method study based on the state of charge estimation. *Int. J. Electrochem. Sci.* **2015**, *10*, 5130–5151.
40. Sepasi, S.; Ghorbani, R.; Liaw, B.Y. Inline state of health estimation of lithium-ion batteries using state of charge calculation. *J. Power Sources* **2015**, *299*, 246–254. [CrossRef]
41. He, W.; Williard, N.; Chen, C.; Pecht, M. State of charge estimation for electric vehicle batteries using unscented kalman filtering. *Microelectr. Reliab.* **2013**, *53*, 840–847. [CrossRef]
42. Zheng, X.-J.; Fang, H.-J. An integrated unscented kalman filter and relevance vector regression approach for lithium-ion battery remaining useful life and short-term capacity prediction. *Reliab. Eng. Syst. Saf.* **2015**, *144*, 74–82. [CrossRef]
43. Yu, J.-B. State-of-health monitoring and prediction of lithium-ion battery using probabilistic indication and state-space model. *IEEE Trans. Instrum. Meas.* **2015**, *64*, 2937–2949.

44. Miao, Q.; Cui, H.-J.; Zhou, X. Remaining useful life prediction of the lithium-ion battery using particle filtering. *J. Chongqing Univ.* **2013**, *36*, 47–52, 60.
45. Xing, Y.; Ma, E.W.M.; Tsui, K.L.; Pecht, M. An Ensemble Model for Predicting the Remaining Useful Performance of Lithium-ion Batteries. *Microelectr. Reliab.* **2013**, *53*, 811–820. [CrossRef]
46. Liu, D.-T.; Pang, J.-Y.; Zhou, J.-B.; Peng, Y.; Pecht, M. Prognostics for state of health estimation of lithium-ion batteries based on combination Gaussian process functional regression. *Microelectr. Reliab.* **2013**, *53*, 832–839. [CrossRef]
47. Li, F.; Xu, J.-P. A new prognostics method for state of health estimation of lithium-ion batteries based on a mixture of Gaussian process models and particle filter. *Microelectr. Reliab.* **2015**, *55*, 1035–1045. [CrossRef]
48. Yi, J.; Shen, J.N.; Shen, J.-F. State of health estimation of lithium-ion batteries: A multiscale Gaussian process regression modeling approach. *Aiche J.* **2015**, *61*, 1589–1600.
49. Tang, S.; Yu, C.; Wang, X.; Guo, X.; Si, X. Remaining useful life prediction of Lithium-Ion batteries based on the Wiener process with measurement error. *Energies* **2014**, *7*, 520–547. [CrossRef]
50. Dalal, M.; Ma, J.; He, D. Lithium-ion battery life prognostic health management system using particle filtering framework. *Proc. Inst. Mech. Eng. Part J. Risk Reliab.* **2011**, *225*, 81–90. [CrossRef]
51. Walker, E.; Rayman, S.; White, R.E. Comparison of a particle filter and other state estimation methods for prognostics of lithium-ion batteries. *Diss. Theses Gradworks* **2013**, *287*, 1–12. [CrossRef]
52. Pola, D.; Navarrete, H.F.; Orchard, M.E.; Rabie, R.S.; Cerda, M.A.; Olivares, B.E.; Silva, J.F.; Espinoza, P.A.; Perez, A. Particle-Filtering-Based Discharge Time Prognosis for Lithium-Ion Batteries With a Statistical Characterization of Use Profiles. *IEEE Trans. Reliab.* **2015**, *64*, 1–11. [CrossRef]
53. Wang, D.; Yang, F.; Tsui, K.L.; Zhou, Q.; Bae, S.J. Remaining Useful Life Prediction of Lithium-Ion Batteries Based on Spherical Cubature Particle Filter. *IEEE Trans. Instrum. Meas.* **2016**, in press. [CrossRef]
54. Miao, Q.; Xie, L.; Cui, H.; Liang, W.; Pecht, M. Remaining useful life prediction of lithium-ion battery with unscented particle filter technique. *Microelectr. Reliab.* **2013**, *53*, 805–810. [CrossRef]
55. Goebel, K.; Saha, B.; Saxena, A.; Celaya, J.R.; Christophersen, J.P. Prognostics in battery health management. *IEEE Instrum. Meas. Mag.* **2008**, *11*, 33–40. [CrossRef]
56. Lei, Z.-G.; Zhang, C.-N.; Li, J.-Q. Research on Thermal Characteristics of EVs Lithium—Ion Battery. *J. Power Supply* **2014**, *5*, 83–87.
57. Li, P.; An, F.-Q.; Zhang, J.-B.; Wang, H.-R. Temperature sensitivity of lithium-ion battery: A review. *J Automot. Saf. Energy* **2014**, *5*, 224–237.
58. Selman, J.R.; Hallaj, S.A.; Uchida, I.; Hirano, Y. Cooperative research on safety fundamentals of lithium batteries. *J. Power Sources* **2001**, *97–98*, 726–732. [CrossRef]
59. Xing, Y.; Ma, E.W.M.; Tsui, K.L.; Pecht, M. Battery management systems in electric and hybrid vehicles. *Energies* **2011**, *4*, 1840–1857. [CrossRef]
60. Han, X.; Ouyang, M.; Lu, L.; Li, J. Cycle Life of Commercial Lithium-Ion Batteries with Lithium Titanium Oxide Anodes in Electric Vehicles. *Energies* **2014**, *7*, 4895–4909. [CrossRef]
61. Ma, Z.-Y.; Jiang, J.-C.; Zhang, W.-G.; Wang, Z.-G.; Zheng, L.-F.; Shi, W. Research on Path Dependence of Large Format LiMn2O4 Battery Degradation in Thermal Aging. *Trans. China Electrotech. Soc.* **2014**, *29*, 221–227.
62. Li, Y.; Hu, Y.; Liu, Q.-G. Influence of discharge rate on cycling performance of lithium-ion battery. *Chin. J. Power Sources* **2006**, *6*, 488–491. [CrossRef]
63. Xue, Y. A car-following model with stochastically considering the relative velocity in a traffic flow. *Acta Phys. Sin.* **2003**, *52*, 2750–2756.
64. Yang, Q.; Liu, Y.-S. Robust Adaptive Observer for the Charge of Battery with Charging and Discharging Uncertainties. *J. Chongqing Univ.* **2015**, *47*, 1009–3087.