

Enhanced online identification of battery models exploiting data richness

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Abstract—The equivalent circuit model (ECM) is a commonly used control-oriented model onboard the battery management system (BMS) of electric vehicles (EVs). Parameter online identification is a demanding task that directly influences control precision. This article proposed a modified recursive least squares (RLS) method that selects the data richest point for parameter identification. In this model, Fisher information matrix and Cramér-Rao bound are used to evaluate the data richness. The final algorithms solve the operational limitations of RLS algorithms, enabling a reliable online model parameter identification under real-world dynamic conditions. The identified model parameters from the dynamic stress test (DST) of an NCM battery are verified by terminal voltage and state of charge (SoC) estimation.

Index Terms—Model parameter identification, RLS, sensitivity analysing

I. INTRODUCTION

Safety and reliability of the battery pack are two core considerations in the design of electric vehicles [1]. Conventional BMS systems that rely solely on sensor signals are no longer suitable for EV applications due to the increasing number and energy of cells inside the battery pack. Therefore, model-based BMS is introduced to evaluate more comprehensive battery states, including state-of-charge (SoC), state-of-health (SoH) and remaining useful life (RUL) [2]. Many modelling approaches are introduced in the literature, which can be categorized into physical-based models, data-driven models, and hybrid models [3]. The choice of models dramatically depends on desired resolution and available computational source. Up to date, the most effective and commonly used approach for battery online state estimation is to use the ECM model.

ECM is a family of lumped parameter models that use a series of electronic components to simulate the battery dynamic response under various excitation [4, 5]. As for model parameters, some exist in all models, such as open circuit voltage (OCV) and internal resistance, indicating thermo-dynamic properties and ohmic resistance, respectively. Others are used to simulate battery polarisation, and hysteresis effect, such as resistance-capacitance (RC) pair and their modified versions [6, 7]. It is important to note that all the model parameters and not only a function of battery SoC but also related to

SoH. Battery degradation is a path-dependency phenomenon, which means separately considering and then summing the stress factors is not feasible to describe battery parameter change trajectory [8]. Charging/discharging rate, temperature, driving patterns, other operational conditions and even their trend and order all contribute to battery degradation [9, 10]. Online model parameter identification is thus a necessary requirement and emerges as a major barrier in applying the ECM to the BMS onboard EV in order to guarantee long-term safety usage.

Before introducing a novel parameter identification method, two overlooked aspects, structural identifiability and parameter sensitivity, must be considered [11]. The former determines whether a model parameter can be uniquely identified. In this study, “parameter identifiable” refers to structural identifiability, while “practical identifiability” is considered as part of data sensitivity [12]. From the perspective of control engineering, the ECM is a single-input-single-output system that receives a current signal as an input and outputs a corresponding voltage signal. Given a model circuit structure, the relationship between input and output is possible to be described mathematically. In theory, a more complex ECM may be suitable for a wider range of scenarios, such as high loading, but this does not guarantee model parameter identifiability. Structural identifiability presumes noise-free data, it can be theoretically evaluated regardless of the data condition. Alavi et al. analyzed four different ECM models - the Rint model, Thevenin model, dual polarisation (DP) model, and Randles model - and proved that all of them are locally identifiable, with a finite number of solutions [13]. Moreover, the Rint model and Thevenin model are globally identifiable, with all parameters can be uniquely identified. Compared to the Rint model, the existence of one RC pair allows the description of polarization, although this ability is weaker than that of the DP model [14]. Unfortunately, all ECMs with hysteresis elements are structurally non-uniquely identifiable, which is impossible for online identification [15].

Parameter sensitivity is particularly important for real-world applications since only sensitive parameters can be accurately identified. In practice, given the same estimation error, a more sensitive parameter will lead to lower output error and make

the following state estimation performance better. Except for model structure, the parameter variance (noise and model error) and insufficient excitation are the majority of reasons for worth practical parameter identifiability [16]. In other words, a specific model parameter can be more easily and accurately identified under specific excitation with particular frequency and amplitude [17]. In previous studies, many methods have been applied for analysing the sensitivity of model parameters to the input signals via derived-based methods such as Hessian matrix eigenvalue [18, 19], Fisher matrix eigenvalue [20–22] and Cramér-Rao bound [17, 23] and sensitivity matrix rank. These studies make it possible to perform a posterior analysis of numerical practical identifiability based on the local sensitivity to unknown parameters.

