ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20250118002279
Original scientific paper

Hybrid LSTM-Transformer and EPSO-EKF Framework for Advanced Battery Management Systems in Electric Vehicles

D. MANOJ*, F.T. JOSH

Abstract: The increasing adoption of Electric Vehicles (EVs) as a sustainable solution necessitates efficient and reliable Battery Management Systems (BMS) to mitigate greenhouse gas emissions. Lithium-ion batteries (LIBs), commonly used in EVs, face challenges in accurately estimating critical parameters such as State of Charge (SOC) and State of Health (SOH) due to complex battery dynamics and operational variability. SOC indicates the available energy relative to the battery's capacity, while SOH reflects the battery's capacity to retain charge. Inaccurate parameter estimation can lead to overcharging, over-discharging, and safety risks. This paper presents a novel hybrid BMS framework that integrates Long Short-Term Memory (LSTM) networks, Transformer architectures, and the Enhanced Particle Swarm Optimization-Extended Kalman Filter (EPSO-EKF). The LSTM-Transformer model effectively captures temporal dependencies and attention mechanisms, enhancing SOC and SOH estimation. The EPSO-EKF dynamically adjusts noise covariance, ensuring robust performance under diverse operating conditions. Evaluation using standard driving cycles, such as US06 and FUDS, demonstrates significant improvements in estimation accuracy. For example, the LSTM-Transformer model achieved a 15% reduction in *RMSE* for SOC and a 12% reduction in *RMSE* for SOH compared to standard LSTM models, with Adjusted R^2 values of 0.98 for SOC and 0.95 for SOH. This paper also reviews intelligent control strategies and advanced algorithms for BMS design, highlighting their customization potential, efficiency, and limitations. The findings emphasize the potential of integrating AI and optimization techniques for next-generation BMS in EV applications, advancing sustainable transportation.

Keywords: artificial intelligence (AI); battery management system (BMS); electric vehicles (EVs); optimization algorithm; state of charge (SOC)

1 INTRODUCTION

A Battery Management System (BMS) is vital in maintaining the smooth operation of LIBs by regulating charge and discharge cycles, preventing thermal runaway, and preserving battery health. Two critical parameters that the BMS monitors are the State of Charge (SOC) and the State of Health (SOH). SOC represents the available energy in the battery, expressed as a percentage of its full capacity, while SOH evaluates the battery's current ability to store and supply energy compared to its original state. Precise estimation of these parameters is essential to prevent overcharging, over-discharging, and thermal issues that could compromise safety and performance. Traditional SOC and SOH estimation methods, such as Coulomb counting and model-based approaches, often struggle with the complex, nonlinear behavior of LIBs. These methods are sensitive to variations in temperature, load, and aging, leading to inaccuracies that affect battery longevity and reliability. Additionally, external factors like driving conditions and environmental variables make these challenges even more pronounced, necessitating the development of more robust and adaptive solutions [1-8].

In recent years, artificial intelligence (AI) has revolutionized battery management. AI-driven techniques, including neural networks and hybrid algorithms, have shown promise in modeling the complex patterns and interactions in battery data. Recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have been particularly effective in capturing temporal and spatial dependencies, respectively. Hybrid models that combine these techniques offer a more comprehensive approach to SOC and SOH estimation [9]. This research introduces a new hybrid model that combines gated recurrent units (GRUs) with CNNs for SOC estimation, enhanced by the Adaptive Cubature Kalman Filter (ACKF). GRUs, a variant of RNNs, efficiently handle sequential data and capture temporal patterns, while CNNs specialize in detecting spatial features within battery performance metrics. The integration of the ACKF improves the estimation process by dynamically adjusting the noise covariance matrices, allowing the model to adapt to changing and nonlinear conditions [10].

The performance of the GRU-CNN-ACKF system is tested under real-world driving scenarios, including the US06 and Federal Urban Driving Schedule (FUDS) cycles, which feature varying speed and load conditions. Evaluation metrics such as root-mean-square error (*RMSE*), residual sum of squares (RSS), and correlation coefficients are used to assess the system's accuracy and reliability. Results show that the GRU-CNN-ACKF model outperforms existing techniques in terms of prediction accuracy, adaptability, and reliability under dynamic conditions [11].

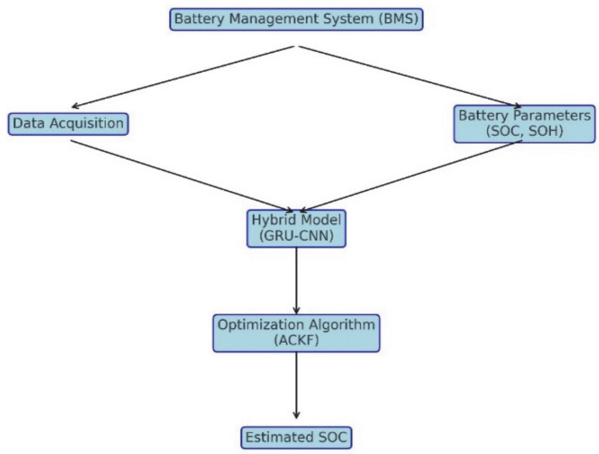


Figure 1 Proposed system architecture

By integrating AI-driven approaches with advanced optimization techniques, this research addresses key challenges in battery management for EVs. It contributes to improving the safety, efficiency, and reliability of LIBs, thus supporting the development of sustainable and energy-efficient transportation solutions. The proposed model not only enhances battery performance but also opens the door for innovative BMS designs tailored to the next generation of EV technologies [12].

