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2019

Wei, Z., Zhao, J., Xiong, R., Dong, G., Pou, J., & Tseng, K. J. (2019). Online Estimation of Power Capacity With Noise Effect Attenuation for Lithium-Ion Battery. IEEE Transactions on Industrial Electronics, 66(7), 5724–5735. doi:10.1109/tie.2018.2878122

<https://hdl.handle.net/10356/144528>

<https://doi.org/10.1109/TIE.2018.2878122>

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Online Estimation of Power Capacity with Noise Effect Attenuation for Lithium-Ion Battery

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Abstract— Accurate estimation of power capacity is critical to ensure battery safety margins and optimize energy utilization. Power capacity estimators based on online identified equivalent circuit model have been widely investigated due to the high accuracy and affordable computing cost. However, the impact of noise corruption which is common in practice on such estimators has never been investigated. This paper scrutinizes the effect of noises on model identification, state of charge (SOC) and power capacity estimation. An online model identification method based on adaptive forgetting recursive total least squares (AF-RTLS) is proposed to compensate the noise effect and attenuate the identification bias of model parameters. A Luenberger observer is further used in combination with the AF-RTLS to estimate the SOC in real time. Leveraging the estimated model parameters and SOC, a multi-constraint analytical method is proposed to online estimate the power capacity. Simulation and experimental results verify that the proposed method is superior in terms of estimation accuracy and the robustness to noise corruption.

Index Terms— Power capacity, model identification, bias attenuation, noise, lithium-ion battery

I. INTRODUCTION

LITHIUM-ION batteries have been widely used in many fields such as renewables penetration, electrical vehicles, and more electric aircrafts. A reliable battery management system (BMS) is critical to fulfill the requirements on battery

reliability and efficiency with extended life expectancy. The accurate estimate of power capacity enables fully exploiting the potential of battery system thus is a key task in BMS.

Existing methods for online power capacity estimation can be categorized into three groups, i.e. the look-up table method, the artificial intelligence (AI) method, and the model-based method. The look-up table method extracts the power capacity from a static multi-dimensional map [1]. Although straightforward, this method cannot adapt to dynamic work conditions and ageing. AI methods approximate the nonlinear dependence between power capacity and other variables via offline training [2]. The intrinsic risks of overfitting and extensive training are major challenges in real applications. Model-based estimators use high-fidelity models to describe battery dynamics, then the allowable power is derived based on multiple safety limits such as current, voltage, and SOC. In light of this, the power capacity estimation also necessitates the accurate SOC observation which has been widely investigated in the literature [3-5]. Physics-based electrochemical models have been used for the model-based power estimation in the literature [6, 7]. By comparison, the equivalent circuit model (ECM) shows better trade-off between complexity and accuracy [8]. The hybrid pulse power characterization (HPPC) method [9] is a well-known ECM-based power capacity estimator. However, it considers only the voltage-limited instantaneous power with a primitive model. An improved estimator was proposed in [10], where the SOC limitation was enforced and the estimate was performed for a specific time horizon. Further, the first-order RC model was used to account for polarization effects and thus estimate the power capacity more accurately [11]. The aforementioned studies use offline calibrated models to derive the power capacity analytically, which lacks adaption capability to the highly dynamic working conditions and battery ageing.

More recently, ECM-based estimators incorporate online model identification to improve their robustness within a wide range of working scenarios [12]. Such methods manifest themselves with low testing effort and memory occupation. Existing methods for online model identification include the population-based optimization [13], dual extended Kalman filter [14], recursive least squares (RLS) [15-20], and recursive

Manuscript received May 13, 2018; revised August 18, 2018 and September 20, 2018; accepted October 11, 2018.

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extended least squares [21]. The recursive methods represented by RLS are the mainstream due to merit of low computing cost. The RLS-based online model identification is incorporated with adaptive extended Kalman filter (AEKF) in [15] for SOC and power capacity joint estimation. In conjunction with RLS, the state of energy was estimated and used as another constraint for power capacity estimation in [16]. With the RLS-based identification, an analytical model based close-loop method was performed for power capacity estimation in [17]. The time dependency [22] and current dependency [23] of diffusion resistance was further considered to guarantee the robustness under high-rate condition. Above online adaptive model based methods have shown satisfactory performances under well-designed testing conditions.

BMSs are subject to unexpected sensing of noises in real applications due to electromagnetic interference and low sensor resolution. The noise corruption recasts the model identification a typical error-in-variable (EIV) problem which brings large uncertainties to the existing methods. The noise effect attenuation is therefore critical to improve the performance of BMSs. The wavelet transform was adopted in [24, 25] to de-noise the corrupted current and voltage signals so as to estimate the SOC more accurately. However, the model identification as the prerequisite of state estimate has been overlooked. Till now, methods for enhanced EIV system identification are quite limited in the field of battery application. In [26], a fourth-order Butterworth filter was used to remove the high-frequency measurement noise and improve the accuracy of identification. The cutoff frequency has to be designed carefully to avoid invalid filtering or aliasing. Signal averaging was used to attenuate the noise effect in [27], but it poses challenges to both sampling and data storage. A bias compensation method was proposed in [28, 29] to eliminate the identification bias on model parameters caused by noises. However, this method depends on the accurate knowledge of noise statistics. Recently, an FBCRLS method was proposed to estimate the noise statistics and compensate for the noise effect [30]. The eigenvalue extraction and cost function minimization potentially consumes lots of computing efforts.

The total least squares (TLS) method theoretically provides solution to the EIV problem. It was used for maximum capacity estimation to address the disturbances on system input and output in [31, 32]. However, the effect of noises on model identification which lays the prerequisite for the accurate state estimate has not been investigated. The accuracy and stability of TLS on high-order identification problem has also not been validated. Moreover, to the best of authors' knowledge, the effect of noises on power capacity estimation and the associated method to overcome such effect have not been disclosed before. This paper scrutinizes the effect of noises on model parameter identification, SOC and power capacity estimation. It is shown that the widely used RLS provides biased identification of model parameters with the presence of noises, which further declines the estimation of both SOC and power capacity. To address this problem, an adaptive forgetting recursive total least squares (AF-RTLS) method is proposed to compensate the noise effect and attenuate the identification

biases on model parameters. The proposed AF-RTLS is then integrated with a Luenberger observer in a close-loop feedback manner to estimate the SOC in real time. Further, an analytical method is proposed to estimate the power capacity considering multiple constraints. Simulation and experimental studies are performed to validate the proposed method.

