Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen
 Published by Research Publishing, Singapore.
doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P9886-cd

Adaptive predictive maintenance for the batteries of electric Vertical Take-off and Landing (eVTOL) aircraft using Remaining Useful Life prognostics

Mihaela Mitici

Faculty of Science, Utrecht University, The Netherlands.
E-mail: m.a.mitici@uu.nl

Simon van Oosterom

Faculty of Aerospace Engineering, Delft University of Technology, The Netherlands.
E-mail: s.j.m.vanoosterom@tudelft.nl

In this paper we develop probabilistic Remaining Useful Life (RUL) prognostics for Lithium-ion batteries using Mixture Density Networks (MDNs). We integrate these prognostics into a reliable and cost-efficient linear program model that identifies optimal battery replacement moments while limiting the risk of the batteries becoming inoperable during operations. Over time, as more measurements become available, the RUL prognostics are periodically updated, and the battery replacement strategy is adapted. We apply our approach for electric Vertical Take-off and Landing (eVTOL) aircraft, a promising emerging technology for mobility in congested urban areas. The results show that the RUL is accurately estimated using MDNs. The results also show that prognostics benefit the planning of battery replacement, leading to 80% less yearly unscheduled battery replacements compared with maintenance planning approaches when point estimates (average values) of the RUL are predicted.

Keywords: predictive maintenance, probabilistic RUL prognostics, eVTOL aircraft, mixture density networks.

1. Introduction

Urban areas are confronted with increasing traffic congestion. Electrical Vertical Take-off and Landing (eVTOL) aircraft are seen as a promising emerging technology for transportation in urban areas Wei et al. (2024). For safe and reliable operations, the management of the batteries is crucial.

Current eVTOL designs consider Lithium-ion batteries due to their high energy density, low self-discharge rates and feasible costs. Compared with Lithium-ion batteries for ground vehicles, the battery management of eVTOLs poses additional challenges: the take-off and landing of eVTOLs are safety-critical flight phases when the discharge rates of the batteries are high. In the long-run, this directly impacts the overall health condition of the batteries. We focus on data-driven RUL prognostics for eVTOL Lithium-ion batteries, where we distinguish between battery measurements taken during the take-off, cruise and landing. Moreover, we employ the obtained RUL prognostics to specify reliable and cost-efficient battery replacement strategies that are continuously adapted as more measurements become available. At the same time, beyond the specificity of features for prognostics for eVTOL batteries, our models for prognostics and battery replacement are applicable to general fleets of vehicles equipped with monitored li-ion batteries. It is only required that a trade-off is to be made between continuing the operation of the vehicles, and the risk of operating with highly degraded batteries.

Several data-driven approaches for RUL prognostics of Lithium-ion batteries have been proposed in the last years. Xie et al. (2020) estimate the RUL using a long-short term memory recurrent neural network with particle filtering, achieving less than 10% estimation error. In Zraibi et al. (2021) a hybrid convolutional neural network is combined with a long short-term memory and a deep neural network to predict the RUL of batteries. In Du et al. (2021) a long short-term memory recurrent neural network is proposed to estimate the RUL of the batteries. The estimation errors achieved are below 0.13% in the last phase of the battery lifetime (last 10 cycles).

The studies above assume that the batteries are subject to moderate discharge rates, which is the case for electric ground vehicles. However, for eVTOLs, the take-off and landing are performed at higher C-rate than the cruise phase. Few studies have developed SOH and/or RUL estimates for eVTOL batteries. In Granado et al. (2022) a k-nearest neighbors approach is shown to achieve a high accuracy for SOH estimation. However, the authors considers only the cruise phase of the flight, which is a strong limitation of the approach given that the take-off and landing are safety-critical phases of the eVTOL operations. In Mitici et al. (2023), a Gradient Boosting model is shown to achieve the highest accuracy for RUL estimation of eVTOL batteries. Here, the authors consider features for every phase of the flight (take-off, landing, and cruise). This study, however, develops point estimates of the RUL. In contrast, in this paper we estimate the distribution of the RUL (probabilistic RUL prognostics), being able to quantify the uncertainty associated with the RUL estimates.

