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Reliable Online Parameter Identification of Li-Ion Batteries in Battery Management Systems Using the Condition Number of the Error Covariance Matrix

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ABSTRACT Monitoring the state of health (SOH) for Li-ion batteries is crucial in the battery management system (BMS), for their efficient and safe use. Due to time-varying battery parameters and insufficient computation capability of the BMSs, computationally efficient online parameter identification is practically required. So, a simple equivalent circuit model (ECM) based recursive least squares (RLS) parameter identification algorithm has been widely used. However, it has long been acknowledged that this algorithm suffers from wind-up problem when the input current doesn't provide sufficient excitation. It causes numerical instability and then induces large sensitivity of identified parameter values to the noise or truncation error of sensor data, leading to large parameter identification errors. In this work, a new reliable version of ECM based RLS, called a condition number based recursive least squares (CNRLS) algorithm, is proposed to avoid large errors due to insufficient excitation by monitoring the condition number of the error covariance matrix If the condition number is greater than a certain prescribed value, currently identified parameters are considered unreliable and hence the proposed algorithm uses stored internal variables previously computed with sufficiently exciting input current, leading to small condition number of the error covariance matrix. Accordingly, the forgetting factor is also adjusted to give a larger weight to such stored internal variables in order to overcome the insufficient excitation of the input current. It is shown with a1-RC equivalent circuit model that the proposed CNRLS algorithm is more noise-tolerant and accurate than two benchmarks including the standard RLS and adaptive forgetting factor RLS (AFFRLS) in terms of mean absolute errors, with almost the same computing cost.

INDEX TERMS Battery management system, condition number based recursive least squares, state of health.

I. INTRODUCTION

Li-ion batteries have been used in many applications. Accordingly, for efficient and safe battery usage, monitoring their state of health (SOH) and state of charge (SOC) is very important in the battery management system (BMS). To accurately estimate SOH and SOC, the parameters of the battery model under consideration must be accurately identified. So far, several Li-ion battery models have been developed, with different accuracy and computation burden. Tt is very important to choose a proper model requiring moderate computational burden for parameter identification in consideration of hardware limitations of BMS.

Two models have often been used to estimate SOH and SOC of Li-ion batteries: electrochemical battery models and equivalent circuit models (ECMs), and so the corresponding parameter identification problems have also been investigated in a variety of approaches.

Several studies have been conducted for parameter identification of the electrochemical battery models [1]–[8].

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Although an electrochemical model is very helpful for observing physical phenomena inside a Li-ion battery, its parameter identification essentially needs time-consuming and computationally demanding techniques such as machine learning or meta-heuristic algorithms because electrochemical models consist of complicated nonlinear partial differential equations with several boundary conditions. Such sophisticated models make it difficult to identify battery parameters using a simple and closed-form formula. Therefore, considering the fact that time-varying battery parameters have to be identified online with typically low computational BMSs, electrochemical models are not suitable.

Conventionally, ECMs have been used for various functions in BMSs due to their simple structure and the small number of involved parameters. Despite of their simplicity, because of their acceptably high capability to represent battery's physical phenomena, they have been successfully applied to complicated problems such as optimal charging strategies [9], [10] or internal short circuit detection algorithms [11]. For online ECM-based parameter identification, well-established Kalman filters (KFs) have long been used [12]–[15], which are composed of two computational stages of prediction and update in each iteration. Furthermore, KFs can be more simplified for ECM based parameters identification, resulting in recursive lease squares (RLS) algorithms without the update step of the former and hence do not require inversion of a matrix [16]. Such simplification works well since battery model parameters are slowly varying, and hence the ECM parameter identification performance of RLS has very little difference from that of the KF.

For practical implementation, the RLS-based algorithms have been widely used in the battery parameter identifications [17]–[21]. However, it has long been known that RLS-based algorithms suffer from a numerical instability problem called a wind-up problem. That is, when the system considered is less excited and hence the resulting parameter identification error covariance matrix becomes very large, the identified parameters tend to be very sensitive to the numerical truncation errors and the sensor noises [22]. In other words, the wind-up problem may provide very large parameter identification errors due to inevitable numerical and sensing errors. To address the wind-up problem, some research has been carried out, which aims to improve the standard RLS by changing the forgetting factors according to the parameter identification errors [21]–[23] or the trace of the covariance matrix [24]. However, such works have not directly measured such numerical instability of wind-up problem in a quantitative way, and thus have not alleviated it effectively. Some works have directly reduced the effect of the sensing noise on the parameter identification error [25]–[28], but the noise statistics has to be known before the parameter identification [26], which is often not the real-world case; or the noise statistics has to be estimated during the parameter identification [25], [27], [28], which requires large computation burden.

