UTM UNIVERSITI TEKNOLOGI MALAYSIA
INTERNATIONAL JOURNAL OF INNOVATIVE COMPUTING
ISSN 2180-4370
Journal Homepage : https://ijic.utm.my/

Hybrid Wavelet-PCA and DNN-LSTM-Kalman Framework for Robust State-of-Charge Estimation Using Minimal Sensors

Nur Mohamed Mohamud[1], Siti Mahfuza Saimon[2*] & Shahrin Md Ayob[3]
Department of Electrical Power Engineering,
Faculty of Electrical Engineering, Universiti Teknologi Malaysia
81310 UTM Johor Bahru, Johor, Malaysia
Email: nurmohamedmohamud@graduate.utm.my[1], sitimahfuza@utm.my[2], e-shahrin@utm.my[3]

Submitted: 15/9/2025. Revised edition: 28/11/2025. Accepted: 5/1/2026. Published online: 28/7/2026
DOI: https://doi.org/10.11113/ijic.v16n1-2.688

***Abstract*—An accurate prediction of state of charge (SOC) is essential for the operational performance and durability of lithium (Li)-ion battery systems in electric vehicles. Its accuracy in dynamic operation, however, is often limited by noise sensitivity, drift buildup and rest-conditioning dependence of conventional procedures such as Coulomb counting and open-circuit voltage. This work presents a two-stage hybrid framework for SOC estimation to overcome these limitations. The first stage includes wavelet transform denoising and principal component analysis (PCA) to enhance the quality of signal, eliminate redundant information, and achieve a signal-to-noise ratio (SNR) improvement up to 77.9 dB with 95% variance retention. The second stage combines a deep neural network (DNN)–long short-term memory (LSTM) model with Kalman filtering to capture nonlinear temporal dynamics and generate smoothed SOC predictions. Experimental results show that the root mean squared error (RMSE) of baseline SOC estimation methods was 21.8%, while that of the proposed method was only 0.52%, achieving over forty-fold accuracy improvement. The proposed framework demonstrates strong robustness under noisy and dynamic operating conditions and can be further extended to state of health (SOH) prediction by incorporating battery degradation features, enabling predictive maintenance and enhancing long-term reliability in battery management systems.**

***Keywords*—State of Charge, Kalman Filter, DNN–LSTM, Battery Management System, Wavelet Transform, Principal Component**

I. INTRODUCTION

Precise estimation of the state of charge (SOC) is vital for the safety, performance and lifespan of lithium (Li)-ion batteries in electric vehicles (EVs). Conventional estimators such as Coulomb Counting (CC) and Open-Circuit Voltage (OCV) are widely used because they require minimal computational resource and few sensors. However, they exhibit low noise tolerance and are highly sensitive to initialization errors and noise or capacity variations resulting from different operating conditions [1]. To mitigate these weaknesses, various Kalman filter-based algorithms, including the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) have been developed [2]. These approaches can handle certain uncertainties and improve estimation stability, but they remain sensitive to parameter mismatches and linearization errors, especially when applied to aged batteries with non-linear system behavior.

Further research has focused on adaptive Equivalent Circuit Models (ECMs) and hybrid machine-learning techniques. A time-varying adaptive ECM insensitive to temperature offset was proposed in [3], while Gaussian Process Regression (GPR) combined with Adaptive Kalman Filtering (AKF) was introduced in [4] to enhance open-circuit voltage (OCV) estimation. In addition, hysteresis modelling was improved using Recursive Least Squares (RLS) in [5] , and a Temporal Convolutional Network (TCN) integrated with an ECM was employed in [6] to compensate for nonlinear system relationships. These adaptive approaches reduced estimation errors to below 2% root mean square error (RMSE) but required noise-free sensor data and incurred significant computational cost, limiting real-time applicability.

Numerous hybrid models combining ECMs with neural networks have also been investigated to further improve robustness. A two-resistor-capacitor ECM combined with a Backpropagation Neural Network (BPNN) was presented in . [7] for semi-solid-state batteries, achieving an RMSE of less than 0.5% under Urban Dynamometer Driving Schedule (UDDS) conditions. Similarly, a hybrid Coulomb Counting–Unscented Kalman Filter (CC–UKF) approach with improved drift correction was proposed in [8] , while the Grasshopper Optimization Algorithm (GOA) combined with a Double Adaptive Unscented Kalman Filter (DAUKF) was employed in [9] for simultaneous estimation of SOC and state of health (SOH). Despite their high accuracy, these methods remain dependent on noise-free measurements and exhibit limited robustness under real-world driving conditions.

