히스테리시스 현상을 고려한 확장칼만필터를 이용한 새로운 납축전지의 충전상태 추정방법

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Novel State-of-Charge Estimation Technique of the Lead-acid Battery by Using EKF Considering Hysteresis Phenomenon

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ABSTRACT

State-of-Charge (SOC) is one of the most important indicators for the battery management system. Thus its precise estimation is crucial not only for effectively utilizing the energy but also preventing critical situations from happening to the powertrain of the vehicle. However, lead-acid battery is time-variant and highly nonlinear, and the hysteresis phenomenon causes large errors in estimating SOC. This paper proposes a novel SOC estimation technique for the lead-acid battery by using Extended Kalman Filter (EKF) considering hysteresis effect. The validity of the proposed technique is verified through the experiments.

1. Introduction

Lead-acid batteries are widely used for automotive applications such as forklifts, golf carts and small electric vehicles. Thus the precise estimation of the SOC is very important for reliable running of them. As is well known, however, due to the complicated battery structure and the influence factors it is not easy to exactly calculate the SOC. The estimation of the SOC of the lead-acid battery is affected by many factors simultaneously. Especially, the lead-acid batteries are highly non-linear and its parameter change is sensitively dependent on factors such as ambient temperature, aging, history of the usage, Peukert effect, current level, and SOC. In addition, the hysteresis phenomenon of the lead-acid battery can cause large error in estimating the SOC.

In this paper a novel estimation technique for the SOC of the lead-acid batter by using Extended Kalman filter considering hysteresis effect is proposed. In the proposed method a simplified Thevenin based model of the battery is used to estimate the SOC for the lead-acid battery[1]. The model takes into account the diffusion effect and the parameter variation according to SOC. Also the hysteresis effect is considered by measuring the charge throughput of the partial cycle.

2. Battery modeling

2.1 Battery modeling

Basically, the lead-acid battery can be accurately modeled by an open circuit voltage (OCV), a series resistance, and two parallel of resistance and capacitance(R-RC-RC). In the model the second R-C network represents the diffusion phenomenon which causes a second overvoltage on the electrode potential called “diffusion overvoltage” varying very slowly. It is considered that the voltage drop on R-RC connection is eliminated after three minutes and the terminal voltage of the lead-acid battery is reached to the equilibrium condition after three hours of relaxation time. In order to reduce the computation, the second RC connection can be modeled by a weighting factor together with the OCV at the three minutes and three hours relaxation.

The hysteresis of the lead-acid batteries is the deviation of the measured OCV and the OCV which corresponds to the average acid concentration caused by horizontal and vertical gradients of the acid concentration. It creates two fundamental equilibrium-potential curves, OCV charge and OCV discharge curve during the full cycle of charge and discharge. When the battery is under the non-monotonous load condition, the OCV curve is not only varied along with these two curve but transited from the charge curve to discharge curve and vice versa. Some approaches have been proposed to take it into account for the estimation of the SOC such as average OCV, Takacs' hysteresis model or one-state hysteresis modeling[1]. However, these approaches are complex thereby causing the low speed of computation and impractical for lead-acid battery applications.

In this research a novel SOC estimation technique is proposed by using EKF considering hysteresis effects. The developed estimation technique adopts a modified Randle’s circuit with an OCV component considering diffusion factor ζ and hysteresis factor α as the lead-acid battery model illustrated in Fig. 1. The diffusion is modeled by measuring the OCV vs. SOC relationship with different relaxation time and the hysteresis effects is modeled by calculating the OCV transition by normalized integration of the charge throughput of the partial charge/discharge cycle[2].

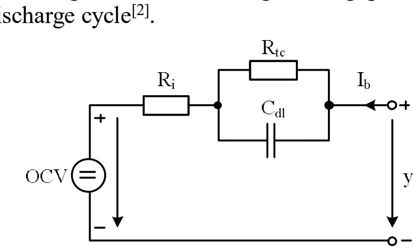

Fig. 1. Selected model for the lead-acid battery

2.2 Parameter extraction for the proposed method

A 12V-70Ah Solite AGM70L-DIN battery is used for the tests. The current pulse and curve fitting technique are applied to the measurement results to extract the model parameters. The variation of the parameters and components according to SOC are modeled by the fifth order polynomial function. Fig 2 shows the OCV vs. SOC measurements results with different relaxation time (3min and 3hr). It also shows the partial cycle test for investigating the hysteresis performed as follows. Firstly the fully charged battery is discharged continuously to 38% of SOC then charged back to the value of 77% of SOC by pulses of 4% of SOC each. And then the battery is discharged again to 38% of SOC with the same pulse.

