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TR2014-056 June 2014

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American Control Conference (ACC), 2014

Fast UD Factorization-Based RLS Online Parameter Identification for Model-Based Condition Monitoring of Lithium-ion Batteries

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***Abstract*—This paper proposes a novel parameter identification method for model-based condition monitoring of lithium-ion batteries. A fast UD factorization-based recursive least square (FUDRLS) algorithm is developed for identifying time-varying electrical parameters of a battery model. The proposed algorithm can be used for online state of charge, state of health and state of power estimation for lithium-ion batteries. The proposed method is more numerically stable than conventional recursive least square (RLS)-based parameter estimation methods and faster than the existing UD RLS-based method. Moreover, a variable forgetting factor (VF) is included in the FUDRLS to optimize its performance. Due to its low complexity and numerical stability, the proposed method is suitable for the real-time embedded Battery Management System (BMS). Simulation and experimental results for a polymer lithium-ion battery are provided to validate the proposed method.**

***Index Terms*—Fast UD recursive least square (FUDRLS), lithium-ion battery, parameter identification, variable forgetting factor (VF)**

I. INTRODUCTION

Lithium-ion batteries have gained more pervasive use in numerous applications from electronics to power tools due to their high energy and power densities and long cycle life [1]. However, the concerns of using lithium-ion batteries are reliability and performance degradation due to low thermal stability and aging process. Therefore, a battery management system (BMS) is required to monitor and control the conditions of batteries [2]. A key function of the BMS is to monitor the state of charge (SOC), state of health (SOH), instantaneous available power (i.e., SOP), parameters including impedance and capacity, etc., during operation [3]. It is well-understood that the online parameters and states can only be reconstructed, typically, from model-based estimation methods due to absence of sensors for direct measurements of these quantities. The goal of parameter estimation/identification is to capture time-varying parameters of a real-time battery model, which is used for condition monitoring of lithium-ion batteries, such as SOC, SOH [3], and SOP [4] estimation.

A variety of real-time battery parameter estimation methods have been developed, which, in general, can be classified into two categories: Kalman filter-based methods and linear least square regression based-methods. In the first category, linear Kalman filter [4], joint extended Kalman filter (JEKF) [5], dual extended Kalman filter (DEKF) [6], and dual sigma point Kalman filter (SPKF) [7] have been used to estimate parameters and states of a state-space battery model simultaneously. In general, the Kalman filter-based methods provide an accurate solution. However, the estimation error can be large when the process noise and the measurement noise are uncorrelated with zero mean white Gaussian and their covariance values are not properly defined. Moreover, they incur high computational complexity, thus may be difficult to implement in real-time embedded systems.

Linear least square regression based-methods are by far most widely used to estimate parameters of a battery model due to their low computational cost and relatively high accuracy. In order to perform online estimation of time-varying parameters, recursive least square (RLS) [8], [9] and moving window least square (MWLS) [10], [11] have been introduced with an exponential forgetting factor (EF). Recently, a Bierman's UD factorization-based RLS estimation method with an EF [12] has been proposed to solve the digital computer implementation problem of RLS. However, it has drawbacks such as wind-up when a data vector is not persistently exiting [13] as well as nonoptimal tracking ability and noise influence due to the constant forgetting factor [13].

This paper proposes a parameter estimation method called fast UD recursive least square (FUDRLS), which is an alternative matrix form of the Bierman's UD update equations [14] by using a matrix triangularization method [15]. This approach will be more attractive to be used in embedded systems due to a pipeline implementation and

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extension to vector measurements [16]. The proposed method is more numerically stable than conventional RLS-based parameter estimation and faster than the existing UD RLS-based method. Furthermore, a VF method is included to address limitations of the EF method. The proposed parameter identification algorithm is suitable for real-time embedded BMS due to low complexity and easy implementation. The proposed method is validated by simulation and experimental results for a polymer lithium-ion battery.

II. THE BATTERY MODEL

An accurate battery model is important to obtain a precise estimation of those parameters. In addition, a balance between the accuracy and complexity of the battery model should be considered for real-time condition monitoring in embedded systems. In general, electrical circuit battery models are suitable for embedded system applications due to the low complexity and the ability of predicting battery cell current-voltage (I-V) dynamics [17]. The hysteresis effect [18], which shows an equilibrium difference between battery charging and discharging, is a fundamental phenomenon of batteries. It was also demonstrated that the first-order resistor-capacitor (RC) model with a hysteresis, as shown in Fig. 1, provides a good balance between model accuracy and complexity [19].

