Lithium-ion Battery Remaining Useful Life Estimation Based on Nonlinear AR Model Combined with Degradation Feature

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ABSTRACT

Long term prediction such as multi-step time series prediction is a challenging prognostics problem. This paper proposes an improved AR time series model called ND-AR model (Nonlinear Degradation AutoRegression) for Remaining Useful Life (RUL) estimation of lithium-ion batteries. The nonlinear degradation feature of the lithium-ion battery capacity degradation is analyzed and then the non-linear accelerated degradation factor is extracted to improve the linear AR model. In this model, the nonlinear degradation factor can be obtained with curve fitting, and then the ND-AR model can be applied as an adaptive data-driven prognostics method to monitor degradation time series data. Experimental results with CALCE battery data set show that the proposed nonlinear degradation AR model can realize satisfied prognostics for various lithium-ion batteries with low computing complexity.

1. INTRODUCTION

With high energy density, high galvanic potential, wide temperature range, low self-discharge rate and long lifetime, the lithium-ion battery has been widely used in mobile communications, electric vehicles, aerospace electronics and almost all of the industrial fields with energy supply etc. The lithium-ion battery has gradually become the key techniques for many important areas and industrial applications(Bhaskar Saha & Kai Goebel, 2009) (Jingliang Zhang & Jay Lee, 2011) (Wei He, Nicholas Williard, Michael Osterman, & Michael Pecht, 2011). Due to the safety management, charging and discharging control, capacity degradation of the lithium-ion battery, capacity fade and remaining useful life(RUL) estimation of lithium-ion batteries has become a hotspot and challenge problem in the fields of reliability, automatic test, power sources, and electric vehicles, etc. As a result, lithium-ion battery RUL estimation and prediction became the hot issues in electronic prognostics and health management (PHM) (K. Goebel, B. Saha, A. Saxena, J. R. Celaya, & J. P. Christophersen, 2008) (F. Rufus & S. Lee, 2008).

At present, among the various approaches of battery State of Charge(SOC) estimation and RUL prediction, it can be generally classified into two categories: data-driven (or statistical data-driven) and model based (Jingliang Zhang & Jay Lee, 2011) (Xiao-Sheng Si, Wenbin Wang, Chang-Hua Hu, & Dong-Hua Zhou, 2011). There are lots of research work focusing on performance degradation, SOC/SOH assessment, RUL estimation for the lithium-ion battery (Bhaskar Saha, Kai Goebel, & Jon Christophersen, 2009) (Bhaskar Saha, Kai Goebel, Scott Poll, & Jon Christophersen, 2009) (Enrico Zio, & Giovanni Peloni, 2011) (Achmad Widodo, Min-Chan Shim, Wahyu Caesarendra, & Bo-Suk Yang, 2011). Especially for the lithium battery prognostics, the prediction uncertainty, and the applicability of the model-based (physics based model, chemistry model, etc.) and data-driven methods have always been the challenge problems in this area.

Lots of researchers such as Bhaskar Saha and Kai Goebel and others researchers in the Prognostics Center of Excellence (PCoE) of the NASA AMES Center achieved the battery RUL prediction as well as the uncertainty representation and management with particle filter(PF) algorithm (Bhaskar Saha, Kai Goebel, & Jon Christophersen, 2009) (Bhaskar Saha, Kai Goebel, Scott Poll, & Jon Christophersen, 2009). Moreover, the Artificial Neural Networks (ANN) (Jie Liu, Abhinav Saxena, Kai Goebel, Bhaskar Saha, & Wilson Wang, 2010), Extended Kalman Filter (EKF) (Lijun Gao, Shengyi Liu, & Roger A. Dougal, 2002), Support Vector Machine (SVM) (Bhaskar Saha, Kai Goebel, Scott Poll, & Jon Christophersen, 2007), Relevance Vector Machine (RVM) (B. Saha, S. Poll, & K. Goebel, 2007), Gaussian Process Regression (GPR) (Bhaskar Saha, Kai Goebel, & Jon Christophersen, 2009) and other machine learning and statistical algorithms are applied in lithium-ion battery prognostics. At the same time, lots of physical model, chemistry model and other related empirical model are developed or applied in the battery RUL estimation.