RLS algorithms with forgetting factors are a widely used parameterisation technology for online applications [24, 25]. However, RLS always suffer from numerical instability. When the system is under insufficient excitation (e.g. content current), the parameter error covariance tends to an enormous value, making the parameter identification result highly sensitive to numerical errors and sensor noise [26]. Thus fail to guarantee convergence. In previous studies, many modification methods have been proposed, such as tuning the forgetting factor according to parameter identification errors [27] and condition number-based RLS [26]. However, these methods do not address the excitation issue directly. Furthermore, the inherent characteristics of the ECM model limit the accuracy of RLS under real-world conditions, where excitations occur randomly and may occasionally be sensitive to parameters. In this study, we introduced a sensitive analysis-based RLS for parameter identification in the online environment. The Fisher information matrix is adopted to quantitatively evaluate the sufficiency of excitation and then select the most informative data to update the Thevenin model parameters with confidence. A three-time scale parameter identification method with Cramér-Rao bound as data sufficiency indicator is introduced in section II. In section III, the discrete form Thevenin model is presented. The section III detailed discusses the RLS with forgetting factor and Fisher information matrix. Parameter verification is shown in section V in terms of terminal voltage and SoC estimation.

II. FRAMEWORK FOR PARAMETER IDENTIFICATION IN THREE TIMESCALES

The proposed method aims to select the most sensitive data for model parameter identification in order to overcome the limitation of the RLS algorithm. The process of the proposed algorithms is shown in Figure 1. To avoid frequent parameter changes that can degrade the system stability, the model parameters are updated every 1% change in SoC to maintain robustness and stability due to the model parameter change is sluggish. Therefore, the final result for the BMS is a lookup table rather than a time series. This semi-online approach allows for enough time to wait for highly sensitive data to occur and also enables the lookup table to evolve over

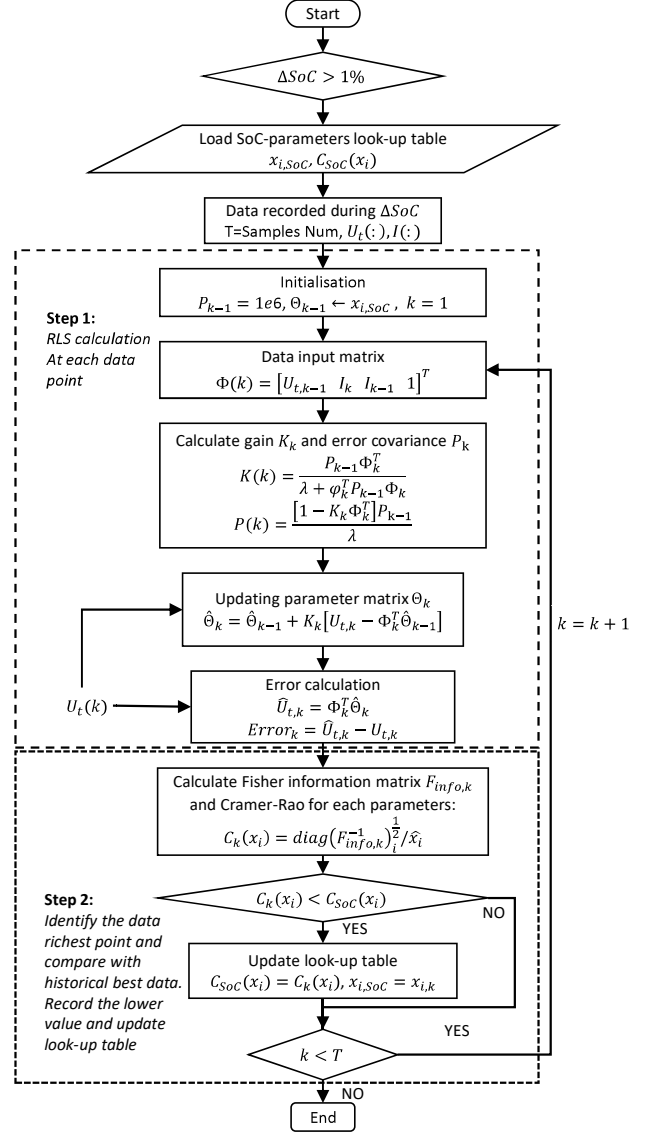


Fig. 1. Diagram of sensitive analysis-based RLS for model parameter identification

time whenever better data becomes available. The proposed algorithms are divided into three time regions:

