

A Hybrid Approach towards Remaining Useful Life Prediction of Li-ion Batteries of UAVs

Dharmaraja Selvamuthu*, Ritam Dasgupta, Ayush Sharma

Department of Mathematics, IIT Delhi, New Delhi 110016, India

*Corresponding author: dharmar@maths.iitd.ac.in

Abstract—We present a hybrid approach for predicting the remaining useful life (RUL) of Li-ion batteries in unmanned aerial vehicles (UAVs). Our current method integrates an LSTM network with an Adaptive Kalman Filter to model nonlinear battery degradation trends and to refine predictions by mitigating sensor noise. Experimental evaluation on a NASA dataset demonstrates that the proposed approach effectively captures the degradation pattern in early operating cycles, though performance degrades in later cycles due to increased variability in battery behavior. Our contributions include the development of a framework that combines deep learning with Kalman Filtering for UAV battery health prediction, as well as a detailed analysis of the method's performance under real-world conditions. Emphasis is put on online learning and light computations to potentially allow for real-time SoH prediction in UAV batteries. Future work may focus on enhancing this framework by incorporating a Residual GRU architecture and an Unscented Kalman Filter (UKF) to improve long-term prediction accuracy and robustness.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have evolved into critical assets in both military and civilian sectors, with applications in defense, logistics, and environmental monitoring [1]. Their increasing autonomy is largely driven by artificial intelligence (AI), which enhances reliability through predictive maintenance and obstacle avoidance [2].

The efficiency of UAVs is directly tied to their power sources, with lithium-ion (Li-ion) batteries being the most widely used because of their high energy density and rechargeability [3]. However, these batteries degrade over time, leading to performance deterioration and increased failure risk [4]. This degradation highlights the importance of predictive maintenance strategies to ensure UAV longevity and operational reliability [5].

Traditional battery health monitoring methods, such as voltage-based State of Charge (SoC) tracking, have limitations in capturing nonlinear aging effects [6]. Recent advancements incorporate hybrid approaches that integrate data-driven models with physics-based filtering techniques to improve predictive accuracy [7]. Deep learning models, including Long Short-Term Memory (LSTM) networks, have shown great results in predicting complex battery degradation trends [8].

State-space estimation methods, particularly Kalman Filtering (KF), have been widely used for battery health tracking, providing real-time corrections by reducing noise in sensor

measurements [9]. Deep learning architectures, such as CNN-BiLSTM models, have further improved lithium-ion battery State of Health (SoH) estimation [10].

Alternative statistical models, such as Naive Bayes, have been explored for robust RUL estimation, offering a lower computational cost than deep learning approaches [6]. Advanced physics-based models have also been proposed, integrating state-space modeling with deep learning for enhanced battery degradation tracking [11]. Additionally, CNN-based models have demonstrated effectiveness in extracting features from multi-channel charge profiles for improved SOH prediction [12].

This research introduces a hybrid approach that integrates Long Short-Term Memory (LSTM) deep learning with Kalman Filtering (KF) to improve UAV battery Remaining Useful Life (RUL) estimation. LSTM networks are particularly effective in modeling nonlinear time-series data, as they include a memory cell that can maintain information for long periods, hence making them suitable for sequential data processing [8]. However, despite their advantages, LSTMs are sensitive to sensor noise and real-time operational variations, which can reduce prediction accuracy.

To address these challenges, Kalman Filtering has been extensively used in battery health estimation because of its ability to provide real-time correction of battery state estimation by mitigating sensor noise and measurement inaccuracies [9]. While Kalman Filters are excellent for state-space estimation, they struggle to model long-term dependencies in battery degradation trends. Therefore, combining LSTM's ability to learn temporal degradation patterns with Kalman Filtering's capability for real-time correction results in a powerful hybrid model.

This integration ensures that the LSTM model captures complex degradation patterns from historical charge-discharge cycles, while the KF refines predictions by continuously adjusting estimates based on incoming sensor data. Such a fusion enhances predictive accuracy, mitigates sensor drift, and enables reliable real-time battery health monitoring, making it particularly valuable for UAV applications where operational reliability is critical [5].

