A Fusion Method Based on Unscented Particle Filter and Minimum Sampling Variance Resampling for Lithium-ion Battery Remaining Useful Life Prediction

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ABSTRACT

It is important to predict the capacity of lithium-ion battery for future cycles to assess its health condition and to estimate remaining useful life (RUL). Particle filter approaches are widely applied into the estimation of battery capacity. However, after several iterations, the degeneracy and impoverishment of particles can cause unreliable and inaccurate prediction results in particle filter (PF). In this paper, a fusion method is proposed by integrating unscented Kalman filter (UKF) and minimum sampling variance resampling (MSVR) into the standard PF for RUL prediction of batteries. The UKF is employed to generate the proposal distribution of particles, which is used by PF to calculate the weights of particles. Next, the MSVR algorithm is introduced for performing resampling procedure to improve the performance. Finally, the performance of the proposed method is validated and compared to other predictors with four different battery datasets from NASA. According to the results, the integrated method has high reliability and prediction accuracy.

1. INTRODUCTION

Lithium-ion battery is a promising power source for many systems, such as spacecraft, aircraft, and electric vehicles (Xing, Ma, Tsui & Pecht, 2011). However, the performance of batteries gradually deteriorates with cycling and aging of batteries is an inevitable problem (He, Williard, Chen & Pecht, 2014, Xing, Ma, Tsui & Pecht, 2013). Therefore, an accurate prognosis for the remaining useful life (RUL) of Lithium-ion batteries is desired for these applications (Walker, Rayman & White, 2015). RUL of a battery is defined as the useful life of the battery at a particular time of operation (Dong, Jin, Lou & Wang, 2014). In order to track the degradation and predict RUL of batteries, the gradual decreasing capacity is chosen as an indicator of degradation performance.

In the literature, many approaches for RUL prediction of batteries have been proposed. Regression algorithms such as support vector machine (SVM) and relevance vector machine (RVM) were applied to Lithium-ion battery health condition analysis (Nuhic, Terzimehic, Soczka-Guth, Buchholz & Dietmayer, 2013, Widodo, Shim, Caesarendra & Yang, 2011). Besides this kind of pure data-driven methods, model-based filtering approaches are developed to monitor the Lithium-ion battery State-of-Health (SOH) and predict the RUL, such as Kalman filters (KF) (Andre, Appel, Soczka-Guth & Sauer, 2013, Gregory, 2004, Plett, 2004, Plett, 2004) and particle filters (PF) (He, Williard, Osterman & Pecht, 2011, Miao, Xie, Cui, Liang & Pecht, 2013, Bhaskar Saha, Goebel, Poll & Christophersen, 2009). In (Walker, 2015), PF is believed to perform a more accurate estimation of states than unscented Kalman filter (UKF). Moreover, PF is able to deal with more general system models than a KF (Dong, 2014), especially when the system is nonlinear. Consequently, it has been widely applied to battery SOH monitoring and RUL prediction. However, the estimation error is a bit big due to the degeneracy of the particles (Miao, 2013), which means all but a few importance weights tend towards zero. Resampling algorithm can not only solve the problem of particle degeneracy , but also overcome the particle impoverishment issue. That is, most of the particles are

duplicated from the same few ancestors, suffering from a problem of the same nature as degeneracy (Li, Villarrubia, Sun, Corchado & Bajo, 2015).

In this paper, a fusion method for Lithium-ion battery RUL prediction based on unscented particle filter (UPF) and minimum sampling variance resampling (MSVR) is proposed to improve the prediction accuracy and stability. UKF and MSVR algorithms are integrated into the standard PF to mitigate the degeneracy and impoverishment phenomenon.

The rest of this paper is organized as follows. Section 2 summarizes the related PF, UKF and UPF algorithms. The fusion method and battery data are introduced in the section 3. Section 4 gives the comparison results of UPF with systematic resampling (UPF-SR), PF-MSVR and UPF-MSVR, respectively. Conclusions are drawn in section 5.