All of the RUL estimation framework became an effective and practical approach for lithium battery degradation analysis and estimation. However, in the complicated operating conditions, to obtain the model or to identify the model parameters is very difficult for physical model or chemistry model. The drawback is that it does not consider the varied operation condition for on-line application. In the other hand, most of the data-driven prognostics algorithm are of high computing complexity, it is hard to realize or compute for some simple application.

To develop efficient RUL estimation method for the real-time prognostics of lithium batteries, this paper proposes an improved AR time series prediction model based on analyzing the nonlinear degradation of capacity of lithium batteries. This paper first introduces the basic principle of the AR model, and then with the battery RUL estimation experiment, the "accelerated" degradation factor is extracted based on the experimental result. The improved so-called ND-AR model is described to achieve satisfied long term prediction of the status of lithium battery. Experimental results with the CALCE battery data set show that the algorithms can be effectively applied to RUL prognostics for lithium battery capacity degradation with better performance in both efficiency and accuracy.

2. AR Time Series Prediction Model

Time series analysis and prediction based on stochastic process theory and mathematical statistics has been widely applied in signal processing, intelligent information analysis and PHM etc. In the engineering field, the AR model is used more extensive than the MA model and the ARMA model, because the parameter identification of the AR model is relatively simple, as well as the computing load is small. Furthermore, it has already proved the MA model and ARMA model can be equivalent by higher order AR model (Jianqing Fan, & Qiwei Yao, 2003). The degradation of battery capacity data is based on observations and calculated time-series data, it can take advantage of the AR model in time series analysis techniques to study.

2.1. The AR Model

The AR model is first proposed for time series analysis. For time series $\{x_t\}$,

$$\begin{cases} x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + a_t \\ \phi_p \neq 0 \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t \varepsilon_s) = 0, s \neq t \\ Ex_s \varepsilon_t = 0, \forall s < t \end{cases} \tag{1}$$

It is defined as AR model of p order as AR(p). The latter three constraints in equation (1) can be omitted. At this time, the AR model is described as the time series $\{x_t\}$ can equals to the linear function of the historical value and random noise.

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + a_t \tag{2}$$

Here the ϕ is the coefficient of autoregression, p is the order of the model. $a_t, t = 0, \pm 1, \cdots$ is the independent white noise sequence with mean zero and variance σ^2. In the AR(p) model, the number of the parameters is p+2, the parameters are the order p, coefficients $\phi_1, \phi_2 \cdots, \phi_p$ and σ_a^2.

It can be seen from the equation (2) that the AR model is linear prediction function.

2.2. The Order and Parameters Estimation for AR Model

While the AR model is applied to time series prediction, the selection of the order the model is a key factor. Because the coefficients $\{\phi_p\}$ are relevant to the order p, to obtain the reasonable coefficients $\{\phi_p\}$, we should first select the suitable order for the AR model.

In this paper, the AIC (Akaike Information Criterion, AIC) method (Akaike H, 1974) is applied for the determination of the model order. The AIC method is defined as follows.

$$AIC(p) = N \ln \sigma_p^2 + 2p \tag{3}$$

Here the p is the determination of the model order, n is the number of the data sample, σ_p^2 is the prediction variance of p order model.

The methods for parameters estimation of the AR model includes the least square estimation, Maximum Likelihood Estimation, Yule-Wallker method (autocorrelation method), the Burg method and covariance method, etc. In this paper, the Burg algorithm that can directly calculate the parameters with the observed time series is applied to realize parameters estimation of the AR model. This algorithm can avoid the priori estimation of the autocorrelation function, as a result, the computing is simple, and the real-time performance is excellent. Especially, the Burg algorithm is suitable for the parameters estimation of short time series, which meets the demand of the battery remaining useful life estimation.

