Adaptive recursive least squares for online parameter identification in lithium-ion battery models

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Abstract

Accurate online parameter identification is fundamental to the reliable operation of battery management systems (BMS) in electric vehicles. This paper proposes an Adaptive Forgetting Factor Recursive Least Squares (AFFRLS) algorithm for real-time identification of equivalent circuit model (ECM) parameters in lithium-ion batteries. A Thevenin-type ECM is adopted and discretized using the bilinear (Tustin) transformation, yielding a linear regression structure amenable to recursive estimation. The identified parameters ohmic resistance R_0, polarization resistance R_P, and polarization capacitance C_P are updated to compute the estimated battery terminal voltage U_{est}. Three algorithms standard Recursive Least Squares (RLS), Forgetting Factor RLS (FFRLS), and the proposed AFFRLS are comparatively evaluated under the highly dynamic Urban Dynamometer Driving Schedule (UDDS) current profile applied to a commercial LG 18650HG2 NMC lithium-ion cell. Simulation results show that AFFRLS achieves the lowest maximum absolute voltage error of 2.68%, compared with 4.09% for RLS and 3.45% for FFRLS, while maintaining an RMSE of 0.13%, which is comparable to that of FFRLS at 0.12%. These results indicate that the adaptive forgetting factor mechanism improves worst-case tracking performance during abrupt current transients while preserving competitive overall estimation accuracy. With an explicit saturation mechanism to constrain the forgetting factor within [0.95, 1.0], AFFRLS provides a promising and computationally lightweight candidate for online ECM parameter identification in embedded BMS applications.

Keywords: *Lithium-ion battery, Recursive Least Squares, Adaptive forgetting factor, Equivalent circuit model, Battery management system*

Abbreviations

LS	Least Squares
RLS	Recursive Least Squares
AFFRLS	Adaptive Forgetting Factor Recursive Least Squares
FFRLS	Forgetting Factor Recursive Least Squares
BMS	Battery Management System
ECM	Equivalent Circuit Model
UDDS	Urban Dynamometer Driving Schedule
EV	Electric Vehicle
SoC	State of Charge
RMSE	Root Mean Square Error
MaxAE	Maximum Absolute Error
SOH	State of Health
OCV	Open-Circuit Voltage
EKF	Extended Kalman Filter
UKF	Unscented Kalman Filter
NMC	Nickel Manganese Cobalt

1. Introduction

The rapid global adoption of electric vehicles (EVs) has intensified demands on battery management systems (BMS) to ensure the safety, efficiency, and longevity of lithium-ion battery packs. Central to BMS operation is the real-time estimation of key battery states, most notably the state of charge (SOC) which directly determines remaining driving range, prevents overcharge and over-discharge events, and underpins energy management strategies. Reliable SOC estimation, in turn, depends critically on the availability of an accurate and continuously updated battery model whose parameters faithfully reflect the instantaneous electrochemical and thermal condition of the cell [1], [2], [3]. Unlike measurable electrical quantities such as current and voltage, SOC is an internal state that cannot be directly observed. Model-based estimation methods using Equivalent Circuit Models (ECMs) are widely adopted because they offer a favorable trade-off between physical interpretability and computational complexity. Nevertheless, the accuracy of ECM-based SOC estimation strongly depends on the fidelity of model parameters, including ohmic resistance and polarization components [4], [5], [6]. In practical energy storage applications, these parameters are not constant. They vary with temperature, operating conditions, and especially with electrochemical aging. Resistance growth and changes in polarization dynamics progressively occur during cycling, leading to model–plant mismatch when fixed parameters identified offline are used. This mismatch propagates into SOC estimation errors and may compromise both performance and long-term reliability of the energy storage system. Therefore, adaptive online parameter identification is crucial for maintaining model consistency over the battery lifetime [7], [8], [9]. Recursive Least Squares (RLS) algorithms have been widely employed for online parameter estimation due to their fast convergence and relatively low computational burden. However, classical RLS tends to accumulate outdated information, which limits its tracking capability under time-varying conditions. The Forgetting Factor RLS (FFRLS) addresses this limitation by introducing a fixed forgetting factor to attenuate the influence of historical data. Nevertheless, its performance strongly depends on the appropriate selection of the forgetting factor, creating a trade-off between responsiveness and noise robustness. [10], [11],

