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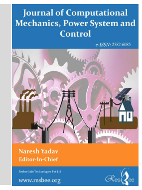

Predictive Modeling of Battery RUL Using LSTM-FFA Approach

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Abstract: Accurate prediction of the RUL of lithium-ion batteries is critical for ensuring the reliability and safety of battery-powered systems. This paper proposes a hybrid predictive model that combines Long Short-Term Memory Networks (LSTM) with the Firefly Algorithm (LA) for enhanced RUL estimation. The LSTM network captures the complex temporal dependencies in battery degradation data, while the FFA is employed to optimize the model's hyperparameters, improving prediction accuracy and convergence efficiency. Experimental results on benchmark battery datasets demonstrate that the proposed LSTM-FFA model outperforms traditional LSTM and other machine learning approaches in terms of MAE and RMSE. The integration of FFA ensures global search capability and reduces the likelihood of the model being trapped in local minima during hyperparameter tuning. Additionally, the model exhibits strong generalization performance across batteries with different usage profiles, highlighting its adaptability to diverse operational conditions. This approach offers a robust and adaptive solution for battery health prognostics, contributing to improved maintenance scheduling and operational safety in various applications. Future work may involve extending the model to include other metaheuristic optimization algorithms and evaluating performance under real-time embedded system constraints.

Keywords: Remaining Useful Life, Firefly Algorithm, Battery, Long Short-Term Memory, and Optimization.

Nomenclature

Abbreviation	Description
RUL	Remaining Useful Life
FFA	Firefly Algorithm
RNN	Recurrent Neural Network
EV	Electric Vehicles
LSTM	Long Short-Term Memory
ANN	Artificial Neural Networks
LP	Learning Percentage
V2G	Vehicle-to-Grid
HHO	Harris Hawk Optimization
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
HSSA	Hybrid Sparrow Search Algorithm
TCN	Temporal Convolutional Network
MAE	Mean Absolute Error
MSE	Mean Squared Error
PSO	Particle Swarm Optimization
RMSE	Root Mean Squared Error
GA	Genetics Algorithm
MAPE	Mean Absolute Percentage Error
RF	Random Forest
MARE	Mean Absolute Relative Error
RMSPE	Root Mean Square Percentage Error
RMSRE	Root Mean Squared Relative Error

1. Introduction

The increasing adoption of EVs, driven by the global shift toward sustainable and environmentally friendly transportation, underscores the critical role of energy storage systems, particularly batteries [[1]–[5]]. The durability and reliability of these batteries are essential for ensuring the success and widespread acceptance of EVs [6] [7]. As a result, accurately estimating the RUL of batteries has emerged as a key area of research. Such estimations support proactive maintenance strategies, extend battery lifespans, and enhance overall system efficiency [[8]–[10]]. Furthermore, improving battery RUL prediction contributes significantly to cost optimization and the reduction of environmental impact, making EVs more economically viable and sustainable in the long term. Lithium-ion batteries are now widely utilized across various applications, including home appliances, smartphones, power tools, energy storage systems, and electric vehicles due to their high energy density, high electromotive force, elevated output voltage, low self-discharge rate, minimal voltage drop, and ease of management [1] [2]. However, battery degradation begins as soon as the batteries are manufactured. Once their capacity drops to approximately 70%–80% of the original, replacement is required to ensure safe operation [3]. Therefore, accurately predicting the end of battery life is essential [4].