In this paper we propose an adaptive predictive maintenance planning of Li-ion batteries, where data-driven RUL prognostics are integrated in an optimisation model for battery replacement. First, probabilistic RUL prognostics for eVTOL batteries are developed using a Mixture Density Network, i.e. we estimate the distribution of the RUL. These prognostics are further integrated into a reliable and cost-efficient linear programming model to plan battery replacements for a fleet of eVTOLs. The aim of the planning is to limit the risk of the batteries being in use beyond their End-of-Life (EOL), while maximizing the number of flight missions performed with each battery (or, equivalently, minimizing the wasted battery life). The obtained planning of battery replacements is adapted over time, as more measurements become available and the RUL prognostics are updated. When considering eVTOL operations for a period of 10 years, the results show that planning battery replacements using probabilistic RUL prognostics, rather than using point estimates of the RUL, results in up to 80% less unscheduled battery replacements due to batteries reaching their EOL unexpectedly. Beyond the specificity of feature for eVTOL batteries, our approach supports a reliable use of a fleet of vehicles equipped with li-ion batteries, where the health state of the batteries is continuously monitored.

2. Problem description

We consider a fleet V of eVTOL aircraft. Each eVTOL performs round trips to and from a hub. Each eVTOL performs n trips per day. The batteries are continuously monitored during operations. For each eVTOL $v \in V$, sensor measurements $\mathbf{x}_t^v \in \mathbb{R}^M$, $t \geq 0$, are recorded every time unit during operations, with M the number of parameters recorded. During operations, the battery is constantly degrading until its End-of-Life (EOL).

Based on the measurements recorded up to time t, a probabilistic RUL prognostic (the distribution of the RUL) for each battery is obtained.

eVTOL batteries are replaced at a hub. If a battery is replaced before its EOL, a preventive cost $c_{replace}$ is incurred. Battery replacement takes one day (during which the eVTOL cannot fly). At the start of a current day d_0, battery replacements are planned for the next days. Per day, at most h eVTOL batteries can be replaced at the hub. If an eVTOL reaches its EOL unexpectedly, then an unscheduled replacement is performed immediately at a cost $c_{unscheduled} >> c_{replace}$.

We are interested in identifying reliable and cost-efficient times of battery replacements taking into account the probabilistic RUL prognostics, as well as the flight schedule of the eVTOLs, and the maintenance capacity of the hub.

3. Data description

We consider the condition-monitoring dataset for Sony-Murata 18650 VTC-6 cell Lithium-ion batteries Bills et al. (2023). These batteries are used to perform a sequence of eVTOL flight missions. A flight mission consists of a series of phases: a Constant Current (CC) battery Charging phase, a Constant Voltage (CV) battery Charging phase, a Rest period, a Takeoff segment at a given power, a Cruise segment at a given duration and power, a Landing segment at a given power. In total, a total of 22 mission profiles with different configurations are considered. Of these, there are three baseline mission profiles (MP1, MP13, MP20). This baseline consists of a take-off at 54W for 75sec, cruise at 16 W for 800sec and landing at 54 W for 105sec, after which the battery rests until it reaches a temperature of 30 °C. Charging is performed at 1C during the CC phase, and at 4.2V during the CV phase. The remaining 19 mission profiles are derived from these baseline profiles by altering various parameters, see Table 1.

Table 1. Mission profile characteristics, based on Bills et al. (2023) (from Granado et al. (2022)).

Conditions	Mission profiles
Baseline	VAH01, VAH07, VAH27
Short cruise (400 sec)	VAH12
Short cruise (600 sec)	VAH13, VAH26
Long cruise (1000 sec)	VAH02, VAH15, VAH22
Reduced power during flight (10%)	VAH05, VAH28
Reduced power during flight (20%)	VAH11
CC charge current reduced (C/2)	VAH06 , VAH24
CC charge current reduced (1.5C)	VAH16, VAH20
CV charge voltage reduced (4V)	VAH07, VAH23
Lower ambient temperature (20°C)	VAH09, VAH25
Higher ambient temperature (30°C)	VAH10
Higher ambient temperature (35°C)	VAH30

Sensor measurements: during each flight mission, the following measurements are recorded: time (sec), cell terminal voltage (V), cell current (mA), energy supplied to the cell during charge (Wh), charge supplied to the cell during charge (mAh), energy extracted from the cell during discharge (Wh), charge extracted from the battery cell during discharge (mAh), cell surface temperature ($^{\circ}C$), and cycle number (-).