The rest of this paper is structured as below. In Section II, we review existing methodologies for UAV battery health estimation, covering both machine learning and model-based

approaches. Section III details the proposed hybrid framework, describing the integration of LSTM networks with Kalman Filtering for accurate RUL prediction. Section IV presents experimental validation, including dataset selection, model training, and performance evaluation metrics. Finally, Section V discusses the implications of the results, summarizes key conclusions and outlines possible future research directions.

II. RELATED WORK

We conducted a wide literature review of previous work in preparation for this report. First, we considered working on maintainability prediction of entire UAV systems. The problem of maintainability prediction in Unmanned Aerial Vehicles (UAVs) has been extensively studied, with various approaches focusing on system-wide diagnostics and failure analysis. MIL-HDBK-472, a military handbook on maintainability prediction, provides a standardized framework for estimating failure rates, repair times, and operational availability of UAV components [4]. It outlines quantitative methodologies for evaluating subsystem reliability, emphasizing the need for detailed component-level data to perform accurate failure mode analysis. However, while these methodologies are robust, their implementation requires extensive information about every UAV subsystem, making them less practical when dealing with systems where only partial data is available [1].

Among UAV subsystems, the battery is one of the most critical components, as it directly impacts mission endurance, operational safety, and overall UAV reliability. A battery failure mid-flight can lead to catastrophic consequences, including mission failure or vehicle loss [13]. Therefore, battery health monitoring has emerged as a key research area, with a particular emphasis on Remaining Useful Life (RUL) prediction. Traditional RUL estimation approaches often rely on voltage monitoring and impedance analysis, but these methods fail to fully capture the nonlinear aging effects of lithium-ion (Li-ion) batteries, necessitating more advanced predictive models [5].

Existing research on battery health estimation falls into two primary categories: state-space models (SSMs) and data-driven models. State-space models use mathematical representations of battery degradation dynamics, allowing real-time tracking of internal battery states such as State of Charge (SOC), State of Health (SOH), and internal resistance. For example, Kalman Filtering (KF) and its advanced variants (e.g., Unscented Kalman Filter (UKF)) have been widely applied to Li-ion battery diagnostics. Sun et al. demonstrate that UKF-based approaches enhance state estimation by compensating for sensor noise and model uncertainties, leading to improved accuracy in battery lifetime prediction [9]. Similarly, structured State Space Models (SSMs) have been explored for long-sequence battery SOH estimation, offering an alternative to conventional filtering techniques [11].

In contrast, data-driven models leverage machine learning and deep learning techniques to extract complex degradation patterns from historical charge-discharge cycles. Ng et al.

propose a Naive Bayes approach for robust RUL prediction, demonstrating that statistical models can effectively handle battery performance variations [6]. Meanwhile, deep learning techniques, such as Long Short-Term Memory (LSTM) networks, have shown great performance in capturing long-term dependencies in battery degradation trends [8].

Recent advancements have also introduced hybrid models that combine machine learning with physics-based estimation techniques. Choi et al. demonstrate that Convolutional Neural Networks (CNNs) can extract multi-channel features from charge-discharge curves, improving SOH estimation accuracy [12]. Similarly, CNN-BiLSTM architectures have been employed for RUL prediction, effectively capturing both spatial and temporal degradation features [10].

As the field progresses, a growing body of research suggests that hybrid approaches, integrating LSTMs with Kalman Filtering (KF), can provide highly accurate and real-time adaptable RUL estimations. By integrating LSTM's ability to model long-term dependencies with KF's real-time correction mechanisms, researchers can achieve robust, adaptive battery health monitoring for UAV applications [7].

This review highlights the evolution from traditional failure mode analysis to modern, data-driven and hybrid RUL estimation techniques. While SSMs provide interpretable, physics-based insights into battery degradation, deep learning models leverage complex data structures to uncover hidden degradation patterns. Future research is likely to focus on fusing physics-based and AI-driven methods, further improving the accuracy and reliability of UAV battery health prediction.

