# Data-driven and dynamic multi-criteria decision support system for corrective maintenance of aircraft structural damages

## Master of Science Thesis

Natalia Elías Ortega

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# Data-driven and dynamic multi-criteria decision support system for corrective maintenance of aircraft structural damages

## Master of Science Thesis

by

Natalia Elías Ortega

to obtain the degree of Master of Science
at the Delft University of Technology,
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TU Delft

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This report marks the end of my studies at Delft University of Technology, as it is the final delivery to get my MSc in Aerospace Engineering. TU Delft has given me many opportunities that have shaped me into the person I am today, both personally and professionally. In Delft, I met many inspiring smart people, adapted to a new culture (and weather), learned a lot of new skills, and found a place in which I feel at home. Furthermore, I also enjoyed making the most out of my student time during my Bachelor and Master: being very active in a student association, doing an Erasmus minor in Toulouse, and an internship abroad in Brasil. After 6 years of hard work, I can say that coming to Delft when I was only 17 years old was one of the best decisions I have taken.

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Natalia Elías Ortega
Delft, August 2020

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# List of Abbreviations

| | |
|---|---|
| A/C | Aircraft |
| AHP | Analytic Hierarchy Process |
| ANP | Analytic Network Process |
| BDT | Boolean Decision Tree |
| BIC | Bayesian Information Criterion |
| BWM | Best-Worst Method |
| CD | Calendar Days |
| CDF | Cumulative Distribution Function |
| CI | Confidence Interval |
| DM | Decision-Maker |
| DSS | Decision Support System |
| EASA | European Union Aviation Safety Agency |
| ELECTRE | Elimination and Choice Expressing Reality |
| FAA | Federal Aviation Administration |
| FC | Flight Cycles |
| FH | Flight Hours |
| GRP | Generalised Renewal Process |
| HPP | Homogeneous Poisson Process |
| MCDM | Multi-Criteria Decision-Making |
| MLE | Maximum Likelihood Estimator |
| NHPP | Non-Homogeneous Poisson Process |
| OR | Operations Research |
| PDF | Probability Density Function |
| PROMETHEE | Preference Ranking Organization Method for Enrichment Evaluation |
| SRM | Structural Repair Manual |
| TOPSIS | Technique for Order Preference by Similarity to Ideal Solution |
| VIKOR | Multicriteria Optimization and Compromise Solution |
| WSM | Weighted Sum Method |

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# Introduction

Complex decisions need to be taken daily in aircraft Maintenance, Repair & Overhaul (MRO) organisations. Despite the fast-paced development of predictive aircraft maintenance techniques in the past years [4], it is not possible to completely eliminate unexpected structural damage occurrences due to their stochastic nature. In real-life maintenance operations, the initial maintenance plan experiences the addition of non-routine tasks due to the occurrence of unplanned failures. After the occurrence of an unplanned failure, a corrective maintenance diagnostic or troubleshooting needs to be performed to understand the scope of the problem and develop different solution scenarios or repair options. An effective solution needs to be provided in a short time horizon (in the order of hours) to repair the failure within specified airworthiness requirements and to minimise the possible consequences (cost, downtime, cancellations, etc). In this stage, effective decision-making plays a key role. Current industry practices lack a systematic approach to decision-making, failing to identify, compare and update all the possible repair options in a structured and exhaustive manner due to the dynamic and complex environment. This leads to losses of time and the selection of sub-optimal decisions. Given these issues, the research objective is formulated as follows:

> *"To improve the situational awareness of aircraft maintenance planners by providing a fast, systematic and dynamic decision support tool for repair or replace decisions after an externally-induced structural damage"*

The tool should increase the planner's situational awareness by providing within few minutes: 1) a complete list of feasible repair decision options, 2) a ranking of these decision options, and 3) a systematic approach for dynamic decision iteration. Furthermore, the tool should be easy to understand by the decision-makers. Therefore, methods that are easy to comprehend according to existing literature should be selected. In addition, the tool should provide a fast recommendation based on both the specific scenario and the decision-maker priorities. The total time to provide a recommendation including the processing time of the tool and introduction of required user inputs should be in the order of minutes.

To achieve the research objectives, a novel hybrid Multi-Criteria Decision Support System (DSS) is proposed in this research, combining a Boolean Decision Tree (BDT), the Bayesian Best-Worst Method (BWM), and the Weighted Sum Method (WSM). The main steps of the proposed model are shown in Figure 1. In Step I, damage and repair limits information is collected. Feasible time slots to plan non-routine maintenance actions are determined in Step II. Then, a complete list of repair options is generated in step III using a BDT. The decision-makers' judgement is taken into account via standard criteria weights determination in Step IV. Furthermore, the DSS is data-driven, as historical data is used to evaluate the different repair options in Step V. Finally, the repair options are ranked using WSM in Step VI and a recommended option is shown to the decision-maker. This recommendation is updated when the operational conditions change.

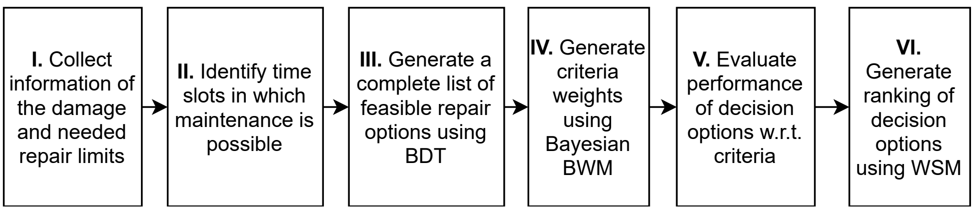


Figure 1: Steps of the DSS model

The thesis report is divided into three parts. In part I, the research paper written as the result of this research is presented. The research paper includes explanations of the methodology, case study, results, and sensitivity analysis. Part II contains a literature study performed before the start of the research which set the basis of the research, including the research question. Finally, Part III adds supporting work related to the scientific paper presented in Part I. This includes databases information, validation & verification, reliability analysis results, and further sensitivity analysis.

