Journal of Energy Storage 142 (2026) 119523

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Review Article

Battery management in electric aviation: A bibliometric review of technologies, regulations, and international collaborations

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ARTICLE INFO

Keywords:
Electric aircraft
Lithium-ion battery
Neural networks
State-of-charge
Temperature prediction
Urban air mobility

ABSTRACT

This paper presents a bibliometric analysis of research trends and gaps in battery management systems (BMS) for electric aviation, spanning 1997 to December 2024. Based on 500 publications, the study identifies academic collaborations, regulatory frameworks, thematic evolutions, and research hotspots. It also highlights the field's most critical documents, countries, authors, and affiliations. The results reveal three major research phases: foundational development (1997–2016), rapid growth (2017–2022), and advanced multidisciplinary exploration (2023–December 2024). UAVs emerge as a central focus throughout, with increasing emphasis on electrical take-off and landing (eVTOL) aircraft in the later stages. Machine learning (ML), fuzzy logic approaches for power and thermal control, and predictive models for state estimation and problem diagnostics are among the most significant breakthroughs in the domain. However, significant challenges persist in this research domain, including the absence of clear regulatory frameworks for ML integration, the scarcity of onboard BMS models for large-scale aircraft, and insufficient predictive models for thermal management in eVTOL aircraft. Additionally, limited international collaboration, particularly from the United States, restricts the potential for data diversity and global innovation. This review provides a roadmap for future research, emphasizing the need for adaptive, real-time BMS models, stronger international partnerships, and policy standardization to accelerate the field of electric aviation.

1. Introduction

1.1. Thermal and environmental challenges in electric aviation

Electrification in aviation is a critical turning point in the industry's quest to reduce carbon emissions and achieve sustainability. Globally, there is an increasing trend of switching to electric propulsion systems in support of attempts to address climate change and meet international carbon reduction goals, such as those established by the Paris Agreement [1–3]. Electric propulsion is especially beneficial for short-range and urban mobility applications since traditional aircraft technologies are inefficient and environmentally harmful [4,5]. Electric vertical take-off and landing (eVTOL) aircraft and unmanned aerial vehicles (UAVs) are the most prominent examples of this change. These vehicles facilitated more efficient, quieter, and environmentally friendly urban air mobility (UAM) solutions [6,7]. The adoption of electrification also aligns with the rapid advancements in renewable energy integration, battery technologies, and power management systems, rendering electric aviation increasingly viable and feasible [8,9]. By utilizing energy from renewable sources and eliminating direct emissions during flight, these technologies help reduce the environmental impact of aviation. Furthermore, electric propulsion technologies enhance energy efficiency, save maintenance costs, and simplify aircraft design [10].

Battery technologies represent a crucial element of UAVs, eVTOL aircraft, electric aircraft, and hybrid-electric aircraft (HEA). However, batteries pose numerous thermal and electrical challenges related to

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https://doi.org/10.1016/j.est.2025.119523
Received 26 June 2025; Received in revised form 29 October 2025; Accepted 17 November 2025
Available online 25 November 2025

aviation's unique and demanding operational conditions. UAVs demand a balance of energy and power density to enable mobility and long-duration duties, usually constrained by weight concerns [11,12]. eVTOL aircraft, on the contrary, necessitate a high-power density for short energy bursts during take-off and landing, emphasizing agility while optimizing weight and power tradeoffs [13,14]. Lastly, to do long-distance cruising with increased weight tolerance, HEA aims for high energy density [15,16]. Moving on to thermal problems, UAV performance is significantly hampered by low and fluctuating temperatures, especially at altitudes of up to 3000 m, where temperatures can range from −10 °C to −30 °C. Due to higher internal resistance and decreased discharge rates, lithium-ion (li-ion) batteries, which are often used in UAVs, may lose 20–30 % of their capacity under these circumstances [17]. eVTOL aircraft, which generally fly below 1500 m for urban mobility, confront ambient temperatures ranging from −10 °C to 40 °C. To maintain operating temperatures between 15 °C and 35 °C, eVTOL aircraft batteries need strong cooling technologies, such as liquid cooling and phase-change materials (PCM) [18]. Operating at elevations between 10,000 and 30,000 ft (3000 and 9000 m), HEA experiences temperatures as low as −40 °C. By decreasing ion mobility and total energy capacity, extremely low temperatures can have a significant effect on battery efficiency [15].

UAVs and eVTOL aircraft travel at elevations where pressure implications are minimal. However, HEA can operate at significantly higher altitudes that reach 30,000 ft. Low-pressure conditions have a significant influence on the status and performance of li-ion batteries, notably in operations such as high-altitude flying in HEA aircraft, with pressure dropping below 20–60 kPa [19–21]. Reduced pressure affects the battery's thermal characteristics by decreasing the convective heat dissipation coefficient, forcing the internal temperature to increase rapidly [22]. Consequently, batteries can achieve thermal runaway (TR) states at lower ignition temperatures and considerably shorter periods than standard ambient pressure conditions. Extremely low pressures, reaching 30 kPa, expedite the initiation of TR and deteriorate thermal stability due to the rapid rupturing of safety valves and the premature release of flammable gases [23]. Another notable effect of low pressure on LIBs is rapid propagation behavior, which impairs the stability of battery modules in arrangements like those found in aircraft. Sun et al. [24] discovered that decreased convective heat transfers associated with reduced pressure (primarily around 20 kPa) deteriorate heat dissipation. This elevates internal cell temperatures more rapidly at localized spots during TR than a uniform temperature distribution.

1.2. Battery management in electric aviation

In electric aviation, battery management and thermal management are often discussed together, yet they serve different but complementary functions. The battery management system (BMS) primarily governs the electrical, computational, and diagnostic aspects of the battery pack, including electrical state estimation, power regulation, balancing, and fault detection [11,25]. Conversely, the battery thermal management system (BTMS) focuses on maintaining the battery within its optimal temperature range through active or passive heat dissipation techniques, ensuring thermal uniformity and preventing TR [26,27]. While their objectives differ, electrical control versus thermal regulation, both systems are interdependent. The BTMS often operates as a physical subsystem coordinated by the BMS, forming an integrated system that ensures electrical stability, thermal safety, and an overall efficient battery performance under the demanding conditions of electric aviation [28].

BMS in aviation focuses on battery state estimation, charging/discharging, and instantaneous power regulation in the demanding nature of these applications. Advanced machine learning (ML), fuzzy logic, and filtering techniques are the imperative solutions to the complex nature of these applications [29,30]. However, all these techniques encounter critical challenges that affect their performance and effectiveness. Firstly, electric aircraft certification, training validation, and model verification must be considered in real-world flight scenarios, as environmental conditions significantly influence batteries [31]. Therefore, Shen et al. [32] trained, validated, and tested their radial basis function neural network (RBFNN) model utilizing datasets from practical electric buses rather than lab-based datasets. Furthermore, BMS that facilitate online learning are more accurate and effective in dealing with the dynamic nature of UAVs, eVTOL aircraft, and HEA [33–35]. The continuous modification of model parameters is crucial in applications where environmental changes are widespread [36]. One of the studies used artificial neural networks (ANN) and online learning to identify the equivalent circuit models' parameters and accurately estimate the battery state-of-charge (SOC) [37]. While these online models boost prediction accuracy, the corresponding computational time increases accordingly. To tackle this issue, Khaleghi et al. [38] integrated similarity-based models to predict battery health and prognosis regardless of aging patterns. This technique relies solely on historical cases with known failure data to make predictions, eliminating the need for explicitly defined failure criteria. As a result, it reduces computational burden and facilitates real-time operation.

BTMS, on the other hand, focuses on increased cooling capacity, reduced weight, drag, and power consumption [39]. UAVs commonly operate at altitudes where low air density limits cooling efficiency, necessitating innovative approaches. Gong et al. [40] demonstrated that boosting air stoichiometry in air-cooled fuel cell stacks allows UAVs to achieve heat dissipation while adding minimal weight, an essential factor for long-duration missions. Recognizing the need for weight-efficient alternatives, Guibert et al. [41] proposed thermo-electrochemical topology optimization to reduce heat resistance in tiny battery layouts. This method is especially valuable for eVTOL aircraft applications, where small battery packs require precise heat dissipation to minimize performance degradation during rapid discharge. In HEA, studies indicate that liquid cooling, ram-air (RA) cooling, outer mold line cooling, heat exchangers, and the utilization of fuel as a heat sink are the most effective heat transfer techniques [42–45]. Among all these technologies, liquid cooling has the most significant heat collection-to-size ratio [46]. This makes it the most popular and effective cooling technique proposed for HEA, with a high technology readiness level (TRL) (>7) [47]. On the other hand, emerging techniques such as thermoelectric heat sinks are being studied for their tremendous potential to minimize fuel consumption and promising thermal management capabilities [48].

1.3. Objective and scope of the study

Given the growing interest and significant increase in research on BMS for electric aviation, including their critical roles in UAVs, eVTOL aircraft, and HEA, there is a pressing need to systematically evaluate the evolution, trends, and gaps in this domain. Therefore, this review presents a comprehensive bibliometric analysis confined to BMS/BTMS in electric aviation. The presented data is explored under a core lens that focuses on BMS power/energy functions and metrics such as SOC, state-of-health (SOH), state-of-power (SOP), and other safety indicators. Additionally, the study discusses emerging trends and developments in BTMS architectures and controls, including air, liquid, hybrid, and passive cooling. To limit the scope of the study, papers focusing primarily on battery chemistry/materials and general electric propulsion without an aviation BMS/BTMS component were excluded from the core analysis. Their use was restricted only to referencing for context where necessary or to demonstrate the evolution of the domain. The main contributions of this work are as follows: (1) providing a comprehensive quantitative overview of research trends and thematic evolution specific to BMS for UAVs, eVTOL aircraft, and HEA, offering an evidence-based foundation for understanding advancements in power and thermal regulation; (2) identifying key research gaps and priorities in power and thermal management through a structured, data-driven approach, ensuring actionable recommendations; (3) assessing regulatory frameworks to identify gaps and opportunities for standardized guidelines supporting safe integration of advanced BMS in electric aviation; and (4) analyzing global collaboration networks to uncover institutional and regional disparities, thereby identifying opportunities for fostering international and interdisciplinary partnerships.

This bibliometric study is organized into five sections, covering the evaluation and analysis of trends and gaps in BMS in electric aviation. The rest of this paper is as follows: Section 2 presents the bibliometric methodology used in this study, covering data collection approaches, visualization tools, and analysis techniques. Section 3 is the core section of this paper, with all the results and discussions affiliated with authors, institutions, countries, keywords, and themes. Section 4 discusses the domain's challenges and research gaps and suggests recommendations for future research directions. Finally, Section 5 summarizes this study's main conclusions, key contributions, and limitations.

2. Methodology

The numerous benefits of bibliometrics have rendered it an increasingly common method for researchers to investigate their research domain. Unlike purely narrative approaches, this analysis leverages tangible visualizations, such as keyword co-occurrence maps, thematic development charts, and co-authorship networks, offering objective and reproducible insights into the field. This research intends to use bibliometrics to more effectively evaluate current and future trends in BMS of electric aviation and UAM applications. Fig. 1 depicts the methodology used in conducting the bibliometric analysis of BMS techniques and technologies of electric propulsion systems of aviation. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) technique was utilized to collect organized and clear bibliometric information [49–51]. Furthermore, providing detailed definitions of the bibliometric techniques helps overcome the interpretability and black-box problem often associated with science mapping. It ensures that the results are grounded in measurable network-based indicators rather than only software-generated visuals. This transparency enhances the credibility of the analysis. It also improves reproducibility, allowing other researchers to replicate the study and validate the findings across co-occurrence, thematic mapping, thematic evolution, and citation-based analyses.