III. METHODOLOGY

We propose a hybrid framework for predicting the RUL of lithium-ion batteries using the NASA dataset. Our approach combines an LSTM-based predictive model with an Adaptive Kalman Filter (AKF) to refine predictions. The framework comprises three main stages: data selection and preprocessing, LSTM-based next-step prediction with online training, and adaptive Kalman filtering for denoising the predictions.

A. Data Selection and Preprocessing

The NASA Prognostics Center of Excellence (PCoE) dataset [3], [14] provides detailed cycle data in MATLAB .mat files, including various sensor measurements (voltage, current, temperature) and capacity values that serve as a proxy for the battery's state of health (SOH). Our preprocessing steps include:

- 1) **Extraction:** Selecting only the discharge cycles.
- 2) **Normalization:** Applying Min-Max scaling to ensure all features are on a consistent scale.
- 3) **Segmentation:** Dividing the data into sequential input-output pairs using a sliding window approach (e.g., a look-back of 10 cycles) where the target is the capacity of the subsequent cycle.

B. LSTM-based Next-Step Prediction and Training Process

Recent research indicates that deep learning architectures, particularly recurrent neural networks (RNNs), outperform traditional statistical models in RUL estimation [8]. Among RNN variants, LSTM networks have demonstrated great performance in handling long-term dependencies in sequential battery degradation data [7]. Unlike feedforward networks, LSTMs can retain historical information through memory cells, enabling better modeling of degradation trends.

A critical factor in improving RUL prediction is multi-channel profiling, where multiple sensor features (e.g., voltage, current, temperature) are used instead of a single input channel [12]. Studies have shown that incorporating multiple features into an LSTM framework leads to more robust SOH predictions, as different parameters degrade at different rates and provide complementary information [9]. Feature selection plays a crucial role in improving model generalization, and techniques such as correlation analysis are used to determine the most informative variables for the network [6].

The LSTM model is trained on sequences of past battery cycles, where each input consists of a multi-channel time series, and the predicted SOH or RUL [10] is the output. The loss function used is Mean Squared Error, and the Adam optimizer is used due to its adaptive learning capabilities. A dropout layer is introduced to mitigate overfitting, ensuring that our model remains stable across different battery types.

Key aspects of our training process include:

- **Input Reshaping:** The data is reshaped into a 4D tensor to capture the sequential structure of the battery cycles.
- **Model Architecture:** The model consists of stacked LSTM layers followed by dense layers, allowing the network to learn complex temporal degradation patterns.
- **Online Learning:** The training process is conducted in an online fashion, updating the model with each new cycle. This approach ensures that the model continuously adapts to the latest degradation trends.
- **Regularization:** Dropout layers are incorporated to reduce overfitting and improve generalization.

C. Adaptive Kalman Filtering for Refined Predictions

Despite the strong modeling capabilities of the LSTM network, the predictions may still contain high-frequency noise due to sensor uncertainties. To address this, we refine the LSTM outputs using an Adaptive Kalman Filter (AKF). The classical Kalman Filter is based on the following two steps:

a) Prediction Step::

$$\hat{x}_{k|k-1} = A \hat{x}_{k-1|k-1}, \quad (1)$$

$$P_{k|k-1} = A^2 P_{k-1|k-1} + Q, \quad (2)$$

where:

- $\hat{x}_{k|k-1}$ is the predicted state at time k ,
- $P_{k|k-1}$ is the predicted error covariance,
- A is the state transition coefficient (assumed to be close to 1), and
- Q is the process noise covariance.

b) Update Step::

$$K_k = \frac{P_{k|k-1} H}{H^2 P_{k|k-1} + R}, \quad (3)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - H \hat{x}_{k|k-1}), \quad (4)$$

$$P_{k|k} = (1 - K_k H) P_{k|k-1}, \quad (5)$$

where:

- K_k is the Kalman gain,
- z_k is the measurement (the LSTM prediction),
- H is the measurement coefficient (set to 1), and
- R is the measurement noise covariance.