- 1) RLS operates at each time point
- 2) Fisher information matrix calculation at each 1% change in SoC
- 3) The look-up tables evolve with progression through cycles

Once the data from 1% change is received, the model parameter from the reserved look-up table and corresponding data-sufficient indicator inputs as the initial condition. In Step 1, the recursive nature of the RLS algorithm requires it to be run at each data point. The calculation of the Fisher information matrix requires a series of data to calculate the output variance. Thus, step 2 calculates the Cramér-Rao bounds as the data-sufficient indicator. Within this range, the most

sensitive data for each parameter is different and therefore selected individually, rather than considering all parameters simultaneously and choosing a single data point [28]. As a result, each corresponding model parameter is selected to represent the average model parameters within this SoC range. However, it is not guaranteed that the theoretically optimal data point will appear in the acquired data. Thus, the value of the data sufficient index is compared with the historical lowest value (C_{SoC}). If a lower value appears, the look-up table is updated; otherwise, the original value is preserved. This process allows the look-up table to evolve over time until all model parameters are selected from the globally richest data points.

III. BATTERY MODELLING

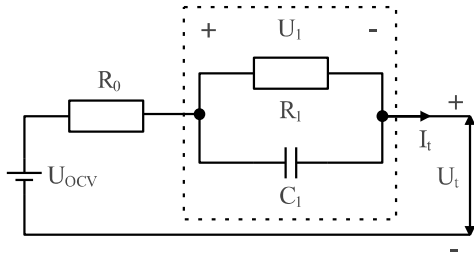


Fig. 2. Diagram of the Thevenin model

As shown in Figure 2 is the Thevenin model. A voltage source represents the open circuit voltage (U_{OCV}), a resistance R_0 indicate internal resistance and one RC pair (R_1 & C_1) describes the polarization behaviours. U_t , and U_1 indicate the terminal voltage and voltage of the RC pair, respectively. In this study, we define the discharge current as the positive value. Therefore, the state-space function of the Thevenin model is:

$$\begin{cases} U_t = U_{OCV} - iR_0 - U_1 \\ \dot{U}_1 = I/C_1 - U_1/R_1C_1 \end{cases} \quad (1)$$

Applying Laplace transformation the transfer function $G(s)$ is:

$$G(s) = \frac{E(s)}{I(s)} = - \left(R_0 + \frac{R_1}{1+s\tau} \right) \quad (2)$$

where, $E(s) = U_t - U_{OCV}$, τ is the time constant that equal to R_1C_1 . In practice, the transfer function always employs a discrete form with sample time T due to the sensor data being acquired as a series of points. Here, the bilinear transformation is adopted:

$$s = \frac{2}{T} \frac{1-z}{1+z} \quad (3)$$

The discrete form of Equation (2) can be written as:

$$G(z^{-1}) = \frac{\theta_2 + \theta_3 z^{-1}}{1 - \theta_1 z^{-1}} \quad (4)$$

where,

$$\begin{aligned} \theta_1 &= \frac{2\tau - T}{T + 2\tau} \\ \theta_2 &= -\frac{TR_0 + TR_1 + 2R_0\tau}{T + 2\tau} \\ \theta_3 &= -\frac{TR_0 + TR_1 - 2R_0\tau}{T + 2\tau} \end{aligned}$$

Besides, the OCV drop is insignificant within two continuous sampling steps. Thus, it is reasonable to approximate $U_{OCV,k} = U_{OCV,k-1}$. A uniform discrete form used for parameter identification is:

$$U_{t,k} = \Phi_k \Theta_k \quad (5)$$

Where,

$$\begin{aligned} \Phi_k &= [U_{t,k-1} \quad I_k \quad I_{k-1} \quad 1] \\ \Theta_k &= [\theta_1 \quad \theta_2 \quad \theta_3 \quad U_{OCV}(1 - \theta_1)]^T \end{aligned}$$