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[12]. Adaptive Forgetting Factor RLS (AFFRLS) further enhances adaptability by dynamically adjusting the forgetting factor according to prediction errors. This mechanism enables improved tracking of resistance drift and polarization variation during dynamic operation. Although parameter identification algorithms such as RLS, FFRLS, and AFFRLS have been widely studied, systematic quantitative comparisons among these three algorithms for battery model parameter estimation under realistic load profiles remain limited in the energy storage literature [10], [12]. In this study, a comprehensive comparative analysis of the RLS, FFRLS, and AFFRLS algorithms is conducted for the online parameter identification problem of the first-order Thevenin battery model. The identified parameters are then used to compute the battery terminal voltage and are validated using the experimental dataset of the LG 18650HG2 battery under the UDDS driving cycle [13], [14], [15]. The main contributions of this paper are summarized as follows:

1. A complete online parameter identification framework is formulated, integrating Thevenin ECM discretization via the bilinear transformation, linear regression reformulation for recursive identification, and closed-form parameter recovery from identified discrete coefficients.
2. Three recursive identification algorithms RLS, FFRLS, and AFFRLS are implemented and systematically compared within a unified simulation environment, ensuring fair benchmarking under identical initialization and input conditions.
3. An adaptive forgetting factor update law based on instantaneous prediction error is proposed and validated, enabling automatic adjustment of memory length in response to changing battery dynamics.
4. Quantitative evaluation against the publicly available McMaster University LG 18650HG2 UDDS dataset confirms that AFFRLS achieves superior terminal voltage estimation accuracy, establishing its suitability for real-time BMS deployment.

2. Battery modeling

2.1 Equivalent Circuit Models (ECM)

ECM is the most widely used battery models for online Electric vehicle applications [16], [17], [18] due to its low-order structure, typically consisting of an SOC-dependent open-circuit voltage (OCV) source, an internal resistance, and one or several RC branches that capture polarization dynamics. Despite its simplicity, ECM can accurately reproduce terminal voltage–current behavior within the practical operating range. Owing to its compact state-space representation, ECM is particularly suitable for online estimation algorithms such as RLS, EKF, UKF, and dual-filter frameworks, enabling simultaneous parameter identification (e.g., R_0 , R_i , C_i , and the OCV–SOC relationship) and real-time SOC estimation [19], [20]. Compared with detailed electrochemical models (e.g., DFN/P2D), ECM involves significantly fewer parameters and avoids the need to identify difficult-to-measure physical quantities such as diffusion coefficients or reaction rate constants [21], [22]. This substantially reduces computational burden and facilitates implementation on embedded BMS hardware [23]. In contrast, thermal and electro-thermal models primarily describe temperature dynamics and require additional thermal parameters that are often challenging to determine accurately [24]. Moreover, the electrical submodel in electro-thermal formulations is typically based on an ECM, and thermal models alone do not provide sufficient information for SOC estimation without coupling to an electrical model [25]. Therefore, when the primary objective is real-time online estimation of electrical parameters and SOC, ECM represents a practical and computationally efficient modeling choice compared to more complex electrochemical or thermal models.

2.2 Thevenin First-Order Model

Among commonly used equivalent circuit models such as Rint, RC, PNGV and dual-polarization variants, Thevenin-type structures provide a favorable balance between modelling accuracy and computational simplicity, offering sufficiently accurate voltage dynamics for real-time BMS implementation [26].

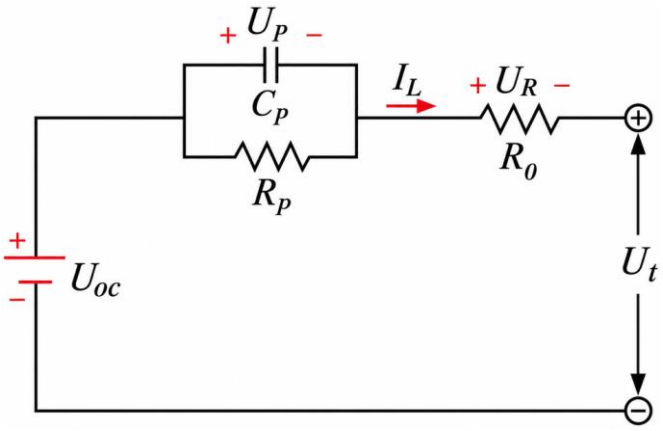


Figure 1: Equivalent circuit diagram of the Thevenin model

By applying Kirchhoff's Voltage Law (KVL) and Kirchhoff's Current Law (KCL) to the equivalent circuit, the continuous-time dynamic equations of the battery can be derived as follows:

$$U_t(t) = U_{oc}(\mathrm{SoC}) - \mathrm{U}_p(t) - I(t)R_0 \tag{1}$$

$$\frac{dU_p(t)}{dt} = -\frac{1}{R_pC_p}U_p(t) + \frac{1}{C_p}I(t) \tag{2}$$

Where U_t denotes the terminal voltage, U_p represents the polarization voltage across the RC network, and $I(t)$ is the load current (positive during discharge). R_0 is the ohmic resistance, while $\mathrm{R_p}$ and $\mathrm{C_p}$ characterize the polarization dynamics of the Thevenin model.