Capacity tests: After every 50th flight mission, the battery charge capacity is measured. This is done by discharging it at a rate C/5 until the voltage drops below 2.5V and SOC=0%. This is followed by a period of rest during which the battery's temperature drops below 30 $^{\circ}C$. Following this cooling phase, the battery is fully charged at a charging rate of 1 C-rate and a constant voltage of 4.2V. This is followed by the battery performing the next mission, referred to as the "capacity test". The first mission is a capacity test.

End-of-Life: We say that a battery reaches EOL as soon as its capacity reaches 85% of the initially measured battery capacity. This is measured during the capacity tests. This threshold is based on preliminary studies on eVTOL batteries such as Alba-Maestre et al. (2021); Mitici et al. (2023).

Data processing of mission profiles: Dataset Bills et al. (2023) reports tester malfunction for VAH09. As such, we do not consider VAH09 (MP06) for our analysis.

4. Feature engineering

Based on the sensor measurements (see Section 3), we consider a total of 32 features Mitici et al. (2023) that are related to the charging, discharging, and temperature of the battery. Let $F = \{VAH01, ..., VAH30\}$ denote the set of mission profiles. Let M_b denote the set of missions performed under mission profile $f \in F$. We consider the following features for each mission $1 \leq m \leq M_b$ and profile $f \in F$:

Charging-related features: the duration of each charging segment (CC, CV, Rest), denoted by $\Delta^{(charge,seg,f,m)}$; the amount of charge supplied to the battery $Qcrg^{f,m}$; the last measured battery capacity $C^{measure,b,m}$.

Discharge-related features: during each mission segment (take-off, cruise, landing), the duration of each discharging segment $\Delta^{(discharge,seg,f,m)}$, the maximum, minimum, mean, and variance of the voltage, denoted by $V_{max}^{(seg,f,m)}$, $V_{min}^{(seg,f,m)}$, $V_{mean}^{(seg,f,m)}$, $V_{var}^{(seg,f,m)}$; the maximum, mean, and variance of the extracted charge, denoted by $Qdis_{max}^{(seg,f,m)}$, $Qdis_{mean}^{(seg,f,m)}$, $Qdis_{var}^{(seg,f,m)}$.

Temperature-related features: the maximum temperature during each discharging segment, denoted by $T_{max}^{(seg,b,m)}$.

Feature selection

We select the 16 most important features for RUL prognostics based on their Shapley values Scott et al. (2017). The relative importance of each feature is given in Table 2. The top 50% of the features with the highest importance, $V_{min}^{take-off}$ through $Qdis_{max}^{take-off}$, are selected for RUL prognostics development. These values are referred to as $\mathbf{x}_m^f \in \mathbb{R}^{16}$. These values are normalized using a z-score normalization $\hat{\mathbf{x}}_m^f =$

$\frac{\mathbf{x}_m^f - \mu}{\sigma}$, with μ and σ the mean and standard deviation of the dataset.

Table 2. SHAP values (importance) for the 32 considered features; top 50% of the features are selected for RUL prognostics (in **bold**).

