Battery status estimation using extended belief rule base with novel rule reduction method

H Z Zhu, M Q Xiao, J F Li and Zh Zh Liu.

ATS Lab, Air Force Engineering University, Xi’an 710038, China.

E-mail: Haizhzhu@hotmail.com.

Abstract. The status estimation for lithium battery is playing more and more important role in preventing the catastrophic failure of the system. The traditional data-driven methods treat the battery status estimation as a black box, which denies interpretability of the health status estimation process. Originated from belief rule base (BRB) methods, the extended belief rule base (EBRB) broadened the possible application areas of BRB. By transferring measured data into extended belief rules, EBRB combines the advantages of accuracy from data driven methods and interpretability from belief rule based methods. This paper employs EBRB to deal with battery status estimation problem. Moreover, in this paper, we proposed a novel rule reduction method to optimize the performance of EBRB. The effectiveness of the proposed method is verified by the data of spacecraft applied batteries. Comparison among the proposed method, conventional EBRB and BP neural network is given in this paper to further illustrate the performance of the proposed method.

1. Introduction
Lithium batteries have been widely used in aviation and aerospace equipment, which are mainly safety-critical devices [1]. With the increase of using time, the health status of battery gradually deteriorate until failure. If the status of battery is not real-timely monitored, some unexpected failure may result in complete fail of the whole task [2]. Thus, monitoring and estimating the status of batteries is playing a more and more important role in preventing catastrophic failures. The health status of battery is usually represented by their capacity [3]. However, it is impossible to directly measure the capacity of batteries in working aviation equipment and on-orbit space equipment. By monitoring signals, such as operating voltage, current, temperature and working time, the current statue of battery can be inferred. The capacity of battery is mostly measured by the operating time from a certain working high level voltage to a relative low level voltage. Additionally, the working temperature also influence the status of battery. For that the aforementioned parameters can be easily measured and transferred through sensors, the status of operating battery is possibly obtained by constructing the model to represent the no-linear relationship between the battery status and signals.

Currently, many state-of-art machine learning algorithms can be used to address the health status estimation problem. However, these methods are facing challenges when dealing with fuzzy or incomplete information. Moreover, some methods such as Artificial Neural Network (ANN) are regarded as a black-box, which denies interpretation [4]. The extended belief-rule-based (EBRB) system, which is based on the structure of IF-THEN rules, is able to handle both qualitative and quantitative information [5]. By transforming the measured data into IF-THEN rules and using
evidential reasoning, the EBRB system, with the character of interpretability, is widely used to address both classification and regression problems [6]. Nevertheless, problem of activating nearly all of the extended belief rules would deteriorate the performance of EBRB system [7]. In this paper, we focus on using EBRB system with rule reduction procedures to address battery status estimation problem.

The reminder of this paper are as follows. The second section would introduce the basic theory of EBRB system. After that, the experiment data of batteries, provided by National Aeronautics and Space Administration(NASA), is utilized to verify the effectiveness of the proposed method [8]. The conclusion and is given at the end of this paper.

2. Extended belief-rule-based system

2.1. Rule generation

Let \( \{U_i, U_2, \ldots, U_M\} \) be the antecedent attributes and \( \{A_{i,j}, \alpha_{i,j}^k\}; j = 1, \ldots, J_i \) be the \( j \)th reference values of the \( i \)th attribute. The \( k \)th extended belief rule can be expressed as:

\[
R_k : \text{IF } U_i \text{ is } \{A_{i,j}, \alpha_{i,j}^k\} \text{ and } U_j \text{ is } \{A_{j,l}, \alpha_{j,l}^k\} \text{ then } Y \text{ is } \{Y_m, \beta_m^k\},
\]

where \( \alpha_{i,j}^k \) and \( \beta_m^k \) subject to \( \sum_{j=1}^{J_i} \alpha_{i,j}^k \leq 1 \) and \( \sum_{m=1}^{N} \beta_m^k \leq 1 \), respectively.

We suppose that the parameters measured by the sensors are in the form of \( x_k = \{x_{k,1}, x_{k,2}, \ldots, x_{k,M}\} \) and the utility values of \( A_{i,j} \) are represented by \( u(A_{i,j}) \), which can be given by experts or generated from measure data. The extended belief rules can be generated through:

\[
S(x_{i,j}) = \{\{A_{i,j}, \alpha_{i,j}^t\}; j = 1, \ldots, J_i\}
\]

where \( \alpha_{i,j}^t = u(A_{i,j}) - x_{i,j} \) and \( \alpha_{i,j+l}^t = 1 - \alpha_{i,j+l}^t \), if \( u(A_{i,j}) \leq x_{i,j} \leq u(A_{i,j+l}) \). \( \alpha_{i,j}^t = 0 \) for \( t = 1, \ldots, J_i \) and \( t \neq j, j+1 \).

After the generation of extended belief rule base, the similarity between input measured data and the kth extended belief rule can be calculated by:

\[
S^k(x_i, U_j) = \sum_{j=1}^{J_i} \alpha_{i,j}^t \left( 1.0 - \min_{u(A_{i,j})} \left\{ u(A_{i,j}) \right\} \right)
\]

The activation weight of the kth extended belief rule is:

\[
w_k = \theta_k \prod_{j=1}^{J_i} \left( \sum_{i=1}^{M} \theta_i \prod_{j=1}^{J_i} \left( S^j(x_i, U_j) \right)^2 \right)^{1/2} \text{ and } \delta_i = \delta_i \left( \max_{j=1, \ldots, M} \{\delta_{i,j}\} \right)^{1/2}
\]

2.2. Rule reduction

According to the original EBRB theory, the extended belief rules, whose activation weights are greater than zero, are activated for the evidential reasoning. However, this scheme would result in activating nearly all of the rules in the base, which would bring relative high computational cost. Moreover, activating oversize rules may deteriorate the performance of EBRB system. In this paper a rule reduction method is proposed downsize the computation cost of status estimation using the original EBRB system.

