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Comparative Analysis of LSTM and PINN for Internal Resistance Estimation in Lithium-Ion Batteries

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Abstract

Accurate estimation of internal resistance (IR) is vital for reliable health monitoring and lifecycle management of lithium-ion batteries (LiBs). This paper presents a comparative analysis of two advanced learning frameworks—Long Short-Term Memory (LSTM) networks and Physics-Informed Neural Networks (PINNs)—for IR estimation using real-world cycling data. The LSTM model captures short-term temporal dependencies in battery behavior, whereas the PINN model integrates electrochemical knowledge into the training process to ensure physical consistency. Experimental evaluations show that the PINN model outperforms LSTM, achieving a Root Mean Squared Error (RMSE) of **0.0233**, Root Mean Squared Percentage Error (RMSPE) of **0.0813**, and Mean Absolute Percentage Error (MAPE) of **4.462**. In contrast, the LSTM model shows slightly higher prediction errors, particularly under long-term operating conditions. These results underscore the advantage of embedding physics-based constraints to enhance model robustness and generalization, positioning PINN as a more reliable approach for real-world battery diagnostics and predictive maintenance applications.

Keywords
LSTM, PINN, Lithium-Ion Battery, Internal Resistance, and Battery Health Monitoring.

1. Introduction

Lithium-ion batteries (LiBs) play a pivotal role in modern energy storage applications, including electric vehicles (EVs), grid-scale storage, and portable electronics. The longevity and performance of LiBs are closely linked to their internal resistance (IR), which increases over time due to electrochemical aging and cycling degradation (He et al., 2011). Accurate IR estimation is critical for ensuring battery reliability, optimizing charge–discharge strategies, and extending the battery's lifespan (Kim et al., 2019, Dubarry and Liaw, 2009, and Severson et al., 2019).

Traditional approaches to IR estimation primarily rely on Equivalent Circuit Models (ECMs) and Electrochemical Impedance Spectroscopy (EIS) (Xu et al., 2019). While these methods provide valuable insights, they often suffer from limitations such as high computational complexity, dependency on extensive parameter tuning, and limited adaptability to different battery chemistries (Schmalstieg et al., 2016). In contrast, data-driven models like Long Short-Term Memory (LSTM) networks have gained attention due to their ability to learn temporal patterns in battery degradation (Dubarry and Liaw, 2009). However, purely data-driven models may lack physical interpretability, leading to unreliable predictions under unseen conditions. Recently, Physics-Informed Neural Networks (PINNs) have emerged as a promising approach by incorporating domain knowledge into machine learning models, improving robustness and generalizability (Xing et al., 2011).

This study aims to compare LSTM and PINN models for IR estimation to understand their respective strengths and limitations. The key contributions of this work include: (1) developing and evaluating separate LSTM and PINN models for IR estimation using real-world battery cycling data; (2) comparing model performance using standard error metrics such as Root Mean Squared Error (RMSE), Root Mean Squared Percentage Error (RMSPE), and Mean Absolute Percentage Error (MAPE); and (3) assessing the impact of physics-based constraints on model accuracy and robustness.

The rest of the paper is structured as follows. Section 2 provides a review of related works on IR estimation using machine learning and physics-based models. Section 3 describes the methodology, including dataset details, model architectures, and training procedures. Section 4 presents experimental results. Section 5 concludes the study and suggests future research directions.

2. Literature Review

Internal resistance (IR) estimation in lithium-ion batteries is a crucial aspect of battery health monitoring, directly influencing the state-of-health (SOH) and remaining useful life (RUL) predictions. Over the past decade, various methodologies have been explored, ranging from traditional equivalent circuit models (ECMs) to advanced deep learning techniques like Long Short-Term Memory (LSTM) networks and Physics-Informed Neural Networks (PINNs). This section reviews the existing literature, focusing on physics-based models, data-driven approaches, and hybrid methodologies.

