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Review article

# A review and bibliometric analysis of intelligent techniques for advanced battery state estimation in aviation propulsion systems

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ABSTRACT

This review assesses advanced battery state estimation techniques for electric aviation, focusing on machine learning (ML), filtering methods, and fuzzy-based energy management strategies. Aviation batteries face unique challenges, including extreme fluctuations in power demand and significant variations in temperature and pressure across flight phases. These conditions disturb battery behavior and complicate state of charge (SOC), state of health (SOH), and remaining useful life (RUL) estimations. Filtering methods such as Kalman and particle filters demonstrate resistance to noise and dynamic loads. However, their application remains mostly limited to unmanned aerial vehicles (UAVs), with minimal studies addressing hybrid-electric aircraft (HEA) and none focused on electric vertical takeoff and landing (eVTOL) aircraft. ML techniques, including deep and hybrid models, offer adaptability under harsh conditions. Nevertheless, most studies rely on non-benchmarked or static-temperature datasets, limiting real-world relevance, especially in eVTOL aircraft applications. Transformer models outperform traditional deep learning approaches in low temperatures, showing promise for HEAs. Fuzzy-based techniques, while less suited for regression tasks, are widely adopted for energy management due to their ability to incorporate expert-defined logic via membership functions and rule-based control. However, most hybrid fuzzy systems lack interpretability evaluation, which poses a barrier to certification and deployment. This review highlights critical gaps, including the insufficient aviation-specific datasets, the underutilization of lithium polymer batteries in intelligent models, and the need for adaptive, context-aware estimation architectures tailored to dynamic aviation missions.

## 1. Introduction

The need for advanced batteries has grown exponentially in recent years, driven by the increasing integration of electric propulsion into emerging aviation technologies. These technologies include unmanned aerial vehicles (UAVs), electric vertical take-off and landing (eVTOL) aircraft, and hybrid-electric aircraft (HEA). UAVs have become essential across industries, from agricultural monitoring and package delivery to defense applications like surveillance and disaster response [1,2]. Their utility has driven rapid technological innovation, with electric propulsion at the forefront due to its low noise, operational flexibility, and reduced maintenance requirements [3]. Similarly, eVTOL aircraft are revolutionizing urban air mobility by enabling short-distance, on-demand transportation, aligning with global priorities for reducing urban congestion and emissions [4,5]. These aircraft promise quieter operations and greater efficiency than conventional transport methods, making them highly attractive for urban logistics and passenger mobility. HEA, designed primarily for regional and short-haul routes, aims to reduce emissions by blending traditional engines with electric propulsion. This combination improves fuel efficiency and reduces greenhouse gas emissions, making these aircraft pivotal in efforts to decarbonize aviation [6–8]. As the adoption of these aviation

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technologies grows, so does the demand for reliable, high-performing batteries that can meet operational challenges. This dependency underscores the critical role of batteries in enabling these transformative applications and their broader implications for the future of sustainable aviation [9,10].

Aviation applications such as UAVs, eVTOL aircraft, and HEA operate in dynamic and challenging environments, which place extraordinary demands on their propulsion systems and batteries. UAVs, often deployed at varying altitudes, experience temperature extremes and low-pressure conditions that degrade battery capacity by up to 30%, particularly in missions requiring prolonged endurance at high altitudes [11,12]. eVTOL aircraft are designed for repetitive high-power cycles during take-off and landing, creating significant thermal stress and accelerating degradation, which compromises both battery safety and performance if not managed effectively [13]. HEA faces even harsher challenges at cruising altitudes, where temperatures can fall below -40°C, impairing ion mobility and energy efficiency. Effective thermal management systems are critical to maintaining battery functionality under such extreme conditions [14–16]. Across all platforms, propulsion batteries must balance high energy density, power output, and operational longevity while withstanding these environmental stressors. Monitoring state of charge (SOC), state of power (SOP), state of health (SOH), and remaining useful life (RUL) under these conditions is vital to maintaining reliability and preventing performance degradation. Meeting these requirements demands advanced, real-time battery management systems (BMS) capable of handling the rigorous conditions faced in aviation applications.

Advanced state estimation techniques are crucial in addressing the operational challenges presented by aviation applications. SOC, SOP, and SOH are essential metrics for battery management. They provide insights into energy reserves, power delivery capacity, and long-term reliability. Accurate estimations of these metrics allow real-time energy management, preventing failures such as unexpected power depletion, thermal runaway (TR), or capacity fade [17]. Predictive state estimation models are particularly valuable, enabling optimization of battery usage across diverse flight phases, from high-power demands during ascent to energy conservation during cruising [18–20]. HEA benefits from integrated algorithms that coordinate power-sharing between batteries and auxiliary energy systems, improving overall efficiency [21]. In UAVs and eVTOL aircraft, state estimation facilitates adaptive energy allocation and thermal management, extending operational life while maintaining performance [22,23]. As aviation continues to adopt electric and hybrid-electric propulsion, advanced state estimation techniques are crucial in safety, performance optimization, and experimental deployment.

Filtering-based techniques, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), are foundational tools for battery state estimation in aviation applications. These techniques are particularly effective at modelling nonlinear battery dynamics and mitigating the impact of noisy sensor data, which are prevalent challenges in aerial systems [24–27]. EKF is widely used in UAVs for real-time SOC monitoring, providing accurate insights into battery performance and enabling efficient energy allocation throughout complex missions [28,29]. On the other hand, HEA benefits significantly from particle filters, which excel in integrating power systems involving multiple energy sources, such as batteries and fuel cells, while effectively managing non-Gaussian noise [30]. These filtering methods enable real-time corrections and adaptive performance management, ensuring that batteries maintain safety, reliability, and efficiency even under the most demanding operating conditions.

Machine Learning (ML) has emerged as a transformative tool in battery state estimation, offering innovative solutions for the complex demands of aviation. Unlike traditional methods, ML algorithms excel at capturing nonlinear battery dynamics and adapting to the rapidly changing operating conditions characteristic of aviation applications. Shallow, deep, and hybrid architectures are effective in predicting SOC, SOP, and SOH with high accuracy, even in challenging environments [31–35]. In UAVs, ML models dynamically optimize energy usage by predicting battery performance during extended missions, reducing energy waste, and improving operational endurance [36]. eVTOL aircraft leverage Reinforcement learning (RL) and shallow architectures to adapt to rapid power demands during take-off and hover, maintaining energy efficiency and reliability under high stress [37]. HEA benefits from predictive models that optimize power-sharing between batteries and auxiliary systems, minimizing energy losses and enhancing overall efficiency during long-haul flights [38]. ML algorithms are inherently adaptive, learning from operational data to refine their predictions. This adaptability makes them valuable for aviation systems, where variability in flight conditions and energy demands is the norm.

Fuzzy logic-based techniques offer a complementary solution to aviation energy management by addressing uncertainties and variability in dynamic aviation environments [39]. Unlike traditional deterministic models, fuzzy systems excel at interpreting noisy or incomplete data, making them particularly effective for applications such as UAVs and eVTOL aircraft [40–44]. UAVs, for example, experience abrupt transitions in power demand during rapid maneuvers or extended surveillance missions, where fuzzy logic can provide accurate and reliable power allocations based on SOC estimations [45,46]. By combining human-like reasoning with computational precision, fuzzy logic-based techniques enhance the robustness and flexibility of BMS, addressing the unique demands of aviation applications. Their integration into hybrid and ML-based frameworks further broadens their applicability, paving the way for more resilient and adaptive aviation energy systems.

### 1.1. Objective and research scope of the review

Battery failures in electric vehicles (EVs) have raised critical concerns regarding the necessity of accurate and robust BMS. These concerns become significantly more serious in the context of electric aviation. In such high-stakes applications, batteries are exposed to drastic environmental changes that can lead to UAV battery failures, and they must frequently endure extreme power demands that can trigger TR in eVTOL aircraft. For HEA and other passenger aircraft, the consequences of battery malfunctions are far more catastrophic than in ground-based applications. Despite the growing deployment of electrified propulsion in aviation, there is a clear lack of systematic reviews that organize and assess advanced battery state estimation techniques within this domain. Specifically, no comprehensive study critically analyzes the application of ML, fuzzy logic, and filtering-based techniques in electric aviation, with a focus on their technical implementation and the challenges posed by aviation-specific conditions. Therefore, this review emphasizes the critical role of fuzzy-based, ML-based, and filtering-based strategies in improving battery state estimation to address these challenges. The main contributions of this review include: (a) A focused discussion on how the requirements of electric aviation make battery state estimation uniquely challenging, and why solutions used in other domains cannot be directly applied without tailoring. (b) A detailed exploration of fuzzy-based, ML-based, and filtering-based techniques, their recent advancements, and their specific roles in aviation battery state estimation. (c) Identification of research gaps and directions for future work, offering a foundational reference for researchers aiming to innovate in this field.

The paper is organized into seven key sections, with the remaining as follows: Section 2 presents a bibliometric analysis to quantitatively highlight the primary current research focus, potential gaps, and future trends in the domain. Section 3 discusses the unique operational challenges, harsh environmental conditions, and battery requirements in electric aviation. Section 4 provides a review of filtering-based techniques in battery state estimation. Section 5 covers ML-based battery state estimation of aviation propulsion batteries, starting with shallow learning architectures and concluding with transformers. Section 6 covers the key applications and design requirements of fuzzy-based energy management techniques. Finally, Section 7 concludes with insights into future research opportunities and challenges. As shown in Fig. 1, the paper maintains a specific scope and structure throughout the entire analysis process. All the sections and topics center around utilizing ML, fuzzy techniques, and filtering techniques to assess UAVs, eVTOL aircraft, and HEA batteries. This ensures clarity and uniformity in the research objective and scope throughout the paper.

## 2. Bibliometric analysis of the domain

Bibliometric analysis is crucial in identifying research gaps and trends, providing invaluable insights and perspectives. It helps assess knowledge gaps in the domain, track knowledge evolution, and guide research directions. The several benefits of bibliometrics have made it a more popular tool for scholars to study their subjects. Highlighting the domain's key themes and trending keywords is imperative before diving into the systematic review of advanced battery state estimation. This refines and guides the search during database collection. Moreover, instead of relying entirely on traditional reviews, which can be subject to individual interpretation, we integrate bibliometric analysis to provide a quantitative and visual foundation that strengthens and complements the technical review.

### 2.1. Methods and types of reporting

Fig. 2 illustrates the methodology used in conducting the bibliometric analysis of advanced battery state estimation in aviation. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique was utilized to collect organized and transparent data. Scopus, created by Elsevier in 2004, is a valuable database that includes publications dating back to the nineteenth century and extending to the present. Since it is mostly linked with engineering, Scopus was utilized to create bibliographic data in September 2024. To tailor the search query, the "advanced search" tool on Scopus was used. We conducted a topic search to identify papers that included relevant search terms in the title, abstract, or keywords, resulting in 180 documents. Following referencing, these studies undergo a series of identification, search restrictions, and screening to eliminate the ineligible documents and duplicates. This stage culminated in 171 eligible documents for the bibliometric analysis. The study provides the raw bibliometric data as supplementary material in Table S1. Finally, we conducted a bibliometric analysis using VOSviewer and R Bibliometrix.

### 2.2. Scientific output and document classification in the domain

The advanced battery state estimation field has expanded significantly in aviation and aerospace due to the growing demand for effective and convenient electrical systems for such prominent industries. Fig. 3 depicts the progression of scientific production in this subject, beginning with a consistent period from 2007 to 2018, during which research activity was insignificant, with fewer than 10 publications a year. 2019 marked a pivotal milestone, with a significant increase in research output, exhibiting a recognition of the necessity of BMS in aviation. Between 2020 and 2023, this growing pattern intensified tremendously, reaching a peak of nearly 40 publications in 2023. This spike is a result of the industrial developments in electric propulsion technologies and the regulatory concerns that accompany these developments. As demonstrated in Table 1, initial electric aircraft designs were introduced during this time, with the majority restricted to a maximum of two passengers. Following 2022, the area exhibited another breakthrough period, suggesting an extraordinary pace due to the impending commercialization of electric aircraft. Following this peak, a minor decline in the number of documents is observed after 2023, which could indicate a stabilization in research activity as fundamental concerns are investigated and basic knowledge is established. However, the field consistently produces high-quality scientific work, indicating continued attempts to enhance and optimize battery technologies essential for the future of aircraft energy management systems.

The significant industrial interest in electric aircraft, especially in modern cities seeking sustainability, accelerated the investigation of advanced battery state estimation techniques. The investigation began during the development phase and continued in the following phases due to regulatory concerns. The regulatory and safety standards for passenger airplanes are far stricter, which hinders the preliminary adoption of new technology [47–49]. Table 2 shows the contributions of several worldwide standards entities to electric aviation. It outlines the norms and laws regulating ML integration in aviation and the crucial areas that require further attention. The European Union Aviation Safety Agency (EASA) is developing several modules and guidelines to govern the use of ML in aviation applications. The standards address three