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# I

## Scientific Paper

Data-driven and dynamic multi-criteria decision support system for corrective maintenance of aircraft structural damages

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**Abstract**

After the detection of an externally-induced aircraft structural damage, a fast decision needs to be made regarding the planning of corrective maintenance actions. In these situations, several suitable repair options exist. Current industry practices lack a structured approach to identify and analyse the different repair options due to the dynamic and complex environment with competing decision criteria. A novel data-driven and dynamic multi-criteria Decision Support System (DSS) for operational maintenance decisions is proposed in this paper to address this issue. The criteria considered in the DSS are 1) maximisation of aircraft part reliability, 2) minimisation of repair cost, 3) maximisation of aircraft utilization and 4) maximisation of aircraft part life. The relative importance of these decision criteria is determined using expert judgement and the Bayesian Best-Worst Method. The proposed DSS aims to increase the planner's situational awareness by providing: 1) a complete list of feasible repair decision options using a Boolean Decision Tree (BDT), 2) a ranking of these repair options using the Weighted Sum Method (WSM), and 3) a dynamic approach for decision iteration. The proposed DSS is applied to a real-life aircraft maintenance case study of a major European airline. The case study corresponds to an externally-induced outboard flap damage of a Boeing 777. The results show that the DSS provides an informed repair option recommendation to the planner in a few minutes, including both the DSS processing time and the input of the required data. In contrast, current real-life decision-making practices can take in the order of hours to days to evaluate similar decision-making problems due to their unstructured approach. Furthermore, the DSS lead to the identification of feasible repair options that were not considered in real life but had a more beneficial ranking score. These results show the potential of the described DSS, not only in terms of improvement of the planners' awareness by introducing a structured approach to decision-making in a dynamic environment but also by improving agility when taking a decision. As future work, the DSS should be implemented in a wider range of real-life operational case studies to further validate the conclusions reached in this research.

***Keywords:*** *Multi-Criteria Decision-Making, Decision Support System, Weighted Sum Method, Structural Damages, Non-Routine Maintenance, Best-Worst Method, Boolean Decision Tree, Repairable Systems, Generalised Renewal Process*

# 1 Introduction

Maintenance is considered a key strategic element as it ensures airworthiness and influences companies' competitiveness and profitability [2]. In the airline industry, this is evident as aircraft maintenance plays a crucial role in the direct operating cost of an aircraft, representing approximately from 10% to 20% of the total cost [27]. Maintenance caused by an unexpected failure drives a major part of this cost, as it leads to unscheduled corrective maintenance actions.

In real-life maintenance operations, unexpected damages lead to the addition of non-routine tasks to the initially planned maintenance checks. After the occurrence of an unplanned failure, a corrective maintenance diagnostic or troubleshooting needs to be performed to understand the scope of the problem and select a suitable repair option. An effective solution needs to be provided in a short time horizon to repair the failure within the specified airworthiness requirements. At this stage, decision-making plays a key role in minimising the operational and economic consequences of the failure. Current industry practices remark the lack of a structured decision-making approach and insufficient gathering of information in operational aircraft maintenance decisions [10]. The unstructured approach and incomplete gathering of information directly affect the decision-maker's situational awareness. This impacts its ability to generate a complete list of repair options, find correlations, and identify risks while taking the decision. Furthermore, the maintenance scenario nowadays is considered static despite the dynamic nature of the maintenance environment. Dynamically

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adapting the decisions to the operational conditions is hardly used in practice. The repair decision is taken at the moment of failure and different alternatives are uniquely considered when the chosen option is no longer possible. Finally, the human nature of the decision-maker drives the inability to process large amounts of changing, correlated, and contradicting data and constraints simultaneously. This leads to losses of time and the selection of non-optimal solutions. These gaps set the need for a decision-support tool at operational maintenance level.

Given the main gaps introduced earlier, the research objective can be formulated as follows: *"To improve the situational awareness of aircraft maintenance planners by providing a fast, systematic and dynamic decision support tool for repair or replace decisions after an externally-induced structural damage."* The tool should improve all levels of situational awareness presented in Figure 1 and provide the planner with: 1) a complete list of feasible repair decision options, 2) a ranking of these decision options, and 3) a systematic approach for dynamic decision iteration. Furthermore, the tool should be easy to understand by the decision-makers. This goal should be achieved by selecting methods that are easy to comprehend according to existing literature. In addition, the tool should provide a fast recommendation based on the specific scenario and the decision-maker priorities. The total time to provide a recommendation including the processing time of the tool and introduction of required user inputs should be in the order of minutes.

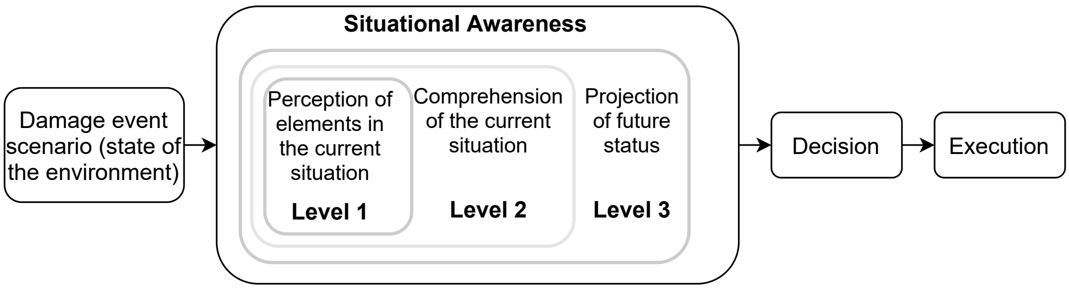


Figure 1: Levels of situational awareness in decision-making adapted from [12]

To achieve this objective a novel Multi-Criteria Decision-Making (MCDM) approach is proposed. MCDM is a branch of Operations Research (OR) that experienced growing popularity in research during the past decades. A multi-criteria approach is selected for this research due to its ability to cope with the competing goals and to evaluate decision options in a structured and fast way. This is applicable in the context of corrective maintenance planning, where multiple competing goals play a role when taking a final operational decision such as direct and indirect costs, reliability, and availability of resources. MCDM methods have been applied successfully in a wide range of industries, including the aviation industry. Despite the growing applications of MCDM in the aviation industry, the number of scientific publications related to aircraft maintenance is very limited [11].

