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An integrated unscented kalman filter and relevance vector regression approach for lithium-ion battery remaining useful life and short-term capacity prediction ☆

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ABSTRACT

The gradual decreasing capacity of lithium-ion batteries can serve as a health indicator for tracking the degradation of lithium-ion batteries. It is important to predict the capacity of a lithium-ion battery for future cycles to assess its health condition and remaining useful life (RUL). In this paper, a novel method is developed using unscented Kalman filter (UKF) with relevance vector regression (RVR) and applied to RUL and short-term capacity prediction of batteries. A RVR model is employed as a nonlinear time-series prediction model to predict the UKF future residuals which otherwise remain zero during the prediction period. Taking the prediction step into account, the predictive value through the RVR method and the latest real residual value constitute the future evolution of the residuals with a time-varying weighting scheme. Next, the future residuals are utilized by UKF to recursively estimate the battery parameters for predicting RUL and short-term capacity. Finally, the performance of the proposed method is validated and compared to other predictors with the experimental data. According to the experimental and analysis results, the proposed approach has high reliability and prediction accuracy, which can be applied to battery monitoring and prognostics, as well as generalized to other prognostic applications.

1. Introduction

Lithium-ion battery is one of the promising power sources for consumer electronics, automotive electric vehicles, and even space systems for its high energy density, lower self-discharge rate, no memory effect, longer cycle life and other advantages. However, the performance of batteries gradually deteriorates with cycling, i.e. aging of batteries is an inevitable problem [1,2]. Failures of lithium-ion batteries could result in performance degradation, economic loss, and even catastrophe. Therefore, it is necessary to supervise the degradation performance of batteries and to evaluate its reliability to obtain the accurate batteries capacity estimation. In order to track the degradation of batteries, the gradual decreasing capacity is chosen as an indicator of degradation performance.

In the literatures, approaches to estimate or predict the capacity of batteries can be categorized into two main approaches, namely model-based filtering approaches and data-driven approaches. Depending on the mathematical representations of the batteries degradation evolution, model-based filtering methods use particle filter (PF), extended Kalman filter (EKF) or unscented Kalman filter (UKF) to estimate the state-of-health (SOH), state-of-charge (SOC) or remaining useful life (RUL) of batteries [3–7]. Hu et al. [8] applied a particle filtering and kernel smoothing approach (PF–KS) for simultaneously estimating the degradation state and the unknown parameters of degrading components, then RUL prediction is obtained by simulating future particles evolutions. Miao et al. [9] introduced unscented particle filter (UPF) for the battery remaining useful life prediction. However, due to the lack of understanding of the degradation evolution, it may not be available to build mathematical model for complex systems. In contrast, when the explicit degradation mechanism is unknown, but sufficient historical data are available, data-driven methods can be used, which are purely based on the extract features from performance data, such as current, voltage, capacity and impedance to predict the batteries health conditions [10–13]. As a result, it is highly dependent on not only the quantity, but also on the quality of historical data. Hu et al. [12] proposed an ensemble approach for the data-driven prognostics with three weighting schemes, which gave more accurate RUL predictions compared to any sole algorithm. Wang et al. [13] used a conditional three parameter capacity degradation model to fit the representative training vectors by employing relevance vector machine, and then the extrapolation of the degradation model is

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used to estimate the remaining useful life of lithium-ion batteries. As Fig. 1 shows, under different available forms of information for the assessment of the evolution to failure of a degrading system, e.g., information on the dynamic model including empirical-based, semi-physical based or physical-based, and observed data sequence related to the degradation of the system, etc., different prognostic methods may be chosen [14,15].

The approaches that are purely model-based filtering and those that are purely data-driven have their respective limitations, with the former relying on the physical model for state prediction and the latter not accounting for the physical process. Hybrid methods are therefore proposed to integrate the strengths of the two types and overcome the limitations. Liao et al. [16] categorized hybrid approaches for prediction into five types. According to category H4 in Ref. [16] and our findings, incorporating model-based filtering approaches and data-driven approaches for the battery prognostic problem can be classified into three types.

The first type develops a data-driven model that is made to compensate the physical state/measurement model. Due to the ever-increasing complexity of the degradation system, it may be tedious or even impossible to obtain a degradation model. It is an alternative to replace the complex physics-based model with a data-driven model. Liu et al. [17] adopted a data-driven nonlinear degradation autoregressive (ND-AR) model as the observation model for regularized particle filter (RPF) to estimate battery RUL. He et al. [1] chose a neural network (NN) model as the battery state of charge measurement model. The UKF was then used to filter out the noise in the NN output and improve the estimation accuracy.

