

Data-Driven Prognostics of LiFePO₄ Battery Remaining Useful Life in Residential Microgrids: A Hybrid Approach Integrating Recursive Least Squares and Long Short-Term Memory

Prognostik Berbasis Data untuk Sisa Masa Pakai Baterai LiFePO₄ pada Mikrogrid Perumahan: Sebuah Pendekatan Hibrida yang Mengintegrasikan Metode Kuadrat Terkecil Berulang dan Jaringan Memori Jangka Panjang-Pendek

^{1,2}Zaenal Abidin, ¹Awang Noor Indra Wardana*), ¹Sunarno

¹Department of Nuclear Engineering and Engineering Physics, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia

²PLN Indonesia Power, Jakarta 12950, Indonesia

*) corresponding email: awang.wardana@ugm.ac.id

Abstract

The growing use of residential photovoltaic systems is increasing the deployment of Lithium Iron Phosphate (LiFePO₄) battery energy storage systems. However, dynamic load demands and frequent cycling accelerate battery degradation. Accurate state-of-health estimation and remaining useful life prediction are critical for operational reliability. This study introduces a hybrid framework that integrates recursive least squares with a long short-term memory network. A first-order Thevenin equivalent circuit model is used to extract physical parameters such as ohmic resistance, polarization resistance, and polarization capacitance. The recursive least squares algorithm, with a forgetting factor of 0.999, adaptively tracks resistance-based State of Health, detecting an increase in ohmic resistance from 26.5 to 37.04 milliohms after 348 cycles. This approach achieves a root-mean-square error of 1.0554% and a coefficient of determination of 0.8354. These parameters are then used to train the long short-term memory network to model degradation trends. The network predicts remaining useful life with a root mean square error of 0.8947% and a coefficient of determination of 0.9553, forecasting lifespans of 511, 953, and 1,310 days for end-of-life thresholds of 80%, 70%, and 60% State of Health, respectively.

Keywords: photovoltaic systems, lithium battery, degradation tracking, lifespan prediction, microgrids

Abstrak

Peningkatan penggunaan sistem fotovoltaik pada sektor residensial mendorong pemanfaatan Battery Energy Storage System (BESS) berbasis baterai Lithium Iron Phosphate (LiFePO₄) untuk menyimpan energi dan meningkatkan fleksibilitas operasi sistem kelistrikan. Namun, tuntutan beban yang dinamis dan siklus pengisian-pengosongan yang sering dapat mempercepat degradasi baterai. Estimasi status kesehatan yang akurat dan prediksi sisa masa pakai sangat penting untuk menjaga keandalan operasional. Penelitian ini memperkenalkan kerangka kerja hibrida yang mengintegrasikan metode kuadrat terkecil rekursif dengan jaringan memori jangka pendek panjang. Model rangkaian ekuivalen Thevenin orde pertama digunakan untuk mengekstraksi parameter fisik seperti hambatan ohmik, hambatan polarisasi, dan kapasitansi polarisasi. Algoritma kuadrat terkecil rekursif, dengan faktor pelupa sebesar 0,999, secara adaptif melacak status kesehatan berbasis hambatan, mendeteksi kenaikan hambatan ohmik dari 26,5 menjadi 37,04 miliohm setelah 348 siklus. Pendekatan ini menghasilkan kesalahan akar kuadrat rata-rata sebesar 1,0554% dan koefisien determinasi sebesar 0,8354. Parameter-parameter tersebut kemudian digunakan untuk melatih jaringan memori jangka pendek panjang dalam memodelkan tren degradasi. Jaringan ini memprediksi sisa masa pakai dengan kesalahan akar kuadrat rata-rata sebesar 0,8947% dan koefisien determinasi sebesar 0,9553, serta memperkirakan masa pakai masing-masing selama 511, 953, dan 1.310 hari untuk ambang batas akhir masa pakai sebesar 80%, 70%, dan 60% dari status kesehatan.

Kata Kunci: sistem fotovoltaik, baterai litium, pelacakan degradasi, prediksi umur, mikrogrid

Paper accepted July 19th, 2026 – paper revised October 6th, 2026 – approved October 7th, 2026

This paper is open access with [CC BY-SA](#) license.



1. Introduction

Renewable energy adoption in Indonesia has increased substantially in recent years. A prominent application is the deployment of rooftop photovoltaic (PV) systems in both residential and commercial buildings. According to the Ministry of Energy and Mineral Resources (MEMR), the cumulative installed capacity of rooftop PV systems in Indonesia reached 446.09 MW in 2025 [1]. Despite this growth, PV systems are inherently intermittent because their output depends on solar irradiance, time of day, and weather conditions. As a result, a reliable Battery Energy Storage System (BESS) is essential for storing surplus energy and supplying it when required. In BESS operation, the State of Health (SoH) serves as a critical indicator for assessing battery condition. However, SoH cannot be measured directly and must be estimated from changes in battery capacity or internal resistance [2]. Additionally, LiFePO_4 batteries have a relatively flat open-circuit voltage (OCV) characteristic, which makes it more difficult to extract health indicators and accurately estimate SoH from voltage measurements [3]. Therefore, a Remaining Useful Life (RUL) prognostic system is necessary to predict the battery's remaining service life until it reaches its End of Life (EoL), thereby enhancing the reliability and operational management of residential BESS.

Because SoH cannot be measured directly, it is typically estimated using empirical measurement-based methods [4],[5], mathematical model-based methods [6]–[9], or data-driven approaches [10]–[13]. Prior research has explored SoH estimation for lithium-ion batteries using Support Vector Regression (SVR), which has demonstrated that kernel-based regression can accurately map health indicators to SoH [10]. Gaussian Process Regression (GPR) based on indirect health indicators has also been shown to provide accurate SoH estimates while quantifying prediction uncertainty [14]. In deep learning, Long Short-Term Memory (LSTM) networks have been widely adopted for battery health prediction due to their capacity to capture long-term degradation patterns from sequential data [15]. Bidirectional Long Short-Term Memory (BiLSTM) networks further improve SoH prediction performance by leveraging temporal information from both forward and backward directions [13]. Among model-based approaches, the Dual Extended Kalman Filter (DEKF) combined with Recursive Least Squares (RLS) has been used to estimate battery states under varying temperature conditions, utilizing internal parameters as degradation indicators of SoH [16]. Additionally, data-driven methods have been developed to simultaneously predict the SoH trajectory and RUL by forecasting future SoH evolution, thereby supporting RUL estimation [17].

