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A novel fusion prognostic approach for the prediction of the remaining useful life of a lithium-ion battery

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Abstract: The lithium-ion battery has been widely used in electronic devices. Remaining useful life (RUL) prediction allows for predictive maintenance of electronic devices, thus reducing expensive unscheduled maintenance. RUL prediction of the lithium-ion battery appears to be a hot issue attracting more and more attention as well as being of great challenge. In this paper, a new fusion prognostic approach based on error-correction is proposed to predict the RUL of lithium-ion battery, which combines unscented Kalman filter (UKF) with BP neural network. Firstly, UKF algorithm is employed to obtain prognosis based on an estimated model and build a raw error series. Next, the error series is utilized by BP neural network to predict the UKF future residuals, which remain zero without consideration. Finally, the prognostic residual is adopted to correct the prognostic result achieved by UKF. According to the remaining useful life prediction experiments for batteries, the fusion method has high reliability and prediction accuracy.

Key Words: Lithium-ion battery, Remaining useful life, Unscented Kalman filter, BP neural network, Error-correction

1 Introduction

The past few decades have witnessed an increasing interest in health monitoring of lithium-ion battery. With the advantages of small size, light weight, high energy and no pollution, the lithium-ion battery has become a widely used power source in electronics field, such as Bluetooth headset, notebook computers, electric cars, satellites, etc. As an essential part of many systems, the fault of lithium-ion battery causes degradation or even becomes failure in the end. Therefore, the prediction of remaining useful life is of great significance [1][2]. For many situations, the gradual decreasing capacity is chosen as an indicator of battery degradation performance, which could be described as a mathematical model [3]. In the existing literatures, approaches to estimate or predict the capacity can be broadly categorized into three approaches, namely model-based approach, data-driven approach and fusion approach [4].

Model-based methods attempt to set up physical models or mathematical models to describe degradation processes of machinery. Then the models are employed to forecast the future performance of machinery and work out the RUL prediction [5][6]. The commonly obtained methods include the Kalman filter, extended Kalman filter, unscented Kalman filter, particle filter, grey model and so on. RK Singleton et al. developed the extended Kalman filter to test the data to predict the RUL of bearing faults under different operating conditions [7]. Miao et al. introduced unscented particle filter into battery remaining useful life prediction [8]. Zhou et al. described the battery capacity degradation with the help of grey model and revised grey model, which is presented to predict the RUL [9]. Consequently, they may work well in RUL prediction.

On the contrary, data-driven methods attempt to derive the degradation process of a machine from measured data using machine learning techniques. These methods rely on the assumption that statistical characteristics of data are relatively consistent unless a fault occurs. They produce RUL prediction results based on history data measured from machinery. Therefore, the prediction accuracy of data-driven methods depends on not only the quantity but also the quality of the history data [5]. The commonly used methods include the artificial neural network (ANN), support vector machine (SVM), relevance vector regression (RVR) and so on[10]. Z Tian et al. developed an artificial neural network approach utilizing both failure and suspension condition monitoring histories and validated in the field of pump bearing [11]. T Feng et al. employed SVM to identify abnormal data and regress raw data [12].

Considering a system with highly reliable physical-based model and also rich in historical data, the third approach named fusion prognostic approach has emerged for lithium-ion battery prognostics. Fusion methods combine models with data to improve the prediction accuracy and real-time prediction capability. Zheng et al. combined UKF with RVR to predict the short-term capacity of batteries [4]. Chang et al. introduced complete ensemble empirical mode decomposition (CEEMD) into the fusion algorithm of UKF and relevance vector machine (RVM) [13]. Consequently, the fusion methods could obtain a better performance than purely model-based methods or purely data-driven methods.

This paper presented a novel fusion prognostic combined UKF and BP network. BP network is applied to predict residuals of UKF, which can ensure the accuracy and reliability of the final RUL prediction results.

The remainder of this paper is organized as follows. Section 2 provides the related model-based approach and data-driven approach for describe the proposed method, and presents the battery degradation model. Section 3 puts forward the novel fusion prognostic method. Section 4 conducts RUL prediction experiments of lithium-ion battery. Conclusions are discussed in Section 5.