To enable online parameter identification, a three-step modeling procedure is adopted. First, the continuous-time Thevenin equivalent circuit model is discretized using the bilinear (Tustin) transformation. This discretization ensures compatibility with sampled measurement data and enables real-time implementation in the battery management system (BMS). As a result, the battery dynamics can be represented in the discrete domain by a first-order transfer function

relating the dynamic terminal voltage $U_t - U_{oc}$ to the input current I.

$$G(z^{-1}) = \frac{Ut(z^{-1}) - Uoc(z^{-1})}{I(z^{-1})} = \frac{b_0 + b_1 z^{-1}}{1 + a_1 z^{-1}} \quad (3)$$

The discrete coefficients a_1, b_0, and b_1 are related to the physical parameters R_0, R_1, and C_1 as follows.

$$a_1 = \frac{T - 2\tau}{T + 2\tau}; b_0 = -\frac{R_0 T + R_1 T + 2R_0\tau}{T + 2\tau}; \quad b_1 = -\frac{R_0 T + R_1 T - 2R_0\tau}{T + 2\tau} \quad (4)$$

To apply the RLS identification algorithm, the transfer function above is transformed into the following regression-based difference equation

$$U_t(k) - U_{oc}(k) = a_1[U_t(k-1) - U_{oc}(k-1)] + b_0 I(k) + b_1 I(k-1) \quad (5)$$

The synthetic influence on the OCV is determined by various factors, including the SOC, working temperature (T_e), and cycle history (H). These factors can all be mathematically represented as functions of time (t). Therefore, the correlation between these factors can be defined as:

$$\frac{dU_{OC}}{dt} = \left(\frac{\partial U_{OC}}{\partial SoC} \frac{\partial SoC}{\partial t} + \frac{\partial U_{OC}}{\partial Tem} \frac{\partial Tem}{\partial t} + \frac{\partial U_{OC}}{\partial H} \frac{\partial H}{\partial t} \right) \quad (6)$$

If the change in SOC during the sampling time is negligible, we can assume that

$$\frac{\partial \mathrm{SOC}}{\partial t} \approx 0.$$

Additionally, as the battery is typically heated or cooled to reach the working temperature, we can assume that the temperature change is relatively small and

$$\frac{\partial T_e}{\partial t} \approx 0.$$

In the long-term usage history, short-term cycles have minimal impact on the cycle history (H) value. Therefore, we can also assume that

$$\frac{\partial H}{\partial t} \approx 0.$$

As a result, we can rewrite Equation (6) as:

$$\frac{dU_{OC}}{dt} = \frac{U_{OC}(k) - U_{OC}(k-1)}{T} \approx 0 \quad (7)$$

$$\Delta U_{OC}(k) = U_{OC}(k) - U_{OC}(k-1) \approx 0 \quad (8)$$

By assuming that $U_{oc}(k) \approx U_{oc}(k-1)$ for a sufficiently small sampling period T.

$$U_t(k) - U_{OC}(k) = -a_1 U_{OC}(k) + a_1 U_t(k-1) + b_0 I(k) + b_1 I(k-1) \quad (9)$$

The discrete transfer function is reformulated into a linear regression structure, allowing the application of recursive identification algorithms such as Recursive Least Squares (RLS), Forgetting Factor RLS (FFRLS), and Adaptive Forgetting Factor RLS (AFFRLS). These algorithms estimate the discrete coefficients a_1, b_0, and b_1 in real time.

$$y(k) = \phi^T(k)\theta(k) \quad (10)$$

Where: $y(k) = U_t(k) - U_{oc}(k)$

$$\theta(k) = [-a_1\ U_{oc}(k), a_1, b_0, b_1]^T$$

$$\phi(k) = [1, U_1(k-1), I(k), I(k-1)]^T \quad (11)$$

Finally, the identified discrete coefficients are converted back into the physical parameters of the battery model R_0, R_p, C_p.

$$R_0 = \frac{b_0 - b_1}{1 - a_1};\ R_p = \frac{2(a_1 b_0 - b_1)}{1 - a_1^2} - R_0\ ;\ C_p = \frac{T(1 + a_1)}{2R_1(1 - a_1)} \quad (12)$$