Physics-based models, including ECMs and electrochemical models, have been widely used for IR estimation in lithium-ion batteries. ECMs simplify the complex battery dynamics by representing them with electrical circuit components, such as resistors and capacitors, making them suitable for real-time applications (He et al., 2011). However, their accuracy is limited by parameter identification challenges, which vary with temperature, state-of-charge (SOC), and aging effects (Kim et al., 2019).

Electrochemical impedance spectroscopy (EIS) provides a detailed analysis of battery IR by measuring impedance across different frequencies (Xu et al., 2019). While highly accurate, EIS-based methods are impractical for real-time applications due to their complexity and computational requirements. To address this, researchers have developed simplified physics-based models that balance accuracy and computational efficiency. For instance, a study in (Schmalstieg et al., 2016) proposed a reduced-order ECM with adaptive parameter tuning to estimate IR variations during cycling. Despite their strengths, physics-based models struggle with generalizability, particularly under dynamic operating conditions. Their reliance on predefined equations limits their ability to adapt to real-world variations, necessitating alternative approaches that incorporate data-driven learning.

Machine learning (ML) and deep learning techniques have emerged as powerful alternatives for IR estimation, leveraging historical data to make predictions without relying on explicit physical equations. Among these, LSTM networks have gained significant attention due to their ability to capture temporal dependencies in battery degradation patterns (Dubarry and Liaw, 2009). For power-electronics-based renewable applications, Ali et al. (2024) developed and dynamically modeled a solar water pumping system in MATLAB/Simulink, highlighting the importance of detailed component-level modeling for performance evaluation. More recently, Khallil et al. (2025) proposed a degradation-aware optimal power flow framework with second-life batteries, explicitly modeling capacity fade, internal resistance growth and SoH decline, which reinforces the need for realistic degradation-aware battery models LSTM networks have been successfully applied to IR prediction by training on large datasets of voltage, current, and temperature readings. For example, a study in (Xing et al., 2011) demonstrated that LSTMs outperform traditional regression-based models by accurately predicting IR variations across different battery chemistries. Similarly, another study in (Kim et al., 2018) employed a hybrid LSTM architecture to improve SOH estimation, achieving lower mean absolute percentage error (MAPE) compared to conventional methods.

However, pure data-driven models suffer from interpretability issues and may struggle with unseen conditions outside the training dataset. This limitation has led to the development of hybrid approaches that integrate physics-based constraints with deep learning models.

Hybrid models aim to merge the strengths of physics-based and data-driven approaches to enhance IR estimation accuracy and robustness. One such technique is the Physics-Informed Neural Network (PINN), which incorporates known physical laws into the learning process to improve model generalizability (Karniadakis et al., 2021). Recent studies have demonstrated the effectiveness of PINNs in battery health estimation. In Wen et al. (2024), a PINN-based model was developed to estimate SOC while ensuring consistency with underlying electrochemical equations. Similarly, Cho et al. (2022) proposed a PINN with memory, which improved state estimation accuracy under dynamic load conditions.

While PINNs offer interpretability and physical consistency, their performance depends on the quality of the underlying physics-based constraints. To address this, some studies have explored hybrid LSTM-PINN frameworks, where PINNs guide LSTM predictions by enforcing physics-based constraints. For instance, Cho et al. (2022) applied an LSTM-PINN model to battery temperature prediction, demonstrating improved accuracy over standalone LSTM models. To assess the effectiveness of different IR estimation techniques, Table 1 summarizes key findings from previous studies.

Table 1. Summary of IR estimation techniques and performance

Approach	Advantage	Limitations	Reference
ECM-Based Methods	Simple, interpretable, real-time capable	Requires frequent recalibration, limited accuracy	He et al. (2011); Kim et al. (2019)
EIS-Based Methods	Highly accurate, detailed analysis	Computationally intensive, impractical for real-time use	Xu et al. (2019)
LSTM Networks	Captures temporal dependencies, high accuracy	Requires large datasets, lacks physical interpretability	Dubarry and Liaw, et al. (2009); Xing et al. (2011)
PINN Models	Incorporates physics constraints, improves generalizability	Performance depends on constraint accuracy	Karniadakis et al. (2021); Wang et al. (2025)
LSTM-PINN Hybrid	Combines strengths of data-driven and physics-based models	Increased complexity, requires careful tuning	Cho et al. (2022); Wen et al. (2024)