2. UNSCENTED PARTICLE FILTER

As a promising state estimation method for nonlinear system, UPF is constructed based on the theories of PF and UKF. In this section, the fundamentals and algorithms of PF and UKF will be reviewed briefly.

2.1. Particle Filter and Bayesian Estimation

Many dynamic systems can be represented by the state space model, which consists of a transition and an observation equation. A general non-linear state space model can be defined as (Arulampalam, Maskell, Gordon & Clapp, 2002):

$$x_k = f(x_{k-1}, v_{k-1}) \tag{1}$$

$$z_k = h(x_h, n_k) \tag{2}$$

Where x_k is the system unobservable states, z_k is the system observation, $f(\cdot)$ and $h(\cdot)$ are the state transition function and the observation function respectively, v_k and n_k are the process noise and observation noise of the system. Generally, to construct a battery RUL prognostic model, we assume that v_k and n_k are the uncorrelated zero-mean white noises of transition and observation with covariance Q and R.

Bayesian estimation is applied to approximate the posterior pdf of the unobservable states x_k based on the sequence of observations $Z_{0:k} = \{z_i, i = 0,1,\cdots,k\}$. Thus constructing the posterior pdf (probability density function) $p(x_k | z_{0:k-1})$ becomes an essential step. For Bayesian filtering approach, the posterior pdf can be calculated through a recursive predicting and updating process.

1. Prediction. Use of the system model to obtain the prior pdf of the state at cycle *k* via Chapman-Kolmogorov equation:

$$p(x_k | z_{0:k-1}) = \int p(x_k | z_{k-1}) \int p(x_{k-1} | z_{0:k-1}) dx_{k-1} \tag{3}$$

2. Update. At time *k*, an observation z_k is available and used to update the prior via Bayes' rule:

$$p(x_k | z_{0:k-1}) = \frac{p(z_k | x_k) p(x_k | z_{0:k-1})}{p(z_k | z_{0:k-1})} \tag{4}$$

Where the normalizing constant

$$p(z_k | z_{0:k-1}) = \int p(z_k | x_k) p(x_k | z_{0:k-1}) dx_k \tag{5}$$

depends on the likelihood function $p(z_k | x_k)$ defined by the observation model.

As a general algorithm based on the recursive Bayesian estimation (Sorenson & Alspach, 1971), PF utilizes a sequential Monte Carlo method to draw samples $\{x_k^{(i)}\}_{i=1}^N$ (also called particles) from a posterior distribution and assigns a weight $\{\omega_k^{(i)}\}_{i=1}^N$ to each particle. The posterior pdf can be noted as

$$p(x_k | z_{1:k}) \approx \sum_{i=1}^{N} \omega_k^i \delta(x_k - x_k^i) \tag{6}$$

The standard PF algorithm is described as follows (Julier & Uhlmann, 1997):

1. Initialization
   Set $k = 0$ and draw particles $x_0^i \sim p(x_0), i = 1,2,\cdots,N$.
2. Importance sampling and weights calculation
   For $i = 1,2,...,N$, draw $x_k^i \sim q(x_k^i | x_{0:k-1}^i, z_{0:k})$. In standard PF, define $q(x_k^i | x_{0:k-1}^i, z_{0:k}) = p(x_k^i | x_{0:k-1}^i)$. Assign the particle a weight according to

$$\omega_k^i = \omega_{k-1}^i p(z_k | x_{k-1}^i) = \omega_{k-1}^i \frac{p(z_k | x_k^i) p(x_k^i | x_{k-1}^i)}{q(x_k^i | x_{k-1}^i, z_k)} \tag{7}$$

Normalize the weights

$$\omega_k^i = \omega_k^i \Big/ \sum_{i=1}^{N} \omega_k^i \tag{8}$$

3. Re-sampling
   If the effective sample size N_{eff} is below the given threshold N_{th}, do the re-sampling procedure. Generally, let $N_{th} = 2/3N$

$$N_{eff} = 1 \Big/ \sum_{i=1}^{N} (\omega_k^i)^2 \tag{9}$$

Draw N particles x_k^i from the current particle set x_k^i, and replace the current set with the new one

$$\varpi_k^i = 1/N \tag{10}$$

4. State prediction
   Calculate the expected state by the equation

$$x_k = \sum_{i=1}^{N} \omega_k^i x_k^i \tag{11}$$

If $k \le T$ (T is the number of the measurements), let $k = k + 1$, turn to step 2; else, end the prediction.