3. Online Parameter identification

3.1 Conventional Recursive Least Squares (RLS) Algorithm

The Least Squares (LS) method belongs to the deterministic theoretical framework and aims to design a filter that estimates a desired signal based on another observed signal. In the context of battery modeling, the objective is to determine the parameter vector θ such that the model best fits the experimental data. Assume that we have a linear system with the observed input vector φ and the measured output y(k) at time step k:

$$y(k) = \phi^T(k)\theta(k) + \xi(k) \quad (13)$$

Here, θ denotes the parameter vector to be estimated, and ξ represents the system noise. At time $n > 0$, the objective is to determine the estimate $\hat{\theta}(n)$ such that the cost function J(n) is minimized.

$$J_{RLS}(k) = \sum_{k=1}^{n} e_n^2(k) \quad (14)$$

With the estimation error defined as:

$$e_n(k) = y(k) - \phi^T(k)\hat{\theta}_n \quad (15)$$

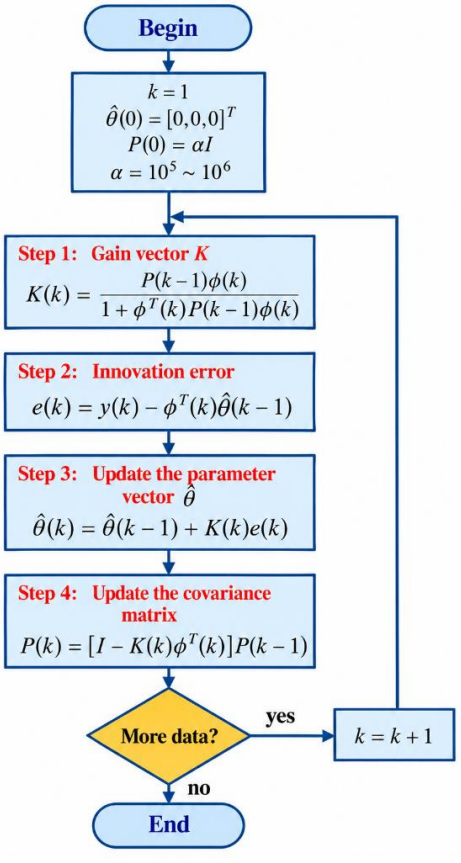


Figure 2: Flowchart of the RLS Algorithm

For practical implementation on a BMS chip, the algorithm must be reformulated into a recursive (R) form through a series of mathematical transformations.

At each time step k, the RLS algorithm sequentially performs the following four matrix algebra operations to update the model parameter vector as shown in **Figure 2**.

3.2 Recursive Least Squares Algorithm with Forgetting Factor (FFRLS)

The standard RLS algorithm is characterized by infinite memory, assigning equal importance to all data from the past (k=1) to the present. However, lithium-ion batteries represent a time-varying system in which the parameters (R, C) continuously change with temperature and the state of charge (SoC). When the accumulated dataset becomes large ($k \to \infty$), a phenomenon known as "data saturation" occurs, causing the covariance matrix to approach zero and consequently reducing the algorithm's ability to track newly emerging variations [27].

To address this limitation, the Forgetting Factor Recursive Least Squares (FFRLS) algorithm introduces a forgetting factor λ $(0.95 \leq \lambda \leq 1)$ to minimize a weighted cost function

$$J_{FFRLS}(k) = \sum_{i=1}^{k} \lambda^{k-i} [y(i) - \phi^T(i)\hat{\theta}(k)]^2 \quad (16)$$

The forgetting factor λplays a critical role in balancing the estimation process:

• When λ is small: The algorithm exhibits short-term memory, enabling it to track rapid parameter variations effectively; however, it becomes more sensitive to noise and thus less stable.

• When λ is large (close to 1.0): The algorithm exhibits long-term memory, which improves noise filtering and enhances stability, but results in a slower response (lag) to instantaneous changes in battery dynamics.