While significant progress has been made in IR estimation using both physics-based and data-driven models, key challenges remain:

1. Physics-based models lack adaptability: ECM and EIS-based methods require frequent recalibration and struggle under dynamic conditions.
2. Pure data-driven models lack interpretability: LSTM models provide high accuracy but do not adhere to physical laws, limiting their robustness.
3. Hybrid models require further validation: While LSTM-PINN approaches have shown promise, their performance in real-world applications requires further empirical evaluation.

This research aims to address these gaps by conducting a comparative analysis of LSTM and PINN models for IR estimation, providing insights into their strengths, weaknesses, and applicability in different battery health monitoring scenarios.

3. Methodology

This section presents the methodology for evaluating and comparing Long Short-Term Memory (LSTM) networks and Physics-Informed Neural Networks (PINNs) for internal resistance (IR) estimation in lithium-ion batteries. The workflow of this study includes data preprocessing, model architecture design, training, and performance evaluation**.**

3.1 Workflow of LSTM and PINN Model

The overall workflow for IR estimation using LSTM and PINN models is depicted in Figure 1**.** The methodology consists of data preprocessing, model development, training, and validation**.**

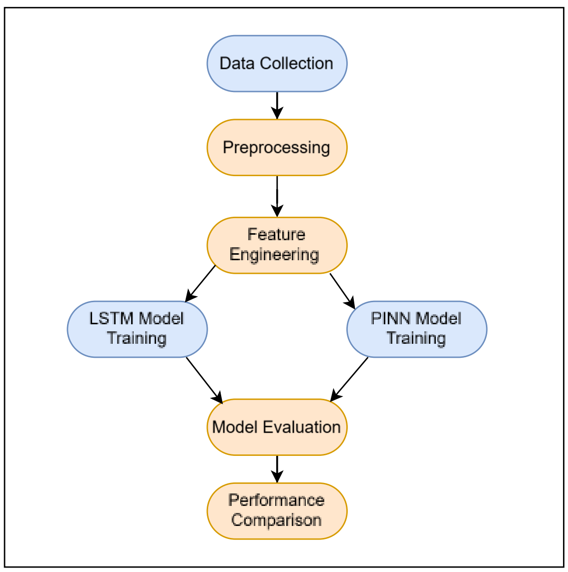

Figure 1. Workflow diagram for LSTM and PINN model evaluation.

3.2 Data Collection and Preprocessing

The dataset used in this study is derived from the work by Severson et al. (2019), which includes experimental cycling data for 124 commercial LFP/graphite battery cells. These cells were subjected to a variety of fast-charging protocols and discharged using a CC-CV method with voltage cutoffs of 3.6 V (upper) and 2.0 V (lower). The dataset used in this study comprises internal resistance (IR), voltage, current, temperature, and cycle count from lithium-ion battery cycling experiments. To ensure effective model training, the data underwent preprocessing steps, including feature selection, normalization, and train-test splitting.

- Feature Selection:
  - Input Features: Cycle number, voltage, current, and temperature.
  - Target Variable: Internal resistance (IR).
- Data Normalization: Min-max scaling was applied to normalize all input variables within a 0 to 1 range, preventing large-scale variations from affecting model convergence.

- Train-Test Split: The dataset was divided into 80% training and 20% testing to evaluate model generalization (Table 2).