2.1. Data collection

Scopus, created by Elsevier in 2004, is an invaluable database that includes various publications released from the nineteenth century to the present. Because the study of BMS in aviation is mainly linked with engineering, Scopus was utilized to create bibliographic data in December 2024. The "advanced search" tool on Scopus was used to tailor the search query, which covered a wide range of document types, including research articles, review articles, and conference papers. A

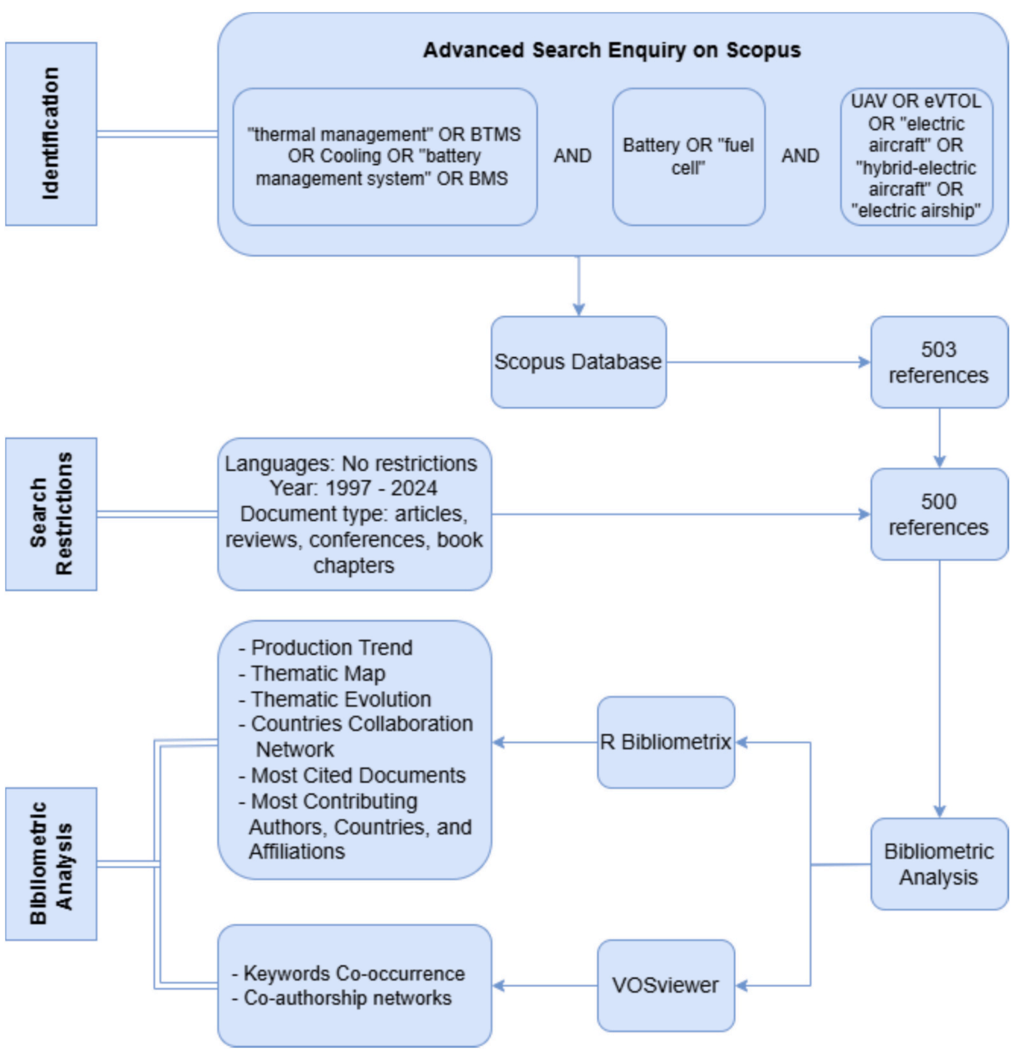

Fig. 1. PRISMA methodology used in the bibliometric analysis.

topic search was used to find documents that contained relevant search terms in the title, abstract, or keywords. Furthermore, no language restrictions were set, with the search covering the period settled as 1997–2024. Following the evaluation of 503 search results, we exported the bibliographic data (affiliations and publishers), abstracts, keywords, and citation information (authors, document titles, source titles, etc.) of the 500 qualified publications as an Excel file for the study. The exact search query and the raw bibliometric data are provided in the supplementary material section.

2.2. Visualization tools

This analytical inquiry employs a rigorous bibliometric technique, combining statistical data and mathematical representations to analyze various elements of the research field thoroughly. Bibliometric tools such as VOSviewer and R Bibliometrix were used to conduct a quantitative study, producing statistical results for the evaluated academic documents. The current research performs a bibliometric analysis of the strategies used in aviation applications using VOSviewer (version 1.6.20) and the Bibliometrix package in R (version 4.3.2). Bibliometrix, established within the R programming environment, is a readily available resource for extensive bibliometric analysis, and its capabilities are expanding rapidly. This tool provides a variety of crucial analysis visualizations, including thematic maps, factorial graphs, most cited articles, sources, affiliations, and countries' collaborations [52,53]. On the other hand, VOSviewer software allows for investigating sophisticated elements of keyword trends and researcher collaboration networks, such as author co-citation, co-authorship, and bibliographic coupling networks. These graphs and figures provide a valuable overview of the current research trends, scientific surge, and potential gaps in the domain [54].

2.3. Bibliometric methods

The bibliometric analysis covered several essential components. To measure the progress of research efforts in BMS of aviation vehicles, publication trends were first examined. The conceptual structure of the subject area was investigated by co-occurrence, thematic mapping, and thematic evolution. These strategies provide insights into the relationships between research themes and predict potential future research directions. Furthermore, the analysis intends to determine the leading countries, research institutes, and publications in the domain to understand the current research focus of the major contributors. The study additionally examined international research collaboration and knowledge exchange methods among different countries to gain a global perspective. Finally, we examined the most frequently cited publications to identify crucial studies significantly impacting the field. These methodologies help researchers determine stakeholders' interests and attributes, in addition to the current state of international collaboration and knowledge exchange. To conclude, using the Scopus database, PRISMA methodology, and verified bibliometric tools such as VOSviewer offers a solid foundation for the study.

The thematic map was constructed through a multi-step process combining co-word analysis, similarity measures, clustering, and the application of Callon's centrality–density framework. This approach is framed and organized also by Cobo et al. [55]. Firstly, a co-occurrence network of keywords was generated, where the equivalence index was used to normalize the strength of association between two terms i and j. According to Van Eck et al. [56], the equivalence index established by Callon et al. [57] is the best normalization measure for co-occurrence frequencies. The equivalence index is defined as:

$$e_{ij} = \frac{c_{ij}^2}{c_i c_j} \tag{1}$$

where c_{ij} is the number of documents in which both keywords i and j co-occur, and c_i and c_j represent the number of documents in which each term appears individually. This normalization ensures that the co-occurrence strength is not biased toward more frequent keywords.

Next, keywords were grouped into clusters representing research themes. Clustering was performed using community detection algorithms (e.g., InfoMap, Louvain), which partition the co-word network into subgroups of strongly associated terms [58]. Finally, each cluster was characterized using Callon's centrality and density measures [57]. Centrality reflects the degree of interaction of a cluster with other clusters and is used as an indicator of a theme's importance in the research field:

$$c = 10 \times \sum e_{kh} \tag{2}$$

where e_{kh} represents the strength of links between cluster k and other clusters h. On the other hand, **density** measures the internal strength of connections within a cluster and indicates the theme's **maturity**:

$$d = 100 \times \frac{\sum e_{ij}}{w} \tag{3}$$

where e_{ij} is the internal link strength between keywords i and j belonging to the cluster, and w is the number of keywords in that cluster.

Moreover, in this study, the distinction between incremental and substantial research was addressed indirectly through a combination of frequency- and citation-based indicators. The co-occurrence and thematic analyses emphasized recurring themes supported by multiple documents, which may reflect incremental advances. Citation-based indicators such as total citations (TC) and average citations (AC) highlighted influential studies that, although they might be less frequent sometimes, represent substantial contributions to the field. This dual consideration allowed the analysis to capture both the breadth of repeated research activity and the depth of highly impactful but less common works.

3. Results and discussion

3.1. General information and production trend

The bibliometric study offers a thorough overview of research on BMS in electric aviation from 1997 to 2024. During this time, 500 documents were published from 264 sources, representing a moderate yearly growth rate of 4 %, as shown in Fig. 2. This research field has received contributions from 1478 authors, demonstrating the diversity and extent of academic activity. Only 23 documents were written independently, explaining the field's strong collaborative nature. The average number of co-authors per document, 4.03, supports this trend, demonstrating the multidisciplinary and collaborative approach necessary to address the issues of energy management and temperature control in electric aviation systems. Furthermore, the 12.2 % foreign co-authorship reflects the global commitment to developing this essential study subject. The topic is distinguished by 1060 author keywords, indicating its large but concentrated subject scope, including theoretical frameworks and practical implementations. The 13,725 references in these publications demonstrate a heavy dependence on previous research, laying a solid platform for additional investigation. The average document age of 4.32 indicates a relatively young and fast-changing area. In contrast, the average number of citations per document is 13.41, indicating the rising academic significance of works in this domain. These data depict a dynamic and collaborative research community tackling one of the most critical issues in sustainable aviation.

The timescale graph of research production on BMS in electric aviation is crucial for bibliometric analysis. It indicates the research's significance and trends in the area. Observing the quantity of publications over time might reveal trends in research efforts and shifts in concentration. Research within a certain period goes through various

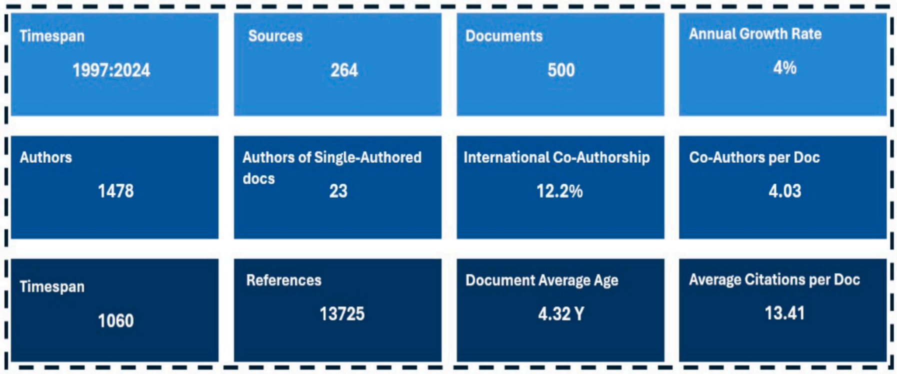

Fig. 2. Primary information of bibliometric data.

growth, peak, and decline stages, allowing researchers to determine the most suitable times for further studies. Moreover, such graphs can help government agencies analyze the growth of an area and formulate related policies. In conclusion, annual scientific production graphs help scholars, policymakers, and investors comprehend a field's evolution and features, allowing for more informed decision-making.

As shown in Fig. 3, the annual scientific output in BMS and BTMS for electric aviation, such as eVTOL aircraft, UAVs, HEA, and electric aircraft, shows an apparent evolution through three different stages: foundational growth (1997–2016), rapid acceleration (2017–2022), and breakthrough (2023–December 2024). Between 1997 and 2016, research activity was modest, indicating the early stages of electric aviation technologies, with general studies having a wide scope. The growth rate in this period, denoted by the graph slope, was 0.26, indicating insignificant growth. Although a minor effort toward industrial cooling mechanisms was introduced in 1997, the need for BMS in electric aviation was initially introduced by Fellner and Loeber [59] in 1999. They discovered that cell behavior is highly vulnerable to ambient temperature, necessitating a BMS tailored to aviation applications. Most publications during this stage focused on fundamental studies of battery chemistry, basic electrical performance, and battery behavior in dynamic ambient conditions [60–62]. However, these early investigations were critical in establishing a foundation for understanding thermal sensitivity, safety thresholds, and cell behavior. Such knowledge later guided the development of advanced aviation BMS and BTMS solutions through a better understanding of cell behavior with respect to ambient conditions. Limited publications during this period can be attributed to technological limitations, such as low battery energy density and thermal safety, along with a lack of industrial demand [63–65].

2017–2022 experienced an exponential increase, with publications exceeding 80/year by 2022 and an average growth rate of 8 documents per year. This acceleration corresponded with advances in li-ion battery technology, a renewed emphasis on sustainable aviation, and significant investment in UAM prototypes by major manufacturers such as Hamilton Aerospace, Zunum Aero, and Volocopter [66–68]. As shown in Table 1, the first electric aircraft designs were launched during this period, with most of the designs being limited to a maximum of 2 passengers. However, some business electric and HEA were manufactured with greater capacities, such as the ZA10 and Eviation Alice [69]. These industrial breakthroughs demanded that researchers move their attention from basic research to practical, scalable solutions for TR avoidance and adaptive cooling systems geared to aircraft batteries. After 2023, the domain reached a breakthrough phase, with over 100 publications per year and a growth rate of 26, indicating an exceptional pace caused by the near commercialization of electric aviation vehicles [70]. Moreover, some crucial industrial partnerships were launched during this period, including the Airbus-Siemens-Rolls-Royce partnership to accelerate the production of the E-Fan X. Such imperative partnerships fund tremendous research and development projects, especially in battery design and advanced BMS.