In Fig 1, the VOC (i.e., the open-circuit voltage OCV), includes two parts. The first part, denoted by $V_{oc}(SOC)$, represents the equilibrium OCV, which is used to bridge the SOC to the cell open-circuit voltage. The second part V_h is the hysteresis voltage to capture the nonlinearity of OCV. The RC circuit models the I-V characteristics and the transient response of the battery cell. Particularly, the series resistance, R_s, is used to characterize the charge/discharge energy losses of the cell; the charge transfer resistance, R_c, and double layer capacitance, C_d, are used to characterize the short-term diffusion voltage, V_d, of the cell; V_{cell} represents the terminal voltage of the cell. Defining $H(i_B) = \exp(-\rho|i_B(k)|T_s)$, a discrete-time state-space version of the real-time battery model is expressed as follows:

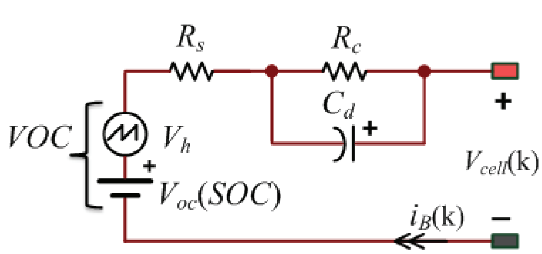


Fig. 1. The first-order RC model with a hysteresis.

$$\begin{bmatrix} SOC(k+1) \\ V_d(k+1) \\ V_h(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \exp(\frac{-T_s}{R_c \cdot C_d}) & 0 \\ 0 & 0 & H \end{bmatrix} \cdot \begin{bmatrix} SOC(k) \\ V_d(k) \\ V_h(k) \end{bmatrix} + \begin{bmatrix} -\eta T_s / C_{\max} & 0 \\ R_c(1-\exp(\frac{-T_s}{R_c \cdot C_d})) & 0 \\ 0 & (H-1)sign(i_B) \end{bmatrix} \cdot \begin{bmatrix} i_B(k) \\ V_{h\max} \end{bmatrix} \quad (1)$$

$$V_{cell}(k) = V_{oc}(SOC) - V_d(k) - R_s \cdot i_B(k) + V_h(k) \quad (2)$$

$$V_{oc}(SOC) = a_0 \exp(-a_1 SOC) + a_2 + a_3 SOC - a_4 SOC^2 + a_5 SOC^3 \quad (3)$$

where η is the Coulomb efficiency (assuming $\eta = 1$); T_s is the sampling period; $i_B(k)$ is the instantaneous current of the battery at the time index k; V_{hmax} is the maximum hysteresis voltage which may be a function of SOC; ρ is the hysteresis parameter, which represents the convergence rate.

Due to the nonlinearity of hysteresis voltage V_h, it is not easy to estimate all parameters. Therefore, a simplified real-time battery model has been used by assuming that VOC is parameterized by $b_1 \cdot SOC + b_0$, which can be expressed as follows [11]:

$$\begin{bmatrix} SOC(k+1) \\ V_d(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & F \end{bmatrix} \cdot \begin{bmatrix} SOC(k) \\ V_d(k) \end{bmatrix} + \begin{bmatrix} \frac{-\eta T_s}{C_{\max}} \\ R_c(1-F) \end{bmatrix} \cdot i_B(k) \quad (4)$$

$$V_{cell}(k) = \begin{bmatrix} b_1 & -1 \end{bmatrix} \begin{bmatrix} SOC(k) \\ V_d(k) \end{bmatrix} - R_s \cdot i_B(k) + b_0 \quad (5)$$

where $F = \exp(-T_s/\tau)$, $\tau = R_c \cdot C_d$ is the time constant of the battery; C_{max} denotes the maximum capacity of the battery.