Many MCDM methods exist and have been used in literature. Some of the most popular MCDM methods are Analytic Hierarchy Process (AHP) [4], Multicriteria Optimization and Compromise Solution (VIKOR) [15], Elimination and Choice Expressing Reality (ELECTRE) [6], Analytic Network Process (ANP) [17], Best Worst Method (BWM) [32], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [21], Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [14], and Weighted Sum Method (WSM) [10]. Even though each method is based on different principles, they all approach decision-making following three similar high-level steps that can be summarised as follows: 1) determination of repair options, 2) selection of decision criteria, and 3) evaluation of each repair option with respect to the decision criteria. The advantages and disadvantages of each method have been studied by several authors [35, 5]. Hybrid MCDM approaches have become very popular to overcome the weaknesses of the individual methods.

In this paper, a hybrid MCDM Decision Support System (DSS) is proposed, combining Boolean Decision Tree (BDT), Bayesian BWM, and WSM. BDT is used to determine a complete list of feasible repair options. Decision trees are a popular tool in decision-making and machine learning, as they represent a sequential decision-making process in a visual way [13]. WSM is used as an aggregation method to generate a ranking of the repair options. The WSM is selected because it is easily understood and used by the maintenance Decision-Makers (DMs). This will accelerate the implementation and acceptance of the tool in real-life operations. WSM requires two inputs: criteria weights and repair options performance ratings. The performance ratings are the result of the evaluation of the performance of each repair option with respect to each criterion. These ratings are data-driven and derived from historical data. The second input is the criteria weights, which indicate the relative importance of each decision criteria. One of the main disadvantages of the WSM is its inability to determine standard weight values, which are assigned arbitrarily [1]. To overcome this limitation, the proposed DSS generates criteria weights based on expert judgement using the Bayesian BWM. The BWM was firstly introduced by [28], who explains the advantages of this method when compared to more popular pairwise comparison methods such as AHP [30]. The BWM is selected over AHP because it leads to less and more reliable pairwise comparisons when compared to AHP by identifying the best and the worst criteria before conducting the comparisons.

This research adds value to the body of knowledge by creating a novel systematic and dynamic framework for operational maintenance repair decision-making which does not solely rely on human judgement but is also data-driven. The main novelties of the DSS in the context of operational aircraft maintenance decision-making are the following: 1) the use of a Bayesian BWM approach for the determination of standard decision criteria, 2) the use of heuristics to re-evaluate the selection of repair options accounting for a dynamic environment with competing resources, and 3) the use of a Generalised Renewal Process (GRP) approach to model imperfect repairs and determine part reliability performance ratings within the context of the proposed hybrid MCDM DSS.

The paper is structured as follows. Firstly, Section 2 describes the problem formulation. Secondly, Section 3 explains the methodology of the DSS presented in this paper, including a proposed approach to deal with dynamic decisions. Thirdly, Section 4 elaborates on the implementation of the proposed DSS to a real-life case study. Fourthly, the main results that follow from the case study are described in Section 5, both for a static and a dynamic scenario. Fifthly, a sensitivity analysis is carried out in Section 6. Finally, Section 7 summarises the main conclusions that follow from this paper and provides recommendations for future research.

## 2 Problem definition

Aircraft maintenance tasks are commonly bundled together in letter checks (A, B, C, and D). These checks are composed of routine and non-routine tasks. Non-routine tasks are more difficult to predict and plan, as they are added to the schedule when unexpected damages are found. The duration and frequency of the routine maintenance checks is dependent on the airline and the type of aircraft. A and C-checks are the most common type of maintenance checks. A-checks are simpler checks carried out within an inspection interval of 2 to 3 months while C-checks are more specialised checks including the main aircraft systems and its frequency is larger, normally every 18 to 24 months. B-checks need to be carried out every 6-8 months in theory, but they are rarely used in practice. The necessary tasks of this check are usually included in previous A-checks. Therefore, B-checks are not considered in the DSS. Finally, D-checks correspond to heavy maintenance. Being the most labour-intensive and comprehensive check, their interval range is from 6 to 10 years [7].

The scope of the research is decision-support for the planning of non-routine maintenance tasks required after unexpected externally-induced structural damages. Structural aircraft damages need to be repaired when found due to airworthiness regulations and, thus, an immediate non-routine repair action when the damage is found is required. In such a scenario, decisions need to be taken fast to minimise disruptions. The immediate repair action performed can be either temporary or permanent. If the executed immediate repair action at $t_0$ is temporary, the structure should be permanently repaired at a deferred maintenance timeslot $t_d$ within allowable limits. Different types of permanent repair actions are available, such as replacing the damaged part with a spare part or undergoing permanent maintenance in the original damaged part. The decision support in this research considers different repair options in terms of the type of repair (permanent repair, temporary repair, replacement of original part with a spare part, etc) and the different timeslot at which the repair actions are scheduled. Furthermore, it accounts for 1) the operational feasibility of the repair options in terms of resources available, and 2) the consequences of the different repair options in terms of cost, reliability, part life, and availability. Recommendations regarding the specific structural repair techniques used to accomplish those repair actions are out of the scope of this research. These techniques are damage-specific and depend on the type of structure and the severity of the damage. In this study, the specific repair techniques required for each damage scenario are considered as an input retrieved from the Structural Repair Manual (SRM).

Due to the dynamic airline environment, the operational scenario can change at any time point between the initial planning decision at $t_0$ and the execution of any deferred tasks. These changes in the initial operational scenario are related to changes in the availability of resources and unexpected damages in other aircraft of the fleet between the time of taking the initial planning decision and the final repair action execution. The decision-making process is therefore a dynamic process, and the repair option recommendation should be updated over time when the operational scenario changes. A structured decision-making approach that is able to cope with dynamic scenarios is needed to achieve effective and informed decision-making in such an operational setting.

