Sustainability and Cost Assessment of Lithium Battery Health Management Strategies for Electric Unmanned Aerial Vehicles

Master of Science Thesis

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Sustainability and Cost Assessment of Lithium Battery Health Management Strategies for Electric Unmanned Aerial Vehicles

Master of Science Thesis

by

P.J. Vossen

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Amsterdam, March 2022

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List of Abbreviations

Abbreviations

ANAC	Agência Nacional de Aviação Civil
BASA	Bilateral Aviation Safety Agreements
BM	Breakdown Maintenance
BMS	Battery Management System
BOL	Beginning-of-Life
CALCE	Center for Advanced Life Cycle Engineering
CBA	Cost-Benefit Analysis
CBM	Condition Based Maintenance
CC/CV	Constant Current and Constant Voltage
CM	Corrective Maintenance
CMT	Certification Management Team
CRA	Cumulative Relative Accuracy
DBM	Detection-Based Maintenance
DES	Discrete Event Simulation
DOC	Direct Operating Costs
DOD	Depth-of-Discharge
DOM	Design-Out Maintenance
EASA	European Aviation Safety Agency
eAV	Electrical Aerial Vehicle
EOD	End-of-Discharge
EOL	End-of-Life
EOP	End-of-Prediction
eUAV	Electrical Unmanned Aerial Vehicle
FAA	Federal Aviation Administration
FBM	Failure-Based Maintenance
FN	False Negative
FP	False Positive
FT	Failure Threshold
GHG	Greenhouse Gas

GWP	Global Warming Potential
ICAO	International Civil Aviation Organisation
IPA	Implementation Procedures for Airworthiness
JAA	Joint Aviation Authority
LCO	Lithium Cobalt Oxide
LFP	Lithium Iron Phosphate
Li-ion	Lithium-ion
Li-Po	Lithium-Polymer
LMO	Lithium Manganese Oxide
LR	Linear Regression
LTO	Lithium Titanate Oxide
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MC	Monte Carlo
MCC	Multistage Constant Current
MdAD	Median Absolute Deviation
MEA	More Electric Aircraft
MLR	Multiple Linear Regression
MSE	Mean Squared Error
MTBF	Mean Time Between Failure
MTBUR	Mean Time Between Unit Replacements
NASA	National Aeronautics and Space Administration
NCA	Nickel Cobalt Aluminum Oxide
NMC	Nickel Manganese Cobalt Oxide
NPV	Net Present Value
OAT	One-at-a-Time
OCV	Open Circuit Voltage
OTS	Off-the-Shelf
PDF	Probability Density Function
PdM	Predictive Maintenance
PH	Prognostic Horizon
PHM	Prognostics and Health Management
PM	Preventive Maintenance
PyBaMM	Python Battery Mathematical Modelling

Q-Q	Quantile-Quantile
RA	Relative Accuracy
RMSE	Root Mean Squared Error
ROI	Return On Investment
RTF	Run-To-Failure
RUL	Remaining Useful Life
SA	Sensitivity Analysis
SEI	Solid Electrolyte Interphase
SHM	Structural Health Monitoring
SNL	Sandia National Laboratories
SOC	State of Charge
SOH	State of Health
SPM	Single Particle Model
SSD	Sample Standard Deviation
TBM	Time-Based Maintenance
TCCA	Transport Canada Civil Aviation
UAV	Unmanned Aerial Vehicle
UBM	Usage-Based Maintenance

Symbols

$\widetilde{Cost}_{BOL}$	BOL costs [€] / flying time [s]
$\widetilde{Cost}_{charge}$	Charging costs [€] / flying time [s]
$\widetilde{CO}_{2,\ BOL}$	BOL emissions [kg] / flying time [s]
$\widetilde{CO}_{2,\ charge}$	Charging emissions [kg] / flying time [s]
$\widetilde{P}_{total}$	Charging power [kWh] / flying time [s]
$CO_{2,\ BOL}$	BOL emissions [kg]
$CO_{2,\ charge}$	Charging emissions [kg]
$Cost_{BOL}$	BOL costs [€]
$Cost_{charge}$	Charging costs [€]
d_{max}	Maximum target distance [m]
d_{min}	Minimum target distance [m]
d_{target}	Target distance [m]
I	Current [A]
I_c	Current at cruise [A]
I_l	Current at landing [A]

$I_{t/o}$	Current at take-off $[A]$
P_{total}	Charging power $[kWh]$
Q	Capacity $[Ah]$ or $[C]$
Q_0	Initial capacity at beginning of life $[Ah]$ or $[C]$
Q_{max}	Maximum capacity at a cycle $[Ah]$ or $[C]$
R	Resistance $[\Omega]$
t_c	Time duration of cruise $[s]$
t_l	Time duration of landing $[s]$
$t_{t/o}$	Time duration of take-off $[s]$
V	Voltage $[V]$
V_{exp}	Expected DOD voltage $[V]$
V_{max}	Maximum voltage $[V]$
V_{min}	Minimum voltage $[V]$
V_{req}	Required voltage $[V]$
$V_{SOC\ 30\%}$	Battery voltage when SOC = 30% $[V]$

Introduction

Given the growing use of Lithium batteries in electric Unmanned Aerial Vehicles (eUAV), it is chosen to conduct research regarding battery health management strategies. One of the biggest challenges that the aerospace industry currently faces is the rapid rate of battery degradation which limits a battery's capacity and lifetime. In this report, the application of an eUAV battery health management strategy that reduces the severeness of battery degradation is explored.

A potential method to decrease the battery degradation rate is by minimising the average State of Charge (SOC) and Depth-of-Discharge (DOD) levels. Translating this to eUAV practices, a 'mission-based' battery health management strategy is proposed that charges the battery to the estimated required level of SOC to complete a flight. Moreover, the impact of varying DOD ranges is reviewed by regulating the flying range.

To evaluate the performance of the mission-based strategy, it is compared to two other battery health management approaches that charge the eUAV battery to 100% and 80% SOC. Although a more advanced model is recommended before applying this model to real-life applications, this research provides insights and tools to support operators in exploring and comparing the benefits of battery health management strategies.

The research is carried out as part of a master thesis of the Air Transport Operations track at the Faculty of Aerospace Engineering at Delft University of Technology. This thesis report has the following structure. Part I presents the scientific paper of the research. Thereafter, Part II contains a report of the Literature Study, providing background information on the topic of maintenance in the aerospace industry as well as battery health management and sustainability and cost assessment practices. Lastly, Part III provides supporting work for the research presented in the scientific paper. An elaborate statistical analysis of the model is first provided in Appendix 1, followed by an overview of the model limitations and recommendations for future studies in Appendix 2.

I

Scientific Paper

Sustainability and Cost Assessment of Lithium Battery Health Management Strategies for Electric Unmanned Aerial Vehicles

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Abstract

In this research, a sustainability and cost assessment of battery health management strategies applied to Lithium batteries of an electric Unmanned Aerial Vehicle (eUAV) is performed. A mission-based strategy is proposed with the aim to elongate battery lifetime. With this strategy, the battery is charged to the estimated State of Charge (SOC) level required to complete the next flight. The mission-based strategy is compared to two other strategies: the SOC 100% strategy that always fully charges the battery before flight, and, the SOC 80% strategy that charges that battery to 80% before flying. The three strategies are tested for a variety of flight distances. The battery model is simulated using Python Battery Mathematical Modelling (PyBaMM). A Monte Carlo (MC) simulation is run to review the response to uncertainties in initial battery compositions and operating conditions. Ultimately, the strategies are evaluated on environmental impact, financial costs and flying efficiency. The results show that the mission-based strategy outperforms the SOC 100%, yielding lower emissions and costs and higher flying efficiency performance. However, depending on the range flown, the SOC 80% shows environmental, cost and flying efficiency benefits that challenge the relevance of implementing a mission-based battery health management strategy.

Index Terms — electric Unmanned Aerial Vehicle (eUAV), Monte Carlo (MC), Lithium battery, health management, sustainability

1 Introduction

In line with the sustainability trends, an increase in studies reviewing the use of alternative propulsion systems such as rechargeable batteries is observed [18, 19, 60, 79, 83]. Within the aviation industry, electrically powered aerial vehicles do not only bring along environmental benefits, but also operational advantages such as noise reduction and reactive thrust [17, 83], making them are a popular subject for research.

The prevailing used battery type in aviation is Lithium [56, 60, 68, 78, 79]. The scope of this research is set to Lithium batteries that are widely used in Unmanned Aerial Vehicles (UAVs) [8, 18, 83]. When an UAV is fully electric, it is also referred to as an electric UAV (eUAV). In aviation, UAVs and eUAVs are favoured for a multitude of reasons such as their low operating costs and ability to fly in dangerous or extreme conditions [3, 33, 54, 75]. Applications include military, search and rescue and agricultural operations.

One important field of study for batteries revolves around their performance and reliability, characterised by the battery's capacity and internal resistance [49]. The capacity defines how much energy can be stored in the battery, while the internal resistance sets a limit on the maximum level of power that the battery is able to deliver. Of these two parameters, capacity is commonly used as the main component to evaluate a battery's performance and reliability [89]. These characteristics form the guiding principles for safe flight.

To improve the performance and reliability of eUAV batteries, several different battery health management approaches can be identified. Firstly, most batteries onboard an eUAV are linked to a Battery Management System (BMS) that monitors several parameters including the battery voltage, current, temperature and State of Charge (SOC) [12, 47, 93]. The BMS provides a battery protection by ensuring it does not exceed operating limits. Depending on the level of sophistication, a BMS could also be able to determine the State of Health (SOH) and/or make End-of-Discharge (EOD) and End-of-Life (EOL) estimations. Secondly, in recent years, the benefit of implementing Prognostics and Health Management (PHM) to enhance battery reliability and capabilities is being reviewed [64]. For batteries, PHM focuses on predictions of parameters such as SOC, EOD, SOH and EOL [17, 89].

During one discharge cycle, a battery's available capacity decreases with respect to the maximum capacity at the start of the cycle [9, 89]. This is reflected by the SOC, with a battery's SOC being 100% when it is fully charged. Additionally, the maximum achievable capacity degrades over the course of multiple cycles compared to the battery's initial capacity at Beginning-of-

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Life (BOL). The status of maximum achievable capacity is known as SOH, with a battery having 100% SOH at BOL. The reduction of capacity due to cycling, also known as battery ageing or degradation, does not only affect the system's performance and reliability, but also has environmental and financial consequences as this phenomenon is directly linked to the battery's lifetime [19, 83].

While battery ageing is unavoidable, there are several factors that accelerate the degradation process. For example, for cycle ageing, the severeness of SOH degradation is heavily driven by the operating temperature, rate of current, average SOC and Depth-of-Discharge (DOD) [30, 41, 53, 80, 91]. Here, the average SOC can be regulated by charging to a SOC level below 100%. Furthermore, the DOD relates to the amount of energy extracted from the battery. Regulating these parameters throughout eUAV operations could potentially lead to battery lifetime elongation.

To determine which health management strategy is most beneficial, an assessment of costs is a commonly applied technique to evaluate and compare different strategies [11, 90]. However, other metrics including effectiveness [62], scientific performance [70] as well as sustainability and/or social impact [28, 31] can also be reviewed. The selection and weights of the relevant parameters depend on the topic of concern and stakeholders that are involved.

Following the aforementioned trends of sustainability within aviation, it is chosen to conduct a research on the implementation of health management approaches for eUAV batteries. The research objective is ***to determine the environmental and cost-benefit of a mission-based battery health management strategy for Lithium batteries for electric Unmanned Aerial Vehicles***. Specifically, this research aims to achieve battery lifetime elongation by modelling a mission-based battery health management strategy that minimises the battery's average SOC by charging to a lower SOC before flight. The mission-based strategy is compared to two alternative health management strategies where the battery is always charged to 100% SOC, and a strategy in which the battery is charged to 80% SOC. The strategies are assessed for a set of different DOD ranges to investigate how the distance flown relates to the battery degradation rate. The battery models are tested by running a Monte Carlo (MC) simulation to review the response to small uncertainties. The MC incorporates stochastic inputs to represent battery manufacturing impurities in new batteries [6, 22, 61, 89] and in-flight variations in battery power usage and flying times [65]. Ultimately, an assessment of battery health management strategies' environmental emissions, monetary costs and efficiency with respect to downtime is carried out.

The academic contribution of this study consists of three parts. Firstly, although lower SOC and DOD levels are known to decrease battery degradation rate [30, 91], no literature is found in which this battery health management strategy is applied to eUAV applications. The second contribution lies in the proposed framework to evaluate and compare eUAV battery health management strategies which can be used in future eUAV battery analyses, covering three pillars including sustainability, financial costs and efficiency. Lastly, this research explores the use Python Battery Mathematical Modelling (PyBaMM) [77] to review new eUAV battery lifetime elongation methods. PyBaMM is a simulation package launched in 2021 that is able to efficiently solve battery models in Python. This tool has not been used to model Lithium batteries for eUAV applications before.

This paper has the following structure. First, related work on battery health management research is elaborated on in section 2. Subsequently, the methodology of this study is presented in several separate sections. A description of the mission profile set-up is given in section 3, followed by an elaboration of the framework of the eUAV battery simulation and health management strategies in section 4. Then, section 5 presents the assessment metrics used to review the battery model outputs. To conclude the methodology of this study, a brief overview of the experimental set-up is given in section 6. Section 7 presents the results of the experiment, after which the model is validated by assessing its robustness through the means of a sensitivity analysis in section 8. Finally, the research conclusion and future recommendations are summarised in section 9.

2 Related Work

Model choices for this research are substantiated by findings from literature. The following sections present examples of related work featuring eUAV battery health management and performance evaluation studies. Relevant research regarding battery health and simulation practices are first elaborated on in section 2.1. Secondly, examples of assessment frameworks are given in section 2.2.

2.1 Battery Health

Given the global shift towards more sustainable fuel alternatives, an increase in battery studies is observed [17, 18, 79, 83]. This section first reviews literature concerning battery health management practices related to Lithium batteries in section 2.1.1. Health management applications to enhance a battery system's performance and reliability is first elaborated on, after which sustainability-oriented health management opportunities are highlighted. Then, section 2.1.2 discusses several battery modelling approaches providing substantiation as to why PyBaMM is chosen to model the eUAV batteries in this study.

2.1.1 Battery Health Management

By applying health management to battery systems, operators aim to improve the system's reliability and performance by closely monitoring the battery's capacity and health [14, 23, 49, 54, 89]. For Lithium batteries, it is especially important to monitor both the SOC and SOH, as voltage levels significantly drop when operated beyond their safety limits. For eUAV applications, the SOC threshold is equal to 30% to avoid the precipitous decrease in voltage that occurs beyond the knee point while also ensuring the batteries are able to provide the eUAV sufficient power to perform at least two additional landing attempts [37, 72, 84]. The battery's EOL is defined to be as soon as the SOH reaches 80% as flying with the battery beyond 70 - 80% SOH is considered to be highly unsafe [49, 85, 87, 89]. Alternatively, some researchers such as Viwanathan and Knapp [83] state that internal increase of resistance could define the EOL of an eUAV Lithium battery. For Lithium batteries, this is defined to be when the battery's internal resistance is twice the value it had at BOL [25, 49, 89]. Both capacity and resistance are therefore advised to be taken into account when determining an eUAV's battery's EOL.

Similar to determining the Remaining Useful Life (RUL) of a component for maintenance, most battery health management studies focus on predicting the moment at which the battery reaches EOD and EOL [7, 37, 68, 69, 75]. By incorporating prognostics, experts aspire to move away from relying on fixed flying time and lifetime prescriptions as these are highly conservative [17, 75].

Instead of exclusively applying battery health management methods to improve a battery's reliability, authors such as Iung and Levrat [40], advocate the integration of other factors such as minimal energy consumption or effectiveness. Especially in the view of sustainability, this offers great perspectives. For example, Xu et al. [91] and Gao et al. [30] explored the influence of different SOC and DOD levels on the rate of battery degradation. From their studies, the researchers found that battery ageing is less severe when the battery is cycled at a lower average SOC with minimum DOD ranges. These batteries have, however, been cycled under constant charging and discharging conditions. Subsequently, in this research paper, it is chosen to review how the lifetime of batteries operating eUAV flights would respond to lower SOC and DOD levels. Translating this to a battery health management approach, two aspects are regulated. Firstly, a battery is charged to a lower SOC level before flight (instead of 100%). In order to ensure that the eUAV is safely able to complete it's flight, this initial SOC level should be carefully estimated. In this research, this strategy is referred to as being 'mission-based'. Secondly, the DOD ranges are regulated by flying different distances and seeing how the battery degradation rate responds.

Rather than applying a potentially costly prognostic battery health management strategy, researchers such as Nair and Garimella [58] reviewed the option of setting the BMS limits to a minimum of 20% and maximum of 80% SOC. By doing so, a lower average SOC and DOD is also yielded. This strategy could be inputted as an alternative to always charging to SOC 100% before flight, and is addressed in this research as the SOC 80% strategy.

By decreasing the average SOC and DOD range that an eUAV battery cycles through, the available capacity for flight is also reduced. Nevertheless, this battery health management strategy could still yield significant benefits when combining this charging and flying methodology with other pivotal solutions such as eUAV battery swapping or wireless charging at power lines [29, 51]. Additionally, the effects of average SOC and DOD on battery degradation could provide insightful understandings for optimisation problems concerning eUAV hub location [2] and last-mile delivery models with eUAVs and trucks [32, 57].

2.1.2 Battery Models

Battery health management models can be established with the use of electrochemical or data-driven methods [4, 14, 23, 49, 54, 89]. Commonly, data-driven approaches are favoured since electrochemical models are very complex. Moreover, data-driven approaches are beneficial as they allow the user to include a broad range of parameters such as voltage, current and temperature. A wide variety of data-driven techniques exist including regression, filtering, and machine learning applications.

To promote data-driven battery research, Dos Reis et al. [20] recently published a paper providing an overview of all available open-source Lithium battery data sets. Well-known data sets are for example from the Prognostics Center of Excellence department of National Aeronautics and Space Administration (NASA) [1], Center for Advanced Life Cycle Engineering (CALCE) [27] and Sandia National Laboratories (SNL) [45]. Drawbacks of using these data sets, however, are that the cycling conditions are case-specific and not directly applicable to eUAV operations.

Alternatively, software can be used to model batteries. An advantage of using a simulation programme is its flexibility to tailor battery specifications and cycling throughput values. On the downside, many software tools are difficult to synthesize with other data processing operating systems such as Matlab and Python or require costly licences. Mitigating these shortcomings, a package called 'PyBaMM' was recently launched by a community of researchers [77]. The package allows batteries to be modelled and simulated in a rapid and versatile manner. Users can either choose to exploit readily available Lithium or Lead-Acid battery parameter sets and ageing models, or implement their own models.

To model an eUAV flight, battery data is required. Although some research publications that provide documentation about the power usage for certain eUAV manoeuvres are available [5, 16, 94], these papers lack detailed battery information such as the voltage and current levels the battery outputs during operation. The open-source data set by Rodrigues et al. [65] does specify in-flight energy use and battery cycling information of a DJI Matric 100 eUAV quadcopter. Together with PyBaMM, this battery data is used to generate the flight profiles for the battery model in this study.

2.2 Sustainability and Cost Assessment

An assessment of battery health management strategies can be done to review the benefits associated with each approach. For the aerospace field specifically, however, authors such as Saxena et al. [71] state that the industry lacks a set of standardised performance metrics to evaluate prognostic strategies. Similarly, Liu et al. [50] conclude that battery health management studies can have a variety of main objectives. Hence, this research will combine a set of sustainability and cost assessment parameters that are relevant to evaluate and compare eUAV battery health management approaches.

For this study, the following evaluation metrics are included: environmental impact, financial costs and effectiveness. Each of these parameters is briefly introduced in the following section 2.2.1 to 2.2.3, along with a battery health management example from literature.

2.2.1 Environmental Impact

In recent years, authors such as Franciosci et al. [28] and Ghazi et al. [31] are promoting the use of more sustainability related assessment parameters, instead of solely focusing on financial and technical aspects. Factors they list to assess the environmental impact of a system are for example material resources, energy consumption, noise emissions, pollutant emissions and waste. Ghazi et al. [31] recognise the fact that the establishment of a method to compare the impact of different environmental parameters is a complex task. Often, the opinion of the stakeholders plays an important role in this evaluation process in order to conduct a (weighted) trade-off.

In a study by Koiwanit [44] assessing the environmental impacts of using eUAVs to deliver online shopping, it is estimated that 80% of an eUAV's battery Global Warming Potential (GWP) originates from carbon emissions. Other environmental impact parameters such as abiotic depletion and ecotoxicity are also evaluated, but suffer from incomplete data. The eUAV delivery system is evaluated with the use of a life-cycle analysis that includes the BOL, operation and maintenance and EOL activities. With the use of the CML2001 model [34], the author concludes that the production of parts at BOL sum up to be 99% of the model's total environmental footprint. Similarly, reviewing the life-cycle cost-benefit of a battery storage system, Li et al. [48] concluded that BOL production emissions equal 70-75% of the battery's total emissions, followed by operation emissions and EOL emissions equal to 20-25% and 5%, respectively.

To determine the emissions for production, estimations based on the battery specifications and energy in kWh are commonly made [35, 52, 66]. For operation, charging emissions are often country-based and must therefore be analysed locally [24, 48]. Note that emissions vary vastly depending on each battery type, application and location. Therefore, if possible, it is highly recommended to validate results before drawing conclusions.

On a larger scale, Goodchild and Toy [32] and Stolaroff et al. [76] compared Greenhouse Gas (GHG) emissions yielded from the use of eUAVs versus trucks for last-mile package delivery. Here, when charging an eUAV, they state the importance of considering the efficiency of transferring electricity from the power plant to its motors. On average, the studies suggest that this efficiency factor is equal to 0.78 [32, 76].

2.2.2 Financial Costs

When assessing economic costs, the most obvious main objective is to minimise the total costs. However, van den Bergh et al. [81] point out that other aims such as minimum downtime and minimal delays can also be distinguished. To quantify the costs, Kent and Murphy [42] describe three methodologies: (1) an analogy approach where costs are based on historical or actual data, (2) a parametric method using formulas to cost relations and finally, (3) an engineering estimation concept through the use of an extensive cost breakdown. To review the financial costs over the lifetime of a component, metrics such as Return on Investment (ROI), Payback Period and Net Present Value (NPV) are commonly applied [26, 63, 90].

In the light of reviewing the costs of Lithium battery health management strategies, Liu et al. [50] assessed the economic performance of several battery charging approaches. In their model, the authors included the initial cost of the battery, the charging costs of the battery as well as the resale opportunities at the battery's EOL. In another study, Li et al. [48] analysed the costs of a battery storage system and concluded that the system's life-cycle costs mainly consisted of the initial costs at BOL and charging costs.

2.2.3 Efficiency

In a study reviewing maintenance approaches, Pecht and Rafanelli [62] analysed the effectiveness of a system to take its availability, dependability and capability into account. Here, availability refers to the system being usable at the beginning of a period of desired usage. Moreover, dependability indicates the probability of the system failing during operation. Lastly, the systems capability shows at which level of performance the system is able to carry out its function.

3 Mission Profiles

In the previous sections, an introduction and substantiation of the research topic has been given. The following sections 3, 4, 5 and 6 describe the methodology of this study regarding eUAV flights, battery simulation, performance assessment and MC set-up.

In order to test the battery health management strategies defined for this research, this section presents the framework of the missions that the eUAV executes. To simulate a cycle that a battery undergoes during a flight, eUAV flight data tracked for a DJI Matrice 100 quadcopter by Rodrigues et al. [65] is used. In section 3.1 an overview of the flight layout is presented. Secondly, the flight distance flown is discussed in section 3.2, after which the input data for the flight profiles is elaborated on in section 3.3.

3.1 Flight Outline

To model discharge cycles that an eUAV battery undergoes, flight missions are defined. As the focus of this paper lies on determining the benefit of applying a mission-based approach for eUAV battery health management, a flying plan is proposed during which an eUAV performs 'simple' manoeuvres to reach a randomly assigned 'target'. The eUAV flies to the target by carrying out actions including take-off, cruise and landing. For each flight, the following steps are executed:

1. The eUAV is initially positioned at a hub where it is able to charge its battery.
2. Then, a mission target is randomly generated within the maximum defined distance that the eUAV is able to fly, given the maximum capacity of the battery.
3. Once the target is known, the eUAV flies to the target and back to the hub, by:
    - performing a vertical take-off to the desired cruise altitude,
    - cruising at the set altitude to the target,
    - vertically landing at the target,
    - resting for a short time,
    - executing a vertical take-off to the inputted cruise altitude,
    - cruising at the set altitude back to the charging hub, and,
    - vertically landing at the hub.
4. A new target mission is then generated *(continue to loop from step 1).*

The maximum distance that the eUAV is able to fly is limited by the battery capacity. In the model set-up for this research, the maximum distance is defined conservatively to ensure that the battery is always able to safely complete each flight. The flight distances covered in this research are briefly elaborated on in the next section.

3.2 Flight Distance

In this study, the distance that the eUAV flies is varied to review the impact of DOD on battery degradation for eUAV applications. From literature [30, 91] it is found that smaller DOD ranges result in less severe ageing for batteries cycled under constant discharge protocols. For eUAV battery operations, there are various manners to regulate the DOD such as altering the distance covered, speed flown or payload carried. However, because an amendment in speed or payload is paired with other ageing side-effects due to a change in battery load profiles. Thus, it is chosen to exclusively adjust the cruise distance flown.

The eUAV completes four sets of different ranges to explore the effect of varying the DOD: *mixed, short, medium* and *long* range. The target distance framework is further elaborated on in section 6.

3.3 Flight Data

In the DJI Matrice 100 quadcopter data [65] several flights are monitored exploring the influence of wind, cruise altitude, ground speed and payload weight on the eUAV performance.

The DJI Matrice has a 22.2 V Lithium battery with 4.5 Ah capacity. The quadcopter has a maximum cruise speed equal to 17 ms^{-1} and is able to fly 22 minutes provided it is not carrying a payload.

In order to simulate the battery flights in PyBaMM, the rates of current the battery provides the quadcopter during take-off, cruise and landing are required. Secondly, the time duration of a take-off and landing manoeuvre are quantified. A summary of the mean inputs per flight part is given in Table 1. Both the current and time values have a standard deviation equal to 2.6% [65]. Note that the cruise time is not fixed, as this depends on the target distance that is stochastically generated before each flight.

In order to obtain these data inputs, the DJI Matrice 100 data set is filtered on altitude, payload weight and ground speed. The lowest altitude from the DJI Matrice 100 tests, equal to 25 m, is chosen to allow for a longer residual flight time to explore the influence of flying different DOD ranges. Additionally, following the same reasoning, the payload is set to 0 kg. Finally, the average ground speed of 8 ms^{-1} is used.

Part	**Current**		**Time duration**	
	Symbol	*Value [A]*	*Symbol*	*Value [s]*
Take-off	$I_{t/o}$	23.5	$t_{t/o}$	12.0
Cruise	I_c	21.0	t_c	*variable*
Landing	I_l	19.5	t_l	25.0

Table 1: Flight profile input values

4 Battery Simulation

Now that the mission profiles are defined, this section presents the battery simulation set-up used to cycle the battery throughout the flights. To evaluate the performance of the mission-based battery health management strategy, it is compared to a SOC 100% and SOC 80% strategy. First, section 4.1 describes the general battery model used for simulations in Python. Then,

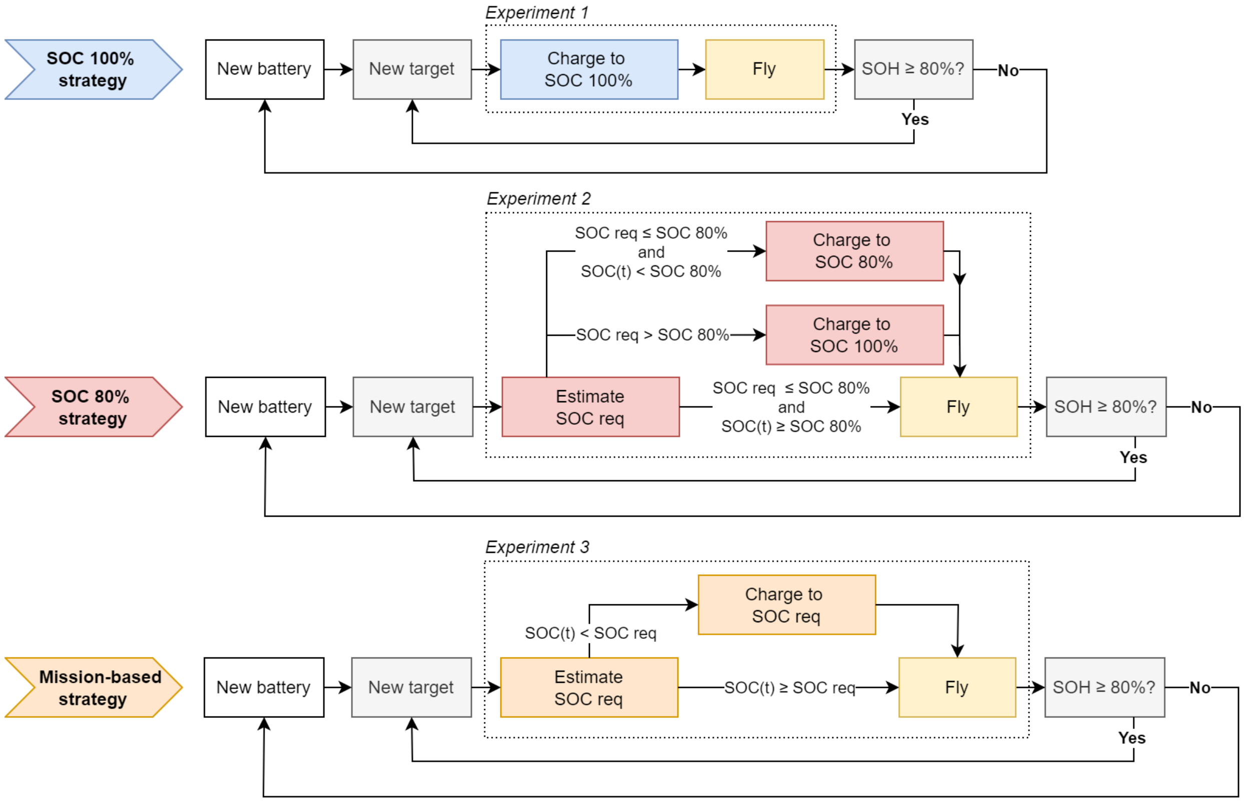


Figure 1: Schematic overview of SOC 100%, SOC 80% and mission-based strategy battery models

the SOC 100%, SOC 80% and mission-based battery health management strategies are elaborated on in section 4.2.

4.1 Battery Modelling

The battery is modelled with the use of the Python package PyBaMM (version 21.10) [77]. To increase computational speed, the battery cells are represented by a Single Particle Model (SPM). It is chosen to replicate the Nickel, Manganese and Cobalt (NMC) Lithium battery using the parameter set provided by Mohtat et al. [55] as this battery cell has similar properties to the DJI Matrice battery used to fly the eUAV described in section 3.3. An overview of the battery parameter values defined by Mohtat et al. [55] is given in Table 21 in Appendix A.

In this model, the Lithium pouch cell from Mohtat et al. [55] has a 4.2 V maximum voltage (V_{max}) and a 3.0 V minimum voltage (V_{min}). The nominal cell capacity is 5.0 Ah. This is slightly more than the 4.5 Ah DJI Matrice battery, enabling the eUAV to fly longer. To reach the 22.2 V delivered by the DJI Matrice batteries, multiple Lithium NMC pouch cells can be placed in series to form a battery pack. To rule out ageing influences between battery cells, however, this model only reviews the performance of a single cell.

Battery ageing is modelled with a Solid Electrolyte Interphase (SEI) kinetic rate equal to $1 \cdot 10^{-14}$ ms^{-1} derived by Yang et al. [92]. Here, the ethylene carbonate reaction is limited following the SEI formation reaction. The battery's EOL is defined when SOH is 80% to avoid a critical voltage drop. The internal resistance is not defined to be the limiting factor as test runs showed that this parameter increased with a maximum of +20% upon reaching 80% SOH.

As PyBaMM is deterministic, several small perturbances are inputted into the model to mirror real-life parameter variation observed in literature. Table 22 in Appendix A lists these non-deterministic errors that applied to the battery chemistry and BMS readings. These stochastic inputs are also briefly addressed in section 6 and further explored when validating the model in section 8.

A schematic flowchart of the steps the battery model undergoes is given in Figure 1. This overview includes three separate steps that are executed depending on the battery health management strategy that is in place. These three strategies are: ***(1) SOC 100%***, ***(2) SOC 80%*** and ***(3) mission-based***. The battery model is almost identical for these strategies, except for the *experiment* that the battery executes for each flight. A detailed description of experiments 1, 2 and 3 is given in section 4.2. Below is a brief description of each step in depicted in Figure 1:

1. **New battery** - a new battery is inputted into the model to be tested until it reaches SOH 80%. The number of batteries that are tested for each strategy is determined by the MC simulation setup which is further discussed in section 6.

2. **New target** - while SOH $\geq$ 80%, new targets are generated for the battery to fly to.

3. **Experiment** - depending on the battery health management strategy (*SOC 100%, SOC 80%* or *mission-based*), the battery is either first charged and then flown, or flown directly.

4. **SOH ≥ 80%** - SOH is checked after each flight:

   i if SOH ≥ 80%, a new target is generated at d_{target} distance and the battery undergoes another cycle.

   ii if SOH ≤ 80%, this battery is discarded and a new battery is inputted in the model to be tested.

Translating the flowchart steps into a simulation model, the skeleton of the battery model developed in Python using PyBaMM is given in Algorithm 1. The following notes apply:

- The normally distributed input values in lines 5, 7, 8 and 17 refer to the specifications listed in Table 22 in Appendix A.
- Flights, *f*, are counted for each mission completed.
- During each flight, the *experiment* run for the simulation in line 27 depends on the battery health management strategy that is in place. Note that in this context, 'experiment' refers to the charge/discharge cycle that the battery undergoes in PyBaMM. The variation in types of simulation experiments are elaborated on in section 4.2.
- After an experiment has been simulated, *sim()*, the battery's inner state has been modified from $battery_f, start$ to $battery_f, end$.
- Finally, when the battery has reached SOH = 80% the *output* solution is a set of flights executed by the inputted battery. The data includes detailed battery state information such as voltage, current and capacity levels for each flight.

4.2 Battery Health Management Strategies

As stated in the previous section, the *experiment* a battery performs during each cycle depends on the strategy that is being evaluated. In this section, the three battery health management strategies ***(1) SOC 100%***, ***(2) SOC 80%*** and ***(3) mission-based*** are described in detail. The frameworks of the experiments associated with each strategy is first given in section 4.2.1. Thereafter, the methodology of the estimation of the required amount of SOC to safely complete a mission is presented in section 4.2.2.

4.2.1 PyBaMM Experiments per Strategy

The definitions of the *experiment* for the SOC 100%, SOC 80% and mission-based strategy are presented in Algorithms 2, 3 and 4, respectively. These experiments are inputted into the main battery model in Algorithm 1 when 'flying = *True*' which starts in line 21.

