Cleaner Engineering and Technology 25 (2025) 100917

Contents lists available at ScienceDirect

Cleaner Engineering and Technology

journal homepage: www.sciencedirect.com/journal/cleaner-engineering-and-technology

Performance enhancement of drone LiB state of charge using extended Kalman filter algorithm

Kamal Anoune[a], Ismail El Kafazi[b], Anas El Maliki[c], Badre Bossoufi[d,*], Badr NASIRI[e], Hana Zekraoui[f], Mishari Metab Almalki[g], Thamer A.H. Alghamdi[h,i], Mohammed Alenezi[h,**]

[a] EMIT Laboratory, Energy & Materials, Instrumentation & Telecom, Physics Department, Faculty of Sciences and Technologies FST-Settat, Hassan First University (UHP), Settat, Morocco
[b] Superior School of Technology in Khenifra, Sultan Moulay Slimane University, Beni Mellal, Morocco
[c] Laboratory of Electronic Systems, Information Processing, Mechanics and Energetics, Faculty of Sciences, University Ibn Tofail, Kenitra, Morocco
[d] LIMAS Laboratory, Faculty of Sciences Dhar El Mahraz, Sidi Mohamed Ben Abdellah University, Fez, Morocco
[e] Laboratory of Optic of Information Processing, Mechanic, Energetic and Electronic, Faculty of Science, University Moulay Ismail, Meknes, Morocco
[f] LGEM Laboratory, Higher Scool of Technology, First Mohammed University, Oujda, Morocco
[g] Department of Electrical Engineering, Faculty of Engineering, Al-Baha University, Alaqiq, 65779-7738, Saudi Arabia
[h] Wolfson Centre for Magnetics, School of Engineering, Cardiff University, CF24 3AA, UK
[i] Electrical Engineering Department, Faculty of Engineering, Al-Baha University, Al-Baha 65779, Saudi Arabia

A R T I C L E I N F O

Keywords:
Extended Kalman filter (EKF)
Lithium-ion battery (LiB)
State-of-charge (SoC)
Hybrid pulse power characterization (HPPC) testing and recursive least squares with forgetting factor (FFRLS)

A B S T R A C T

This study introduces a more accurate approach to managing drone batteries by improving how the state of charge (SoC) is estimated, focusing on energy efficiency and environmental impact. The key innovation lies in developing a mathematical model to assess battery behavior, combined with Hybrid Pulse Power Characterization testing and Recursive Least Squares with Forgetting Factor for parameter identification. To enhance the battery management system, the study integrates the Extended Kalman Filter (EKF), which overcomes the limitations of traditional linear filters and provides more precise SoC estimation. This approach reduces energy waste and extends battery life, directly supporting sustainable engineering practices. A developed MATLAB-based framework ensures real-time monitoring and optimized battery performance, minimizing the risk of power depletion during flight. The results demonstrate that the proposed SoC_EKF method significantly outperforms the conventional SoC_AH approach, achieving a lower estimation error (1.93×10^{-4} vs. 7.21×10^{-4}), leading to improved energy efficiency, reduced carbon footprint, and more reliable, eco-friendly drone operations for clean technology applications.

1. Introduction

1.1. Stat of literature

Drones become among the most extensively researched logistics technologies in recent years. They integrate technical elements corresponding to contemporary developments in the transportation sector and Society; critical attributes like autonomy, adaptability, and agility are essential. Among the primary factors influencing a drone's battery life is the weight of its payload. The larger the payload weight, the more energy the drone will take to fly, hence the shorter the battery life. A payload weighing a few kg is relatively heavy for a drone and will require more energy than a drone without a payload. This reduces the drone's battery life and shorter flight time than flying without a payload. Second, the wind speed can have an impact on the battery life of the drone. Flying against the wind consumes more energy and affects the drone's battery life. Flying with the wind, on the other hand, can enhance battery life, allowing the drone to fly for extended periods. Temperature also has an impact on battery life. When the temperature rises too high, the battery can overheat, shortening its life. As the temperature drops, the battery's capacity diminishes, decreasing performance and lowering overall performance and flight time. Finally, flight height can have an impact on battery life. The more energy the drone requires to maintain stability and continue flying, the shorter its battery

* Corresponding authors.
** Corresponding authors.
E-mail addresses: kamal.anoune@gmail.com (K. Anoune), badre.bossoufi@usmba.ac.ma (B. Bossoufi), AleneziM1@cardiff.ac.uk (M. Alenezi).

https://doi.org/10.1016/j.clet.2025.100917
Received 16 December 2024; Received in revised form 14 February 2025; Accepted 15 February 2025
Available online 26 February 2025

life. As a result, it is critical to consider these aspects when planning drone operations, particularly when transporting a payload, ensuring the drone has sufficient battery life to complete its mission safely and effectively. (Yaacoub et al., 2020). Three significant difficulties must be addressed to make drone operations a predictable energy assessment. Effective drone design focuses on creating reliable and efficient equipment suited to various tasks that can float, be used in a variety of circumstances, and have reliability comparable to airline airliners; this is an enormous task that will require numerous attempts, as well as the creativity and contributions of people to various fields (Andrea, 2014). Moreover, Xia et al., (2023) conducted a study on the routing challenges of drones with load-dependent energy characteristics; they introduced docking hubs as collaborative facilities for trucks and drones, enhancing service coverage. A mixed-integer model was proposed to tackle the complexities associated with nonlinear, load-dependent energy consumption. At the same time, the operational range has traditionally not been a critical issue due to rapid and convenient refueling options; accurately estimating the range for battery-powered vehicles, such as drones, has become essential given their increased diffusion and importance in various domains, such as personal and commercial transportation and surveillance (Baek et al., 2019). In the context of drone operations, energy consumption emerges as a critical constraint that must be addressed to unlock the full potential of maximum range, cost reduction, and accurate SoC estimation. Optimizing energy usage is crucial for extending the operational range of drones, as it determines the distance they can travel and the payload they can transport. To fully leverage drone capabilities, it is essential to implement effective energy management strategies that maximize range while minimizing power consumption. These strategies must account for various factors, including flight dynamics, payload weight, wind conditions, and specific operational requirements (Zhang et al., 2021).

Countless studies reveal that drones have some drawbacks in terms of energy efficiency. Even brief periods of hovering create substantial energy needs, severely limiting a drone's operating radius; Kirschstein et al. (Kirschstein, 2020) study introduces a drone energy consumption model to evaluate energy requirements based on eco-friendly factors and flight configurations. The model estimates the energy needs for a fixed-route package delivery system operating from a central hub, serving a predefined client base. For comparison, drone energy consumption is assessed alongside the energy demands of diesel and electric trucks serving the same clients from an equivalent depot. To enhance the accuracy and reliability of SoC estimation, an auto-regressive moving average model approximates the dynamic characteristics of the battery; this approach compensates for inaccuracies in measuring terminal voltage and discharge current, improving SoC estimation precision and reliability (Liu et al., 2019). Manjarrez et al., (2023) focused on tackling the challenge of estimating the energy requirements for mission performance. Furthermore, Madani et al. (Madani et al., 2018) review different equivalent circuit models and parameter identification techniques utilized in lithium-ion batteries for energy storage; their paper underscores the significance of accurately determining the state of charge, cycle life, and other critical parameters to guarantee lithium-ion batteries' reliable, safe, and cost-effective operation in portable electronics and electric vehicles; they discuss various equivalent circuit models, from simpler ones like the internal resistance model to more intricate ones like the two-time constants model, Thevenin model, PNGV model, and dual polarization model. Additionally, the review explores methods like electrochemical impedance spectroscopy and the tree seeds algorithm, highlighting their relevance in battery management systems. Freja Vandeputte et al., (2023) introduce a parametric estimation method to assess the impedance of lithium-ion batteries, which is essential for determining their SoC, health, and remaining useful life. Unlike electrochemical impedance spectroscopy, a widely used nonparametric technique, this new method employs a fractional order equivalent circuit model to deliver impedance estimates across the entire frequency range of interest rather than limiting itself to specific frequencies; in their parametric approach enables any persistently exciting signal, such as a noise excitation, instead of being confined to sine or multiline signals. The method has been validated through simulations and subsequently applied to measurements of commercial Samsung 48X cells. However, the research primarily concentrates on batteries at rest, meaning at a constant SoC after a relaxation period, showcasing the potential for enhanced impedance analysis in battery management systems. Simone Barcellona and Luigi Piegari (Barcellona and Piegari, 2017) examined the vital importance of battery storage systems in both stationary and mobile applications, particularly emphasizing lithium-ion batteries for their impressive power and energy densities. Precise modeling of these batteries is crucial to accurately predicting their charge and health state. Their paper reviews various battery models and techniques for parameter estimation, underscoring the significance of electric, thermal, and aging modeling. It also introduces a classification method for the different models, dividing them into three primary categories: mathematical, physical, and circuit models. This classification offers a clear framework for understanding the advantages and limitations of each type of model.

