파라미터 식별을 위한 ARX 모델과 히스테리시스와 확산 효과를 고려한 이중 확장 칼만필터의 결합에 의한 AGM 배터리의 SOC/SOH 추정방법

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SOC/SOH Estimation Method for AGM Battery by Combining ARX Model for Online Parameters Identification and DEKF Considering Hysteresis and Diffusion Effects

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ABSTRACT

State of Charge (SOC) and State of Health (SOH) are the key issues for the application of Absorbent Glass Mat (AGM) type battery in Idle Start Stop (ISS) system which is popularly integrated in Electric Vehicles (EVs). However, battery parameters strongly depend on SOC, current rate and temperature and significantly change over the battery life cycles. In this research, a novel method for SOC, SOH estimation which combines the Auto Regressive with external input (ARX) method using for online parameters prediction and Dual Extended Kalman Filter (DEKF) algorithm considering hysteresis is proposed. The validity of the proposed algorithm is verified by the simulation and experiments.

1. Introduction

As the result of the growing awareness of global warming, fossil fuel depletion and the fuel cost escalation, the conventional engine vehicles powered either by gasoline or diesel engines have been replaced by Electric Vehicles (EVs). In current time, ISS system is preferred as the key operating strategy in EVs since it can improve fuel efficiency. For this system, frequent system start and stop is required, thus the batteries, especially AGM battery type received lots of stress from experiencing very different heavy load characteristics.

In order to estimate the SOC and SOH, DEKF approach is favored because of its advances and ability to provide reliable results [1]. Unfortunately, battery parameter characteristic changes over the battery lifetime and depends significantly on the battery operation conditions such as the SOC, the temperature, the current rate and, as the result, the estimation accuracy will be deteriorated as the time goes by. Thus, lots of pretests are required to obtain the information about the parameter variation, and then it is required to provide it to the DEKF to achieve high estimation accuracy. However, it is a kind of time consuming process which is prone to error and requires a lot of instruments and human labors for the tests. Therefore, the online parameters estimation by using ARX method which considers the exogenous variable effect and additive noise can provide large benefit in reducing time and cost for the labor for the pretests and in increasing the accuracy of SOC and SOH estimation even when the parameters of the battery changes [2].

In this research, a novel method which combines DEKF method considering hysteresis and diffusion effect and ARX method is proposed. The DEKF provides the exact information of the Open Circuit Voltage (OCV) of the battery to ARX model and ARX model keep observing the parameters variation by Recursive Least Squares (RLS) with forgetting factor and supply it to the DEKF. In this way, the estimation accuracy can be maintained even if parameters of the battery change. The proposed method is verified by the simulation and experiments.

2. Battery parameter identification by ARX model

The proposed battery electric equivalent circuit consists of OCV connecting in serial with an internal resistance R_i and an R-C parallel branch composing of a charge transfer resistance R_{tc} and a double layer capacitance C_{dl} [3].

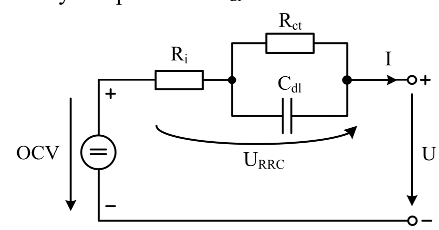

Fig. 1 Selected model for the AGM lead-acid battery

An n^th order linear time variant ARX model which determines the next output value with the previous observation and the prediction error *e(k)* is given in (1) [2].

$$y(k)+a_1 y(k-1)+...+a_n y(k-n)=b_0 u(k) + b_1 u(k-1)+...+b_m u(k-m)+e(k) \quad (1)$$

The transfer function of R_i and R_{ct}–C_{dl} network can be obtained as (2).

$$G(s)=\frac{U_{RRC}(s)}{I(s)}=\frac{(R_i R_{ct} C_{dl})s+(R_i+R_{ct})}{(R_{ct}C_{dl})s+1} \quad (2)$$

By using the transfer function above and the bilinear transformation method, the transfer function of battery system in discrete form with sample time T can be obtained as (3).

$$G(z^{-1})=\frac{(R_i R_{ct} C_{dl})\frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}}+(R_i+R_{ct})}{(R_{ct}C_{dl})\frac{2}{T}\frac{1-z^{-1}}{1+z^{-1}}+1}=\frac{a_2+a_3 z^{-1}}{1+a_1 z^{-1}} \quad (3)$$

Where: $$a_1=\frac{(T-2R_{ct}C_{dl})}{(T+2R_{ct}C_{dl})} \quad (4)$$

$$a_2=\frac{(R_i T+R_{ct}T+2R_i R_{ct}C_{dl})}{(T+2R_{ct}C_{dl})}, a_3=\frac{(R_i T+R_{ct}T-2R_i R_{ct}C_{dl})}{(T+2R_{ct}C_{dl})} \quad (5)$$

