DOI 10.5162/iCCC2026/P47

THE IMPORTANCE OF PREDICTING BATTERY DEGRADATION IN LIGHT ELECTRIC AIRCRAFT

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Abstract
This paper discusses the importance and need for predicting battery degradation in an all-electric battery powered aircraft. This type of aircraft is expected to represent an emission-free alternative to the conventional light aircraft used for pilot training and leisure flying. The drawbacks of limited life-span of batteries, important parameters like total charge capacity and internal resistance which indicate battery health, and the need to define end-of-life (EOL) parameter values are addressed. The importance of analysing the particularities of the mission flown by light planes and the different approaches to model battery cells for battery management system (BMS) algorithms are presented. Further avenues to continue the work are also presented.

1. INTRODUCTION

The aviation industry is responsible for nearly 2% of the global CO_2 and 3% of the global NO_x emissions. This will increase in the foreseeable future together with the demand for air travel [1]. Electric propulsion technology has the potential to curb aircraft emissions and achieve the climate goals set by the commercial aviation industry and different political agendas of the governments and agencies [2]. All-electric propulsion architectures powered solely by batteries produce zero emissions during flight operations. In [3], Pattanyak et al. conducted a comprehensive study reviewing different battery technologies for aviation and concluded that for the foreseeable future lithium-ion (Li-ion) cell chemistries will dominate the battery technology required for electric aviation considering their high gravimetric and volumetric energy and power densities, low self-discharge rate, lower degradation rate, etc. However, the gravimetric and volumetric energy and power density of state-of-the-art Li-ion chemistry is still relatively low compared to conventional fuels or hydrogen. This makes them unpractical for long distance transport aircraft [4]. Electric power trains with Li-ion battery pack are nevertheless suitable for light aircraft used for leisure flying and pilot training such as one shown in Fig. 1.
Such light battery-powered aircraft can reduce the environmental footprint and operating cost of flight school, especially when the electricity used to charge the batteries is generated from renewable energy sources [6].
One of the main challenges in designing battery-powered aircraft is to predict how long the battery pack will last. The knowledge of useful battery life is particularly important from the perspective of certification. With time, the energy and power capacity of a battery pack degrades due to calendar and cycle aging [7]. This prompts the need to accurately monitor battery health, predict degradation, and optimize operation over the whole life cycle to increase the useful life and reliability of the battery pack without compromising the flight safety. The task is not trivial as the aging and degradation of Li-ion batteries is a complex non-linear process and predicting degradation dynamics is challenging [8]. This can be accomplished by intelligent battery management system (BMS) algorithms similar to those used in the automotive sector.
This work explores some important considerations in this regard and proposes an approach on how to address this issue.

2. BATTERY AS A LIFE-LIMITED COMPONENT

Several components and systems in aviation have a limited life span including batteries. As battery cells undergo ageing and degradation, their total charge capacity decreases and internal resistance increases. This happens because of the unwanted side reactions that consume lithium ions and structural deterioration of the electrodes. Thus, they last a limited number of cycles or operational hours before having to be replaced. Batteries are expensive: in mobility applications like electric vehicles (EVs), the battery system is one of the major contributors to the overall cost of an EV, reaching about 40-60% of the total cost price of the vehicle [9]. Study of battery degradation is also very important from the perspective of aircraft operation eco-

FIG 1. Diamond eDA40 aircraft [5]

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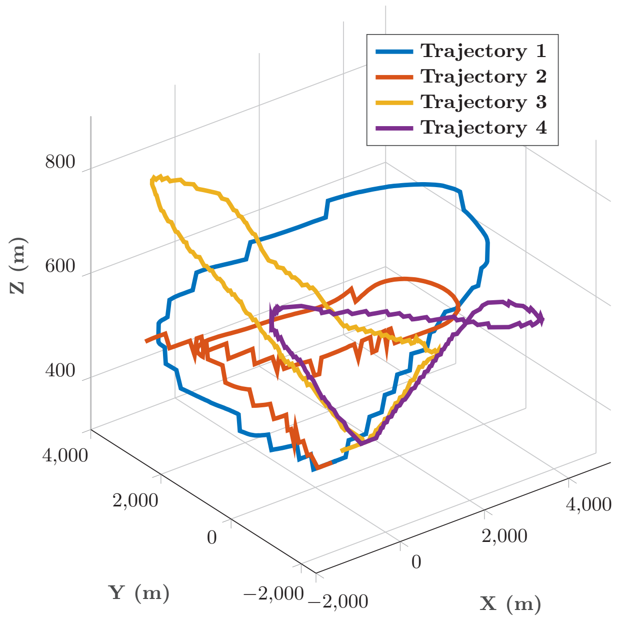

