언센티드 칼만 필터와 파티클 필터에 기반한 리튬 인산철 배터리의 정확한 충전 상태 추정

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Accurate State of Charge Estimation of $LiFePO_4$ Battery Based on the Unscented Kalman Filter and the Particle Filter

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ABSTRACT

An accurate State Of Charge (SOC) estimation of battery is the most important technique for Electric Vehicles (EVs) and Energy Storage Systems (ESSs). In this paper a new integrated Unscented Kalman Filter–Particle Filter (UKF-PF) is employed to estimate the SOC of a $LiFePO_4$ battery cell and a significant improvement is obtained as compared to the other methods. The parameters of the battery is modeled by the second order Auto Regressive eXogenous (ARX) model and estimated by using Recursive Least Square (RLS) method to calculate value of each element in the model. The proposed algorithm is established by combining a parameter identification technique using RLS method with ARX model and an SOC estimation technique using UKF-PF.

1. Introduction

At the present time, many companies under support of governments as well as organization put much effort into developing battery powered electric applications. Lithium ion (Li-ion) batteries are the most preferred and come in many variations, a popular of Li-ion system is the $LiFePO_4$. In order to ensure the high performance, safety and reliable operation of the battery systems, the SOC of the battery has to be observed. The most typical model of the battery is an Equivalent Circuit Model (ECM) consisting of an OCV, indicated by a DC source, and chains of resistances and capacitances. To avoid labor intensive and time consuming pretests, Auto Regressive eXogenous (ARX) model for online battery parameter estimation has been used. In order to track each of battery parameters of the battery model, a significantly low demand of computing cost Recursive Least Square (RLS) algorithm is applied to the ARX model. Most remarkably, the RLS can adapt to the actual changes of the battery over lifespan and working conditions. Typically, since the SOC of the battery cannot be directly measured by the sensors, it is calculated by using current integration. After identifying the model parameters, some methods could be applied to track the SOC of the battery using Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Particle Filter (PF) and etc. In case of EKF and UKF, one major drawback of these methods is the determination of the process and measurement noises which give significant influences on the convergence rate and SOC estimation accuracy. Thus adaptive approach is employed to minimize the effect of these noises. The idea of PF is to describe the battery state as a distribution density function that is generated from a prior distribution, the distribution presents a set of samples in which each of them has its own contribution weight. These samples are transferred to the dynamic system using sampling algorithm to continue updating the distribution by a measurement model. The calculation of the likelihood of the PF is essential, the noise of conventional UKF is independent, for that reason, an adaptive algorithm is employed to estimate the covariance of noises providing prior knowledge for the PF.

2. Battery Modeling

There is a trade-off between simple model and complexity of the computational procedure, it has been proved that the DP model produces the best performance among widely used ECMs. As depicted in Fig. 1. The corresponding relationship between U_{OC} and SOC is determined through SOC-OCV test and the U_{OC} can be defined as a function of SOC. The ARX model was applied for battery parameter and system identification in several papers. A practical equation to determine output value through input values of the 2^{nd} order ARX model with additive noise is

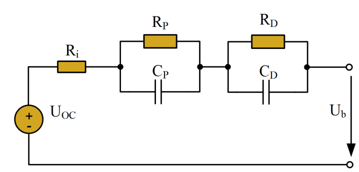

Figure 1. Equivalent circuit model of $LiFePO_4$ battery

given as:

$$y(k) = -a_1y(k-1) - a_2y(k-2) + b_0u(k) + b_1u(k-1) + b_2u(k-2) + e(k) \quad (1)$$