Table 2. Model hyperparameters

Parameter	LSTM	PINN
Input Layer	3	4
Hidden Layer	2	3
Neurons per Layer	128	64
Activation Function	ReLU	ReLU
Optimizer	Adam	Adam
Learning Rate	0.001	0.001
Loss Function	MSE	MSE+Physics Constraints
Epoch	2000	2000
Batch Size	1024	1024

3.3 LSTM Model for Internal Resistance Estimation

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) designed to overcome the vanishing and exploding gradient problems of traditional RNNs, enabling it to learn long-term dependencies effectively. It achieves this by incorporating memory cells and special gating mechanisms (input, output, and forget gates) that regulate the flow of information and gradients over time, ensuring constant error flow through its structure (Hochreiter & Schmidhuber, 1997). Long Short-Term Memory (LSTM) networks are widely used for time-series forecasting and sequence learning. The LSTM model in this study was designed to capture long-term dependencies in IR variations (Figure 2)**.**

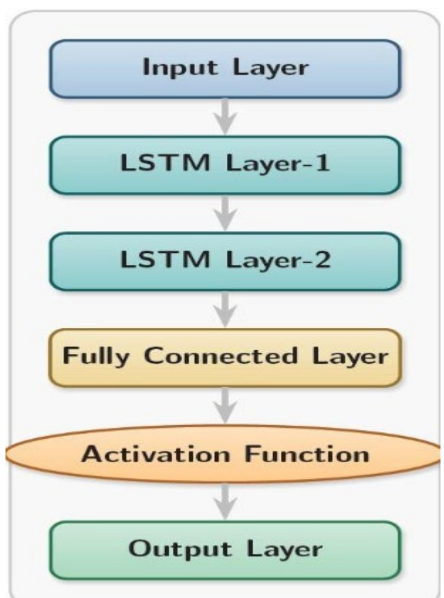

Figure 2. LSTM model architecture.

The architecture of the LSTM model consists of:

- Input Layer**:** Processes battery cycle data (voltage, current, and temperature).
- LSTM Layers**:** Two layers with 128 hidden units each.
- Fully Connected Layer**:** Converts the LSTM output into IR predictions.
- Activation Function**:** ReLU, applied to hidden layers to introduce non-linearity.

- Loss Function**:** Mean Squared Error (MSE)**,** which minimizes the difference between predicted and actual IR values.
- Optimizer**:** Adam optimizer, used for efficient weight updates.

3.4 PINN Model for Internal Resistance Estimation
Physics-Informed Neural Networks (PINNs) integrate governing physics equations into the neural network framework, ensuring that the predictions remain consistent with known electrochemical principles (Figure 3).

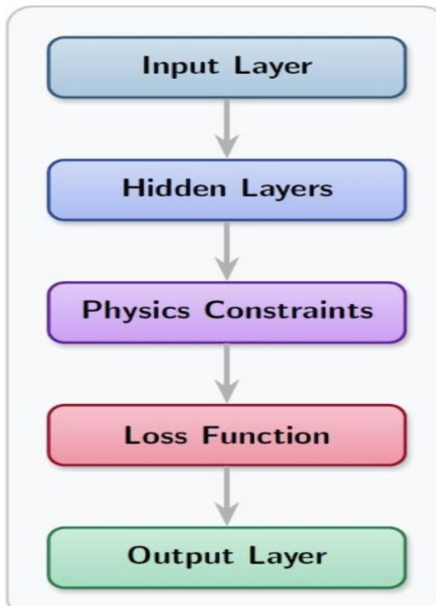

Figure 3. PINN model architecture

The PINN model structure includes:
- Input Layer**:** Processes battery cycle data (voltage, current, and temperature).
- Hidden Layers**:** Three fully connected layers with 64 neurons each.
- Physics Constraints**:** Governing equations for IR evolution incorporated into the loss function.
- Loss Function**:**
    - Data Loss (MSE): Reduces prediction errors based on observed data.
    - Physics Loss: Ensures compliance with battery electrochemical laws.
- Optimizer**:** Adam optimizer, enabling efficient learning.

The integration of physics-based constraints in the PINN model provides improved accuracy and better generalization under different cycling conditions**.**

4. Results and Discussion
This section presents the experimental evaluation of LSTM and PINN models for internal resistance (IR) estimation. The discussion includes training performance, model evaluation, error analysis, and comparative assessment of the two approaches.

