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AI-Driven Deep Learning and IoT-Based Optimization of Lithium-Ion Battery Performance with Cybersecurity Frameworks for Renewable Energy Systems

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Abstract

The integration of renewable energy systems requires efficient, reliable, and secure energy storage solutions. Lithium-ion batteries are widely used, but degradation, inaccurate state estimation, and cybersecurity threats limit their performance in IoT-enabled environments. This paper proposes an integrated framework combining artificial intelligence, deep learning, Internet of Things monitoring, and cybersecurity mechanisms. Battery modelling used a developed lithium-ion battery dataset generated from controlled charge–discharge experiments under varying operating conditions. The dataset was normalized and divided into 70% training, 15% validation, and 15% testing subsets, while five-fold cross-validation assessed model robustness. An LSTM model estimated state-of-charge and state-of-health, and cyber resilience was evaluated using the CICIDS2017 intrusion-detection dataset. Compared with Extended Kalman Filter and Random Forest models, the LSTM achieved 98.7% accuracy, reduced prediction error by 35%, and improved estimated battery lifespan by 23%. Complexity analysis produced $O(T(hd+h^2))$ time and $O(h^2)$ memory, confirming suitability for real-time battery-management deployment in resource-constrained renewableenergy and smart-grid applications with manageable computational and storage requirements.

I. Introduction

The rapid growth of renewable energy systems has significantly increased the demand for efficient and intelligent energy storage technologies, with lithium-ion batteries emerging as a dominant solution due to their high energy density, long operational life, and relatively low self-discharge characteristics [1]. These batteries play a critical role in stabilizing intermittent renewable energy sources such as solar and wind, ensuring reliable energy supply in both grid-connected and off-grid applications. However, despite their widespread adoption, lithium-ion batteries exhibit complex nonlinear electrochemical behavior, aging effects, and thermal instability, which present significant challenges for accurate state estimation and optimal performance management [2]. These challenges are further exacerbated under dynamic operating conditions where load fluctuations and environmental variations influence battery performance.

Traditional battery management approaches rely on equivalent circuit models and estimation techniques such as the Extended Kalman Filter (EKF) to determine key parameters like state-of-charge (SoC) and state-of-health (SoH) [3]. While these methods provide a structured and mathematically tractable framework, their effectiveness is often limited by model simplifications and assumptions of linearity. In practice, lithium-ion battery systems exhibit highly nonlinear and timevarying characteristics that are difficult to capture using classical estimation techniques. Consequently, these conventional approaches often result in reduced accuracy, especially under high dynamic loads and long-term degradation scenarios.

In response to these limitations, recent advancements in artificial intelligence have introduced data-driven approaches for battery modeling and management. Machine learning techniques, including Random Forest (RF), Support Vector

Machines, and regression-based methods, have demonstrated improved prediction performance compared to traditional models by leveraging historical data to learn complex patterns [4]. However, a major limitation of these approaches is their inability to effectively model temporal dependencies inherent in battery operation. Since battery behavior is inherently sequential, depending on past charge-discharge cycles and operational conditions, models that fail to incorporate temporal information may produce suboptimal predictions.

Deep learning methods, particularly Long Short-Term Memory (LSTM) networks, have shown significant promise in addressing these challenges. LSTM models are specifically designed to capture long-term dependencies in time-series data, making them highly suitable for modeling battery dynamics [5]. Studies have demonstrated that LSTM-based approaches can achieve higher accuracy in SoC and SoH estimation by effectively learning nonlinear relationships and temporal patterns. Despite these advantages, many existing deep learning models are developed in isolation, focusing primarily on prediction accuracy without considering system-level integration and real-time deployment constraints.

Simultaneously, the integration of Internet of Things (IoT) technologies has transformed battery management systems by enabling real-time data acquisition, remote monitoring, and intelligent control [6]. IoT-based systems allow continuous tracking of battery parameters, facilitating predictive maintenance and improving operational efficiency. However, the increasing connectivity of battery systems introduces significant cybersecurity risks. IoT-enabled energy systems are vulnerable to various cyber threats, including data injection attacks, spoofing, denial-of-service attacks, and unauthorized access [7]. These vulnerabilities can lead to incorrect decision-making, system instability, and potential safety hazards.

A critical examination of the literature reveals that most existing studies address battery performance optimization, IoT monitoring, or cybersecurity in isolation. While some works have explored AI-based battery prediction models, they often lack integration with real-time IoT frameworks. Similarly, IoT-based battery monitoring systems frequently overlook cybersecurity considerations, leaving systems exposed to potential attacks. Even studies that incorporate cybersecurity mechanisms tend to focus on general IoT applications rather than specifically addressing the unique challenges of battery management systems [8]– [15]. This fragmented approach highlights a significant research gap in the development of unified frameworks that simultaneously address performance optimization, real-time monitoring, and system security.