2.2. Unscented Kalman Filter

Julier and Uhlmann (Julier & Uhlmann, 1997) proposes the UKF algorithm, which employs unscented transformation to transform the state transition equation. The UKF algorithm can be summarized as follows:

1. Initialization

$$\bar{x}_0 = E(x_0), p_0 = E[(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)^T] \tag{12}$$

Augmented initialized state vector and covariance

$$x_0^a = \begin{bmatrix} x_0^T & 0 & 0 \end{bmatrix}^T, p_o^a = \begin{bmatrix} p_0 & 0 & 0 \\ 0 & Q_0 & 0 \\ 0 & 0 & R_0 \end{bmatrix} \tag{13}$$

2. Sigma points and weights calculation

$$x_k^a = \begin{bmatrix} x_k^T & v_k^T & n_k^T \end{bmatrix}^T, p_k^a = \begin{bmatrix} p_k & 0 & 0 \\ 0 & Q_k & 0 \\ 0 & 0 & R_k \end{bmatrix} \tag{14}$$

$$x_{k-1}^a = \begin{bmatrix} \bar{x}_{k-1}^a & \bar{x}_{k-1}^a + \eta\sqrt{p_{k-1}^a} & \bar{x}_{k-1}^a - \eta\sqrt{p_{k-1}^a} \end{bmatrix} \tag{15}$$

$$\eta = \sqrt{n_a + \lambda}, n_a = n_x + n_v + n_n, \lambda = \alpha^2(n_a + k) - n_a \tag{16}$$

$$x_{k-1}^a = \begin{bmatrix} \bar{x}_{k-1}^x & \bar{x}_{k-1}^v & \bar{x}_{k-1}^n \end{bmatrix}^T \tag{17}$$

$$W_0^{(m)} = \frac{\lambda}{n_a + \lambda}, W_0^{(m)} = \frac{\lambda}{n_a + \lambda} + (1 - \alpha^2 + \beta) \tag{18}$$

$$W_0^{(m)} = W_i^{(c)} = \frac{1}{2(n_a + k)}, i = 1, 2, ..., 2n_a \tag{19}$$

3. Time update

$$x_{k|k-1}^x = f\left(x_{k-1}^x, x_{k-1}^v\right) \tag{20}$$

$$\bar{x}_{k-1} = \sum_{i=0}^{2n_a} W_i^{(m)} X_{i,k|k-1}^x \tag{21}$$

$$p_{k|k-1} = \sum_{i=0}^{2n_a} W_i^{(c)} [x_{i,k|k-1}^x - \bar{x}_{k|k-1}][x_{i,k|k-1}^x - \bar{x}_{k|k-1}]^T \tag{22}$$

$$z_{k|k-1} = h\left(x_{k|k-1}^x, x_{k|k-1}^n\right) \tag{23}$$

$$\bar{z}_{k|k-1} = \sum_{i=0}^{2n_a} W_i^{(m)} z_{i,k|k-1} \tag{24}$$

4. Observation update

$$p_{zz} = \sum_{i=0}^{2n_a} W_i^{(c)} [z_{i,k|k-1} - \bar{z}_{k|k-1}][z_{i,k|k-1} - \bar{z}_{k|k-1}]^T \tag{25}$$

$$p_{xz} = \sum_{i=0}^{2n_a} W_i^{(c)} [x_{i,k|k-1}^x - \bar{x}_{k|k-1}][z_{i,k|k-1} - \bar{z}_{k|k-1}]^T \tag{26}$$