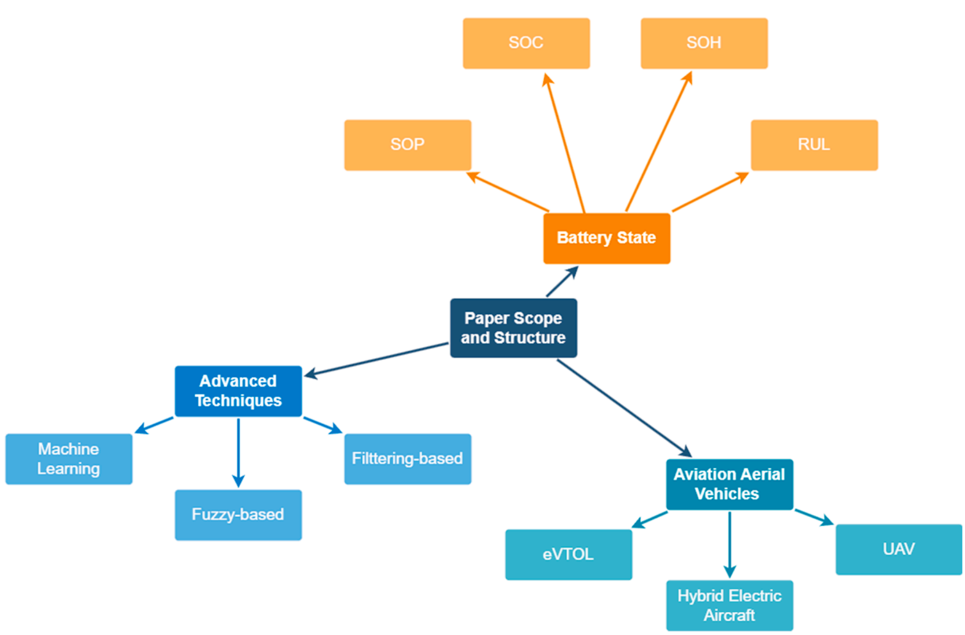



**Fig. 1.** The analysis scope and research objective map.

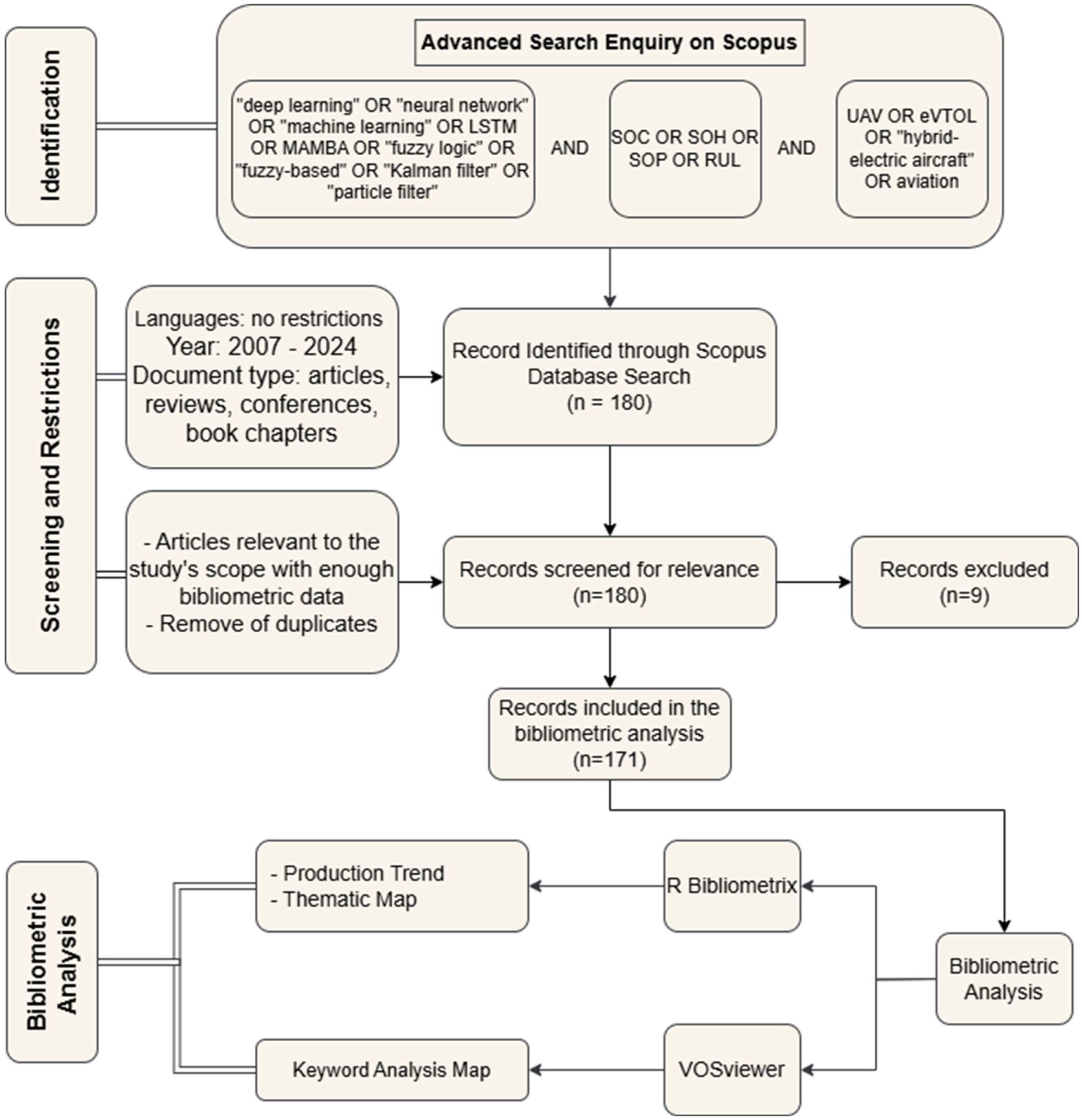



**Fig. 2.** The PRISMA methodology followed in the bibliometric analysis study.

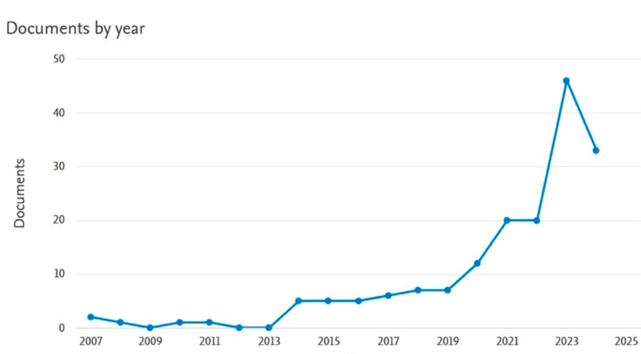



**Fig. 3.** The annual scientific production and production trend of the domain.

**Table 1**
Industrial progress in electric aviation.

| Project | Type | Pax | Year |
|---|---|---|---|
| NASA X-57 Maxwell | Electric | 2 | 2020-2021 |
| Zunum Aero ZA10 | Hybrid-electric | 12 | 2020 |
| Pipistrel Alpha Electro | Electric | 2 | 2018 |
| Kitty Hawk Cora | Electric | 2 | 2022 |
| Airbus Vahana | Electric | 1 | 2020 |
| Boeing Aurora | Electric | 2 | 2020 |
| Volocopter 2X | Electric | 2 | 2018 |
| Eviation Alice | Electric | 9 | 2021 |
| Siemens Extra 330LE | Electric | 2 | 2016 |
| Hamilton Aero | Electric | 1 | 2017 |

issues: lack of predictability, end-user trustworthiness, and model complexity. However, these restrictions do not include overridable, non-overridable decision-making and adaptive models in fully autonomous platforms, leaving a large gap between academic studies and industry implementations [47–51]. Consequently, the balance between model complexity and interpretability remains an important consideration. In aviation, where system failures can have disastrous implications, the necessity for accurate forecasts must be meticulously weighed against the demand for model interpretability. Understanding the logic behind decisions is crucial for trust, validation, and regulatory authorization. Thus, research efforts have amplified in recent years to build

**Table 2**
Standardization bodies in electric aviation and their corresponding ML-related regulations.

| Standardization Body | ML-related Regulations | Relevant Codes / Guidelines |
|---|---|---|
| Federal Aviation Administration (FAA) | • Addresses software and electronic hardware in electric aviation<br>• Lacks central Artificial Intelligence (AI)/ML standardizations and regulations | DO-178, DO-254 |
| Society of Automotive Engineers (SAE) | • Arranges standardization discussions aligned with NASA's framework<br>• Develops civil aircraft systems guidance | SAE ARP 4761, SAE APR 4754A |
| European Union Aviation Safety Agency (EASA) | • Regulates AI/ML use in Urban Air Mobility (UAM)<br>• Issues guidance for ML model training, testing, and deployment<br>• Notes the absence of oversight for unsupervised ML, adaptive models, and non-overridable decision-making | AI Roadmap 1.0, AI Roadmap 2.0 |

reliable systems with a clear framework for regulatory approvals and experimental deployments.

### 2.3. Keyword analysis and research direction

In the domain of advanced battery state estimation in aviation and aerospace applications, the visual representation of keyword networks, shown in Fig. 4, grants an extensive overview of the most important constructs and their interconnections. At the center of the network is the lithium-ion (Li-ion) battery, reflecting the significance of these batteries and their subtypes in electric aviation. Moreover, various linked nodes depict crucial techniques, including EKF and lithium compounds, which prominently connect SOC and SOC estimation approaches, especially to UAVs. Furthermore, ML, neural networks (NN), and SOH are linked, demonstrating their consistent affiliation with SOH estimation in aviation and aerospace applications. This signifies a solid focus on predictive techniques in appraising battery performance and endurance. Fig. 4 (b) demonstrates the UAV's subnetwork with key terms connected to it. UAVs exhibit connections with fuzzy logic, recurrent neural networks (RNNs), and, in other clusters, EKF. This signifies that these are the primary techniques in UAV battery state estimation. On the other hand, the eVTOL aircraft network exhibits close interconnections with random forest (RF), highlighting it as the main technique used in these aircraft, especially in recent years, as indicated by the yellow link.

The thematic map, shown in Fig. 5, categorizes research themes in battery state estimation for aviation and aerospace applications, dividing keywords into four separate quadrants. Basic themes (lower-right quadrant) are those that are extremely relevant to the field but have a lower development density, indicating that they are basic yet demand additional investigation. Battery management systems, UAVs, Li-ion batteries, and forecasts constitute the fundamental elements of this quadrant. These keywords highlight principal topics that are important to the study field but are undeveloped, offering opportunities for further exploration and innovation. Niche themes (upper-left quadrant) are well-developed yet specialized fields. These subjects have been well investigated and have established methodology; however, they may not be widely relevant to the area. To strategically elevate basic themes like BMS and UAVs into the motor quadrant, their research density must increase. This can be achieved by integrating them with established high-density areas such as "learning algorithms", "operational conditions" (aviation-specific), and "estimation techniques". Such combinations broaden their research context but also expose critical implementation gaps. These include the need for interpretable models suitable for regulatory approval, experimental validations in real-world deployments, and enhanced real-time accuracy through technologies like sensor fusion, digital twins, and edge computing. Addressing these layered challenges would solidify their methodological maturity and cross-domain impact, shifting them toward more central, dense themes in the research landscape.

## 3. Overview of battery requirements and environmental conditions of electric aviation

### 3.1. Battery demands in aviation propulsion

Aviation propulsion systems, such as UAVs, eVTOL aircraft, and HEA, have unique energy and power density needs that are determined by their operating objectives and design priorities. As shown in Table 3, UAVs prioritize a balance of energy and power density to facilitate agility and long-duration missions, which are frequently limited by weight sensitivity. eVTOL aircraft, on the other hand, require a high power density for quick energy bursts during take-off and landing, stressing mobility while balancing weight and power trade-offs. HEA, although demanding high power density, prioritizes high energy density to enable long-distance cruising with increased weight tolerance. Each system's endurance and performance requirements underscore the importance of customized battery solutions in fulfilling operational needs. This guarantees efficient, reliable, and safe propulsion across a wide range of aviation applications.

#### 3.1.1. High energy density demands in HEA

HEA requires batteries with a high energy density to fulfill propulsion requirements and attain resilient operational capabilities for regional flights. Their complex system, shown in Fig. 6, combines fuel combustion propulsion with low-density batteries [68]. Low energy density limits range and overall performance, especially in hybrid-electric systems aimed at reducing fuel reliance. Therefore, Finger et al [69] underline the need to strike a balance between battery mass and energy output. Likewise, Marciello et al [70] and Gimenez et al [71] state that sustainability goals, such as those of the Clean Sky 2 project, necessitate high-density batteries that do not significantly increase aircraft weight, which is critical for operating efficiency. Baerheim et al [72] and Figueroa et al [73] emphasize that existing energy density restrictions make both all-electric and hybrid systems only practicable for short-haul routes, implying that a density addition of roughly 500 Wh/kg is required for considerable range enhancements. Similarly, Palaia et al [74] emphasize that reaching such energy density requirements is critical for supporting power and endurance needs in hybrid-electric aviation.

To address these challenges, innovative approaches have been proposed to meet the demanding energy density requirements of hybrid-electric systems. Di Mauro et al [75] investigated structural batteries. These batteries fulfill this demand by integrating energy storage inside structural parts, increasing density without adding unnecessary weight. Batra et al [76] follow by investigating range equations, which show how energy density directly affects flight endurance, hence altering design requirements. Furthermore, Abu Salem et al [77] contend that choosing proper performance measures is critical for balanced hybrid aircraft design, influencing judgments on energy density criteria. These studies collectively reveal that high energy density is necessary for attaining efficient, low-emission hybrid-electric flying, emphasizing its importance in next-generation aviation [78]. These energy density requirements create a distinct challenge in battery state estimation. HEA demands precise, real-time control over energy reserves to manage varying power needs across flight phases. Accurate estimation must assess capacity under fluctuating high-load conditions, where transitions between discharge and recharge can alter the battery's effective energy density. Monitoring internal resistance and capacity fade becomes essential, as these directly impact the battery's ability to maintain

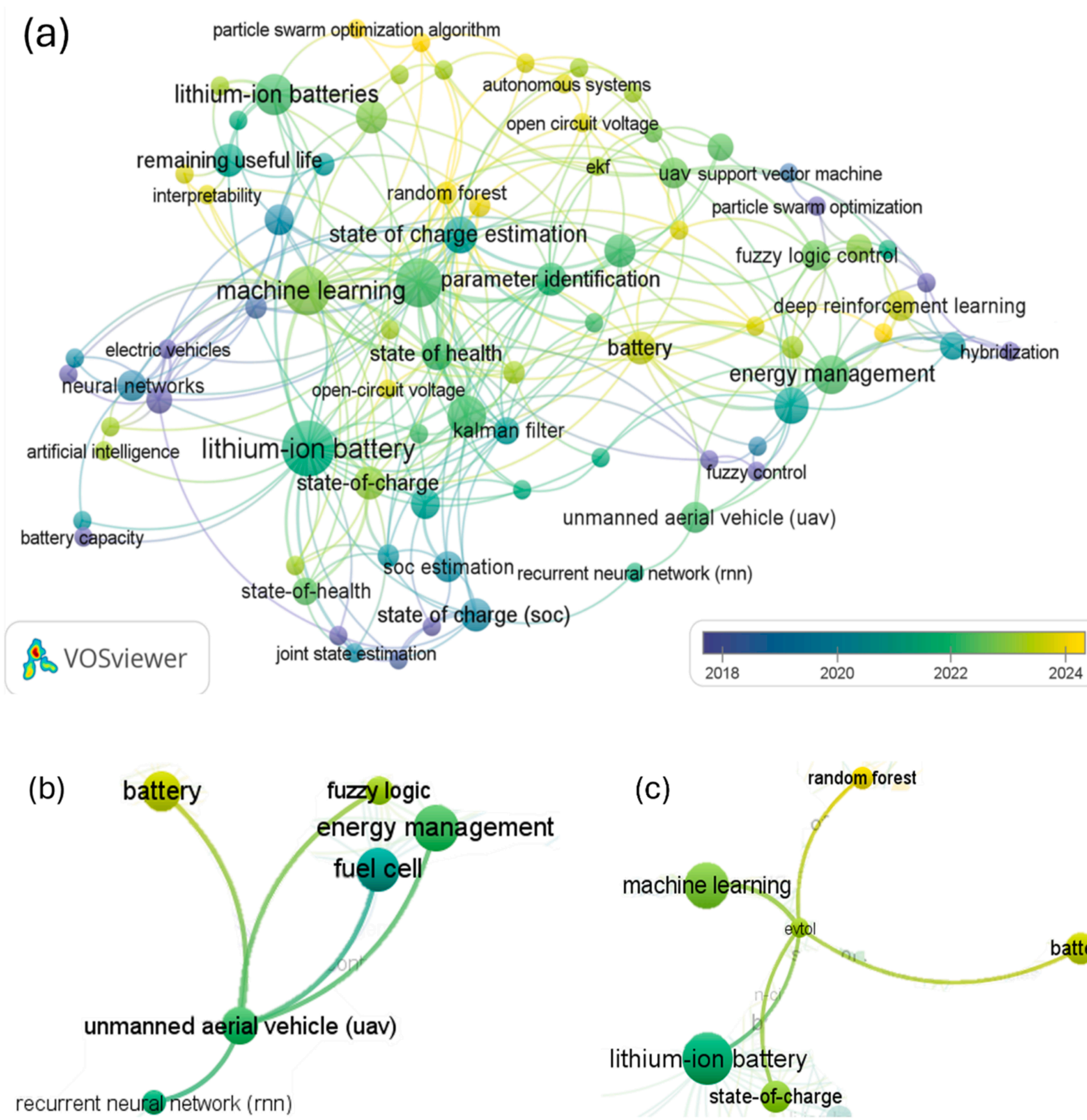



**Fig. 4.** Keyword co-occurrence networks with time overlay. (a) General network highlighting dominant themes across battery SOC/SOH estimation. (b) Focused subnetwork showing research trends related to UAV applications. (c) Focused subnetwork highlighting eVTOL-related research topics.

high energy density and meet sustained performance requirements across cycles.

### 3.1.2. High discharge rate and power demands in eVTOL aircraft

The power requirements for eVTOL aircraft applications are quite high, especially during phases such as take-off, hover, and landing, when quick energy discharge is crucial. As seen in Fig. 7, eVTOL aircraft require up to 900 W/kg during take-off and landing, which is significantly more than the 150-350 W/kg required during cruising. This fluctuation necessitates batteries capable of delivering powerful bursts of power during take-off and landing, followed by consistent energy production during steady cruising. Furthermore, the figure shows that the energy distribution for different flight phases must consider emergency reserves. A portion of battery capacity must be set aside for unexpected situations, such as hovering or redirection maneuvers, to maintain safety and operational reliability under all circumstances [54]. These high-power needs, particularly during vertical liftoff and descent, put a significant load on the battery system, demanding precision energy management to optimize discharge without sacrificing performance.

The variable demand profile depicted in the image emphasizes the need for batteries that can quickly transition between high-power and moderate-power states, which is a distinct requirement for eVTOL aircraft compared to conventional aircraft [79]. To satisfy these requirements, the battery must maintain a consistent voltage output throughout a wide C-rate range, typically peaking above 8C during strenuous stages such as takeoff. Furthermore, as demonstrated, batteries in eVTOL aircraft must be capable of draining considerable capacity in seconds, emphasizing the necessity for extremely high discharge rates and thermal management devices to handle peak loads without overheating [80]. Such high variability in power requirements underscores the need for precision in battery state estimation to predict performance and prevent failure under high-stress cycles accurately. Accurate estimation of parameters like internal resistance and degradation rates becomes critical, as these directly impact the battery’s ability to meet peak power requirements. Moreover, tracking SOC and SOH in real-time allows the system to adapt dynamically to fluctuations, preserving operational integrity and ensuring the system remains within safe discharge limits.

