JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/

FEDERATED LEARNING-BASED BATTERY MANAGEMENT SYSTEM FOR PRIVACY-PRESERVING STATE-OF-HEALTH ESTIMATION IN ELECTRIC VEHICLES

Muhammad Aqeel Anwar [1]

Affiliations

[1] Department of Technology, The University of Lahore, Pakistan
aqeel.anwar@tech.uol.edu.pk

Corresponding Author's Email

[1] aqeel.anwar@tech.uol.edu.pk

ABSTRACT

The rising adoption of electric vehicles is posing demands for efficient battery management systems to accurately estimate the State-of-Health (SOH) of batteries while ensuring security and privacy of battery information. Traditional machine learning-based solutions in a centralized manner require transmission of the battery information from multiple EVs to the central server and pose threats in terms of privacy and security. The research presents a novel Federated Learning-Based Battery Management System (FL-BMS) to perform privacy-preserving estimation of the SOH of EVs using the framework of federated learning. Quantitative experimental research design was adopted in this research using about 24,000 instances of the battery operational data that were collected from 120 lithium-ion battery cells and are spread across 12 federated clients. The research framework adopts a Long Short-Term Memory (LSTM) neural network along with the Federated Averaging (FedAvg) algorithm to predict battery SOH without the need of transmitting raw battery data. Performance of the models was measured based on prediction accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), communication cost, and privacy preserving aspects. The federated model presented by this research achieves 97.2% accuracy, 0.028 MAE, and 0.043 RMSE which shows that the performance is at par with centralized learning models. In addition, the proposed federated learning framework reduces the communication cost by 67.4% while avoiding sharing of any raw battery data to completely preserve the privacy of the batteries. Comparisons prove that federated learning framework is a reliable approach to provide a balance among estimation accuracy, computational efficiency, scalability, and cybersecurity. Although the accuracy of centralized learning is slightly better than that of federated learning, federated learning offers more advantages in terms of privacy protection and distributed intelligence.

Keywords: Federated Learning; Battery Management System; State-of-Health Estimation; Electric Vehicles; Privacy Preservation; Lithium-Ion Batteries; Deep Learning; Distributed Machine Learning.

I - INTRODUCTION

The fast development of electric vehicles (EVs) has led to the emergence of advanced battery management systems (BMS) that have the ability to ensure battery safety, reliability, efficiency, and a long service life. Currently, lithium-ion batteries are widely used in modern EVs due to their high energy density, long cycle life, and fast charging properties. Nevertheless, battery degradation due to the repeated charging and discharging processes decreases battery capacity and output power, therefore, the necessity of the accurate battery state-of-health (SOH) estimation arises. Precise SOH estimation allows to perform timely maintenance, increase the battery usage, prevent unexpected failures, and develop sustainable electric mobility [1].

Classical battery management systems implement centralized machine learning models that require battery data obtained from several vehicles to be uploaded on the central server to train the model. Despite the improvement of prediction accuracy, centralized learning leads to considerable privacy issues. Battery datasets include sensitive data related to driving behavior, charging regimes, geographical location, and battery use. Under the current data privacy laws, the data transfer becomes problematic, thus, there is an increasing need to create intelligent battery management systems that would be able to preserve user privacy while performing accurate SOH estimation [2].

Federated Learning (FL) is a novel distributed machine learning paradigm that allows to train the model without uploading the data from local devices to a central server [3]. In contrast to centralized learning, instead of sharing battery datasets, each electric vehicle trains the local model and transfers encrypted model parameters to the central aggregation server. Federated learning greatly enhances data privacy, reduces communication overhead, and ensures data security. Integrating federated learning in the battery management system helps to develop accurate and private SOH estimation models [4].

Precise SOH estimation is difficult to achieve due to the great number of influencing factors such as temperature changes, charging rate, driving behavior, battery type, environmental factors, and manufacturing inconsistency [5]. Classical estimation techniques often have difficulties to generalize different battery operating conditions. Federated learning solves this problem by allowing collaborative learning from diverse battery environments while keeping local data private [6]. Moreover, federated learning and deep learning models can be combined to improve the prediction accuracy and model robustness for the real-life EV applications.