Thus, a discretized form of (2) can be written as (6).

$$U(k)-OCV(k)+a_1(U(k-1)-OCV(k-1))=a_2 I(k)+a_3 I(k-1) \quad (6)$$

Where, the OCV-SOC model including the hysteresis effect and diffusion effect can be represented by (7) as demonstrated clearly in the previous research [3].

$$\mathrm{OCV}(SOC,\alpha,\zeta)=\alpha\left[(1-\zeta)\mathrm{OCV}_{c3h}(SOC)+\zeta\,\mathrm{OCV}_{c3m}(SOC)\right] + (1-\alpha)\left[(1-\zeta)\mathrm{OCV}_{d3h}(SOC)+\zeta\,\mathrm{OCV}_{d3m}(SOC)\right] \quad (7)$$

The function (6) is the specific form of the ARX model in (1) for the first-order equivalent circuit model as shown in (8).

$$y(k)=-a_1 y(k-1)+b_0 u(k)+b_1 u(k-1) \quad (8)$$

The RLS algorithm is used to estimate the coefficients [2]:

$$L(k)=\frac{P(k-1)\varphi(k)}{\lambda(k)+\varphi^{T}(k)P(k-1)\varphi(k)} \tag{9}$$

$$\hat{\theta}(k)=\theta(k-1)+L(k)[y(k)-\varphi^{T}(k)\hat{\theta}(k-1)] \tag{10}$$

$$P(k)=\frac{1}{\lambda(k)}\left[P(k-1)-\frac{P(k-1)\varphi(k)\varphi^{T}(k)P(k-1)}{\lambda(k)+\varphi^{T}(k)P(k-1)\varphi(k)}\right] \tag{11}$$

Where, $$\varphi(k)=\left[V(k-1)-OCV(k-1),I(k),I(k-1)\right]^{T} \tag{12}$$

$$\theta(k)=\left[a_1(k),a_2(k),a_3(k)\right] \tag{13}$$

After identifying $a_1(k)$, $a_2(k)$, $a_3(k)$, the parameters of the battery model can be determined as:

$$R_i=\frac{a_3-a_2}{a_1-1},\ R_{ct}=\frac{2a_1a_2-2a_3}{(a_1-1)(a_1+1)},\ C_{dl}=\frac{T(a_1-1)^2}{4a_1a_2-4a_3} \tag{14}$$

3. Combination of DEKF and ARX model for the SOC and SOH estimation

The battery parameters estimated by the ARX method in the section 2 is then used for estimating SOC, SOH by DEKF algorithm. The DEKF framework which is described from (15) to (25) contains two EKFs, one of which is the state filter used for estimating SOC, and another is the weight filter used for estimating battery capacity[1]. Nonlinear state-space models can be represented as (15) and (16). The computing procedure for the DEKF can be summarized as follows.

$$\mathbf{x}_{k+1}=\mathrm{f}(\mathbf{x}_k,\mathbf{u}_k,\boldsymbol{\theta}_k)+\mathbf{w}_k\ ,\quad \boldsymbol{\theta}_{k+1}=\boldsymbol{\theta}_k+\mathbf{r}_k \tag{15}$$

$$\mathbf{y}_k=\mathrm{g}(\mathbf{x}_k,\mathbf{u}_k,\boldsymbol{\theta}_k)+\mathbf{v}_k\ ,\quad \mathbf{d}_k=\mathrm{g}(\mathbf{x}_k,\mathbf{u}_k,\boldsymbol{\theta}_k)+\mathbf{e}_k \tag{16}$$

Initialize: $\hat{\boldsymbol{\theta}}_0^+$, $\hat{\mathbf{x}}_0^+$, $\mathbf{P}_{\theta,0}^+$, $\mathbf{P}_{x,0}^+$

Approximation of nonlinear functions: $\mathbf{F}_{k-1}$, $\mathbf{G}_k^x$, $\mathbf{G}_k^\theta$

Time update:

$$\hat{\mathbf{x}}_k^-=\mathbf{f}(\mathbf{x}_{k-1}^+,\mathbf{u}_{k-1},\hat{\boldsymbol{\theta}}_k^-) \tag{17}$$

$$\mathbf{P}_{x,k}^-=\mathbf{F}_{k-1}\mathbf{P}_{x,k-1}^+\mathbf{F}_{k-1}^T+\mathbf{Q}_k^x \tag{18}$$

$$\hat{\boldsymbol{\theta}}_k^-=\boldsymbol{\theta}_{k-1}^+\ ,\quad \mathbf{P}_{\theta,k}^-=\mathbf{P}_{\theta,k-1}^++\mathbf{Q}_k^\theta \tag{19}$$