Here, Φ_k receives the input data, and Θ_k is the parameter matrix in which the model parameters can be derived :

$$\begin{cases} R_0 = \frac{\theta_3 - \theta_2}{1 + \theta_1} \\ R_1 = -2 \frac{\theta_1 \theta_2 + \theta_3}{1 - \theta_1^2} \\ C_1 = -\frac{T(1 + \theta_1^2)}{4(\theta_1 \theta_2 + \theta_3)} \\ U_{OCV} = \frac{\theta_4}{1 - \theta_1} \end{cases} \quad (6)$$

IV. RLS AND FISHER INFORMATION MATRIX

In order to implement a battery parameter estimation method in BMS onboard EVs, the algorithm is needed to be simple and efficient to run in real-time. RLS is a recursive form to solve the least square problem. Once received time series data $[U_{t,0}, \Phi_0], [U_{t,1}, \Phi_1], \dots, [U_{t,k}, \Phi_k]$, RLS tend to find optimized value of Θ via minimising terminal voltage error with the cost function:

$$\Theta = \arg \min_{\Theta} \frac{1}{k} \sum_{t=1}^k (\hat{U}_t(t|\Theta) - U_t)^2 \quad (7)$$

Once the optimized value of Θ is received, the model parameters (R_0, R_1, c_1 and U_{OCV}) can be identified from Equation (6). The detailed process of RLS has been widely discussed in many literature [29–31], and the majority of equations are listed in Algorithm 1. Where e is the prediction error of terminal voltage, K_k is the gain vector, P_k is the covariance matrix. λ is the forgetting factor between 0 to 1, which could discard the old data and assign a large weight to the new data. Here it is set to 0.95.

In RLS, parameter identification relies on the measurement of output signals. The more information contained in the output, the higher quality of the parameter identification results. The Fisher information matrix evaluates the derivative of the output to each model parameter, providing a tool to quantify

Algorithm 1 RLS parameter identification**Input:** Φ_k Θ_{k-1} U_k P_{k-1}

- 1: $e \leftarrow U_{t,k} - \Phi_k \cdot \Theta_{k-1}$
- 2: Gain calculation
 $K_k \leftarrow P_{k-1} \Phi_k^T \cdot [\Phi_k P_{k-1} \Phi_k^T + \lambda]^{-1}$
- 3: Error covariance
 $P_k \leftarrow \frac{1}{\lambda} [1 - K_k \Phi_k] \cdot P_{k-1}$
- 4: Parameter matrix update
 $\Theta_k \leftarrow \Theta_{k-1} + K_k \cdot e$

Output: $\Theta(k)$

the data sufficiency of output [21–23]. The Fisher information matrix is expressed as

$$F_{\text{info},k+1} = \frac{1}{\sigma_y^2} \left(\frac{\partial Y}{\partial(x|\Theta_{k+1})} \right)^T \left(\frac{\partial Y}{\partial(x|\Theta_{k+1})} \right) \quad (8)$$

where σ_y^2 is the variance of the terminal voltage measurement error assumed to be Gaussian. Y is the system output, and x is the model parameters matrix, $[R_0, R_1, C_1, U_{OCV}]$, that need to be identified. Here, Y can be derived from Equation (1):

$$U_{t,k+1} = U_{OCV,k} - i_{R_0,k+1} - e^{-\frac{T}{\tau}} U_{1,k} + i_k R_1 (1 - e^{-\frac{T}{\tau}}) \quad (9)$$

Thus, at time $k+1$

$$\frac{\partial Y}{\partial(x|\Theta_k)} = \begin{bmatrix} \frac{\partial U_t}{\partial R_0} & \frac{\partial U_t}{\partial R_1} & \frac{\partial U_t}{\partial C_1} & \frac{\partial U_t}{\partial U_{OCV}} \end{bmatrix}^T \quad (10)$$

