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Prognostics of Lithium-ion batteries based on state space modeling with heterogeneous noise variances

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ABSTRACT

Prognostics and health management of lithium-ion batteries, especially their remaining useful life (RUL) prediction, has attracted much attention in recent years because accurate battery RUL prediction is beneficial to ensuring high reliability of lithium-ion batteries for providing power sources for many electronic products. In the common state space modeling of battery RUL prediction, noise variances are usually assumed to be fixed. However, noise variances have great influence on state space modeling. If noise variances are too small, it takes long time for initial guess states to approach true states, and thus estimated states and measurements are biased. If noise variances are too large, state space modeling based filtering will suffer divergence. Besides, even though a same type of lithium-ion batteries are investigated, their degradation paths vary quite differently in practice due to unit-to-unit variation, ambient temperature and other working conditions. Consequently, heterogeneity of noise variances should be taken into consideration in state space modeling so as to improve RUL prediction accuracy. More importantly, noise variances should be posteriorly updated by using up-to-date battery capacity degradation measurements. In this paper, an efficient prognostic method for battery RUL prediction is proposed based on state space modeling with heterogeneity of noise variances. 26 lithium-ion batteries degradation data are used to illustrate how the proposed prognostic method works. Some comparisons with other common prognostic methods are conducted to show the superiority of the proposed prognostic method.

1. Introduction

Lithium-ion batteries have been widely used in many electronic products because of their merits including high energy density, good power capability, long lifespan, and environmental friendliness [1]. Battery performance degrades with cycling and aging. Battery failure may result in catastrophic effects, i.e. electrical fire because of battery thermal runaway of a Boeing 787 in 2013, and the recalls of lithium batteries used in notebooks due to circuit defects and overheating in recent years. To keep maintaining high reliability of lithium-ion batteries and help users make a replacement decision, accurate estimation of maximum available battery performance and prediction of remaining battery performance are needed. Battery capacity is commonly chosen as an indicator of battery state of health. Battery failure can be defined as that the capacity of a battery drops below a failure threshold defined by users. Thus, battery remaining useful life (RUL) can be defined as the period between the current cycle and a cycle when the capacity of the battery reaches the failure threshold for the first time [2,3].

To predict battery RUL, many regression based prognostic methods have been proposed in the recent years [4]. In between, state space modeling of RUL prediction attracts much attention because it is able to track battery capacity degradation over time by using the idea of dynamic Bayesian inference. Here, states are parameters of regression models, and they are hidden and can not be directly observed. Measurements are observable battery capacity degradation data and they are used to infer the posterior distributions of the hidden states. Following this idea, many scholars have done good research works along this idea. Burgess [5] built a linear and Gaussian state space model and used Kalman filtering to estimate valve regulated lead acid battery capacity. Then, Burgess projected estimated capacity to future capacity and predicted battery RUL. To extend linear state space modeling to non-linear state space modeling, Saha et al. [6] used an exponential function as an empirical battery capacity degradation model and employed particle filtering to estimate lithium-ion battery capacity. In their successive work [7], they experimentally proved that non-linear state space modeling solved by particle filtering can produce higher RUL prediction accuracy than autoregressive integrated moving average and extended Kalman filtering based prognostic methods. Further, He et al. [8] used the sum of two exponential functions instead of the exponential function as an empirical battery capacity degradation model so as to improve the fitting ability of the previous empirical battery

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degradation model. To enhance the local fitting ability of the sum of two exponential functions, Xing et al. [9] developed the sum of an exponential function and a polynomial function with an order of 2 to form another empirical battery degradation model. In the works of He et al. [8] and Xing et al. [9], particle filtering was used to solve their associated non-linear state space models and predict lithium-ion battery RUL. Because particle filtering has strong ability to solve non-linear state space models by using lots of random particles with their associated weights, it has been widely applied to battery RUL prediction together with other advanced algorithms, such as particle swarm optimization [10], Gaussian process models [11], support vector regression [12], autoregressive model [13], kernel smoothing [14], unscented Kalman filtering [15], spherical cubature Kalman filtering [16], Gauss–Hermite Kalman filtering [17], logistic regression [18], etc.

In the aforementioned prognostic methods, two assumptions are commonly used [5,8,9,15,16]. The first assumption is that additive Gaussian noises are used in state space modeling. Specifically, before the current battery degradation measurement is available, states in state space modeling are driven by additive Gaussian noises, and predicted states are assumed to follow the Gaussian distribution. When the current battery capacity measurement is available, an error between the current measurement and a predicted measurement is assumed to follow the Gaussian distribution. In other words, the Gaussian distribution is used in state space modeling. Under this assumption, it is unnecessary to use particle filtering because Gaussian quadrature [19], such as unscented transform, Gauss–Hermite quadrature, spherical cubature, etc., is sufficiently used to calculate the nonlinear projection/function of the Gaussian distribution. Moreover, the calculation time of Gaussian quadrature is much quick because only a few deterministic sigma points sampled from the Gaussian distribution are used in integration required in dynamic Bayesian inference of state space modeling. Compared with Gaussian quadrature, particle filtering needs lots of random particles to approximate integration required in dynamic Bayesian inference of state space modeling. The second assumption is that noise variances used in state space modeling are assumed to be fixed. In practice, even though a same type of lithium-ion batteries is investigated in battery prognostics, these lithium-ion batteries are heterogeneous and have different battery degradation paths. Moreover, noise variances have great influence on state space modeling. If noise variances are too small, it takes long time to approach true states, and thus estimated states and measurements are biased. If noise variances are too large, filtering will suffer divergence. Consequently, heterogeneity of noise variances should be considered in state space modeling to improve RUL prediction accuracy. More importantly, noise variances should be posteriorly updated when a new battery capacity degradation measurement is available.

