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REVIEW

Diagnosis and prediction of battery life using recurrent neural networks

Diagnóstico y predicción de vida útil de baterías mediante redes neuronales recurrentes

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ABSTRACT

Monitoring the health status (SOH) and predicting the remaining useful life (RUL) of lithium-ion batteries represent critical challenges in chemical and materials engineering. This review analyzes the fundamental role of long-term memory networks (LSTM) as an advanced tool for modeling the temporal degradation of batteries. LSTMs, with their gate architecture that regulates information flow, demonstrate a unique ability to capture nonlinear and long-term dependencies in operational data sequences, overcoming the limitations of traditional methods based on physical models or static machine learning techniques. Analysis of recent applications reveals that hybrid approaches combining LSTMs with Gaussian processes, convolutional networks, or attention mechanisms achieve prediction errors of less than 1 %, establishing new paradigms of accuracy in RUL forecasting. However, the computational complexity of these architectures poses practical challenges for their implementation in real-time battery management systems. The review concludes that LSTMs represent a transformative advance in battery monitoring; however, their industrial adoption will require optimizations in computational efficiency and transfer learning strategies to adapt to diverse chemistries and operating conditions.

Keywords: Artificial Intelligence; Recurrent Neural Networks; Lithium-Ion Batteries; Health Status Monitoring.

RESUMEN

La monitorización del estado de salud (SOH) y la predicción de la vida útil restante (RUL) de baterías de iones de litio representan desafíos críticos en ingeniería química y de materiales. Esta revisión analiza el papel fundamental de las redes de memoria a largo plazo (LSTM) como herramienta avanzada para modelar la degradación temporal de baterías. Las LSTM, con su arquitectura de puertas que regulan el flujo de información, demuestran una capacidad única para capturar dependencias no lineales y de largo plazo en secuencias de datos operativos, superando las limitaciones de métodos tradicionales basados en modelos físicos o técnicas de *Machine Learning* estáticas. El análisis de aplicaciones recientes revela que los enfoques híbridos que combinan LSTM con procesos Gaussianos, redes convolucionales o mecanismos de atención logran errores de predicción inferiores al 1 %, estableciendo nuevos paradigmas de precisión en el pronóstico de RUL. Sin embargo, la complejidad computacional de estas arquitecturas plantea desafíos prácticos para su implementación en sistemas de gestión de baterías (BMS) en tiempo real. La revisión concluye que las LSTM representan un avance transformador en la monitorización de baterías, sin embargo, su adopción industrial requerirá optimizaciones en eficiencia computacional y estrategias de aprendizaje transferencial para adaptarse a diversas químicas y condiciones operativas.

Palabras clave: Inteligencia Artificial; Redes Neuronales Recurrentes; Baterías de Iones de Litio; Monitorización del Estado de Salud.

INTRODUCTION

The diagnosis and prognosis of the useful life of lithium-ion batteries is an essential field of study, given the growing dependence on these electrochemical storage systems in electric mobility, renewable energy integration, and portable devices.[1] Their progressive degradation—manifested by loss of active material, growth of the SEI layer, and increased internal resistance—is a critical technical challenge that directly impacts reliability and operational safety.[2]

Accurate estimation of State of Health (SOH), defined as the percentage of the current capacity relative to the nominal capacity, and Remaining Useful Life (RUL) is essential to ensure safe and efficient operation. These parameters enable predictive maintenance, optimized replacements, and the prevention of catastrophic failures, thereby reducing operating costs and associated risks.[2]

Traditional approaches to estimating SOH/RUL are divided into methods based on physical-mathematical models and techniques based on data.[2,3] The former use representations based on electrochemical principles or equivalent circuits, often combined with Kalman or particle filters.[4] While they provide valuable mechanical information, their applicability is limited by the need for specific calibration and their poor adaptability to variable operating conditions. [5]