$$k_k = p_{xz} p_{zz}^{-1} \tag{27}$$

$$\bar{x}_k = \bar{x}_{k|k-1} + k_k(z_k - \bar{z}_{k|k-1}) \tag{28}$$

$$p = p_{k|k-1} - k_k p_{zz} k_k^T \tag{29}$$

2.3. Unscented Particle Filter

The key point of the UPF algorithm is that the unscented transformation in UKF is employed to generate a proposal distribution. Then the posterior pdf can be obtained considering the latest observation. The algorithm of UPF can be divided into two steps: firstly, apply the UKF algorithm to get the proposal distribution; secondly, use the standard PF algorithm to get the final results. It is described as follows (Miao, 2013):

1. Update particles $\left\{x_k^{(i)}\right\}_{i=1}^N$ with the UKF described in section 2.2 to obtain $\bar{x}_k^i$ and p_k^i.

2. Sample particles $\{x_k^i\}_{i=1}^N$ from the proposal distribution $q\left(x_k^i \middle| x_{1:k-1}^i, z_{1:k-1}\right) = N\left(\bar{x}_k^i, p_k^i\right)$. Follow the standard PF steps described in section 2.1 to get the final particles and weights. The expected state and its covariance can be calculated through:

$$x_k^i = \sum_{i=1}^{N} \omega_k^i x_k^i \tag{30}$$

$$p_k^i = \sum_{i=1}^{N} \omega [x_k^i - x_k^i][x_k^i - x_k^i]^T \tag{31}$$

3. THE FUSION METHOD FOR BATTERY CAPACITY PREDICTION

3.1. Minimum Sampling Variance Resampling

To avoid the degeneracy phenomenon, the resampling procedure is applied in the PF by eliminating small weight particles and duplicating large weight particles. However,

traditional resampling methods will cause most particles gathering around the larger weighted ones, which lead to the loss of diversity and impoverishment. In this paper, a new resampling algorithm is introduced to avoid this problem and known as MSVR (Li, 2015), which can solve the degeneracy phenomenon and keep the diversity of particles. From the comparative result in literature (Li, 2015), the MSVR shows a better performance in sample sizes and processing time than other resampling algorithms, such as multinomial, residual, stratified, and systematic. The MSVR consists of two main steps and the algorithm is described as follows:

1. Each particle is first resampled $Floor(N\omega_k^i)_{i=1:N}$ times, leaving a weight residual $\overset{i}{\omega}_k = \omega_k^i - Floor(N\omega_k^i)$; this step will yield, in total, L particles, where $L = \sum_{i=1}^{N} Floor(N\omega_k^i)$.
2. The particles with relatively large weight residuals, top N-L, will be further sampled one more time each.

Algorithm MSVR

$[\{\overset{i}{x}_k\}_{i=1}^N] = \mathrm{Re}\, sampleMSV[\{x_k^i, \omega_k^i\}_{i=1}^N];$
$n = 0; L = 0;$
For $i = 1:N$
  $N_k^i = Floor(N\omega_k^i);$
  $\overset{i}{\omega}_k = \omega_k^i - N_k^i / N;$
  $L = L + N_k^i;$
End
For $i = 1:N$
  If $\overset{i}{\omega}_k \in TopRank_{N-L}[\{\overset{i}{\omega}_k\}_{i=1}^N];$
    $N_k^i = N_k^i + 1;$
  End
  For $h = 1:N_k^i$
    $n = n + 1;$
    $\overset{i}{x}_k = x_k^i;$
  End
End

Where $Floor(\cdot)$ gives the largest integer not exceeding the content and $TopRank_s[s]$ returns the largest s elements in Set S.