By deeply understanding the battery performance growth procedure, valuable insights can be gained. This understanding enables the testing of battery performance, leading to the identification of Various significant and minor factors that contribute to performance outcomes alongside the associated implications. Practical battery system models for BMS can be developed using a modeling method based on mechanism, semi-experience, or experience. These models provide adequate precision while minimizing complex computations. During operation, adaptive control technology is employed to identify battery system parameters, estimate battery SoC, State of Health (SoH) and State of Function (SoF)," and communicate this information to the drone controller through the grid, supporting this assessment parameter the research conducted by Yuan Chen et al. (Y. Chen et al., 2024b) introduces a hybrid framework to predict battery life accurately, emphasizing feature extraction and advanced optimization methods; they extract eight features from the collected data to establish a connection with the battery's state of health. This framework integrates variational mode decomposition, an enhanced sparrow search algorithm, and multi-kernel support vector regression to tackle data instability, uneven feature distribution, and local optima. The elite chaotic opposition learning strategy and adaptive weights also improve the optimization process. Experimental validation using NASA datasets shows that this proposed method surpasses other algorithms, achieving improvements in SoH estimation accuracy ranging from 0.16% to 1.67% while maintaining stable predictions of remaining helpful life across various starting points (Lu et al., 2013).

Kaiqiang Chen (K. Chen et al., 2024a) et al. conducted a study on accurately estimating the SoC for lithium-ion batteries; their research explores how the precision of parameter identification and temperature fluctuations affect SoC estimation. The authors created a dual polarization model for LIBs, identifying its parameters through a novel genetic factor recursive least square (GFRLS) algorithm. They utilized an extended particle filter (EPF) method based on the identified model for SoC estimation. The study confirmed the model's accuracy across a range of temperatures from −10 to 40 °C, using the federal urban driving schedule for testing; their results showed that the GFRLS and EPF methods significantly enhanced SoC estimation accuracy, achieving an error margin of less than 1.3%, which lays a strong foundation for the reliable operation of battery management systems in various environmental conditions. Furthermore, Alshawabkeh, A. et al. (Alshawabkeh et al., 2024) discuss the growing use of batteries across various applications underscored the need for precise parameter identification and effective modeling, particularly for lithium-ion batteries, which are favored for their high power and energy densities; their works introduce a comprehensive framework that employs the Levenberg–Marquardt algorithm (LMA) to validate and identify parameters of lithium-ion battery models, aiming to enhance the accuracy of SoC estimations by utilizing only discharging measurements within the N-order Thevenin equivalent circuit model; the findings reveal that optimization based solely on discharging data is sufficient for precise parameter estimation; also, it aligns closely with experimental measurements. Alternatively, a relevant study highlights the significance of monitoring internal parameters to ensure lithium-ion batteries' safety and accurately predict their SoC (Wang et al., 2024a), the research presents an enhanced electrochemical thermal coupling model that considers low-temperature degradation and various battery characteristics. It introduces a decoupled deviation strategy for real-time adjustments of current and temperature fluctuations, which improves SOC accuracy; their results indicate a maximum SOC error of 4.57% under challenging test conditions, showcasing its reliability in dynamic settings—moreover, the approach developed by Wang et al. (Wang et al., 2024b) aims to enhance the SoC estimation for lithium-ion batteries, essential for effective battery management systems; they introduce a method that combines particle swarm optimization with an adaptive square root cubature Kalman filter to improve SoC estimation accuracy; the filtering parameters are optimized to achieve precise SoC estimation, and an adaptive window is determined using the PSO algorithm to refine the moving estimation window their results show that the relative error stays under 0.5% when the SoC is stable, and the root mean square error and mean absolute error are 0.0019 and 0.0017, respectively, proving the robustness and adaptability of the method in varying conditions. In another study (Wang et al., 2022), the prediction of the whole-life-cycle SoC for lithium-ion batteries is explored, addressing the challenges posed by variations in internal capacity, working temperature, and current rate, indeed the study proposes an improved feedforward-long short-term memory modeling method to achieve accurate SoC prediction throughout the battery's life cycle by considering current, voltage, and temperature variations, the technique involves an optimized sliding balance window for filtering the measured current. It creates a three-dimensional input matrix using filtered current and voltage. Long-term charging capacity decay tests on two batteries show a significant reduction in capacity, with a decrease of 21.30% and 22.61% after 200 cycles. The maximum SoC prediction error is 3.53%, with RMSE, MAE, and MAPE values of 3.451%, 2.541%, and 0.074%, respectively, confirming the model's effectiveness for whole-life-cycle SOC prediction in battery applications.

This Paper outlines a method for estimating the SoC of batteries that involves several necessary steps. First, creating a battery model tailored for drones using data from Hybrid Pulse Power Characterization tests gives us a more precise understanding of how the battery performs during flight. Then, an Extended Kalman Filter framework for real-time SoC estimation will be implemented, incorporating an online parameter identification algorithm that adjusts to the battery's changing characteristics throughout the flight. This approach helps maintain the accuracy of SoC predictions under different operational conditions. The confrontation of real-world drone flight test data was used to validate and compare the proposed method, showing a notable enhancement in estimation accuracy and reliability. This paper is planned as follows: In the introduction, we outline the problem statement, underscoring the critical role of energy consumption in drone operations. The system modeling section then explores the methods used to estimate drone energy consumption. We then address battery modeling, presenting a mathematical framework for understanding battery behavior alongside applying the HPPC test and the FFRLS method for parameter identification. The subsequent section on nonlinear filtering introduces the Extended Kalman Filter EKF as a robust approach to battery state estimation, offering advantages over traditional linear filters. We then describe the battery system utilized in this study, detailing its importance in enhancing battery performance management. In conclusion, we summarize the primary findings, highlight the contributions of our research, and discuss its broader implications for advancing drone energy consumption and battery management practices.

1.2. Problem statement

SoC estimation is a vital factor in the success of drone operations. It presents a significant hurdle that must be tackled to unlock the full potential of achieving maximum range and cost efficiency. The optimization of energy usage and precise SoC estimation are crucial aspects that directly impact the operational range of drones, determining their coverage distance and payload capability. To fully capitalize on the benefits of drones, we must devise efficient strategies for managing energy that extends range and minimizes power consumption. This issue also applies to aerial drones, where accurate flight range planning is essential to ensure uninterrupted service and prevent battery depletion mid-flight. Precise SoC estimation is critical for dependable power usage modeling. While comprehensive models for drones are available, power is consumed by the battery as a result of non-ideal characteristics of the battery, and they fail to precisely align with the power consumed by the battery due to its non-ideal characteristics. This research seeks to tackle these challenges by introducing an innovative approach for predicting and optimizing drone range. The proposed technique allows for varying levels of accuracy and complexity in both drone and battery models, thereby enhancing capabilities for precise range estimation and effective operational planning.

1.3. Goals and contributions

This paper emphasizes the importance of sustainable engineering solutions and innovative technologies for cleaner production and environmental protection. Our research contributes to the field by introducing an advanced energy management strategy for drones, which focuses on optimizing battery performance and reducing energy consumption. Accurate estimation of the State of Charge is essential for minimizing battery waste, extending battery life, and ensuring effective energy use. These enhancements promote sustainable drone operations by improving energy efficiency, lowering carbon footprints, and facilitating eco-friendly applications such as last-mile logistics, precision agriculture, and environmental monitoring. By incorporating advanced estimation methods like the Extended Kalman Filter, our work supports advancing greener and more dependable drone technologies, directly aiding in cleaner energy management and sustainable engineering practices.

The variety of drone choices significantly impacts how users perceive them. Accurately determining the battery charge level is crucial for effectively modeling power usage. Our study addresses these obstacles and strives to advance innovatively in foreseeing and improving drone range. Our approach caters to varying degrees of precision and intricacy in the drone and battery models, ultimately enhancing the capacity for range estimation and planning. Furthermore, drones are often promoted as an environmentally-friendly means of transportation thanks to their use of batteries. Nevertheless, developing an energy usage model is paramount to accurately depicting the energy needs for specific drone functions. This model considers various parameters such as flight characteristics, payload capacity, environmental conditions, and operational constraints to accurately and accurately. By doing so, this research aims to provide a comprehensive understanding of the impact of energy consumption. The developed energy usage model will also be a valuable tool for optimizing drone performance, prolonging battery life, and improving overall energy efficiency. These advancements contribute to the sustainable and energy-efficient utilization of drones.

