A review on prognostics and health management (PHM) methods of lithium-ion batteries

Article in Renewable and Sustainable Energy Reviews · September 2019

DOI: 10.1016/j.rser.2019.109405

2 authors:

Huixing Meng
Beijing Institute of Technology

Yan-Fu Li
Tsinghua University

A Review on Prognostics and Health Management (PHM) Methods of Lithium-ion Batteries

Huixing Meng, Yan-Fu Li*

Department of Industrial Engineering, Tsinghua University, Beijing, China

---

Abstract

Batteries are prevalent energy providers for modern systems. They can also be regarded as storage units for renewable and sustainable energy. Failures of batteries can bring huge losses in terms of personnel, facility, environment, and reputation aspects. Therefore the accurate health estimation and high availability of batteries is urgently required by corresponding users, distributors, and manufactures. Fortunately, prognostics and health management (PHM) technique has been demonstrated the capability of supporting the improvement of the availability and reliability of batteries. In this paper, we gave a review on the state-of-the-art of the PHM study on batteries. We observed the increase of publication related to battery PHM in the past decade (2009-2018), especially in the past five years. Approaches related to battery performance prognostics are categorized into physics-based, data-driven and hybrid classes. Selection of the battery PHM approach requires to take the user requirement, data availability and degradation mechanisms attainability into consideration. Based on the survey, we also proposed research and development perspectives to conduct further studies on the battery PHM ,including the approach selection, health management, performance evaluation, uncertainty treatment, application economics, as well as environmental issues. We focused on PHM of lithium-ion batteries, given the fact that several publications discussed other types of batteries (e.g., lead-acid batteries).

Keywords: Lithium-ion batteries; Prognostics; Health management; State of health; Remaining useful life

---

*Corresponding author

Email address: liyanfu@tsinghua.edu.cn (Yan-Fu Li)

Acronyms

ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average Model
BHM	Battery Health Management
BMS	Battery Management System
CEEMD	Complete Ensemble Empirical Mode Decomposition
DBN	Dynamic Bayesian Networks
EMD	Empirical Mode Decomposition
EOD	End Of Discharge
EV	Electric Vehicles
FFNN	Feed-Forward Neural Network
GPR	Gaussian Process Regression
GPRNN	Gaussian Process Regression with Neural Networks
HI	Health Indicator
IMMPF	Interacting Multiple Model Particle Filter
LR	Logistic Regression
MKRVM	Multiple Kernel Relevance Vector Machine
OCV	Open Circuit Voltage
PCA	Principal Component Analysis
PF	Particle Filter
PHM	Prognostics and Health Management
PoF	Physics of Failure
RBF	Radial Basis Function
RUL	Remaining Useful Life
RVM	Relevance Vector Machine
SCPF	Spherical Cubature Particle Filter
SOC	State Of Charge
SOF	State Of Function
SOH	State Of Health
SVM	Support Vector Machine
SVR	Support Vector Regression
UKF	Unscented Kalman Filter
UPF	Unscented Particle Filter

1. Introduction

Batteries are prevalent energy providers for modern systems, such as smartphones, laptops, and electric vehicles (EV). Batteries hold the relative high energy density in a confined space. For example, the energy density of lead-acid batteries is around 10∼40Wh/kg [1]. Energy densities of NiCd and lithium-ion batteries are around 50∼75Wh/kg and 100∼200Wh/kg, respectively [1]. Regarding some other types of electrical energy storage systems, supercapacitors hold the energy density around 2.5∼15Wh/kg [2]. The reliability and safety of batteries are thus quite crucial for their users [3, 4]. Reference [3] provided an overview of PHM for lithium-ion batteries, which advocated the importance of battery reliability via accurate estimation of state of health (SOH) and state of charge (SOC). In [4], the authors reviewed the thermal runaway mechanisms of lithium-ion batteries, which emphasized the significance of battery safety. For example, battery safety is a key focus in the design of EV [5]. Battery safety attracts increasing attention from battery consumers and producers. Battery PHM can be helpful for ensuring battery safety.

Failures of batteries can bring loss of power, downtime, and even severe accidents. For example, the short circuit has the risk of leading to temperature increase, and subsequent fire and explosion. In recent years, several accidents have brought significant losses to users, distributors, and manufactures. For examples, battery faults of smartphones have cost Samsung Electronics Co., Ltd. billions of dollars and brought huge of reputation losses in 2016. These faults are generated by design flaws (thin separators and high energy density in batteries) and manufacturing defects [6]. A cargo flight, a Boeing 747-400F operated by United Parcel Service (UPS), crashed because of the fire generated by Lithium-ion (Li-ion) batteries in 2010 [7]. In addition, failures of batteries can lead to recall activities (therefore huge of losses). Recently, due to fire and burn hazards, about 52,600 Li-ion batteries of notebook computers and mobile workstations are recalled in January 2018 [8], around 260,000 Li-ion portable power banks are recalled in March 2018 [9]. Therefore stakeholders expect effective techniques to ensure availability and reliability of batteries.

Owing to complicated electrochemical characteristics and complex working conditions, lithium-ion batteries reveal highly dynamic and nonlinear features [10]. To ensure the required operational performance of lithium-ion batteries, it is necessary to accurately estimate the battery status. Furthermore, to avoid unexpected incidents and subsequent losses, it is helpful to carry out performance prediction of batteries. To meet the accuracy and applicability requirement of battery consumers, prognostics and health management methods are significantly important.

Battery PHM refers to activities to apply PHM approaches in the field of batteries, which includes the prognostics (i.e., health prediction) and health management (e.g., replacement) of batteries. By adopting battery PHM, it enables engineers to obtain and predict the health state of batteries and proactively take measures to maintain the required availability of batteries. Accurate estimation of SOC, SOH, and RUL of batteries is of critical importance for obtaining remaining charge, capacity, and life of batteries. Therefore, it can enable users to timely plan maintenance strategies and conduct disposal and replacement [3].

Prognostics and Health Management (PHM) technique has been widely adopted in different fields to improve and maintain the availability of engineered systems [11, 12, 13]. Reference [11] provided a comprehensive investigation of PHM applied in electronics area. In [12], the researchers discussed in detail the prognostics approaches applied in engineering systems. Comprehensive aspects of prognostics methods are also investigated in [13]. Prognostics aims at predicting the future status of a system, whereas the process of health management uses the information generated as advisory to institute actions to return the system to a healthy state [14]. With growing requirements of high reliability of modern engineered systems, PHM receives increasing attention from academia and industry communities. A significant number of studies on PHM of batteries have been published. We retrieved the journal publications on PHM from the Web of Science database in the past ten years (2009-2018), as shown in Figure 1. We found that research works on PHM have increased steadily from 2010 to 2014 and more rapidly from 2014 to 2018.

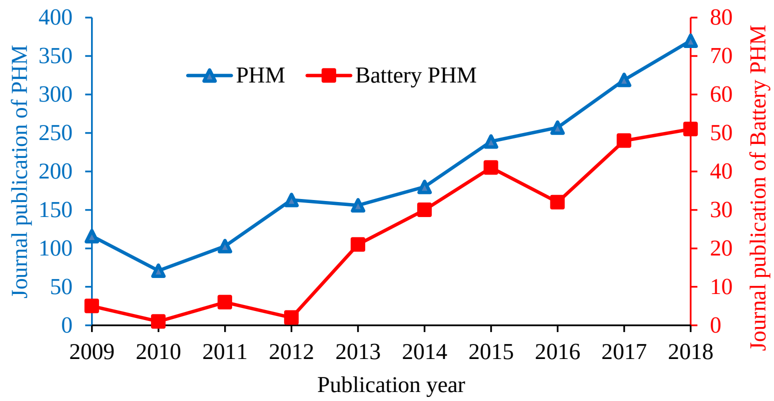

Figure 1: Number of journal publications on PHM in Web of Science.

The objectives of investigating battery PHM is to improve the control, management, and maintenance of batteries and to enable the safe and reliable operation of battery systems [3]. According to our survey, several researchers have conducted literature review on battery PHM. Zhang and Lee [15] reviewed the approaches to predict the capacity, current, voltage, state of charge (SOC), and remaining useful life (RUL) of Li-ion batteries. The review was comprehensive at that time in 2011. However, due to the rapid growth of the research on battery PHM in the past few years (see e.g., the tendency in Figure 1), it is necessary to conduct literature investigation on the articles published in recent years. Liao and Köttig [16] conducted literature review on generic prognostics approaches. To apply advantages of involved prognostics approaches, the authors advocated to use hybrid prognostics approaches to predict RUL of engineered systems, not limited to batteries. Rezvanizaniani et al. [17] reviewed prognostics approaches for EV batteries. The authors considered battery prognostics with focusing on ensuring the EV safety and mobility. Berecibar et al. [18] conducted a review on state of health (SOH) estimation approaches of Li-ion batteries. Their study paid attention to SOH estimation rather than prediction. Shrivastava et al. [10] surveyed particularly the Kalman filter family algorithms for SOC estimation of lithium-ion batteries. Lipu et al. [19] conducted a general review on SOH and RUL estimation of lithium-ion batteries in EVs. Li et al. [20] reviewed mainly the data-driven health estimation and health prognostics of lithium-ion batteries. According to the discussions above, we find that a more comprehensive and up-to-date review on the battery PHM is required. We intend to conduct the literature review by considering both the prognostics and the health management aspects.

Exterior and inner environment (influenced by operation and storage of batteries) can influence the PHM objectives of batteries. For example, wastewater generated by batteries can heavily harm the environment. Therefore the wastewater treatment is an indispensable step in the lifecycle of batteries [21]. Techniques for wastewater treatment normally include the chemical-physical treatment processes and biological ones [22]. Among them, Membrane bioreactors (MBR) is an alternative biological technique for battery wastewater treatment. MBR is composed of a typical activated sludge process (ASP) and membrane separation to maintain biomass [23, 24].

In this paper, we focus on PHM methods of lithium-ion batteries, besides several publications discussed other types of batteries (e.g., lead-acid batteries). Moreover, this manuscript investigated more on PHM methods, rather than empirical PHM from the engineering viewpoint. Although battery chemistry is the basis of the battery exterior performance, we focus on battery PHM from the perspective of battery health performance, rather than the battery chemistry.

The remainder of this article is organized as follows. Section 2 introduces PHM in general. Section 3 reviews the classification of batteries. Section 4 illustrates the application of PHM for batteries. Based on literature review, Section 5 outlines the perspectives for future research in battery PHM. Eventually, Section 6 concludes the article.

2. Prognostics and Health Management

PHM was first coined in 1990s [25, 26, 27, 28], along with the launch of the Joint Strike Fighter (JSF) project of the US army. The initial application of PHM is thus in the military aviation domain. Given the accelerated development of the sensor technology (see e.g., [29]) and prediction algorithms, practitioners have more opportunity to monitor and predict the system status. System stakeholders can thus proactively take measures to avoid severe accidents. Therefore PHM is currently popular in a growing number of domains.

PHM aims to provide actionable information to aid timely decisions [30]. Several PHM-related international standards have already been published. Among them, IEEE Std 1856: 2017 provides guidance for carrying out PHM for electronic systems [14]. It can be extended to other systems, such as the mechanical and energy systems.

Table 1: Prognostics and Health Management (PHM) cycle (adapted from [14]).