Considering these limitations, data-based methods are emerging as a promising alternative, as they learn directly from operating histories without requiring explicit physical modeling. These techniques, which include support vector machines, autoregressive models, and random forests, stand out for their flexibility in adapting to dynamic scenarios. Among them, LSTM recurrent neural networks have demonstrated exceptional capabilities for capturing complex degradation patterns.[2,3]

Long Short-Term Memory (LSTM) networks are an evolution of conventional recurrent networks, designed specifically to model long-range temporal dependencies.[2,6] Their architecture with information gates allows them to retain relevant internal states over long sequences, a crucial feature for representing degradation processes where past events (e.g., discharge depths, thermal exposures) significantly influence future behavior.[7]

This sequential modeling capability positions LSTMs as a privileged tool for battery monitoring. Recent evidence confirms their superiority over traditional methods for SOH estimation and RUL prediction, particularly in identifying nonlinear patterns and complex temporal relationships that conventional techniques miss.[7] Their applicability extends to various operating scenarios, consolidating them as a fundamental component in modern battery management systems. This review analyzes recent literature on the application of LSTM networks to battery diagnostics, examining methodologies, results, comparisons with other approaches, current challenges, and future lines of research. The objective is to describe recent advances in the application of LSTM networks for the diagnosis and prediction of lithium battery life.

DEVELOPMENT

Fundamentals of LSTM networks applied to battery sequences

Long Short-Term Memory (LSTM) networks are an evolution of recurrent neural networks, designed specifically to overcome the long-term memory limitations of conventional RNNs.[2] Their architecture is based on memory cells with three multiplicative gates: the input gate regulates the flow of new information, the forget gate controls the retention of previous information, and the output gate determines the influence of the internal state on the prediction.[8,9] This gate mechanism allows LSTMs to learn complex temporal dependencies by deciding what information to retain or discard over long sequences. In the context of batteries, this capability captures

cumulative effects, such as historical charge cycles or thermal stress events, facilitating the prediction of the evolution of critical parameters, such as capacity and internal resistance.

The adaptability of LSTMs to variable-length sequences and their robustness to noisy data make them ideal tools for analyzing time series of batteries from real operating environments. Nonlinear phenomena such as capacity recovery or degradation plateaus, which challenge linear models, can be learned directly from the data through appropriate network training.[10] This flexibility has established LSTMs as a fundamental component in State of Health (SOH) estimation models—where sequences of operational indicators are mapped to the current capacity value—and Remaining Useful Life (RUL) prediction—where the degradation trajectory is projected until critical thresholds are reached (e.g., SOH < 80 %).

Consequently, LSTMs establish a solid computational framework for modeling temporal degradation processes in electrochemical systems. Their theoretical foundation enables the representation of nonlinear, operation-history-dependent relationships, providing a technical basis for their successful application in battery monitoring and forecasting. The following section examines specific implementations and recent optimizations of LSTM networks for lithium-ion battery diagnosis.

Recent applications of LSTM in Li-ion battery monitoring

Research on LSTM applications in lithium-ion battery monitoring has grown significantly, with numerous studies demonstrating its effectiveness in estimating State of Health (SOH) and predicting Remaining Useful Life (RUL). This section summarizes the most relevant advances, analyzing methodologies, data used, and results obtained.

Pure LSTM models have demonstrated the ability to achieve SOH estimates with remarkable accuracy. Yang et al. reported that an LSTM network trained with charge/discharge cycle data predicted remaining capacity with less error than conventional neural networks in time forecasting.[11] Complementarily, another study[12] applied LSTM to cells under different depths of discharge, obtaining relative errors of less than 2 % even with small data sets, thanks to the exploitation of sequential dependencies. A crucial finding was the transfer of knowledge through the reuse of frozen LSTM layers between different batteries, suggesting that these networks capture general aging features that reduce the need for large volumes of labeled data per cell.