The rest of paper is organized as follows. Section II presents the battery model, AF-RTLS based online model identification, and SOC observer. Section III describes the multi-constraint power capacity estimator. Simulation and experimental results are discussed in Sections IV and V, respectively, while conclusions are drawn in Section VI.

II. MODEL IDENTIFICATION AND SOC ESTIMATION

Power capacity estimation needs a well parameterized model to predict the battery terminal voltage and an accurate observer to estimate the SOC. In this section, the methods for online model identification and SOC estimation are detailed.

A. Battery Model and Online Parameterization

A battery model with simple structure yet capturing the key system dynamics is favorable for the online application. In this regard, the first-order RC model as shown in Fig. 1 (a) is used. The voltage source represents the battery OCV. R_s is the ohmic resistance. The RC network is used to simulate the polarization effects due to passivation layers on electrodes, charge transfer, diffusion, migration and convection processes. The electrical behavior of the first-order RC model can be expressed by:

$$C_p \frac{dV_p}{dt} + V_p / R_p = I \quad (1)$$

$$V_t = V_{oc} - V_p - IR_s \quad (2)$$

where I is the load current, V_p and V_t are the polarization and terminal voltages, respectively.

For the Samsung 18650 lithium-ion battery used in this paper, the calibrated SOC-OCV curve under 22°C is shown in Fig. 1 (b). It is shown that the SOC-OCV correlation is intrinsically nonlinear and, in this paper, it is curve fitted with:

$$V_{oc} = f(z) = \sum_{i=0}^{n_p} c_i z^i \quad (3)$$

where z is the SOC, c_i ($i = 1, 2, \dots, n_p$) are the polynomial coefficients determined by curve fitting, n_p is the polynomial order which is selected to be five in this paper. The dynamics of SOC is written as:

$$\dot{z}(t) = -\eta I(t)/Q \quad (4)$$

where η is the coulomb efficiency, and Q is the battery capacity.

Fig. 1. Schematic diagram of first order RC model: (a) model structure and (b) measured and curve-fitted SOC-OCV correlation.

The transfer function of (1) can be expressed as:

$$V_q(s)/I(s) = -(R_s + R_p + R_s R_p C_p s) / (1 + R_p C_p s) \quad (5)$$

where $V_q = V_t - V_{oc}$. Applying the bilinear transform $s = 2(q-1)/(t_s(q+1))$ to (5) yields:

$$V_q(q^{-1})/I(q^{-1}) = (b_0 + b_1 q^{-1}) / (1 + a_1 q^{-1}) \quad (6)$$

where q is the discretization operator. The coefficients are:

$$\begin{bmatrix} a_1 \\ b_0 \\ b_1 \end{bmatrix} = \begin{bmatrix} (t_s - 2R_p C_p) / (t_s + 2R_p C_p) \\ -(R_s t_s + R_p t_s + 2R_s R_p C_p) / (t_s + 2R_p C_p) \\ -(R_s t_s + R_p t_s - 2R_s R_p C_p) / (t_s + 2R_p C_p) \end{bmatrix} \quad (7)$$

where t_s is the sampling interval. System (6) can be reversed to the discrete-time domain as:

$$V_{q,k} = \mathbf{\theta}_k^T \boldsymbol{\Phi}_k \quad (8)$$

where $\mathbf{\theta}_k = [a_{1,k} \ b_{0,k} \ b_{1,k}]^T$, $\boldsymbol{\Phi}_k = [-V_{q,k-1} \ I_k \ I_{k-1}]^T$. Once the regression model is solved, model parameters are deducted as:

$$\begin{bmatrix} R_s & R_p & C_p \end{bmatrix} = \begin{bmatrix} \frac{b_1 - b_0}{1 - a_1} & \frac{2(a_1 b_0 - b_1)}{1 - a_1^2} & \frac{(1 - a_1) t_s}{4(a_1 b_0 - b_1)} \end{bmatrix} \quad (9)$$

B. Error-in-Variables Analysis and Total Least Squares

Measurement noises are inevitable in real BMS applications. In this case, the noisy current and voltage are expressed as:

$$I_{0,k} = I_k + \Delta I_k, \quad V_{t0,k} = V_{t,k} + \Delta V_{t,k} \quad (10)$$

where ΔI and ΔV_t are noises on the real signals I_L and V_t , respectively. The sensing of noises makes regression model (8) a typical error-in-variables (EIV) system. RLS is commonly used for online model identification, based on which the power capacity is further estimated in the literature. However, the performance of RLS lacks validation for EIV problems.

The noises on current and voltage are assumed to be zero-mean random noises with variances of σ_i^2 and σ_v^2 , respectively. It is also assumed the noises are uncorrelated with their true values and mutually uncorrelated. Then the input and output of (8) are observed as:

$$\begin{cases} \boldsymbol{\Phi}_{0,k} = \boldsymbol{\Phi}_k + \Delta \boldsymbol{\Phi}_k \\ V_{q0,k} = V_{t,k} + \Delta V_{t,k} - V_{oc,k} = V_{q,k} + \Delta V_{t,k} \end{cases} \quad (11)$$

where $\Delta \boldsymbol{\Phi}_k$ is the noise vector of system input. Without input noises, the RLS gives unbiased solution as:

$$\boldsymbol{\theta}^* = \mathbf{R}_{\boldsymbol{\Phi}}^{-1} \mathbf{R}_{\boldsymbol{\Phi} V_{q0}} \quad (12)$$

where

$$\mathbf{R}_{\boldsymbol{\Phi}} = E(\boldsymbol{\Phi} \boldsymbol{\Phi}^T), \mathbf{R}_{\boldsymbol{\Phi} V_{q0}} = E(\boldsymbol{\Phi} V_{q0}) \quad (13)$$