Stages	Steps
Sense	(1) Sensors
Acquire	(2) Data acquisition
	(3) Data manipulation
Analyze	(4) State detection
	(5) Health assessment
	(6) Prognostic assessment
Advise	(7) Advisory generation
Act	(8) Health management

The life cycle of PHM can be illustrated in Table 1. This PHM cycle is composed of eight steps [14]:

- (1) Sensors: This function involves physical sensors and any soft system performance variables available within the system.
- (2) Data acquisition: This function acquires and records the sensor data and health state information from the internal monitors, data bus or recorder of the system.
- (3) Data manipulation: This function processes the data from step (2).
- (4) State detection: This function assesses the state conditions with the comparison of normal operating profiles and generates normal or abnormal condition indicators.
- (5) Health assessment: This function generates information to obtain the SOH of the system.
- (6) Prognostic assessment: This function gives upcoming SOH, remaining performance life, or RUL (usage) indicators.
- (7) Advisory generation: This function gives applicable action strategies to operational and repair crews or exterior systems.
- (8) Health management: This function uses the information generated in advisory generation to institute actions to return the system to a *healthy state*.

Prognostics is the key step of PHM. It is the prediction procedure of the RUL of the object system by modeling the fault propagation by considering the present level of degradation, the load profile, and the future operational and environmental scenarios to estimate the time at which the target system will no more perform its predetermined function [14].

A number of prognostics approaches have been proposed. They can be generally classified into three groups: data-driven, physics-based, and hybrid approaches.

Physics-based approaches use explicit mathematical equations to incorporate physical knowledge about the degradation/failure behaviors of a particular system [31]. Physics-based approaches assume that system behaviors can be characterized analytically and precisely [30, 32]. To develop physics-based models, detailed domain knowledge of underlying the degradation processes leading to failure is therefore required [31]. It can be accurate when the degradation physics knowledge is sufficient and relevant. In terms of a battery, its internal electrochemical process is hardly to be observed [17]. Therefore the degradation process of batteries cannot be described directly in a precise way. Moreover, physics-based models developed in laboratories need to be adapted to the real operating environment, which can be constantly changing and rather different from the laboratory conditions.

Data-driven approaches extract useful features from collected data to characterize the current state and thus to model the degradation trend [33]. By using data-driven approaches, it is un-necessary to model various degradation/failure physics in a precise way, instead, only the collected data is used to predict future RUL. The major limitation of data-driven approaches is the prerequisite of sufficient training data that is indeed relevant to the failure/degradation under study.

Hybrid approaches combine the advantages of both physics-based and data-driven approaches [31]. If a hybrid approach obtains the prior knowledge of physics-based model in the first step, and attains unmeasured process parameters by data-driven approaches in the second step, we call such an approach as series approach [30]. That is, the physics-based model can be updated with new data by using data-driven approaches. If we are able to learn from physics-based and data-driven approaches at the same time, we name such hybrid approaches as parallel ones [30]. That is, data-driven approaches serve as supplement to those cannot be described directly by physics-based models.

Characteristics of prognostics approaches are summarized in Table 2. Data-driven approaches require less accurate mathematical modeling of systems than physics-based approaches. However, data-driven approaches require more data than physics-based ones. An et al. [33] applied a selection tree to determine the appropriate prognostics approach for a specific question. The nodes (e.g. the existence of information, the complexity of degradation behavior, the level of noise) of the tree decide the selection process. The authors compared Artificial neural networks (ANN), Gaussian process regression (GPR), Particle filter (PF) and Bayesian method with a mission of crack growth prediction.

Physics-based and data-driven approaches are also significantly influenced by environment and conditions, such as the availability of sufficient data and physical mechanisms. Regarding physics-based approaches, when physics behaviors of target components are explicitly available, they are more robust to the environment. In terms of data-driven methods, when sufficient useful data is available, data-driven methods are usually applicable. Due to the combination of the benefits of physics-based and data-driven approaches, hybrid approaches are regarded as more applicable when dealing with new environment.

It is necessary to consider dynamic operational and environmental loading conditions, which can significantly affect the accuracy and uncertainty of PHM approaches [11]. Furthermore, it is difficult to guarantee the accuracy of feature extraction procedure for monitoring dataset in real situations [11]. In engineering scenarios, along with various operational and environmental conditions, the monitored data would be much more irregular than laboratory environment [11, 34]. Together with influencing factors like the current degradation degree and load profile, future environmental and operational conditions (such as thermal, mechanical, chemical, and electrical ones) can affect prognostics results [11]. Assuming that a training dataset is obtained with the constant discharge current of a battery, if the discharge current varies in the test (prognostics) period, the prediction error can be generated and prognostics model needs to be updated accordingly. For instance, the charge and discharge cycles of batteries can lead to growth of their surface temperatures. Therefore, to meet the high accuracy requirement of prognostics models, such phenomenon needs to be taken into account. In brief, we need to consider the uncertainty of dynamic environmental loads in prognostics models.

Table 2: Characteristics of prognostics approaches.

Approaches	Advantages	Disadvantages
Physics-based	Accurate to describe degradation/failure behaviors of components, subsystems, and systems; provide knowledge and understanding about the degradation/failure; do not require plenty of data.	Hard to observe the degradation process directly; physics-based models developed in laboratories need to be adapted to simulate the real environment in practice.
Data-driven	Un-necessary to model various degradation/failure physics in a precise way; require little domain knowledge.	Reliance on relevant and quality data; low adaptation to new conditions.
Hybrid	Combine advantages of physics-based and data-driven approaches.	Complexity of the selection, combination and parameter tuning of various methods.

In particular, given the recent rapid development of sensor technology and Internet of Things (IoT), massive real-time data recording and transmitting devices can be utilized for PHM research and applications [35]. Due to its powerful feature learning capability, deep learning has attracted interests from the PHM community [36]. Deutsch and He [35] integrated the deep belief network and feedforward neural network to predict RUL of rotating components. The approach can improve the situation that traditional data-driven approaches are built with shallow learning architectures and explicit model equations. Li et al. [37] conducted the RUL prediction by using a deep convolutional neural network. By applying the presented method, it is not required to know in advance the knowledge of signal processing and prognostics.

3. Batteries

Batteries can be classified into primary and secondary batteries, as shown in Figure 2, according to whether their chemical reactions are reversible or not. Secondary batteries can be further categorized into Lead-acid, Lithium-ion (Li-ion), Nickel-cadmium (NiCd), Nickel metal hydride (NiMH) batteries, Nickel-zinc (NiZn), etc. Among them, Li-ion and Lead-acid batteries have attracted more interests from academia and industry.

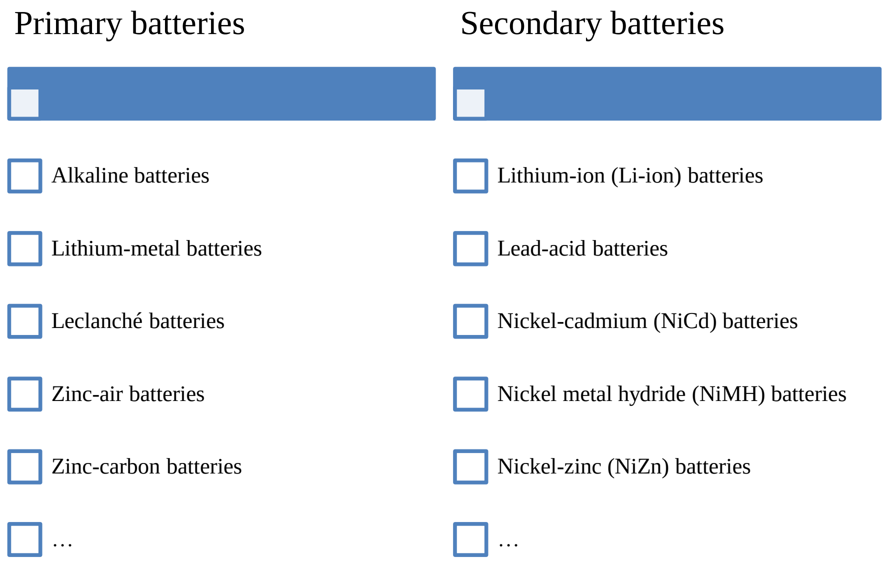

Figure 2: Battery categories.

Li-ion batteries are crucial components of the portable, entertainment, computing and telecommunication equipment [1, 38]. In charging and discharging processes, lithium ions are shuttled between the two electrodes [39]. Li-ion batteries have several attractive superiorities, such as the high energy density, long cycle life, and no-memory effect [40, 41]. They have played a leading role in the energy storage industry and have dominated the consumer market of portable electronics devices [42].

Lead-acid batteries hold the largest market share for rechargeable batteries both in terms of sales value and MWh production [43]. They can serve as industrial batteries for standby, automotive batteries, and motive power [43].

State detection is one necessary step in PHM. For one battery, its status can be evaluated via parameters of SOC, SOH and state of function (SOF) [40, 41, 44].

- SOC corresponds to the stored charge that is available for working, relative to which is available after the battery has been fully charged. SOC describes the battery status, with the comparison of a totally charged one. SOC can be defined as [13]:

$$SOC = 1 - \frac{q_{max} - q_b}{C_{max}} \tag{1}$$

  where q_b is the current charge of the battery, q_{max} is the maximum possible charge of the battery, and C_{max} is the maximum possible capacity of the battery.
- SOH represents the capability of a cell to store the electric energy, in relation to its initial or nominal capabilities. SOH can be regarded as a time-dependent variable with the following expression [13]:

$$SOH = \frac{C_p}{C_i} \tag{2}$$

where C_p is the nominal capacity at the present time, C_i is the nominal capacity at the initial time.

- SOF describes the ability of a battery to satisfy the power demands [41, 44]. SOF of battery is estimated by taking into account its SOC, SOH and operating conditions. SOF can be defined as [41]:

$$SOF = \frac{P - P_d}{P_m - P_d} \tag{3}$$

  where P represents the possible power that the battery can provide, P_d stands for the power demands, P_m denotes the maximum possible supplied power of the battery.

Aforementioned parameters can be estimated by considering specific metrics of batteries, such as the voltage, capacity, current, inner resistance and working temperature. Several data sets for battery PHM study are publicly accessible [45, 46].

4. Prognostics and Health Management of Batteries

According to the classification of PHM approaches in Table 2, we illustrate the PHM approaches for batteries in the similar way.

4.1. Prognostics of batteries

The process of prognostics is normally composed of five steps [16]: measurement, feature extraction, state estimation, state prediction and RUL. In the first step (*measurement*), we can obtain the original measurement data by using sensors. In the second step (*feature extraction*), to decrease the complexity of learning algorithms and increase the robustness of constructed models, we can find a new set of k dimensions that are combinations of the original d dimensions [47]. Note that the second step is optional. In the third step (*state estimation*), we can estimate the state via the measurement models (indirectly evaluate the internal system state with the measurement data) and the deterioration models. In the forth step (*state prediction*), we can predict the state based on the results of the state estimation. Eventually, we can obtain the RUL of targeted components or systems.

In a nutshell, state estimation is used to obtain the *current* health status. Subsequently, state prediction (i.e., prognostics) intends to construct the prognostics model and make prediction of *future* health performance. State estimation and state prediction are indispensable in a prognostics process. Regarding the feature extraction, which is optional according to its application situation. In specific scenarios, it is not necessary to conduct feature extraction according to raw sensor measurement. In [16], feature extraction is declared to be optional for prognostics processes. An example is the health prognostics of lithium-ion batteries. Capacity, which can be monitored directly by a battery tester, is usually regarded as the health index of lithium-ion batteries. Under this assumption, we can carry out health prognostics of lithium-ion batteries without conducting feature extraction.

4.1.1. Physics-based approaches

The internal resistance battery model (R_{int} model) consists of an ideal battery, with the open-circuit voltage (V_{OC}), and a constant internal resistance (R) in the series relationship. The parameters in the R_{int} model change according to SOC, temperature (T), and the direction of current flow (charge or discharge) [48]. Since the voltage response of this model is sensitive to external load changes, this model is applicable assuming that the load conditions are steady [48].