The optimal FFRLS solution derived from the batch least-squares formulation is expressed as

$$\hat{\theta}(k) = \Phi_{\lambda}^{-1}(k)\Theta_{\lambda}(k) \quad (17)$$

To enable online computation without explicitly performing matrix inversion at each time step, the Matrix Inversion Lemma is applied to recursively update the covariance matrix $P(k)$.

$$P(k) = \frac{1}{\lambda}\left[\mathrm{P(k-1)} - \frac{P(k-1)\phi^T(k)P(k-1)}{\lambda + \phi^T(k-1)\phi(k)} \right] \quad (18)$$

In summary, at each time step k, the FFRLS procedure consists of four sequential steps

1. Compute the prediction error

$$e(k) = y(k) - \phi^T(k)\hat{\theta}(k-1) \quad (19)$$

2. Compute the gain vector

$$K(k) = \frac{P(k-1)\phi(k)}{\lambda + \phi^T(k)P(k-1)\phi(k)} \quad (20)$$

3. Update the parameter vector

$$\hat{\theta}(k) = \hat{\theta}(\mathrm{k-1}) + K(\mathrm{k})\,\mathrm{e(k)} \quad (21)$$

4. Update the covariance matrix

$$P(k) = \frac{1}{\lambda}[I - K(k)\phi^T(k)]P(k-1) \quad (22)$$

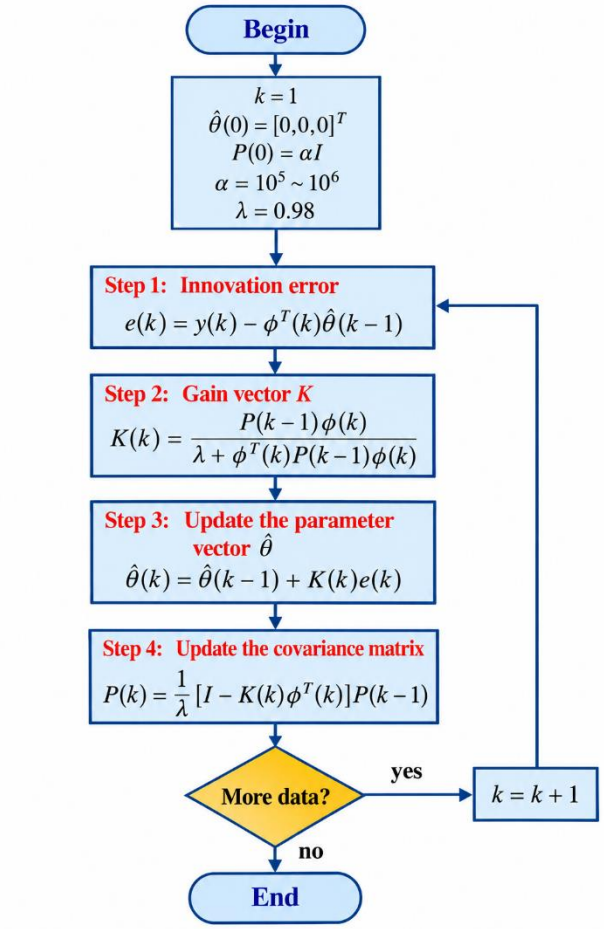


Figure 3: Flowchart of the FFRLS Algorithm

Figure 3 illustrates the flowchart of the FFRLS algorithm. For each new data sample, the algorithm sequentially computes the innovation error, evaluates the gain vector, updates the parameter vector, and revises the covariance matrix using a fixed forgetting factor λ=0,98 until all data samples are processed.

3.3 Adaptive Forgetting Factor Recursive Least Squares (AFFRLS) Algorithm

In conventional RLS algorithms, the forgetting factor is typically set as a constant, which leads to suboptimal performance under the complex and unpredictable operating conditions of lithium-ion batteries. To address this limitation, the proposed approach employs an adaptive forgetting factor that can automatically adjust according to the system's estimation error. The core principle is that when the prediction error becomes large (e.g., due to abrupt parameter variations).

The algorithm reduces the forgetting factor to rapidly discard outdated information and incorporate new data. Conversely, when the error is small, the forgetting factor increases to enhance system stability and maintain consistent correlations with the regression vector and the covariance matrix. The implementation procedure of the adaptive forgetting factor recursive least squares algorithm is illustrated in **Figure 4**

In summary, at each time step k, the AFFRLS procedure consists of five sequential steps with the first four steps are identical to those of the FFRLS algorithm.