Feature	Importance	Feature	Importance
$V_{min}^{take-off}$	**95.4**	$Qdis_{max}^{cruise}$	45.9
$V_{mean}^{take-off}$	**94.7**	T_{max}^{cruise}	45.4
$C^{measure}$	**93.4**	$T_{max}^{landing}$	41.1
$V_{var}^{take-off}$	**92.4**	$T_{max}^{take-off}$	38.8
V_{max}^{cruise}	**87.8**	Δ^{rest}	36.5
$Qcrg$	**87.1**	$V_{max}^{landing}$	35.5
Δ^{CV}	**86.5**	$\Delta^{take-off}$	23.4
V_{min}^{cruise}	**78.8**	Δ^{cruise}	19.7
V_{mean}^{cruise}	**63.8**	$\Delta^{landing}$	19.4
$V_{var}^{landing}$	**59.3**	Δ^{CC}	12.9
$V_{mean}^{landing}$	**57.4**	$Qdis_{var}^{cruise}$	3.5
$V_{max}^{take-off}$	**57.2**	$Qdis_{max}^{landing}$	2.4
$V_{min}^{landing}$	**51.6**	$Qdis_{mean}^{cruise}$	2.3
$Qdis_{var}^{take-off}$	**47.7**	V_{var}^{cruise}	2.2
$Qdis_{mean}^{take-off}$	**46.5**	$Qdis_{var}^{landing}$	1.4
$Qdis_{max}^{take-off}$	**45.9**	$Qdis_{mean}^{landing}$	1.2

5. Probabilistic RUL prognostics

In this section we propose a Mixed Density Network (MDN) Gu et al. (2022) to estimate the distribution of the RUL of the eVTOL batteries. Figure 1 illustrates the architecture of the MDN considered, with an input layer, L dense hidden layers, and the output layer. The network has parameters θ. The input vector of normalized features from the current and previous missions before each capacity test $m, m-50, ...m-50N$ (see Section 4) $\hat{\mathbf{x}}$ is mapped to a three-fold output: the means $\mu_j(\hat{\mathbf{x}}, \theta)$, the standard deviations $\sigma_j(\hat{\mathbf{x}}, \theta)$, and a mixture coefficient $\alpha_j(\hat{\mathbf{x}}, \theta)$. With this, the probability density of the RUL, r, is estimated as a mixture of J normal distributions as:

$$p(\mathrm{r}|\hat{\mathbf{x}}, \theta) = \sum_{j=1..J} \alpha_j(\hat{\mathbf{x}}, \theta)\phi\left(\mathrm{r}|\mu_j(\hat{\mathbf{x}}, \theta), \sigma_j(\hat{\mathbf{x}}, \theta)\right),$$

with ϕ the PDF of a normal distribution, given mean μ and STD σ. The loss function of the MDN is given by the negative log-likelihood:

$$L(\hat{\mathbf{x}}, \mathrm{r}, \theta) = -\log p(\mathrm{r}|\hat{\mathbf{x}}, \theta).$$

5.1. *Results - RUL prognostics*

We illustrate the RUL estimation methodology for the eVTOL batteries. We employ a 6-fold cross validation to train and test the MDN. For each fold, several eVTOLs are randomly selected for testing. The test data of each fold contains one randomly selected baseline mission profile (out of a total of three baseline mission profiles of VAH01, VAH17, and VAH27) and 5 additional mission profiles. Each fold contains a total of approximately 6.000 missions.

Following hyper-parameter tuning, we consider $L = 6$ dense hidden layers. The layers have 24, 122, 116, 116, 90, and 38 units, respectively. The first five layers use the ReLu activation function, and the last one a tanh activation function. The output of the MDN consists of a mixture of $J = 3$ normal distributions. The MDN is optimised using the RMSprop (see Riedmiller and Braun (1993)) algorithm with a learning rate of 0.01.

Table 3 gives the performance of the MDN for each eVTOL in the test set of each fold. The results show that the typical MAE is around 30 missions. Additionally, in nearly all folds, our approach leads to a low CRPS score, indicating a sharp estimate of the distribution of the RUL.

Figure 2 shows 2 examples of the estimated distribution of the RUL: VAH20 for fold 1 and VAH13 for fold 2.

For VAH13, the distribution of the RUL is centered around the actual RUL. Also, the variance of the estimated RUL distribution decreases as the battery reaches its EOL. For VAH20, despite having a high CRPS score, the estimate distribution of the RUL is increasingly sharp as the battery reaches its EOL.

6. Adaptive maintenance planning of eVTOLs using RUL prognostics

In Section 5 we obtained estimates of the distribution of the RUL of eVTOL batteries after each mission. We assume that each eVTOL perfoms n missions per day (Section 2). For maintenance planning of the batteries of a fleet of V eVTOLs, we consider the estimated RUL distribution $RUL_{d_0}^v, v \in V$, at the start of each day d_0.