To model the dynamic behaviors of battery voltages, the Thevenin circuit model (see e.g. [49, 50]) can be applied. It can be applied to estimate a battery's voltage transient in response to the change of current load [17]. A RC network (Resistor-capacitor circuit) can filter signals by blocking certain frequencies and passing others. Therefore more RC circuits can represent more complicated behaviors of batteries. By adding more RC networks, we can enhance the accuracy of the Thevenin circuit model [17]. The Thevenin circuit is comprised of a battery, the internal resistance and a RC network in series.

- A battery, whose open-circuit voltage is regarded as constant.
- The internal resistance (R).
- A RC network.

The electrical circuit equivalent model can be applied for end of discharge (EOD) prediction under reasonable accuracy, but it cannot readily capture the aging effects [13]. As an empirical battery model, its equivalent circuit can represent major dynamics of a battery. The model is composed of four parts (i.e., a capacitance, two RC networks and a resistor) in series.

- A capacitance C_b, nonlinear, holds the charge of the battery and captures the open-circuit potential and concentration overpotential.
- A RC network, R_{sp} and C_{sp} in parallel, captures the main nonlinear voltage drop.
- Another RC network, R_s and C_s in parallel. R_s captures the Ohmic drop.
- A resistor, R_p, models the parasitic resistance that takes the self-discharge into account. The external load is added to both ends of R_p.

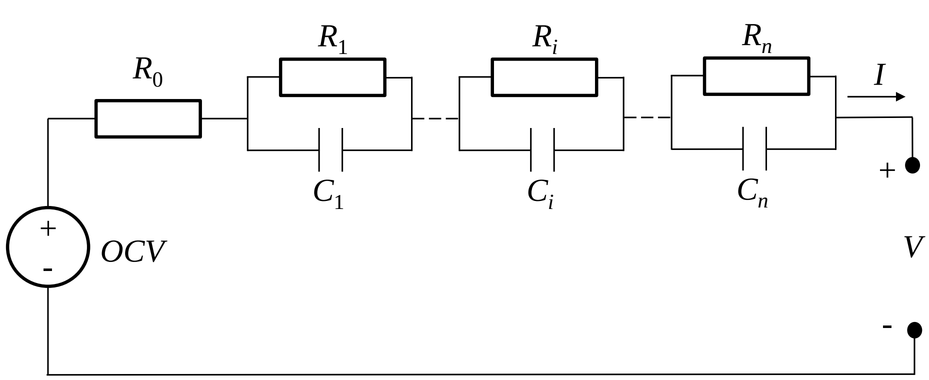

Figure 3: A generic electrical circuit equivalent model.

A generic electrical circuit equivalent model is shown in Figure 3. The terminal voltage V of the battery is depicted as [51, 52]:

$$V = OCV - I\left(R_0 + \sum_{i=1}^{n} R_i\left(1 - \exp(-\frac{t}{R_i C_i})\right)\right) \tag{4}$$

where OCV represents the open circuit voltage of the battery, I denotes the current in the battery, R_0 is the ohmic resistance of the battery, R_i and C_i are polarization resistance and capacitor in ith Resistance-Capacitance (RC) network, respectively. In a nutshellbrief, nRC network is a generic form. Particularly, 0RC is Rint model (i.e., $n = 0$) [48], 1RC is regarded as Thevenin model (i.e., $n = 1$) [49], and 2RC is treated as dual polarization (DP) model (i.e., $n = 2$) [53]. With the increasing number of RC networks, the parameter identification and state estimation can become more difficult [52]. In practice, Rint model, Thevenin model and DP model and their variants are widely applied [53, 54]. Regarding parameter identification of equivalent circuit models, genetic algorithm (GA) can be considered applied to obtained the parameters of equivalent circuit models [52].

Besides the above electric circuit models, the other physics-based prognostics approaches have also been applied. PF has been broadly applied in prognostics of engineering systems, including batteries [55, 56, 57]. The PF process is based on the state transition function f and the measurement function h [58, 59, 60]:

$$x_k = f(x_{k-1}, \boldsymbol{\theta}_k, v_k) \tag{5}$$

$$z_k = h(x_k, w_k) \tag{6}$$

where k represents the time step index, x_k denotes the damage state, $\boldsymbol{\theta}_k$ is a vector of the model parameters, z_k indicates measurement data. v_k and w_k are separately the process and measurement noise. PF is also called the Sequential Monte Carlo (SMC). Interested readers are suggested to refer to [58, 61, 62] for more information of PF in PHM. A Matlab-based tutorial to introduce the PF approach is available in [60]. In their work, An et al. introduced a segment of PF code with a case study of battery degradation.

In addition, PF has been adjusted for the prognostics of battery performance. Wang et al. [55] proposed a methodology for the RUL prediction of Li-ion batteries, on the basis of Spherical Cubature Particle Filter (SCPF). SCPF adapts a spherical cubature integration-based Kalman filter (KF, see e.g. [63]) to generate the importance function of PF. KF assumes that the posterior density at each time step is Gaussian [58]. Miao et al. [64] raised a methodology based on unscented particle filter (UPF) to estimate the RUL of Li-ion batteries. The authors proposed UPF on the basis of PF and Unscented Kalman filter (UKF) (see e.g. [65, 66, 67]). UPF is able to obtain less estimation error than the standard PF. Su et al. [68] applied interacting multiple model particle filter (IMMPF) to determine the RUL of Li-ion batteries. Duong and Raghaven [69] combined the Heuristic Kalman algorithm (HKA) and PF for predicting the RUL of Li-ion batteries. HKA can be used to tackle the sample impoverishment and degeneracy in the standard PF. The prediction results are declared to be more accurate than those of the standard PF.

3D imaging techniques can also be applied to inspect the degradation of batteries. The degradation and failure of Li-ion batteries is strongly associated with the electrode microstructure change upon (de)lithiation [70]. The X-ray tomography approach can observe changes in the microstructure of electrodes to cell performance, and predict degradation processes [70].

Degradation behaviors of batteries have also been studied. Wang et al. [71] studied the aging and degradation of Li-ion batteries with applying the non-destructive electrochemical approaches. They discover that the capacity loss of a battery is heavily influenced by its rate, depth of discharge, and temperature. Xu et al. [72] proposed a semi-empirical Li-ion battery degradation model which can evaluate the battery cell life loss, particularly for offline battery life assessment. The model has been obtained by integrating fundamental theories of battery deterioration, such as the Arrhenius relationship and solid electrolyte interphase (SEI) film formation, and the battery aging test results.

Electrochemcial models are also useful for evaluating battery states. He et al. [73] proposed a physics-based electrochemical model for estimating the SOC of Li-ion batteries. The electrochemical processes are normally established with a group of coupled partial differential equations (PDEs). In order to solve the solid-phase diffusion PDEs, they put forward an optimised projection-based method and moving-window filtering (MWF). The modification of an electrochemical battery model has been proposed to save the computational resources in prognostics [74]. The proposed model can obtain accurate results while reducing the processing time.

Pseudo-Two-Dimensional (P2D) model is a widely-used electrochemical model for lithium-ion batteries [75]. A series of PDEs is employed to describe complex physical and chemical characteristics of batteries. Due to the complexity of P2D model, numerical solutions of parameter identification and simplified version of P2D model are available [76].

4.1.2. Data-driven approaches

In the advent of IoT, data from different devices in batteries is becoming increasingly available. Therefore the applicability of data-driven approaches for battery prognostics is improved as well [77]. Lucu et al. [78] reviewed the self-adaptive aging models for batteries, which include the Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), Relevance Vector Machine (RVM), GPR and ANN.To minimize the testing labors required to develop an accurate aging model, a self-adaptive model can be applied to adapt itself to accommodate better the recently applicable data samples. The authors have also defined criteria for accuracy and computational cost evaluation.

Statistical approaches. Statistical approaches mainly include regression approaches and stochastic approaches. GPR is comprised of a global model and its local departure [33]. Researchers have applied GPR to forecast the battery SOH [77] and estimate the in-situ battery capacity [79]. Zhou et al. [80] used GPR to forecast the SOH of the Li-ion batteries. The proposed GPRNN (Gaussian process regression with neural network) models are declared to be simpler than other mixture methods, such as GPR and multiscale GPR algorithms. GPRNN models are also capable of conducting real-time prognostics. He et al. [81] proposed a multiscale GPR modeling approach to obtain the SOH of Li-ion batteries. The authors applied the wavelet analysis (see e.g. [82]) to decouple the global degeneration, local reconstruction, and variations in the SOH time series. Yu [83] proposed a methodology by integrating GPR and logistic regression (LR) to forecast the RUL of Li-ion batteries. The mean of the results obtained by using LR and GPR is applied.

The other statistical approaches have also been applied for battery prognostics. Based on a bivariate Wiener process (see e.g. [84, 85]), Liu et al. [86] proposed estimated RUL of partially degraded components with two performance characteristics. The researchers tested several Li-ion batteries to testify the provided method. They declared that the suggested method is more robust and accurate. Zhou and Huang [87] proposed a methodology based on empirical mode decomposition (EMD) and ARIMA to estimate the RUL of Li-ion batteries. They validated the methodology with an aging test dataset of Li-ion batteries. Xu et al. [88] proposed a Bayesian hierarchical method by combining discharging and degradation processes to predict EOD. Zhang et al. [89] applied Box-Cox transformation (BCT) to convert the capacity data and to build a model between the transformed capacities and corresponding cycles. This model can therefore be used to forecast the battery RUL. The uncertainties of RUL predictions have been considered with Monte Carlo Simulation (MCS). To predict the EOD by incorporating all discharge cycles, Mishra et al. [90] proposed a Bayesian hierarchical model-based prognostics approach.

Machine Learning approaches. Machine learning (ML) approaches have also been applied for the battery prognostics, such as ANN, Support Vector Machines (SVM), RVM, DBN, etc. These ML approaches have also been integrated with themselves or other methods for the application in more complex situations or the acquirement of more comprehensive results.

ANN learns a way to produce desired outputs by reacting to given inputs [33]. ANN can be used for prognostics on the condition that the relationship between inputs and outputs has been learned sufficiently. The learning process intends to determine *weight* and *bias parameters* between inputs and outputs, as well as *transfer functions* between two adjacent layers. You et al. [91] applied an ANN to estimate the SOH of the EV batteries. The interested data (i.e., the current, voltage and temperature) were obtained from a battery management system (BMS) (see e.g. [92, 93, 94]) on the condition that the batteries are charged/discharged dynamically by considering the driving modes.

ANN has also been combined with other methods for battery prognostics. Zhou et al. [95] proposed a robust prognostics approach to predict the degeneration and estimate the RUL of the proton exchange membrane fuel cell (PEMFC). The autoregressive and moving average (ARMA) model and the time-delay neural network (TDNN) model are integrated to depict the different characteristics in PEMFC degradation voltage data. The linear pattern is initially described by ARMA model. The remaining nonlinear component is simulated and forecasted by TDNN model. To extend the lifetime and reduce the cost of batteries, especially the PEMFC, Liu et al. [96] demonstrated that the combination of different ANN and wavelet decomposition approach can significantly increase the accuracy and stability of the short-term (i.e., time length $\leq$ 50 hours) prognostics.

The other learning algorithms of ANN, for example the extreme learning machine (ELM), have also been applied for the battery prognostics. With the features of randomly choosing the hidden units and analytically deciding the output weights for single hidden layer feed forward neural networks (SLFN), ELM can give better generalization performance at an highly rapid learning speed [97]. ELM has been applied for single-step and multistep predictions [98]. Razavi-Far et al. [98] raised a prognostic scheme for predicting the RUL of Li-ion batteries by considering missing observations. The scheme is composed of pre-processing and prediction modules. When the direct data is insufficient, the observations from a fleet of similar batteries with similar working conditions have been utilized to estimate the RUL of a battery via ELM [99]. Pan et al. [100] proposed a multiple health indicator (HI)-based and machine learning-enabled SOH estimator for PHM. HI can be used to quantify the capacity degradation. An ELM was applied to obtain the correlation of the generated HI and capacity degradation. It is reported that ELM learns fast and is highly accurate, when compared with BP neural netwok.