Analyzing language usage in publications helps comprehend BMS geographical distribution and international collaboration in electric aviation. Although English is the primary language used in prestigious journals, Chinese and Spanish are the most spoken native languages worldwide. Non-native English speakers may encounter a citation rate when publishing articles in languages other than English, a common observation in the academic community [71]. By analyzing the

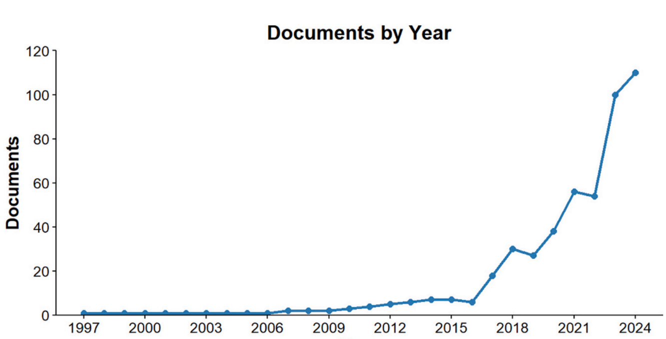

Fig. 3. Annual scientific output of the domain.

Table 1
Some of electric aviation's industrial projects and products.

Project	Country	Type	Category	Pax	Year
Pipistrel Alpha Electro	Slovenia	Electric	General aviation	2	2018
Kitty Hawk Cora Generation 5	USA/New Zealand	Electric	eVTOL aircraft	2	2019
Airbus Vahana	France/USA	Electric	eVTOL aircraft	1	2019
Volocopter 2×	Germany	Electric	eVTOL aircraft	2	2018
Eviation Alice	USA	Electric	Business aircraft	9	2022
Siemens Extra 330LE	Germany	Electric	General aviation	2	2016
Hamilton Aero	New Zealand	Electric	General aviation	1	2017
Eve Air Mobility (Embraer)	Brazil	Electric	eVTOL aircraft	4	2024
The ePlane Company (e200/e200X)	India	Electric	eVTOL aircraft	2	2021
Magnix eCaravan	USA	Electric	Commuter aircraft	9–12	2020
EHang 216	China	Electric	eVTOL aircraft	2	2018
Ampaire Electric EEL	USA	Hybrid	Commuter aircraft	6	2019

predominant language distribution in a field's research, we help researchers who are not proficient with the dominant language and identify possible language challenges they might face. Furthermore, when a study subject includes a range of languages, examining language percentages might indicate trends in cross-cultural research. Furthermore, analyzing language distribution might reveal instances of interdisciplinary study within a topic, as introducing literature in other languages is frequently connected with multidisciplinary research. Thus, investigating the linguistic distribution of publications bears essential importance.

Based on Fig. 4, it is evident that English is the predominant language in scholarly publications, accounting for 97 % of all papers in the field. Chinese ranks second with 2.6 %, and Korean third with 0.4 %. This overwhelming dominance of English reflects its role as the primary medium for global academic communication, ensuring broader visibility, accessibility, and citation potential. However, this linguistic trend may present challenges for researchers interested in contributing to the field but not proficient in English, the dominant language. For non-native English-speaking researchers, the language barrier can be a significant obstacle to engaging with existing literature and disseminating their findings effectively. While publishing in English maximizes impact and facilitates cross-border collaboration, it inherently limits accessibility for scholars from regions where English proficiency is not widespread. This barrier may discourage contributions from talented researchers whose work could enrich the field but lacks the exposure afforded by English-language publications.

3.2. Country, institution, and personnel analysis

Identifying countries, institutions, and authors of BMS in electric aviation literature offers numerous purposes. The analysis evaluates international collaboration in this discipline, allowing academics to locate possible collaborators and promote global knowledge exchange and partnerships. Examining the institutions engaged in this research helps identify those with considerable impact. This information will help academic institutions and government organizations identify opportunities to collaborate with prominent entities. Acknowledging authors who have contributed significantly to electric aviation's BMS is crucial for policymakers to identify prospective mentors and expert advisers. In conclusion, analyzing countries, academic institutions, and authors provides a better knowledge of the global scene, key contributors, and trends in the research. This offers researchers and government bodies essential insights, advancing electric aviation's research and development. This examination is crucial for the field's advancement and growth.

3.2.1. Analysis of the most contributing countries and their scientific collaborations

Based on the analysis of 500 documents, the data reveals significant contributions from diverse countries, reflecting the global importance of developing efficient and reliable BMS technologies to support sustainable air mobility. The research output is concentrated in regions firmly committed to advancing aviation electrification, such as North America, Europe, and Asia, where established research institutions and robust industrial ecosystems foster innovation. At the same time, contributions from emerging economies demonstrate growing interest in the field, indicating a shift toward more inclusive global participation.

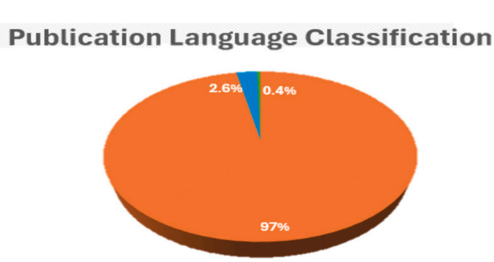

Fig. 4. Language classification of publications.

Fig. 5 depicts the geographical distribution of scientific papers on BMS for electric aircraft, with the United States (U.S.) and China as the primary contributors. The U.S. has the most publications, more than 140, followed by China, which has over 100. This supremacy is due to these nations' robust research ecosystems, industrial capacities, and strong policy frameworks, pushing advances in aviation electrification [72–75]. In the US, initiatives such as NASA's advanced air mobility (AAM) Program and significant investments by companies like Joby Aviation, Beta Technologies, and Archer Aviation have created a fertile ground for research and innovation in battery technologies. Additionally, the U.S. Department of Energy's focus on developing advanced battery systems, particularly for high-density applications, aligns with the demands of electric aviation. These efforts emphasize the integration of safe, lightweight, and high-performance batteries into the next generation of aircraft, fostering collaboration between academia and industry [76]. On the other hand, China has made significant progress through government-backed projects like Made in China 2025, which focuses on battery innovation and transportation electrification. The emergence of Chinese enterprises like EHang, a pioneer in autonomous eVTOL aircraft, has prompted significant research into BMS technology. China's concentration on UAM and its leading position in global lithium battery manufacturing give it a strategic advantage [77,78]. This highlights the critical influence of the US and China in advancing BMS technologies for electric aviation. Understanding the drivers behind their high research output, such as key policies, large-scale projects, and industrial priorities, provides valuable insight into the field's strategic directions. It reveals where innovation thrives, whether in areas like high-density energy storage, advanced thermal management, or scalable battery systems tailored for aviation applications.

Beyond the US and China, countries such as Germany, the United Kingdom (UK), Italy, and France also contribute significantly to the research landscape of BMS in electric aviation, reflecting their strong industrial ecosystems and academic excellence in advanced engineering and sustainable technologies. The prominence of European countries underscores the continent's concerted efforts to decarbonize aviation within frameworks such as the European Green Deal and the Flightpath 2050 vision, which prioritize electrification and hybrid-electric systems [79,80]. These nations play a vital role in global collaborations, further expanding the scope and impact of BMS research. Germany's position, for instance, can be attributed to its robust aerospace and automotive sectors, which intersect with battery innovation. Initiatives like the electric flight demonstrator program and significant investments by companies like Airbus and Lilium have positioned Germany as a leader in developing high-performance BMS technologies for eVTOL aircraft and electric aircraft [81]. Moreover, Germany's expertise in energy storage systems extends from its automotive successes, translating into cutting-edge solutions for aviation. Similarly, South Korea's presence among the top contributors is tied to its dominance in li-ion battery manufacturing and its push for innovation in energy storage systems. LG Energy Solution and Samsung SDI are pivotal in advancing battery technologies, focusing on lightweight, energy-dense systems [82]. South Korea's contributions demonstrate how a country's industrial strength in battery production can pivot into aviation applications, highlighting a path for others to follow in aligning industry and research for sustainable air mobility.

According to Fig. 6, the notable academic efforts in the domain by Europe, Asia, and North America have culminated in numerous active global scientific collaborations. China and the UK's partnership in battery technology, for instance, is essentially motivated by a shared interest in the advancement of UAVs [83–87]. Both countries strongly emphasize BMS, which is critical for assuring the reliability and effectiveness of UAV power systems. Their principal collaborative research efforts are focused on developing air-cooling technologies and adaptive

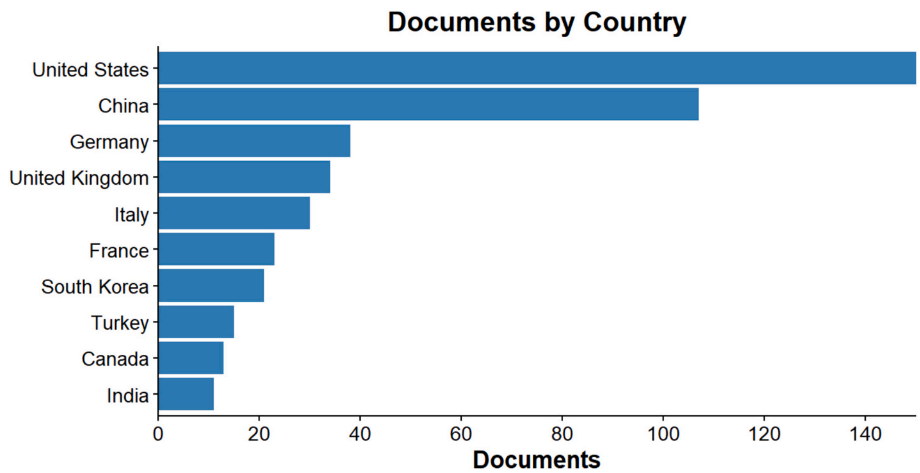

Fig. 5. Total number of documents of the most contributing countries in the domain.

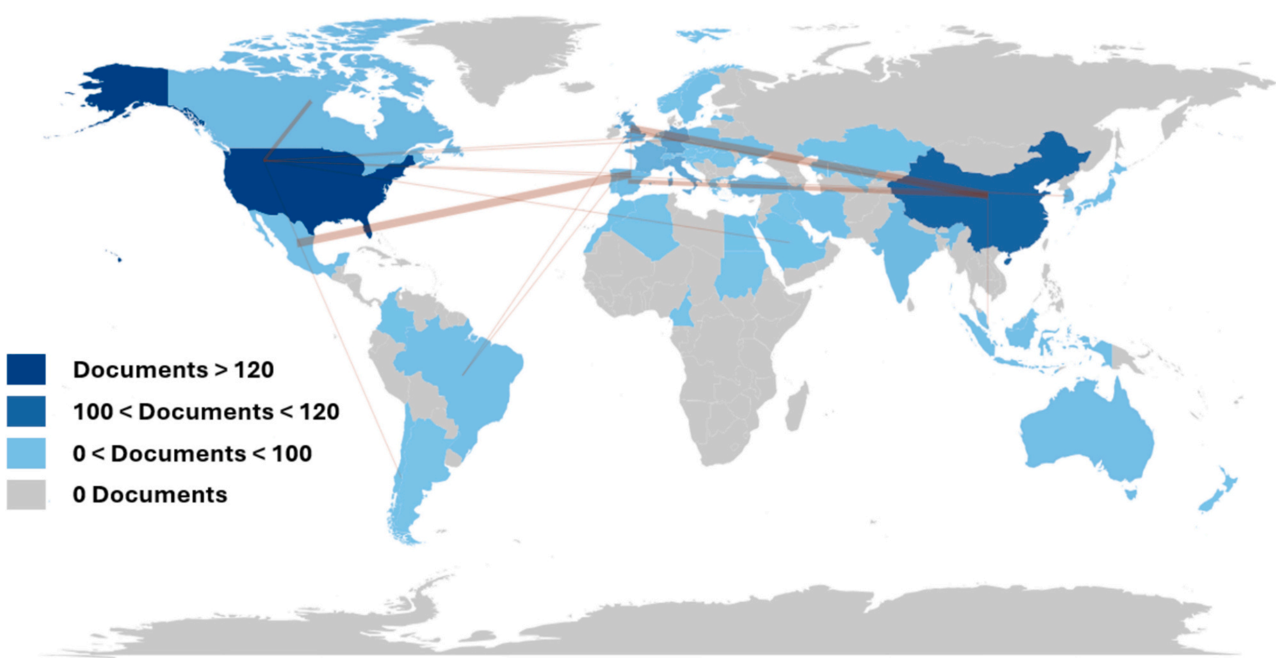

Fig. 6. International collaboration network of the domain.

battery parameter identification, including accurate prediction of the SOC, SOP, and SOH to improve battery performance and durability [88,89]. Similarly, several collaborations between China and Spain are driven by the mutual interest in UAV BMS technologies. However, these collaborations are concentrated on battery parameter identification using advanced techniques such as unscented Kalman filters (UKF), with the absence of any collaborative studies related to BTMS [17,30]. On the other hand, the US, the most contributing country in the domain, exhibits fewer active collaborations than China. This is attributed to U.S. organizations' preference for fostering internal collaborations between the universities, major government agencies (e.g., NASA, DOE), and private companies (e.g., Tesla, Boeing) over international partnerships. Ampaire's ongoing significant work with NASA, Boeing, and GE in developing fully electric and HEA is a testament to that [90].