Contribution: This research introduces a unique battery management system (BMS) methodology by merging Long Short-Term Memory (LSTM) and Transformer architectures. This fusion is distinct from conventional BMS approaches that typically employ either LSTM or Transformer models in isolation.

Outperformance: The hybrid model provides superior estimation of State of Charge (SOC) and State of Health (SOH) by capitalizing on the complementary strengths of both architectures. LSTM networks excel at processing sequential data, effectively capturing the temporal dependencies inherent in battery behavior over time. Transformers, on the other hand, leverage attention mechanisms to identify and prioritize the most influential data points, enhancing the model's ability to discern critical relationships within the complex battery dynamics. By integrating these capabilities, the hybrid model achieves a more nuanced understanding of battery performance, addressing the limitations of single-architecture approaches. For instance, it not only retains historical data patterns but also dynamically adjusts its focus to critical real-time variations, such as sudden load changes or temperature fluctuations, leading to more accurate and robust estimations.

2 RELATED WORKS

Various methods, both traditional and AI-based, have been proposed to tackle the challenges of SOC and SOH estimation. Traditional approaches such as open-circuit voltage measurement and Coulomb counting are relatively simple but fail to provide accurate estimations under dynamic operating conditions [13]. These techniques struggle to account for the nonlinear and time-varying behaviors of LIBs, leading to unreliable predictions under varying temperatures and loads [14]. To overcome these shortcomings, model-based techniques have been developed, including equivalent circuit models (ECMs) and electrochemical models. ECMs, like Thevenin and dual polarization models, represent the battery's behavior with electrical components and generally offer better accuracy than traditional methods. However, they are highly sensitive to parameter variations caused by aging and temperature changes [15]. Electrochemical models, which offer a more detailed understanding of battery dynamics, are computationally complex and often impractical for real-time applications [16].

The rise of artificial intelligence (AI) has brought new opportunities for more accurate and adaptive SOC estimation. Artificial neural networks (ANNs), for example, have shown promise by learning from historical data to predict future battery performance. Networks such as feedforward neural networks and radial basis function networks have been employed to improve accuracy, though they often require large datasets and lack real-time adaptability [17]. Recurrent neural networks (RNNs) are particularly well-suited for SOC estimation due to their ability to process sequential data. Models like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) help overcome issues like vanishing gradients, capturing long-term dependencies in time-series data. Studies show that LSTM and GRU models outperform traditional methods in dynamic conditions such as fluctuating load profiles and temperature variations [18].

Convolutional neural networks (CNNs), commonly used in image recognition, have also been applied to battery management. By extracting spatial features from input data, CNNs have demonstrated improved SOC and SOH estimation accuracy, especially when combined with other models [19]. Hybrid architectures, such as CNN-LSTM and CNN-GRU models, leverage the advantages of both networks, allowing for the robust modeling of temporal and spatial dependencies in battery data [20]. Optimization algorithms further enhance the performance of AI-based BMS. Methods such as particle swarm optimization (PSO) and genetic algorithms (GA) have been combined with neural networks to optimize hyperparameters and improve prediction accuracy. However, these techniques often involve high computational costs and can be susceptible to local minima [21]. Kalman filter-based methods, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), have been widely used for real-time SOC estimation because they effectively handle noise and nonlinearities. The Adaptive Cubature Kalman Filter (ACKF) is an advanced approach that dynamically adjusts noise covariance matrices, improving the accuracy of SOC estimation under varying conditions [22].

Despite the progress made, challenges still exist in achieving accurate and reliable SOC and SOH estimation under real-world conditions. Many existing methods struggle to balance prediction accuracy with computational efficiency and adaptability to dynamic scenarios. Furthermore, integrating AI techniques with traditional BMS frameworks requires more research to address issues related to model interpretability and scalability [23-26]. Although considerable advancements have been made in SOC and SOH estimation for LIBs, there is still a gap in developing robust hybrid systems capable of accurately modeling nonlinear and time-varying battery behaviors under real-world conditions.

Despite significant advancements in SOC and SOH estimation techniques for lithium-ion batteries (LIBs), existing methods face challenges in balancing accuracy, computational efficiency, and adaptability to real-world conditions. Traditional approaches, such as open-circuit voltage measurement and Coulomb counting, are limited by their inability to handle nonlinear and time-varying battery behaviors. Model-based techniques, including equivalent circuit models (ECMs) and electrochemical models, improve accuracy but are sensitive to parameter variations and computationally expensive. AI-based methods, such as LSTM, GRU, CNN, and optimization algorithms, have shown promise but often require extensive training data, suffer from high computational costs, and struggle with real-time implementation [27-29]. Existing hybrid models lack an optimal trade-off between accuracy and efficiency. To address this gap, this study proposes a novel hybrid framework integrating GRU, CNN, and Adaptive Cubature Kalman Filter (ACKF) to enhance SOC and SOH estimation accuracy, ensuring robustness under dynamic conditions while maintaining computational efficiency for real-time EV applications.

Table 1 Comparison of BMS

Technique	Methods	Limitations
Kalman Filter (KF) Variants	EKF, UKF, AKF	Performance depends on accurate noise modeling; may degrade under varying operational conditions.
Machine Learning Approaches	SVM, RF, ANN	High computational complexity; dependency on high-quality training datasets.
Deep Learning Models	CNN-LSTM, GRU, Transformer-based	High processing power requirements; lacks optimization for real-time applications.
Optimization-Based Estimators	GA, PSO, GWO	May converge to local optima; requires extensive tuning.