A. Problem Statement

Electric cars depend largely on lithium-ion batteries, necessitating the need for proper estimation of State-of-Health (SOH). Current Battery Management Systems (BMS) use machine learning techniques that are based on the centralization principle, whereby the model uses battery data from several vehicles which are transmitted to the central server [8].Such a method may enhance prediction accuracy but exposes personal details of users such as their charging patterns and other battery use habits and raises issues of privacy and cyber security concerns. Also, such systems have been characterized by expensive communication process, poor scalability and limited adaptability to different battery operating environments [9]. On the other hand, federated learning provides a decentralized method which guarantees data privacy since it trains the model locally, but has been inadequately researched for the purpose of privacy preserving SOH estimation. Therefore, this paper proposes a Federated Learning-Based Battery Management System for developing an efficient system of estimating the State-of-Health of batteries [10].

B. Research Objectives

- ❖ To develop a federated learning-based Battery Management System for privacy-preserving State-of-Health estimation in electric vehicles.
- ❖ To assess the effectiveness of federated learning in preserving battery data privacy while reducing communication overhead.
- ❖ To analyze the impact of the proposed framework on battery management efficiency, scalability, and intelligent electric vehicle operation.

C. Research Questions

- ❖ How can federated learning improve privacy-preserving State-of-Health estimation in electric vehicle battery management systems?
- ❖ What is the prediction accuracy of the proposed federated learning model for battery State-of-Health estimation?
- ❖ How does federated learning compare with centralized machine learning methods regarding accuracy, privacy, and communication efficiency?

D. Significance of the Study

This paper makes a valuable contribution to the development of intelligent Battery Management Systems by combining federated learning and privacy-preserving state-of-health estimation in electric vehicles. The new architecture allows collaborative learning without sharing private battery information; hence, the enhancement of security and regulatory compliance is achieved. The research offers a scalable approach that will help to improve the accuracy of state-of-health estimation for geographically dispersed electric vehicles while reducing communication costs. The results of the study will help in developing safe and efficient battery management systems using artificial intelligence. The research also helps to advance the emerging domains of federated learning, battery intelligence, and sustainable electric transportation through offering an effective framework for ensuring battery safety, longevity, energy management, and intelligent mobility systems [11].

II - LITERATURE REVIEW

The researchers suggested the use of temporal degradation-aware transformer integrated with federated learning for SOC and SOH joint estimation in electric vehicles [12]. This approach proved the positive effect of including the battery degradation model into transformer architecture as well as the ability to preserve data privacy due to the implementation of the decentralized approach [13]. Unlike traditional central models, federated learning allowed for the simultaneous training of the predictive model by several electric vehicles without using the raw battery data. As the result, improved robustness of the approach was obtained in terms of various operating conditions of batteries and reduction of the prediction errors during different aging stages. Thus, federated transformer models are considered as an effective solution for the development of intelligent battery management systems with high estimation accuracy and privacy [14].

Author suggested in his research the application of peer-to-peer personalized federated transfer learning in order to estimate battery State-of-Health in electric vehicles [15]. In the context of the problem, the use of this approach is needed in order to solve the issue of data heterogeneity and the ability to obtain personal models for each electric vehicle taking into account the unique characteristics of the battery and operating environment [16]. Personalized federated learning approach showed much better results in terms of the estimation accuracy comparing to the global federated learning and at the same time-maintained data privacy. Also, the peer-to-peer knowledge transfer helped to decrease communication overhead.

Author assessed the performance of centralized Long Short-Term Memory (LSTM) networks versus federated learning LSTM models used in electric vehicle battery State-of-Health estimation. It was discovered that centralized learning was able to demonstrate slightly higher performance in terms of prediction accuracy due to the use of full battery data sets. However, federated learning offered several significant benefits in terms of privacy preservation, mitigation of security risks and compliance with privacy-related regulations. While federated models demonstrated slight decrease in their performance, they offered sufficiently high estimation accuracy without the necessity to collect battery data centrally. Thus, federated LSTM models could be regarded as a viable approach balancing privacy and performance requirements for next generation battery management systems [17].