SVM has been applied for the battery prognostics as well. SVM solves nonlinear issues by transforming the data into a higher feature space, where a problem becomes linear [101, 102]. Zhou et al. [103] applied ANN and SVM separately on infrared images (i.e., surface temperature profiles) to evaluate the cycle life of Li-ion polymer batteries. Their study showed that these two models can obtain similar results, while the SVM models require longer testing time. Gao and Huang [104] used multi-kernel SVM, which is based on the polynomial and radial basis kernel functions, to forecast the RUL of Li-ion batteries. The researchers applied the particle swarm optimization to search essential parameters of the multi-kernel SVM model.

When SVM is applied for regression tasks, it is named SVR. SVR is one of the most popular regression approaches [105]. Due to the capability of describing the nonlinear correlation of input and output data, SVR is suitable for prediction tasks [106]. Ma et al. [105] put forward a methodology for SOH prediction of Li-ion batteries by applying the feature fusion and SVR. The authors applied the sliding window to extract features from different views during the discharge process of Li-ion batteries. Wang and Mamo [106] proposed a hybrid SVR and differential evolution (DE) model to increase the accuracy of RUL prediction for Li-ion batteries. DE has been applied to attain the kernal parameters of SVR.

RVM, as a sparse Bayesian approach for the kernel regression, carries out regression in a probabilistic way [107]. The sparsity characteristic of the RVM regression model permits to carry out predictions for novel observations in an efficient way [107]. RVM has the identical function form of SVM. Nevertheless, it is capable for providing the probabilistic classification. Based on the health features generated from the charging profile (including the voltage, current and temperature profiles), the remaining capacity of Li-ion batteries has been estimated by using RVM [108]. The grey rational analysis and principal component analysis (PCA) have been used to extract and optimize the related health features.

RVM has been integrated with other methods for battery prognostics. Li et al. [109] employed mean entropy and RVM to estimate the RUL of Li-ion batteries. The authors applied the mean entropy to attain the optimal embedding dimension for the correct time series regeneration. They applied RVM subsequently to forecast the SOH and RUL of Li-ion batteries. Zhang et al. [110] proposed a methodology based on the EMD denoising method and multiple kernel relevance vector machine (MKRVM) to evaluate the capacity of the Li-ion battery. The noise-free capacity data can be obtained by applying the EMD denoising approach with the measured capacity data. Based on the noise-free capacity data, its capacity predicting model can thus be established by using MKRVM. Liu et al. [111] applied an optimized RVM to predict the RUL of Li-ion batteries. The extracted HI with battery discharging voltage difference (DVD) is optimized, with the Box-Cox transformation, to retrofit the performance in the RUL prediction. RVM is subsequently applied to indirectly estimate RUL by considering the extracted and optimized HI.

The other ML approaches, such as the Dynamic Bayesian Networks (DBN, see e.g. [112, 113, 114]), have been applied for battery prognostics as well. He et al. [115] applied DBN to evaluate the online SOH of Li-ion batteries. The researchers treated SOC as the hidden states in DBN. They utilized terminal voltages of Li-ion batteries as observations, which are convenient in real applications.

Most recently, Severson et al [116] applied data-driven techniques to predict the battery cycle life. They predict battery life based on early life cycles (i.e., first 100 cycles) and classified batteries with first 5 cycles. High level of accuracy is attained, partially owing to feature extraction from discharge voltage curves. In [117], the random forest regression method is used for battery health prognostics. The features are extracted from the charging voltage-capacity profile. They compared obtained results with those from GPR and incremental capacity analysis.

To carry out data-driven PHM for batteries, we can also learn or employ algorithms applied in other domains, such as PHM studies of bearing and gearbox. In [118], RUL prediction of bearings has been conducted by deep neural networks (DNN). In this work, a denoising autoencoder-based DNN is applied to classify signals of monitored bearings into several degradation stages. Subsequently, shallow neural networks-based regression models are proposed for corresponding degradation stages. Eventually, regression results from different models are smoothed to obtain RUL. In [119], the short frequency Fourier transform (SFFT) is utilized to attain the time-frequency domain information. The multi-scale feature extraction is carried out by applying the convolutional neural networks (CNN).

4.1.3. Hybrid approaches

Hybrid approaches for battery prognostics are mainly related to the PF-related and KF-related approaches. PF can be applied jointly with other approaches to predict the battery RUL. Xing et al. [120] proposed an ensemble approach by integrating an empirical exponential and a polynomial regression models to forecast the RUL of

Li-ion batteries. Parameters are adjusted by applying PF in the model. Dong et al. [121] proposed a framework of on-line short-term (e.g., several-step-ahead) SOH evaluation and long-term RUL forecasting by applying the Brownian motion based deterioration model and PF. The framework treated the capacity degeneration as the traveling distance of a Brownian particle in a time interval. PF can estimate the drift parameter of the Brownian motion. Yu [122] presented a battery health prognostics approach on the basis of the Bayesian-inference probabilistic (BIP) indication and state-space model (SSM) that combines LR and PF. Li and Xu [123] integrated GPR and PF to forecast the SOH of Li-ion batteries. Mixture of Gaussian process (MGP) is firstly applied to learn the statistical properties of the deterioration process. On the basis of the parameter distribution in the degradation process, PF is used to estimate battery SOH. Liao and Köttig [16] applied SVR and PF for prognostics of batteries. Sbarufatti et al. [56] presented an approach for the adaptive prognostics of Li-ion battery terminal voltage. The authors integrated PF and the radial basis function (RBF) neural networks (see e.g. [124, 125, 126]), where PF can ascertain the parameters of RBF dynamically. The algorithm can adapt to the changing dynamics generated by the battery aging effect. Cadini et al. [127] proposed an hybrid approach, by integrating PF and multilayer perception (MLP) neural networks, for prognostics of batteries. PF is used to recursively determine the posterior probability density function (pdf) of the MLP parameters.

For a linear system with Gaussian noise, PF reduces itself to KF [128]. Based on an iteratively renewed RVM integrated with the KF algorithm, Song et al. [129] predicted the RUL of Li-ion batteries. The authors applied KF to optimize an estimator, generated by RVM, with a physical degradation model. Subsequently, they added the optimized estimator as an online sample. By integrating UKF, complete ensemble empirical mode decomposition (CEEMD) and RVM, Chang et al. [130] raised a hybrid method to obtain the RUL of Li-ion batteries. They initially obtained a prognostics result and a raw error series by using UKF. They updated the raw error series by utilizing CEEMD. Based on the novel error series, prognostic error is predicted by using RVM. Prognostics results attained by UKF are updated by the prognostics error. Bai et al. [131] integrated a feed-forward neural network (FFNN) (see e.g. [132, 133]) and KF to depict the battery system dynamics. They testified the proposed method subsequently with a set of the battery experimental data. Misyris et al. [134] estimated SOC for Li-ion Batteries with an accurate hybrid approach. In their work, the Fast Upper-triangular and Diagonal Recursive Least Squares (FUDRLS) with varying forgetting factors and the Approximate Weighted Total Least Squares (AWTLS) algorithms have been applied to identify parameters and estimate capacities. The Coulomb Counting (CC), Linear Kalman Filter (LKF) and open circuit voltage (OCV)-based methods have been utilized to estimate the SOC.

The other hybrid approaches have also been applied for the battery prognostics. Wang et al. [135] used RVM and a capacity deterioration model to estimate the RUL of Li-ion batteries. They applied relevance vectors to discover representative training vectors. Those training vectors, together with the nonlinear least squares regression, are utilized to calculate the parameters of the battery capacity deterioration model.

A hybrid method, the improved bird swarm algorithm optimization least squares support vector machine (IBSA-LSSVM), has been proposed to estimate the RUL of Li-ion batteries [136]. IBSA is applied to determine the optimum parameters of the LSSVM model. The method is declared to obtain higher prediction accuracy and stability.

We summarize the above prognostics approaches for batteries in Table 3.

4.2. Health management of batteries

Health management is the procedure of decision-making and action implementation on the basis of the evaluation of the SOH derived from health monitoring and future application scenarios of the system [14]. Besides the prognostics, health management is another indispensable part for PHM. With the advanced warning of impending failures, we are able to apply prognostics results for maintenance plan and contingency mitigation [16]. Several researchers treat the battery health management (BHM) as BMS [18, 141, 142]. BMS can measure and estimate the functional status of a battery [93]. It has been applied to ensure the battery a safe, reliable, and cost-efficient solution. In addition, BHM can make future operational policies for the usage management and lifetime extension, maintenance costs reduction, and safety incidents prevention [93].

In the operation of batteries, it is required to take into account the health management. The degradation behavior of the electrochemical energy storage (EES, a.k.a. batteries) affects its operational decisions and economic assessments [143]. Perez et al. [144] developed a combined economic-degradation model to evaluate the effects of operational strategies on the total revenue, multi-service portfolios, deterioration, and lifespan of energy storage plants. The storage management strategy of Li-ion batteries, by considering the economic analysis and charging/discharging management, is helpful for the day-ahead optimal operation scheduling of the micro grid [145]. The optimal schedule is applied to minimize the operation cost of the micro grid, as well as the battery depreciation cost.

Maintenance actions for batteries mainly include the repair and replacement. For example, an IEEE *Recommend Practice* is available for the maintenance of the Valve-Regulated Lead-Acid (VRLA) batteries [146]. Maintenance is used to ensure a sound status of the battery in its life cycle, thus to fulfill the required reliability and availability [147]. Battery maintenance should be performed with the specialized knowledge of batteries and the safety precautions involved [146]. Once there is a faulty cell in a battery pack, we need to replace it. Battery replacement criteria includes the battery capacity, service test results, new load requirements, abnormally high temperature, etc. [146]. Replacement cells, if applied, need to ensure that their electrical characteristics are compatible with already existed cells and are testified prior to installation [146]. Due to the inherent aging effect, the capacity of the degraded battery is usually lower than a new one [148]. Therefore it is necessary to select proper replacement cells to avoid the electrical imbalance [148].

The operation and maintenance of batteries have to be considered integrally if necessary. An optimal management/schedule is capable of decreasing the operational costs and expanding the lifespan of batteries. The objective function of such an

Table 3: Introductory summarization of prognostics approaches for batteries.