# 3 Methodology

The methodology proposed to address the described aircraft operational maintenance problems is described in this section. The DSS has been implemented using Python programming language and Jupyter notebook. The purpose of using Jupyter notebook is to create an interactive environment easy to visualise and understand by the decision-maker. The DSS framework is presented in Figure 2. The framework consists of four different layers: criteria, database, model, and user interface. This type of DSS architecture is commonly found in literature [22] [8]. First, the different layers of the DSS architecture are explained in Section 3.1. Then, four of the DSS steps of the model layer are described in detail: Step VI in Section 3.2, Step III in Section 3.3, Step IV in Section 3.4 and, Step V in Section 3.5. Finally, the DSS dynamic approach is explained in Section 3.6.

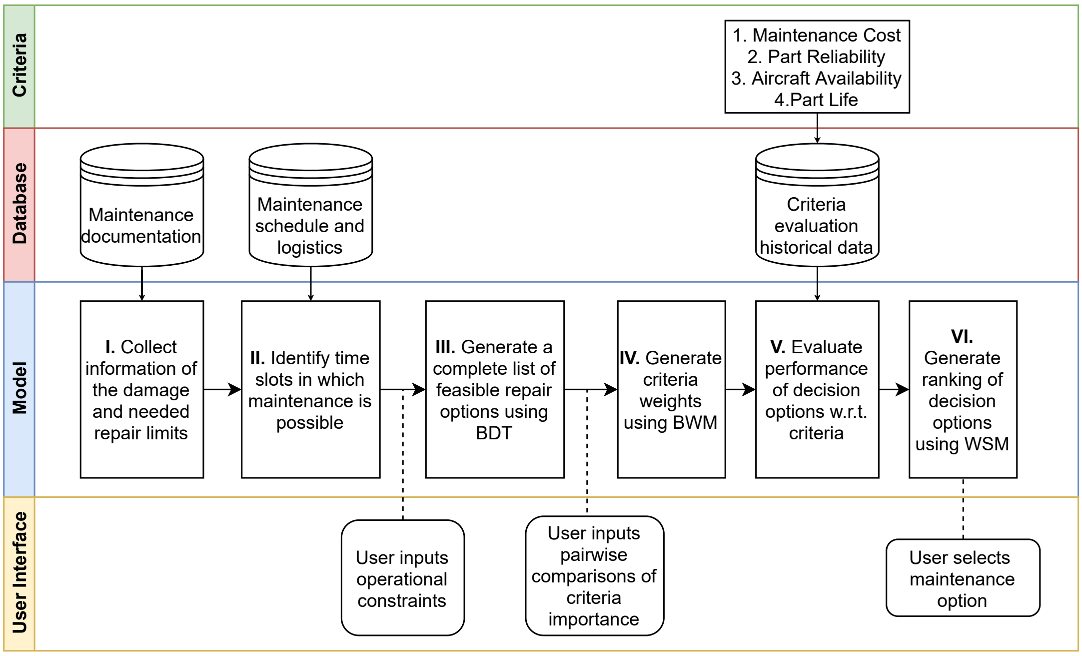


Figure 2: Decision Support System Framework

## 3.1 Layers

This section elaborates on the different layers of the DSS presented in Figure 2: 1) criteria, 2) database 3) model and 4) user interface.

### DSS Layer 1: Criteria

Four decision criteria are selected, which were found to be of importance in aerospace maintenance decision-making literature [36, 27, 10] and have been further validated using expert opinions through a questionnaire. More information about the questionnaire can be found in Appendix 1. An overview of each criterion is found below:

- **Maximisation of aircraft part reliability**: This refers to the probability of a certain component not experiencing a failure from the moment of repair until the next repair event. The greater the probability of survival of the repaired part to the next repair opportunity (for example, next A-check), the better the rating of this criterion will be. These probabilities are generated using a Generalised Renewal Process (GRP) modelled with historical data and using sequential event probabilities. All decision alternatives considered are within regulation limits.
- **Minimisation of repair cost**: This criterion refers to the direct cost incurred by the repair. This includes the materials cost, labour costs, and hangar costs.

- **Maximisation of aircraft utilization**: This criterion intends to give preference to repair alternatives that are performed in months of the year in which the aircraft utilization is lower (low season), in order to maximise aircraft utilization during high season months.
- **Maximisation of aircraft part life**: This criterion gives preference to options in which the aircraft parts are used for a longer time before being replaced or repaired (after a temporary repair and within safety regulations). This contributes in the long term to cost reduction.

**DSS Layer 2: Database**

The database layer contains all the necessary inputs for the DSS. An explanation of each of the elements in this layer is found below:

- **Maintenance documentation**: This database contains data that aids in understanding the specific damages and ensures the decision recommendation will comply with regulations. This database is based on the SRM, which contains specific information on the required repair steps and limits necessary to maintain airworthiness in aircraft structures. The SRM is issued by the aircraft manufacturer and approved by the corresponding regulatory body, such as the European Union Aviation Safety Agency (EASA) or the Federal Aviation Administration (FAA).
- **Maintenance schedule and logistics**: This database is used to input the fleet-specific inspection intervals of the aircraft in which the unexpected damage is found, including the aircraft utilization and preliminary maintenance schedule.
- **Criteria evaluation historical database**: Historical data is the base of the different models proposed for the evaluation of each of the decision criteria. This historical data is assumed to be a good predictor of the future in the context of the research.

**DSS Layer 3: Model**

The model layer consists of the following six steps:

**I** **Collect damage information**: This step gathers scenario-specific repair information from the SRM and ensures the DSS complies with airworthiness regulations by ensuring the required repair time limits are met. The output of this step is the required repair tasks and the time limits within the repair needs to be carried. These times can be indicated in Flight Cycles (FC), Flight Hours (FH), and Calendar Days (CD). Whichever time limit is met first drives the constraint.