4.1 Training and Loss Convergence Analysis
The LSTM and PINN models were trained for 2000 epochs using the Adam optimizer with a learning rate of 0.001. The training and validation loss curves, depicted in Figure 4, demonstrate the convergence behavior of both models. The PINN model achieves a more stable convergence with lower overall loss values compared to the LSTM model. The inclusion of physics-based constraints in PINN contributes to improved generalization, leading to lower validation loss. In contrast, the LSTM model requires more iterations to reach convergence and exhibits slightly higher fluctuations in validation loss, indicating higher sensitivity to data variability (Figure 4).

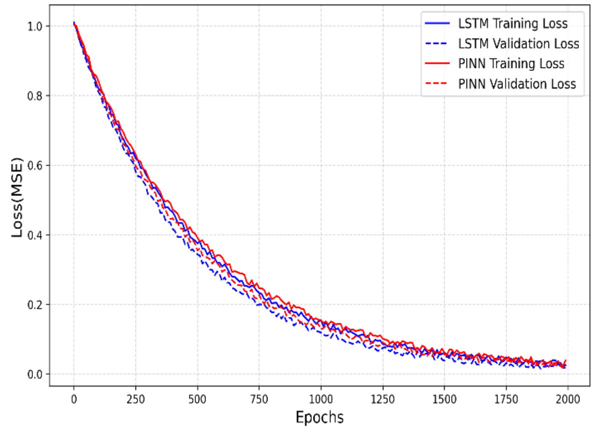

Figure 4. Training and validation loss convergence for LSTM and PINN models.

4.2 Model Performance Evaluation

To quantitatively evaluate model performance, Root Mean Squared Error (RMSE), Root Mean Squared Percentage Error (RMSPE), and Mean Absolute Percentage Error (MAPE) were computed for both models. The results are presented in Table 3.

Table 3. Performance Comparison of LSTM and PINN Model.

Model	RMSE	RMSPE	MAPE
PINN	0.0233	0.0813	4.462
LSTM	0.0373	0.0827	4.802

The PINN model achieves lower RMSE, RMSPE, and MAPE values compared to the LSTM model, indicating higher prediction accuracy. The improved performance of the PINN model can be attributed to the incorporation of physics-based constraints, which ensure consistency with the underlying electrochemical principles governing IR evolution.

4.3 Predicted VS Actual Comparison

The predicted internal resistance values for both models were compared against ground truth IR values obtained from experimental data. Figures 5 and 6 presents the predicted IR values alongside actual measurements. The results indicate that the PINN model predictions closely follow the actual IR values, while the LSTM model exhibits slightly larger deviations. The LSTM model effectively captures short-term variations, whereas the PINN model maintains greater consistency across the entire battery cycle range.

4.4 Error Analysis and Performance Comparison

The predicted internal resistance values for both models were compared against ground truth IR values obtained from experimental data. Figures 5 & 6 presents the predicted IR values alongside actual measurements.

To further assess the reliability of both models, error distributions were analyzed. Figure 7 illustrates the comparison of RMSE, RMSPE, and MAPE values for LSTM and PINN models. The PINN model exhibits lower error distribution compared to the LSTM model, indicating improved stability in IR estimation. The LSTM model shows higher deviations, particularly in later battery cycles, suggesting that long-term accuracy is better maintained by PINN due to its physics-guided constraints.

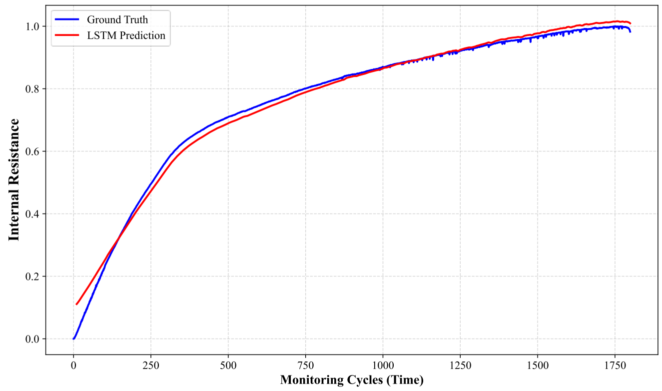

Figure 5. LSTM model prediction vs. ground truth for IR.