III. ELECTRICAL PARAMETER IDENTIFICATION OF LITHIUM-ION BATTERY

Because battery parameters change due to variations of the SOC, temperature, and charge/discharge current rate, etc., online parameter estimation algorithm is required. The FUDRLS method is employed to identify the internal parameters of the electrical circuit model which include the electrical impedances R_s, R_c, and C_d. The z-transfer function of (4) and (5) is given [20]:

$$\frac{V_{cell}(z) - b_0}{i_B(z)} = C(zI_{2\times 2} - A)^{-1} B + D = \frac{x_3 + x_4 z^{-1} + x_5 z^{-2}}{1 + x_1 z^{-1} + x_2 z^{-2}} \quad (6)$$

where

$$A = \begin{bmatrix} 1 & 0 \\ 0 & F \end{bmatrix}, B = \begin{bmatrix} \frac{-T_s}{C_{\max}} \\ R_c(1-F) \end{bmatrix}, C = [b_1 \ -1], \quad D = -R_s \quad (7)$$

$$\begin{cases} x_1 = -F-1, x_2 = F, x_3 = -R_s, x_4 = \frac{-b_1 T_s}{C_{\max}} + R_c(F-1) + R_s(F+1) \\ x_5 = R_c(1-F) + F\left(\frac{b_1 T_s}{C_{\max}} - R_s\right) \end{cases} \quad (8)$$

The corresponding difference equation is given:

$$\begin{aligned} V_{cell}(k) = & -x_1 \cdot V_{cell}(k-1) - x_2 \cdot V_{cell}(k-2) + x_3 \cdot i_B(k) \\ & + x_4 \cdot i_B(k-1) + x_5 \cdot i_B(k-2) + b_0(1 + x_1 + x_2) \end{aligned} \quad (9)$$

Because $(1+x_1+x_2)$ is zero and x_1 is $(-x_2-1)$, (9) can be reformulated into the regression form of the input/output relationship.

$$[V_{cell}(k)-V_{cell}(k-1)] = x_2 \cdot [V_{cell}(k-1)-V_{cell}(k-2)] + x_3 \cdot i_B(k) + x_4 \cdot i_B(k-1) + x_5 \cdot i_B(k-2) = \phi^T(k) \cdot \theta \quad (10)$$

where the regressor is $\phi^T(k)=\{[V_{cell}(k\text{-}1)\text{-}V_{cell}(k\text{-}2)],\ i_B(k),\ i_B(k\text{-}1),\ i_B(k\text{-}2)\}$ and the vector of the parameters to be estimated is $\theta=[x_2, x_3, x_4, x_5]^T$. The FUDRLS algorithm is designed to estimate the vector θ from which the internal parameters of the electrical circuit model can be uniquely determined. The parameter identification algorithms need to check the estimated parameters. The abnormal values of the estimated internal parameters due to low quality of the input signal will be discarded (i.e., abnormal condition) and then, the previously estimated parameters will be used until the estimated parameters are in the scope of predefined values (i.e., normal condition).

The RLS-based methods can be improved by using the forgetting factor [9]. When the value of forgetting factor is small, its tracking ability to time-varying parameters will be improved at the expense of sensitivity to noises; while the forgetting factor is large, its tracking ability will be poor but robust to the noise. The RLS technique with an exponential forgetting (EF) has been used [9] and [12]. The main drawback of the EF method is the wind-up, which is result from a non-persistently exciting data vector [13], nonoptimal tracking ability, and noise corruption due to the constant forgetting factor [13]. Instead, the VF methods aim to improve the estimation by optimally changing the forgetting factor. The main mechanism is: a smaller forgetting factor will be employed for the large prediction error; a larger forgetting factor will be used when the prediction error is small. In this paper, a simple VF is proposed in (11) according to the time-averaged estimation of the square of posterior error, $e(k)$, which is given by (12).

$$\lambda(k+1) = \left[1 - \frac{v(k)}{\sigma_0^{\,2} N_0}\right], \quad \lambda_{\min} \le \lambda \le \lambda_{\max} \quad (11)$$

$$v(k) = \delta \cdot v(k-1) + (1-\delta) \cdot e(k)^2 \quad (12)$$

where λ is a forgetting factor; δ is weighting factor to be a quantity between $\lambda_{\min}$ and $\lambda_{\max}$; v is time-average expressions of $e(k)^2$; the parameter $\sigma_0^{\,2}$ is the mean value of the variance of the prediction error obtained from the method implemented in the FUDRLS with constant forgetting factor (e.g., λ = 0.98) assuming that expected noise variance is much smaller than $\sigma_0^{\,2}$ [21]; N_0 represents the memory length (e.g., N_0=50 corresponding to mean forgetting factor of 0.98); $\lambda_{\max}$ (e.g., 0.999) and $\lambda_{\min}$ (e.g., 0.95) denote maximum forgetting factor and minimum forgetting factor, respectively. A similar approach has been proposed in [21]. The main difference from [21] is that the mean value of posterior errors of the moving window buffer has been replaced to (12) resulting in simple as well as $v(0)$ is set to be $\sigma_0^{\,2}$. Calculated $\lambda(k+1)$ will be used in next time step $(k+1)$.