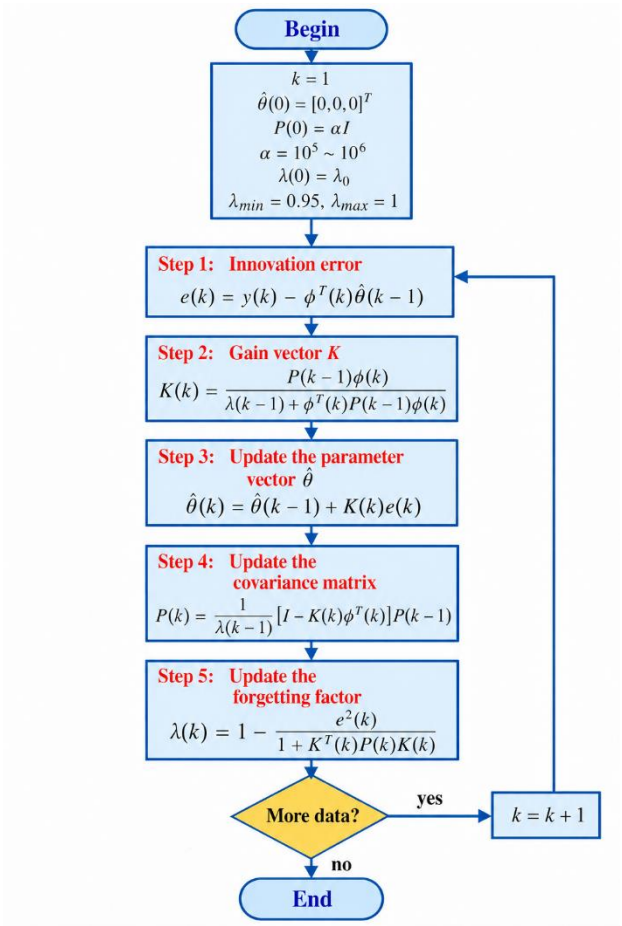


Figure 4: Flowchart of the AFFRLS Algorithm

Step 5: Update the forgetting factor

$$\lambda(k) = 1 - \frac{e^2(k)}{1 + K^T(k)P(k)K(k)} \quad (23)$$

The actual forgetting factor used in the AFFRLS update is then constrained as:

$$\lambda(k) = \min\left(\lambda_{max}, max\left(\lambda_{min}, \lambda(k)\right)\right) \quad (24)$$

where $\lambda_{min} = 0.95$ and $\lambda_{max} = 1.0$. This clipping operation ensures that the forgetting factor remains positive and bounded during large transient prediction errors.

4. Simulation and Results

4.1 Simulation Scenario and Initialization Parameters

To validate the effectiveness of the proposed approaches, the system was implemented in the MATLAB/Simulink environment. Three parameter identification algorithms (RLS, FFRLS, and AFFRLS) were configured to process the same input data stream and provide the parameters (R0, R1, C1) for calculating the estimated terminal voltage U_{est}. The obtained results were then compared and evaluated against a benchmark dataset provided by McMaster University (Canada) and hosted on the Mendeley Data repository [13]. The dataset records the current–voltage dynamic responses of lithium-ion batteries under highly dynamic operating conditions that emulate the real-world UDDS driving cycle of electric vehicles. UDDS (Urban Dynamometer Driving Schedule) is a standard EPA (U.S.) driving cycle designed to simulate urban driving conditions, characterized by continuously varying load currents, including acceleration phases (high discharge current), regenerative braking (short-term charging), and random idle periods. The highly dynamic nature of the UDDS cycle provides an ideal condition for evaluating the tracking capability of adaptive algorithms [24]. The experimental subject is the commercial LG 18650HG2 battery cell. This battery employs an NMC cathode and a graphite–silicon anode chemistry, optimized for applications requiring high discharge power

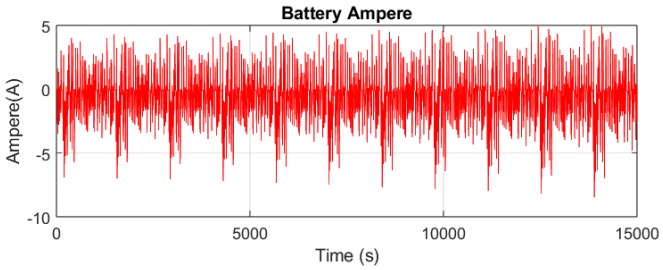


Figure 5: Current Profile of the UDDS Driving Cycle

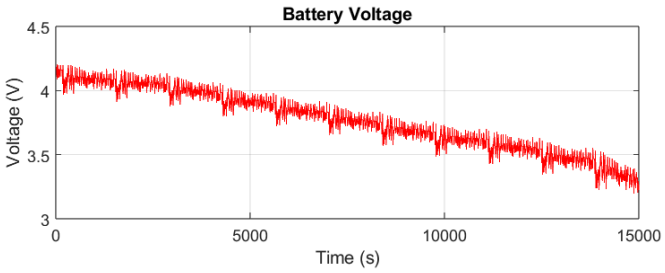


Figure 6: Voltage Profile of the UDDS Driving Cycle

Table 1: Technical Specifications of the LG 1865HG2 Lithium-ion battery

Parameter	Value/Description
Product Name	LG 18650HG2 (LGDBHG21865)
Chemical Composition	Li[NiMnCo]O2 (H-NMC) / Graphite + SiO
Nominal Capacity	3.0 Ah
Nominal Voltage	3.6 V
Maximum charge voltage	4.2 V
Cut-off Voltage (End Voltage)	2.0 V
Maximum Continuous Discharger Current	20 A
Energy Density	240 Wh/kg
Experimental Data Source	McMaster University, Canada [13]