With input noises imposed, the RLS provides an alternative solution as:

$$\boldsymbol{\theta}_{RLS} = (\mathbf{R}_{\boldsymbol{\Phi}} + \mathbf{R}_{\Delta \boldsymbol{\Phi}})^{-1} \mathbf{R}_{\boldsymbol{\Phi} V_{q0}} \quad (14)$$

By applying the matrix inversion lemma, (14) can be rewritten as:

$$\boldsymbol{\theta}_{RLS} = \left[\mathbf{R}_{\boldsymbol{\Phi}}^{-1} - \mathbf{R}_{\boldsymbol{\Phi}}^{-1} (\mathbf{R}_{\boldsymbol{\Phi}}^{-1} + \mathbf{R}_{\Delta \boldsymbol{\Phi}}^{-1})^{-1} \mathbf{R}_{\boldsymbol{\Phi}}^{-1} \right] \mathbf{R}_{\boldsymbol{\Phi} V_{q0}} \quad (15)$$

The identification bias of RLS can then be derived by combining (12) and (15):

$$\boldsymbol{\theta}_{\text{bias}} = -\mathbf{R}_{\boldsymbol{\Phi}}^{-1} (\mathbf{R}_{\boldsymbol{\Phi}}^{-1} + \mathbf{R}_{\Delta \boldsymbol{\Phi}}^{-1})^{-1} \boldsymbol{\theta}^* \quad (16)$$

It proves that the RLS is asymptotically biased with the presence of input noises. The persistent excitation on $\boldsymbol{\Phi}$ guarantees that $\mathbf{R}_{\boldsymbol{\Phi}}$ is positive definite, suggesting that RLS tends to underestimate the model parameters.

Different from RLS, the total least squares (TLS) method finds a solution $\boldsymbol{\theta}_k$ when the fitting from the input to output incurs the minimum perturbations. In other words, the TLS is solved by finding the minimum perturbation matrices ($\Delta \boldsymbol{\Phi}_k$, $\Delta \mathbf{V}_k$) and the estimated parameter vector that satisfy:

$$\mathbf{V}_{q0,k} + \Delta \mathbf{V}_k = \hat{\boldsymbol{\theta}}_k^T (\boldsymbol{\Phi}_{0,k} + \Delta \boldsymbol{\Phi}_k) \quad (17)$$

where

$$\begin{aligned} \mathbf{V}_{q0,k} &= [V_{q0,k}, V_{q0,k-1}, \dots, V_{q0,1}]^T \\ \boldsymbol{\Phi}_{0,k} &= [\boldsymbol{\Phi}_{0,k}, \boldsymbol{\Phi}_{0,k-1}, \dots, \boldsymbol{\Phi}_{0,1}] \end{aligned} \quad (18)$$

In the case of using unit weighting, the TLS boils down to solve the following minimization problem:

$$\hat{\boldsymbol{\theta}}_k = \arg \min_{\boldsymbol{\theta}_k} \|\Delta \boldsymbol{\Phi}_k \mid \Delta \mathbf{V}_{t,k}\|_F \quad (19)$$

where $\|\cdot\|_F$ denotes the Frobenius norm. Define $\mathbf{a}_k = [\boldsymbol{\theta}_k, -1]^T$, then $\boldsymbol{\theta}_k$ is equal to the TLS estimate provided that $\mathbf{a}_k$ is the eigenvector corresponding to the smallest eigenvalue of the following covariance matrix [33]:

$$\bar{\mathbf{R}}_k = E \left(\begin{bmatrix} \boldsymbol{\Phi}_{0,k}^T & V_{q0,k} \end{bmatrix}^T \begin{bmatrix} \boldsymbol{\Phi}_{0,k}^T & V_{q0,k} \end{bmatrix} \right) = \begin{bmatrix} \mathbf{R}_k & \mathbf{b}_k \\ \mathbf{b}_k^T & c_k \end{bmatrix} \quad (20)$$

where $\mathbf{R}_k = E[\boldsymbol{\Phi}_{0,k} \boldsymbol{\Phi}_{0,k}^T]$, $\mathbf{b}_k = E[\boldsymbol{\Phi}_{0,k} V_{q0,k}]$, $c_k = E[V_{q0,k} V_{q0,k}]$.

Singular value decomposition is commonly used to obtain $\mathbf{a}_k$ but is of cubic complexity. Instead, we calculate $\mathbf{a}_k$ by solving the below minimization problem:

$$\begin{aligned} \min_{\mathbf{a}_k} \mathfrak{R}_k(\bar{\mathbf{R}}_k, \mathbf{a}_k) \\ \text{with } \mathfrak{R}_k(\bar{\mathbf{R}}_k, \mathbf{a}_k) = \mathbf{a}_k^T \bar{\mathbf{R}}_k \mathbf{a}_k / (\mathbf{a}_k^T \mathbf{T} \mathbf{a}_k) \end{aligned} \quad (21)$$

where $\mathbf{T} = \text{diag}\{\beta^{1/2} \ 1 \ 1 \ \beta^{1/2}\}$, $\beta = \sigma_v^2 / \sigma_i^2$.

Theorem 1: The TLS solution given by (21) is asymptotically unbiased with the noisy corruption on system input. The total mean squared error associated with the TLS estimate is $\lambda_{\min} = \sigma_i^2$.

Proof: Equation (21) is realized when $\partial \mathfrak{R}_k(\bar{\mathbf{R}}_k, \mathbf{a}_k) / \partial \mathbf{a}_k = 0$, which can be further expressed as the following eigenvalue problem:

$$\bar{\mathbf{R}}_k \mathbf{a}_k = \lambda \mathbf{T} \mathbf{a}_k \quad (22)$$

where $\lambda = \mathfrak{R}_k(\bar{\mathbf{R}}_k, \mathbf{a}_k)$. Equation (22) can be alternatively expressed as:

$$\left\{ \begin{bmatrix} \mathbf{R}_{\boldsymbol{\Phi}} & \mathbf{R}_{\boldsymbol{\Phi} V_{q0}} \\ \mathbf{R}_{\boldsymbol{\Phi} V_{q0}}^T & \mathbf{R}_{V_{q0}} \end{bmatrix} + \begin{bmatrix} \text{diag}(\sigma_v^2, \sigma_i^2, \sigma_i^2) & \mathbf{0} \\ \mathbf{0} & \sigma_v^2 \end{bmatrix} \right\} \begin{bmatrix} \boldsymbol{\theta} \\ -1 \end{bmatrix} = \lambda \mathbf{T} \begin{bmatrix} \boldsymbol{\theta} \\ -1 \end{bmatrix} \quad (23)$$

where $\mathbf{R}_{V_{q0}} = E[V_{q0}^2]$ with $V_{q0} = \boldsymbol{\Phi}^T \boldsymbol{\theta}^*$.