The integration of LSTM with other techniques has led to hybrid approaches that improve accuracy and robustness. Zhao et al.[3]combined LSTM with Gaussian processes (GPR) for joint SOH/RUL prediction, where LSTM predicts health indicator trajectories that feed into the GPR model. When validated with the four-cell NASA dataset, they achieved SOH errors below 1 % and RUL errors below one cycle. Similarly, the CNN-LSTM combination has proven effective at extracting spatial features (e.g., voltage waveforms), which are then processed temporally by the LSTM. More complex architectures incorporate transfer learning[13] or bidirectional LSTMs (Bi-LSTM), seeking synergies between local pattern capture and long-term trend modeling.[2]

The incorporation of attention mechanisms represents a qualitative advance in the evolution of LSTMs. Xu et al.[14] developed a model with spatiotemporal attention that separates long-term degradation characteristics from short-term fluctuations, applying double spatial attention (to weight indicators) and temporal attention (to focus on specific stages). This approach proved superior to traditional LSTMs, even in the face of phenomena such as capacity regeneration. In RUL prediction, Chen et al.[15] proposed a hybrid architecture that combines transductive LSTM (TLSTM) with dilated convolutions, spatial attention, and evolutionary optimization. Their multi-channel approach (using voltage, current, and temperature) reduced prediction errors by 10-14 %, achieving an MAPE of 0,5-1 % in validation tests using NASA data. Although computational complexity poses challenges for implementation in BMS, these works set new benchmarks for accuracy.

The versatility of LSTMs extends to specific applications such as diagnosis using load curve segments,[16] stacked models for fast charging,[17] or fusion with Kalman filters. The common denominator is the ability to adapt to various types of input while maintaining errors within a few percentage points, substantially outperforming traditional methods, where errors of 5-10 % were common.[3] This accuracy has established LSTMs as a central component in modern data-driven battery management systems.

Comparison between LSTM and other diagnostic methods

Battery diagnostics using LSTM must be contextualized within the broader spectrum of available methodologies, ranging from physical model-based approaches to advanced artificial intelligence techniques. This section presents a comparative analysis of the strengths and limitations of LSTM compared to these alternative methods.

Physical/model-based methods

Approaches based on physical models, such as electrochemical models (e.g., the pseudo-2D particle model) or equivalent circuits combined with Kalman filters, offer the unique advantage of providing physical insights into degradation mechanisms. However, their development and calibration require specialized knowledge and are costly, and they exhibit significant limitations when operating conditions deviate from the original calibration scenarios.[2] In contrast, LSTM-based techniques have greater generalization capabilities by learning directly from experimental data, avoiding the need for detailed physical modeling for each battery chemistry. This advantage is mitigated by the "black box" nature of LSTMs, which sacrifices physical interpretability for gains in accuracy and operational flexibility.

Other Machine Learning Techniques

Classic methods such as support vector machines, random forests, and autoregressive models have demonstrated limited ability to capture complex temporal dependencies, often requiring manual feature engineering to incorporate the temporal dimension. LSTMs overcome this limitation by automatically modeling temporal sequences, learning temporal dynamics directly from the data. Comparative studies such as that by Bhattacharjee et al.[18] confirm that LSTMs identify degradation trends more accurately than SVM or ARIMA, especially in non-smooth patterns with fluctuations and discontinuities. Although techniques such as XGBoost or LightGBM can achieve good performance with specialized features, they generally require more tuning and do not capture temporal dependencies as naturally as LSTMs.