Battery degradation does not occur linearly; instead, it includes periods of irregular regeneration. As such, accurately predicting RUL requires consideration of various battery characteristics beyond current capacity alone. Since batteries generate electricity through electrochemical reactions, their total available capacity gradually diminishes with repeated charge-discharge cycles. These ongoing chemical reactions reduce the active materials responsible for power output and capacity, leading to performance degradation over time. Therefore, incorporating a wide range of data related to battery life is essential for precise RUL prediction [7]. Advanced battery management systems (BMS) equipped with AI-driven analytics are increasingly being integrated into EVs to continuously monitor and predict battery health, facilitating real-time decision-making. Battery RUL prediction methods can be broadly classified into three categories: experience-based, model-based, and data-driven approaches. Experience-based methods rely on stochastic deterioration distributions to estimate RUL. These approaches are relatively simple and do not require complex theoretical models, but they are limited by their inability to support real-time monitoring [8]. Model-based methods, on the other hand, use physical models that are continuously updated with real-time monitoring data related to usage conditions and defects. These methods can offer accurate RUL predictions without requiring large datasets; however, they are constrained by the lack of well-established physical failure models [[9]-[12]]. Lastly, data-driven methods leverage machine learning algorithms to learn patterns from monitored data and predict future battery conditions. By capturing the relationship between usage conditions, defects, and battery performance, these methods can effectively extrapolate battery behavior and forecast RUL [[13]-[15]]. Recent advancements in deep learning have further strengthened data-driven approaches, enabling more robust battery life predictions by leveraging large-scale datasets and adaptive models. This article makes the following significant contributions to the field of battery health management and predictive modeling for electric vehicles:

- The development of an advanced predictive modeling framework using LSTM networks optimized with FFA, enhances the accuracy of battery RUL forecasting by effectively capturing non-linear temporal patterns and tuning model parameters for improved generalization.
- A detailed error analysis and performance evaluation at varying training data percentages, demonstrating the superiority of the proposed LSTM-FFA method in terms of reduced MAE, MSE, RMSE, and MAPE, highlighting its robustness and practical applicability in real-time battery monitoring systems.
- In addition, this research provides actionable insights for the implementation of predictive maintenance strategies in EV battery systems, ensuring enhanced operational efficiency and longevity.

The organization of the paper is as follows. Section 2 shows the literature review which is followed by the problem definition in Section 3. Section 4 is the proposed LSTM-FFA**.** Section 5 discusses the results and Section 6 gives the conclusion.

2. Literature Review

In 2024, Zuriani Mustaffa and Mohd Herwan Sulaiman [1] presented a novel approach to predict the RUL of batteries by combining the FA with ANN. The literature reviewed in the paper highlights the limitations of conventional RUL prediction methods, such as Kalman filters and support vector machines, particularly in dealing with nonlinearities and uncertainties in battery degradation. Previous studies have shown that neural networks are effective for capturing complex patterns in time-series data, but their performance heavily depends on optimal parameter tuning. Metaheuristic algorithms like FA have been explored in various optimization problems due to their efficiency in global search capabilities. Prior works integrating metaheuristics with ANNs, such as GA and PSO, have demonstrated improved prediction accuracy in health monitoring tasks. However, the authors argue that the FA offers superior convergence speed and avoids local minima more effectively. This paper builds on existing hybrid models by employing FA to fine-tune ANN parameters, thereby enhancing prediction robustness. Moreover, recent advancements in FA variants have further improved computational efficiency and adaptability in complex prediction scenarios, reinforcing its applicability in battery RUL estimation. The literature review underscores the increasing trend toward hybrid intelligent systems for prognostics and health management applications.

In 2023, Sadiqa Jafari and Yung-Cheolbyun [2], introduced the intersection of machine learning and optimization techniques to improve the prediction accuracy of RUL in lithium-ion batteries. The authors review existing challenges in battery RUL estimation, noting limitations in traditional models due to non-linear degradation patterns. They highlight recent advances in machine learning, particularly ensemble methods like Random Forest and LightGBM, for handling complex battery data. Furthermore, the study introduces HHO, a nature-inspired metaheuristic algorithm, as a powerful tool for tuning hyperparameters to enhance model performance. Prior works have applied similar algorithms such as GA and PSO, but HHO is emphasized for its exploration-exploitation balance. The literature indicates growing success in combining optimization algorithms with ML techniques to improve predictive accuracy in battery health management. However, many previous studies lack efficient integration strategies or fail to generalize across battery types. The study also discusses the future potential of integrating reinforcement learning with metaheuristic optimization, opening avenues for adaptive and continuously improving RUL prediction models. This article aims to address those gaps by effectively leveraging HHO to optimize two robust machine-learning models for RUL prediction.