1.4. Methodology

Our approach to determining the operating ranges of drones starts with gathering vital information about the drones and their batteries. This involves looking at important mechanical and electrical features, such as motor specifications, total weight, and aerodynamic drag, all of which affect power usage and overall flight efficiency. By examining these factors, we can better understand the energy needs of various drone models. We also analyze the electrical characteristics of individual battery cells and how they fit into the battery pack to evaluate energy storage capacity accurately. We use a battery modeling technique that considers power conversion efficiency to improve our range estimates. We utilize voltage and current waveforms to gauge the state of charge and the potential flight range. A key part of this model is capturing the power consumption patterns based on different payloads and incorporating this into a simulation framework. This allows for a thorough assessment of battery performance in real-world flight scenarios, deepening our insight into energy dynamics and battery life during operation.

2. System modeling

2.1. Drones' energy modeling

Several factors must be considered when determining the optimal operating conditions for a drone, including the drone's type, battery capacity, and weather conditions. The battery life of a drone is influenced by multiple variables, such as payload weight, wind speed, temperature, and flight altitude, which are crucial in determining the drone's energy requirements. To ensure reliable operation, it is vital to verify that the drone's battery has enough power to complete a round trip, even with the added weight of the payload and potential environmental influences of the payload and any unpredictable weather conditions. Moreover, the flight path should be planned to avoid obstacles, including buildings, power lines, and trees. The route should also avoid flying over densely populated areas or sensitive sites such as airports, and finally, weather conditions can have a noteworthy influence on drone operations. It is essential to check the weather before each flight and avoid flying in adverse conditions.

The research work carried out by Anderea (Andrea, 2014) This approach has produced substantial insights into the techno-economic analysis of drone operations under these specifications. Andrea's research has concentrated on identifying the primary factors influencing the cost-effectiveness and profitability of drone usage in this framework. Specifically, the study examines how factors such as the drone's purchase and operational costs impact overall financial feasibility, battery life, payload weight, and operating environment, as well as the profitability of drone operations. His research has also explored the potential applications of drones with such specifications. For example, drones with a payload of 2 kg and a range of 10 km with a speed of 30 km/h can be used for errands such as aerial photography, surveying, and package delivery. The present research looked at the potential economic impact of using drones for these tasks and has found that they can significantly reduce costs and improve efficiency compared to traditional methods. The power consumption in "kW" can be approached by:

$$P_{Cons} = \frac{(m_p + m_v)v}{370\eta r} + P_{elec} \tag{1}$$

To calculate the power consumption in "kW," the following approximation can be used in (1) where m_p represents the payload mass in "kg," m_v: denotes the vehicle mass in "kg," r signifies the lift-to-drag ratio, η\etaη indicates the motor and propeller power transfer efficiency, P_{elec} Represents the electronic power consumption in "kW," and v represents the cruising velocity in "km/h. The input parameters for this design are as follows: m_p is set to 2 "kg", m_v is set to 4 "kg" for the drone mass, r is set to 3 for a pessimistic scenario representing a drone skilled in vertical departure and landing, η is assumed to be 0.5 for power transfer efficiency, P_{elec} is estimated to be 0.1 "kW" for the power consumed by the electronics, and the cruising velocity can range from 0 to 45 "km/h". Please note that the velocity is not converted to "m/s". Additionally, a study (Andrea, 2014) This suggests that these parameter values and cruising velocity directly affect the drones' power consumption.

Based on (1), a nested loop calculates power consumption for each velocity and payload mass combination. The results are stored in the P_{Cons} Matrix. Then, a 3D plot is created in "Fig. 1". using the mesh function to visualize the drone's power consumption as a function of its cruising velocity and payload mass. Consequently, these values lead to a power consumption of "0.59 kW". An approximation can estimate the worst-case energy prerequisite in "kWh." Through targeted calculations and careful considerations, the maximum energy demand that the system may experience can be calculated. This estimation is essential for selecting the correct capacity and sizing of energy storage systems, as it supports optimal performance and ensures reliable operation in varying conditions. For further details, refer to (2).

$$P_{Cons}(\text{worst}) = \frac{d}{1 - HWF}\left(\frac{(m_p + m_v)}{370\eta r} + \frac{P_{elec}}{v}\right) \tag{2}$$

The maximum range, represented by "d" in kilometers, is influenced by the HeadWind Factor (HWF), which quantifies the ratio between headwind speed and the drone's airspeed. To illustrate, let us examine some sample values: if the maximum range varies between "2–25 km," with an airspeed range from "0–45 km/h" and a headwind speed of "30 km/h," the HWF plays a crucial role in determining the feasible distance the drone can cover under these conditions.

In " Fig. 2, " the graph shows multiple lines, each representing a different maximum range value. The x-axis represents the cruising velocity in km/h, and the y-axis represents the power consumption in kW.

By analyzing this graph, one can gain insights into the drone's power consumption behavior based on varying velocities and maximum ranges. This information can be valuable in designing the drone's power system and estimating its operational capabilities.

- Power Consumption Trend: As the cruising velocity increases, power consumption generally increases. This is expected since higher velocities require more energy to overcome air resistance and maintain forward motion.
- Maximum Range Influence: Each line in the graph represents a different maximum range value. Comparing the lines, we can observe that the overall power consumption tends to be higher as the maximum range increases. This is because longer ranges require more energy to cover the distance.
- Sensitivity to Headwind Factor: The HeadWind Factor is two-thirds of the ratio between headwind speed and airspeed. Although the specific HWF value does not appear explicitly in the graph, it is

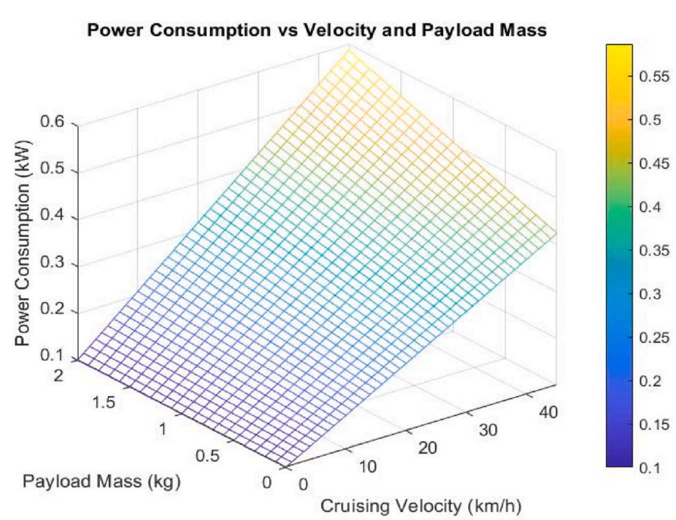

Fig. 1. Power consumption of drones as a function of velocity and payload mass.

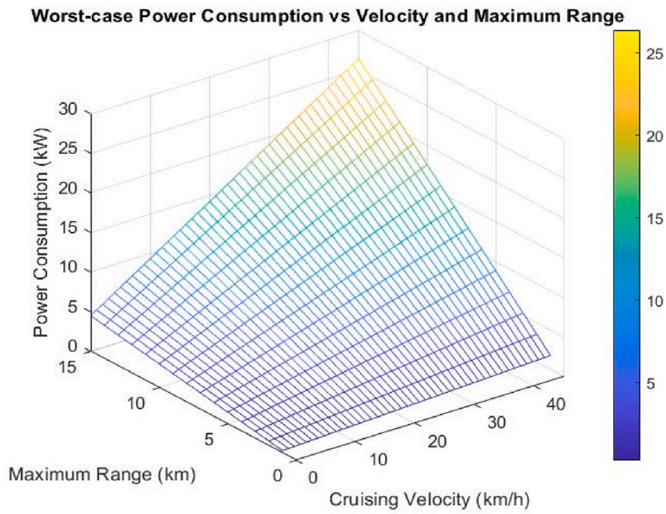

Fig. 2. Analysis of worst-case power consumption concerning velocity and maximum range.

treated as a constant factor in power consumption calculations, influencing overall energy requirements. Nonetheless, the graph provides an understanding of the power consumption trend under different velocities and ranges, regardless of the HWF value.

$$E_{Cost}(km) = \frac{C_{elec}}{Char_{eff}}\left(\frac{(m_p + m_v)}{370\eta r} + \frac{P_{elec}}{v}\right) \tag{3}$$

The average energy cost per kilometer can become near to C_{elec} represents the electricity cost at approximately "0,12 $/kWh" and $Char_{eff}$ denotes the charging efficiency, estimated at around 0.8."

Analyzing this graph "Fig. 3" can help gain insights into the relationship between cruising velocity and the average energy cost per kilometer for the given parameters. This information can help understand drones' energy efficiency and make informed decisions regarding operation and cost considerations.

The trend in energy cost can be explained as follows: as cruising velocity increases, the energy cost per kilometer tends to decrease. This reduction is primarily due to the more efficient use of power over distance at higher speeds. overhand, payload and vehicle mass influence higher velocities, which results in covering more distance in less time and reducing the energy cost per kilometer. On the other hand, payload and vehicle mass influence energy cost; higher mass values can increase energy consumption and, consequently, the energy cost per kilometer.