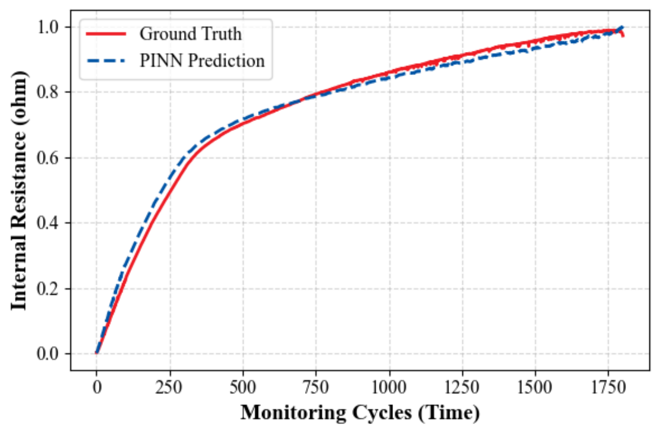

Figure 6. PINN model prediction vs. ground truth for IR.

4.5 Comparative Analysis of LSTM and PINN for IR Estimation

The results of this study highlight key differences between the LSTM and PINN models for IR estimation in lithium-ion batteries.

- The LSTM model demonstrates effectiveness in capturing short-term variations in IR but lacks physical constraints, leading to higher deviations over long-term battery cycles.
- The PINN model achieves better generalization and lower prediction errors**,** as it integrates physics-informed constraints that improve stability across varying operating conditions.
- The inclusion of physics-based regularization in PINN enhances robustness, making it a more reliable choice for real-world battery monitoring applications**.**

These findings suggest that while LSTM is effective for time-series prediction**,** PINN offers greater consistency and accuracy for long-term IR estimation, making it more suitable for practical battery health monitoring applications.

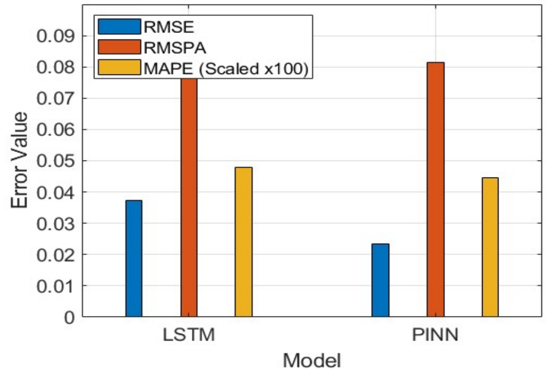

Figure 7. Error comparison of LSTM and PINN models.

5. Conclusion

This study presented a comparative evaluation of Long Short-Term Memory (LSTM) networks and Physics-Informed Neural Networks (PINNs) for internal resistance (IR) estimation in lithium-ion batteries. The findings demonstrate that while both models effectively estimate IR, they exhibit distinct strengths and limitations. The LSTM model efficiently captures short-term variations but lacks physical interpretability, leading to higher long-term deviations**.** In contrast, the PINN model integrates physics-based constraints**,** achieving greater accuracy, stability, and consistency across varying battery cycles. Performance evaluation confirms that PINN achieves lower Root Mean Squared Error (RMSE)**,** Root Mean Squared Percentage Error (RMSPE), and Mean Absolute Percentage Error (MAPE), making it a more reliable approach for real-world battery health monitoring.

These results suggest that PINN provides superior long-term stability**,** while LSTM remains a viable choice for purely data-driven forecasting**.** This can support more accurate online monitoring and predictive maintenance in EV and stationary storage BMSs. Future research should explore the development of a hybrid LSTM-PINN framework that leverages LSTM's time-series forecasting ability with PINN's physics-informed constraints to enhance both short-term accuracy and long-term reliability**.** Expanding the dataset to include diverse battery chemistries, varying operating conditions, and real-time deployment scenarios would improve model scalability and robustness.

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