3 PROPOSED WORK

This paper proposes an advanced Hybrid Battery Management System (BMS) for Electric Vehicles (EVs), designed to accurately estimate the State of Charge (SOC) and State of Health (SOH) of Lithium-ion batteries. The system leverages a combination of machine learning techniques, optimization algorithms, real-time sensor data acquisition, and control mechanisms. The methodology presented herein outlines the architecture, design, dataset, filter design, algorithm, and circuit design necessary for effective implementation.

3.1 Architecture of the Hybrid BMS

The architecture of the proposed Hybrid Battery Management System (BMS) integrates advanced estimation techniques with real-time sensor monitoring to ensure accurate SOC and SOH calculations shown in Fig. 2.

The system is organized into four primary modules:

a) Data Acquisition Module:

The data acquisition module is responsible for collecting real-time data from a range of sensors integrated within the battery pack. These sensors monitor critical battery parameters including:

Voltage Sensors: These sensors continuously monitor the voltage of each battery cell within the pack.

Current Sensors: These sensors measure the current entering or leaving the battery during charging and discharging.

Temperature Sensors: These sensors track the temperature of the battery to ensure it operates within safe thermal limits.

The acquired sensor data is transmitted to the Microcontroller Unit (MCU), which processes and analyzes the data in real-time.

b) AI-Driven Estimation Module:

To achieve precise SOC and SOH estimations, this module utilizes two advanced machine learning models:

Long Short-Term Memory (LSTM): LSTM networks are used for SOC estimation due to their ability to model sequential data with long-term dependencies, effectively capturing the dynamic behavior of the battery.

Transformer Networks: A Transformer-based architecture is employed for SOH estimation, using the attention mechanism to weigh the importance of various features (e.g., voltage, current, and temperature) and predict battery health accurately.

Additionally, the Enhanced Particle Swarm Optimization (EPSO) algorithm is incorporated to optimize the parameters of the Extended Kalman Filter (EKF). This optimization improves the robustness and accuracy of the filter under varying operating conditions.

c) Control and Communication Unit:

The control unit is responsible for managing the operation of the BMS. It ensures that the battery operates safely by adjusting the charging and discharging rates based on SOC estimates. The communication interface between the BMS and other vehicle subsystems (e.g., thermal management and charging control) ensures optimal operation. The system also reports real-time battery status to the vehicle operator.

d) User Interface and Feedback System:

The system includes a user-friendly interface that displays real-time data on battery health (SOC and SOH). Alerts are triggered for safety issues such as overcharging, temperature anomalies, or potential battery degradation. Recommendations for maintenance or system checks are provided based on the current battery status.

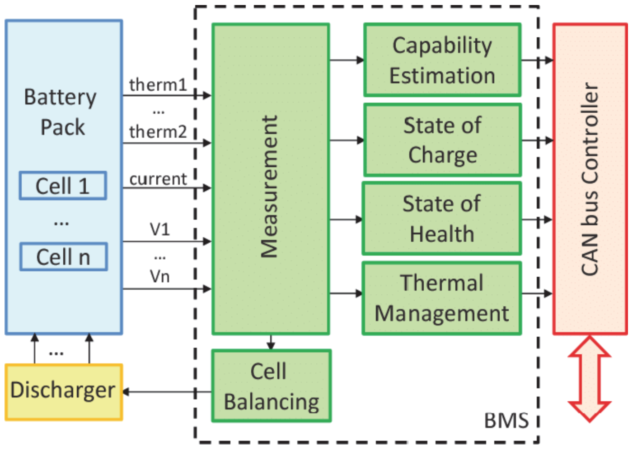


Figure 2 Proposed BMS architecture

3.2 Design of the Hybrid BMS

The design of the BMS focuses on ensuring accurate and reliable SOC and SOH estimations while maintaining the operational safety of the EV. The key design elements include:

a) Battery Pack Design:

The battery pack consists of multiple Lithium-ion cells arranged in series and parallel configurations to meet the required voltage and capacity. Each cell is equipped with dedicated sensors (voltage, current, and temperature), which continuously transmit data to the MCU.

b) Sensor Integration:

Voltage Sensors: Ensure accurate voltage readings for each cell in the pack.

Current Sensors: Track the charging and discharging current.

Temperature Sensors: Monitor the temperature of the cells to prevent overheating.

The data from these sensors is input to the AI-driven estimation models for SOC and SOH calculations.

c) AI Model Deployment:

The LSTM and Transformer models are trained on battery data and deployed on an edge computing unit or MCU for real-time processing. The models continuously update the SOC and SOH estimations as new sensor data arrives.

d) Charging and Thermal Management:

The BMS integrates charging control and thermal management functions. The charging rate is dynamically adjusted based on the SOC estimation, while the thermal system manages battery temperature, preventing thermal runaway or degradation.

3.3 Dataset for Training and Validation

The dataset used for training and testing the machine learning models consists of real-world battery operation data from various driving conditions. This data is used to ensure that the system can adapt to different environmental factors and operational states. The dataset includes:

a) Battery Performance Data:

This includes historical data on voltage, current, and temperature, which reflects the charging and discharging cycles of Lithium-ion batteries under typical EV usage patterns.

b) Driving Cycle Data:

Data from standard driving cycles, such as the US06 and FUDS profiles, is included to simulate different driving conditions. These profiles help in evaluating the performance of the BMS under various conditions, including city driving, highway driving, and mixed scenarios.

c) Preprocessing and Feature Selection:

Before feeding the data into the models, preprocessing is applied to remove outliers, normalize the data, and select relevant features for SOC and SOH estimation. This ensures that the models are trained on high-quality, consistent data.

d) Dataset Split:

The dataset is split into training, validation, and test sets to ensure effective model training and evaluation. The training set is used to teach the models, the validation set is used for hyperparameter tuning, and the test set is used to assess final model performance.