2.2. Battery modeling

The battery system theatres a crucial role in electric vehicles, making sophisticated battery models essential for optimizing energy processes and design (Anoune et al., 2018). Cutting-edge battery models and estimation techniques are necessary for drone flight time estimation and range prediction. In existing literature, battery models are generally categorized into three main types: mathematical models, electrochemical models, and Electrical Equivalent Circuit Models (ECM). Due to the complexities involved in parameter identification and the high computational demands of mathematical and electrochemical models, this study adopts an ECM approach to assess battery performance more efficiently (Shrivastava et al., 2019).

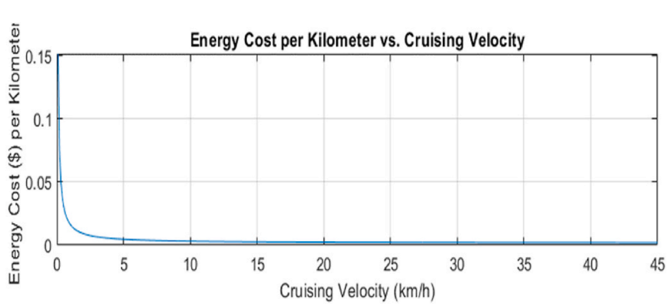

Fig. 3. Energy Cost per Kilometer vs. Cruising Velocity.

2.2.1. Mathematical model

An Electrical Equivalent Circuit Model comprises resistors, capacitors, and voltage or current sources. This configuration provides a balanced trade-off, achieving a suitable compromise between modeling accuracy and computational simplicity. Due to its effectiveness, the ECM shown in "Fig. 4" is considered a standard in the electronic design field.

Estimating the SoC relies heavily on accurately representing its dynamic characteristics through an equivalent model. Thevenin's model offers a solution by combining a parallel R.C. circuit integrated into the Rint model to overcome its limitations in representing the dynamic behavior of Li-ion batteries. This enhanced model is illustrated in "Fig. 4," where the terminal voltage is indicated as U_{L} and the ohmic voltage is represented by U_{R}, with R_0 serving as the internal ohmic resistance. The R.C. circuit includes a polarization resistor, R_p, and a polarization capacitor, C_p, which accurately represents the polarization effect in Li-ion batteries. The voltage across the polarization component is denoted by U_p. Using Kirchhoff's law, Equation (4) describes this equivalent circuit's voltage and current relationships (Xu et al., 2021).

$$\begin{cases} U_L = U_{oc} - IR_0 - U_p \\ \dot{U}_p = -\dfrac{1}{C_pR_p}U_p + \dfrac{1}{C_p}I \end{cases} \tag{4}$$

2.2.2. Parameter estimation

In this subsection, we introduce the HPPC test and the Recursive FFRLS algorithms as real-time battery parameter estimation tools. The HPPC test follows a structured sequence of steps: initially, it establishes the OCV-SOC relationship, which is crucial for accurate battery modeling. Additionally, this test aids in determining parameter values for the equivalent circuit model using an offline parameter identification approach. The HPPC process begins by placing the battery cell in a temperature-controlled chamber at 25 °C for 4 h. Following this stabilization period, a constant 1C current is applied to the cell until it reaches a voltage of 4.2V, preparing it for subsequent characterization steps. Following this, the voltage is reserved fixed at 4.2V, pending the current decreases under ≤0.05C. The cell is then permitted to respite for 1 h. Next, the cell is initially discharged at a current of 1C until it reaches an SoC of 90%. After a 1-h resting period, the cell is further discharged with a 3C current for 10 s, tracked by a rest period of 30 s. Subsequently, a 2.25C current is applied for another 10 s. This sequence is systematically repeated at different SoC levels, starting at 80% and proceeding in 10% increments to 10%. Subsequently, a sextic polynomial referred to (5) is utilized to fit the relationship accurately, where $k_0 \sim k_6$ are the constants

$$V_{ocv} = k_0 + k_1Soc + k_2Soc^2 + k_3Soc^3 + k_4Soc^4 + k_5Soc^5 + k_6Soc^6 \tag{5}$$

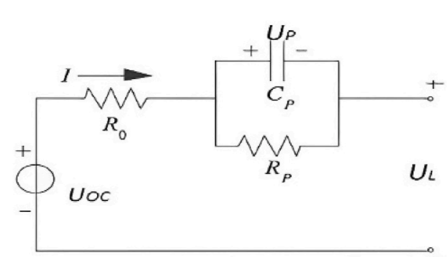

Fig. 4. Electric circuit model for batteries.

2.2.3. HPPC test

In the context of parameter approximation for LiB, the FFRLS algorithm plays a crucial role. It is employed alongside the HPPC test to estimate LiB's parameters accurately. The FFRLS algorithm is a recursive estimation technique that continually updates parameter values based on measured data. It takes into account the dynamic characteristics of LiB and adjusts the parameter estimates accordingly. Including an overlooking feature in the algorithm allows for a balance between the effect of new facts and the significance of past facts, preventing outdated information from overly impacting the parameter estimation process. Beyond selecting a suitable battery model, ensuring accurate parameter estimation is equally crucial for reliable SoC estimation. This study employs the well-established Fast Fourier Recursive Least Squares (FFRLS) method for identifying key parameters such as R_0 (internal resistance), RP, and CP (Shi et al., 2022)(M. Wu et al., 2020). The following outlines the derivation process: Following the application of the Laplace transform to Equation (6) (Lai et al., 2022)(Qin et al., 2022), the Thevenin model can be expressed in the frequency domain as

$$U_t(s) - U_{oc}(s) = I_t\ (s)\left(R_0 + \frac{R_p}{1 + R_pC_ps}\right) \tag{6}$$

Where s represents "frequency operator". By introducing $E_t(s) = U_t(s) - U_{oc}(s)$ transfer function can be represented as:

$$G(s) = \frac{U(s) - U_{oc}(s)}{I(s)} = \left(R_0 + \frac{R_p}{1 + R_pC_ps}\right) \tag{7}$$

This work utilizes the well-established bilinear transformation technique to discretize the transfer function. The specific formulation employed is presented below.

$$s = \frac{2}{T_s}\frac{1 - z^{-1}}{1 + z^{-1}} \tag{8}$$

Where discretization operator z is Ts is set to 1, the discrete form of Equation (G(s)) can be expressed as:

$$G(z^{-1}) = \frac{a_2 - a_3z^{-1}}{1 + a_1z^{-1}} \tag{9}$$

These coefficients a_1, a_2 *and* a_3 are formulated as:

$$\begin{cases} a_1 = \dfrac{2R_pC_p - 1}{2R_pC_p + 1} \\ a_2 = \dfrac{R_0 + R_p + 2R_0R_p}{2R_pC_p + 1} \\ a_3 = \dfrac{R_0\Delta t + R_p\Delta t - 2R_0R_p\Delta t}{2R_pC_p + 1} \end{cases} \tag{10}$$

The model's functionality depends on the following parameters:

$$\begin{cases} R_0 = \dfrac{a_2 - a_3}{1 - a_1} \\ R_p = \dfrac{2(a_1a_2 + a_3)}{1 + a_1^2} - \dfrac{a_2 - a_3}{1 - a_1} \\ C_p = \dfrac{(1 + a_1)^2}{4(a_1a_2 + a_3)} < listbend > \end{cases} \tag{11}$$

2.3. Nonlinear filter: extended Kalman filter (EKF)

By estimating the SoC, the BMS theatres significantly enhance the performance and reliability of electric vehicles such as drones. Battery performance is significantly influenced by complex factors such as self-discharge, discharge current, and the natural aging of battery cells, all of which contribute to inaccuracies in measurement and estimation. The Ampere-hour "A.H." method is commonly adopted to mitigate these issues for its straightforward approach to SoC estimation. Despite its simplicity, the A.H. method can be error-prone in real-world applications, where external influences like noise and random interference lead to cumulative errors over time. Various algorithms have been proposed and examined in the literature to correct these random discrepancies. (Jung et al., 2019); (Kamal et al., 2018); (Maliki et al., 2024).

Model-based techniques, particularly the equivalent circuit model, are frequently employed for more accurate SoC estimation. Among these techniques, the Kalman filter is popular due to its effectiveness in linear systems. However, the standard Kalman filter is often insufficient since battery systems exhibit nonlinear characteristics. Advanced adaptations such as the EKF have been developed to address the limitations of linearity. The EKF method is widely adopted in battery management because it reduces convergence time and provides accurate SoC estimations under diverse operational conditions. However, it does introduce a higher computational burden on the BMS.

