Extending Battery Life via Load Sharing in Electric AirCraft

George K. Anthony* and Nathaniel Cooper† and Jarrett Peskar‡
University of South Carolina, Columbia, SC, 29208

Austin Downey§
University of South Carolina, Columbia, SC, 29208

Kristen Booth¶
University of South Carolina, Columbia, SC, 29208

Electric Aircraft have the potential to revolutionize short-distance air travel with lower operating costs and simplified maintenance. However, due to the long lead-time associated with procuring batteries and the maintenance challenges of replacing and repairing batteries in electric aircraft, there are still unanswered questions related to the true long-term operating costs of electric aircraft. This research examines using a load-sharing system in electric aircraft to optimally tune battery degradation in a multi-battery system such that the battery life of a single battery is extended. The active optimization of energy drawn from multiple battery packs means that each battery pack reaches its optimal replacement point at the same time; thereby simplifying the maintenance procedure and reducing cost. This work uses lithium iron phosphate batteries experimentally characterized and simulated in OpenModelica for a flight load profile. Adaptive agents control the load on the battery according to factors such as state of charge, and state of health, to respond to potential faults. The findings in this work show the potential for adaptive agents to selectively draw more power from a healthy battery to extend the lifespan of a degraded battery such that the remaining useful life of both batteries reaches zero at the same time. Simulations show that dual battery replacement can be facilitated using the proposed method when the in-service battery has a remaining useful life of greater than 0.5; assuming that the replacement battery it is paired with has a remaining useful life of 1.0. Limitations of the proposed method are discussed within this work.

I. Nomenclature

RUL	=	remaining useful life
SOC	=	state of charge
SOH	=	state of health
EOL	=	end of life

II. Introduction

Electric airplanes have emerged as a promising solution to address the challenge of sustainable transportation, offering reduced carbon emissions, lower noise levels, and enhanced energy efficiency. All-electric and hybrid-electric power systems have shown promise in other fields of transportation. For these systems, the lifespan of batteries is key to further development; particularly when fast charging is considered [1]. Safety is of utmost importance in aviation, and batteries pose unique safety challenges [2, 3]. Issues such as thermal runaway and off-gassing need to be addressed to ensure the safe operation of electric aircraft. Robust battery management systems and effective safety protocols are essential for mitigating these risks.

*Graduate Research Assistant, AIAA Member, Department of Mechanical Engineering, University of South Carolina, Columbia, SC 29208, USA.
†Graduate Research Assistant, Mechanical Engineering, University of South Carolina, Columbia, SC 29208, USA.
‡Graduate Research Assistant, Department of Mechanical Engineering, University of South Carolina, Columbia, SC 29208, USA.
§Associate Professor, AIAA Member, Department of Mechanical Engineering, Department of Civil, and Environmental Engineering, University of South Carolina, Columbia, SC 29208, USA, Contact Author austindowney@sc.edu.
¶Assistant Professor, Department of Electrical Engineering, University of South Carolina, Columbia, SC 29208, USA.

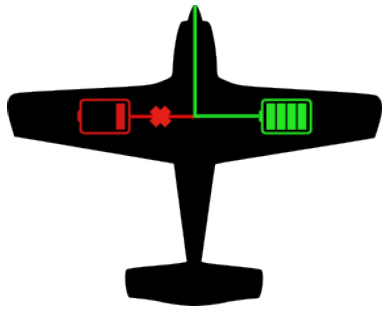


Fig. 1 Diagram of a plane with a simulated fault in a single battery of a dual-battery system.

Maintenance related to batteries caused by their inevitable degradation are critical factors in the operational costs and reliability of electric aircraft [1]. Frequent charging and discharging cycles may be required to maintain high airframe availability. Moreover, high power demands during flight can accelerate battery degradation. Ensuring the longevity of batteries while maintaining optimal performance is a significant challenge. Digital twins offer the ability to track the state of various electric aircraft subsystems in real-time. When combined with remaining useful life (RUL) forecasting tools [4], they offer the potential to optimally manage the degradation and maintenance of batteries.