### 3.1.3. Energy density and power density demands in UAVs

Unlike eVTOL aircraft and HEA, UAVs impose a significant versatility in operating conditions and battery demands. UAVs are classified

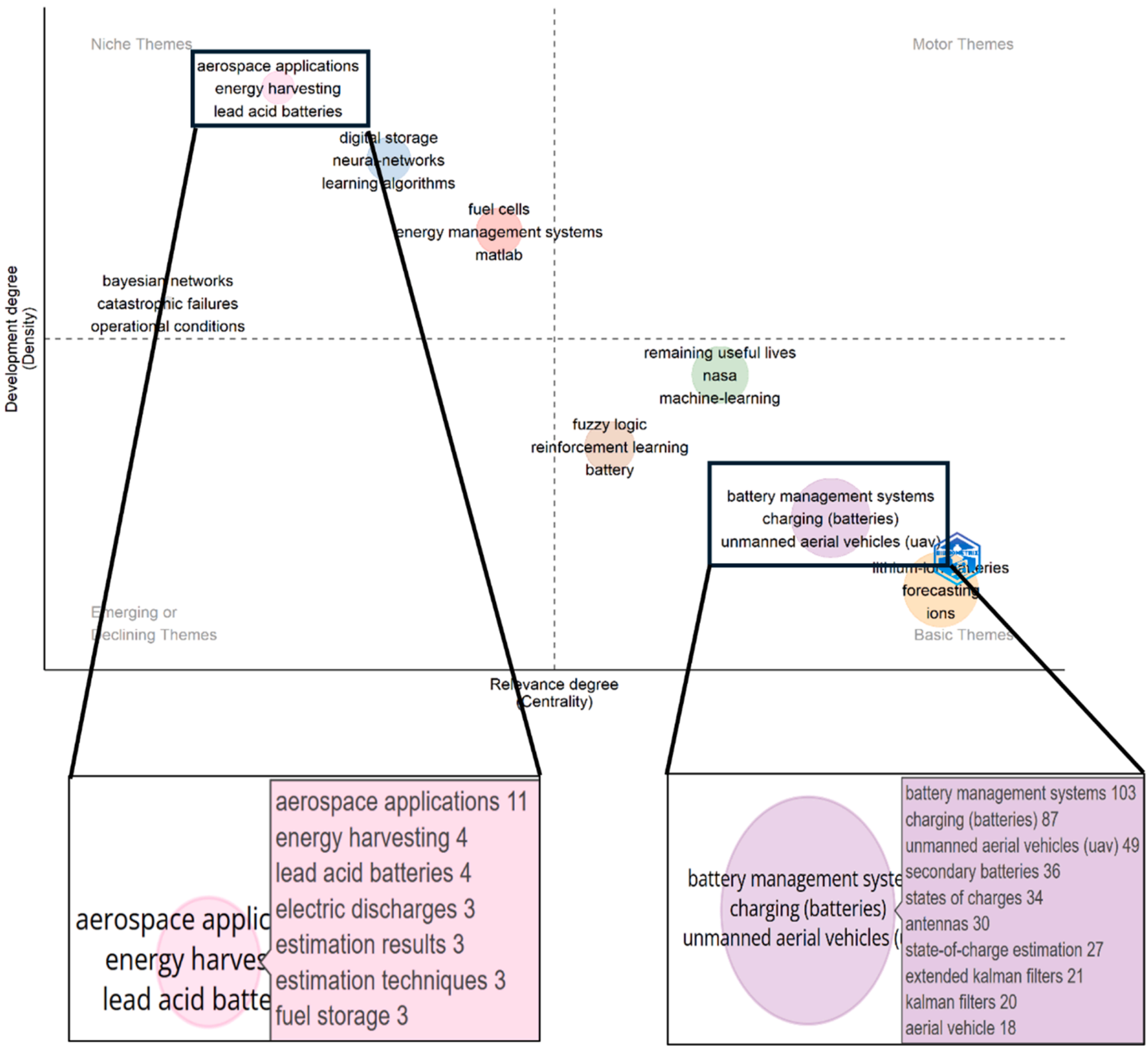



**Fig. 5.** Thematic map of the domain showing the niche, emerging, motor, and basic themes of the domain.

into various clusters based on their speed, operating conditions (temperature and pressure), altitude, etc. Since such technologies are utilized in critical domains such as military activities and surveillance, a single UAV is sometimes used to navigate and operate in dramatically changing conditions where temperature, pressure, and altitudes rapidly change during the flight [5,81]. Therefore, UAVs' batteries require special energy and power density capabilities to adapt to such challenging and fluctuating demands. UAV missions frequently include long flight periods, necessitating energy densities of ~250 Wh/kg to enable continuous power for intra-city short to medium-range distances [52,82].

This demand for endurance is consistent with the energy density-focused criteria common in HEA, which favour long-haul efficiency and cruising range. However, UAVs require a high-power density, typically 250-500 W/kg, to enable the fast bursts of energy required for quick manoeuvres, take-offs, and stability control, all of which are vital in dynamic and frequently unexpected airborne situations [52,83]. In contrast, eVTOL aircraft, which are primarily designed for urban transportation, place a greater emphasis on power density to handle fast, high-energy phases like as vertical take-off and landing, when instantaneous energy delivery is critical. Once airborne, eVTOLs switch to lower-power modes, lessening the focus on sustained energy density. HEA, on the other hand, prefer energy density above power density since their primary operating phases include sustained, effective cruising without demanding fast power changes [84]. UAVs, compared to eVTOL aircraft and HEA, require a balanced combination of power and energy densities to function flexibly across different flight characteristics, ranging from expanded cruising to rapid manoeuvres [85]. Therefore, the battery choice in such a critical and demanding application is significantly challenging. As shown in Table 4, most batteries either offer a high power density or a high energy density. Li-ion and lithium polymer (Li-Po) batteries are the only two practical batteries that possess both characteristics [86].

Li-Po batteries possess high power and energy densities, making them effective for the weight constraints of electric aviation applications, especially UAVs [87,88]. However, their low oxidative stability prevents them from extended operations. As the electrolyte's stability is low, it breaks down when exposed to high voltages or oxidizing

**Table 3**
Battery demands for UAVS, eVTOL aircraft, and HEA.

| Feature | UAVs | eVTOL aircraft | HEA | References |
|---|---|---|---|---|
| Energy Density | ~250 Wh/kg for 30 minutes at 1 kW discharge | ~250 Wh/kg for ~230 km range | (650–800 Wh/kg) for ~1100 miles | [52–56] |
| Power Density | ~500 to sustain lift and payload | 200–900 W/kg depending on flight stage (hover or cruise) | 400–1000 W/kg) depending on the hybridization level | [52,54,57,58] |
| Endurance Requirements | High (for extended missions up to 90+ mins) | Moderate (urban flights under 1 hour) | Very High (long-haul cruising) | [59–61] |
| Maneuverability Demands | High, requiring rapid power bursts for agility | High during take-off/landing, but reduced in cruise | Low to Moderate, stable cruise focus | [62–64] |
| Weight Sensitivity | High, as lighter batteries enhance flight duration | Moderate, balance of weight and power for VTOL | Moderate, as larger frames can support more weight | [65–67] |

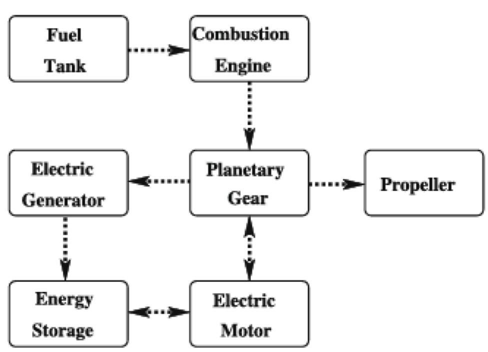



**Fig. 6.** The propulsion system of HEA [68].

conditions. Consequently, the battery will not be able to handle constant charge/ discharge cycling without major performance degradation. Post-mortem analysis of solid-state polymer electrolyte cells is hindered by the difficulty of recovering and separating electrode and electrolyte components, limiting comprehensive diagnostics of degradation [89]. Therefore, current research is highly oriented towards studying this behavior and designing material-based innovations to address these challenges [90–92]. Li-Po batteries' underexplored behavior and modeling in extreme and dynamic environments make it risky to run experiments in extreme conditions in electric aviation. Consequently, most current Li-Po datasets are EV-based, with limited discharge loads and environmental conditions [93,94]. ML and Kalman filters (KF) demand large, high-resolution datasets for training and testing. As research addresses the safety and degradation issue of Li-Po, researchers will start running experiments in these conditions and form datasets. These datasets will drive innovations in ML and KF-based BMS.

The current high costs of Li-Po and solid-state batteries is driven mainly by expensive materials, complex manufacturing processes, and limited production scale [95,96]. As the industrial demands increase, research and development will address challenges. These costs are projected to decline significantly over the next decade. Li-Po batteries will benefit from ongoing developments in electrolyte stabilization and more efficient production methods [97,98]. Advancements in material science, notably transitioning from scarce metals such as cobalt and nickel to abundant alternatives like iron-based cathodes (e.g., $FeCl_3$), can dramatically reduce cathode costs to as low as 1–2% of current benchmarks [99]. Costs might further decrease with the increasing adoption of UAVs and eVTOL aircraft, especially in surveillance and military [100,101]. These declining costs will enable broader integration into UAV and eVTOL systems, significantly shaping future battery technology choices in electric aviation by balancing performance, safety, and affordability.

With these battery technology breakthroughs aimed at supporting the high electrical demands of electric aviation, there is a growing need to revisit how SOC is estimated. These new or modified batteries often exhibit different electrochemical and thermal behavior compared to conventional cells, making traditional estimation methods less reliable. As battery architecture evolves to deliver higher performance, its internal dynamics become more complex and less predictable under varying operating conditions. This shift underscores the need to develop SOC estimation techniques that can accommodate the characteristics of these advanced batteries. Failing to do so risks compromising performance and safety, particularly in applications where precision is critical. Therefore, studying and designing new SOC estimation frameworks that align with the behavior of modern battery systems is essential. This ensures accurate monitoring and efficient energy management in next-generation electric aviation.

### 3.2. Thermal and pressure challenges of batteries in aviation

#### 3.2.1. Effects of temperature on propulsion batteries

UAVs, eVTOL aircraft, and HEA face significant performance challenges in low and fluctuating temperatures, especially at altitudes up to 3,000 meters, where temperatures can range from -10°C to -30°C. Under these conditions, Li-ion batteries, commonly used in these applications, experience increased internal resistance and reduced chemical reaction rate. At low temperatures, the chemical reaction rate at the electrode–electrolyte interface slows down significantly due to reduced charge transfer kinetics, leading to increased activation polarization. Low temperatures exacerbate capacity fade by amplifying the impact of high activation energies and mismatches between the anode and cathode. This effect is minimized when both electrodes have balanced activation energies [102]. Although activation and ohmic polarization increase in these conditions, anode concentration polarization is the main element limiting Li-ion battery performance at low ambient temperatures [103]. As shown in Fig. 8 (a), at extremely low temperatures (-15°C), like those encountered in electric aviation, the anode's solid-phase concentration polarization constitutes 65% of electrode polarization. This is due to an increased lithium-ion concentration gradient caused by slow ion diffusion in the active material [104]. Consequently, these batteries can experience a 20-30% drop in capacity, as presented in Fig. 8 (b). The figure demonstrates the discharge characteristics of a battery at 1 A at temperatures of -10°C, 10°C, and 25°C, demonstrating how temperature influences battery performance. At -10°C, the battery's terminal voltage drops the fastest, exhibiting a capacity loss and culminating in the shortest discharge period [105–107]. This capacity loss, also shown in part (c), leads to SOC overestimation by conventional physics-based techniques.

To mitigate the consequences of SOC overestimation, studies introduced model improvements to equivalent circuit modeling (ECM) and electrochemical modeling. Model improvements are temperature corrections that account for these temperature-related variations in battery internal resistance and chemical reaction rates. Firstly, ECM is commonly used to estimate SOC by representing battery behavior with electrical components, but its accuracy is affected by temperature. To address this, improved second-order RC models have been developed with temperature-corrected parameters (R0, R1, C1, C2), using

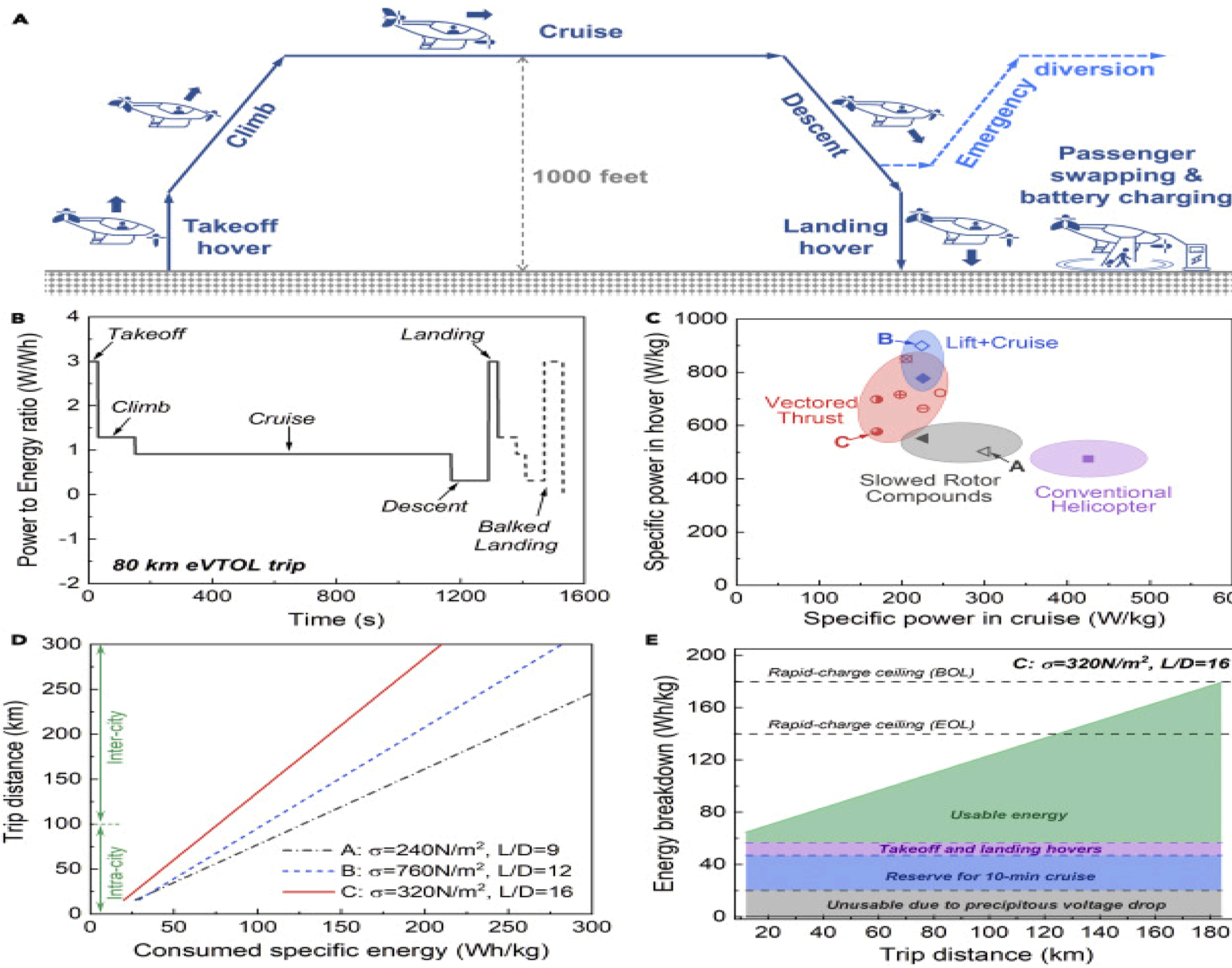



**Fig. 7.** Power demands phases in eVTOL aircraft with specific power requirements, energy consumption relative to distance, and energy breakdown [54].

**Table 4**
Electrical characteristics of different battery alternatives for UAVs [86].

| | Battery Type | | | | | |
|---|---|---|---|---|---|---|
| | Pb-acid | NiMH | Li-ion | NiCAD | Alkaline | Li-Po |
| Nominal cell voltage (V) | 2.1 | 1.2 | 3.6-3.85 | 1.2 | 1.3-1.5 | 2.7-3 |
| Specific Energy (Wh/kg) | 30-40 | 60-120 | 100-265 | 40-60 | 85-190 | 100-265 |
| Specific Power (W/kg) | 180 | 250-1000 | 250-340 | 150 | 50 | 245-430 |
| Cycle life | <350 | 180-2000 | 400-1200 | 2000 | Non-rechargeable | 500 |
| Cost ($/Wh) | 0.6975 | 0.8546 | 0.9361 | 2.6778 | 1.6727 | 2.3095 |

interpolation and polynomial fitting methods. The results indicate that these models achieve superior performance compared to conventional ECM [108]. Building on this, Xu et al [109] constructed a temperature-dependent second-order RC equivalent circuit model where each parameter (R0, R1, R2, C1, C2, and VOC) is expressed as a function of both SOC and ambient temperature. As shown in Fig. 9, internal resistance and capacitance surfaces were experimentally identified under varying temperatures using hybrid pulse power characterization (HPPC) tests and then interpolated to derive continuous temperature-corrected mappings, which are embedded into the model for dynamic correction. Nevertheless, this enhanced model demanded Kalman filtering to achieve the desired error margins of ±20 mV and SOC errors within ±0.4. Similarly, improvements in electrochemical modelling link thermal dynamics with electrochemical processes, including fluctuations in diffusion, charge transfer, and heat generation. Advanced models, such as electrochemical-thermal coupling and thermal-neural hybrids, improve accuracy during dynamic thermal situations by resolving nonlinear relationships between temperature and battery state variables [110–112].