This study introduces a hybrid framework for estimating the physical parameters of LiFePO_4 batteries and predicting their long-term degradation using an equivalent circuit model (ECM). The ECM output is processed by the Recursive Least Squares (RLS) algorithm to estimate model parameters and extract physics-informed health indicators. Concurrently, an LSTM network is utilized to capture nonlinear degradation dynamics and project the SoH trajectory for RUL prediction. This research advances practical battery prognostics by employing real-world operational data collected from a residential microgrid equipped with a LiFePO_4 -based BESS, a context that has received limited attention in existing literature, which primarily focuses on laboratory datasets or electric vehicle applications. Accordingly, this work addresses a significant research gap by developing a hybrid physics-informed, data-driven framework that integrates RLS for online SoH parameter estimation with LSTM for long-term degradation forecasting and RUL prediction using actual operational data.

2. Methodology

2.1 Residential BESS Prototype

The research object of this study is a 5 kWh residential BESS. The system is powered by a 5.98 kWp solar PV array connected to a 5 kW inverter, which then supplies electricity to the Safety Center building. In addition, the system is connected to the PLN utility grid, which serves as a backup power source when the energy generated by the solar PV system and the battery is insufficient to meet the load demand. The configuration of the proposed residential microgrid system is illustrated in Figure 1.

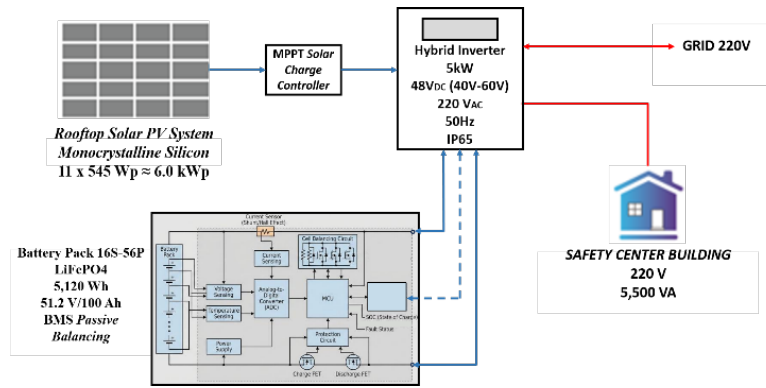


Figure 1. Residential microgrid system architecture

A 5 kWh energy storage capacity allows the battery to supply a 1 kW load for approximately 5 hours, a 2 kW load for 2.5 hours, or a 5 kW load for about 1 hour under ideal operating conditions. To extend battery lifespan, the system is generally operated at a Depth of Discharge (DoD) of approximately 80%, yielding a usable energy capacity of around 4 kWh.

2.2 Real-World Dataset

The dataset analyzed in this study was collected from a 5 kWh residential BESS prototype utilizing LiFePO₄ batteries over an 18-month operational period, spanning October 2024 to April 2026. The pack-level dataset comprises time-series measurements recorded at 5-minute intervals, yielding 288 samples per day. Across approximately 548 days of operation, this results in a theoretical total of 157,824 data points for each measured parameter. Data was obtained directly from the residential BESS during operation and include battery terminal voltage, charging and discharging current, output power, State of Charge (SoC), battery temperature, cumulative charging energy, and cumulative discharging energy. Before model development, the dataset underwent comprehensive preprocessing to ensure quality and consistency. Preprocessing steps included timestamp synchronization, outlier removal, handling of missing values, noise filtering, data normalization, and segmentation. These procedures resulted in a clean, consistent, and standardized dataset suitable for parameter estimation and remaining useful life (RUL) prognostic modeling.

2.3 Battery Modeling using Equivalent Circuit Model (ECM)

In battery modeling, ECM provides an effective balance between dynamic modeling accuracy and computational efficiency. The ECM represents the battery's internal characteristics, including ohmic resistance, polarization effects, and energy storage behavior, using fundamental electrical components such as voltage sources, resistors, and capacitors. In this study, a first-order Thevenin ECM (1-RC) is adopted because it can accurately capture the transient response of the battery while maintaining low computational complexity and enabling straightforward parameter identification. As illustrated in Figure 2, the model consists of an Open Circuit Voltage (OCV) source, an ohmic internal resistance (R_0), and a single polarization branch composed of a resistor (R_1) and a capacitor (C_1).

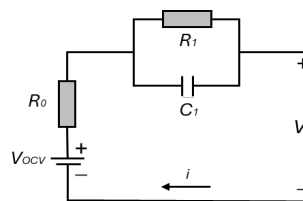


Figure 1. Thevenin 1-RC Model

Physically, the ohmic resistance (R_0) represents the instantaneous voltage loss caused by the internal resistance of the electrolyte, current collectors, connectors, and electrode materials. Meanwhile, the R_1 - C_1 branch models the electrochemical polarization phenomenon responsible for the transient voltage response during battery charging and discharging processes. Based on the first-order Thevenin equivalent circuit model, the relationship between the battery terminal voltage and its internal parameters can be expressed as follows:

$$V_t = OCV(SOC_t) - I_t R_0 - V_{p,t} \quad (1)$$

where V_t denotes the measured battery terminal voltage, and $OCV(SOC_t)$ is the OCV as a function of SoC. The parameter R_0 represents the ohmic internal resistance, which accounts for the voltage losses associated with the electrolyte, electrodes, and battery connectors. The variable I_t denotes the battery current, where a positive current corresponds to the discharging process and a negative current corresponds to the charging process. The term $V_{p,t}$ represents the polarization voltage across the RC branch, which characterizes the electrochemical polarization effects occurring during battery charging and discharging.

The dynamics of the polarization voltage across the RC branch are expressed as follows:

$$\frac{dV_p}{dt} = -\frac{1}{R_1 C_1} V_p + \frac{1}{C_1} I_t \quad (2)$$

where R_1 denotes the polarization resistance and C_1 represents the polarization capacitance. Together, these parameters define the system as time constant, $R_1 C_1$, which characterizes the transient response of the battery. Equation (2) indicates that the polarization voltage increases when current flows into or out of the battery and gradually decays exponentially toward its steady-state value when the battery is in a rest or idle condition. Since the experimental data were recorded at a discrete sampling interval of $\Delta t = 300$ s, the continuous-time model in Equation (2) was discretized using the exact exponential solution, yielding the following discrete-time coefficients:

$$a = e^{-\frac{\Delta t}{R_1 C_1}} \quad (3)$$

$$b = R_1(1 - a) \quad (4)$$

The a coefficient represents the decay factor, which characterizes the exponential decay of the polarization voltage in the RC branch, whereas the coefficient b describes the contribution of the battery current to the evolution of the polarization voltage at each sampling interval. Using these coefficients, the polarization voltage dynamics in the discrete-time domain can be expressed as follows:

$$V_{p,k} = aV_{p,k-1} + bI_{k-1} \quad (5)$$

Equation (5) indicates that the polarization voltage at time step k depends on both the polarization voltage and the battery current from the previous sampling interval. Accordingly, the discrete-time battery terminal voltage can be expressed as

$$V_k = OCV_k - R_0 I_k - V_{p,k} \quad (6)$$

where V_k denotes the measured battery terminal voltage at time step k , while OCV_k is OCV obtained from the OCV-SoC relationship. The voltage drops caused by the ohmic internal resistance are represented by the term $R_0 I_k$, whereas $V_{p,k}$ accounts for the dynamic polarization effect of the battery. By substituting Equation (5) into Equation (6), the following discrete-time terminal voltage model is obtained:

$$V_k = OCV_k - R_0 I_k - aV_{p,k-1} - bI_{k-1} \quad (7)$$

Equation (7) represents the discrete-time first-order Thevenin equivalent circuit model (1-RC), which describes the relationship among the battery terminal voltage, current, and polarization effects. However, the state variable $V_{p,k-1}$ cannot be measured directly. Therefore, a parameter identification algorithm, such as RLS, is required to estimate the model parameters from the measured voltage and current data.