Based on the above two experiments, a new equation for SOC estimation of the lead-acid battery including the diffusion and hysteresis factor as follows.

$$\mathrm{OCV}(SOC,\alpha,\zeta)=(1-\alpha)\mathrm{OCV_d}(SOC,\zeta)+\alpha\,\mathrm{OCV_c}(SOC,\zeta)\quad(1)$$

The $\mathrm{OCV_c}$ /$\mathrm{OCV_d}$ at charge/discharge is defined by the following equations with the relaxation time t_w.

$$\mathrm{OCV_c}(SOC,\zeta)=(1-\zeta)\mathrm{OCV_{c3h}}(SOC)+\zeta\,\mathrm{OCV_{c3m}}(SOC)\quad(2)$$

$$\mathrm{OCV_d}(SOC,\zeta)=(1-\zeta)\mathrm{OCV_{d3h}}(SOC)+\zeta\,\mathrm{OCV_{d3m}}(SOC)\quad(3)$$

The factors are calculated as follows.

$$\zeta(t_w)=\exp\left(\frac{180-t_w}{\tau}\right)\quad(4)$$

$$\alpha=v\alpha_1+(1-v)\alpha_2\quad(5)$$

where, $0\le\alpha_1,\alpha_2\le 1$

Charge state, $\alpha_1=\int(h_1\eta_i I/C_b)dt,\ \alpha_2=\int(h_2\eta_i I/C_b)dt$ (6)

Discharge state, $\alpha_1=\int(h_2\eta_i I/C_b)dt,\ \alpha_2=\int(h_1\eta_i I/C_b)dt$ (7)

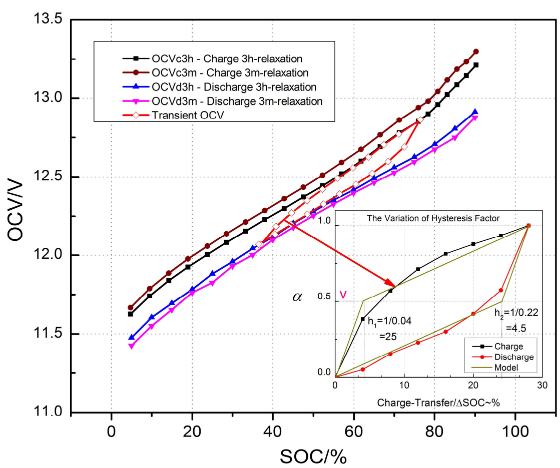

Fig. 2. Experimental data for OCV, hysteresis and diffusion

3. SOC estimation algorithm using EKF

3.1 Implementation of the Extended Kalman Filter

The EKF computing procedure for the nonlinear discrete-time system is given as follows.

$$\mathbf{x}_{k+1}=\mathbf{f}(\mathbf{x}_k,\mathbf{u}_k)+\mathbf{w}_k\quad(8)$$

$$\mathbf{y}_k=\mathbf{g}(\mathbf{x}_k,\mathbf{u}_k)+\mathbf{v}_k\quad(9)$$

Initialization, $\hat{\mathbf{x}}_0^+=\mathbf{E}[\mathbf{x}_0],\ \hat{\mathbf{P}}_0^+=\mathbf{E}\left[(\mathbf{x}_0-\hat{\mathbf{x}}_0^+)(\mathbf{x}_0-\hat{\mathbf{x}}_0^+)^T\right]$ (10)

Approximation $\mathbf{F}_k=\partial\mathbf{f}(\mathbf{x}_k,\mathbf{u}_k)/\partial\mathbf{x}_k\big|_{x_k=\hat{x}_k^+}$ (11)

$$\mathbf{G}_k=\partial\mathbf{g}(\mathbf{x}_k,\mathbf{u}_k)/\partial\mathbf{x}_k\big|_{x_k=\hat{x}_k^-}\quad(12)$$

Time update $\hat{\mathbf{x}}_k^-\approx\mathbf{f}(\mathbf{x}_{k-1}^+,\mathbf{u}_{k-1})$ (13)

$$\mathbf{P}_k^-=\mathbf{F}_{k-1}\mathbf{P}_{k-1}^+\mathbf{F}_{k-1}^T+\mathbf{Q}_k\quad(14)$$

