

Maximizing energy efficiency in drones through accurate state of charge estimation using extended Kalman filter

Kamal Anoune¹, Anas El Maliki², Merouan Belkasmi³

¹EMIT Laboratory, Energy & Materials, Instrumentation & Telecom, Physics Department, Faculty of Sciences and Technologie FST-Settat, Hassan First University (UHP), Settat, Morocco

²Laboratory of Electronic Systems, Information Processing, Mechanics and Energetics, Faculty of Sciences, University Ibn Tofail, Kenitra, Morocco

³LERMA Laboratory, International University of Rabat (UIR), Sala Al Jadida, Morocco

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ABSTRACT

This paper delves into the critical aspect of managing energy consumption in drone operations to achieve the utmost range and ensure accurate state of charge (SoC) estimation. Effective energy management is pivotal in determining the operational range of drones, allowing for longer distances and heavier payloads. The integration of precise energy estimation algorithms into operational planning extends the range of drones, facilitating swift, environmentally-conscious missions for sustainable and efficient logistics solutions. The paper introduces a mathematical model to understand energy consumption and battery behavior in drones, utilizing the hybrid pulse power characterization test and recursive least square with forgetting factor for parameter identification. To overcome the limitations of linear filters, the paper employs the accurate extended Kalman filter (EKF) in the nonlinear filter section. The EKF significantly enhances the battery management system by furnishing precise SoC data. The study evaluates two SoC estimation techniques: SoC-AH (ampere-hours) and SoC_EKF, using root mean square error for comparison. The SoC_EKF technique demonstrates higher accuracy, boasting a lower errors value of 0.78%, thus making it superior for precise drone battery SoC estimation. These findings contribute to the improved performance, reliability, and overall safety of drones.

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Corresponding Author:

Kamal Anoune

LMIET Laboratory, Physics Department, Faculty of Sciences and Technics FST-Settat

Hassan 1st University

Settat, Morocco

Email: kamal.anoune@gmail.com, kamal.anoune@uhp.ac.ma

1. INTRODUCTION

In recent years, drones have emerged as one of the most extensively researched logistics technologies, incorporating technical elements that align with modern transportation and societal developments, including autonomy, adaptability, and agility. The first factor influencing a drone's battery life is the payload weight. Heavier payloads require more energy to fly, resulting in shorter battery life. For instance, a few kilograms of payload can significantly reduce the drone's flight time compared to flying without any payload. Additionally, wind speed affects battery life, as flying against the wind consumes more energy while flying with the wind can extend flight time. Temperature also plays a crucial role; high temperatures can lead to battery overheating, and low temperatures reduce battery capacity and overall performance. Furthermore, flight height influences battery life, as maintaining stability and continuous flight demands more energy, resulting in shorter battery life.

Considering these aspects becomes critical when planning drone operations, especially with payloads, to ensure the drone has sufficient battery life to complete tasks safely and effectively. Drones find extensive use in remote guidance and encompass a variety of vehicles, including submarines and land-based autonomous vehicles. Notably, hybrid-wing drones, a recent addition to the market, possess fixed and rotary-wing capabilities, enabling rapid destination reach through gliding and utilizing four rotors for hovering [1], [2]. Achieving operational drones requires addressing three significant challenges through automation research: vehicle design, positioning and routing, and vehicle coordination. The vehicle design aspect involves creating equipment that is not only efficient but also capable of hovering and adapting to various scenarios while maintaining reliability comparable to commercial airliners. This ambitious task demands numerous iterations, necessitating the collaboration and contributions of experts from diverse fields to bring forth innovative solutions [3]. Numerous studies reveal that drones have some negative limitation related to estimation of disposable energy. Kirschstein *et al.* [4] introduces an energy usage model tailored for drones, aiming to delineate the energy needs for drone deliveries based on environmental conditions and flight patterns. The model is subsequently employed to gauge the energy consumption of a stationary package delivery system, which operates from a designated depot and serves a specific number of clients. A comparative analysis is conducted between drone energy consumption and the energy requirements of diesel and electric trucks that cater to the same clients from a similar depot. To bolster the accuracy and dependability of SoC estimation, the dynamic attributes of a lithium-ion battery (LiB) are approximated through an auto-regressive and moving average model. This model effectively compensates for potential discrepancies stemming from voltage and discharge current measurements, thereby elevating the precision and reliability of state of charge (SoC) estimation [5].

Gaining profound insights into LiB performance and its underlying instrument offers valuable knowledge. Such understanding facilitates battery performance testing, enabling the identification of several factors that impact performance and the governing laws behind their influence. To develop practical battery system models for battery management systems (BMS) [6], modeling methods can be employed. These models provide satisfactory accuracy while minimizing complex computations. During operation, adaptive control technology is utilized to identify battery system parameters, estimate critical battery states such as SoC, state of health (SoH), and state of function (SoF), and detect faults. This information is then communicated to the vehicle manager over network, ensuring the vehicles' safe and dependable operation [7]. In their research, Xia *et al.* [8] conducted a study focused on the routing problem of drones featuring load-dependent characteristics. The researchers introduced docking hubs as collaborative facilities for trucks and drones, effectively expanding the service coverage. To handle the complexities arising from nonlinear load-dependent energy consumption, they proposed a mixed-integer model. While predicting the operational range for drones has not been a significant challenge due to fast and readily available refueling options, accurately estimating the driving or flying range for battery-operated vehicles has become crucial. This increased importance arises from the widespread adoption of battery-operated vehicles in countless areas [9]. Addressing energy consumption becomes a fundamental constraint in realm of drone operations, unlocking full possible of achieving maximum range, cost reduction, and accurate SoC estimation. Optimizing energy usage directly influences drones' operational range, determining the distance they can cover and the payload they can carry. To fully harness the benefits of drones, it is imperative to develop efficient energy management strategies that maximize range while minimizing power consumption. These strategies necessitate considering numerous factors, including flight dynamics, payload weight, wind conditions, and operational requirements. Developing an accurate energy estimation algorithm and integrating it into operational planning enable drones to extend their operational range, facilitating rapid and environmentally friendly operations. Ultimately, this contributes to advancing sustainable and efficient last-mile logistics solutions.