Firstly, the reference values of the battery status should be given by experts or generated by the measured training data. For example, the status of batteries and the corresponding reference values can
be \{\text{very good, 2.1}\}, \{\text{good, 1.9}\}, \{\text{medium, 1.75}\}, \{\text{bad, 1.65}\}, \{\text{very bad, 1.4}\} and \{\text{fail, 1.2}\}. If the measured capacity of a battery is 1.3, then the status is estimated to be fail. Thus, the sample data can be represented as \(x_{j,1}^l, x_{j,2}^l, \ldots, x_{j,m}^l, D_j\), where the \(D_j\) is the battery status. After that, we suppose that the number of samples from the \(l\)th status is \(p_l\). The \(l\) status center can be calculated through:

\[
C_l = \left\{x_{c,j,1}^l, x_{c,j,2}^l, \ldots, x_{c,j,m}^l\right\} = \left\{\sum_{j=1}^{p_l} x_{j,1}^l p_l^{-1}, \sum_{j=1}^{p_l} x_{j,2}^l p_l^{-1}, \ldots, \sum_{j=1}^{p_l} x_{j,m}^l p_l^{-1}\right\}, j = 1, 2, \ldots, p_l
\]  

(5)

Suppose \(x_q\) is the measured signal of an operating battery, the distance form it to the \(l\)th center is calculated by:

\[
d_{l,q} = \left(\sum_{a=1}^{m} (x_{q,a} - x_{c,a}^l)^2\right)^{1/2}
\]  

(6)

We construct a \(m\)-dimensional hypersphere, whose center and radius of the center are \(x_q\) and \(\min(d_{l,q})\), to select the measured signal-related training data. The extended belief rules, whose corresponding training data are within the constructed hypersphere, are supposed to be activated. Compared to the original EBRB method, whereby nearly all of the extended belief rules are activated, the proposed method is able to reduce the size of rules to a tighter and more accurate range.

2.3. Evidential reasoning

By integrating all of the activated extended belief rules, the estimated distribution of the operating battery is obtained by:

\[
\beta_n = \mu \left[\prod_{k=1}^{l} \left(\omega_k \beta_k^k + 1 - \omega_k \sum_{i=1}^{N} \beta_i^k\right)\right] \prod_{k=1}^{l} \left(1 - \omega_k \sum_{i=1}^{N} \beta_i^k\right)^{1-\left(k\right)} \prod_{k=1}^{l} \left(1 - \omega_k \sum_{i=1}^{N} \beta_i^k\right)^{1-\left(k\right)}
\]  

(7)

\[
\mu = \left[\sum_{k=1}^{N} \prod_{k=1}^{l} \left(\omega_k \beta_k^k + 1 - \omega_k \sum_{i=1}^{N} \beta_i^k\right)\right]^{-1} \prod_{k=1}^{l} \left(1 - \omega_k \sum_{i=1}^{N} \beta_i^k\right)^{-1}
\]  

(8)

Additionally, let \(r_n\) denote the \(n\)th reference value. The estimated capacity of the operating battery is calculated by:

\[
f(x) = \sum_{n=1}^{l} r_n \beta_n
\]  

(9)

3. Experiments

In this section, the measured data of batteries provided by NASA is utilized verify the effectiveness of the proposed method. In the given data, the discharging and charging data are provided. In our study, only the former one is utilized. In the experiments, the battery numbered B0005 and B0006 are used as training data and B0007 is utilized to test the performance of the proposed method.

3.1. Information abstraction

From the provided data, two indicator named equal discharge voltage difference time interval(TIEDV) and mean operating temperature(MOT) are abstracted form the raw measured data[9,10]. The TIEDV refers to the time interval the battery takes from a high voltage level to a low one during the discharging process. In our study the high voltage level and the low one are supposed as 3.6V and 3.2V, respectively. The MOT refers to the mean operating temperature of the aforementioned period.
The abstracted information of B0005 as well as the real capacity measured in the experimental condition are as showed in figure 1. The x-axis represents the number of cycles of discharge.

![Figure 1. The abstracted information from original data.](image1)

### 3.2. Estimated result of the EBRB system

The results using original EBRB (EBRB output), EBRB with rule reduction method (RR-EBRB output) and the BP neural network (Network output) are as showed in figure 2, whereby the real output are as depicted using the blue line.

![Figure 2. Estimated results using different algorithms.](image2)

It is noticeable that compared with the original EBRB, our proposed method is closer to the real output. This is because that the original would activate almost all of the extended belief rules in the rule base, which is quite an inaccurate way. Using the EBRB with rule reduction, we can downsize the computational cost as well as activate customized extended belief rules for the input query data. Also compared with the BP neural network, we can figure out that the neural network has relative better performance in the starting period. However, with the increase of charging cycle, the result of the
network becomes worse than that of EBRB with rule reduction. To further compare the results of different methods, we calculated the accumulative error of the aforementioned methods, which are as showed in figure 3.

![Figure 3](image_url)

**Figure 3.** Accumulative error using different algorithms.

The accumulative error of the 3 methods used in our study shows that the proposed method outperforms BP neural network as well as greatly improves the accuracy of the original EBRB method.

4. Conclusion

In this study, we proposed a rule reduction method for the original EBRB method. The proposed can downsize the computational cost as well as activate appropriate extended belief rules for query data. The experiment shows that the proposed method can more accurately estimate the status of operating battery.

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