Algorithm 1 Skeleton of the battery model using PyBaMM

1: **Input** model ← *SPM*
2: **Input** model ← *ec reaction limited*

3: **Input** parameter ← *Lithium-ion Mohtat2020*
4: **Input** parameter ← *SEI kinetic rate Yang2017*
5: **Input** parameter ← $capacity_{f=0}$, *normal*(μ,σ)

6: **Input** electrode ← *Lithium-ion ElectrodeSOH*
7: **Input** electrode ← *Vmin, normal*(μ,σ)
8: **Input** electrode ← *Vmax, normal*(μ,σ)

9: $f = 0$
10: $battery_{f=0}$ ← *model, parameter, electrode*

11: **while** SOH ≥ 80% **do**
12: new_mission = *True*
13: flying = *False*
14: mission_complete = *False*

15: **if** new_mission = *True* **then**
16: d_{target} ← *random target within range*
17: parameter ← *SEI kinetic rate normal*(μ,σ)

18: new_mission = *False*
19: flying = *True*
20: **end if**

21: **if** flying = *True* **then**
22: **if** $f = f_0$ **then**
23: $battery_{f,start}$ ← $battery_{f=0}$
24: **else**
25: $battery_{f,start}$ ← $battery_{f-1,end}$
26: **end if**
27: experiment ← d_{target}
28: $battery_{f,end}$ ← sim($battery_{f,start}$, *experiment*)
$f \leftarrow f + 1$

29: flying = *False*
30: mission_complete = *True*
31: **end if**

32: **if** mission_complete = *True* **then**
33: SOH ← $capacity_{f,end}/capacity_{f=0}$

34: mission_complete = *False*
35: new_mission = *True*
36: **end if**
37: **end while**

38: **Output** model ← *solution*

For the SOC 100%, SOC 80% and mission-based strategy, the experiments includes charging ('Charge') and in flight ('Fly') discharging commands that PyBaMM uses to cycle the battery. These two processes are further elaborated on below. Note that both the SOC 80% and mission-based battery health management strategy allow the eUAV to fly directly if it has sufficient SOC from the previous flight.

Charge
The battery cell is charged following a standard Constant Current Constant Voltage (CC/CV) protocol. The CC/CV charging steps inputted in the *experiment* are presented in Algorithm 5. The SOC_{start} values derived for the SOC 100%, SOC 80% and mission-based strategy are first converted to V_{start}V, as PyBaMM requires voltage inputs to charge the battery. Then, the battery is charged at 1C until V_{start}V (CC step) and held at V_{start}V until C/50 (CV step).

Algorithm 2 SOC 100% battery strategy - *Experiment 1*

$\text{SOC}_{start} \leftarrow 100\%$
if flying $=$ *True* **then**
  experiment $\leftarrow$ *Charge*(SOC_{start})
  experiment $\leftarrow$ *Fly*(d_{target})
end if

Algorithm 3 SOC 80% battery strategy - *Experiment 2*

if flying $=$ *True* **then**
  Estimate $\text{SOC}_{req} \leftarrow d_{target},\ SOH$

  if $\text{SOC}_{req} > 80\%$ **then**
    $\text{SOC}_{start} \leftarrow 100\%$
    experiment $\leftarrow$ *Charge*(SOC_{start})
    experiment $\leftarrow$ *Fly*(d_{target})

  else if $\text{SOC}_{req} \leq 80\%$ and $\text{SOC(t)} < 80\%$ **then**
    $\text{SOC}_{start} \leftarrow 80\%$
    experiment $\leftarrow$ *Charge*(SOC_{start})
    experiment $\leftarrow$ *Fly*(d_{target})

  else
    experiment $\leftarrow$ *Fly*(d_{target})

  end if
end if

Algorithm 4 Mission-based battery strategy - *Experiment 3*

if flying $=$ *True* **then**
  Estimate $\text{SOC}_{req} \leftarrow d_{target},\ SOH$
  if $\text{SOC(t)} < \text{SOC}_{req}$ **then**
    $\text{SOC}_{start} \leftarrow SOC_{req}$
    experiment $\leftarrow$ *Charge*(SOC_{start})
    experiment $\leftarrow$ *Fly*(d_{target})
  else
    experiment $\leftarrow$ *Fly*(d_{target})
  end if
end if

Fly
As described in the mission profile part in section 3, a flight consists of multiple steps in order to fly from the hub, to the target and back to the hub. These steps are presented in Algorithm 6. The target distance (d_{target}) is converted to cruise time (t_c) with the use of the set 8 ms^{-1} ground speed. The current throughput rates applied during take-off ($I_{t/o}$), cruise (I_c) and landing (I_l), as well as the times to perform take-off ($t_{t/o}$) and landing (t_l) are in line with the DJI Matrice values observed in literature [65] as listed in Table 1 which is stochastically generated with a standard deviation equal to 2.6% for each flight.

Algorithm 5 CC/CV charge in *experiment*

$\text{V}_{start} \leftarrow \text{SOC}_{start}$

$$\text{Charge}(V_{start}) \leftarrow \begin{Bmatrix} \textit{Charge at 1C until } V_{start}V, \\ \textit{Hold at } V_{start}V \textit{ until C/50} \end{Bmatrix}$$

Algorithm 6 Fly in *experiment*

$\text{t}_c \leftarrow \text{d}_{target}$

$$\text{Fly}(\text{d}_{target}) \leftarrow \begin{Bmatrix} \textit{Discharge at 0.1A for 3s,} \\ \textit{Discharge at } I_{t/o} \textit{ A for } t_{t/o} \textit{ s,} \\ \textit{Discharge at } I_c \textit{ A for } t_c \textit{ s,} \\ \textit{Discharge at } I_l \textit{ A for } t_l \textit{ s,} \\ \textit{Discharge at 0.1A for 3s,} \\ \textit{Rest for 3 minutes} \end{Bmatrix}$$

4.2.2 Estimation of Required State of Charge

Both the SOC 80% and mission-based strategy estimate the required SOC for the eUAV to complete the flight before flying. The establishment of this estimation is done using Linear Regression (LR) and Multiple Linear Regression (MLR). Because PyBaMM requires voltage as an input for charging practices, it is required to translate SOC to voltage levels, whilst keeping in mind that the voltage relation changes as the battery ages [72].

Equation 1 gives the formula used in the battery health management models to derive the required voltage level (V_{req}) for the SOC 80% and mission-based battery health management strategy. This method is based on an approach presented by Viswanathan et al. [84]. The V_{req} is the voltage level to which the battery must be charged to safely complete the mission. In this equation, $V_{SOC\ 30\%}$ is the voltage at which the battery has 30% SOC. The expected DOD voltage based on the inputted target distance is represented by V_{exp}.

$$V_{req} = V_{SOC\ 30\%} + V_{exp} \tag{1}$$

Voltage for 30% SOC ($V_{SOC\ 30\%}$)
The level at which $V_{SOC\ 30\%}$ is incorporated because

30% SOC is the minimum SOC threshold that the battery must have to ensure safe flight [37]. The determination of the $V_{SOC\ 30\%}$ level is given in Algorithm 7.

The number of batteries tested to determine the $V_{SOC\ 30\%}$ levels for different SOH states, along with the corresponding number of data points, is listed in Table 2. The simulations are run with the battery and BMS specifications listed in Table 21 and 22 in Appendix A. To capture the $V_{SOC\ 30\%}$ values on the voltage curves as the battery ages, the battery is cycled from its minimum to its maximum voltage until SOH = 80%. The battery's SOH is reviewed at the start and end of each cycle, c. The cycling experiment in line 17 is given in Algorithm 8. To ensure that the battery ageing process is similar to the battery model used for flying, the same CC/CV charging approach is used to charge the batteries.

After the model output values for $V_{SOC\ 30\%}$ from 100 batteries at different SOH stages have been gathered, a LR is performed through regression in Python. For this LR, the battery's SOH is inputted due to the fact that the batteries' voltage level curves decrease as the battery degrades. Equation 2 is yielded to calculate $V_{SOC\ 30\%}$. This LR equation has an R^2 value of 0.432.

$$V_{SOC\ 30\%} = 0.397 \cdot SOH + 3.30 \tag{2}$$

Expected Voltage (V_{exp})
Secondly, the V_{exp} is added to the determined $V_{SOC\ 30\%}$. In order to derive the voltage DOD for a variety of distances flown, the model described in Algorithm 1 is used. Naturally, a higher V_{exp} relates to a longer flight distance. Again, this voltage model is simulated with the battery and BMS inputs listed in Table 21 and 22 in Appendix A are simulated. The total number of batteries tested is listed in Table 2. In this model, the SOC 100% experiment described in Algorithm 2 is inputted into the battery simulations. The number of data points outputted from these runs is significantly more compared to the $V_{SOC\ 30\%}$ model due to the longer lifetime as a result of a smaller DOD.

For V_{exp}, two variables are fed into the MLR, namely SOH and target distance. The SOH is inputted in order to account for the change in voltage curves as the battery ages, while the target distance (d_{target}) is used to determine what the DOD of the battery voltage will be. The regression results in Equation 3 which can be used to determine V_{exp}. The R^2 value of this MLR equation is 0.857.

$$V_{exp} = -0.0861 \cdot SOH + 0.0003 \cdot d_{target} + 0.195 \tag{3}$$

Voltage level	**Number of batteries**	**Data points**
$V_{SOC\ 30\%}$	1000	4442
V_{exp}	100	9067

Table 2: Voltage level tests

Algorithm 7 LR required SOC
- *Model for Voltage at which SOC = 30% ($V_{SOC\ 30\%}$)*

1: **Input** model ← *SPM*
2: **Input** model ← *ec reaction limited*

3: **Input** parameter ← *Lithium-ion Mohtat2020*
4: **Input** parameter ← *SEI kinetic rate Yang2017*
5: **Input** parameter ← $capacity_{f=0}$, *normal*(μ,σ)

6: **Input** electrode ← *Lithium-ion ElectrodeSOH*
7: **Input** electrode ← *Vmin, normal*(μ,σ)
8: **Input** electrode ← *Vmax, normal*(μ,σ)

9: $c = 0$
10: $\text{battery}_{f=0}$ ← *model, parameter, electrode*

11: **while** SOH ≥ 80% **do**
12: **if** $c = c_0$ **then**
13: $\text{battery}_{c,start} \leftarrow battery_{c=0}$
14: **else**
15: $\text{battery}_{c,start} \leftarrow battery_{c-1,end}$
16: **end if**
17: $\text{battery}_{c,end} \leftarrow \text{sim}(battery_{c,start},\ experiment)$
$c \leftarrow c + 1$
18: SOH ← $capacity_{c,end}/capacity_{c=0}$
19: **end while**

20: **Output** model ← *solution*

Algorithm 8 LR required SOC
- *Experiment for $V_{SOC\ 30\%}$*

1: $\text{experiment} \leftarrow \left\{ \begin{array}{l} \textit{Charge at 1C until } V_{max}V, \\ \textit{Hold at } V_{max}V \textit{ until C/50,} \\ \textit{Discharge at 1C until } V_{min}V, \\ \textit{Rest for 3 minutes} \end{array} \right\}$

5 Sustainability and Cost Assessment

After a MC simulation of the batteries has been run, an assessment is performed comparing the SOC 100%, SOC 80% and mission-based eUAV battery health management strategies. In total, three pillars are assessed: *environmental impact, financial costs,* and, *efficiency.* These factors are explained in more detail in section 5.1, 5.2 5.3, respectively. The assessment of the results evaluates these three pillar separately as a trade-off requires additional stakeholder information to determine the weight of each parameter.

5.1 Environmental Impact

The environmental impact related to longevity and energy consumption are reviewed. These are sustainability factors derived from literature [28, 31, 40] and chosen due to the availability of data. The environmental impact is quantified through carbon emissions, as these make up for 80% of a battery's Global Warming Potential (GWP) score [44]. The calculations of the carbon emissions are presented hereafter.

The carbon emissions that arise from the BOL production processes ($CO_{2,BOL}$ $[kg]$) account for the waste and longevity sustainability component. These emissions are determined using Equation 4. In this equation, battery's energy at BOL (E_{BOL} $[kWh]$). The average E_{BOL} for the batteries inputted in this model in PyBaMM is 0.0190 kWh. The BOL carbon emissions ($CO_{2,\ BOL\ kWh}$ $[kg/kWh]$) equal 143.7 kg of carbon per kWh battery capacity. This is derived from averaged BOL emission data for lithium batteries with NMC chemistry as the values of the BOL CO_2 emissions strongly vary per source [35, 52]. The EOL emissions are disregarded due to a lack of consistency in data and situational influences [38, 46].

$$CO_{2,\ BOL} = E_{BOL} \cdot CO_{2,\ BOL\ kWh} \tag{4}$$

During operation, the energy consumption throughout the activity of charging is closely monitored and translated to carbon emissions ($CO_{2,charge}$ $[kg]$) with Equation 5. Here, the total charging power (P_{total} $[kWh]$) is reviewed for each battery health management strategy. The efficiency of transferring electricity (η) from the power plant to the drone motors is set to 0.78 [32, 76]. Moreover, charging carbon emissions ($CO_{2,\ charge\ kWh}$ $[kg/kWh]$) associated with a mixed-use of green and grey electricity in the Netherlands are implemented into the model. This results in 0.49 kg CO_2 per kWh electricity used. [13, 15].

$$CO_{2,\ charge} = P_{total} \cdot \frac{1}{\eta} \cdot CO_{2,\ charge\ kWh} \tag{5}$$

5.2 Financial Costs

Secondly, similar to the environmental impact, the financial costs of a battery at BOL, throughout operation and EOL can be considered for assessment [81]. EOL costs, however, are again disregarded as these are complex to determine in view of inconsistency of data and battery specification dependencies [38, 66]. For the SOC 80% and mission-based strategy, an investment cost also applies to initially establish, verify and validate the predictive approach [26]. In this study, however, the investment cost is neglected due to a lack of data. Consequently, the costs' ROI or Payback Period are also not assessed. By neglecting battery health management investment costs, the financial assessment of the mission-based and SOC 80% strategy is more optimistic. The equations to evaluate the remaining costs for the battery at BOL and during operation are discussed below.

The battery BOL costs ($Cost_{BOL}$ [€]) can be determined by either through an analogy approach reviewing average costs per kWh or with a parametric method by averaging Off-the-Shelf (OTS) products. As costs per kWh vary [48], it is chosen to use the off-the-shelf price of the Lithium batteries used to model the eUAV flight mission profiles in section 3, which is equivalent to € 199 [21].

To operate an eUAV battery, operation and maintenance costs mainly consist of energy consumption costs during charging [48]. To determine the charging costs ($Cost_{charge}$ [€]) Equation 6 is used with the average electricity cost ($Cost_{charge\ kWh}$ [€$/kWh$]) in the Netherlands as of 1 May 2021 [59], equal to € 0.23 per kWh. In this equation P_{total} and η refer to the same charging power in kWh and electricity transfer process efficiency, respectively, as used in Equation 5.

$$Cost_{charge} = P_{total} \cdot \frac{1}{\eta} \cdot Cost_{charge\ kWh} \tag{6}$$

5.3 Efficiency

The last assessment parameter used to assess the battery health management strategies is efficiency which is related to the availability of the battery [62, 81]. Here, the 'downtime' of the battery health management strategies during the activity of charging are compared to the flight times. Naturally, a low downtime is desired, yielding a higher efficiency. To determine the efficiency of a strategy, Equation 7 is applied. Here, $Total\ flight\ time$ refers to the sum of the time the battery is used to fly, and $Total\ time$ represents the sum of the flying and charging time each battery undergoes.

$$Efficiency = \frac{Total\ flight\ time}{Total\ time} \tag{7}$$

Depending on the stakeholders involved, efficiency could be reflected in operational costs. This is, however, case-specific and beyond the scope of this study.

6 Experimental Set-up

Sections section 3 to 5 provided background information for the mission profiles, battery model and sustainability and cost assessment framework. In this section, the experimental set-up of this research is elaborated on. Details concerning the stochastic generation of mission targets is first presented in section 6.1, followed by an overview of the MC simulation set-up in section 6.2.

6.1 Mission Targets

During a flight, the eUAV is modelled to fly from the hub to a mission target and back. The minimum distance (d_{min}) to a target to is positioned 20 m from the hub such that the eUAV approximately covers the same distance horizontally as vertically. The maximum distance that the eUAV is able to fly is governed by the battery characteristics and flight profiles. The battery in PyBaMM has a capacity of 5.0 Ah. Following the flight instructions in which the battery provides sufficient energy for the eUAV to fly to a randomly assigned target location and back to the hub while also maintaining a SOC level above the 30% threshold, the maximum target distance (d_{max}) is defined to be 1000 m.

To analyse the influence of the battery DOD cycled through by each eUAV battery, four target distance ranges are defined. An overview of the minimum and maximum distance (d_{min} and d_{max}) associated with each range is given in Table 3. The minimum distance of the *short* range equals the minimum distance inputted into the *mixed* battery model, while the maximum distance of the *long* distance is the same as the maximum range flown by the eUAV for the *mixed* set of missions. For each range, targets are generated following a uniform distribution such that each mission target has an equal chance of being visited.

Range	d_{min} [m]	d_{max} [m]
Mixed	20	1000
Short	20	346
Medium	347	673
Long	674	1000

Table 3: Target distance ranges

6.2 Monte Carlo

To run the MC simulations, the battery model is tested using the SOC 100%, SOC 80% and mission-based strategy. Table 4 provides an overview of the number of batteries tested per strategy and range.

Range	SOC 100%	SOC 80%	Mission-based
Mixed	1000	1000	1000
Short	300	300	300
Medium	300	300	300
Long	300	300	300

Table 4: Number of batteries tested per strategy and range

The *mixed* target distance is initially tested for 1000 batteries. A statistical analysis presented in supporting work [86], is carried out to verify if the MC simulations of the independent battery runs converge to stable means. The total sum of target distances flown by each battery is reviewed as missions targets are stochastically generated as an 'input' to the battery model. The results show that the total sum of target distances flown by each battery for the SOC 100%, SOC 80% and mission-based strategy for the *mixed* range stabilises after approximately 300 runs. Hence, it can be concluded that sufficient MC simulations have been run. For the *short, medium* and *long* range tests, the MC simulations are run 300 times to decrease the total run time.

For the MC simulations for the *mixed, short, medium* and *long* range tests using the SOC 100%, SOC 80% and mission-based strategy, the following stochastic inputs are incorporated in the runs:

The MC incorporates stochastic inputs to represent battery manufacturing impurities in new batteries [6, 22, 61, 89] and in-flight variations in battery power usage and flying times [65].

- ***Initial battery parameters***
  Each battery that is newly inputted into the model, has the following stochastic initial properties as listed in Table 22 in Appendix A: initial capacity, initial maximum voltage and initial minimum voltage.
- ***In-flight variations***
  Every battery cycles through random flights depending on the target locations generated. Each mission, the current and time required to complete a take-off, cruise and landing manoeuvre varies around the mean value presented in Table 1 with a standard deviation equal to 2.6% [65]. Furthermore, the SEI kinetic rate constant depends on the battery health and is normally distributed using the inputs provided in Table 22 in Appendix A. Finally, the BMS reading errors for voltage, SOC and SOH which are presented in Table 22 in Appendix A, vary each flight affecting for example the determination of EOL at 80% SOH.

6.3 Sustainability and Cost Assessment

To assess the environmental impact and financial costs of the battery models, the output is reviewed for 'battery lifetime' and 'battery usage'. A brief description of these two characteristics is given below:

- ***Battery lifetime***
  Here, the impact of battery lifetime concerning BOL practices is assessed. From the sustainability and cost assessment parameters presented in section 5, the review of battery lifetime performance includes $CO_{2,\ BOL}$ and $Cost_{BOL}$. The EOL practices are disregarded due to lack of data.

  In order to ensure that the SOC 100%, SOC 80% and mission-based output values are on the same scale, the BOL emissions and costs are expressed per total flying time flown per battery ($\widetilde{CO_{2,\ BOL}}$ [kg/s] and $\widetilde{Cost_{BOL}}$ [€/s]). Both these two parameters relate to the number of batteries used per flying time ($\widetilde{B}$), which will be discussed in the results in section 7.
- ***Battery usage***
  The evaluation of battery usage focuses on the performance during operation. From section 5 the parameters $CO_{2,\ charge}$ and $Cost_{charge}$ are incorporated to review the impact of charging. Also, the efficiency of flying versus downtime is included.

  Again, to effectively compare the SOC 100%, SOC 80% and mission-based results, the emissions and costs parameters are reviewed per flying time ($\widetilde{CO_{2,\ charge}}$ [kg/s] and $\widetilde{Cost_{charge}}$ [€/s]). These two metrics both relate to the total charge used per flying time per battery ($\widetilde{P}_{total}$ [kWh/s]), which is used to evaluate the battery usage performance in the next section. The flying efficiency results for battery usage can be compared directly.

7 Results

In this section, the results for battery health management strategies are presented. The results of the 1000 batteries tested for the *mixed* range are first discussed in section 7.1, after which the results of the 300 batteries simulated for the *short, medium* and *long* range are elaborated on in section 7.2. Finally, conclusions regarding the effect of regulating the average SOC and DOD on sustainability and cost performance is discussed in section 7.3.

Parameter	**Mission-based vs. SOC 100%**	**Mission-based vs. SOC 80%**
$\widetilde{B}$	-20.1%	-5.7%
$\widetilde{P}_{total}$	-6.4%	-5.2%
Efficiency	+2.8%	-6.9%

Table 5: Relative mean Battery Usage and Battery Lifetime performance of 1000 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for mixed range

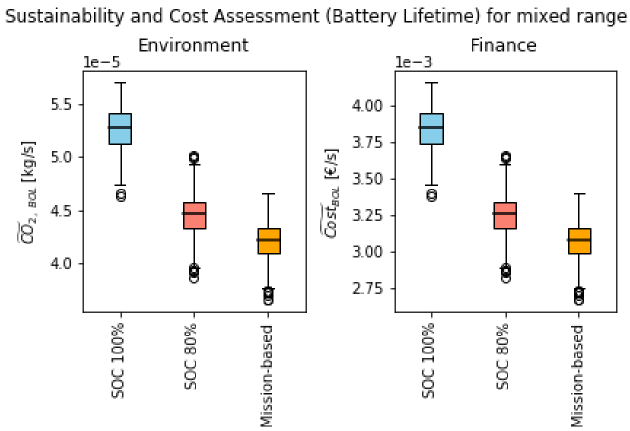


Figure 2: Sustainability and Cost Assessment - Battery Lifetime results of 1000 batteries tested through Monte Carlo simulation for the SOC 100%, SOC 80% and mission-based strategy for mixed range

7.1 Mixed Range

First, section 7.1.1 elaborates on the evaluation with respect to battery lifetime in which the BOL emissions and costs are assessed. Secondly, section 7.1.2 presents the outcome of the battery usage assessment concerning emissions and costs of charging as well as the flying efficiency results.

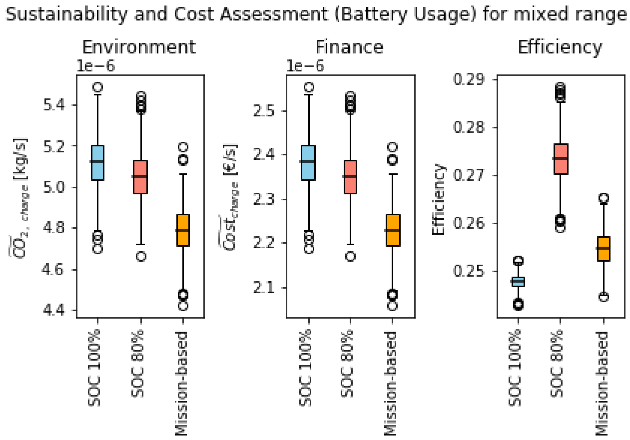


Figure 3: Sustainability and Cost Assessment - Battery Usage results of 1000 batteries tested through Monte Carlo simulation for the SOC 100%, SOC 80% and mission-based strategy for mixed range

7.1.1 Battery Lifetime

It is expected that the mission-based health management strategy yields a longer battery lifetime due to the lower average SOC level. This implies that this model requires fewer batteries per flying distance flown ($\widetilde{B}$) before reaching EOL at 80% SOH. A longer lifetime results in a relative decrease in BOL emissions and costs.

In order to compare if there is a significant difference in the average battery lifetime for the SOC 100%, SOC 80% and mission-based strategy, the hypotheses in Table 6 and Table 7 are tested for batteries used per flying time ($\widetilde{B}$). From a statistical analysis performed in supporting work [86] it is concluded that the $\widetilde{B}$ output of the models follow a normal distribution. Hence, the hypotheses are tested for $\alpha = 1\%$ using an unpaired one-sided T-test.

Mission-based vs. SOC 100% - **mixed range**
H_0: $\widetilde{B}_{\ mission-based} \geq \widetilde{B}_{\ SOC\ 100\%}$
H_1: $\widetilde{B}_{\ mission-based} < \widetilde{B}_{\ SOC\ 100\%}$

Table 6: **Hypothesis** $\widetilde{B}$ - Mission-based vs. SOC 100% strategy for mixed range

The relative mean $\widetilde{B}$ performance from the MC simulations for the SOC 100% and mission-based strategy is displayed in Table 5. When comparing the independent samples of $\widetilde{B}$ paired with both strategies, it is observed that the mission-based approach requires approximately **20.1%** less $\widetilde{B}$ with 100% confidence [86]. Hence, H_0 for $\widetilde{B}$ in Table 6 is rejected.

From these results, it can be concluded that the mission-based battery health management strategy yields a longer battery lifetime with respect to the SOC 100% method. The battery life elongation as a result of applying the mission-based strategy is attributed to the fact that the battery is cycled around a lower average SOC.

Mission-based vs. SOC 80% - **mixed range**
H_0: $\widetilde{B}_{\ mission-based} \geq \widetilde{B}_{\ SOC\ 80\%}$
H_1: $\widetilde{B}_{\ mission-based} < \widetilde{B}_{\ SOC\ 80\%}$

Table 7: **Hypothesis** $\widetilde{B}$ - Mission-based vs. SOC 80% strategy for mixed range

The relative average $\widetilde{B}$ from the SOC 80% and mission-based strategy MC simulations is displayed in Table 5. When comparing the $\widetilde{B}$ for these two strategies and reviewing the statistical analysis presented in supporting work [86], it is concluded with 100% confidence that the mission-based strategy has **5.7%** reduced $\widetilde{B}$. Hence, H_0 for $\widetilde{B}$ in Table 7 is rejected. Again, the conclusion can be drawn that the mission-based battery health management strategy results in battery lifetime elongation compared to the SOC 80% method.

Translating $\widetilde{B}$ into $\widetilde{CO_{2,\ BOL}}$ and $\widetilde{Cost_{BOL}}$ it can be reviewed how the BOL results for the SOC 100%, SOC 80% and mission-based strategy compare. The $\widetilde{CO_{2,\ BOL}}$ and $\widetilde{Cost_{BOL}}$ results for the strategies are depicted in Figure 2.

7.1.2 Battery Usage

During the operation, the batteries' charging CO_2 emissions and costs and flying efficiency are assessed. The mission-based battery health management strategy is anticipated to perform better than the SOC 100% strategy for all three parameters. Below, the amount of energy required to charge the batteries per flying distance flown ($\widetilde{P}_{total}$) and efficiency of the flying time to the total time are assessed.

To evaluate the model outputs for the *mixed* range, the following sets of hypotheses listed in Table 8 to 11 are defined for $\widetilde{P}_{total}$ and *Efficiency* per battery. From supporting work [86] a statistical analysis shows that both outputs follow a normal distribution for the SOC 100%, SOC 80% and mission-based models. The hypotheses listed below are tested for $\alpha = 1\%$ with an unpaired one-sided T-test.

Mission-based vs. SOC 100% - **mixed range**
H_0: $\widetilde{P}_{total,\ mission-based} \geq \widetilde{P}_{total,\ SOC\ 100\%}$
H_1: $\widetilde{P}_{total,\ mission-based} < \widetilde{P}_{total,\ SOC\ 100\%}$

Table 8: **Hypothesis** $\widetilde{P}_{total}$ - Mission-based vs. SOC 100% strategy for mixed range

Mission-based vs. SOC 100% - **mixed range**
H_0: $Efficiency_{\ mission-based} \leq Efficiency_{\ SOC\ 100\%}$
H_1: $Efficiency_{\ mission-based} > Efficiency_{\ SOC\ 100\%}$

Table 9: **Hypothesis** *Efficiency* - Mission-based vs. SOC 100% strategy for mixed range

From the relative outcome of the MC simulations presented in Table 5, it can be concluded that the mission-based battery health management strategy results in a lower $\widetilde{P}_{total}$ and higher flying efficiency. The mission-based $\widetilde{P}_{total}$ is reduced with **6.4%** of compared to the SOC 100% approach, while the efficiency increases by **2.8%**. The improved battery usage performance is the result of the fact that the battery is merely charged to the estimated amount of charge. Both the samples for $\widetilde{P}_{total}$ and *Efficiency* differ with 100% confidence as presented in supporting work [86], implying that both H_0 hypotheses in Table 8 and Table 9 are rejected.

Mission-based vs. SOC 80% - **mixed range**
H_0: $\widetilde{P}_{total,\ mission-based} \geq \widetilde{P}_{total,\ SOC\ 80\%}$
H_1: $\widetilde{P}_{total,\ mission-based} < \widetilde{P}_{total,\ SOC\ 80\%}$

Table 10: **Hypothesis** $\widetilde{P}_{total}$ - Mission-based vs. SOC 80% strategy for mixed range

Mission-based vs. SOC 80% - **mixed range**
H_0: $Efficiency_{\ mission-based} \leq Efficiency_{\ SOC\ 80\%}$
H_1: $Efficiency_{\ mission-based} > Efficiency_{\ SOC\ 80\%}$

Table 11: **Hypothesis** *Efficiency* - Mission-based vs. SOC 80% strategy for mixed range

The average results of the MC simulations presented in Table 5 show the mission-based battery health management strategy results in a lower total power used for charge per mission time flown ($\widetilde{P}_{total}$). The $\widetilde{P}_{total}$ for the mission-based approach is reduced with **5.2%** compared to the SOC 80% strategy. However, despite this improved charging performance, the mission-based outputs a **6.9%** lower efficiency with respect to the SOC 80% strategy. This is explained by the fact that the strategy skips charging when SOC$_{req}$ $\leq$ 80% and SOC(t) $\geq$ 80%, which is frequently yielded after having charged to SOC 100% for the previous flight. Therefore, the overall conclusion stands that the H_0 for $\widetilde{P}_{total}$ in Table 10 is rejected with 100% confidence [86], while the H_0 for *Efficiency* in Table 11 is failed to be rejected.

For the sustainability and cost assessment of each battery, the sum of charging power per time flown ($\widetilde{P}_{total}$) is translated in to $\widetilde{CO_{2,\ charge}}$ and $\widetilde{Cost_{charge}}$. Moreover, the flying efficiency is directly assessed. The battery usage results per battery run through the MC simulations for the SOC 100%, SOC 80% and mission-based strategy are displayed in Figure 3.

7.2 Short, Medium and Long Range

Reviewing different distance ranges flown, the mission-based battery strategy is expected to perform better than the SOC 100% and SOC 80% model for both 'battery lifetime' and 'battery usage' related parameters. Moreover, the short range distance is expected to yield the best results due to minimum battery degradation influenced by DOD.

In a statistical analysis presented in supporting work [86], it is concluded that the results for the SOC 100%,

Parameter	**Short**		**Medium**		**Long**	
	Mission-based vs. SOC 100%	*Mission-based vs. SOC 80%*	*Mission-based vs. SOC 100%*	*Mission-based vs. SOC 80%*	*Mission-based vs. SOC 100%*	*Mission-based vs. SOC 80%*
$\widetilde{B}$	-34.3%	-15.1%	-19.9%	+5.5%	-10.9%	-10.8%
$\widetilde{P}_{total}$	-9.7%	-0.8%	-7.4%	-6.1%	-4.5%	-4.5%
Efficiency	+6.8%	+2.6%	+1.5%	-15.6%	+0.6%	+0.5%

Table 12: Relative mean Battery Usage and Battery Lifetime performance of 300 batteries tested through Monte Carlo simulation comparing the SOC 100%, SOC 80% and mission-based strategy per short, medium and long range

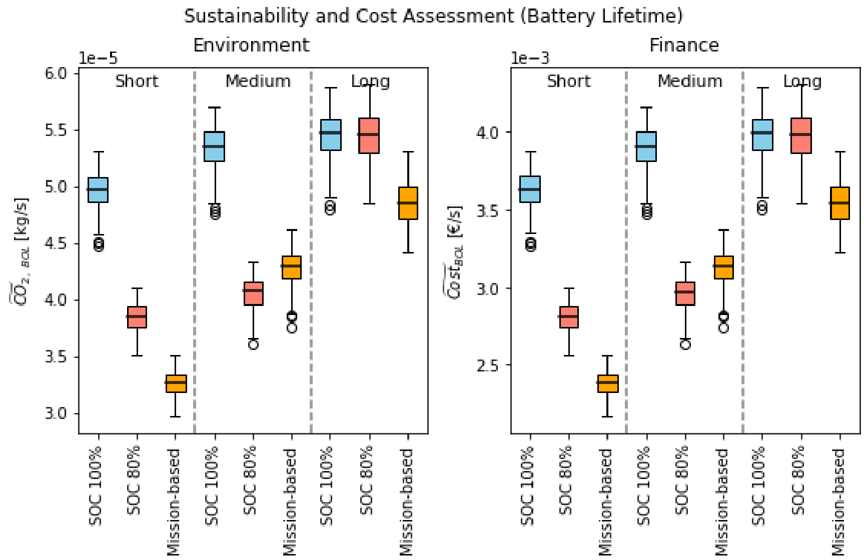


Figure 4: Sustainability and Cost Assessment - Battery Lifetime results of 300 batteries tested through Monte Carlo simulation for the SOC 100%, SOC 80% and mission-based strategy for short, medium and long range

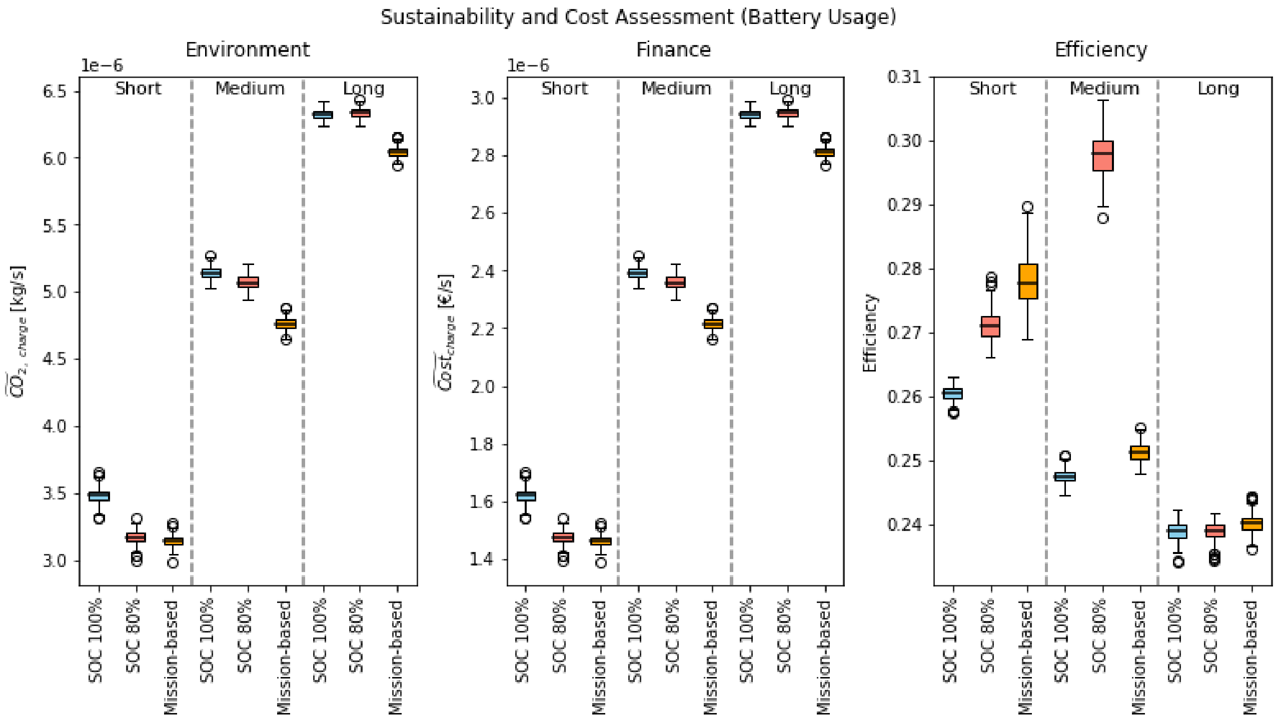


Figure 5: Sustainability and Cost Assessment - Battery Usage results of 300 batteries tested through Monte Carlo simulation the for SOC 100%, SOC 80% and mission-based strategy for short, medium and long range

SOC 80% and mission-based strategy are normally distributed and can thus be evaluated with an unpaired one-sided T-test. The hypotheses for the short, medium and long range results are tested for $\alpha = 1\%$. Here, *Output* refers to the performance of $\widetilde{B}$, $\widetilde{P}_{total}$ and *Efficiency*. An improved performance corresponds to a lower $\widetilde{B}$ and $\widetilde{P}_{total}$, and higher *Efficiency* output.