The UDRLS is a UD factorization algorithm to solve digital computer implementation problem of RLS, which preserves the positive covariance P by updating the U, upper triangular and D diagonal matrices, thus the numerical stability has been improved [14]. Conventional Bierman's UD method was implemented to estimate parameters of a lithium-ion battery [12]. An alternative matrix form of Bierman's UD update equations has been developed by using matrix triangularization method [15], called Gentleman's UDRLS. Using Gentleman's UDRLS, a directive forgetting factor has been included in [16]. We propose Gentleman's UDRLS with the variable forgetting factor to solve the regression (10). In order to implement FUDRLS, the regression matrix $\phi^T(k)$ is combined with y= $[V_{cell}(k)\text{-}V_{cell}(k\text{-}1)]$ to produce an augmented matrix: $\Phi^T(k)=\{[V_{cell}(k\text{-}1)\text{-}V_{cell}(k\text{-}2)],\ i_B(k),\ i_B(k\text{-}1),\ i_B(k\text{-}2),\ y\}$.

The FUDRLS algorithm is implemented in the following steps:

Step 1: The algorithm starts. Set the initial values for θ , P_0= $\delta I= U_0 D_0 U_0^T$, $\lambda(0)$, and $K = [0,0,0,0,0]^T$

$$U_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & \theta_1 \\ 0 & 1 & 0 & 0 & \theta_2 \\ 0 & 0 & 1 & 0 & \theta_3 \\ 0 & 0 & 0 & 1 & \theta_4 \\ 0 & 0 & 0 & 0 & -1 \end{bmatrix}, \quad D_0 = \delta \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Step 2: Read a new data $V_{cell}(k)$ and $i_B(k)$.
Step 3: Compute $f=U_0^T\Phi(k)$.
Step 4: Initialize $r(0)=\lambda$.
Step 5.1: Compute the parameters Gentleman's transformation of following loops:

    for h=1,2,…5
        $r(h) = r(h\text{-}1) + D_0(h,h)f(h)^2$
        $D(h,h) = D_0(h,h)r(h\text{-}1) /(\lambda r(h))$
        $\alpha(h) = -f(h)$
        $\beta(h) = D_0(h,h)f(h)/r(h)$
        $K(h)= \beta(h)$
    end loop h

Step 5.2: Compute the Gentleman's transformation of following loops:

    for j=2,…5
        for i=1:j-1
            $U(i,j)=U_0(i,j)+ \alpha(j)K(i)$
            $K(i) = K(i)+ \beta(j)U(i,j)$
        end loop i
    end loop j

Step 6: Update θ=[$U(1,5)$, $U(2,5)$, $U(3,5)$, $U(4,5)$]^T , U_0= U, D_0= D.
Step 7: Convert θ to internal parameters and update λ.
Step 9: Check whether estimated parameters are within the predefined range of values.
Step 10: Update the internal parameters.

where δ is an initial covariance value (e.g., 10^5). The sequences of r and K iteratively compute the prediction error covariance and the gain vector, respectively.

IV. VALIDATION

Simulation and experimental studies are carried out to validate the proposed parameter identification algorithm for a polymer lithium-ion battery subject to various pulse current operations. Comparisons with existing methods such as traditional RLS and UDRLS are also provided to show the advantages of the proposed algorithm in terms of tracking ability, accuracy and computational cost. The nominal capacity, nominal voltage and cutoff voltage of a single battery are 5 Ah, 3.7 V and 2.5 V, respectively. The proposed method is implemented in MATLAB on a computer. In the simulation study, the battery model includes a first-order RC electrical circuit model with the pre-defined true electrical circuit values and the OCV-SOC function (3). The algorithms are implemented based on the simplified model (4)-(5). The parameters of the OCV-SOC function (3) are listed in Table I [17]. For the experimental study, the true values of electrical parameters are unknown. Therefore, we compare the true voltage and the true SOC values with the estimated values from the parameter estimation algorithms. The experimental data of the cell voltage, current, and SOC are collected from a battery tester under the ambient temperature. Then, the measured cell voltage and current from the battery tester are used by the proposed method for real-time electrical impedance, and SOC estimation for a polymer lithium-ion battery.