The optimization of energy consumption plays a critical role in determining the operational range and payload capacity of drones. To fully harness the potential benefits of drones, efficient energy management strategies must be developed to maximize range while minimizing power usage. This challenge also extends to aerial drones, where precise flight range planning is essential to ensure continuous service and prevent battery depletion during flights. Accurate estimation of the SoC through an effective BMS is crucial for reliable power usage modeling. However, existing comprehensive drone models may not precisely align with the actual energy strained from LiB due to its non-idealities. To address these issues, this research presents a novel contribution focused on predicting and optimizing drone range. The proposed approach offers flexibility in accommodating varying levels of accuracy and complexity in both drone and battery models, resulting in improved range estimation and planning capabilities. Additionally, drones are often hailed as energy-efficient transportation options, given their battery-powered operation. However, to ensure an accurate representation of energy requirements for specific drone applications, we have developed a MATLAB program based on extended Kalman filter (EKF) to precisely estimate battery charge.

The paper follows a structured organization as follows: In the introduction, the problem statement is highlighted, emphasizing the significance of energy consumption in drone operations. Moving to the system

modeling section, the focus shifts to the modeling of drones' energy consumption, offering insights into the approach used for estimating energy usage in drones. Next, the paper delves into battery modeling, presenting a mathematical model for characterizing battery behavior. Additionally, the utilization of the hybrid pulse power characterization (HPPC) test and the recursive least square with forgetting factor (FFRLS) for parameter identification in battery modeling is introduced. In nonlinear filter section, the implementation of EKF is discussed, serving as a powerful tool for battery state estimation, and overcoming the limitations of linear filters. Subsequently, an overview of BMS employed in the study is provided, highlighting its role in effectively managing and optimizing battery performance. Finally, the paper concludes by summarizing the key points, emphasizing the contributions made by the research, and discussing the broader implications of the study in the field of drone energy consumption and battery management.

2. METHOD

The proposed approach for estimating the operational range of drones involves the gathering of both drone and battery data. The drone data encompasses mechanical and electrical characteristics that influence power consumption, such as motor power, weight, and aerodynamic drag. This data provides valuable insights into the energy requirements of different drone types. On the other hand, battery data focuses on the electrical properties of the battery cell and its scaling for the battery pack, enabling a comprehensive understanding of the energy storage capabilities.

To estimate the drone's range, a battery model is formulated, taking into consideration power conversion efficiency. By analyzing voltage and current waveforms, the model calculates the battery's SoC and, consequently, the drone's range. The methodology is designed to be adaptable to various drone types and also takes into account variables like weather conditions. It incorporates efficiency trade-offs and adjustments, including speed control mechanisms, to optimize power consumption and maximize the drone's operational range. This approach ensures a comprehensive estimation of the drone's range and provides insights for enhancing flight performance and efficiency.

2.1. Battery modeling

Battery storage system holds paramount importance in electric vehicles, calling for the utilization of sophisticated battery models to refine energy processes and design. In tasks such as estimating drones' flight duration and predicting their operational range, advanced lithium-ion battery (LiB) models and estimation techniques play a crucial role. Existing literature outlines three primary categories of LiB models: mathematical, electrochemical, and electrical equivalent circuit models (ECMs). Considering the complexities associated with parameter identification and the computational demands of mathematical and electrochemical models, we have opted for an ECM to emulate battery performance. This decision enables us to strike a harmonious balance between precision and computational efficiency, rendering it well-suited for practical applications in both drones and electric vehicles [10], [11].

2.1.1. Mathematical model

An ECM consists of resistors, capacitors, and voltage or current sources, providing a reasonably balanced deals among accuracy and simplicity. In domain of electronic design, the ECM depicted in Figure 1 is widely recognized as a standard configuration due to its effectiveness and practicality. Accurately estimating the SoC of LiBs hinges on the precise representation of its dynamic characteristics using an equivalent model.

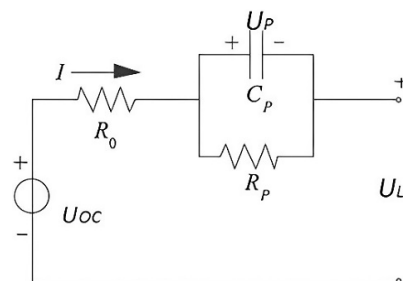


Figure 1. Electric circuit model for batteries

Thevenin's model offers a promising solution by incorporating a Rint model with a parallel RC circuit, effectively addressing the limitations of the Rint model, which fails to capture the dynamic properties of Li-

ion batteries. As depicted in Figure 1, this model visualizes the terminal voltage as U_L , the ohmic voltage as U_R , and the ohmic internal resistance as R_0 . The RC circuit includes a polarization resistor R_p and a polarization capacitor C_p , effectively characterizing the polarization effect in Li-ion batteries, with the voltage across the polarization element denoted as U_p . By employing Kirchhoff's law, in (1) establishes the voltage and current representations within the equivalent circuit, enabling an improved and more accurate estimation of the battery's SoC. These advanced modelling technics own a big possibility for enhancing battery management systems and optimizing battery performance in numerous applications, including electric vehicles and portable electronic devices [12].

$$\begin{cases} U_L = U_{oc} - IR_0 - U_p \\ \dot{U}_p = -\frac{1}{C_p R_p} U_p + \frac{1}{C_p} I \end{cases} \quad (1)$$