The results of the mission-based strategy compared to the SOC 100% approach are first discussed in section 7.2.1. Subsequently, the results of the mission-based compared to the SOC 100% strategy are evaluated in section 7.2.2. Finally, the results of the different ranges are compared in section 7.2.3.

7.2.1 Mission-based vs. SOC 100%

To review if the mission-based strategy is better than the SOC 100% approach, hypotheses for the *short, medium* and *long* range are presented in Table 13, 14 and 15, respectively.

Mission-based vs. SOC 100% - **short range**
H_0: $Output_{\ mission-based} \leq Output_{\ SOC\ 100\%}$
H_1: $Output_{\ mission-based} > Output_{\ SOC\ 100\%}$

Table 13: **Hypothesis** *Output* - Mission-based vs. SOC 100% strategy for short range

Mission-based vs. SOC 100% - **medium range**
H_0: $Output_{\ mission-based} \leq Output_{\ SOC\ 100\%}$
H_1: $Output_{\ mission-based} > Output_{\ SOC\ 100\%}$

Table 14: **Hypothesis** *Output* - Mission-based vs. SOC 100% strategy for medium range

Mission-based vs. SOC 100% - **long range**
H_0: $Output_{\ mission-based} \leq Output_{\ SOC\ 100\%}$
H_1: $Output_{\ mission-based} > Output_{\ SOC\ 100\%}$

Table 15: **Hypothesis** *Output* - Mission-based vs. SOC 100% strategy for long range

From the relative mean battery lifetime and usage results presented in Table 12, Figure 4 and 5 the following conclusions are drawn. The mission-based approach yielded better results than the SOC 100% for all three distance ranges.

Short range
Battery lifetime for the mission-based strategy is improved significantly as it shows the lowest $\widetilde{B}$. For battery usage, the P_{total} is reduced with and efficiency is increased. Compared to the *medium* and *long* range, it becomes apparent that the battery lifetime and usage is most affected in the *short* range. This is the result of the shorter distances flown that result in a longer lifetime and minimal charging activity corresponding to a lower $\widetilde{P}_{total}$ and higher efficiency. Concluding these results and a T-test presented in supporting work [86], the H_0 for the **short** range in Table 13 can be rejected with 100% confidence.

Medium range
With the mission-based strategy, the battery lifetime and usage yield improved results compared to the SOC 100% strategy. Here, similar values to the performance in *mixed* distance are observed. Based on the output of these results and a T-test [86], the H_0 for the **medium** range in Table 14 is rejected with 100% confidence.

Long range
The mission-based strategy yields less $\widetilde{B}$ than the SOC 100% approach. Furthermore, the $\widetilde{P}_{total}$ is improved and an efficiency that is also a little higher. Contrarily to the other distance ranges, though, the difference in performance of the mission-based and SOC 100% strategy for the *long* distance is less evident. This is due to the fact that when flying to targets that are positioned further away, the mission-based strategy is required to charge to a SOC level that is closer to 100%. From these results and the T-test output [86], H_0 for **long** range in Table 15 can successfully be rejected with 100% confidence.

7.2.2 Mission-based vs. SOC 80%

The hypotheses to evaluate the performance of the mission-based strategy compared to the SOC 80% approach for the *short, medium* and *long* range are presented in Table 16, 17 and 18, respectively.

Mission-based vs. SOC 80% - **short range**
H_0: $Output_{\ mission-based} \leq Output_{\ SOC\ 80\%}$
H_1: $Output_{\ mission-based} > Output_{\ SOC\ 80\%}$

Table 16: **Hypothesis** *Output* - Mission-based vs. SOC 80% strategy for short range

Mission-based vs. SOC 80% - **medium range**
H_0: $Output_{\ mission-based} \leq Output_{\ SOC\ 80\%}$
H_1: $Output_{\ mission-based} > Output_{\ SOC\ 80\%}$

Table 17: **Hypothesis** *Output* - Mission-based vs. SOC 80% strategy for medium range

Mission-based vs. SOC 80% - **long range**
H_0: $Output_{\ mission-based} \leq Output_{\ SOC\ 80\%}$
H_1: $Output_{\ mission-based} > Output_{\ SOC\ 80\%}$

Table 18: **Hypothesis** *Output* - Mission-based vs. SOC 80% strategy for long range

Comparing the relative mean battery lifetime and usage results presented in Table 12, Figure 4 and 5 the following conclusions are drawn for the mission-based and SOC 80% strategy.

Short range
The mission-based strategy shows a better $\widetilde{B}$ than the SOC 80% strategy. For battery usage, the $\widetilde{P}_{total}$ is only slightly reduced, which suggest that both strategies charge to similar SOC levels. The efficiency of the mission-based strategy is however still higher because the average required SOC for short ranges is very low, resulting in the battery regularly skipping charging before a flight. From these results and a T-test elaborated on in supporting work [86], H_0 for the **short** range in Table 16 is rejected with 100% confidence.

Medium range
For the medium range, the mission-based strategy is not superior to the SOC 80% strategy, which goes against the hypothesis formulated above. The results show that the SOC 80% strategy yields a better $\widetilde{B}$ and efficiency. An explanation for this could be the fact that the eUAV battery regularly skips charging due to the toggle between SOC 100% and 80%. As a result, battery degradation is less severe and efficiency is significantly increased. When analysing the charging power $\widetilde{P}_{total}$, however, the mission-based strategy outperforms the SOC 80% approach. To conclude, the H_0 for the **medium** in Table 17 is only partially rejected, as only the mission-based strategy only outperformed SOC 80% for $\widetilde{P}_{total}$ during operation. The confidence levels for the T-tests are presented in supporting work [86].

Long range
The mission-based strategy results in a lower $\widetilde{B}$ compared to the SOC 100% approach. Also, the $\widetilde{P}_{total}$ is and efficiency are improved. Based on the T-test results [86], H_0 for the **long** range in Table 18 is rejected with 100% confidence. The results show that for *long* distance, the SOC 80% strategy performs very similar to the SOC 100% approach. This is due to the fact that 80% SOC is insufficient to safely complete a mission to the target in the *long* range, forcing the battery to almost always charge to 100%.

7.2.3 Distances

Per strategy, the performance of *short* compared to *medium* and *long* distance is evaluated to review the influence of DOD. The hypotheses for testing the impact of the distance are presented in Table 20. It is expected that the *short* distance outperforms the *medium* and *long* range model due to battery lifetime elongation as a result of a smaller DOD.

Distance - short vs. medium and long range
H_0: *Output* $_{short} \leq$ *Output* $_{medium,\ long}$
H_1: *Output* $_{short} >$ *Output* $_{medium,\ long}$

Table 20: **Hypothesis** *Output* - Distance short vs. medium and long range

Reviewing the battery lifetime and usage sustainability and cost assessment results in Table 19, Figure 4 and 5, several conclusions are drawn.

Battery lifetime
When comparing the battery lifetime output within each strategy, it is observed that the *short* range yields the best battery lifetime performance compared to *medium* and *long* target distance range. This is in line with the expectations and shows that a smaller DOD results in a longer battery life. Furthermore, it becomes apparent that decreasing the DOD elongates the lifetime most significantly for mission-based strategy compared to the SOC 100% and SOC 80% strategy because the batteries with the mission-based approach are cycled around a lower average SOC.

Battery usage
For battery usage, the results show that $\widetilde{P}_{total}$ yields the lowest results for the *short* distance, which supports the hypothesis stated above. The amount of charge used during battery lifetime decreases with approximately the same order of magnitude for each strategy. The reason that the charge required for the total mission time flown decreases, originates from the fact that the battery suffers from less severe battery ageing, implying that a eUAV battery is able to fly longer. For the flying efficiency for the SOC 80% strategy, however, the value is highest for the *medium* range, instead of the *short* range. The high efficiency for the SOC 80% range is attributed to the SOC 100% and 80% toggle mentioned previously.

Concluding the findings above, the H_0 in Table 20 for **distance** is partially rejected, because the flying efficiency with the SOC 80% strategy for *medium* distance outperforms the other ranges. The T-test results are presented in supporting work [86].

7.3 Discussion

A concluding discussion of the results of this study is given in the following sections. The benefit of applying a mission-based battery health management strategy by minimising the average SOC and DOD is first elaborated on in section 7.3.1 and 7.3.2, respectively. Then, general sustainability and cost assessment findings are discussed in section 7.3.3. Throughout the section, several recommendations for future studies are provided. A more elaborate overview of this study's limitations and suggestions for further analysis is given in supporting work [86].

7.3.1 Average State of Charge

From the *mixed* range simulations, it is concluded that the mission-based study which cycles the battery around a lower average SOC by charging to a beforehand estimated required SOC, yields better results. However, it must be noted that it cannot be ruled out that this performance is solely the result of cycling

	SOC 100%		SOC 80%		Mission-based	
Parameter	*Short vs. Medium*	*Short vs. Long*	*Short vs. Medium*	*Short vs. Long*	*Short vs. Medium*	*Short vs. Long*
$\widetilde{B}$	-7.0%	-8.8%	-5.2%	-29.4%	-23.7%	-32.8%
$\widetilde{P}_{total}$	-32.3%	-45.0%	-37.5%	-50.0%	-34.0%	-48.0%
Efficiency	+5.3%	+9.1%	-8.9%	+13.5%	+10.7%	+15.8%

Table 19: Relative mean Battery Usage and Battery Lifetime performance of 300 batteries tested through Monte Carlo simulation comparing short, medium and long range per strategy

around a lower SOC, as the influence of skipping charging must not be neglected. By applying the mission-based strategy, benefits are yielded across eUAV *battery lifetime* parameters with respect to emissions and costs.

Secondly, during eUAV operation for the *mixed* distance, the mission-based methodology yields the least power required for charging. This is due to the fact that the battery is merely charged to the estimated SOC required to complete the next flight, or is immediately used to fly if the battery already has sufficient charge. Regarding flying efficiency, however, the SOC 80% strategy performs best. This is the result of the SOC 80% strategy's toggle between SOC 80% for shorter and SOC 100% for longer distances. This leads to the eUAV regularly having sufficient SOC to complete the next mission without being charged beforehand. It could therefore be argued that the need for a mission-based model is challenged, considering the fact that the SOC 80% is relatively simple to apply.

Although the SOC 80% and mission-based strategy improve battery lifetime and usage performance, it could be argued that implementing these battery health management strategies is risk-prone due to the reduced available capacity for flight. For future studies it is therefore recommended to include a safety assessment parameter. Moreover, the reliability of the strategies could be increased by establishing a more advanced SOC estimation model that accounts for an elaborate set of factors such as wind, altitude, payload and flight speed.

7.3.2 Depth of Discharge

By varying the distance flown by the eUAV for a *short, medium* and *long* range, the effect of varying the DOD of that the battery cycles through is explored. From the model output, it is concluded that the mission-based battery health management strategy outperforms the SOC 100% strategy for all three distance ranges. The *battery lifetime* is most significantly affected for the *short* range, as this distance pairs with a smaller DOD, a lower average SOC and regular skipping of charging practices. During *battery usage*, the power for charging is reduced for the mission-based strategy as the battery suffers from less severe battery ageing, implying that a eUAV battery is able to fly longer. Lastly, the flying efficiency is increased due to the fact that the battery is either charged to a lower SOC, or can immediately be inputted to fly given it already has sufficient charge from the previous flight.

Comparing the mission-based strategy to the SOC 80% approach, it is concluded that the SOC 80% yields benefits for the *medium* range. For this distance, the SOC 80% strategy resulted in a better *battery lifetime* yielding lower emissions and costs. Moreover, the flying efficiency was significantly increased for *battery usage*. This improved performance is the result of the SOC 80% regularly skipping the charging step when the eUAV has sufficient charge from the previous flight.

Given the difference in sustainability and cost assessment results for the *mixed, short, medium* and *long* range, a recommendation for future research is to review the optimal flying distance to maximise battery lifetime and usage performance.

Note that if the environmental and financial assessment results would be specified over target distance flown instead of total flying time, a different output is yielded. For the short range, this implies that a eUAV travels less cruise distance per flight, but still has to perform the same take-off and landing manoeuvres requiring relatively more charge per target distance flown. As a result, the results for the short range would not outperform the other ranges for battery lifetime and battery usage.

7.3.3 Sustainability and Cost Assessment

Comparing the *battery lifetime* to the *battery usage* results, it becomes apparent that the environmental and financial costs at BOL have the largest impact. For the *mixed* range, the $\widetilde{CO_{2,\ BOL}}$ emissions for approximately 91.1%, 89.8% and 89.8% of the total emissions for the SOC 100%, SOC 80% and mission-based battery health management strategy, respectively. For the economic costs, the $\widetilde{Cost_{BOL}}$ approximately sum up to equal 99.9% of the total costs for all three strategies. This is in line with the findings described in literature, and suggest that battery lifetime could be considered prime focus point by operators.

The second discussion point revolves around the seemingly low battery usage efficiency rate across all strategies and distances flown. This output is attributed to the CC/CV charging protocol that is inputted into the model. Due to the applied charging C-rate and method, the charging time is approximately twice as long as the discharging practices, yielding a low flying efficiency rate. Applying a different charging methodology would influence the magnitude of this parameter, which must be taken into account when using the same framework to other battery models.

Finally, when analysing the distributions of the battery lifetime and usage graphs depicting the charging emissions, costs and flying efficiency, the following points stand out. For the emissions and costs boxplots, similar distributions for the SOC 100%, SOC 80% and mission-based strategy are observed. For flying efficiency, however, the SOC 80% and mission-based strategy show a wider spread of flying efficiency results compared to the SOC 100% approach. This is caused to the SOC 80% and mission-based strategy set-up in which the battery is not charged before flight if it has sufficient SOC from the previous mission. This becomes strongly apparent for short range flights which require less charge to safely complete a mission.

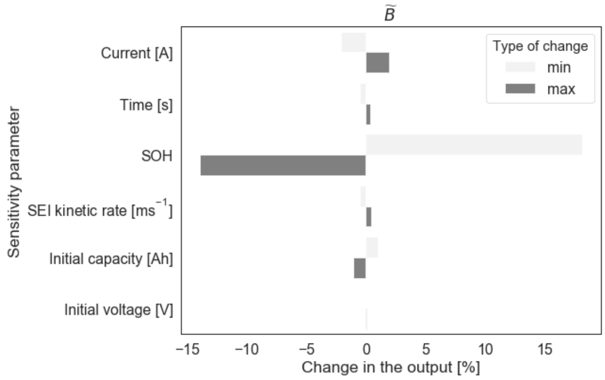


Figure 6: Sensitivity Analysis for Battery Lifetime - relative change in *output* of $\widetilde{B}$ (battery used per flying time) for SOC 100% strategy

8 Validation

Validation of the battery model is done through a Sensitivity Analysis (SA). Due to the absence of real data to compare the model output, a SA is one of the few methods to validate functional frameworks [10, 39, 67]. By running a SA, the robustness of a model is checked. For future studies, it is recommended to validate the model with real eUAV battery data.

The result of a change in inputs is reviewed both with respect to *logic* and *sensitivity.* A One-at-a-Time (OAT) analysis [10] is performed to review how the output responds to a change of a single input while keeping the other inputs constant. The inputs that are varied are those that are stochastically generated for each battery and flight, listed in Table 22 in Appendix A. Each input is tested OAT for their minimum and maximum value. Depending on their distribution, this is either equal to the minimum or maximum value of the uniform distribution, or ±95% confidence interval value for normally distributed variables.

In the interest of speeding up the computational time, the SOC 100% methodology is used to validate the battery model. Moreover, the MC is run for 300 runs for each sensitivity parameter as the mean target distance covered by each eUAV battery stabilised for this number of simulations. A verification of this is given in statistical analysis in supporting work [86].

In Figure 6 and 7, the tornado plots of the SA results for battery lifetime and usage are depicted. The mean results of the model outputs for the minimum or maximum sensitivity parameters varied OAT are compared to the average results for a model in which all sensitivity parameter inputs are fixed at their mean. These validation outputs for battery lifetime are first discussed in section 8.1, followed by the battery usage results in section 8.2.

8.1 Battery Lifetime

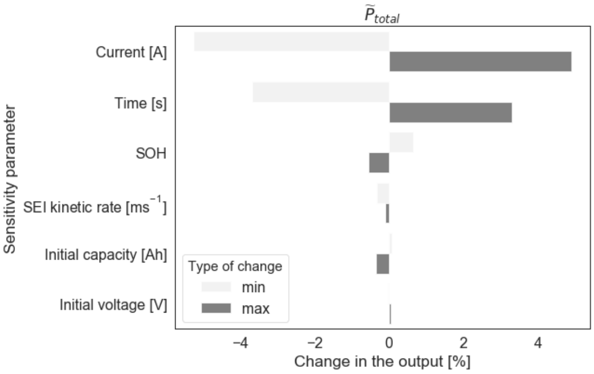
For battery lifetime, Figure 6 shows that the minimum and maximum settings for SOH have the biggest influence on the batteries used per flying distance flown ($\widetilde{B}$). This tells us that with respect to lifetime, the model is more sensitive to the BMS error than the other stochastic inputs. The relation between the SOH sensitivity parameter and lifetime is in line with expectations. If the BMS consequently reads a lower SOH than the actual value, the battery is terminated at an earlier stage. Contrarily, if a higher SOH is gone by, the battery is terminated later than the real SOH 80% threshold, resulting in an elongated lifetime. For $\widetilde{B}$, the minimum SOH input value results in a larger change in output deviation than the maximum value. This is because the flying time sums up to equal a relatively larger fraction for a shorter compared to at a longer lifetime which is governed by the CC/CV charging protocol.

For the remaining sensitivity parameters, the battery lifetime results display logical results. The battery performs more flights per battery when for minimum current throughput and flying time manoeuvre duration, yielding a lower $\widetilde{B}$. This is due to a decrease in ageing severeness as a result of lower current rates during discharge and smaller DOD. Moreover, lower SEI kinetic rate values result in longer battery life. On the contrary, the eUAV battery is able to complete more flights on average when the maximum initial capacity is inputted into the model. Finally, the initial voltage parameter shows a negligible difference when comparing the minimum and maximum inputted values to the mean.

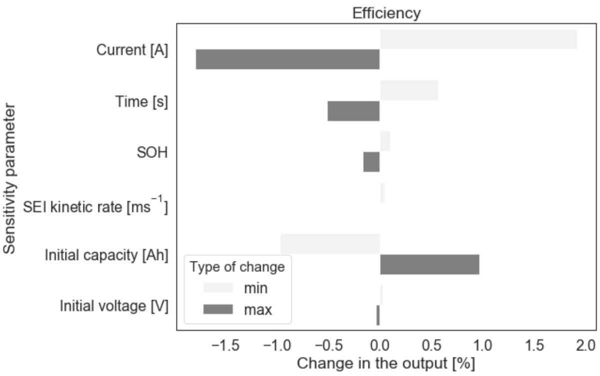
8.2 Battery Usage

The $\widetilde{P}_{total}$ and flying efficiency SA tornado plots are shown in Figure 7a and 7b, respectively. The average output of results varies marginally for battery usage. The influence of each sensitivity parameter is discussed below.

The flying current and time duration sensitivity values have a large influence on the resulting $\widetilde{P}_{total}$ and flying efficiency. This is logical, as battery ageing is expected to be less severe for lower current rates and DOD levels, resulting in a longer lifetime which pairs with smaller $\widetilde{P}_{total}$ values. For flying efficiency, minimum current and time values yield a higher efficiency. This is attributed to the fact that the batteries require



(a) $\widetilde{P}_{total}$ (charging power used per flying time)



(b) *Efficiency*

Figure 7: Sensitivity Analysis for Battery Usage - relative change in *output* for SOC 100% strategy

less charging time on average, which results in a higher flying efficiency because charging takes relatively long due to a lower current rate during the CC phase.

The maximum SOH reading error implies that batteries are operated longer which yields a higher total flying time per battery. Hence, the $\widetilde{P}_{total}$ for each battery decreases. However, the flying efficiency is also decreased, as more flights are flown which pair with relatively longer charging time. Furthermore, from the tornado plots it is concluded that the $\widetilde{P}_{total}$ and flying efficiency is hardly related to the SEI kinetic rate.

The initial capacity of the eUAV battery has a relatively large influence on the flying efficiency output. The reason for this is not trivial and requires further analysis. For $\widetilde{P}_{total}$, a higher initial capacity results in more charging power required to reach a fully charged state. This is linked to the longer lifetime presented in the SA plot for $\widetilde{B}$. Finally, the initial voltage level has a negligible influence on the SA results.

9 Conclusions and Recommendations

This research reviews the environmental and cost-benefit of applying a mission-based battery health management strategy to Lithium batteries used in an electric Unmanned Aerial Vehicle (eUAV). By applying the mission-based strategy, the eUAV battery is charged to the estimated State of Charge (SOC) level required to successfully complete a flight. The performance of the mission-based strategy is compared to two other approaches where the battery is either charged to 100% SOC or SOC 80%. The strategies are tested for several different flight ranges (*mixed, short, medium* and *long)* to explore the influence of varying the Depth-of-Discharge (DOD). The motivation to research this topic originated from the hypothesis that cycling a battery at a lower average level of SOC and smaller DOD ranges results in a longer battery lifetime, which is especially important from a sustainability perspective.

The research is carried out with a Nickel, Manganese and Cobalt (NMC) Lithium battery model simulated with the Python Battery Mathematical Modelling (PyBaMM) package. A Monte Carlo (MC) simulation is used to review how the model responds to uncertainties in initial battery characteristics and in-flight variations. The eUAV battery performs flights including a take-off, cruise and landing manoeuvre, during which it flies there and back to stochastically generated targets. Ultimately, the performance of the mission-based strategy is compared to the SOC 100% and SOC 80% approach by executing a sustainability and cost assessment. Here, the environmental and financial costs related to the batteries' lifetime and usage are assessed. Furthermore the efficiency of flying is evaluated.

Comparing the mission-based strategy to the SOC 100% and SOC 80% model for the *mixed* distance, a decrease in emissions and costs is observed. Regarding flying efficiency that aims to minimise downtime, however, the SOC 80% performs best. Additionally, like the mission-based strategy, the SOC 80% approach outperforms the SOC 100% strategy for all assessment parameters. These results could challenge the significance of implementing a mission-based battery health management strategy, as the SOC 80% method is relatively simple to establish. Reviewing the results of the *short, medium* and *long* range flights, it is concluded that battery lifetime and usage results are significantly improved for a battery flying short range flights.

Although a more advanced model is advised before applying this model to real-life eUAV applications, this study provides insights with respect to how a mission-based battery health management strategy could yield environmental, financial and flying efficiency benefits. Addressing the shortcomings described in section 7 and 8, the foremost focus point for future recommendations of the model include the incorporation of a safety assessment parameter. Moreover, it is advised to extend the model by including inputs such as wind, speed, altitude and payload settings. Finally, it is recommended to validate the model with real-life experiments. Here, it is especially advised to review the Battery Management System's (BMS) accuracy of determining the battery's SOH, as this sensitivity parameter resulted in the most significant relative output changes.

To conclude, this study analysed the benefit of applying a mission-based battery health management strategy with the use of a simulated Lithium battery model in PyBaMM. The mission-based methodology, battery model and sustainability and cost assessment framework can support operators in evaluating and comparing the performance of different battery health management strategies.

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Appendices

A Appendix A - Battery model specifications

Pouch cell	
Nominal capacity $[Ah]$	5.0
Minimum voltage $[V]$	3.0
Maximum voltage $[V]$	4.2
Thickness $[mm]$	4.0
Length $[mm]$	132
Width $[mm]$	90
Positive electrode	
Material	NMC:CB:PVDF (94:3:3)
Number of double sided electrode sheets	14
Negative electrode	
Material	Graphite:PVDF (95:5)
Number of double sided electrode sheets	15
Separator	
Material	Polyethylene (PE)
Electrolyte	
Material	1 M $LiPF_6$
Organic solvent in electrolyte	2% EC:EMC (3:7)

Table 21: Lithium battery specifications [55]

Parameter	**Source**	**Distr.**[1]	**Value**
Initial battery parameters			
Initial capacity $[Ah]$	[61]	Normal	$\mu = 5$, $\sigma = 1.3\%$
Initial minimum voltage $[V]$	[22]	Normal	$\mu = 3.0$, $\sigma = 0.01\%$
Initial maximum voltage $[V]$	[22]	Normal	$\mu = 4.2$, $\sigma = 0.01\%$
Battery ageing parameters			
SEI kinetic rate constant $[ms^{-1}]$	[6]	Normal	1.0 >SOH >0.9: $\mu = 1 \cdot 10^{-14}$, $\sigma = 1.5\%$ 0.9 >SOH >0.8: $\mu = 1 \cdot 10^{-14}$, σ = -0.055*SOH + 0.051
Battery Monitoring System			
Voltage $[V]$	[36, 88]	Uniform	Error margin = ± 1.0%
SOC	[43, 74]	Uniform	Error margin = ± 2.0%
SOH	[73, 82]	Uniform	Error margin = ± 2.5%

[1] Distr. = Distribution (probability)

Table 22: Battery and BMS non-deterministic error model inputs

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II

Literature Study
previously graded under AE4020

1
Introduction

Maintenance is an important process in aviation to ensure safety and reliability requirements are met [41, 68]. Studying maintenance procedures has become a popular subject for many other reasons such as the minimisation of financial costs and improvement of efficiency [6, 73, 87, 102]. Commonly applied types of maintenance are Corrective Maintenance (CM), scheduled maintenance and Predictive Maintenance (PdM) [6, 124]. The most basic approach is CM, which is a reactive maintenance approach [41]. Scheduled maintenance is a proactive strategy that is structured by time- or usage-based intervals [53, 121], which is widely applied due to its simplicity and efficiency for planning extensive checks [1, 68]. Currently, PdM is increasingly applied within the maintenance domain. PdM, also known as Prognostics and Health Management (PHM) [119], is a preventive approach that monitors a component's performance to provide maintenance prognostics [74]. By incorporating predictive maintenance, the objective is to improve a system's reliability and safety while reducing monetary costs, increasing availability and elongating component lifetime [48, 111, 116]. To guide the decision-making process for which maintenance strategy is optimal for a given system, a Cost-Benefit Analysis (CBA) can be performed [54].

The aim of this study is to review the current literature on PHM practices in the aerospace industry, in order to set up a research that will contribute to this topic. Moreover, appropriate CBA methodologies are explored. This research is performed as part of an MSc thesis at the Faculty of Aerospace Engineering at Delft University of Technology. The thesis objective is to execute a CBA analysing the performance of a PHM approach. The fundamental building blocks of executing the thesis project are also covered in this report.

Part IIA evaluates the available literature on PHM. First, chapter 2 reviews the different types of maintenance techniques. For predictive maintenance, although the diagnostic part of such an approach is well established, the prognostic component requires further development [72, 110]. Moreover, given the current shift to more sustainable practices, a shortcoming is observed with respect to PHM studies on electric Aerial Vehicles (eAVs). Specifically, the rest of the report addresses PHM practices related to batteries, given their critical power supply role [19]. As batteries for large aircraft are not yet widely available [19, 125], this study focuses on electric Unmanned Aerial Vehicles (eUAVs). For eUAVs, Lithium batteries are most commonly used [28, 107, 118]. Hence, an in-depth analysis of Lithium battery health management methodologies is performed in chapter 3. Subsequently, chapter 4 discusses general performance metrics to evaluate predictive algorithms. Finally, maintenance costs as well as cost-benefit parameters are elaborated on in chapter 5. Here, the inclusion of sustainability parameters is also addressed.
Building on the findings in Part IIA a thesis project is defined. Part IIB first presents the problem statement in chapter 6. Here, the main objects, scope and research sub-questions are summarised. To perform the research, a brief overview of the project methodology and timeline is given in chapter 7.

PART IIA

2
Aircraft Maintenance

In this chapter, all topics directly related to aerospace maintenance is discussed. First, a general overview of the evolution of aircraft maintenance and important factors that need to be taken into account are elaborated on in section 2.1. Secondly, section 2.2 provides a detailed breakdown of the different types of maintenance strategies that exist. Here, the maintenance types corrective, preventive and predictive maintenance are specifically focused on. Finally, a conclusion of research gaps is drawn in section 2.3, highlighting the challenges and literature gaps encountered throughout aerospace maintenance practices.

2.1. General Background

The development and improvement of aircraft maintenance schedules is an ongoing process. Over the past couple of decades, the number of publications on this topic has grown significantly. For aircraft maintenance, Van den Bergh et al. [124] perceived a steady increase from approximately 10 to 30 papers issued yearly over a duration of 20 years compared to 1995. Moreover, for machine prognostics in general, Lei et al. [74] showed that the number of publications grew steadily from around 10 to over 200 pieces each year over 20 years compared to 1996, resulting in a total of 1426 papers. On the one hand, this is driven by the airworthiness of aviation. Aircraft safety is an important factor within the aviation industry, as a lack of integrity could lead to fatal accidents [41]. On the other hand, maintenance costs make up for approximately 10 - 20 % of an air carrier's total budget [6, 73, 87, 102]. Hence, optimising maintenance costs is beneficial.

In this section, the aspects of safety in aviation are first discussed in subsection 2.1.1. Then, relevant organisations and principles related to safety and maintenance are presented in subsection 2.1.2.

2.1.1. Safety in Aviation

As mentioned above, safety is an important factor within aviation. For safety-related to aeronautics, a distinction is made between the following types: man, environment and machine safety [41]. The first category, **man**, includes all people that are actively involved with flight operations such as the pilots, maintenance labourers and air traffic controllers. For **environment**, all external aspects that are related to air traffic are considered. For example, this category refers to meteorological conditions, communications and traffic zones. Finally, **machine** includes safety regarding aircraft construction. This last type is also known as **airworthiness**, which is especially relevant for maintenance. According to the Italian RAI-ENAC Technical Regulations, airworthiness is defined to be "the possession of the necessary requirements for flying in safe conditions, within allowable limits".

The airworthiness of aircraft depends on several factors including the materials, design and manufacturing process and operations and maintenance activities performed. Although aviation is often referred to as the safest mode of transport [35, 84], Duarte et al. [35] stress the importance of the continuation of research concerning flight safety. In their paper, several studies are addressed that support the thesis that failure analyses are of high importance concerning aircraft system safety.
Not only on the technical front but also from a social point of view, further development is important. Lack of communication between parties, such as the manufacturer and operator or an aircraft, can have a negative

influence on maintenance processes [50] or even result in fatal accidents [35]. If component failures are not communicated to the manufacturer, the design cannot be adjusted to correct these errors. Conversely, the maintainability of aircraft highly depends on the technical support given by the manufacturer to the operators and maintenance engineers. The percentage of accidents assigned to be the result of human errors vary vastly per study, ranging from 21% [128] to 96% [59]. However, it must be noted that human errors can be classified into several different stages, starting at an organisational level that ultimately influences all maintenance actions performed at lower stages [120]. Nevertheless, it can be concluded that the assurance of airworthiness is a joint effort between all parties that are related to aviation practices.

2.1.2. Organisations and Regulations

Aviation developed rapidly around World War I and World War II. In order to monitor technological developments, the International Civil Aviation Organisation (ICAO) was established in 1947 [41]. The ICAO's aim was to set up techniques and principles for international aviation to ensure safe and efficient service. Ultimately, the ICAO delivered 18 annexes that each cover air navigation-related subjects. Here, recommended maintenance practices are predominantly discussed in Annex 6 'Operation of Aircraft', Annex 8 'Airworthiness of Aircraft' and Annex 16 'Environmental Protection'.

Subsequently, authorities were established to ensure that airworthiness standards were actually met [41]. The authorities have the task to prescribe requirements and procedures, to inform all air navigation parties and control that the prescriptions are followed up. These regulations apply for aircraft design, manufacturing and material organisations, as well as air navigation operators. Finally, an airworthiness authority has the task of certificating materials and organisations. To stimulate cooperation between authorities, Bilateral Aviation Safety Agreements (BASA) were initialised. When concerning aircraft airworthiness, an additional document Implementation Procedures for Airworthiness (IPA) is developed to ensure all standards are met. Here, specific protocols are defined including activities related to aircraft design, production, repair and other technical operations.

Different authorities exist, partially newly established and partially evolved from former organisations [41]. Most authorities operate on a national level, but steps are being made to harmonise these air navigation regulations. For example, in 2016, the Certification Management Team (CMT) was officially founded [84] [32] consisting of four of the largest aviation authorities being the Federal Aviation Administration (FAA) in the United States, Transport Canada Civil Aviation (TCCA), Agência Nacional de Aviação Civil (ANAC) in Brasil and finally the European Aviation Safety Agency (EASA), that took control over the no longer existing Joint Aviation Authority (JAA) in 2007 [101]. The aim of the is to further develop and implement aviation regulations and policies globally in an efficient and effective manner.

2.2. Maintenance Types

Maintenance was introduced to improve the reliability of a system [65]. A common maintenance topic that is often elaborated on by researchers, are aircraft engines. Van den Bergh et al. [124] state that engines are safety-critical systems and therefore considered to be very important for maintenance. Engines are also very complex and expensive [102], making them an important maintenance factor to consider. Engine maintenance is performed at a specialised facility, usually depending on the type of engine. Hence, it is important to take engine maintenance into account for scheduling.

Not just engines but entire aircraft are subject to maintenance to improve the performance and reliability of a system. Different maintenance strategies exist which are further elaborated on in this section. In Figure 2.1, a breakdown tree of existing maintenance types is given. The main two categories that the types of maintenance can be distinguished, are Corrective Maintenance (CM) and Preventive Maintenance (PM) [53]. The difference between these categories is that CM is reactive, whereas PM is proactive.

The maintenance abbreviations in Figure 2.1 are:

- **DOM** - Design-Out Maintenance
- **FBM** - Failure-Based Maintenance
- **RTF** - Run to Failure
- **BM** - Breakdown maintenance
- **TBM** - Time-Based Maintenance

- **UBM** - Usage-Based Maintenance
- **CBM** - Condition Based Maintenance
- **CBM+** - CBM, including a reliability analysis
- **PdM** - Predictive Maintenance
- **DBM** - Detection-Based Maintenance
- **PHM** - Prognostics & Health Management

The definitions of these maintenance policies are discussed throughout this section.