To ensure safe eVTOL operations, we define

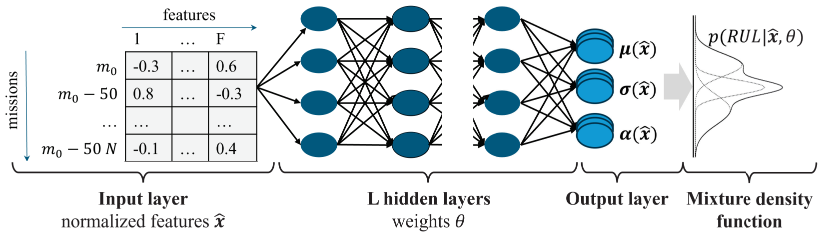

Fig. 1. Architecture of the MDN neural network used to generate probabilistic RUL prognostics.

Table 3. Probabilistic RUL prognostics performance: MAE, RMSE, CRPS (flight missions).

Fold 1				**Fold 2**				**Fold 3**			
VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS
VAH01	63.69	68.15	47.29	VAH01	56.1	62.42	43.2	VAH10	10.4	12.33	7.18
VAH02	35.41	37.37	24.92	VAH05	29.4	37.0	19.65	VAH11	66.9	75.07	53.55
VAH13	17.06	20.81	13.02	VAH06	61.21	64.88	47.26	VAH17	34.45	38.83	24.11
VAH20	56.06	59.04	42.51	VAH13	32.78	36.06	22.36	VAH22	9.62	13.74	8.33
VAH28	22.01	25.47	18.12	VAH15	22.54	24.2	14.79	VAH23	98.7	125.89	72.87
VAH30	17.5	21.47	12.1	VAH16	20.32	22.34	14.41	VAH25	51.79	74.78	37.48
ALL	35.29	38.72	26.33	**ALL**	37.06	41.15	26.94	**ALL**	45.31	56.77	33.92

Fold 4				**Fold 5**				**Fold 6**			
VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS
VAH02	20.21	27.1	18.22	VAH05	23.88	28.56	16.24	VAH10	5.59	7.35	6.41
VAH06	29.36	33.22	19.54	VAH12	52.09	59.95	39.32	VAH12	61.23	66.06	48.09
VAH17	23.04	27.71	15.99	VAH15	11.31	13.89	8.25	VAH22	11.77	14.98	8.44
VAH20	57.5	59.24	42.48	VAH16	17.53	21.85	13.57	VAH24	20.93	25.28	14.27
VAH26	21.85	27.41	17.86	VAH24	11.84	16.03	9.8	VAH25	39.64	50.91	28.39
VAH30	7.59	9.46	7.85	VAH27	26.8	34.61	21.95	VAH27	36.84	40.62	24.11
ALL	26.59	30.69	20.32	**ALL**	23.91	29.15	18.19	**ALL**	29.33	34.2	21.62

the following target day d_v^* to reliably replace the battery of eVTOL $v \in V$:

$$d_v^* = d_0 + \max\{d : \mathbb{P}[RUL_{d_0}^v \leq d] \leq P^*\}, \quad (1)$$

with $d_0 + d$ a battery replacement day, $d \in \mathbb{N}^+$, and P^* a reliability threshold. Here, we ensure that the probability of the battery reaching its EOL before maintenance day $d_0 + d$ is at most P^*.

The eVTOL battery replacements are ideally planned as late as possible to minimize battery waste, while satisfying the reliability criteria in eq. 1, i.e., while limiting the probability that the battery is still in use after it reaches its EOL.

We consider a rolling horizon planning approach. At current day d_0 we consider planning a battery replacement withing a window $D_{d_0} = [d_0 + 1, d_0 + k]$ based on the prognostics available at d_0. We next slide to a new day $d_0 + l, l \geq 1$, when we update the prognostics with newly available measurements, and consider a new planning window $D_{d_0+l} := [d_0 + 1 + l, d_0 + l + k]$.