In this paper, a new reliable version of RLS, called a condition number based recursive least squares (CNRLS) algorithm, is developed for low computational and real-time ECM parameter identification without knowing any prior knowledge about the noise statistics. To overcome the wind-up problem, the proposed CNRLS algorithm adaptively updates the internal variables according to the condition number of the parameter identification error covariance matrix, which is a direct and accurate measurement of numerical stability. More specifically, the key strategy is that the CNRLS stores in memory the identified parameter values and their error covariance matrix when the condition number is small and then uses them when the condition number becomes large. In addition, the proposed CNRLS can avoid a matrix inversion operation required for computing the condition number of a parameter error covariance matrix, by exploiting the recursion of inverse matrices arising from RLS. The advantages of the proposed CNRLS is summarized as follows:

- Low computational burden
  - Simple ECM, no matrix inversion operation, no computation for estimating noise statistics
- High accurate of parameter identification
  - Direct quantification of the numerical stability (sensitivity of parameter identification error to the noise and truncation error) with matrix condition number and its efficient remedy without any prior information of noise statistics.

The proposed CNRLS is validated by comparing its performance with two benchmarks, including standard RLS and adaptive forgetting factor RLS (AFFRLS) [21]. AFFRLS is chosen as a benchmark in this work because it has been proven to have high parameter identification accuracy and low computational burden, which is suitable for use in real BMS hardware. To reflect a real BMS environment, Gaussian noise is added to the data used in the validation. The proposed CNRLS turns out to be superior to the two benchmarks in terms of relative mean absolute errors at almost the same computing cost.

The remainder of the paper is organized as follows: Section II and III introduce the condition number of a matrix and the RLS algorithm, respectively. In Section IV, the CNRLS is proposed for 1-RC ECM parameter identification. Section V shows the validation with the simulation results and provides its discussion. In Section VI, the conclusion is drawn.

II. MATRIX CONDITION NUMBER

The matrix conditon number of a square matrix $A \in \mathbb{R}^{n\times n}$ is defined as follows:

$$\kappa(A) = \|A\| \left\|A^{-1}\right\| \tag{1}$$

where $\|A\|$ means any submultiplicative matrix norm of A. If x is a solution of a linear equation

$$Ax = b \tag{2}$$

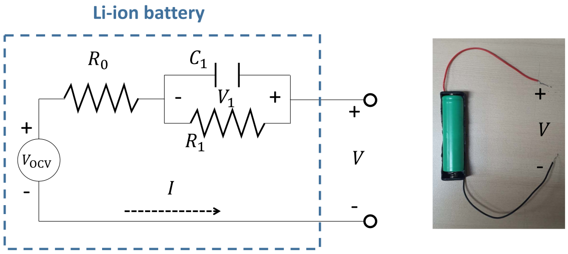

FIGURE 1. 1-RC equivalent circuit model (ECM).

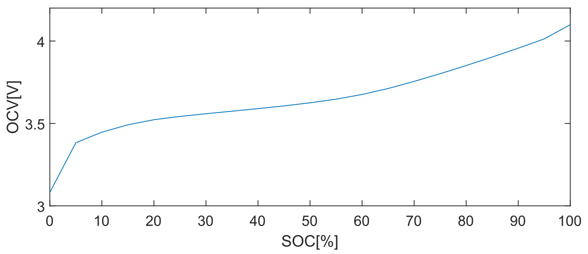

FIGURE 2. Experimental SOC-OCV relationship.

where $b \in \mathbb{R}^{n\times 1}$, and $x + \Delta x$ is a solution to a linear equation

$$(A + \Delta A)(x + \Delta x) = (b + \Delta b), \quad (3)$$

The following inequality holds under some assumptions [29]:

$$\frac{\frac{\|\Delta x\|}{\|x\|}}{\frac{\|\Delta b\|}{\|b\|} + \frac{\|\Delta A\|}{\|A\|}} \leq \kappa(A) \quad (4)$$

which means that $\kappa(A)$ is an upper bound on how much the solution to the linear equation $Ax = b$ can change according to the perturbation of A and $b \in \mathbb{R}^{n\times 1}$. The proof of (4) is presented in [29]. It is noted that if the condition number $\kappa(A)$ in the inequality (4) is large, even small errors of A and b are likely to cause large errors of the solution x.