Although the domain includes numerous technologically developed countries, such as China, the U.K., and Spain, it lacks collaborations between these developed countries and some emerging developing countries. Firstly, as shown in Table 1, most industrial prototypes or operating industrial solutions are developed by developed countries such as the U.S, China, and Germany. This provides a significant advantage for these countries to collect vast amounts of data under actual ambient and flight conditions [91,92]. This data is the fundamental element of a data-driven BMS [93]. On the other hand, developing countries, although having some theoretical solutions tested by domestic startups and companies, still have limited industrial operators in the field compared to developed countries. Consequently, they will have fewer opportunities to acquire data that is crucial for their solutions, resulting in slower progress. Over time, the slower progress will widen the gap between them and developed countries, resulting in asymmetry in innovation progress [94]. Furthermore, with the rapid growth of the field, researchers are working on battery designs and optimization with a significant range suitable for cross-border flights [95]. Since these aircraft might be traveling between countries in the future, batteries will encounter significantly dynamic environmental conditions. Without data sharing between developed and developing countries to train and validate the data-driven models, BMS will struggle to adapt to the real-time environmental changes [96]. Although the tests can still be conducted in controlled lab environments, having real-time data from actual test flights is superior and more effective.

Data sharing is an effective framework that, although requiring meticulous planning, is driven by several essential factors. Batteries in electric aircraft operate under highly dynamic and safety-critical conditions, where high discharge rates make them particularly sensitive to ambient temperature and pressure variations [96]. In EVs, by contrast, batteries operate at much lower discharge rates relative to their capacity, causing their performance characteristics to remain largely stable under normal environmental changes, except in extreme climates [97]. This distinction makes aviation applications far more dependent on accurate environmental modeling and broader data availability to ensure reliability and safety. Since most current flights remain domestic, a data-sharing framework is not an immediate necessity. However, the rapid advancement of electric aviation and ongoing improvements in battery technology are expected to lead to cross-country operations with wider environmental diversity [98]. Establishing such a framework early serves as a precautionary measure, avoiding future challenges related to delayed certification or costly adaptation of unstandardized systems once the issue materializes [99]. Beyond improving adaptability, data sharing also plays a vital role in expanding the knowledge base for institutions and researchers without access to flight prototypes, allowing them to validate and refine models using real-world data rather than relying solely on controlled laboratory experiments [100].

A similar pattern has already been documented in other battery applications, where resource-rich countries in the global south remain largely excluded from the most advanced stages of technological innovation [101,102]. Despite their abundance of natural resources, countries such as Argentina, Bolivia, and Chile contribute minimally to patenting and technology development, while a small group of technologically advanced economies dominate innovation and industrial deployment. This imbalance is reinforced by weak research–industry linkages in these countries, limited absorptive capacity, and insufficient participation in international collaboration networks [101]. Consequently, developing countries risk remaining confined to the role of raw material suppliers, while a small group of economies continue to accumulate technological and commercial advantages [102]. Projecting this observation to the domain of electric aviation BMS, there is a concern of adopting a similar structural asymmetry. Developed countries, supported by industrial operators and certified prototypes, might maintain leadership by generating real-world data and validating advanced models. On the contrary, developing countries may have limited contributions with less impact on industrial practice. If unaddressed, this imbalance could translate from a concern into a reality.

3.2.2. Analysis of the most contributing affiliations

Table 2 reveals a global divide in research strategies, highlighting differences in institutional priorities between quantity and quality. The U.S. emerges as a highly active player, with four institutions represented and a focus on impactful research. For instance, NASA Ames Research Center achieves a notable AC of 13.8 with 13 publications. At the same time, Georgia Institute of Technology excels with an AC of 18.8, emphasizing high-value contributions. This demonstrates the U.S.'s ability to balance productivity and influence. China dominates in terms of publication volume, led by Northwestern Polytechnical University with 17 publications, although its AC of 5.0 suggests a focus on visibility over impact. However, the Beijing Institute of Technology stands out with an AC of 21.8, showing a strong commitment to producing highly influential work within a publication-driven system. Beihang University offers a balanced approach, with 16 publications and an AC of 7.0. European institutions prioritize quality over quantity. Cranfield University in the UK achieves the highest AC of 23.9, emphasizing impactful research despite having only 10 publications. Similarly, Politecnico di Torino in Italy maintains an impressive AC of 16.0, underlining Europe's tradition of academic rigor. In contrast, Germany's Deutsches Zentrum für Luft- und Raumfahrt, with an AC of 0.7, shows limited citation visibility, potentially due to a focus on specialized fields.

Table 2
Primary information of the most contributing institutions in the domain.

Affiliation	Country	Publications	TC	AC
Northwestern Polytechnical University	China	17	85	5.0
Beihang University	China	16	112	7.0
NASA Ames Research Center	USA	13	179	13.8
Deutsches Zentrum fur Luft-und Raumfahrt	Germany	11	8	0.7
University of Illinois Urbana-Champaign	USA	10	41	4.1
Cranfield University	UK	10	239	23.9
Politecnico di Torino	Italy	10	160	16.0
The Ohio State University	USA	9	51	5.7
Beijing Institute of Technology	China	9	196	21.8
Georgia Institute of Technology	USA	9	169	18.8

Understanding the research emphasis of the most prominent institutions in the field, and thus, the trend of the field, requires analyzing their research content. Research on hybrid-electric propulsion systems at "Cranfield University" focuses on thermal management issues, including weight considerations and heat transfer efficiency, which are crucial for aviation performance and safety [103]. Furthermore, fuzzy logic-based Equivalent Consumption Minimization techniques (F-ECMS) are integrated into their energy management techniques to maintain battery SOC and improve fuel economy in hybrid-electric systems for UAVs [85]. Designing and testing hybrid fuel cell/battery propulsion designs for long-endurance UAVs and eVTOL aircraft employing hardware-in-the-loop frameworks and high-fidelity simulation is another crucial area of research in this institute [104,105]. Similarly, the "Beijing Institute of Technology" focuses on advanced fuzzy logic-based energy management strategies for hybrid-electric UAVs, utilizing a fuzzy state machine (FSM) framework to optimize dynamic power sharing among fuel cells, batteries, and photovoltaics. Their research implements online fuzzy control algorithms coupled with state-based decision-making to enhance real-time energy efficiency, fuel utilization, and power stability across mission-specific profiles [23,106]. The focus on adaptive fuzzy-based control approaches, encompassing some for precise SOC regulation and multi-source integration, is consistent with Cranfield University's research on fuzzy logic-driven BMS optimization, establishing the foundation for future collaborations to improve intelligent BMS for electric aviation and UAVs. Finally, the most influential articles at "The Georgia Institute of Technology" highlight the computational and model complexity challenges in electric propulsion battery health and temperature predictions [107]. Consequently, multiple studies at "NASA Ames Research Center" propose reduced-order models, offering cost-effective and feasible models with reduced higher fidelity. This could also encourage future collaborations between the two institutes, considering the U.S. tendency for internal collaborations [108,109].

3.2.3. Analysis of the most contributing authors

Table 3 provides insights into key contributors to the field of BMS in electric aviation, highlighting diverse research focuses and varying levels of influence. Zhang Xiaohui emerges as a prominent figure, with a high AC of 29.8 across six publications, primarily in UAV and fuel cell integration, signaling a strong emphasis on hybrid-electric aviation technologies [110,111]. Similarly, Liu Li, with an AC of 25.7, has contributed significantly to UAV and fuel cell advancements, suggesting a strong intersection of fuel cell research with BMS for electric aviation [112]. Karakok Tahir's focus on li-ion batteries and PCM, combined with an AC of 24.5, underscores the importance of nanofluids in advancing PCM in BTMS of electric aviation [27,113–115]. Ozge Yetik's leading eight publications on li-ion batteries and BMS reflect the growing importance of advanced prediction models that utilize ML techniques such as ANN in the field [116]. Likewise, the integration of other ML techniques (e.g., deep neural network (DNN), long short-term memory (LSTM) in BMS research, demonstrated by Jean-Christophe Ponsart and

Table 3
Most contributing authors in the domain with their primary information.

Author	Research Focus	Publications	AC	Activeness period
Yetik, Ozge	• Li-ion batteries • PCM	8	18.5	2020–2024
Liu, Li	• Fuel cell • UAV	7	25.7	2016–2024
Ponsart, Jean-Christophe	• DNN, LSTM	7	11.7	2017–2023
Farhad, Siamak	• Li-ion batteries • BMS • Lithium molecular entity	6	18.3	2018–2021
Karakok, Tahir	• Li-ion batteries • PCM	6	24.5	2020–2022
Zhang, Xiaohui	• Fuel cell • UAV	6	29.8	2016–2024
Astorga-Zaragoza C.M	• Battery state estimation	5	15.8	2017–2019
Hashemi, Seyed	• Li-ion batteries • SOC estimation	5	22.0	2018–2021
Kazula, Stefan	• Propulsion systems • machine design	5	2.0	2023–2024
Kulkarni, Chetan	• DNN, LSTM • Li-ion BMS	5	12.0	2018–2024

Chetan Kulkarni, indicating a trend toward predictive battery performance and state estimation [117,118].

As shown in Fig. 7, the connection between Hashemi, Seyed, and Farhad, Siamak, represents a pivotal hub within the largest co-authorship network, highlighting their influence in advanced engineering systems, particularly in energy optimization and ML applications. This group's prominence provides a strong platform for expanding collaborations with other researchers. For instance, their shared interest in advanced BMS aligns with the expertise of Liu, Li, Zhang, and Xiaohui, who specialize in ML models and fuzzy-based techniques for energy systems. As the U.S. (Farhad group) and China (Liu group) are global epicenters for battery research with substantial financial investments, a collaboration between these two groups could yield groundbreaking results, such as novel ML models for battery diagnostics and optimization. Moreover, since much of these two research groups' contributions focus on UAV technologies, they could further engage with Astorga-Zaragoza, C.M., whose work on lithium-polymer batteries and energy consumption modeling requires updates. Sharing data and methodologies could enable comparative studies on the efficiencies and reliabilities of li-ion versus lithium-polymer batteries. Such an initiative would enhance energy models for UAV applications while bridging research silos across nations.