To enhance safety and preserve the life of batteries in electric aircraft, this paper explores using adaptive agents to share the load between multiple batteries in an aircraft by looking at the status and health of each battery in real-time and adjusting power routing and sourcing on the fly. For example, an aircraft with two batteries may experience a fault event that creates premature degradation on one of the batteries as seen in Fig. 1. Now the battery has to be replaced. After replacement, there will be two batteries with different states of health. If nothing is done the batteries will continue to operate with uniform power draw, creating an irregular maintenance schedule for the aircraft. In this work, we propose a method where the adaptive agent will prioritize drawing power from the battery with a higher SOH (State of Health) to degrade it faster than the battery that has already consumed a larger portion of its useful life. This allows the RUL to even out between battery packs, reducing unnecessary strain on the older cells as seen in Fig. 2.

Data used for these adaptive agents can also be used to track the condition of batteries for streamlined maintenance and increased battery life. Wang et al., [5] showed that SOH can be tracked using only the constant voltage segment of the charge cycle. This work first introduces the multi-agent control scheme and uses OpenModelica v1.21 [6] to model a stand-in system for an electric aircraft. This work introduces a multi-agent approach for real-time power sharing in electric aircraft. The contribution of this work is in proposing a method to potentially solve a problem presented by the maintenance of an electric aircraft. This paper observes how this method works and identifies additional changes that need to be made to further explore to streamline the maintenance of electric aircraft systems.

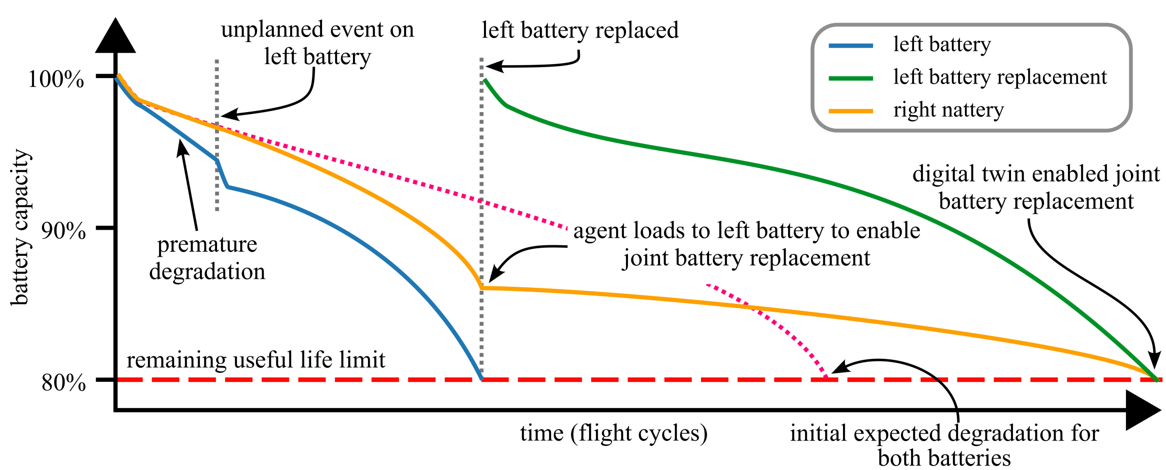


Fig. 2 Scenario of battery fault showing how the optimal usage of a replacement battery could enable two batteries to be replaced at the same time.