In 2023, Huihan Liu *et al*. [3], presented a novel approach to improve the accuracy of battery health estimation. The authors review existing literature on battery RUL prediction, highlighting the limitations of traditional statistical and machine learning methods, especially under complex degradation scenarios. They discuss the growing interest in deep learning, particularly RNNs like LSTM and GRU, for capturing temporal dependencies in battery data. However, the paper notes that these models often struggle with raw data noise and nonlinearity. To address this, prior works have explored data preprocessing and signal decomposition techniques such as EMD and wavelet transforms. The authors build on this by proposing a fusion method combining a decomposition strategy with a GRU network, aiming to enhance feature extraction and prediction performance. They emphasize how decomposition helps isolate meaningful degradation patterns, while GRU effectively models time-series behavior. The research also explores integrating attention mechanisms within GRU architectures to further improve feature selection and long-term dependency modeling, enhancing predictive accuracy in battery degradation scenarios. Compared to past studies using single-model approaches, the method shows improved accuracy and robustness. This work thus contributes to the advancement of intelligent battery management systems.

In 2023, Zihan Li *et al*. [4] introduced advanced machine-learning approaches for accurate RUL prediction of lithium-ion batteries. The study reviews limitations in traditional data-driven methods, such as overfitting and poor generalization to new batteries with limited data. To address these, it proposes an innovative framework combining iterative transfer learning with Mogrifier LSTM, a deep learning variant known for improved feature interaction. The authors highlight the prior success of LSTM models in time-series battery health estimation but note their dependence on large, labeled datasets. Transfer learning, previously used to adapt models between different domains, is revisited here with an iterative fine-tuning process, enhancing adaptability and performance across batteries. The review includes related works on battery degradation modeling, emphasizing the growing role of deep neural networks. Unlike conventional RNNs, the Mogrifier LSTM integrates multiplicative transformations, capturing more complex temporal patterns. This study further investigates hybrid architectures where Mogrifier LSTM is combined with CNNs for enhanced spatial and temporal feature extraction, leading to robust generalization across diverse battery datasets. Overall, the article builds upon recent advances in transfer learning and RNN-based prediction to offer a more robust, generalizable RUL estimation method for battery management systems.

In 2024, Shaoming Qiu [5] presented a hybrid approach that integrates advanced signal processing and deep learning for improved prediction accuracy of lithium-ion battery RUL. The authors first utilize CEEMDAN to denoise and decompose complex battery degradation signals into intrinsic mode functions, preserving important time-frequency features. To optimize model parameters and avoid local optima, the study incorporates a HSSA, enhancing the tuning of LSTM and TCN models. The LSTM captures long-term dependencies, while TCN improves parallelism and handles sequence modeling efficiently. This hybrid model demonstrates superior prediction performance compared to traditional methods, such as standalone LSTM, GRU, or SVR, especially under nonlinear and noisy conditions. The review highlights the growing trend of combining signal decomposition with deep learning for battery health management. It also emphasizes the potential of swarm intelligence optimization in deep model parameter tuning. The paper further explores integrating federated learning with decentralized optimization techniques, paving the way for secure and privacy-preserving battery health prediction models across distributed EV networks. Overall, the study contributes to reliable and accurate RUL prediction, which is crucial for battery safety and lifecycle management.