Measurement update:

$$\mathbf{K}_k^x=\mathbf{P}_{x,k}^-\left(\mathbf{G}_k^x\right)^T\left[\mathbf{G}_k^x\mathbf{P}_k^-\left(\mathbf{G}_k^x\right)^T+\mathbf{R}_k^x\right]^{-1} \tag{20}$$

$$\hat{\mathbf{x}}_k^+=\mathbf{x}_k^-+\mathbf{K}_k^x\left[U_k-\mathbf{g}\left(\hat{\mathbf{x}}_k^-,\mathbf{u}_k,\hat{\boldsymbol{\theta}}_k^-\right)\right] \tag{21}$$

$$\mathbf{P}_{x,k}^+=\left(\mathbf{I}-\mathbf{K}_k^x\mathbf{G}_k^x\right)\mathbf{P}_{x,k}^- \tag{22}$$

$$\mathbf{K}_k^\theta=\mathbf{P}_{\theta,k}^-\left(\mathbf{G}_k^\theta\right)^T\left[\mathbf{G}_k^\theta\mathbf{P}_k^-\left(\mathbf{G}_k^\theta\right)^T+\mathbf{R}_k^\theta\right]^{-1} \tag{23}$$

$$\hat{\boldsymbol{\theta}}_k^+=\boldsymbol{\theta}_k^-+\mathbf{K}_k^\theta\left[U_k-\mathbf{g}\left(\hat{\mathbf{x}}_k^-,\mathbf{u}_k,\hat{\boldsymbol{\theta}}_k^-\right)\right] \tag{24}$$

$$\mathbf{P}_{\theta,k}^+=\left(\mathbf{I}-\mathbf{K}_k^\theta\mathbf{G}_k^\theta\right)\mathbf{P}_{\theta,k}^- \tag{25}$$

4. Experiment setup and Evaluation

In order to validate the proposed algorithm, a dynamic charge discharge current profile is applied to the battery for the validation process. The battery used for the test is a 12V, 70Ah Solite AGM70L – DIM battery and it is connected to the bipolar DC power supply NF BP4610. A program created in Labview automatically controls the output of the bipolar DC supply and records the voltage and current of the battery by a sensing circuit and a NI myDAQ Device from National Instruments. The initial value of the SOC was given as 50% instead of 100% to verify the convergence of the estimated SOC to the true SOC value. It is clear that the estimated SOC tracks the SOC reference well and the estimation error is less than 5% as shown in Fig. 5. To guarantee the operation of DEKF algorithm for estimating the battery capacity, a pulse current cycle test comprised of a sequence of discharge pulses and relaxation followed by a sequence of charge pulses and relaxation for the same type of battery was conducted. The capacity estimation with three different initial values was performed and the results are shown in Fig. 6. Three different initial capacity values used in the simulation are 0.79Cn, 1.19Cn, 1.0Cn. In all three cases, the estimated value of the capacity converges to the real capacity value (0.98Cn) within 3% error. The results indicate that the proposed estimation algorithm works successfully.

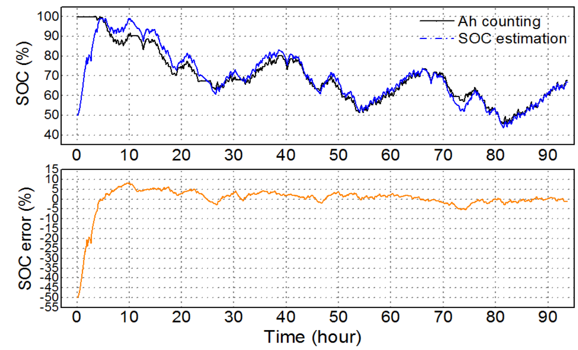

Fig. 5 SOC estimation results and its error

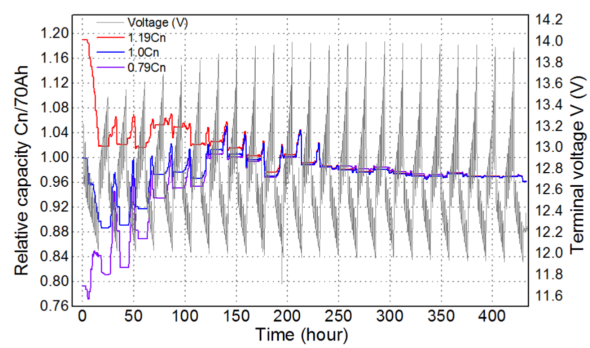

Fig. 6 SOH estimation result with three different initial values of the battery capacity

5. Conclusions

This work proposed a novel technique for estimating the SOC and the SOH of the Lead-acid battery based on the combination of online battery parameters identification with ARX model and the DEKF algorithm including OCV hysteresis and diffusion model. With the help of proposed method, the time and labor for the battery pretests can be significantly saved, since any change in the battery parameters would be detected by the ARX all the time and used for updating the battery model for the DEKF. The obtained results reveal that the proposed method works accurately and it is suitable for the battery management system such as an ISS system.

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