Even with improved physics-based models, most studies integrated advanced battery state estimation techniques to achieve promising accuracies. Advanced battery state estimation techniques are crucial for handling the distinct and demanding operational conditions of UAVs, eVTOL aircraft, and HEAs. An accurate estimate of factors such as SOC, SOH, and SOP enables these aircraft to retain performance and safety despite temperature variations and significant power requirements. Low temperatures can lower capacity by up to 30% in UAVs, but accurate state estimation minimizes power loss mid-flight by offering real-time modifications [113]. Likewise, SOC and SOH estimates are utilized by eVTOL aircraft, which frequently experience high-discharge cycles in vertical takeoff and landing, to control battery thermal conditions and avoid overheating [114]. Advanced state estimation algorithms can

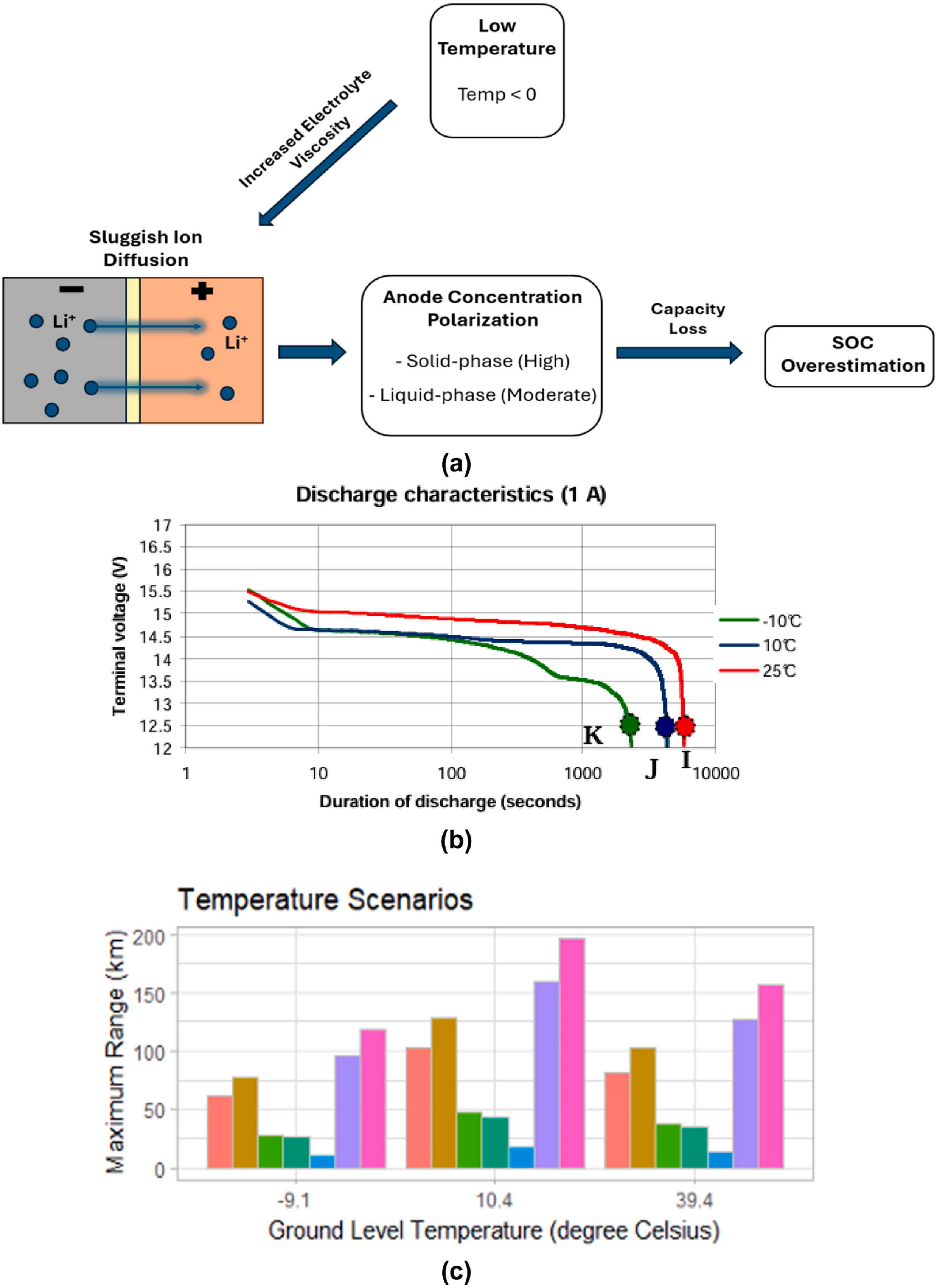



**Fig. 8.** Impact of low temperatures on Li-ion battery performance. (a) Shows how reduced ion diffusion increases anode polarization, causing capacity loss and SOC overestimation. (b) Displays discharge profiles at -10°C, 10°C, and 25°C, with colder conditions leading to faster voltage drop [106]. (c) Highlights reduced UAV/eVTOL range at lower ambient temperatures [107].

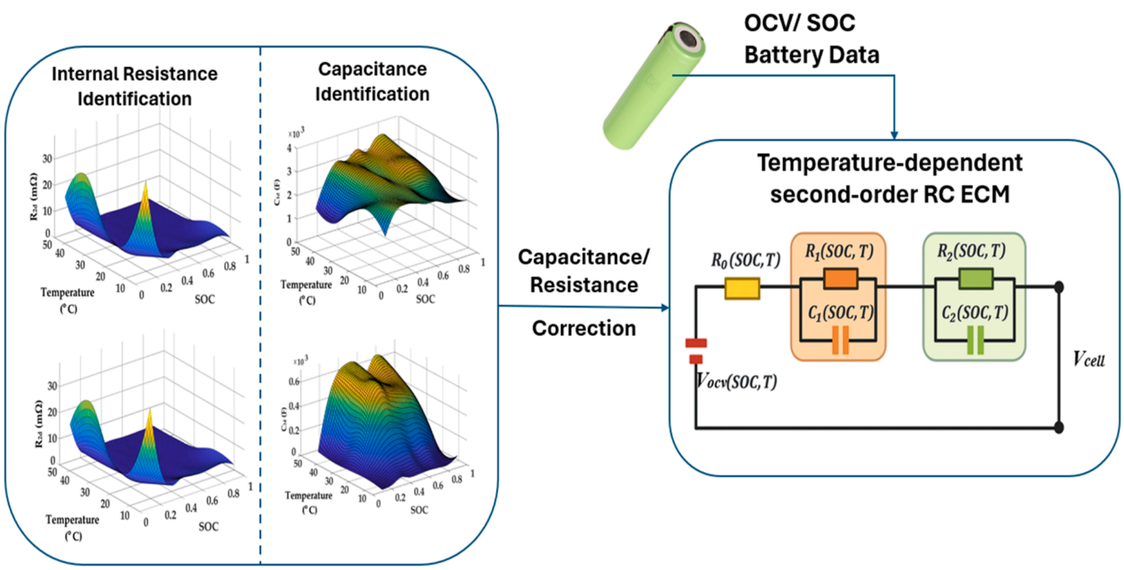



**Fig. 9.** Temperature-dependent second-order RC model with corrected resistance and capacitance parameters ($R_0$, $R_1$, $R_2$, $C_1$, $C_2$, VOC) identified across SOC and temperature to improve SOC estimation accuracy under varying thermal conditions.

balance power between batteries and fuel cells in HEA flying at high altitudes with ambient temperatures as low as -40°C, sustaining energy production under harsh conditions [68]. Thus, comprehensive battery state estimation directly contributes to the operating efficiency, safety, and lifetime of electric and hybrid aerial vehicles in challenging conditions.

### 3.2.2. Effects of low pressures on propulsion batteries

Most UAVs and eVTOL aircraft operate at altitudes where pressure effects are acceptable. On the other hand, HEA functions in tremendously higher altitudes, reaching up to 30,000 ft. Low-pressure conditions have a substantial influence on battery state and performance, particularly in applications such as high-altitude flight in HEA, where pressure can drop to 20-60 kPa. As shown in Fig. 10, reduced pressure affects battery state estimation in three different aspects. Firstly, it induces notable changes in battery capacity fading, causing implications in SOH and RUL estimation [115]. Moreover, it increases ohmic and reaction resistances, affecting SOC estimation [116]. Lastly, it accelerates TR initiation, significantly disrupting battery parameters and state estimation [117].

Low-pressure environments significantly affect the internal resistance and capacity fade dynamics of lithium-ion batteries, introducing serious challenges to accurate state estimation. These conditions increase both ohmic and charge-transfer resistances, as demonstrated in

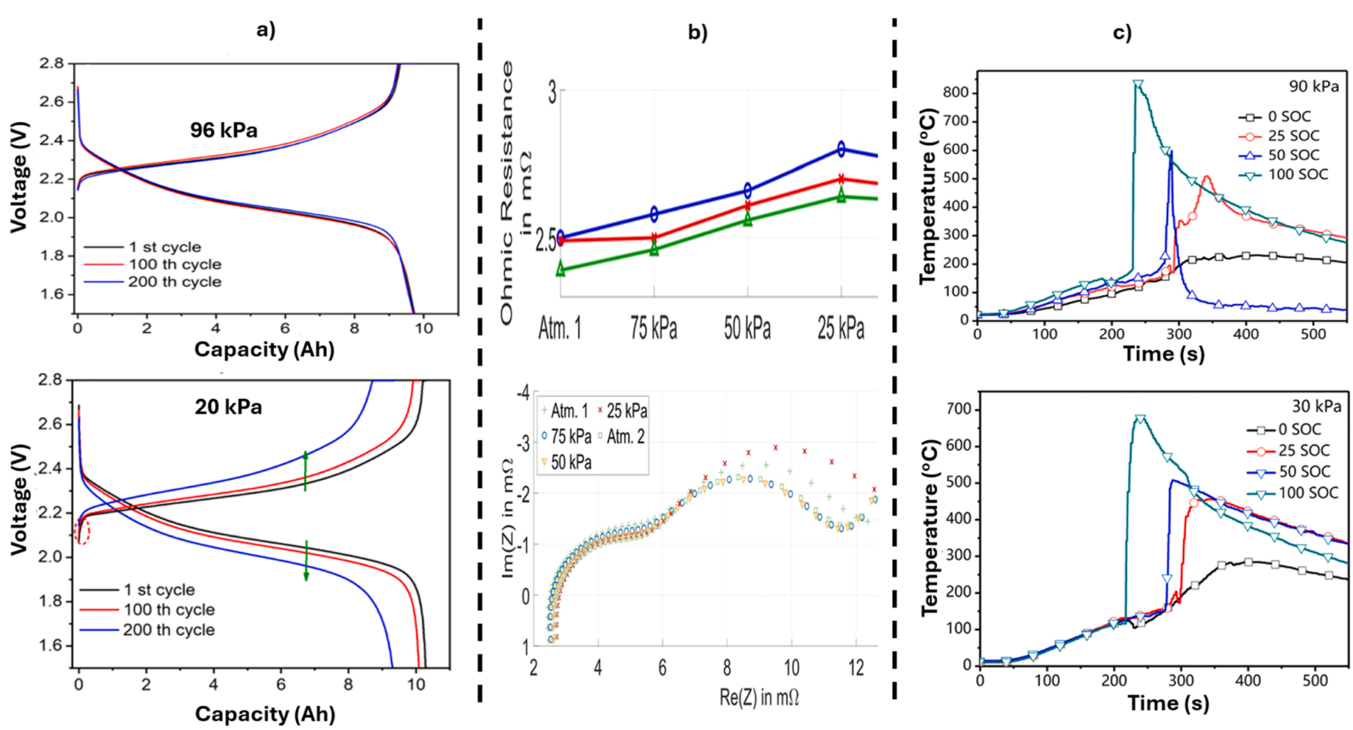



**Fig. 10.** Effect of low-pressure conditions on battery state estimation in three aspects: (a) Aging and capacity fade (SOH and RUL estimation) [115] (b) Ohmic and reaction resistances (SOC estimation) [116] (c) TR behavior in terms of ignition time and safety valve rupture (SOC, SOH, and TR relationship) [117].

Fig. 12a and Fig. 12 (b). Xie et al [118] reported a 6.2% and 46% rise in ohmic and charge-transfer resistances, respectively, when operating at 60 kPa compared to standard pressure. Such increases in internal resistance distort the voltage response during operation, which is a critical input for most SOC estimation algorithms. If these resistance variations are not dynamically compensated for, SOC estimations drift, particularly under load transitions and thermal gradients. Furthermore, pressure-induced thermal stress accelerates parasitic reactions and lithium plating, resulting in increased capacity fading. Hoenicke et al [116] noted that even at 25 kPa, resistance rise and cell deformation were evident in NMC pouch cells, directly correlating with energy loss. This degradation trajectory is not linear. Xie et al [119] observed that capacity fade rates increased from 0.5% to 17.4% as pressure drops from 96 kPa to 30 kPa. Such instability complicates SOH and RUL estimations, which depend on consistent degradation modeling. Tang et al [120] emphasized that these conditions shift the baseline of degradation prediction, making long-term forecasting unreliable without thermal-pressure coupling. These alterations in battery behavior highlight the vulnerability of conventional physics-based battery state estimation techniques in aviation applications.

Furthermore, low-pressure conditions influence battery thermal behaviour by lowering the convective heat dissipation coefficient, causing the internal temperature to rise more quickly [121]. In these conditions, batteries can attain TR states at lower ignition temperatures and in shorter timeframes than under normal pressure settings. Research indicates that pressures as low as 30 kPa hasten the beginning of TR, compromising thermal stability owing to faster rupturing of safety valves and early release of flammable gases [122]. SOC and SOH are inextricably connected to TR concerns, particularly in low-pressure settings. In an increased SOC level, the TR onset temperature drops, resulting in a shorter ignition time and higher peak temperatures under high SOC levels, as shown in Fig. 12(c). For example, experiments using NCM523/graphite batteries at SOC values of 30%, 50%, and 100% show that increased SOC speeds up TR, increases heat release rates, and intensifies flammable gas emissions. Higher SOC batteries are more vulnerable to TR at high-altitude or low-pressure environments, where less oxygen and heat dissipation might increase safety issues [117,122,123]. These extreme thermal conditions alter the voltage–SOC relationship, introduce rapid fluctuations in internal resistance, and accelerate electrochemical degradation, all of which disrupt standard SOC estimation algorithms. As a result, accurately estimating SOC under low-pressure, TR-prone environments becomes significantly more challenging, requiring advanced models that dynamically adapt to evolving thermal and electrochemical states.

## 4. Filtering-based approaches for aviation battery state estimation

As electric aviation evolved, the need for real-time, accurate battery state estimation became paramount. Traditional physics-based methods, while grounded in electrochemical theory, began to show limitations in these applications. Their inherent lag in dynamic response made them less suitable for aerial missions, where vehicles transition quickly between flight phases or maneuver. Although certain adaptations, including the Fast Open Circuit Voltage (Fast-OCV) technique, were proposed to accelerate estimation, these approaches remained highly sensitive to noise introduced by fluctuating loads, temperature shifts, and varying discharge rates. To overcome these drawbacks, filtering-based techniques began to emerge, most notably Kalman filtering. KF provided a powerful tool for integrating noisy real-time data with model predictions, allowing for continuous correction and adaptation during operation. Their ability to track hidden states with minimal delay and correct sensor noise and model uncertainty made them a natural evolution from traditional methods. This transition marked a critical advancement, where filtering techniques became foundational. Table 5 highlights the key Kalman filtering techniques used in battery state estimation in electric aviation. The Kalman filtering techniques used in battery state estimation in aviation can be grouped into four main techniques: EKF, UKF, double Kalman filters (DKF), and sigma-point Kalman filters (SPKF). Notably, most of these techniques are applied to UAVs, with a minor electric aircraft, and a complete absence of eVTOL aircraft.

**Table 5**
Summary of the main KF techniques with their applications and limitations.

| Main Kalman Filter Type | Variants/ Extensions | Application Focus | Limitations |
|---|---|---|---|
| EKF | • Adaptive extended Kalman filter (AEKF)<br>• EKF + recursive least squares (RLS) | SOC estimation in UAVs | Struggles with ambient pressure and temperature variations |
| UKF | • Adaptive unscented Kalman filter (AUKF)<br>• Square root unscented Kalman filter (SRUKF) | SOC estimation under varying loads and mission profiles | Struggles with ambient pressure and temperature variations |
| DKF | DKF + EFK | Accurate SOC near full discharge | Lacks performance tests in dynamic ambient conditions |
| SPKF | SPKF + ECM | Handles temperature and aging factors (potential use in HEA) | Lacks performance tests in low pressure conditions |

SOC estimation is a critical challenge in UAV applications, as previously discussed, and KF techniques have proven effective in addressing some of these challenges [124]. These filters offer robust estimation by handling minor system non-linearities, real-time dynamic load variations, and noise [125–128]. Among these techniques, the combination of EKF and DKF in the study by Chen et al [129] significantly enhances SOC accuracy, particularly during the critical last 20% of battery discharge. This dual-filter mechanism capitalizes on real-time parameter modifications and state monitoring, attaining accurate SOC estimations that are indispensable for optimizing UAV flight durations in constantly changing loads. Studies utilizing EKF for SOC prediction in UAVs exhibited remarkable accuracy in battery pack assessment. He et al [125] proposed a hybrid SOC estimation method for UAV battery systems, integrating a fast OCV-based Rint model with an AUKF to improve real-time estimation accuracy. The approach used least squares fitting for parameter identification and a batch-mode UKF for enhanced noise handling. The approach maintained SOC estimation errors below 3% in different mission profiles and varying current loads. For SOH estimation.