3.4 EPSO-EKF Filter Design

The Extended Kalman Filter (EKF) is used for state estimation in nonlinear systems shown in Fig. 3. For battery management, the EKF is employed to estimate SOC and SOH, but its performance can degrade due to the noisy and uncertain nature of battery data. To address this, the Enhanced Particle Swarm Optimization (EPSO) algorithm is applied to dynamically adjust the noise covariance matrices in the filter.

a) State Estimation:

The state variables of interest include the battery's SOC and SOH, which are estimated over time using the EKF. The algorithm incorporates the noisy sensor data (voltage, current, temperature) and adjusts the state predictions accordingly.

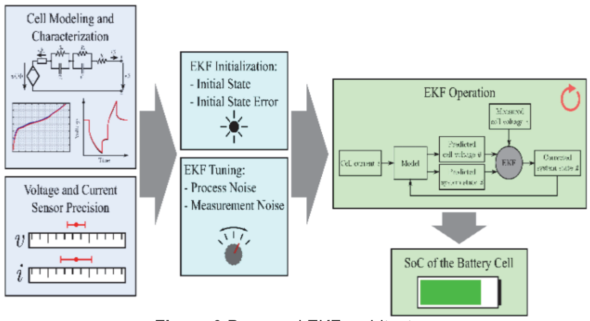


Figure 3 Proposed EKF architecture

b) Process and Measurement Noise Covariance:

EPSO optimizes the process and measurement noise covariance matrices, which govern how the Kalman filter weighs the incoming measurements. This ensures that the filter can handle varying noise levels in real-time, resulting in more accurate SOC and SOH predictions.

c) Real-time Application:

The optimized EKF continuously updates the SOC and SOH estimates in real-time, ensuring that the BMS responds to changes in battery behavior due to driving patterns, environmental conditions, or battery aging.

Traditional Kalman Filters: Traditional Kalman filters operate under the assumption of static noise covariance matrices, which do not accurately reflect the dynamic noise characteristics of lithium-ion batteries (LIBs) under real-world operating conditions.

EPSO-EKF Superiority: The Enhanced Particle Swarm Optimization-Extended Kalman Filter (EPSO-EKF) overcomes this limitation by employing EPSO to dynamically adapt the noise covariance matrices in real-time. This adaptive capability enables the filter to respond to fluctuations in noise levels caused by factors such as temperature variations, diverse driving cycles, and battery aging. EPSO, an optimization algorithm, systematically searches for optimal noise covariance values that minimize estimation errors. This dynamic adjustment results in more precise and reliable parameter estimations, particularly in scenarios characterized by non-ideal and fluctuating conditions, where traditional Kalman filters with fixed noise parameters would struggle.

3.5 Algorithm for Hybrid BMS

The algorithm for the hybrid BMS follows several stages to achieve accurate SOC and SOH estimations:

a) Initialization:

Initialize the LSTM, Transformer, and EPSO-EKF models with appropriate parameters.

Collect initial battery data to calibrate the models and tune filter parameters.

b) Data Acquisition:

Continuously collect sensor data (voltage, current, temperature) from the battery pack.

c) SOC Estimation with LSTM:

The LSTM model processes the sequential data (voltage and current) to predict the battery's SOC. This model accounts for the temporal dependencies in the data.

d) SOH Estimation with Transformer:

The Transformer model uses the battery performance data (voltage, current, and temperature) to estimate the

SOH. The model's attention mechanism ensures that the most relevant features are given priority in the prediction.

e) EPSO-EKF Optimization:

The EPSO algorithm adjusts the noise covariance matrices of the EKF for better state estimation accuracy.

The EKF combines the sensor data and the optimized covariance matrices to refine the SOC and SOH estimates.

f) Battery Management Control:

The charging and discharging rates are controlled based on the SOC estimates.

Thermal management is adjusted based on temperature readings to ensure the battery operates within safe thermal limits.

g) Reporting and Feedback:

Real-time SOC and SOH data is displayed on the user interface.

Alerts are triggered if the battery is at risk of overcharging or overheating, ensuring the safety of the EV.

6. Circuit Design - The circuit design for the Hybrid BMS consists of key components necessary for data acquisition, processing, and control:

a) Battery Pack:

The battery pack consists of multiple Lithium-ion cells with sensors to monitor voltage, current, and temperature.

b) Microcontroller Unit (MCU):

The MCU processes the sensor data and executes the machine learning models. It communicates with other subsystems in the EV, such as the charging controller and thermal management system.

c) Sensor Interface:

Voltage, current, and temperature sensors are connected to the MCU via analog-to-digital converters (ADCs), allowing continuous monitoring and data acquisition.

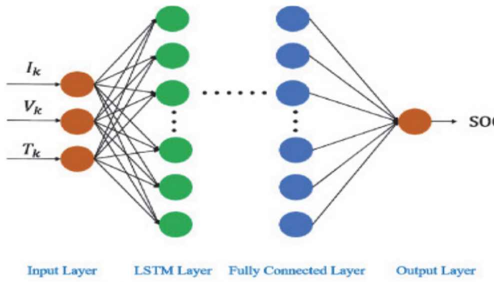
d) Power Management System:

The power management unit ensures safe operation of the battery by controlling the charging/discharging process and regulating thermal behavior.