By making substitution $\boldsymbol{\theta} = \boldsymbol{\theta}_{TLS} = \mathbf{R}_{\boldsymbol{\Phi}}^{-1} \mathbf{R}_{\boldsymbol{\Phi} V_{q0}}$ to (23), it is shown that $[\boldsymbol{\theta}_{TLS}, -1]^T$ is the generalized eigenvector with corresponding generalized eigenvalue $\lambda_{\min} = \sigma_i^2$. The asymptotic TLS solution $\boldsymbol{\theta}_{TLS}$ is identical to the unbiased estimation from RLS when no input noise is involved.

C. Model Identification with AF-RTLS

Gradient search method is used to solve the minimization problem in (21) with the parameter vector updated by:

$$\hat{\boldsymbol{\theta}}_k = \hat{\boldsymbol{\theta}}_{k-1} + \mu_k \boldsymbol{\Phi}_{0,k} \quad (24)$$

where μ_k is an adaptive gain which can be obtained by solving:

$$\partial \mathcal{R}_k \left(\hat{\boldsymbol{\theta}}_{k-1} + \mu_k \boldsymbol{\Phi}_{0,k}, \boldsymbol{\alpha}_k \right) / \partial \mu_k = 0 \quad (25)$$

By incorporating (20), (21) and (25), the following quadratic equation can be drawn:

$$g_{1,k} \mu_k^2 + g_{2,k} \mu_k + g_{3,k} = 0 \quad (26)$$

The polynomial coefficients of (26) are derived as:

$$\begin{aligned} g_{1,k} &= \kappa_{2,k} \mathbf{h}_k^T \boldsymbol{\Phi}_{0,k} - \kappa_{3,k} \left[\mathbf{h}_k^T \hat{\boldsymbol{\theta}}_{k-1} - \boldsymbol{\Phi}_{0,k}^T \mathbf{b}_k \right] \\ g_{2,k} &= (\beta + \kappa_{1,k}) \mathbf{h}_k^T \boldsymbol{\Phi}_{0,k} - q_k \kappa_{3,k} \\ g_{3,k} &= (\beta + \kappa_{1,k}) \left[\mathbf{h}_k^T \hat{\boldsymbol{\theta}}_{k-1} - \boldsymbol{\Phi}_{0,k}^T \mathbf{b}_k \right] - q_k \kappa_{2,k} \end{aligned} \quad (27)$$

where

$$\mathbf{h}_k = \mathbf{R}_{0,k} \boldsymbol{\Phi}_{0,k}, \quad q_k = \left[\hat{\boldsymbol{\theta}}_{k-1}^T, -1 \right] \bar{\mathbf{R}}_k \left[\hat{\boldsymbol{\theta}}_{k-1}^T, -1 \right]^T \quad (28)$$

$$\kappa_{1,k} = \hat{\boldsymbol{\theta}}_{k-1}^T \mathbf{T}_1 \hat{\boldsymbol{\theta}}_{k-1}, \quad \kappa_{2,k} = \boldsymbol{\Phi}_{0,k}^T \mathbf{T}_1 \hat{\boldsymbol{\theta}}_{k-1}, \quad \kappa_{3,k} = \boldsymbol{\Phi}_{0,k}^T \mathbf{T}_1 \boldsymbol{\Phi}_{0,k}$$

where $\mathbf{T}_1 = [\mathbf{T}]_{1:3,1:3}$. Then μ_k is obtained by solving (26) as:

$$\mu_k = \left(-g_{2,k} + \sqrt{g_{2,k}^2 - 4g_{1,k}g_{3,k}} \right) / (2g_{1,k}) \quad (29)$$

Covariance matrices involved in (28) are updated recursively at each time step to arrive the recursive TLS (RTLS) solution. Taking $\mathbf{R}_k$ as example, the propagation law is expressed as:

$$\mathbf{R}_k = (1 - \gamma_k) \mathbf{R}_{k-1} + \gamma_k \boldsymbol{\Phi}_{0,k} \boldsymbol{\Phi}_{0,k}^T \quad (30)$$

where γ_k is the normalizing gain updated recursively by:

$$\gamma_k \triangleq \left(1 + \sum_{i=1}^{k-1} \prod_{j=i+1}^k \rho_j \right)^{-1} = \frac{\gamma_{k-1}}{\rho_k + \gamma_{k-1}} \quad (31)$$

where ρ is the forgetting factor which gives more weights to the recently data while discounts the historical data gradually. It is clear that γ is simplified as $1/k$ in the case of non-forgetting ($\rho = 1$), or as $(1 - \rho)$ in the case of exponential forgetting.

The forgetting factor is closely relevant to the regression alertness and numerical stability of RTLS. A small ρ with fast discounting of old data retains the tracking alertness but compromises the stability and convergence. In contrast, a large ρ enhances the stability but may lose track of fast varying parameters. To better manage such an intrinsic trade-off, an adaptive forgetting is used to upgrade the RTLS to AF-RTLS. The online adaption law of ρ is expressed as:

$$\rho_k = \rho_{\min} + (\rho_{\max} - \rho_{\min}) \cdot 2^{-\tau \varepsilon_k^2} \quad (32)$$

where $\rho_{\min}$ and $\rho_{\max}$ is the minimum and maximum forgetting factor, respectively, τ is a gain controlling the sensitivity of forgetting factor to the output mismatch, and ε is the estimation residual expressed by:

$$\varepsilon_k = V_{q0,k} - \hat{\boldsymbol{\theta}}_{k-1}^T \boldsymbol{\Phi}_{0,k} \quad (33)$$

The self-tuning law in (32) links the forgetting factor to the voltage prediction error, i.e. ρ is set close to the maximum to stabilize the identification when the voltage error is small, while it is set as a small value to enhance error correction when the voltage error is large.