TABLE I: BATTERY MODEL PARAMETERS [17]

a_0	-0.852	a_1	63.867
a_2	3.692	a_3	0.559
a_4	0.51	a_5	0.508

A. *Simulation Study*

We first use simulated data from the developed battery model to verify FUDRLS with the proposed variable forgetting factor (λ_{min} = 0.9 and λ_{max} = 0.99). A conventional RLS [9] and an UDRLS [12] algorithm are implemented with an EF (λ = 0.98) to compare the proposed FUDRLS. We set initial electrical parameters as R_s = 0.1 ohm, R_c = 0.021 ohm, and C_d = 1900 F. In order to check tracking ability, the parameter R_s has been changed after time 950 seconds from 0.08 ohm to 0.075 ohm. Fig. 2(a)-(c) compare the true and estimated electrical parameters of the battery cell model driven by a pulse current cycle shown in Fig. 2(d). Right after a step change of R_s at time 950 seconds, all algorithms fail to track. However, it has been shown that the FUDRLS with the VF converges to the true values faster after parameter changes than others by reducing forgetting factor. On the other hands, other algorithms using EF converge slowly due to relatively high EF values. Also, Table II illustrates comparison of the performance in terms of accuracy as root mean square error (RMSE) and computational cost as simulation time on a computer using Intel® Core™2 Duo CPU T6600@2.2GHz, 64-bit OS. The results show that the proposed FUDRLS parameter identification algorithm works the best in terms of accuracy

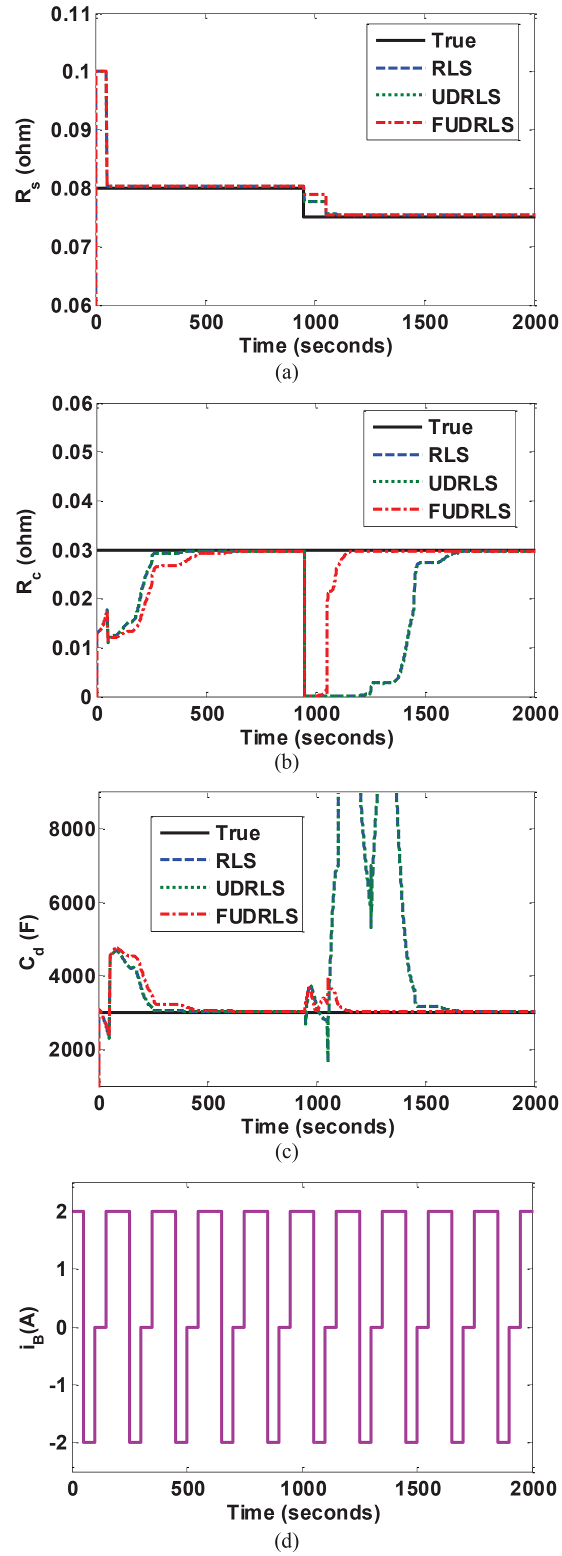


Fig. 2. Comparison of true and estimated electrical parameters of the battery cell model estimated by using the online RLS, UDRLS, and FUDRLS algorithms: (a) R_s, (b) R_c, (c) C_d, and (d) a pulse current cycle applied to the battery.