2.4 RLS Algorithm for Parameter Identification

In this study, the first-order Thevenin equivalent circuit model (1-RC) is identified online using the RLS algorithm. The primary objective of the identification process is to estimate the model parameters, namely the ohmic resistance (R_0), polarization resistance (R_1), and polarization capacitance (C_1), which vary according to the battery operating conditions. The RLS algorithm recursively updates these parameters whenever new measurement data become available, enabling continuous tracking of battery characteristics under varying current profiles, operating temperatures, and degradation levels.

$$y_k = \phi_k^T \theta_k + \varepsilon_k \quad (8)$$

where the model output is defined as

$$y_k = OCV_k - V_k \quad (9)$$

and the regressor vector is given by

$$\phi_k = \begin{bmatrix} y_{k-1} \\ I_k \\ I_{k-1} \end{bmatrix}, \theta_k = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} \quad (20)$$

In Equation (8), y_k denotes the model output, which is defined as the difference between OCV and the measured battery terminal voltage. The regressor vector ϕ_k consists of the previous model output, the current battery current, and the battery current from the previous sampling interval, whereas θ_k represents the regression parameter vector to be recursively estimated. The RLS algorithm estimates the regression parameter vector $\theta = [a, b_0, b_1]^T$, which does not directly represent the physical parameters of the battery. Therefore, a parameter transformation is performed to recover the equivalent circuit parameters of the first-order Thevenin model. The parameter b_0 corresponds to the ohmic resistance R_0 , while R_1 is obtained from the relationship between the regression coefficients and the discrete-time RC dynamics. The polarization capacitance C_1 is subsequently calculated from the RC time constant $\tau = -\Delta t / \ln(a)$, thereby enabling the regression parameters to be interpreted as physically meaningful battery characteristics. The term ε_k denotes the modeling error or measurement noise. To enable the model to continuously adapt to variations in battery characteristics during the degradation process, the parameters are recursively updated using the RLS algorithm with a forgetting factor. The parameter update is governed by the following equations:

$$K_k = \frac{P_{k-1} \phi_k}{\lambda + \phi_k^T P_{k-1} \phi_k} \quad (31)$$

$$\theta_k = \theta_{k-1} + K_k (y_k - \phi_k^T \theta_{k-1}) \quad (12)$$

$$P_k = \frac{1}{\lambda} (P_{k-1} - K_k \phi_k^T P_{k-1}) \quad (13)$$

where K_k denotes the RLS gain, P_k is the parameter covariance matrix, and λ is the forgetting factor, which controls the sensitivity of the algorithm to newly acquired measurement data. The forgetting factor satisfies $0 < \lambda \leq 1$, where values closer to unity provide more stable parameter estimates, whereas smaller values enable the algorithm to respond more rapidly to changes in battery characteristics. To construct a health indicator with a standardized scale, the estimated internal resistance is converted into the Resistance-based State of Health (SoH_R) using the following equation:

$$SoH_R = 100 - \left(\frac{R_0 - R_{0,BOL}}{R_{0,BOL}} \right) \times (100 - SoH_{limit}) \quad (44)$$

Equation (14) represents a linear resistance-based degradation mapping that converts the relative increase in ohmic resistance into an equivalent SoH indicator. The mapping assumes that the battery starts from 100% SoH at the Beginning of Life (BoL) and gradually decreases as the internal resistance increases. The scaling factor $(100 - SoH_{limit})$ defines the degradation range between the BoL condition and the selected End-of-Life (EoL) threshold adopted in this study. The initial R_0 value is obtained from the RLS estimation from the initial phase up to the steady state. The determination of SoH_{limit} uses three thresholds: 80% as a conservative industry standard, 70% as the operational limit for this study, and 60% to evaluate the maximum technical lifespan limit before significant degradation occurs.

2.5 Long Short-Term Memory (LSTM) Network

After the battery health parameters have been estimated using RLS algorithm, the resulting Health Indicator (HI) time series is used as the input to LSTM network to predict the future battery degradation trend. LSTM is adopted because of its ability to capture long-term dependencies, making it well suited for modeling the

nonlinear degradation behavior of batteries driven by their operational history. At each time step, the LSTM network receives a sequence of Health Indicator values and processes them through four fundamental components: the forget gate, input gate, cell state, and output gate. The forget gate determines which information from the previous memory state should be retained or discarded, and is mathematically expressed as

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (55)$$

where x_t denotes the input vector at time step t , h_{t-1} is the hidden state from the previous time step, and W_f , U_f , and b_f represent the weight matrices and bias vector of the forget gate, respectively. The sigmoid activation function, $\sigma(\cdot)$, produces values in the range of 0 to 1, indicating the proportion of information retained from the previous cell state. The new information to be stored in the memory cell is then computed as follows:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (66)$$

and the candidate cell state is computed as

$$\tilde{C}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (77)$$

The input gate controls the amount of new information that is incorporated into the cell memory, whereas $\tilde{C}_t$ represents the candidate cell state generated by the hyperbolic tangent ($\tanh$) activation function. The cell state is then updated by combining the retained information from the previous cell state with the newly generated information according to

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (88)$$

where C_t denotes the cell state at time step t , and the symbol $\odot$ represents the element-wise multiplication. Subsequently, the output gate determines the information to be propagated to the next layer (or the next time step) and is computed as follows:

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (99)$$

which produces the hidden state

$$h_t = o_t \odot \tanh(C_t) \quad (20)$$

The resulting hidden state provides a temporal feature representation learned by the LSTM network, capturing the degradation patterns embedded in the Health Indicator sequence. These learned features are subsequently used to predict the future health condition of the battery. The output of the LSTM network is employed to forecast the Health Indicator at the next timestep, which can be expressed as

$$\widehat{HI}_{t+1} = f_{LSTM}(HI_{t-n+1}, \dots, HI_t) \quad (210)$$

where $\widehat{HI}_{t+1}$ denotes the predicted Health Indicator at the next timestep obtained from the LSTM network using the historical Health Indicator sequence. The Remaining Useful Life (RUL) is then estimated as the time remaining from the current operating condition until the predicted Health Indicator reaches the predefined End-of-Life (EoL) threshold, as expressed by

$$RUL = t_{EOL} - t_{current} \quad (22)$$

In this study, HI is derived from SoH_R estimated using the RLS algorithm. Consequently, the LSTM network does not directly utilize the measured current or voltage signals as inputs. Instead, it learns the battery degradation behavior from the temporal evolution SoH_R , enabling accurate forecasting of the degradation trajectory and estimation of the RUL until the predefined EoL threshold is reached.