III. RECURSIVE LEAST SQUARES

Recursive least squares (RLS) is an recursive algorithm for solving the least squares (LS) problem of finding the parameters $\theta \in \mathbb{R}^{n\times 1}$ of a linear regression model

$$d_t = \theta^T \varphi_t \quad (5)$$

where $d_t \in \mathbb{R}^{1\times 1}$ is an output and $\varphi_t \in \mathbb{R}^{n\times 1}$ is an input of the linear model. From given time series data $[\varphi_0, d_0], [\varphi_1, d_1], [\varphi_2, d_2], \ldots, [\varphi_t, d_t], \ldots$, RLS tries to find θ so that the following cost function is minimized:

$$e(t) = \sum_{k=0}^{t} \lambda^{t-k}(d_k - \theta^T \varphi_k)^2 \quad (6)$$

where the so called forgetting factor λ is a real number between 0 and 1. λ assigns bigger weights to the present data compared to the past data when computing the output error. The small λ indicates that RLS can effectively deal with time-varying θ_t since large amounts of the past data are forgotten to find the optimal θ. It can be easily shown that the optimal solution θ_t minimizing $e(t)$ is obtained from the following algebraic equation:

$$\Phi_t \theta_t = \Psi_t \quad (7)$$

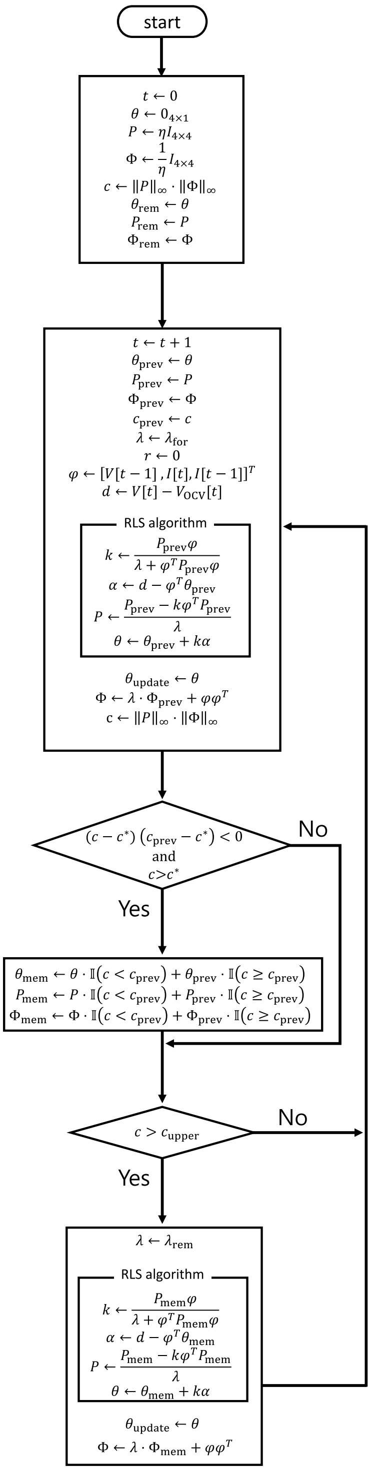

FIGURE 3. Flow chart of the proposed CNRLS. (c is the condition number of the covariance matrix P or $\kappa(P)$).