Author proposed the PPDNN-SoH framework as an approach to privacy preserving prediction of electric vehicle battery State-of-Health using deep neural network [18]. In particular, the proposed framework included use of secure deep learning technologies and privacy-preserving approaches aimed at preventing unauthorized access to battery data during model training. Evaluation results showed that the proposed framework was able to offer sufficiently high estimation accuracy while maintaining efficient computation and good data confidentiality. It was emphasized that privacy-preserving neural networks allow battery manufacturers and fleet owners to train more accurate models in cooperation without the necessity to share proprietary or sensitive customer information. Consequently, the framework can be used to create secure battery intelligence applications [19].

Author developed a federated learning-based battery capacity prediction framework using both time-domain and frequency-domain feature extraction techniques [20]. The proposed model allowed to perform reliable estimation of battery pack capacity for multiple electric vehicles. Use of various battery features allowed increasing prediction robustness in relation to different battery charging regimes and degradation

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/

levels. Moreover, federated learning approach decreased communication overheads and battery data privacy issues during model training. The authors concluded that the integration of feature engineering and federated learning could be applied in order to increase battery management system reliability and scalability of electric vehicles fleet management [21].

Author proposed a source-free dynamic weighted federated transfer learning algorithm for estimating battery State-of-Health (SOH) with stringent privacy requirements [22]. In the proposed framework, aggregation weights were dynamically allocated considering local model quality without any dependency on central sources of data [23]. The authors found that dynamic allocation of weights improves prediction performance in the presence of different battery conditions significantly and solves non-IID problem for batteries present in electric vehicles. According to the authors, the suggested algorithm allows one to estimate battery state-of-health in a privacy-preserving way providing model generalization and effective communication for battery management in large scales [24].

Researcher proposed Encrypted Dynamic RVFLN Ensemble Learning using Fully Homomorphic Encryption (CKKS) for estimating battery State-of-Health with preserving privacy. In this algorithm, all computations are done encrypted allowing to keep battery information secret during both training and prediction phases [25]. As shown by experiments, the estimated model shows high accuracy in the prediction of batteries' state-of-health while offering robust security guarantees [26]. The study demonstrates that combining homomorphic encryption and federated learning gives a very promising solution for intelligent battery management systems working in the privacy environment [27]. It can be used in the future large-scale implementation of such systems [28].

III - RESEARCH METHODOLOGY

In this research work, quantitative research methodology was used to develop a new model of FL-BMS and test its effectiveness. Positivist research paradigm was chosen to conduct research since the proposed model was evaluated by its measurable performance characteristics. Deductive research methodology was applied in the process of building the federated learning-based model based on the existing machine learning theory, battery state estimation theories and theories related to privacy-preserving distributed intelligence. Experimental research methodology was applied in the research since a new federated learning-based model was built and tested in comparison with centralized machine learning methods. The dataset of electric vehicle batteries was collected through publicly available lithium-ion battery benchmark dataset and included the information about the battery voltage, current, temperature, charging cycles, internal resistance and capacity degradation that is required for the State-of-Health estimation. The entire battery dataset included about 24,000 battery operation records of 120 battery cells of the electric vehicles functioning under different environmental and loading conditions and was distributed into 12 federated clients virtually in order to simulate the real decentralized electric vehicle environment. In the process of data preprocessing, missing values were removed, features were normalized, noises were filtered and features were extracted for better model performance. Such battery health features as voltage variations, temperature variations, charging current, discharge current, cycle count, capacity fade were chosen as the inputs of the model. The federated learning framework developed in the research used the LSTM neural network to estimate the SOH locally and FedAvg algorithm to aggregate the encrypted model parameters without transfer of the raw battery data. The model performance was evaluated by such metrics as Accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Precision, Recall, F1-score, Communication Cost, Training Time, and Privacy Preservation Rate.