2.1.2. Hybrid pulse power characterization (HPPC) method for parameter identification

The hybrid pulse power characterization (HPPC) method stands as a pivotal technique in comprehensively characterizing LiB. It involves subjecting the battery to a series of hybrid pulse power profiles, essentially a set of distinct current pulses with varying magnitudes and durations, while concurrently measuring the battery's response in terms of voltage and current. This method operates under varying conditions, encompassing different load levels, charging, and discharging cycles, to gather an expansive dataset. HPPC conditions encompass a spectrum of scenarios, simulating real-world usage patterns by integrating abrupt changes in load conditions, rapid charging, and discharging. Through this controlled yet diverse dataset, HPPC facilitates the extraction of critical parameters that significantly influence LiB behavior. Parameters obtained through HPPC encapsulate vital attributes such as internal resistance, capacity, and voltage response at varying SoC. Method enables the derivation of critical battery model parameters like open circuit voltage (OCV) versus SoC relationship, which forms the fundamental basis for predicting the battery's behavior under different operating conditions. This method not only aids in enhancing battery model accuracy but also plays a crucial role in predicting battery behavior and performance across a range of real-world scenarios.

The battery model is developed using parameters derived from characterization. Extracting these parameters requires a series of characterization tests, following established standards and research methodologies [13]. Initially, the capacity test determines the battery's effective nominal capacity through a standard charge and discharge test. The second OCV test, is conducted to extract the OCV-SoC relationship and battery model parameters. This approach deviates from employing the hybrid pulse power characterization (HPPC) test, as the study exclusively focuses on the standard C-rate. Baccouche *et al.*'s research [14] emphasizes accurate modeling of the nonlinear OCV-SoC relationship crucial for adaptive Li-ion battery operation. This model, employing five parameters within double exponential and quadratic functions, closely aligns with experimental curves, boasting a mere 1 mV fitting error. It covers wide temperature ranges, accounts for OCV voltage hysteresis, and when integrated into EKF for SoC estimation, significantly minimizes execution time and reduces estimation error to 3%, outperforming other models at 5%. Rigorous experiments validate the model's reliability and precision across diverse loads and temperatures.

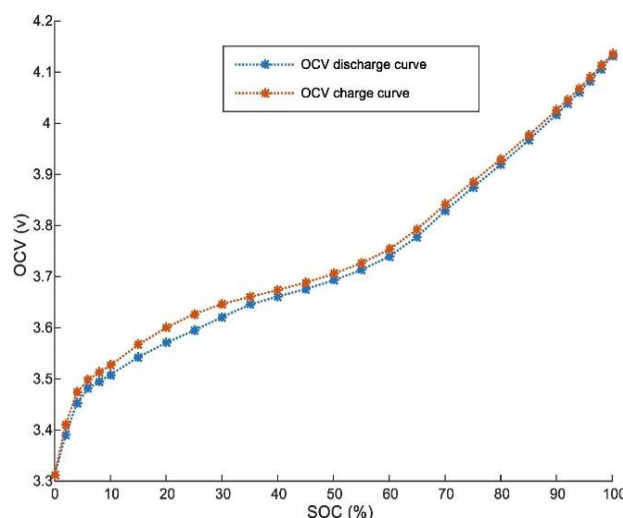


Figure 2. Experimental OCV-SOC curves at 25 °C

Figure 2 illustrates the experimental OCV discharge test [14]. The test involves initially fully charging the battery, followed by discharging current pulses equivalent to 5% of the SoC step. This is interspersed with a 30-minute rest time to ensure complete cell discharge and stabilize the OCV at a consistent value. Extracting OCV points at different SoC levels is essential to construct the analytical model representing the mapping between OCV and SoC

HPPC test involves several key steps. Firstly, it is employed to establish the (OCV-SoC) connection, and it also serves to identify parameter values from ECM derived through the offline parameter identification method [15]. The HPPC test commences by placing the battery cell in at 25 °C for four hours. Subsequently, constant current of 1C is applied to the cell until it reaches a voltage of 4.2 V, which is then maintained until the current decreases to $\leq 0.05C$. After 1 hour break, cell is discharged with a 1C current until it reaches a SoC of 90%. Following another 1-hour break, the cell is further discharged with a 3C current for 10 seconds, followed by a 30-second rest period. Lastly, the cell is loaded with a 2.25C current for 10 seconds. This sequence is repeated for various SoC values, ranging from 80% to 10%. Subsequently, a sextic polynomial (2) is employed to accurately fit the relationship where $k_0 \sim k_6$ are the constants.

$$V_{ocv} = k_0 + k_1 SoC + k_2 SoC^2 + k_3 SoC^3 + k_4 SoC^4 + k_5 SoC^5 + k_6 SoC^6 \quad (2)$$

By utilizing the HPPC test in conjunction with advanced fitting algorithms, the battery's parameters can be accurately determined in real-time, providing valuable insights for battery management and performance optimization in practical applications.

2.1.3. FFRLS algorithm

In addition to the careful selection of an appropriate battery model, ensuring compatible parameters is of equal importance. To assess the impact of different OCV-SoC curves on SoC estimation individually, it is logical to mitigate the influence of pulse input method (PIM) outcomes related to Ohmic resistance and the RC network on SoC estimation. Consequently, this study utilizes the widely accepted fast Fourier recursive least squares (FFRLS) method for the identification of key parameters [16], [17], specifically R_0 , R_p , and C_p . The derivation processes are outlined as follows. Applying the Laplace transformation to (3) [18], [19], the frequency-domain function of the Thevenin model can be expressed as in (3):

$$U_t(s) - U_{oc}(s) = I_t(s) \left(R_0 + \frac{R_p}{1 + R_p C_p s} \right) \quad (3)$$

where s denotes the frequency operator. By introducing $E_t(s) = U_t(s) - U_{oc}(s)$ transfer function can be represented as in (4):

$$G(s) = \frac{U(s) - U_{oc}(s)}{I(s)} = \left(R_0 + \frac{R_p}{1 + R_p C_p s} \right) \quad (4)$$

to convert the transfer function into a discrete form, this paper employs the commonly used bilinear transformation, with the formulation provided in (5).