3. Nonlinear Degradation AR Model for Battery Remaining Useful Life Estimation

In this part, the AR model is applied to achieve the battery RUL estimation with the long term time series prediction. Based on the prediction result, the unsuitability for the nonlinear degradation of lithium battery RUL estimation is analyzed. At last, the nonlinear degradation AR model for battery RUL estimation is proposed to expect better prognostics results.

3.1. Lithium-ion Battery RUL Estimation based on AR Model

Before the modeling to the Lithium battery capacity data with AR model, the order and the parameters of the AR model should be determined. From the experience perspective, the order value of the AR model should not be more than 10. The order p value could be optimized and determined using the AIC criterion according to the evaluation precision.

According to equation (3), when the order p increases from one gradually, $AIC(p)$ will got the minimum value for certain p value. The corresponding p is the suitable order of the AR model.

Here we conduct analysis using the NASA battery data set (B. Saha, & K. Goebel, 2007), the battery No. 05 is selected as modeling data set, the order of the AR model with AIC method. Figure 1 and Table 1 shows the AIC value while the order p varies from 1 to 10.

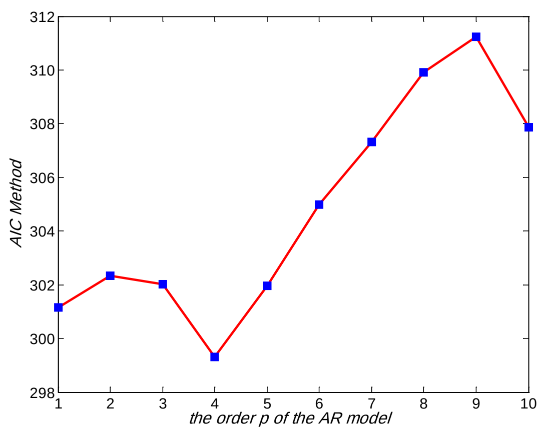

Figure 1. the order of the AR model with AIC method for NASA battery No. 05

From the figure 1 and Table 1, we can conclude that the best order p value for the battery degradation data is 4 while the corresponding AIC obtains the most optimized value. After the determination of the order p, if the prediction starting point is T cycle, we could realize the parameters estimation with Burg algorithm to the observed capacity data Capacity (1: T), and then the prediction could be implemented with the AR model.

Order *p*	AIC Value
1	201.6376
2	198.5693
3	200.7816
4	196.6361
5	203.1455
6	205.2109
7	205.4390
8	206.8059
9	207.0218
10	202.0553

Table 1. the order of the AR model with AIC method for NASA battery No. 05

Figure 2 shows the battery remaining useful life estimation result (the battery No. 05 of NASA PCoE Center) with different starting point with 4-order AR model. The detail prediction result is shown as Table 2.

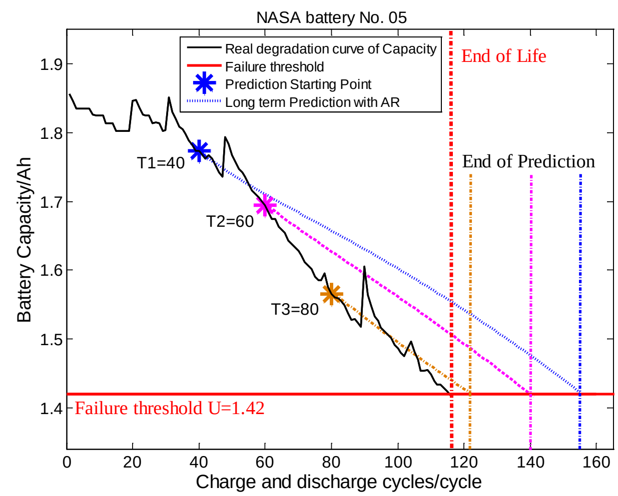

Figure 2. the battery RUL estimation at different starting point with AR model(NASA battery No. 05)

Starting point	End of Prediction (cycle)	RUL prediction result(cycle)	prediction error(cycle)
T1=40	154	114	38
T2=60	140	80	24
T3=80	122	42	6

Table 2. Error comparison of long term prediction with AR model at different starting point

In the experiment, the prediction is fulfilled at three different starting points respectively: T1 = 40cycle, T2 = 60cycle and T3 = 80cycle (marked in the figure 2). The EoL (End of Life) of the battery No. 05 is about 116 cycle as shown in the Fig 2. We defined that when the capacity of the battery degraded to the 70% of its SOC, the battery reaches its EoL (in the experiment, while the capacity of the battery degraded to 1.42Ah, we define as the End of Life). We can see that different prediction results are obtained at different prediction starting points.