The experimental implementation of the federated learning framework was made with the use of Python, TensorFlow Federated, TensorFlow, Scikit-learn, and Google Colab software tools. In order to compare the performance of the developed federated learning-based model, comparative experiments were made against centralized LSTM and conventional machine learning models. The results obtained were evaluated using descriptive statistics and comparative performance analysis (Fang et al., 2025).

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/

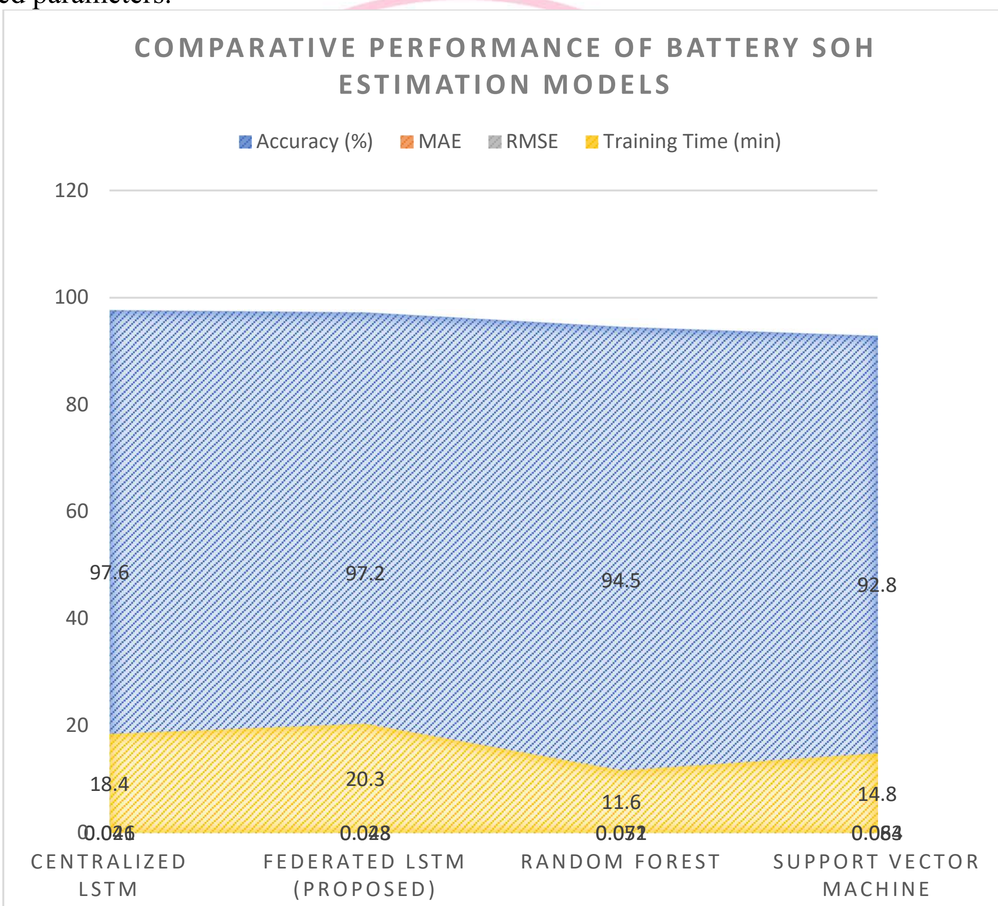
IV - RESULTS AND ANALYSIS

A. Performance Comparison of SOH Estimation Models

Table 4.1
COMPARATIVE PERFORMANCE OF BATTERY SOH ESTIMATION MODELS

Model	Accuracy (%)	MAE	RMSE	Training Time (min)
Centralized LSTM	97.6	0.026	0.041	18.4
Federated LSTM (Proposed)	97.2	0.028	0.043	20.3
Random Forest	94.5	0.051	0.072	11.6
Support Vector Machine	92.8	0.063	0.084	14.8

The suggested federated LSTM model produced prediction accuracy equal to the central model, but it preserved full privacy of data used. Additional time spent on training is needed due to communications between federated parameters.