Measurement update $\mathbf{K}_k=\mathbf{P}_k^-\mathbf{G}_k^T\left[\mathbf{G}_k\mathbf{P}_k^-\mathbf{G}_k^T+\mathbf{R}_k\right]^{-1}$ (15)

$$\hat{\mathbf{x}}_k^+=\mathbf{x}_k^-+\mathbf{K}_k\left[\mathbf{y}_k-\mathbf{g}(\hat{\mathbf{x}}_k^-,\mathbf{u}_k)\right]\quad(16)$$

$$\mathbf{P}_k^+=(\mathbf{I}-\mathbf{K}_k\mathbf{G}_k)\mathbf{P}_k^-\quad(17)$$

3.2 Estimation of the SOC with EKF

The state space derivation of the model can be found elsewhere, thus it is not included here for convenience. The state space equations are shown in Eqs. (18) and (19).

$$\begin{pmatrix} z_{k+1}\\ V_{Cdl\,k+1}\end{pmatrix}=\begin{pmatrix}1 & 0\\ 0 & 1-\dfrac{\Delta t}{R_{tc}C_{dl}}\end{pmatrix}\begin{pmatrix} z_k\\ V_{Cdl\,k}\end{pmatrix}+\begin{pmatrix}-\dfrac{\eta_i\Delta t}{C_b}\\ \dfrac{\Delta t}{C_{dl}}\end{pmatrix}I_k+w_k\quad(18)$$

$$y_k=\mathrm{OCV}(z_k,\zeta_k,\alpha_k)-V_{Cdl\,k}-R_iI_k+v_k\quad(19)$$

where, z_k is the SOC at step k and

$$\mathrm{OCV}(z_k,\zeta_k,\alpha_k)=(1-\alpha_k)\begin{bmatrix}(1-\zeta_d)\mathrm{OCV_{d3h}}(z_k)\\ +\zeta_d\,\mathrm{OCV_{d3m}}(z_k)\end{bmatrix}+\alpha_k\begin{bmatrix}(1-\zeta_c)\mathrm{OCV_{c3h}}(z_k)\\ +\zeta_c\,\mathrm{OCV_{c3m}}(z_k)\end{bmatrix}\quad(20)$$

In a comprehensive form of fifth order polynomial equation,

$$\mathrm{OCV}(z_k,\zeta_k,\alpha_k)=\sum_{i=0}^{5}a_{i,k}z_k{}^i\quad(21)$$

where, $a_{i,k}=(1-\alpha_k)\left[\zeta_k ad3m_{i,k}+(1-\zeta_k)ad3h_{i,k}\right]$
$+\alpha_k\left[\zeta_k ac3m_{i,k}+(1-\zeta_k)ac3h_{i,k}\right]$ (22)

4. Experimental results and discussion

The experiments were conducted with two EKF estimation algorithms simultaneously, the one with taking into account the hysteresis effect and the other without it. As seen in Fig. 3, the large errors occur when the charge/discharge turns over if the hysteresis effect is not taken into account. Especially error becomes almost 16% in the state of discharge after the charge. It can be seen in the figure that the errors becomes smaller (within 5%) when the hysteresis is taken into account.

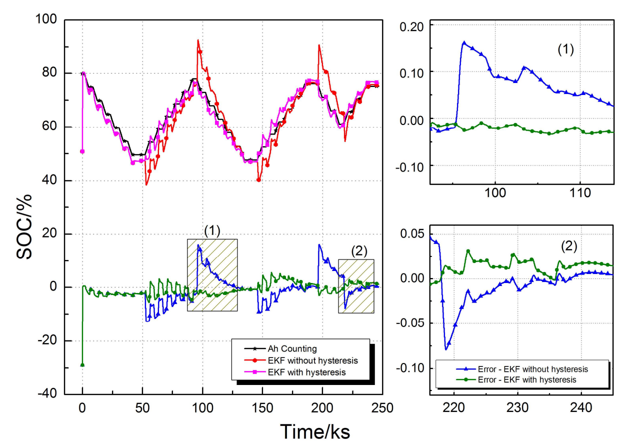

Fig. 3. Estimation results of the estimation with and without hysteresis

5. Conclusion

A novel estimation technique for the State-of-Charge of the lead-acid battery by using EKF considering hysteresis and diffusion effect has been proposed and applied to the AGM battery. The observed error during the charge/discharge cycle was within 5%, thereby validating the proposed method.

References

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[2] M. A. Roscher and D. U. Sauer, "Dynamic electric behavior and open-circuit-voltage modeling of LiFePO4-based lithium ion secondary batteries," Journal of Power Sources, vol. 196, pp. 331-336, 2011.