**II** **Identify maintenance timeslots**: Once the necessary repair and time limits are known for the damage scenario, the available slots to perform the non-routine maintenance tasks need to be identified. The time horizon for feasible slots identification is any time between the damage event and the regulatory repair time limit. The model assumes that non-routine maintenance tasks can be performed during line maintenance and scheduled letter checks (A, C, and D-checks). The fleet-specific letter-check interval and the introduction date of each aircraft are used to generate an assumed maintenance schedule in this study, as the routine maintenance schedule of the fleet was not available for the research.

**III** **Generate a list of repair options**: Using a BDT approach a complete list of repair options is generated in this step.

**IV** **Generate criteria weights using BWM**: The relative importance of each criterion in the form of criteria weights is generated using expert judgement and the Bayesian BWM. Expert judgement data is gathered via a questionnaire filled out by 10 aircraft maintenance industry and academia experts.

**V** **Generate performance ratings**: This step evaluates the performance of each decision option generated in Step III with respect to each decision criteria.

**VI** **Rank decision options using WSM**: Using the criteria weights and performance ratings generated in Steps IV and V, a final ranking of repair options is generated in this step using the WSM.

**DSS Layer 4: User interface**

The last layer of the DSS is the user interface, which represents the user interaction with the model. Machine-human interaction is used in this approach, as the DSS aim is not to replace but to support the planner with the decision-making. This interaction is achieved with a Jupyter notebook in which the user will 1) be presented with information of each step in the model and the results (both in narrative and graphical forms) and 2) specify required user inputs. Three user inputs are needed: 1) answers to scenario-specific operational questions for the BDT, 2) pairwise comparisons of the criteria importance for standard criteria weights determination, and 3) final repair decision after the repair options have been ranked by the DSS.

### 3.2 Ranking of repair options using WSM

For a given operational maintenance scenario, the WSM is used to rank the complete list of feasible decision options generated using BDT. The multi-criteria problem can be formulated as can be seen in Equations 1, 2, 3, 4 and 5 [16]. An overview of the model parameters can be seen in Table 1. Equation 1 shows the definition of the performance matrix. The parameter $m$ is the total number of decision criteria which in this research is four, while $p$ refers to the total number of repair options which is scenario dependent. The final ranking score for each repair option is calculated using Equation 4. The ranking score $R_i^{WSMscore}$ depends both on the criteria weights $w_j$ and on the individual normalised ratings $n_{ij}$ of each repair option $o_i$ with respect to each repair criteria $c_j$ as specified in Equation 4. The repair option $o_i$ with the highest ranking score $R_i^{WSMscore}$ corresponds to the recommended repair option for the given scenario as can be seen in Equation 5.

To calculate the individual normalised ratings $n_{ij}$, the performance ratings $r_{ij}$ need to be normalised. Normalisation is necessary to have significant results, as each criterion rating has different units which are not comparable. Different normalisation techniques can be used, namely (1) linear max, (2) linear max-min, (3) linear sum, (4) vector normalisation, (5) logarithmic normalisation, and (6) fuzzification. For this study, the linear min-max normalisation technique was selected due to its highest discrimination power among different repair options. This is because the linear min-max technique generates values in the range from 0 to 1. To ensure a logically correct performance rating for the repair options with respect to the decision criteria Equations 2 and 3 are used to normalise the results. Equation 2 is used for beneficial criteria (aircraft part reliability, aircraft utilization, and aircraft part life) while Equation 3 is used for non-beneficial criteria (repair cost) [37].

$$O = \begin{array}{c c} & \begin{array}{cccc} c_1 & c_2 & \cdots & c_m \end{array} \\ \begin{array}{c} o_1 \\ o_2 \\ \vdots \\ o_p \end{array} & \begin{pmatrix} n_{11} & n_{12} & \cdots & n_{1m} \\ n_{21} & n_{22} & \cdots & n_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ n_{p1} & n_{p2} & \cdots & n_{pm} \end{pmatrix} \end{array} \tag{1}$$

$$\text{Beneficial: } n_{ij} = \frac{r_{ij} - r_j^{min}}{r_j^{max} - r_j^{min}} \tag{2}$$

$$\text{Non-beneficial: } n_{ij} = \frac{r_j^{max} - r_{ij}}{r_j^{max} - r_j^{min}} \tag{3}$$

$$R_i^{WSMscore} = \sum_{j=1}^{m} w_j n_{ij}, \quad i = 1, 2, ..., p; \quad \text{with } \sum_{j=1}^{m} w_j = 1, \quad w_j \in (0, 1) \tag{4}$$

$$R_*^{WSMscore} = \max_i \sum_{j=1}^{m} w_j n_{ij} \tag{5}$$

Table 1: WSM model parameters

| Parameter | Description |
|---|---|
| $O$ | Performance matrix |
| $m$ | Total number of decision criteria |
| $p$ | Total number of repair options |
| $o_i$ | Repair option number $i$ |
| $c_j$ | Decision criteria number $j$ |
| $n_{ij}$ | Normalised performance rating of option $i$ with respect to criteria $j$ |
| $w_j$ | Weight of the relative importance of criteria $j$ |
| $r_{ij}$ | Performance rating of option $i$ with respect to criteria $j$ |
| $r_j^{max}$ | Maximum value of the performance ratings of criteria $j$ |
| $r_j^{min}$ | Mininum value of the performance ratings of criteria $j$ |
| $R_i^{WSMscore}$ | WSM Ranking score of repair option $i$ |
| $R_*^{WSMscore}$ | WSM Ranking score of the recommended repair option |

The following sections elaborate on the models used to generate the repair options $o_i$, the criteria weight vector $W = [w_1, w_2, ..., w_m]$, and the performance ratings $r_{ij}$ necessary to calculate the WSM ranking scores.