3.2. Analysis of Nonlinear Degradation of Lithium-ion Battery

From the Table 2, we can see that, at the early stage (T=40) and medium-term (T=60) the RUL prediction results are not satisfied. Although the AR model could be applied to realize trend prediction in time series analysis, the AR model is still a linear method. To analyze the degradation trend of the lithium battery, we could find that with the degradation process developing, the degradation rate will accelerate with the increasing cycle number.

So we can see that the prediction function could not track the "accelerated" degradation process. It means that with the development of the degradation with the charging and discharging, it shows an accelerated degradation trend from the lifetime monitoring data. Especially, at the early stage and medium stage, the RUL prediction result could not satisfy the real application.

3.3. Nonlinear Degradation AR Model

To solve the poor prediction accuracy and improve the RUL estimation performance with AR model, the "accelerated" degradation factor should be considered. To implement more precise degradation trend tracking, an accelerated factor could be modify the un-matching of the AR model. To check the un-matching phenomenon carefully, we can find that with the degradation process develops (the degradation cycle increases), the degree of the un-matching strengthens.

The accelerated degradation characteristics above can be understood as follows. With the charging and discharging cycle, the inner lithium-ion decreases and the resistance increases. With this degradation process developed, the degradation trend will be accelerated with the increasing of the inner resistance. As a result, the power loss will be gradually increased leading the accelerated degradation process.

With this accelerated degradation factor, the linear AR time series prediction value could be supplemented. Moreover, with this idea, the high efficiency of the AR model could be kept well. According to the analysis above, we proposed an improved battery RUL estimation approach with AR model combined with nonlinear degradation process (accelerated degradation process with the cycle increasing). We call this approach as nonlinear degradation AR model (ND-AR model). The ND-AR model is defined as follows.

An "accelerated" factor is add to the AR model output to match the battery degradation process:

$$x_t = K_T \times [\phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + a_t] \qquad (4)$$

Here the K_T is the "accelerated" factor. Considering the accelerated factor is correlated to the degradation cycle, we define the K_T as follows considering the nonlinear degradation process analyzed above.

$$K_T = \frac{1}{1 + a * (k + b)} \qquad (5)$$

In equation (5), k is the prediction step, and the K_T become the time varied accelerated factor with the prediction process.

While the parameters estimation of the AR model is fulfilled, the parameters in equation (5) could be obtained by curve fitting or least square estimation.

4. Experimental and Discussion

4.1. Battery Data set

The battery data set is from the CALCE of University of Maryland. The lithium-ion batteries were tested to discover the degradation of the capacity. The cycling of the batteries was implemented with the Arbin BT2000 battery testing system under room temperature. The 1.1Ah rated capacity of batteries are adopted in the experiment with the discharging current (0.45A that the discharging speeds is 0.5C) (Wei He, Nicholas Williard, Michael Osterman, & Michael Pecht, 2011). The battery capacity degradation of different batteries are shown as Figure 3.