Categories	Sub-categories	Approaches
Physics-based approaches	Circuit models	Internal resistance model [48]
		Thevenin circuit model [49]
		Battery equivalent circuit [13]
	PF	PF [60, 64, 55, 61, 62, 56, 57, 122]
		SCPF [55]
		UPF [64, 137, 138]
		IMMPF [68]
		Heuristic Kalman optimized PF [69]
	Others	X-ray tomography [70]
		Electrochemcial models [73]
Data-driven approaches (Statistical ones)	GPR	GPR [77, 79, 139]
		GPRNN [80]
		Multiscale GPR [81]
		GPR and LR [83]
	Others	Bivariate Wiener process [86]
		EMD and ARIMA [87]
		Bayesian hierarchical method [88]
Data-driven approaches (ML ones)	ANN	ANN [91, 103]
		ARMA and TDNN [95]
		ANN and wavelet decomposition [96]
		ELM [98, 99, 100]
	SVM	SVM [103]
		Multi-kernel SVM [104]
	SVR	SVR and DE [106]
		SVR and Multiple-view feature fusion [105]
	RVM	Mean entropy and RVM [109]
		Rational analysis, PCA and RVM [108]
		EMD and MKRVM [110]
		Optimized RVM [111]
	Others	DBN [115]
Hybrid approaches	PF-related	PF and LR [122]
		PF and GPR [123]
		PF and RBF neural networks [56]
		PF and MLP neural networks [127]
		PF and SVR [140, 16, 57]
	KF-related	KF and FFNN [131]
		KF and RVM [129]
		UKF, CEEMD and RVM [130]
		LKF, CC and OCV [134]
	Others	RVM and capacity degradation model [135]
		IBSA and LSSVM [136]

optimization model is to maximize the lifespan and minimize the downtime cost. The constraints are the degradation rates, the working environment and the operational modes of batteries. The downtime cost is related to the failure-detection cost, the maintenance cost, as well as the test cost. The maintenance cost is dependent on the cell value, repair crew expense, logistics expense, time delay, etc. Bordin et al. [149] raised the linear programming models for the optimum management of storage units (especially the batteries) in off-grid systems. The developed methodology considered the battery degradation cost and replacement cost in the optimization models. They discussed how the operational modes of an off-grid power system can affect the aging costs of batteries. He et al. [143] proposed an intertemporal decision framework, which includes the replacement options, to generate the optimal solution for maximizing the life-cycle profit of EES. The framework has considered the operating (including short, mid, and long terms) and planning phases of EES.

5. Discussions

With the continuous evolution of engineered systems, their increasing complexity and dynamics add difficulties to the battery PHM. Simultaneously, the risk of failure propagation can bring new challenges for current PHM activities. Therefore there are efforts remain to improve current PHM methods. For instance, we need to propose optimal maintenance strategies by considering the uncertainties of prognostics results and system operations.

5.1. Approach selection for prognostics

In the prognostics domain, due to the different system complexities, data availabilities and application constraints, there is no accepted best model to estimate RUL [16]. However, one algorithm can outperform another one in a particular situation [13]. The comparison of the prognostic algorithms for predicting RUL of batteries can be found in [150].

To select appropriate approaches for battery PHM, we need to consider the requirements from the users and decision makers, such as the working environment, the accuracy and the period of time to be predicted. Operations research (OR) methods can be applied to select optimal methods by considering the cost and benefit. For example, to choose suitable approaches for battery prognostics, we can adopt the analytical hierarchical process (AHP) (see e.g. [151, 152, 153, 154]) to support the multiple criteria decision analysis.

In this manuscript, PHM methods in the literature are usually discussed with specific types of commercial batteries in case studies. These methods are not necessarily applicable to other classes of batteries, even naturally to the identical type of batteries (e.g., different manufacturers or variant chemical concentrations of electrodes and electrolytes). However, when confronted with a new battery case, the review work can be helpful by considering differences of target batteries and those in literature, working conditions, accuracy requirement, and data availability.

5.2. Health management

Significant efforts have been devoted to prognostics in the battery PHM studies, that is, the estimation of current situations and the prediction of future scenarios. However, it is far from integrated for PHM. We need to consider the health management as an indispensable part of PHM. Due to the pervasive application of batteries and difficulties encountered in accidents, we need to devote more efforts to the domain of battery emergency management, which to our knowledge has not been sufficiently researched. With the prepared handling strategies, we can reduce the potential losses effectively and efficiently. To ensure the stable working of systems in both nominal operation and emergency scenario, we can investigate the efficient and resilient management of spare parts and emergency supplies. In addition, we can establish an integrated deployment model of system operation and spare parts management by taking into account prognostics results and maintenance strategies. By considering the spare parts, requirements, uncertainty levels, component importance, manufacturing characteristics and distribution efficiency, we can propose a prediction model of spare parts requirements. To effectively cope with emergency incidents, we need to re-schedule system maintenance activities and provide dynamic emergency strategies, including the personnel deploy and emergency supplies.

5.3. Performance evaluation

Performance evaluation of PHM includes the assessment of PHM methods and the evaluation of PHM results. PHM methods are the approaches as we discussed in Section 4. PHM results are the prognostics outcomes and maintenance strategies that can be obtained by using the PHM methods.

On the one hand, we can assess the PHM methods in several aspects, such as the algorithm convergence, the computational complexity, the cost-benefit risk, and the ease of the algorithm certification [30]. For example, we need to evaluate different prognostics approaches by considering above aspects before their applications.

On the other hand, we can evaluate the PHM results through the verification and validation activities. Regarding the verification, which is a *quality control* process [13], we need to review if the PHM results can fulfill the basic PHM principles as we discussed in Section 2. In terms of the validation, which is a *quality assurance* process [13], we can check if the PHM results can meet the specific accuracy and precision requirements.

5.4. Uncertainty treatment

Due to the incomplete knowledge of systems, lack of the accurate sensing, variability of future operating and loading conditions [13], it is necessary to consider the uncertainty in PHM process. If the uncertainty in prognostics were not considered, the prediction would be useless for the decision making [13]. A key aspect of prognostics is not only to predict future values of related variables but also to express their uncertainties (aleatory and epistemic) associated with these values [77, 128].

By considering the uncertainties generated from current states, future states, modeling and prediction, we can determine the importance measures of components. By taking into account the maintenance cost and the operability, we can propose a decision model for operation and maintenance. Robust optimization applies several approaches for protecting decision-makers against the parameter ambiguity and the stochastic uncertainty[155, 156]. Therefore we can also develop robust optimization scheme to deal with PHM uncertainties. By considering different working scenarios and unstable system inputs, we can put forward a robust maintenance/operation optimization to meet availability requirements of equipment. In this way, we can maximize the equipment RUL and minimize the cost of operation and maintenance.

5.5. Economics of application

To commercialize the application of PHM in engineering domains, it is necessary to provide PHM solutions with low cost and high performance. The effectiveness and efficiency of PHM needs to be economically viable [157]. For example, we can acquire benefits of prognostics in the life cycle of a system, including the processes of design and development, production, operations, logistics support, as well as the maintenance [158]. The cost of prognostics include the acquisition and installation costs, implementation costs, changes in business practices, and the cost of product redesign [158]. Return on investment (ROI) is a popular metrics that can be applied in a cost benefit quantitative analysis [159, 158].

5.6. Environmental issue

Battery industry can bring various environmental pollutants, including toxic gases, greenhouse gas emissions, and hazardous waste in the battery lifecycle [160]. Therefore the environmental issue has to be taken into account. Environmental issues related to lithium-ion batteries include the working environment and wastewater issue. For example, in the usage (charging/discharging) phase, lithium-ion batteries can bring additional heat to the surrounding environment, which has the risk of leading to fire and explosion, and subsequent chemical harm to the environment. In the disposal phase, such as those batteries replaced by novel ones, it is required to take environmental effect into consideration. Related decision-making should be responsible to the whole society, rather than merely high availability of lithium-ion batteries. Among them, wastewater issue related to batteries cannot be neglected, which should be an obbligato part of the battery lifecycle.

Overall, it has to be mentioned that PHM of batteries has its advantages and drawbacks, as is listed in Table 4. By using PHM, it enables us to obtain and predict the battery health. By utilizing prognostics results, engineers can proactively take measures (e.g., terminate and replace related batteries) to maintain the battery availability and forbid unexpected incidents. Adversely, it also takes significant efforts to conduct credible ROI analysis. And it also requires detailed electrochemical knowledge to explain, verify and update the PHM models of batteries.

Table 4: A summary of the advantages and drawbacks of battery PHM.

Advantages	Drawbacks
- Prognostics mission can benefit from the advancement of sensor technology and availability of efficient algorithms and computation resources.	- In a laboratory, it would be easier to obtain health parameters for PHM. In practice, it costs money in PHM implementation. Credible analysis of return on investment (ROI) of PHM is necessary for decision-makers for practical application.
- Health performance and RUL of batteries can be predicted according to the current status.	- It requires sophisticated electrochemical domain knowledge to explain, verify and update PHM models of batteries.
- Prognostics results enable engineers to proactively take measure to optimize mission and replacement strategies, even to forbid severe accidents.	

6. Conclusion

In this paper, we reviewed literature related to battery PHM methods, particularly prognostics methods of lithium-ion batteries. There exists no individual perfect approach for battery PHM, due to the advantages and constraints of each approach. Selection of an approach requires to take the user requirement, data availability and degradation mechanisms attainability into consideration. Three types of battery prognostics approaches are thoroughly discussed. Regarding data-driven prognostics approaches, they highly rely on the quality and quantity of monitoring data and feature engineering techniques. However, they are relatively free from detailed domain knowledge. In terms of physics-based prognostics approaches, they can work with limited data. Nevertheless, sophisticated knowledge of aging mechanisms is required instead. Hybrid approaches can be regarded as a generalization of data-driven and physics-based approaches.

In a nutshell, the review showed that, with complex battery systems, working conditions and monitored data, machine learning-based data-driven approaches are becoming more and more conducive. Hybrid approaches, by integrating data-driven and physic-based methods, are also promising in the domain of battery PHM. Based on the review study, we proposed research and development perspectives to conduct further studies on the battery PHM, which include the approach selection, health management, performance evaluation, uncertainty treatment, application economics, as well as environmental issues.

References

[1] J.-M. Tarascon, M. Armand, Issues and Challenges Facing Rechargeable Lithium Batteries, Nature 414 (2001) 359–367.

[2] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, Y. Ding, Progress in electrical energy storage system: A critical review, Progress in Natural Science 19 (3) (2009) 291 – 312.

[3] S. Saxena, Y. Xing, M. G. Pecht, PHM of Li-ion Batteries, in: Prognostics and Health Management of Electronics, 2018, pp. 349–375.

[4] X. Feng, M. Ouyang, X. Liu, L. Lu, Y. Xia, X. He, Thermal runaway mechanism of lithium ion battery for electric vehicles: A review, Energy Storage Materials 10 (2018) 246–267. doi:10.1016/j.ensm.2017.05.013.

[5] J. Deng, C. Bae, J. Marcicki, A. Masias, T. Miller, Safety Modelling and Testing of Lithium-ion Batteries in Electrified Vehicles, Nature Energy 3 (4) (2018) 261–265.

[6] P. Mozur, Galaxy Note 7 Fires Caused by Battery and Design Flaws, Samsung Says , https://www.nytimes.com/2017/01/22/business/samsung-galaxy-note-7-battery-fires-report.html, [accessed 16-Nov-2018] (2017).

[7] General Civil Aviation Authority of the United Arab Emirates, Uncontained Cargo Fire Leading to Loss of Control Inflight and Uncontrolled Descent Into Terrain, Tech. rep., United Arab Emirates (2010).

[8] The U.S. Consumer Product Safety Commission, HP Recalls Batteries for Notebook Computers and Mobile Workstations Due to Fire and Burn Hazards, https://www.cpsc.gov/recalls/2018/hp-recalls-batteries-for-notebook-computers-and-mobile-workstations-due-to-fire-and-burn-hazards, [accessed 16-Nov-2018] (2018).

[9] The U.S. Consumer Product Safety Commission, Amazon Recalls Portable Power Banks Due to Fire and Chemical Burn Hazards (Recall Alert), https://www.cpsc.gov/Recalls/2018/amazon-recalls-portable-power-banks-due-to-fire-and-chemical-burn-hazards-recall-alert, [accessed 16-Nov-2018] (2018).

[10] P. Shrivastava, T. K. Soon, M. Y. I. B. Idris, S. Mekhilef, Overview of model-based online state-of-charge estimation using kalman filter family for lithium-ion batteries, Renewable and Sustainable Energy Reviews 113 (2019) 109233. doi:10.1016/j.rser.2019.06.040.