The EKF achieves first-order polynomial precision by ignoring higher-order terms, allowing it to provide reliable state estimates across various operating environments. However, improvements are still required to make this approach suitable for complex monitoring needs, especially when dealing with large Li-ion battery packs. Implementing EKF for SoC estimation requires a linearized state-space model updated around the most recent estimates. This model is then applied using linearized Kalman filter "LKF" equations, where the input is the charge or discharge current, and the output is the battery voltage (Hossain et al., 2022) (Takyi-Aninakwa et al., 2022) In the case of nonlinear systems, a discrete state-space model can be constructed to capture the battery system's dynamic behaviors and improve the precision of SoC estimations.

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + d_k \\ y_k &= Cx_k + Du_k + s_k \end{aligned} \tag{12}$$

The dynamics of Lithium-ion Battery "LiB" behavior can be represented using a discrete state-space model formulated through the following equations:

$$\begin{aligned} x_{k+1} &= f(x_k, u_k) + d_k \\ y_k &= g(x_k, u_k) + s_k \end{aligned} \tag{13}$$

Where, $f(x_k, u_k)$ and $g(x_k, u_k)$ represent nonlinear state evolution and measuring functions, respectively. By integrating the state equation and considering measurement noise, the model can be expressed as follows:

$$\begin{aligned} x_{k+1} &= \widehat{A}_kx_k + f(\widehat{x}_k, u_k) - \widehat{A}_k\widehat{x}_k + d_k \\ y_k &= \widehat{C}_kx_k + g(\widehat{x}_k, u_k) - \widehat{C}_k\widehat{x}_k + s_k \end{aligned} \tag{14}$$

Building on the linearization approach discussed previously, it becomes clear that the EKF effectively addresses the constraints of the LKF by integrating the system model's nonlinear characteristics within both the state prediction and correction phases.

The EKF uses nonlinear battery models to forecast the system state and output. At each time step k, the EKF applies a linearization of the nonlinear battery model around the predicted state $\widehat{A}_k\widehat{x}_k$. This process generates the matrices. $\widehat{A}_k$, $\widehat{B}_k$, and $\widehat{C}_k$. These are essential for updating the covariance matrix, as it is simulated with state estimation errors and computing the Kalman gain. These matrices provide a foundation for refining the filter's predictive accuracy, as they capture the local behavior of the nonlinear system around the current state. In this way, the EKF mitigates the limitations of linearization inherent to the LKF by embedding a nonlinear model of the battery system, leading to enhanced state estimation accuracy and overall performance (Wang et al., 2020) (C. Wu et al., 2023).In the context of SoC estimation, the EKF is used due to its adaptability to the battery's dynamic behavior. Initial parameter values for the estimation process are established as follows:

$$\begin{cases} P_0 = \begin{bmatrix} 1e^{-1} & 0 \\ 0 & 1e^{-1} \end{bmatrix} \\ Q = \begin{bmatrix} 2e^{-8} & 0 \\ 0 & 5e^{-3} \end{bmatrix} \\ \quad R = 2e^{-1} \end{cases} \tag{15}$$

Our three-part model in "Fig. 5" begins with data initialization. If possible, the FFRLS algorithm and HPPC test data determine initial values for critical variables impacting load state prediction that mention specific variables.

The second part, the Thevenin model, performs parameter estimation (Step A) followed by SoC-OCV calculation (Step B) to estimate terminal voltage. Finally, the third part utilizes the EKF algorithm for SoC estimation. This two-step process involves calculating predicted and current states, incorporating initial noise values (Q and R), and using a state filter to determine the final estimated SOC (El Maliki et al., 2024).

3. Result and discussion

In this study, we used the results obtained from an experimental flight test conducted with a Y6 hexacopter in "Fig. 6" by Boukoberine et al., (2021) The hexacopter drone was powered by a compact battery from 3D Robotics. It featured three Y-shaped arms, each fitted with two counter-rotating propellers that provided lift, acceleration, and stability. The airframe also included several autonomous flight modes, improving its versatility and adaptability for different applications.(Foster, 2014).

Our primary goal was to precisely capture the power profile associated with the load and incorporate it as an input within our simulation study. This approach allowed us to understand battery performance better and evaluate energy consumption under realistic flight conditions. By implementing accurate SoC estimation, we aimed to assess how the battery behaves and performs in operational scenarios, providing insights into its efficiency and endurance during actual flight missions.

We thoroughly evaluated the energy consumption profile through experimental tests with drones, focusing on analyzing current load characteristics and the ampere-hour-based state of charge for the drones involved. As illustrated in "Fig. 7," each test drone began with a fully charged battery. However, as the flight distance increased and speed varied, environmental factors—particularly wind speed—significantly impacted the energy consumption patterns and altered the input current. We applied the previously described empirical method to estimate the SoC, which allowed us to dynamically assess the remaining battery life under different operational conditions. The SoC estimation results are presented along with a detailed analysis of the current load profile, offering insights into the energy demands of drones at various flight stages. This method clarifies how changing environmental and operational factors influence energy efficiency and battery usage.

The proposed SoC estimation model consists of three crucial parts in the estimation process. First, the Data Input stage involves initializing the necessary input data for the model. Utilizing the Recursive FFRLS algorithm along with the HPPC test, the initial values for key system *variables* k_0 through k_6, and parameters such as R_0 (ohmic resistance), R_p (polarization resistance), and C_p (polarization capacitance) are precisely determined. These foundational values are essential for accurately predicting the load state and ensuring reliable SoC estimation.

Fig. 8 showcases the main components and their interactions within

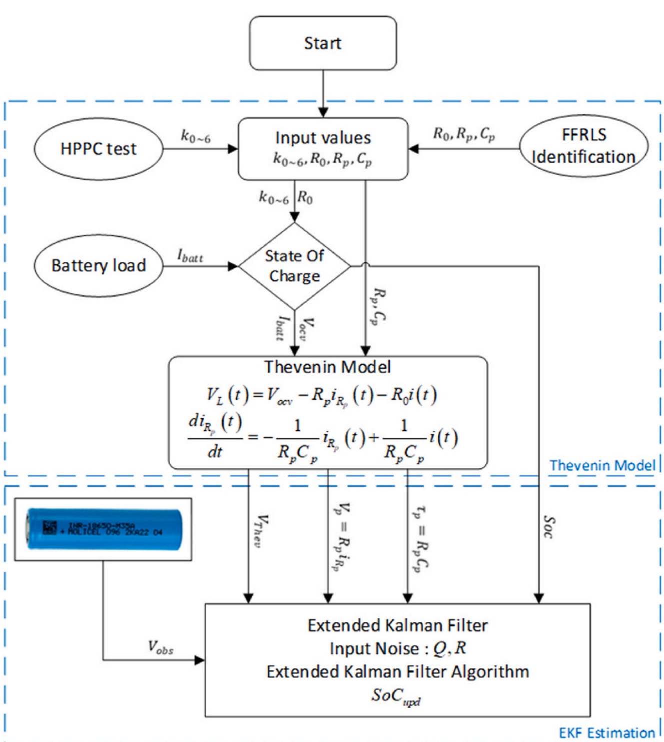

Fig. 5. Flowchart calculation.

Fig. 6. 3D Robotics RTF Y6 (Foster, 2014).

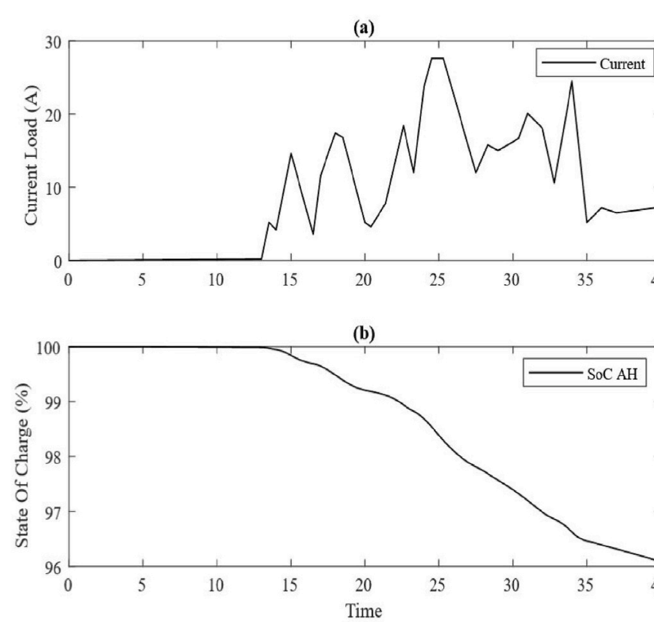

Fig. 7. Analysis of current load profile and ampere-hour-based SoC (SoC) for the drones under Investigation.