$$s = \frac{2}{T_s} \frac{1 - z^{-1}}{1 + z^{-1}} \quad (1)$$

Where z is the discretization operator and T_s is set to 1 in this paper. Moreover, the discrete form of equation (G(s)) can be expressed as in (6).

$$G(z^{-1}) = \frac{a_2 - a_3 z^{-1}}{1 + a_1 z^{-1}} \quad (6)$$

these coefficients a_1 , a_2 , and a_3 are formulated as in (7).

$$\begin{cases} a_1 = \frac{2R_p C_p - 1}{2R_p C_p + 1} \\ a_2 = \frac{R_0 + R_p + 2R_0 R_p}{2R_p C_p + 1} \\ a_3 = \frac{R_0 \Delta t + R_p \Delta t - 2R_0 R_p \Delta t}{2R_p C_p + 1} \end{cases} \quad (7)$$

The model parameters can be expressed as in (8).

$$\begin{cases} R_0 = \frac{a_2 - a_3}{1 - a_1} \\ R_p = \frac{2(a_1 a_2 + a_3)}{1 + a_1^2} - \frac{a_2 - a_3}{1 - a_1} \\ C_p = \frac{(1 + a_1)^2}{4(a_1 a_2 + a_3)} \end{cases} \quad (8)$$

2.2. Energy modeling of drones

Drone operation is affected by a multitude of factors, encompassing the drone type, battery capacity, and weather conditions. Several factors can impact the battery life of a drone, such as payload weight, wind speed, temperature, and flight altitude. Ensuring that the drone's battery has sufficient power for the round trip, accounting for payload and unpredictable weather conditions, is crucial. Careful planning of the flight path is necessary to avoid obstacles like buildings, power lines, and trees, as well as densely populated areas and sensitive sites like airports. Additionally, climate conditions, such as velocity, temperature, and precipitation, can significantly affect drone performance and stability. Checking the weather forecast before each flight and avoiding adverse conditions is essential. Anderea [3] conducted valuable research on the techno-economic analysis of drone operations with such specifications. The study focused on understanding key factors impacting the cost and profitability of drone operations in this context, including drone cost, battery life, payload weight, and operating environment. Furthermore, the research explored the potential applications of drones with these specifications. The power consumption in kW can be approximated by the research findings.

$$P_{\text{Cons}} = \frac{(m_p + m_v)v}{370\eta r} + P_{\text{elec}} \quad (9)$$

The power consumption in kW can be calculated using the following approximation, as shown in (9). Furthermore, a study by Anderea provides parameter values, where the cruising velocity has a direct impact on the power consumption of the drones (see Table. 1). Figure 3 illustrates the power consumption (P_{Cons}) for various combinations of payload mass and cruising velocity using the given input parameters. The 3D bar plot visually represents power consumption trends across different payload masses and cruising velocities. The overview of the data indicates the size of the matrix and a minimum, maximum, mean, and standard deviation of power consumption. The optimal operating point is identified as the payload mass and cruising velocity combination with the lowest power consumption, while the worst operating point is the combination with the highest power consumption. The 3D bar plot helps visualize how power consumption changes with varying payload masses and cruising velocities, providing valuable insights into power consumption behavior.

Table 1. Input parameter

Parameter	Description	Value
P_{Cons}	Power consumption in kW	
P_{elec}	Power consumption of electronics in kW	0.1 kW
m_p	m_p represents the payload mass in kg	2 kg
m_v	Vehicle mass in kg	4 kg
v	Cruising velocity in km/h	from 0 to 45 km/h
r	Represents the lift-to-drag ratio	3
η	Power transfer efficiency	0.5

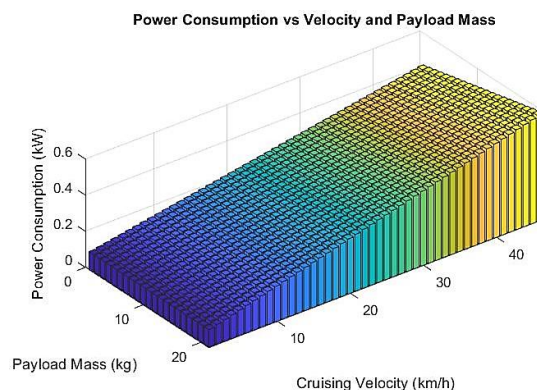


Figure 3. Power consumption of a drone as a function of velocity and payload mass

To derive an estimation of the worst-case energy requirement in kilowatt-hours (kWh), a practical approach can be utilized. By employing precise calculations and thoughtful considerations, it becomes feasible to approximate the system's highest energy demand it might encounter. This estimation holds significant importance in determining the suitable capacity and sizing of energy storage systems, ensuring optimal performance and dependable operation in (10).

$$P_{\text{Cons}}(\text{worst}) = \frac{d}{1-\text{HWF}} \left(\frac{(m_p+m_v)}{370\eta r} + \frac{P_{\text{elec}}}{v} \right) \quad (10)$$