2.6 Equivalent Cycle Calculation

Because the BESS operates under irregular, partial charge–discharge profiles driven by PV generation and household load, the cycle count was expressed as the equivalent full cycle (EFC) based on energy throughput, rather than by counting individual charge–discharge events [18]. For each day i , the discharged energy was obtained from the cumulative discharging energy recorded by the BESS, or equivalently by integrating the discharge power over the sampling interval:

$$E_{\text{dis},i} = E_{\text{dis,cum}}(t_{i,\text{end}}) - E_{\text{dis,cum}}(t_{i,\text{start}}) = \sum_{k \in i} P_{\text{dis},k} \Delta t \quad (23)$$

where $t_{i,\text{start}}$ and $t_{i,\text{end}}$ denote the first and last timestamps of day i . The equivalent cycle count accumulated up to day d is then calculated as:

$$N_{\text{eq}}(d) = \sum_{i=1}^d \frac{E_{\text{dis},i}}{E_{\text{ref}}} \quad (24)$$

where E_{ref} is the reference energy capacity of the battery. One equivalent cycle corresponds to a cumulative discharge equal to E_{ref} , regardless of how this energy is distributed over partial cycles. The relationship between RUL in cycle units and day units is bridged by the operational usage frequency or average daily cycle count, where cycle RUL indicates the electrochemical capacity limit until reaching EoL while day RUL reflects real-world operational time dynamically influenced by DoD variations, ambient temperature, and calendar aging components running concurrently with cyclic processes.

3. Results and Discussion

3.1 SoH Estimation Performance

Before parameter estimation with the RLS algorithm, the dataset was grouped by battery operating temperature using temperature binning to reduce the impact of thermal variations on estimated internal resistance. Throughout the observation period, battery operating temperatures ranged from 25°C to 45°C and were divided into four bins: 25–30°C, 30–35°C, 35–40°C, and 40–45°C, each with a width of 5°C. This preprocessing ensured that estimated resistance parameters primarily reflected intrinsic degradation due to battery aging, rather than transient fluctuations from temperature changes. As a result, temperature-dependent effects on battery impedance characteristics were reduced, yielding more consistent and reliable parameter identification, as shown in Figure 3.

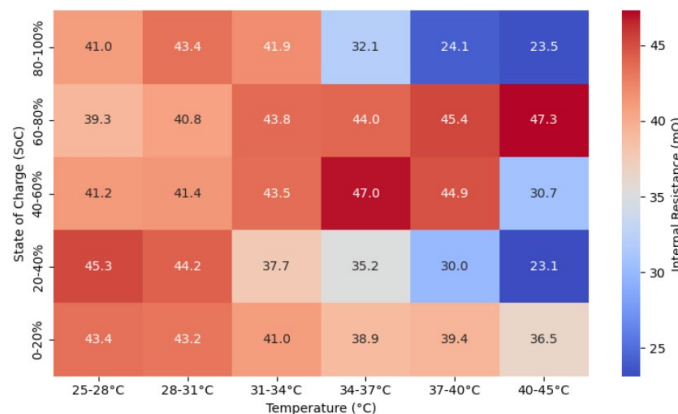


Figure 3. Data binning temperature

After the temperature binning process, the battery was modeled by deriving the mathematical formulation of the first-order Thevenin ECM (1-RC ECM). The function of the SoC–OCV curve in ECM modeling is to map the non-linear relationship between the open-circuit voltage and the State of Charge, allowing R_0 and polarization voltage parameters to be accurately estimated at each operating point of SoC. The comparison between the model output and the measured battery response is presented in Figure 4.

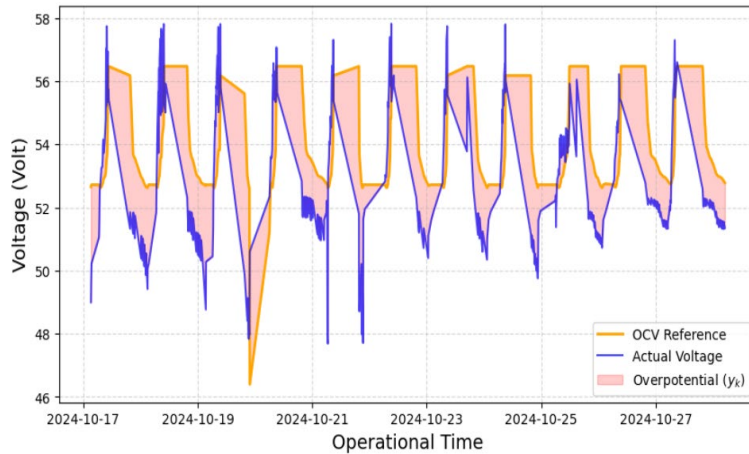


Figure 4. Comparison of OCV and measured battery terminal voltage for overpotential extraction

Figure 4 presents the sampled battery terminal voltage profile together with the reference OCV. The OCV ranges from approximately 46.5 V to 56.5 V, measured directly on the battery in the laboratory under no-load conditions. Whereas the measured terminal voltage exhibits a wider variation, ranging from approximately 47.0 V to 57.8 V, following the battery charging and discharging conditions. The difference between these two voltage profiles corresponds to the overpotential (y_k), which increases during periods of significant current variation. Pronounced overpotential peaks are observed during rapid transitions between charging and discharging operations, while under low-current or rest conditions, the terminal voltage gradually converges toward the OCV curve. To evaluate the sensitivity of the RLS algorithm to parameter adaptation, six forgetting factor (λ) values were investigated: 0.950, 0.975, 0.985, 0.990, 0.995, and 0.999. The forgetting factor is a key parameter in the RLS algorithm because it determines the trade-off between parameter adaptability and estimation stability. Smaller values of λ assign greater weight to recent measurements, enabling faster tracking of battery parameter variations at the expense of increased sensitivity to measurement noise. Conversely, values of λ closer to unity produce smoother and more stable parameter estimates but reduce the algorithm's responsiveness to battery degradation. Therefore, the selection of an appropriate forgetting factor plays a critical role in the accuracy and robustness of SoH_R estimation.