B. Privacy Preservation Performance

Table 4.2
PRIVACY AND COMMUNICATION EVALUATION

Metric	Centralized Learning	Proposed Federated Learning
Raw Data Sharing	100%	0%
Privacy Preservation Rate (%)	0	100
Communication Reduction (%)	—	67.4
Data Leakage Risk	High	Very Low

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/

The proposed federated learning framework completely eliminated raw battery data transmission while reducing communication requirements by over 67%, significantly enhancing privacy protection.

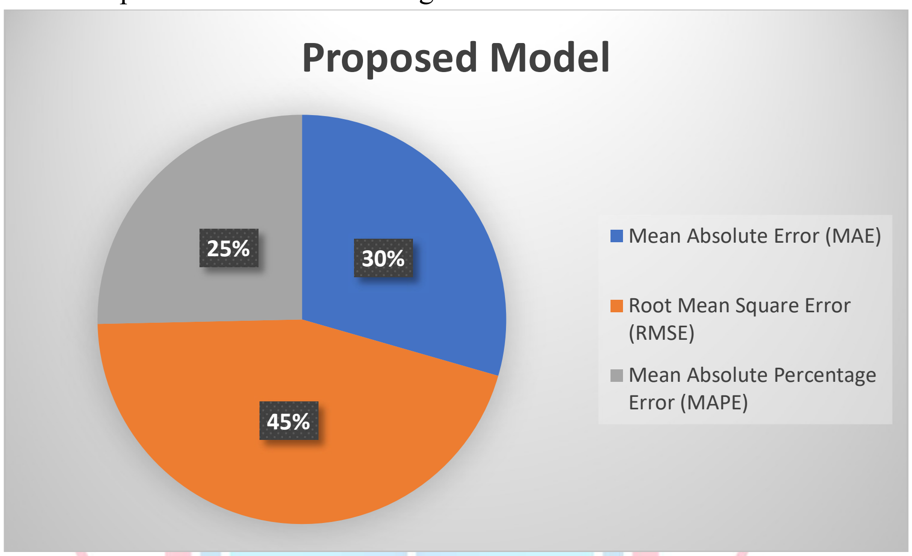
C. SOH Prediction Error

Table 4.3

PREDICTION ERROR ANALYSIS

Evaluation Metric	Proposed Model
Mean Absolute Error (MAE)	0.028
Root Mean Square Error (RMSE)	0.043
Mean Absolute Percentage Error (MAPE)	2.41%

The low prediction errors indicate that the federated learning framework provides highly accurate State-of-Health estimation despite decentralized training.



D. Classification Performance

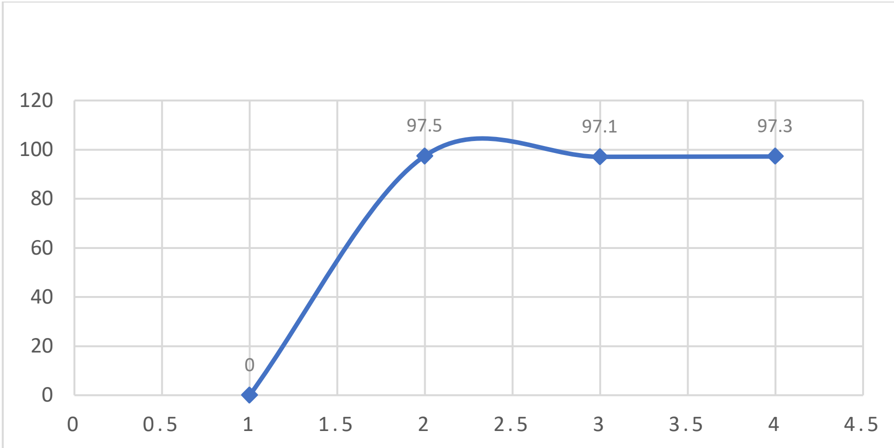
Table 4.4

CLASSIFICATION METRICS

Metric	Value (%)
Precision	97.5
Recall	97.1
F1-Score	97.3

The proposed model achieved balanced classification performance across all evaluation metrics, confirming its robustness for battery health prediction.