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2 Basic theory

2.1 Unscented Kalman filter

UKF is a model-based filtering algorithm on account of discrete system, which specializes in dealing with uncertainty and nonlinearity. UKF is the most typical method of Sigma Point Kalman Filter (SPKF) which adopts unscented transformation (UT) [14]. Consider the following general non-linear state space model:

$$\begin{cases} x_{k+1} = f(x_k) + \omega_k \\ y_k = h(x_k) + \nu_k \end{cases} \tag{1}$$

where $x_k \in R^n$ is the unobservable state transition vector at cycle k, $y_k \in R^m$ is the system observation which is treated as the health indicator (HI) , $f(\bullet)$ and $h(\bullet)$ is the non-linear system state transition function and measurement function of the mathematical model, $\omega_k \in R^n$ and $\nu_k \in R^m$ is adopted to indicate the system noise which are uncorrelated zero-mean Gaussian noise with covariance S_k and R_k.

Calculating the mean $\bar{y}$ and the covariance P_{yy} of the system model $y_k = f(x_k)$ is the key step in the filtering of non-linear system. Sigma points $x_k (k = 0,1,...,2n)$ are constructed to have the same mean and covariance as x, $mean\{x_k\} = \bar{x}$ and $\operatorname{cov}\{x_k\} = P_{xx}$. Then the mean and covariance of propagated sigma points are, $mean\{y_k\} = \bar{y}$ and $\operatorname{cov}\{y_k\} = P_{yy}$ .The specific steps are as follows:

The sigma points and corresponding weights are constructed by:

$$X^i = \begin{cases} \bar{x}, i = 0 \\ \bar{x} + (\sqrt{(n+\lambda)P_{xx}})^i, i = 1,...,n \\ \bar{x} - (\sqrt{(n+\lambda)P_{xx}})^i, i = n+1,...,2n \end{cases} \tag{2}$$

$$\omega^i = \begin{cases} \dfrac{\lambda}{n+\lambda}, i = 0 \\ \dfrac{1}{2(n+\lambda)}, i = 1,...,2n \end{cases} \tag{3}$$

where λ is an adjustable proportionality factor $(\sqrt{(n+\lambda)P_{xx}})^i$ means the ith column of the matrix square root of the weighted covariance matrix [4].

The prediction step is:

$$\begin{aligned} & X^i_{k|k-1} = f(X^i_{k-1|k-1}), i = 0,...,2n \\ & Y^i_{k|k-1} = h(X^i_{k|k-1}), i = 0,...,2n \\ & \hat{x}_{k|k-1} = \sum_{i=0}^{2n} \omega^i X^i_{k|k-1} \\ & \hat{y}_{k|k-1} = \sum_{i=0}^{2n} \omega^i Y^i_{k|k-1} \\ & P_{k|k-1} = S_k + \sum_{i=0}^{2n} \omega^i (X^i_{k|k-1} - \hat{x}_{k|k-1})(X^i_{k|k-1} - \hat{x}_{k|k-1})^T \end{aligned} \tag{4}$$

The update step is:

$$\begin{aligned} & P_{yy} = R_k + \sum_{i=0}^{2n} \omega^i (Y^i_{k|k-1} - \hat{y}_{k|k-1})(Y^i_{k|k-1} - \hat{y}_{k|k-1})^T \\ & P_{xy} = \sum_{i=0}^{2n} \omega^i (X^i_{k|k-1} - \hat{x}_{k|k-1})(Y^i_{k|k-1} - \hat{y}_{k|k-1})^T \\ & \hat{x}_{k|k} = \hat{x}_{k|k-1} + P_{xy} P_{yy}^{-1} (y_k - \hat{y}_{k|k-1}) \\ & P_{k|k} = P_{k|k-1} - P_{xy} P_{yy}^{-1} P_{yy} (P_{xy} P_{yy}^{-1})^T \end{aligned} \tag{5}$$

2.2 BP neural network

BP neural network is a multilayer feed-forward network trained by error backpropagation algorithm. The learning rule of BP network is obtaining the steepest descent method. The back-propagation network is employed to continuously adjust the weights and thresholds in order to achieve the network with the minimum sum of squared errors [15]. As shown in Fig. 1, the topology structure of BP network includes input layer, hidden layer and output layer.

