Machine learning-based prediction for state-of-health of lithium-ion battery used for eVTOL aircraft in urban air mobility

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Abstract

The future and spread of the Urban Air Mobility (UAM) largely relies on aircraft capable of fully electric vertical take-off and landing (eVTOL). The main power source of these vehicles for the propulsion system is the lithium-based batteries in general. Since an aircraft requires more dynamic power than ground-based vehicles. Battery aging that occurs during the long-term use of batteries should be considered much more for the safe and efficient mission of the eVTOL in UAM. Since battery aging cannot be measured directly, predictive methods are implemented and the state of health (SOH) of a battery is an important parameter to predict battery aging. In this study, a machine learning-based regression approach is applied to predict the state of health of the lithium-ion battery of eVTOL. For this purpose, the Random Forest, Decision Tree, and Polynomial Regression algorithms were tested on a public open dataset (only for the VAH01 mission) consisting of take-off, cruising, and landing flight phases for a lithium-ion battery of eVTOL. Additionally, 2nd, 3rd, and 4th-degree Polynomial algorithms were implemented and compared with each other and with other two regression algorithms. As a result, while the mean absolute error (MAE) for the Random Forest algorithm is 1.29 for the same problem in the literature, it was obtained as 0.95 in this study. In addition, to predict SOH, the lowest MAE was provided as 0.7 in the 2nd Polynomial algorithm among the entire algorithms implemented in this study.

1 Introduction

The term 'urban air mobility (UAM)' refers to cargo delivery, emergency management, and passenger mobility in metropolitan cities and surrounding [1][2]. Among the various aircraft configurations, VTOL-type (Vertical Take-Off and Landing) vehicles stand out as the most suitable choice for UAM, eliminating the need for traditional runways [3]. The academic and commercial research on VTOL-type aircraft is currently focused on three main areas: the propulsion system, autonomy, and conceptual design, with major companies like Uber Elevate, Hyundai, eHANG, Boeing-Aurora Transmitive, Grab, LILIUM, Supernal, Airbus, and BLADE actively involved in this trend.[4][5].

Fully-electric propulsion systems used in urban air mobility are especially attractive considering of environmental sustainability of VTOL aircrafts [6][7]. They may consist of a single energy source or a hybrid system (mono application of battery, fuel cell, solar cell, and supercapacitor or hybridisation of them). Considering energy/power density, response time, and cost, lithium-based batteries are the best option for non-hybrid propulsion systems of fully-electrical VTOL (eVTOL) aircraft [8].

The development and widespread use of eVTOL vehicles heavily relies on batteries as a key technology. The critical considerations for lithium-based batteries in eVTOL vehicles encompass their designed lifespan, efficiency, and the assurance of safe operation during missions [9]. Thus, the reliable and efficient missions of eVTOLs rely on battery management systems (BMS) in practice. Moreover, air vehicles have a more dynamic power demand characteristic than on-ground vehicles. In other words, a eVTOL vehicle needs higher power demand in the take-off flight phase compared to other flight phases (landing and cruise) [10]. This situation accelerates battery aging, which, over time, causes unreliable missions, connection losses, and inefficient flights in eVTOL vehicles. [11]. As a result, eVTOL vehicles in urban air mobility require a BMS to ensure the safety and efficiency of their missions. The BMS includes battery state indicators that cannot be measured directly, such as state of charge (SOC), state of health (SOH), state of function (SOF), state of temperature (SOT), remaining useful life (RUL), state of power (SOP), as well as aging and degradation prediction.

The state of health (SOH) is defined as the rate of actual measured capacity to rated capacity, and it indicates the decrease in the capacity due to the battery aging. There are many SOH estimation studies for on-ground electric vehicles (they are summarized in References [12] and [13]). However, due to the scarcity of publicly available data and the difficulty of collecting data, there are limited studies for aircrafts. For electric vehicles, publicly available battery test data are summarized in Reference [14]. Accordingly, Fredericks et al. [15] share the battery (consisting of 22 cells) measurement data of an eVTOL vehicle. This data set is important as it covers all flight phases and many different flight missions of the eVTOL vehicle in the UAM. Using this dataset, Granado et. al. [16] performed the battery SOH estimation with Linear Regression, Support Vector Machines, k-Nearest Neighbours (kNN), Random Forest, and Gradient-Boosted Trees regression-based machine learning algorithms. They concluded that kNN is the most suitable algorithm in terms of the accurate prediction (test-$R^2 \approx 0.98$) and the low training time (1 µs/point). In the same dataset, Mitici et. al. [17] applied various machine-learning algorithms (Support Vector regression (SVR), Random Forrest (RF) regression, Gaussian Process regression (GPR), Extreme Gradient Boosting (XGBoost), and Multi-layer Perceptron (MLP)) for battery SOH and RUL estimation. They stated that Random Forest Regression and Extreme Gradient Boosting algorithms are well suitable for battery RUL and SOH estimation. Based on the literature search, it can be deduced that studies about the battery performance prediction of a VTOL vehicle for UAM seem to be limited to these two studies. However, there are some studies related to battery performance prediction in unmanned aerial vehicles designed for different missions (example of [18-24]).