[11] M. G. Pecht, M. Kang, Prognostics and Health Management of Electronics: Fundamentals, Machine Learning, and the Internet of Things, Wiley-IEEE Press, 2018.

[12] N.-H. Kim, D. An, J.-H. Choi, Prognostics and Health Management of Engineering Systems, Springer, 2017.

[13] K. Goebel, M. Daigle, A. Saxena, S. Sankararaman, I. Roychoudhury, J. R. Celaya, Prognostics – The Science of Prediction, CreateSpace Independent Publishing Platform, 2017.

[14] IEEE Std 1856 IEEE Standard Framework for Prognostics and Health Management of Electronic Systems (2017).

[15] J. Zhang, J. Lee, A Review on Prognostics and Health Monitoring of Li-ion Battery, Journal of Power Sources 196 (15) (2011) 6007–6014.

[16] L. Liao, F. Köttig, Review of Hybrid Prognostics Approaches for Remaining Useful Life Prediction of Engineered Systems, and an Application to Battery Life Prediction, IEEE Transactions on Reliability 63 (1) (2014) 191–207.

[17] S. M. Rezvanizaniani, Z. Liu, Y. Chen, J. Lee, Review and Recent Advances in Battery Health Monitoring and Prognostics Technologies for Electric Vehicle (EV) Safety and Mobility, Journal of Power Sources 256 (2014) 110–124.

[18] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. V. Mierlo, P. V. den Bossche, Critical Review of State of Health Estimation Methods of Li-ion Batteries for Real Applications, Renewable and Sustainable Energy Reviews 56 (2016) 572 – 587.

[19] M. S. H. Lipu, M. A. Hannan, A. Hussain, M. M. Hoque, P. J. Ker, M. H. M. Saad, A. Ayob, A review of state of health and remaining useful life estimation methods for lithium-ion battery in electric vehicles: Challenges and recommendations, Journal of Cleaner Production 205 (2018) 115–133. doi:10.1016/j.jclepro.2018.09.065.

[20] Y. Li, K. Liu, A. M. Foley, A. Zlke, M. Berecibar, E. Nanini-Maury, J. Van Mierlo, H. E. Hoster, Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review, Renewable and Sustainable Energy Reviews 113 (2019) 109254. doi:10.1016/j.rser.2019.109254.

[21] H. Dahodwalla, S. Herat, Cleaner production options for lead-acid battery manufacturing industry, Journal of Cleaner Production 8 (2) (2000) 133 – 142. doi:https://doi.org/10.1016/S0959-6526(99)00314-5.

[22] R. L. Droste, R. L. Gehr, Theory and practice of water and wastewater treatment, John Wiley & Sons, 2018.

[23] S. Judd, The MBR book: principles and applications of membrane bioreactors for water and wastewater treatment, Elsevier, 2010.

[24] A. Sepehri, M.-H. Sarrafzadeh, Effect of nitrifiers community on fouling mitigation and nitrification efficiency in a membrane bioreactor, Chemical Engineering and Processing - Process Intensification 128 (2018) 10–18. doi:10.1016/j.cep.2018.04.006.

[25] G. Smith, J. B. Schroeder, S. Navarro, D. Haldeman, Development of a Prognostics and Health Management Capability for the Joint Strike Fighter, in: 1997 IEEE Autotestcon Proceedings, 1997, pp. 676–682.

[26] W. Scheuren, K. Caldwell, G. Goodman, A. Wegman, Joint Strike Fighter Prognostics and Health Management, in: 34th AIAA/ASME/SAE/ASEE Joint Propulsion Conference and Exhibit, 1998, p. 3710.

[27] A. Hess, L. Fila, The Joint Strike Fighter (JSF) PHM Concept: Potential Impact on Aging Aircraft Problems, in: IEEE Aerospace Conference Proceedings, Vol. 6, 2002, pp. 3021–3026.

[28] A. Hess, G. Calvello, T. Dabney, PHM a Key Enabler for the JSF Autonomic Logistics Support Concept, in: 2004 IEEE Aerospace Conference Proceedings, Vol. 6, IEEE, 2004, pp. 3543–3550.

[29] S. Cheng, M. H. Azarian, M. G. Pecht, Sensor Systems for Prognostics and Health Management, Sensors (Basel) 10 (6) (2010) 5774–5797.

[30] K. Javed, R. Gouriveau, N. Zerhouni, State of the Art and Taxonomy of Prognostics Approaches, Trends of Prognostics Applications and Open Issues Towards Maturity at Different Technology Readiness Levels, Mechanical Systems and Signal Processing 94 (2017) 214 – 236.

[31] M. Pecht, R. Jaai, A Prognostics and Health Management Roadmap for Information and Electronics-rich Systems, Microelectronics Reliability 50 (3) (2010) 317 – 323.

[32] M. Pecht, Prognostics and Health Management of Electronics, John Wiley & Sons, Ltd, 2008.

[33] D. An, N. H. Kim, J.-H. Choi, Practical Options for Selecting Data-driven or Physics-based Prognostics Algorithms with Reviews, Reliability Engineering & System Safety 133 (2015) 223 – 236.

[34] B. Yang, Y. Lei, F. Jia, S. Xing, An intelligent fault diagnosis approach based on transfer learning from laboratory bearings to locomotive bearings, Mechanical Systems and Signal Processing 122 (2019) 692–706. doi:10.1016/j.ymssp.2018.12.051.

[35] J. Deutsch, D. He, Using Deep Learning-Based Approach to Predict Remaining Useful Life of Rotating Components, IEEE Transactions on Systems, Man, and Cybernetics: Systems 48 (1) (2018) 11–20.

[36] Y. Lin, X. Li, Y. Hu, Deep Diagnostics and Prognostics: An Integrated Hierarchical Learning Framework in PHM Applications, Applied Soft Computing 72 (2018) 555 – 564.

[37] X. Li, Q. Ding, J.-Q. Sun, Remaining Useful Life Estimation in Prognostics Using Deep Convolution Neural Networks, Reliability Engineering & System Safety 172 (2018) 1 – 11.

[38] G. Zubi, R. Dufo-Lpez, M. Carvalho, G. Pasaoglu, The Lithium-ion Battery: State of the Art and Future Perspectives, Renewable and Sustainable Energy Reviews 89 (2018) 292 – 308.

[39] J. Oudenhoven, R. Vullers, R. Van Schaijk, A Review of the Present Situation and Future Developments of Micro-Batteries for Wireless Autonomous Sensor Systems, International Journal of Energy Research 36 (12) (2012) 1139–1150.

[40] I. S. Kim, A Technique for Estimating the State of Health of Lithium Batteries Through a Dual-Sliding-Mode Observer, IEEE Transactions on Power Electronics 25 (4) (2010) 1013–1022.

[41] L. Lu, X. Han, J. Li, J. Hua, M. Ouyang, A Review on the Key Issues for Lithium-ion Battery Management in Electric Vehicles, Journal of Power Sources 226 (2013) 272–288.

[42] J. Lu, T. Wu, K. Amine, State-of-the-art Characterization Techniques for Advanced Lithium-ion Batteries, Nature Energy 2 (3) (2017) 17011.

[43] G. J. May, A. Davidson, B. Monahov, Lead Batteries for Utility Energy Storage: A Review, Journal of Energy Storage 15 (2018) 145–157.

[44] P. Shen, M. Ouyang, L. Lu, J. Li, X. Feng, The Co-estimation of State of Charge, State of Health, and State of Function for Lithium-Ion Batteries in Electric Vehicles, IEEE Transactions on Vehicular Technology 67 (1) (2018) 92–103.

[45] NASA, The Prognostics Center of Excellence (PCoE), https://ti.arc.nasa.gov/tech/dash/groups/pcoe/, [accessed 16-Nov-2018] (2018).

[46] CALCE, Center for Advanced Life Cycle Engineering, University of Maryland, https://web.calce.umd.edu/batteries/data.htm, [accessed 16-Nov-2018] (2018).

[47] E. Alpaydn, Introduction to Machine Learning, The MIT Press, 2010.

[48] V. Johnson, Battery Performance Models in ADVISOR, Journal of Power Sources 110 (2) (2002) 321 – 329.

[49] Z. M. Salameh, M. A. Casacca, W. A. Lynch, A Mathematical Model for Lead-acid Batteries, IEEE Transactions on Energy Conversion 7 (1) (1992) 93–98.

[50] M. Chen, G. A. Rincon-Mora, Accurate Electrical Battery Model Capable of Predicting Runtime and I-V Performance, IEEE Transactions on Energy Conversion 21 (2) (2006) 504–511.

[51] X. Lai, Y. J. Zheng, T. Sun, A comparative study of different equivalent circuit models for estimating state-of-charge of lithium-ion batteries, Electrochimica Acta 259 (2018) 566–577. doi:10.1016/j.electacta.2017.10.153.

[52] X. Lai, W. Gao, Y. Zheng, M. Ouyang, J. Li, X. Han, L. Zhou, A comparative study of global optimization methods for parameter identification of different equivalent circuit models for li-ion batteries, Electrochimica Acta 295 (2019) 1057–1066. doi:10.1016/j.electacta.2018.11.134.

[53] H. He, R. Xiong, H. Guo, S. Li, Comparison study on the battery models used for the energy management of batteries in electric vehicles, Energy Conversion and Management 64 (2012) 113–121. doi:10.1016/j.enconman.2012.04.014.

[54] H. Mu, R. Xiong, Chapter 1 - modeling, evaluation, and state estimation for batteries, in: H. Zhang, D. Cao, H. Du (Eds.), Modeling, Dynamics and Control of Electrified Vehicles, Woodhead Publishing, 2018, pp. 1 – 38.

[55] D. Wang, F. Yang, K.-L. Tsui, Q. Zhou, S. J. Bae, Remaining Useful Life Prediction of Lithium-ion Batteries Based on Spherical Cubature Particle Filter, IEEE Transactions on Instrumentation and Measurement 65 (6) (2016) 1282–1291.

[56] C. Sbarufatti, M. Corbetta, M. Giglio, F. Cadini, Adaptive Prognosis of Lithium-ion Batteries based on the Combination of Particle Filters and Radial Basis Function Neural Networks, Journal of Power Sources 344 (2017) 128–140.

[57] J. Wei, G. Dong, Z. Chen, Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-ion Batteries Using Particle Filter and Support Vector Regression, IEEE Transactions on Industrial Electronics 65 (7) (2018) 5634–5643.

[58] M. Arulampalam, S. Maskell, N. Gordon, T. Clapp, A Tutorial on Particle Filters for Online Nonlinear/non-Gaussian Bayesian Tracking, IEEE Transactions on Signal Processing 50 (2) (2002) 174–188.

[59] E. Zio, G. Peloni, Particle Filtering Prognostic Estimation of the Remaining Useful Life of Nonlinear Components, Reliability Engineering & System Safety 96 (3) (2011) 403–409.

[60] D. An, J.-H. Choi, N. H. Kim, Prognostics 101: A Tutorial for Particle Filter-based Prognostics Algorithm using Matlab, Reliability Engineering & System Safety 115 (2013) 161 – 169.

[61] M. Jouin, R. Gouriveau, D. Hissel, M.-C. Péra, N. Zerhouni, Particle Filter-based Prognostics: Review, Discussion and Perspectives, Mechanical Systems and Signal Processing 72 (2016) 2–31.

[62] D. E. Acuña, M. E. Orchard, Particle-filtering-based Failure Prognosis via Sigma-points: Application to Lithium-ion Battery State-of-charge Monitoring, Mechanical Systems and Signal Processing 85 (2017) 827–848.

[63] B. Sinopoli, L. Schenato, M. Franceschetti, K. Poolla, M. Jordan, S. Sastry, Kalman Filtering with Intermittent Observations, IEEE Transactions on Automatic Control 49 (9) (2004) 1453–1464.