To better handle the non-stationary noise in our predictions, we adapt the noise covariances dynamically:

$$R_k = \frac{1}{N} \sum_{j=k-N+1}^k (z_j - \hat{x}_{j|j-1})^2, \quad (6)$$

$$Q_k = (1 - \alpha) Q_{k-1} + \alpha (K_k (z_k - \hat{x}_{k|k-1}))^2, \quad (7)$$

where:

- N is the window size used to compute residual statistics,
- α is the adaptation rate,
- R_k is the updated measurement noise covariance, and
- Q_k is the updated process noise covariance.

These adaptive equations allow the filter to dynamically adjust its sensitivity to new measurements, thereby smoothing the LSTM predictions and reducing high-frequency noise while preserving the overall degradation trend.

D. Summary

Our hybrid approach integrates the strengths of LSTM networks for capturing complex, nonlinear degradation patterns with the robustness of Adaptive Kalman Filtering for noise reduction. The LSTM model is trained using an online, sliding-window strategy to continuously adapt to new battery cycles, while the AKF refines these predictions by dynamically estimating the noise covariances. This combination provides accurate and smooth RUL estimates in real time, which is essential for effective battery prognostics. Furthermore, the online learning approach enables the model to quickly incorporate the latest battery performance data, allowing for timely updates to the state-of-health predictions. Coupled with the computationally light adaptive Kalman filter, this strategy supports real-time monitoring and decision-making for UAV batteries, enhancing both reliability and operational safety.

IV. EXPERIMENTAL RESULTS

A. Dataset Description

The dataset employed in this study comprises four lithium-ion batteries (Battery #5, #6, #7, and #18), each tested under three operational conditions: charging, discharging, and impedance measurement, all conducted at standard room temperature.

Charging was performed using a constant current (CC) of 1.5A until the voltage of the battery increased to 4.2V. After reaching this threshold, the process shifted to a constant

voltage (CV) phase, holding the voltage steady at 4.2V while the current declined to 20mA. Discharging followed a constant current (CC) protocol set at 2A, with termination voltages varying across the batteries: 2.7V for Battery #5, 2.5V for Battery #6, 2.2V for Battery #7, and 2.5V for Battery #18.

Impedance analysis was performed using electrochemical impedance spectroscopy, i.e., EIS, across a frequency range spanning from 0.1Hz to 5kHz. The batteries were subjected to continuous charge-discharge cycling to accelerate degradation, while impedance data was collected to monitor changes in internal electrochemical properties as aging progressed. The experiment concluded once the batteries met the predefined end-of-life (EOL) condition, which was specified as a 30% decline in nominal capacity, reducing from 2Ahr to 1.4Ahr.

This dataset serves as a resource for forecasting both the remaining charge within a given discharge cycle and the remaining useful life (RUL) of the batteries.

Each recorded cycle includes data corresponding to charging, discharging, and impedance assessments. The primary parameters captured in the dataset are:

- **Voltage_measured:** Measured terminal voltage (V)
- **Current_measured:** Output current supplied by the battery (A)
- **Temperature_measured:** Internal battery temperature (°C)
- **Current_charge:** Charge or discharge current from the power source or load (A)
- **Voltage_charge:** Voltage at the charging source or load (V)
- **Time:** Time series corresponding to the cycle (s)
- **Capacity:** Measured battery capacity (Ahr) during discharge cycles

Impedance data includes additional fields such as estimated electrolyte resistance and charge transfer resistance.

B. Justification for Selecting Discharge Data

For this study, we focused only on the discharge cycles and excluded the impedance and charge cycles. The reasons for this decision are:

- Discharge cycles provide the most direct and relevant information about battery degradation and remaining useful life (RUL).
- Impedance data requires specialized electrochemical analysis, which was beyond the scope of our current implementation.
- The charge cycle can contribute valuable insights, but its inclusion requires additional preprocessing and modeling adjustments, which we plan to incorporate in future work.

C. Data Preprocessing and Exploration

The dataset had a complex structure, requiring significant effort to properly extract, align, and format the data for preprocessing and training. Some key preprocessing steps included:

- 1) Extracting relevant discharge cycle data from the MATLAB files.