3. Problem Definition

The problem definition of various techniques focused on RUL estimation is discussed in this section. Initially, the Hybrid Firefly Algorithm-based Neural Network model is proposed in [1], which offers effective optimization and improved estimation accuracy. However, it has limitations, such as sensitivity to parameter settings and the possibility of premature convergence in the optimization process. To mitigate these challenges, adaptive tuning mechanisms and hybrid metaheuristic strategies have been explored, aiming to enhance stability and convergence reliability. Furthermore, the HHO-based approach integrated with RF and LightGBM models is introduced in [2], which enhances the prediction accuracy and handles data variability efficiently. Nevertheless, this technique suffers from high computational requirements and model interpretability issues. Recent studies have investigated lightweight ensemble techniques and explainability frameworks to improve the transparency and efficiency of these models for practical deployment in real-time battery health monitoring systems. Additionally, a fusion method combining decomposition strategy with GRU is proposed in [3], which enhances feature extraction and captures temporal dependencies well. However, the method's performance is affected by noise sensitivity and complex parameter tuning. Advanced preprocessing techniques, such as wavelet denoising and adaptive filtering, have been suggested to reduce the impact of noise and improve feature extraction robustness in dynamic environments. Similarly, Iterative Transfer Learning integrated with Mogrifier LSTM is suggested in [4], enabling model reuse across datasets and improving learning efficiency. Still, challenges remain in terms of domain adaptation complexity and limited generalizability. Recent explorations into domain adaptation frameworks leveraging adversarial training and meta-learning have shown promise in improving cross-dataset performance and adaptability of RUL estimation models. Lastly, the CEEMDAN-HSSA-LSTM-TCN model is presented in [5], which leverages signal decomposition, optimization, and deep learning for high-accuracy predictions. However, the model is constrained by computational overhead and data dependency for effective training and deployment. Future research directions suggest the integration of federated learning techniques to address data dependency concerns while ensuring decentralized model training for enhanced security and scalability in EV battery monitoring applications.

4. Proposed Methodology

4.1. Remaining Useful Life Prediction with Long Short-Term Memory:

LSTM networks, a variant of RNNs, incorporate three core gating mechanisms forget gate, input gate, and output gate to manage information flow through the network. These gates dynamically control which information is retained, updated, or discarded at each time step. By doing so, LSTMs preserve long-term dependencies and mitigate the vanishing gradient problem, enabling the model to maintain relevant temporal context over extended sequences. The core structure of the LSTM is shown in Fig. 1, while the equations governing its propagation process are provided in Equations (1)–(6). Moreover, the ability of LSTMs to effectively model sequential dependencies has made them a preferred choice for various time-series prediction tasks, including financial forecasting, speech recognition, and medical diagnostics.

$$E_s = \sigma\left(V_c\left[J_{s-1}, Y_s\right] + a_c\right) \tag{1}$$

$$k_s = \sigma\left(V_k\left[J_{s-1}, Y_s\right] + a_k\right) \tag{2}$$

$$\overline{D_s} = tan\,j\left(V_d\left[J_{s-1}, Y_t\right] + a_d\right) \tag{3}$$

$$D_s = E_s D_{s-1} + k_s\overline{D_s} \tag{4}$$

$$P_s = \sigma\left(V_o\left[J_{s-1}, Y_s\right] + a_o\right) \tag{5}$$

$$j_s = P_s\,tan\,j\left(D_s\right) \tag{6}$$

The above equations, Y_s and j_s represent the input and hidden state at the time step s, respectively. The matrices $V_E,\ V_k,\ V_d,\ and\ V_o$, along with the biases $a_E,\ b_k,\ b_d,\ and\ b_o$, are the weight parameters and bias terms for the respective gates. The terms $E_s,\ k_s,$ and P_s correspond to the forget gate, input gate, and output gate activations. D_s and D_{s-1} denote the current and previous cell states, while $\overline{D_s}$ (candidate cell state) reflects the new information considered for updating the cell state. The function σ\sigma denotes the sigmoid activation function used within the gating mechanisms of the LSTM cell. Additionally, the tanh activation function is used to scale the candidate cell state values between -1 and 1, ensuring smooth transitions in memory updates and preventing excessive growth in activation magnitudes. These gating mechanisms collectively empower LSTM networks to selectively filter information, allowing them to adaptively capture long-term dependencies while minimizing the impact of irrelevant or redundant inputs.