3.2. Battery Degradation Model

In this study, four battery datasets labeled #5 #6 #7 and #18 from the NASA Ames Prognostics Center of Excellence (B Saha & Goebel, 2007) were selected to demonstrate the effectiveness of the proposed fusion method. Fig.1 shows the degradation curve of the four batteries. The end of life for all batteries is considered to be below 70% of their rated capacity. Thus, the threshold value is set as 1.38Ah. Given that the capacity of battery #7 is always greater than the present failure threshold 1.38 Ah, the value is set 74.5% of its rated capacity (Dong, 2014). Based on fitting the battery degradation data, a battery capacity fading model is established by Saha and Goebel (Bhaskar Saha & Goebel, 2009) as:

$$C_{k+1} = \eta_c C_k + \beta_1 \exp(-\beta_2 / \Delta t_k) \tag{32}$$

Where C_k is the battery capacity of cycle k, β_1 and β_2 are the model parameters, η_c is the coulomb efficiency and Δt_k represents the rest time from cycle k to $k+1$.
Corresponding to our case, the model parameters (β_1, β_2) are need to be estimated. η_c and Δt_k are set 0.997 and 0.7 in this paper. Therefore, the state-space model can be established as:

$$x_k = [\beta_{1,k}; \beta_{2,k}; C_k] \tag{33}$$

$$\begin{aligned} x_{k+1} &= x_k + w_k \\ &= \begin{bmatrix} \beta_{1,k+1} = \beta_{1,k} + w_{k1} \\ \beta_{2,k+1} = \beta_{2,k} + w_{k2} \\ C_{k+1} = \eta_c C_k + \beta_{1,k} \exp(-\beta_{2,k} / \Delta t_k) + w_{k3} \end{bmatrix} \\ z_k &= C_k + v_k \end{aligned} \tag{34}$$

Where x_k denotes the state vector containing model parameters, z_k denotes the capacity observation, w_k and v_k are the state noise and the measurement noise respectively.

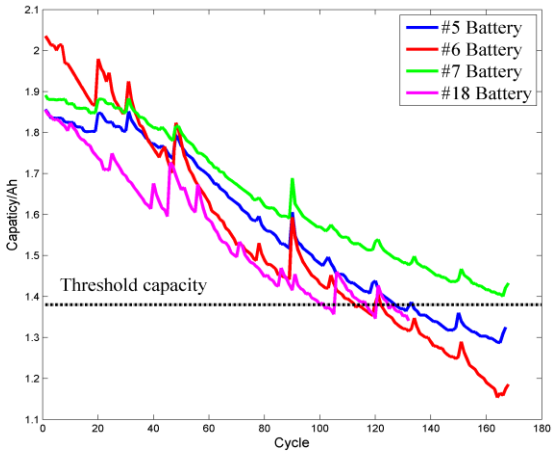

Figure 1. The degradation curve of four batteries.

3.3. The Fusion Method

To avoid problems of degeneracy and impoverishment of particles, for model-based filtering approaches, the key steps

are choosing reasonable proposal distribution and selecting effective resampling algorithm. Combined with UPF and MSVR, the implementation flowchart of the proposed fusion method for battery RUL estimation is shown in fig.2. The fusion method is typically divided into the following two steps:

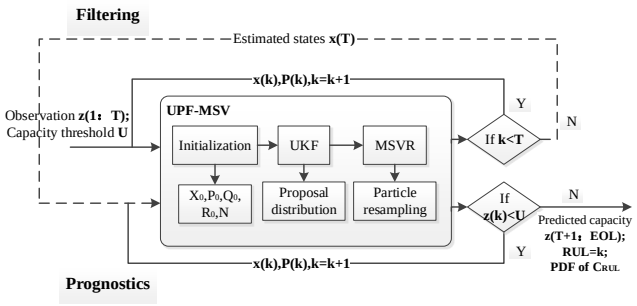

Figure 2. Schematic diagram of the proposed UPF-MSVR method

1. Filtering: state estimation.

   Given the prediction starting point is from step *T*, then the capacity data *z(1： T)* is used for performing model parameters estimation by UPF-MSVR with the empirical degradation model.