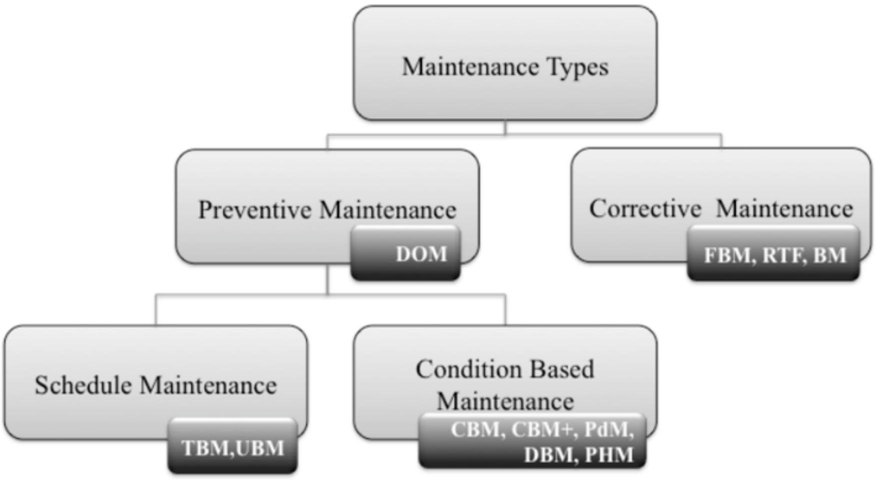

Figure 2.1: Breakdown Tree of Maintenance Types [53]

First, subsection 2.2.1 elaborates on the principles of CM. Then, several approaches within PM are discussed in subsection 2.2.2, including scheduled and unscheduled maintenance types. Finally, subsection 2.2.3 explores several integrated maintenance approaches.

2.2.1. Corrective Maintenance

The most basic type of maintenance is Corrective Maintenance (CM), also known as Failure Based Maintenance (FBM), Run-To-Failure (RTF) or Breakdown Maintenance (BM), as shown in Figure 2.1. This is a maintenance type that is carried out after a fault is detected and therefore considered to be reactive [6, 24, 53, 124]. Failures occur unexpectedly, implying that CM is an unscheduled maintenance type [6, 53].

There are several reasons why CM is considered undesirable:

- **Reliability**
  Depending on the severity of the failure condition and how critical the component is, implementing the CM strategy may lead to fatal accidents [41, 100].
- **Availability**
  During maintenance, a component or entire vehicle is not available for use. Unscheduled maintenance may affect an operation schedule and cause undesired downtime resulting in an increase in operator costs [15, 99].
- **Secondary damages**
  Letting a component run-to-failure, secondary damages or failures may be inflicted to other components, resulting in higher total maintenance costs or even critical situations [24, 67].

Nevertheless, for some non-critical components, CM may be the most cost-effective maintenance strategy [53]. Depending on the system, CM may therefore be determined to be the optimal maintenance type.

2.2.2. Preventive Maintenance

In contrast to the corrective type, Preventive Maintenance (PM) has the aim to restore the system level of perfection by performing maintenance before failure has occurred [68]. By applying this maintenance strategy for critical components, the system's reliability is improved [99].

Design-Out Maintenance (DOM), as depicted in Figure 2.1, is not a synonym for PM, but a stand-alone category [36]. In this strategy, the design of a component is altered to account for shortcomings discovered during the component's usage.

Scheduled maintenance is often used as a synonym for PM [124]. However, there are also several other types of unscheduled PM that exist. These scheduled and unscheduled types of PM are presented in the following subsections.

2.2.2.1. Scheduled Maintenance

Two types of scheduled maintenance can be distinguished. Time-Based Maintenance (TBM) is a PM type of maintenance that is linked to fixed time intervals [65]. The second type is Usage-Based Maintenance (UBM), which is based on relevant usage parameters such as flight hours.

Obligatory scheduled checks have been defined by Federal Aviation Administration (FAA) to monitor the airworthiness of an aircraft, referred to as A-, B-, C- and D-checks [124]. These are checks that the operator is obliged to carry out after a specific number of flight hours or calendar days, varying in time interval duration and maintenance extensiveness.
TBM schemes are based on past failure time data to ensure safety requirements are met [72]. However, Acktert [1] concludes that using fixed TBM schemes are not beneficial for cases where the component failure is not dominant. Moreover, Lee et al. [72] argue that TBM is not effective if the current health state of the component is not taken into account. This motion is backed by Andreacchio et al. [6] who point out that TBM is not effective if for example CM has been performed within a scheduled time interval.

2.2.2.2. Condition Based Maintenance

Remedying the shortcomings for TBM mentioned above, Condition Based Maintenance (CBM) recommends maintenance based on the observed health status of a system or component [48, 65, 116, 121]. As CBM is a PM type, components are repaired or replaced before the event of total failure. The item's health is continuously monitored with the use of sensors. This activity of collecting data through sensors is called **condition monitoring** [65]. Repairing the system or component is done on an unscheduled basis.

In Figure 2.1, CBM+ and Detection-Based Maintenance (DBM) are also depicted as maintenance types. These strategies are very similar to CBM. CBM+ is more elaborate than CBM with a stronger focus on prognostics and reliability [14]. In DBM, condition monitoring is done through operator observations [126], instead of system monitors.

In the ISO-13374 documentation, Condition Monitory and Diagnostics of Machines [94], the process of CBM is stated to consist of the following six parts:

1. data acquisition,
2. data handling,
3. state determination,
4. health assessment,
5. prognostics, and
6. recommendation.

Common condition monitoring techniques include acoustic emission analysis, vibration monitoring and thermography mapping [50, 65, 121]. Three different monitoring data types are typically recognised: **value** (e.g. single measurement of temperature), **waveform** (e.g. sound wave) and **multidimensional** (e.g. 2D image) [65]. The sensor choice takes the criteria such as the installed weight and damage detection capabilities into account.
Data acquisition can either be done continuously or periodically, the latter commonly chosen as this set-up is less expensive and less susceptible to noise. A disadvantage of periodic condition monitoring is however the risk of missing a failure. Thus, research regarding the monitoring interval is very important [33, 121].

Condition monitoring accuracy is increased by combining information obtained through multiple sensors

monitoring the same system [65]. To avoid errors, data is always first cleaned before data analysis is done. To combine data input from multiple sensors, data-level, feature-level or decision-level fusion methods are used. Depending on the acquired data, reduction techniques and or regression or time series analyses are applied.
A health monitoring technique that is closely related to condition monitoring, is called Structural Health Monitoring (SHM) [121]. This method originates from inspecting structures and uses non-destructive testing techniques to determine the structure's health. SHM mainly focuses on increasing the probability of detecting a failure and can use active or passive sensors [33]. Here, active sensors represent those that detect damages by sending a signal and reviewing the results, while passive sensors detect signals that are generated by failures without external excitation.

Summarising steps 1 to 6 mentioned above, CBM consists of a diagnostic and an advisory phase [94, 116]. Diagnostic methods revolve around the mapping of the condition monitoring information to the machine fault, which can be done manually or automatically (e.g. statistics or artificial intelligence driven) [65]. Manual methods require high expertise. However, while an automatic approach is more simple, the lack of data slows down the development of data-driven models.
The diagnostic part is well established. However, the second part of CBM concerning the health analysis and advisory step are less well-developed and thus have limited applied examples [121]. During the prognostics phase, the Remaining Useful Life (RUL) is determined by combining the health assessment insights with knowledge obtained from past degradation trends. Furthermore, the probability of failure before the next TBM check is computed. Maintenance is planned when the prognostics indicate that a predefined critical threshold is passed [72, 74, 116]. Prognostic methods are based on a physical model, data-driven analysis or a hybrid combination of both approaches [37].

In Figure 2.2, a graphical depiction is given of the RUL prediction process [74]. At t_{FPT} (first prediction time, predefined through statistical analysis) a prediction is made of the RUL, represented by the green line. The probability density function (PDF) determines the confidence interval, expressing the range of time in which the End-of-Life (EOL) is predicted to occur. In this figure, the real-life component health is depicted by the red continuous line. The actual t_{EOL} (time of EOL) is finally reached when the health passes the set Failure Threshold (FT).

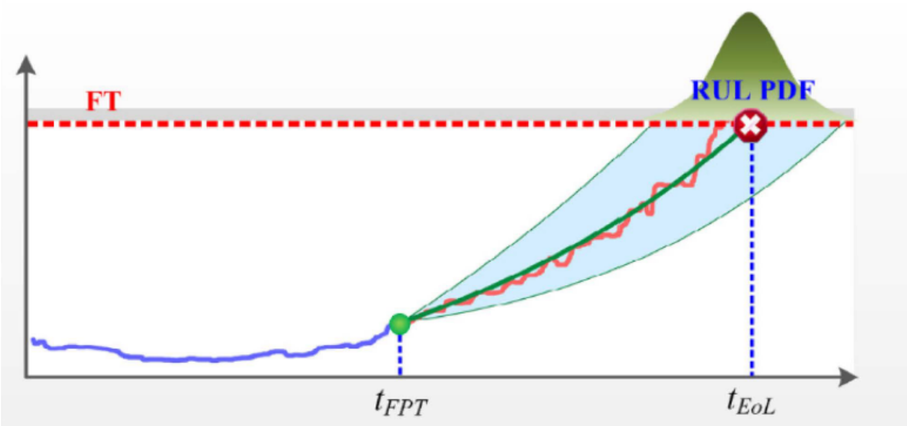

Figure 2.2: Determination of the Remaining Useful Life in Predictive Maintenance [74]

RUL predictions are done multiple times throughout the component's lifetime. Based on the evaluation of the data, with the aim to repair the component before failure occurs, a maintenance recommendation is given [65]. A drawback of CBM is that the maintenance moments cannot be plannend [48, 116].

2.2.2.3. Predictive Maintenance

Following up on CBM, Predictive Maintenance (PdM), which is also a type of unscheduled maintenance, takes the prognostics phase one step further [48, 116]. PdM is also referred to as Prognostics and Health Management (PHM) [119]. The aim of prognostics is to improve maintenance through for example the enhancement of safety and reliability, the reduction of costs and the increase of availability and elongation of a component's lifetime [65, 111, 121]. Moreover, authors such as Franciosi et al. [43] and Hoang et al. [58] point out that using prognostics also has potential to reduce the environmental impact of maintenance.

Similar to CBM, PdM monitors the health of a component or system through condition monitoring [74]. Moreover, event data is collected to include information regarding the components usage and maintenance activities. Like in CBM, prognostics are made by evaluating the monitored data and predicting the RUL of the component. Again, RUL predictions can be data-driven or based on a modelled approach, or a combination of these methodologies [37, 72, 74].

What distinguishes PdM from CBM, however, is the planning component that PdM can incorporated [48, 116]. Busse et al. [22] refer to two types of PdM prognostics. The maintenance can either be executed immediately (known as 'trigger strategies') or it can be planned ahead (referred to as 'planning strategies'). Here, a cost analysis is done to evaluate whether the trigger or planning strategy is more beneficial. Hence, it becomes apparent that in PdM tries to synchronize operation and maintenance activities such that the system's downtime is near-zero [72]. Furthermore, with PdM, a TBM scheduled maintenance plan of a given component may be altered as the time since the last maintenance activity has changed, which is not considered in CBM [50]. By taking the overall scheme of the system into account, PdM aims to achieve cost-effective maintenance schedules, whereas CBM cannot be planned [48, 116].

2.2.3. Integrated Approach

Instead of implementing merely one of the above-described types (CM or PM) as an aviation maintenance strategy, aircraft undergo a combination of these maintenance types [124]. A corrective approach is necessary when a defected fault has occurred, while preventive and predictive strategies are implemented to increase availability and reduce costs.

Reviewing the effectiveness of maintenance schemes is an important research topic [48, 121]. Tinga et al. [121] researched the similarities and differences of three maintenance disciplines: CBM, SHM and PHM. In their paper, they stress the benefit of combining the three approaches in order to enhance the overall maintenance effectiveness. Instead of using only data-driven approaches to provide maintenance prognostics, an integration with a physical model-based approach yields a better understanding of the system's health.

Another example that focuses on combining multiple types of maintenance strategies, is given by Andreacchio et al. [6]. In their research they state that PM schedules do not take unscheduled CM activities into account, resulting in premature aircraft asset replacement. As a solution for this problem, they propose the implementation of a Cyber-Physical Systems (CPS) approach to enhance aircraft asset utilisation and reduce replacement costs.

2.3. Research gaps

Based on the reviewed literature, two main gaps are identified. The first shortcoming is regarding prognostics, which is discussed in subsection 2.3.1. The second gap is concerning the type of aerial vehicles that are commonly researched, which is elaborated on in subsection 2.3.2.

2.3.1. Prognostics

As stated in subsection 2.2.2, the diagnostics part within PdM is already well established, while prognostics still require further research. Saxena et al. [110] and Lee et al. [72] point out that prognostic concepts are often inconsistent and ambiguous and lack standard definitions and that more research is required regarding the prediction of a system's performance and degradation. Furthermore, for data-driven prognostics, they stress that the shortage of data impedes the verification and validation phase required to evaluate prognostic theories.

2.3.2. Electric Aerial Vehicles

Recently there has been an increase in the usage of electric propulsion systems as these are more sustainable compared to conventionally fuel propelled aircraft [28, 118]. In addition to the sustainable advantages, electric power has control and operational advantages such as responsive thrust and noise reduction [27, 125]. Thus it is not surprising to see that there is a growth in research regarding battery development for aviation, focusing on rechargeable batteries.

For maintenance, the most apparent difference between conventionally fuelled and electrically propelled aviation practices revolves around batteries [19]. Despite the increase in the use of electric propulsion systems, limited literature is found on battery PHM practices applied within the aviation industry.

In the interest of sustainability, battery PHM is chosen for more in-depth analysis in the following chapter. Batteries are used in More Electric Aircraft (MEA), electrical Aerial Vehicles (eAVs) and electrical Unmanned Aerial Vehicles (eUAVs) [19, 28, 118]. MEA are aircraft in which all non-propulsive systems are run on electric power, while eAVs and eUAVs are fully electric. Although all three types are electrically powered, it is chosen to focus on eUAVs in this study due to the availability of battery data. Small batteries are already widely used to power eUAVs, while battery compositions for MEA and eAVs are not yet widely available [19, 125]. Hence, throughout the rest of this literature study, battery practices for eUAVs are reviewed.

3

Battery Health Management

Based on the research gap findings within the scope of aircraft maintenance, presented in subsection 2.3.1 and 2.3.2, deeper analysis of health management for batteries used in eUAVs is recommended. Literature on this subject is explored in this chapter.

First, in section 3.1, the relevance of reviewing battery health management for eUAVs is highlighted. Secondly, several types of batteries are briefly addressed in section 3.2. Thirdly, section 3.3 explains the most important battery characteristics related to health monitoring. Then, several battery health monitoring example approaches are reviewed in section 3.4. In section 3.5, several battery data and simulation tool sources are briefly listed. Finally, the main research gaps from this chapter are summarised in section 3.6.

3.1. Relevance

As previously addressed in subsection 2.3.2, electric power sources are increasingly used in aerial vehicles. While electrically powered non-propulsive systems are common in practice, the low energy density of batteries is still the biggest obstacle for large electrically propelled aircraft [125]. Currently, for fully electrical flight, batteries are merely able to achieve an energy density that is 60 times smaller than the energy density related to kerosene [19].

For smaller eUAVs, batteries are more frequently used as a power source for both non-propulsive and propulsive systems. eUAVs are favourable for several reasons [8, 52, 60, 61, 85, 113] including the fact that they have lower operating costs, lower environmental impact and are able to execute missions in extreme or dangerous environments compared to manned aircraft. Furthermore, eUAVs play important roles in a diverse range of activities including military missions, search and rescue operations, security patrols, agriculture tasks and mapping exercises.

Jing and Haifeng [29] and Rezvanizaniani et al. [104] reviewed the feasibility of implementing prognostic technologies of PHM to improve the battery health management capabilities and reliability for eUAVs and electric vehicles, respectively. For batteries, prognostic practices for example include predicting the moment when the battery reaches End-of-Discharge (EOD) and End-of-Life (EOL). However, future challenges they recognised are listed below, implying that this topic requires further research.

- shortage of understanding in technologies,
- difficulty in realising real-time data processing,
- challenge in filtering data,
- complexity in representing and managing uncertainty related to the safety throughout battery life, and
- lack of data for validation and verification.

3.2. Battery Type

Several different types of batteries exist. Batteries are categorised into the following classes [90]:

1. **Primary** - Discarded after used, these batteries can only be discharged once.
2. **Secondary** - Rechargeable batteries.
3. **Reserve** - Batteries that are activated when necessary and that can be stored over long periods of time.

The most common battery type in aviation is Lithium as these batteries are lightweight, have a high energy density, have a low discharge rate (implying their charge holds longer) and are characterised by a relatively long total lifetime [28, 90, 95, 107, 117, 118]. Lithium batteries are secondary type cells, and thus rechargeable.

Multiple different types of Lithium batteries exist. The first sort is Lithium-ion (Li-ion), which has several compositions related to the active materials present for the cathode and anode within the battery [66]. The active materials within the Li-ion battery result in small battery characteristics discrepancies [47]. The second type is Lithium-Polymer (Li-Po), which is a solid-state battery, implying that it uses solid polymer as an electrolyte [23].
An overview of the most common Li-ion battery types (name, abbreviation and scientific formula) is given in Table 3.1, along with a hexagonal spider graph of their characteristics in Figure 3.1 [23]. In this figure, the following characteristics are depicted:

1. **Specific energy** - Capacity related to run time.
2. **Specific power** - Ability to output a high current load.
3. **Safety** - Stability of chemical processes within the battery.
4. **Performance** - Usage performance at cold and hot temperatures.
5. **Life span** - Lifetime and cycle life.
6. **Cost** - Material, manufacturing and quality control expenses.

From the hexagonal diagrams, it becomes apparent that LMO batteries have a moderate overall performance. The types LCO, NMC and NCA show outstanding specific energy performance while LFP and LTO batteries have the best life span characteristics. Battery performance is similar for most types, though LTO batteries excel in this area. For specific power, the highest throughput is provided by LFP types. The safest performance is provided by LFP and LTO types. The battery costs are approximately equal for LCO, LMO, NMC and LFP batteries. From the charts, it can clearly be concluded that LTO types are the most expensive [23].
Depending on the battery application, different performance characteristics are desired. It is therefore important to evaluate the power source requirements before choosing a battery type.

Li-Po batteries are very similar to Li-ion batteries, though there are several small discrepancies. Compared to Li-ion types, Li-Po batteries have a slightly higher energy density and can be manufactured more thinly. Li-Po casing is able to be flexible, which further reduces the overall weight of the battery composition. The disadvantage of Li-Po batteries is that they are more costly [23].

In a study on eUAV batteries, Eleftheroglou et al. [37] state that they chose to research Lithium-Polymer batteries as they are easily monitored. Subsequently, the authors point out that Lithium batteries, in general, are relevant study cases as they commonly do not function well once voltage levels drop past a critical threshold, which is further elaborated on in section 3.3. Hence, it is useful to study indicators that predict the future performance of battery power systems.

3.3. Battery Characteristics

In order to understand the types of battery health management that can be applied, it is important to review the general background information regarding battery characteristics. First, battery performance and reliability is reviewed in subsection 3.3.1. Here, battery charge curves throughout a charge and discharge cycles are evaluated. Then, in subsection 3.3.2, battery degradation over multiple cycles is discussed.

3.3.1. Performance and Reliability

Battery performance and reliability are characterised by its capacity and internal resistance [78]. Capacity relates to how long the battery can provide energy, while the internal impedance limits the maximum power

Name	Abbreviation	Formula
Lithium Cobalt Oxide	LCO	$LiCoO_2$
Lithium Manganese Oxide	LMO	$LiMn_2O_4$
Lithium Nickel Manganese Cobalt Oxide	NMC	$LiNiMnCoO_2$
Lithium Iron Phosphate	LFP	$LiFePO_4$
Lithium Nickel Cobalt Aluminum Oxide	NCA	$LiNiCoAlO_2$
Lithium Titanate	LTO	Li_2TiO_3

Table 3.1: Overview of common Lithium-ion battery types listing the name, abbreviation and formula [23]

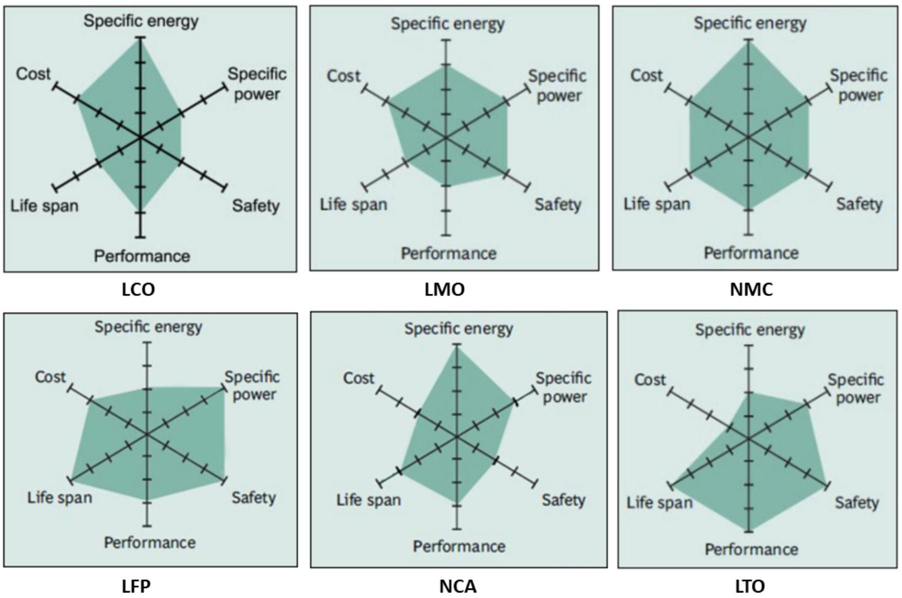

Figure 3.1: Hexagonal spider graphics of performance characteristics for Lithium-ion battery types LCO, LMO, NMC, LFP, NCA and NMC, showing specific energy, specific power, safety, performance, life span and cost [23]

level the battery is able to provide. According to Williard et al. [129], from these two parameters, the battery's capacity is the main characteristic used for performance and reliability evaluation.

Capacity is the electrical charge (Q) measured in the battery, expressed in Coulombs [C] or Ampere-Hours [Ah] [129]. To indicate a battery's performance and reliability, the maximum discharge capacity (Q_{max}) is typically referred to, as this shows the total amount of charge that a fully charged battery is able to deliver to its entirely discharged state. Hence, capacity is important as it determines how long the eUAV can fly. Not all batteries are identical, hence batteries' true Q_{max} values are distributed around the manufacturer's average capacity estimation [129]. When working with large data sets, such distributions are often represented by means of a normal distribution which is characterised by a specific mean and variance [31]. Baumhöfer et al. [13] also showed that this is the case for the initial capacity of a set of identical Lithium batteries.

Internal resistance (R), also referred to as internal impedance, is expressed in Ohm [Ω]. This parameter influences the maximum achievable throughput Current (I), measured in [A], within the system. A higher resistance results in restricted current, a drop in voltage and temperature rises within the battery [23]. For hybrid electric vehicles, resistance is an important performance indicator as an increase in battery impedance leads to lower acceleration capabilities or higher fuel usage [86]. For eUAVs, the maximum achievable power level is especially important for the take-off phase, as this requires the most power [125].

In the context the of current rate, the term C-rate is regularly used [23]. If a battery is discharged at 1C, it implies that when fully charged, it can provide a specific level of constant current for 1 hour. The level of current it can constantly discharge is governed by the initial Beginning-of-Life (BOL) battery capacity.

A battery's Q_{max} changes over time within a discharge cycle, affecting the power system's performance and reliability. This is more elaborately discussed in subsequent sections. Contrarily, the R within a discharge cycle is almost constant, leading to no major effects [23].

3.3.1.1. State of Charge

The State of Charge (SOC) refers to the remaining available charge of a system. For eUAVs, the mission duration is critical information to determine if the SOC is sufficient to complete the mission [129]. The SOC of a battery is 100% when it is fully charged, and defined to be 0% when it is fully discharged [20].

A battery's SOC is related to the voltage and current during a charge or discharge process as well as the battery's electrochemical properties. The SOC is defined by Equation 3.1, where $Q(t)$ is the capacity at any given moment of time and Q_{max} is the nominal capacity at the beginning of the current cycle [26].

$$\text{SOC}\ (t) = \frac{Q(t)}{Q_{max}}\% \tag{3.1}$$

Within a cycle, the decay of SOC over time is related to the voltage. For an open circuit, this relationship is called Open Circuit Voltage (OCV) hysteresis [10]. The variation of OCV with respect to SOC is highly non-linear [98]. Lithium batteries exhibit hysteretic behaviour both during charge and discharge cycles. However, the curves of these two processes differ slightly, as can be seen in Figure 3.2 [11]. For LFP batteries, the shape of this curve in Figure 3.2 is very typical. Note that the arrows in the graph represent the hysteresis orientation depending on whether the battery is undergoing a charge (SOC from 0 to 100%) or discharge (SOC from 100 to 0%) cycle. Baronti et al. [11] point out that LFP batteries are widely used due to their steady OCV throughput for SOC levels between 20 and 80%, which is very different from lead-acid battery behaviour. This OCV hysteresis curve differs slightly depending on the active materials, but all Lithium batteries exhibit similar flat OCV trajectories. For NMC battery types, for example, the OCV curve is slightly more slanted between 20% and 100% [134].

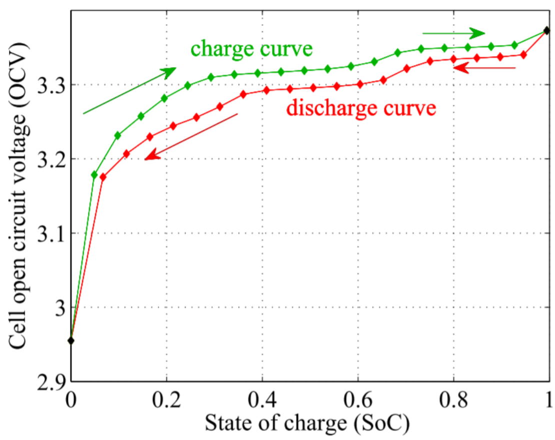

Figure 3.2: Typical Open Circuit Voltage hysteretic behaviour of a Lithium Iron Phosphate battery subject to a charge and discharge process at 20Ah [11]

The rate of SOC decrease within a cycle depends on the eUAV's power consumption throughout a mission. The flight load profile is therefore very important to accurately determine the required SOC needed to execute the mission. Saha et al. [108] characterised the typical flight load profile for eUAVs during flight which is depicted in Figure 3.3. Here, as previously stated, it can clearly be seen that take-off and landing required the most power.
Other parameters that influence power consumption are temperature, weight, density altitude, wind direction and flying velocity [12, 113].
The SOC can be determined through either an offline or online approach [20]. In the offline method, historical data is analysed to provide an accurate SOC prediction. With an online approach, real-time metrics are directly translated to a SOC estimation. Commonly these approaches are combined, such that the model is first trained using past data after which the online method can be applied [37].

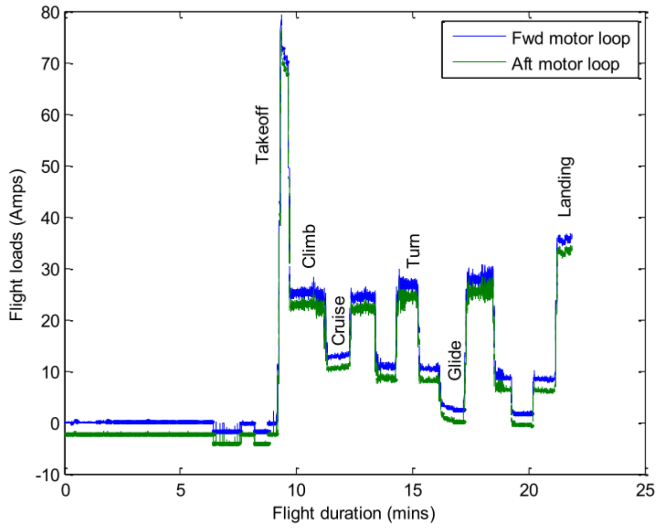

Figure 3.3: Typical eUAV flight load during flight [108]

3.3.1.2. End-of-Discharge

The battery's End-of-Discharge (EOD) is at the end of the discharge cycle when SOC = 0% [17]. The SOC can be used to determine the EOD, which is similar to the estimation process of RUL presented in subsection 2.2.2. During operation, eUAV battery monitoring of SOC is done to ensure safe flight by observing and predicting if the battery has sufficient charge to complete the mission. Instead of letting the battery run to 0% charge, a capacity threshold is set **before** battery failure at 0% charge [85]. For Lithium batteries, this critical threshold is set to be when the battery has 30% SOC [60, 61, 112]. As authors Hogge et al. [60] point out, operating am eUAV with less than 30% SOC is defined to be high risk. This is due to the sudden voltage drop that occurs soon after passing the 30% SOC level, as can be seen in Figure 3.2, called the ‘knee point’ [112]. Upon reaching the critical threshold of 30% SOC, the batteries still have sufficient power to perform a minimum of two landing attempts safely [60].

3.3.2. State of Health

A battery's capacity and internal resistance change over time, affecting the battery's health. The battery's State of Health (SOH) is used as a metric to show the power source's number of remaining cycles before EOL [129]. The SOH is calculated using Equation 3.2, with Q_{max} being the nominal capacity at the start of a cycle and Q_0 the initial capacity at the battery's BOL [12].

$$\text{SOH}\ (t) = \frac{Q_{max}(t)}{Q_0}\% \tag{3.2}$$

Batteries degrade over time, this process is called ageing. As a consequence, two main characteristics change [12, 20]. Firstly, batteries suffer from **capacity loss**. This is due to the reduction in the available amount Lithium within the battery, resulting in a shorter discharge time for the same output current. Secondly, batteries experience an **increase in internal impedance** which causes the battery output voltage to decrease. For Lithium batteries, these health indicators degrade independently from each other [66].
Although some authors such as Viswanathan and Knapp [125] state that it is unknown whether capacity fade or resistance increase will be the limiting factor for eUAV applications, some researchers in the eUAV field only use SOH = 80% as the EOL threshold [96, 97, 129].
Two types of ageing categories exist:

- **Calendar ageing**
  This type of ageing includes all degradation that is not dependent on charge/discharge battery cycles [66]. Calendar ageing results in battery capacity loss that behaves according to a power law over time [78]. Moreover, this degradation process is weighted by the storage level of SOC and environment temperature [12, 78].

- **Cycle ageing**

> This ageing kind is related to the charge/discharge cycles of a battery and many other different parameters, making it difficult to estimate or predict. Variables include cycle number, cycle duration, temperature, current rate, voltage range, Depth-of-Discharge (DOD) and average cycling SOC. Here, DOD is the range of SOC (ΔSOC) throughout the charge/discharge cycle of the battery [12, 78].

Saxena et al. [112] reviewed data-driven PHM approaches for batteries. After cycling the batteries (charge/discharge), the ageing phenomena described above can clearly be deduced. Using NASA's prognostic battery dataset [2], the researchers' findings are depicted in Figure 3.4. For one single battery, the same discharge process is repeated during which the battery starts at a discharge voltage of 4.2 V and is cut off at 2.7 V.
Within one cycle, a similar discharge curve to the Lithium discharge trajectory in Figure 3.2 is observed. Then, as the cycles progress, the discharge curves in Figure 3.4 slowly shift. In the graph, it can be seen that cycles number 2 and 588 begin at the same discharge voltage at time = 0 s. Then, as time progresses, cycle 588 shows a steeper decrease and ultimately reaches the discharge cut-off voltage sooner than the battery did in cycle 2. Also, the battery's knee point has shifted to a slightly lower voltage level.

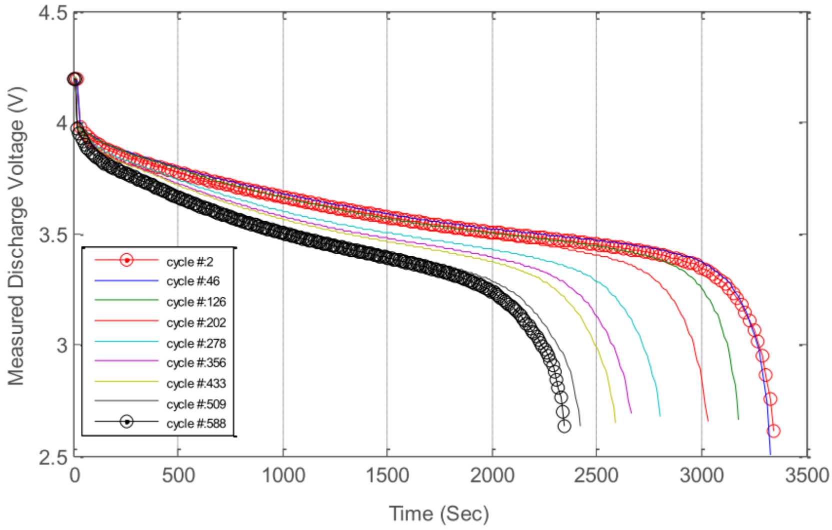

Figure 3.4: Discharge cycles at different battery life stages for constant load profiles from one single Lithium battery [112]

Battery ageing is unavoidable. Nonetheless, there are several parameters that accelerate this degradation process. Below, the effect of temperature, current rate, SOC and DOD on battery degradation are presented [47, 66, 83, 123, 132]. Then, it is briefly described how these parameters relate to eUAV applications.

1. **Temperature**
   In practice, Lithium batteries can be operated between -20 and +60°C, while the temperature region from +15 to +35°C is considered to be optimal. For temperatures below 0°C, lower temperatures cause expedited battery degradation. On the contrary, for temperatures above 0°C, higher temperature levels lead to accelerated capacity loss and impedance gain. Temperatures affect battery ageing both during operation and rest. During active use of the battery, however, Xu et al. [131] point out the importance and complexity of decoupling temperature rise with other parameters such as rate of discharge.
   For storage, temperature ageing effects can more easily be decoupled. In a study by Keil et al. [66] the impact of higher temperatures during a battery's resting period is highlighted. For different Lithium chemical compositions (NCA, NMC and LFP), the study showed that higher storage temperatures lead to accelerated capacity degradation and an increase in internal resistance.

2. **Current rate during charge and discharge process**
   High values of load current lead to accelerated battery ageing. For Lithium batteries, Ning et al. [93] found that the battery degradation is significantly influenced by the C-rate of the discharge cycles. When the battery was cycled at 1C discharge rate, the capacity loss was 9.5% after 300 cycles. In contrast, for 2C and 3C discharge rates the capacity degradation was 13.2 and 16.9%, respectively.

3. **Depth-of-Discharge (DOD)**
   Larger DODs during charge and discharge cycles lead to accelerated battery capacity loss.
   Xu et al. [132] researched the effect of various different SOC % ranges during Lithium battery cycling. In Figure 3.5 it can clearly be seen that the smallest DOD interval (65-75%) results in the least battery capacity fade, while the battery cycled at the largest DOD (25-100%) shows the most severe degradation.

4. **Average State of Charge (SOC) during operation and resting level**
   Batteries operated around high SOCs and/or stored at high SOC levels during rest period, show accelerated battery degradation [47, 66]. For Lithium batteries the capacity reduction is accelerated and depending on the active material types, the internal resistance growth is further stimulated.
   For the same DOD of 20% SOC, Gao et al. [47] concluded that battery capacity decrease is significantly more around higher SOCs (80-100%) compared to lower SOCs (0-20%), as depicted in Figure 3.6. Note the ‘clusters' of degradation behaviour trends, as the battery capacity fades similarly for the DODs ranges 20-40%, 40-60% and 60-80%, while intervals 0-20% and 80-100% deviate significantly. In this figure, ‘equivalent full cycles' are cycles that where the capacity throughput is normalised with the nominal battery capacity, such that different DOD can be compared.

For eUAV applications, regulating these above-mentioned parameters is not always trivial. For temperatures, studies show that operating eUAVs in extreme temperatures strongly affects the battery performance. For example, Li et al. [76] concluded that both high and low temperatures have a significant impact on eUAV battery degradation. Unfortunately, the location at which the mission must be executed cannot always be chosen. For charging strategies, however, regulating the temperature is more realisable. Though conclusions by Liao et al. [79] suggest that the charging temperature has a less significant effect on capacity degradation compared to the discharging temperature.