The maximum range, represented by "d" and measured in kilometers, is influenced by the head wind factor (HWF), which signifies the ratio of headwind to airspeed. To illustrate with numerical examples: Let's assume a maximum range varying from 2 to 25 km, an airspeed range from 0 to 45 km/h, and a headwind of 30 km/h. The graph in Figure 4 illustrates multiple lines representing the worst-case power consumption for an aerial vehicle system, considering different combinations of cruising velocity and maximum range. The results demonstrate that power consumption increases with higher cruising velocities and maximum ranges, attributed to the heightened energy requirements for propulsion and electronics. For example, at a cruising velocity of 30 km/h and a maximum range of 10 km, the worst-case power consumption is approximately 8.5 kW. As the cruising velocity increases to 45 km/h and the maximum range extends to 15 km, the power consumption peaks at around 12.3 kW. This analysis emphasizes the significance of optimizing flight parameters to minimize power demands and progress efficiency and endurance of the aerial vehicle system. Additionally, the power consumption trend reveals that higher cruising velocities generally lead to increased power consumption due to greater air resistance. The sensitivity to the head wind factor (HWF), which is assumed as 2/3 of the headwind-to-airspeed ratio, is not explicitly depicted in the graph; however, it is considered a constant factor in the power consumption equation. Next, let's consider the economic aspect: Energy cost per kilometer compared to cruising velocity.

$$E_{\text{Cost}}(\text{km}) = \frac{C_{\text{elec}}}{\text{Char}_{\text{eff}}} \left(\frac{(m_p+m_v)}{370\eta r} + \frac{P_{\text{elec}}}{v} \right) \quad (11)$$

An estimation of the average energy cost per kilometer can be represented as C_{elec} is the cost of electricity à 0.12 \$/kW h and Char_{eff} is charging efficiency (about 0.8).

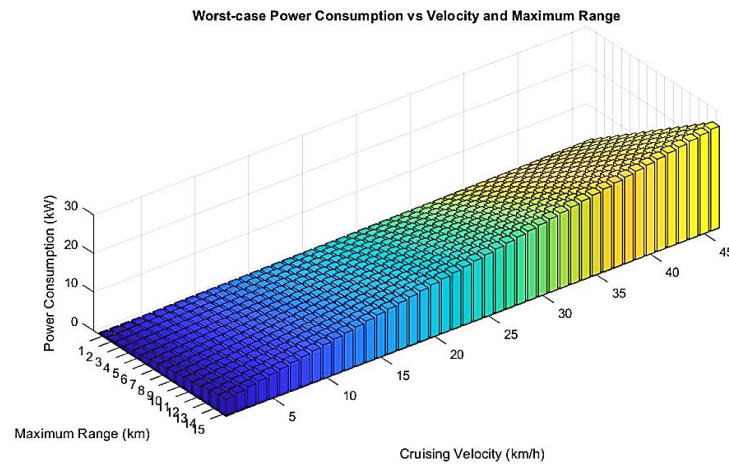


Figure 4. Worst-case power consumption vs. velocity and maximum range

Figure 5 illustrates the energy cost per kilometer (E_{Cost}) for an aerial vehicle system, considering various cruising velocities within the range of 0 to 45 km/h. The results show that as the cruising velocity increases, the energy cost per kilometer generally decreases. For instance, at a low cruising velocity of 5 km/h, the energy cost is approximately \$0.022 per kilometer. However, as the cruising velocity rises to 30 km/h, the energy cost reduces to around \$0.008 per kilometer. This inverse relationship is due to higher cruising velocities resulting in better energy efficiency and lower energy consumption per kilometer. The analysis emphasizes the economic benefits of optimizing cruising velocities for cost-effective operations, wherein higher speeds can lead to significant savings in energy expenses per kilometer traveled [8], [20].

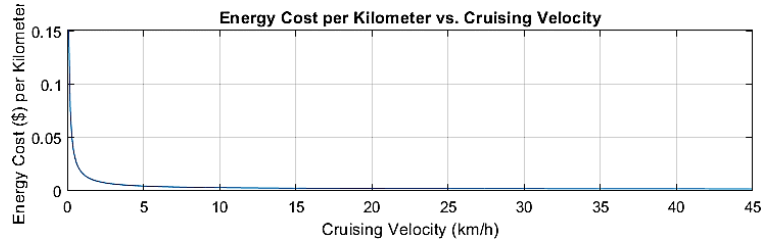


Figure 5. Energy cost per kilometer vs. cruising velocity

2.3. Nonlinear filter: Extended Kalman filter (EKF)

Estimating SoC is decisive for enhancing the performance and reliability of drones. However, SoC estimation is heavily influenced by complex issues such as self-discharge, discharge current, and battery aging, which can lead to imprecise results. To tackle this challenge, several SoC estimation methods have been developed. One commonly used approach is the ampere-hour (AH) method, chosen for its simplicity. Yet, in practical applications, this method is susceptible to errors arising from factors like noise and random interference, which accumulate over time. To address these random errors, various model-based algorithms have been proposed [21].

Model-based methods, such as the equivalent circuit model, are commonly employed for SoC estimation. The Kalman filter is a widely utilized model, but its applicability is limited to linear systems. To address the nonlinearity in battery systems, researchers have developed extensions like the extended Kalman filter (EKF) [22], [16], [23]. While the EKF reduces convergence time and accurately estimates system states under various operating conditions, it comes at the cost of augmented computational load on LiB management system. EKF achieves accurate SoC estimation through first-order polynomial accuracy, achieved by discarding higher-order terms. However, for complex system monitoring, especially in Li-ion battery packs, further improvements are necessary. To estimate SoC using the EKF, a linearized state-space model must be utilized near the latest estimate. This model is then combined with linear Kalman filter (LKF) equations, with the charge/discharge current serving as input and the battery voltage as output. This comprehensive approach is essential for achieving precise and reliable SoC estimation in complex battery systems [24], [25].

When dealing with a nonlinear system, the formulation of the discrete state-space model equation becomes more intricate, as it must account for the dynamic behavior of LiB. Discrete state-space model considers relationships between the system's states, inputs, and outputs at discrete time intervals. Incorporating the system dynamics into this equation is essential to accurately capture the nonlinearities and complexities inherent in the system's behavior. By accounting for the dynamics, the discrete state-space model provides a more comprehensive representation, enabling precise modeling and estimation of the system's states and responses over time. This approach is particularly valuable when dealing with nonlinear systems, such as complex battery dynamics in real-world applications, where accurate modeling and estimation are critical for efficient and reliable operation.