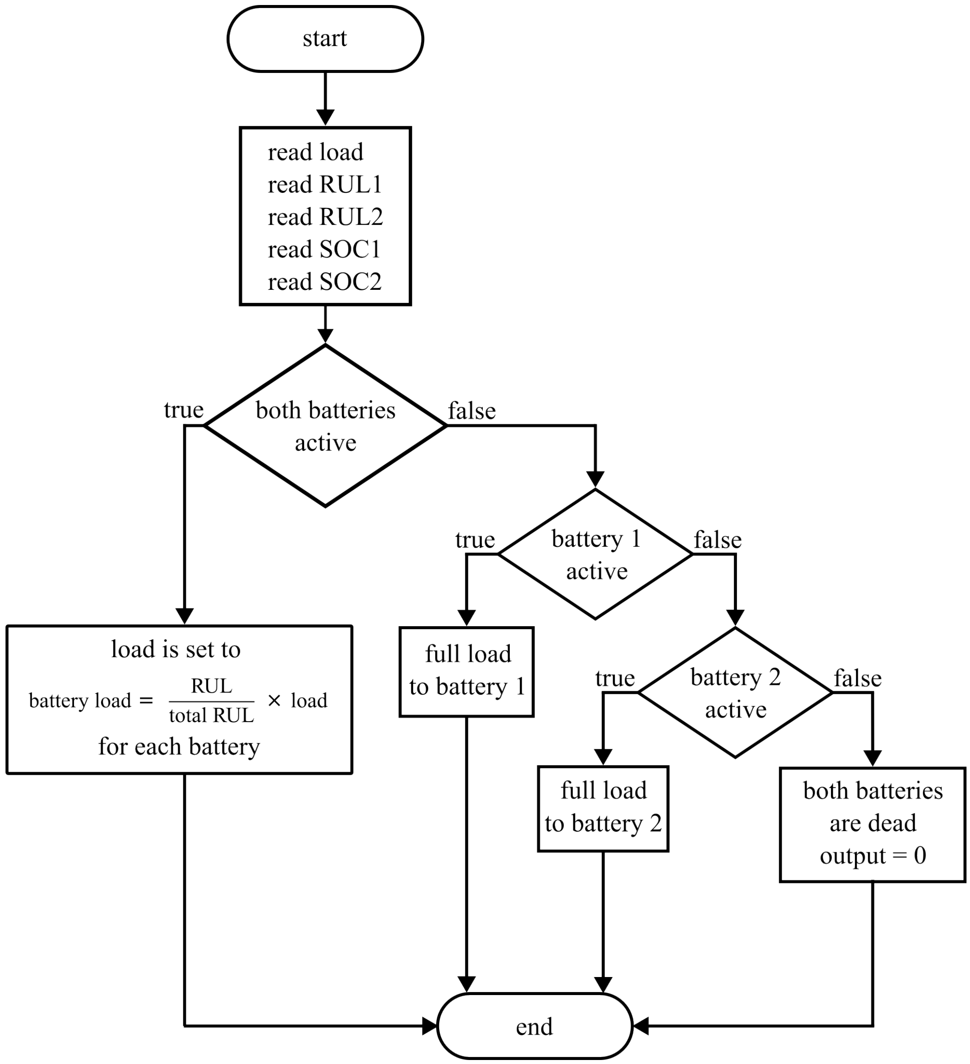


Fig. 3 Flow chart of the basic logic of adaptive agent.

III. Methodology

The aircraft architecture developed and tested in this paper consists of a pair of battery packs, supplying the load to an electric motor powering a small general aviation aircraft, as shown in Fig. 1. Each battery has a battery management system, allowing for easy tracking of temperature, state of charge (SOC), SOH, and RUL. These variables are used for the calibration of the adaptive agent. SOC is tracked using coulomb counting while the RUL is calculated using an equivalent cycle approach based on the battery datasheet. The agent is the decision maker and acts autonomously, constrained by the requirement to source enough power to the motor.

The agent is designed to adjust the load by comparing the RUL and SOC between two batteries as diagrammed in Fig. 3. The figure shows the process of comparing the two RULs and then scaling the load based on the ratio. If the agent detects a SOC has reached zero or been fully charged, it fully directs the load to the remaining battery. Reducing the load of a battery with a lower SOH can potentially reduce the time it takes for the battery to reach EOL and hit the knee gap where the battery's capacity dramatically declines. Mathematically, this is represented as:

$$\text{battery load} = \left(\frac{\text{RUL}}{\text{total RUL}}\right) \times \text{load} \tag{1}$$

where RUL is the batteries RUL and total RUL is the sum of all battery RULs in the system.