2. Prognostics: RUL prediction.

   The prediction is implemented after cycle *T* with the estimated state *x(T)* and the capacity threshold *U*. when the predicted capacity *z(k)* reaches *U*, then the RUL is calculated as the time between the prediction starting cycle *T* and the end of life (EOL) cycle.

4. REMAINING USEFUL LIFE PREDICTION AND PERFORMANCE ANALYSIS

In order to evaluate the forecasting accuracy, three different performance indices are introduced, including root mean square error (RMSE), mean absolute percentage error (MAPE) and R^2 coefficient, which are given by:

$$RMSE=\sqrt{\frac{1}{N}\sum_{k=1}^{N}(C_k-C_k)^2} \tag{35}$$

$$MAPE=\frac{1}{N}\sum_{k=1}^{N}\left|\frac{C-C_k}{C_k}\right|\times 100\% \tag{36}$$

$$R^2=1-\frac{\sum_{k=1}^{N}(C_k-\overline{C}_k)^2}{\sum_{k=1}^{N}(C_k-\overline{C}_k)^2} \tag{37}$$

Where C_k denotes the actual battery capacity, $\overline{C}$ denotes the predicted battery capacity, and $\overline{C}_k$ is the mean of actual battery capacity sequence. For R^2 coefficient, the closer the R^2 value is near to 1， the better performance of the method is.

In addition, the error of RUL and relative accuracy (RA) is defined as follows:

$$E_{RUL}=\left|RUL_{true}-RUL_{predicted}\right| \tag{38}$$

$$RA=1-\frac{\left|RUL_{true}-RUL_{predicted}\right|}{RUL_{true}} \tag{39}$$

Where RA is used to measure the prediction accuracy, which represents the bigger the value, the higher the prediction accuracy. For comparison, UPF-SR method and PF-MSVR methods are employed in this research.

In the study, the number of particles was set at 200 and the inspection cycle was chosen as 60 for four batteries. The actual capacity data and the predicted results by different methods at inspection cycle are plotted in fig.3-fig.6. It is seen that the proposed UPF-MSVR method outperforms the UMP-SR and PF-MSVR methods for predicting RUL. Table 1 gives the prediction performance comparisons in terms of RUL prediction errors, RA, RMSE, MAPE and R^2. By comparing the results from these three methods, UPF-MSVR is observed to be more accurate because its E_{RUL} is smaller than the other two and its RA is largest. In addition, as mentioned above, the R^2 coefficient of the proposed approach has the best performance. Compared with the result in literature (Miao, 2013, Zheng & Fang, 2015) , the proposed method also shows outstanding performance in RUL prediction.

Table 1. Comparison of capacity prediction performance for four batteries

No.	Method	E_{RUL}	RA	RMSE	MAPE	R^2
5	PF-MSVR	7	0.8971	0.0563	0.0242	0.9126
	UPF-SR	10	0.8529	0.0402	0.0199	0.9553
	UPF-MSVR	2	0.9706	0.0262	0.0130	0.9811
6	PF-MSVR	15	0.7170	0.0526	0.0292	0.9561
	UPF-SR	5	0.9057	0.0443	0.0238	0.9690
	UPF-MSVR	3	0.9434	0.2550	0.0187	0.9770
7	PF-MSVR	17	0.7848	0.0630	0.0271	0.8460
	UPF-SR	16	0.7975	0.0477	0.0197	0.9115
	UPF-MSVR	7	0.9114	0.0284	0.0126	0.9687
18	PF-	5	0.875	0.054	0.026	0.877

	MSVR		0	1	0	0
	UPF-SR	7	0.8250	0.0436	0.0204	0.9201
	UPF-MSVR	5	0.8750	0.0343	0.0144	0.9505

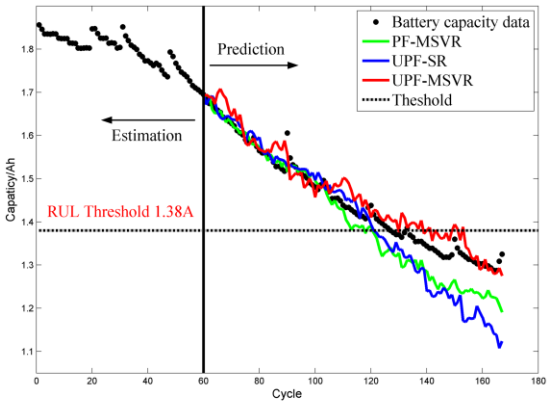

Figure 3. Prediction results for #5 battery.