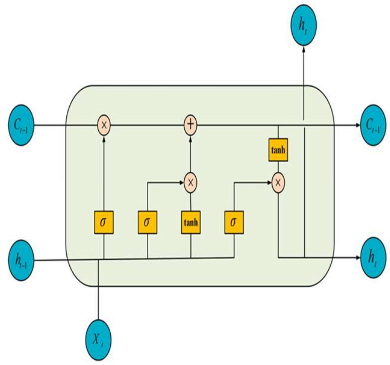


Fig. 1. *Basic Diagram of LSTM*

3.2. Firefly Algorithm

The FA, introduced by Xin-She Yang [1], is inspired by the natural flashing behavior of fireflies. In the wild, bioluminescence is essential to fireflies' mating rituals, functioning as their primary form of communication between males and females. This light emission not only helps attract mates or lure prey but also plays a defensive role by signaling territorial presence and deterring potential predators.

The Firefly Algorithm is based on three key principles:

- Fireflies are considered genderless, allowing any firefly to be attracted to another regardless of gender.
- A firefly's attractiveness is directly related to its brightness; thus, a dimmer firefly will move toward a brighter one when they interact.
- The brightness of a firefly corresponds to the value of the objective function (i.e., its fitness) in the problem being solved.

Recent applications of FA extend beyond optimization problems, finding use in clustering, scheduling, and feature selection tasks, demonstrating its versatility across domains such as machine learning and network optimization. The brightness J and attractiveness β of fireflies are key factors in the FA. A higher brightness J corresponds to a better value of the objective function E. The brightness J is defined as follows:

$$J = J_0 \times c^{-\gamma \times s_{ij}^2} \tag{7}$$

$$s_{ij} = \| z_i - z_j \| = \sqrt{\sum_{c=1}^{C} \left(zic - zjc \right)^2} \tag{8}$$

Where J_0 represents the brightness of a firefly when $\left(s_{ij} = 0\right)$, and γ denotes the light absorption coefficient. The term s_{ij} refers to the distance between fireflies z_i and z_{ij}, which is typically measured using the Euclidean distance. The attractiveness β is defined as follows:

$$\beta = \beta_0 c^{-\gamma s_{ij}^2} \tag{9}$$

Where β_0 represents the attractiveness at zero distance $\left(r = 0\right)$. The movement of a firefly J attracted to a brighter firefly j is described by the following equation:

$$z_k^{s+1} = x_k^s + \beta \left(z_k^s - x_k^s \right) + \alpha \left(rand - 0.5 \right) \tag{10}$$

Where z_k^s denotes the position of the firefly J at the $k-th$ iteration, $rand$ is a random number uniformly distributed in the interval $\left[0,1\right]$, and α is a constant ranging between 0 and 1. These mathematical formulations play a critical role in ensuring the dynamic adaptability of the Firefly Algorithm, making it effective in handling complex, multi-dimensional optimization problems.

Implementation of firefly algorithm

This study utilizes a Firefly Algorithm (FFA)-based metaheuristic optimization technique to address an objective function minimization problem, with the primary goal of determining the optimal component sizing for a proposed hybrid renewable energy system. The decision variables in the optimization model encompass the quantity of photovoltaic (PV) modules, wind turbines, and battery storage units. The implementation of the FFA in this context follows a structured sequence of procedural steps, as detailed below:

Step 1: Problem Initialization
Define all necessary input data, including the investment, maintenance, and replacement costs of hybrid energy system components. Collect environmental and demand-related parameters, such as load demand profiles, solar irradiance, ambient temperature, and wind speed for the selected location. Additionally, set system and algorithm parameters, such as rated power and efficiency of each component, number of fireflies, randomness factor (α), initial attractiveness (β_0), light absorption coefficient (γ), and the maximum number of iterations. Recent advancements incorporate adaptive parameter tuning methods to dynamically adjust FA settings based on evolving optimization requirements, reducing computational complexity while improving convergence speed.