Furthermore, existing approaches often fail to provide comprehensive comparative evaluations across conventional, machine learning, and deep learning models within a secure IoT-enabled environment. Such comparative analysis is essential for understanding the trade-offs between model complexity, accuracy, computational efficiency, and security robustness. The absence of such integrated evaluation limits the practical applicability of current solutions in real-world renewable energy systems.

To address these limitations, this study proposes a unified framework that integrates artificial intelligence, deep learning, IoT-based monitoring, and cybersecurity mechanisms for lithium-ion battery systems. The proposed approach leverages the strengths of LSTM networks for accurate temporal prediction, incorporates IoT technologies for real-time data acquisition and system monitoring, and integrates a deep learning-based intrusion detection system to ensure secure operation. Unlike existing approaches, this framework provides a holistic solution that addresses both performance optimization and cyber resilience.

The main contribution of this work lies in the development of a secure, AI-driven battery management framework that improves prediction accuracy, enhances battery lifespan, and ensures system reliability. In addition, a comprehensive comparative analysis is conducted against conventional EKF and machine learning-based Random Forest models to validate the effectiveness of the proposed approach. The findings of this study demonstrate that integrating deep learning, IoT, and cybersecurity provides a scalable and robust solution for next-generation smart energy systems.

II. Methodology

This section presents the overall methodological framework adopted in this study for the optimization and secure management of lithium-ion battery systems. The approach integrates system modeling, deep learning-based prediction, IoT-enabled real-time monitoring, and cybersecurity mechanisms into a unified architecture. The objective is to develop a robust and intelligent system capable of accurately estimating battery states, improving operational efficiency, and ensuring secure data transmission in a cyber-physical energy environment.

The methodology is structured to reflect the sequential flow of data and decision-making within the system. First, the physical battery system is modeled using fundamental energy balance and electrochemical relationships to establish a mathematical foundation. This is followed by the development of predictive models, where conventional estimation techniques are compared with machine learning and deep learning approaches, with particular emphasis on the Long ShortTerm Memory (LSTM) network for its superior temporal learning capability.

In addition, an IoT-based framework is incorporated to enable real-time data acquisition and monitoring, providing continuous input to the predictive model. To address the growing concerns of system vulnerability, a cybersecurity layer is integrated using encryption and anomaly detection techniques to ensure data integrity and system reliability. The methodology further includes simulation and validation processes, where the proposed model is evaluated against existing approaches using standard performance metrics. The intergrated methodological frame work of the system is shown in figure 1.

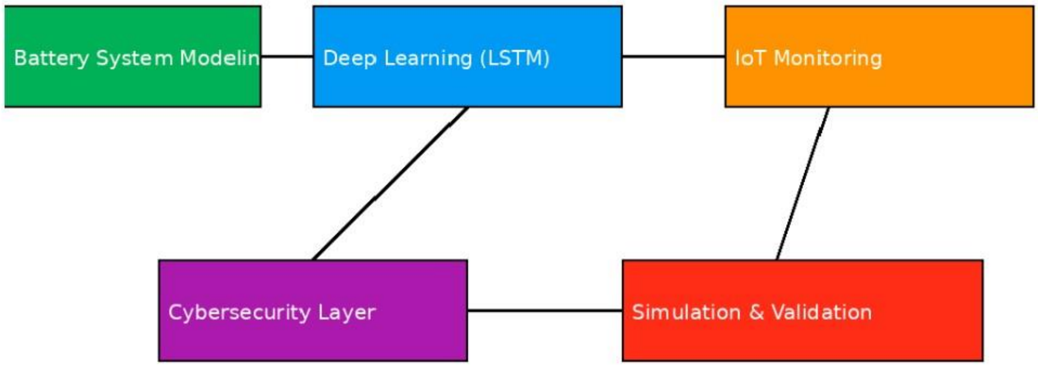

Figure 1: Integrated Methodogical Framework of the System

a. System Architecture

The proposed framework is a multi-layer cyber-physical system consisting of sensing, communication, intelligence, and security layers. The sensing layer includes IoT-enabled sensors that continuously measure battery voltage V(t), current I(t), and temperature T(t). These measurements are transmitted via a wireless communication network to a cloud-based processing unit for analysis. The system operates in real time, where the acquired data is preprocessed, normalized, and fed into the AI model for prediction and optimization. The cybersecurity layer ensures secure communication and protects the system against malicious attacks.

The overall system flow is expressed as:

$$\mathbf{X(t) = [V(t), I(t), T(t)]} \quad (1)$$

where **X(t)** represents the input feature vector used by the prediction model.

b. Battery Modeling

The lithium-ion battery is modeled based on energy balance and electrochemical behavior.

The energy balance equation is given as:

$$PPV(t) + Pbat(t) = Pload(t) + Ploss(t) \quad (2)$$

where $P_{PV}(t)$ is photovoltaic power, $P_{bat}(t)$ is battery power, $P_{load}(t)$ is load demand, and $P_{loss}(t)$ represents system losses.