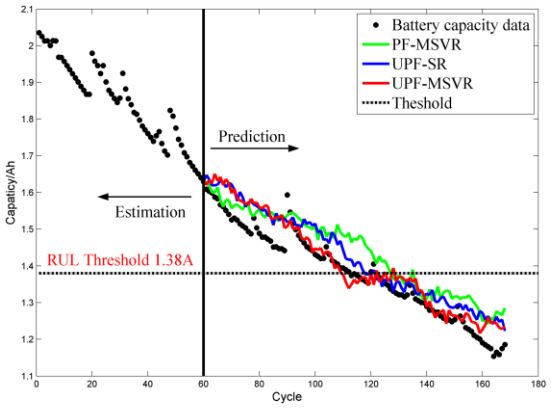

Figure 4. Prediction results for #6 battery.

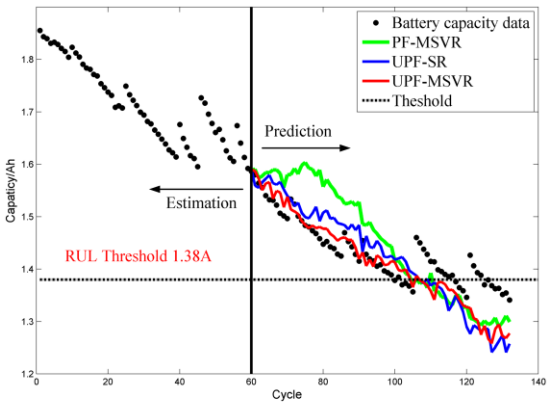

Figure 5. Prediction results for #7 battery.

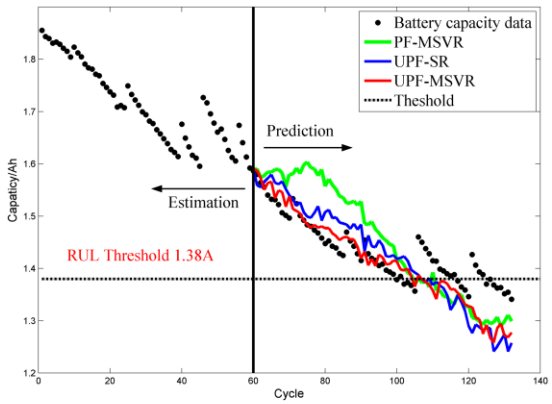

Figure 6. Prediction results for #18 battery.

5. CONCLUSIONS

Lithium-ion batteries play a more and more important role in our daily life. Accurate prediction of battery capacity can not only protect battery from overcharge or discharge, but also provide RUL for maintenance decision. To provide more accurate prediction of battery RUL and improve the performance, the proposed fusion method employs the UKF to generate the posterior distribution of particles for PF, then the MSVR is implemented to resample particles to avoid the degeneracy and impoverishment. From the results presented in section 4, the accuracy of the UPF-MSVR for battery RUL prognostics is validated, and it outperforms the UPF-SR and PF-MSVR with a smaller prediction error. Data of four different batteries, respectively #5, #6, #7 and #18, are used to demonstrate the reliability of the method. Future works include the investigation of the physical models for different types of batteries and the application of the proposed integrated method to other types of battery.

REFERENCES

Andre D, Appel C, Soczka-Guth T, Sauer DU. (2013). Advanced mathematical methods of SOC and SOH estimation for lithium-ion batteries. *Journal of power sources*;vol. 224, pp. 20-7.