Comprehensive reviews have summarized both classical and advanced SOC and SOH estimation methods, including OCV lookup, Coulomb counting, Kalman filtering, and adaptive modeling [10]. Key challenges identified include dependence on clean sensor data, parameter sensitivity, and high computational demand. While adaptive and distributed techniques proposed in [11,12,13] improved adaptability and scalability, most existing methods still experience performance degradation when exposed to real-world noise and dynamic operating conditions. This highlights the need for a robust and computationally efficient SOC estimation framework capable of handling practical uncertainties.

To address these challenges, this study proposes a two-stage hybrid framework that integrates wavelet based denoising and principal component analysis (PCA) guided feature optimization with deep neural network (DNN) and long short-term memory (LSTM) models enhanced by Kalman filtering. The proposed method improves signal quality, achieving up to 77.9 dB signal to noise ratio (SNR) with 95% variance retention, while capturing nonlinear temporal dynamics and stabilizing prediction accuracy. It achieves at least an order of magnitude improvement over baseline methods, reducing SOC estimation error from 21.8% RMSE to 0.52%. The results demonstrate that combining signal enhancement with hybrid deep learning modelling provides a robust, efficient, and accurate SOC estimation approach for practical battery management system (BMS) applications, paving the way for future SOH prediction and predictive maintenance in EVs.

II. Methodology

Fig. 1 depicts the overall flow of the proposed hybrid approach for SOC estimation. The process originates with experimental data (comprising current, voltage, temperature, and time) measured from an EV battery system. From these measurements, reference SOC values are first established using CC and OCV-SOC relationships. The data then enters the two-stage framework. The first stage consists of pre-processing, where wavelet de-noising and PCA are applied to remove signal noise, ensuring that only noise-resistant features are retained. In the second stage, this extracted signals are fed into a hybrid DNN–LSTM model integrated with a Kalman filter. This model is designed to accurately estimate SOC under nonlinear and dynamic operating conditions. Finally, the workflow concludes with an evaluation layer, where the accuracy of the estimated SOC is validated against the reference values using RMSE. This step confirms the robustness and accuracy of the model in real time.

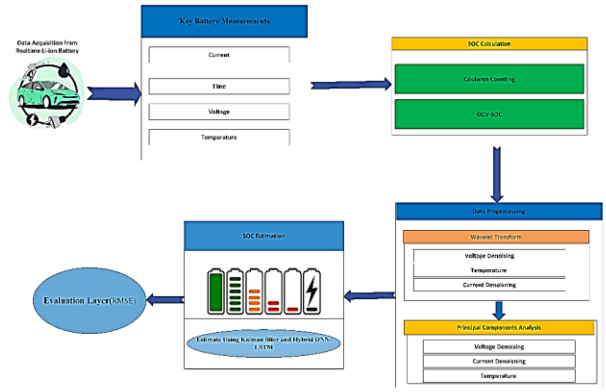

Fig. 1. Proposed SOC estimation framework integrating pre-processing (wavelet + PCA) and hybrid modelling (DNN–LSTM + Kalman Filter)

A. Data acquisition and preparation

The reliability of SOC and SOH estimation depends mostly on the quality of experimental data used. In practice, such data must capture the complex and dynamic behavior of Li-ion batteries when operating under real conditions. The raw measurements provided the basis for feature extraction as well as for the design of the estimation algorithms. Notably, the dataset did not include direct SOC or SOH labels, instead, reference values for training and validation were reconstructed offline from the measured battery signals.

B. Experimental dataset

In this study, the experimental data was acquired from one Murata US18650VTC5D Li-ion cell which has a nominal voltage at 3.6 V and rated capacity of 2.8 Ah. The cell was evaluated in the laboratory, following the charging and discharging protocols, both under constant currents (1C, i.e., 2.8 A). The cutoff voltage was 4.2 V for charging, and 2.5 V for discharging with motivation to ensure safe operation and to capture the full available capacity of the cell.