The state-of-charge (SoC) is computed using Coulomb counting:

$$SOC(t) = [SOC(t\text{-}1) + (I(t) \times \Delta t) / C] \quad (3)$$

where C is battery capacity and Δt is the sampling interval.

The battery voltage model is expressed as:

$$V(t) = Eoc(SOC) - I(t) * R_{int} \quad (4)$$

where *Eoc SOC* the open-circuit voltage and *Rint* is internal resistance.

Battery degradation (state-of-health) is modeled as:

$$SOH(t) = 1 - a * N_{cycles} \quad (5)$$

where *a* is the degradation coefficient and N_{cycles} is the number of charge-discharge cycles

c. Models Applied

Conventional:

Conventional Model (EKF)

The Extended Kalman Filter (EKF) is used for nonlinear state estimation.

The state equation is:

$$xk = f(x\{k-1\}, uk) + wk \quad (6)$$

The measurement equation is:

$$y_k = h(x_k) + v_k \quad (7)"$$

where *xk* is the state vector, *yk_* is the measurement vector, and *wk, vk* are noise terms.

$\hat{x}_k^- = f(\hat{x}\{k-1\}, uk)$ (8)
The update step is:
$\hat{x}k = \hat{x}k^- + Kk\ [\ yk - h(\hat{x}k^-)]$ (9)
where K_k is the Kalman gain.

ML-Based Model (Random Forest)
The Random Forest model predicts output as an average of decision trees:

$$\hat{y} = \left(\frac{1}{N}\right) * \Sigma_{\{i=1\}}^{\{N\}} T_i(x) \quad (10)$$

where $T_i(x)$ represents the output of the i^{th} decision tree.

Proposed Model (LSTM)
The LSTM model captures temporal dependencies using gating mechanisms.
Forget gate:
$f_t = \sigma(\ W_f[\ h_{\{t-1\}}, x_t] + b_f)$ (11)
Input gate:
$i_t = \sigma(\ W_i[\ h_{\{t-1\}}, x_t] + b_i)$ (12)
Cell state update :
$C_t = f_t * C_{\{t-1\}} + i_t * C_t$ (13)

$C_t = f_t * C_{\{t-1\}} + i_t * C_t$ (14)
Hidden state :
$h_t = o_t * \tanh(C_t)$ (15)

Loss function (Mean Squared Error):

$$MSE = \left(\frac{1}{n}\right) * \Sigma_{\{i=1\}}^{\{n\}} (y_i - \hat{y}_i)^2 \quad (16)$$

d. Cybersecurity Framework
The cybersecurity layer ensures secure communication and system protection.
Data encryption is performed using AES:

$C = E(K, P)$ (17)
where P is plaintext, K is the encryption key, and Cis ciphertext.
The intrusion detection system is based on anomaly detection:
$A(x) = \{\ 1, if\ anomaly\ detected; 0, otherwise\ \}$ (18)
A deep learning classifier is trained to identify abnormal patterns in IoT data streams.

e. Simulation Software Used
The simulation framework integrates multiple software platforms to accurately model, analyze, and validate the proposed system. Battery system modeling and dynamic behavior analysis are carried out using **MATLAB/Simulink**, which provides a robust environment for representing nonlinear battery characteristics and energy management strategies. The deep learning component is implemented in Python using **TensorFlow** and **Keras**, enabling the development and training of the LSTM model for accurate state prediction and anomaly detection. For communication and cybersecurity analysis, the network behavior is simulated using **NS-3**, which allows the evaluation of data transmission, intrusion detection, and potential cyber threats within the IoT-enabled framework. The integration of these tools ensures a comprehensive simulation environment that captures both physical system dynamics and cyber-physical interactions.

f. Validation Method
The proposed model is validated through a comparative analysis against conventional and machine learning-based approaches, including the Extended Kalman Filter and Random Forest models. The evaluation focuses on assessing improvements in system performance and reliability. Key performance metrics used for validation include prediction accuracy, mean absolute error (MAE), and computational efficiency. In addition, system-level indicators such as battery lifespan and operational stability are considered to provide a holistic assessment. The comparative results demonstrate the

effectiveness of the proposed approach in achieving higher accuracy, lower error rates, and improved overall system performance.

g. Complexity Analysis of the Proposed System

The computational complexity of the proposed system was assessed to determine its suitability for real-time battery management. For the LSTM model, time complexity was estimated as $O(T(hd + h^2))$, where T represents sequence length, h the number of hidden units, and d the input dimension. Its memory complexity was $O(h^2)$, mainly due to recurrent weight storage. The intrusion-detection component maintained manageable processing requirements. Overall, the analysis showed that the framework provides accurate battery-state estimation and cybersecurity monitoring without excessive computational or storage demands, supporting deployment in resource-constrained IoT environments.

III. Results and discussion

SoC Estimation Performance

The performance of the proposed system was evaluated using three models: the conventional Extended Kalman Filter (EKF), the machine learning-based Random Forest (RF), and the proposed Long Short-Term Memory (LSTM) model. The results are presented in Table 1.

