적응형 Unscented 칼만필터를 이용한 플러디드 납축전지의 SOC 추정

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SOC Estimation of Flooded Lead Acid Battery Using an Adaptive Unscented Kalman Filter

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ABSTRACT

Flooded lead acid batteries are still very popular in the industry because of their low cost as compared to their counterparts. State of Charge (SOC) estimation is of great importance for a flooded lead acid battery to ensure its safe working and to prevent it from over-charging or over-discharging. Different types of Kalman Filters are widely used for SOC estimation of batteries. The values of process and measurement noise covariance of a filter are usually calculated by trial and error method and taken as constant throughout the estimation process. While in practical cases, these values can vary as well depending upon the dynamics of the system. Therefore an Adaptive Unscented Kalman Filter (AUKF) is introduced in which the values of the process and measurement noise covariance are updated in each iteration based on the residual system error. A comparison of traditional and Adaptive Unscented Kalman Filter is presented in the paper. The results show that SOC estimation error by the proposed method is further reduced by 3 % as compared to traditional Unscented Kalman Filter.

Index Terms – Flooded Battery, State of Charge Estimation, Adaptive Unscented Kalman Filter.

1. Introduction

There are different types of batteries available in the market such as Li-Ion, Lead-Acid and Nickel-Cadmium etc. Among the lead acid batteries, flooded batteries are also widely used due to their low cost and long life[1]. The flooded batteries are available in both serviceable and maintenance free styles. A battery management system is vital for flooded lead acid batteries to maximize their performance, ensure their safety and extend their life span. The state of charge (SOC) estimation of a battery is one of the fundamental requirements of the battery management system. Different approaches have been proposed to predict the battery SOC but the most widely accepted algorithm is by using Kalman Filter. To make the estimation more accurate different types of Kalman Filters (KF) are developed and used previously. One of the refined form is Unscented Kalman Filter. All the Kalman Filter uses values for Gaussian noises which are calculated based on trial and error method for any particular system. Usually in traditional KF systems these values remain constant throughout the estimation operation. It has been analyzed that these values can vary practically because of the certain changing parameters in a nonlinear system. Therefore there is a need to update the values of such noises depending upon the dynamics of the system[2].

In this research, an Adaptive Unscented Kalman Filter (AUKF) is proposed for SOC estimation of flooded lead acid battery. The overall working of AUKF is similar to UKF except that the process noise and the measurement noise are adaptively updated in each iteration based on the residual system error of the system. So as the dynamics of the system changes due to external factors then the system also changes the gain of the filter by adjusting the noise covariance matrices. A comparison of traditional UKF and adaptive UKF is presented and results are plotted together which shows that AUKF is better in terms of estimation accuracy and convergence to the right value.

2. Battery Modeling

Fig. 1 represents the selected model for flooded lead acid battery. It consists of Open Circuit Voltage (OCV) connecting in serial with an internal resistance R_i and a RC parallel branch of a charge transfer resistance R_{tc} and a double layer capacitance C_{dl} The hysteresis and diffusion effects are directly included in the OCV and the procedure to model them is described in our previous work[3].The parameters of the battery are estimated online by using ARX algorithm[3].

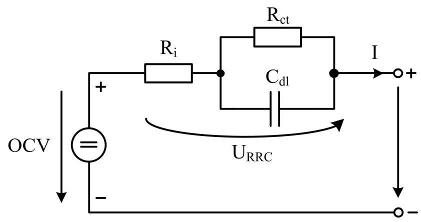

Fig. 1 Selected model for the lead-acid battery

3. SOC Estimation using AUKF

2.1 Implementation of Unscented Kalman Filter

The UKF computing procedure for the nonlinear discrete-time system is given as follows:

$$x_k = f(x_{k-1}, u_k) + w_k \tag{1}$$

$$y_k = h(x_k, u_k) + v_k \tag{2}$$

Initialization:

$$\bar{x}_0 = E(x_0),\ P_0 = E[(x_0 - \bar{x}_0).(x_0 - \bar{x}_0)^T] \tag{3}$$

Generation of Sigma Points:

$$\sqrt{P_{k|k-1}} = \mathrm{chol}(P_{k|k-1}) \tag{4}$$

$$\chi_{k-1} = \left[\bar{x}_{k-1},\ \bar{x}_{k-1} + \sqrt{(L+\lambda).P_{k-1}}\ ,\ \bar{x}_{k-1} - \sqrt{(L+\lambda).P_{k-1}}\right] \tag{5}$$