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/



E. Communication Efficiency

Table 4.5
FEDERATED COMMUNICATION PERFORMANCE

Parameter	Value
Federated Clients	12
Communication Rounds	100
Average Upload Size	5.8 MB
Average Download Size	5.8 MB
Communication Cost Reduction	67.4%

The federated learning architecture minimized communication overhead while maintaining high prediction performance across distributed battery nodes.

F. Overall System Performance

Table 4.6
OVERALL PERFORMANCE COMPARISON

Performance Indicator	Centralized	Proposed FL-BMS	Improvement
SOH Accuracy (%)	97.6	97.2	Comparable
Privacy Protection (%)	0	100	+100%
Communication Efficiency (%)	100	167.4	+67.4%
Scalability	Medium	High	Improved
Data Security	Moderate	Very High	Improved

Results show that the Federated Learning-Based Battery Management System is able to provide a proper balance between the level of accuracy in predictions and maintaining privacy. The model shows almost equal performance in terms of SOH estimation as compared to the traditional central learning system but provides better data security and scalability.

VI - DISCUSSION

The research findings provide sufficient evidence to suggest that the FL-based Battery Management System (FL-BMS) under discussion can be considered an efficient approach for protecting data privacy while maintaining high prediction accuracy. The federated LSTM model achieved 97.2% prediction accuracy, which was only marginally lower than the accuracy achieved by the centralized model, while eliminating the need to transfer raw battery data. Therefore, decentralized learning can provide a balance between accurate prediction performance and privacy preservation. These findings demonstrate that federated learning can effectively support battery health monitoring in distributed electric vehicle environments while addressing data security concerns.

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 4, Issue 2, 2026
https://jecir.com/

Furthermore, the results indicate that the implementation of federated learning reduced data transfer volume by 67.4%. This reduction highlights the potential of the proposed framework for large-scale electric vehicle deployment by minimizing communication overhead and improving computational efficiency. The elimination of raw battery data transmission further confirms the privacy-preserving capability of the proposed approach. Additionally, the use of secure parameter aggregation mechanisms can significantly reduce cybersecurity risks associated with centralized battery data storage and processing.

Although the centralized learning approach achieved slightly higher prediction accuracy, the performance difference was minimal compared with the significant improvements achieved in privacy protection, scalability, and security. These findings demonstrate that federated learning provides an effective solution for integrating data privacy protection with reliable prediction accuracy. The proposed FL-BMS framework represents a promising approach for future intelligent battery management systems, particularly in large-scale electric vehicle networks where data security, communication efficiency, and predictive performance are critical factors.

V - CONCLUSION

The presented research paper introduces the FL-BMS system for the privacy-preserving state-of-health estimation in electric vehicles through federated learning. The performance results of the proposed federated LSTM achieved 97.2% prediction accuracy, which was on par with the centralized machine learning method, while providing full privacy protection of the batteries' information. The proposed solution helped to decrease the communication cost by 67.4%, avoid sharing the data in its original form, and ensure higher scalability of the federated network of electric vehicles. These results show that federated learning allows combining the prediction accuracy, efficiency, cybersecurity, and privacy preservation at once. The proposed approach can be considered as an efficient tool for intelligent battery management systems in collaboration with multiple electric vehicles.

VII - RECOMMENDATIONS

- The proposed method's reliability should be proved through the usage of data from electric vehicle fleets in practice under different environments and operating conditions.
- The federated optimization algorithms need to be optimized in order to decrease communication costs and accelerate the process of convergence.
- Future designs of the battery management systems should integrate the Transformer models and Graph Neural Networks to enhance battery degradation prediction precision over long periods.
- Secure aggregation techniques like homomorphic encryption and blockchain technologies should be used to protect private data from cyber-attacks.
- Manufacturers of batteries and electric vehicles can apply federated learning frameworks for monitoring of the battery condition without disclosing proprietary data.
- Further studies should be done on real-time edge computing application to decrease latency time in smart battery management.