FIG 2. Flight trajectories of a light aircraft [11]

nomics. Thus, there is a need to determine its initial use end-of-life point in a better way.
The common practice followed in the automotive industry is to replace the battery pack once its energy storage capacity degrades to 70-80% of the value at the beginning-of-life (BOL). This degradation to 80% of the BOL energy storage capacity is called the end-of-life (EOL) point for a battery pack. Saxena et al. [10] showed that batteries in electrical vehicles continue to meet the performance requirements of the daily user even when energy storage capacity has degraded to a value well below 80% and the power delivering capacity has been degraded down to 30%. They conclude that accepted practice of retiring batteries when energy storage capacity has degraded to 80% is inaccurate, and should be done when the battery pack no longer meets the user requirement. This retired battery might then be used for a second-life stationary application.
This prompts the need to investigate and define the EOL parameters for the battery pack in a light electric aircraft as the dynamics of load profile and operating conditions are very different compared to automotive and it is a mandatory requirement for certification.

3. EFFECTS OF THE MISSION PROFILE

To investigate its degradation, it is important to identify the operating conditions which the battery pack will be subjected to during its life cycle. As mentioned in 1, such light electric aircraft can be used for leisure flying and pilot training, and their mission profile can vary a lot. This is unlike commercial aircraft, which usually fly similar profiles during their whole operational life. During flight training missions, aircraft usually remain in the vicinity of the airfield doing traffic pattern training. This leads to very frequent cycles between idle and full power. While flying, it can encounter stochastic conditions like turbulence, emergency maneuvers, etc. Several flights can be flown during a day which might require repeated charging of batteries. All these factors can affect battery performance and health.
Obtaining load profiles for a light electric aircraft is challenging because operational data of such aircraft is not publicly available. Some information about mission trajectories of light conventional aircraft can be extracted from data used for aircraft surveillance, like Automatic Dependent Surveillance Broadcast (ADS-B) or Mode S. In such surveillance technique, aircraft automatically transmit their identity, position, speed, etc., derived from onboard systems to other aircraft in the vicinity and ground air traffic control stations to avoid mid-air collision, and for air traffic monitoring and management [12].
Many datasets are publicly available and can be used for generating and analyzing flight trajectory patterns. One such trajectory dataset for light general aviation (GA) was collected and made available by Patrikar, et al. using an on-site ADS-B receiver at Pittsburgh-Butler Regional Airport (ICAO location indicator KBTP), near the city of Pittsburgh in Pennsylvania, USA [11]. Few mission trajectories flown by light conventional aircraft are shown in Fig. 2. It can be seen that even though the aircraft take off and land on the same airfield, their mission trajectories can be very different. For example, trajectories 1 and 2 have steps in the flying pattern indicating that multiple climb, cruise and descent maneuvers with steep pitch angles were performed during the flight. Such maneuvers have an impact on the power drawn from the battery pack and this needs to be taken into consideration when defining the constraints to optimize battery pack design, performance, and life.

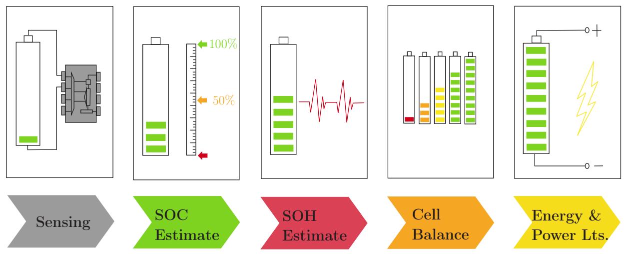

FIG 3. BMS Workflow [13]