$y(k)$ and $u(k)$ indicate the system output and input, respectively. A compact form of the Eq. (1) can be written as a linear regression:

$$y(k) = \psi^T(k)\,\vartheta(k-1) + e(k) \quad (2)$$

Where the Eq. (2) subsequently gives:

$$\vartheta(k) = [\, a_1;\, a_2;\, b_0;\, b_1;\, b_2 \,] \quad (3)$$

$$\psi(k) = [-y(k-1),\, -y(k-2),\, u(k),\, u(k-1),\, u(k-2)]^T \quad (4)$$

On the other hand, a transfer function given by the Laplace equation for the battery impedance can be deduced in the s domain as:

$$G(s) = \frac{U_{Imp}(s)}{I_b(s)} = \frac{U_b(s) - U_{OC}(s)}{I_b(s)} = R_i + \frac{R_P}{1 + s.R_P.C_P} + \frac{R_D}{1 + s.R_D.C_D} \quad (5)$$

Eventually:

$$G(s) = \left(K_1.s^2 + \frac{K_5}{K_2}.s + \frac{K_4}{K_2}\right) \Big/ \left(s^2 + \frac{K_3}{K_2}.s + \frac{1}{K_2}\right) \quad (6)$$

Where:

$$K_1 = R_i;\; K_2 = R_P.C_P.R_D.C_D;\; K_3 = R_P.C_P + R_D.C_D;\; K_4 = R_i + R_P + R_D$$
$$K_5 = R_i.R_P.C_P + R_i.R_D.C_D + R_P.R_D.C_D + R_D.R_P.C_P \quad (7)$$

The basic forward Euler transformation method providing a simple yet accurate approximation with small step interval T_s is employed for discretization computation. Substitute $s = (1-z^{-1})/(T_s.z^{-1})$ Into Eq. (5), the discrete transfer function is obtained as follows:

$$G(z) = (b_0 + b_1.z^{-1} + b_2.z^{-2})/(1 - a_1.z^{-1} - a_2.z^{-2}) \quad (8)$$

A differential equation indicating the time domain relationship between input and output is as follows:

$$U_b(k) - U_{OC}(k) = -a_1.(U_b(k-1) - U_{OC}(k-1)) - a_2.(U_b(k-2) - U_{OC}(k-2)) + b_0.I_b(k) + b_1.I_b(k-1) + b_2.I_b(k-2) \quad (9)$$

The above function indicates the 2^{nd} order ARX model of Eq. (1) for the battery ECM in Fig. 1, thus the parameters of this system can be identified by RLS method. The calculation procedure of the RLS can be found in many textbooks and papers.

3. Proposed State Estimation Method

In the UKF and PF, an accurate measurement equation is essential for accurate estimation which is directly influenced. By considering the SOC of the battery cell as a member of the state model, state space of the proposed battery model can be represented as:

$$x_{k+1} = A_k.x_k + B_k.u_k + w_k;\ \ y_k = C_k.x_k + D_k.u_k + v_k \tag{10}$$

And in form of discrete time Equations as:

$$x_{k+1} = \begin{bmatrix} U_{P,k+1} \\ U_{D,k+1} \\ z_{k+1} \end{bmatrix} = \begin{bmatrix} 1\text{-}T_s/(R_P.\ C_P) & 0 & 0 \\ 0 & 1\text{-}T_s/(R_D.\ C_D) & 0 \\ 0 & 0 & 1 \end{bmatrix} . \begin{bmatrix} U_{P,k} \\ U_{D,k} \\ z_k \end{bmatrix} + \begin{bmatrix} T_s/C_P \\ T_s/C_D \\ \eta_I.C_n \end{bmatrix} . \begin{bmatrix} I_{b,k} \end{bmatrix} + w_k \tag{11}$$

$$U_{b,k} = U_{OC,k}(z_k)\text{-}\ I_{b,k}.R_i\ \text{-}\ U_{P,k}\ \text{-}\ U_{D,k} \tag{12}$$

Where, z_k is the SOC of the battery, η_I and C_n are the Coulomb efficiency and the actual capacity of the battery cell, respectively. The UKF algorithm based SOC estimation can be applied as follows:

1. Determine Scaling and Weights

$$\alpha,\ \beta,\ \kappa\ (default),\ n;\ \ \lambda = \alpha^2.(n+\kappa)+n \tag{13}$$

$$W_0^m = \lambda/(n+\lambda);\ W_0^c = \lambda/(n+\lambda)+1\text{-}\alpha^2+\beta$$
$$W_i^m = W_i^c = 1/[2(n+\lambda)];\ i=1,2,\dots 2n \tag{14}$$

2. Initialization:

$$\bar{x}_0 = E(x_0);\ \ P_0 = E[(x_0\text{-}\ \bar{x}_0).(x_0\text{-}\ \bar{x}_0)^T] \tag{15}$$

3. Generate the Sigma-point:

$$\sqrt{P_{k-1}} = chol\ (P_{k-1}) \tag{16}$$

$$\chi_{k-1} = \begin{bmatrix} \hat{x}_{k-1} & \hat{x}_{k-1}+\sqrt{L+\lambda}\sqrt{P_{k-1}} & \hat{x}_{k-1}\text{-}\sqrt{L+\lambda}\sqrt{P_{k-1}} \end{bmatrix} \tag{17}$$

4. Prediction transformation:

$$\chi^i_{k|k-1} = A_k.\hat{x}^i_k + B_k.u_k + w_k;\ i=0,1,2\dots 2n \tag{18}$$

$$\hat{x}_{k|k-1} = \sum_i^{2n} W_i^m\ \chi^i_{k|k-1} \tag{19}$$

$$P_{k|k-1} = Q_{k-1} + \sum_i^{2n} W_i^c \left[\chi^i_{k|k-1}\text{-}\hat{x}_{k|k-1}\right]\left[\chi^i_{k|k-1}\text{-}\hat{x}_{k|k-1}\right]^T \tag{20}$$

5. Observation transformation

$$\psi^i_{k|k-1} = C_k.\hat{x}^i_k + D_k.u_k + v_k;\ \ \hat{y}_{k|k-1} = \textstyle\sum_i^{2n} W_i^m\ \hat{\psi}^i_{k|k-1} \tag{21}$$

$$P_x^{yy} = R_k + \sum_i^{2n} W_i^c \left[\psi^i_{k|k-1}\text{-}\hat{y}_{k|k-1}\right]\left[\psi^i_{k|k-1}\text{-}\hat{y}_{k|k-1}\right]^T \tag{22}$$

$$P_x^{xy} = \sum_i^{2n} W_i^c \left[\chi^i_{k|k-1}\text{-}\hat{x}_{k|k-1}\right]\left[\chi^i_{k|k-1}\text{-}\hat{x}_{k|k-1}\right]^T \tag{23}$$

6. Measurement update

$$K_k = P_k^{xy}[P_k^{yy}]^{-1};\hat{x}_k = \hat{x}_{k|k-1}+K_k.(y_k\text{-}\hat{y}_{k|k-1});P_k = P_{k|k-1} + K_k.P_k^{yy}.K_k^T \tag{24}$$

Particle filter method assumes that the state space can be modeled with independent output as represented in Eq. (11, 12). The state space variables are estimated by PF through a probability distribution $p(x_k|y_k)$ that provides the probabilities of possible values of the true state. The standard PF is expressed as follows:

1. Initialization: randomly draw N initial particle for SOC. Draw particles $x_0^i \sim p(x_0);\ i=1,\ 2,\dots\ N$.

2. Sampling and weight calculation: from the distribution, the particles are sampled from the distribution and have been updated with new observation information and then a new sample is obtained.