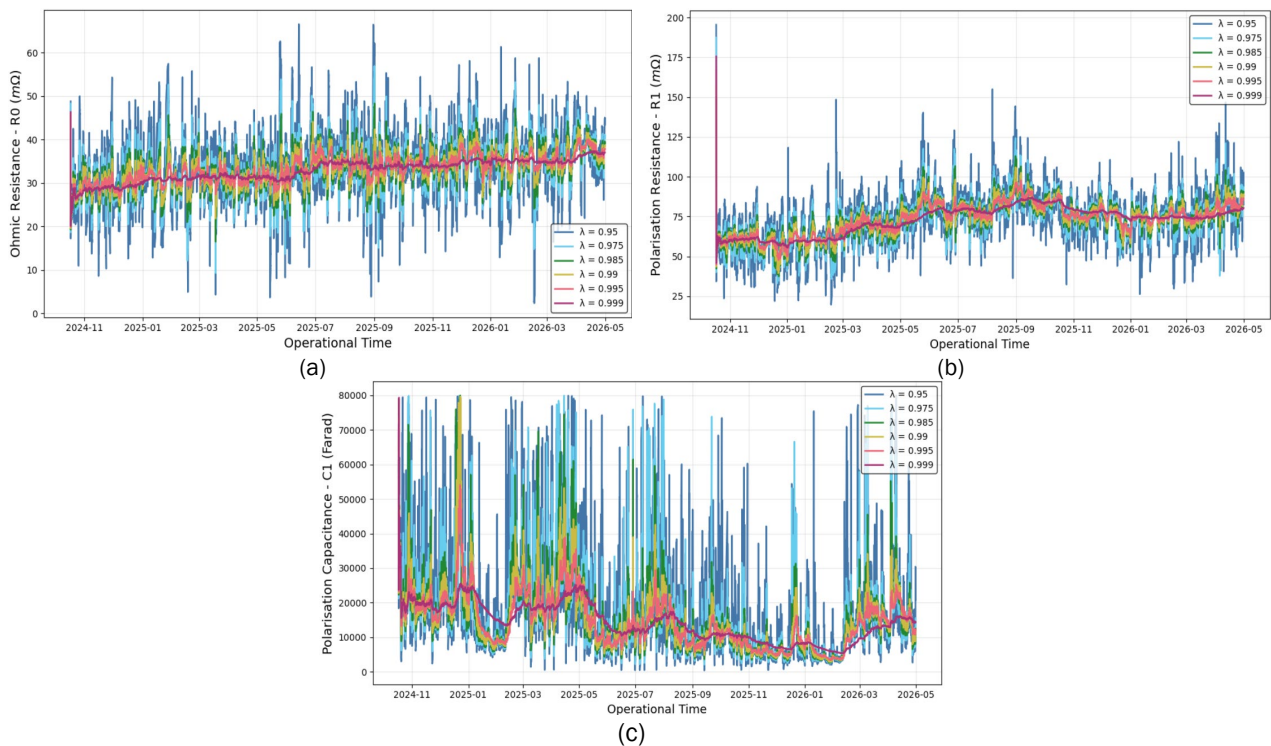


Figure 5. RLS parameter estimation under different forgetting factor values, (a) R_0 trajectory, (b) R_1 trajectory, (c) C_1 trajectory

Figure 5 presents the ECM parameter identification results obtained using RLS algorithm with different forgetting factor values ($\lambda = 0.950 - 0.999$). As shown in Figure 5(a), the estimated ohmic resistance (R_0) ranges from approximately 20 to 40 m Ω and exhibits a gradual increasing trend, reaching about 36–38 m Ω at the end of the observation period. The choice of forgetting factor significantly affects the smoothness of the estimated parameters. Smaller values of λ produce more responsive estimates with larger fluctuations, whereas $\lambda = 0.999$ yields a smoother and more stable trajectory. The gradual increase in R_0 indicates progressive battery degradation caused by the growth of the internal ohmic resistance during long-term operation.

As illustrated in Figure 5(b), the polarization resistance (R_1) generally varies between 55 and 85 m Ω and also shows an increasing trend over time. Although several transient spikes exceeding 150 m Ω are observed, particularly for smaller forgetting factor values, all estimation results exhibit a consistent degradation pattern. In contrast, Figure 5(c) shows that the polarization capacitance (C_1) exhibits substantially larger variations than the resistance parameters, ranging from approximately 5,000 to 25,000 F, with occasional peaks approaching 80,000 F under certain operating conditions. Compared with R_0 and R_1 , the estimated C_1 is more sensitive to current dynamics, resulting in greater estimation fluctuations. Subsequently, the estimated internal resistance (R_0) is converted into the Resistance-based State of Health (SoH_R) using Equation (14). The resulting of SoH_R estimation is presented in Figure 6.

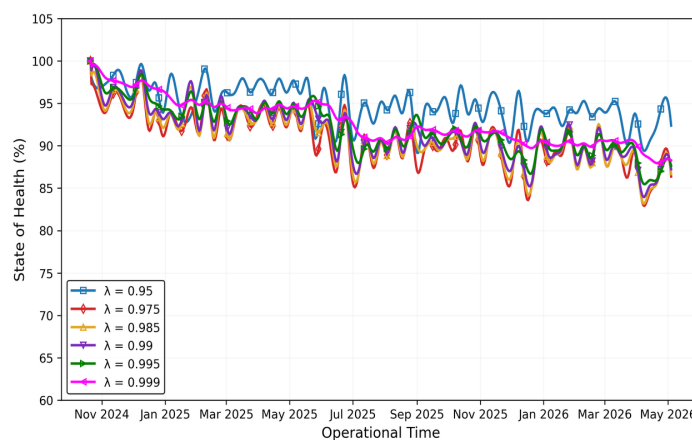


Figure 6. Resistance-based SoH estimation using different forgetting factor values

Figure 6 presents SoH_R estimated using the RLS algorithm with different forgetting factor values ($\lambda = 0.950 - 0.999$). Throughout the observation period from October 2024 to April 2026, all estimation trajectories exhibit a gradual decline in SoH from approximately 99–100% at the beginning of the monitoring period to approximately 88–90% at the end, corresponding to an overall battery degradation of about 10–12%. The most pronounced decline occurs during the middle to late stages of operation, which is consistent with the progressive increase in internal resistance caused by battery aging. The forgetting factor has a significant influence on the stability of the SoH_R estimation. The trajectory obtained with $\lambda = 0.950$ exhibits larger fluctuations and generally predicts slightly higher SoH values than the other configurations. In contrast, $\lambda = 0.995$ and $\lambda = 0.999$ produce smoother and more consistent estimation trajectories, providing a more reliable representation of the long-term battery degradation process. These results indicate that larger forgetting factor values are more suitable for constructing a stable HI, thereby improving the quality of the input sequence for LSTM model used in RUL prognostics.