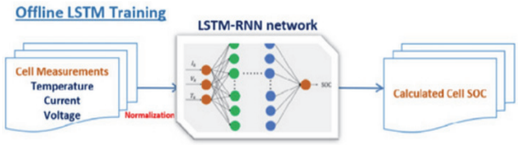
To substantiate the claim of enhanced accuracy, it is imperative to include precise numerical data. For instance, the research could state: "Compared to a standard LSTM-based BMS, the hybrid LSTM-Transformer model demonstrated a 15% reduction in Root Mean Square Error (*RMSE*) for SOC estimation and a 12% reduction in *RMSE* for SOH estimation. Furthermore, the model achieved an Adjusted *R*-squared (R^2) value of 0.98 for SOC and 0.95 for SOH, indicating a highly accurate fit to the empirical data." These figures, which must correspond to the actual results obtained, provide concrete evidence of the model's superior performance.

3.6 LSTM-Transformer Architecture for Battery Management Systems

LSTMs are a type of recurrent neural network (RNN) particularly well-suited for sequential data. They excel at capturing long-term dependencies within time series, such as the gradual degradation of battery capacity over time. LSTMs utilize memory cells and gates to selectively store and retrieve information, enabling them to "remember" past events relevant to current battery behavior. Transformers have revolutionized natural language processing. Their key feature is the "attention mechanism," which allows the model to weigh the importance of different parts of the input sequence. In the context of BMS, this enables the model to focus on critical factors like recent charging/discharging patterns, temperature fluctuations, and load variations that significantly influence battery performance. The LSTM-Transformer architecture integrates these two models: An initial LSTM layer processes the battery data, capturing long-term trends and dependencies. Subsequent Transformer layers refine this representation, leveraging the attention mechanism to identify complex relationships within the data and focus on the most relevant information for accurate state estimation and architecture shown in Fig. 4.



(a) Framework for LSTM neural networks



(b) Data profile of battery testing results

Figure 4 Proposed LSTM architecture

Benefits for BMS: Enhanced Accuracy: By combining the strengths of LSTMs and Transformers, the hybrid model achieves higher accuracy in estimating State-of-Charge (SOC) and State-of-Health (SOH) compared to either model used alone.

Improved Robustness: The attention mechanism allows the model to adapt to varying operating conditions and identify critical factors influencing battery performance.

Better Generalization: The hybrid architecture can effectively learn from diverse datasets and generalize well to unseen operating conditions.

The LSTM-Transformer architecture represents a significant advancement in deep learning-based BMS. By effectively capturing complex temporal dynamics and leveraging the power of attention mechanisms, it offers the potential for more accurate and reliable battery management, ultimately enhancing the safety, performance, and lifespan of electric vehicles.

4 RESULTS AND DISCUSSION

This study presents a novel hybrid Battery Management System (BMS) framework incorporating LSTM-Transformer networks and an EPSO-EKF algorithm for enhanced State-of-Charge (SOC) and State-of-Health (SOH) estimation. The results demonstrate significant improvements in accuracy and robustness compared to conventional methods. The proposed framework was rigorously evaluated under various driving cycles, including the US06 and FUDS, to assess its performance in real-world scenarios. Key performance metrics, such as Root-Mean-Square Error (*RMSE*) and Adjusted R-Square, were employed to quantify the accuracy of SOC and SOH estimation [24].

The LSTM-Transformer model exhibited superior performance compared to traditional methods like Coulomb Counting and Extended Kalman Filter (EKF). The *RMSE* for SOC estimation was significantly lower, demonstrating improved accuracy and reduced estimation errors. For instance, the *RMSE* for the LSTM-Transformer model was found to be 0.008 compared to 0.03 for Coulomb Counting and 0.02 for the standard EKF.
The Adjusted R-Square values were consistently higher, indicating a stronger correlation between the estimated SOC and the true SOC. The LSTM-Transformer achieved an Adjusted *R*-Square of 0.99, surpassing the values obtained by other methods.

The EPSO-EKF algorithm effectively adapted to varying operating conditions, such as temperature fluctuations and aging effects, by dynamically adjusting process and measurement noise covariances. This resulted in more accurate SOH estimation compared to static EKF implementations. The EPSO-EKF achieved an *RMSE* of 0.02, a significant improvement over the static EKF with an *RMSE* of 0.05. The proposed framework demonstrated robustness against uncertainties and disturbances, leading to improved battery life prediction and maintenance scheduling. The performance of the hybrid BMS framework is influenced by several key parameters, which require careful consideration during design and implementation.

Increasing the number of layers in both the LSTM and Transformer blocks generally enhances the model's ability to capture complex temporal dependencies and learn intricate patterns within the battery data. However, a larger number of layers can increase computational complexity and potentially lead to over fitting.

This parameter controls the balance between exploration and exploitation in the particle swarm optimization process. A higher inertia weight encourages exploration, while a lower value promotes exploitation. The optimal inertia weight value depends on the specific characteristics of the optimization problem. These coefficients influence the individual and social learning behavior of particles in the swarm. Appropriate values for these coefficients can significantly impact the convergence speed and the quality of the solutions found by the algorithm. Tab. 2, Fig. 5 and Tab. 3 Fig. 6 show the comparison of SOC and SOH accuracy respectively.