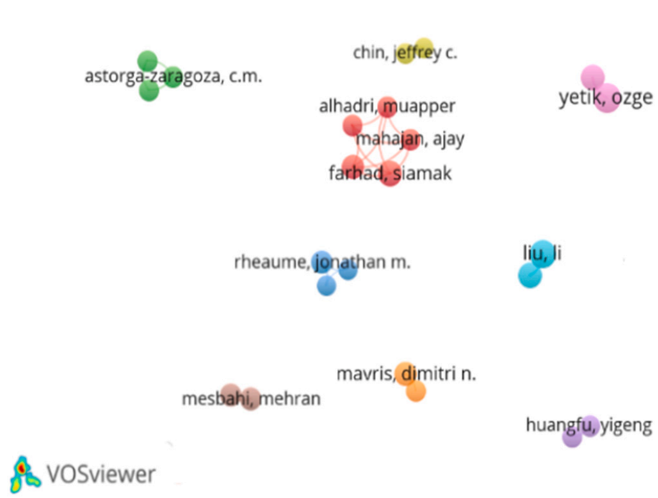

Fig. 7. Co-authorship network of the leading research groups in the domain, showing different research groups contributing to the domain.

3.3. Key research areas of focus in the domain

There are several reasons for examining the most influential publications in electric aviation's BMS. Firstly, it assists in pinpointing the research frontiers and popular themes in this field, which helps academics determine which areas are grabbing significant attention and where there could be gaps for potential contributions. Second, influential studies usually include excellent experimental design, data analysis, and methodology, providing other researchers who wish to improve their research skills with helpful learning materials. Additionally, researchers might highlight possible future collaborations by contacting the authors of these imperative papers in the field. Collaborative efforts frequently accelerate research advancement, particularly in multidisciplinary or international collaborations. Furthermore, scholars can choose their study issues and directions with the help of these paramount studies [119].

Table 4 highlights the most influential documents contributing to the domain of BMS for electric aviation, revealing critical insights into how the field has evolved, the dominance of Chemali et al. [120,121], with the highest TC (595 and 565) and AC/year (74.38 and 70.63), underscores a pivotal shift toward using ML techniques like LSTM and DNN for precise SOC estimation. These contributions signal the increasing importance of real-time, data-driven models in managing complex battery systems, aligning with the high-stakes demands of electric aviation [122,123]. In contrast, Brejle and Martins [124], focusing on electric propulsion's practical and theoretical challenges, reflects the necessity of bridging system-level considerations with battery management [125]. Interestingly, Mathew et al. [126] and Ure et al. [127] emphasize UAV battery optimization, suggesting the early focus of the field on reducing downtime and improving charging efficiency, which was foundational to the practical adoption of electric aviation technologies [128–131]. Recent works, like Yang et al. [13], focus on broader system requirements for eVTOL aircraft, including energy density and safety, showcasing the domain's expansion beyond UAVs to larger-scale applications. While Tariq et al. [132] and Shiau et al. [133] may have lower citation metrics, their contributions to BMS architectures and solar power integration reflect an enduring focus on sustainability and hybrid systems.

3.4. Research hotspots and gaps

Analyzing keyword co-occurrence networks and the thematic evolution of keywords is highly effective in identifying research gaps and hot topics in a domain. Studying current challenges, such as policy challenges (regulatory ambiguities or misaligned global standards), technical challenges (complex integration, data inconsistencies, or security vulnerabilities), and scalability challenges (managing increased complexity with growing datasets or broader applications), offers critical insights into the field's limitations. Understanding these challenges and exploring emerging solutions enables researchers to pinpoint areas of opportunity, track evolving trends, and effectively guide innovation to address the pressing needs within the domain.

3.4.1. Keyword co-occurrence analysis

Keyword analysis is a practical approach for summarizing significant concepts in a particular study subject offering insight into the principal emphasis of studies throughout a given period. Mapping research hotspots helps discover new trends and understand the present research direction within a domain. The rising frequency of particular keywords over time indicates a growing interest in certain subjects rendering it beneficial in suggesting novel investigation paths. Furthermore examining annual fluctuations in keywords helps identify topics that get constant academic interest allowing scholars to make more informed

Table 4
Most cited documents in the domain covering their year of publication, TC, AC per year, and key findings and main contributions.

Paper	Year	TC	AC/year	Key findings
Chemali et al. [121]	2018	595	74.38	The study presents a novel approach utilizing RNN with LSTM to accurately estimate the SOC of li-ion batteries. It demonstrates how the LSTM-RNN can precisely estimate SOC and express battery parameter relationships in real time without filters, battery models, or inference systems like UKFs.
Chemali et al. [120]	2018	565	70.63	Battery SOC is estimated using deep feedforward neural networks (DFNN), in which SOC is directly linked to battery parameters. The model is trained in versatile data to simulate the UAV's operation conditions.
Brelje and Martins [124]	2019	467	66.71	The study examines industrial products, prototypes, and theoretical investigations to compile a list of potential benefits and drawbacks of electric propulsion.
Mathew et al. [126]	2015	141	12.82	The study suggests an approach to effectively optimizing and controlling the charging of UAV batteries, a crucial element of BMS. Simulation using battery models demonstrated the effectiveness of the proposed approach.
Lee et al. [134]	2014	130	10.83	The study introduces an active power management system (PMS) that regulates power based on a UAV's supply and demand. The system responds to UAVs' dynamic power requirements while maintaining a SOC of 45 %.
Benzaquen et al. [107]	2021	120	24.00	The paper reviews the most critical challenges of electric hybrid-electric propulsion in aviation. It individually studies the main components of electric aviation vehicles, including batteries and power converters
Ure et al. [127]	2015	119	10.82	The study proposes a BMS for UAVs that optimizes the charging process, reducing UAV downtime and simultaneously allowing for multiple battery charging.
Yang et al. [13]	2021	115	23.00	The study comprehensively analyses eVTOL aircraft battery requirements, encompassing battery energy density, specific energy, power requirements, safety, etc. The paper is an asset for those aiming to understand the differences between electric vehicles (EVs) and eVTOL aircraft battery requirements.
Tariq et al. [132]	2016	109	12.11	The paper reviews the evolution of more electric aircraft (MEA) power systems' architectures and BMS and discusses some SOC and battery health management estimation techniques.
Shiau et al. [133]	2009	108	6.35	The paper proposes a solar power management system and BMS for a UAV's lithium polymer battery. The system delivers the required power to onboard computers and electronic devices.

selections regarding their areas of emphasis. This strategy may lead to individual and collaborative research efforts ensuring they align with the academic community's goals.

The keyword co-occurrence network, shown in Fig. 8 for BMS in electric aircraft research, provides a rich visual representation of research patterns, identifying essential themes and their relationships. Larger nodes in the graph reflect keywords that are important in the domain, whereas smaller nodes show less common but significant concepts. Different colors signify diverse clusters, each emphasizing a particular area of interest in the scientific field. The thickness of the lines linking the nodes, known as edge weight, indicates the strength of the co-occurrence of terms, demonstrating how closely they are related in academic investigations. This network assists in comprehending the structure of the field by highlighting major research areas and their relationships. Although the figure shows several clusters, three significant clusters can be highlighted: the UAV cluster (green), the electric aircraft and battery management cluster (blue), and the thermal management cluster. These clusters work together to understand the field's core research topics comprehensively.

The UAV cluster highlights essential developments in improving energy management tactics to improve UAV performance and sustainability. The cluster mainly consists of hybrid power systems, energy management, and fuzzy logic (shown as a node without a label). Although li-ion batteries exhibit remarkable specific power (250–340 W/kg), batteries possess relatively low specific energies that allow small UAVs to operate for an average of 90 min only [135,136]. By dynamically shifting power modes to satisfy mission objectives, hybrid power systems combine batteries with complementing energy sources like fuel cells, offering operational flexibility [17,137,138]. Energy management techniques, driven by real-time data SOC, allow for effective utilization of energy resources, resulting in stable and extended flight periods in UAV operations where durability is critical [139]. Using fuzzy logic in UAV systems solves the issues of unpredictable and dynamic operational settings, enabling adaptive decision-making for operations like shifting between energy sources or optimizing charging phases [140–142]. For instance, Bai et al. [29] developed a fuzzy-based composite energy management approach for UAVs that utilizes the resilience and adaptability of fuzzy logic control-equivalent consumption minimum strategy (FLC-ECMS). The FLC-ECMS approach decreases fuel consumption and the difference between the initial and final SOC values during the mission, keeping the battery SOC within the allowable range. Similarly, Yang et al. [143] established a fuzzy logic-based BMS for hybrid UAVs driven by fuzzy logic's remarkable capabilities in maintaining optimum fuel consumption and high SOC. The management achieved an optimal fuel consumption exceeding 85 % while maintaining the SOC levels within the perfect threshold. The popularity of hybrid UAVs and the necessity for effective energy management strategies shape the terms' co-occurrence in this cluster.

The electric aircraft and battery management system's cluster depicts the tight connection of these terms with SOC, fault diagnosis, and ML. One of the fundamental functions of the BMS in electric aircraft is to monitor SOC and keep it within ideal ranges. This is critical for maintaining operational efficiency and avoiding overcharging or deep draining, which can significantly impact battery performance and durability [144–146]. Furthermore, fault diagnostics appear to be another essential component of BMS performance. TR, sensor errors, and voltage imbalances may all arise in electric aircraft's dynamic and frequently harsh operating conditions. However, diagnosing these errors can be challenging owing to the inherent nonlinearity and complexity of battery systems [39,147,148]. ML shows promising potential in addressing these challenges. However, further research on interpretability and validation is necessary before it can be widely accepted for industrial deployment. By leveraging advanced algorithms, ML enables the BMS to detect patterns, predict faults, and adapt SOC management strategies in real time, ensuring safety and efficiency in electric aircraft operations. The most frequently used ML algorithms in electric aviation applications are RNN-LSTM, random forests (RF), DNN, support vector machine (SVM), back propagation neural networks (BPNN), and transformers.

Table 5 outlines various ML algorithms utilized in studies related to electric aviation's BMS, focusing on their application in managing SOC, SOH, SOP, state of temperature (SOT), and remaining useful life (RUL).

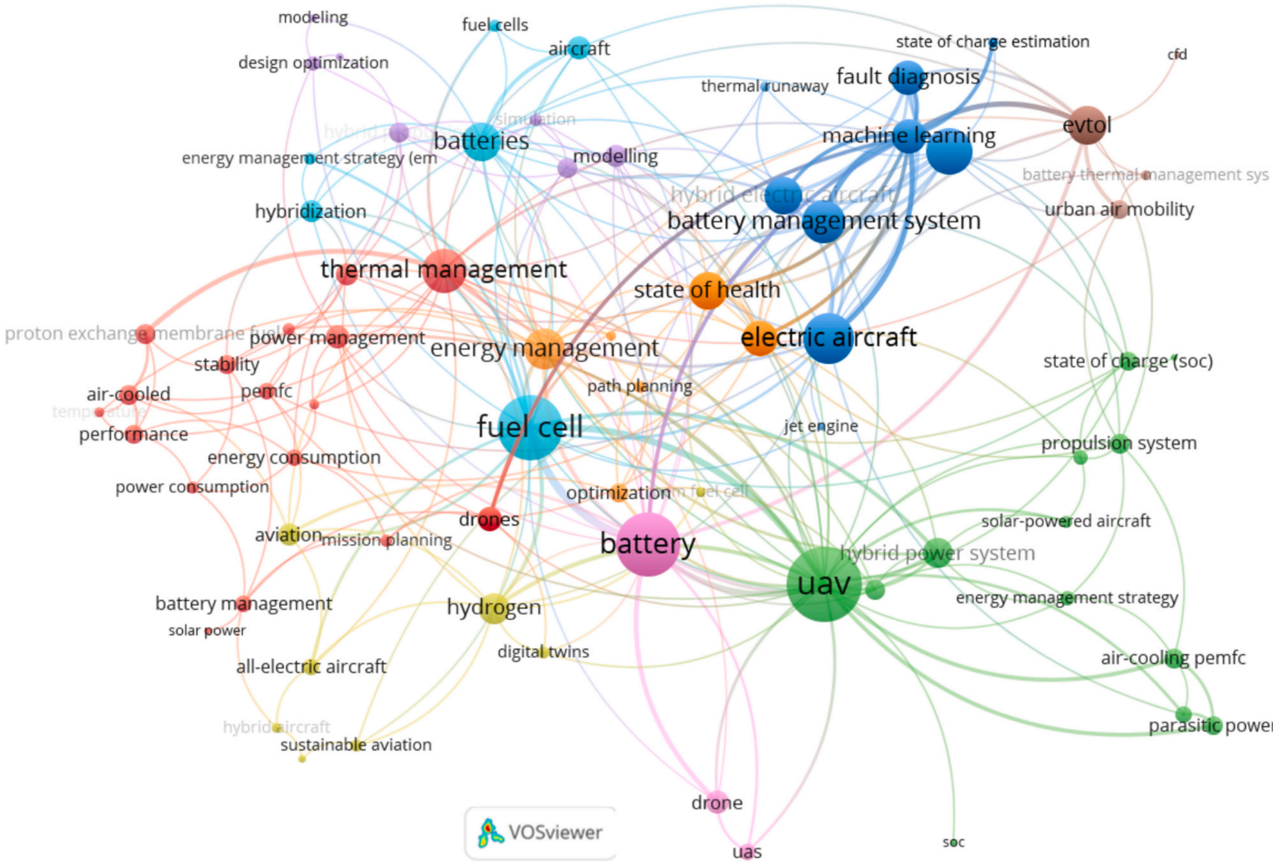

Fig. 8. Co-occurrence network exhibiting the main clusters of the domain.