where

$$\Phi_t = \sum_{k=0}^{t} \lambda^{t-k} \varphi_k \varphi_k^T \quad (8)$$

$$\Psi_t = \sum_{k=0}^{t} \lambda^{t-k} \varphi_k d_k \quad (9)$$

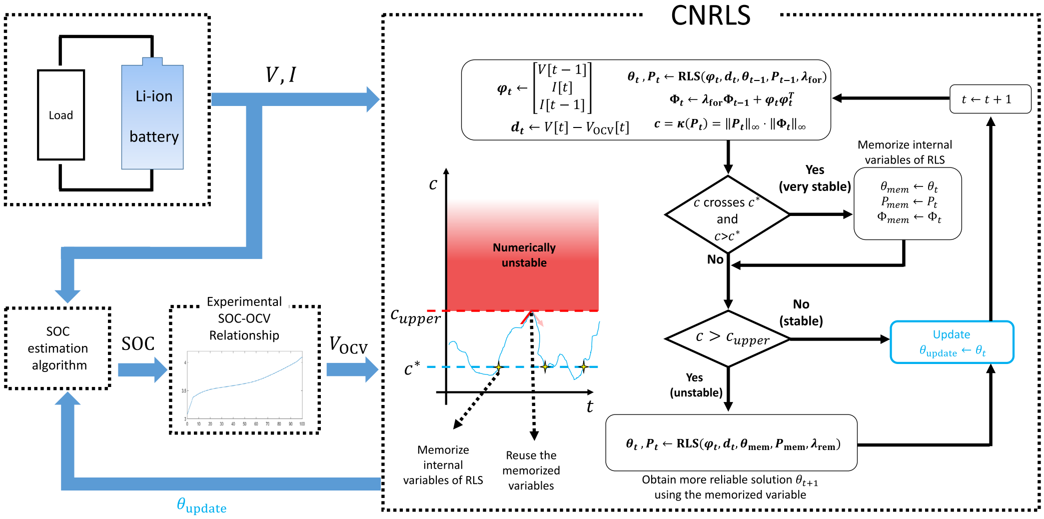

FIGURE 4. Overall view of the proposed CNRLS and its key strategy. ($c = \kappa(P)$ is the condition number of the error covariance matrix P of θ).

Applying the matrix inversion formula yields the following RLS:

$$k_t \leftarrow \frac{P_{t-1}\varphi_t}{\lambda + \varphi_t^T P_{t-1}\varphi_t} \tag{10}$$

$$\alpha_t \leftarrow d_t - \varphi_t^T \theta_{t-1} \tag{11}$$

$$P_t \leftarrow \frac{P_{t-1} - k_t\varphi_t^T P_{t-1}}{\lambda} \tag{12}$$

$$\theta_t \leftarrow \theta_{t-1} + k_t\alpha_t \tag{13}$$

where $P_t = [\Phi_t]^{-1}$ is the error covariance matrix [16]. The recurrence relation of the inverse of the error covariance matrix, $\Phi_t = [P]^{-1}$ can be written as:

$$\Phi_t = \varphi_t\varphi_t^T + \lambda\Phi_{t-1} \tag{14}$$

IV. CONDITION NUMBER BASED RECURSIVE LEAST SQUARES FOR THE PARAMETER IDENTIFICATION OF THE LI-ION BATTERIES

A. EQUIVALENT CIRCUIT MODEL OF THE LI-ION BATTERIES

In this paper, as one of widely-used equivalent circuit models (ECMs), 1-RC model is employed as shown in Figure 1. Specifically, I, V, and V_{OCV} denote the current, the voltage, and the open circuit voltage (OCV), respectively. OCV is generally assumed to be a function of SOC. The ECM parameters are assumed to be dependent on only SOH not SOC, which still provides an accurate ECM [30]–[34]. In this paper, the SOC-OCV relation is obtained from slow charge or discharge operations (Fig. 2). Setting $x = \begin{bmatrix} V_1 \end{bmatrix}$ as a state, $u = \begin{bmatrix} I \end{bmatrix}$ as an input and $y = \begin{bmatrix} V - V_{OCV} \end{bmatrix}$ a state-space model for this ECM can be expressed as follows:

$$\frac{d}{dt}x = Ax + Bu \tag{15}$$

$$y = Cx + Du \tag{16}$$

where

$$A = \begin{bmatrix} -\frac{1}{R_1C_1} \end{bmatrix}, B = \begin{bmatrix} \frac{1}{C_1} \end{bmatrix}, C = \begin{bmatrix} 1 \end{bmatrix}, D = \begin{bmatrix} R_0 \end{bmatrix},$$

The continuous-time state-space model in (15)-(16) can be discretized as follows:

$$x[t+1] = A_d x[t] + B_d u[t] \tag{17}$$

$$y[t] = C_d x[t] + D_d u[t] \tag{18}$$

where

$$\begin{aligned} A_d &= e^{\Delta t A} = \left[\exp\left(-\tfrac{\Delta t}{R_1C_1}\right) \right], \\ B_d &= \left(\int_0^{\Delta t} e^{At}dt \right) B = \left[R_1 \left(1 - \exp\left(-\tfrac{\Delta t}{R_1C_1}\right) \right) \right], \\ C_d &= C = \begin{bmatrix} 1 \end{bmatrix}, \\ D_d &= D = \begin{bmatrix} R_0 \end{bmatrix}, \\ y[t] &= D = \begin{bmatrix} V[t] - V_{OCV}[t] \end{bmatrix}, \\ u[t] &= D = \begin{bmatrix} I[t] \end{bmatrix}, \\ x[t] &= D = \begin{bmatrix} V_1[t] \end{bmatrix}, \end{aligned}$$

and Δt is a time step. Applying z-transform to the discrete-time state-space model equations in (17)-(18) yields

$$\begin{aligned} \frac{Y(z)}{U(z)} &= C_d(zI - A_d)^{-1}B_d + D_d \\ &= \frac{a_2 + a_3z^{-1}}{1 - a_1z^{-1}} \end{aligned} \tag{19}$$

where $V(z)$ and $I(z)$ are the z-transforms of V_t and I_t, respectively, and

$$\begin{aligned} a_1 &= \exp\left(-\frac{\Delta t}{R_1C_1}\right), \\ a_2 &= R_0, \\ a_3 &= R_1\left(1 - \exp\left(-\frac{\Delta t}{R_1C_1}\right)\right) - R_0\exp\left(-\frac{\Delta t}{R_1C_1}\right), \end{aligned}$$