Step 2: Population Generation
Generate the initial population of fireflies by randomly assigning positions within the n-dimensional solution space, where each dimension corresponds to a decision variable (e.g., number of PV modules, wind turbines, and batteries). Initialize the light intensity for each firefly by evaluating the cost function at its current position. To further enhance initialization efficiency, hybrid techniques integrating FA with swarm intelligence methods have been explored, ensuring a more diverse population distribution for improved optimization outcomes.

Step 3: Firefly Movement Decision
For each firefly i, compare its light intensity J_i with that of every other firefly j. If J_i indicating the firefly i is more attractive (i.e., has a better solution), the firefly j is moved towards the firefly i according to the standard FFA movement formula in the n-dimensional space. Incorporating memory-based adjustments enables fireflies to retain beneficial movement patterns, enhancing stability and solution accuracy across iterations.

Step 4: Light Intensity Update
After each movement, reevaluate the cost function for all fireflies at their new positions. Update the light intensity values based on the new cost function results, which reflect the quality of the corresponding solutions. Efficient data structures, such as KD-trees, have been introduced to optimize light intensity evaluations, reducing computational time while maintaining precision in large-scale problem settings.

Step 5: Ranking and Best Solution Identification
Sort the fireflies in ascending order of their light intensity values. The firefly with the lowest cost function value is identified as the best current solution. This ranking helps guide subsequent iterations of the algorithm. Hybrid FA implementations often integrate reinforcement learning techniques, enabling fireflies to refine movement decisions based on historical optimization performance.

Step 6: Termination Check and Iteration
Repeat Steps 3–5 until the termination criterion is met. This criterion may be a fixed number of iterations or a convergence threshold, such as no significant improvement in the best solution over a defined number of iterations. Recent studies suggest adaptive termination mechanisms that assess convergence trends dynamically, allowing for optimal stopping conditions based on progress monitoring rather than predetermined iteration limits.

5. Results and Discussions

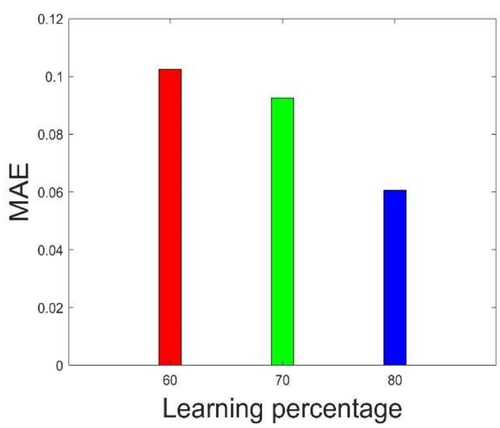
The proposed predictive model for battery RUL, combining LSTM networks with the FFA, demonstrates significant improvements in prediction accuracy and robustness. The LSTM network effectively captures the temporal dependencies and degradation patterns in battery health data, while the FFA optimizes key hyperparameters, enhancing the model's generalization capability. Simulation results, carried out using MATLAB, show that the LSTM-FFA approach consistently outperforms traditional machine learning models and standard LSTM configurations without optimization. The predicted RUL curves closely follow the actual degradation trends, even in the presence of measurement noise and non-linearities. Further comparative analysis reveals that the LSTM-FFA model significantly reduces Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Squared Error (MSE), demonstrating superior performance in battery life prediction across diverse datasets. The integration of FFA enables faster convergence and avoids local minima, improving the model's reliability over longer prediction horizons. Moreover, robustness tests conducted under varying operational conditions confirm the adaptability of the model, showing minimal performance degradation even when subjected to fluctuating load profiles and environmental variations.