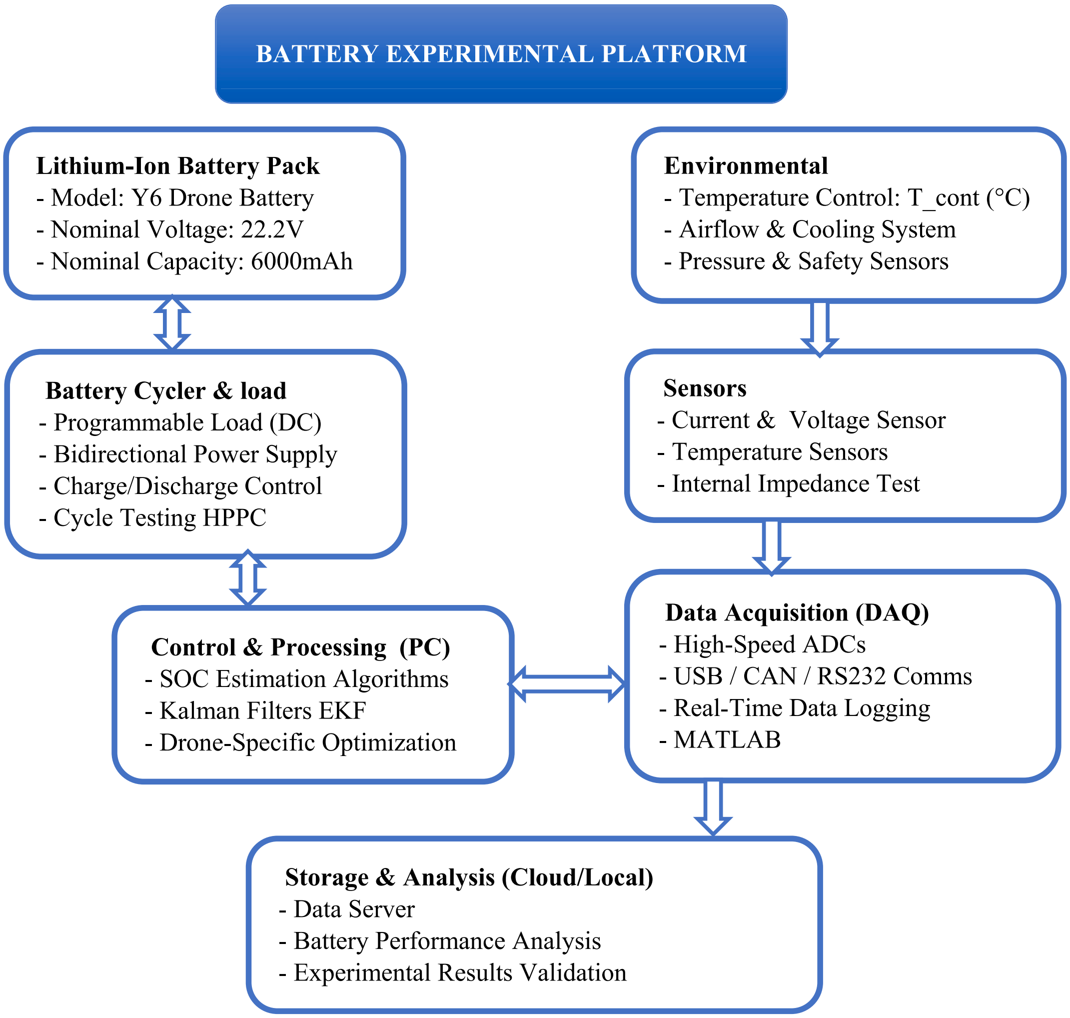

Fig. 8. Diagram illustrating the battery experimental platform.

the experimental setup aimed at assessing the performance of the battery management system in drones. This platform features a lithium-ion battery pack that powers the drone's propulsion system and is monitored by a battery management system for real-time SoC estimation. The battery pack connects to a voltage and current measurement system to gather vital parameters such as voltage, current, and temperature, which are crucial for precise SOC and health estimation. Data from these sensors is sent to a processing unit employing algorithms like the EKF for SOC estimation and parameter identification techniques to model the battery's behavior accurately. Furthermore, the platform incorporates a charging and discharging controller that manages battery usage during flight tests, ensuring optimal performance and longevity. The experimental platform is also linked with a flight controller, enabling real-world testing of the battery system during drone operations, which provides essential feedback for enhancing the battery management strategy.

The 3D Robotics Y6 Drone is utilized as the platform for real-world flight validation in this study. This hexacopter drone features autonomous flight capabilities, making it an excellent choice for testing and validating the battery SoC estimation model. The Y6 drone operates on lithium-ion, which aligns well with the proposed EKF-based SOC estimation framework. Incorporating this drone into the experimental setup enables practical verification of the proposed SOC estimation methods during actual flight operations (He et al., 2021).

The key technical specifications of the battery cell used in the Y6 drone are as follows:

The HPPC test is specifically employed to establish the correlation between the battery's OCV and SoC (see Table 1). This test subjects the battery to a sequence of hybrid pulse power profiles to simulate real-world load conditions. The resulting data is then fitted to a sixth-order polynomial function, allowing for an accurate mathematical representation of the relationship between the Li-ion battery's OCV and its SoC. Modeling this relationship is vital for comprehending battery behavior and predicting its performance across varying load scenarios. The values for k_0 through k_6, are detailed in "Table 2," providing an apparent reference for these critical parameters (He et al., 2021):

System parameter identification is applied to determine if the model parameters align with the OCV-SOC curve. This process involves extracting fundamental values that define the battery's behavior over various charge states. The resulting parameters, derived using the Recursive FFRLS algorithm, are summarized in Table 3. These parameters are essential for refining the model's accuracy and enhancing its

Table 1
the key technical specifications of the battery cell.

Specification	Details
Battery type	Lithium-ion
Nominal voltage	22.2v (6s configuration)
Capacity	6000mAh
Anode material	Graphite
Cathode material	Lithium nickel manganese cobalt oxide (NMC, $LiNiMnCoO_2$)
Electrolyte	$LiPF_6$in ethylene carbonate (EC) and dimethyl carbonate (DMC)

Table 2
results of OCV-SOC fitting at 25 °C.

k_0	k_1	k_2	k_3	k_4	k_5	k_6
3.353	2.478	− 9.902	19.01	− 14.44	2.351	1.319

Table 3
Model parameters at 25 °C.

$R_0(\Omega)$	$R_P(\Omega)$	$C_P(F)$
0.0703	0.0481	750.6747

predictive capability under different operational conditions.

Fig. 9 presents a graph with three curves illustrating the SoC for the system under study. The first curve displays the observed SoC, reflecting the actual measured SoC values and serving as a reference benchmark for evaluating the accuracy of the other two curves. This observed curve provides a basis for comparison, enabling an assessment of how well the modeled estimations align with the real-world data.

- The second curve, labeled SoC_EKF, represents the SoC estimated using the Extended Kalman Filter. This curve aligns closely with the observed SoC, delivering a high-precision estimation by leveraging advanced filtering and state estimation techniques. The SoC_EKF effectiveness stems from its ability to account for dynamic system changes, offering superior accuracy in SoC predictions.
- In contrast, the third curve, labeled SoC_AH, represents the SoC estimated through the Ampere-hour (A.H.) counting method. Although the SoC_AH curve provides a reasonable approximation of the SoC, it does not reach the precision level achieved by the SoC_EKF. The Ampere-hour method calculates SoC based on accumulated charge or discharge, which is simpler but may introduce slight errors, particularly over extended operation periods.
- As time progresses, the discrepancies between the actual observed and estimated SoC curves (SoC_EKF and SoC_AH) tend to grow. This drift indicates a gradual reduction in estimation accuracy for both methods. Potential sources of these errors include battery aging effects, which alter battery performance over time; measurement noise and uncertainties, which may affect sensor readings; and inherent limitations in the estimation algorithms. These factors contribute to a cumulative error that becomes more noticeable with extended usage, highlighting the need for periodic recalibration or adjustment of the estimation models to maintain accuracy.

According to "Fig. 10," the Ampere-hour "A.H." method provides a reasonably moderate estimation of SoC, although it is somewhat less precise than the EKF method. The estimated error for SoC_AH can be as high as 0.00134451, whereas the error for SoC_EKF is lower at 0.000315187.

It can be concluded that SoC.

- The Ampere-hour "A.H." method offers a reasonable estimation of the SoC; however, it demonstrates slightly lower accuracy than the SoC estimation achieved through the Extended Kalman Filter "SoC_EKF".
- The SoC_AH method estimates the SoC using ampere-hour counting techniques. However, this approach can introduce a certain error level into the estimation process due to cumulative inaccuracies and sensor noise.
- The Root Mean Square Error "RMSE" counts the average magnitude of discrepancies between the estimated SoC values and the actual observed values, providing a reliable metric for assessing estimation accuracy. In this context:
  - For SoC_AH, the RMSE value is 7.2150×10^{-4}).