### 3.3 Identification of feasible repair options using BDT

To identify a complete list of repair options for a given structural damage scenario a BDT is used. This corresponds to step III of the DSS model. Feasibility is ensured by only generating options compliant with the information gathered from the SRM in Step I of the DSS. As previously explained, aircraft structural damages need immediate action, to ensure aircraft integrity and comply with regulations. When a structural damage is found, the aircraft needs to be grounded and the damaged part needs to undergo an immediate corrective repair before the aircraft can re-start normal operations. The immediate repair can be either temporary or permanent. If the immediate repair is temporary, a follow-up permanent repair needs to take place within regulated time limits found in the SRM.

A summary of all the possible maintenance repair or replace actions for externally-induced aircraft structural damages is gathered in Table 2. These have been identified as general options for any scenario, but their feasibility and the timeslots at which the actions can be performed depend on the operational conditions of each damage scenario. Options 1 and 5 correspond to temporary actions, which need to be followed up by a permanent repair or replace action. In the case of option 1, the temporary action is a repair on the original damaged part, which can be followed up by any of the permanent actions in Table 2, namely options 2, 3, or 4. On the other hand, in option 5 the original damaged structure is replaced temporarily by a leased part, while the original part is undergoing a permanent repair. Then, at a later timeslot $t_D$, the leased part is uninstalled and the permanently repaired original part is installed. Options 2, 3, and 4 correspond to permanent repair actions, which do not need a follow-up. Option 2 consists of a permanent repair on the original structure. Options 3 and 4 consider the replacement of the damaged structure. In option 3 the original structure is replaced by a spare part. A spare part is a part that is purchased new from a supplier. If the required spare part is not in stock, some time is required for its delivery. Depending on the severity of the damage in the original structure, the new spare part can be purchased at a discounted price by exchanging it for the original part. In option 4 the original structure is replaced by a part exchanged from another aircraft of the fleet. Such an option is used in practice when the donor aircraft is undergoing a C or D-check. The original aircraft can restart operations with the exchanged part, while the original damaged part will be installed in the donor aircraft once it is permanently repaired.

The described options are general to every situation. To determine the list of feasible solutions for a specific scenario, a BDT is created as shown in Figure 3. Each branch of the tree corresponds to different operational conditions, which are selected by the user answering simple yes/no questions. The order of the questions in the tree has been decided aiming to minimise the number of questions that need to be answered by the user. The BDT has two parts, depicted as two dashed rectangles. The green dashed rectangle corresponds to questions related to immediate conditions at $t_0$. This part of the tree is only answered once, as it is used to determine the immediate repair action, which needs to be executed at $t_0$. On the other hand, the questions in the blue dashed rectangle need to be repeated as many times as possible maintenance time-slots $t_{D_s} = [t_{D_1}, t_{D_2}, ..., t_{D_S}]$. The possible maintenance slots in which the non-routine tasks can be planned were identified in Step II of the DSS model. By gathering all the BDT output repair options lists (one per available deferred slot), the final list of all feasible repair options for a given scenario is generated. Once the immediate repair action has been executed and $t > t_0$, an immediate repair action option will not be needed anymore. As a result, the rightest branches of the BDT only have options at $t_D$ in contrast with the options at $t_0 + t_D$ observed in the left branches.

Table 2: List of the different types of maintenance options

| Maintenance Option | Type | Action | Follow-up | Time |
|---|---|---|---|---|
| **1** | Temporary | Repair on original | Permanent | Immediate |
| **2** | Permanent | Repair on original | None | Immediate or deferred |
| **3** | Permanent | Replace original with spare | None | Immediate or deferred |
| **4** | Permanent | Replace original with exchanged part | Install repaired original on donor aircraft | Immediate or deferred |
| **5** | Temporary | Replace original with leased part | Uninstall lease and install repaired original | Immediate and deferred |