For current rates during the charging cycle of a battery, dedicated charging schedules could improve battery life. Klein et al. [69] explain that the most common charging method for Lithium batteries is using a Constant Current and Constant Voltage (CC/CV) approach. Manufacturers state the limits for CC/CV charging methods, as exceeding the prescribed values during a charging cycle leads to accelerated battery degradation. Exploring other charging schedules for electric vehicles such as Multistage Constant Current (MCC), researchers Liu et al. [80] explored the application of MCC for energy and cost optimisation purposes by finding current values where battery degradation is least severe.
Reviewing the current rates during the discharge process for eUAVs is less trivial due to the fact that the load current usage range of freedom is limited as this is determined by the mission profile [108]. For example, for take-off and landing a certain amount of power and thus current rate is required. During cruise, the velocity of the eUAV could be chosen such that the current rate is most optimal.

The DOD and average SOC relate to the amount of capacity available for flight. In order to reduce the DOD a battery undergoes, the distance the eUAV flies in between charging moments must be decreased. To achieve a lower average SOC, the battery should be charged to a SOC level below 100%. The challenge in this charging strategy is to be able to accurately predict the amount of charge required to complete a mission. This prediction is similar to EOD predictions, further described in subsection 3.4.3.
Though decreasing the DOD and avg SOC may elongate battery lifetime, it simultaneously limits the distance that the eUAV can cover. Nonetheless, several studies could provide solutions to this problem. Firstly, Bocewicz et al. [18] research the option of setting up a network of mobile battery swapping stations to optimise a routing problem with eUAVs travel paths. Another potential solution is proposed by Lu et al. [81], who review the use of powerlines to charge eUAVs during a mission through a wireless power transfer method. Similarly, Galkin et al. [45] research a combination of these innovative methods to ensure continuous eUAV operations. Their solution incorporates the option of swapping the eUAVs or their batteries, transferring power wirelessly or improving the battery energy density. Thirdly, optimal eUAV hub location problems are commonly addressed, such as in a research by Aurambout et al. [7]. In this study the authors review the economic viability of placing hubs in different locations, but such optimisation models could also incorporate other criteria such as sustainability. Finally, there are several studies such as a research by Goodchild and Toy [51] and Moshref-Javadi et al. [91] that evaluate the option of using UAVs in a last-mile delivery model with trucks, which would also allow for shorter flying distances.

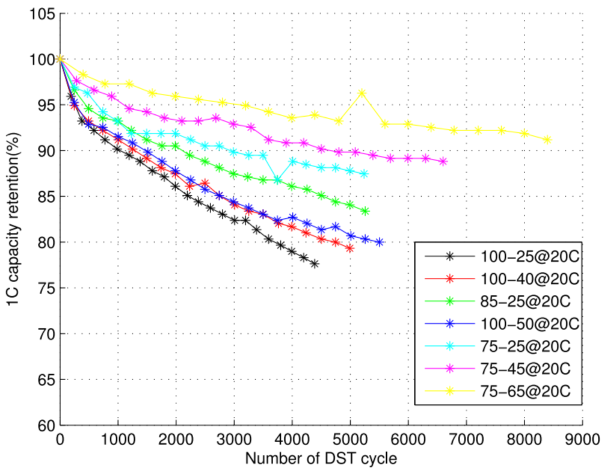

Figure 3.5: Lithium-ion battery capacity retention behaviour related to different Depth-of-Discharge ranges during battery Dynamic Stress Testing (DST) [132]

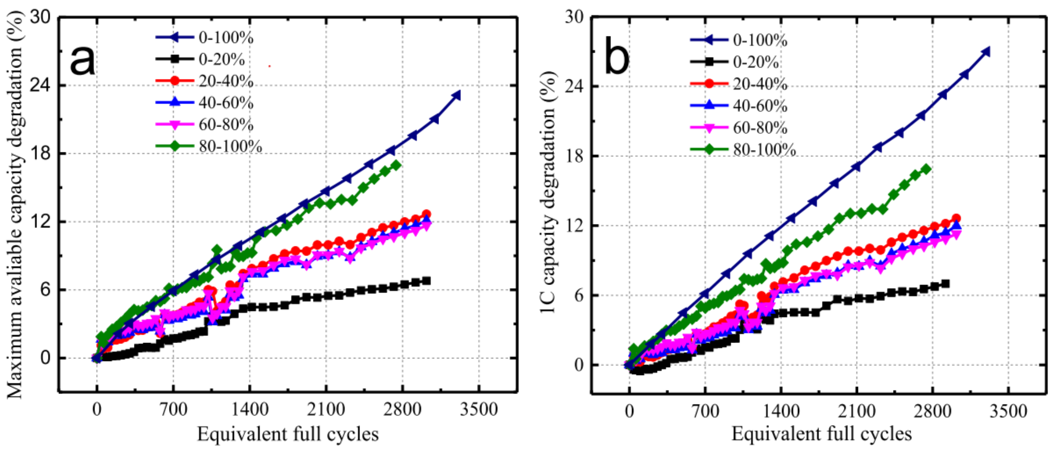

Figure 3.6: Lithium-ion battery capacity loss due to different Depth-of-Discharge ranges, showing (a) maximum available capacity degradation, (b) nominal capacity degradation [47]

3.3.2.1. End-of-Life

The battery EOL is defined to be when SOH = 0% [12]. Operating the battery until 0% is however considered to be highly unsafe. Therefore, the useful life of a battery is defined to be until SOH = 70% or 80%, or when the internal resistance has doubled its initial value compared to at the beginning of life [39, 78, 129]. Operating the eUAV beyond this SOH point is dangerous, as the battery capacity may suddenly drop. The battery is therefore often considered as 'failed' when it reaches the critical SOH level between 80% [34, 78, 129].

3.4. Battery Health Management

Several studies have been done reviewing battery health management. Monitoring a battery's health is important to improve reliability and performance. eUAV battery health management aspects include determining the SOC and SOH, charging the rechargeable battery to ensure the system has sufficient charge to execute the next mission and ultimately replacing the battery when SOH < 80%.

First, the Battery Management System (BMS) that monitors the battery's health onboard most eUAVs is discussed in subsection 3.4.1. Then, different battery health management strategies are discussed in the following subsections 3.4.2 and 3.4.3. Finally, a general overview of battery health monitoring challenges is given in subsection 3.4.4.

3.4.1. Battery Management System

Most Lithium applications have a Battery Management System (BMS) to ensure that the battery remains within safe limits [23]. For example, the BMS will not let a battery charge beyond SOC = 100%. Depending on the battery usage application, the range of safe SOC levels may vary. Given the increased rate of battery degradation for higher SOC levels, it can be beneficial to set a lower maximum SOC level. For example, in a study with photovoltaic systems, the limits 20 and 80% are set as the minimum and maximum SOC levels, respectively [92].

The BMS monitors various parameters such as temperature, battery voltage and current and more [23, 75, 135]. The level of sophistication of a BMS varies. The basic features are providing the battery protection by ensuring operating limits are not exceeded, as well as determining the SOC. More sophisticated types of BMS are also able to show the SOH and make EOD or EOL predictions.

For eUAVs, size, weight and cost constraints are important drivers. Hence, researchers such as Sierra et al. [113] stress the need for efficient BMS computational resources while maintaining high accuracy. Moreover, despite recent BMS advancements, determining the battery SOH remains a challenge [23, 75]. This is due to the fact that the SOH is not a readily measurable output. Furthermore, extensive electrochemical models used to accurately determine SOH are often too computationally intensive to incorporate into a BMS. Finally, the most accurate SOC and SOH readings can be done when a battery is cycled from a fully charged to a fully discharged state. In reality, however, this is not always possible due to mission profile constraints and the SOC = 30% safety boundary for eUAV operations.

3.4.2. Scheduled Battery Health Management

The simplest form of battery health management is by using a 'scheduled' approach [23, 27, 113]. Here, within one discharge cycle, the eUAV's safe range of flying time is predefined before flight. Furthermore, the battery is regarded as unsafe to be used after a predetermined number of charge/discharge cycles. These estimations for flying time and useful lifetime cycles is based on past data.

When applying this battery health management approach, several undesirable traits arise [23, 27, 113]. Firstly, by using a fixed flying time, missions times are typically highly conservative, forcing the eUAV to stick to shorter missions. On the other hand, the other extreme would be that fatal accidents occur by disregarding the battery health that has potentially significantly degraded over time, implying that the available flying time has decreased with respect to the initial predetermined maximum available flight duration. Finally, for the SOH, similar problems come forward. The set number of battery cycles is either too safe or extremely dangerous. Currently, to avoid hazardous situations, engineers recognise that batteries are commonly replaced too soon [23].

3.4.3. Predictive Battery Health Management

Recognising the shortcomings of applying simple battery health management approaches to batteries, researchers are exploring predictive strategies. Researchers focus on various aspects within the topic of battery PHM, looking into topics such as EOD prediction and ageing mechanisms.

Estimation and prediction of SOC, EOD, SOH and EOL for eUAVs is important because these vehicles usually have cost constraints as well as weight and size restrictions [20, 113]. Prognostics play an important role in monitoring the battery's health and capacity [129]. Ultimately, accurate EOD estimation is the only protection against unexpected battery failure during flight [37]. When comparing battery monitoring to CM, the 'value' data type is typically considered, as parameters such as voltage and charge are commonly used to determine the battery charge and/or health status.

Methods to estimate the SOC include voltage models, coulomb counting and data-driven approaches [26, 129]. For SOH, similar techniques can be used including, for example, electrochemical, analytical, statistical models or data-driven mechanisms [12, 78]. For both SOC and SOH, determination approaches can also have a hybrid form combining for example model-based and data-driven techniques. These hybrid models often incorporate the benefits from both the physics and data-drive models, giving them optimal performance [26].

Mansouri et al. [85] state that RUL prediction for eUAVs is often done through data-driven methods as

physics-based approaches require a very high level of expertise. Batteries are non-linear electrochemical systems and behave dynamically over time, making them complex systems to comprehend.
Machine learning, regression, filtering and stochastic processes are often used as data-driven methods [85]. Two types of data-driven methods are recognised by Eleftheroglou et al. [37]. Most commonly, one overarching predictive model is built. The second method consists of building several simpler models and then combining these outputs.

Although battery PHM have come a long way, many researchers still recognise this as a subject for improvement. Accurately determining and predicting the SOC and SOH of a battery is extremely complex due to the influence of many different parameters such as operating environment, cycling profile and the non-linearity of electrochemical processes [26, 98]. For eUAVs, data-driven techniques are commonly chosen as electrochemical battery models are complex and require expert knowledge [29, 78]. Also, aviation electronics with eUAVs form a compounded integrated system, making it difficult to insert CM technologies. Finally, data-driven approaches are beneficial as they have the ability to include many different parameters such as voltage, temperature and current levels. They have a high computational efficiency and are flexible, implying that they are able to adjust to dynamic settings.

Currently, researchers recognise a **problem concerning SOC and SOH estimations**. If the SOC and SOH levels are not known with absolute certainty, accurate predictions for EOD and EOL for eUAVs cannot be made [27, 113, 135]. As a result, flight plans are decidedly conservative, implying that only those missions are executed that fall well within the estimated EOD range. Improving SOC predictions would be beneficial because this enables longer flight plans to be flown. With more accurate SOH predictions, the battery could be used for more cycles instead of being replaced too soon before reaching SOH = 80% which is regularly the case in reality [23].

For battery health management, several prognostic elements exist. Throughout charge and discharge cycles, the predictive system is required to [27, 78]:

1. accurately determine the actual charge (SOC) in the battery,
2. determine the required battery charge needed to safely complete a mission,
3. predict the battery's EOD,
4. forecast the battery ageing over time, and
5. estimate the battery's EOL.

Case Studies

As a remaining flying time example, Hogge et al. [61] verify their method that predicts the amount of charge a battery has left to perform a mission. Flying with SOC <30% was considered highly unsafe. Thus, the researchers conducted ground-based simulated testing to train the model. The flight time prognostics are firstly dependent on accurate online SOC estimations. Then, based on a predefined flight plan with set power loads, a future power demand prediction for the motor is done. To represent a real-life mission, parasitic battery loads are also accounted for in online estimations. Finally, the future flight plan battery discharge profile is predicted.

On the same topic, Saha et al. [107] present a PHM framework for Lithium eUAV batteries based on Bayesian learning techniques with the aim to predict the EOD within a cycle. They address several different flight operation regimes including take-off, cruise, turns and landing to accurately represent a mission. Throughout the mission, the PDF of the EOD is continuously updated. Based on these calculations it can successfully be determined if the eUAV is able to complete the flight safely.

Another example is given by Sierra et al. [113] who present a battery management system for rotatory-wing eUAVs that provides an accurate estimation of the SOC and EOD time of Lithium batteries. In this study, a prognostic framework based on models assisted by Bayesian methods is used. By evaluating the SOC and EOD parameters, decisions regarding the flight plan can effectively be made.

For capacity degradation and EOL estimation, Birkl et al. [17] look into the electrochemical properties of battery degradation and validate that Lithium battery capacity loss is linked to properties such as loss of lithium inventory and loss of active materials. The authors propose a model that is able to predict the trajectory of changes of these properties within an acceptable margin. Incorporating such forecasting techniques enables users to keep track of the battery's SOH and, by doing so, ensure safe operation. In theory, their diagnostic tool is applicable for all types of Lithium batteries. Future work includes applying this real-time to commercial Lithium batteries.

When exploring research done on predictive battery health strategies that aim to maximise battery lifetime, little literature is found concerning eUAVs. For electric vehicles in the automotive industry, Valentina et al. [123] recognise the influence that charging has on Lithium battery degradation and stresses the importance of defining a methodology for users to promote battery lifetime elongation. On the same topic of electric vehicles, Abdullah et al. [3] acknowledge the impact that charging methods have on battery degradation and discover that introducing rest periods during battery charging reduces the degradation process.

3.4.4. Challenges

Throughout battery health management and prognostic studies, researchers define various challenges that decelerate the development and progress of these subjects. These oppositions are listed below.

- **Noisy data**
  For all predictive battery health management methods, the accuracy and reliability of the prognostics are dependent on the input data. Raw data is generally noisy and requires manipulations before it can be used to identify trends and generate predictions [85, 129]. Filtering techniques are used to clean the data in order to use it for forecasting. It is important to continuously evaluate and further develop the applied filtering methods to improve the performance of the predictive model.

- **Nominal capacity**
  To set up a useful predictive battery health management system, it is important to accurately determine the battery's SOC based on readily available performance metrics. Deriving the SOC from real-time input remains one of the toughest challenges in battery health management due to the intertwinement of many parameters and complexity of electrochemical compositions [26, 98, 129]. Prognostics for EOD and EOL cannot be done if the output of this fundamental step of determining SOC is not reliable.

- **Flying plans**
  The rate of SOC decrease is highly dependent on the eUAV's flight plan. The power consumption differs depending on the flying manoeuvre, making EOD predictions a complex task [108, 113]. For example for eUAVs, the absolute level of power consumption is higher during landing than during cruise, as shown in Figure 3.3. Predefining the eUAV's flight plan is therefore very important, such that specific flight actions can be taken into consideration when estimating the EOD.

- **Flying conditions**
  Anticipating the diverse range of varying flying conditions that an eUAV may encounter, remains a challenge for predicting the battery's EOD [12, 85, 108, 113]. As stated in section 3.3, the SOC decrease rate varies depending on the power demand which is influenced by a diverse set of parameters including the external temperature, wind and density altitude.

- **Ageing**
  Battery ageing remains a problem, as this brings along uncertainty in battery PHM [12, 61, 132]. The rate of battery degradation is dependent on a large set of parameters, making it very complex to predict. Currently, studies mainly focus on battery capacity loss and internal resistance increase as ageing phenomena. In practice, ageing is related to many more events. Also, in order to benefit from degradation predictive models, future work is required to develop a real-time ageing estimator.

- **Cost-Benefit Analysis**
  Limited literature is found regarding Cost-Benefit Analyses (CBAs) of battery health management methods. Several overviews are given of advantages and disadvantages of different types of batteries [95], as well as comparative studies on various prognostic approaches [78]. However, no material is found that focuses on comparing two battery health management techniques for the same kind of battery. Quantifying battery health management costs is complex but essential in order to make justified charging strategy decisions.

3.5. Battery Data and Simulation Tools

To conduct a research in the field of batteries, it is important to verify that there is sufficient data and/or simulation tools available. A brief overview of potential sources is given in this section.

In a recent paper, don Reis et al. [34] listed all Lithium data sources. The most commonly used battery cycling data sets are:

1. **NASA Prognostics Center of Excellence department**
   This NASA battery data set [2] is the first publicly available battery data set, showing cycling data for 34 Lithium 18650 cells and 28 LCO 18650 cells with a nominal capacity of 2.0 and 2.2 Ah, respectively. The battery cells undergo cycling for a range of different temperatures, charge and discharge regimes. The experiments are stopped until a SOH level is reached between 50-80%.
2. **Center for Advanced Life Cycle Engineering (CALCE)**
   The CALCE data sets [42] feature LCO, LFP, and NMC chemistries of Lithium batteries with varying dimensions and different capacities (2.0, 2.23, 1.1, 1.35, 1.5). The data sets investigate different DODs, C-rates and ranges for partial charge/discharge until SOH = 80% is reached.
3. **Sandia National Laboratories (SNL)** Sandia National Laboratories (SNL) offer multiple 18650 cells with LFP, NCA and NMC compositions. The battery cells are cycled under different temperatures and DODs (0-100%, 20-80%, 40-60%). All batteries are charged according to the manufacturer guidelines at 0.5C, and discharged at different currents (0.5C, 1C, 2C, 3C) until EOL is reached at SOH = 80%.

Although there are a few other data sources available, these are not relevant for eUAV battery health management applications. For example, some data sets focus on calendar ageing, fast charging protocols or have very specific usage applications. The authors [34] recognise the lack of Lithium battery data and call for more open-source data sets to stimulate further battery research.

Instead of using data sets, it is also possible to use battery simulation tools. A benefit of using a simulation programme instead of a data set, is that it can be tailored to represent an eUAV application more accurately. Many simulation programmes, however, require expensive licenses and/or are difficult to integrate with programming languages such as Python and Matlab. To mitigate these shortcomings, a group of researchers launched the Python package 'PyBaMM' in 2019 [115]. PyBaMM is a tool to simulate battery models fast and flexibly. It can be used to solve models using readily available Lithium battery cell specifications or has the option to input new battery parameter sets. Batteries can be cycled through simple calling functions (for example, "Discharge at 1C until 3.0V"), or by means of a detailed excel input cycle data set. The package has an open-source collaboration platform on GitHub [103].

3.6. Research Gaps

In this chapter, fundamental understandings of Lithium batteries used in electrical aviation are listed. Deriving accurate battery characteristics such as SOC and SOH are crucial in order to enable safe flight. Concurrently, if the real-time SOC and SOH are accurately determined, batteries could be used for longer flights and more charge/discharge cycles, respectively.

Summarising the main points of interest for further analysis, it is clear there is a need for more accurate predictions of SOC, required charge, EOD, battery ageing and EOL. Addressing all these topics, however, would be out of scope for one thesis research. Hence, in the interest of sustainability, it is chosen to focus on a battery health management strategy that aims to elongate the battery lifetime by minimising the DOD and average SOC at which the battery is cycled, discussed in subsection 3.3.2. Applying this to eUAV applications has not been previously done in literature. Thus, this research could provide interesting insights for the aviation industry. Moreover, evaluating the other prognostic elements such are predicting SOC and SOH does not contribute to combatting battery degradation.

A more detailed description of the proposed thesis research topic regarding battery DOD and average SOC minimisation is presented in Part IIB of this report. Before providing a detailed overview of the thesis experimental setup, two additional topics related to prognostic models are discussed in the following chapters. In order to execute the research, battery health monitoring prognostics are required related to estimating the amount of charge required to complete a mission. Methods to evaluate the required charge prediction method are discussed in chapter 4. Then, in 5, a method to compare the benefits of different battery health management strategies is presented.

4
Performance Evaluation

Evaluation of the predictive technique's performance is essential to determine which methodology is most beneficial for a given component or system. In the thesis research proposed in Part IIB of this report, one/multiple of these metrics can be used to evaluate the performance of the model that predicts the amount of battery charge required to complete an eUAV mission, as briefly described in section 3.6.

Despite the fact that performance metrics vary depending on the type of system or applicable requirements, a survey done by Saxena et al. [109] showed that most metrics are related to the accuracy and precision of a method. In industries such as finance where reference prediction models are readily available, metrics such as Mean Square Error (MSE), Mean Absolute Deviation (MAD), Median Absolute Deviation (MdAD) and Mean Absolute Percentage Error (MAPE) are often used. These metrics can also be used to measure the accuracy of a model in the aerospace industry.
Within PdM and PHM, Saxena et al. [109] point out that there is a lack of standard definitions. In the authors' opinion, the methodologies are often ambiguous and inconsistent. Moreover, the shortcomings of model verification and validation are stressed. Establishing a set of performance metrics to evaluate the PdM and PHM approaches would enable straightforward assessment and comparison between models. These statements are also backed by Chang [26] who claims that setting up an accurate evaluation method and/or measurement of performance is required to determine which models best predict SOC trajectories and other battery characteristics.

Nine performance metrics are defined by Saxena et al. [110] to evaluate data-driven prognostic algorithms for maintenance in domains such as aerospace, automotive, electronics, nuclear and medicine. Performance metrics are required in order to evaluate the model to ultimately avoid the occurrence of False Positives (FP) and/or False Negatives (FN).

First, the difference between accuracy and precision is addressed in section 4.1. Then, a brief description is given about FP and FN in section 4.2. Subsequently, the evaluation metrics are presented in the following section 4.3. Finally, several challenges are addressed in section 4.4, as well as a brief conclusion of how performance evaluation metrics can be used in battery health management research.

The description of the terms and notations that are used throughout the sections in this chapter are listed in Table 4.1.

4.1. Accuracy and Precision

While the terms 'accuracy' and 'precision' are often used interchangeably, there is a fundamental difference between the two definitions. Accuracy refers to the average error distance between the predicted and actual RUL. High accuracy is defined when these errors are small. Precision, on the other hand, refers to the spread between the predicted RULs. Most desired are cases that have both a high accuracy and precision level [22, 56].

Name	Abbreviation
X	Number of units under testing
i_P	First time index i within set ℓ that a prediction is made
i_{EOP}	Last time index i within set ℓ that a prediction is made (EOP is End-of-Prediction)
i_{EOL}	Actual time index i that the component reaches its End-of-Life
ℓ	Total time set of moments i at which predictions are made, $\ell = \vert(i\vert P \leq i \leq EOP)\vert$
$\Delta^X(i)$	Error between the estimated and the true RUL at time point i for a given component for time set l
$r^X(i)$	Estimated RUL for the X^{th} unit under testing at time point i using the prognostic algorithm
$r_*^X(i)$	True RUL for the X^{th} unit under testing at time point i provided that the data is available

Table 4.1: Overview terms and notations for prognostic data-driven algorithm evaluation metrics [110]

4.2. False Positives and False Negatives

A prediction that incorrectly gives an alert that failure is near, is called a False Positive (FP). This is considered an unacceptable early estimation if a predefined range r_{FP} is violated, as shown in Equation 4.1 [109]. On the other hand, False Negatives (FNs) are the result of late predictions, as defined in Equation 4.2 [109]. Here, the FN occurs when the critical range r_{FN} is exceeded.

$$FP = \begin{cases} 1 & \text{if} \quad \Delta^X(i) > r_{FP} \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

$$FN = \begin{cases} 1 & \text{if} \quad -\Delta^X(i) > r_{FN} \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

When evaluating an algorithm, FNs are typically penalised more severely as late predictions may result in fatal accidents.

4.3. Performance Metrics

Specifically, the evaluation standards focus on models estimating the RUL of a component. Ideally, evaluation metrics are unitless as this enables easy comparison of performance from different models.

The metrics are built upon findings in a previous survey done by Saxena et al. [109] regarding all existing evaluation metrics for prognostic use cases. After reviewing the metrics, nine methods are selected and proposed for common predictive algorithm evaluation. These evaluation standards are also used for the assessment of prognostic models made by other authors such as Hogge et al. [60], Busse et al. [22] and Saha et al. [108]. These metrics are discussed in subsection 4.3.1 to 4.3.9.

4.3.1. Average Bias

The average bias metric is one of the most important methods to determine the accuracy of a prediction. The average bias is calculated using Equation 4.3 [110], averaging the errors made per prediction at all times after the prediction is made for a total set of l time indices that an estimation of the RUL is made.

$$B_\ell = \frac{1}{\ell} \sum_{i=1}^{\ell} \Delta^X(i) \tag{4.3}$$

Using this metric, positive and negative errors cancel each other out. Also, the influence of outliers is not mitigated.

4.3.2. Sample Standard Deviation

To evaluate the precision of a prediction, the Sample Standard Deviation (SSD) is often used. This metric quantifies variability with respect to the sample mean. The SSD is determined with Equation 4.4 [110]. Note that SSD only applies to normal distributions. In this formula, m is the mean of the sample set of errors.

$$SSD = \sqrt{\frac{\sum_{i=1}^{\ell} (\Delta(i) - m)^2}{\ell - 1}} \tag{4.4}$$

4.3.3. Mean Squared Error

The Mean Squared Error (MSE) addresses both the accuracy and precision of a model. Unlike most evaluation metrics, MSE is not unitless. Thus, comparing two systems' MSEs must be done carefully. The MSE determines the average of the squared prediction errors and therefore takes both positive and negative errors into account. The metric is calculated using Equation 4.5 [110].

$$MSE = \frac{1}{\ell}\sum_{i=1}^{\ell}\Delta(i)^2 \tag{4.5}$$

As a metric, MSE is sensitive to non-normal data and the presence of outliers. Moreover, MSE is unreliable for small samples of data.

The Root Mean Squared Error (RMSE) is a derivative of the MSE, which measures the accuracy of a function. The RMSE is calculated by taking the root function of MSE and is commonly used by researchers.

4.3.4. Mean Absolute Percentage Error

For prognostics, it is important to take the time at which the prediction is made, into account. Prediction errors made closer to a component's EOL are therefore often weighted heavier than those made at the beginning of a component's lifetime. The Mean Absolute Percentage Error (MAPE) weighs the prognostic errors with the RULs and then averages these absolute percentage errors. The formula for MAPE is given in Equation 4.6 [110].

$$MAPE = \frac{1}{\ell}\sum_{i=1}^{\ell}\left|\frac{100\Delta(i)}{r_*(i)}\right| \tag{4.6}$$

Using MAPE is only relevant for ratio-scaled data that have a meaningful zero. Furthermore, severe penalties are given when forecasts exceed the actual EOL compared to those that are less than the real EOL.

4.3.5. Prognostic Horizon

The Prognostic Horizon (PH) reflects on the difference between i_p and i_{EOP}, specifying a tolerable error bound (α). By using PH, predictions are reliable as it focuses on estimates that fall within specified limits close to the actual EOL. When comparing multiple data-driven models, the algorithm with a larger PH is desired. The PH is defined by Equation 4.7 [110].

$$PH = i_{EOP} - i_P\ , \quad \text{with } i = \min\left\{j \mid (j \in \ell) \wedge \left(r_*(1-\alpha) \le r^l(j) \le r_*(1+\alpha)\right)\right\} \tag{4.7}$$

For example, if $\alpha = 5\%$, then the PH will indicate when then the algorithm starts predicting the EOL within 5% confidence bound of the actual EOL.

4.3.6. $\alpha - \lambda$ Performance

Similar to PH, the $\alpha - \lambda$ performance metric can be used to determine if a prediction adheres to specified performance levels. For this metric, the horizon λ is defined as a percentage of the total RUL, measured from time point i_P. Moreover, the accuracy of the estimation is evaluated with the use of α which forms a cone around the actual RUL trajectory r_*^X, as can be seen in Figure 4.1. In this graph, $\alpha = 0.2$ implying that the metric reviews whether the prediction adheres to the 20% accuracy range. Equation 4.8 shows how predicted RUL, r^X, is evaluated. In this formula, $t_\lambda = i_P + \lambda(i_{EOP} - i_P)$.

$$[1-\alpha]\cdot r_*(t) \le r^X(t_\lambda) \le [1+\alpha]\cdot r_*(t) \tag{4.8}$$

4.3.7. Relative Accuracy

The Relative Accuracy (RA) metric is similar to $\alpha - \lambda$ performance. However, with RA the accuracy level is measured instead of determining if data points fall within an accuracy range. Algorithms with a high RA are desirable, as this implies that predictions are accurate. Using Equation 4.9 [110], the RA of a model is determined. Again, in this formula, $t_\lambda = i_P + \lambda(i_{EOP} - i_P)$.

$$RA_\lambda = 1 - \frac{\left|r_*(t_\lambda) - r^X(t_\lambda)\right|}{r_*(t_\lambda)} \tag{4.9}$$

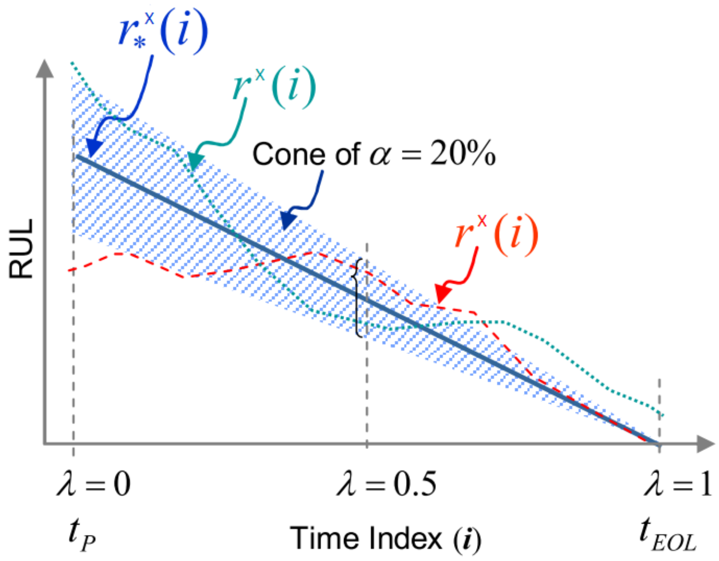

Figure 4.1: Schematic figure of the $\alpha - \lambda$ prognostic algorithm evaluation metric with $\alpha = 0.2$ [110]

4.3.8. Cumulative Relative Accuracy

If the RA of a model is evaluated multiple times, the results can be aggregated by using the Cumulative Relative Accuracy (CRA) metric. This parameter represents the normalised weighted sum of the RA measured at specific points of time. The CRA is calculated by using Equation 4.10 [110], in which w is the assigned weight. Usually, higher weights are assigned to predictions done closer to the EOL.

$$CRA_\lambda = \frac{1}{\ell} \sum_{i=1}^{\ell} w\left(r^X\right) RA_\lambda \tag{4.10}$$

4.3.9. Convergence

This metric is used to quantify if and how well the accuracy and/or precision of a model improves over time. In Figure 4.2, three example cases are depicted that have different convergence rates. The metric $M(i)$ represents the performance of a system. For each case, the centroid is defined as (x_c, y_c). Convergence is quantified using Equation 4.11 [110]. When the Euclidean distance between the graph's origin and the prognostic case curve's centroid is low, a high convergence is defined.

$$\begin{aligned} C_M &= \sqrt{(x_c - t_P)^2 + y_c^2} \\ \mathrm{x_c} &= \frac{\frac{1}{2}\sum_{i=i_P}^{i_{EOP}} \left(t_{i+1}{}^2 - t_i^2\right) M(i)}{\sum_{i=i_P}^{i_{EOP}} (t_{i+1} - t_i) M(i)}, \text{ and} \\ \mathrm{y_c} &= \frac{\frac{1}{2}\sum_{i=i_P}^{i_{EOP}} (t_{i+1} - t_i) M(i)^2}{\sum_{i=i_P}^{i_{EOP}} (t_{i+1} - t_i) M(i)}. \end{aligned} \tag{4.11}$$

4.4. Conclusion

One of the main challenges for evaluating predictive models is the vast number of metrics that are used throughout literature. Aside from the nine metrics presented in section 4.3, there is an even more elaborate summary of existing evaluation methods presented in another study by Saxena et al. [109]. Deciding which metrics are most suitable, is a complex task. Each prognostic model is unique, making it difficult to choose one metric to evaluate and compare different systems.

When evaluating the nine metrics for prognostic algorithms discussed above, Saxena et al. [110] state that

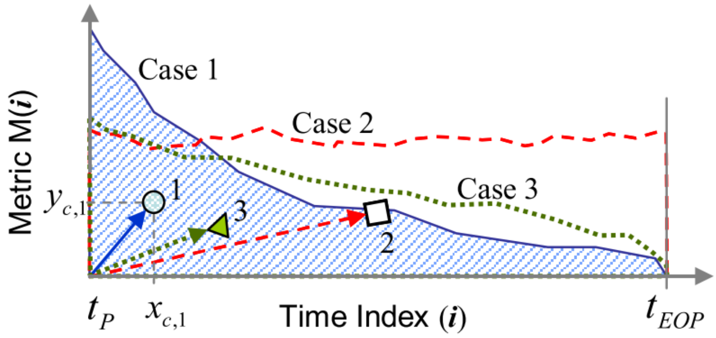

Figure 4.2: Schematic figure of the convergence prognostic algorithm evaluation metric showing three cases that converge at different rates [110]

future work is required to investigate the possibility to define a single performance metric that covers all the predictive model's aspects. Currently, using a combined set of multiple evaluation metrics is recommended to properly evaluate and compare algorithms.
Unfortunately, similar to shortcomings mentioned in chapter 2 and 3, Saxena et al. [111] stress that lack of data delays the ability to further develop evaluation metrics suitable for all types of maintenance prognostics on a large scale.

To evaluate prognostic battery health management strategies, one or multiple of these performance metrics can be applied. Providing that the errors are normally distributed, the metrics SSD and MSE can be used to determine the precision and accuracy of the error, respectively. If this is not the case, other metrics must be applied.

5
Cost-Benefit Analysis

A Cost-Benefit Analysis (CBA) is an effective method to evaluate and compare systems on metrics other than accuracy and precision. For maintenance, a CBA provides support for deciding which maintenance strategy is most beneficial for a specific system [54].
In order to determine the benefits of the battery charging strategy in which battery DOD and average SOC are minimised, described in section 3.6, a CBA can be executed. Through a CBA, the performance can be compared to the output of for example a simple battery charging strategy in which the battery is always charged to full charge.

Often, a CBA is immediately associated with financial costs. Although this is often the case, other metrics are also used such as the effectiveness of maintenance [54], the scientific performance of a model [109] or the social and/or environmental impact that a strategy has [49]. For the aerospace industry, the metrics for CBAs are still immature [110]. These CBA parameters are first discussed in section 5.1. Then, the second part of this chapter, section 5.2, discusses essential steps that need to be taken in order to successfully conduct a CBA. Note that both these sections can be used to conduct a general CBA for a wide variety of aviation related maintenance practices. To draw the relevant CBA aspects that can be used to analyse eUAV battery health management strategies, a concluding summary of this chapter is given in section 5.3.

5.1. Parameters

In this section, several CBA parameters are presented. First, monetary costs functions are elaborated on in subsection 5.1.1. Secondly, maintenance effectiveness is reviewed in subsection 5.1.2. Then, in subsection 5.1.3 the scientific performance of a maintenance strategy is discussed. Finally, subsection 5.1.4 and 5.1.5 focus on social and environmental CBA parameters.

5.1.1. Financial Costs

For prognostic maintenance strategies, several different types of economic factors can be used to conduct a CBA. The most evident main object is to minimise maintenance costs. However, other related objectives such as minimal delays, minimum repair time duration and optimal utilisation of resources can also be included [124]. It must be noted that economic factors are often difficult to demarcate as many maintenance operations are intertwined with other activities. Van den Bergh et al. [124] refer to a long list of parameters such as availability, flight scheduling, crew assignment and legal matters that have their own associated costs that may be affected by a specific maintenance activity.