Table 5
ML algorithms used in advanced BMS of electric aviation batteries.

Algorithm	Characteristics	Performance metrics	Benchmark datasets	Aircraft type	Papers
RNN-LSTM	• High accuracy with smaller datasets. • Resistance to ambient conditions' fluctuations. • Used in SOC, SOH, SOP, RUL, and SOT	RMSE: 0.1–0.19	• NASA HIRF [150] • Fricke et al. [151] • Bills et al. [152]	UAV, eVTOL aircraft	[121–123,153–157]
RF	• Accurate battery aging estimation regardless of loading conditions (better than SVM). • Used in SOC, RUL, and SOH estimation.	RMSE: 0.000985–1.8	• NASA HIRF [150] • Fricke et al. [151] • Bills et al. [152]	UAV, eVTOL aircraft	[123,158,159]
DNN	• Offers high accuracy in different ambient temperatures. • Provides computational efficiency compared to the other algorithms. • Mainly suited for SOC estimation.	RMSE: 0.029–0.087	• NASA HIRF [150] • Fricke et al. [151] • Bills et al. [152]	UAV, eVTOL aircraft	[120,123,155,160]
SVM	• Supports system integration (can run onboard). • More accurate in SOH estimation compared to SOC.	RMSE: 0.017–0.087	• NASA HIRF [150] • Fricke et al. [151] • Bills et al. [152]	UAV, eVTOL aircraft	[158,159]
BPNN	• Relatively accurate SOC estimation compared to model complexity. • Higher interpretability compared to LSTM and other deep learning architectures.	RMSE: 0.108	• NASA, Bole et al. [161]	Potential use in aviation	[162]
Transformers	• Very effective in low temperature environments. • Effective in harsh testing protocols	RMSE: 0.1–0.15	Kollmeyer 18650pf dataset [163]	Potential use in aviation due to low ambient temperature validation	[164,165]

Note: NASA HIRF and Bills eVTOL datasets listed in this table are publicly available at the provided sources and were utilized in the reviewed studies. The preprocessing procedures reported by the original authors typically involved filtering incomplete cycles, normalizing voltage/current profiles, and segmenting data into training and testing sets.

Notably, all algorithms have been applied to UAVs and eVTOL aircraft, underscoring the significant focus on smaller, potentially autonomous electric aircraft in current research. This trend reflects the growing interest and rapid development in these areas, driven mainly by their promising applications in UAM and autonomous operations. However, the table also reveals a significant research gap, as there are no studies applying these ML techniques to hybrid-electric and commercial electric aircraft. This gap is attributed to the complexity and scale of commercial airplanes and HEA, which pose more significant challenges in data collection and algorithm implementation than smaller UAVs and eVTOL aircraft [149].

A primary obstacle to the deployment of ML in electric aviation batteries is the limited availability of domain-specific datasets. Unlike the automotive sector, where several public datasets are established benchmarks, aviation-oriented datasets remain scarce. Most existing collections were acquired under ground-level or automotive conditions and do not capture the unique environmental and operational profiles of UAVs, eVTOL aircraft, and HEA [166–168]. For instance, few datasets account for low-pressure conditions at altitude, rapid thermal transients during climb and descent, or dynamic load cycles during hover and vertical take-off [169]. Even the datasets labeled for eVTOL aircraft testing are typically gathered at constant temperatures, failing to reflect real mission profiles where dynamic temperature conditions exist [152]. This mismatch severely restricts the generalizability of ML models, as they may exhibit strong performance under laboratory settings yet fail under flight conditions. Another consequence is the lack of standardized benchmarking. Many studies evaluate algorithms on private datasets, making results incomparable across architectures and complicating fair assessment of progress [121,170,171]. To support reliable adoption, the community requires curated aviation-specific benchmark datasets that capture multi-environment stressors and allow systematic comparison.

Another pressing challenge in applying ML to electric aviation batteries lies in the tension between predictive horizon requirements, real-time deployment, and interpretability. Accurate SOC, SOH, and RUL estimation often demands long prediction horizons and large input windows to capture degradation trends and transient behaviors [172]. However, increasing the horizon length or sequence depth dramatically raises computational latency, making real-time deployment on resource-constrained BMS impractical [173,174]. For instance, LSTM and transformer-based models achieve high accuracy with extended horizons. Still, their complexity exceeds the onboard processing capacity of avionics-grade embedded systems, particularly under strict timing constraints during dynamic flight phases such as take-off or emergency descent. To mitigate this, researchers shorten the prediction horizon or simplify the model, but this trade-off reduces accuracy and reliability [175,176]. This trade-off poses a significant challenge in important applications that cannot tolerate delays, such as TR prediction. A summary of the key challenges associated with ML integration in electric aviation batteries is presented in Fig. 9.

Furthermore, regulatory and safety requirements for passenger aircraft are considerably more stringent, which might slow the experimental deployment of new technologies [177–179]. Table 6 highlights the contributions of some global standardization entities in electric aviation. It presents the codes and regulations governing ML integration with the critical areas that need further emphasis. The European Union Aviation Safety Agency (EASA) has been developing several modules and standards to guide the use of ML in aviation applications. The standards address the issues of lack of predictability, end-user distrust, and model complexity. Nevertheless, these regulations do not cover overridable, non-overridable decision-making and adaptive models in fully autonomous systems, posing a significant gap between research studies and industrial applications [25,177,180]. Therefore, the trade-off between model complexity and interpretability remains a critical issue. Where complex ML models such as RF and RNN offer promising accuracy, interpreting and dealing with such complexity is challenging for some operators and engineers. In aviation, where system failures can have fatal consequences, the need for accurate predictions must be carefully balanced against the requirement for model interpretability, as understanding the rationale behind decisions is critical for trust,

Table 6
Global standardization entities in the electric aviation field.

Standardization	ML-related regulations	Related codes
Federal Aviation Administration (FAA)	• Addresses software and electronic hardware in electric aviation. • Lacks central Artificial intelligence (AI)/ML standardizations and regulations.	DO-178, DO-254
Society of Automotive Engineers (SAE)	• Arrange meetings to compare global standardization to NASA's framework. • Development guidelines for civil aircraft systems	SAE ARP 4761, SAE APR 4754A
EASA	• Addresses AI/ML applications in UAM. • Provide assessment guidelines for ML model training, testing, and actual use. • Lacks standardization toward unsupervised ML, non-overridable decision-making, and adaptive models.	AI Roadmap 1.0, AI Roadmap 2.0

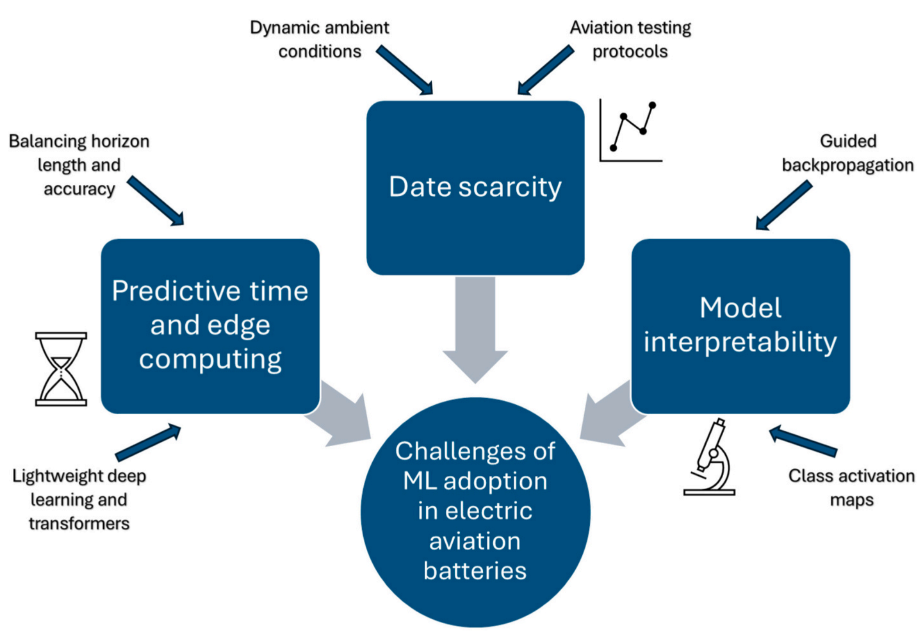

Fig. 9. Summary of the key challenges faced by ML integration in electric aviation BMS with the primary solutions that can tackle these challenges.

validation, and regulatory approval.

The third and last cluster is thermal management, exhibiting paramount keywords such as power management and air-cooling. Power management is critical for electrical aviation batteries, as UAVs and eVTOL aircraft require tremendous discharge power during take-off, landing, and maneuvering [181–183]. This discharge power could reach 8 C during certain stages, especially in eVTOL aircraft, where take-off/landing demands high-power motors and electrical supply [13]. Discharge power is the main contributing factor for battery temperature elevation. According to an optimization study by Mishra and Mishra [184], in comparison to the electrical arrangement, tab width, tab depth, and busbar height, discharge rate has the most significant impact on maximum pack temperature (44 %). This interplay between power and thermal management highlights a critical connection within the domain, as identified through co-occurrence mapping. Although liquid cooling offers high heat load capacity, the weight and size constraints in UAVs and eVTOL aircraft restrict its use and limit performance. Therefore, enhancing and optimizing the current air-cooling designs remains the primary research focus in UAVs and eVTOL aircraft. This is evident by the appearance of air-cooling solely in the co-occurrence network [185–187]. Table 7 summarizes electric aviation's three main cooling mechanisms, demonstrating the current research focus, challenges, and limitations. Despite their promising performance, the results depict a notable research production shortage in passive cooling techniques such as PCM and RA cooling. This could be attributed to the bias toward established active cooling systems, which provide better temperature control [188,189]. Additionally, integrating control algorithms, such as ML architectures, is more difficult in PCM compared to liquid and air cooling [26].

3.4.2. Thematic map and thematic evolution

The thematic map in Fig. 10 provides a structured view of the research landscape for BMS in electric aviation. It categorizes the themes into four quadrants based on their degree of development (density) and relevance (centrality). Each quadrant represents a stage of maturity and importance, helping to understand the current focus and future directions in this domain. The size of each circle in the thematic map reflects the frequency of keywords grouped within that cluster, meaning larger circles represent themes that appear more often across the dataset. A minimum occurrence threshold of five appearances per thousand documents was applied to filter out keywords that were too rare to establish meaningful co-occurrence links. This restriction prevents fragmented or unstable clusters and ensures that the thematic map highlights themes with sufficient representation in the literature. The position on the map (maturity and importance) is determined and quantified separately by centrality relationships presented in Eqs. (1)–(3).

The niche themes quadrant encompasses highly developed areas with limited connectivity to broader themes, indicating specialized yet narrowly focused research. Key terms in this quadrant are energy management strategy (EMS), adaptive neuro-fuzzy inference systems (ANFIS), and hybrid auxiliary power unit (APU). These topics emphasize advanced control strategies and hybrid system integration, which hold the potential for optimizing energy usage in aviation. However, their niche placement indicates that further efforts are needed to integrate these advancements into the broader electric aviation landscape. In contrast, the motor themes quadrant identifies highly developed and relevant topics, making them central to advancements in electric aviation. Notable terms include thermal management system, battery modeling, air cooling, thermal management, and HEA. These themes highlight the critical importance of efficient heat dissipation and accurate modeling for ensuring the reliability and safety of aviation battery systems. Including HEA signals the industry's ongoing commitment to sustainable aviation technologies, marking this quadrant as a priority for researchers and industry stakeholders. The basic themes quadrant represents foundational concepts that, while not highly developed, are essential for building advanced systems. Prominent terms in this category include fuel cell batteries, UAVs, and more electric aircraft. These topics lay the groundwork for further advancements, particularly in energy storage and electrified propulsion systems. The focus on fuel cell batteries highlights the potential for cleaner energy sources. At the same time, the presence of UAVs and more electric aircraft indicates the growing interest in electrifying aviation for various applications.