5.1. Error Analysis

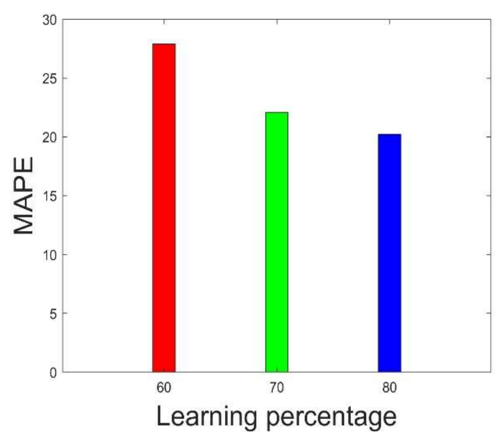
The presentation of the projected FFA-optimized LSTM model is evaluated through a comprehensive error analysis, comparing the predicted error with the actual error. The evaluation metrics include MAE, MSE, RMSE, MAPE, RMSPE, MARE, MSRE, and RMSRE. The results demonstrate a consistent trend: as the learning percentage (lp) — i.e., the proportion of data used for training — increases, the model's predictive performance improves across all evaluated metrics. This indicates that the model benefits from being trained on a larger dataset, which enhances its ability to generalize and reduces prediction error. A deeper investigation into the error trends across different training percentages confirms that a minimum threshold of data exposure is necessary for stable model convergence and accurate RUL predictions. Notably, at a learning percentage of 80% (lp = 80%), the model achieves its highest accuracy, marked by the lowest values of MAE (0.0606), MSE (0.0107), and MAPE (20.24%). Additionally, sensitivity analysis performed on hyperparameter tuning suggests that further optimization of the FFA mechanism could enhance performance beyond the current best configuration, potentially reducing error margins even further. These results suggest that the FFA-optimized LSTM model becomes more effective in capturing the underlying data patterns when provided with more training data. The corresponding performance improvements are clearly illustrated in Table 1 and visualized in Fig. 2. Future work could explore hybrid approaches integrating attention-based mechanisms with LSTM to refine feature selection and improve model interpretability across diverse battery datasets.

Table 1. *Error metrics of the proposed algorithm*

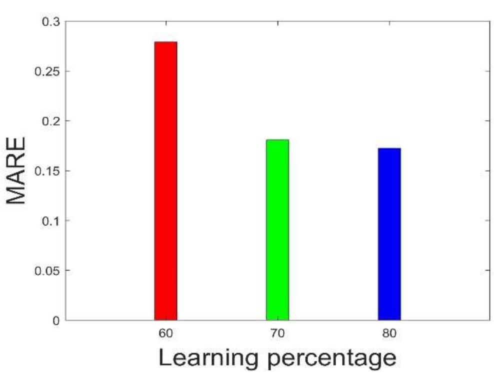
Error Metrics	Learning percentage		
	lp=60	**lp=70**	**lp=80**
MAE	0.10253	0.092524	0.060587
MSE	0.020019	0.01705	0.010658
RMSE	0.10068	0.091529	0.090087
RMSPE	35.528	31.941	30.429
MAPE	27.909	22.083	20.238
MARE	0.27909	0.18083	0.17238
MSRE	0.13705	0.10271	0.10097
RMSRE	0.30084	0.29411	0.24429