4. BATTERY CELL MODELS FOR BMS ALGORITHMS

As described in section 1, the task of predicting battery degradation is not trivial and it is accomplished by intelligent BMS algorithms. Values of voltage, temperature, and current from each cell are measured in real-time using appropriate sensors and communicated to the BMS. These values are used to estimate the state-of-charge (SOC), state-of-health (SOH), perform cell balancing, and compute energy and power limits. The workflow of BMS is shown in Fig. 3. Battery management algorithms perform these estimations using observers which are mathematical models of the battery cells. SOC and SOH estimations are performed for each cell in the pack. Based on the number of cells connected in series and parallel, cell balancing is performed, and then energy and power limits of the pack are computed. The cell models used for such estimations can be physics-based, data-driven, or a combination of both.
SOH is indicated by analyzing two parameters: total charge capacity and internal resistance of the cells. They provide an estimate of the total energy storage and power delivering capacities. As the battery pack undergoes aging and degradation, the total charge capacity and the internal resistance of the cells change. Obtaining a good estimate of these values is crucial [14]. BMS SOH algorithms accomplish this with the help of observers. This makes an accurate cell model necessary.

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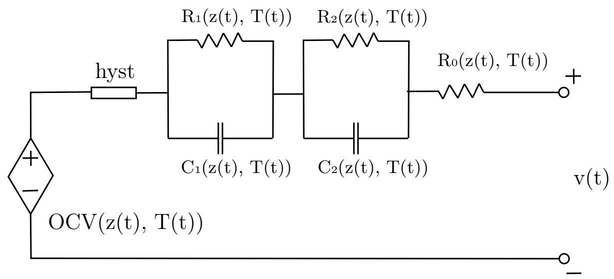

FIG 4. ECM

Physics-based models are developed using the partial differential equations that govern various electrochemical reactions occurring in the electrodes and electrolytes of the cell. Such models have higher fidelity, as they aim to capture all key behaviours of the cell to provide high accuracy, but they are very expensive computationally [15]. This renders them unsuitable for real-time applications.

The second category of models are data-driven models in which experimental data is used to parameterize a predefined model structure and validate behaviour. These models depend on the design of the experiments and quality of the data available. In this category there are two subtypes. The first one uses experimental data to fit empirically derived equations to infer input-output relationships. Such models are simple and easy to implement, but they are of low fidelity and have high inaccuracies. It is also difficult to interpret their parameters physically. These are also known as black-box models. This category also includes Artificial Intelligence based models which have become very popular in the recent years because of their better performance compared to conventional black-box models but they are not considered in this study because of the limitations in certifying them according to stringent aviation standards. The second category consists of lumped-parameter equivalent circuit models (ECM). These models use different electrical circuit elements to mimic the behaviour of an actual battery cell. The simplest model consists of an ideal voltage source connected in series to a resistance. Such models are static in nature and used for preliminary sizing and design studies. Higher fidelity ECMs take into account the dynamic effects by connecting one or more parallel RC networks or some other circuit elements in series or parallel to the series resistance and voltage source. These additional elements characterize the dynamic behaviour of various electrochemical processes happening inside a cell. Such ECMs have found traction on BMS applications since they offer a good trade-off between accuracy and computational effort, while maintaining a strong physical correlation between the model parameters and actual electrochemical processes within the battery cell [16].

Many comprehensive studies have been conducted to compare different ECMs. Hu, et al. did a comparative study of 12 ECMs for Li-ion battery cells in [15]. In [16], Nejad, et al. compared 7 different types of ECMs for real-time estimation of Li-ion battery states. In [17] and [18] different ECMs were investigated for their application to EV. In [19], Tran et al. developed a comprehensive ECM to incorporate effects of SOH, SOC, and temperature on model parameters.

Based on the literature review, a dual polarization ECM with one hysteresis element was selected for further study. The model structure is shown in Fig. 4. It is important to include the hysteresis element in the model to avoid SOC estimation errors. Hysteresis is a phenomenon which causes the difference in the charge and discharge OCV curves for same SOC. This phenomenon is shown in Fig. 5 using experimental data of A123 Li-ion cell collected by by Xing, et al. which is publicly available. Table 1 summarizes the root mean square error between charge and discharge OCV-SOC data for different temperatures.