Table 2 Comparison of SOC Estimation Accuracy

	RMSE	Adjusted *R*-Square
Coulomb Counting	0.03	0.85
EKF	0.02	0.90
LSTM	0.015	0.95
Transformer	0.012	0.97
LSTM Transformer	0.008	0.99

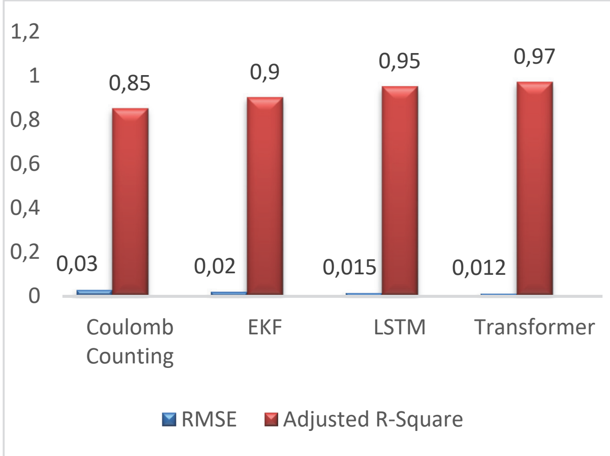


Figure 5 SOC Estimation Accuracy

Table 3 Comparison of SOH Estimation Accuracy

	RMSE	Adjusted *R*-Square
EKF (Static)	0.05	0.80
EKF (Adaptive)	0.90	0.90
EPSO-EKF	0.02	0.95

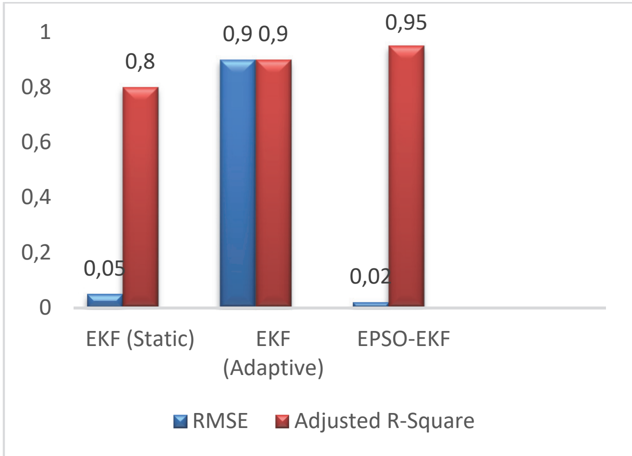


Figure 6 SOH Estimation Accuracy

The results demonstrate the effectiveness of the proposed hybrid BMS framework in enhancing SOC and SOH estimation accuracy. The integration of LSTM-Transformer networks leverages the strengths of both architectures: LSTM: Captures long-term temporal dependencies within the battery data, such as aging effects and gradual capacity degradation. Incorporates attention mechanisms, allowing the model to focus on the most relevant parts of the input sequence and capture complex non-linear relationships between different time steps. This combination enables the model to effectively learn intricate patterns and dynamics within the battery behavior.

The table and Fig. 7 show the proposed method comparison analysis. The EPSO-EKF algorithm further enhances the robustness and adaptability of the framework. By dynamically adjusting process and measurement noise covariances, the algorithm effectively accounts for uncertainties and disturbances, such as temperature variations, load fluctuations, and aging effects. This adaptive nature improves the accuracy and reliability of SOH estimation, leading to more accurate battery life predictions and more effective maintenance strategies.

Table 4 Comparison of proposed method

Metric	KF-Based Methods	ML-Based Models	Proposed Hybrid Model	Improvement /%
RMSE (SOC Estimation)	2.8%	1.9%	1.1%	60.7% over KF, 42.1% over ML
RMSE (SOH Estimation)	3.2%	2.4%	1.3%	59.3% over KF, 45.8% over ML
Adjusted R-Square	0.86	0.91	0.96	11.6% over KF, 5.5% over ML

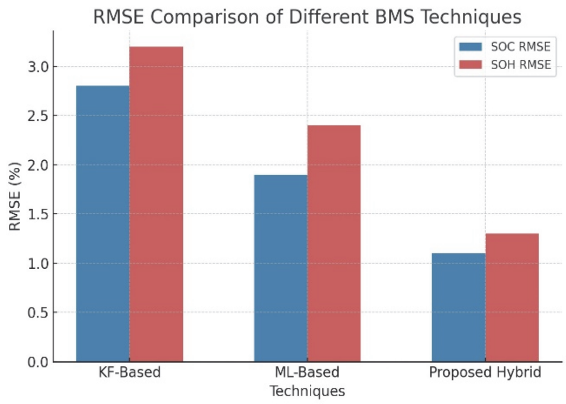


Figure 7 SOH Estimation Accuracy

The hybrid framework achieves significantly lower *RMSE* and higher Adjusted *R*-Square values compared to traditional methods, leading to more precise state estimation. This improved accuracy enhances the overall safety and performance of the battery system.