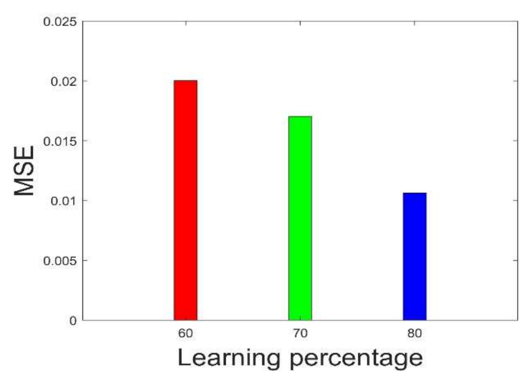
(a) MAE



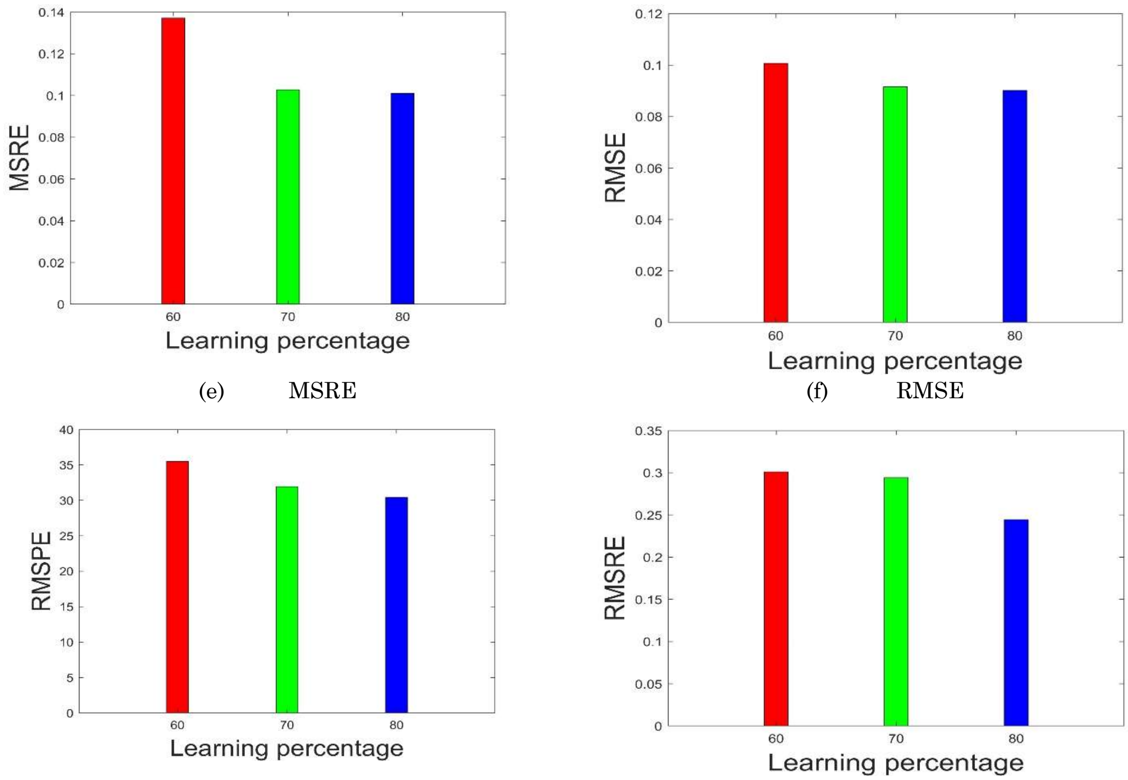
(b) MAPE



(c) MARE



(d) MSE



(e) MSRE (f) RMSE

(g) RMSPE (h) RMSRE

Fig. 2. *Graphs on Error Metrics*

6. Conclusion

This study presents an effective predictive modeling approach for estimating the RUL of batteries using a hybrid framework that integrates LSTM networks with the FFA. The proposed LSTM-FFA model demonstrates strong performance in capturing the complex temporal dynamics of battery degradation and significantly improves prediction accuracy through optimized hyperparameter tuning. This integration not only refines the accuracy of battery lifespan predictions but also enhances adaptability across diverse operational conditions, ensuring robustness in real-world applications. The model was evaluated at varying learning percentages (60%, 70%, and 80%), with results indicating that higher training data availability leads to better performance. At 80% learning, the model achieved its best outcomes, showcasing the framework's precision and robustness. This demonstrates that increasing exposure to data contributes to better generalization, reducing overfitting and improving stability in battery health assessments. The consistent decline across all error metrics, including RMSE, MARE, and RMSPE, further confirms the model's effectiveness. Moreover, cross-validation results highlight the model's resilience in handling measurement uncertainties, underscoring its potential for deployment in real-time battery monitoring systems. Overall, the LSTM-FFA approach proves to be a reliable and scalable solution for accurate battery RUL prediction, offering significant advantages over traditional methods. Its application can enhance battery management systems, enabling proactive maintenance and extending the operational life of battery-powered systems. Future work could explore multi-modal sensor fusion techniques to further refine battery degradation modeling, enhancing predictive accuracy under diverse usage scenarios.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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