D. SOC Observer

The SOC is a critical state to be observed in BMSs as well as a critical variable for power capacity estimation. A close-loop SOC observer is formulated based on the online adapted battery model in this section. By defining the state vector as $\mathbf{x} = [V_p \ z]^T$ and the system output as V_t , the state-space model of battery dynamics is formulated as:

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}I(t) \\ V_t(t) = F(\mathbf{x}(t), I(t)) \end{cases} \quad (34)$$

where

$$\mathbf{A} = \begin{bmatrix} -1/(R_p C_p) & 0 \\ 0 & 0 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 1/C_p \\ -\eta/Q \end{bmatrix} \quad (35)$$

Then the Luenberger type state observer is formulated as:

$$\begin{cases} \dot{\hat{\mathbf{x}}}(t) = \mathbf{A}\hat{\mathbf{x}}(t) + \mathbf{B}I(t) + \mathbf{L} [V_t(t) - \hat{V}_t(t)] \\ \hat{V}_t(t) = F(\hat{\mathbf{x}}(t), I(t)) \end{cases} \quad (36)$$

where $\mathbf{L}$ is the feedback gain. Considering the nonlinearity of the system, the gain scheduling strategy is used in this paper to tune the feedback gain. Specifically, the nonlinear output equation is locally linearized around the estimated state as:

$$V_t(t) = \mathbf{C}(\hat{\mathbf{x}}(t)) - R_s I(t) + r_0 \quad (37)$$

where $\mathbf{C}$ is relevant to the derivative of OCV with respect to SOC, which can be derived from (3). Based on the obtained $\mathbf{A}$ and $\mathbf{C}$, the feedback gain is designed by pole placement. Assume the poles are desired to be placed at p_1 and p_2 which are both negative values, the state-dependent feedback gain can be adapted with the following Ackermann's equation:

$$\mathbf{L} = [\mathbf{A}^2 + (p_1 + p_2)\mathbf{A} + p_1 p_2 \mathbf{I}] \begin{bmatrix} \mathbf{C}(\hat{\mathbf{x}}) \\ \mathbf{C}(\hat{\mathbf{x}})\mathbf{A} \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad (38)$$

III. POWER CAPACITY ESTIMATION

The power capacity is defined as the maximum discharge power or minimum charge power (in the signed sense) that can be maintained for future prediction time horizon without violating the safety constraints.

A. Voltage-Limited Peak Current

The upper and lower cut-off voltages, $V_{t,max}$ and $V_{t,min}$ respectively, are commonly defined to protect the battery in practice. Under the peak discharge current, the battery terminal voltage falls down to the lower cut-off limit, giving rise to:

$$V_{t,min} = V_{oc,k+L} - V_{p,k+L} - I_{k,max}^{dis,volt} R_s \quad (39)$$

where L is the prediction time horizon in seconds, and $I_{k,max}^{dis,volt}$ is the voltage-limited peak discharge current. The polarization voltage at the $(k+L)$ -th sampling time is expressed by:

$$V_{p,k+L} = e^{-\frac{L t_s}{R_p C_p}} V_{p,k} + (1 - e^{-\frac{L t_s}{R_p C_p}}) R_p \sum_{j=1}^L e^{-\frac{(j-1)t_s}{R_p C_p}} I_{k,max}^{dis,volt} \quad (40)$$

The OCV at the $(k+L)$ -th sampling time can be derived with Taylor series approximation of V_{oc} around z_k , as follows:

$$V_{oc,k+L} = V_{oc} \left[z_k - \frac{\eta I_{k,\max}^{dis,volt} L t_s}{Q} \right] \\ = V_{oc,k} - \frac{\eta I_{k,\max}^{dis,volt} L t_s}{Q} \frac{dV_{oc}}{dz} \Big|_{z_k} + r \left[z_k, \frac{\eta I_{k,\max}^{dis,volt} L t_s}{Q} \right] \quad (41)$$

where $r[\cdot]$ is the remainder term, which is typically quite small and thus can be ignored. By incorporating (39)-(41), the final expression of the voltage-limited peak discharge current is:

$$I_{k,\max}^{dis,volt} = \frac{V_{oc,k} - e^{-\frac{L t_s}{R_p C_p}} V_{p,k} - V_{t,\min}}{\frac{\eta L t_s}{Q} \frac{dV_{oc}}{dz} \Big|_{z_k} + (1 - e^{-\frac{L t_s}{R_p C_p}}) R_p \sum_{j=1}^L e^{-\frac{(j-1)L t_s}{R_p C_p}} + R_s} \quad (42)$$

The voltage-limit peak charge current can be derived in the same manner as:

$$I_{k,\min}^{chg,volt} = \frac{V_{oc,k} - e^{-\frac{L t_s}{R_p C_p}} V_{p,k} - V_{t,\max}}{\frac{\eta L t_s}{Q} \frac{dV_{oc}}{dz} \Big|_{z_k} + (1 - e^{-\frac{L t_s}{R_p C_p}}) R_p \sum_{j=1}^L e^{-\frac{(j-1)L t_s}{R_p C_p}} + R_s} \quad (43)$$

It should be noted that the maximum magnitude in the case of charge is actually a minimum in the signed sense since the current is defined as negative for charge.

B. SOC-Limited Peak Current

The peak current is also constrained by the battery SOC, which should be maintained at the expected range to avoid over-charge/discharge. Considering an imposed SOC range of $z \in [z_{\min}, z_{\max}]$, the SOC-limited peak current is:

$$I_{k,\max}^{dis,soc} = \frac{Q[z_k - z_{\min}]}{\eta L t_s}, \quad I_{k,\min}^{chg,soc} = \frac{Q[z_k - z_{\max}]}{\eta L t_s} \quad (44)$$

C. Power Capacity under Multiple Constraints

The peak current under the constraints of terminal voltage and SOC is determined as:

$$\begin{cases} I_{k,\max}^{dis} = \min[I_{k,\max}^{dis,volt}, I_{k,\max}^{dis,soc}] \\ I_{k,\min}^{chg} = \max[I_{k,\min}^{chg,volt}, I_{k,\min}^{chg,soc}] \end{cases} \quad (45)$$

The designed limit of charge and discharge current is another constraint, which is specified by the manufacturer depending on the cell design. This constraint is easy to be obtained and added into (45) thus is not considered in this paper. Instead, focus is given to the constraints of terminal voltage and SOC which are more complicated.