Considering the above two discussions, in this paper, an efficient prognostic method for battery RUL prediction is proposed. The main contributions of this paper are summarized as follows. Firstly, following the previous research works, we still use additive Gaussian noises to drive state and measurement predictions in state space modeling. As explained previously, Gaussian quadrature is sufficiently used in Gaussian integration required by dynamic Bayesian inference of state space modeling. To reduce calculation time increased by the large number of random particles in particle filtering, we use unscented transform as a demonstration of Gaussian quadrature to sample a few deterministic sigma points from the Gaussian distribution used in state space modeling. Other options include Gauss–Hermite quadrature, spherical cubature, etc. Secondly, because unscented transform is able to transmit a few deterministic sigma points through a non-linear state space model, dynamic Bayesian inference on noise variances in the framework of Kalman filtering [20] is still effective in non-linear state space modeling used in battery RUL prediction. Considering this view, we posteriorly update noise variances over time when a new battery capacity degradation measurement is available.

The rest of this paper is organized as follows. The problem of state space modeling of battery RUL prediction is formulated in Section 2. The proposed prognostic method is presented in Section 3. The results obtained by using the proposed prognostic method are shown in Section 4. Moreover, comparisons with other prognostic methods are conducted in the same section. Conclusions are drawn in the last section.

2. The problem formulation of state space modeling of battery RUL prediction in the previous research works

For state space modeling of battery RUL prediction, it is necessary to establish a state space model as follows:

State function

$$\mathbf{x}_k = g(\mathbf{x}_{k-1}, k) + \mathbf{v}_k, \tag{1}$$

Measurement function

$$y_k = f(\mathbf{x}_k, k) + w_k, \tag{2}$$

where $\mathbf{v}_k$ is an additive state noise vector at iteration k and it follows the Gaussian distribution with a mean vector $\mathbf{0}$ and a covariance matrix $\mathbf{Q}_{k-1}$; $\mathbf{x}_{k-1}$ is a state vector posteriorly estimated at iteration $k-1$; $\mathbf{x}_k$ is a predicted state vector at iteration k before the current measurement y_k is available; $w_k$is an additive Gaussian measurement noise with a mean 0 and a variance q_{k-1}^2 at iteration k; $g(\cdot)$ and $f(\cdot)$ are linear/non-linear functions. In the previous state space modeling of battery RUL prediction [5,8,9,15,16], the state and measurement functions shown in Eqs. (1) and (2) are simplified as follows:

State function

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{v}, \tag{3}$$

Measurement function

$$y_k = f(\mathbf{x}_k, k) + w. \tag{4}$$

The mathematical meaning of Eq. (3) is that the predicted state vector $\mathbf{x}_k$directly evolves from a prior state vector/posterior state vector $\mathbf{x}_{k-1}$ at iteration $k-1$ by using the Gaussian random walk before the current measurement y_k is available. Obviously, the predicted state vector $\mathbf{x}_k$ follows the Gaussian distribution with a mean vector $\boldsymbol{m}_{k-1}$ and a covariance matrix $\boldsymbol{P}_{k-1} + \mathbf{Q}_{k-1}$. Here, $\boldsymbol{m}_{k-1}$ and $\boldsymbol{P}_{k-1}$ are the mean vector and the covariance matrix of the posterior state vector $\mathbf{x}_{k-1}$ at iteration $k-1$, respectively. Moreover, in Eq. (3), it is assumed that the additive state noise vector $\mathbf{v}_k$ always has a fixed covariance matrix $\mathbf{Q}_{k-1} = \mathbf{Q}$, which is not posteriorly updated over time. The same assumption is applied to the variance $q_{k-1}^2 = q^2$ of the additive Gaussian measurement noise. For RUL prediction of lithium-ion batteries, the non-linear function $f(\cdot)$ is established by goodness of fit. Some candidates for the non-linear function $f(\cdot)$ include an exponential function [6,15], the sum of two exponential functions [8], the sum of an exponential function and a polynomial function with an order of 2 [9], etc. Theoretically, the more the number of states/parameters used in the non-linear function, the better goodness of fit. However, the increase of the number of states may cause the overfitting problem and complicate state space modeling of battery RUL prediction. Therefore, selection of a proper non-linear function $f(\cdot)$ depends on the requirement of users and battery degradation trends. If the increase of the number of states only increases goodness of fit a little, it is preferable to use a simpler function, such as the exponential function, to avoid the overfitting problem.

In the previous state space modeling of battery RUL prediction, particle filtering is applied to solve the state space model provided by Eqs. (3) and (4) so that the posterior distribution of $\mathbf{x}_k$ can be iteratively estimated when the current measurement y_k is available. The main idea of