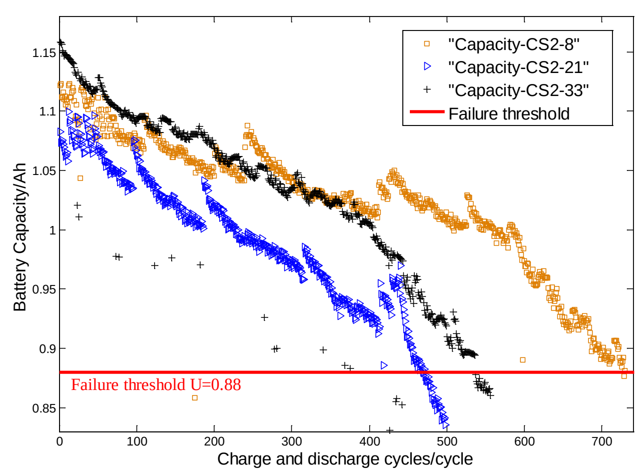

Figure 3. the capacity degradation of different batteries (CALCE battery data)

4.2. Parameters Estimation

The parameters of AR model containing the order p and other parameters are determined using the same method as described in section 3.1. The order p value equals to 4 while the model gets best prediction performance.

With the curve fitting method, the parameters a and b in the ND-AR model are estimated, a=1.5e-7, b=100.

The other parameters are obtained with Burg algorithm to the observed capacity degradation BCm (1: T) with the modeling process.

4.3. Battery RUL estimation with ND-AR model

Figure 4, Figure5, and Figure 6 show the prediction result for various lithium battery capacity degradation data with the ND-AR model proposed in this paper. From Fig.4, Fig5, and Fig.6, we can conclude that the capacity degradation process under different testing and operating condition is forecasted precisely with the proposed ND-AR model. The prediction and estimation of RUL will be beneficial for the process control and maintenance of the lithium batteries.

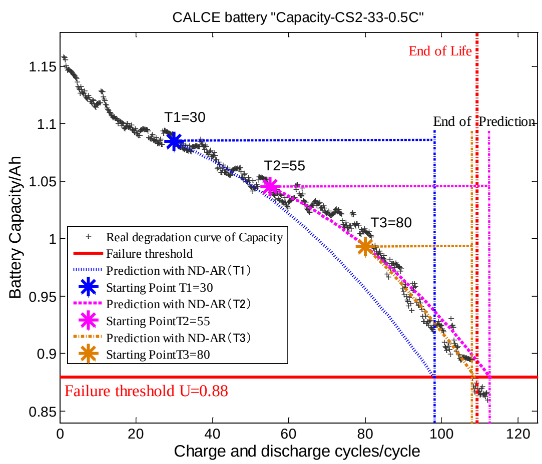

Figure 4. the battery RUL estimation at different starting point with ND-AR model(CALCE battery“Capacity-CS2-33-0.5C”)

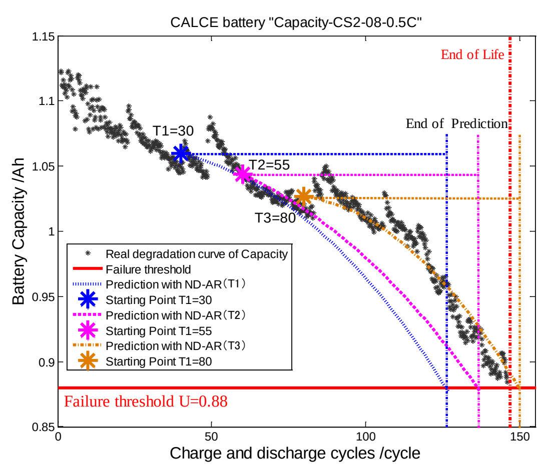

Figure 5. the battery RUL estimation at different starting point with ND-AR model(CALCE battery“Capacity-CS2-08-0.5C”)

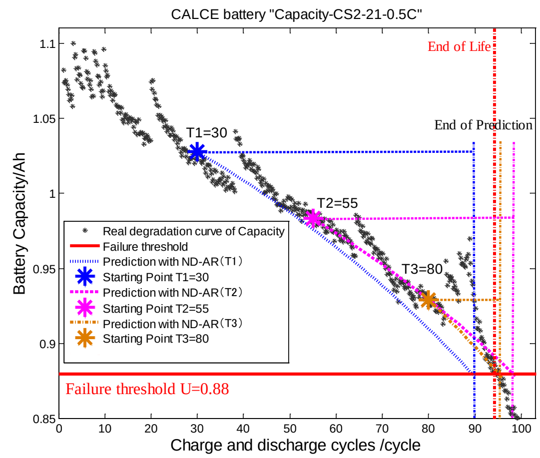

Figure 6. the battery RUL estimation at different starting point with ND-AR model(CALCE battery“Capacity-CS2-21-0.5C”)

4.4. Results analysis and comparison

To evaluation the proposed ND=AR model, we compare the battery RUL estimation results of both AR and ND-AR model. The prediction result is shown as figure 6 for one of testing battery.