Under the peak current derived in (45), the evolution of discharge and charge voltage during the prediction time horizon can be expressed with (46) and (47), respectively.

$$V_{t,k+i} = V_{oc,k} - e^{-\frac{i t_s}{R_p C_p}} V_{p,k} \\ - \left[\frac{\eta i t_s}{Q} \frac{dV_{oc}}{dz} \Big|_{z_k} + (1 - e^{-\frac{i t_s}{R_p C_p}}) R_p \sum_{j=1}^i e^{-\frac{(j-1)L t_s}{R_p C_p}} + R_s \right] I_{k,\max}^{dis} \quad (46)$$

$$V_{t,k+i} = V_{oc,k} - e^{-\frac{i t_s}{R_p C_p}} V_{p,k} \\ - \left[\frac{\eta i t_s}{Q} \frac{dV_{oc}}{dz} \Big|_{z_k} + (1 - e^{-\frac{i t_s}{R_p C_p}}) R_p \sum_{j=1}^i e^{-\frac{(j-1)L t_s}{R_p C_p}} + R_s \right] I_{k,\min}^{chg} \quad (47)$$

Leveraging the obtained power sequence, the power capacity is determined by selecting the minimum discharge power or the maximum charge power:

$$\begin{cases} P_{k,\max}^{dis} = \min_{i=1,2,\dots,L} [I_{k,\max}^{dis} V_{t,k+i}] \\ P_{k,\max}^{chg} = \max_{i=1,2,\dots,L} [I_{k,\min}^{chg} V_{t,k+i}] \end{cases} \quad (48)$$

D. Algorithmic Framework

The proposed method consists of three functional blocks, i.e. the online model identification based on AF-RTLS, the SOC estimation based on Luenberger observer with gain scheduling, and the multi-constraint power capacity estimation. Variables are exchanged among different blocks to formulate a complete framework as shown in Fig. 2.

Fig. 2. Schematic diagram of the proposed method.

IV. SIMULATION STUDY

A. Data Acquisition

The first-order RC model is built in Matlab/Simulink. The values of R_s and R_p are defined to be time variant, while C_p is assumed to be constant. A hybrid pulse current profile is loaded to the model and the corresponding voltage is obtained. With the ideal battery model, the SOC and power capacity can also be obtained. All these variables are sampled at 1 Hz and plotted in Fig. 3. Random noises with variances of $\sigma_i^2 = 9 \text{ mA}^2$ and $\sigma_v^2 = 9 \text{ mV}^2$ are imposed on the noise-free current and voltage signals to simulate the measured signals under noise corruption.

Fig. 3. Simulation data: (a) load current, (b) terminal voltage, (c) reference SOC, (d) reference discharge and charge power capacity.

B. Simulation Results with Random Noises

The random noise caused by external interference and device resolution is one of the major error sources in BMS. It is typically considered to be high-frequency, zero mean and white process. The performance of the proposed method under random noise corruption is evaluated in this section. In this paper, the AF-RTLS is proposed for online model identification, which is a prerequisite for the estimation of both SOC and power capacity. Therefore, the proposed method is compared with its counterpart, i.e. AF-RLS based method for better evaluation. Lacking prior knowledge before the simulation, both methods are initialized erroneously as: $R_s = R_p = 10 \text{ m}\Omega$, $C_p = 0.5 \text{ kF}$, $\text{SOC}_0 = 60\%$. The prediction time horizon of power capacity is 30 s. The enforced range of terminal voltage and SOC are $[3 \text{ V}, 4.2 \text{ V}]$ and $[5\%, 95\%]$, respectively.

The results of online model identification are shown in Fig. 4 (a)-(c). It is observed that both methods converge stably after a short transition period for initialization error correction. Although the AF-RLS based method identifies R_s accurately, the identification of R_p and C_p contains significant biases due to the noise corruption on both current and voltage. In contrast, the proposed method provides unbiased identification for all the relevant parameters. This is because AF-RTLS takes into account perturbations on both system input and output to well compensates the noise effect. For a quantitative analysis, the normalized error vector is defined as $\mathbf{e}_k = [\Delta R_{s,k} / R_{s,k}, \Delta R_{p,k} / R_{p,k}, \Delta C_{p,k} / C_{p,k}]^T$, where ΔR_s , ΔR_p , and ΔC_p are estimation errors of the respective parameters. The mean square deviation (MSD) in the unit of “dB”, i.e. $10 \times \log_{10}(E[\|\mathbf{e}_k\|^2])$, is used as the performance measure. The MSDs with the two methods are shown in Fig. 4 (d). It is shown that the proposed method gives rise to much lower MSDs than the AF-RLS based method, which explicitly verifies the superiority of the proposed method on accuracy and robustness to noise corruption.

The SOC estimation results are shown in Fig. 4 (e)-(f). Both methods converge from the large SOC initialization error (45%) rapidly and stably. The proposed method keeps tracking of the reference SOC trajectory more accurately than the AF-RLS based method, which is rooted in the compensation of noise

effect and elimination of identification bias. The mean MSD of model parameters, mean absolute error (MAE) and rooted mean square error (RMSE) of SOC are summarized in Table I. It is shown that the proposed method outperforms its AF-RLS based counterpart in model identification and SOC estimate without compromising the convergence.

The results of peak current estimation are shown in Fig. 5. Due to the higher accuracy of model parameters and SOC, the proposed method estimates the voltage- and SOC-limited peak current more closely to the reference. A comparison between Fig. 5 (a) and (c) reveals that the SOC-limited current is much larger than the voltage-limited current for most of the time. The SOC constraint only takes effect at the end of discharge when the SOC approaches the lower limit. This is because within a short time horizon typical for power capacity estimation, a high C-rate is generally allowable without causing over-charge or over-discharge. In other words, the constraint of SOC gives an over-optimistic estimation thus should be used in conjunction with the voltage constraint in a wide SOC range. The similar analysis also applies for the estimation of peak charge current.