The recorded parameters include:

(i) Voltage (V): instantaneous terminal voltage of the cell,

(ii) Current (A): applied charge or discharge current,

(iii) Temperature (°C): measured at multiple points and recorded as minimum, maximum, and average values,

(iv) Capacity (Ah, Wh): accumulated charge/discharge capacity during cycling,

(v) Timestamp: time-based recording interval for synchronization.

The key specifications of the Murata US18650VTC5D cell are summarized in Table I.

TABLE I. CELL SPECIFICATION OF LITHIUM ION BATTERY

Battery Type	Li-Ion Murata
Model	US18650VTC5D
Nominal Capacity	2.8 Ah
Nominal Voltage	3.6 V
Charging Voltage	4.2 V
Minimum Operating Voltage	2.5 V
Charging Method	Constant Current, Constant Voltage (CV)
Weight Dimension	46.7 g
Nominal Capacity	Diameter – 18.5 mm
Nominal Voltage	Height – 65.25 mm

C. Derivation of SOC

The dataset lacked measured SOC values, so reference SOC values were derived offline using CC with OCV correction. This method integrates current over nominal capacity and uses feedback between voltage and OCV–SOC to mitigate drift. These reference SOC values serve as ground truth for training and testing a hybrid DNN–LSTM and Kalman filter model, distinct from the SOC prediction process. The baseline SOC was established from the OCV–SOC relationship specified in the dataset, confirmed by prior studies under equilibrium conditions. Due to the impracticality of measuring OCV during dynamic cycling, an offline OCV–SOC curve was utilized. Terminal voltage data was denoised with a wavelet technique, and the cleaned signal was interpolated along the OCV–SOC curve to create a reliable reference SOC profile, enabling consistent model accuracy assessment under varying charging and discharging conditions.

The SOC is calculated using the following equation:

$$SOC(t) = SOC(0) - \frac{1}{C_n}\int_0^t I(t) \quad (1)$$

Where, $SOC(0)$ is initial SOC (100% at fully charged state), C_n is nominal capacity (2.8 Ah), and $I(t)$ is measured current at time t (positive for charging, negative for discharging). For discrete data samples, SOC is obtained from:

$$SOC(k) = SOC(k-1) - \frac{I(k)\Delta t}{C_n} \quad (2)$$

Where Δt is at sampling interval. To improve robustness, OCV-SOC calibration data were used to periodically correct drift in calculated SOC values, providing more reliable reference targets.

D. Signal preprocessing and feature extraction

As the raw battery signals collected from laboratory tests may contain measurement noises, fluctuations and redundancies, which can explicitly lower the accuracy of machine learning-based models. Thus, it is important to make sure the SOC and SOH estimation are reliable through pre-processing and feature extraction. In this study, two principal methods were used, wavelet transform for noise reduction and PCA for feature optimization.

1) Wavelet transform for noise reduction

The measured voltage, current, and temperature signals inevitably contain high-frequency noise due to sensor imperfections and environmental disturbances. To suppress these effects while preserving essential signal characteristics, the discrete wavelet transform was employed. A signal $x(t)$ can be expressed using wavelet decomposition as

$$x(t) = \sum_k c_{jo,k}\phi_{jo,k}(t) + \sum_{j=jo}^{j}\sum_k d_{j,k}\psi_{j,k}(t) \quad (3)$$

Where $\phi_{jo,k}(t)$ and $\psi_{j,k}(t)$ are the scaling and wavelet functions, $c_{jo,k}$ and $d_{j,k}$ are the approximation and detail coefficients, j is the decomposition level, and k is the translation index. By filtering the detail coefficients, noise was effectively removed.

2) Principal Component Analysis for feature extraction

Battery data sets typically contain correlated signals (such as the voltage and current profiles) which may become repeated and add to model complexity. To lower the dimension while preserving important information, PCA was applied. PCA projects original variables to a new set of orthogonal variables (principal components) which are linear combinations of the original features. Given a dataset X with zero-mean, PCA is computed by solving the eigen value decomposition of the covariance matrix (C):

$$C = \frac{1}{n-1}X^T X \quad (4)$$

$$C\omega i = \lambda i \omega i \quad (5)$$

Where λ_i is the eigenvalue representing the variance explained by the i^{th} principal component and ωi is the corresponding eigenvector. The first few principal components that capture the majority of variance (≥95%) were selected and used as inputs for model training. This reduces noise sensitivity, eliminates redundancy, and improves computational efficiency in the SOC and SOH estimation models.