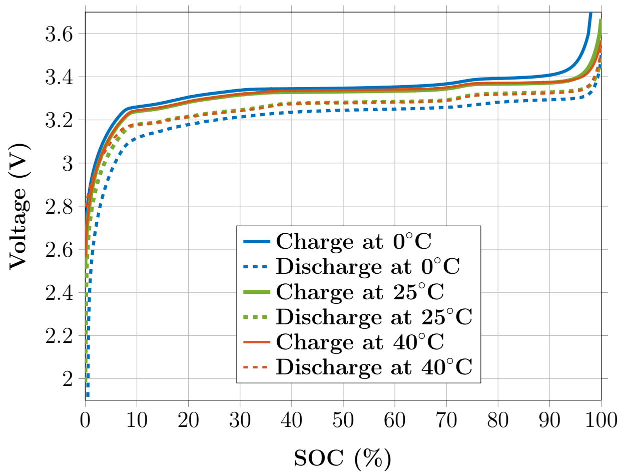

FIG 5. OCV vs SOC curves [20]

Temperature (°C)	OCV RMSE (V)
-10	0.2132
0	0.1980
20	0.1319
25	0.0638
30	0.1282
40	0.0614
50	0.2244

TAB 1. RMSE between charge and discharge OCV curves at different temperatures [20]

5. NEXT STEPS

The preliminary discussion presented in this paper will be elaborated further in the future. The main avenues of development are a more informed determination of the expected operational profiles of a light aircraft. This will be done by detailed analysis of open-source ADS-B data of light aircraft and consultation with the operators of light aircraft (flight schools, flight clubs) and manufacturers of some of the light electric airplanes already certified or about to be. Once the operational profiles of light aircraft are identified, they will be used to generate synthetic cell cycling data to parameterize the ECM proposed in this paper. The parameterized ECM will then be used to develop BMS algorithms for predicting battery pack degradation to optimize its operation with objective to increase battery life.

6. CONCLUDING REMARKS

This paper discussed the importance of predicting battery degradation during the operational life of a batterypowered light aircraft. It was discussed how the individual characteristics of the different operational profiles of this class of airplane represent a particular challenge in the safe and reliable operation of the batteries. The importance of modeling battery cells to create BMS algorithms used for estimating battery health and predicting degradation was highlighted since this could maximize the useful life of the battery. This study also explored the different types of cell models which could be used as observers in BMS algorithms and selected a model relevant to the use application presented in this study.

References

[1] J. Mukhopadhaya and B. Graver. Performance analysis of regional electric aircraft. *International Council of Clean Transportation white paper*, 2022.

[2] V.P. Joshi, R. Cepeda-Gomez, and T. F. Geyer. Optimal sizing and energy management of a battery to support a fuel cell powered regional electric aircraft during take-off phase. In *AIAA AVIATION FORUM AND ASCEND*, 2024. DOI: 10.2514/6.2024-3702.

[3] Tavish Pattanayak and Dimitri Mavris. Battery technology for sustainable aviation: a review of current trends and future prospects. *Applied Energy*, 397:126356, 2025. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2025.126356.

[4] A. T. Isikveren, A. Seitz, P. C. Vratny, C. Pornet, K. O. Plötner, and M. Hornung. Conceptual studies of universally-electric systems architectures suitable for transport aircraft. *DeutscherLuft und RaumfahrtKongress, DLRK, Berlin*, 2012.

[5] Diamond Aircraft Industries, 2025. https://www.diamondaircraft.com/en/flight-school-solution/aircraft/eda40/overview/.

[6] Nicolò Avogadro and Renato Redondi. Demystifying electric aircraft's role in aviation decarbonization: Are first-generation electric aircraft cost-effective? *Transportation Research Part D: Transport and Environment*, 130:104191, 2024. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2024.104191.