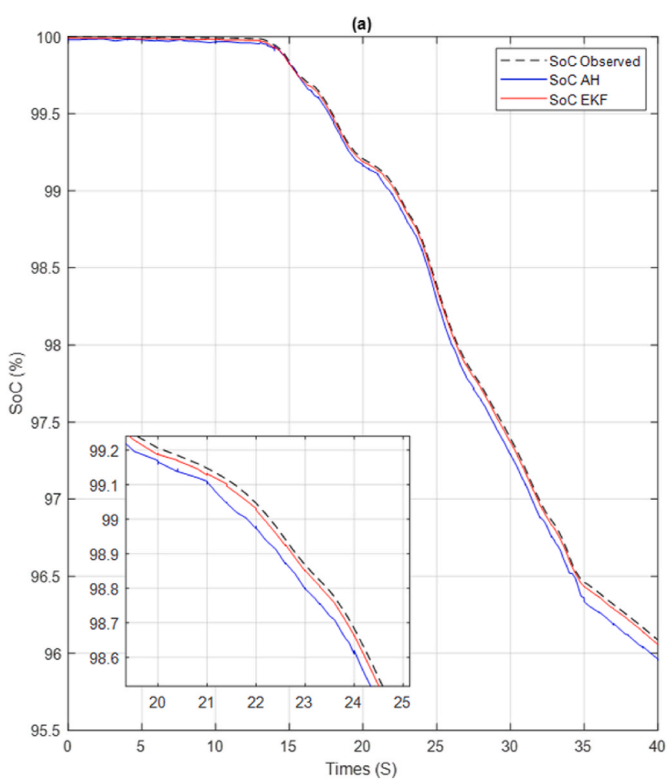

Fig. 9. Comparison of SoC estimation using the Extended Kalman Filter (SoC_EKF) with the Ampere-hour method (SoC_Ah).

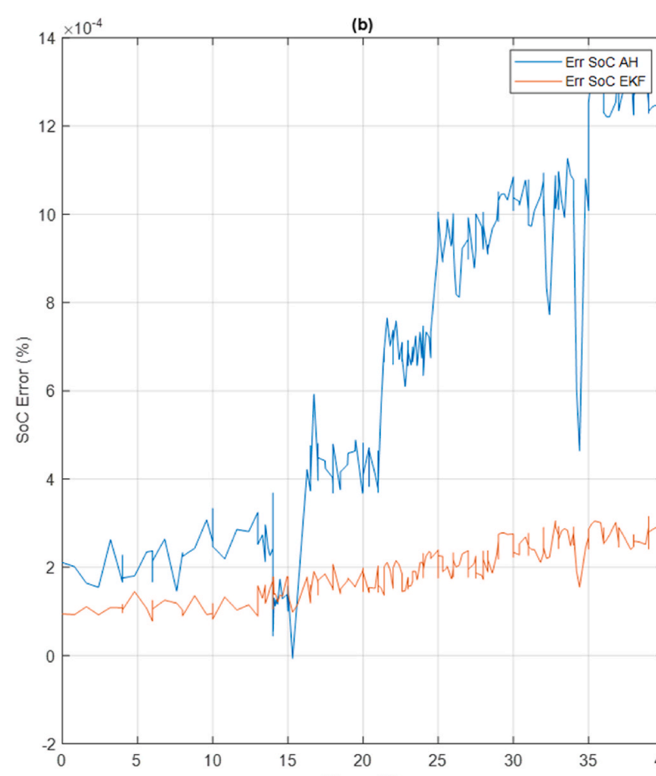

Fig. 10. Registered errors detected between SoC_AH and the estimated SoC_EKF.

- For SoC_EKF, the RMSE value is 1.9329×10^{-4}).

- Comparing the RMSE values, we can observe that the SoC_EKF estimation process has a lower RMSE value, indicating higher accuracy than the SoC_AH estimation process.

Considering the overall results, the SoC_EKF method delivers highly precise estimations of the SoC but requires more significant computational resources, making processing power more demanding. In contrast, the SoC_AH method presents a more practical and computationally efficient option, offering a satisfactory level of accuracy that may be suitable for less resource-intensive applications.

4. Conclusion

In this study, we created an advanced battery management system for drones, emphasizing precise State of Charge estimation to optimize energy use and improve operational efficiency. Our research presents a detailed mathematical model for evaluating battery performance and energy consumption, backed by Hybrid Pulse Power Characterization tests and Recursive Least Squares with Forgetting Factor for parameter identification. To overcome the shortcomings of linear filtering techniques, we employed the Extended Kalman Filter for nonlinear SoC estimation, which greatly enhances accuracy and reliability. The comparative analysis between the SoC_AH and SoC_EKF estimation methods revealed that the EKF method offers greater accuracy, with RMSE values of 1.93×10^{-4} for SoC_EKF compared to 7.21×10^{-4} for SoC_AH. These findings indicate that SoC_EKF minimizes estimation errors and enables real-time, accurate SoC monitoring. This improved battery state estimation prevents power depletion during drone operations and enhances battery performance across different environmental and load conditions. In addition to enhancing energy efficiency, our findings have important implications for sustainable drone operations. They contribute to longer battery life, minimize energy waste, and promote eco-friendly logistics, agriculture, and surveillance uses. This research marks progress toward creating more dependable and energy-efficient drones for contemporary technological applications. This paper also emphasizes the significance of sustainable engineering solutions and innovative technologies aimed at cleaner production and lowering carbon footprints. By incorporating advanced estimation techniques such as the EKF, our research fosters the development of greener and more reliable drone technologies to create energy-efficient drones for environmentally friendly applications.

CRediT authorship contribution statement

Kamal Anoune: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ismail El Kafazi:** Writing – original draft, Visualization, Formal analysis. **Anas El Maliki:** Software, Resources, Project administration, Formal analysis, Data curation. **Badre Bossoufi:** Validation, Supervision, Software, Resources. **Badr NASIRI:** Software, Resources, Project administration. **Hana Zekraoui:** Writing – review & editing. **Mishari Metab Almalki:** Visualization, Validation, Supervision, Software. **Thamer A.H. Alghamdi:** Validation, Software, Resources. **Mohammed Alenezi:** Methodology, Investigation, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors express heartfelt appreciation to their colleagues and professors for their unwavering support and guidance during the research, playing a pivotal role in shaping and enhancing the quality of this academic paper.

Data availability

Data will be made available on request.