Table 1 summarizes the effect of different forgetting factor (λ) values on the SoH_R estimation. As the forgetting factor increases, the estimated final internal resistance (R_0) decreases and becomes more stable, from 44.59 m Ω at $\lambda = 0.950$ to 37.04 m Ω at $\lambda = 0.999$. Consequently, the estimated final SoH_R increases from 86.48% to 88.08%, indicating that larger forgetting factor values provide more consistent degradation estimates that better reflect the actual battery condition. In terms of estimation accuracy, increasing the forgetting factor substantially improves the model performance. The RMSE decreases from 5.3577% to 1.0554%, the MAE decreases from 4.1127% to 0.8077%, and the MAPE decreases from 4.4969% to 0.8704%. Meanwhile, the coefficient determination (R^2) increases significantly from 0.0598 to 0.8354, indicating a much stronger agreement between the estimated and actual degradation trends. Although all scenarios require only a very short computational time (0.0026–0.0057 s), the differences are negligible. Therefore, $\lambda = 0.999$ is selected as the optimal forgetting factor, as it provides the highest estimation accuracy, the most stable parameter identification, and a negligible computational cost, making it well suited for generating a reliable Health Indicator for subsequent LSTM-based RUL prognostics.

Table 1. Comparison of RLS output parameters under different forgetting factor values

Parameter	Forgetting factor (λ)					
	$\lambda = 0.95$	$\lambda = 0.975$	$\lambda = 0.985$	$\lambda = 0.990$	$\lambda = 0.995$	$\lambda = 0.999$
Initial R_0 (m Ω)	30.74	26.13	26.01	26.17	26.35	26.5
Final R_0 (m Ω)	44.59	40.96	39.48	38.64	37.87	37.04
Final SoH _R (%)	86.48	82.97	84.47	85.71	86.88	88.08
RMSE (%)	5.3577	5.4756	4.1421	3.1793	2.0663	1.0554
MAE (%)	4.1127	4.2948	3.2951	2.5683	1.6745	0.8077
MAPE (%)	4.4969	4.8198	3.6423	2.8131	1.8238	0.8704
R^2	0.0598	0.1427	0.2486	0.3668	0.5794	0.8354
Computational time (second)	0.005668	0.003543	0.002652	0.002609	0.003517	0.003452

3.2 RUL Prognostic Performance

The LSTM model was employed to perform long-term forecasting of the SoH_R trajectory obtained from the ECM-RLS framework. The model input consisted of the HI generated from the ECM-based battery modeling and RLS parameter estimation, while the model output was the predicted future SoH_R trajectory until the predefined EoL thresholds of 80%, 70%, and 60% were reached. The prognostic model was implemented using a two-layer stacked LSTM architecture. To obtain the optimal prognostic performance, a sequential hyperparameter tuning strategy was adopted, consisting of two evaluation stages: Scenario A, which optimized the number of hidden units, and Scenario B, which optimized the learning algorithm (optimizer). In Scenario A, three stacked LSTM architectures were evaluated, representing lightweight (16–8 neurons), moderate (32–16 neurons), and relatively larger (64–32 neurons) network configurations. The first LSTM layer was configured with `return_sequences = True` to preserve temporal information for the subsequent LSTM layer. In addition, a dropout rate of 20% was applied after each LSTM layer to reduce the risk of overfitting. Based on the experimental results, the architecture yielding the lowest RMSE, MAE, MAPE, and computational time, together with the highest R^2 , was selected for the second evaluation stage.

In Scenario B, three widely used optimization algorithms Adam (Adaptive Moment Estimation), RMSprop (Root Mean Squared Propagation), and SGD (Stochastic Gradient Descent) were investigated to identify the most stable weight-update strategy. Furthermore, a fully connected Dense layer containing 16 neurons with the ReLU activation function was employed to capture nonlinear relationships from the LSTM outputs before producing the final SoH_R prediction through a single-neuron output layer. The performance comparison of all hyperparameter configurations evaluated in Scenarios A and B is summarized in Table 2.

Table 2. Performance comparison of LSTM hyperparameter configurations

Scenario	Model ID	Hidden units (Layer 1 & 2)	Optimizer	RMSE (%)	MAE (%)	MAPE (%)	R^2	Computational time (second)
Scenario A	M1.1	16 – 8	Adam	0,7422	0,5558	0,6444	0,8872	0,601362
	M1.2	32 - 16	Adam	0,9605	0,6692	0,7775	0,9118	0,200149
	M1.3	64 -32	Adam	0,8947	0,65	0,7542	0,9553	0,206641
Scenario B	M3.1	64 -32	Adam	0,8947	0,65	0,7542	0,9553	0,206641
	M3.2	64 -32	RMSprop	0,8871	0,6484	0,7527	0,9372	0,125035
	M3.3	64 -32	SGD	0,8699	0,7147	0,8267	0,9392	0,446784

The sequential evaluation of the LSTM model revealed distinct performance characteristics across the tested configurations. In Scenario A, which investigated different network architectures (hidden units) while maintaining the Adam optimizer, Model M1.1 with the smallest architecture (16–8 hidden units) achieved the lowest prediction errors, with an RMSE of 0.7422%, MAE of 0.5558%, and MAPE of 0.6444%. However, it yielded the lowest coefficient of determination ($R^2 = 0.8872$) and required the longest computational time (0.601362 s), indicating that its limited network capacity was insufficient to effectively capture the long-term degradation dynamics of the battery. Increasing the network capacity to Model M1.2 (32–16) and Model M1.3 (64–32) substantially improved the goodness of fit, with the R^2 values increasing to 0.9118 and 0.9553,

respectively. Although Model M1.3 exhibited a slightly higher RMSE (0.8947%) than Model M1.1, its considerably higher R^2 demonstrates a superior capability to capture the overall SoH_R degradation trend. Moreover, Model M1.3 achieved a significantly shorter computational time (0.206641 s), making it the most suitable hidden-unit configuration for the subsequent optimizer evaluation in Scenario B.

In Scenario B, the optimization focused on the learning algorithm while fixing the network architecture to the best-performing configuration identified in Scenario A (64–32 hidden units). Three optimization algorithms, namely Adam, RMSprop, and SGD, were comparatively evaluated. Among them, Model M3.3 using the SGD optimizer achieved the lowest RMSE (0.8699%) with an R^2 of 0.9392, but required the longest computational time (0.446784 s) due to the relatively slower convergence behavior of SGD. In contrast, Model M3.2 was employing the RMSprop optimizer exhibited the most balanced overall performance, achieving an RMSE of 0.8871%, MAE of 0.6484%, MAPE of 0.7527%, and an R^2 of 0.9372, while outperforming the Adam optimizer in terms of prediction error.