Traditional KF approaches, and some of their adaptive variants, neglect or struggle with temperature variations. Although they resist noise and adapt to electrical load dynamics, they fail to account for extreme ambient conditions. Temperature variation had a significant influence on the KF models, as shown in Fig. 11. At low temperatures, the batteries became considerably polarized, reducing the accuracy of the battery model. Consequently, the estimation accuracy for SOC reduced marginally, with a maximum error of around 2.8%. Moreover, the solution lacked online or real-time estate estimations, as the model was only tested in offline scenarios [130]. Uhm and Kim [131] proposed an Adaptive Robust Extended Kalman Filter (AREKF) for SOC estimation in small UAVs, integrating a modified Shepherd battery model. Their approach outperformed typical Adaptive AEKF under dynamic loads and non-Gaussian noise, achieving superior results with errors below 3%. The approach also greatly reduced fluctuations in remaining flying time (RFT) forecasts. However, the study neglects temperature variations and battery ageing, limiting its adaptability to electrical loading only. Therefore, due to these limitations and improper assumptions, studies

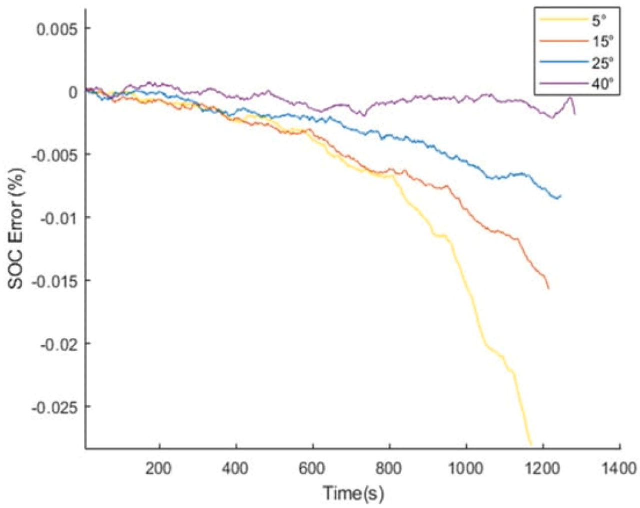



**Fig. 11.** SOC estimation error with respect to time and under different operation temperature [130].

introduced adaptive techniques and correction layers that account for these limitations.

KFs' adaptive variants are instrumental in managing battery performance under dynamic environmental conditions. This is achieved by incorporating a temperature correction layer to account for temperature-sensitive internal battery parameters. Fig. 12 categorizes recent methods used to enhance the temperature adaptability of KF-based SOC estimators. Semi-empirical models embed temperature effects into OCV behavior by empirically calibrating battery responses across multiple temperatures, facilitating interpolation instead of static maps [132,133]. ML-based correction layers, such as multilayer perceptrons (MLPs) and radial basis function neural network (RBFNN), fully substitute the ECM. These models are trained using voltage, current, and temperature inputs and are often optimized using noise-injected training to enhance robustness across thermal domains [134,135]. Another approach integrates an NN that estimates degradation-related factors, which are then injected into UKF to tune its estimation process [136]. Optimization-based techniques, such as particle swarm optimization (PSO), adapt internal parameters like resistance and capacity in real-time, especially in cold-start or low-pressure scenarios. PSO is used to minimize RMSE by tuning the model during significant thermal variations [137,138]. Finally, adaptive filtering structures, including adaptive particle filters (APF) and robust EKF variants, improve estimation under temperature transients by adjusting noise covariances or learning from batch-mode sensor data [139]. Each technique strengthens the filter's resilience to thermal non-linearity at different layers of the estimation pipeline.

Particle filtering techniques have also emerged as a pivotal tool in aviation battery state estimation due to their ability to handle non-linearities, noise, and dynamic operational conditions [140,141]. Tang et al [142] developed a particle filter (PF)-based method integrated with a power transfer model to predict the end-of-discharge (EOD) time for UAV Li-ion batteries. By leveraging a state-space model and dynamically updating parameters using an Adam optimization algorithm, the method achieved superior prediction accuracy, particularly under varying flight states, making it highly relevant for real-time UAV energy management. Zhang et al [143] enhanced traditional PF approaches by introducing an F-distribution particle filter (FPF) combined with a kernel smoothing algorithm for RUL prediction. This innovation addressed particle weight degeneration and uncertainty issues, significantly improving prediction stability and accuracy in aviation-specific applications, as validated using NASA battery datasets. Luan et al [30] extended particle filter adaptability with an APF that integrated a dual-polarization equivalent circuit model and real-time temperature-sensitive parameter updates using PSO. This approach achieved robust SOC estimation even under rapid thermal variations, a common challenge in aviation environments. However, the same model vulnerability, exhibited by KF algorithms, to low temperatures is observed in this model as demonstrated in Fig. 13. Therefore, the use of fast temperature correction adaptive particle filter (FTC-APF) could tackle this issue and improve model accuracy.

Estimation techniques should perform effectively at extremely low pressures to be used in more electric aircraft (MEA) or HEA traveling at high altitudes. The domain exhibits a noticeable gap in studies testing the effectiveness of KF and its variants in low-pressure environments. For instance, Laurin et al [133] developed a method using an SPKF model combined with a detailed aging model and an equivalent circuit to track battery degradation in MEA. Their semi-empirical ageing model

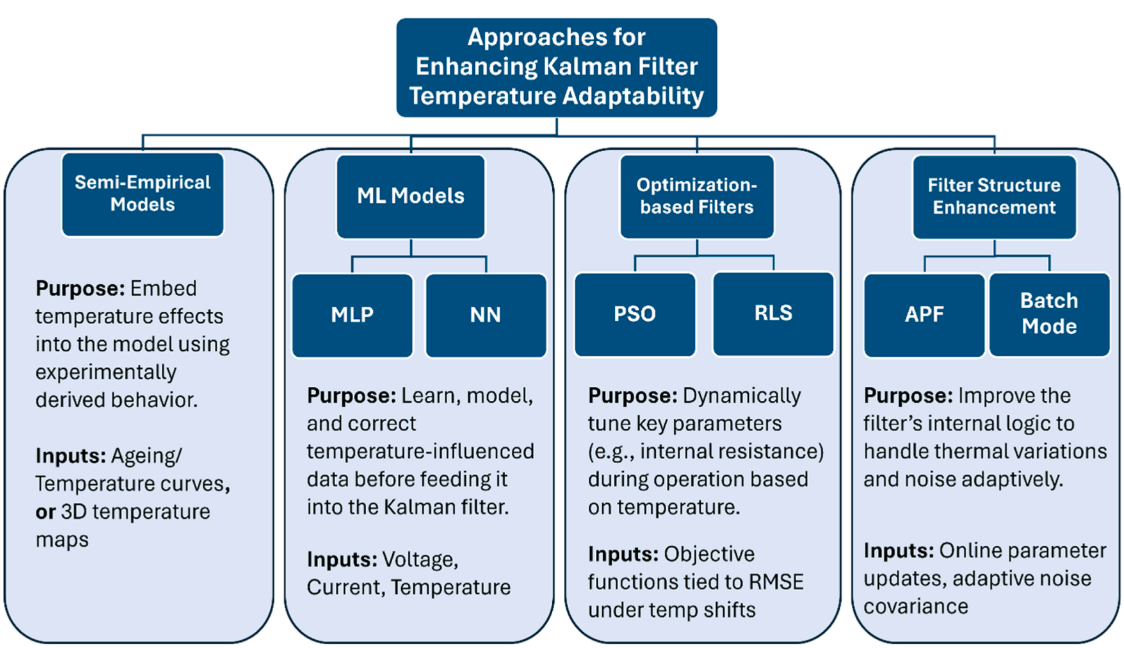



**Fig. 12.** Categorization of recent methods for enhancing Kalman Filter temperature adaptability in SOC estimation.

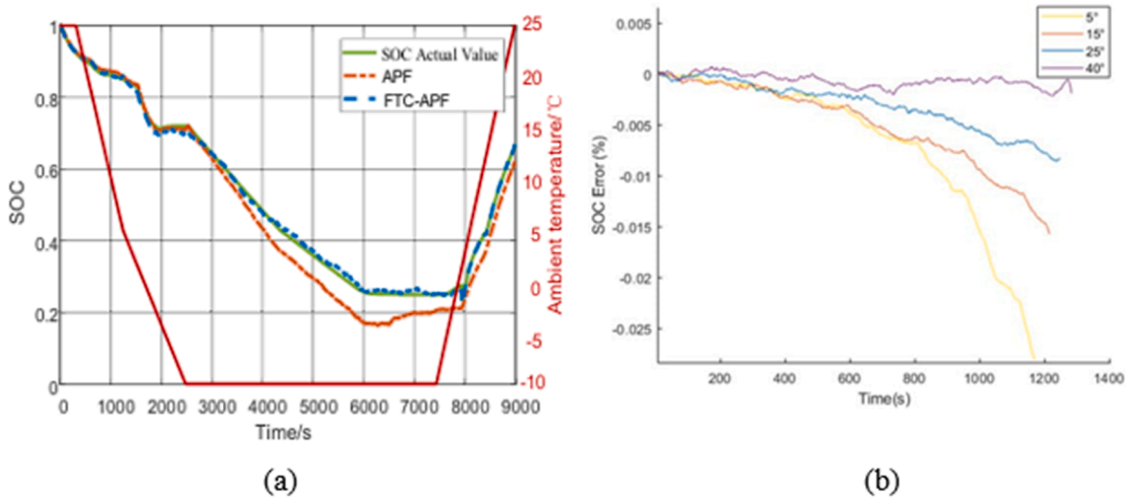



**Fig. 13.** Performance evaluation and comparison of filtering techniques and their vulnerabilities to low and rapidly varying temperatures as in (a) the accuracy of SOC estimation accuracy using APF [30] and (b) SOC estimation error using EKF [130].

kept SOH estimation errors below 2%, even across various temperatures and aging profiles. Nevertheless, the study neglected the indirect effect of pressure on internal parameters, raising concerns about the performance of this method in actual MEA environments. Li et al [138] is the only study that investigated KFs in low-pressure environments. They used PSO to improve KF performance in an ECM for lithium titanate batteries at different ambient pressures. The PSO allowed the KF to adapt its parameters in real time, which makes it capable of handling changes caused by low-pressure environments. The resilience of the ECM-based estimation in aviation settings was demonstrated by its achievement of absolute SOC errors of 2% at 96 kPa and 30 kPa. Thus, adding optimization layers or modifying the physics-based models to account for pressure would potentially facilitate the use of KFs in MEA or HEA. Further research is needed to address this gap before implementing KFs in MEA or HEA.

## 5. ML-based approaches for aviation battery state estimation

ML architectures for battery state estimation in HEA, eVTOL aircraft, and UAVs differ significantly in terms of processing needs, data requirements, and performance. Shallow learning models, including backpropagation neural networks (BPNN), random forest (RF), k-Nearest Neighbour (KNN), support vector regression (SVR), support vector machine (SVM) and dynamic mode decomposition (DMD), are lightweight and effective on small datasets, which makes them ideal for eVTOL aircraft with limited onboard resources. However, they suffer in highly nonlinear, dynamic environments and are frequently unreliable under extremely harsh situations such as HEA missions. Deep learning architectures such as typical deep neural networks (DNN), long short-term memory (LSTM), gated recurrent unit (GRU), extreme learning machine (ELM), and evolving Elman neural network (EENN) perform well in dynamic environments, capturing temporal dependencies and voltage drifts, especially during flight phase transitions. This comes at the expense of enormous datasets and significant computational power, which may be unfeasible in energy-constrained aircraft applications. Hybrid approaches include Adaptive Neuro-Fuzzy Inference System with Deep Belief Network (ANFIS-DBN), ANFIS-Artificial Neural Network (ANFIS-ANN), and Physics-Informed Gaussian process regression (GPR). These architectures combine physics-based models and ML to improve interpretability and robustness in low-temperature and long-duration missions. Despite their high performance, hybrid models are typically more difficult and time-consuming to build. Table 6 summarizes the advantages, disadvantages, and applications of ML architectures for battery state estimation in electric aviation. Moreover, Table 7 presents a summary of recent progress in ML-based battery state estimation studies.

### 5.1. Shallow learning architectures in aviation battery state estimation

Shallow learning models, including BPNN, RF, and data-driven

**Table 6**
The advantages and disadvantages of ML-based aviation battery state estimation techniques.

| ML Subset | Advantages | Disadvantages | Application and architectures | References |
|---|---|---|---|---|
| Shallow Learning | • Effective with small datasets.<br>• Low computational demand fits UAVs/eVTOL limits.<br>• Safer, as some offer uncertainty estimates.<br>• Transparent models, meeting aviation regulations. | • Struggles with flight transitions and nonlinearities<br>• Struggles in extreme ambient conditions.<br>• Not adaptive to load variations, common in HEA.<br>• Limited in long-term battery degradation trends. | UAVs (BPNN, DMD, Typical DNN) eVTOL aircraft (RF, KNN, SVR, SVM) | [144–146] |
| Deep Learning | • Capture SOC/SOH under dynamic loads and conditions<br>• LSTM/GRU handles low-temp voltage drifts.<br>• Model transitions across takeoff, cruise, and descent with temporal memory. | • Require large datasets.<br>• High computational cost.<br>• Sensitive to noise<br>• Difficult to interpret, posing a safety and regulatory challenge. | UAVs (LSTM, ELM, GRU)<br>General Aerospace (EENN) | [147–150] |
| Hybrid | • Combine physics/fuzzy logic with data-driven ML approaches for adaptability.<br>• Perform well in low temperatures, even with data scarcity.<br>• Stable in long-duration HEA or MEA missions. | • Complex to design and tune.<br>• Longer development time compared to physics-based techniques.<br>• High computational cost in hybrid energy systems. | General aviation (ANN-ANFIS, Physics-informed GPR)<br>MEA (ANFIS-DBN) | [151–153] |

**Table 7**
Summary of ML-based studies on aviation battery state estimation, including models, performance, datasets, and estimated parameters.

| Article | ML Architecture | Performance | Testing Dataset | Estimated Parameters |
|---|---|---|---|---|
| Mao et al [154] | BPNN with Levy-flight PSO | RMSE: 0.108 | NASA, Bole et al [155] | SOC |
| Phung et al [37] | RF Regression | RMSE: 0.000985 | Bills et al [156] eVTOL aircraft dataset | SOC |
| Mitici et al [157] | SVR, RF, GPR | **SVR:** MAE: 1.48 RMSE: 2.2 **RF:** MAE: 1.33 RMSE: 1.8 **GPR:** MAE: 1.48 RMSE: 2.27 | Bills et al [156] eVTOL aircraft dataset | SOH, RUL |
| Javid et al [158] | Adaptive Online GRU | RMSE: 1.08 | Xing et al [159] | SOC |
| Chemali et al [160] | LSTM | Constant Temperature (0 °C): MAE: 2.088 RMSE: 2.444 Varying Temperature (10 to 25 °C): MAE: 1.606 RMSE: 2.038 | Personal data. Protocol: LA92, US06 | SOC |
| Wang and Yang [161] | ELM, BPNN, SVM | ELM RMSE: 0.0344 BPNN RMSE: 0.085 SVM RMSE: 0.0873 | Personal Data | SOC |
| Zhu et al [162] | Domain Adaptation Convolutional neural network (CNN) | RMSE: 0.8 – 3 Depending on the tested dataset | Xing et al [163] and He et al [164] | SOH |
| Nascimento et al [165] | Hybrid Physics-Informed NN | RMSE: 0.031 | NASA [166] | RUL |
| Granado et al [167] | SVM, KNN, RF | SVM RMSE: 0.0172 KNN RMSE: 0.014 RF RMSE: 0.0198 | Bills et al [156] eVTOL aircraft dataset | SOH |
| Kohtza and Wang [168] | Physics-Informed GPR (Hybrid) | RMSE: 3.6192 | Personal Data. Protocol: Ekstrom et al [169] | SOH |
| Shibl et al [170] | DNN, LSTM, RF | DNN RMSE: 0.0276 LSTM RMSE: 0.1517 RF Classification Accuracy: 0.92 | Kollmeyer [171] 18650PF Panasonic Dataset | SOC, SOH (classification, not regression) |

decomposition methods, continue to provide accurate and computationally efficient SOC estimation in aviation systems. These methods have fewer or no hidden layers, no deep feature extraction, while offering fast training with limited data. Yang et al [172] introduced an improved BPNN optimized using a GA-PSO algorithm, enhancing the robustness and accuracy of SOC predictions for aviation batteries through efficient synchronous sampling of internal resistance. Mao et al [154] used a BPNN optimized with a Levy-flight PSO algorithm to improve SOC prediction accuracy by addressing the randomness and complexity of Li-ion battery datasets. Furthermore, Tameemi et al [173] used DMD for real-time voltage collapse detection in Li-ion batteries, which improved SOC monitoring precision and dependability in UAVs by adjusting swiftly to major voltage fluctuations, thereby supporting crucial decision-making in high-risk situations. The DMD technique exhibited superior battery state estimation capabilities compared to linear discriminant analysis (LDA). Phung et al [37] applied RF regression for SOC estimation in eVTOL aircraft, achieving an RMSE of 0.000985 and $R^2$ of 0.9996 by effectively addressing the nonlinear relationships between features. The consistency observed in extended cruise, power reduction, short cruise, and constant current conditions, as shown in Fig. 14, highlights the model's robustness and adaptability to varying battery usage profiles, making it highly suitable for eVTOL aircraft and UAV applications where dynamic energy demands are common.