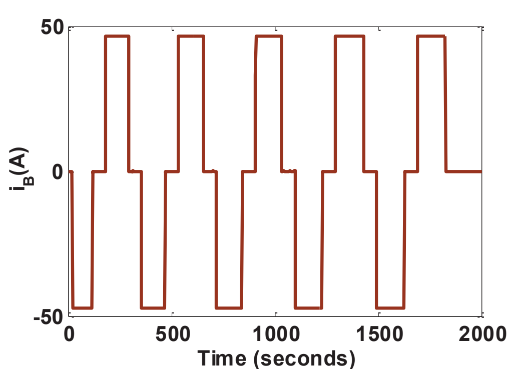
and computational speed.

TABLE II: SIMULATION TIME AND RMSE RESULTS FOR PARAMETER IDENTIFICATION ALGORITHM

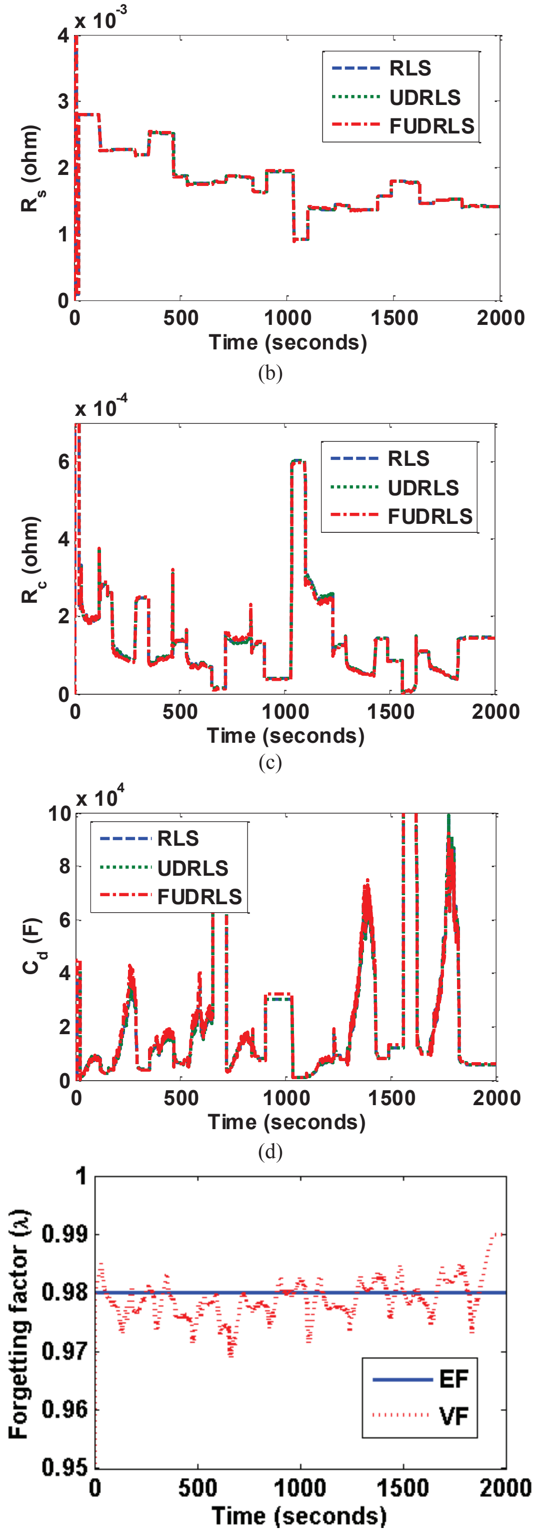
	RLS	UDRLS	FUDRLS
Simulation time (seconds)	0.1315	0.1358	0.1062
Rs (ohm)	0.0039	0.0039	0.0039
Rc (ohm)	0.0142	0.0142	0.0085
Cd (F)	2,668	2,668	445