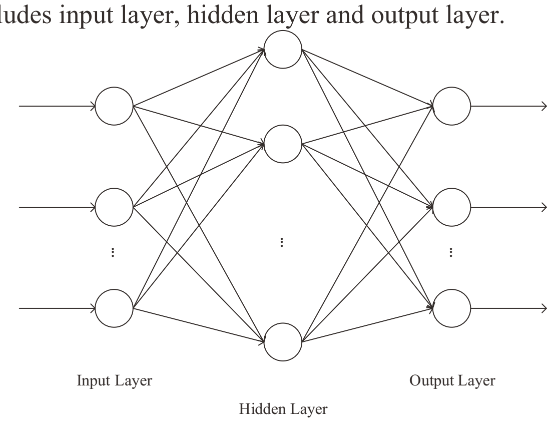

Fig.1 Diagram of BP neural network

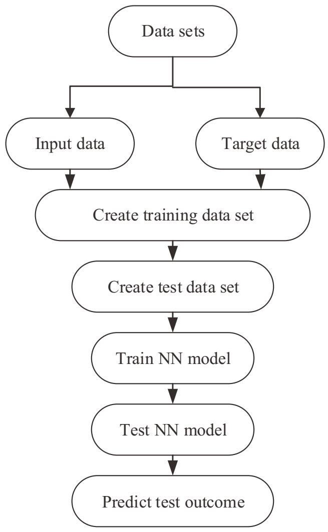

Fig. 2. Computational steps of neural network

BP network is trained by repeatedly presenting a series of input/output pattern sets to the network. The network gradually “learns” the input/output relationship of interest by adjusting the weights to minimize the error between the actual and predicted output patterns of the training set [16]. The trained network is usually examined through a separated set of data called the test set to monitor its performance and validity. When the mean squared error (MSE) of the test set reaches a minimum, network training is considered complete and the weights are fixed. Fig. 2 shows the computational steps for building a network model using qualification test data and using the test outcomes.

The error of BP network is:

$$E=\frac{1}{2}\sum_{k=1}^{p}(d_k-y_k)^2 \tag{6}$$

where d_k is the desired output and y_k is the actual output.

The weight modifier is:

$$\Delta\omega_{jk}=-\eta\frac{\partial E}{\partial\omega_{jk}} \tag{7}$$

where η is learning step, ω_{jk} is weights among layers, $\Delta\omega_{jk}$ is the weight modifier, which is adjusted by total error.

2.3 Battery degradation

The actual capacity of lithium-ion battery is declining with the aging time. The end of life for batteries is specified to be below 80% of their rated values [17]. The battery capacity degradation model can be represented by a 2-dimensional exponential model as follows:

$$Q_k=a_k\cdot\exp(b_k\cdot k)+c_k\cdot\exp(d_k\cdot k) \tag{8}$$

where Q_k is the battery capacity at cycle *k*, a_k , b_k , c_k , d_k are the model parameters at cycle *k*.

In this paper, the state-space model can be set as:

$$\begin{aligned} x_k &= [a_k,b_k,c_k,d_k] \\ x_k &= x_{k-1}+w_k \\ Q_k &= a_k\cdot\exp(b_k\cdot k)+c_k\cdot\exp(d_k\cdot k)+v_k \end{aligned} \tag{9}$$

where x_k is the state vector established by model parameters, w_k is the state noise and v_k is the measurement noise which are both Gaussian noise with zero mean.

3 The fusion algorithm

The fusion method consists of two parts: model-based prediction and data-driven prediction. The schematic diagram of the proposed approach is shown in Fig.3. Firstly, estimate and update the states and model parameters iteratively until the end of monitor (EOM) at cycle T_{EOM} . The capacity data (1: T_{EOM}) is obtained to perform model parameters estimation by UKF with the battery degradation model. Generate the residual data before T_{EOM} as history samples to train BP network:

$$\begin{cases}\tilde{x}_{j+1}=f(\hat{x}_j)\\ \tilde{y}_j=h(\hat{x}_j),\ j=0,...,T_{EOM}\end{cases} \tag{10}$$
$$e_j=y_j-\tilde{y}_j$$

where $\tilde{x}_k$ is the state vector and $\tilde{y}_k$ is measurement data produced by the UKF model, e (1: T_{EOM}) are the training residual data. Then, train the BP network model to predict the future evolution of the UKF residuals.

Next, implement the prediction after cycle T_{EOM} . Predict the raw battery capacity by UKF. In the meanwhile, predict the raw corresponding residual by BP network algorithm. Take the consideration of the discrepancy exists between the BP network predicted value and the real value, the update residual is calculated as follows:

$$\hat{e}_k=\frac{\mu}{i}e_{k-1}+(1-\frac{\mu}{i})\tilde{e}_k \tag{11}$$

where $\hat{e}_k$ is the final residual data used to correct the UKF prediction, $\tilde{e}_k$ is the predicted value by the BP algorithm, $\mu\in(0,1)$ is an adjustable coefficient.