Prediction Transformation:

$$\chi^{(i)}_{k|k-1} = f(\chi^{(i)}_{k|k-1}, u_k), \qquad i=0,1,..,2L \tag{6}$$

$$\hat{x}^-_k = \sum_{i=0}^{2L} W^{(i)}_m \cdot \chi^{(i)}_{k|k-1} \tag{7}$$

$$P^-_k = \sum_{i=0}^{2L} W^{(i)}_c (\chi^{(i)}_{k|k-1} - \hat{x}^-_k)(\chi^{(i)}_{k|k-1} - x^-_k)^T + Q_w \tag{8}$$

Observation Transformation:

$$\psi^{(i)}_{k|k-1} = h(\chi^{(i)}_{k|k-1}, u_k) \tag{9}$$

$$\hat{y}^-_k = \sum_{i=0}^{2L} W^{(i)}_m . \psi^{(i)}_{k|k-1} \tag{10}$$

$$P^{yy}_k = \sum_{i=0}^{2L} W^{(i)}_c (\psi^{(i)}_{k|k-1} - \hat{y}^-_k)(\psi^{(i)}_{k|k-1} - y^-_k)^T + R_v \tag{11}$$

$$P^{xy}_k = \sum_{i=0}^{2L} W^{(i)}_c (\chi^{(i)}_{k|k-1} - \hat{x}^-_k)(\psi^{(i)}_{k|k-1} - y^-_k)^T \tag{12}$$

Measurement Update:

$$G_k = P_k^{xy}(P_k^{yy})^{-1} \tag{13}$$

$$\hat{x}_k = x_k^- + G_k(y_k - \hat{y}_k^-) \tag{14}$$

$$P_k = P_k^- - G_k P_k^{yy} G_k^T \tag{15}$$

3.2 Adaptive Unscented Kalman Filter

The process noise Q_w and the measurement noise R_v are used in Eqs. (8) & (11) and plays an important role in the calculation of Kalman gain. For traditional UKF, both Q_w and R_v are taken as constant by finding their values by trail and error method. In AUKF, both Q_w and R_v are adaptively updated in each iteration based on the residual system error and are calculated as:

$$Q_w = G_k F_k G_k^T \tag{16}$$

$$R_v = F_k + \sum_{i=0}^{2L} W_c^{(i)} (\psi_{k|k-1}^{(i)} - y_k)(\psi_{k|k-1}^{(i)} - y_k)^T \tag{17}$$

$$F_k = \frac{1}{L} \sum_{i=k-L_w+1}^{k} e_i e_i^T \tag{18}$$

Here e_i is the residual error of the system at time step i and L represents the window size of the covariance matching.

For a battery system, state space equation for the AUKF can be given as:

$$\begin{pmatrix} SOC_{k+1} \\ V_{Cdl\,k+1} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 - \frac{\Delta t}{R_{ct} C_{dl}} \end{pmatrix} \begin{pmatrix} SOC_k \\ V_{Cdl\,k} \end{pmatrix} + \begin{pmatrix} -\frac{\Delta t}{C_n} & \frac{\Delta t}{C_{dl}} \end{pmatrix}^T I_k + w_k \tag{19}$$

$$V_k = OCV - V_{Cdl,k} - R_i I_k + v_k \tag{20}$$

The detail of the battery model, hysteresis modeling, diffusion modeling and above equations can be found in our previous work[4].

4. Experimental Setup and Evaluation

For experimentation, a 90Ah, 12V sealed flooded lead acid battery from Sebang Company is used. The battery is placed in a temperature chamber to maintain its temperature at 25℃. To verify the proposed algorithm a random current profile is applied on the battery as shown in the Fig. 2. In the applied current profile, the SOC of the battery varies from 100 % to about 50% and it also has both charging & discharging regimes so that hysteresis modeling can also be verified as lead acid batteries have a significant hysteresis phenomenon. A Labview program controls the output of a bipolar DC supply and also records the voltage and current of the battery by a sensing circuit and data acquisition device from National Instruments. At start the initialization of estimated SOC was 50 % instead of 100 % to verify the convergence of the estimated SOC to the true SOC value.