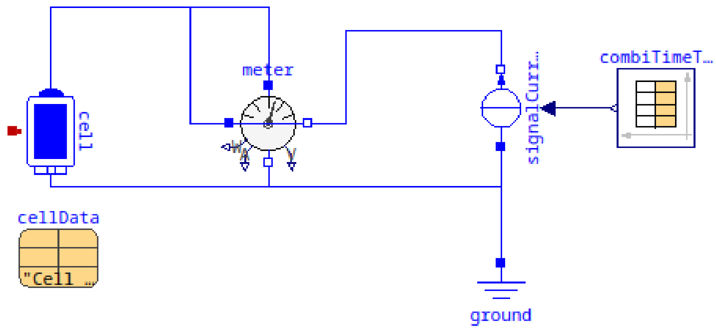


Fig. 4 OpenModelica model of a single 26650 cell used for experimental validation.

The agent also helps identify additional efficiencies and calibrate the use of batteries for optimal performance. The adaptive agent adjusts based on four inputs into the battery as seen in Fig. 3. One limitation of this configuration is that if the load is too unbalanced, it can rapidly discharge one battery faster than the other. This allows the aircraft to continue to operate, but it loses the redundancy of having two batteries. This loss of redundancy is a safety concern because the remaining battery is also the one with a lower SOH.

The operational state of the batteries is tracked by a state variable to prevent any dangerous discharge. The system constantly verifies it is only pulling from an active battery. When a battery enters a discharged or faulted state, the adaptive agent no longer asks it to provide a load to the system. This prevents any dangerous use of the batteries that would damage the system. Any active batteries in the system are used and calculated towards the remaining power capacity.

The OpenModelica model is used to find the limits of the proposed load sharing methodology under different RUL configurations. A 75% of full power load is tested, emulating the expected max load of an aircraft leaving excess capacity for a power reserve [1]. The starting RULs are adapted as well. The experiment emulates a plane with two batteries where one battery fails at a different RUL and has a new battery replacing the old one. This gives the plane one battery at 1 RUL and another at a lower RUL. The new battery is replaced at 0.8, 0.6, 0.4, and 0.2 RUL to see how the system reacts differently to the difference in Battery RUL.

A LiFeP 22650 is chosen for this simulation because it is a cylindrical cell, so it is not affected by the atmospheric pressure difference of operating on an aircraft, and its long voltage plateau allows it to provide a reliable voltage over its SOC. A model of a 26650 lithium-ion battery cell was developed using the standard OpenModelica electrical libraries, pictured in Fig. 4. The primary components were 1) a single 26650 cell, 2) a "cell data" record containing all the pertinent parameters for the battery model, 3) a variable current load representing the aircraft motor, and 4) voltage, current, and power meters. The model can easily be scaled from a single cell to a full stack of arbitrary size by specifying the number of cells to be connected in parallel and series.

Parameterization of the model was done by experiment and review of the literature. A used lithium iron phosphate (model LFP26650P manufactured by K2 Energy) with an SOH was used in all experiments. Manufacturer specifications of the cell are given in Table 1. Because of the degraded state of the battery, the maximum capacity was approximately 85% of its nominal capacity of 2.5 Ah or 2.21 A-hr. The two most important parameters in characterization were the SOC-OCV curve and the cell's internal resistance.

Table 1 K2 LFP26650P manufacturer specifications.