The scalar expression in (19) can be rewritten in a vector and matrix form as follows:

$$V[t] = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} V[t-1] \\ I[t] \\ I[t-1] \end{bmatrix} \tag{20}$$

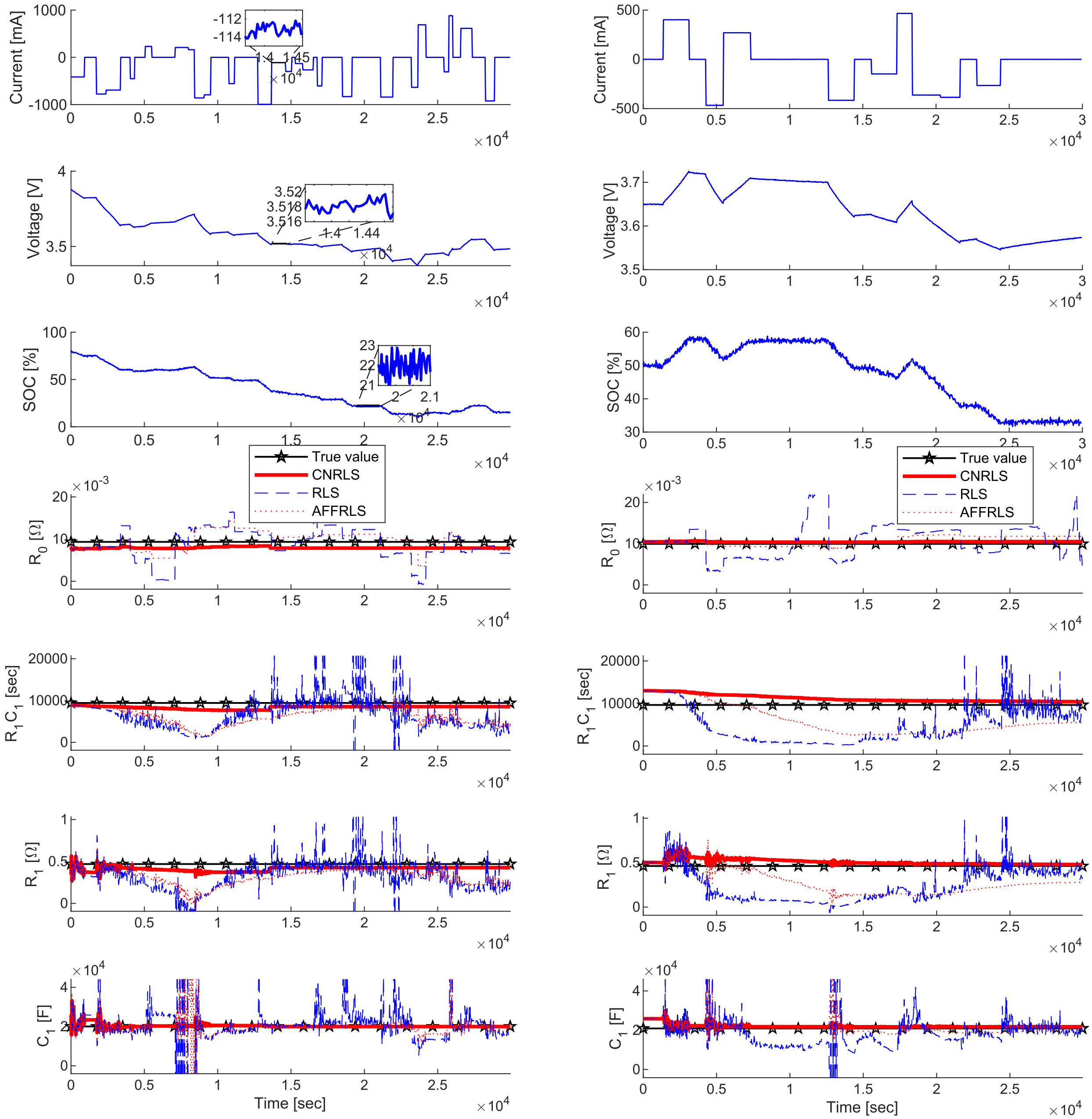

FIGURE 5. Performance comparison of the proposed CNRLS with the RLS and AFFRLS.

where $V[t]$, $[a_1, a_2, a_3]^T$, and $[V[t-1], I[t], I[t-1]]^T$ correspond to d_t, θ, and φ_t in (5), respectively.