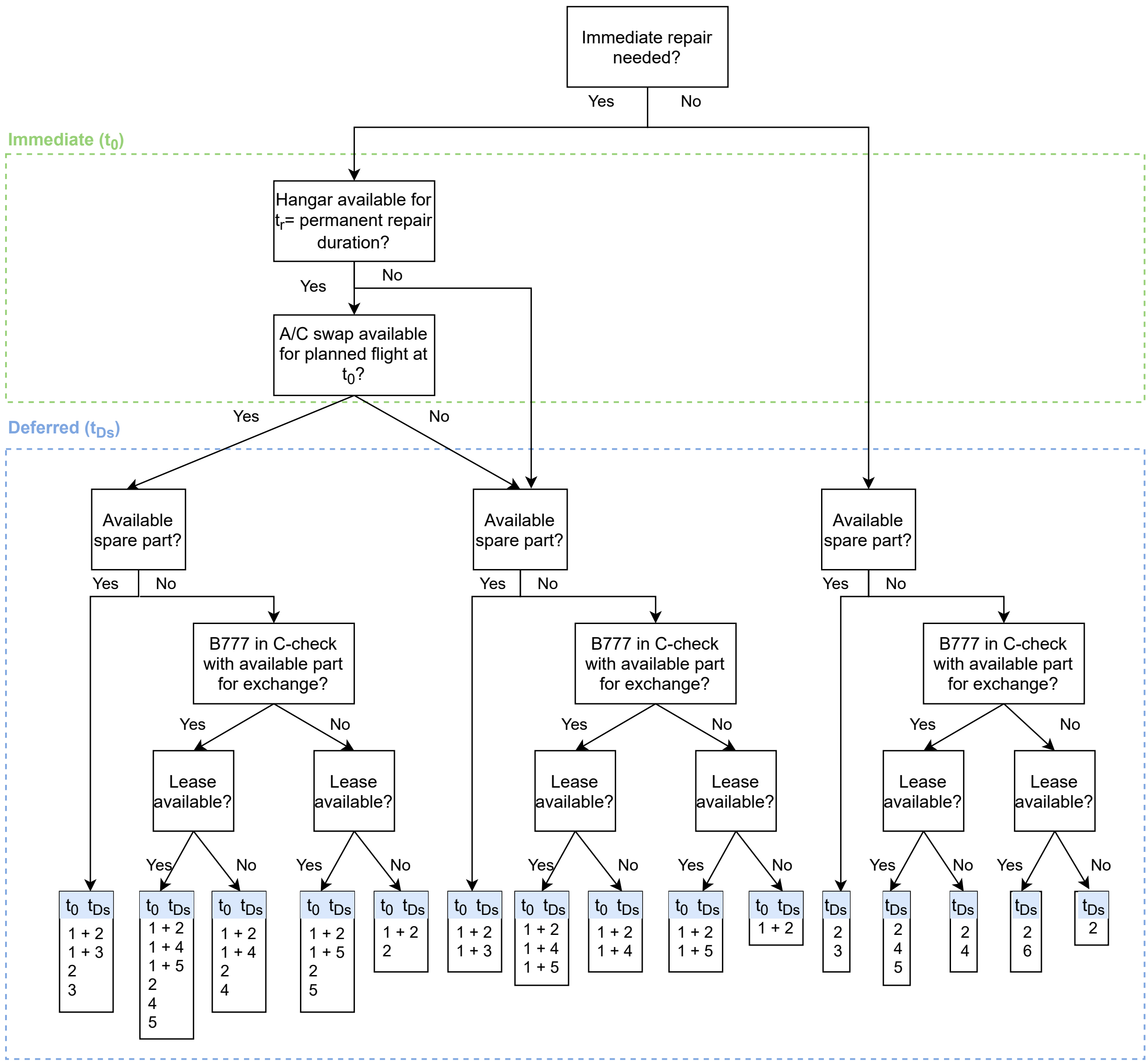


Figure 3: Boolean Decision Tree for non-routine maintenance option identification (based on Table 2)

### 3.4 Determination of criteria weight vector using the Bayesian BWM

This section elaborates on Step IV of the DSS model, explaining the approach followed to calculate the weight vector $W = [w_1, w_2, ..., w_m]$ introduced in Section 3.2. This step assesses the relative importance of the different criteria in the decision-making process and can have a big influence on the final recommended decision. In this study, a Bayesian BWM approach is selected as MCDM preference elicitation method. This method was recently developed by M. Mohammadi in 2020 [25] and it is based on the linear BWM model which was first developed by J. Rezaei [29]. The BWM is based on pairwise comparisons. The Bayesian approach is used in this study instead of the original BWM in order to account for group decision-making. This is decided as, in practice, different parties will be involved in the operational maintenance decision-making process.

Assuming $k = [1, 2, ..., K]$ decision-makers (DMs) evaluate a set of decision criteria $C = [c_1, c_2, ..., c_m]$ to find their relative importance, the main Bayesian BWM steps to find a standard group criteria weight vector $w^{agg}$ are summarised below. More details about the Bayesian BWM can be found in [25].

**Step 1** Each DM selects the most important (Best $c_B^k$) and least important (Worst $c_W^k$) criterion.

**Step 2** DM input pairwise comparisons of the best criterion $c_B^k$ compared to the other criteria. This generates the vector $A_B^k = [a_{B1}^k, a_{B2}^k, ..., a_{Bm}^k]$. $a_{Bm}^k$ refers to the relative importance of the best criterion $c_B^k$ when compared with another criterion $m$. The comparisons are given on a scale from 1 to 9, as indicated in Table 3.

Table 3: Scale used for the BWM pairwise comparisons.

| Importance values | Explanation |
|---|---|
| **1** | Both compared criteria have the same importance |
| **3** | Moderated favoured towards one criterion over the other |
| **5** | Essential or strong importance towards one criterion over the other |
| **7** | Demonstrated importance towards one criterion over the other |
| **9** | Absolute importance |
| **2, 4, 6, 8** | Intermediate values |

**Step 3** DMs input pairwise comparisons between every criterion compared to the worst criterion $c_W^k$. This generates the vector $A_W^k = [a_{1W}^k, a_{2W}^k, ..., a_{mW}^k]$. $a_{mW}^k$ refers to the relative importance of criterion $m$ when compared with the selected worst criterion $c_W^k$. The 1 to 9 scale shown in Table 3 is also used in this step.

**Step 4** The Bayesian model is described in this step. The graphical probabilistic model can be seen in Figure 4. The square nodes represent the model inputs from Steps 2 and 3, while the circle nodes represent the variables that will be estimated. The arrows represent dependency. this means that, for example, $w_k$ depends both on $A_W^k$ and $A_B^k$. The variables inside the blue rectangle are iterated for each DM. Based on this, the group decision joint probability distribution can be seen on the left-hand side of Equation 6. This is proved to be equivalent to the right-hand side of the equation after applying Bayes' theorem, the conditional independence shown in Figure 4, and the chain rule. Then, the distribution of each element on the right-hand side of Equation 6 needs to be specified. In his paper, Majid Mohammadi [25] proves that a multinomial distribution is appropriate to model $A_W^k|w^k$ and $A_B^k|w^k$ as stated in Equation 7 and Equation 8. The weight vector has two constraints: the values should sum one ($\sum w^k = 1$) and they should be non-negative ($w^k \in (0, 1)$). The Dirichlet distribution is an adequate distribution to model the weights, as it complies with these constraints. The last element that needs to be specified in Equation 6 is $w^k|w^{agg}$. This can be estimated as seen in Equation 9, where $w^{agg}$ is the distribution mean and $\gamma$ is the non-negative concentration parameter which is modelled using a gamma distribution with shape parameter a and scale parameter b. $w^{agg}$ is defined in Equation 10 as the prior distribution and is also modelled using a Dirichlet distribution. Its parameter $\alpha$ is equal to 1 as the prior distribution should be non-informative so that the effect on the posterior distribution is minimum. Finally, the posterior distribution is found using Markov Chain Monte Carlo methods, as the model does not have a close form solution [25]. The final output is the aggregated criteria weight vector $w^{agg} = [w_1, w_2, ..., w_m]$ and the posterior distribution of individual decision-makers.