Other neural networks

Within deep learning, LSTMs coexist with alternative architectures such as GRUs, CNNs, and Transformers. GRUs, a simplified version of LSTMs, can achieve similar performance in some applications, though specific studies on batteries suggest that LSTMs retain advantages in highly nonlinear degradation scenarios.[19] For example, Sheikhani et al.[20] demonstrated the superiority of LSTM over GRU and feed-forward networks in predicting SOH until total failure. Pure CNNs, although effective for feature extraction, lack the inherent ability to model temporal dependencies, motivating hybrid CNN-LSTM architectures that leverage the strengths of both approaches.[21] Transformers are emerging as a promising alternative due to their ability to capture very long-term dependencies, although their high complexity and data requirements limit their practical applicability. Hybrid Transformer-LSTM strategies seek to balance this dichotomy, using Transformers for feature extraction and LSTM as the predictive backbone.(2)

This comparison shows that selecting the optimal method depends critically on the balance between physical interpretability, computational requirements, data availability, and required accuracy, with LSTMs being particularly suitable for applications where capturing complex

temporal dependencies is a priority.

FINAL CONSIDERATIONS

The application of LSTM networks has established itself as an effective paradigm for diagnosing and predicting lithium-ion battery life, demonstrating capabilities superior to traditional methods. The reviewed evidence confirms that these architectures achieve SOH estimates with minimal errors and RUL predictions with remarkable accuracy, significantly outperforming approaches based on physicochemical models and conventional machine learning techniques. This advantage stems from their inherent ability to model the nonlinear, operation-history-dependent dynamics that characterize electrochemical degradation processes.

Recent methodological developments show a clear trend toward hybrid architectures that combine LSTM with complementary components. Integration with convolutional networks, attention mechanisms, and probabilistic methods has enabled incremental improvements in predictive performance, achieving previously unattainable levels of accuracy. However, this sophistication comes with greater computational demands and data requirements, creating new challenges for practical implementation in embedded battery management systems (BMS).

Future developments must critically address computational efficiency, generalization across different battery chemistries, and the interpretability of predictions. The integration of these techniques with adaptive control and predictive maintenance strategies will optimize operation and extend service life. However, their industrial implementation will require solutions that balance complexity and practicality. LSTMs have thus set a new standard in battery monitoring, positioning themselves as a fundamental component in the next generation of intelligent energy management systems.

BIBLIOGRAPHIC REFERENCES

1. Juan OS, Moisés J. Modelos de diagnóstico predictivos de SOH (State of Health) de baterías. 2022 Sep 19. Disponible en: http://addi.ehu.eus/handle/10810/58716

2. Xu G, Xu J, Zhu Y. LSTM-based estimation of lithium-ion battery SOH using data characteristics and spatio-temporal attention. PLOS ONE. 2024 Dec 26;19(12):e0312856. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0312856

3. Zhao J, Zhu Y, Zhang B, Liu M, Wang J, Liu C, et al. Method of Predicting SOH and RUL of Lithium-Ion Battery Based on the Combination of LSTM and GPR. Sustainability. 2022 Jan;14(19):11865. https://www.mdpi.com/2071-1050/14/19/11865

4. Benavides Flores MI. Determinación de indicadores de estado de salud de baterías de ion-litio, mediante el uso de espectroscopía de impedancia electroquímica y caracterización del término de la vida útil basado en la generación de calor dada por la impedancia interna. 2018. Disponible en: https://repositorio.uchile.cl/handle/2250/153342

5. Artificial intelligence for estimating State of Health and Remaining Useful Life of EV batteries: A systematic review. ICT Express. 2025 Aug 1;11(4):769-89. https://www.sciencedirect.com/science/article/pii/S240595952500075X

6. Pérez Sepa MA, Angueta Ponce AV, Guasumba Maila JE, Calero Torres DA. Estimación de la vida útil de las baterías de los vehículos híbridos causas y consecuencias. Dominio de las Ciencias. 2022;8(2):770-81. https://dialnet.unirioja.es/servlet/articulo?codigo=8637987

7. Rout S, Samal SK, Gelmecha DJ, Mishra S. Estimation of state of health for lithium-ion

batteries using advanced data-driven techniques. Scientific Reports. 2025 Aug 19;15(1):30438. https://www.nature.com/articles/s41598-025-93775-y