Shallow learning models, such as decision trees and boosting ensembles, remain relevant for SOH and RUL estimation due to their simplicity, interpretability, and low computational load. Mitici et al [157] introduced an ML framework tailored to eVTOL aircraft applications, incorporating mission-phase-specific discharge rates (like take-off versus cruise) as core features. By employing RF and extreme gradient boosting models, they achieved an RMSE of 1.3%, which allows accurate SOH tracking, critical in high-demand aviation environments where battery conditions fluctuate frequently. Granado et al [167] demonstrated highly accurate long-term SOH forecasting ($R^2 > 0.97$) for eVTOL aircraft applications using KNN and gradient boosted trees, confirming its effectiveness in aviation contexts with high-load and mission-variable profiles as shown in Fig. 15. KNN exhibited an outstanding validation score and less noisy predictions.

Shallow architectures struggle with fluctuating and transitional conditions, frequently encountered by eVTOL aircraft. However, these architectures, especially RF and KNN, achieved remarkable SOC and SOH estimations in eVTOL aircraft applications. This result contrasts with the characteristics and performance limitations of these architectures. This exceptional performance is justified by the dataset used in training and testing these architectures. As shown in Table 7, all the studies that implemented shallow learning in eVTOL aircraft applications used the Bills et al [156] dataset. This dataset highly replicates the power demands of a typical eVTOL aircraft mission. Nevertheless, it lacks a fundamental aspect in terms of environmental conditions. The data is acquired by running the batteries at a set of different yet constant temperatures, neglecting the transitional and dynamic nature of these missions. To illustrate, the authors conducted three distinct experiments to examine the temperature effect (at 20 °C, 30 °C, and 35 °C). However, they did not include an experiment that captures the transitional thermal behavior occurring during take-off and landing, where the temperature progressively rises from 20 °C to 30 °C. This omission of transitional conditions undermines the dataset's ability to replicate real eVTOL aircraft missions. Moreover, we cannot generalize the results since all studies used the same dataset. The dataset also lacks data on low-temperature ranges encountered by eVTOL aircraft in winter or at high altitudes. As a result, shallow models may appear to perform exceptionally well under static conditions but are likely to underperform when exposed to realistic, dynamic datasets.

### 5.2. Deep learning architectures in aviation battery state estimation

Deep learning–based BMS architectures are increasingly addressing the limitations of traditional SOC estimation under dynamic thermal and operational conditions. RNN, LSTM, GRU, and ELM offer advanced temporal real-time modeling and generalization capabilities for SOC estimation in complex UAV missions [174,175]. Deep feedforward NNs excel in temperatures from −20 °C to 25 °C, including transitional profiles encountered in UAV missions. The models demonstrated the ability to generalize across both seen and unseen temperature ranges

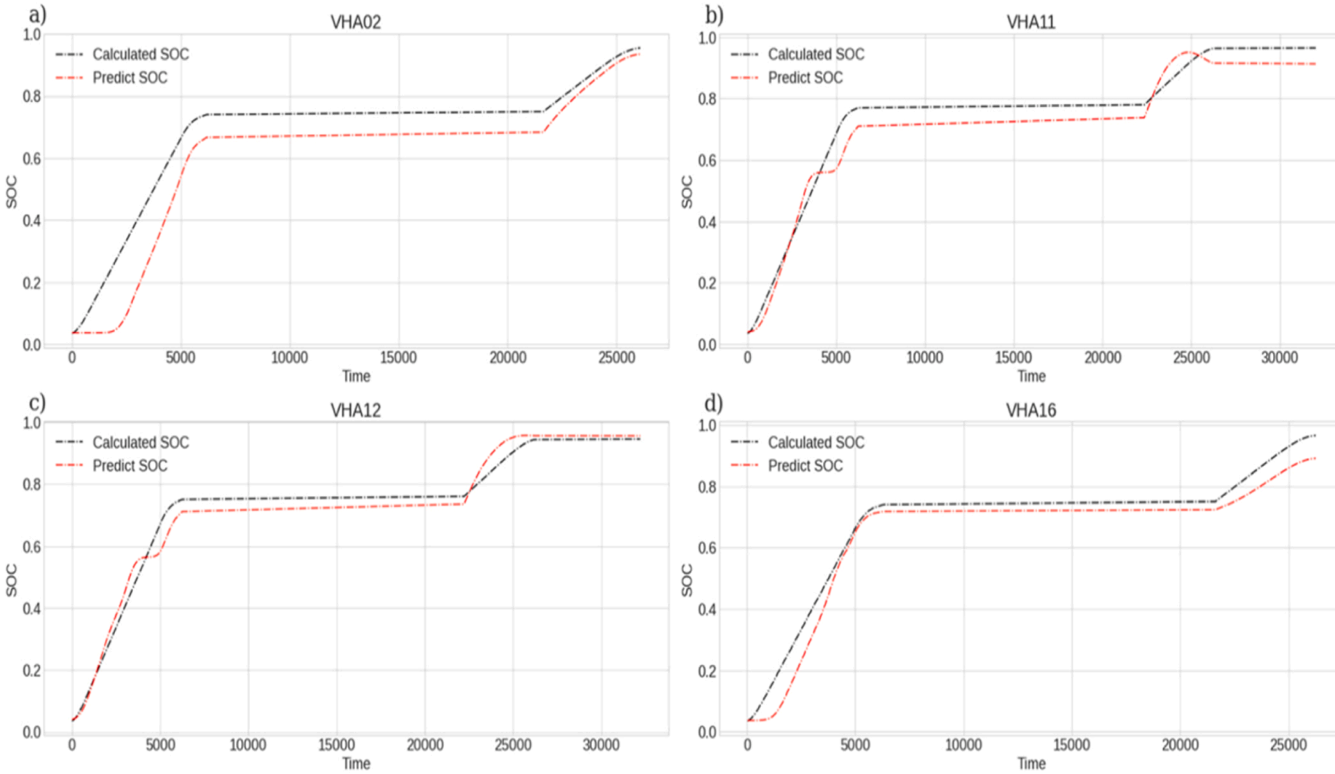



**Fig. 14.** RF SOC predictions vs. calculated SOC under varied conditions: a) extended cruise, b) power reduction during discharge, c) short cruise, and d) constant current charge [37].

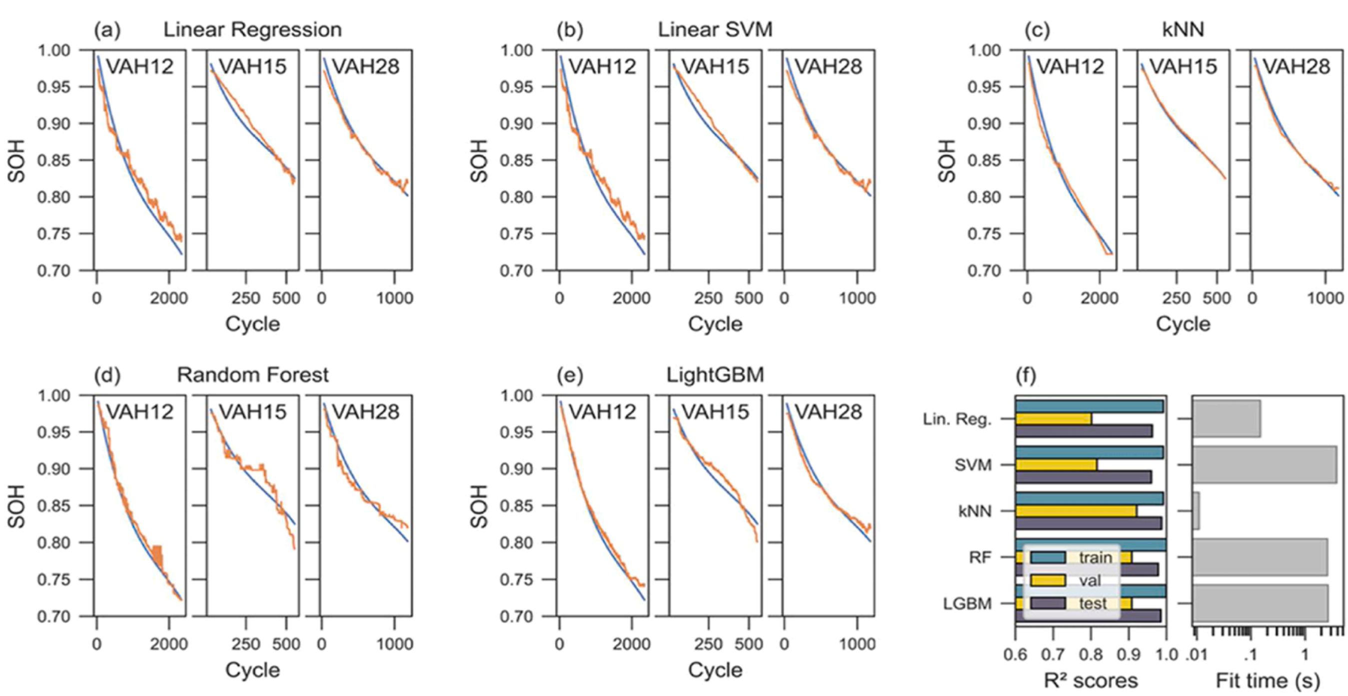



**Fig. 15.** Actual and predicted SOH values concerning cycles for the test set, showing superior KNN prediction, validation (R scores), and noise capabilities [167].

without requiring separate estimators or filtering layers [176]. Shibl et al [170] developed an ML-based BMS that estimated UAV battery SOC using a DNN architecture. This method attained a SOC prediction with an RMSE of 0.0276 when trained and tested with datasets at a temperature range of -20 °C to 20 °C. Expanding on this concept, LSTM networks can capture temporal patterns within battery signals, achieving a mean absolute error of 2.088% at constant temperature and 1.606% under varying conditions, thereby reinforcing the adaptability of deep learning models to fluctuating environments [160]. Further advancing adaptability, GRUs exhibit promising real-time and self-learning characteristics. These architectures offer online self-adjustment of internal weights during flight, enabling real-time adaptation to abrupt shifts in power demand and environmental factors such as altitude and temperature gradients [158]. With precise model design, this adaptability to temperature variations and self-learning capabilities addresses the dynamic nature of UAVs.

In SOH estimation, deep learning-based models are widely used to capture nonlinear degradation patterns in aviation batteries, particularly under irregular cycles and variable loads. Zhang et al [177] employed EENN to predict SOH for satellite Li-ion batteries, using a unique feature, time series of equal discharging voltage difference (TSEDVD), to assess capacity degradation in complex cycling scenarios. Although designed for satellite batteries, this method adapts well to UAVs experiencing irregular cycles. On the other hand, Zhu et al [162] proposed a cross-domain SOH prediction model utilizing domain adaptation techniques. This model uses convolutional NNs and maximum mean discrepancy (MMD) loss, successfully transferring trained models across battery types while preserving accuracy, which is essential for diverse aviation operations with mixed battery profiles. With the ability to capture these non-linearities, deep learning models offer effective degradation characterization for UAV dynamic flights.

In automotive contexts, deep learning architectures also excel in RUL estimation in electric aviation setups. Chen et al [178] introduced a hybrid deep learning model for predicting the RUL of Li-ion batteries, integrating a channel attention mechanism with an LSTM network. The channel attention mechanism enhances the model's ability to extract relevant features, particularly under limited data conditions, by focusing on local data characteristics and mitigating capacity rebound effects during charge-discharge cycles. Tested on NASA and CALCE datasets, the model showed high accuracy and robustness across varied prediction starting points, which supports its adaptability to aviation applications that rely on precise RUL forecasting for critical power systems. Li et al [179] proposed a hybrid model combining LSTM and Elam neural networks (ENN) to predict Li-ion battery RUL. Using Empirical Mode Decomposition (EMD), they separated the high- and low-frequency components of the capacity degradation data, applying LSTM for the low-frequency, long-term trends and the Elman network for the high-frequency fluctuations. Although initially developed for EVs, the model demonstrated strong predictive performance on unseen NASA datasets, with a prediction error of only 2.7%.

The adaptability of these deep learning algorithms is often attributed to architecture design, such as whether a model utilizes recurrent memory (e.g., LSTM) or attention mechanisms to respond to temporal and contextual variations. However, the quality and diversity of the input data play an equally critical role. Voltage, current, and temperature inputs are the foundation of nearly all SOC/SOH prediction models. These inputs carry indirect information about flight phase transitions, environmental stress, and operational intent. For example, rapid current changes can indicate take-off or landing phases, while prolonged low current may suggest cruise. Temperature variations can reflect altitude or ambient conditions, and energy discharge trends can imply mission intensity or duration. However, despite their richness, these signals can be ambiguous or misleading. A current spike may stem from onboard equipment activation rather than a flight maneuver. Similarly, elevated temperatures could result from self-heating or internal resistance rather than external stress. Similarly, long discharge patterns may occur in both low-altitude loitering and high-altitude transit, making inference difficult without corroborating data. These limitations highlight that while input features can offer contextual cues, they are not definitive. This introduces a level of uncertainty that must be addressed through either an architecture-level solution, such as attention weighting and temporal filtering, rule-based algorithms (similar to fuzzy logic) for

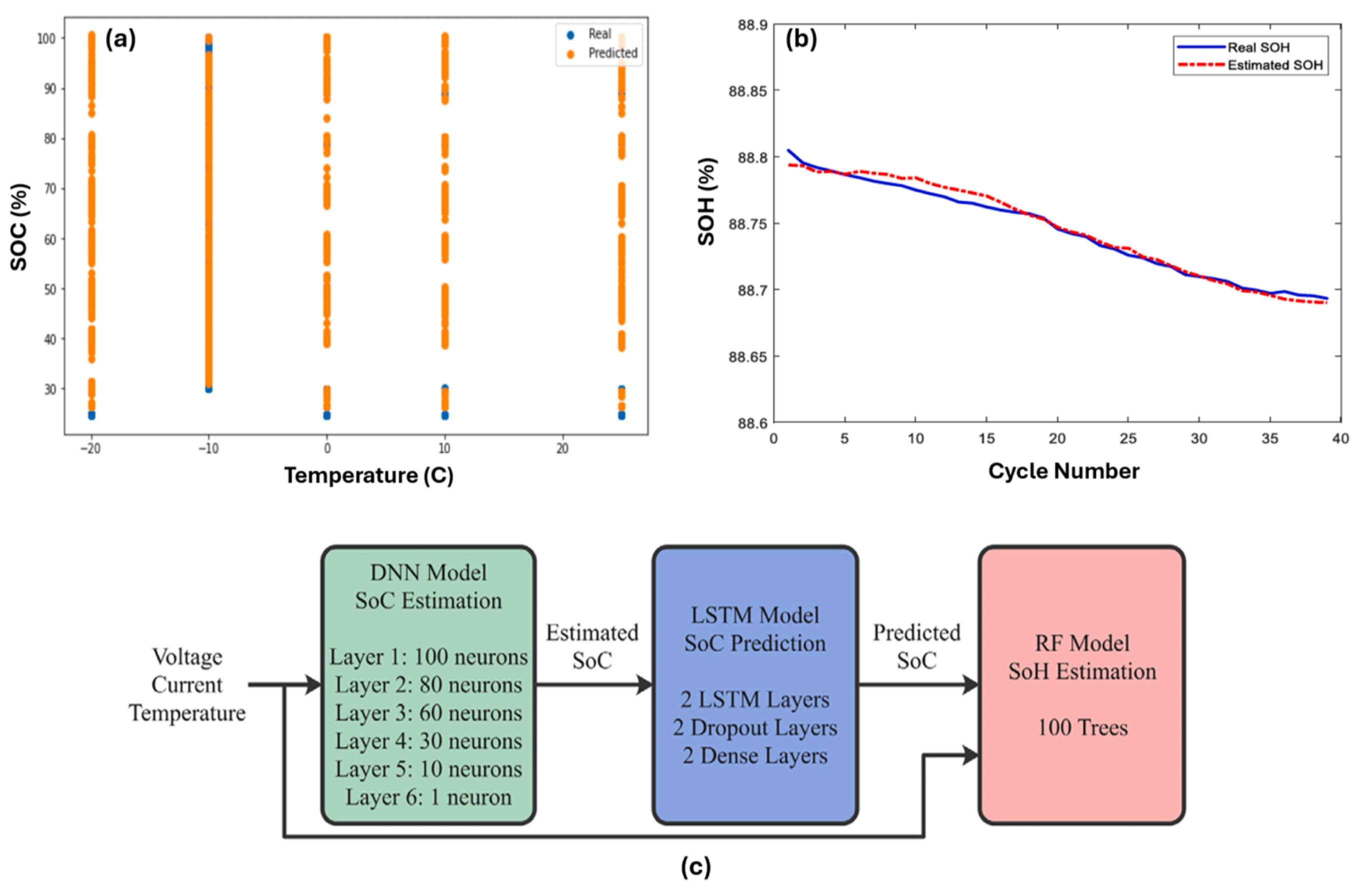
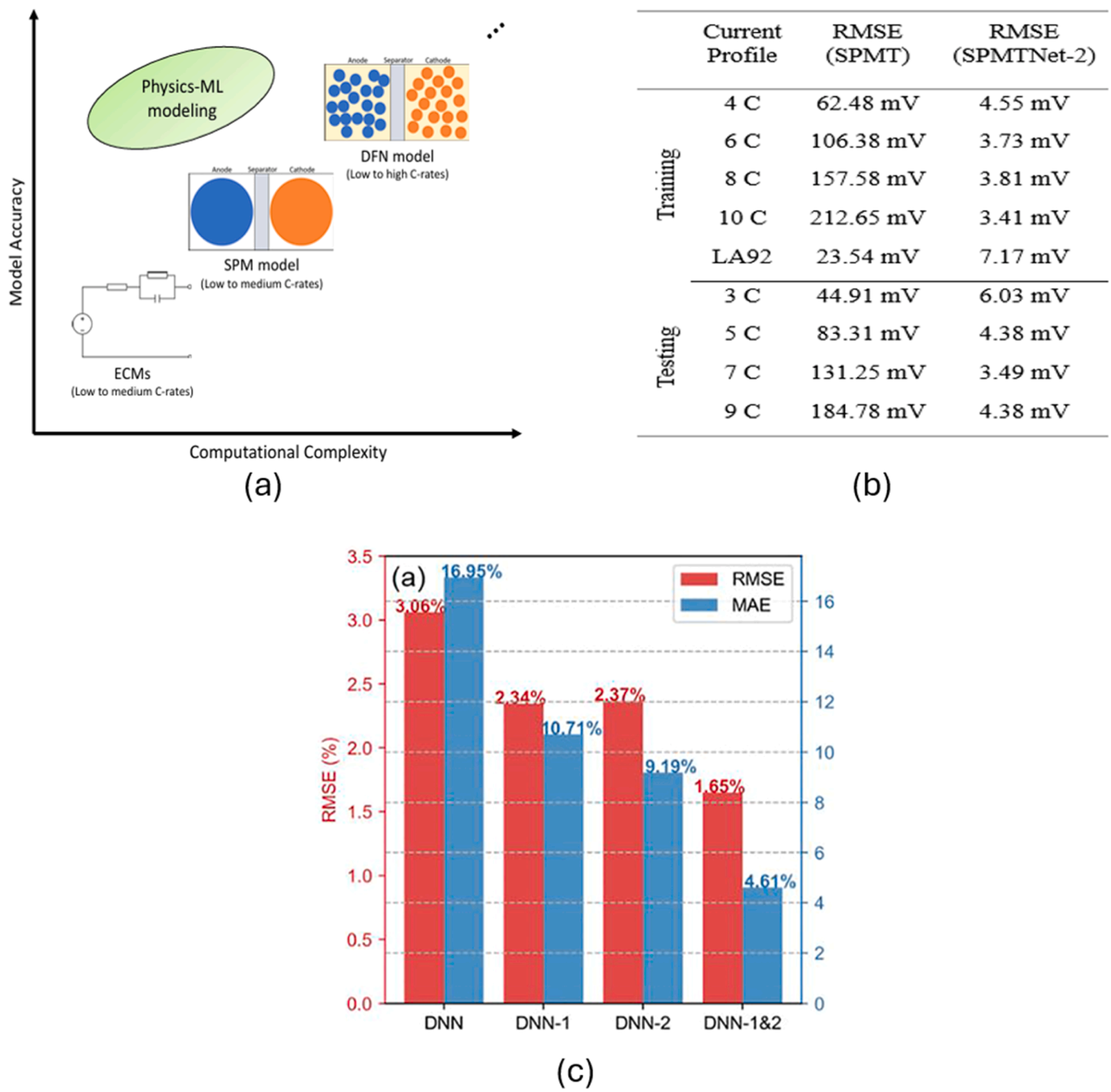