The second type uses a data-driven approach to predict the future trend of measurement values. During the prediction period without new measurements, the predicted measurements from the data-driven approach could be used as new measurements for the filtering-based approach. Liu et al. [18] proposed a data-model fusion approach to improve the prediction performance. A data-driven predictor was used to predict the future battery measurements, which incorporated into PF for long-term prediction. In Ref. [16], two data-driven models were used. One was applied as a measurement model to establish the mapping between the battery internal state and the measurement. The other was used to predict future measurements which were fed into the PF to predict the battery RUL.

The third type uses data-driven methods to estimate the model parameters for the physical-based methods to predict. Saha et al.

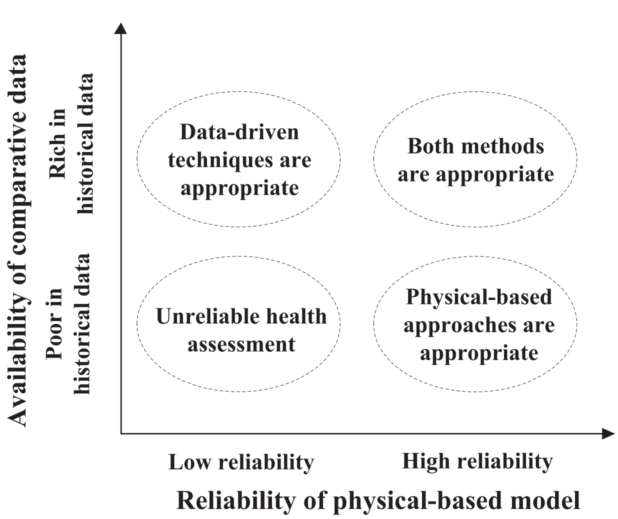

Fig. 1. Comparison of model-based approaches and data-driven approaches.

[19,20] used RVR to estimate the parameters for the battery model, which were fed into the PF or Rao–Blackwellized particle filter (RBPF) to predict the battery RUL. He et al. [21] applied the Dempster–Shafer theory (DST) to select the initial model parameters, and then Bayesian Monte Carlo (BMC) was used to update the model parameters and predict the RUL through battery capacity monitoring. In the above examples, the PF-based approaches are widely used for battery prognosis and RUL prediction. However, these works only concern the RUL prediction but the battery capacity during the prediction is missed. Moreover, most of these researches focus on the prediction accuracy without considering the requirements of efficiency and calculation complexity for practical applications.

Meanwhile, UKF is another booming method for nonlinear state estimation for its strong capability of handling uncertainty and less computational complexity. The UKF employs the features of the KF but utilizes the unscented transform (UT) method to deal with the nonlinear terms. The Kalman filter can also perform predictions and has been researched for prognostic applications [22-24]. However, it forecasts the system state by using the degradation model and the last known state and covariance without updating the state and covariance during the prediction process. Juricek et al. [23] and Zamanizadeh et al. [24] used KF as a predictor for abnormal situation prediction, which set the KF residuals to be zero and the state and covariance to be invariant for all future values. Therefore, KF is unable to adapt to the model variation. The UKF is confronted with the same situation due to the system degradation. However, although data-driven approaches can carry out prediction, but since the system dynamics change over time in real applications, the trained data-driven model may not be able to carry out accurate predictions without various dynamics taken into account during the prediction process.

Motivated by references [16,19], in this paper, an integrated UKF-RVR method is proposed to improve the multi-step-ahead prediction accuracy and real-time prediction capability of battery capacity and RUL. Due to the high accuracy and robustness for nonlinear system estimation with low computational complexity, UKF is used to estimate and adjust the system states and hence to track the battery degradation process. However, since prediction involves future time horizons, it goes beyond the scope of filtering applications. The RVR model is utilized to provide the future evolution of the UKF residuals. Taking the RVR forecast error into account, we employ both the last known residual value and the predicted residual values from RVR model by allocating the time-varying weight values according to the prediction steps. And then the forecast residual information can be used for UKF continuously updating the battery model parameters during the prediction process. The predicted residuals play a role to guide the system states back to reasonable values; otherwise, a large discrepancy between the actual and the estimated states is introduced if the residuals are set to be zero for future prediction. The effectiveness of the developed approach was tested using four different batteries degradation data. The results demonstrate its prediction accuracy, which outperforms other predictors. Moreover, both the UKF and the RVR are much simpler methods compared to PF and NN, which are more suitable to be applied in practical forecasting.

The remainder of this paper is organized as follows. Section 2 summarizes the related model-based filtering approach and data-driven approach. In Section 3, the integrated method is illustrated. The application of the proposed approach to batteries capacity prediction is introduced in Section 4. The performance of the proposed method compared to that of the single model-based filtering method and data-driven method predictions is also demonstrated in Section 4. Conclusions are discussed in Section 5.