First, high-level descriptions of maintenance costs for different strategies are given. Then, the most common methods to evaluate financial costs are discussed in the following subsections.

5.1.1.1. Maintenance Costs

Maintenance costs are complex to determine due to the many related factors. Kent and Murphy [67] define three methods to build simplified models that can be used to represent the financial costs: an analogy, parametric, and engineering estimation method.

- **Analogy**
  Estimation of cost based on actual and historical data. The data may concern information from a similar existing or alternative recommended technique.

- **Parametric**
  Approximation using 'cost estimating relationships' that are either statistical or mathematical formulas relating to one or multiple of the system characteristics.

- **Engineering**
  Technique in which a detailed cost breakdown is made. The costs for the individual components are then combined to form an engineering estimate.

Compared to aircraft, MEA and eAVs have a reduced cost [125, 127]. This cost reduction is related to a decrease in operation, maintenance and fuel costs. Accurate saving estimates have not yet been made due to the uncertainty of battery technologies.

Unmanned Aerial Vehicles (UAVs), either battery or fuel-powered, also have a significantly lower overall cost [8]. Although operating costs are generally substantially lower (approximately 40% of an aircraft's operational cost), not all UAVs costs are less. For example, UAVs require surveillance and radio communication systems that may be even more extensive than a manned aircraft. Additionally, a control station may be required that can be either ground, air or sea-based. Secondly, although UAVs are smaller and weigh significantly less, their structure can consist of a similar number of components that come with comparable manufacturing costs. UAV maintenance costs are estimated to equal 20% of a manned aircraft cost.

Corrective Maintenance
The costs of a failure consists of the component repair costs and the downtime costs [15]. The actual repair costs are relatively easy to compute as this usually consists of quantifiable expenses such as material, equipment, workplace and labour costs. Downtime, however, is more complicated as this is related to the system's business value and any potential effects it has on other parameters such as delay and customer satisfaction. Most models assume there is no fixed cost for corrective maintenance this method is already being applied in practice and does not require any additional investments.

Scheduled Maintenance
Costs for PM consist of two parts [15]. Firstly, maintenance costs apply for maintenance carried out on a periodic basis. Secondly, failure costs (equal to costs for corrective maintenance) are induced in the occurrence of an unexpected failure. The probability of an unexpected failure arising in between scheduled maintenance checks and the costs that are paired with such an event, can be simulated using for example a Monte Carlo approach. Similar to corrective maintenance, authors assumed that no fixed costs are associated with PM.

Predictive Maintenance
For PdM, investment and operating costs are required [15, 40, 130]. As an investment, costs are made during the development, verification, and validation phase of the maintenance model. These costs include labour fees, but also all expenses related to software and administrative costs. Moreover, all additional hardware costs must be considered, including new sensor technologies, electronics, and testing facilities implied expenses. During operation, the costs consist of performing the prognostic analyses, maintaining the system, and physically repairing the system.

Costs for FP and FN must also be considered [15, 40]. For an FP, when a near failure is wrongly alerted, expenses consist of system downtime and any additional inspection cost factors. If a failure alert is missed due to an FN, failure costs equal to corrective maintenance are included.

5.1.1.2. Evaluation Methods
To review the financial costs related to a maintenance strategy, various metrics exist. Below, the parameters return on investment, payback period and net present value are detailed.

Return on Investment

For PdM and other prognostic maintenance strategies, an investment is required before being able to physically apply and use the maintenance method. The Return on Investment (ROI) is most commonly used to evaluate the financial benefit of an investment and is calculated using Equation 5.1 [40]. Here, the central fraction is the classical finance ROI definition, while the right ratio is the ROI applied for PHM assessment equation.

$$ROI = \frac{Return - Investment}{Investment} = \frac{Avoided\ Cost}{Investment} - 1 \tag{5.1}$$

If ROI is larger than 0, there is a cost-benefit [40, 130]. Though in some cases, a ROI that is less than 0 may still be beneficial, if for example availability of the system is a lot higher and if this factor has not been included in the cost calculations.

In a study for NASA, Kent and Murphy [67] claimed that implementing prognostics for aircraft maintenance of structures results in a ROI of 0.58 within 3 years time, assuming that there is a 35% decrease in maintenance requirements.

Typically, businesses calculate different cost scenarios for conducting maintenance and then apply the setting for which the highest ROI is achieved [40]. For example, in a study done by Banks and Merenich [9], sensitivity analyses showed that the highest ROI was achieved for prognostics incorporating the longest time horizon.

Payback Period
Another method used to evaluate finances, is the Payback Period. This metric assesses the risk associated with the maintenance strategy as it indicates the time period it takes until the return is equal to the investment costs (ROI = 0) [130].

To determine the Payback Period expressed in months for a PHM strategy, Equation 5.2 [130] can be used. Here, T is the application time of the PHM approach.

$$Payback\ Period = \frac{Investment}{Monthly\ Benefit} = \frac{12T}{ROI + 1} \tag{5.2}$$

Net Present Value
The Net Present Value (NPV) is another parameter regularly used to evaluate economic factors as it indicates the value that the investment of implementing prognostics adds to the investor. The NPV is calculated using Equation 5.3 [102]. In this formula, t refers to the time during the total time period T that has passed. Over time, a positive ΔNPV (NPV > 0) indicates that there is a financial benefit [102].

$$NPV = Initial\ Costs + \sum_{t=1}^{T} \frac{Cash\ Flow\ at\ t}{(1 + Discount\ Rate)^t} \tag{5.3}$$

5.1.2. Effectiveness
Instead of calculating economic costs, some studies focus on the difference in the effectiveness of maintenance strategies. As stated previously, a negative ROI can still imply that the maintenance strategy is more desirable if, for example, the system effectiveness is higher.

According to Pecht and Rafanelli [99], effectiveness is determined by reviewing the availability, dependability and capability of a system. Availability refers to the probability that the system is able to operate at the beginning of the usage period. Dependability is related to the probability that the system does not fail during operation. Finally, capability measures the product performance. The effectiveness is calculated through Equation 5.4 [99].

$$Effectiveness = Availability \cdot Dependability \cdot Capability \tag{5.4}$$

Another commonly used term for 'dependability', is 'reliability'. For maintenance, to measure the reliability of a system, metrics like Mean Time Between Failure and its ratio to metric Mean Time Between Unit Replacements (MTBF/MTBUR) are applied [110].

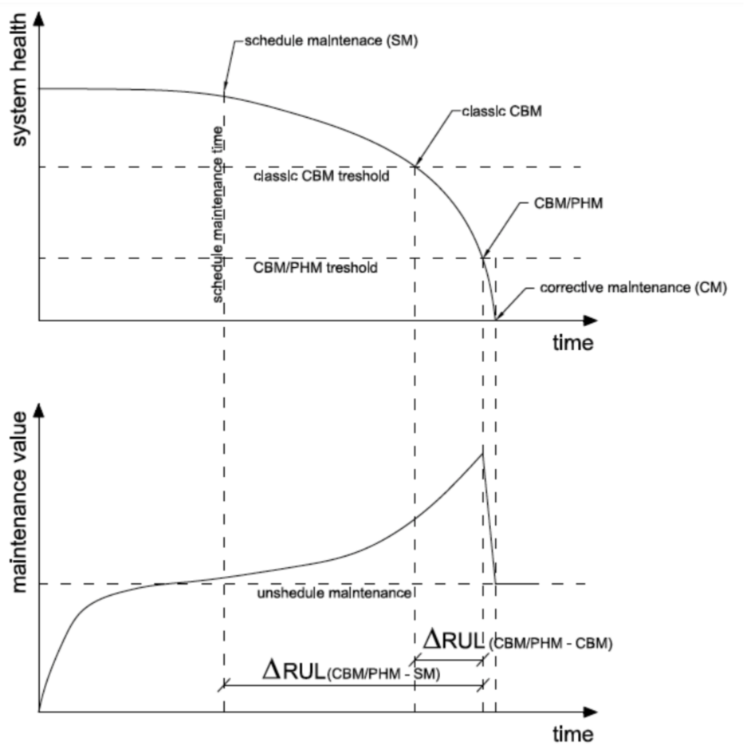

Figure 5.1: Analysis of value for different maintenance strategy levels [53]

For Lithium batteries, Gandoman et al. [46] research the characterisation of failure models for Lithium batteries for electric vehicles and identify that understanding these modes is important for reliability assessment. According to their study, the loss of active anode materials contributes most to the reliability of the battery. Williard et al. [129] go about a similar approach and highlight that the chemical composition of Lithium batteries is crucial when designing the power source for reliability. In addition to assessing reliability during the design stage, the operation stage is reviewed. Here, the battery capacity is most commonly used to evaluate reliability and performance.

Other parameters may also be used to indicate the system effectiveness. Haddad et al. [54] refer to system effectiveness as maintenance value that is determined by parameters such as downtime, unpredictability and occurrence of catastrophic failures.

Inspired by their work, Guillén et al. [53] created a graph showing the maintenance value as a function of time, which is depicted in Figure 5.1. The chart also reflects the system health along the same timeline. In the graph, the maintenance types scheduled maintenance (TBM), CBM, CBM/PHM combined and corrective maintenance are marked. Here, unscheduled maintenance is defined to be the same as corrective maintenance.
The graph clearly shows that the highest maintenance value is achieved by using the CBM/PHM strategy. Furthermore the difference between scheduled and unscheduled maintenance is negligibly small as although fatal accidents are more likely for the unscheduled approach, scheduled maintenance faces the problem of high downtimes and early replacements (large unused RUL).

5.1.3. Scientific Performance

Another method to evaluate and compare maintenance strategies is by reviewing their accuracy and precision [109]. Methodologies to do this have been discussed in chapter 4. Note that these metrics are designed to evaluate prognostic algorithms are and therefore not useful to compare two different types of maintenance strategies. For example, these metrics could be used to determine which PdM algorithm performs best, but not to determine whether a corrective maintenance or PdM strategy should be applied.

Busse et al. [22] state that cost savings depend on the accuracy and precision of a prognostic model. For models with higher accuracy and precision, a larger cost reduction is observed. This can be assigned to the fact that low prognostic accuracy and precision result in maintenance that is either carried to early or too late.

5.1.4. Social Impact

Another metric that can be used to select the most beneficial maintenance strategy, is social impact [49]. This is not a common parameter to include, though it is still very relevant to take into consideration. Social measures that could be evaluated are for example personnel safety, health, and wage, as well as general employment issues, government regulations and stakeholder participation.

Setting up a method to compare these social impact factors is not straightforward. Ghazi et al. [49] propose an approach with fuzzy rules by translating modes from $very\ low$ to $very\ high$ to a numerical scale that ranges from 0 to 1. The authors then determine which leading factors must be taken into consideration for the CBA, after which a weighted trade-off is conducted.

5.1.5. Environmental Impact

An upcoming factor to do take into account when conducting a CBA, addresses the sustainability aspect of the problem. Authors such as Franciosi et al. [44] and Ghazi et al. [49] state that current maintenance decision methods are solely focused on conventional parameters related to economical or technical features. The authors focus on general industrial and manufacturing industries, not just specifically the aerospace domain. With the current shift towards technologies that have a smaller environmental impact, more research on this topic related to maintenance is required.

The term 'green maintenance' is used in literature [4, 43, 44] to represent maintenance strategies that aim to minimise the negative impact on the environment. According to Iung [64], the integration of sustainability in maintenance is advocated by the upcoming trend in implementing PHM methodologies. By looking at the system as a whole instead of only focusing on one small component, prognostics are shifting from only reviewing the RUL to other matters such as energy consumption and/or efficiency. Here, it is essential that maintenance is not seen as an aftermarket service but rather an imminent and continuous process to enhance the overall system performance.

Environmental factors that can be considered when choosing a maintenance strategy are [43, 49, 64]:

- Energy consumption
- Pollutive emissions (air, water and soil)
- Noise emissions
- Material resources
- Material longevity and waste upon disposal
- Environment management

Similar to subsection 5.1.4, comparing different types of sustainability parameters within a CBA is complex, as different factors can be weighted differently depending on the stakeholders' preference. It is important to determine a CBA method beforehand to avoid confusion.

5.2. Experimental Setup

In order to determine which maintenance strategy is most beneficial, an analysis is performed. Before conducting the CBA, several steps need to be taken.
The experimental setup parts related to a CBA are discussed in the subsections below. Firstly, lifecycle cost data types are elaborated on in subsection 5.2.1. Subsequently, different system modelling analysis approaches are presented in subsection 5.2.2. Then, CBA parameter choice and trade-off methodologies are discussed in subsection 5.2.3. Finally, subsection 5.2.4 touches upon common assumptions applied for maintenance strategy CBAs.

5.2.1. Data

In order to determine the lifecycle cost of a system, Kent and Murphy [67] recognise three types of data categories: technical, programmatic and cost data. These types are briefly explained below.

- **Technical**
  This data type includes the specifications for engineering, operational attributes and performance

characteristics. Here, the reliability and maintainability of the system are mainly focused on.

- **Programmatic**
  Programmatic data consist of the facts and/or assumptions concerning the system. These data points are related to several activities including the utilisation of the system as well as the logistics and support concepts.

- **Cost**
  Items such as labour, equipment and material costs are categorised under cost data. This data type includes the facts and/or assumptions regarding the monetary value of the resources and/or consumption requirements.

5.2.2. Analysis

In order to conduct a CBA, separate systems following a specific maintenance strategy are modelled. The following subsections describe typical analysis methods to model systems.

5.2.2.1. Scenario Analysis

The simplest way to model a system is by using a scenario analysis [124]. Scenario analyses can be used for exploratory or decision orientated research based on qualitative and/or quantitative information [122]. Scenario cases can also be used to perform sensitivity analyses, to investigate how a model responds to different scenario inputs [21]. Often, these models are simple and not computational heavy. The downside is that scenario analyses are often less suitable to evaluate stochastic elements and perform detailed analysis on relationships between events.

5.2.2.2. Discrete Event Simulation

As the title of this simulation suggests, Discrete Event Simulation (DES) models operations as a discrete set of time points. DES can be used for several types of models including determination of the maintenance cost, availability, reliability and scheduling [5]. Usually, DES represent deterministic models. A DES model requires several inputs including an initial state, a time variable to order the events in chronological order, the types of events that may occur and the changes required to yield the different statuses [16].
For example, Hölzel et al. [62] used DES to conduct a CBA on lifecycle costs for aircraft using CBM and PHM maintenance strategies versus conventional TBM approaches.

5.2.2.3. Monte Carlo Simulation

Monte Carlo (MC) simulations are similar to DES, but instead of representing deterministic systems, MC simulations are mostly used to model uncertainty. In an MC simulation, several different events can be statistically modelled, each with their own Gaussian distribution [54]. Random samples are generated to analyse all possible scenarios [50]. Hence, MC is often applied to analyse the range of all possible outcomes for a given maintenance strategy.
In a study done by Wu et al. [130], MC simulation is used to model a system in order to perform a CBA while covering all uncertainties that may occur.

For maintenance modelling, MC simulation techniques could be used to model the uncertainties such as unexpected delays, varying maintenance repair rates and the availability of equipment or workforce personnel [124] .

5.2.3. Cost-Benefit Model

In order to conduct a CBA, the relevant cost parameters along with a trade-off method need to be selected.

From the CBA parameters presented in section 5.1, a selection can be made based on the interest of the stakeholders. In most cases, a financial factor is included to minimise monetary costs and (if applicable) determine if the investment is worthy.
With the current shift towards more sustainable practices, including a review of the environmental impact linked to specific maintenance practice is recommended [44, 49]. For example, for maintenance of eUAV batteries, multiple sustainability parameters such as energy consumption and waste could be included.

As briefly touched upon in subsection 5.1.4 and 5.1.5, comparing different types of CBA parameters is not straightforward. Within for example parameter types 'social and environmental impact', it is challenging to compare different cost factors as different weights can be applied to reflect the importance of the parameter. The CBA process is further complicated when additional cost parameters such as financial cost and maintenance effectiveness are included.

Typically, a trade-off method is used to reach an ultimate number to determine an optimal strategy. Trade-offs are essential in order to justify the choice of a preferred strategy in an objective manner.
Although the outcome of the trade-off is important, Daniels et al. [30] state that the documentation of the trade-off is the most critical part, including the relevant CBA parameters, scoring functions and input values. In their study, the authors provide several standard trade-ff methods. Figures of merit are used to represent specific quantifiable items that are of interest to determine if and how well a strategy satisfies the stakeholder's requirements. Weights are often included to classify the importance of the parameters that are being evaluated.

Finally, a sensitivity analysis can be performed to analyse the contribution of each CBA parameter [30, 57]. Pareto's distribution shows that in most cases, 80% of the strategy's performance can be traced down to 20% of the parameters. A Pareto analysis can also be used to review trade-offs for multi-objective optimisation problems. Optimal Pareto solutions provide the best solution for all cost functions related to a CBA.

5.2.4. Assumptions

Several researchers state relevant assumptions when evaluating the cost-benefit results of different maintenance techniques. A selection of these assumptions is briefly discussed below.

In a CBA study comparing sensor based with scheduled maintenance for aircraft done by Dong and Kim [33], an assumption is made that sensors do not need to be replaced throughout the aircraft's lifetime. Furthermore, the authors assume that the sensors are error-free. Lastly, the use of real-time CM data is critically reviewed. Although using such a data set is thorough, it brings along many complications in reality. Using real-time data is impractical from a wiring perspective. Prognostic calculations would be done from a ground-based station, thus wireless sensors would be required. However, and the use of wireless sensors comes at a cost as the sensors' weight is higher. Secondly, the use of real-time data is undesirable as processing all the sensor data is time-consuming.

Another crucial assumption that is often implemented in a CBA, is the assumption that a maintenance prognosis is always correct. Haddad et al. [54] incorporate such an assumption in choosing the best PHM approach by elongating the operation time past the RUL prediction. Here, the benefit of an extended RUL is compared to increased downtimes if the component is repaired at a sooner moment in time. Recognising that PHM prognostics are not perfect, the authors assume an error rate equal to 0.05 implying that there is a 5% probability that the PHM provides a wrong prediction of RUL.

For maintenance, the assumption that a component is 'as good as new' after having been repaired is also sometimes applied. Gilabert et al. [50] include such an assumption when a replacement or refurbishment maintenance activity is performed as soon as a component is nearing its EOL. But researchers can also choose to assume this after regular maintenance has been carried out.
For Lithium batteries, assuming that the battery charge is 'as good as new' after charging, would imply that the SOH of the battery is assumed to remain constant. As the SOH degrades significantly over time, assuming the battery that has run a large number of charge/discharge cycles returns to a restored level of perfection equal to the level at BOL could lead to fatal accidents and is therefore not recommended.

Finally, conducting a CBA for maintenance strategies addressing a single aircraft or UAV will result in different insights compared to models accounting for an entire fleet. For a conventional aircraft fleet model, extra costs for, for example, flight scheduling, maintenance routing and crew assignment are included when the total network of multiple systems is reviewed as opposed to an individual aircraft. Assumptions regarding the fleet size must therefore be stated beforehand. Furthermore, sensitivity analyses can be performed to evaluate different scenarios [124].

5.3. Conclusion

In this section, the CBA parameters related to battery health management strategies are first discussed, after a high-level overview of a relevant experimental setup is given.

Parameters

For a CBA on maintenance strategies for eUAV batteries during which different charging approaches are compared, the parameters 'financial costs', 'effectiveness' and 'environmental impact' are most relevant [45, 77, 80, 114]. When assessing battery health management strategies, it is important to account for the efficiency of transferring power from the power plant to the grid, to the battery and finally, to the eUAV propulsion system. Goodchild and Toy [51] find that this total effiency factor is 0.79. Similarly, Stolaroff et al. [114] state that this efficiency is 0.77.

For **financial costs**, the total costs consist of the BOL battery costs, the operation and maintenance costs and the EOL costs. These three costs are briefly discussed below.

1. **Beginning-of-Life costs**
For batteries, the BOL costs are usually determined either by analysing off-the-shelf prices or by calculating the costs based on average price per kWh data [77].

2. **Operation and maintenance costs**
For simple charging strategies, operation and maintenance costs of battery systems mainly consist of electricity costs used to charge the battery [77]. These can also be determined by using open-source price per kWh data, which changes over time and is country-specific in Europe [38]. A detailed breakdown between peak and off-peak electricity prices can be used to distinguish charging activities that occur during the day or at night [80]. When including prognostics, costs described in subsection 5.1.1 apply.

3. **End-of-Life**
Recently, there has been an increase in papers addressing battery recycling and second-life practices [63, 71, 88]. Though the total amount of batteries that are being recycled or reused is increasing, this is not yet standard practice. Furthermore, though waste is reduced, recycling techniques often bring along the use or emissions of other unsustainable materials [63, 106]. Lithium EOL battery costs are complex to determine due to the inconsistency in data and dependency on many factors such as battery specifications, usage application and location, and can hence be disregarded.

Depending on the interest of the stakeholders it can be chosen to simply compare the total sum of the financial costs, or to apply evaluation methods such as the ROI. For batteries specifically, however, it may be difficult to accurately determine the investment costs for prognostics as this is not yet a standard practice.

The **effectiveness** of a battery health management strategy can be measured through the formula presented in Equation 5.4. For simplicity, the dependability and capability of the battery can be neglected, as for eUAV applications the battery SOC will always be kept above 30%, and the SOH above 80%, as described in chapter 3. The 'availability' of the battery, however, may vary depending on the applied charging strategy. Galkin et al. [45] use the downtime per UAV to determine how efficient each model is.

For **environmental impact**, the parameters 'energy consumption', 'material longevity and waste' are most relevant. In a study assessing the environmental impact of a UAV package delivery model, Koiwanit [70] found that of the total Global Warming Potential (GWP), 80% consisted of carbon emissions. Thus, for the battery life cycle factors 'energy consumption' and 'material longevity and waste', carbon emissions will closely be evaluated.
Firstly, the energy consumed during the charging cycles of the battery can continuously be monitored and differs between charging methods. Emissions per kWh in the Netherlands, for example, are a mixture of emissions derived from sustainable 'green' and 'grey' electricity [25], on average resulting in 0.49 kg carbon emissions per kWh consumed electricity.
Secondly, material longevity refers to the battery lifetime that is affected by the applied charging strategy. Emissions arising from this parameter are related to BOL and EOL activities. For BOL, emissions are usually expressed in kg or carbon per kWh battery. On average, BOL production GWP emissions account for 99%

of the total battery life cycle emissions [70]. Data for Lithium battery production emissions vary between 35 and 250 kg per kWh [55, 82, 106]. For EOL, as mentioned above, recycling and reuse practices are not yet standard. Hence, recycling and reuse applications can be disregarded from this study.

Experimental Setup

For the experimental setup of the CBA, the data can be retrieved from example studies or open-source data centres. Some exemplary sample data has been presented above per parameter 'financial costs', 'effectiveness' and 'environmental impact'. For the analysis, an MC simulation can be run to test how the battery health management strategies respond to uncertainty. Throughout the CBA, it is essential to state all assumptions and acknowledge their impact on the CBA results. Due to the fact that no standard CBA framework for battery health management approaches exists, it can be chosen to retrieve a single final CBA score through the use of a trade-off method, a sensitivity analysis and/or review of the model's Pareto efficiency.

PART IIB

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6

Problem Statement

Based on the literature gaps discussed in Part IIA of this Literature Study, a Cost-Benefit Analysis (CBA) comparing several battery health management strategies for electric Unmanned Aerial Vehicles (eUAVs) Lithium batteries is proposed. First, a summary of the research gaps found in Part IIA of this report is presented in section 6.1. Secondly, the project outline of the proposed thesis research is elaborated on in section 6.2. Finally, section 6.3 lists the research questions of the cost-benefit analysis.

6.1. Research Gaps

Throughout this Literature Study, several shortcomings in available maintenance and battery health management research studies have been addressed. These research gaps are shortly summarised below.

1. **Battery Health Management**
   Reviewing maintenance studies, it can be concluded that there is a significant difference in the number of research papers regarding conventionally fuelled aircraft compared to electrical Aerial Vehicles (eAVs) health monitoring strategies. With the current shift towards more sustainable alternatives, there is an increase in eAV applications. Thus, it is beneficial to further investigate and improve eAV health monitoring approaches.
   Given the main distinction from fuelled aircraft and the critical role of a eAV's power source, it is chosen to focus on health management methodologies for batteries. As batteries for large eAVs are not yet widely available, smaller electric Unmanned Aerial Vehicles (eUAV) battery applications will be considered.

2. **Prognostics**
   Within the aerospace industry, Prognostic & Health Management (PHM) methodologies are increasingly being applied. Also in the field of batteries, prognostic practices are progressively being developed. For both general maintenance and battery health management strategies, however, the prognostic part requires further development. Authors call for an improvement in consistency within prognostics, more data acquisition, and an enhancement in performance for estimations and prediction methods and stress the importance of verifying and validating theories.

3. **Sustainability**
   Although studies have proven that the average State of Charge (SOC) and Depth of Discharge (DOD) levels influence battery ageing processes, little research has been done applying this knowledge to eUAV battery models. Especially in the light of developing more sustainable battery health management methods, developing and evaluating charging schedules that aim to elongate battery lifetime, is of interest.

4. **Cost-Benefit Analysis**
   In order to determine which battery health management strategy is optimal for a given system, a Cost-Benefit Analysis (CBA) can be conducted. Currently, there is no set framework to review and compare different types of battery health management strategies to determine which method is optimal when considering CBA parameters such as financial costs, effectiveness and sustainability.

6.2. Research Outline

The main research aim is to **review battery health management methods for eUAV batteries**, particularly focusing on a PHM approach. In the thesis research, a **simple battery charging approach** will be compared to a **more advanced prognostic strategy**. The performance of the methods will ultimately be evaluated by means of an CBA.

To evaluate both charging approaches in a fair manner, identical lists of missions target locations will be generated and executed in the same order by both the simple and the prognostic battery health management model. A more detailed description of these two strategies is given below.

In the first **simple SOC 100%** strategy, the eUAV battery always starts from 100% SOC level. For this model, battery degradation is expected to be most severe due to the high average SOC level. In contrast, the second **prognostic varying SOC** battery health management approach aims to decrease the rate of degradation. This is achieved using a predictive approach to determine the minimum SOC level that the battery needs to complete the next mission. By charging the battery to a lower SOC, the battery is protected from severe battery degradation. The required charge predictions are based on previous flying data using for example a regression or machine learning technique.

For both approaches, the predefined maximum flight time is chosen such that the battery always operates within SOC safety limits by maintaining a SOC level between 30 and 100%. Furthermore, capacity degradation is chosen as the indication parameter for the battery's State of Health (SOH). A battery is always replaced when its SOH drops below 80%. This is monitored by the Battery Management System (BMS).

The two proposed battery health management methods are briefly summarised below. These steps are repeated until the set list of missions has been complete.

1. **Simple SOC 100% charging model**
   - Predefined maximum flight time which is never exceeded.
   - The battery is charged to 100% SOC before the next mission.
   - The battery is replaced when SOH < 80%.
2. **Prognostic varying SOC charging model**
   - Predefined maximum flight time which is never exceeded.
   - The required battery charge is predicted for the next mission based on the known target location.
   - Before the next mission, the current battery SOC is evaluated.
   - Then...
     i. if the battery has sufficient charge to complete the next mission, the battery is directly used for the next flight, or,
     ii. if the battery has insufficient charge to complete the next mission, the battery is charged until the predicted required SOC level before the next mission.
   - The battery is replaced when SOH < 80%.

The scope of the research will focus on one eUAV system that must execute all the missions. By doing so, the impact of charging strategies can directly be linked to the degradation of the battery. It can be assumed that the number of available batteries for replacement is unlimited. To review the effect of different DOD on battery ageing, the two battery charging strategies will be tested for several mission ranges (short, medium, long). This is further elaborated on in chapter 7.

Additionally, case studies where the battery health management approach for example charges the battery before each flight to a lower maximum SOC level equal to 80% can be performed to review the sensitivity of the simple and prognostic charging strategies. Ultimately, the battery health management methods will be evaluated on several performance characteristics, including financial costs, effectiveness and sustainability.

6.3. Research Questions

The main research question is:

What is the sustainability and cost-benefit of simple versus prognostic battery health management strategies for Lithium batteries for electric unmanned aerial vehicles?

The following sub-questions are defined to conduct the research:

1. What is the sustainability and cost-benefit of using the simple SOC 100% battery health management charging strategy?
   i. After how many cycles is the Lithium battery replaced?
2. What is the sustainability and cost-benefit of using the prognostic varying SOC battery health management charging strategy?
   i. What is the performance predictive required SOC level model?
   ii. After how many cycles is the Lithium battery replaced?
3. What are the optimal settings to minimise battery ageing for Lithium batteries?
   i. What is the optimal average State of Charge level during operation?
   ii. What is the optimal Depth of Discharge level during operation?

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7

Methodology and Project Timeline

In this chapter, a high-level outline of the project methodology is presented in section 7.1. Then, in section 7.2 these methodology phases are broken down into smaller tasks which are shown in a Gantt Chart.

7.1. Methodology

To build the battery health management models, the first part of the research consists of the approach preparations to develop the model, discussed in subsection 7.1.1. Then, the actual establishment of the model is addressed in subsection 7.1.2. Lastly, the final phase of the project is defined in subsection 7.1.3 during which the results are analysed, validated and conclusions are drawn.

7.1.1. Model Preparation

In order to develop the battery health management models for the Lithium eUAV batteries, available literature, data sets, simulation tools and open-source codes are reviewed. For the prognostic model, a data-driven approach is chosen due to the complexity of using an electrochemical physics of failure based model. Furthermore, data-driven techniques are desirable due to their computational efficiency and flexibility.

To simulate a battery's SOC and SOH, literature and data are analysed. A Lithium battery data set or simulation tool is chosen to simulate the battery decrease in charge during flight and degradation over time.

To build the simple and prognostic method, typical battery health management strategies for Lithium batteries are analysed. Literature and data supporting maximum flying time and useful lifetime values are summarised to determine predefined battery standards. For the PHM approach, open-source predictive algorithms are reviewed to gain a deep understanding of applicable methods.

7.1.2. Model Development

In this part, the two battery health management strategies, presented in section 6.2, are simulated. The model is developed in Python programming language.

The simple strategy is developed with the use of the literature findings regarding maximum flying time and lifetime cycles are translated into a simulation model.
For the PHM methodology, the predictive algorithms to predict the amount of charge required to fly a specific distance. In this way, the average SOC is reduced. The prognostic model can finally be evaluated using precision and accuracy performance metric such as Mean Squared Error (MSE) and Standard Deviation (SSD).

A set of three different mission areas are defined, in order to compare different battery DOD ranges. The maximum range within the largest mission area is set to be equal to the distance that can be travelled with $\Delta SOC = 70\%$, such that a battery is always able to deliver sufficient charge to go from the hub to the target and back to the hub for charging. This 70% SOC target value is defined by the minimum SOC threshold of 30% required to perform two additional landing attempts if required. Flight profiles are stochastically generated randomly anywhere within either the short, medium or long-range to represent a diverse set of missions.

Moreover, a set of 'mixed' missions of targets located in all three ranges can be generated. By differentiating these mission distances, the battery's DOD is intrinsically varied. Hence, the DOD's effect on battery ageing can be evaluated.
In order to compare the strategies, the sustainability and cost-benefit analysis model is prepared. Then, the two battery health management approaches are finally applied to the large set of mission profiles to evaluate their performance in the final phase of the project.

7.1.3. Results Analysis, Validation and Conclusion

In this last phase, the results of applying either the simple or PHM battery charge strategy to a statistically simulated set of mission profiles are analysed. To determine if the outcome of the models can be considered correct, the data is validated. Finally, conclusions for the sustainability and cost-benefit analysis can be drawn.

7.2. Project Timeline

Translating the research methodology into a project timeline, a total of six phases are defined. These parts are briefly elaborated on below in subsection 7.2.1 to 7.2.3. A Gantt chart depicting the timeline schedule of these six phases is shown in Figure 7.1.

7.2.1. Phase 1

This part of the project consists of the **model preparation**, discussed in subsection 7.1.1. In this first phase, the following project parts are completed within the first three weeks:

- Exploring battery data and simulation tool sources.
- Deciding on a battery data source or simulation programme.
- Simulating the battery.

7.2.2. Phase 2 and 3

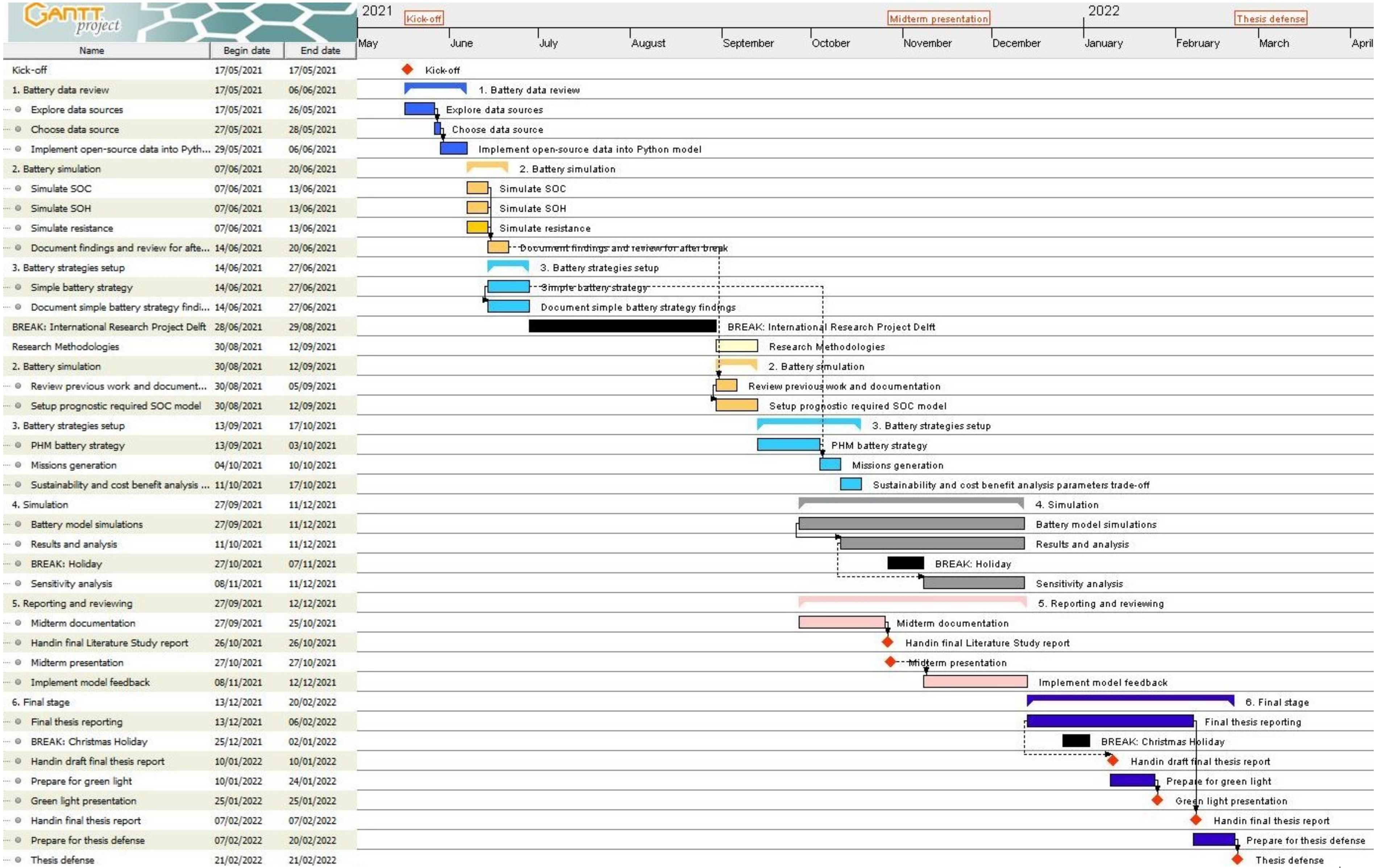
Phases 2 and 3 of the project represents the **model development**, presented in subsection 7.1.2. This section runs for approximately 10 weeks, during which the following parts are carried out:

- Simulating the battery SOC and SOH.
- Defining of prognostic algorithms for the required amount of battery charge.
- Setting up the simple and prognostic battery health management strategy simulation models.
- Generating stochastic mission profiles.
- Constructing sustainability and cost-benefit analysis trade-off parameters and methodology.