- 2) Aligning time-series data to ensure consistency across cycles.
- 3) Normalizing voltage, current, and capacity values using Min-Max scaling.
- 4) Handling missing or inconsistent data values.
- 5) Reshaping the data into a format suitable for sequence-based learning.

Exploratory Data Analysis (EDA) was conducted to understand data trends and relationships. Figure 1 [15] illustrates the battery capacity degradation over cycles.

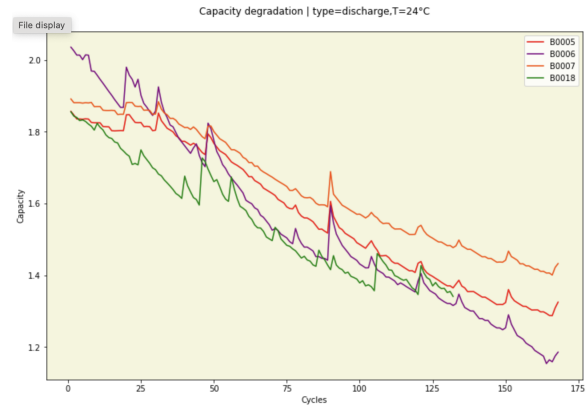


Fig. 1. Battery capacity degradation over charge-discharge cycles.

D. Training Process

To model battery degradation, we implemented a Long Short-Term Memory (LSTM) network trained on discharge cycle data. The model configuration was as follows:

- **Input:** Sequential time-series data spanning 10 consecutive cycles.
- **Network Architecture:** Two stacked LSTM layers with 64 and 32 units, each followed by dropout layers to mitigate overfitting, and a fully connected dense layer for generating predictions.
- **Activation Function:** Rectified Linear Unit (ReLU).
- **Optimization and Loss Metric:** Adam optimizer with Mean Squared Error as the loss criterion.

A comparison between actual and predicted capacity values using the full data is shown in Figure 2.

E. Results and Analysis

The trained LSTM model successfully captured the capacity degradation trend.

This model uses the entire dataset for both training and prediction purposes. It required significant restructuring of the data for training and inference. Earlier cycles served as input data for forecasting the capacity of the following cycles. The model performed well in early cycles but exhibited deviations in later cycles due to increased variance in battery behavior.

The LSTM predictions were then smoothed using Adaptive Kalman Filtering as shown in Figure 3.

Potential improvements include:

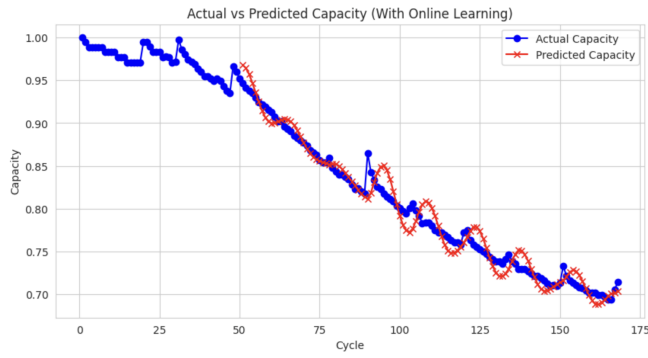


Fig. 2. Comparison of actual vs. LSTM predicted capacity

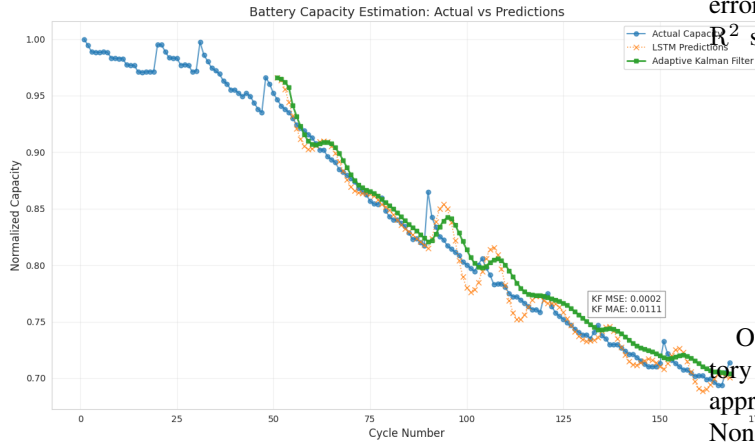


Fig. 3. Comparison of actual capacity, LSTM predictions and Kalman-smoothed predictions

- Incorporating charge cycle data to enhance prediction accuracy.
- Experimenting with different sequence lengths and feature engineering.