Specification	Value
Diameter, mm	0.046653
Length, mm	0.031821
Cell Capacity at C/5, A-hr	0.028593
Weight, g	0.023320
Operating Temperature, °C	-20 to 60

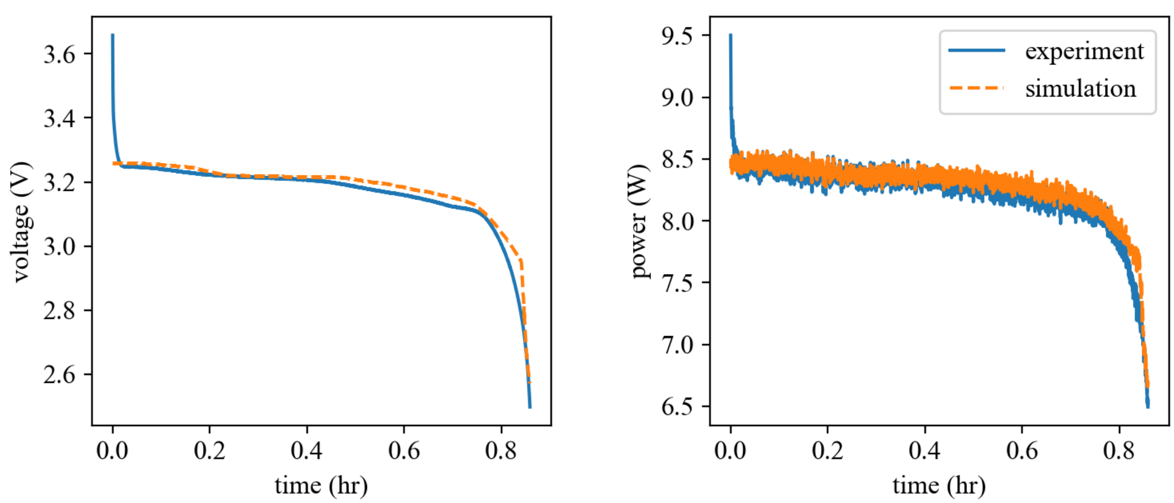
Table 2   26650 cell internal resistance.

Ambient Temperature, °C	Resistance, mΩ
20	46.653
30	31.821
40	28.593
50	23.320
T_{amb}	69.184 exp(-0.022 T_{amb})

The SOC-OCV curve for a battery mapped the open circuit voltage (OCV), the cell's voltage when disconnected from any current load, to the cell's state of charge (SOC), ranging from zero to 1. In Chin et. al. [7], the authors developed a comprehensive electro-thermal model of a similar 26650 $LiFePO_4$ cell, including the SOC-OCV curve. Data from this curve was tabulated and entered as the cell's SOC-OCV curve. The model then was bench-marked by simulating a full discharge cycle at 5 A and comparing the result to the discharge curve provided by the manufacturer. A nominal (0.001 Ω) resistance was assumed. The results showed generally good agreement, matching to within 5% during the constant voltage part of the curve. The SOC-OCV curve of Chin therefore was deemed adequate.

To estimate the cell's internal resistance, a series of pulse tests were run at a series of different ambient temperatures (20, 30, 40, and 50 °C). In each, the cell was charged at 6 A and discharged at 3 A three times. For each discharge cycle, the cell's voltage drop was measured and the resistance was estimated from Ohm's Law. The calculated resistances from each pulse were then averaged to give an overall value at each temperature. Full results are given in Table 2. To estimate the resistance at an arbitrary ambient, the result for each ambient was fit to an exponential curve, giving:

To validate the model, a set of discharge tests was conducted measuring the cell's voltage and power, with the measured current being directly input as the current load of the simulated cell. As in the section on cell resistance, these tests were conducted at 20, 30, 40, and 50 °C. A representative example of the results at 50 °C is shown in Fig. 5 (a) (cell voltage) and Fig. 5 (b) (power). In general, excellent agreement is shown for SOC greater than 0.1 (greater than 2800 seconds). The elbow observed below this threshold is likely an artifact of the SOC-OCV curve and could be corrected with additional testing. At the lower ambients, this divergence began slightly earlier; this was due to the resistance calculations being less reliable at lower temperatures [7].