[7] Yaqi Li, Wendi Guo, Daniel-Ioan Stroe, Hongbo Zhao, Peter Kjær Kristensen, Lars Rosgaard Jensen, Kjeld Pedersen, and Leonid Gurevich. Evolution of aging mechanisms and performance degradation of lithium-ion battery from moderate to severe capacity loss scenarios. *Chemical Engineering Journal*, 498:155588, 2024. ISSN: 1385-8947. DOI: https://doi.org/10.1016/j.cej.2024.155588.

[8] Ruihe Li, Niall Kirkaldy, Fabian Oehler, Monica Marinescu, Gregory Offer, and Simon O'Kane. The importance of degradation mode analysis in parameterising lifetime prediction models of lithium-ion battery degradation. *Nature Communications*, 16, 03 2025. DOI: 10.1038/s41467-025-57968-3.

[9] H. Proff. Study: The key role of battery costs in automotive, 2023. https://www.deloitte.com/de/de/Industries/automotive/research/study-key-role-of-battery-costs-in-automotive.html.

[10] Samveg Saxena, Caroline Le Floch, Jason MacDonald, and Scott Moura. Quantifying ev battery end-of-life through analysis of travel needs with vehicle powertrain models. *Journal of Power Sources*, 282:265–276, 2015. ISSN: 0378-7753. DOI: https://doi.org/10.1016/j.jpowsour.2015.01.072.

[11] Jay Patrikar, Brady Moon, Sourish Ghosh, Jean Oh, and Sebastian Scherer. TrajAir: A General Aviation Trajectory Dataset. 6 2021. DOI: 10.1184/R1/14866251.v1.

[12] Junzi Sun, Joost Ellerbroek, and Jacco Hoekstra. Flight extraction and phase identification for large automatic dependent surveillance–broadcast datasets. *Journal of Aerospace Information Systems*, 14:1–6, 08 2017. DOI: 10.2514/1.I010520.

[13] Munish Manas, Ravish Yadav, and Rajesh Kumar Dubey. Designing a battery management system for electric vehicles: A congregated approach. *Journal of Energy Storage*, 74:109439, 2023. ISSN: 2352-152X. DOI: https://doi.org/10.1016/j.est.2023.109439.

[14] Gregory L. Plett. Extended kalman filtering for battery management systems of lipb-based hev battery packs: Part 2. modeling and identification. *Journal of Power Sources*, 134(2):262–276, 2004. ISSN: 0378-7753. DOI: https://doi.org/10.1016/j.jpowsour.2004.02.032.

[15] Xiaosong Hu, Shengbo Li, and Huei Peng. A comparative study of equivalent circuit models for li-ion batteries. *Journal of Power Sources*, 198:359–367, 2012. ISSN: 0378-7753. DOI: https://doi.org/10.1016/j.jpowsour.2011.10.013.

[16] S. Nejad, D.T. Gladwin, and D.A. Stone. A systematic review of lumped-parameter equivalent circuit models for real-time estimation of lithium-ion battery states. *Journal of Power Sources*, 316:183–196, 2016. ISSN: 0378-7753. DOI: https://doi.org/10.1016/j.jpowsour.2016.03.042.

[17] Xiaofeng Ding, Donghuai Zhang, Jiawei Cheng, Binbin Wang, and Patrick Chi Kwong Luk. An improved thevenin model of lithium-ion battery with high accuracy for electric vehicles. *Applied Energy*, 254:113615, 2019. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2019.113615.

[18] Merve Tekin and M. İhsan Karamangil. Comparative analysis of equivalent circuit battery models for electric vehicle battery management systems. *Journal of Energy Storage*, 86:111327, 2024. ISSN: 2352-152X. DOI: https://doi.org/10.1016/j.est.2024.111327.

[19] Manh-Kien Tran, Manoj Mathew, Stefan Janhunen, Satyam Panchal, Kaamran Raahemifar, Roydon Fraser, and Michael Fowler. A comprehensive equivalent circuit model for lithium-ion batteries, incorporating the effects of state of health, state of charge, and temperature on model parameters. *Journal of Energy Storage*, 43:103252, 2021. ISSN: 2352-152X. DOI: https://doi.org/10.1016/j.est.2021.103252.

[20] Yinjiao Xing, Wei He, Michael Pecht, and Kwok Leung Tsui. State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures. *Applied Energy*, 113:106–115, 2014. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2013.07.008.