E. SOC estimation framework

Precise monitoring of the SOC is regarded as one of the most important aspects in battery management that can represent the available energy capacity and guarantee the safety of electric vehicle systems. In the work, SOC estimation was performed using a hybrid model, DNN–LSTM model and Kalman filtering. The hybridization takes advantage of the learning ability of the DNN–LSTM for extracting nonlinear temporal dependencies from battery data, and the Kalman filter updates provide recursive corrections to mitigate estimation drift and noise in the measurement.

The DNN–LSTM architecture was designed for learning nonlinear from the preprocessed signals. Measuring data of voltage, current and temperature (after wavelet denoising and PCA feature optimization) were utilized for model input and the resulted SOC reference (from CC with model based OCV correction) was employed as training target.

The model consists of:

(i) DNN hidden layers: capturing complex interactions between features.

(ii) LSTM layers: to capture temporal dependencies among sequential charge–discharge cycles.

The LSTM cell operations (forget gate f_t, input gate $\dot{u}_t$, output gate o_t, cell state C_t,, and hidden state h_t) are defined by the following equations:

$$f_{t=}\sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{6}$$

$$\dot{u}_t = \sigma\left(W_f[h_{t-1}, x_t] + b_i\right) \tag{7}$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C \tag{8}$$

$$C_t = f_t . C_{t-1} + \dot{u}_t . \tilde{C}_t \tag{9}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = o_t . \tanh(C_t) \tag{11}$$

Where x_t is the input feature vector, σ is the signoid activation function, and W and b are trainable weight matrices and bias vectors, respectively. The network was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Early stopping and dropout regularization were applied to prevent overfitting.

1) Kalman filter integration

While the proposed DNN–LSTM is capable of capturing temporal relationships, it is still sensitive to cumulative drift errors due to long sequence exposure or noisy signals. In order to eliminate this limitation, we refined the DNN–LSTM output, using a Kalman filter.

The terminal voltage feedback is considered for the predicted SOC correction by the Kalman filter with respect to the OCV–SOC through. It works in the following two steps:

(i) Prediction Step:

$$S\hat{O}C^-(k) = S\hat{O}C(K-1) - \frac{I(k)\Delta t}{C_n} \tag{12}$$

$$P^-(k) = P(k-1) + Q \tag{13}$$

(ii) Correction step:

$$K(k) = \frac{P^-(k)}{P^-(k) + R} \tag{14}$$

$$S\hat{O}C(k) = \hat{O}C^-(k) + K(k)[V_{meas}(k) - V_{pred}(k)] \tag{15}$$

$$P(k) = (1 - K(k)P^-(k) \tag{16}$$

Where:

$S\hat{O}C(k)$= corrected SOC estimate

$I(k)$ = measured current,

$V_{meas}(k)$ = measured terminal voltage

$V_{pred}(k)$ = predicted voltage from OCV-SOC curve,

C_n= nominal capacity(2.8Ah)

Q, R = process and measurement noise covariances

$K(k)$ = Kalman gain.

This recursive correction ensures that the SOC estimate remains stable and accurate, even under noisy operating conditions.

III. Results and Discussion

A. Correlation analysis and data visualization

The raw battery data was initially examined for signal characteristics and variable relationships. Scatter plots and histograms in Fig. 2 verified uniform distributions in voltage, current and temperature respectively. The correlation heatmap in Fig. 3 showed a highly negative relationship between voltage and current (r = −0.71), followed by the moderate relation between current and temperature (r = −0.35). Results add importance to pre-processing step for redundancy elimination and noise attenuations due to sensor errors.