8. Verdin-Tavares AL, Bravo-Valtierra EM, Cárdenas-Valdez JR, Calvillo-Téllez Á. Medidor IoT del estado de salud de baterías. Pädi Boletín Científico de Ciencias Básicas e Ingenierías del ICBI. 2023 Nov 30;11:62-6. https://repository.uaeh.edu.mx/revistas/index.php/icbi/article/view/11430

9. Rincón Maya CJ. Modelo predictivo para la vida útil restante de un componente crítico de un vehículo eléctrico. 2024. Disponible en: https://hdl.handle.net/10495/38460

10. Sarasketa Zabala E. A novel approach for lithium-ion battery selection and lifetime prediction. Mondragon Unibertsitatea; 2014. Disponible en: https://research.science.eus/documentos/5fed2b435ef74402109ada45

11. A novel Gaussian process regression model for state-of-health estimation of lithium-ion battery using charging curve. Journal of Power Sources. 2018 Apr 30;384:387-95. https://www.sciencedirect.com/science/article/abs/pii/S0378775318302398

12. Yao L, Wen J, Xu S, Zheng J, Hou J, Fang Z, et al. State of Health Estimation Based on the Long Short-Term Memory Network Using Incremental Capacity and Transfer Learning. Sensors (Basel). 2022 Oct 15;22(20):7835.

13. Liu J, Luo P, Shen J. Bearing Fault Prognosis Method Based on Priori Knowledge-Enhanced Particle Filter. Disponible en: https://onlinelibrary.wiley.com/doi/10.1155/2022/8634753

14. Xu G, Xu J, Zhu Y. LSTM-based estimation of lithium-ion battery SOH using data characteristics and spatio-temporal attention. PLoS One. 2024;19(12):e0312856.

15. Chen S, Fang X. Remaining useful life prediction of lithium–ion batteries via spatial attention TLSTM and dilated CNN with evolutionary optimization. Scientific Reports. 2025 Sep 2;15(1):32340. https://www.nature.com/articles/s41598-025-17610-0

16. Qian K, Li Y, Zou Q, Cao K, Li Z. SOH and RUL Estimation for Lithium-Ion Batteries Based on Partial Charging Curve Features. Energies. 2025 Jan;18(13):3248. https://www.mdpi.com/1996-1073/18/13/3248

17. Yayan U, Arslan AT, Yucel H. A Novel Method for SoH Prediction of Batteries Based on Stacked LSTM with Quick Charge Data. Applied Artificial Intelligence. 2021 May 12. https://www.tandfonline.com/doi/abs/10.1080/08839514.2021.1901033

18. Bhattacharjee S, Maity S, Sen R, Chatterjee S. Class Biased Sarcasm Detection Using Variational LSTM Autoencoder. In: Mandal L, Tavares JMRS, Balas VE, editors. Proceedings of International Conference on Computational Intelligence, Data Science and Cloud Computing. Singapore: Springer Nature; 2022. p. 289-97.

19. Olivares Rubio BE. Sistema de pronóstico para el estado-de-salud de acumuladores de energía basado en filtro de partículas y caracterización estadística de fenómenos de regeneración. 2012. Disponible en: https://repositorio.uchile.cl/handle/2250/111463

20. Sheikhani A, Agic E, Moghadam MH, Andresen JC, Vesterberg A. Lithium-Ion Battery SOH Forecasting: From Deep Learning Augmented by Explainability to Lightweight Machine Learning Models. In: 2024 IEEE 29th International Conference on Emerging Technologies and Factory Automation (ETFA). 2024. p. 1-4. https://ieeexplore.ieee.org/abstract/document/10710794

21. Sheikhani A, Agic E. Lithium-Ion Battery SOH Forecasting With Deep Learning Augmented By Explainable Machine Learning. 2024. Disponible en: https://urn.kb.se/resolve?urn=urn:nbn:se:mdh:diva-67618

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