Where,

$$\begin{cases} \frac{\partial U_t}{\partial R_0} = -I_{k+1} \\ \frac{\partial U_t}{\partial R_1} = -U_{1,k} e^{-\frac{T}{\tau}} \cdot \frac{T}{R_1 \hat{\tau}} + i_k \left(1 - e^{-\frac{T}{\tau}} \cdot \frac{\hat{\tau} + T}{\hat{\tau}} \right) \\ \frac{\partial U_t}{\partial C_1} = -e^{-\frac{T}{\tau}} \left(\frac{i_k T}{\hat{C}_1^2} + \frac{U_1 T}{\hat{C}_1^2 \hat{R}_1} \right) \\ \frac{\partial U_t}{\partial U_{OCV}} = 1 \end{cases} \quad (11)$$

Here, $\hat{\tau}$, $\hat{R}_1$, $\hat{C}_1$ are RLS estimates. Considering extracting sensitivity information from the Fisher information matrix, the Cramér-Rao bound introduces a judgement index to represent the best achievable variance of the estimation error [17, 23]. It establishes the lowest estimation covariance of an unbiased estimator via the inverse of the Fisher information matrix:

$$\text{cov}_{\text{est}}(x_i) \geq \bar{\sigma}^2(x_i) = \text{diag}(F_{\text{info}}^{-1})_i \quad (12)$$

Here, the $\sigma^2(x_i)$ is the Cramér-Rao bound for the i^{th} model parameters which is represented by the i^{th} diagonal value of the F_{info}^{-1} . A smaller value indicates a better identification result, thus the corresponding excitation can be regarded as a sufficient input. It is clear that the estimation result is affected by the variance of measured terminal voltage and ECM inherent characteristics (differential derivatives relationship). In this study, the normalized Cramér-Rao bounds are employed

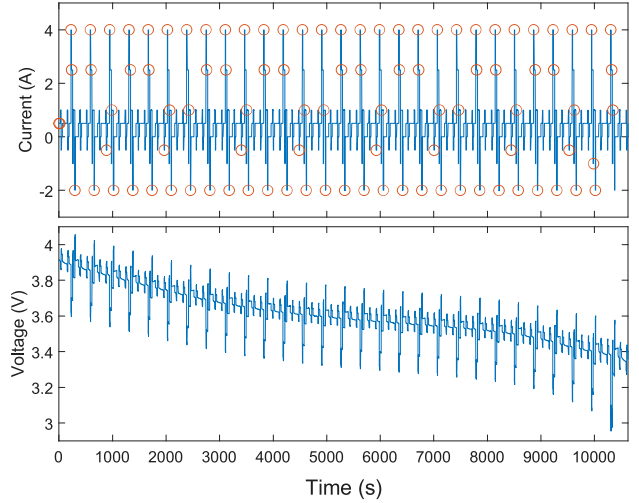


Fig. 3. Raw data of current and voltage (blue line) and R_0 sensitivity data (orange circuit)

as data sufficient indicator for each model parameter, which is expressed as:

$$C(x_i) = \bar{\sigma}(x_i) = \text{diag}(F_{\text{info}}^{-1})_i^{1/2} / \hat{x} \quad (13)$$

V. ALGORITHMS VERIFICATION

In order to generate a reliable look-up table for BMS, it is necessary to be able to accurately track terminal voltage and estimate SoC. In this study, DST results from the Center for Advanced Life Cycle Engineering (CALCE) are utilized for identification and verification using Matlab/Simulink 2022a. The raw data is shown in Figure 3. The resulting ECM parameter look-up table is excited with the original current signals, and the terminal voltage response is compared with the original measured data for verification. An adaptive Extended Kalman filter (AEKF) algorithm is then employed to estimate the SoC, with the true value calculated using a column counting method.

The parameter identification results from the original RLS algorithm and sensitivity analysis-based methods are shown in Figure 4 by the orange and blue lines, respectively. The original RLS algorithm exhibits a larger amount of fluctuation, even incorrect values of the identified parameters, which can lead to errors in subsequent state estimation and result in divergence. The main reason for this is insufficient excitation during the dynamic test. The proposed methods can avoid fluctuation and generate a stable look-up table. However, a single cycle does guarantee the overall best results. For example, the selected data points for R_0 are shown in 3 with the orange circuit. Based on Equation (11), the highest current, the higher sensitivity. Although all of the highest pulse data are successfully selected, many SoC regions do not exist the highest current thus compromising the estimation quality. Besides, the amplitude of pulse data also affects the battery polarization behaviour. This can explain why C_1 still exist many fluctuations. These sensitivity related issues can be

solved among cycles. Nevertheless, the identified parameter is still sufficient to support other BMS functions only when a single cycle data is used.