For long-term RUL prognostics, the primary consideration is the model's ability to accurately preserve the overall degradation trajectory rather than minimizing point-wise prediction errors alone. In this regard, Model M3.1, which employs the Adam optimizer with a 64–32 hidden-unit architecture, demonstrated the best overall performance by achieving the highest coefficient of determination ($R^2 = 0.9553$), while its prediction errors remained comparable to those of the RMSprop-based model. The superior R^2 indicates that the model more faithfully captures the long-term degradation trend, thereby reducing error accumulation during iterative multi-step forecasting. Therefore, Model M3.1 was selected as the optimal prognostic model and subsequently used to iteratively project the future SoH_R trajectory for RUL estimation. The resulting RUL prognostic trajectories obtained using the 64–32 hidden-unit architecture with the Adam optimizer are presented in Fig. 7.

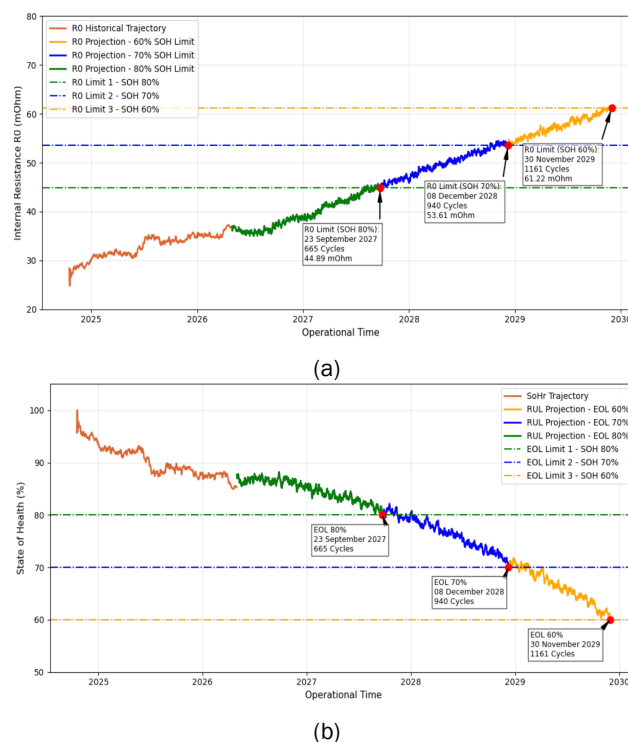


Figure 7. LSTM-Based RUL Prognostics: (a) R_0 prognostics, and (b) SoH_R Prognostics

Figure 7 illustrates the LSTM-based RUL prognostic results using the ohmic internal resistance (R_0) as the degradation indicator. The model successfully projects the battery degradation trend continuously beyond the end of the historical observation period in 2026. The historical trajectory shows an increase in R_0 from approximately 26.83 mΩ at the beginning of the observation period to 36.31 mΩ at the end of the training dataset. Subsequently, the LSTM model predicts that the internal resistance will continue to increase nonlinearly, reaching 44.89 mΩ on 23 September 2027, corresponding to the predefined 80% EoL threshold. Beyond this point, the resistance growth continues progressively, reaching 53.61 mΩ on 8 December 2028 for the 70% EoL threshold and further increasing to 61.22 mΩ on 30 November 2029 for the 60% EoL threshold. This degradation trajectory indicates that the battery aging mechanism progresses gradually, which is consistent with the characteristics of LiFePO₄ batteries, where internal resistance increases over time due to cumulative charge–discharge cycling and electrochemical degradation. Since the LSTM uses iterative multi-

step forecasting, errors accumulate with the forecast horizon, and the reported metrics (computed on observed data) do not reflect long-horizon errors. The RUL estimates are therefore extrapolations with increasing uncertainty at longer horizons and have not yet been validated against actual EoL data.

For comparison, the LSTM was benchmarked against the Gated Recurrent Unit, or GRU, a simplified variant of the LSTM architecture that retains the ability to model temporal dependencies. The LSTM better follows the long-term degradation trend, as indicated by its higher R^2 , namely 0.9553 versus 0.8627 for the GRU. In contrast, the GRU achieved slightly better prediction accuracy, with an RMSE of 0.697% versus 0.8947% for the LSTM, an MAE of 0.5536% versus 0.6500%, and a MAPE of 0.6018% versus 0.7542%, as well as a shorter computational time. Since long-term prognostics prioritizes preserving the overall degradation trajectory over minimizing point-wise errors, the LSTM was selected as the prognostic model.

4. Conclusion

The results of this study demonstrate that the first-order Thevenin 1-RC model successfully represents the dynamic characteristics of the LiFePO_4 battery in a residential microgrid system through the estimation of physical parameters, including the ohmic resistance (R_0), polarization resistance (R_1), and polarization capacitance (C_1). The identified parameters provide a reliable basis for internal resistance tracking and real-time battery SoH estimation. The implementation of the RLS algorithm with a forgetting factor mechanism significantly improves the accuracy of SoH_R estimation. Among the evaluated configurations, $\lambda = 0.999$ achieved the best performance, with an RMSE of 1.0554%, MAE of 0.8078%, MAPE of 0.8707%, and $R^2 = 0.8354$. The proposed approach successfully tracked the increase in ohmic resistance (R_0) from 26.5 m Ω to 37.04 m Ω , corresponding to a reduction in SoH_R to 88.08% after 348 equivalent cycles. Furthermore, the LSTM-based prognostic model, utilizing degradation features extracted from the RLS estimation, the optimized LSTM model successfully projected the future SoH_R trajectory and estimated the RUL under predefined EoL threshold scenarios. The optimized LSTM model achieved an RMSE of 0.8947%, MAE of 0.6500%, MAPE of 0.7542%, and $R^2 = 0.9553$. The model predicted the battery EoL thresholds at 511 days for $\text{SoH}_R = 80\%$, 953 days for $\text{SoH}_R = 70\%$, and 1,310 days for $\text{SoH}_R = 60\%$, demonstrating the effectiveness of the proposed hybrid ECM-RLS-LSTM framework for battery health monitoring and long-term prognostics in residential BESS applications.

These predictions are extrapolations and have not yet been validated against actual EoL data, which remains a limitation of this study. Future work is recommended to apply a Variable Forgetting Factor (VFF-RLS) algorithm so that λ can adapt automatically to dynamic load transients in the microgrid, yielding stable internal resistance estimates without losing responsiveness. Future studies are also encouraged to incorporate ambient temperature compensation and to integrate uncertainty quantification methods, such as Bayesian Neural Networks or Monte Carlo Dropout, into the LSTM or GRU models to provide uncertainty intervals for RUL predictions. In addition, the RUL predictions should be validated against actual end-of-life data and tested on more battery units.