In this study, the SOH prediction of a lithium-ion battery for the eVTOL aircraft in Reference 5 was performed using machine learning-based algorithms. In this context, algorithms such as Random Forest, Decision Tree, and Polynomial regression were applied to the datasets in Reference [15]. In addition, hyperparameter tuning studies were carried out for these machine learning regression algorithms. Among these algorithms, the 2nd-order Polynomial algorithm provided the lowest mean absolute error (MAE). The novelty of this study is the application of the Decision Tree and Polynomial algorithms to this data set for the first time, as well as the application of the hyperparameter tuning and finding the best degree for the Polynomial regression. To summarize, this study makes the following contributions:

1- A lower Mean Absolute Error than Ref. [17] was obtained by tuning the hyperparameters of the Random Forrest regression algorithm for mission profile VAH01. Therefore, we have achieved more accurate results for the SOH prediction of the battery compared to the recent literature.

2- The performances of 2nd, 3rd, and 4th-degree Polynomial algorithms were compared with each other for SOH prediction. Accordingly, the lowest MAE was provided by the 2nd-degree Polynomial algorithm. In addition, this MAE value (0.72) is the lowest value for the VAH01 mission according to the literature [17].

3-For the mission profile VAH01, Decision Tree regression and Polynomial algorithm were used first-time to predict the SOH of the battery in this study.

4- Finally, this study contributes by providing the opportunity for comparison and validation to the literature in that there are very few studies on SOH prediction of lithium-ion batteries of the eVTOL vehicles.

5- The SOH of lithium-ion battery is estimated using 4-fold cross-validation in this study, while 5-fold validation method is employed in the literature ([17]).

2 Data description

2.1. Dataset

For machine learning-based SOH prediction, was used the dataset available at [15]. This dataset was collected for an eVTOL vehicle by researchers at Carnegie Mellon University in 2018-2019 and consists of 22 flight missions. Of these, VAH01, VAH17, and VAH27 are baseline flight missions, and other mission data sets consist of according to different cruising flight times, thermal chamber temperatures, CC (constant current) charge currents, and CV (constant voltage) charge voltages. In this study, SOH prediction studies based on machine learning were carried out only for the VAH01 flight mission, and it is planned to be applied to all flight missions as the extension of this study. Figure 1 shows a representative flight profile for the baseline flight mission VAH01. The flights consist of take-off, cruising, and landing flight phases for every mission.

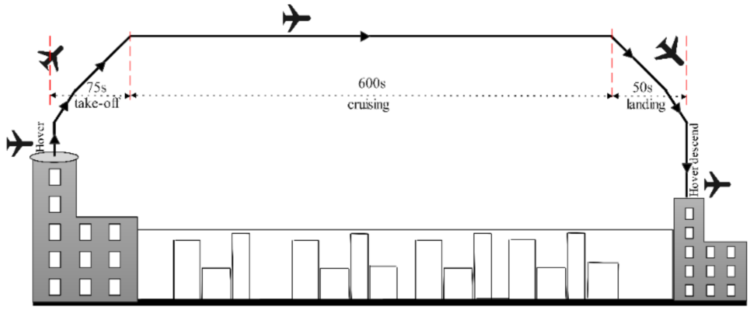

Figure 1: The basic VAH01 flight mission of the eVTOL vehicle.