V. DISCUSSION & FUTURE DIRECTIONS

A. Discussion

The results indicate that our LSTM-based approach effectively captures the overall trend of battery capacity degradation across discharge cycles. However, as seen in **Figure 2**, which depicts LSTM predictions with online learning, the model exhibits increased fluctuations in later cycles. This suggests that while the LSTM is capable of learning early-stage degradation patterns, it can become unstable when facing the higher variance characteristic of prolonged battery usage.

Although our hybrid approach performs well on the NASA dataset, further field validation under real UAV flight conditions is required before immediate deployment [16]. Moreover, UAVs are resource-constrained platforms with limited onboard compute and power, so lightweight prognostic architectures (e.g. LSTMs or GRUs with Kalman Filter architectures) are preferable to heavier networks [17], [18]. Finally, reliance solely on the standard NASA dataset may limit

generalization to diverse operational environments; techniques such as domain adaptation have been shown to mitigate this “dataset shift” and improve cross-environment RUL accuracy [19].

By contrast, **Figure 3** highlights the effect of applying an Adaptive Kalman Filter (AKF) to the LSTM outputs. In this scenario, the AKF reduces high-frequency noise, yielding smoother predictions that remain close to the actual capacity values in later charging-discharging cycles. This improvement indicates that an adaptive filtering technique can address the LSTM’s tendency to oscillate when battery degradation becomes more stochastic.

Table I summarizes the performance metrics before and after applying filtering. Although the MSE (mean squared error) remains the same, the mean absolute error (MAE) and R^2 score illustrate subtle differences in predictive behavior.

TABLE I
PERFORMANCE COMPARISON

Metric	Before Filtering	After Filtering
MSE	0.0002	0.0002
MAE	0.0094	0.0111
R^2 Score	0.9701	0.9675

Overall, the LSTM captures the general degradation trajectory but struggles with local instabilities, whereas the AKF approach proves valuable for mitigating these fluctuations. Nonetheless, the filtered predictions can sometimes introduce a slight bias, highlighting the need for continued refinement of both the modeling and filtering strategies.

B. Future Directions

Moving forward, we plan to focus on two key enhancements to improve the robustness and accuracy of battery capacity predictions:

- **Enhanced Filtering with UKF:** In future work, we plan to explore the Unscented Kalman Filter (UKF) as an alternative to our current adaptive filtering techniques. The UKF’s ability to handle nonlinearities through the unscented transform could provide more accurate state estimation, especially given the inherently nonlinear nature of battery degradation processes. Although it may introduce additional computational complexity, its potential for improved smoothing and robustness makes it a promising avenue for enhancing battery state-of-health predictions. This approach is expected to offer improved smoothing without introducing excessive bias, particularly in the later stages of battery life.
- **Advanced Temporal Modeling with Residual GRUs:** To better capture the nonlinear and long-term dependencies inherent in battery aging, we will explore residual Gated Recurrent Units (GRUs). By integrating residual connections into the GRU architecture, we hope to overcome issues such as vanishing gradients and improve the model’s ability to track complex degradation patterns

over extended cycles. GRUs use two gates instead of the three present in LSTMs, which can also lead to faster training and inference, one of our core goals.

Additional directions include expanding the feature set by incorporating data from charge cycles, employing more sophisticated hyperparameter optimization techniques, and developing robust online learning mechanisms that adapt in real-time as new data becomes available. These advancements aim to address the limitations observed in the current work, ultimately leading to more accurate and stable battery state-of-health estimation models.