B. *Experimental Study*

The parameter identification algorithms as mentioned in the simulation study can be used for online SOC estimation. The parameter identification algorithm has been used to update electrical parameters of the full state-space model on which a conventional EKF is designed to perform the SOC estimation [22] using the measured data of the polymer lithium-ion battery. In the EKF design, the system's process noise covariance matrix, and measurement noise covariance matrix are defined as 0.16 and 0.25, respectively. The parameters of the OCV-SOC function of the polymer lithium-ion battery are obtained under the ambient temperature. The SOC and the capacity are initially set with a wrong initial SOC of 0.5 and the maximum capacity of 5 Ah for the state-space model in (1), respectively; the true initial SOC and maximum capacity of the battery are 0.8 and 4.732 Ah, respectively. In order to set initial SOCs for the test battery cells, the battery was first fully charged and rest for one hour. Then the cells are discharged using a small current (e.g., 0.2 A) to the desired initial SOC values. The parameter identification algorithms and EKF are executed in (e.g., T_s = 1 second) to keep track of the fast time varying electrical parameters and SOC. The battery was operated by a dynamic high pulse current cycle (i_B = 10C) shown in Fig. 3(a). Fig. 3(b)-(d) show the electrical parameters of the battery estimated by using the online parameter identification algorithms as well as Table III illustrates comparison of the performance in terms of accuracy as root mean square error (RMSE) and computational cost as a computational time. The results indicate that the accuracy is quite similar so that the values of VF in FUDRLS are closed to EF (λ = 0.98) as shown in Fig. 3(e). However, FUDRLS is the fastest among them.



(a)



(b) (c) (d) (e)

Fig. 3. Estimated electrical parameters and SOC on the experimental data: (a) a pulse current cycle applied to the battery, (b) Rs, (c) Rc, (d) Cd, (e) forgetting factors (λ).

Next, An EKF is implemented with constant electrical parameters to compare the EKF with the proposed FUDRLS which offers the real-time parameters. We set constant electrical parameters as R_s = 0.003 ohm, R_c = 0.0004 ohm, and C_d = 60000 F by trial-and-error in an effort to reduce the estimation error. Fig. 4 compares the estimated SOCs with

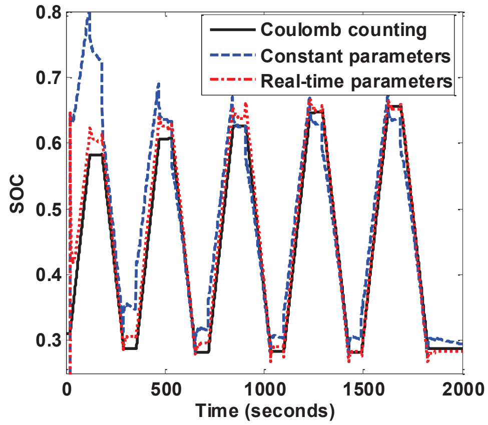


Fig. 4. Comparison of Coulomb counting and estimated SOCs of the battery cell.

Coulomb counting SOC by assuming that the Coulomb counting indicates the true measured SOC value. It has been shown that the estimated SOCs match the measured value although the initial SOC is set wrong in the both methods. However, the result shows that the proposed algorithm works better than the EKF with constant parameters in terms of convergence speed and accuracy by updating internal parameters of the state-space model. The maximum SOC difference is about 3% after 1000 seconds while about 6% of the EKF with constant parameters. Therefore, these results clearly show that the proposed algorithm offers relatively accurate real-time electrical parameters with a low computational cost for SOC estimation algorithms.

TABLE III: COMPUTATIONAL TIME AND RMSE RESULTS FOR PARAMETER IDENTIFICATION ALGORITHM

	RLS	UDRLS	FUDRLS
Computational time (seconds)	0.1166	0.1256	0.0972
V_{cell} (V)	0.00312	0.00312	0.00311
SOC	0.03682	0.03682	0.03678

V. CONCLUSION

This paper has presented an improved RLS-based parameter identification algorithm for a real-time battery model. The proposed FUDRLS with a variable forgetting factor method has been implemented in MATLAB and validated by simulation and experimental results for a polymer lithium-ion battery. The proposed method can be applied to any types of SOC estimation algorithms. Moreover, estimated electrical parameters (e.g., R_s) can be used as an indicator of SOH (e.g., power fade) by comparing electrical parameters of a new battery. Due to low complexity and high accuracy, the proposed method can be suitable for real-time embedded battery management systems in various applications, such as EVs and PHEVs.

REFERENCES

[1] Y. Nishi, “Lithium ion secondary batteries; past 10 years and the future,” *Journal of Power Sources*, vol. 100, no. 1-2, pp. 101-106, 2001.