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

The expression of discrete state-space model equation, which incorporates system's dynamics, takes the following form:

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

Incorporating the nonlinear state transition function $f(x_k, u_k)$ and measurement function $g(x_k, u_k)$, where x_k represents state variables and u_k denotes input variables, the state equation can be formulated. Additionally, considering measurement noises, we can further express in (14).

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

Upon considering the discussed linearization process, it becomes evident that EKF effectively overcomes limitations of linear Kalman filter (LKF) by integrating the nonlinear system model into both the state

prediction and correction steps. EKF effectively utilizes nonlinear LiB modeling to predict both the system state and output. At each time step k , the nonlinear LiB modelling is linearized based on the predicted state \hat{x}_k^- to derive the matrices \hat{A}_k , \hat{B}_k , and \hat{C}_k . These matrices are crucial in calculating and updating the covariance matrix of the state estimation errors, as well as in determining the Kalman gain.

In essence, the EKF overcomes the challenges of linearization encountered in LKF by skillfully incorporating the nonlinear battery model. By doing so, it ensures accurate state estimation and improved overall performance. This integration of nonlinear battery models in the EKF enables the filter to handle the complexities and variations present in real-world battery systems, providing reliable and precise state estimations even in dynamic and challenging conditions. Thus, the EKF stands as a powerful tool for state estimation in BMS, enhancing performance and reliability of LiBs applications [26], [27]. Even though EKF estimation is utilized for SoC estimation, initial values of Kalman parameters are strongminded in following manner:

$$P_0 = \begin{bmatrix} 1e^{-1} & 0 \\ 0 & 1e^{-1} \end{bmatrix}, Q = \begin{bmatrix} 2e^{-8} & 0 \\ 0 & 5e^{-3} \end{bmatrix} \text{ and } R = 2e^{-1} \quad (15)$$

3. RESULTS AND DISCUSSION

For this study, we leveraged the outcomes derived from an experimental drone flight test conducted by the team of Chen *et al.* [28], due to the nonlinear nature of batteries, accurately estimating real flight time can be challenging, as many battery models do not account for all non-ideal characteristics. In their research, they present a battery-aware model designed to provide a precise analysis of drone energy consumption. Our primary objective was to accurately capture the power profile associated with the load and utilize it as an input profile in our simulation study. This allowed us to gain insights into the battery's performance and its energy consumption in real-world flight scenarios by ensuring precise SoC estimation. We conducted an in-depth analysis of energy consumption during an experimental drone test, as depicted in Figures 6 and 7. Our focus centered on scrutinizing the current load profile and Ampere-hours of SoC for the drones under investigation. Initially, as shown in Figure 6, the drones operated with fully charged batteries. However, as flight conditions evolved, including variations in drone velocity and external factors like wind speed, the energy load profile was directly affected, leading to alterations in input current. To estimate SoC, we applied an empirical method detailed in the preceding section, and the results of SoC estimation are presented alongside the current load analysis.

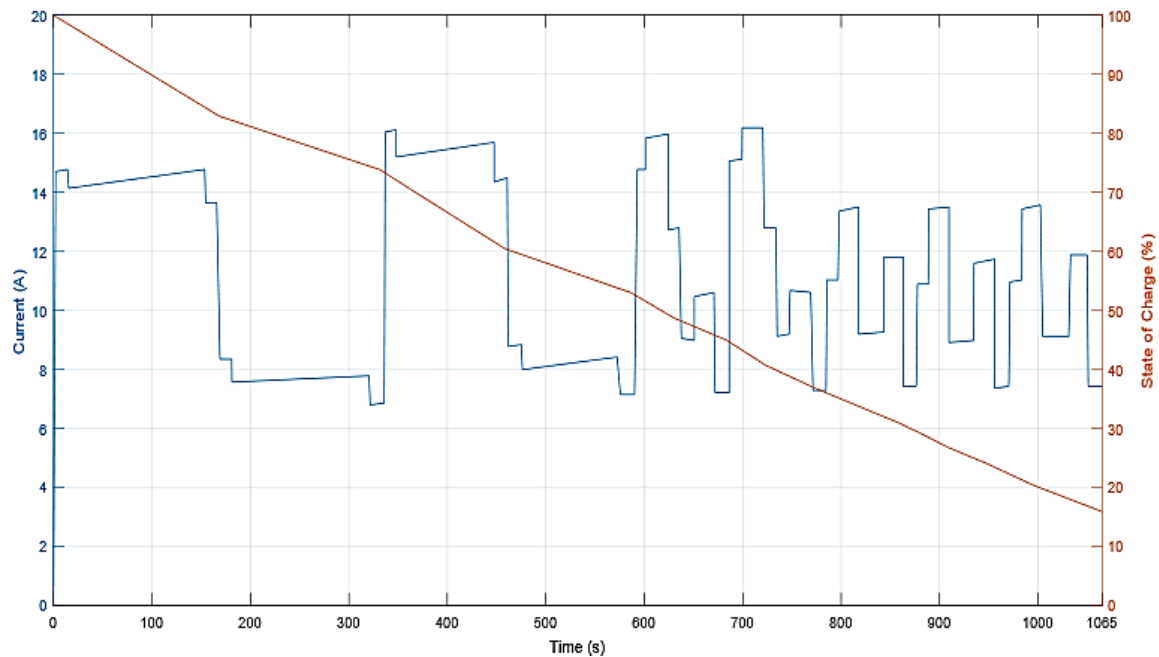


Figure 6. Evaluation of present load profile and Ampere-hours SoC for examined drones [28]