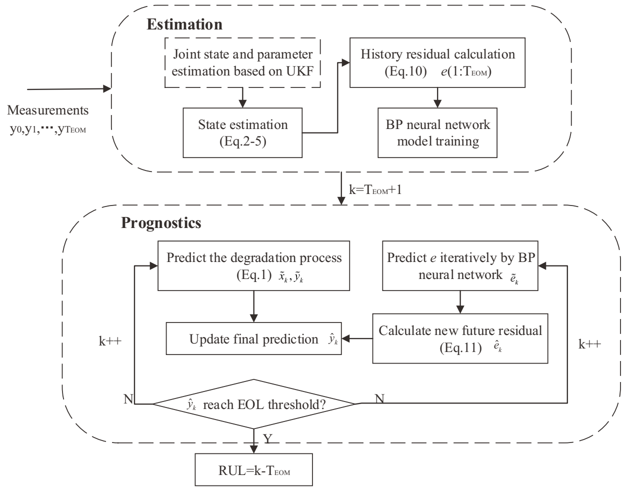

Fig.3. Flowchart of the proposed method

Finally, apply the results of two predictors to update the measurements. Calculate the predicted battery capacity for each cycle until the capacity reaches the end of life (EOL). The RUL is the time between EOM cycle and EOL cycle.

4 Experiment and result analysis

4.1 Experiment

In this study, four batteries labeled A1, A2, A3 and A4 from the Center for Advanced Life Cycle Engineering of University of Maryland are chosen randomly to validate the effectiveness of the proposed approach. Normalize all battery capacity data by:

$$\begin{aligned} Q &= \hat{Q}/\hat{Q}_{\mathrm{r}} \\ \tilde{Q} &= Q\cdot Q_{\mathrm{r}} \end{aligned} \tag{12}$$

where $\hat{Q}$ and $\hat{Q}_r$ are the real capacity and rated capacity, Q is the data applied in the simulation, $\tilde{Q}$ is the predicted capacity which is anti-normalization data of the simulation results.

Set the EOM threshold to be 90% of the rated capacity and the EOL threshold to be 80% of the rated capacity. Capacity data before cycle T_{EOM} is the known data. The accuracy of BP neural network prediction is closely linked with the quality of data, so the known data could not reflect the later degradation of battery. Therefore, results of proposed method are only compared with the purely UKF method.

4.2 Result analysis

In order to evaluate the forecasting accuracy, we define three indicators, including error indicator (EI), relative accuracy (RA), root mean square error (RMSE):

$$\begin{aligned} EI &= \left|RUL_{true}-RUL_{predicted}\right| \\ RA &= 1-\frac{\left|RUL_{true}-RUL_{predicted}\right|}{RUL_{true}} \\ RMSE &= \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(Q_k-\hat{Q}_k\right)^2} \end{aligned} \tag{13}$$

The predicted RUL and indicators are shown in Table 1. The prediction capacities of four batteries are displayed in Fig.4-7.

Table 1: Prediction results for A1, A2, A3, A4

	method	RUL (true)	RUL (pre)	EI	RA	RMSE
A 1	UKF	48	54	6	87.5%	0.0119
	UKF-BP	48	51	3	93.75%	0.0051
A 2	UKF	39	40	1	97.44%	0.0249
	UKF-BP	39	40	1	97.44%	0.0060
A 3	UKF	53	62	9	83.02%	0.0183
	UKF-BP	53	58	5	90.57%	0.0115
A 4	UKF	15	--	--	--	0.1177
	UKF-BP	15	18	3	80%	0.0165

For battery A1, the EOM cycle is set to be 153. Compared with the UKF method, the fusion method is more precise and can output a relative reasonable RUL. For battery A2, the EOM cycle is set to be 93. It is seen that both the results of two approaches are closely to the real values and calculate the same RUL. Considering the RMSE indicator, the fusion approach has a slight advantage because of the tiny RMSE. So, the prediction accuracy of the fusion method is much higher than the pure method.