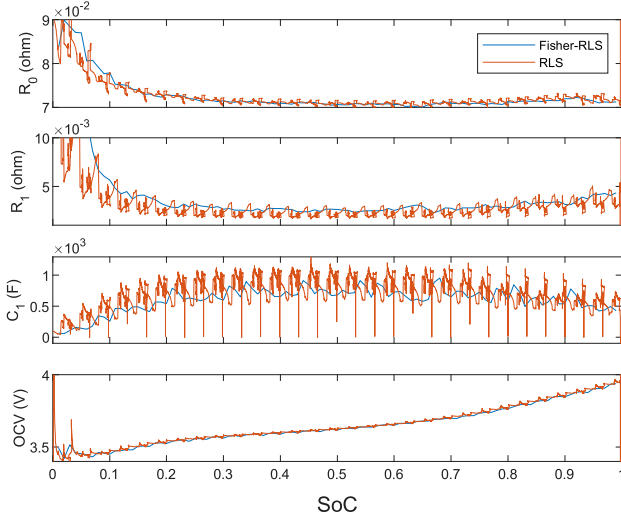


Fig. 4. Comparison of RLS and Fisher-RLS results

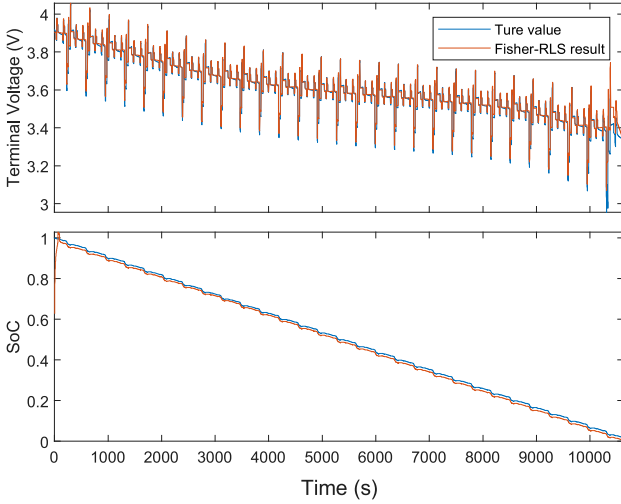


Fig. 5. Terminal voltage verification results and SoC estimation results

The verification results are shown in Figure 5. The estimations results are evaluated by Root Mean Square Error (RMSE) following:

$$RMSE = \sqrt{\frac{\sum_{t=1}^T (y(t) - \hat{y}(t))^2}{T}} \quad (14)$$

Utilising the same excitation, terminal voltage and state of charge (SoC) estimation can both follow the true value. AEKF is sensitive to the model parameters, even with the wrong initial value (60% SoC) the SoC estimation can fast converge to the true value. Their RMSE results are shown in Table 1.

TABLE I
RMSE OF TERMINAL VOLTAGE AND SoC ESTIMATION

Measurement	Estimation	RMSE
U_t	$\hat{U}_t$	0.033 2
SoC	$\hat{SoC}$	0.015 2

VI. CONCLUSION

A key challenge in implementing a battery model onboard BMS is model parameter identification. In an online environment, the cell-to-cell imbalance, range of environmental, and cell conditions require an online model parameter identification process. An inherent and often overlooked problem is the sufficiency of the excitation signal.

In this study, we propose a data sensitivity-based method for selecting the best data points for model parameter identification using the Fisher information matrix and the Cramér-Rao bound. This approach overcomes the operational limitations of the conventional RLS algorithm, enabling a reliable and robust online model parameter identification for BMS. For real-world applications, this method can generate a reliable look-up table to support other functions. In this paper, this has been demonstrated over a discharge cycle, and will potentially be extended further in future work. The estimated model parameters can accurately estimate terminal voltage and SoC with RMSE of 3.32% and 1.52%, respectively.

It is worth noting that this study only addresses the question of whether the data is sufficient for model parameter identification. The true values of the parameters are also sensitive to environmental conditions (such as temperature) and the health of the battery. These variables are not considered in this paper and will be the focus of our future work.

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