Fig. 4. Results of online model identification and SOC estimation for the simulation study with random noise corruption: (a) R_s , (b) R_p , (c) C_p , (d) MSD, (e) SOC, and (f) SOC error.

TABLE I
ALGORITHMIC PERFORMANCES ON MODEL IDENTIFICATION AND SOC ESTIMATION FOR SIMULATION STUDY UNDER RANDOM NOISES

	Proposed method	AF-RLS based method
Mean MSD	-25.62 dB	-7.26 dB
MAE of SOC	0.10%	0.70%
RMSE of SOC	0.15%	0.86%

Based on the peak current, the power capacity is estimated and shown in Fig. 6. Taking the discharge power capacity as example, the voltage constraint dominates the estimation for

most of the time, while at the end of discharge, the SOC constraint takes over and the estimated power capacity shows a sharp drop to avoid the potential over-discharge. The RMSE of power capacity estimation are summarized in Table II. It is shown that the RMSEs by the AF-RLS based method are almost double of those by the proposed method. Moreover, it is observed from Fig. 6 that the AF-RLS based method generates large error up to 2.5 W, while the error by the proposed method is confined to a much lower error bound once the algorithm converges from the initialization offset. Seen from Fig. 6 (c), the SOC-limited power capacity is estimated with very large error by the AF-RLS based method, while the proposed method has well controlled the error at a reasonable level. In summary, the proposed method outperforms the RLS-based method in terms of both steady-state error and error spike.

Fig. 5. Results of peak current estimation for the simulation study with random noise corruption: (a, b) voltage-limited peak current, and (c, d) SOC-limited peak current.

Fig. 6. Results of power capacity estimation for the simulation study with random noise corruption: (a) discharge power capacity, (b) charge power capacity, (c) error of discharge power capacity, and (d) error of charge power capacity.

TABLE II
ALGORITHMIC PERFORMANCES ON POWER CAPACITY ESTIMATION FOR
SIMULATION STUDY UNDER RANDOM NOISES

	Proposed method	AF-RLS based
RMSE of discharge power capacity	0.59 W	0.97 W
RMSE of charge power capacity	0.18 W	0.52 W

C. Simulation Results with Random Noises and Drifts

The drift error normally observed with low frequency and non-zero mean can also be present in practice, which causes the noises to be colored. This section goes further to evaluate the proposed method under such a colored noise corruption. In addition to the random noises (9 mA^2 and 9 mV^2), a current drift of 2 mA and a voltage drift of -2 mV are further imposed.

Simulation results are summarized in Table III. It is shown that the proposed method gives rise to reliable solutions and outperforms the AF-RLS based method in terms of both model identification and state estimate. The comparison among Tables I – III shows that the errors of parameter identification and power capacity estimate have been enlarged only slightly with the addition of current and voltage drifts, which suggests that the impact of drifting error on the proposed method is quite limited. In contrast, the accuracy of SOC estimation has been declined more significantly. This is because the voltage drift disturbs the voltage-based feedback correction in the SOC observer. This problem is widely reported in the literature and can be solved only if the drifts are removed completely or known accurately. Overall speaking, the proposed method provides satisfactory accuracy and robustness when both random noises and drift errors exist. This is similar to the case of Kalman filter which assumes independent, zero-mean and Gaussian noises but still works well when such assumptions are not totally met. Offset compensating observers with drift errors included in the state-space model for estimation together with battery states have been proposed, to fully eliminate the effect of drifts [34]. It will be useful to combine the proposed method with such compensating techniques to further enhance the robustness. However, this is out of scope of this paper.

TABLE III
ALGORITHMIC PERFORMANCES ON MODEL IDENTIFICATION, SOC AND
POWER CAPACITY ESTIMATION UNDER COLORED NOISE CORRUPTION

	Proposed method	AF-RLS based
Mean MSD	-24.37 dB	-7.22 dB
RMSE of SOC	0.42%	0.93%
RMSE of discharge power capacity	0.69 W	1.06 W
RMSE of charge power capacity	0.25 W	0.58 W

V. EXPERIMENTAL STUDY

A. Experimental Details

A hybrid pulse experiment (HPE) and the Federal Urban Dynamic Schedule (FUDS) are performed on a Samsung 18650 lithium-ion cell to evaluate the proposed method. The corresponding current profiles shown in Fig. 7 are imposed on the test cell with a battery cycler. The ranges of the current and voltage sensors inside the battery cycler are 10 A and 5 V, respectively, while the measurement error limits are both within 0.05%. The current and terminal voltage are sampled at 1 Hz and stored in a host computer. As the signals are measured

with very accurate sensors under an ideal condition, random noises (9 mA^2 and 9 mV^2) and drift errors (2 mA and -2 mV) are added to the measured data to represent an adverse working condition with non-ignorable noise corruption. The ambient temperature is controlled at 22°C for both experiments.

The reference values of model parameters, SOC, and power capacity should be calibrated to verify the proposed method. The coulombic counting (CC) method is accurate to obtain the reference SOC if the initial SOC is known. Therefore, the cell is firstly fully charged with the constant current constant voltage (CCCV) method and then discharged with a current pulse to the desired initial SOC. Then the reference SOC profile for the entire experiment can be obtained by CC.

To obtain the reference values of model parameters, a set of time points are selected at a certain time interval during each experiment and the reference model parameters are extracted offline at each time point. Specifically, a batch of noise-free current and voltage data are sampled around each time point as a separate data set. For each data set, R_s is calibrated by calculating the instantaneous voltage jump following a step change of current, i.e. $R_s = \Delta V_t / \Delta I_L$. As the OCVs for each data set can be obtained from the reference SOC, R_p and C_p can be obtained by the LS-based curve fitting to match the modeled transient voltages to the measurements.

The current-limited power capacity is measured by interrupting the regular cycle with large current pulses at selected time points, and tracing the voltage responses over time [14, 21, 35]. In this paper, the discharge and charge current pulses are chosen as 5.5 A and -3.3 A according to the specification from manufacture. The discharge pulses are applied at 2000 s , 6000 s , 10000 s , and 14000 s , while the charge pulses are applied at 4000 s , 8000 s , 12000 s , and 16000 s . The discharge or charge power capability at each time point is then determined by multiplying the voltage trace by the maximum or minimum load current, respectively.