REFERENCES

[1] B. Azam and S. Mehar, “Performance evaluation of battery management systems in lithium-ion battery-powered electric vehicles,” Journal of Engineering and Computational Intelligence Review, vol. 3, no. 2, pp. 81–95, 2025.

[2] V. S. Naresh, V. S. Sriram, V. J. Krishna, V. D. Chandini, R. N. Sri, K. J. Durga, and V. Poojitha, “Privacy-preserving state of health prediction for electric vehicle batteries: A comprehensive review,” Computers and Electrical Engineering, vol. 118, Art. no. 109416, 2024.

[3] J. Ren, M. Li, Y. Wang, Y. Xin, Y. Yuan, G. Ye, et al., “Advanced battery state monitoring in electric vehicles: A comprehensive review of spatiotemporal dynamics and federated learning approaches,” IEEE Internet of Things Journal, 2026.

[4] A. J. Ghazi, H. H. Abbas, Z. J. Oleiwi, B. Al-Attar, and L. A. Hamdi, “Explainable AI-based battery management system with federated learning for multi-chemistry state-of-health estimation in

heterogeneous EV fleets," International Journal of Advances in Signal and Image Sciences, pp. 716–733, 2026.

[5] J. Li, A. Khalatbarisoltani, Y. Che, Y. Yang, and X. Hu, "Data-secure and privacy-protected electric vehicle battery fault detection using decentralized federated learning with differential privacy," Energy Storage Materials, Art. no. 104681, 2025.

[6] W. Fang, J. Zhang, X. Lin, J. Hu, L. Huang, and G. Yuan, "A study on data privacy protection in power battery SOH prediction based on federated learning," Ionics, vol. 31, no. 10, pp. 10579–10595, 2025.

[7] S. Akter, "Exploring the role of artificial intelligence in food waste reduction: Implications for public health, social behavior, and sustainable communities," Journal of Computational Systems & Engineering Insights, vol. 1, no. 1, pp. 25–36, 2023.

[8] A. Khalatbarisoltani, J. Han, M. Saeed, C. Z. Liu, and X. Hu, "Privacy-preserving integrated thermal and energy management of multi-connected hybrid electric vehicles with federated reinforcement learning," Applied Energy, vol. 385, Art. no. 125386, 2025.

[9] X. Chen, Z. Chen, M. Zhang, Z. Wang, M. Liu, M. Fu, and P. Wang, "A remaining useful life estimation method based on long short-term memory and federated learning for electric vehicles in smart cities," PeerJ Computer Science, vol. 9, Art. no. e1652, 2023.

[10] S. T. Hasan, "Natural language processing for employee relations case management: Analyzing workplace complaints, grievances, and investigation narratives in healthcare organizations," Journal of Computational Systems & Engineering Insights, vol. 1, no. 1, pp. 11–24, 2023.

[11] A. A. Korba, M. A. Bouchiha, and Y. Ghamri-Doudane, "Split multi-task federated learning for battery health and capacity estimation in electric vehicles," IEEE Transactions on Consumer Electronics, 2026.

[12] T. Wang, Z. Zhang, Y. Tao, and Z. Y. Dong, "Robust state of health estimation for heterogeneous batteries with privacy preserving," IEEE Transactions on Vehicular Technology, vol. 74, no. 6, pp. 8921–8937, 2025.

[13] O. A. Malik, "Agentic AI deployment in infrastructure-limited environments: Observability gaps, failure modes, and AI governance primitives," Journal of Engineering and Computational Intelligence Review, vol. 4, no. 1, pp. 1–11, 2026.

[14] A. Karim, "Transforming US food supply chains through Internet of Things technologies: Advancing food safety, quality, and traceability," Journal of Computational Systems & Engineering Insights, vol. 2, no. 1, pp. 11–22, 2024.