B. PARAMETER IDENTIFICATION USING CONDITION NUMBER BASED RECURSIVE LEAST SQUARES

The strategy of the newly proposed parameter identification algorithm, called a condition number based recursive least squares(CNRLS) in this paper, is simple to implement. The proposed CNRLS stores in memory the identified parameters and their convariance matrices calculated from RLS when it operates with high numerical robustness, and then it reuses the stored ones when it operates with low numerical robustness. Such a numerical robustness-seeking strategy provides reliable identified parameters at all times. As mentioned in the section II, for a given linear equation $Ax = b$, small condition number of A means that its solution is highly reliable. As in such a linear equation, the condition number of the covariance matrix P_t in (7) is important for how much reliable the solution θ_t is. Therefore, the proposed CNRLS stores in memory the RLS variables (P_t, θ_t) when $\kappa(P_t)$ is small, and reuses them when $\kappa(P_t)$ is large, to obtain the reliable θ_t at all times. The flow chart for the key idea behind CNRLS is drawn in Fig. 4.

The involved design parameters of the CNRLS are as follows:

- c^*: Φ, P, and θ in (7), (12), and (13) are stored in memory the moment when $c = \kappa(P)$ have just exceeded or just become smaller than c^*. More specifically, the values of

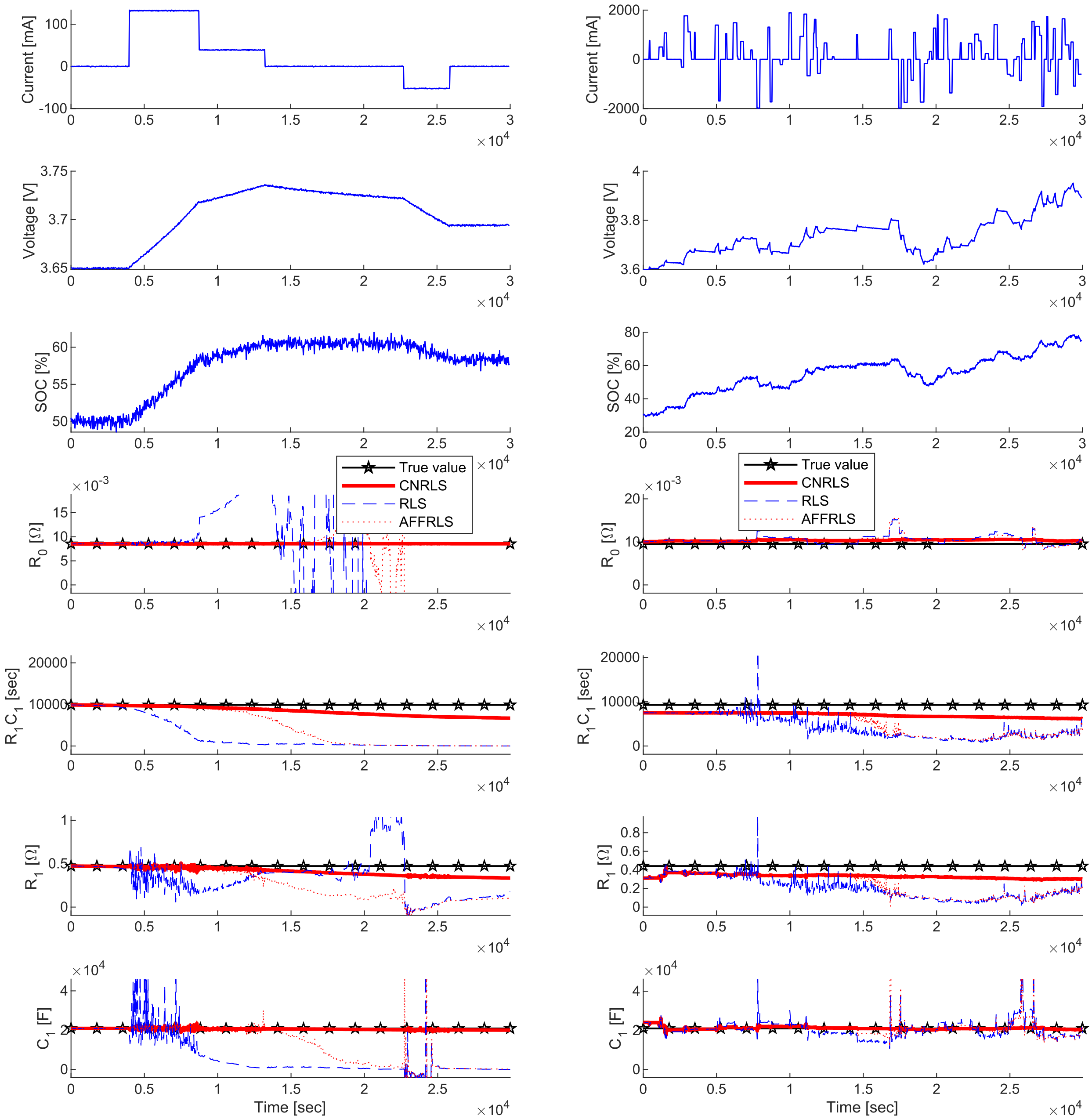

FIGURE 6. **Performance comparison of the proposed CNRLS with the RLS and AFFRLS.**

c right before and right after that moment are compared to each other and then only Φ, P, and θ corresponding to the smaller c value are stored for better numerical robustness as shown in Fig. 3.

- c_{upper}: Φ_{mem}, P_{mem}, and θ_{mem} stored in memory, are reused when $c = \kappa(P_t)$ becomes greater than c_{upper}.
- λ: This is the forgetting factor used in the parameter θ update by RLS.
- λ_{for}: This is set to be smaller than 1. It has the same role as forgetting factor in the original RLS. Generally, λ has a value of λ_{for} at most of iterations.
- λ_{rem}: This is set to be greater than 1. λ has a value of λ_{rem} to put much weight on the stored Φ_{mem}, P_{mem}, and θ_{mem} computed earlier with high numerical robustness, which occurs when they are used to obtain a reliable solution θ_t. At the first iteration after that, λ has a value of $\lambda_{for}/\lambda_{rem}$ to give bigger weight back to the current data. After that, λ_{for} is used as λ until $c = \kappa(P)$ becomes greater than c_{upper} as shown in Fig. 3.