REFERENCES

- [1] B. J. de Oliveira Martins Franco and L. C. S. Góes, "Failure analysis methods in unmanned aerial vehicle (uav) applications," in *Proceedings of COBEM 2007: 19th International Congress of Mechanical Engineering*. Brasília, DF, Brazil: ABCM, 2007.
- [2] Y. Koç, "Reliability analysis of tactical unmanned aerial vehicle (uav)," Master's thesis, Middle East Technical University, Ankara, Turkey, 2017.
- [3] B. Saha, E. Koshimoto, C. C. Quach, S. L. Vazquez, E. F. Hogge, T. H. Strom, B. L. Hill, and K. Goebel, "Predicting battery life for electric uavs," AIAA Technical Conferences, Tech. Rep., 2013.
- [4] *MIL-HDBK-472: Military Standardization Handbook - Maintainability Prediction*. Washington, D.C.: Department of Defense, 1966.
- [5] E. C. Ozkat, O. Bektas, M. J. Nielsen, and A. la Cour-Harbo, "A data-driven predictive maintenance model to estimate rul in a multi-rotor uas," *International Journal of Micro Air Vehicles*, vol. 15, pp. 1–14, 2023.
- [6] S. S. Ng, Y. Xing, and K. L. Tsui, "A naive bayes model for robust remaining useful life prediction of lithium-ion battery," *Applied Energy*, vol. 118, pp. 114–123, 2014.
- [7] S. Reimann, J. Amos, E. Bergquist, J. Cole, J. Phillips, and S. Shuster, "Uav for reliability," University of Minnesota - Twin Cities, Aerospace Vehicle Design, Tech. Rep., December 2013.
- [8] I. Obisakin and C. V. Ekeanyanwu, "State of health estimation of lithium-ion batteries using support vector regression and long short-term memory," *Open Journal of Applied Sciences*, vol. 12, pp. 1366–1382, 2022.
- [9] F. Sun, X. Hu, Y. Zou, and S. Li, "Adaptive unscented kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles," *Energy*, vol. 36, pp. 3531–3540, 2011.
- [10] Y. Tian, J. Wen, Y. Yang, Y. Shi, and J. Zeng, "State-of-health prediction of lithium-ion batteries based on cnn-bilstm-am," *Batteries*, vol. 8, p. 155, 2022.
- [11] J. I. Olalde-Verano, S. Kirch, C. Pérez-Molina, and S. Martin, "Samba: State of health prediction of li-ion batteries using mamba state space models," *arXiv preprint*, 2024.
- [12] Y. Choi, S. Ryu, K. Park, and H. Kim, "Machine learning-based lithium-ion battery capacity estimation exploiting multi-channel charging profiles," *IEEE Access*, vol. 7, pp. 75 143–75 157, 2019.
- [13] E. Petritoli, F. Leccese, and L. Ciani, "Reliability and maintenance analysis of unmanned aerial vehicles," *Sensors*, vol. 18, no. 9, p. 3171, 2018.
- [14] B. Saha and K. Goebel, "Battery data set," 2007, nASA Prognostics Data Repository, NASA Ames Research Center, Moffett Field, CA.
- [15] L. Zhang, T. Ji, S. Yu, and G. Liu, "Accurate prediction approach of soh for lithium-ion batteries based on lstm method," *Batteries*, vol. 9, p. 177, 2023.
- [16] Y.-H. Chang, Y.-C. Hsieh, Y.-H. Chai, and H.-W. Lin, "Remaining-useful-life prediction for li-ion batteries," *Energies*, vol. 16, no. 7, p. 3096, 2023.
- [17] Y. Wang, X. Feng, F. Li, Q. Xian, Z.-H. Jia, Z. Du, and C. Liu, "Lightweight visual localization algorithm for uavs," *Scientific Reports*, vol. 15, p. 6069, 2025.
- [18] H. Li, Z. Yin, and C. Chen, "Delay minimization for bac-noma offloading in uav networks," *Sensors*, vol. 25, no. 1, p. 84, 2025.
- [19] K. Tran, B. Huynh, T. Le, L. Pham, and V.-R. Nguyen, "Hybridonet-adapt: A domain-adapted framework for accurate lithium-ion battery rul prediction," *Mechanical Systems and Signal Processing*, 2024, in press.