The emerging themes in BMS for electric aviation emphasize cutting-edge innovations that can address future efficiency, safety, and sustainability challenges. Central to these themes are eVTOL aircraft, ML, LSTM, and fuzzy logic control. eVTOL aircraft represent a transformative solution for UAM but demand advanced thermal and battery management due to high power-density requirements and rapid charge-discharge cycles. ML, particularly algorithms like LSTM, provides predictive insights into battery health, thermal anomalies, and lifecycle optimization by leveraging real-time data. Additionally, fuzzy logic control enables adaptive decision-making in nonlinear conditions, allowing for precise thermal regulation and improved energy efficiency.

Table 7
Main battery thermal management techniques in electric aviation.

Cooling mechanism	Components	Main features	Challenges and limitations	Studies
Air cooling	Fans, airflow channels, heat sinks, cooling fins, temperature sensors, and control system	• Simple and lightweight • Effective for batteries and fuel cells • No leakages or any hazardous coolant. • Sensitive to fins and airflow channel design, offering research opportunities	• Limited heat load capacity. • Scalability: mainly suitable for only UAVs and small eVTOL aircraft	[40,83,185–187,190–195]
Liquid cooling	Coolant, pump, heat exchanger, flow channels, cold plates, and control interface	• High heat load capacity • More uniform cooling: no hotspots • Scalability: suitable for high discharge power applications in large eVTOL aircraft and HEA	• Complexity and increased weight due to pumps and other components' weight • Risk of leakages, especially of hazardous coolants • Higher installation and maintenance cost	[18,196–200]
Passive cooling	PCM, RA	• PCM possesses high thermal storage capacity (applications with high melting enthalpy) • Energy-efficient and cost-effective • Compact and lightweight • RA is quite effective in high aircraft speed applications	• Repeated phase change in PCM degrade the material over time (10 years) • Low melting enthalpy PCMs have a narrow operating temperature range • High initial investment cost • RA cooling is highly sensitive to unpredictable air temperature, pressure, and density. • Intake and exhaust RA ducts could induce drag	[201–204]

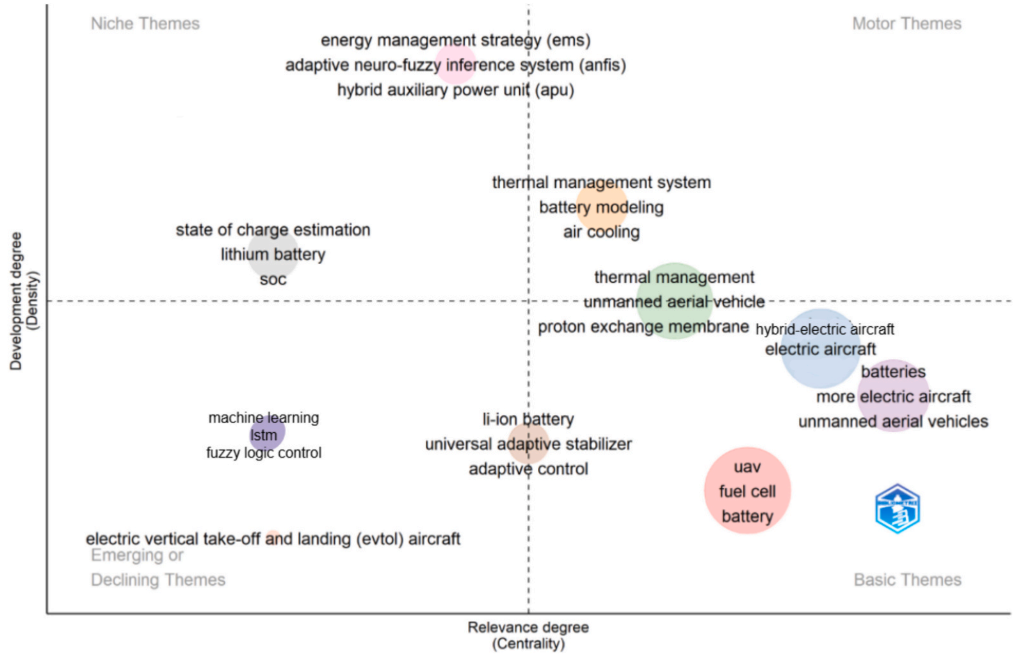

Fig. 10. Thematic map of the niche, basic, motor, and emerging themes in the domain.

These technologies enhance operational reliability and scalability, which is critical for meeting the high demands of electric aviation. Addressing these emerging areas can significantly advance safety, reduce downtime, and optimize energy usage, fostering a sustainable future for urban air transportation and beyond.

The chord diagram, shown in Fig. 11, represents the thematic evolution of the field and the interconnections between its key themes. It is part of a series of three diagrams: the first (a) captures the initial research period from 1997 to 2016, the second (b) spans 2017 to 2022, and the third (c) represents developments from 2023 to December 2024. In the first period (1997–2016), the connections between themes were relatively straightforward, reflecting a focused approach to addressing foundational challenges. Over time, these connections grew more complex in the second and third periods, illustrating the field's natural shift toward multidisciplinary exploration. UAVs appeared as a recurring subject throughout the research landscape during all stages. A prominent link between UAVs and heat transfer management, in part (a), shows thermal regulation as a significant difficulty, even with more miniature battery packs at that time [205–207]. The lack of li-ion batteries and the prevalence of terminology like "hydrogen" indicate an early emphasis on fuel cells when li-ion technology was still in its early stages [208,209]. This time laid the framework for the field's future growth, allowing it to become more integrated and diverse.

The second research period (2017–2022) marks a significant thematic evolution, as reflected in the diagram's increasing complexity and interconnectedness. Unlike the initial period, which focused on more-electric aircraft reliant on conventional fuels, this stage introduced a clear shift toward electric aircraft, signaling the field's transition from exploratory stages to integrating fully electric propulsion systems. This evolution signifies increased technological confidence and breakthroughs in battery technology, making electric aircraft increasingly viable and essential for research. This is also attributed to the appearance of li-ion batteries since these batteries partially addressed the energy and power density challenges [210,211]. The introduction of "state-of-charge" and "battery management system" depicts the field's focus on managing these new battery technologies. "state-of-charge" emphasizes precisely calculating battery capacity in real-time, which is crucial for maximizing performance, extending battery life, and assuring safety. The term "battery management system" emphasizes this transformation since BMS technology became critical to controlling the increasingly complex energy systems necessary for electric aircraft. This age also saw UAVs retain a prominent presence but with deeper links, showing their incorporation into more extensive networks.

The final research period (2023–December 2024) highlights the presence of advanced techniques for BMS, particularly in thermal and power management. Techniques such as ML and fuzzy logic have emerged as dominant methodologies in electric aviation BMS, showcasing the field's shift toward data-driven and adaptive systems. A notable trend in this period is the presence of eVTOL aircraft, reflecting ongoing research efforts to address their unique energy demands. While the first eVTOL aircraft was slated for launch in 2018, extensive testing revealed significant power and thermal management challenges. The unique requirements of eVTOL aircraft, such as managing discharge powers up to 8C, necessitate a specialized BMS tailored for these high-power systems. Although BMS studies for UAVs and EVs are well-established, eVTOL aircraft demand bespoke thermal and power optimization solutions. Nevertheless, most current studies emphasize battery state estimation over thermal management and temperature prediction, pointing to an area needing further exploration. Despite databases like those formed by Bills et al. [152], there remains a scarcity of ML models explicitly designed for eVTOL aircraft systems.

4. Future recommendations and direction

In this section, we have synthesized findings from the latest research and literature on BMS in the context of electric aviation while addressing the limitations and challenges inherent to this field. Considering the gaps and constraints in BMS technology, this overview highlights future research opportunities and critical directions for advancing BMS solutions in electric aviation. The aim is to equip researchers and engineers with a concise reference for understanding the scope of ongoing development and emerging priorities in this rapidly evolving sector. A summary of the challenges is presented in Fig. 12.

4.1. Policy enhancement and filling the gap between research and the industry

The primary challenges in fostering ML applications in aviation

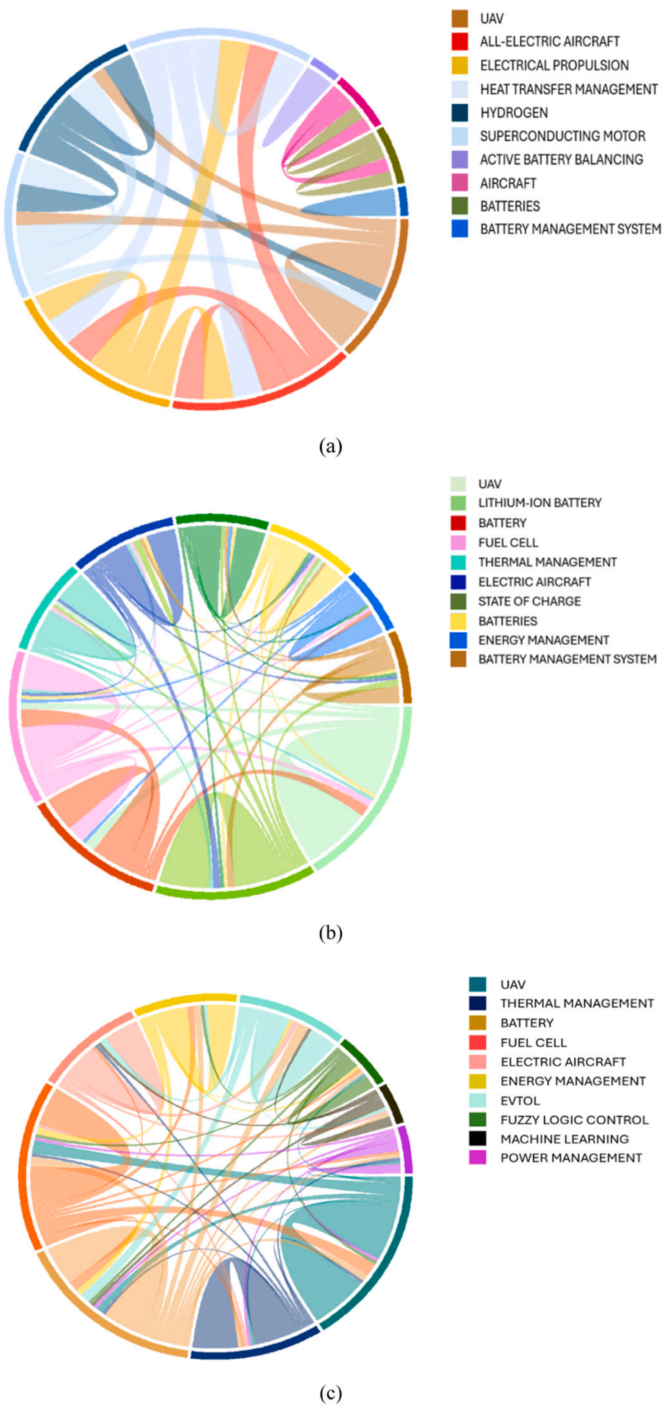

Fig. 11. Chord diagram representing the thematic evolution of the domain: (a) first period (1997–2016), (b) second period (2017–2022), and (c) third period (2023–December 2024).

revolve around adapting assurance frameworks to address learning-specific processes, improving explainability and robustness, and establishing user trust in the opaque and unpredictable nature of AI/ML systems [212]. To address these challenges, future research should focus on creating frameworks that align with safety-critical requirements. Researchers should develop adaptive assurance frameworks tailored to ML, addressing learning-based system uncertainties, such as dynamic safety certification processes that evolve with real-world data. Explainability techniques should be refined to make ML decisions transparent and interpretable, enabling policymakers to assess risk confidently. Additionally, researchers should prioritize creating scalable and standardizable risk-assessment models that quantify the residual risks of AI systems coupled with simulation-based tools to validate these assessments under realistic scenarios. Lastly, developing harmonized global guidelines for ML lifecycle management and integrating continuous monitoring and safety assurance is critical to bridging the gap between research, implementation, and regulatory acceptance in aviation.