[64] Q. Miao, L. Xie, H. Cui, W. Liang, M. Pecht, Remaining Useful Life Prediction of Lithium-ion Battery with Unscented Particle Filter Technique, Microelectronics Reliability 53 (6) (2013) 805–810.

[65] S. J. Julier, J. K. Uhlmann, New Extension of the Kalman Filter to Nonlinear Systems, in: Proceedings of SPIE - The International Society for Optical Engineering, Vol. 3068, Orlando, FL, USA, 1997, pp. 182 – 193.

[66] W. He, N. Williard, C. Chen, M. Pecht, State of Charge Estimation for Electric Vehicle Batteries using Unscented Kalman Filtering, Microelectronics Reliability 53 (6) (2013) 840–847.

[67] H. He, R. Xiong, J. Peng, Real-time Estimation of Battery State-of-charge with Unscented Kalman Filter and RTOS μCOS-II Platform, Applied Energy 162 (2016) 1410–1418.

[68] X. Su, S. Wang, M. Pecht, L. Zhao, Z. Ye, Interacting Multiple Model Particle Filter for Prognostics of Lithium-ion Batteries, Microelectronics Reliability 70 (2017) 59–69.

[69] P. L. T. Duong, N. Raghavan, Heuristic Kalman Optimized Particle Filter for Remaining Useful Life Prediction of Lithium-ion Battery, Microelectronics Reliability 81 (2018) 232–243.

[70] P. R. Shearing, Batteries: Imaging Degradation, Nature Energy 1 (11) (2016) 1–2.

[71] J. Wang, J. Purewal, P. Liu, J. Hicks-Garner, S. Soukazian, E. Sherman, A. Sorenson, L. Vu, H. Tataria, M. W. Verbrugge, Degradation of Lithium-ion Batteries Employing Graphite Negatives and Nickel-cobalt-manganese Oxide + Spinel Manganese Oxide Positives: Part 1, Aging Mechanisms and Life Estimation, Journal of Power Sources 269 (2014) 937 – 948.

[72] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, D. S. Kirschen, Modeling of Lithium-Ion Battery Degradation for Cell Life Assessment, IEEE Transactions on Smart Grid 9 (2) (2018) 1131–1140.

[73] W. He, M. Pecht, D. Flynn, F. Dinmohammadi, A Physics-Based Electrochemical Model for Lithium-ion Battery State-of-Charge Estimation Solved by an Optimised Projection-Based Method and Moving-Window Filtering, Energies 11 (8).

[74] G. Paez, M. Orchard, C. Kulkarni, K. Goebel, A Hybrid Battery Model for Prognostics in Small-size Electric UAVs, in: 2018 PHM Society Conference.

[75] A. Tulsyan, Y. Tsai, R. B. Gopaluni, R. D. Braatz, State-of-charge estimation in lithium-ion batteries: A particle filter approach, Journal of Power Sources 331 (2016) 208–223. doi:10.1016/j.jpowsour.2016.08.113.

[76] Z.-Y. Liu, K. Yang, Z.-H. Wei, L.-Y. Yao, Electrochemical model of lithium ion battery with simplified liquid phase diffusion equation, Acta Physica Sinica 68 (9). doi:10.7498/aps.68.20190159.

[77] R. R. Richardson, M. A. Osborne, D. A. Howey, Gaussian Process Regression for Forecasting Battery State of Health, Journal of Power Sources 357 (2017) 209 – 219.

[78] M. Lucu, E. Martinez-Laserna, I. Gandiaga, H. Camblong, A Critical Review on Self-adaptive Li-ion Battery Ageing Models, Journal of Power Sources 401 (2018) 85–101.

[79] R. R. Richardson, C. R. Birkl, M. A. Osborne, D. Howey, Gaussian Process Regression for In-situ Capacity Estimation of Lithium-ion Batteries, IEEE Transactions on Industrial Informatics.

[80] D. Zhou, H. Yin, P. Fu, X. Song, W. Lu, L. Yuan, Z. Fu, Prognostics for State of Health of Lithium-Ion Batteries Based on Gaussian Process Regression , Mathematical Problems in Engineering 2018 (2018) 1–11.

[81] Y.-J. He, J.-N. Shen, J.-F. Shen, Z.-F. Ma, State of Health Estimation of Lithium-ion Batteries: A Multiscale Gaussian Process Regression Modeling Approach, AIChE Journal 61 (5) (2015) 1589–1600.

[82] C. Torrence, G. Compo, A Practical Guide to Wavelet Analysis, Bulletin of the American Meteorological Society 79 (1) (1998) 61–78.

[83] J. Yu, State of Health Prediction of Lithium-ion Batteries: Multiscale Logic Regression and Gaussian Process Regression Ensemble, Reliability Engineering & System Safety 174 (2018) 82–95.

[84] Z.-S. Ye, Y. Wang, K.-L. Tsui, M. Pecht, Degradation Data Analysis Using Wiener Processes With Measurement Errors, IEEE Transactions on Reliability 62 (4) (2013) 772–780.

[85] X.-S. Si, W. Wang, C.-H. Hu, M.-Y. Chen, D.-H. Zhou, A Wiener-process-based Degradation Model with a Recursive Filter Algorithm for Remaining Useful Life Estimation, Mechanical Systems and Signal Processing 35 (1-2) (2013) 219–237.

[86] T. Liu, Z. Pan, Q. Sun, J. Feng, Y. Tang, Residual Useful Life Estimation for Products with Two Performance Characteristics based on a Bivariate Wiener Process, Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability 231 (1) (2017) 69–80.

[87] Y. Zhou, M. Huang, Lithium-ion Batteries Remaining Useful Life Prediction based on a Mixture of Empirical Mode Decomposition and ARIMA model, Microelectronics Reliability 65 (2016) 265–273.

[88] X. Xu, Z. Li, N. Chen, A Hierarchical Model for Lithium-Ion Battery Degradation Prediction, IEEE Transactions on Reliability 65 (1) (2016) 310–325.

[89] Y. Zhang, R. Xiong, H. He, M. G. Pecht, Lithium-ion Battery Remaining Useful Life Prediction With BoxCox Transformation and Monte Carlo Simulation, IEEE Transactions on Industrial Electronics 66 (2) (2019) 1585–1597.

[90] M. Mishra, J. Martinsson, M. Rantatalo, K. Goebel, Bayesian Hierarchical Model-based Prognostics for Lithium-ion Batteries, Reliability Engineering & System Safety 172 (2018) 25–35.

[91] G.-w. You, S. Park, D. Oh, Real-time State-of-health Estimation for Electric Vehicle Batteries: A Data-driven Approach, Applied Energy 176 (2016) 92–103.

[92] Y. Xing, E. W. M. Ma, K. L. Tsui, M. Pecht, Battery Management Systems in Electric and Hybrid Vehicles, Energies 4 (11) (2011) 1840–1857.

[93] H. Rahimi-Eichi, U. Ojha, F. Baronti, M. Y. Chow, Battery Management System: An Overview of Its Application in the Smart Grid and Electric Vehicles, IEEE Industrial Electronics Magazine 7 (2) (2013) 4–16.

[94] B. G. Carkhuff, P. A. Demirev, R. Srinivasan, Impedance-Based Battery Management System for Safety Monitoring of Lithium-Ion Batteries, IEEE Transactions on Industrial Electronics 65 (8) (2018) 6497–6504.

[95] D. Zhou, A. Al-Durra, K. Zhang, A. Ravey, F. Gao, Online Remaining Useful Lifetime Prediction of Proton Exchange Membrane Fuel Cells Using a Novel Robust Methodology, Journal of Power Sources 399 (2018) 314–328.

[96] H. Liu, J. Chen, D. Hissel, H. Su, Short-term Prognostics of PEM Fuel Cells: A Comparative and Improvement Study, IEEE Transactions on Industrial Electronics.

[97] G.-B. Huang, Q.-Y. Zhu, C.-K. Siew, Extreme Learning Machine: Theory and Applications, Neurocomputing 70 (1-3) (2006) 489–501.

[98] R. Razavi-Far, S. Chakrabarti, M. Saif, E. Zio, An Integrated Imputation-prediction Scheme for Prognostics of Battery Data with Missing Observations, Expert Systems with Applications 115 (2019) 709–723.

[99] R. Razavi-Far, S. Chakrabarti, M. Saif, E. Zio, V. Palade, Extreme Learning Machine Based Prognostics of Battery Life, International Journal on Artificial Intelligence Tools 27 (8).

[100] H. Pan, Z. L, H. Wang, H. Wei, L. Chen, Novel Battery State-of-health Online Estimation Method Using Multiple Health Indicators and an Extreme Learning Machine, Energy 160 (2018) 466–477.

[101] J. Han, M. Kamber, J. Pei, Data Mining: Concepts and Techniques, Third Edition, Elsevier, 2012.

[102] J. Liu, Y.-F. Li, E. Zio, A SVM Framework for Fault Detection of the Braking System in a High Speed Train, Mechanical Systems and Signal Processing 87 (2017) 401–409.

[103] X. Zhou, S.-J. Hsieh, B. Peng, D. Hsieh, Cycle Life Estimation of Lithium-ion Polymer Batteries using Artificial Neural Network and Support Vector Machine with Time-resolved Thermography, Microelectronics Reliability 79 (2017) 48–58.

[104] D. Gao, M. Huang, Prediction of Remaining Useful Life of Lithium-ion Battery based on Multi-kernel Support Vector Machine with Particle Swarm Optimization, Journal of Power Electronics 17 (5) (2017) 1288–1297.

[105] C. Ma, X. Zhai, Z. Wang, M. Tian, Q. Yu, L. Liu, H. Liu, H. Wang, X. Yang, State of Health Prediction for Lithium-ion Batteries using Multiple-view Feature Fusion and Support Vector Regression Ensemble, International Journal of Machine Learning and Cybernetics 10 (9) (2018) 22692282.

[106] F.-K. Wang, T. Mamo, A Hybrid Model based on Support Vector Regression and Differential Evolution for Remaining Useful Lifetime Prediction of Lithium-ion Batteries, Journal of Power Sources 401 (2018) 49–54.

[107] C. Hu, G. Jain, C. Schmidt, C. Strief, M. Sullivan, Online Estimation of Lithium-ion Battery Capacity using Sparse Bayesian Learning, Journal of Power Sources 289 (2015) 105–113.

[108] J. Lee, D. Kwon, M. Pecht, Reduction of Li-ion Battery Qualification Time Based on Prognostics and Health Management, IEEE Transactions on Industrial Electronics 6 (9) (2019) 7310–7315.

[109] H. Li, D. Pan, C. L. P. Chen, Intelligent Prognostics for Battery Health Monitoring Using the Mean Entropy and Relevance Vector Machine, IEEE Transactions on Systems Man Cybernetics-Systems 44 (7) (2014) 851–862.

[110] C. Zhang, Y. He, L. Yuan, S. Xiang, Capacity Prognostics of Lithium-Ion Batteries using EMD Denoising and Multiple Kernel RVM, IEEE Access 5 (2017) 12061–12070.

[111] D. Liu, J. Zhou, H. Liao, Y. Peng, X. Peng, A Health Indicator Extraction and Optimization Framework for Lithium-Ion Battery Degradation Modeling and Prognostics, IEEE Transactions on Systems Man Cybernetics-Systems 45 (6) (2015) 915–928.

[112] Z. Liu, Y. Liu, B. Cai, D. Zhang, C. Zheng, Dynamic Bayesian Network Modeling of Reliability of Subsea Blowout Preventer Stack in Presence of Common Cause Failures, Journal of Loss Prevention in the Process Industries 38 (2015) 58–66.