The initialization parameters are consistently configured to ensure fairness in the comparison:

- ***Model parameter vector***: $\theta_0 = [0,0,0]^T$

- ***Error covariance matrix:*** $(P_0): P_0 = 10^6.I$

This large value reflects the initial uncertainty of the parameters, allowing the algorithm to converge rapidly once the first measurement data become available.

- ***Forgetting factor configuration (λ):***

+ Conventional RLS: $\lambda = 1.0$

+ FFRLS: $\lambda = 0.98$

+ AFFRLS: Automatically adjusted within the range $\lambda \in [0.95;1.0]$.

4.2 Error Evaluation Criteria

The performance of the algorithms is quantified by comparing the estimated Voltage (U_{est}) with the reference voltage (U_t) over the entire dataset consisting of N samples, using the following three statistical metrics:

1. *Maximum Absolute Error (Max Error): Evaluates the largest deviation (worst-case scenario):*

$$MaxError(\%) = 100 \frac{\max_{k=1..N} | U_{est}(k) - U_t(k) |}{U_{Nom}} \quad (25)$$

2. *Root Mean Square Error (RMSE): Evaluates the stability and dispersion of the estimation error*

$$RMSE(\%) = 100 \frac{\sqrt{\frac{1}{N}\sum_{k=1}^{N}(U_{est}(k) - U_t(k))^2}}{U_{Nom}} \quad (26)$$

4.3 Results and Discussion

To validate the effectiveness of the proposed approaches, the simulation system generated the terminal voltage responses U_{est} and the instantaneous estimation errors of the three algorithms: RLS, FFRLS, and AFFRLS Figures 7, Figures 8, and Figures 9 respectively illustrate the estimated voltage U_{est} trajectories of the three algorithms compared with the actual values throughout the UDDS operating cycle. In addition to the qualitative evaluation based on graphical observations, the accuracy of each algorithm is quantitatively assessed through the summarized error table presented below. Table II reports two key performance metrics Maximum Error (Max Error) and Root Mean Square Error (RMSE) for each algorithm, providing a reliable dataset for detailed analysis

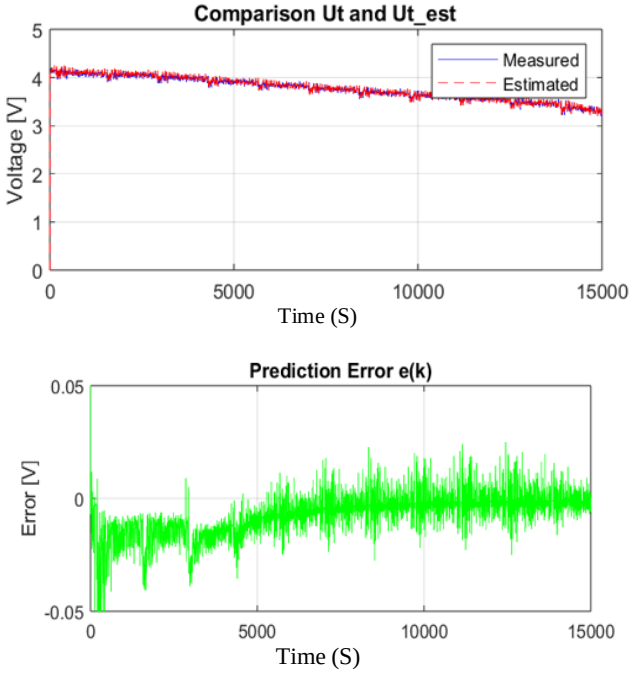


Figure 7: Model Parameter Estimation Results Using the RLS Algorithm.