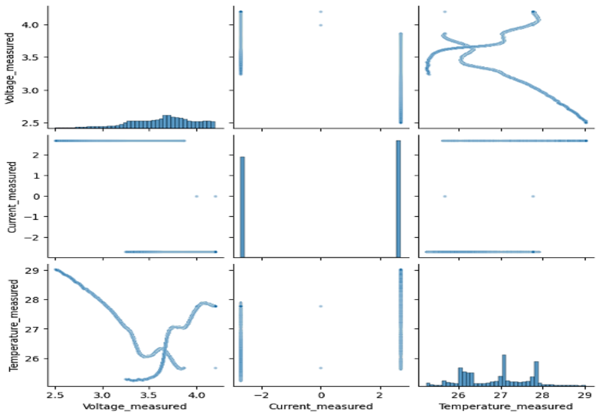

Fig. 2. Scatter plots and histograms

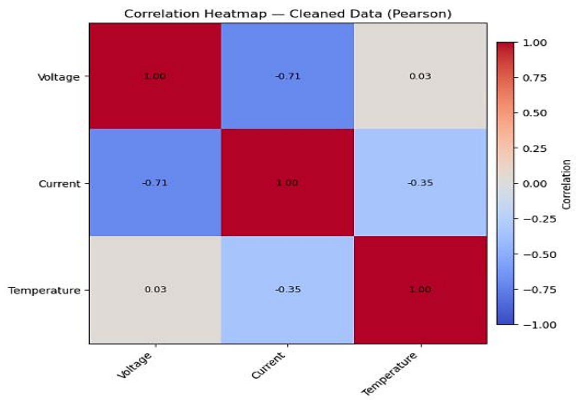

Fig. 3. Correlation heatmap

B. Wavelet denoising performance

Voltage, current and temperature signals were decomposed by wavelet transform (db4) to remove noise in the data and extract dynamical structures. Comparisons of raw and denoised signals are presented in Figs. 4–6, indicating good de-noising result. Quantitative analysis (Tables II–IV) supported a significant increase in SNR. The maximum SNR was found to be 76.6, 77.9 and 56.9 dB for voltage, temperature and current at their optimal thresholds respectively. These findings support efficiency of wavelet denoising as a preprocessing step.

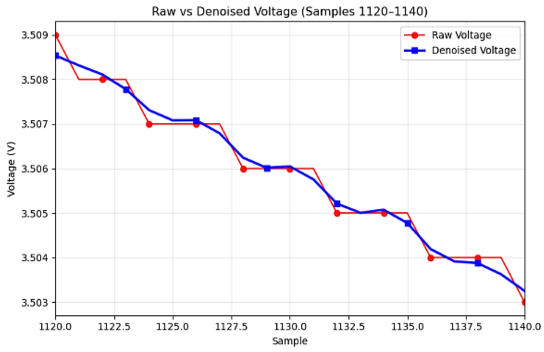

Fig. 4. Voltage raw and denoised signals

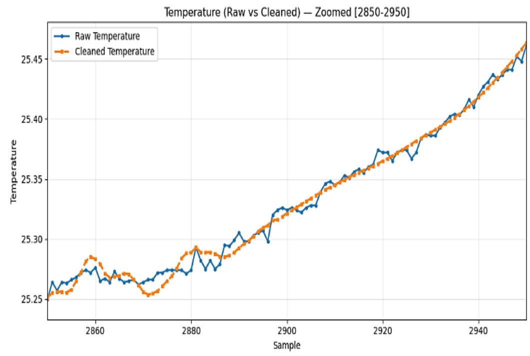

Fig. 5. Temperature raw and denoised signals

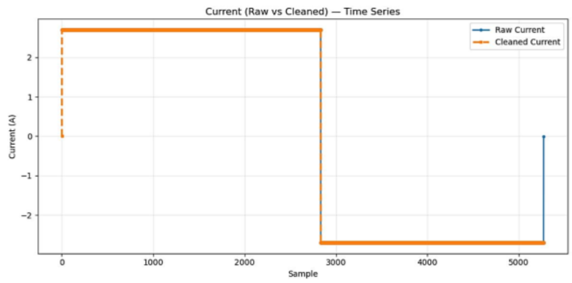

Fig. 6. Current raw and denoised signals

TABLE II. DENOISING PERFORMANCE (CLEANED VOLTAGE)

Denoising Level	Threshold	PowerNoise_Denoised	SNR_dB
1	0.01	2.887×10^{-7}	7.662×10^{1}
2	0.05	5.136×10^{-6}	6.412×10^{1}
3	0.1	1.785×10^{-5}	5.871×10^{1}
4	0.15	3.609×10^{-5}	5.565×10^{1}
5	0.2	5.955×10^{-5}	5.348×10^{1}

TABLE III. DENOISING PERFORMANCE (CLEANED TEMPERATURE)

Denoising Level	Threshold	PowerNoise_Denoised	SNR_dB
1	0.01	1.180×10^{-5}	7.788×10^{1}
2	0.05	2.283×10^{-4}	6.501×10^{1}
3	0.1	7.270×10^{-4}	5.998×10^{1}
4	0.15	1.473×10^{-3}	5.691×10^{1}
5	0.2	2.359×10^{-3}	5.487×10^{1}