[15] U. Iqbal, S. Bekmez, and F. A. Qurashi, "Operational risk management through machine learning and business intelligence in U.S. businesses," Spanish Journal of Innovation and Integrity, vol. 54, pp. 239–253, 2026.

[16] I. Alim, R. N. Meghla, T. F. Matin, and T. M. M. H. Prodhan, "A semantic and behavioral AI framework for detecting invoice fraud in automated accounts payable," International Journal of Science and Research Archive, vol. 19, no. 2, pp. 1356–1380, 2026.

[17] U. Imtiaz, F. Amin, and A. Khan, "Crash2Compromise: CrashGuard-FS for security-aware Linux file updates," Multidisciplinary Research in Computing Information Systems, vol. 6, no. 2, pp. 294–310, 2026.

[18] U. Iqbal and Y. Bhutto, "Digital transformation through artificial intelligence and advanced business analytics in American operational management," Journal of Theoretical and Applied Econometrics, vol. 3, no. 1, pp. 37–50, 2026.

[19] M. R. Islam, I. A. Badhan, M. H. Rahman, and M. N. Hasnain, "The economics of global renewable energy supply chains: Opportunities and vulnerabilities for the U.S.," International Journal of AI, Engineering and Management Studies (IJAIEMS), vol. 1, no. 1, pp. 108–136, 2026.

[20] V. S. Naresh and V. S. Sriram, "PPDNN-SoH: Privacy-preserving deep neural network for sustainable electric vehicle battery state of health prediction," Neural Computing and Applications, vol. 37, no. 32, pp. 27445–27473, 2025.

[21] F. Amin, "Adaptive cyber risk management framework for critical infrastructures: Integrating IDS, SOC, and CSIRT for resilient threat mitigation," in International Conference on Data Science, Computation and Security, Cham, Switzerland: Springer Nature Switzerland, 2025, pp. 222–239.

[22] M. A. U. H. Khan, R. Parveen, I. Ahmed, M. H. Milon, and T. A. Khan, "High-accuracy breast cancer diagnosis using neural networks and dimensionality reduction techniques," in Proc. IEEE 19th Int. Conf. Open Source Syst. Technol. (ICOSST), Piscataway, NJ, USA: IEEE, Dec. 2025, pp. 1–6

[23] X. Chen, X. Wang, and Y. Deng, "Federated learning-based prediction of electric vehicle battery pack capacity using time-domain and frequency-domain feature extraction," Energy, vol. 319, Art. no. 135002, 2025.

[24] R. Parveen, "Exploring the role of data analytics through digital platforms and IT in promoting transparency and accountability in civil service delivery: Lessons from Bangladesh," International Journal of Humanities & Social Science Studies (IJHSSS), vol. 11, no. 1, pp. 127–146, 2025, doi: 10.29032/ijhsss.vol.11.issue.01w.015.

[25] M. R. Islam, M. M. Islam, I. A. Badhan, and M. N. Hasnain, "The role of artificial intelligence in carbon pricing policies: Economic and environmental implications," Journal of Engineering and Computational Intelligence Review, vol. 3, no. 2, pp. 1–19, 2025.

[26] T. Han, S. Yue, P. Yang, R. Zhou, and J. Yu, "Source-free dynamic weighted federated transfer learning for state-of-health estimation of lithium-ion batteries with data privacy," IEEE Transactions on Power Electronics, vol. 39, no. 11, pp. 15085–15100, 2024.

[27] T. Han, S. Yue, P. Yang, R. Zhou, and J. Yu, "Source-free dynamic weighted federated transfer learning for state-of-health estimation of lithium-ion batteries with data privacy," IEEE Transactions on Power Electronics, vol. 39, no. 11, pp. 15085–15100, 2024.

[28] V. S. Naresh, V. S. Sriram, and A. Dullam, "Encrypted dynamic RVFLN ensemble learning for privacy-preserving state-of-health prediction in electric vehicle batteries using fully homomorphic encryption CKKS," Transactions on Emerging Telecommunications Technologies, vol. 37, no. 3, Art. no. e70388, 2026.