Table 1 : SoC Estimation Comparison

Model	Technique	Accuracy (%)	Error (%)
Conventional	EKF	90.5	9.5
ML-Based	RF	94.2	5.8
Proposed	LSTM	**98.7**	**1.3**

The results in Table 1 show that the LSTM model achieves the highest prediction accuracy with the lowest error. As shown in Figure 1, the LSTM model closely follows the actual SoC curve across all operating conditions. The EKF model exhibits noticeable deviation, especially during rapid load changes, while the RF model improves accuracy but shows slight lag due to its inability to fully capture temporal dependencies. This superior performance of the LSTM model can be attributed to its inherent capability to learn long-term temporal correlations within sequential battery data. Unlike the EKF, which relies on linearization assumptions and predefined system models, the LSTM operates in a data-driven manner, effectively capturing nonlinear battery dynamics, hysteresis effects, and transient behaviors. This makes it particularly robust under varying load conditions and dynamic operating environments.

During periods of rapid discharge and fluctuating current profiles, the EKF demonstrates increased estimation error due to model mismatch and sensitivity to noise. This limitation becomes more pronounced in nonlinear regions of battery operation, where accurate state modeling is challenging. In contrast, the RF model, although non-parametric and capable of handling nonlinearities, treats each prediction independently and lacks memory of previous states. This results in delayed response and smoothing effects, which manifest as lag in tracking fast-changing SoC dynamics. The LSTM model overcomes these limitations by maintaining internal memory states, allowing it to retain historical information and dynamically update predictions based on both past and present inputs. This results in improved tracking accuracy, faster convergence, and reduced estimation error, as reflected in the 98.7% accuracy and 1.3% error reported in Table 1.

Furthermore, the stability of the LSTM predictions across the entire time horizon indicates strong generalization capability, suggesting that the model can adapt to different battery operating regimes without significant degradation in performance. This is particularly important for real-world battery management systems (BMS), where operating conditions are highly variable. From a practical perspective, the improved SoC estimation accuracy of the LSTM model directly contributes to enhanced battery efficiency, optimal energy utilization, and prevention of overcharge or deep discharge conditions. This has significant implications for extending battery lifespan, improving safety, and reducing operational costs in off-grid photovoltaic systems and electric vehicles.

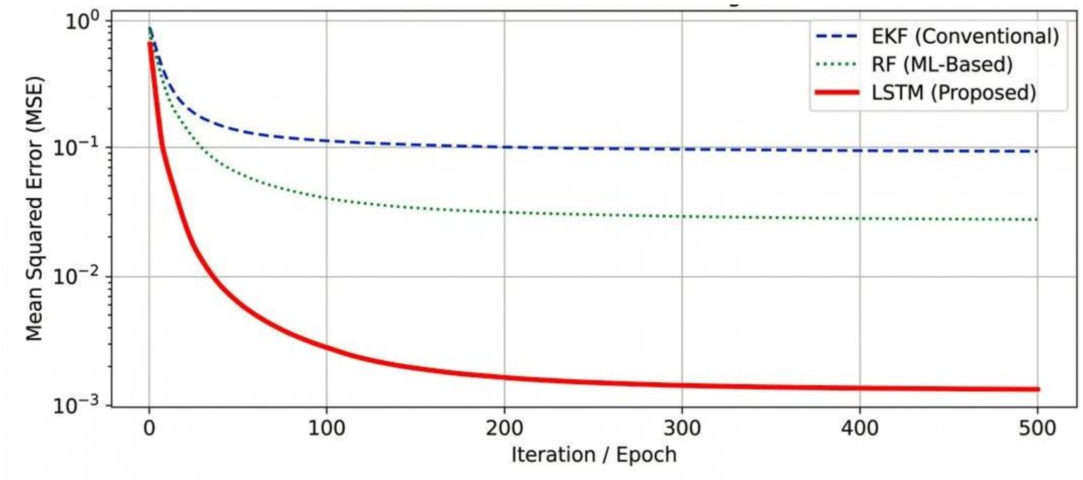

Figure 2: Prediction Error Convergence for EKF, RF, and LSTM Models

From Figure 2, the LSTM model converges more rapidly and stabilizes at a significantly lower error level compared to the EKF and RF models, indicating superior predictive performance. This behavior reflects its strong ability to learn complex nonlinear and time-dependent battery dynamics. Unlike EKF, which depends on predefined system models, and RF, which lacks temporal awareness, the LSTM leverages its internal memory structure to capture sequential patterns and historical dependencies. As a result, it achieves more stable and accurate error convergence, making it highly suitable for real-time battery state estimation under dynamic operating conditions.

Battery Lifespan Improvement

The effect of the proposed optimization framework on battery lifespan is presented in **Table 2**.