7.2.3. Phase 4, 5 and 6

The final project phases combined have the longest duration of roughly 16 weeks. This part includes the **results analysis, validation and conclusion**, addressed in subsection 7.1.3, as well as the documentation of the midterm and final thesis report. Furthermore, the midterm presentation, green light and final thesis presentation take place in this last section. To summarise, the following topics are covered:

- Simulating the battery health management strategies and analysing and validating the results
- Drawing conclusions from the sustainability and cost-benefit analysis.
- Performing sensitivity analyses.
- Drafting the midterm and ultimately the final thesis report.
- Presenting methodology and findings during a midterm and final thesis presentation.



Name	Begin date	End date
Kick-off	17/05/2021	17/05/2021
1. Battery data review	17/05/2021	06/06/2021
Explore data sources	17/05/2021	26/05/2021
Choose data source	27/05/2021	28/05/2021
Implement open-source data into Pyth...	29/05/2021	06/06/2021
2. Battery simulation	07/06/2021	20/06/2021
Simulate SOC	07/06/2021	13/06/2021
Simulate SOH	07/06/2021	13/06/2021
Simulate resistance	07/06/2021	13/06/2021
Document findings and review for afte...	14/06/2021	20/06/2021
3. Battery strategies setup	14/06/2021	27/06/2021
Simple battery strategy	14/06/2021	27/06/2021
Document simple battery strategy findi...	14/06/2021	27/06/2021
BREAK: International Research Project Delft	28/06/2021	29/08/2021
Research Methodologies	30/08/2021	12/09/2021
2. Battery simulation	30/08/2021	12/09/2021
Review previous work and document...	30/08/2021	05/09/2021
Setup prognostic required SOC model	30/08/2021	12/09/2021
3. Battery strategies setup	13/09/2021	17/10/2021
PHM battery strategy	13/09/2021	03/10/2021
Missions generation	04/10/2021	10/10/2021
Sustainability and cost benefit analysis ...	11/10/2021	17/10/2021
4. Simulation	27/09/2021	11/12/2021
Battery model simulations	27/09/2021	11/12/2021
Results and analysis	11/10/2021	11/12/2021
BREAK: Holiday	27/10/2021	07/11/2021
Sensitivity analysis	08/11/2021	11/12/2021
5. Reporting and reviewing	27/09/2021	12/12/2021
Midterm documentation	27/09/2021	25/10/2021
Handin final Literature Study report	26/10/2021	26/10/2021
Midterm presentation	27/10/2021	27/10/2021
Implement model feedback	08/11/2021	12/12/2021
6. Final stage	13/12/2021	20/02/2022
Final thesis reporting	13/12/2021	06/02/2022
BREAK: Christmas Holiday	25/12/2021	02/01/2022
Handin draft final thesis report	10/01/2022	10/01/2022
Prepare for green light	10/01/2022	24/01/2022
Green light presentation	25/01/2022	25/01/2022
Handin final thesis report	07/02/2022	07/02/2022
Prepare for thesis defense	07/02/2022	20/02/2022
Thesis defense	21/02/2022	21/02/2022

Figure 7.1: Project timeline in the form of a Gantt Chart

III

Appendices

1
Statistical Analysis

A statistical analysis of the results and validation output presented in the scientific paper in Part I of this thesis report is presented below. The following elements are reviewed:

- ***Monte Carlo (MC)*** - the stabilisation of the mean target distance covered by each eUAV battery is checked.
- ***Distribution of Sustainability and Cost Assessment results*** - the distributions of the $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ variables are reviewed for normality to determine if a t-test can be applied. This is done by visually inspecting the histrograms of the results, as well as by running Shapiro-Wilk tests and reviewing Quantile-Quantile (Q-Q) plots for variables that show uncertain Shapiro-Wilk outputs. The Shapiro-Wilk test is a powerful method to check the normality of the distributions [89].

  From the histogram graphs, $\widetilde{CO}_{2,\ BOL}$ and $\widetilde{Cost}_{BOL}$ are both related to $\widetilde{B}$ tested with Shapiro-Wilk tests. Furthermore, $\widetilde{CO}_{2,\ charge}$ and $\widetilde{Cost}_{charge}$ link to $\widetilde{P}_{total}$. The $Efficiency$ distributions are assessed separately with Shapiro-Wilk tests.
- ***Statistical T-test*** - an overview of the p-values for each unpaired one-sided T-test applied to test the hypotheses presented in the scientific paper in Part I.

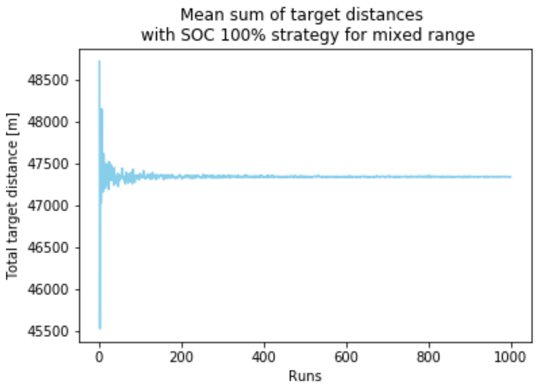
The MC, distributions and T-tests for the mixed, short, medium and long range distance results are first analysed in section 1.1, 1.2, 1.3 and 1.4, respectively. Thereafter, the MC plots of the validation results are presented in section 1.6.

1.1. Mixed range

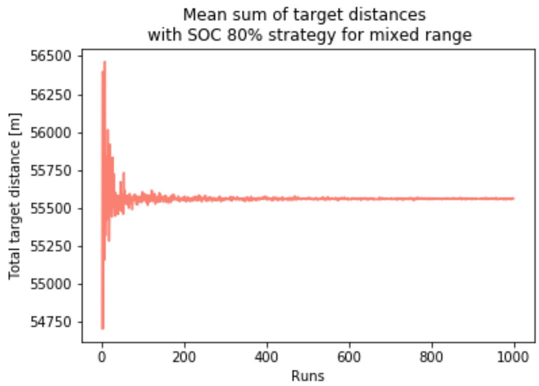
The MC graphs for the mixed range are first discussed. Then, the normality of the results is checked. Finally, the T-test outputs of the tested hypotheses are elaborated on.

1.1.1. Mixed range - Monte Carlo

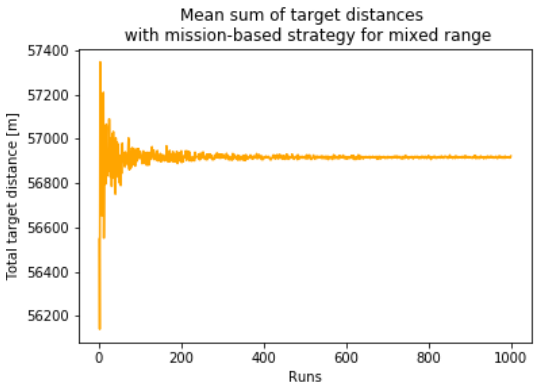
The MC graphs of the 1000 eUAV batteries tested with the SOC 100%, SOC 80% and mission-based strategy for the mixed range are displayed in Figure 1.1. From the graphs, it is concluded that sufficient batteries are tested as the means converge after approximately 300 runs. It can be seen that the mission-based strategy mean takes the longest to converge due to the bigger variance in battery lifetime, resulting in a larger spread in total distance flown. Due to the convergence of means after 300 runs for all three battery health management strategies, it is chosen to run the MC simulations a total of 300 times for the remaining short, medium and long range to speed up computational running time.



(a) SOC 100% strategy



(b) SOC 80% strategy



(c) Mission-based strategy

Figure 1.1: Stabilisation of mean distance results of 1000 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for mixed range

1.1.2. Mixed range - Distribution of Sustainability and Cost Assessment results

From the histogram graphs for battery lifetime and battery usage presented Figure 1.9 and 1.10, respectively, it can be seen that the sustainability and cost assessment results seem to follow normal distributions.

Reviewing the Shapiro-Wilk normality check tests in Table 1.1, it is concluded that all outputs except $\widetilde{B}$ for the SOC 100% and mission-based strategy are normally distributed. Zooming in on these parameters, Q-Q plots are generated to review how severe the outputs deviate from a normal distribution. The Q-Q plots in 1.2a and 1.2b show that the set of $\widetilde{B}$ for the SOC 100% and mission-based strategy are 'sufficiently normal' to apply T-tests.

1.1.3. Mixed range - Statistical T-tests

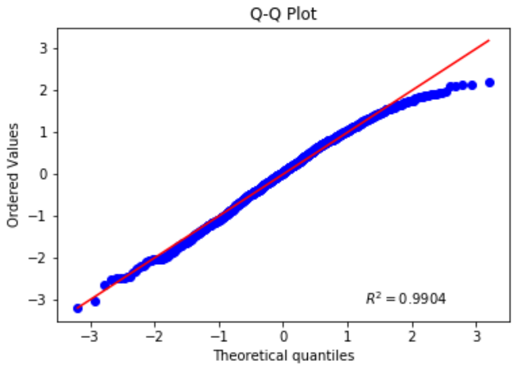
To test the hypotheses presented in the scientific paper in Part I, Table 1.2 provides a summary of the p-values retrieved from the unpaired one-sided T-tests tested for the mixed range. From the results, it is concluded that the mission-based strategy outperforms the SOC 100% strategy for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$. Secondly, the mission-based strategy performs better than the SOC 80% strategy for $\widetilde{B}$ and $\widetilde{P}_{total}$. However, the SOC 80% results for $Efficiency$ are higher than the mission-based strategy.

$\widetilde{B}$ - mixed range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.990	$1.66\cdot 10^{-6}$	False
SOC 80%	0.999	0.664	True
Mission-based	0.992	$4.41\cdot 10^{-5}$	False

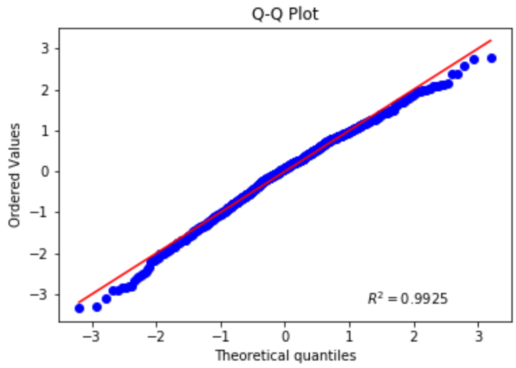
$\widetilde{P}_{total}$ - mixed range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.998	0.291	True
SOC 80%	0.999	0.835	True
Mission-based	0.999	0.940	True

$Efficiency$ - mixed range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.999	0.748	True
SOC 80%	0.999	0.844	True
Mission-based	0.999	0.705	True

Table 1.1: Shapiro-Wilk normal test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 1000 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for mixed range



(a) $\widetilde{B}$ for SOC 100% strategy



(b) $\widetilde{B}$ for mission-based strategy

Figure 1.2: Quantile-Quantile (Q-Q) plots for outputs of 1000 batteries tested through Monte Carlo simulation for mixed range

$\widetilde{B}$ - mixed range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

$\widetilde{P}_{total}$ - mixed range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

$Efficiency$ - mixed range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	1.000

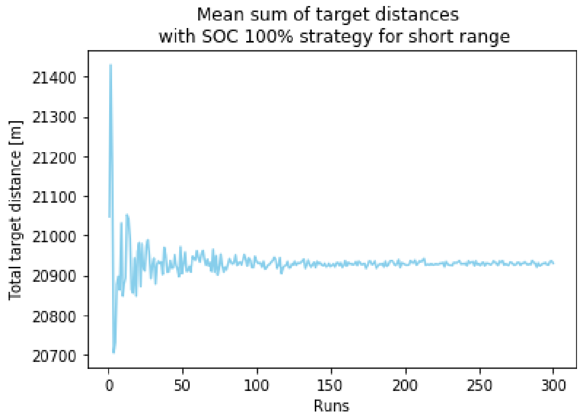
Table 1.2: Unpaired one-sided T-test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 1000 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for mixed range

1.2. Short range

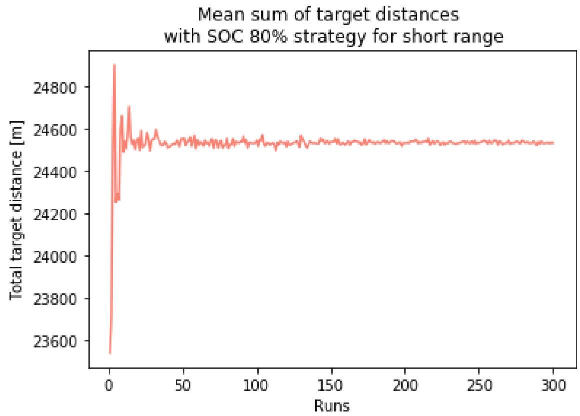
In this section, the statistical analysis of the MC simulations, normality and T-test results are given for the short range.

1.2.1. Short range - Monte Carlo

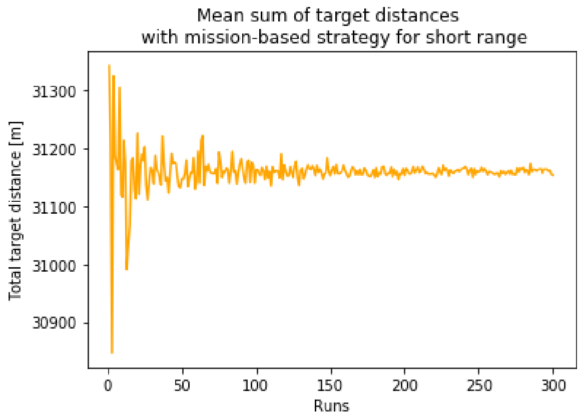
The MC plots for the short range distance for the SOC 100%, SOC 80% and mission-based strategy are depicted in 1.3a, 1.3b and 1.3c, respectively. The graphs show that the mean target distance flown stabilises, implying that sufficient MC runs are simulated.



(a) SOC 100% strategy



(b) SOC 80% strategy



(c) Mission-based strategy

Figure 1.3: Stabilisation of mean distance results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for short range

1.2.2. Short range - Distribution of Sustainability and Cost Assessment results

The distributions of the battery lifetime and usage results for the short range are presented in histograms in Figure 1.11 and 1.12. From Shapiro-Wilk test results listed Table 1.3 it is concluded that $\widetilde{B}$ outputs for the SOC 100% and SOC 80% strategies are not normally distributed. Moreover, the $Efficiency$ results for the SOC 80% strategy does not follow a normal distribution. Reviewing the Q-Q plots for these parameters in Figure 1.4, however, it is concluded that the distributions are 'sufficiently normal' to apply T-tests.

1.2.3. Short range - Statistical T-tests

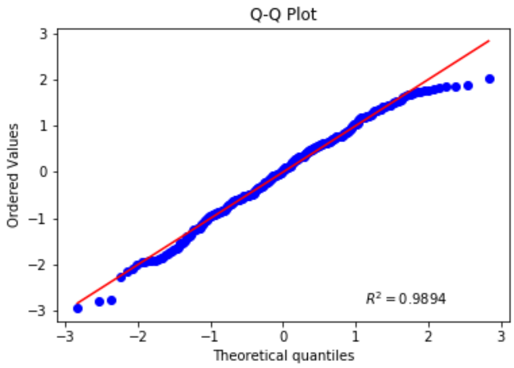
The results of the unpaired one-sided T-tests reviewed for the short range are presented in Table 1.4. From these p-values results, it is concluded that the mission-based strategy performs better than the SOC 100% and SOC 80% approach for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$.

$\widetilde{B}$ - short range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.988	0.012	False
SOC 80%	0.984	0.002	False
Mission-based	0.992	0.103	True

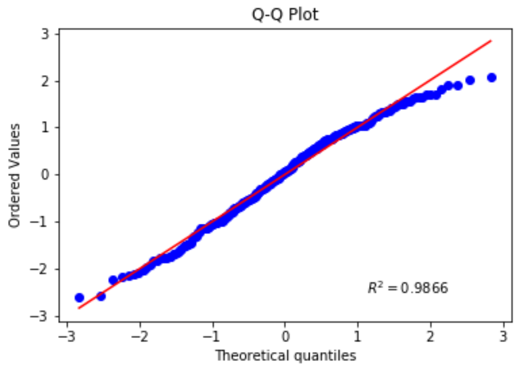
$\widetilde{P}_{total}$ - short range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.997	0.796	True
SOC 80%	0.994	0.317	True
Mission-based	0.995	0.379	True

$Efficiency$ - short range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.997	0.800	True
SOC 80%	0.986	0.005	False
Mission-based	0.993	0.189	True

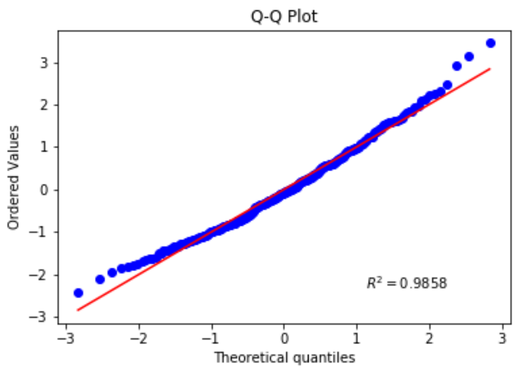
Table 1.3: Shapiro-Wilk normal test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for short range



(a) $\widetilde{B}$ for SOC 100% strategy



(b) $\widetilde{B}$ for SOC 80% strategy



(c) $Efficiency$ for SOC 80% strategy

Figure 1.4: Quantile-Quantile (Q-Q) plots for outputs of 300 batteries tested through Monte Carlo simulation for short range

$\widetilde{B}$ - short range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

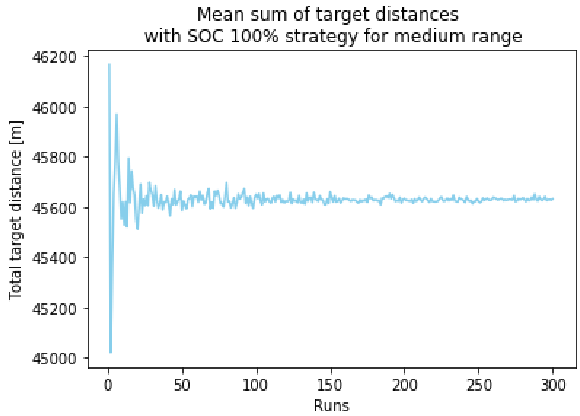
$\widetilde{P}_{total}$ - short range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

$Efficiency$ - short range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

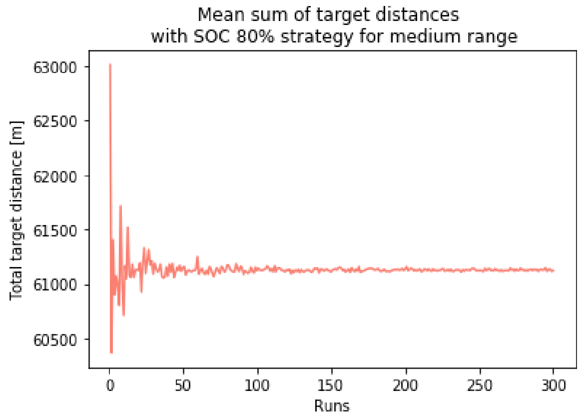
Table 1.4: Unpaired one-sided T-test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for short range

1.3. Medium range

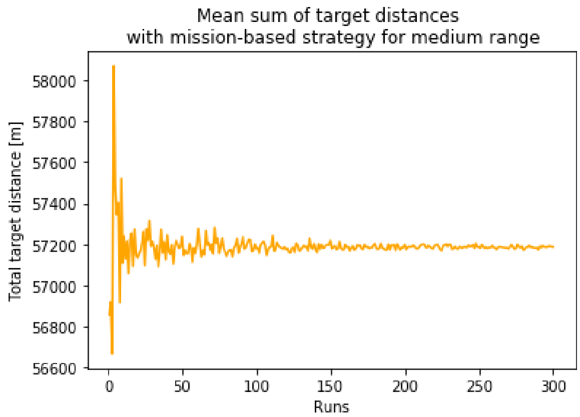
For the medium range, the MC simulation plots are first discussed. Then, the results are checked for normality. Lastly, the T-test outputs are presented.



(a) SOC 100% strategy



(b) SOC 80% strategy



(c) Mission-based strategy

Figure 1.5: Stabilisation of mean distance results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for medium range

1.3.1. Medium range - Monte Carlo

The MC plots for the medium range for the SOC 100%, SOC 80% and mission-based strategy are displayed in 1.5a, 1.5b and 1.5c, respectively. From these figures, it can be concluded that sufficient MC simulations are run, because the means for each plot converge to a stable value.

1.3.2. Medium range - Distribution of Sustainability and Cost Assessment results

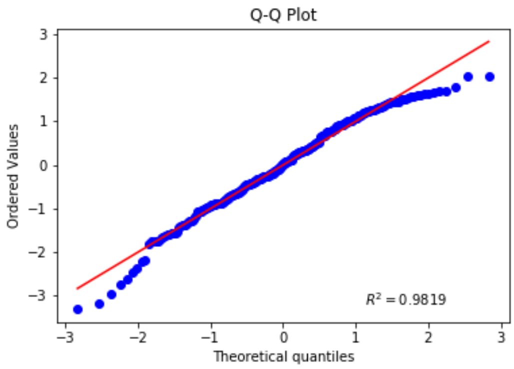
The results for the sustainability and cost assessment results for the medium range are given in Figure 1.13 and 1.14. The Shapiro-Wilk results presented in Table 1.5 show that the distributions for $\widetilde{B}$ for all three strategies are not normally distributed. Additionally, the $\widetilde{P}_{total}$ results for the SOC 80% strategy do not follow a normal distribution. From the Q-Q plots presented in Figure 1.6, however, it is concluded that the results are distributed 'sufficiently normal' for T-tests to be applied.

$\widetilde{B}$ - medium range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.981	0.001	False
SOC 80%	0.982	0.001	False
Mission-based	0.981	$4.74 \cdot 10^{-4}$	False

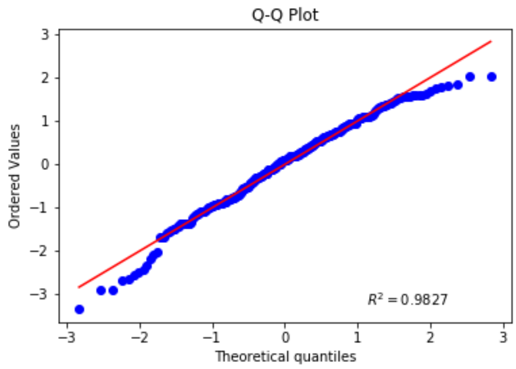
$\widetilde{P}_{total}$ - medium range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.993	0.136	True
SOC 80%	0.988	0.013	False
Mission-based	0.996	0.751	True

$Efficiency$ - medium range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.996	0.602	True
SOC 80%	0.998	0.979	True
Mission-based	0.997	0.804	True

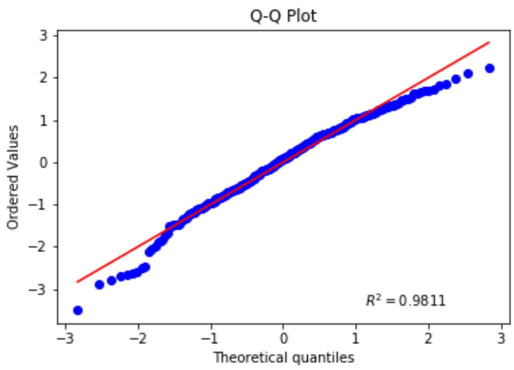
Table 1.5: Shapiro-Wilk normal test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for medium range



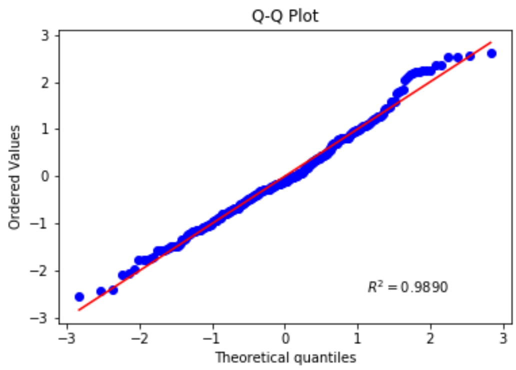
(a) $\widetilde{B}$ for SOC 100% strategy



(b) $\widetilde{B}$ for SOC 80% strategy



(c) $\widetilde{B}$ for mission-based strategy



(d) $\widetilde{P}_{total}$ for SOC 80% strategy

Figure 1.6: Quantile-Quantile (Q-Q) plots for outputs of 300 batteries tested through Monte Carlo simulation for medium range

1.3.3. Medium range - Statistical T-tests

Table 1.6 provides an overview of the p-values derived from the unpaired one-sided T-tests performed for the medium range. Here, it is concluded that the mission-based strategy performs better than the SOC 100% strategy for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$. When comparing the mission-based strategy to the SOC 80% strategy, however, the results show that the mission-based strategy merely outputs an improved $\widetilde{P}_{total}$.

$\widetilde{B}$ - medium range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	1.000

$\widetilde{P}_{total}$ - medium range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

$Efficiency$ - medium range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	1.000

Table 1.6: Unpaired one-sided T-test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for medium range

1.4. Long range

Below, the MC results for the long range are discussed. Then, the outputs are checked for normality, after which an overview of the T-test results is given.

1.4.1. Long range - Monte Carlo

From the MC plots for SOC 100%, SOC 80% and mission-based strategy for long range shown in 1.7a, 1.7b and 1.7c, respectively, it is concluded that sufficient MC simulations are run.

1.4.2. Long range - Distribution of Sustainability and Cost Assessment results

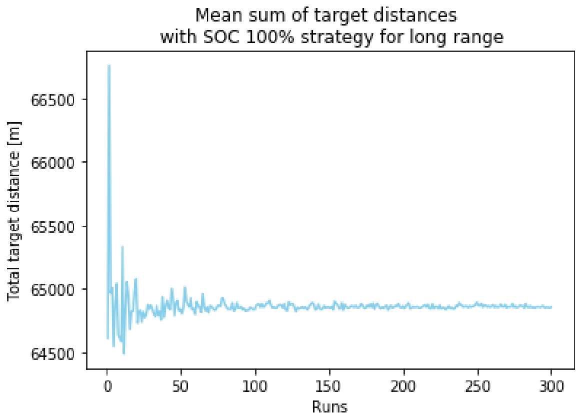
The histograms of the battery lifetime and usage performance for the long range are presented in Figure 1.15 and 1.16. In Table 1.7 the Shapiro-Wilk test results for the long range are given. Here, it becomes apparent that the $\widetilde{B}$ output for the SOC 100% strategy is not normally distributed. Also, the SOC 100% and mission-based $\widetilde{P}_{total}$ results do not follow a normal distribution. Lastly, this is also the case for the SOC 80% $Efficiency$ results. For these parameters, Q-Q plots are generated. From the Q-Q graphs depicted in Figure 1.8 it is concluded that the results are 'sufficiently normal' in their distributions for T-tests to be applied.

$\widetilde{B}$ - long range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.981	0.001	False
SOC 80%	0.991	0.074	True
Mission-based	0.992	0.111	True

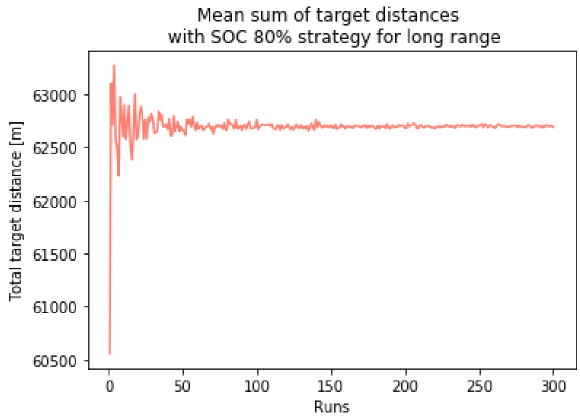
$\widetilde{P}_{total}$ - long range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.990	0.046	False
SOC 80%	0.996	0.664	True
Mission-based	0.990	0.033	False

$Efficiency$ - long range			
Strategy	**W**	**p-value**	**Normal**
SOC 100%	0.994	0.228	True
SOC 80%	0.979	$1.85 \cdot 10^{-4}$	False
Mission-based	0.996	0.690	True

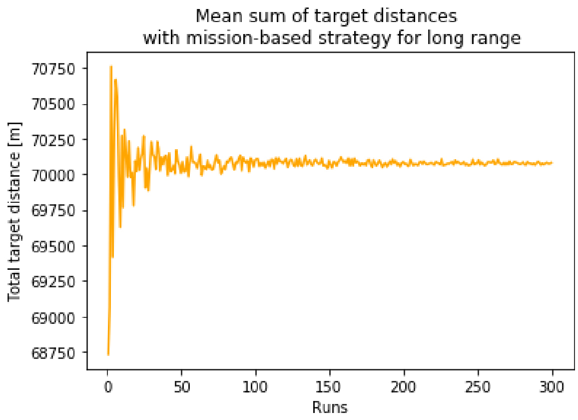
Table 1.7: Shapiro-Wilk normal test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for long range



(a) SOC 100% strategy



(b) SOC 80% strategy



(c) Mission-based strategy

Figure 1.7: Stabilisation of mean distance results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for long range

1.4.3. Long range - Statistical T-tests

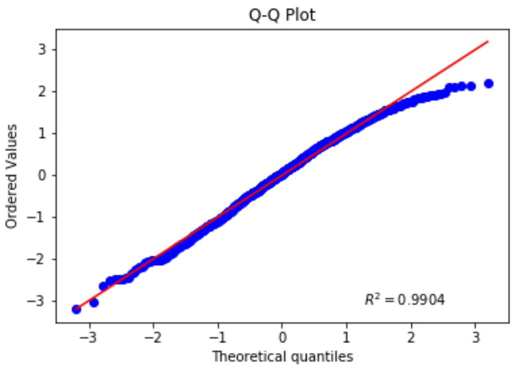
The unpaired one-sided T-test results for the hypotheses tested for the long range are presented in Table 1.8. For the long range, the mission-based strategy performs better than the SOC 100% and SOC 80% strategy across all assessment parameters $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$.

$\widetilde{B}$ - long range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

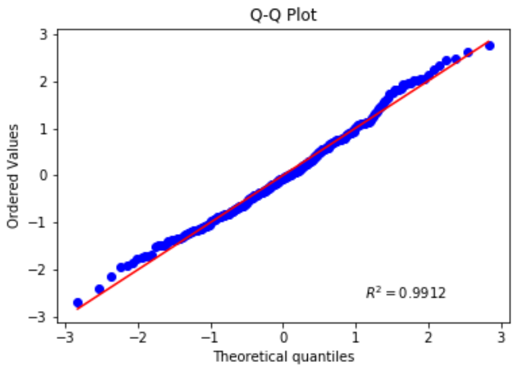
$\widetilde{P}_{total}$ - long range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

$Efficiency$ - long range		
Strategy A	**Strategy B**	**p-value**
SOC 100%	Mission-based	0.000
SOC 80%	Mission-based	0.000

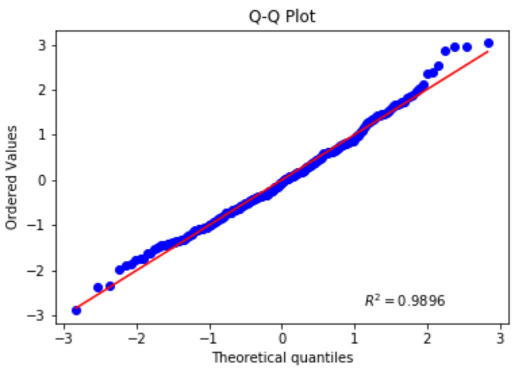
Table 1.8: Unpaired one-sided T-test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for long range



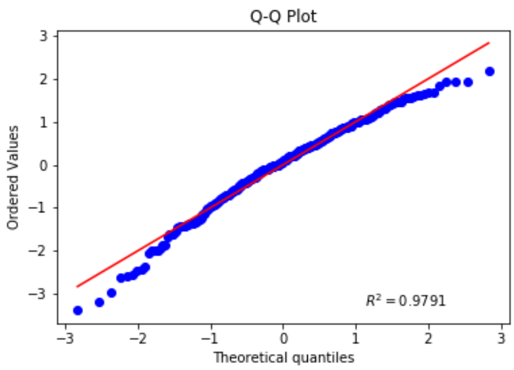
(a) $\widetilde{B}$ for SOC 100% strategy



(b) $\widetilde{P}_{total}$ for SOC 100% strategy



(c) $\widetilde{P}_{total}$ for mission-based strategy



(d) $Efficiency$ for SOC 80% strategy

Figure 1.8: Quantile-Quantile (Q-Q) plots for outputs of 300 batteries tested through Monte Carlo simulation for long range

1.5. Distances - Statistical T-tests

In the scientific paper, the hypothesis that the short range distance outperforms the medium and long range distance within each strategy is tested. Table 1.9 presents the p-values for each test. Here, it is concluded that the short range yields better results than the medium and long range for the SOC 100% and mission-based strategy for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$. However, the SOC 80% range results show that the medium range $Efficiency$ has a better performance than the short range distance. For $\widetilde{B}$ and $Efficiency$, the SOC 80% short range does perform better than the other distances.