The values of c^* and c_{upper} must be carefully chosen by considering their effects on parameter-tracking performance and numerical stability. Generally, c^* is set to be small enough so that the CNRLS can identify the battery prameters with high numerical robustness. However, too small c^* leads to the bad parameter-tracking performance while c is larger than c^*, since Φ_{mem}, P_{mem}, and θ_{mem} are rarely updated.

With small c_{upper}, the solution θ_t tends to be computed with high numerical robustness because of the frequent use of Φ_{mem}, P_{mem}, and θ_{mem}, but too small c_{upper} causes the bad parameter-tracking performance since the past data is preferred over the recent one. Too large c_{upper} leads to the poor numerical stability, since Φ_{mem}, P_{mem}, and θ_{mem} are rarely reused.

One of very practical features of the proposed CNRLS is that the condition number computation does not require the matrix inversion with highly computational complexity. As seen in the following condition number:

$$\kappa(P) = \|P\| \left\|P^{-1}\right\| = \|P\| \, \|\Phi\| \tag{21}$$

the condition number $\kappa(P)$ is easily computed without inversion operation, from P and Φ that are recursively computed from the previous ones. The recursion for Φ is given in (14). In (21), the ∞-norm is employed for calculating the condition number. It can be said that the proposed CNRLS is very suitable for use in the BMS with low computational resources. The detailed work flow diagram of the CNRLS is illustrated in Fig. 3.

V. RESULTS AND DISCUSSIONS

It is assumed that CNRLS is used with a SOC estimation algorithm (Fig. 4). The validation of CNRLS is carried out with random pulse current profiles with four different ECM parameter sets (Fig. 5 and 6). To provide more insight about application of the proposed CNRLS to real BMS, the performance of the proposed CNRLS is compared with that of two RLS-based parameter identification methods including the standard RLS and adaptive forgetting factor RLS (AFFRLS) [21] which has been judged to be successfully applicable to real BMS hardware. The parameter sets are chosen by sampling from Gaussian distributions whose means are reference ECM parameter values in [35]. To reflect the real-world sensing noise and SOC estimation error, zero-mean Gaussian noise is added to the true values of current, voltage and SOC ($\sigma_{\text{current}} = 0.5$ [mA], $\sigma_{\text{voltage}} = 0.5$ [mV], $\sigma_{\text{SOC}} = 0.5$ [%]).