4.2. Foster more ML-based studies for large-scale electric and hybrid-electric aircraft

As presented earlier, ML models, such as LSTM-RNN, SVM, DNN, and RF, exhibit remarkable capabilities in predicting and managing the battery's temperature and state. These capabilities encouraged significant research on implementing these techniques in the dynamic and fluctuating nature of UAVs and eVTOL aircraft. However, the analysis reveals a notable gap in implementing these models in large-scale electric or HEA. Several studies highlight battery management challenges in HEA operating in very low pressure and temperature, yet a few utilize ML techniques to address these challenges. For instance, Xie et al. [213], Zu et al. [214], Jia et al. [215], and Fu et al. [216] studied the effect of low pressure and temperature on the propagation of TR and the early rupture of the safety, and how the process involves multiple parameters (SOC, SOH, etc.). With their capabilities to handle such sophisticated relationships, ML algorithms would play a pivotal role in mitigating TR and other thermal-related risks [217–219]. Therefore, research into ML-based BMS for electric and HEA is a promising research direction, considering the significance of low-pressure/low-temperature conditions on batteries. However, these studies should effectively tackle overfitting issues, especially with the data limitations in HEA applications. This indicates that the issue of data availability should be addressed initially before conducting an extensive investigation of these techniques. Moreover, the analysis should extend beyond functional performance to address real-time deployment constraints, considering the predictive time horizon challenges of ML models [173,174].

4.3. More algorithm-based research on thermal management in eVTOL aircraft

Conventional cooling and thermal management techniques face several challenges due to the complex and dynamic nature of eVTOL aircraft applications. The power and energy density of the batteries would drop significantly as the temperature drops from ambient to -7°. On the other hand, elevated ambient poses significant safety hazards [13]. Therefore, advanced temperature prediction techniques would tackle this critical challenge and offer adaptive management techniques, minimizing localized hotspots and improving the cooling system's efficiency and power consumption [220,221]. Current research on eVTOL aircraft emphasizes utilizing ML and other algorithm-based techniques for battery power management and state estimation. The research field necessitates more studies applying similar techniques for BTMS and temperature predictions, considering the significance of this aspect. Leveraging advanced techniques like transfer learning can enable efficient model training with limited datasets, accelerating progress in BTMS and thermal prediction research. Researchers should also focus on domain adaptation techniques to ensure that models trained on smaller eVTOL aircraft datasets generalize effectively to larger, more diverse systems.

4.4. Foster more international collaborations between contributors

Strengthening international collaboration networks emerges as a decisive recommendation for advancing research in electric aviation and its BMS. Evidence from global co-patenting studies clearly demonstrates that collaboration across borders leads to measurable improvements in

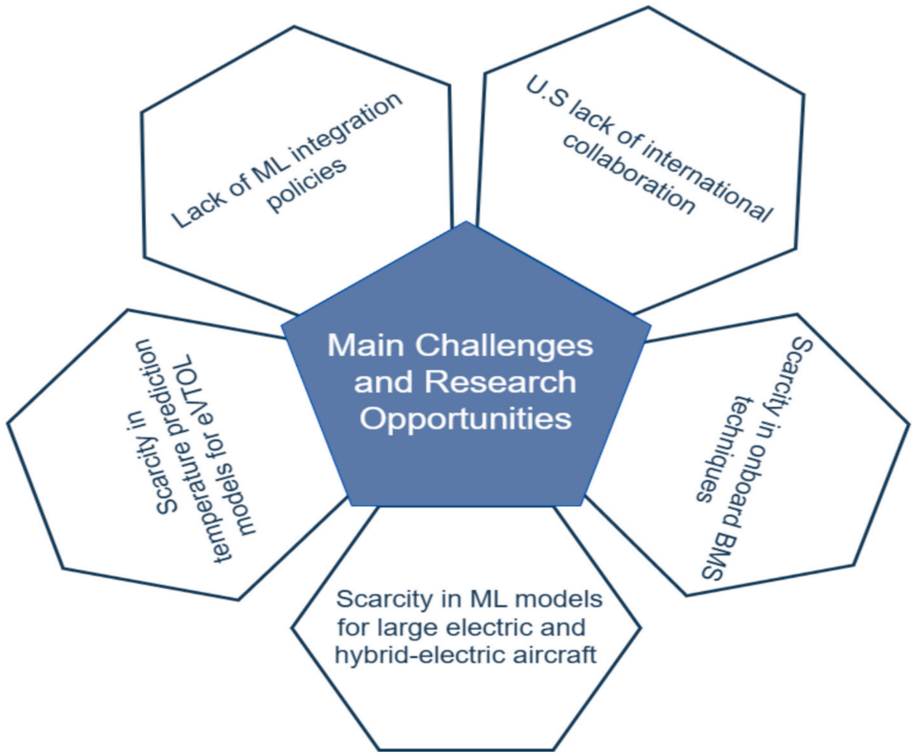

Fig. 12. Summary of the main challenges and research opportunities in the domain grouped into five main categories and potential research directions.

innovation quality, particularly when firms and institutions from different countries engage in joint knowledge creation [222]. As the visualizations of global patent networks reveal in Fig. 13, firms embedded in the largest connected component of global networks increased over time, illustrating that innovation ecosystems have become more interdependent across nations. Crucially, firms with foreign partners show stronger innovation performance compared to those working in isolation, underscoring the importance of bridging fragmented clusters into cohesive, cross-national networks [223]. For the BMS in the electric aviation domain, where scaling from theoretical research to industrial application requires extensive data, rigorous testing, and harmonized standards, international collaboration can accelerate progress by pooling resources, broadening experimental contexts, and distributing costs. This is evident by the advantageous effect of international collaborations in the individual fields (electric aviation and battery research) [101,102,224,225].

The U.S. has the most contributions in the domain, with a tremendous publication volume and industrial investments. The country has a blend of experienced industrial companies, such as Boeing, promising emerging startup companies, such as Zunum Aero, and several well-known academic institutions interested in the domain. Nevertheless, despite its exceptional internal activity, it exhibits inactive global research collaboration. Collaboration between well-known U.S. research institutions, industrial partners, and international research groups would yield mutual benefits. For instance, Liu's research group, as shown in Fig. 7, could benefit from the practical experience of major U.S. industrial entities, which test their adaptive fuzzy management systems in actual environments and collect more valuable data. In return, the

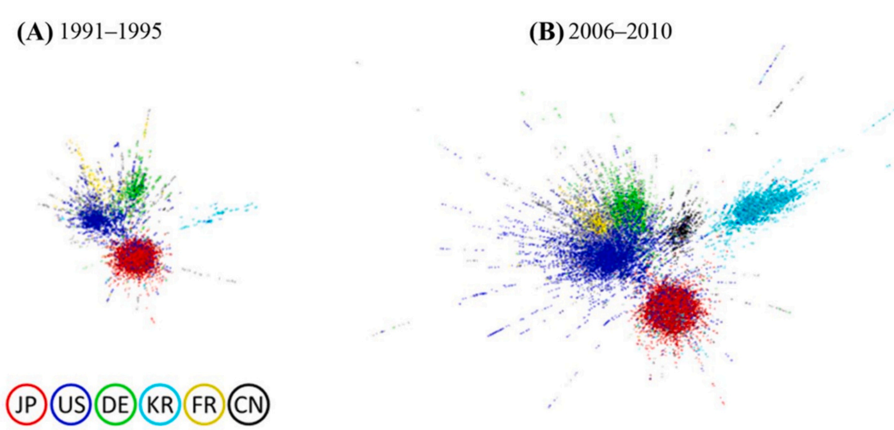

Fig. 13. Global co-patenting network for the periods 1991–1995 and 2006–2010. Each dot represents a firm, with colors indicating the country: Japan (red), US (blue), Germany (green), South Korea (light blue), France (yellow), and China (black). The spatial position of the dots reflects their collaborative connections. Firms that appear closer together belong to the largest connected component, where firms are directly or indirectly linked. Firms positioned farther away represent fragmented or weakly connected sub-networks [222]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

electric aircraft models, shown in Table 1, can benefit from the advanced BMS developed by such active research groups [110,226].

4.5. Develop more onboard BMS

According to Raoofi and Yildiz [25], SVM is the only ML technique that offers onboard battery state estimation. Similarly, this bibliometric review defines an apparent deficiency in studies designing onboard BMS where model parameters can change during operation and according to environmental conditions. This is a crucial element since electric aircraft, unlike EVs, experience dynamic environments where preset model parameters are often inaccurate [33,110]. Furthermore, for a BMS to be considered effective in onboard management, it must incorporate elements beyond battery-specific functions. Key considerations include system integration with avionics, real-time communication with flight control systems, and compliance with aerospace standards. Robust cybersecurity protocols are also essential to protect against potential breaches that could compromise operational safety. Additionally, energy optimization algorithms tailored for mission profiles, lightweight hardware to reduce system weight, and redundancy mechanisms to ensure reliability during failures are crucial [9,84].

5. Conclusion

5.1. Summary of main results

This bibliometric analysis provides a comprehensive review of research on BMS in electric aviation. We analyzed 500 publications from 1997 to 2024, looking at publication countries, institutions, prominent authors, frequently cited documents, research trends, keywords, thematic evolutions, and future research directions. The investigation identified the following traits and patterns in BMS for electric aviation.

The annual scientific output in the domain appeared to evolve through three stages: foundational growth (1997–2016), rapid acceleration (2017–2022), and breakthrough (2023–present), with a peak in 2024. The United States has the most publications (over 140), followed by China (over 120). China demonstrates worldwide collaboration traits, whereas the United States prioritizes domestic collaborations. Aside from these two countries, Germany, the UK, Italy, and France are significant suppliers and partners. The keyword co-occurrence network identifies three major clusters: the UAV, the electric aircraft and battery management, and the thermal management cluster. These clusters included multiple vital keywords such as "machine learning", "fuzzy logic", "hybrid power systems", "fault diagnosis", "power management", and "air-cooling". The current research focus includes ML-based battery state estimation, active UAVs BMS, charging and discharging optimization, and power management demands in eVTOL aircraft.

5.2. Contributions of the study

This study provides a quick guide for researchers to understand the extent of research in the BMS of electric aviation. According to the study, future research should focus on assurance frameworks to address learning-specific processes, improving explainability and robustness, and establishing user trust in the opaque and unpredictable nature of AI/ML systems to accelerate policy approvals and protocols. Moreover, the research field necessitates more studies applying similar techniques for BTMS and temperature predictions, considering the significance of this aspect. Furthermore, research into advanced and adaptive ML-based BMS of electric and HEA is a promising research direction, considering the importance and limited publication volume. Collaboration between well-known U.S. research institutions, industrial partners, and global research groups would yield mutual benefits. Finally, the analysis highlights an apparent deficiency in studies designing onboard BMS where model parameters can change during operation and according to environmental conditions.

5.3. Study limitations

This study conducted a bibliometric analysis of BMS in electric aviation research papers, yielding several research findings. However, the research findings have certain limitations in the following aspects. Firstly, the data in this study were obtained from the Scopus database, excluding potential sources such as the Web of Science, which may result in some omissions in the dataset. Secondly, this study primarily ranked countries, institutions, and researchers based on the number of published papers as a comparative metric. A high number of publications for an author may not necessarily represent a strong influence in the field, and outstanding researchers with lower publication numbers may have been overlooked. Nevertheless, considering TC and AC as complementary criteria in many sections mitigates the consequences of this limitation. The next step will be considering citation counts as an elementary criterion for filtering and ranking.

CRediT authorship contribution statement

Abdeen Osman: Writing – review & editing, Visualization, Methodology. **Aghyad Al Tahhan:** Writing – original draft, Methodology. **Tariq Younes:** Writing – review & editing, Conceptualization. **Mohamad Ramadan:** Writing – review & editing, Conceptualization. **Mohammed Ghazal:** Writing – review & editing, Supervision. **Mohammad Alkhedher:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

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

Acknowledgment

This research is supported by ASPIRE, the technology program management pillar of Abu Dhabi's Advanced Technology Research Council (ATRC), via the ASPIRE VRI (Virtual Research Institute) Award.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.est.2025.119523.

Data availability

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

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