**Fig. 16.** Summary of a hybrid deep learning pipeline for SOC and SOH estimation using voltage, current, and temperature inputs; (a) shows temperature-aware SOC estimation via a DNN [170], (b) illustrates accurate SOH tracking using EENN outputs [177], and (c) depicts the full architecture integrating DNN, LSTM, and RF models for sequential prediction [170].

improved interpretation of the inputs, or sensor fusion and phase labeling when available. Fig. 16 summarizes the performance, adaptability, and model input of deep learning models in SOC and SOH estimations.

### 5.3. Hybrid ML architectures for battery state estimation

Battery state estimation in electric aviation platforms must account for dynamic loads, high power demands, and extreme environmental conditions, particularly low temperatures and fluctuating pressure levels. Hybrid models, which merge physics-based formulations with data-driven learning architectures, have emerged as strong candidates for addressing these complex problems [180,181]. Fig. 17 synthesizes comparative findings from recent studies that benchmark hybrid models against both purely physics-based and ML architectures. Fig. 17 (a) maps each model class according to its computational complexity and accuracy. Physics-based models, including the Single Particle Model with Thermal coupling (SPMT) and Doyle–Fuller–Newman (DFN), excel in theoretical rigor but are computationally demanding and rigid in dynamic flight conditions. DNN architectures, on the other hand, are accurate and flexible but often come with a computational cost. Hybrid models, such as SPMTNet-2, integrate physical laws within NN, offering high accuracy and moderate computational cost. As shown in Fig. 17 (b), Tu et al [182] conducted a performance comparison between SPMTNet-2 and SPMT across discharge rates of 4C to 10C. The hybrid model consistently achieves lower RMSE, demonstrating superior




| | Current Profile | RMSE (SPMT) | RMSE (SPMTNet-2) |
|---|---|---|---|
| Training | 4 C | 62.48 mV | 4.55 mV |
| | 6 C | 106.38 mV | 3.73 mV |
| | 8 C | 157.58 mV | 3.81 mV |
| | 10 C | 212.65 mV | 3.41 mV |
| | LA92 | 23.54 mV | 7.17 mV |
| Testing | 3 C | 44.91 mV | 6.03 mV |
| | 5 C | 83.31 mV | 4.38 mV |
| | 7 C | 131.25 mV | 3.49 mV |
| | 9 C | 184.78 mV | 4.38 mV |

**Fig. 17.** Comparative analysis of battery state estimation approaches for electric aviation: (a) computational cost vs. accuracy for ECMs, physics-based, and hybrid models [182] (b) RMSE comparison showing SPMTNet-2's superior performance across various C-rates [182] (c) error metrics highlighting the enhanced cold-temperature performance of hybrid DNN architectures [183].

tracking of SOC under aggressive current demands similar to those demanded by eVTOL aircraft and HEA. Finally, Fig. 17 (c) evaluates performance at 10°C, where hybrid DNNs (DNN-1 and DNN-2) outperform standalone DNNs in both RMSE and MAE. This confirms their robustness under cold climate operation, critical for UAVs and eVTOL aircraft missions at altitude or in winter conditions [183].

Physics-informed ML models, which combine physical modeling, signal processing, or architectural layering with ML algorithms, have shown strong performance when data is noisy, scarce, or system dynamics are complex. Nascimento et al [165] developed a hybrid physics-informed NN model that combines reduced-order physics equations, such as the Nernst and Butler-Volmer equations, with data-driven layers to enhance SOH prediction accuracy. This model bridges gaps between theoretical predictions and observed data by integrating domain knowledge with data-driven learning, demonstrating suitability for UAV applications with limited data availability and highly variable load cycles. Kohtza and Wang [168] proposed a physics-informed ML model based on GPR to estimate SOH using partial voltage charging curves. The model overcomes data scarcity by generating training datasets through a 1D finite element physics model, enabling it to address capacity estimation and health management tasks effectively. Fricke et al [184] developed a hybrid physics-informed NN model to predict SOC and SOH. The model integrates GPR with electrochemical principles to map cumulative energy and load levels to battery capacity, obtaining robust performance across a wide range of thermal stressors and load fluctuations.

Hybrid models that combine ML architectures with fuzzy logic offer superior precision and robustness for SOC estimation in multi-source aviation systems. This technology improved efficiency by managing power needs across many energy sources, reducing battery wear during long-duration missions. Babu et al [185] combined artificial neural networks (ANN) and ANFIS models for SOC estimation, achieving an RMSE of 0.0004, significantly outperforming individual methods and demonstrating the benefits of hybrid approaches in precision-demanding applications like aviation. The model, shown in Fig. 18, comprises three main aspects: data collection and acquisition, ANN Falgorithm, and ANFIS algorithm. This arrangement is rarely used in predictive models; however, it achieved the highest accuracy among all the other techniques. Similarly, Kamal et al [186] developed a hybrid ANFIS-DBN system for SOC estimation in MEA, tested during emergency power scenarios, and simulated cyber-attacks. The model ensured reliable SOC control and power availability, enhancing aviation system resilience under critical and high-risk conditions. However, both studies lacked any interpretability metrics or evaluation, which is crucial in aviation. ANFIS models and deep learning models are known for their vulnerability to interpretability [187]. Conducting interpretability metrics such as rule relevance, rule quantity, and fuzzy set distinguishability is imperative [188,189]. To improve interpretability, reduce the number of rules and parameter complexity, enforce semantic constraints on membership functions, and merge similar rules via clustering and dimensionality reduction. Additionally, optimization techniques such as gradient descent and evolutionary algorithms are applied to fine-tune system parameters while preserving structural transparency [190,191].

### 5.4. Transformer-based architectures

Transformer-based techniques operate through a self-attention

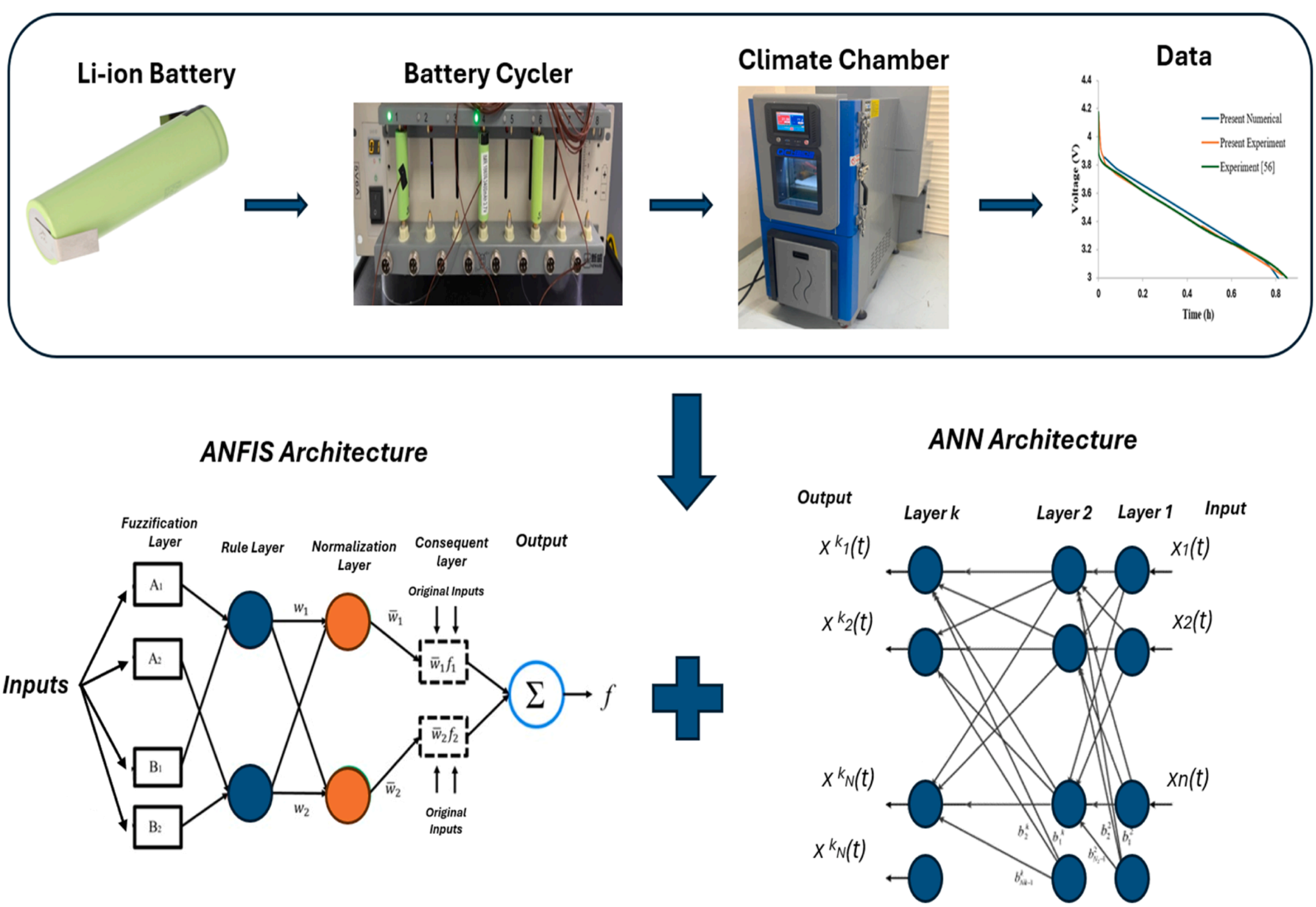



Fig. 18. Workflow and architecture of a hybrid SOC estimation model combining ANFIS and ANN: experimental data are collected using a battery cycler and climate chamber, then processed through a dual-layered architecture.

mechanism that enables the model to capture dependencies between all elements in an input sequence, regardless of their relative positions. This is achieved by projecting input tokens into queries, keys, and values, and computing attention scores as scaled dot products between queries and keys. These scores are used to weight the corresponding values, allowing the model to focus selectively on different parts of the sequence. This mechanism is executed in parallel across all time steps, eliminating the need for recurrence and enabling efficient processing of long sequences [192,193]. As shown in Fig. 19, each transformer layer consists of multi-head self-attention, which allows the model to attend to different representation subspaces simultaneously, followed by a position-wise feedforward NN that introduces non-linearity and depth [194]. To retain sequence order information, absent due to the parallel structure, positional encodings are added to the input embeddings. The stacked layers progressively build hierarchical feature representations, capturing both local and global temporal patterns. This architecture facilitates superior modeling of long-term dependencies and complex temporal structures, making transformers highly effective for tasks involving sequential data, such as time series prediction, language modeling, and increasingly, energy system forecasting.

Transformer-based models outperform typical ML approaches for estimating battery SOC and SOH, considering their ability to comprehend long-range temporal relationships and quickly analyze sequential data. RNN and LSTM models rely on sequential data processing and frequently struggle with disappearing gradients in lengthy sequences. In contrast, transformers utilize a self-attention mechanism that enables them to consider interactions between all time steps simultaneously. This parallelism not only accelerates training but also increases accuracy by focusing on the most important sections of the input sequence [195,196]. Moreover, transformer architectures have demonstrated superior generalization across diverse datasets, including NASA Ames Prognostics Data Respiratory, often outperforming LSTM- and CNN-based methods in both SOC and SOH prediction, as shown in Table 8 [197]. NASA datasets are widely used in the training and testing of ML models for electric aviation applications. Therefore, the results shown in the table, although not specifically tailored for electric aviation, demonstrate the promising performance of transformers and their potential for such dynamic applications.

**Table 8**
Performance of transformer-based architecture when tested with NASA Ames Prognostics Data [197].

| Dataset | Error Index | LSTM | Bi-LSTM | SVR | Transformer |
|---|---|---|---|---|---|
| NASA Ames Prognostics | RMSE | 1.716 | 2.226 | 16.662 | 0.872 |
| | MAE | 1.674 | 2.147 | 16.296 | 0.799 |
| | $R^2$ Score | 0.998 | 0.998 | 0.361 | 0.994 |
| | Max Error | 7.245 | 6.958 | 8.245 | 6.697 |

Transformers have shown exceptional potential in addressing one of the most critical challenges in aviation battery management: accurate SOC estimation under low-temperature conditions. UAVs, HEA, and eVTOL aircraft often operate in environments where battery temperature fluctuates drastically, impairing conventional models' ability to maintain reliable SOC estimates. Transformer-based models such as iTransformer-SQL-AdamP have demonstrated superior accuracy and robustness in extreme scenarios. To illustrate, Wang et al [198] reported that their transformer network achieved the lowest MAE of 0.416% for SOC and 0.395% for state of energy (SOE) at 0 °C, with $R^2$ values near 1, even across extreme temperature conditions (–20 °C to 45 °C). This indicates the model's ability to generalize effectively across diverse thermal states, which is crucial for aviation applications where battery performance is mission-critical. Additionally, the hybrid prompt-driven large language model (LLM) proposed by Bian et al [199] leverages hard-soft prompt encoding and side adapter networks to dynamically adjust to SOC fluctuations, enhancing performance in harsh, sub-zero environments. Chen et al [200] and Gong et al [201] confirmed the superior performance of transformer-based frameworks compared to traditional deep models in extremely low temperatures. Table 9 compares the performance of transformers and Enformers to other deep learning architectures [200].