[2] N. Chaturvedi, R. Klein, J. Christensen, J. Ahmed, and A. Kojic, “Algorithms for advanced battery management systems for advanced battery management systems,” *IEEE Control Systems Magazine*, vol. 30, no. 3, pp. 49-68, 2010.

[3] A. Eddahech, O. Briat, and J. Vinassa, “Real-time SOC and SOH estimation for EV Li-ion cell using online parameters identification,” in *Proc. IEEE Energy Conversion Congress and Exposition*, Sept. 15-20, 2012, pp. 4501-4505.

[4] L. W. Juang, P. J. Kollmeyer, and R. D. Lorenz, “Implementation of online battery state-of-power and state-of-function estimation in electric vehicle applications, in *Proc. IEEE Energy Conversion Congress and Exposition*, Sept. 15-20, 2012, pp. 1819-1826.

[5] H. Fang, Y. Wang, Z. Sahinoglu, T. Wada, and S. hara, “Adaptive robust estimation of state of charge for lithium-ion batteries,” in *Proc. American Control Conference*, 2013, pp. 3491-3497.

[6] G. L. Plett, “Extended Kalman filtering for battery management systems of LiPBbased HEV battery packs – Part 3. State and parameter estimation,” *Journal of Power Sources*, vol. 134, no. 2, pp. 262-276, 2004.

[7] G. L. Plett, “Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2: Simultaneous state and parameter estimation,” *Journal of Power Sources*, vol. 161, pp. 1369-1384, 2006.

[8] M. A. Roscher, O. S. Bohlen, and D. U. Sauer, “Reliable state estimation of multicell lithium-ion battery systems,” *IEEE Transactions on Energy Conversion*, vol. 26, pp. 737-743, 2011.

[9] W. Gao, M. Jiang, and Y. Hou. “Research on PNGV model parameter identification of LiFePO4 Li-ion battery based on FMRLS,” In *Proc. IEEE Industrial Electronics and Applications (ICIEA)*, 2011, pp. 2294-2297.

[10] C. R. Gould, C. M. Bingham, D. A. Stone, and P. Bentley, “New battery model and state-of-health determination through subspace parameter estimation and state-observer techniques,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 8, pp. 3905-3916, 2009.

[11] T. Kim, W. Qiao, and L. Qu, “Online SOC and SOH estimation for multicell lithium-ion batteries based on an adaptive hybrid battery model and sliding-mode observer,” in *Proc. IEEE Energy Conversion Congress and Exposition*, Sept. 15-19, 2013, pp. 292-298 .

[12] X. Tang, X. Mao, J. Lin, and B. Koch, “Li-ion battery parameter estimation for state of charge,” in *Proc. American Control Conference*, 2011, pp. 941-946.

[13] T. R. Fortescue, L. S. Kershenbaum and B. E. Ydstie, “Implementation of self-tuning regulators with variable forgetting factors,” *Automatica*, vol. 17, pp. 831-835, 1981.

[14] G. J. Bierman, *Factorization methods for discrete sequential estimation*, Courier Dover Publications, 2006.

[15] J. M. Jover and T. Kailath, “A parallel architecture for Kalman filter measurement update and parameter estimation,” *Automatica*, vol. 22, pp. 337-346, 1986.

[16] L. Chisci and E. Mosca, “Parallel architectures for RLS with directional forgetting,” *International Journal of Adaptive Control and Signal Processing*, vol. 1, no.1, pp. 69-88, 1987.

[17] T. Kim and W. Qiao, “A hybrid battery model capable of capturing dynamic circuit characteristics and nonlinear capacity effects,” *IEEE Transaction on Energy Conversion*, vol. 26, no. 4, pp. 1172-1180, Dec. 2011.

[18] M. A. Roscher, O. Bohlen, and J. Vetter, “OCV hysteresis in Li-ion batteries including two-phase transition materials,” *International Journal of Electrochemistry*, vol. 2011, 2011.

[19] X. Hu, S. Li, and H. Peng. “A comparative study of equivalent circuit models for Li-ion batteries,” *Journal of Power Sources*, vol. 198, pp. 359-367, 2012.

[20] F. Haugen, “Discrete-time signals and systems,” TechTeach, http://techteach.no, Tech. Rep., 2005.

[21] A. Gupta, “Performance evaluation of adaptive polynomial filtering algorithms for time-varying parameter estimation,” Master thesis, Thapar University, 2011.

[22] G. Plett, “Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs Part 1. Background,” *Journal of Power Sources*, vol. 134, no. 2 pp.252-261, 2004.