Table 1 represents the relative mean absolute error (RMAE) of each ECM parameters identified by using RLS, AFFRLS and CNRLS in the validation (Fig. 5 and 6). RMAE is defined as:

$$\text{RMAE}(\%) = \frac{1}{\sum_{i=1}^{4} T_i} \sum_{i=1}^{4} \sum_{t=1}^{T_i} \frac{\left|\beta_{\text{ECM},i} - \hat{\beta}_{\text{ECM},i,t}\right|}{\beta_{\text{ECM},i}} \times 100(\%) \tag{22}$$

where $\beta_{\text{ECM},i}$ is the true value of a ECM parameter ($\beta_{\text{ECM}} \in \{R_0, R_1C_1, R_1, C_1\}$) of the i-th ECM parameter set, $\hat{\beta}_{\text{ECM},i,t}$ is its identified value and T_i is the number of time steps of each algorithm in the validation step. Average RMAE of parameters and the computing cost of each algorithm are summarized in Fig. 7. The computing cost is characterized by the time it takes to execute each algorithm for 3×10^4 [sec] time-series data by using 3.60 [GHz] CPU and 48 [GB] DRAMs (Fig. 5 and 6).

TABLE 1. Relative mean absolute error of ECM parameters in the validation (Fig. 5 and 6).

ECM parameters	Algorithm		
	RLS	AFFRLS	CNRLS
R_0 [Ω]	288.48 %	87.11 %	7.32 %
R_1C_1 [sec]	58.72 %	45.17 %	16.73 %
R_1 [Ω]	48.70 %	42.06 %	15.22 %
C_1 [F]	40.33 %	22.03 %	3.22 %

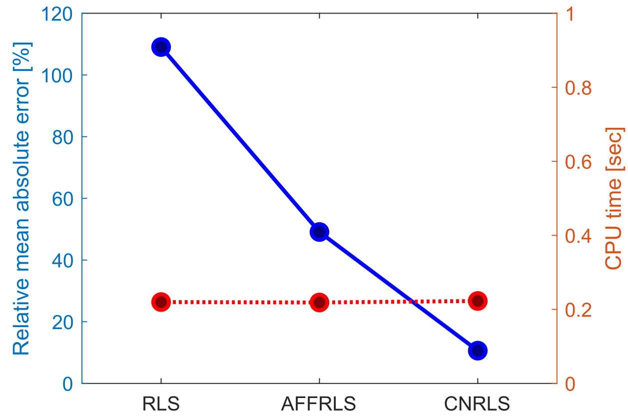

FIGURE 7. Average relative mean absoloute error of ECM parameters and the CPU time to execute each algorithm.

In the validation results, the CNRLS has the smaller parameter identification error than the two benchmarks. When there is the insufficient excitation of input data, both benchmarks show wind-up problem [22], which leads to high sensitivity of the parameter identification error to the data noise and, finally, to the large parameter identification error. Furthermore, such a problem makes the two benchmark algorithms identify ECM parameters as negative values, which is physically infeasible (Fig. 5 and 6). However, the proposed CNRLS identifies the ECM parameters with low errors because of its ability to maintain the high numerical stability. Such ability makes the CNRLS more robust to the noise than the two benchmarks. Additionally, the CNRLS has almost the same computing cost as the two benchmarks (Table 7), which means that the CNRLS can be practically applied to the commercial BMS hardware with low computation power like the two benchmarks [21]. Considering the fact that AFFRLS has been judged as a successful parameter identification algorithm for the use in real BMSs [21] and noisy data is used in the simulation validation of this work, it is believed that the proposed CNRLS can be successfully applied to the real BMS environment. There is high variation of errors among parameters (Table 1), which is believed to be caused by the different identifiability among parameters.

VI. CONCLUSION

A new reinforced version of recursive least squares (RLS) with enhanced reliability, called a condition number based

RLS (CNRLS) throughout this paper, is proposed to effectively identify the equivalent circuit model parameters of a Li-ion battery even when excitation of the input current is insufficient. The proposed CNRLS algorithm is shown to have more reliable performance with less computation burden since it employs a simple ECM and it captures the reliability of the obtained results from the condition number of the identification error covariance matrix. Such a practical CNRLS algorithm is expected to be successfully applied to many real BMSs that have low computing power and hence require low computational complexity. To provide more comprehensive information on the Li-ion batteries such as parameter identifiability, aging modes, and faults, the parameter identification method will be improved by adopting a data-driven approach for more elaborate battery models such as electrochemical models, as the future work.

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