Arulampalam MS, Maskell S, Gordon N, Clapp T. (2002). A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *Signal Processing, IEEE Transactions on*;vol. 50(2), pp. 174-88.

Dong H, Jin X, Lou Y, Wang C. (2014). Lithium-ion battery state of health monitoring and remaining useful life prediction based on support vector regression-particle filter. *Journal of Power Sources*;vol. 271, pp. 114-23.

Gregory LP. (2004). Extended Kalman filtering for battery management systems of LiPB-based HEV battery

packs: Part 1. Background. *Journal of Power Sources*;vol. 134(2), pp. 252-61.

He W, Williard N, Chen C, Pecht M. (2014). State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation. *International Journal of Electrical Power & Energy Systems*;vol. 62, pp. 783-91.

He W, Williard N, Osterman M, Pecht M. (2011). Prognostics of lithium-ion batteries based on Dempster–Shafer theory and the Bayesian Monte Carlo method. *Journal of Power Sources*;vol. 196(23), pp. 10314-21.

Julier SJ, Uhlmann JK, editors. (Year), New extension of the Kalman filter to nonlinear systems. *AeroSense'97*. 1997: International Society for Optics and Photonics.

Li TC, Villarrubia G, Sun SD, Corchado JM, Bajo J. (2015). Resampling methods for particle filtering: identical distribution, a new method, and comparable study. *Frontiers of Information Technology & Electronic Engineering*;vol. 16(11), pp. 969-84.

Miao Q, Xie L, Cui H, Liang W, Pecht M. (2013). Remaining useful life prediction of lithium-ion battery with unscented particle filter technique. *Microelectronics Reliability*;vol. 53(6), pp. 805-10.

Nuhic A, Terzimehic T, Soczka-Guth T, Buchholz M, Dietmayer K. (2013). Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods. *Journal of Power Sources*;vol. 239, pp. 680-8.

Plett GL. (2004). Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification. *Journal of power sources*;vol. 134(2), pp. 262-76.

Plett GL. (2004). Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation. *Journal of Power sources*;vol. 134(2), pp. 277-92.

Saha B, Goebel K. (2007). Battery data set. *NASA AMES prognostics data repository*;vol., pp.

Saha B, Goebel K, editors. (Year), Modeling Li-ion battery capacity depletion in a particle filtering framework. *Proceedings of the annual conference of the prognostics and health management society*. 2009.

Saha B, Goebel K, Poll S, Christophersen J. (2009). Prognostics methods for battery health monitoring using a Bayesian framework. *Instrumentation and Measurement, IEEE Transactions on*;vol. 58(2), pp. 291-6.

Sorenson HW, Alspach DL. (1971). Recursive Bayesian estimation using Gaussian sums. *Automatica*;vol. 7(4), pp. 465-79.

Walker E, Rayman S, White RE. (2015). Comparison of a particle filter and other state estimation methods for prognostics of lithium-ion batteries. *Journal of Power Sources*;vol. 287, pp. 1-12.

Widodo A, Shim M-C, Caesarendra W, Yang B-S. (2011). Intelligent prognostics for battery health monitoring based on sample entropy. *Expert Systems with Applications*;vol. 38(9), pp. 11763-9.

Xing Y, Ma EW, Tsui K-L, Pecht M. (2013). An ensemble model for predicting the remaining useful performance of lithium-ion batteries. *Microelectronics Reliability*;vol. 53(6), pp. 811-20.

Xing Y, Ma EW, Tsui KL, Pecht M. (2011). Battery management systems in electric and hybrid vehicles. *Energies*;vol. 4(11), pp. 1840-57.

Zheng X, Fang H. (2015). An integrated unscented kalman filter and relevance vector regression approach for lithium-ion battery remaining useful life and short-term capacity prediction. *Reliability Engineering & System Safety*;vol. 144, pp. 74-82.

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