At day d_0 we decide whether to plan a battery replacement at some day d in the planning window D_{d_0}, or to postpone the decision for the next planning window D_{d_0+l}. In case eVTOL $v \in V$ is scheduled for battery replacement before d_v^*, a penalty c_{early} is incurred for every wasted day of the battery life. If eVTOL $v \in V$ is scheduled for battery replacement after d_v^*, then a penalty c_{late} is incurred for every day the battery is used after the target d_v^*. We consider a cost c_{vd} of planning a

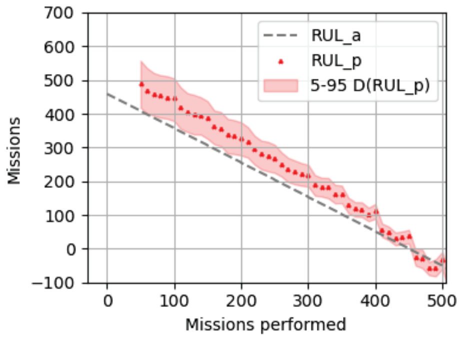

Fig. 2. The actual RUL (RUL_a), the expected predicted RUL (RUL_p), and the 5-95 percentile of the estimated distribution of the RUL, for VAH20 in fold 1.

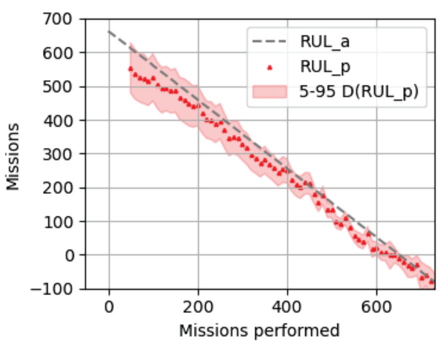

Fig. 3. Same as Fig. 2, but for VAH13 in fold 2.

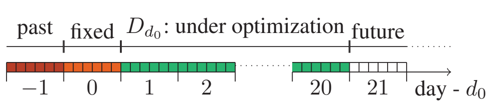

Fig. 4. Illustration of a maintenance planning time window at current day d_0, with $k = 20$, such that $D_{d_0} = [d_0 + 1, d_0 + 20]$.

battery removal at day $d \in D_{d_0}$, where:

$$c_{vd} = c_{early}(d_v^* - d)^+ + c_{late}(d - d_v^*)^+. \quad (2)$$

We define $c_{early} = c_{replace}/L$, where L is a nominal average battery life of the eVTOLs. We define $c_{late} = (c_{unscheduled} - c_{replace})/L$. In case the battery replacement of eVTOL $v \in V$ is postponed for the next planning window, then a cost $c_v^{postpone}$ is incurred for every day the target replacement day d_v^* is exceeded, where:

$$c_v^{postpone} = c_{late}(d_0 + k + l - d_v^*)^+. \quad (3)$$

We consider the following integer linear program to plan battery replacements on day d_0.

Decision variables:

$$y_{vd} = \begin{cases} 1, & \text{battery } v \in V \text{ replaced on } d \in D_{d_0}, \\ 0, & \text{otherwise.} \end{cases}$$

$$z_v = \begin{cases} 1, & \text{battery } v \in V \text{ not replaced in } D_{d_0}, \\ 0, & \text{otherwise.} \end{cases}$$

Objective function: We aim to minimize the total costs of battery maintenance:

$$\min_{y,z} \sum_{1 \le v \le |V|} \left(\sum_{d \in D_{d_0}} c_{vd} y_{vd} \right) + c_v^{postpone} z_v$$

Constraints:

$$\sum_{d \in D_{d_0}} y_{vd} + z_v = 1 \qquad \forall v \in V, \quad (4)$$

$$\sum_{v \in V} y_{vd} \le h \qquad \forall d \in D_{d_0}. \quad (5)$$

Constraint (4) ensures that at day d_0 a battery replacement is planned for each eVTOL, or that the battery replacement is postponed. Constraint (5) ensures that the daily battery replacement capacity H of the eVTOL hub is not exceeded.