TABLE IV. DENOISING PERFORMANCE (CLEANED CURRENT)

Denoising Level	Threshold	PowerNoise_Denoised	SNR_dB
1	0.01	1.459×10^{-5}	5.698×10^{1}
2	0.05	3.081×10^{-4}	4.372×10^{1}
3	0.1	1.004×10^{-4}	3.858×10^{1}
4	0.15	2.046×10^{-3}	3.547×10^{1}
5	0.2	3.470×10^{-3}	3.317×10^{1}

C. Principal component analysis (PCA)

PCA was adopted to reduce redundancy and compact features after denoising. The scree plot in Fig.7 indicated that three principal components (PCs) explained 95% of the total variance. The PCA biplot in Fig. 8 demonstrated that voltage, current and temperature were quite different along the first two PCs, which verify the feasibility of preserving key phenomena related to battery behavior.

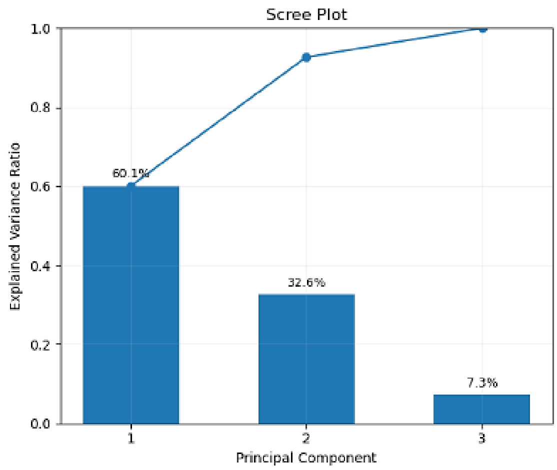

Fig. 7. Scree plot

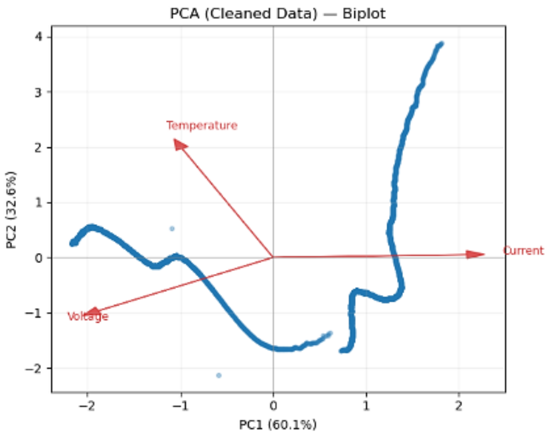

Fig. 8. Biplot

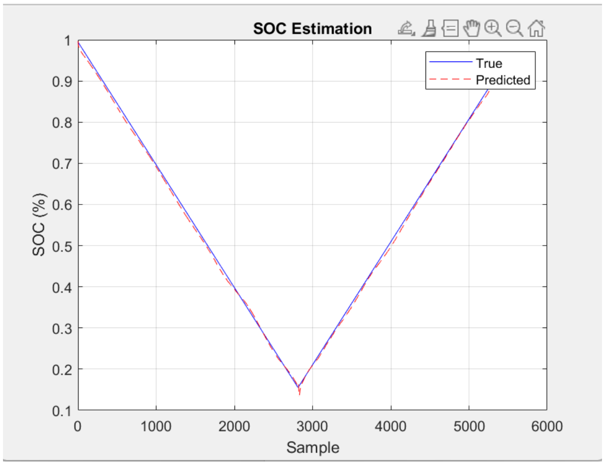

Fig. 10. The SOC result of the proposed hybrid DNN–LSTM–Kalman model compared with the true SOC values.

D. Hybrid DNN–LSTM with Kalman filter

1) Baseline SOC Estimation

This baseline estimate of SOC was conducted with no explicit advanced pre-processing and hybrid modeling. By comparison, as in Fig. 9, the estimation for SOC significantly deviated from the real characteristic especially during a phase of discharge and recovering. The resulting error was 21.8% RMSE, a value many times larger than what is acceptable for real-life battery management. This suboptimal performance also demonstrates the limitation of traditional estimation algorithms under noisy and dynamic environments.