Likelihood calculation

$$p(y_k|x_k^i) = \frac{1}{\sqrt{2\pi R_k^2}} exp\left(\frac{y_k\text{-}(C_k.x_k^i + D_k.u_k + v_k)}{R_k^2}\right) \tag{25}$$

Assign particle a weight

$$\omega_k^i = \omega_{k-1}^i.p(y_k|x_k^i) \tag{26}$$

The distribution calculation

$$p(x_k|y_{k-1}) = \sum_{i=1}^{N} \omega_{k-1}^i.(A_{k-1}.\hat{x}_k^i + B_{k-1}.u_k + w_{k-1}) \tag{27}$$

Normalize the weight

$$\omega_k^i = \omega_k^i \Big/ \sum_{i=1}^{N} \omega_{k-1}^i \tag{28}$$

Where R_k is covariance of the measurement noise.

3. Re-sampling: optionally at each time, take N samples from the set where probability to take sample i is $\omega_{k|k}^i$.

If the effective sample size N_{eff} is under the threshold

$$N_{eff} = 1 \Big/ \sum_{i=1}^{N} (\omega_k^i)^2 \tag{29}$$

Replace current set by a new one

$$\tilde{\omega}_k^i = 1/N \tag{30}$$

4. State prediction:

Calculate the state by

$$\tilde{x}_k = \sum_{i=1}^{N} \tilde{\omega}_k^i.\tilde{x}_k^i \tag{31}$$

The closer $y_k = C_k.x_k + D_k.u_k + v_k$ is to y_k (measured value), the higher the likelihood of x_k, each particle has its own weight differently. The resampling will sample more the values those have higher probability rather than lower ones, thus, it tightens the distribution to the more likely one than others. In this paper, we propose a combined SOC estimation method by using UKF-PF. In accordance with Eq. (25), the likelihood calculation is essential and based on prior measurement noise covariance R_k of the UKF. However, in UKF, the noises are assumed to be independent and be additive accompanying with covariance values which can lead to larger and divergent error. Thus, the adaptive UKF is employed to estimate the noise covariance values according to the following equations:

$$F_k = \textstyle\sum_{j=k-q+1}^{k} e_j\,e_j^T;\ \ Q_k = K_k.F_k.K_k^T \tag{32}$$

$$R_k = F_k + \sum_i^{2n} W_i^c \left[\psi^i_{k|k-1}\text{-}\hat{y}_{k|k-1}\right]\left[\psi^i_{k|k-1}\text{-}\hat{y}_{k|k-1}\right]^T \tag{33}$$

Where e and q are the voltage residual of the battery model and window size for covariance matching, respectively.

5. Experimental Verification

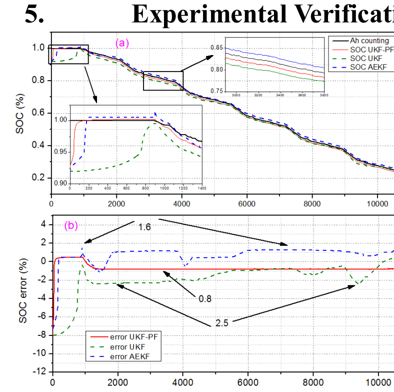

Figure 2. Estimation results under dynamic current
(a) SOC estimation results of the different methods.
(b) SOC estimation errors

In Fig. 2(a), 2 more different algorithms UKF and AEKF are used with the aforementioned current loading profile to verify the estimation accuracy of the proposed method. Fig. 2(a) indicates the tracking results of the SOC estimation by UKF, AEKF and UKF-PF; as above mentioned the Ah counting method is employed as a reference. It is clear to see that the proposed method gives a fastest convergence over the others. The maximum SOC estimation error of the proposed UKF-PF is around 1% while the UKF and AEKF are 2.5% and 1.6%; respectively.

6. Conclusions

In this study, a reliable high accuracy SOC estimation algorithm of LFP battery has been proposed. The joint estimation algorithm combining ARX-RLS for parameter identification with the integrated UKF-PF has been proposed. Comparison of the proposed method and others were conducted, the UKF-PF method obtains superior performance in term of convergence rate and estimated SOC value. The proposed method is able to provide a reliable battery state estimation algorithm for LFP battery system in EVs, HEVs, PHEVs as well as ESS.

References

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