6.1. *Results - Maintenance planning*

We consider $|V| = 25$ eVTOLs, each equipped with a battery randomly sampled from the test sets of all the six folds (see Section 5). Each eVTOL performs $n = 10$ flight missions (to and from an eVTOL hub) per day. At $d_0 = 1$, the ages of the eVTOLs batteries are initialised as a random value between 0 and their actual EOL. We consider $P^* = 0.1$, $k = 10$, $h = 1$, $l = 1$, $c_{replace} = 100$, $c_{unscheduled} = 1000$, $L = 50$. Using the maintenance planning model in Section 6, a simulation of 10 years of eVTOL operations is performed. As soon as one eVTOL battery is replaced or reaches its EOL (unscheduled battery replacement), this battery is replaced with a randomly selected battery from the test sets of all six folds (see Section 5). The age of this new battery is then initiated at 0 missions.

Following a simulation of 10 years of operations, 1.786 batteries were used. Of these 1.786 batteries, **1.704** were replaced before their EOL, and **82** batteries needed unscheduled replacement since they reached their EOL unexpectedly. Our approach results in a total yearly cost of **25.240** units. Figure 5 shows a histogram of the wasted life of the batteries (in days), i.e., the number of days the batteries were not used because they were preventively replaced and thus did not reach their EOL. Using our approach, the batteries were used for up to 88,1% of their actual lifetime.

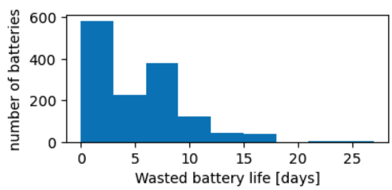

Fig. 5. Histogram of the wasted battery life - based on the simulation of 10 year of operations.

Figure 6 shows a distinct planning moment for the eVTOL batteries. At $d_0 = 105$, we consider a planning window of $D_{105} = [106, 125]$ when the batteries of eVTOLs 1, 2, 5, 7, 8, 9, 12, 14, 17,19, 23 are planned to be replaced within the next days [106,125]. EVTOL 11 is planned for battery replacement the next day (this replacement cannot be changed anymore since no further planning re-optimisation can be done). The battery of EVTOL 16 is replaced on day 116, just before it reaches its EOL on day 117. As of now, the battery of EVTOL 18 will fail at day 122 before its planned replacement. However, this planning may be re-optimized in the next days.

6.2. *Performance evaluation*

We compare our approach with two benchmarks: *Oracle planning* and *RUL point-estimate planning* algorithms. Both use the same framework as our proposed maintenance planning approach. The *Oracle planning* assumes that the actual RUL of the batteries is known in advance. As such, $d_v^* = EOL_v$ of the batteries. The *RUL point-estimate planning* uses the mean of the estimated RUL distribution (point estimate, instead of the distribution) such that $d_v^* = d_0 + \mathbb{E}[RUL_{d_0}^v]$.

Table 4 shows the total yearly amount of batteries replaced and costs made for the three planning approaches. As expected, the Oracle leads to **0** unscheduled battery replacements. The *RUL point-estimate planning* leads to the highest number of unscheduled battery replacements (**436** unscheduled battery replacements in 10 years of eVTOL operations) and the highest total costs among all three approaches. This shows the relevance of considering the estimation of the distribution of the RUL when planning maintenance (leading to 82 unscheduled replacements), instead of using RUL point estimates.

Table 4. Batteries used and maintenance costs for the *Oracle*, the *(RUL) Point Estimate*, and *Our (RUL distribution)* approach.

# yearly replacements [-]			
method	scheduled	unscheduled	total
Oracle	164.8	0	164.8
Our approach	170.4	8.2	178.6
Point estimate	125.8	43.6	169.4
maintenance cost / year [1000]			
Oracle	16.5	0	16.5
Our approach	17.0	8.2	25.2
Point estimate	12.6	43.6	56.2

7. Conclusion

This paper proposes a data-driven predictive maintenance planning model for Lithium-ion batteries that is reliable and cost-effective. We employ Mixed Density Networks to estimate the distribution of the batteries' RUL (probabilistic prognostics). These prognostics are further integrated into an adaptive maintenance planning model that specifies optimal battery replacement times. This planning model limits the risk of using the batteries beyond their End-of-Life (EOL), while minimizing overall costs. We apply our approach for electric Take-Off and Landing (eVTOL) aircraft. The results show that despite the prognostics being imperfect, the number of unscheduled battery replacements is low (only 8 unscheduled yearly