2.2. Baseline mission profiles and capacity tests

Each flight mission profile data in Reference [15] consists of 10 variables: time (s), voltage (V), current (A), charge energy (Wh), charge capacity (mAh), discharge energy (Wh), discharge capacity (mAh), cell temperature (˚C), cycle number, and cycle segment. The VAH01 flight profile has 847 missions and 17 capacity tests. The mission that comes after every 50th mission is called a capacity test. In other words, the capacity tests are realized on 0., 51., 101...., and 801. missions. In this study, as implemented in Reference [24], the 17 capacity tests were taken into account for the SOH prediction of the battery. In a capacity test, the remaining battery charge after the previous flight is decreased to 0% SOC at a constant discharge rate of C/5 until the voltage decreases below 2.5 V. After that, the battery is charged to 100% SOC at a constant charging rate of 1 C-rate and a constant voltage of 4.2 V (Figure 1). This process is repeated for each capacity test (after every 50 missions). All missions of the eVTOL vehicle are carried out according to the following seven phases. In addition, 1st capacity test of the VAH01 is given as before (left) and during (right) flight in Figure 2.

1-CC charging phase: The battery is charged in 1 C-rate until voltage approach 4.2 V.

2-CV charging phase: This phase continues with a constant voltage of 4.2 V until current of the battery is under C/30.

3-1st resting phase: This phase lasts until the battery cell temperature is 35 ˚C.

4-Take-off phase: The eVTOL vehicle stars take-off that continue 75 seconds in total. The take-off phase has 54 W discharge power, 5 C-rate, and 1.12 Wh discharge energy.

5-Cruising phase: In the cruising flight phase of the eVTOL, the battery has 800 s duration, 16 W discharge power, and 3.55 Wh discharge energy.

6-Landing phase: In the cruising flight phase of the eVTOL, the battery has 105 s duration, 54 W discharge power, 5-C rate, and 1.57 Wh discharge energy.

7-2nd resting phase: This phase lasts until the battery cell temperature is 27 ˚C.

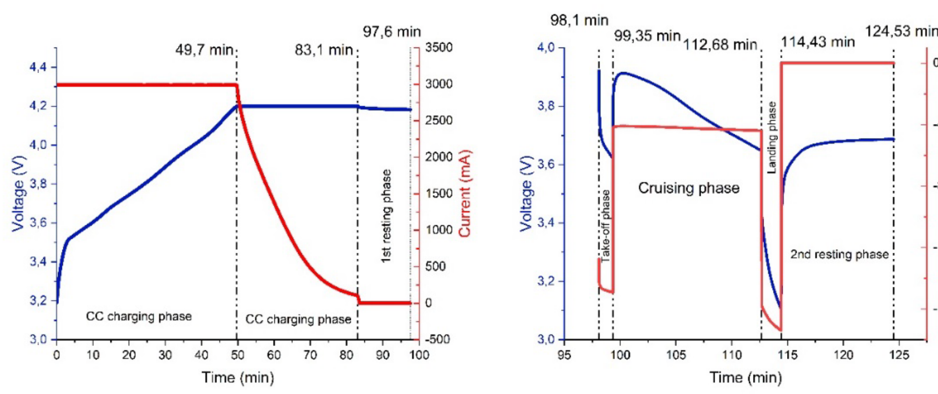

Figure 2: Pre-flight (left) and during-flight (right) phases of the 1st capacity test in VAH01 mission.

3 Methodology

3.1. Definition of State-of-Health

The SOH of a battery is the ratio of the measured charge capacity to the nominal charge capacity. Since the nominal capacity of the battery used in the dataset is slightly smaller than the capacity value in the first capacity test. For this reason, the capacity in the first capacity test is considered instead of the nominal capacity for the SOH calculation in this study [17]. Eventually, the following Equation 1 can be used for the calculation of SOH.

$$SOH^{m,c} = \frac{max_i(Qcharge_i^{m,c})}{max_i(Qcharge_i^{m,0})} x100 \tag{1}$$

Where $Qcharge_i^{m,c}$ represents the maximum measured capacity in a capacity test c of missin profile m. $Qcharge_i^{m,0}$ represents the battery capacity in the first capacity test. Here, m is the number of missions and c is the number of capacity tests.

3.2. Data preparing and definitions of the features for SOH prediction

Mitici et al. [17] determined that 21 of the 33 features in the data set were highly important for SOH prediction of the battery. In this study, SOH prediction was performed using these 21 features for the VAH01 mission profile (see Table 1). VAH01 consists of 17 capacity tests and 847 missions. These 21 features are obtained from the data set of VAH01 mission for each capacity test and were used to train and test algorithms for the prediction of the SOH of the battery. After calculating these 21 features for 17 capacity tests, the SOH of the battery was estimated using these data.