(a)   (b)

Fig. 5   Experimental vs. simulated results for: (a) voltage, and (b) power.

Table 3 RUL equalization results.

RUL1 Start Value	RUL2 Start Value	Equalization Result	Final RUL1	Final RUL2
1	0.8	Success	0	0
1	0.6	Success	0	0
1	0.5	Success	0	0
1	0.4	Fail	0.2	0
1	0.2	Fail	0.6	0

IV. Results

When given batteries with varying SOH values it was found that the limits of the current method of load sharing correction could be determined. The load of 75% nominal capacity limited the amount of RUL correction per flight cycle. For the scenarios of RUL2 as 0.8, 0.6, and 0.5 the agent was able to equalize the RULs without ever losing redundancy of using both batteries this is indicated as success in Table 3. When a load equal to 0.75 of its capacity was given to the battery, the agent prioritized the load and was able to equalize both RULs without losing redundancy as long as battery 2's RUL was more than 0.5 at the time of replacement. When battery 2's starting RUL was lower than 0.50 the agent was unable to equalize the RULs effectively. This resulted in the older battery reaching zero RUL before the other.

Once the starting RUL2 was lower than 0.5 the limits of this load equalization strategy were seen. When the first battery ran out of charge, it continued to strain the other battery. As seen in Fig. 6 the first battery rapidly discharged so the second battery had to take on the full load. This was cause for concern because the redundancy of having a two-battery system was lost. Although the RULs were not able to meet at zero, the batteries with the lower SOH were able to perform 50% more flights before reaching EOL than if there had been no adaptive load sharing. The agent was able to narrow the gap between the two batteries and will be able to match the RULs at zero after one or two more replacements. A RUL2 value of 0.5 was the minimum value that can be corrected with this approach and a consistent 75% load.

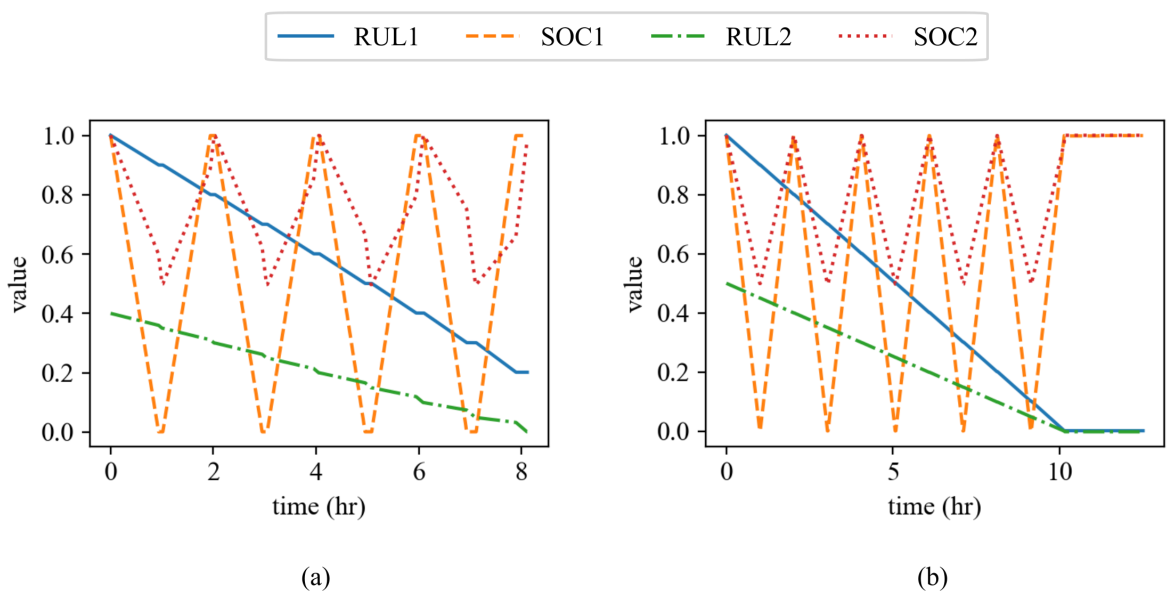


Fig. 6 Load sharing experiment for low starting RULs, showing: (a) RUL2 = 0.4, and (b) RUL2 = 0.5.