References

Alshawabkeh, Ashraf, Matar, Mustafa, Almutairy, Fayha, 2024. Parameters identification for lithium-ion battery models using the Levenberg–Marquardt algorithm. World Electric Vehicle Journal 15 (9), 406. https://doi.org/10.3390/wevj15090406.
Andrea, Raffaello, 2014. Guest Editorial can drones deliver? IEEE Trans. Autom. Sci. Eng. 11 (3), 647–648. https://doi.org/10.1109/TASE.2014.2326952.
Baek, Donkyu, Chen, Yukai, Bocca, Alberto, Bottaccioli, Lorenzo, Di Cataldo, Santa, Gatteschi, Valentina, Pagliari, Daniele Jahier, et al., 2019. Battery-aware operation range estimation for Terrestrial and aerial electric vehicles. IEEE Trans. Veh. Technol. 68 (6), 5471–5482. https://doi.org/10.1109/TVT.2019.2910452.
Barcellona, Simone, Piegari, Luigi, 2017. Lithium ion battery models and parameter identification techniques. Energies 10 (12). https://doi.org/10.3390/en10122007.
Boukoberine, Mohamed Nadir, Zia, Muhammad Fahad, Mohamed, Benbouzid, Zhou, Zhibin, Donateo, Teresa, 2021. Hybrid Fuel cell powered drones energy management strategy improvement and Hydrogen Saving using real flight test data. Energy Convers. Manag. 236 (March), 113987. https://doi.org/10.1016/j.enconman.2021.113987.
Chen, Kaiqiang, Pang, Hui, Nan, Wenzhi, Wang, Fengbin, Yang, Sitian, Liu, Jiahao, 2024a. Parameter identification and state of charge estimation for lithium-ion batteries under Wide temperature range. Ionics 30 (2), 847–862. https://doi.org/10.1007/s11581-023-05352-w.
Chen, Yuan, Duan, Wenxian, He, Yigang, Wang, Shunli, Fernandez, Carlos, 2024b. A hybrid data driven framework considering feature extraction for battery state of health estimation and remaining useful life prediction. Green Energy and Intelligent Transportation 3 (2), 100160. https://doi.org/10.1016/j.geits.2024.100160.
Foster, Jeff, 2014. 3D Robotics RTF Y6 Multicopter, 2014. https://www.provideocoalition.com/3d-robotics-y6/.
He, Zhigang, Li, Yaotai, Sun, Yanyan, Zhao, Shichao, Lin, Chunjing, Pan, Chaofeng, Wang, Limei, 2021. State-of-Charge estimation of lithium ion batteries based on adaptive Iterative extended Kalman filter. J. Energy Storage 39 (September 2020), 102593. https://doi.org/10.1016/j.est.2021.102593.
Hossain, M., Haque, M.E., Arif, M.T., 2022. Kalman filtering techniques for the online model parameters and state of charge estimation of the Li-ion batteries: a comparative analysis. J. Energy Storage 51 (August 2021), 104174. https://doi.org/10.1016/j.est.2022.104174.
Jung, Sunghun, Jo, Yonghyeon, Kim, Young Joon, 2019. Flight time estimation for continuous surveillance missions using a Multirotor UAV. Energies 12 (5). https://doi.org/10.3390/en12050867.
Kamal, Anoune, Bouya, Mohsine, Astito, Abdelali, Abdellaha, Abdellatif Ben, 2018. A design and sizing of a hybrid PV-Wind-Grid system for electric vehicle charging platform. In: The Second International Workshop on Transportation and Supply Chain Engineering - IWTSCE'18. https://doi.org/10.1051/matecconf/201820000008.
Kirschstein, Thomas, 2020. Comparison of energy demands of drone-based and Ground-based Parcel delivery services. Transport. Res. Transport Environ. 78 (December 2019), 102209. https://doi.org/10.1016/j.trd.2019.102209.
Lai, Xin, Weng, Jiahui, Huang, Yunfeng, Yuan, Ming, Yao, Yi, Han, Xuebing, Zheng, Yuejiu, 2022. A Joint state-of-health and state-of-energy estimation method for lithium-ion batteries through combining the Forgetting factor recursive least squares and Unscented Kalman filter. Measurement: Journal of the International Measurement Confederation 205 (August), 112187. https://doi.org/10.1016/j.measurement.2022.112187.
Liu, Zheng, Dang, Xuanju, Jing, Benqin, Ji, Jianbo, 2019. A novel model-based state of charge estimation for lithium-ion battery using adaptive robust Iterative cubature Kalman filter. Elec. Power Syst. Res. 177 (June), 105951. https://doi.org/10.1016/j.epsr.2019.105951.
Lu, Languang, Han, Xuebing, Li, Jianqiu, Hua, Jianfeng, Ouyang, Minggao, 2013. A review on the key issues for lithium-ion battery management in electric vehicles. J. Power Sources 226, 272–288. https://doi.org/10.1016/j.jpowsour.2012.10.060.
Madani, Seyed Saeed, Schaltz, Erik, Kær, Søren Knudsen, 2018. A review of different electric equivalent circuit models and parameter identification methods of lithium-ion batteries. ECS Trans. 87 (1), 23–37. https://doi.org/10.1149/08701.0023ecst.
Maliki, Anas El, Benlafkih, Abdessamad, Anoune, Kamal, Hadjoudja, Abdelkader, 2024. Reduce state of charge estimation errors with an extended Kalman filter algorithm. Int. J. Electr. Comput. Eng. 14 (1), 57–65. https://doi.org/10.11591/ijece.v14i1.pp57-65.
Manjarrez, Luis H., Ramos-Fernández, Julio C., Espinoza, Eduardo S., Lozano, Rogelio, 2023. Estimation of energy consumption and flight time margin for a UAV mission based on Fuzzy systems. Technologies 11 (1), 1–25. https://doi.org/10.3390/technologies11010012.
Qin, Shuai, Qin, Dongchen, Wu, Hongxia, Wang, Tingting, Chen, Jiangyi, Wang, Peizhuo, 2022. State of charge estimation of lithium-ion power battery based on online parameter identification method and BP Neural Network. Int. J. Electrochem. Sci. 17 (1), 220138. https://doi.org/10.20964/2022.01.05.

Shi, Na, Chen, Zewang, Niu, Mu, He, Zhijia, Wang, Youren, Cui, Jiang, 2022. State-of-Charge estimation for the lithium-ion battery based on adaptive extended Kalman filter using improved parameter identification. J. Energy Storage 45 (September 2021), 103518. https://doi.org/10.1016/j.est.2021.103518.

Shrivastava, Prashant, Kok Soon, Tey, Idris, Mohd Yamani Idna Bin, Mekhilef, Saad, 2019. Overview of model-based online state-of-charge estimation using Kalman filter Family for lithium-ion batteries. Renew. Sustain. Energy Rev. 113 (June), 109233. https://doi.org/10.1016/j.rser.2019.06.040.

Takyi-Aninakwa, Paul, Wang, Shunli, Zhang, Hongying, Li, Huan, Xu, Wenhua, Fernandez, Carlos, 2022. An optimized relevant long short-term memory-Squared gain extended Kalman filter for the state of charge estimation of lithium-ion batteries. Energy 260 (August), 125093. https://doi.org/10.1016/j.energy.2022.125093.

Vandeputte, Freja, Hallemans, Noël, Kuzhiyil, Jishnu Ayyangatu, Saniee, Nessa Fereshteh, Widanage, Widanalage Dhammika, Lataire, John, 2023. Frequency domain parametric estimation of fractional order impedance models for Li-ion batteries. IFAC-PapersOnLine 56 (2), 4325–4330. https://doi.org/10.1016/j.ifacol.2023.10.1803.

Wang, Shunli, Fernandez, Carlos, Yu, Chunmei, Fan, Yongcun, Cao, Wen, Stroe, Daniel Ioan, 2020. A novel charged state prediction method of the lithium ion battery packs based on the Composite equivalent modeling and improved Splice Kalman filtering algorithm. J. Power Sources 471 (June), 228450. https://doi.org/10.1016/j.jpowsour.2020.228450.

Wang, Shunli, Gao, Haiying, Takyi-Aninakwa, Paul, Guerrero, Josep M., Fernandez, Carlos, Qi, Huang, 2024a. Improved multiple feature-electrochemical thermal coupling modeling of lithium-ion batteries at low-temperature with real-time coefficient correction. Protection and Control of Modern Power Systems 9 (3), 157–173. https://doi.org/10.23919/pcmp.2023.000257.

Wang, Shunli, Takyi-Aninakwa, Paul, Jin, Siyu, Yu, Chunmei, Fernandez, Carlos, Stroe, Daniel Ioan, 2022. An improved feedforward-long short-term memory modeling method for the whole-life-cycle state of charge prediction of lithium-ion batteries considering current-voltage-temperature variation. Energy 254, 124224. https://doi.org/10.1016/j.energy.2022.124224.

Wang, Shunli, Zhang, Shaojie, Wen, Sufang, Fernandez, Carlos, 2024b. An accurate state-of-charge estimation of lithium-ion batteries based on improved particle swarm optimization-adaptive square root cubature Kalman filter. J. Power Sources 624 (June). https://doi.org/10.1016/j.jpowsour.2024.235594.

Wu, Chunling, Hu, Wenbo, Meng, Jinhao, Xu, Xianfeng, Huang, Xinrong, Cai, Lei, 2023. State-of-Charge estimation of lithium-ion batteries based on MCC-AEKF in non-Gaussian noise environment. Energy 274 (February), 127316. https://doi.org/10.1016/j.energy.2023.127316.

Wu, Muyao, Qin, Linlin, Wu, Gang, Shi, Chun, 2020. State of charge estimation of lithium ion battery based on a new linear online model. In: *Chinese Control Conference, CCC* 2020-July, pp. 5282–5286. https://doi.org/10.23919/CCC50068.2020.9189457.

Xia, Yang, Zeng, Wenjia, Zhang, Canrong, Yang, Hai, 2023. A Branch-and-Price-and-Cut algorithm for the vehicle routing problem with load-dependent drones. Transp. Res. Part B Methodol. 171 (March), 80–110. https://doi.org/10.1016/j.trb.2023.03.003.

Xu, Wenhua, Wang, Shunli, Jiang, Cong, Fernandez, Carlos, Yu, Chunmei, Fan, Yongcun, Wen, Cao, 2021. A novel adaptive dual extended Kalman filtering algorithm for the Li-ion battery state of charge and state of health Co-estimation. Int. J. Energy Res. 45 (10), 14592–14602. https://doi.org/10.1002/er.6719.

Yaacoub, Jean Paul, Noura, Hassan, Salman, Ola, Ali, Chehab, 2020. Security analysis of drones systems: Attacks, limitations, and Recommendations. Internet of Things (Netherlands) 11, 100218. https://doi.org/10.1016/j.iot.2020.100218.

Zhang, Juan, Campbell, James F., Sweeney, Donald C., Hupman, Andrea C., 2021. Energy consumption models for delivery drones: a comparison and assessment. Transport. Res. Transport Environ. 90 (December 2020), 102668. https://doi.org/10.1016/j.trd.2020.102668.