Feature	Description	Unit
$V_{var}^{take-off}$	Variance voltage during take-off	V
$V_{min}^{take-off}$	Min. voltage during take-off	V
Δ^{CC}	Duration CC charging	s
Δ^{CV}	Duration CV charging	s
$V_{mean}^{take-off}$	Mean voltage during take-off	V
Δ^{rest}	Duration rest phase after charging	s
$T_{max}^{landing}$	Max. battery cell surface temperature during landing	˚C
T_{max}^{cruise}	Max. battery cell surface temperature during cruise	˚C
V_{min}^{cruise}	Min. voltage during cruise	V
$T_{max}^{take-off}$	Max. battery cell surface temperature during take-off	˚C
V_{max}^{cruise}	Max. voltage during cruise	V
$V_{var}^{landing}$	Variance voltage during landing	V
$V_{max}^{take-off}$	Max. voltage during take-off	V
$Qdis_{max}^{take-off}$	Max. discharge capacity during take-off	Ah
$Qdis_{min}^{take-off}$	Min. discharge capacity during take-off	Ah
$\Delta^{take-off}$	Duration take-off flight phase	s
$Qdis_{mean}^{take-off}$	Mean discharge capacity during take-off	Ah
$Qdis_{min}^{cruise}$	Min. discharge capacity during cruise	Ah
$Qdis_{var}^{landing}$	Variance discharge capacity during landing	Ah
$V_{min}^{landing}$	Min. voltage during landing	V
$Qdis_{var}^{take-off}$	Variance discharge capacity during take-off	Ah

Table 1: Features used in the prediction of battery SOH.

3.3. Performance metric

Mean Absolute Error (MAE) was used to compare the performance of the machine learning algorithms used to predict the state of health. MAE represents the average of absolute errors, and being close to zero means that the predictive ability of the model is robust. For SOH prediction of the battery, the MAE calculation of each mission and their average are given in Equations 2 and 3, respectively.

$$MAE_{SOH}^{m} = \frac{1}{C^m}\sum_{i=1}^{C^m}\left|SOH^{m,i} - \widehat{SOH}^{m,i}\right| \tag{2}$$

$$MAE_{SOH} = \frac{1}{M}\sum_{j=1}^{M} MAE_{SOH}^{j} \tag{3}$$

where, SOH and $\widehat{SOH}$ represent true SOH and predicted SOH of the battery, respectively (m: the number of missions and c: the number of capacity tests). The MAE_{SOH}^{m} and MAE_{SOH} represent mean absolute error at mission profile m and mean absolute error for the entire mission, respectively. Additionally, M and C state the total number of mission and total number of capacity tests, respectively.

4 Results and discussion

The predicted battery SOH results for the Random Forest (RF) algorithm are given in Table 2. Accordingly, the MAE for the default RF algorithm was 1.21, while after the hyperparameters were tuned, the MAE decreased to 0.95. For the same algorithm and the same flight mission (VAH01), the 0.95 value is lower than as in the literature (approximately 1.06, please see Reference [17]). By hyperparameter tuning, the prediction of 1st capacity test is reasonably improved from 95.31% (for default parameter setting) to 96.33% on this algorithm. While the true battery SOH was 83.83% in the 12th capacity test, it was the best prediction amongst SOH predictions as 83.78% by the tuning the hyperparameters of the random forest algorithm on this capacity test. On the last capacity test, the predicted SOH was obtained as 81.70% for default hyperparameters, however this is optimised to 81.16% by the tuning of these hyperparameters.

Algorithm	Capacity Tests	True SOH (%)	Predicted SOH (%)	MAE	Hyperparameters
Random Forest (default)				1.21	N. Estimators:100
	1 st	100	95.31		Min. Samples Split:2
	4 th	91.85	91.79		Min. Samples Leaf:1
	8 th	87.45	87.13		Max. Depth:None
	12 th	83.83	84.09		Bootstrap:True
	16 th	80.98	81.70		Max. Features:'auto'
					Random State:0
					Criteration:MSE
Random Forest (tuning)				0.95	N. Estimators:100
	1 st	100	96.33		Min. Samples Split:2
	4 th	91.85	91.45		Min. Samples Leaf:1
	8 th	87.45	86.99		Max. Depth:None
	12 th	83.83	83.78		Bootstrap:True
	16 th	80.98	81.16		Max. Features:'auto'
					Random State:0
					Criteration:MSE

Table 2: SOH prediction results for the Random Forest algorithm.