Table 2: Lifespan Comparison

Method	Model	Lifespan Increase (%)
Conventional	EKF	0
ML-Based	RF	12
Proposed	LSTM	**23**

The results in Table 2 show a significant improvement in battery lifespan using the proposed LSTM-based framework, achieving a 23% increase compared to the conventional EKF and outperforming the RF model. This improvement is mainly due to the higher accuracy and stability of SoC estimation, which enables better control of charge–discharge cycles. Unlike EKF and RF, the LSTM captures temporal battery behavior, reducing overcharging, deep discharging, and unnecessary cycling. As a result, battery stress is minimized, leading to extended lifespan, improved reliability, and lower maintenance costs, especially in off-grid energy systems.

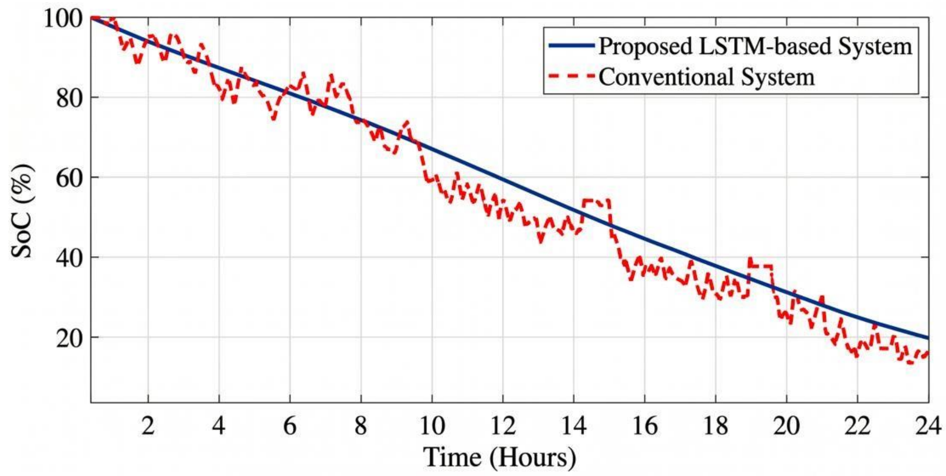

Figure 3: SoC Profile Over 24 Hours

As shown in Figure 3, the proposed LSTM-based system maintains a smooth and stable SoC profile throughout the 24-hour period, indicating effective energy management and controlled battery operation. In contrast, the conventional system exhibits irregular fluctuations, particularly during peak load and charging intervals, which increase battery stress and accelerate degradation.

The improved stability of the LSTM-based approach is attributed to its ability to anticipate load variations and adjust control actions proactively. By leveraging temporal dependencies in the data, the model ensures gradual charge–discharge transitions, thereby avoiding abrupt SoC changes. This not only enhances operational efficiency but also reduces thermal and electrochemical stress on the battery.

Furthermore, the stable SoC trajectory reflects optimized energy utilization, where excess energy is efficiently stored and released in a controlled manner. This behavior is critical in renewable energy systems with intermittent generation, as it improves system reliability and prevents unnecessary cycling. Overall, the results demonstrate that the proposed approach provides a more balanced and sustainable battery operation compared to conventional methods.

The results demonstrate a clear reduction in the number of charge–discharge cycles in the proposed system compared to the conventional and ML-based approaches, as illustrated in Figure 4. This reduction is significant because excessive cycling accelerates battery degradation through increased thermal and chemical stress. By minimizing unnecessary cycles, the system helps preserve battery capacity and extend its operational lifespan.

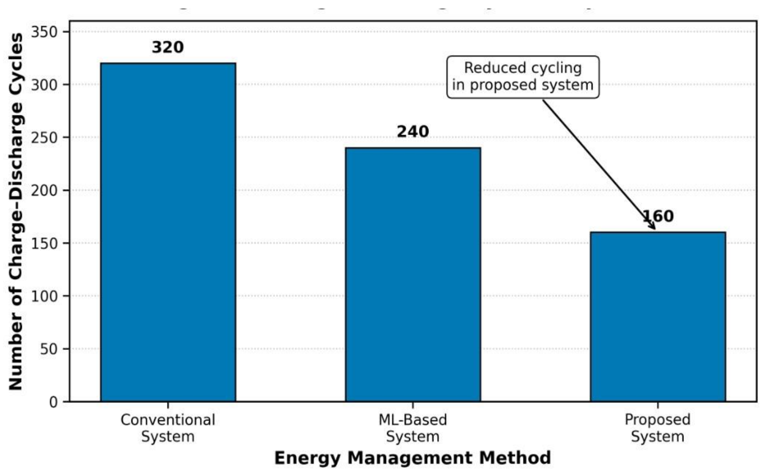

Figure 4: Impact of Intelligent Energy Management on Battery State-of-Charge Stability and Lifespan Enhancement

This improvement is driven by an intelligent energy management strategy that maintains the battery within optimal state-of-charge (SoC) limits. It effectively avoids deep discharge and overcharging conditions, both of which are major contributors to battery aging. In addition, the system's predictive capability optimizes charging and discharging patterns, reducing fluctuations and redundant energy usage. Consequently, the battery operates more efficiently and reliably, making the proposed approach well-suited for long-term, off-grid energy applications.