Although transformer-based models have demonstrated exceptional

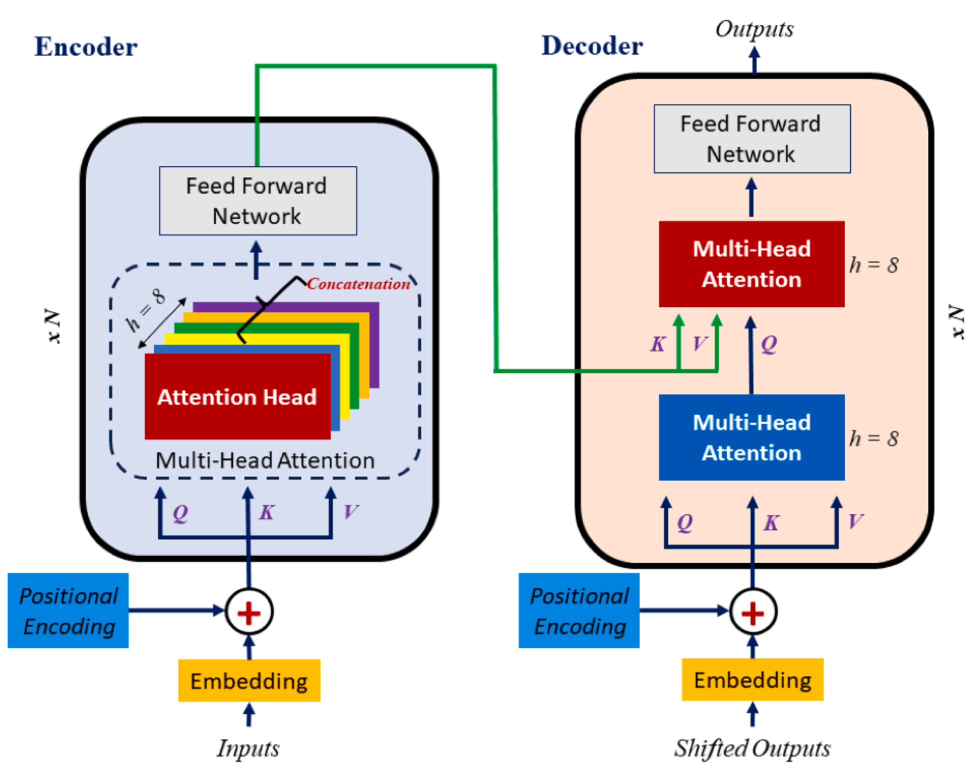



**Fig. 19.** The transformer architecture comprises encoder and decoder blocks with multi-head attention and feedforward layers [194].

**Table 9**
Performance comparison of transformer-based architectures tested at –20 °C and in various driving cycles [200].

| Model | HWFET-UDDS | | LA92-US06 | | US06 -HWFET | |
|---|---|---|---|---|---|---|
| | MAE | RMSE | MAE | RMSE | MAE | RMSE |
| DNN | 3.214 | 3.215 | 3.356 | 3.376 | 3.261 | 3.268 |
| CNN | 0.112 | 0.113 | 0.259 | 0.299 | 0.264 | 0.270 |
| Fully convolutional network (FCN) | 0.093 | 0.099 | 0.266 | 0.299 | 0.187 | 0.192 |
| LSTM | 0.108 | 0.109 | 0.125 | 0.129 | 0.163 | 0.166 |
| GRU | 0.106 | 0.108 | 0.112 | 0.124 | 0.148 | 0.152 |
| BiGRU-AT | 0.088 | 0.089 | 0.112 | 0.127 | 0.130 | 0.133 |
| CNN+LSTM | 0.116 | 0.118 | 0.134 | 0.151 | 0.199 | 0.202 |
| CNN-BiLSTM-AT | 0.104 | 0.107 | 0.124 | 0.137 | 0.152 | 0.155 |
| **Transformer** | **0.107** | **0.108** | **0.142** | **0.152** | **0.142** | **0.154** |
| **Enformer** | **0.057** | **0.067** | **0.062** | **0.075** | **0.063** | **0.069** |

performance in SOC and SOH estimation, particularly with NASA datasets and under extreme thermal conditions, their direct application in electric aviation contexts such as UAVs, HEA, and eVTOL aircraft remains limited. Despite their robustness in volatile environments, there is a noticeable gap in the literature explicitly connecting transformers to aviation-specific BMS. This disconnect may stem from two underexplored technical challenges: the substantial data requirements and the high computational cost associated with transformer architectures. These constraints pose barriers to implementation in aviation platforms, which often operate with limited onboard computational resources and face difficulties in collecting large, high-quality battery datasets. Future research should prioritize addressing these limitations by using lightweight transformer variants and data-efficient learning strategies. For example, integrating prompt tuning or adapter-based fine-tuning could allow the use of pretrained transformers with minimal additional data and computational overhead, making them more feasible for deployment in real-time aviation environments. Tackling these two issues directly could unlock the full potential of transformer models for highly reliable SOC and SOH estimation in next-generation electric aircraft.

## 6. Fuzzy-based approaches for energy management in aviation

Designing fuzzy-based systems includes several stages, as shown in Fig, but designing membership functions is the most important [202, 203]. Membership functions are mathematical curves that define the input's membership degree. The curve specifies the extent to which an input, such as ambient temperature, belongs to a fuzzy concept [204, 205]. To illustrate, after designing a suitable membership function that defines a low ambient temperature in an HEA, a 20°C could belong to this fuzzy concept (low ambient temperature) by 0.2 (10%) only. However, when designing a membership function for an EV, the same temperature would result in a membership degree of 0.6. Therefore, carefully designing membership functions is crucial in electric aviation propulsion systems. The trapezoidal membership function is the most popular in electric aviation energy management. This function offers computational efficiency, better tuning characteristics, and enhanced interpretability, which are imperative in UAVs, eVTOL aircraft, and HEAs. However, for real-time flight missions, the manually designed membership functions are assisted by data-driven tuning methods such as fuzzy C-means and PSO [39]. The fuzzified inputs to these functions vary based on the application. Nevertheless, the input to these functions is usually battery SOC, SOH, discharge current, and voltage. Although highlighting SOC and SOH is counterintuitive, the use of fuzzy logic in most electric aviation applications is for energy and power management rather than battery state estimation [45,206,207], (Fig. 20).

Fuzzy logic approaches fall short of direct SOC and SOH estimation for electric aviation vehicles, owing to their limited capability to handle regression problems [208]. These systems are fundamentally rule-based and rely on manually set membership functions, making them effective for classification and control tasks [209–211]. Accurate real-time regression is crucial in electric aircraft, as battery systems operate under unpredictable conditions, shifting power demands, temperature changes, and flight phase transitions. Fuzzy systems lack the dynamic learning and adaptation needed to simulate these nonlinear, time-dependent processes [212,213]. Unlike Kalman-based filters,

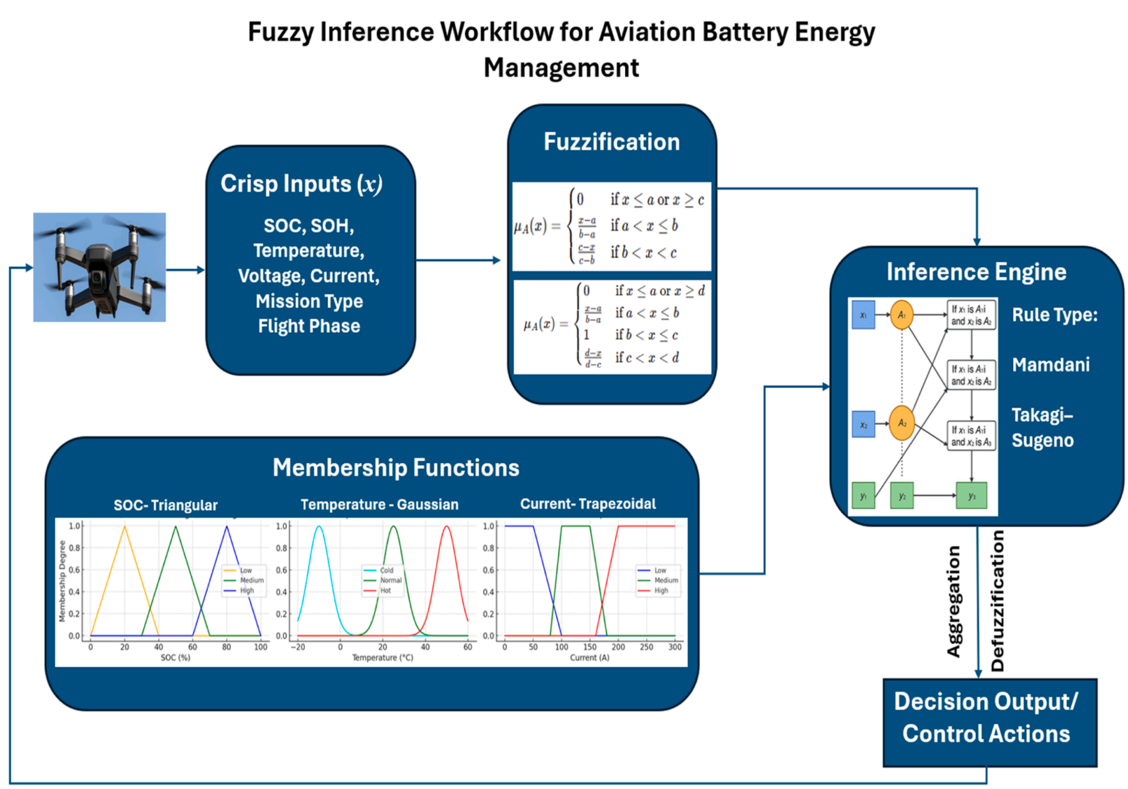



**Fig. 20.** Fuzzy-based energy management maps, with inputs, membership functions, fuzzy rules, and output control actions.

which integrate system models with sensor feedback, or ML models that can learn complex input–output mappings from data, fuzzy logic systems do not generalize well across diverse operating scenarios. This becomes a critical limitation in aviation, where reliability and precision are imperative. Additionally, fuzzy logic offers no inherent mechanism for measuring uncertainty or tracking temporal changes, which are vital for regression predictive models. As a result, while fuzzy logic may still be useful in strategic decision-making activities, it lacks the depth and robustness required for direct SOC and SOH estimation in high-stakes, dynamic applications, such as electric aviation.

Fuzzy logic techniques have shown significant promise in optimizing energy management strategies for aviation, especially in hybrid-electric propulsion systems [214]. In one study, Bai et al [215] introduced a fuzzy logic control-equivalent consumption minimum strategy (FLC-ECMS) that dynamically balances power distribution between engines and batteries. This method reduced fuel consumption and emissions by over 18% in UAVs. Similarly, Zhu et al [216] proposed a fuzzy logic-based energy management strategy for a fixed-wing eVTOL aircraft. By combining fuzzy logic with the ideal operating line (IOL) concept, they optimized power allocation between generators and batteries. This significantly improved fuel economy and system efficiency in simulations under mission-specific profiles . Moreover, Zhang et al [207] developed a fuzzy state machine (FSM) energy management strategy integrating fuzzy logic and state-machine controls. This approach effectively managed power flow among multiple sources, photovoltaics, fuel cells, and batteries, optimizing energy use and extending UAV endurance compared to traditional thermostat strategies. These studies collectively underscore the flexibility and robustness of fuzzy logic in addressing the complexities of aviation power systems, particularly in hybrid configurations.

In addition to hybrid systems, fuzzy logic techniques have shown significant potential in fully electric systems, particularly for precise energy estimation and efficient mission planning [217]. Manjarrez et al [206] introduced a Takagi–Sugeno fuzzy system combined with PSO to dynamically estimate energy consumption and available flight time for UAV missions. The method utilizes trapezoidal membership functions to define the fuzzy sets within the Takagi–Sugeno system. Then, Fuzzy C-Means clustering is applied to compute the membership degrees based on the relative distance of inputs to cluster centers, enabling adaptive rule activation. This approach accounted for real-time variations in energy requirements by continuously refining model parameters, achieving prediction errors of 2%. In another study, Karunarathne et al [218] developed a fuzzy logic control strategy for fully electric UAV systems. The approach utilized a dual-controller system to regulate energy flow between power converters and the battery, ensuring stable SOC and effective load balancing. By dynamically adjusting to fluctuating energy demands, the system optimized energy distribution across mission phases, enhancing endurance and operational reliability.

## 7. Conclusion and recommendation

The review provided a detailed assessment of advanced battery state estimation techniques tailored for aviation, with key conclusions emphasizing the interplay between operational demands and technological innovations. The analysis revealed that electric aviation applications exhibit three characteristics that distinguish them from other battery applications. Aviation batteries undergo extreme fluctuations in power and energy demands across various flight phases. Moreover, UAVs, eVTOL aircraft, and HEA operate in extreme temperature and pressure fluctuations that alter the internal properties of the battery and disturb battery state estimation. This demands special algorithms and datasets that are designed, built, and tested in these unique conditions.

To address these challenges, filtering methods, including advanced Kalman and particle filters, demonstrated resistance to noise and power dynamics. Moreover, their adaptive extensions have proven effective in some dynamic environmental conditions. Studies mainly implement KF techniques in UAV applications, with a minor presence of studies addressing HEA, and a complete absence of eVTOL aircraft. The investigation concluded that the absence is due to the clear gap in research testing these techniques in extremely low-pressure conditions and significantly high discharge power. Adaptable hybrid techniques could be the solution to this, as traditional KFs are vulnerable to ambient conditions. Studies integrate temperature correction layers into KF models to enhance their temperature adaptability. We grouped these layers into 4 categories: semi-empirical models, ML models, optimization techniques, and filter enhancement techniques. Applying similar correction layers for pressure effect adaptability will accelerate progress and experimental deployment of these techniques in HEA and large-scale eVTOL aircraft.

ML models sealed this gap by offering a wider range of architectures suitable for UAVs, eVTOL aircraft, and HEA. Shallow learning architectures, such as RF, BPNN, and SVR, exhibit promising performance in eVTOL aircraft applications. Nevertheless, we observed that all studies applying them to eVTOL aircraft have used the same dataset. This dataset, although replicating eVTOL aircraft power demands, maintains constant (not transient) temperature throughout the experiments, neglecting temperature dynamics. Consequently, we expect these models to underperform when tested in a more practical dataset that considers temperature transitions during flight phases. Deep learning architectures, such as LSTM and GRU, are effective in UAV applications as they offer superior adaptability to ambient environmental conditions and power dynamics. They accurately estimate battery parameters under extreme and fluctuating temperatures. However, we noticed that studies lack testing with benchmarked datasets, as most studies test their models on personal datasets. Moreover, most of their adaptive models incorporate physics-based inputs only, such as voltage, current, and temperature. Although these inputs provide feedback on the flight phases and environmental conditions, they ignore context-aware inputs such as mission type. Unlike traditional ML techniques, hybrid ML models offer prediction accuracy in extreme conditions with data scarcity. As studies test them in high discharge powers and extremely low temperatures, they sustain their accuracy. Finally, Transformer models outperform typical deep learning architectures when tested in low temperatures. Lightweight transformers can provide an accurate and computationally efficient solution for HEAs operating in these conditions.

Finally, the investigation revealed that fuzzy-based approaches are not widely used for battery state estimation in electric aviation batteries. We justified this by the relative vulnerability of purely fuzzy-based techniques to dynamic regression tasks such as SOC and SOH estimations. However, these techniques are widely used in power allocation, decision-making, and energy management. Unlike KFs and ML architectures, fuzzy-based techniques highly incorporate the human factor. Experts form membership functions and rule-based relationships based on their knowledge, experience, and skills. Therefore, combining fuzzy-based techniques with other data-driven techniques has achieved promising results. Nevertheless, we observed that most studies on hybrid fuzzy-based techniques lack interpretability metrics. As interpretability is the major concern slowing regulatory approvals and experimental deployment of these techniques, we expected interpretability to be a pivotal research focus.

This review provides the following specific areas and gaps, discovered in advanced battery state estimation in aviation applications:

- Despite the outstanding energy and power densities offered by Li-Po batteries, which are ideal for UAVs and eVTOL aircraft, there is a notable lack of research integrating ML-based, KF-based, and fuzzy-based approaches for their state estimation, leaving a critical gap in optimizing their performance and reliability.
- The unique power, temperature, and pressure demands of electric aviation offer an opportunity for researchers to obtain new datasets, specifically tailored to aviation. These datasets are the cornerstone

for future developments and industrial deployment of estimation techniques.

- Most KF studies focused on UAVs, while neglecting eVTOL aircraft and HEA. Studying and optimizing KFs' performance in low-pressure environments will accelerate the adoption of these techniques in HEA.
- Shallow models in eVTOL aircraft applications should be tested with datasets simulating the transitional nature of eVTOL aircraft missions. Since a foundational dataset is present, researchers can replicate these experiments while tuning the only missing element (transient temperature conditions).
- In UAVs, researchers should focus on testing their deep learning models on benchmarked datasets for better conclusions and generalization.
- The field requires greater focus on adaptive and context-aware algorithms that can incorporate flight transitions and mission type as model inputs. This gap is particularly critical for eVTOL aircraft and UAVs operating in dynamic and variable mission profiles.
- The lack of interpretability research targeting hybrid neuro-fuzzy models in electric aviation reveals a significant gap. This underscores the need to evaluate current interpretability techniques and innovate solutions specifically tailored to operational and regulatory requirements of the aviation domain.
- Transformer-based techniques outperformed traditional deep learning techniques in low-temperature environments. However, studies should be tailored to electric aviation applications in terms of battery properties and testing protocols to confirm reliability.

## CRediT authorship contribution statement

**Abdeen Ahmed Osman:** Writing – original draft, Visualization, Methodology. **Mahmoud Z. Mistarihi:** Writing – review & editing, Funding acquisition. **Mohamad Ramadan:** Writing – review & editing, Conceptualization. **Mohammed Ghazal:** Writing – review & editing, Supervision. **Mohammad Alkhedher:** Writing – review & editing, Supervision, Project administration.

## 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.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rineng.2025.106741.

## Data availability

No data was used for the research described in the article.

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