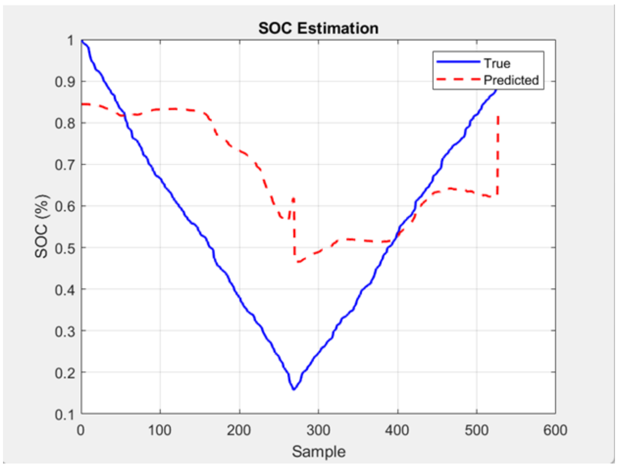

Fig. 9. Baseline SOC estimation

2) Hybrid DNN–LSTM with Kalman Filtering

The developed hybrid model was first trained with wavelet-denoised and PCA-optimized inputs. As we can see from Fig. 10, the estimated content profile was consistent with the true profile and showed impressive accuracy (RMSE of 0.52%, more than 40-fold improvement over baseline). The hybrid approach effectively combined:

E. Discussion

The results validate the efficiency of the proposed two-stage framework. The significant reduction in RMSE from 21.8% (baseline) to 0.52% (proposed model) demonstrates a clear synergy between the signal pre-processing and hybrid modelling stages. The wavelet denoising stage is a critical component. By attenuating high-frequency noise from the voltage, current, and temperature signals, it provides a refined input signal to the deep learning model. This allows the DNN-LSTM to model the battery's core nonlinear temporal dynamics more effectively, as the underlying patterns are no longer obscured by stochastic sensor disturbances. The subsequent PCA optimization further enhances this process by eliminating data redundancy, thereby improving model efficiency.

This synergistic effect explains the framework's superior performance over methods that presuppose ideal or noise-free inputs. While many recent advanced methods (Kadem & Kim, 2023, Fan *et al.*, 2025) focus on enhancing the ECM model itself, their performance often degrades in the presence of noisy signals. The proposed framework, by contrast, is specifically designed to handle such noise, demonstrating superior robustness. In terms of computational complexity and real-time feasibility, the wavelet transform and PCA model training represent a one-time, offline computational cost. The trained inference model (DNN-LSTM and Kalman filter) is computationally efficient and viable for implementation on practical BMS applications.

However, the model formulation still depends on well-tuned wavelet parameters and network hyperparameters for best performance in a different battery chemistry and drive cycle. Despite this, the framework demonstrates high potential for scalability and adaptation. The pre-processing pipeline is inherently adaptable, and the model can be extended to other critical estimation tasks, such as the SOH estimation mentioned previously. This approach achieves a compelling balance of robustness and accuracy, making it highly amenable to real-time electric vehicle BMS applications.

IV. Conclusion

A two-stage hybrid framework was proposed in this work for precise SOC estimation of Li-ion batteries. The first stage used wavelet transformation to remove measurement noise and PCA to decrease redundancy, creating noise-resistant and feature-enhanced inputs. The second stage developed a hybrid DNN–LSTM with Kalman filter model that used temporal sequence learning and stability filtering to predict reliable SOC values. Experimental results showed that conventional methods resulted in a high error rate of 21.8% (RMSE) and were therefore not feasible for real-time battery management. In comparison, the hybrid framework leads to an RMSE of 0.52%, which is a more than 40-fold accuracy enhancement. This remarkable improvement illustrates the real-world impact of integrating signal enhancement and hybrid deep learning, delivering a robust and practical approach for SOC estimation in dynamic operating conditions. Future areas for investigation should focus on enhancing generalization by investigating lighter-weight networks, adaptive thresholding, and real-time learning. Addressing these challenges will be crucial for applying the model across different battery chemistries and drive cycles without extensive re-tuning. These advancements are anticipated to assist with the realization of intelligent and adaptive BMS for next-generation EVs

Acknowledgments

The authors would like to acknowledge the financial supports from Universiti Teknologi Malaysia for the funding under Potential Academic Staff (PAS) (Q.J130000.2723.04K07).

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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