The battery SOH prediction results carried out with the Decision Tree algorithm are presented in Table 3. After tuning the hyperparameters of this algorithm, the MAE dropped from 2.35 to 2.64. By hyperparameter tuning, the prediction of 1st capacity test is significantly improved from 90.50% (for default parameter stetting) to 95.09% on this algorithm. In the last capacity test (in 16-th capacity test), the actual SOH and the predicted SOH for the tuned Decision Tree algorithm were calculated as 80.98% and 82.31%, respectively.

Algorithm	Capacity Tests	True SoH (%)	Predicted SoH (%)	MAE	Hyperparameters
Decision Tree (default)				2.64	Splitter:best
	1 st	100	90.50		Min. Samples Split:2
	4 th	91.85	93.33		Min. Samples Leaf:1
	8 th	87.45	86.83		Max. Depth:None
	12 th	83.83	85.26		Random State:0
	16 th	80.98	80.81		Criteration:MSE
Decision Tree (tuning)				2.35	Splitter:best
	1 st	100	95.09		Min. Samples Split:5
	4 th	91.85	89.96		Min. Samples Leaf:1
	8 th	87.45	86.37		Max. Depth:2
	12 th	83.83	86.37		Random State:0
	16 th	80.98	82.31		Criteration:MSE

Table 3: SOH prediction results for the Decision Tree algorithm.

The SOH prediction results of the Polynomial Regression algorithm are presented in Table 4. 2nd, 3rd, and 4th order Polynomial Regression algorithms were compared in terms of MAE and predicted SOH. Accordingly, the MAE for the 2nd, 3rd and 4th order Polynomial Regression algorithms was calculated as 0.72, 0.83, and 1.04, respectively. In this study, the lowest MAE among the algorithms applied for SOH prediction was obtained with the 2nd order Polynomial Regression (by 0.72).

Algorithm	Number of Cyle	True SOH	Predicted SOH	MAE
Polynomial Regression (2nd order)				0.72
	0	100	99.46	
	4	91.85	93.36	
	8	87.45	86.92	
	12	83.83	84.31	
	16	80.98	80.4	
Polynomial Regression (3rd order)				0.83
	0	100	99.34	
	4	91.85	93.41	
	8	87.45	86.91	
	12	83.83	84.34	
	16	80.98	80.11	
Polynomial Regression (4th order)				1.04
	0	100	99.20	
	4	91.85	93.36	
	8	87.45	86.91	
	12	83.83	84.42	
	16	80.98	79.19	

Table 3: Results for the Polynomial Regression algorithm.

The comparison of the algorithms applied in this study and the literature is given in terms of MAE in Table 4. The lowest MAE value is attained with the application of 2nd order Polynomial Regression which is called quadratic model.

Algorithm	MAE	Ref.
Polynomial Regression (2nd order)	0.72	This study
Decision Tree	2.35	This study
Random Forest	0.95	This study
Random Forest	1.29	[17]
SVR	1.09	[17]
XGBoost	1.20	[17]
GPR	1.18	[17]
MLP	2.14	[17]

Table 4: MAE comparison for SOH prediction of the battery in VAH01 mission.

5 Conclusions

In this study, using the publicly available battery performance dataset of an eVTOL vehicle, state of health prediction of the lithium-ion battery was performed with regression-based machine learning algorithms. This dataset has 22 different flight missions with different flight phase demand powers (take-off, cruise, landing), ambient temperature, and cruise duration. Among these flight missions, SOH prediction for the VAH01 mission was performed with Random Forest, Decision Tree, and Polynomial Regression algorithms. Consequently, the conclusions and contributions of this study can be given as follows:

1- In this study, Decision tree and Polynomial Regression algorithms have been applied for the first time for the SOH prediction of the battery on this data set.

2-Among the Random Forest, Polynomial Regression, and Decision Tree algorithms used in this study for SOH prediction of the lithium-ion battery, the lowest MAE was achieved as 0.72 by the 2nd order Polynomial Regression algorithm. This MAE value is lower than the MAE values provided by other algorithms applied in the literature for the SOH prediction of battery on the VAH01 mission profile (please see Table 4).

3- For SOH estimation, 2nd, 3rd, and 4th order Polynomial Regression algorithms were compared, and the MAE values for these algorithms were 0.72, 0.83, and 1.04, respectively.

In the continuation of this study, the authors plan to estimate SOH, temperature, and RUL for all flight missions in the data set using the machine learning algorithms implemented in this study. In addition, domain adaptation and domain generalization studies will be carried out on this data set.

Acknowledgement

A support application was made to the Scientific and Technological Research Council of Türkiye (TUBITAK) for this study.

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