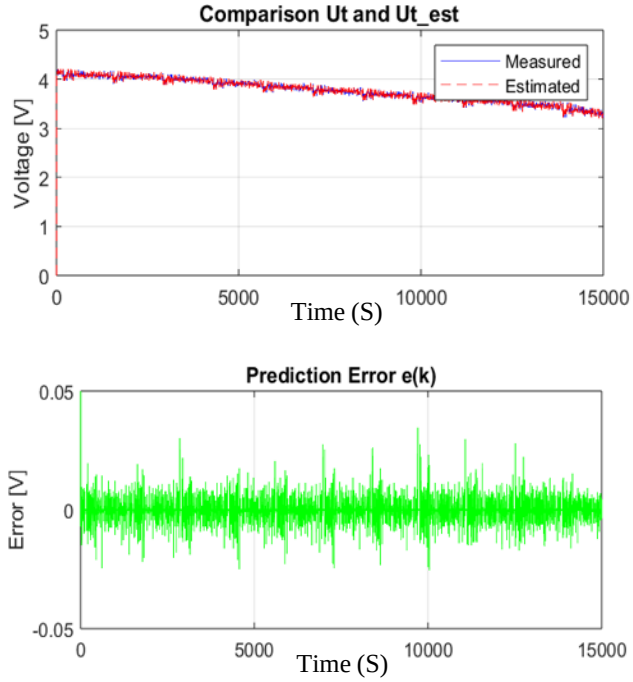


Figure 8: Model Parameter Estimation Results Using the FFRLS Algorithm

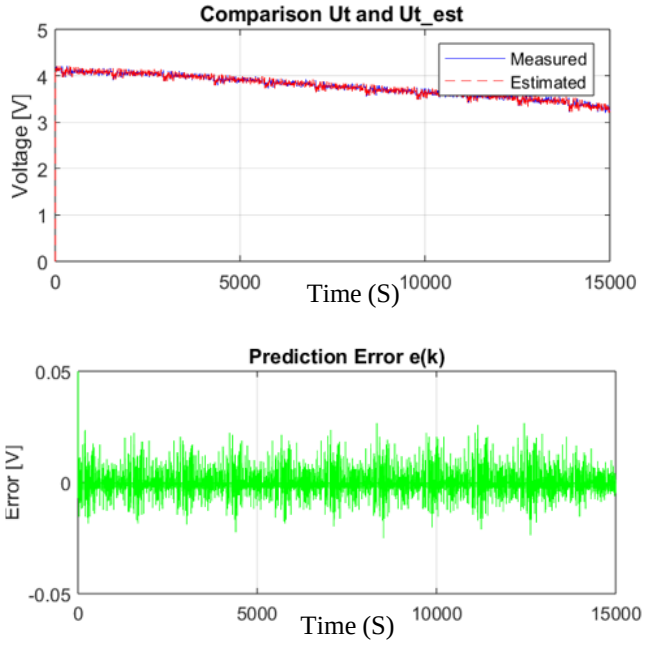


Figure 9: Model Parameter Estimation Results Using the AFFRLS Algorithm

Table 2: Voltage Estimation Results Using of RLS, FFRLS, and AFFRLS

Algorithm	MaxAE (%)	RMSE (%)
RLS	4.09	1.00
FFRLS	3.45	0.12
AFFRLS	2.68	0.13

- The adaptive parameter identification approach based on AFFRLS achieved the lowest maximum voltage estimation

error (2.68%), outperforming both conventional RLS (4.09%) and FFRLS (3.45%).

- The introduction of a forgetting factor mechanism significantly improves the tracking capability of recursive estimation algorithms under highly dynamic operating conditions such as the UDDS driving cycle.
- The AFFRLS algorithm demonstrates superior adaptability to time-varying battery parameters, particularly resistance and polarization dynamics, which are affected by load fluctuations.

Simulation results confirm that adaptive forgetting factor strategies effectively balance responsiveness and noise robustness, enabling more stable estimation performance in practical battery management systems.

5. Conclusion and Future works

This paper presents a comparative evaluation of RLS, FFRLS, and AFFRLS for online parameter identification of a first-order Thevenin equivalent circuit model of an LG 18650HG2 lithium-ion battery under the UDDS driving cycle. The results show that AFFRLS achieves the lowest maximum absolute voltage error, reducing the worst-case deviation compared with both RLS and FFRLS, while maintaining an RMSE comparable to FFRLS. This indicates that the adaptive forgetting factor is particularly beneficial under highly dynamic current profiles, where abrupt transients can cause rapid changes in the effective battery parameters. However, the present study remains simulation-based and focuses primarily on terminal voltage reconstruction. The use of OCV information and the sampling assumptions should be explicitly considered when transferring the method to a fully embedded BMS implementation. Future work will focus on closed-loop validation, integration with SOC/SOH estimation algorithms such as EKF, experimental implementation on embedded hardware, and evaluation under different temperatures, aging levels, and battery chemistries.

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