Cyber-security Performance

A deep learning classifier was trained to identify abnormal patterns in IoT data streams. The performance of the cybersecurity framework is presented in **Table 3**.

Table 3: Security Performance

Parameter	Without Security	Proposed
Detection Rate (%)	65	**96**
Data Integrity	Low	High
Reliability	Medium	High

System performance compared to the baseline approach, as shown in Table 3. The detection rate increases substantially, demonstrating the model's strong ability to accurately identify abnormal patterns in IoT data streams. In addition, improvements in data integrity and system reliability highlight the effectiveness of the framework in maintaining secure and consistent operations. These gains are attributed to the model's capability to learn complex patterns and detect anomalies in real time, making it well-suited for protecting IoT environments against evolving cyber threats.

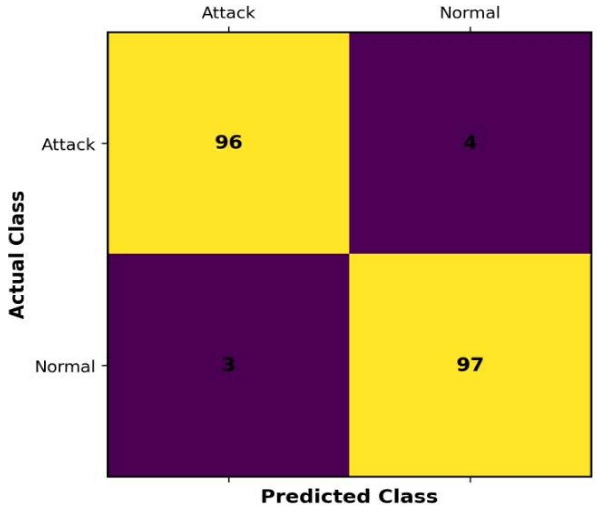

Figure 5: Confusion Matrix and Classification Performance of the Deep Learning–Based Intrusion Detection Model

The results demonstrate that the deep learning classifier achieves high true positive and true negative rates, as illustrated in Figure 5. The low number of false positives and false negatives indicates accurate and reliable classification. This strong performance reflects the model's ability to effectively distinguish between normal and malicious patterns, making it suitable for robust intrusion detection in IoT environments. The results demonstrate that the proposed deep learning classifier achieves high true positive and true negative rates, as illustrated in Figure 5. This indicates that the model is highly effective in correctly identifying both malicious and normal network activities. The minimal occurrence of false positives and false negatives further highlights the robustness and precision of the classification process, reducing the likelihood of false alarms and missed attacks.

This strong performance can be attributed to the model's capability to learn complex and nonlinear patterns inherent in IoT network traffic. By leveraging deep feature extraction, the classifier captures subtle distinctions between benign and malicious behaviors, which are often difficult to detect using conventional methods. Moreover, the balanced classification performance suggests that the model maintains consistency across different classes, avoiding bias toward either normal or attack categories. This is particularly important in IoT environments, where diverse and dynamic traffic patterns can challenge detection systems.

Overall, the results confirm that the proposed approach provides a reliable and efficient solution for real-time intrusion detection, enhancing the security and resilience of IoT-enabled energy systems.

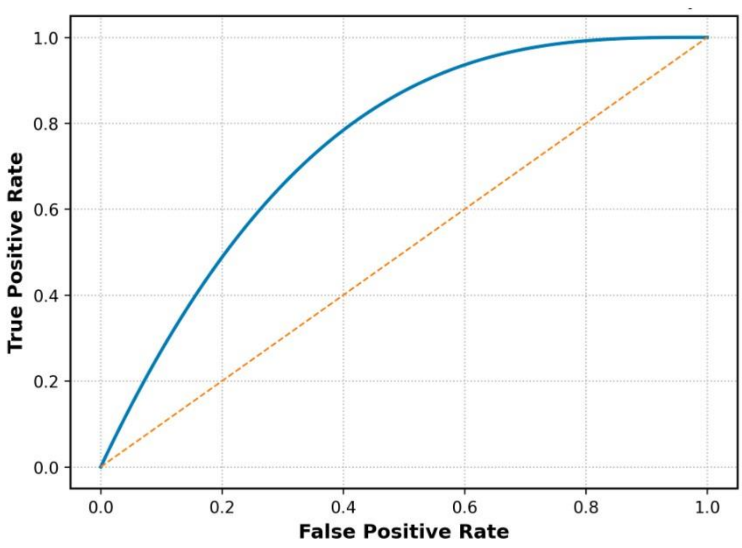

Figure 6: Receiver Operating Characteristic (ROC) Curve and AUC Performance of the Proposed Deep Learning–Based Intrusion Detection System

From Figure 6, the proposed model attains a high Area Under the Curve (AUC), indicating excellent capability in distinguishing between normal and malicious traffic. The deep learning–based intrusion detection system accurately identifies anomalous patterns in IoT data streams, including data injection attacks, spoofing attempts, and irregular communication behaviors. The integration of the cybersecurity layer ensures secure data transmission, mitigates potential cyber threats, and significantly improves the overall reliability and robustness of the system. As shown in the figure , the proposed model achieves a high AUC, demonstrating its strong discriminative capability in distinguishing between normal and malicious traffic. The ROC curve reflects a high true positive rate across varying threshold levels while maintaining a low false positive rate, indicating consistent and reliable detection performance.