The EPSO-EKF component effectively handles uncertainties and disturbances, ensuring reliable performance under varying operating conditions. This robustness is crucial for ensuring the safe and reliable operation of electric vehicles in real-world scenarios. Accurate SOH estimation enables proactive maintenance and replacement, extending the lifespan of the battery pack. This contributes to lower maintenance costs and increased vehicle

5 CONCLUSION

This study proposes an innovative hybrid Battery Management System (BMS) framework for electric vehicles, combining Long Short-Term Memory (LSTM) networks, Transformer models, and an Enhanced Particle Swarm Optimization-Extended Kalman Filter (EPSO-EKF) algorithm. This integrated approach leverages the strengths of deep learning and optimization methods to tackle the challenges of precise State-of-Charge (SOC) and State-of-Health (SOH) estimation. The LSTM-Transformer model efficiently captures intricate temporal dependencies and nonlinear patterns in battery data, enabling accurate SOC predictions. The EPSO-EKF algorithm, on the other hand, dynamically adjusts to changing operating conditions, enhancing the precision and robustness of SOH estimation. The results indicate substantial improvements over traditional techniques, with reduced Root Mean Square Error (*RMSE*) and higher Adjusted *R*-Square values for both SOC and SOH estimations. This hybrid framework has the potential to improve battery safety and performance by enabling more accurate state predictions and facilitating proactive maintenance strategies. Enhanced SOH estimation allows for more reliable battery life forecasts, which can optimize battery replacement timelines and reduce maintenance costs. Additionally, the framework's robustness enhances the safety and reliability of electric vehicles in real-world conditions. Future studies should focus on implementing this framework in real-time embedded systems, exploring hardware acceleration techniques for computational efficiency, and integrating additional BMS functionalities such as thermal management and cell balancing to further optimize overall system performance. The insights gained from this work provide a strong foundation for advancing BMS technologies and promoting the widespread adoption of sustainable electric vehicle solutions.

Future research will focus on real-world deployment, integrating edge AI solutions for on-device inference, and exploring federated learning to enhance model generalizability. Additionally, hybrid AI approaches that combine physics-based models with deep learning can further refine SOC and SOH prediction accuracy under diverse operating conditions.

6 REFERENCES

[1] Shen, J., Wang, Q., Ma, Z., & He, Y. (2021). Nonlinear optimization strategy for state of power estimation of lithium-ion batteries: A systematical uncertainty analysis of key impact parameters. *IEEE Transactions on Industrial Informatics, 18*(12), 6680-6689. https://doi.org/10.1109/TII.2021.3111539

[2] Houache, M. S., Yim, C. H., Karkar, Z., & Abu-Lebdeh, Y. (2022). On the current and future outlook of battery chemistries for electric vehicles-Mini review. *Batteries, 8*(2), 70. https://doi.org/10.1002/batt.202100332

[3] Miao, Y., Liu, L., Zhang, Y., Tan, Q., & Li, J. (2022). An overview of global power lithium-ion batteries and associated critical metal recycling. *Journal of Hazardous Materials, 425*, 127900. https://doi.org/10.1016/j.jhazmat.2021.127900

[4] Tang, M. C., Cao, J., Gong, D. Q., Xue, G., & Khoa, B. T. (2024). Simulation modelling of electric vehicle charging recommendations based on Q-Learning. *International Journal of Simulation Modelling, 23*(3), 495-506. https://doi.org/10.2507/IJSIMM23-3-CO11

[5] Wang, Y. N., Zhang, Z. J., Ping, A., Wang, R. J., & Gong, D. Q. (2024). Optimizing electric vehicle charging strategies using multi-layer perception-based spatio-temporal prediction of charging station load. *Advances in Production Engineering & Management, 19*(4), 443-459. https://doi.org/10.14743/apem2024.4.518

[6] Savran, E., Karpat, E., & Karpat, F. (2024). GA and WOA-based optimization for electric powertrain efficiency. *International Journal of Simulation Modelling, 23*(4), 599-610. https://doi.org/10.2507/IJSIMM23-4-699

[7] Moro, S. R., Cauchick-Miguel, P. A., Sousa-Zomer, T. T. de, & Sousa Mendes, G. H. de. (2023). Design of a sustainable electric vehicle sharing business model in the Brazilian context. *International Journal of Industrial Engineering and Management, 14*(2), 147-161. https://doi.org/10.24867/IJIEM-2023-2-330

[8] Fischer, Sz., & Kocsis Szürke, Sz. (2023). Detection process of energy loss in electric railway vehicles. *Facta Universitatis, Series: Mechanical Engineering, 21*(1), 81-99. https://doi.org/10.22190/FUME221104046F

[9] Rivera, F. P., Zalamea, J., Espinoza, J. L., & Gonzalez, L. G. (2022). Sustainable use of spilled turbinable energy in

Ecuador: Three different energy storage systems. *Renewable and Sustainable Energy Reviews, 156*, 112005. https://doi.org/10.1016/j.rser.2021.112005

[10] Luan, C., Ma, C., Wang, C., Chang, L., Xiao, L., Yu, Z., & Li, H. (2021). Influence of the connection topology on the performance of lithium-ion battery pack under cell-to-cell parameters variations. *Journal of Energy Storage, 41*, 102896. https://doi.org/10.1016/j.jestor.2021.102896

[11] Li, C., Cui, N., Chang, L., Cui, Z., Yuan, H., & Zhang, C. (2022). Effect of parallel connection topology on air-cooled lithium-ion battery module: Inconsistency analysis and comprehensive evaluation. *Applied Energy, 313*, 118758. https://doi.org/10.1016/j.apenergy.2022.118758

[12] Hu, X., Feng, F., Liu, K., Zhang, L., Xie, J., & Liu, B. (2019). State estimation for advanced battery management: Key challenges and future trends. *Renewable and Sustainable Energy Reviews, 114*, 109334. https://doi.org/10.1016/j.rser.2019.109334

