University of Wollongong

Research Online

Australian Institute for Innovative Materials -
Papers

Australian Institute for Innovative Materials

1-1-2014

SOC estimation for LiFePO₄ battery in EVs using recursive least-squares with multiple adaptive forgetting factors

Van Huan Duong

University of Wollongong, vhd931@uowmail.edu.au

Hany A. Bastawrous

University of Wollongong, hany@uow.edu.au

Kai Chin Lim

University of Wollongong, kcl502@uowmail.edu.au

Khay Wai W. See

University of Wollongong, kwsee@uow.edu.au

Peng Zhang

University of Wollongong, pengz@uow.edu.au

See next page for additional authors

Follow this and additional works at: <https://ro.uow.edu.au/aiimpapers>

Part of the [Engineering Commons](#), and the [Physical Sciences and Mathematics Commons](#)

Research Online is the open access institutional repository for the University of Wollongong. For further information contact the UOW Library: research-pubs@uow.edu.au

SOC estimation for LiFePO4 battery in EVs using recursive least-squares with multiple adaptive forgetting factors

Abstract

This work presents a novel technique which is simple yet effective in estimating electric model parameters and state-of-charge (SOC) of the LiFePO4 battery. Unlike the well-known recursive least-squares-based algorithms with single constant forgetting factor, this technique employs multiple adaptive forgetting factors to provide the capability to capture the different dynamics of model parameters. The validity of the proposed method is verified through experiments using actual driving cycles.

Keywords

estimation, lifepo4, battery, evs, recursive, least, soc, squares, factors, multiple, adaptive, forgetting

Disciplines

Engineering | Physical Sciences and Mathematics

Publication Details

Duong, V. H., Bastawrous, H. A., Lim, K. C., See, K. W., Zhang, P. & Dou, S. X. (2014). SOC estimation for LiFePO4 battery in EVs using recursive least-squares with multiple adaptive forgetting factors. Connected Vehicles and Expo (ICCVE), 2014 International Conference on (pp. 520-521). United States: Institute of Electrical and Electronics Engineers.

Authors

Van Huan Duong, Hany A. Bastawrous, Kai Chin Lim, Khay Wai W. See, Peng Zhang, and S X. Dou

SOC Estimation for LiFePO₄ Battery in EVs Using Recursive Least-Squares with Multiple Adaptive Forgetting Factors

V. H. Duong, *Student Member, IEEE*, H. A. Bastawrous, *Member, IEEE*,

K. C. Lim, *Student Member, IEEE*, K. W. See, P. Zhang, and S. X. Dou

Institute for Superconducting and Electronic Materials, University of Wollongong, NSW, Australia

Abstract- This work presents a novel technique which is simple yet effective in estimating electric model parameters and state-of-charge (SOC) of the LiFePO₄ battery. Unlike the well-known recursive least-squares-based algorithms with single constant forgetting factor, this technique employs multiple adaptive forgetting factors to provide the capability to capture the different dynamics of model parameters. The validity of the proposed method is verified through experiments using actual driving cycles.

Keywords- State-of-Charge, LiFePO₄ Battery, Recursive Least Square, Multiple Adaptive Forgetting Factors

I. INTRODUCTION

Electric vehicles have been well recognized because of their contribution in the promising future of emission-free transportation means. The core of the electric vehicles is the battery storage system which plays an important role in the safety and price of the vehicles. Therefore, there is a necessity to develop an effective battery management system in the field of electrification. Various advanced methods have been proposed and applied to cope with difficulties in estimating the states of battery in the storage system [1].

Among these effective methods, recursive least-squares (RLS) algorithm applied on electrical-equivalent battery model has been well proposed and implemented in the battery management system in order to estimate the states of the LiFePO₄ battery online [1, 2]. In order to adapt with dynamic changes of the battery under driving cycles, RLS with a constant forgetting factor has been used. However, the parameters to be estimated for the battery model have different dynamic characteristics. Hence, assigning a single constant forgetting factor may not provide accurate estimations of all battery model parameters and will likely cause divergence in the estimation. To further improve the performance of RLS algorithm, a novel technique employing multiple adaptive forgetting factors is proposed for the first time in this paper.

II. BATTERY MODEL AND ESTIMATION ALGORITHM

A. Battery Model

In order to accurately model the LiFePO₄ battery, an equivalent circuit consisting of an open-circuit voltage (OCV) source, an internal resistance, and two networks of resistance and capacitance (R-RC-RC) connected in series is required [3]. However, this model requires heavy computations due to

Fig. 1 Electrical model for LiFePO₄ battery

the presence of two capacitors. To simplify the model for the sake of fast and feasible implementation, it can be transformed into the one which is depicted in Fig. 1. A detailed explanation of the validity and effectiveness of this transformation can be found elsewhere [4].