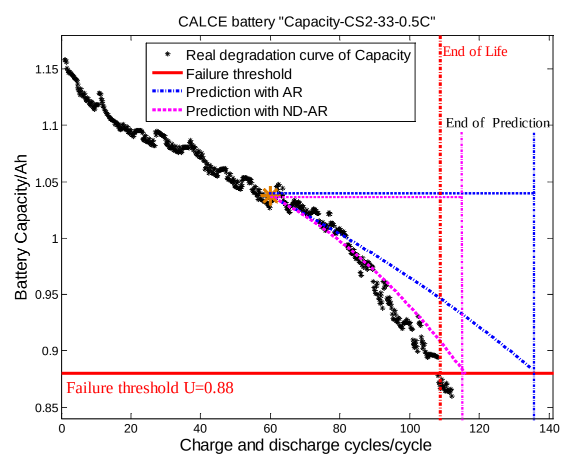

Figure 7.the battery RUL estimation at different starting point with ND-AR model(CALCE battery Capacity-CS2-33-0.5C)

From the figure 7, we can conclude that compared to the basic AR model, the proposed ND-AR model can realize more satisfied prediction result at the same starting point.

To evaluate the comparison result quantitatively, we adopt the Mean Absolute Error(MAE) and Root Mean Square Error (RMSE) and Error of RUL estimation to analyze the prediction results with two methods.

The definition of MAE:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x(i) - \overline{x}(i)\right| \tag{6}$$

RMSE:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x(i) - \bar{x}(i)\right]^2} \qquad (7)$$

Error of RUL:

$$E_{RUL} = \left|RUL_{real} - RUL_{prediction}\right| \qquad (8)$$

Here n the number of prediction data set, $x(i)$ is the real value of testing and monitoring of battery capacity, $\bar{x}(i)$ is the prediction value. In the experiment, k is the prediction steps from the starting point.

The detail result is shown as Table 3.

Index of batteries	**CALCE No. 8**	**CALCE No. 21**	**CALCE No. 33**
MAE of ND-AR	0.0060	0.0057	0.0066
MAE of AR	0.0304	0.0287	0.0317
RMSE of ND-AR	0.0113	0.0105	0.0126
RMSE of AR	0.0349	0.0316	0.0397
E_{RUL} of ND-AR	10	8	7
E_{RUL} of AR	34	27	28

Table 3.Comparison of AR and ND-AR model for battery RUL prediction

From the Table 3, we can find that, the prediction MAE, RMSE and Error of RUL of the ND-AR model are superior than the AR model for various lithium battery.

5. Conclusions

This paper explores an improved nonlinear degradation AR model for battery remaining useful life estimation. The main contribution of this research can be concluded that: (1) low computing complexity AR time series model is applied for battery remaining useful life prediction with the monitoring and testing data, the real-time performance of the proposed method is high. (2) The “accelerated” nonlinear degradation feature of the battery capacity fade is analyzed based on experiment. (3) A nonlinear degradation factor is extracted to combined with standard AR time series prediction model to realize better RUL estimation result and more precisely prediction result could be fulfilled. With the experiment we can conclude that the improved model is suitable for cycle life estimation of the lithium battery as well as low computing application. This proposed NA-AR lithium-ion battery RUL prognostics method shows better prospective in industrial application comparing with RUL prediction based on linear AR model or other time series prediction methods.

6. Future Work

In future, we will consider the uncertainty representation ability of the proposed time series based data-driven method. The dynamic parameters training and models fusion for battery with complex operating condition should be focused in the future research work.

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