The proposed SoC estimation model comprises three essential components, each component is necessary for estimation process. First part is data input step, where the input data is initialized. To achieve this, the model utilizes the FFRLS algorithm and conducts the HPPC test. Through this process, the initial values of system variables $k_0 \sim k_6$ and parameters (R_0, R_p, C_p) are carefully determined. These values form the fundamental basis for predicting the load state, thereby ensuring accurate and reliable SoC estimation. Next, the HPPC algorithm is employed to establish the correlation between OCV and SoC of LiBs. The HPPC test involves subjecting the battery to a series of hybrid pulse power profiles, which generates valuable data about the battery's behavior. This resulting data is then fitted using a polynomial function of order 6. By fitting the data with a polynomial equation, the model accurately models the rapport between LiBs OCV and its SoC. This information is crucial to predict battery's behavior and facilitates the prediction of its performance under different load conditions. The coefficients $k_0 \sim k_6$, as shown in Table 2, are derived from this fitting process [29].

The system parameter identification is used to obtain model parameter according to the OCV-SoC curve. The result of parameters based on the FFRLS algorithm is given in Table 3. The graph labeled as Figure 7 illustrates three distinct curves portraying the SoC of the studied system. The first curve represents the observed SoC, showcasing actual measured SoC values and serving as the reference for comparison. The second curve, labeled as SoC extended Kalman filter (SoC_EKF), closely follows the observed SoC curve, indicating a highly accurate SoC approximation. SoC_EKF employs advanced estimation techniques to improve the precision. On the other hand, the third curve represents the SoC Amper hours (SoC_AH). While the SoC_AH curve provides an acceptable estimation of the SoC, it falls slightly short of achieving the same level of accuracy as the SoC_EKF. The SoC_AH relies on Amper hours techniques to estimate the SoC, which may introduce some degree of error during the estimation process.

As time progresses, it becomes apparent that the differences between the observed SoC and the estimated SoCs increase significantly. This trend indicates a deterioration in the accuracy of both the SoC_EKF and the SoC_AH over time. Several factors could contribute to these increasing errors, including battery aging, measurement uncertainties, and limitations in the estimation algorithms employed.

Table 2. OCV-SoC fitting results 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

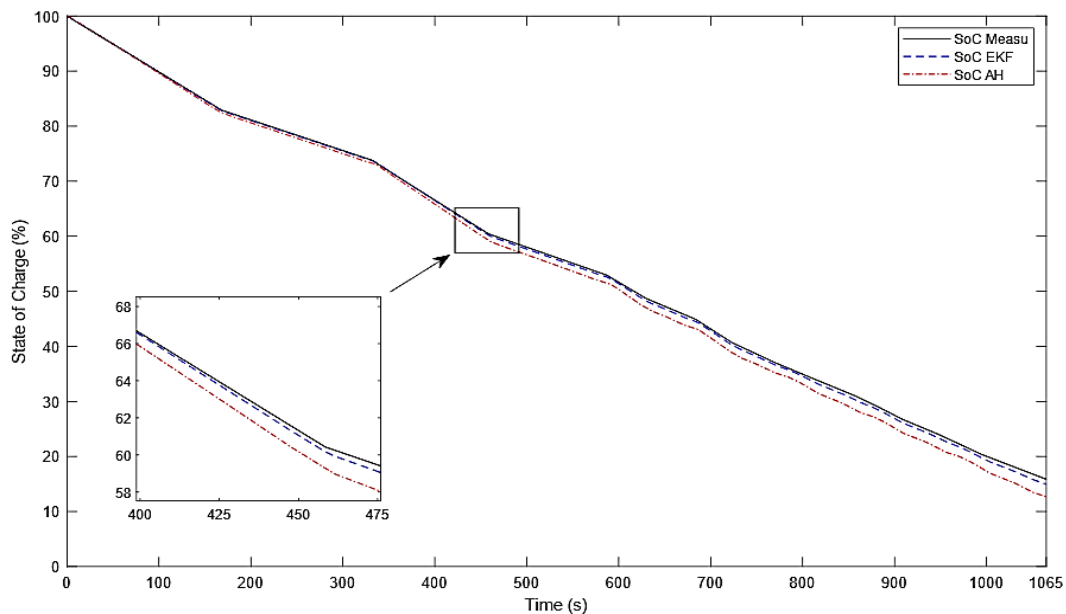


Figure 7. SoC_EKF estimation compared with SOC_Ah estimation

According to Figure 8, the EKF method provides an accurate estimation of the SoC, with a lower root mean squared error (RMSE) value 0.78% making it superior for precise drone battery SoC estimation. These findings contribute to enhanced drone performance, reliability, and overall safety. In conclusion, SoC_AH

offers an acceptable estimation of the SoC, but it is slightly less accurate compared to SoC_EKF. This is because SoC_AH utilizes ampere-hours techniques for estimation, which introduces some degree of error during the process. To measure the amount value of differences among the estimated SoC versus actual values, the RMSE is employed, resulting in an RMSE value ($0.78\text{e-}04$) for SoC_EKF. The overall results underscore a deal between accuracy and computational complexity in selecting an estimation technique for real-world applications. The SoC_EKF method offers highly accurate estimations but may require more computational resources, while the SoC_AH method provides a more practical and computationally efficient alternative with an acceptable level of accuracy.