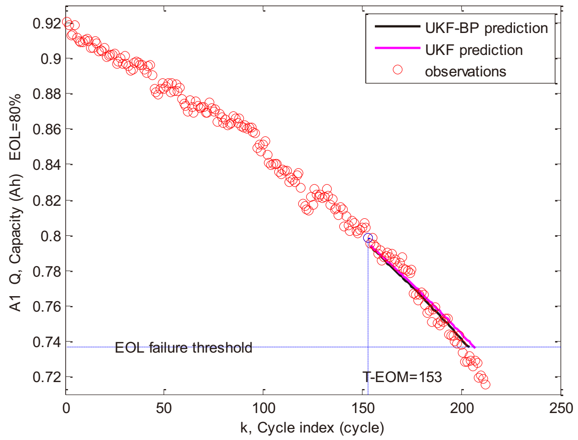

Fig.4. Battery A1 capacity RUL prediction

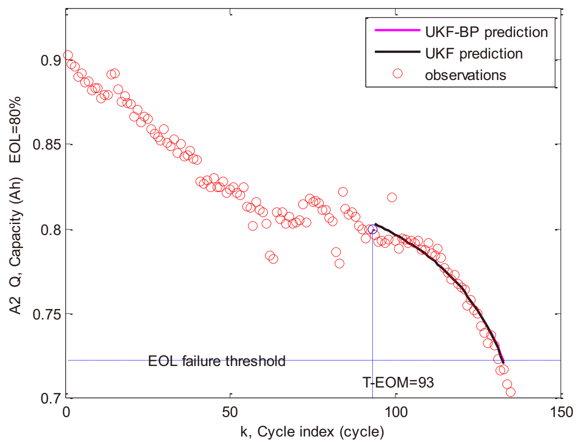

Fig.5. Battery A2 capacity RUL prediction

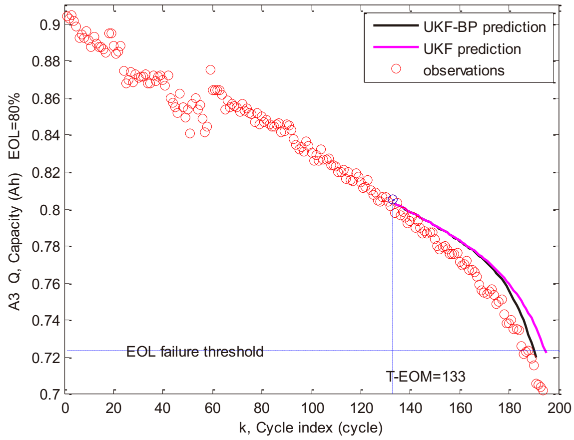

Fig.6. Battery A3 capacity RUL prediction

For battery A3, the EOM cycle is set to be 133. Two prediction curves are a little away from the true profile which caused by the degradation uncertainty. In the early prediction, the error of two prediction results are increasing. As time goes on, the fusion approach results begin back to the real degradation, yet the error of UKF prediction is bigger and bigger. Therefore, the integrated approach can provide more accurate RUL prediction results.

For battery A4, the number of capacity is so small that we can't fitting an accurate curve and can't predict the capacity correctly as other three batteries. The EOM cycle is set to be 32. It is seen that the single algorithm is unable to predict the RUL of the lithium-ion battery. The prediction performance of the proposed method is still reliable.

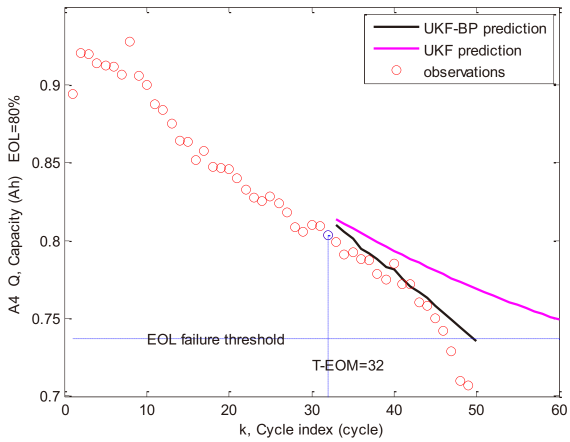

Fig.7. Battery A4 capacity RUL prediction

5 Conclusion

This paper proposes a novel fusion approach based on error-correction to predict the remaining useful life of lithium-ion battery, which fuses unscented Kalman filter (UKF) and BP neural network. The simulation indicates that the proposed method can achieve a good RUL prediction result. However, there are still some limitations in the proposed method. For example, our intention of calculate the EOL cycle is to assume a monotonic degradation trend. In some real cases, however, the degradation trends are actually nonmonotonic or even change abruptly. In these cases, the proposed method is unable to predict the accurate capacity

[5]. Therefore, much research work is still needed to establish more robust degradation models.

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