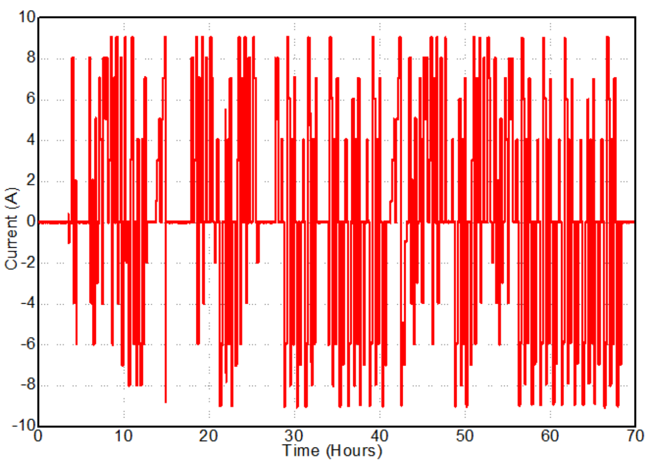

Fig. 2 Random charge/discharge current applied on the battery

Fig. 3 shows the comparison of SOC estimation by traditional UKF and adaptive UKF. For traditional UKF, both R_v and Q_w are taken as constant throughout the estimation process as shown in Table 1 while AUKF adaptively updates both R_v and Q_w depending upon the residual voltage error of the model. The SOC estimation result shows that the AUKF is fast in terms of convergence to the right value. The adaptive UKF takes about half time to converge to the right SOC as compared to traditional UKF. After converging to the right SOC, the dynamics of the AUKF slows down due to which its SOC error is quite smaller than that of traditional UKF.

Table 1 Values of different Parameters for traditional UKF

Parameter	Value
$\mathbf{Q_w}$	$\begin{pmatrix} 1E\text{-}9 & 0 \\ 0 & 1E\text{-}9 \end{pmatrix}$
$\mathbf{P_o}$	$\begin{pmatrix} 1E\text{-}5 & 0 \\ 0 & 1E\text{-}5 \end{pmatrix}$
$\mathbf{R_v}$	0.05

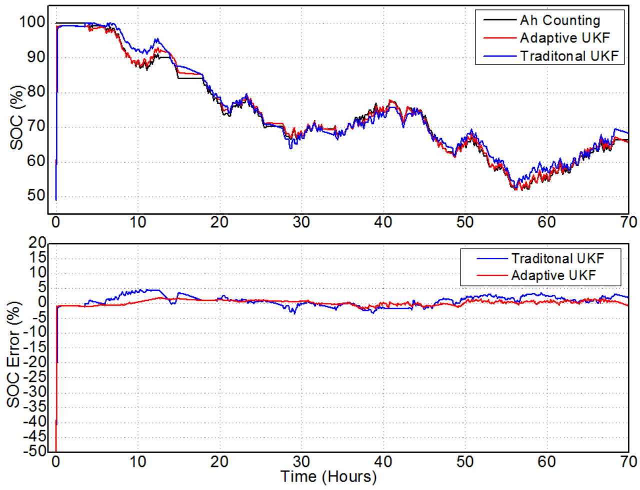

Fig. 3 Comparison of SOC estimation results by traditional and Adaptive Unscented Kalman Filters

The maximum SOC estimation errors by traditional and adaptive UKF are 5% and 2 % respectively. So, SOC error is further reduced by 3 % in AUKF as compared to traditional UKF. The results indicates that adaptive adjusting covariance values of measurement and process noise is highly beneficial to the enhancement of the SOC estimation accuracy.

5. Conclusion

This work proposed an adaptive UKF algorithm for the SOC estimation of a flooded lead acid battery. The obtained results reveal that the proposed AUKF has better performance in terms of convergence time to the right value and SOC estimation error. The proposed adaptive UKF algorithm has reduced the SOC estimation error by 3 % as compared to traditional UKF algorithm.

References

[1] Retrieved from http://www.frost.com/prod/servlet/market-insight-print.pag?docid=SBRD-575K2N

[2] B. Xia, H. Wang, Y. Tian, M. Wang, W. Sun and Z. Xu, State of charge estimation of lithium-ion batteries using an adaptive cubature kalman filter, energies (2015) 5916-5936.

[3] N.T. Tran, K. Hung, P.V. Long, A.B. Khan and W. Choi, SOC/SOH estimation of AGM VRLA by combining ARX model for parameters estimation and DEKF considering hysteresis and diffusion effects, in the IEEE conference on Power Electronics, 2015, 1169-1175.

[4] A.B. Khan and W. Choi, Hysteresis Modeling of the sealed flooded lead acid battery for soc estimation, in Conference of the Korean Institute of Power Electronics, July 2016, 309-310.