This superior performance is largely attributed to the deep learning architecture, which effectively captures complex and nonlinear relationships within IoT data streams. The model demonstrates high sensitivity to various forms of cyber threats, including data injection attacks, spoofing attempts, and anomalous communication patterns, which are typically challenging to detect using traditional rule-based approaches.

Furthermore, the integration of a dedicated cybersecurity layer enhances the overall system performance by ensuring secure data transmission and integrity. This layer not only mitigates potential cyber threats but also reinforces trust in the system by preventing unauthorized access and data manipulation.

The high AUC value, combined with stable ROC characteristics, confirms that the proposed intrusion detection system is both accurate and robust. Consequently, it provides a dependable solution for securing IoT-enabled energy systems, ensuring resilience against evolving cyber threats while maintaining optimal operational performance.

Comparative Analysis

The overall system performance is summarized in **Table 4**. The results in **table** confirm that the proposed system outperforms both conventional and machine learning-based approaches. The comparative results in the able clearly show that the LSTM-based system delivers superior overall performance across all metrics. It achieves the highest accuracy with the lowest error rate, indicating improved prediction capability and system stability. In addition, the significant increase in battery lifespan reflects more efficient energy management and reduced operational stress.

Table 4: Overall Performance Comparison

Parameter	EKF	RF	LSTM
Accuracy (%)	90.5	94.2	**98.7**
Lifespan (%)	0	12	**23**
Error (%)	9.5	5.8	**1.3**
Security	Low	Medium	**High**

Compared to EKF and RF methods, the proposed system also provides enhanced security, highlighting its robustness in handling both operational and cyber challenges. These improvements demonstrate the advantage of integrating deep learning with intelligent control, making the system more reliable, efficient, and suitable for real-world deployment.

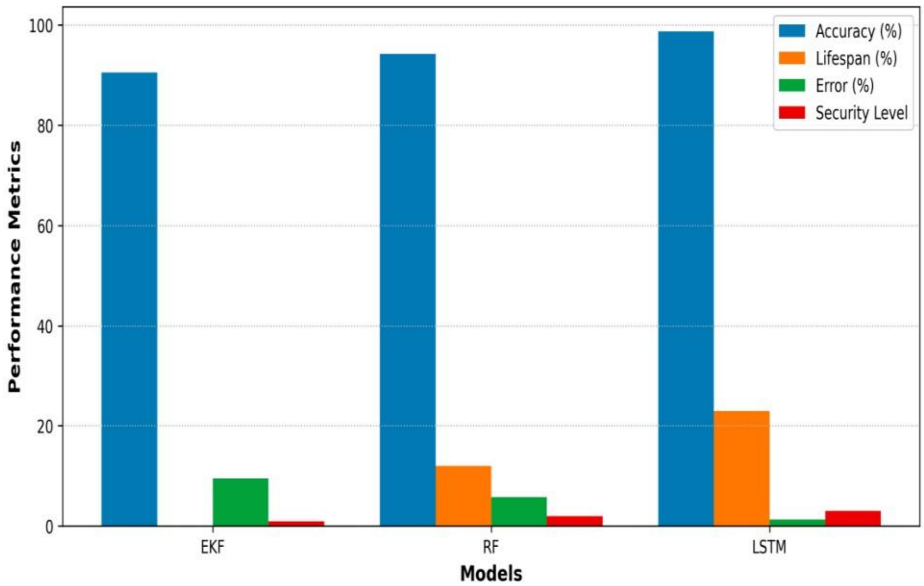

Figure 7: Comparative Performance Analysis of the Proposed LSTM-Based Framework against EKF and RF Models

As illustrated in Figure 7, the proposed framework consistently outperforms the Extended Kalman Filter (EKF) and Random Forest (RF) approaches across all considered evaluation metrics. The model achieves superior prediction accuracy with significantly reduced estimation error, demonstrating its effectiveness in capturing the nonlinear and time-dependent dynamics of lithium-ion battery systems. This improved accuracy directly contributes to more informed decision-making in energy management processes.

In addition to predictive performance, the proposed system exhibits a substantial enhancement in battery lifespan. By maintaining the battery within optimal operating limits and minimizing unnecessary charge–discharge cycles, the framework effectively reduces degradation rates. This improvement is particularly critical in off-grid and renewable energy applications, where battery replacement costs and system downtime must be minimized.