$\widetilde{B}$ - short, medium and long range		
Strategy	**Distances**	**p-value**
SOC 100%	Short vs. Medium	0.000
SOC 100%	Short vs. Long	0.000
SOC 80%	Short vs. Medium	0.000
SOC 80%	Short vs. Long	0.000
Mission-based	Short vs. Medium	0.000
Mission-based	Short vs. Long	0.000

$\widetilde{P}_{total}$ - short, medium and long range		
Strategy	**Distances**	**p-value**
SOC 100%	Short vs. Medium	0.000
SOC 100%	Short vs. Long	0.000
SOC 80%	Short vs. Medium	0.000
SOC 80%	Short vs. Long	0.000
Mission-based	Short vs. Medium	0.000
Mission-based	Short vs. Long	0.000

$Efficiency$ - short, medium and long range		
Strategy	**Distances**	**p-value**
SOC 100%	Short vs. Medium	0.000
SOC 100%	Short vs. Long	0.000
SOC 80%	Short vs. Medium	1.000
SOC 80%	Short vs. Long	0.000
Mission-based	Short vs. Medium	0.000
Mission-based	Short vs. Long	0.000

Table 1.9: Unpaired one-sided T-test results for $\widetilde{B}$, $\widetilde{P}_{total}$ and $Efficiency$ outputs of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for short, medium and long range

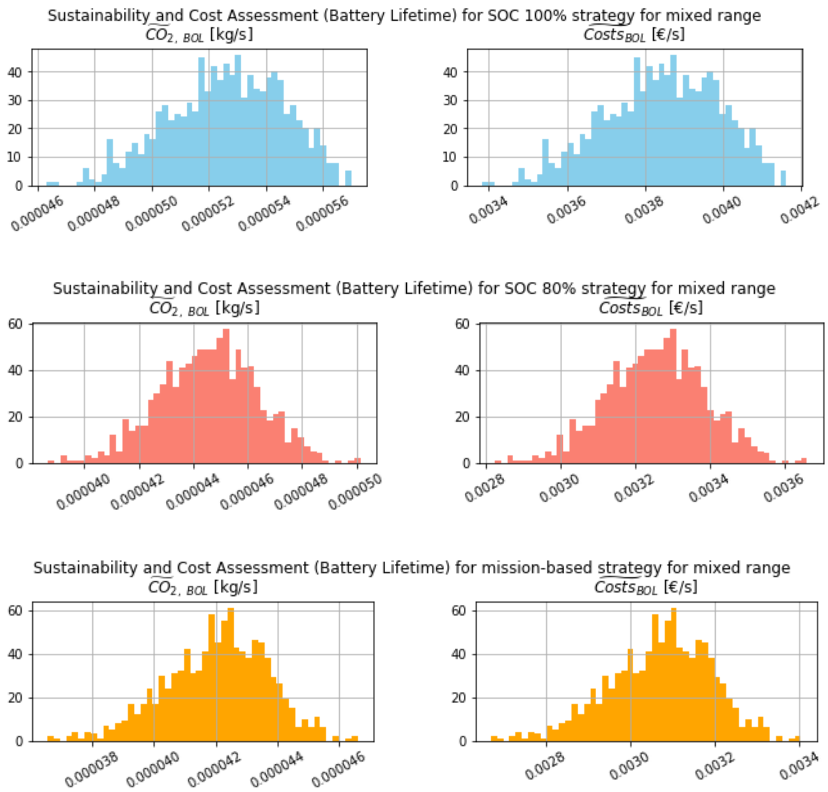


Figure 1.9: Distribution of Sustainability and Cost Assessment (Battery Lifetime) results of 1000 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for mixed range

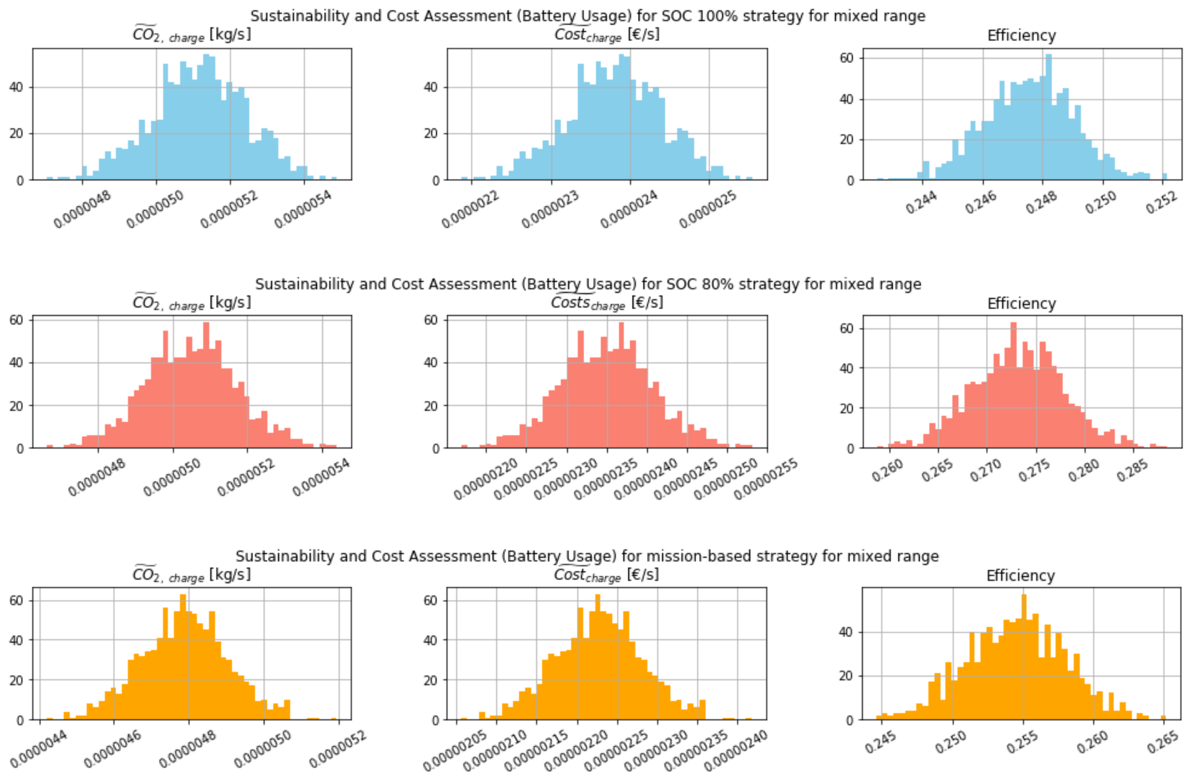


Figure 1.10: Distribution of Sustainability and Cost Assessment (Battery Usage) results of 1000 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for mixed range

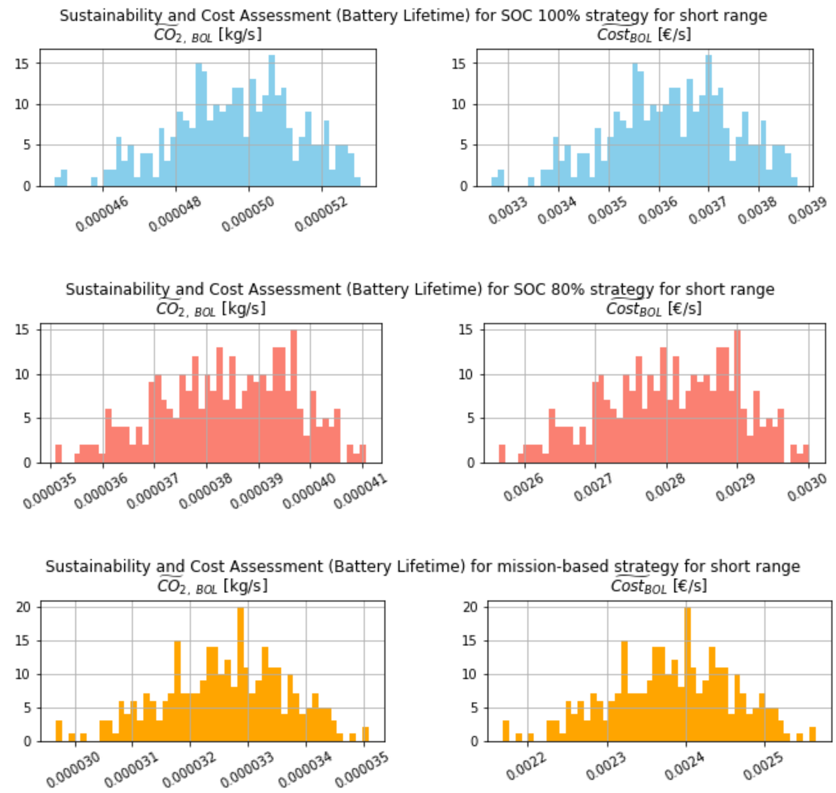


Figure 1.11: Distribution of Sustainability and Cost Assessment (Battery Lifetime) results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for short range

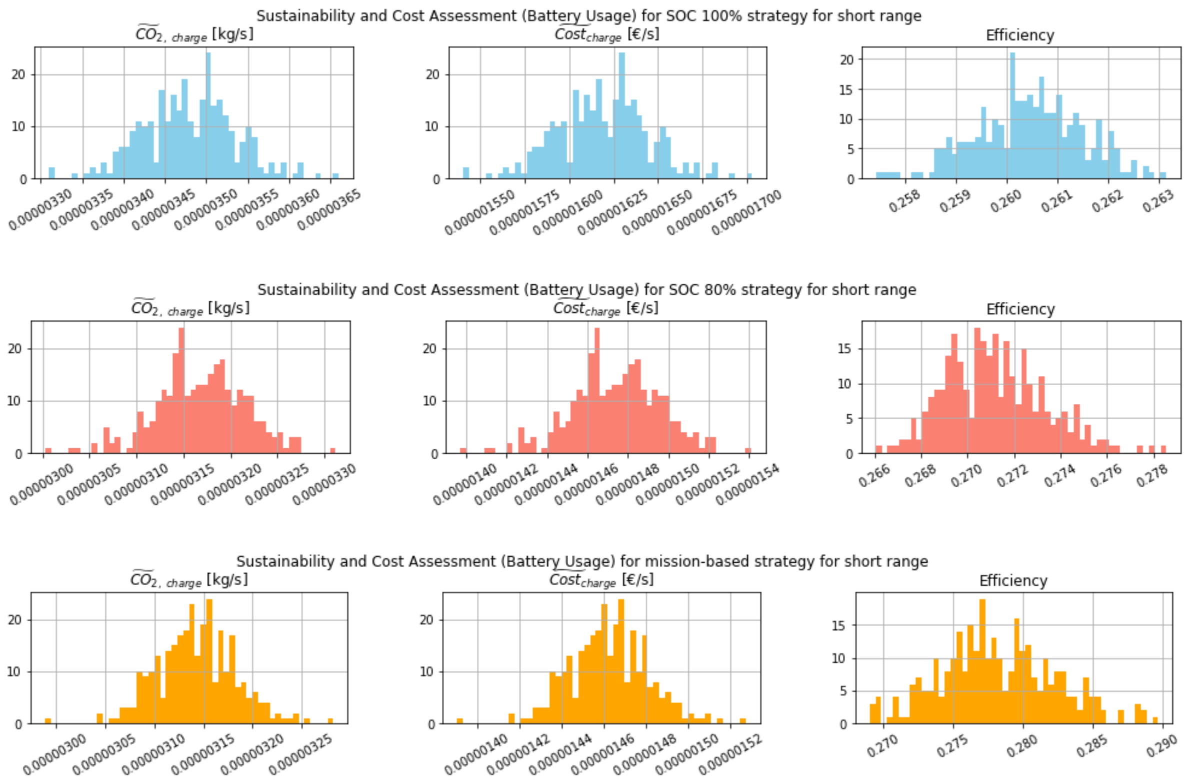


Figure 1.12: Distribution of Sustainability and Cost Assessment (Battery Usage) results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for short range

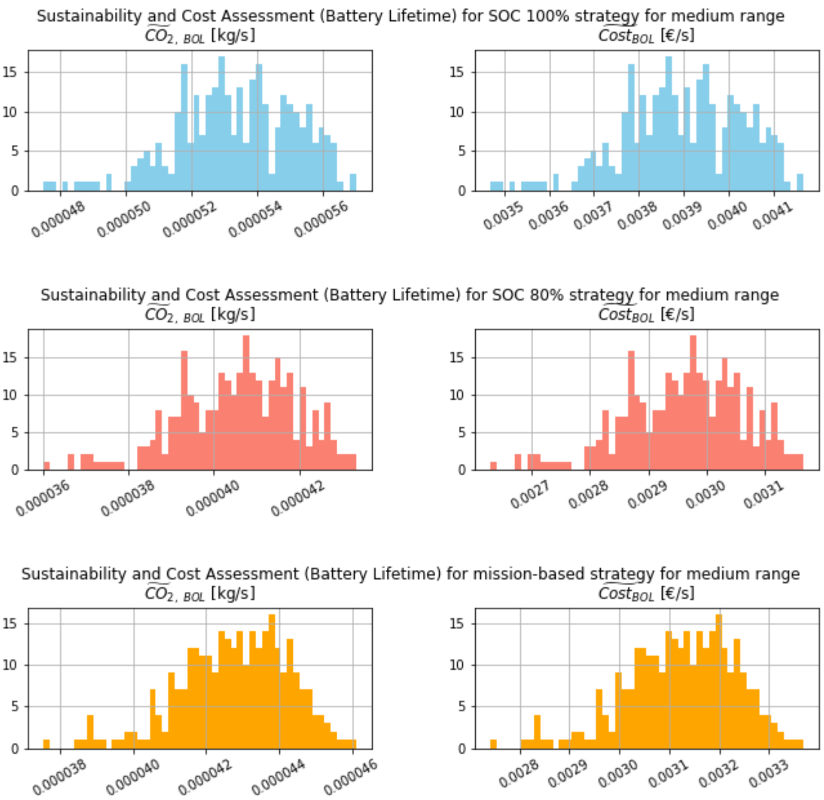


Figure 1.13: Distribution of Sustainability and Cost Assessment (Battery Lifetime) results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for medium range

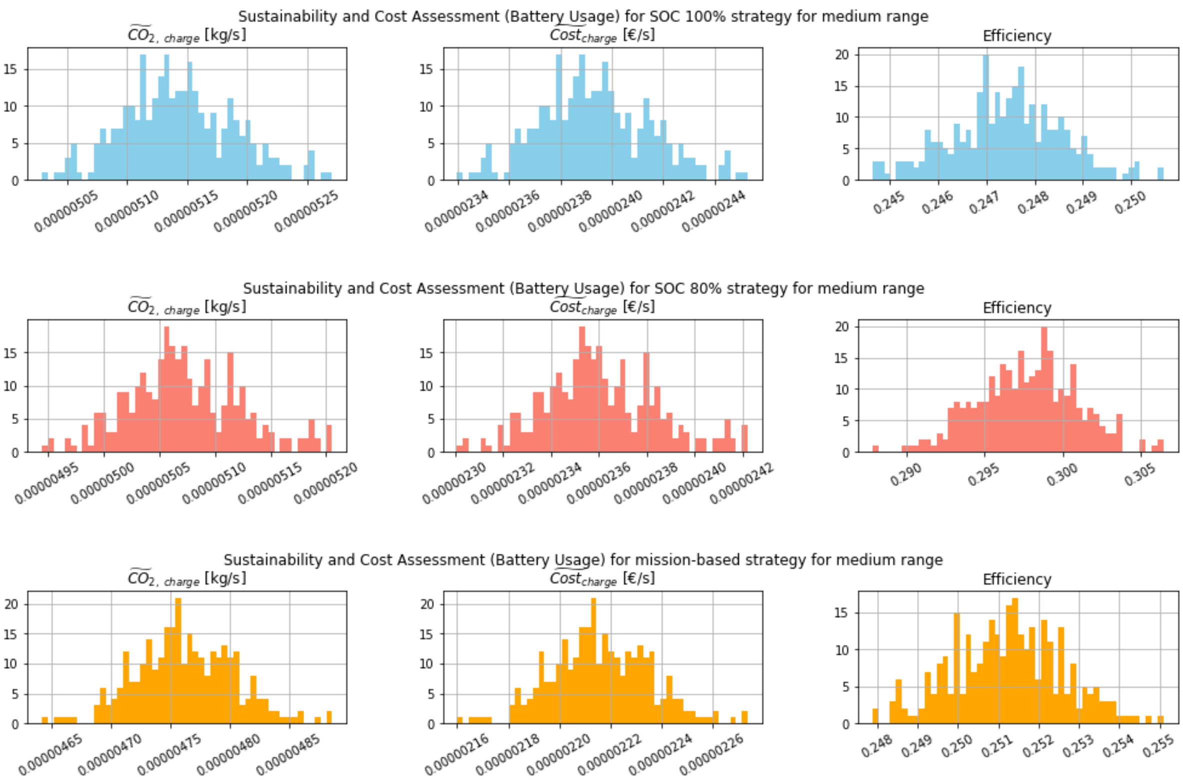


Figure 1.14: Distribution of Sustainability and Cost Assessment (Battery Usage) results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for medium range

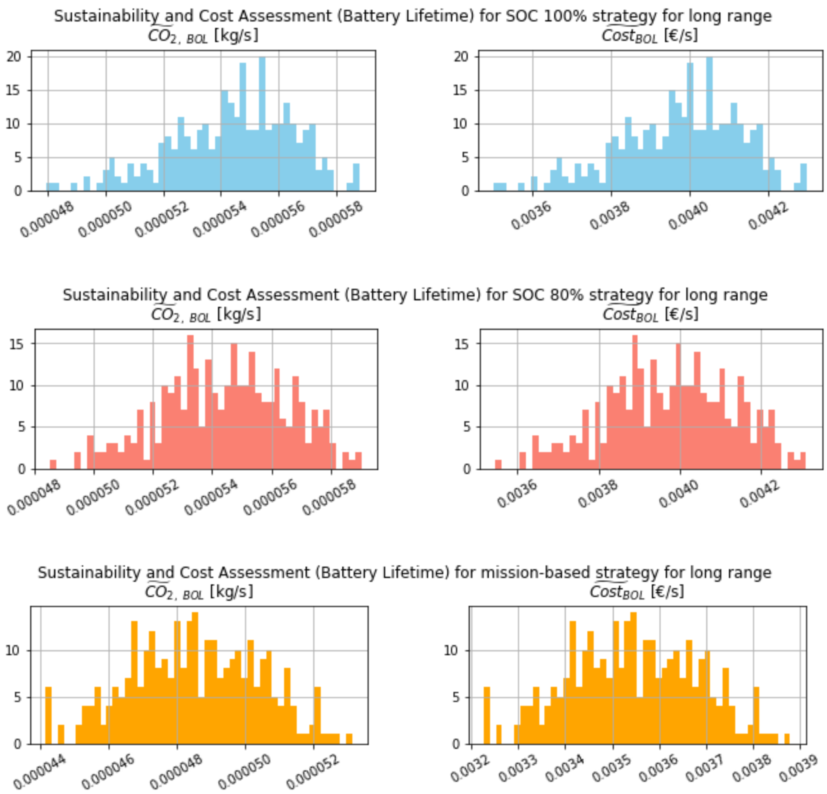


Figure 1.15: Distribution of Sustainability and Cost Assessment (Battery Lifetime) results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for long range

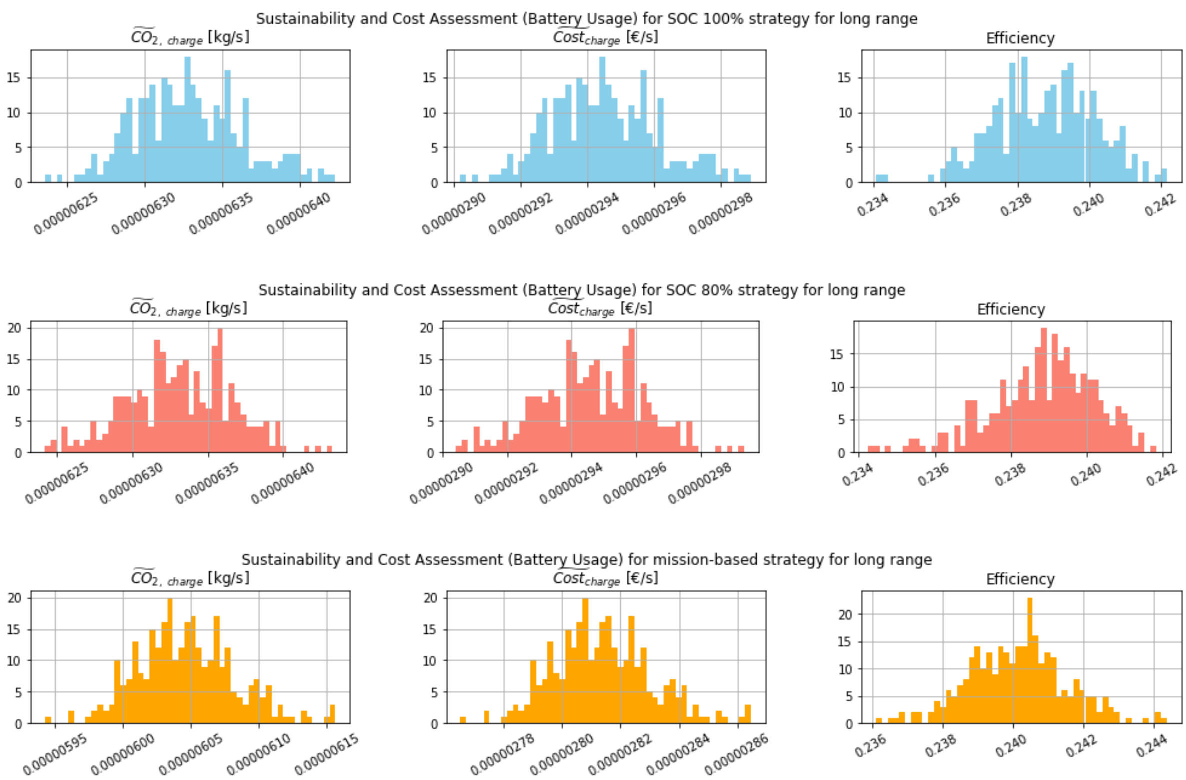
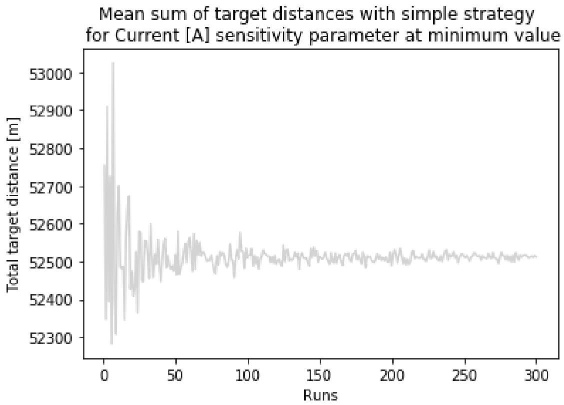


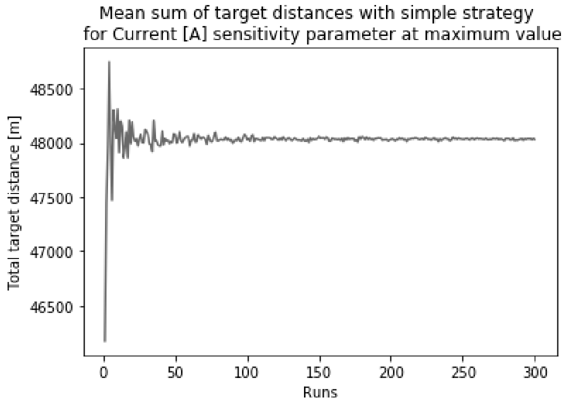
Figure 1.16: Distribution of Sustainability and Cost Assessment (Battery Usage) results of 300 batteries tested through Monte Carlo simulation for SOC 100%, SOC 80% and mission-based strategy for long range

1.6. Validation results

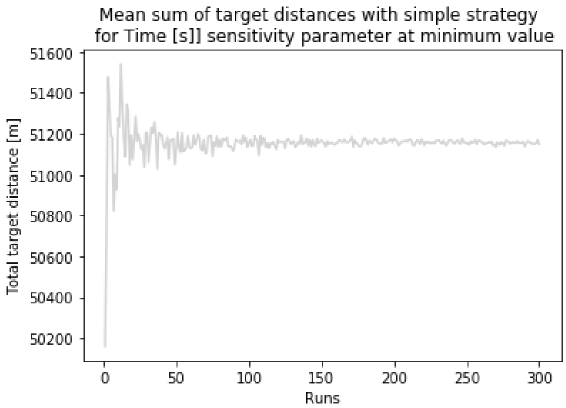
Now that the results for the mixed, short, medium and long range distances have been analysed, this section reviews the outputs of the validation simulations. To validate the model, several sensitivity analyses are run. In Figure 1.17 and 1.18, the MC plots show that the mean target distance flown by each battery converge to a stable value for each sensitivity parameter tested. Therefore, it is concluded that sufficient runs have been simulated.



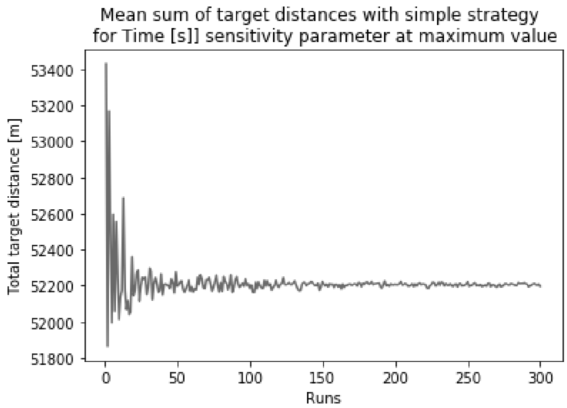
(a) Current [A] with minimum value



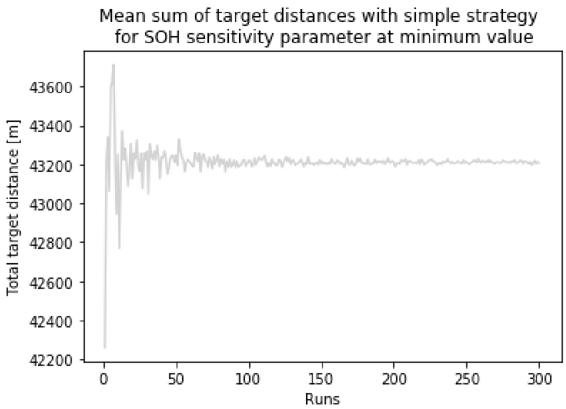
(b) Current [A] with maximum value



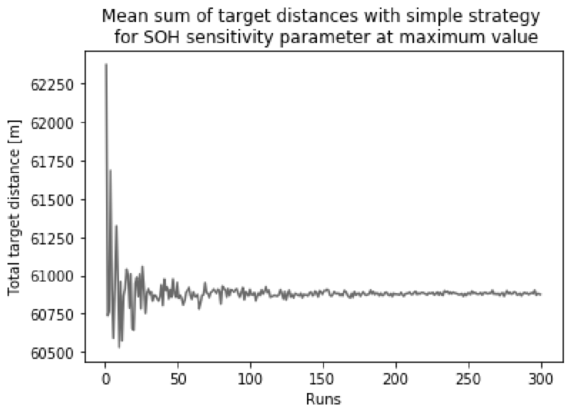
(c) Time [s] with minimum value



(d) Time [s] with maximum value

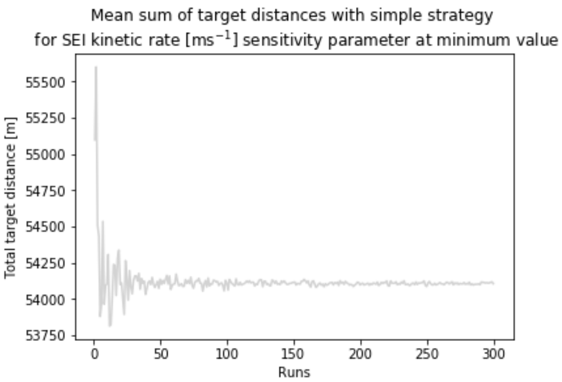


(e) SOH with minimum value

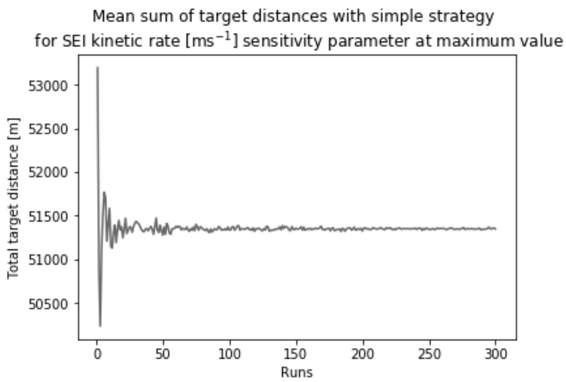


(f) SOH with maximum value

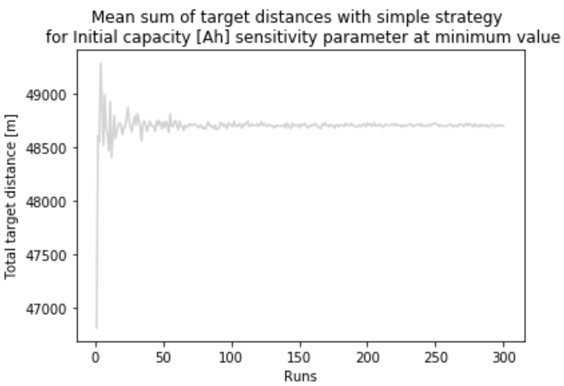
Figure 1.17: Sensitivity Analysis (Part 1) - Stabilisation of mean distance flown per battery through Monte Carlo runs per sensitivity parameter varied for minimum and maximum values



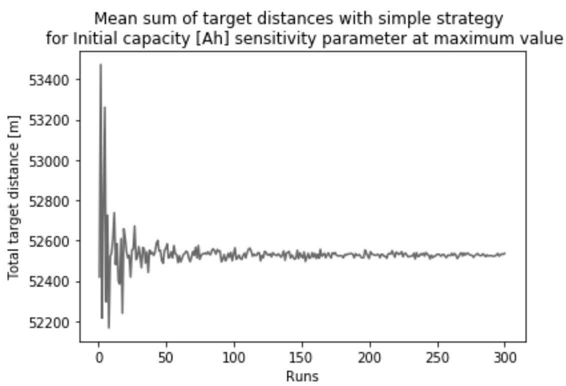
(a) SEI kinetic rate [ms^{-1}] with minimum value



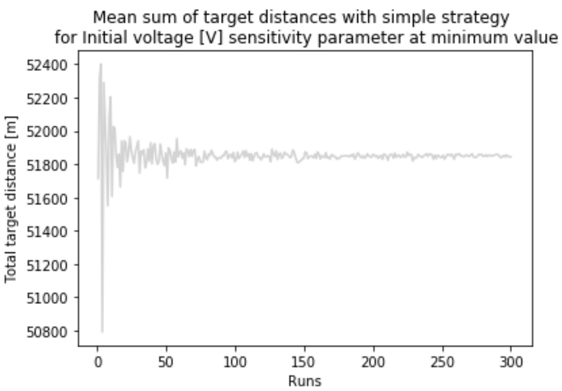
(b) SEI kinetic rate [ms^{-1}] with maximum value



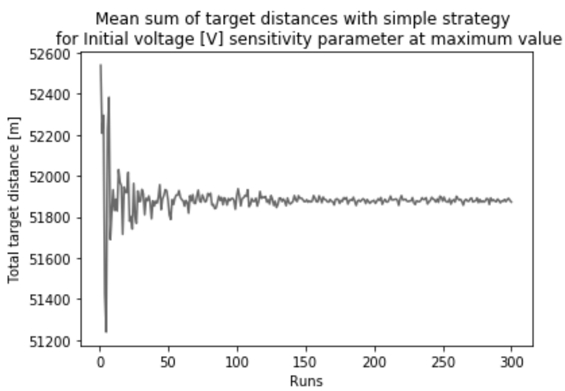
(c) Initial capacity [Ah] with minimum value



(d) Initial capacity [Ah] with maximum value



(e) Initial voltage [V] with minimum value



(f) Initial voltage [V] with maximum value

Figure 1.18: Sensitivity Analysis (Part 2) - Stabilisation of mean distance flown per battery through Monte Carlo runs per sensitivity parameter varied for minimum and maximum values

2
Research Limitations and Recommendations

A review of the limitations of this study originating from assumptions and other external factors is given below. The mission profiles are first discussed in section 2.1. Secondly, the battery model and health management strategies are reviewed in section 2.2 and 2.3. Lastly, limitations of the sustainability and cost assessment are briefly addressed in section 2.4

2.1. Mission Profiles

In order to establish the mission profiles, DJI Matrice 100 quadcopter flying data from the research by Rodrigues et al. [105] is used. Translating this into the battery model used for this study, several shorting comings are listed below.

The derived current throughput and time duration values from their study are implemented into the experiments in PyBaMM as constant values throughout a manoeuvre. However, the accuracy of the research's model would be increased if this is inputted as a so-called 'drive cycle' which specifies the current rate for smaller time periods (for example per second). In addition, the eUAV modelled flight only consists of simple manoeuvres. To more closely replicate real-life eUAV flights, additional movements including turns should be included, as well as more variation in flying plan settings such as speed, altitude and payload. Although these two limitations decrease the accuracy of the model compared to a real-life eUAV application, it is not expected that the results would be significantly influenced.

Finally, apart from the 2.6% standard deviation inputted in the current and time period values, this model does not account for environmental influences such as wind which would considerably influence the eUAV battery operating conditions. Although the SOC 80% and mission-based battery health management strategy showed an improved battery lifetime and usage performance compared to the SOC 100% approach, operators could argue that mission safety is reduced due a reduction of available battery capacity for flight. The model would be improved when more data is inputted into the mission-based strategy such that external factors such as wind are accounted for. An assessment parameter reflecting on flight safety could also be implemented to evaluate the performance of the mission-based model.

2.2. Battery Model

For the battery model, several uncertainties are identified. Foremostly, the non-deterministic errors that are inputted in the MC simulations originate from several different researches and may therefore be case specific. Depending on the battery and BMS used, the battery and non-deterministic model inputs in should be adjusted accordingly.

Additionally, this model incorporates battery ageing by using the SEI kinetic rate equal derived by Yang et al. [133]. For Lithium batteries, this is the dominating degradation phenomenon while SOH > 80%. For more accurate results, Lithium plating could also be included in the model.

To model an eUAV battery, multiple battery cells that form a battery pack could be analysed, instead of using single battery cells. It is important to review the performance of a battery pack as battery degradation is more severe compared to single cells. To model this is, however, very complex to model as interrelated ageing modes arise related parameters such as temperature and resistance. Nonetheless, due to the large demand for such models, PyBaMM is currently developing a separate module called ‘Liionpack’ which could potentially be used.

The last battery model limitation that became apparent during the MC simulations, is the high computational power required to run through the model. On average, one battery MC iteration took 45 minutes to complete. This is a highly constraining factor when testing the model in the SA and case studies, resulting in the MC simulations only being run 300 times. Especially for SA which is performed to validate the model, the computational intensity restrained the variation of tests executed. Executing other SA experiments such as an extensive variance decomposition to review how the output is affected by multiple stochastic inputs, for example, would enhance the certainty of the conclusions about the robustness of the model.

Despite the fact that the accuracy of the battery model is reduced by these battery model assumptions, the overall performance of the battery health management strategies is not expected to change.

2.3. Battery Health Management Strategies

The biggest limitation of PyBaMM is the absence of a SOC function which creates an obstacle of twofold. First of all, when simulating charging operations, PyBaMM takes voltage values as input instead of SOC levels. For the SOC 100% charging strategy, this is not an issue as the battery can always be charged to the initially defined maximum voltage. However, for the SOC 80% and mission-based battery health management strategy, the SOC to which the battery model needs to be charged varies, implying that these SOC values are required to be converted to voltage levels.

Secondly, the lack of a standard SOC function results in another limitation, namely in the setup of the SOC 80% and mission-based model. To estimate the required SOC to complete a flight, data from SOC 100% charging model is used. Here, the SOC required to complete a certain flight is again translated to voltage values. Because Lithium batteries are characterised by an S-shaped discharge voltage curve, this leads to small discrepancies. Effectively, this means that for example 40% SOC DOD does not yield the same voltage DOD when starting from 100% SOC compared to lower mission-based values such as 70%. Due to the S-shaped voltage curves, the mission-based model overestimates the expected voltage DOD.

In this model, SOC conversion to voltage levels is done through regression using SOH and target distance as an input. But as battery electrochemical relations are complex, an regression is supposedly not able to capture the intricacy of SOC couplings. Moreover, PyBaMM brings along the constraint that the SOH cannot be determined during operation and only at the start and end of each flight. Alternatively, other approaches such as Machine Learning could yield higher accuracy.

2.4. Cost-Benefit Analysis

The last set of limitations revolves around the assessment of the model outputs. These limitations are attributed to the lack of battery specific data. For the environmental impact, the values of the BOL CO_2 emissions strongly vary per source. Moreover, a more extensive analysis of other sustainability parameters such as material resources, waste and EOL impact would enhance the thoroughness of the analysis. In the financial cost bucket, the costs of EOL practices as well as investment of setting up the mission-based and SOC 80% battery health management strategy are neglected. By disregarding the SOC estimation investment costs, the financial results of the mission-based and SOC 80% strategy are slightly optimistic. Lastly, the sustainability and cost assessment lacks a single final ‘score’ which combines the outcome of the environmental, financial and efficiency assessments.

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