B. Estimation Algorithm

In order to apply the proposed RLS technique, an autoregressive exogenous (ARX) model is required. To do so, firstly the transfer function of the battery impedance is expressed in s-domain as follows:

$$G(s) = \frac{U_{RR}(s)}{I(s)} = R_0 + \frac{R_1}{1 + sR_1C_1} \quad (1)$$

where U_{RR} represents the dynamic voltage drop of the battery across the series resistance and the RC section. Then, the system is discretised with a sampling time T_s through the simple forward-difference transformation to avoid complexity. Finally, the ARX model is formulated as below:

$$y_k = \theta_k^T \cdot \phi_k \quad (2)$$

$$\text{where } \theta_k = [b_{0,k}; \quad b_{1,k}; \quad a_{1,k}; \quad OCV_k] \quad (3)$$

$$\phi_k = [I_k; \quad I_{k-1}; \quad (OCV_{k-1} - y_{k-1}); \quad 1] \quad (4)$$

$$b_0 = R_0 \quad (5)$$

$$b_1 = -R_0 + \frac{T_s}{C_1} + \frac{T_s \cdot R_0}{R_1 \cdot C_1} \quad (6)$$

$$a_1 = \frac{T_s}{R_1 \cdot C_1} - 1 \quad (7)$$

For the conventional RLS, usually a single forgetting factor λ is assigned for all the parameters although the dynamic behaviour of each parameter is different from the others under the same conditions of current, voltage, and temperature of the battery. This might result in an inaccurate parameters identification which consequently causes a poor SOC estimation. To avoid this issue, we propose to employ

Fig. 2 Test bench configuration

multiple adaptive forgetting factors $\lambda_{i,k}$ in the computation procedure of the RLS estimation as follows [5, 6]:

$$\lambda_{i,k} = 1 - \frac{1}{1 + \frac{\zeta_i}{\phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k}}} \quad (8)$$

$$L_{i,k} = \frac{P_{i,k-1} \cdot \phi_{i,k}}{\lambda_{i,k} + \phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k}} \quad (9)$$

$$P_{i,k} = \frac{1}{\lambda_{i,k}} (1 - L_{i,k} \cdot \phi_{i,k}^T) P_{i,k-1} \quad (10)$$

$$\theta_k = \theta_{k-1} + L_{mul,k} (y_k - \phi_k^T \cdot \theta_{k-1}) \quad (11)$$

$$\text{where } L_{mul,k} = \frac{1}{1 + \sum_{i=1}^4 \frac{P_{i,k-1} \cdot \phi_{i,k}^2}{\lambda_{i,k}}} \begin{bmatrix} P_{1,k-1} \cdot \phi_{1,k} / \lambda_{1,k} \\ P_{2,k-1} \cdot \phi_{2,k} / \lambda_{2,k} \\ P_{3,k-1} \cdot \phi_{3,k} / \lambda_{3,k} \\ P_{4,k-1} \cdot \phi_{4,k} / \lambda_{4,k} \end{bmatrix} \quad (12)$$

$L_{mul,k}$ and $L_{i,k}$ are the updated gain of estimated parameters vector θ_k and its component, respectively. Similarly, $\lambda_{i,k}$ and $P_{i,k}$ are the forgetting factor and the covariance error of each component of vector θ_k while ζ_i is the tuning parameter for each forgetting factor.

III. EXPERIMENTAL RESULTS

A 40Ah LiFePO₄ battery is used for the experiments which are carried out at 20°C. The test bench configuration is illustrated in Fig. 2. A programmable Bitrode machine with very high accuracy is used to charge/discharge the battery with maximum current of 500A and maximum voltage of 12V. Current pulses are applied to construct the battery's characteristic curve of OCV versus SOC. Then, experiments using current patterns and battery terminal voltage of actual driving cycle are conducted to verify the validity of the proposed technique as shown in Fig. 3. The battery parameters are directly identified based on the estimation of the parameters vector θ_k . The SOC is obtained from the estimated OCV via a look-up table built from the experimental OCV-SOC curve. It can be seen in Fig. 4 (a) that estimation of the resistance R_0 is constant after convergence which perfectly describes the limited conductance of the contact, the inter-cell connections, and the electrolyte. In Fig. 4 (b), the estimation of the charge-transfer resistance R_l is dynamic corresponding

Fig. 3 Actual driving cycle load profile: (a) Current, (b) Voltage

Fig. 4 Experimental results: (a-c) parameters estimation; (d) SOC estimation

to the change of the current amplitude and SOC as expected. Fig. 4 (d) shows the result of SOC estimation obtained by the proposed method compared to the reference SOC obtained from Coulomb counting with an accurate initial value. As can be seen, the estimated SOC tracks the reference value well with root-mean-square error (RMSE) of 0.019.

IV. CONCLUSION

In this work, the RLS technique with multiple adaptive forgetting factors has been proposed for the estimation of the dynamic parameters and SOC of LiFePO₄ battery. The validity of the method has been confirmed by accurate SOC estimation results with RMSE of 0.019. In addition, the feasibility of this method has been proven by the simplicity of the model and the light scalar computations in algorithm.

REFERENCES

- [1] W. Waag, et al., Journal of Power Sources, vol. 258, pp. 321-339, 2014.
- [2] H. He, et al., Energy, vol. 39, pp. 310-318, 2012.
- [3] L. Long, et al., INTELEC IEEE 33rd International, pp. 1-9, 2011.
- [4] V.-H. Duong, et al., The Trans. of the KIPE, vol. 19, pp. 139-146, 2014
- [5] D. C. Huynh, et al., Power and Energy IEEE conf., pp. 444-449, 2010.
- [6] A. Vahidi, et al., Vehicle System Dynamics, vol. 43, pp. 31-55, 2005.