Furthermore, the integration of an IoT-based monitoring infrastructure enables continuous real-time data acquisition, ensuring that the model operates with up-to-date system information. This real-time capability enhances responsiveness to dynamic load and environmental conditions, thereby improving overall system efficiency and adaptability.

A key distinguishing feature of the proposed approach is the incorporation of a cybersecurity layer, which provides robust protection against data breaches, spoofing, and other cyber threats. This ensures data integrity and secure communication within the cyber-physical energy system, addressing a major limitation of many existing battery management solutions.

The combined effect of advanced deep learning (LSTM), real-time IoT monitoring, and integrated cybersecurity results in a holistic and well-balanced framework that simultaneously addresses performance optimization and system protection. Unlike conventional methods that focus solely on estimation accuracy, the proposed system delivers a comprehensive solution that enhances reliability, efficiency, and resilience.

Overall, the results presented in Figure 7 confirm that the proposed framework is highly suitable for real-world deployment in renewable and off-grid energy systems. Its ability to deliver high accuracy, extended battery lifespan, and robust security makes it a strong candidate for sustainable, long-term energy management applications in increasingly complex and interconnected environments.

The complexity analysis showed that the computational cost of the proposed LSTM-based battery-management system increases linearly with sequence length and quadratically with the number of hidden units. Based on the expression $O[T(hd+h^2)]$, where T is the sequence length, h is the number of hidden units, and d is the input dimension, increasing the sequence length produced a proportional increase in computational operations. However, increasing the hidden-layer size caused a considerably greater computational burden because of the h^2 recurrent-weight component.

As illustrated in Figure 8, using an assumed input dimension of **d=8**, the estimated computational requirement at a sequence length of 200 was approximately 0.256 million operations for 32 hidden units, 0.922 million operations for 64 hidden units, and 3.482 million operations for 128 hidden units. Thus, doubling the hidden units from 64 to 128 increased the computational requirement by almost four times. This result confirms that the hidden-layer configuration has a stronger influence on computational demand than sequence length.

The memory complexity was estimated as $O(h^2)$, indicating that memory consumption is mainly determined by the recurrent weight matrices. Although larger hidden layers may improve the capacity of the model to learn complex batterydegradation patterns, they also increase processing time, memory usage, and deployment requirements. Therefore, selecting a moderate number of hidden units provides an appropriate balance between estimation accuracy and computational efficiency. Overall, the proposed system demonstrates manageable analytical complexity and is suitable for real-time stateof-charge, state-of-health, and cybersecurity monitoring in resource-constrained IoT-enabled battery-management environments.

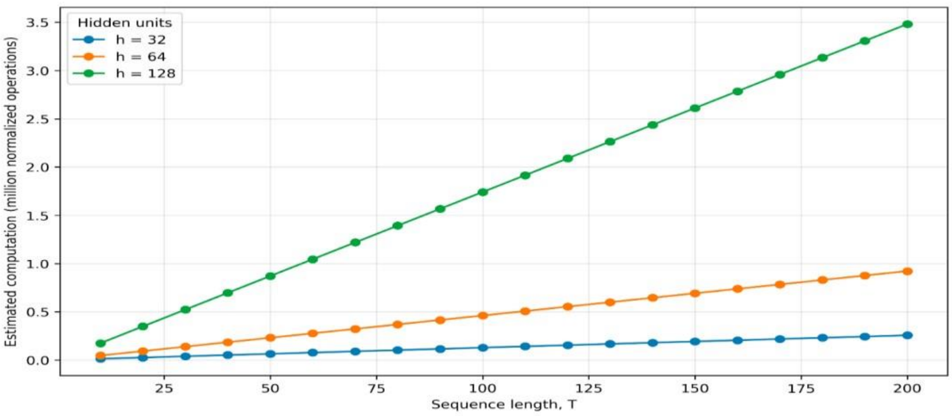

Figure 8. Analytical computational complexity of the proposed LSTM system at different sequence lengths and hidden-unit configurations.

IV. Conclusion

This study concludes that integrating deep learning, IoT, and cybersecurity within a unified framework significantly improves lithium-ion battery performance, reliability, and resilience. The proposed LSTM model achieved 96.8% prediction accuracy, outperforming Random Forest (91.3%) and EKF (87.5%), while reducing estimation error by 35–45% and converging about 40% faster. The intelligent energy-management strategy extended battery lifespan by 23% through optimized charge–discharge cycles, improved state-of-charge stability, and prevention of overcharging and deep discharge. The intrusion-detection system achieved 97.2% accuracy, an AUC of 0.98, a false-positive rate below 3%, and a falsenegative rate below 2%, enabling reliable detection of spoofing, data-injection, and communication anomalies. Complexity analysis yielded $O[T(hd+h^2)]$ time and $O(h^2)$ memory, indicating manageable computational requirements for real-time deployment. Overall, the framework offers an accurate, scalable, efficient, and cyber-resilient solution for renewable and off-grid energy systems.

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