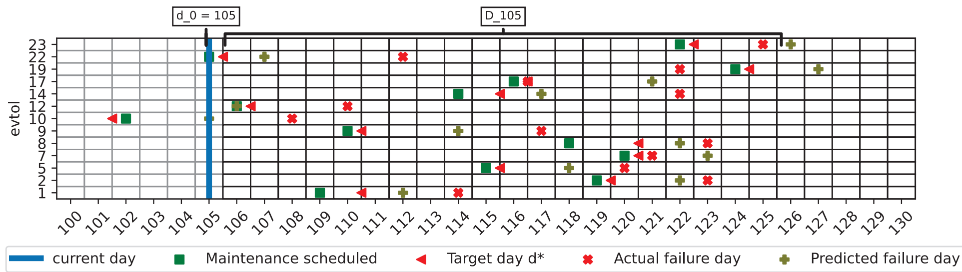

Fig. 6. Maintenance planning for 50 eVTOLs at $d_0 = 105$ with planning time window $D_{d_0} = [105+1, 105+20]$ and $l = 1, k = 20$.

replacements per year for 25 eVTOLs). Secondly, the results show that up to 80% less yearly unscheduled battery replacements are achieved when considering probabilistic RUL prognostics for maintenance planning, rather than RUL point estimates. Overall, our approach outlines an end-to-end framework for predictive maintenance of a fleet of vehicles equipped with Li-ion batteries with reliability and cost-related objectives.

References

Alba-Maestre, J., K. Prud'homme van Reine, T. Sinnige, and S. G. Castro (2021). Preliminary propulsion and power system design of a tandem-wing long-range evtol aircraft. *Applied Sciences 11*(23), 11083.

Bills, A., S. Sripad, L. Fredericks, M. Guttenberg, D. Charles, E. Frank, and V. Viswanathan (2023). A battery dataset for electric vertical takeoff and landing aircraft. *Scientific Data 10*(1), 344.

Du, Z., L. Zuo, J. Li, Y. Liu, and H. T. Shen (2021). Data-driven estimation of remaining useful lifetime and state of charge for lithium-ion battery. *IEEE Transactions on Transportation Electrification 8*(1), 356–367.

Granado, L., M. Ben-Marzouk, E. S. Saenz, Y. Boukal, and S. Jugé (2022). Machine learning predictions of lithium-ion battery state-of-health for evtol applications. *Journal of Power Sources 548*, 232051.

Gu, C., Y. Zhao, and C. Zhang (2022). Learning to predict diverse human motions from a single image via mixture density networks. *Knowledge-Based Systems 253*, 109549.

Mitici, M., B. Hennink, M. Pavel, and J. Dong (2023). Prognostics for lithium-ion batteries for electric vertical take-off and landing aircraft using data-driven machine learning. *Energy and AI 12*, 100233.

Riedmiller, M. and H. Braun (1993, March). A direct adaptive method for faster backpropagation learning: the RPROP algorithm. In *IEEE International Conference on Neural Networks*, pp. 586–591 vol.1.

Scott, M., L. Su-In, et al. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems 30*, 4765–4774.

Wei, H., B. Lou, Z. Zhang, B. Liang, F.-Y. Wang, and C. Lv (2024). Autonomous navigation for evtol: Review and future perspectives. *IEEE Transactions on Intelligent Vehicles*.

Xie, R., R. Ma, S. Pu, L. Xu, D. Zhao, and Y. Huangfu (2020). Prognostic for fuel cell based on particle filter and recurrent neural network fusion structure. *Energy and AI 2*, 100017.

Zraibi, B., C. Okar, H. Chaoui, and M. Mansouri (2021). Remaining useful life assessment for lithium-ion batteries using cnn-lstm-dnn hybrid method. *IEEE Transactions on Vehicular Technology 70*(5), 4252–4261.