References

- [1] Directorate General of New and Renewable Energy and Energy Conservation, Ministry of Energy and Mineral Resources of the Republic of Indonesia, *Laporan Kinerja Direktorat Jenderal EBTKE Tahun 2025*, Jakarta, Indonesia, 2026. [Online] Available : <https://www.esdm.go.id/content-laporan-kinerja-ditjen-ebtke-tahun-2025.pdf> [Accessed: Oct. 6, 2026].
- [2] S. A. Hasib, S. Islam, R. K. Chakraborty, M. J. Ryan, D. K. Saha, M. H. Ahamed, S. I. Moyeen, S. K. Das, M. F. Ali, M. R. Islam, Z. Tasneem, F. R. Badal, "A comprehensive review of available battery datasets, RUL prediction approaches, and advanced battery management," *IEEE Access*, vol. 9, pp. 86166–86193, 2021. <https://doi.org/10.1109/ACCESS.2021.3089032>
- [3] J. Chen, Y. Hu, Q. Zhu, H. Rashid, and H. Li, "A novel battery health indicator and PSO-LSSVR for LiFePO_4 battery SOH estimation during constant current charging," *Energy*, vol. 282, Art. no. 128782, 2023. <https://doi.org/10.1016/j.energy.2023.128782>
- [4] M. Novak and M. Mikolasek, "State of Health estimation of lithium-ion batteries based on incremental capacity and pulse analysis," in 2023 13th European Space Power Conference, ESPC 2023, Institute of Electrical and Electronics Engineers Inc., 2023. <https://doi.org/10.1109/ESPC59009.2023.10298169>
- [5] C. R. Liou, K. C. Sou, Y. C. Hsieh, C. C. Huang, P. I. Pan, C. Y. Wu, L. Y. Sung, K. Y. Chang, F. J. Liang, "State of Health estimation for LiFePO_4 batteries using incremental capacity analysis," in Conference Record - IAS Annual Meeting (IEEE Industry Applications Society), Institute of Electrical and Electronics Engineers Inc., 2025. <https://doi.org/10.1109/IAS62731.2025.11061672>

- [6] S. Liu, Y. Hu, J. Li, S. Luo, S. Zhang, Y. Li, M. Hou, X. Chen, W. Yi, C. Lu, "State of Charge estimation of lithium battery based on improved unscented Kalman filter," in 2024 IEEE 10th International Conference on Underwater System Technology: Theory and Applications, USYS 2024, Institute of Electrical and Electronics Engineers Inc., 2024. <https://doi.org/10.1109/USYS62456.2024.11116367>
- [7] J. B. Kondru and Y. P. Obulesu, "Estimation of State of Charge and State of Health in aged lithium-ion battery performance: an extended Kalman filter approach for predictive modelling," in Proceedings of the 3rd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems, ICPEICES 2024, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 819–823. <https://doi.org/10.1109/ICPEICES62430.2024.10719350>
- [8] M. Zhong, B. Jiang, H. Zhou, Y. Chen, M. Yuan, and Y. Zhou, "Combined online estimation of state-of-charge and state-of-health of lithium-ion power battery based on dual extended Kalman filters," in Proceedings - 2023 China Automation Congress, CAC 2023, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 1599–1604. <https://doi.org/10.1109/CAC59555.2023.10450502>
- [9] S. Wang, K. Ou, W. Zhang, and Y. X. Wang, "A state-of-charge and state-of-health joint estimation method of lithium-ion battery based on temperature-dependent extended Kalman filter and Deep Learning," IEEE Transactions on Industrial Electronics, vol. 72, no. 1, pp. 570–579, 2025. <https://doi.org/10.1109/TIE.2024.3409912>
- [10] G. K. Suhas, S. Ashwini Singh, V. Trupthi, P. V. Keerthishree, N. R. Deepak, and R. Loganathan, "Estimating the State of Health of lithium-ion batteries using support vector regression," in 3rd IEEE International Conference on Mobile Networks and Wireless Communications, ICMNWC 2023, Institute of Electrical and Electronics Engineers Inc., 2023. <https://doi.org/10.1109/ICMNWC60182.2023.10435916>
- [11] S. Patil, S. M. Havaladar, R. K. Bhavana, S. Mathad, and K. R. Patil, "Lithium-ion battery State of Health estimation using Support Vector Regression (SVR)," in IEEE 1st International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics, AIKIE 2023, Institute of Electrical and Electronics Engineers Inc., 2023. <https://doi.org/10.1109/AIKIE60097.2023.10390075>
- [12] C. Ma and C. Ren, "A hybrid Neural Network model for lithium-ion battery health state based on data-driven approach," in Proceedings of the 37th Chinese Control and Decision Conference, CCDC 2025, Institute of Electrical and Electronics Engineers Inc., 2025, pp. 2059–2064. <https://doi.org/10.1109/CCDC65474.2025.11090855>
- [13] K. Chen, H. Pang, G. Lin, F. Wang, W. Nan, and J. Du, "An accurate BiLSTM data-driven model for SoH prediction of lithium batteries based on health indicators," in 2024 IEEE Transportation Electrification Conference and Expo, Asia-Pacific, ITEC Asia-Pacific 2024, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 423–428. <https://doi.org/10.1109/ITECAsia-Pacific63159.2024.10738549>
- [14] D. Y. Reddy, B. Routh, A. Patra, and S. Mukhopadhyay, "Gaussian Process Regression based State of Health estimation of lithium-ion batteries using indirect battery health indicators," in 2021 IEEE International Conference on Prognostics and Health Management, ICPHM 2021, Institute of Electrical and Electronics Engineers Inc., Jun. 2021. <https://doi.org/10.1109/ICPHM51084.2021.9486519>
- [15] W. He, R. Zhang, X. Wang, S. Wang, and A. I. Gavrilo, "Lithium battery health state prediction based on LSTM," in 2025 IEEE 20th Conference on Industrial Electronics and Applications, ICIEA 2025, Institute of Electrical and Electronics Engineers Inc., 2025. <https://doi.org/10.1109/ICIEA65512.2025.11148424>
- [16] Q. Li, H. Chen, S. Cai, L. Wang, H. Gu, and M. Zheng, "State estimation of lithium-ion battery at different temperatures based on DEKF and RLS," in Proceedings of the 16th IEEE Conference on Industrial Electronics and Applications, ICIEA 2021, Institute of Electrical and Electronics Engineers Inc., Aug. 2021, pp. 1619–1624. <https://doi.org/10.1109/ICIEA51954.2021.9516414>
- [17] M. Bellomo, S. Giazitzis, S. Badha, F. Rosetti, E. Ogliari, A. Dolara, F. Grimaccia, "A novel data-driven approach for the simultaneous prediction of State of Health trajectory and remaining useful life in lithium-ion batteries," Proceedings - 24th IEEE International Conference on Environment and Electrical Engineering and 8th I and CPS Industrial and Commercial Power Systems Europe, IEEEIC/I and CPS Europe 2024, Institute of Electrical and Electronics Engineers Inc., 2024. <https://doi.org/10.1109/IEEEIC/ICPSEurope61470.2024.10751417>
- [18] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, "Modeling of lithium-ion battery degradation for cell life assessment," IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 1131–1140, 2018. <https://doi.org/10.1109/TSG.2016.2578950>