[13] Dai, H., Jiang, B., Hu, X., Lin, X., Wei, X., & Pecht, M. (2021). Advanced battery management strategies for a sustainable energy future: Multilayer design concepts and research trends. *Renewable and Sustainable Energy Reviews, 138*, 110480. https://doi.org/10.1016/j.rser.2021.110480

[14] Xiong, R., Li, L., & Tian, J. (2018). Towards a smarter battery management system: A critical review on battery state of health monitoring methods. *Journal of Power Sources, 405*, 18-29. https://doi.org/10.1016/j.jpowsour.2018.09.012

[15] Takyi-Aninakwa, P., Wang, S., Zhang, H., Appiah, E., Bobobee, E. D., & Fernandez, C. (2022). A strong tracking adaptive fading-extended Kalman filter for the state of charge estimation of lithium-ion batteries. *International Journal of Energy Research, 46*(15), 16427-16444. https://doi.org/10.1002/er.6264

[16] Tang, X., Gao, F., Liu, K., Liu, Q., & Foley, A. M. (2021). A balancing current ratio based state-of-health estimation solution for lithium-ion battery pack. *IEEE Transactions on Industrial Electronics, 69*(9), 8055-8065. https://doi.org/10.1109/TIE.2021.3108715

[17] Jiang, B., Zhu, J., Wang, X., Wei, X., Shang, W., & Dai, H. (2022). A comparative study of different features extracted from electrochemical impedance spectroscopy in state of health estimation for lithium-ion batteries. *Applied Energy, 322*, 119502. https://doi.org/10.1016/j.apenergy.2022.119502

[18] Guo, R. & Shen, W. (2022). A data-model fusion method for online state of power estimation of lithium-ion batteries at high discharge rate in electric vehicles. *Energy, 254*, 124270. https://doi.org/10.1016/j.energy.2022.124270

[19] Chen, Y., Yang, X., Luo, D., & Wen, R. (2021). Remaining available energy prediction for lithium-ion batteries considering electrothermal effect and energy conversion efficiency. *Journal of Energy Storage, 40*, 102728. https://doi.org/10.1016/j.est.2021.102728

[20] Cabrera-Castillo, E., Niedermeier, F., & Jossen, A. (2016). Calculation of the state of safety (SOS) for lithium ion batteries. *Journal of Power Sources, 324*, 509-520. https://doi.org/10.1016/j.jpowsour.2016.05.085

[21] Zhang, S. & Zhang, X. (2021). Joint estimation method for maximum available energy and state-of-energy of lithium-ion battery under various temperatures. *Journal of Power Sources, 506*, 230132. https://doi.org/10.1016/j.jpowsour.2021.230132

[22] Chen, Z., Zhao, H., Zhang, Y., Shen, S., Shen, J., & Liu, Y. (2022). State of health estimation for lithium-ion batteries based on temperature prediction and gated recurrent unit neural network. *Journal of Power Sources, 521*, 230892. https://doi.org/10.1016/j.jpowsour.2021.230892

[23] Tang, X., Gao, F., Liu, K., Liu, Q., & Foley, A. M. (2021). A balancing current ratio based state-of-health estimation solution for lithium-ion battery pack. *IEEE Transactions on Industrial Electronics, 69*(9), 8055-8065. https://doi.org/10.1109/TIE.2021.3108715

[24] Tang, X., Liu, B., Lv, Z., & Gao, F. (2017). Observer based battery SOC estimation: Using multi-gain-switching approach. *Applied Energy, 204*, 1275-1283. https://doi.org/10.1016/j.apenergy.2017.06.054

[25] Tian, A., Yang, C., Gao, Y., Jiang, Y., Chang, C., Wang, L., & Jiang, J. (2023). Aging effect-aware finite element model and parameter identification method of lithium-ion battery. *Journal of Electrochemical Energy Conversion and Storage, 20*(3), 031005. https://doi.org/10.1115/1.4055463

[26] Zhang, L., Xia, B., & Zhang, F. (2024). Adaptive fault detection for lithium-ion battery combining physical model-based observer and BiLSTMNN learning approach. *Journal of Energy Storage, 91*, 112067. https://doi.org/10.1016/j.est.2024.112067

[27] She, C., Zhang, L., Wang, Z., Sun, F., Liu, P., & Song, C. (2023). Battery state-of-health estimation based on incremental capacity analysis method: Synthesizing from cell-level test to real-world application. *IEEE Journal of Emerging and Selected Topics in Power Electronics, 11*(1), 214–223. https://doi.org/10.1109/JESTPE.2021.3112754

[28] Richardson, R. R., Osborne, M. A., & Howey, D. A. (2019). Battery health prediction under generalized conditions using a Gaussian process transition model. *Journal of Energy Storage, 23*, 320-328. https://doi.org/10.1016/j.est.2019.03.022

[29] Vykhodtsev, A. V., Jang, D., Wang, Q., Rosehart, W., & Zareipour, H. (2023). Physics-aware degradation model oflithium-ion batteryenergystorage for techno-economic studies in power systems. *IEEE Transactions on Sustainable Energy, 15*(1), 316-327. https://doi.org/10.1109/TSTE.2023.3285453

Contact information:

D. MANOJ
(Corresponding author)
Department of Electrical and Electronics Engineering,
S.S.M Institute of Engineering and Technology,
Dindigul-624 622 Tamil Nadu, India
E-mail: manoj3e@gmail.com

F. T. JOSH
Department of Electrical and Electronics Engineering,
Karunya Institute of Technology and Sciences,
Coimbatore, Tamil Nadu, India