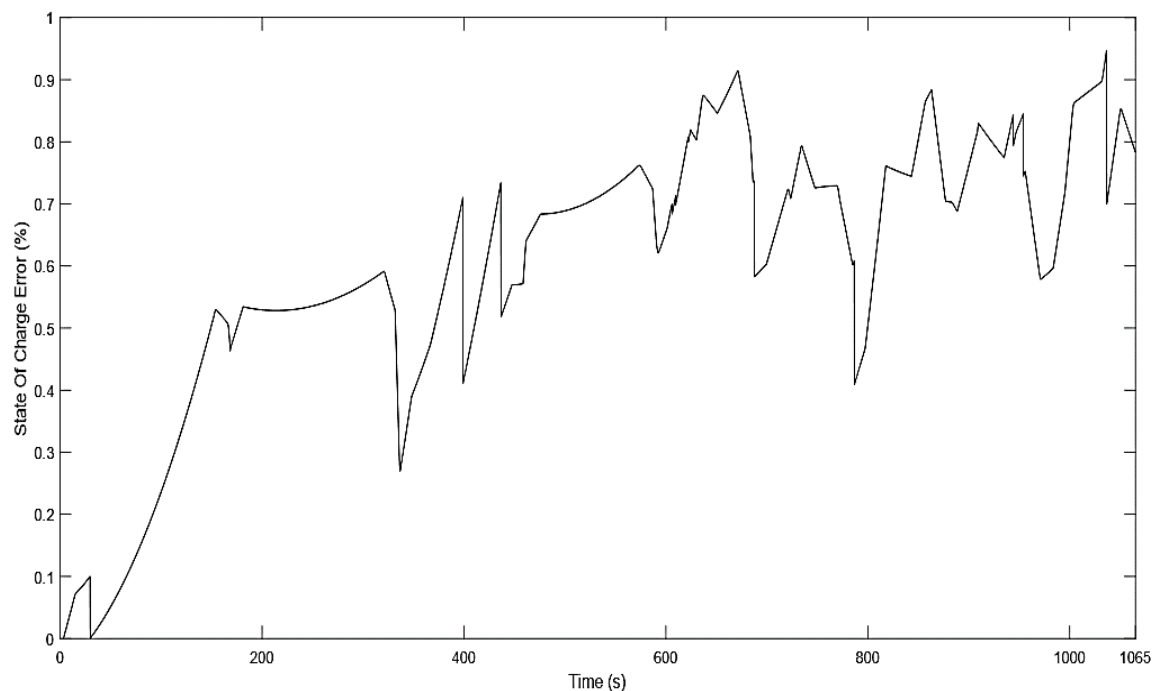


Figure 8. Errors between the observed SoC and the estimated SoCs

4. CONCLUSION

Addressing energy consumption in drone operations is paramount for maximizing range, reducing costs, and accurately estimating the SoC. Optimizing energy usage is crucial in determining drones' operational range and payload capacity, enabling them to cover greater distances and carry heavier loads. By integrating precise energy estimation algorithms into operational planning, drones can extend their range and facilitate rapid, eco-friendly missions. Recently, LIBs have gained significant attention due to their sustainable development. Nevertheless, accurately measuring SoC of LIBs remains a challenge for ensuring their safe operation.

In this paper, we delve into drones' energy consumption modeling and present a mathematical model for their energy consumption and battery behavior. We introduce the HPPC test and FFRLS for parameter identification. In the nonlinear filter section, we focus on implementing an accurate EKF for battery state estimation, surpassing the limitations of linear filters. The EKF algorithm provides precise SoC data, enhancing the BMS by enabling more accurate monitoring and optimization of battery performance. In our study, we present our findings, along with a comprehensive analysis and results interpretation. We investigate the accuracy of SoC estimation techniques: ampere-hours and extended Kalman filter. The study result demonstrates that while ampere-hours estimation provides an acceptable SoC estimation, it is slightly less accurate compared to extended Kalman filter estimation. The ampere-hours technique introduces some degree of error during the estimation process. Finally, we employed the RMSE, a amount magnitude of differences between estimated SoC values and actual values, resulting in an RMSE value of 0.78% for extended Kalman filter estimation. These results highlight the superiority of the SoC_EKF technique in providing more precise estimates of the SoC for drone batteries.

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BIOGRAPHIES OF AUTHORS






Dr. Kamal Anoune    is currently serving as an assistant professor in the Faculty of Sciences and Technics (FST-Settat) at Hassan First University in Settat, Morocco. Previously, he held the position of assistant professor at EMSI-Rabat, an integral part of the esteemed Honoris United Universities between 2020 and 2023. With a distinguished academic background and Ph.D. in optimization of PV-wind-battery-based micro-grid systems, Dr. Anoune stands as a leading expert in the field of sustainable energy. His contributions extend to cutting-edge areas, including smart-grid technology, energy auditing, green hydrogen research, energy storage systems, and battery management systems (BMS). Driven by an unwavering dedication to advancing these critical domains, he is committed to fostering a greener and more sustainable future. Dr. Anoune's influential impact is evident through his numerous patents, publications, and innovations, with a specific focus on energy storage technologies and BMS. He plays an active role in scientific committees and serves as a program committee (PC) session chair member for various international conferences, contributing significantly to the shaping of renewable energy solutions on a global scale. He can be contacted at email: kamal.anoune@gmail.com.



Anas El Maliki    received a B.S. degree in fundamental physics studies from Mohammed V University of Rabat, in 2014 and an M.S. degree in physics and new technology from Hassan II University of Casablanca, in 2017. Currently working toward a Ph.D. degree in energy storage and sustainable energy at Ibn Tofail University Kenitra. He can be contacted at email: anas.elmaliki@uit.ac.ma.



Dr. Merouan Belkasmî    is presently an assistant professor at the International University of Rabat, where he imparts his extensive knowledge in the fields of electronics, renewable energy, and energy conservation. He earned his Ph.D. from Mohamed V University in Rabat, solidifying his expertise in these domains. Dr. Belkasmî's research contributions have significantly advanced the understanding of electronic systems, with a particular emphasis on renewable energy technologies and energy storage solutions. His work stands as a testament to his dedication towards sustainable energy solutions. He can be contacted at email: belkasmimerouan@gmail.com.