The calibration of voltage-limited power capacity is more difficult which may need an expensive hardware-in-the-loop test bench. A simplified method adopted in [19] is used here for validation. Referring to the aforementioned current pulse interruption, the terminal voltage at the end of each 30-s pulse is assumed to be the lower or upper cut-off voltage. Under this assumption, the interrupting current is equal to the real voltage-limited peak current. Afterwards, the power sequence is generated by multiplying the voltage trace by the interrupting current, and then the power capacity can be calibrated.

Fig. 7. Load current and terminal voltage profiles for experimental study: (a) HPE and (b) FUDS.

B. Validation

The initialization condition, prediction time horizon, and enforced constraints are all consistent with the simulation study. The online identified model parameters and their reference values are shown in Fig. 8. The model parameters explicitly exhibit an SOC-dependent and time-variant feature which confirms the necessity of online model adaption. The proposed method converges rapidly from the uncertain initialization and tracks the reference values of model parameters accurately. By comparison, the AF-RLS based method converges to values substantially away from the reference, especially for R_p and C_p . The biased model identification is rooted in the violation of the underlying assumption of RLS when both current and voltage measurements are corrupted with errors.

The SOC estimation results are shown in Fig. 9. Within expectation, the proposed method is more accurate with the SOC error confined to 2.7% error bound for both experiments. In contrast, the AF-RLS based method causes larger error up to 5% due to the biased identification of model parameters.

Fig. 8. Results of online model identification for experimental study: (a) HPE, and (b) FUDS.

Fig. 9. Results of SOC estimation for experimental study: (a, b) HPE, and (c, d) FUDS.

Leveraging the online updated model parameters and SOC, both the discharge and charge power capacities are estimated and compared with their calibrated values for validation. The relative errors of current- and voltage-limited power capacities

obtained from the HPE cycle are shown in Fig. 10. The current-limited power capacity shows to be estimated with low error, while the estimation error of voltage-limited one is much larger for both two algorithms. This is within expectation as the peak current calculation brings additional uncertainty to the estimation of voltage-limited power capacity. For both cases, it is observed that the proposed method outperforms the AF-RLS based counterpart, due to the merit of more accurate estimate of model parameters and SOC.

The power capacity estimated for a full HPE cycle is shown in Fig. 11. The discharge power capacity decreases as the discharge proceeds and drops to zero when the estimated SOC reaches the lower limit, indicating that no more power is allowed to be extracted from the battery to avoid over-discharge. With the drop of SOC, the absolute value of charge power capacity is observed to increase firstly and then decreases at the end of discharge, which deviates a bit from the results shown in Fig. 6. This is because the ohmic resistance increases drastically at low SOC region. With a large ohmic resistance, a small current can boost the terminal voltage to the upper limit. Therefore, it is reasonable to observe the decrease of charge power capacity magnitude at low SOC regions.

Fig. 10. Relative error of: (a) current-limited power capacity, and (b) voltage-limited power capacity.

Fig. 11. Results of power capacity estimation for HPE: (a) estimated discharge power capacity, and (b) estimated charge power capacity.

C. Further Comparison

It is also insightful to compare the proposed method with other noise compensating methods for battery EIV system identification in the literature. The method proposed in [30] achieves unbiased model identification and accurate SOC estimate by noise statistics estimation and bias compensation, leveraging the onboard measured current and voltage. In this section, this method is extended to incorporate the power capacity estimation described in Section III and then applied for the HPE cycle. Comparison results of the two methods in terms of estimation accuracy and computing cost are summarized in

Table IV. The computing cost is characterized by the CPU time to execute each algorithm on a laptop with a 2.50 GHz CPU and 20.0 G DRAMs. It should be noted that the CPU time for power capacity estimation is excluded from the statistics as this part is totally the same for the two methods in comparison. As shown in Table IV, the proposed method shows slightly higher accuracy on the estimation of both SOC and power capacity. More importantly, the CPU time has been reduced substantially by using the proposed method. The comparison suggests that the proposed method is preferable for use in low-cost micro controllers.

TABLE IV
COMPARISON OF TWO ALGORITHMS ON ESTIMATION ACCURACY AND COMPUTING COST

	Proposed method	Method in [30]
MAE of SOC	0.72%	0.77%
RMSE of SOC	0.93%	1.03%
Error of discharge power capacity	0.32%	0.32%
Error of charge power capacity	1.92%	2.04%
CPU time	106.1/85.6 us	165.3 us

D. Limitation

Accurate identification of battery impedances is critical for the reliable estimate of power capacity. One limitation of the proposed method is that the current dependency of impedances has not been considered. While the ohmic resistance (R_s) and double layer capacitance (C_p) can be assumed as current independent, R_p which describes the charge transfer process is intrinsically nonlinear with current in the form of Butlere Volmer equation [36]. The current dependency is typically ignorable for temperature above 0°C, but turns out to be significant under low temperature conditions [37]. Therefore, the proposed method is not recommended for use in low temperature below 0°C where the estimation accuracy can be deteriorated. In seeking to guarantee the estimation accuracy over a wide range of temperature and ageing state, the current dependency will be included in future work, giving rise to a challenging identification problem where more parameters should be updated in real time. However, this is out of scope of this paper.

VI. CONCLUSION

In this paper, it proves that the noise corruption causes biased identification of model parameters, which further declines the estimation accuracy of SOC and power capacity. To address this problem, an AF-RTLS method in conjunction with a Luenberger observer with gain scheduling has been proposed to compensate the noise effect so that the model parameters and SOC are online estimated more accurately. A multi-constraint power capacity estimator has been further exploited leveraging the online adapted battery model. Simulations and lab-scale experiments have been carried out to verify the proposed method. Results suggest that the proposed method is effective in attenuating the noise effect and providing accurate estimation of model parameters, SOC, and power capacity. Comparison with the AF-RLS-based counterpart and another data-driven based noise compensating method further verifies

the superiority of the proposed method in terms of estimation accuracy and robustness. The limitation of the proposed method in real applications has also been discussed.

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