V. Conclusion

This research presents an approach to adjusting the battery load for a more efficient maintenance strategy. The findings showed the potential that agents could enable a more efficient maintenance strategy by altering the load of batteries and tracking the operating and remaining useful life of the batteries. By prioritizing the healthier battery, it was possible to extend the life of the aged battery and return to a more normal operation over time. Aligning the battery's SOH allows for a streamlined maintenance cycle.

This study observed one approach to load-sharing two batteries for an electric aircraft. Some clear disadvantages to this approach should be explored further. For systems with one battery with a low RUL, the agent caused one battery to discharge to zero much faster than the other battery. A loss of redundancy brings up several safety concerns for the operation of an aircraft as loss of power is catastrophic for a plane with nowhere to land. This research studied the maximum load of 75% of its total capacity. However, operating the battery under smaller loads would potentially offer more flexibility and operational advantages for the agent and should be investigated further. The current agents were tasked with having the RULs meet at zero. Future work should investigate having the RULs equalize earlier and then degrading together in parallel. This system also didn't account for the additional strain placed on a battery that went beneath 20% SOC. In practice, this method of degradation might have put more unnecessary wear on the batteries than intended.

References

[1] Yang, X.-G., Liu, T., Ge, S., Rountree, E., and Wang, C.-Y., "Challenges and key requirements of batteries for electric vertical takeoff and landing aircraft," *Joule*, Vol. 5, No. 7, 2021, pp. 1644–1659. https://doi.org/10.1016/j.joule.2021.05.001.

[2] Ma, Y., Teng, H., and Thelliez, M., "Electro-Thermal Modeling of a Lithium-ion Battery System," *SAE International Journal of Engines*, Vol. 3, No. 2, 2010, pp. 306–317. https://doi.org/10.4271/2010-01-2204.

[3] Lee, S., Cherry, J., Safoutin, M., McDonald, J., and Olechiw, M., "Modeling and Validation of 48V Mild Hybrid Lithium-Ion Battery Pack," *SAE International Journal of Alternative Powertrains*, Vol. 7, No. 3, 2018, pp. 273–287. https://doi.org/10.4271/2018-01-0433.

[4] Lui, Y. H., Li, M., Downey, A., Shen, S., Nemani, V. P., Ye, H., VanElzen, C., Jain, G., Hu, S., Laflamme, S., and Hu, C., "Physics-based prognostics of implantable-grade lithium-ion battery for remaining useful life prediction," *Journal of Power Sources*, Vol. 485, 2021, p. 229327. https://doi.org/10.1016/j.jpowsour.2020.229327.

[5] Wang, Z., Zeng, S., Guo, J., and Qin, T., "Remaining capacity estimation of lithium-ion batteries based on the constant voltage charging profile," *PLOS ONE*, Vol. 13, No. 7, 2018, p. e0200169. https://doi.org/10.1371/journal.pone.0200169.

[6] OpenModelica Association, *OpenModelica User's Guide*, 2023. URL https://openmodelica.org/doc/OpenModelicaUsersGuide/1.21/.

[7] Chin, C., Gao, Z., and Zhang, C., "Comprehensive electro-thermal model of 26650 lithium battery for discharge cycle under parametric and temperature variations," *Journal of Energy Storage*, Vol. 28, 2020, p. 101222. https://doi.org/10.1016/j.est.2020.101222.

Acknowledgments

This work is supported by the NASA thorough grant 521536-SC. This work is also partially supported by the National Science Foundation, United States Grant number 2237696. The support of NASA and the NSF is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NASA or the National Science Foundation.