[113] B. Cai, Y. Liu, M. Xie, A Dynamic-Bayesian-Network-Based Fault Diagnosis Methodology Considering Transient and Intermittent Faults, IEEE Transactions on Automation Science and Engineering 14 (1) (2017) 276–285.

[114] N. Khakzad, G. Landucci, G. Reniers, Application of Dynamic Bayesian Network to Performance Assessment of Fire Protection Systems During Domino Effects, Reliability Engineering & System Safety 167 (2017) 232 – 247.

[115] Z. He, M. Gao, G. Ma, Y. Liu, S. Chen, Online State-of-health Estimation of Lithium-ion Batteries using Dynamic Bayesian Networks, Journal of Power Sources 267 (2014) 576–583.

[116] K. A. Severson, P. M. Attia, N. Jin, N. Perkins, B. Jiang, Z. Yang, M. H. Chen, M. Aykol, P. K. Herring, D. Fraggedakis, M. Z. Bazant, S. J. Harris, W. C. Chueh, R. D. Braatz, Data-driven prediction of battery cycle life before capacity degradation, Nature Energy 4 (2019) 383–391. doi:10.1038/s41560-019-0356-8.

[117] Y. Li, C. Zou, M. Berecibar, E. Nanini-Maury, J. C. W. Chan, P. van den Bossche, J. Van Mierlo, N. Omar, Random forest regression for online capacity estimation of lithium-ion batteries, Applied Energy 232 (2018) 197–210. doi:10.1016/j.apenergy.2018.09.182.

[118] M. Xia, T. Li, T. Shu, J. Wan, C. W. d. Silva, Z. Wang, A two-stage approach for the remaining useful life prediction of bearings using deep neural networks, IEEE Transactions on Industrial Informatics 15 (6) (2019) 3703–3711. doi:10.1109/TII.2018.2868687.

[119] X. Li, W. Zhang, Q. Ding, Deep learning-based remaining useful life estimation of bearings using multi-scale feature extraction, Reliability Engineering & System Safety 182 (2019) 208–218. doi:10.1016/j.ress.2018.11.011.

[120] Y. Xing, E. W. M. Ma, K.-L. Tsui, M. Pecht, An Ensemble Model for Predicting the Remaining Useful Performance of Lithium-ion Batteries, Microelectronics Reliability 53 (6) (2013) 811–820.

[121] G. Dong, Z. Chen, J. Wei, Q. Ling, Battery Health Prognosis using Brownian Motion Modeling and Particle Filtering, IEEE Transactions on Industrial Electronics 65 (11) (2018) 8646–8655.

[122] J. Yu, State-of-Health Monitoring and Prediction of Lithium-Ion Battery Using Probabilistic Indication and State-Space Model, IEEE Transactions on Instrumentation and Measurement 64 (11) (2015) 2937–2949.

[123] F. Li, J. Xu, A New Prognostics Method for State of Health Estimation of Lithium-ion Batteries based on a Mixture of Gaussian Process Models and Particle Filter, Microelectronics Reliability 55 (7) (2015) 1035 – 1045.

[124] W. Pedrycz, Conditional Fuzzy Clustering in the Design of Radial Basis Function Neural Networks, IEEE Transactions on Neural Networks 9 (4) (1998) 601–612.

[125] M. Er, S. Wu, J. Lu, H. Toh, Face Recognition with Radial Basis Function (RBF) Neural Networks, IEEE Transactions on Neural Networks 13 (3) (2002) 697–710.

[126] B. Li, X. Rui, Vibration Control of Uncertain Multiple Launch Rocket System using Radial Basis Function Neural Network, Mechanical Systems and Signal Processing 98 (2018) 702–721.

[127] F. Cadini, C. Sbarufatti, F. Cancelliere, M. Giglio, State-of-life Prognosis and Diagnosis of Lithium-ion Batteries by Data-driven Particle Filters, Applied Energy 235 (2019) 661–672.

[128] K. Goebel, B. Saha, A. Saxena, J. R. Celaya, J. P. Christophersen, Prognostics in Battery Health Management, IEEE Instrumentation & Measurement Magazine 11 (4) (2008) 33–40.

[129] Y. Song, D. Liu, Y. Hou, J. Yu, Y. Peng, Satellite Lithium-ion Battery Remaining Useful Life Estimation with an Iterative Updated RVM Fused with the KF Algorithm, Chinese Journal of Aeronautics 31 (1) (2018) 31–40.

[130] Y. Chang, H. Fang, Y. Zhang, A New Hybrid Method for the Prediction of the Remaining Useful Life of a Lithium-ion Battery, Applied Energy 206 (2017) 1564–1578.

[131] G. Bai, P. Wang, C. Hu, A Self-cognizant Dynamic System Approach for Prognostics and Health Management, Journal of Power Sources 278 (2015) 163–174.

[132] J. Ilonen, J. Kamarainen, J. Lampinen, Differential Evolution Training Algorithm for Feed-forward Neural Networks, Neural Processing Letters 17 (1) (2003) 93–105.

[133] M. Hassan, M. Hamada, Performance Comparison of Feed-Forward Neural Networks Trained with Different Learning Algorithms for Recommender Systems, Computation 5 (3).

[134] G. Misyris, D. I. Doukas, T. A. Papadopoulos, D. P. Labridis, V. G. Agelidis, State-of-Charge Estimation for Li-ion Batteries: A More Accurate Hybrid Approach, IEEE Transactions on Energy Conversion 34 (1) (2019) 109–119.

[135] D. Wang, Q. Miao, M. Pecht, Prognostics of Lithium-ion Batteries based on Relevance Vectors and a Conditional Three-parameter Capacity Degradation Model, Journal of Power Sources 239 (2013) 253–264.

[136] L.-L. Li, Z.-F. Liu, M.-L. Tseng, A. S. F. Chiu, Enhancing the Lithium-ion Battery Life Predictability Using a Hybrid Method, Applied Soft Computing 74 (2019) 110–121.

[137] X. Zhang, Q. Miao, Z. Liu, Remaining Useful Life Prediction of Lithium-ion Battery Using an Improved UPF Method based on MCMC, Microelectronics Reliability 75 (2017) 288–295.

[138] H. Zhang, Q. Miao, X. Zhang, Z. Liu, An Improved Unscented Particle Filter Approach for Lithium-ion Battery Remaining Useful Life Prediction, Microelectronics Reliability 81 (2018) 288–298.

[139] D. Yang, X. Zhang, R. Pan, Y. Wang, Z. Chen, A Novel Gaussian Process Regression Model for State-of-health Estimation of Lithium-ion Battery Using Charging Curve, Journal of Power Sources 384 (2018) 387–395.

[140] H. Dong, X. Jin, Y. Lou, C. Wang, Lithium-ion Battery State of Health Monitoring and Remaining Useful Life Prediction based on Support Vector Regression-Particle Filter, Journal of Power Sources 271 (2014) 114–123.

[141] L. Tao, J. Ma, Y. Cheng, A. Noktehdan, J. Chong, C. Lu, A Review of Stochastic Battery Models and Health Management, Renewable and Sustainable Energy Reviews 80 (2017) 716 – 732.

[142] G. Sierra, M. Orchard, K. Goebel, C. Kulkarni, Battery Health Management for Small-size Rotary-wing Electric Unmanned Aerial Vehicles: An Efficient Approach for Constrained Computing Platforms, Reliability Engineering & System Safety 182 (2019) 166 – 178.

[143] G. He, Q. Chen, P. Moutis, S. Kar, J. F. Whitacre, An Intertemporal Decision Framework for Electrochemical Energy Storage Management, Nature Energy 3 (5) (2018) 404–412.

[144] A. Perez, R. Moreno, R. Moreira, M. Orchard, G. Strbac, Effect of Battery Degradation on Multi-Service Portfolios of Energy Storage, IEEE Transactions on Sustainable Energy 7 (4) (2016) 1718–1729.

[145] Z. Zhang, J. Wang, X. Wang, An Improved Charging/discharging Strategy of Lithium Batteries Considering Depreciation Cost in Day-ahead Microgrid Scheduling, Energy Conversion and Management 105 (2015) 675–684.

[146] IEEE Std 1188-2005 - IEEE Recommended Practice for Maintenance, Testing, and Replacement of Valve-Regulated Lead-Acid (VRLA) Batteries for Stationary Applications (2005).

[147] P. Munoz-Condes, M. Gomez-Parra, C. Sancho, M. A. G. San Andres, F. Javier Gonzalez-Fernandez, J. Carpio, R. Guirado, On Condition Maintenance Based on the Impedance Measurement for Traction Batteries: Development and Industrial Implementation, IEEE Transactions on Industrial Electronics 60 (7) (2013) 2750–2759.

[148] L. H. Saw, Y. Ye, A. A. Tay, Integration Issues of Lithium-ion Battery into Electric Vehicles Battery Pack, Journal of Cleaner Production 113 (2016) 1032 – 1045.

[149] C. Bordin, H. O. Anuta, A. Crossland, I. L. Gutierrez, C. J. Dent, D. Vigo, A Linear Programming Approach for Battery Degradation Analysis and Optimization in Offgrid Power Systems with Solar Energy Integration, Renewable Energy 101 (2017) 417–430.

[150] B. Saha, K. Goebel, J. Christophersen, Comparison of Prognostic Algorithms for Estimating Remaining Useful Life of Batteries, Transactions of the Institute of Measurement and Control 31 (3-4) (2009) 293–308.

[151] M. Malik, S. Abdallah, M. Hussain, Assessing Supplier Environmental Performance: Applying Analytical Hierarchical Process in the United Arab Emirates Healthcare Chain, Renewable and Sustainable Energy Reviews 55 (2016) 1313 – 1321.

[152] R. P. Singh, H. P. Nachtnebel, Analytical Hierarchy Process (AHP) Application for Reinforcement of Hydropower Strategy in Nepal, Renewable and Sustainable Energy Reviews 55 (2016) 43 – 58.

[153] A. I. AbdelAzim, A. M. Ibrahim, E. M. Aboul-Zahab, Development of an Energy Efficiency Rating System for Existing Buildings using Analytic Hierarchy Process The Case of Egypt, Renewable and Sustainable Energy Reviews 71 (2017) 414 – 425.

[154] M. Azizkhani, A. Vakili, Y. Noorollahi, F. Naseri, Potential Survey of Photovoltaic Power Plants using Analytical Hierarchy Process (AHP) Method in Iran, Renewable and Sustainable Energy Reviews 75 (2017) 1198 – 1206.

[155] A. Ben-Tal, A. Nemirovski, Robust Optimization - Methodology and Applications, Mathematical Programming 92 (3) (2002) 453–480.

[156] D. Bertsimas, D. B. Brown, C. Caramanis, Theory and Applications of Robust Optimization, SIAM Review 53 (3) (2011) 464–501.

[157] W. Wang, M. Pecht, Economic Analysis of Canary-Based Prognostics and Health Management, IEEE Transactions on Industrial Electronics 58 (7) (2011) 3077–3089.

[158] B. Sun, S. Zeng, R. Kang, M. G. Pecht, Benefits and Challenges of System Prognostics, IEEE Transactions on Reliability 61 (2) (2012) 323–335.

[159] K. Feldman, T. Jazouli, P. A. Sandborn, A Methodology for Determining the Return on Investment Associated with Prognostics and Health Management, IEEE Transactions on Reliability 58 (2) (2009) 305–316.

[160] A. R. Dehghani-Sanij, E. Tharumalingam, M. B. Dusseault, R. Fraser, Study of energy storage systems and environmental challenges of batteries, Renewable and Sustainable Energy Reviews 104 (2019) 192–208. doi:10.1016/j.rser.2019.01.023.