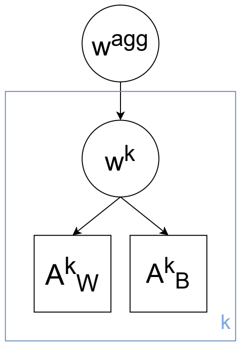


Figure 4: Graphical Bayesian BWM model adapted from [25]

$$P(w^{agg}, w^{1:K}|A_B^{1:K}, A_W^{1:K}) = P(w^{agg}) \prod_{k=1}^{K} P(A_W^k|w^k)P(A_B^k|w^k)P(w^k|w^{agg}) \tag{6}$$

$$A_W^k|w^k \sim \text{multinomial}(w^k) \tag{7}$$

$$A_B^k|w^k \sim \text{multinomial}(1/w^k) \tag{8}$$

$$w^k|w^{agg} \sim Dir(\gamma \times w^{agg}) \quad \text{with } \gamma = gamma(a, b) \tag{9}$$

$$w^{agg} \sim Dir(\alpha) \quad \text{with } \alpha = 1 \tag{10}$$

**Step 5** Finally, a credal ranking is generated. The credal ranking is a set of all the criteria pairs $(c_i, c_j)$ ranked. Furthermore, it shows to which extent the DMs prefer certain criterion over another $(P(c_i > c_j))$. This is important in the maintenance decision-making problem at hand, to understand how certain the superiority of one criterion over another is, in a context where different DMs can differ significantly in opinions. The confidence of $c_i$ being superior to $c_j$ is calculated with Equation 11, where Q is the total number of MCMC samples from $P(w^{agg})$ (posterior distribution of $w^{agg}$). The confidence level $c_i > c_j$ is complementary to the confidence of $c_j > c_i$ as can be seen in Equation 12 [25]. This means that if, for example, criterion $c_i$ is more important than criterion $c_j$ with a confidence of 0.90, the confidence of criterion $c_j$ being more important than criterion $c_i$ is 0.10. Therefore, one criterion $c_i$ is superior to another criterion $c_j$ when the confidence level $P(c_i > c_j)$ is higher than 0.5.

$$P(c_i > c_j) = \frac{1}{Q} \sum_{q=1}^{Q} I_{(w_i^{agg_q} > w_j^{agg_q})} \text{with } I = \begin{cases} 1, & \text{if } w_i^{agg_q} > w_j^{agg_q} \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

$$P(c_i > c_j) + P(c_j > c_i) = 1 \tag{12}$$

## 3.5 Rating of the repair options w.r.t. the decision criteria

This section elaborates on Step V of the DSS model. It explains the approach followed to calculate the performance ratings $r_{ij}$ which are used to calculate the WSM ranking scores. As was explained in Section 3.2, these ratings are normalised afterward using the linear min-max normalisation technique. The tool is data-driven as the performance ratings are determined based on historical non-routine maintenance data. The following sections will elaborate on the modelling approach for each of the different decision criteria: reliability, cost, availability, and structure life.

### 3.5.1 Criterion 1: Aircraft part reliability

The first criterion considered in the decision support tool is component reliability. The performance rating for this criterion consists of the probability of the damaged structure not experiencing a failure from the moment of the initial repair action until the next repair opportunity after the structure has undergone permanent maintenance. To calculate these probabilities for each repair option, a stochastic point process model is used, namely the Generalised Renewal Process (GRP) [20]. Perfect repairs (as-good-as-new) or imperfect repairs (as bad as old) are the most common assumptions for reliability analysis in literature. These assumptions are modelled using the Homogeneous Poisson Process (HPP) and the Non-Homogeneous Poisson Process (NHPP) respectively [26]. However, in practice, most repairs are imperfect and will restore the structure to a worse than new better than old condition. The GRP can model this type of imperfect repairs in repairable systems using the concept of virtual age and repair effectiveness [31]. Modelling imperfect repairs is of specific interest in this research, as different types of repair and replace options present different repair effectiveness.

The structure virtual age is calculated with Equation 13, which is known in reliability analysis literature as Kijima Type II model [19]. From this formula, it can be seen that a repair effectiveness $q$ of 1 corresponds to a minimal repair while a repair effectiveness $q$ of 0 corresponds to a perfect repair. Values between 0 and 1 refer to imperfect repairs. The closer to 0, the more effective the repair was to restore the structure to as-good-as-new state. The repair effectiveness values assumed for the different repair types considered in this study are gathered in Table 4.

$$V_n = q \cdot (V_{n-1} + X_n) \quad \text{with } X_n = t_n - t_{n-1} \tag{13}$$

Table 4: Repair effectiveness assumptions for GRP model

| **Maintenance type** | **Repair effectiveness $q$** |
|---|---|
| 1. Temporary repair on the original part | 0.9 |
| 2. Permanent repair on the original part | 0.3 |
| 3. Replace by spare part | 0.1 |
| 4. Replace by exchanged part | 0.5 |
| 5. Replace by lease | 0.2 |

To calculate the reliability performance rating of each of the repair options generated by the BDT Equation 14 is used [24]. For the repair options consisting of two repair actions, for example, a temporary repair action at $t_0$ and a permanent repair action at $t_D$, the final rating is calculated by multiplying the individual survival probabilities, as repair intervals can be assumed to be independent [10, 33]. In this example, the individual intervals considered are [$t_0$,$t_D$] and [$t_D$,$t_{AorC}$], with $t_{AorC}$ being the time at which the next A or C check is scheduled for the aircraft under consideration after the permanent repair option is executed. The given formula assumes a Weibull distribution able to model deteriorating and improving failure behaviour. However, by using a different formula for the intensity function $\lambda(V_n)$ different distributions can be used. More information on the reliability analysis can be found in Appendix 2.

$$P(N(V_n) = k) = \frac{e^{V_n \lambda(V_n)} (V_n \lambda(V_n))^k}{k!} \quad \text{with } \lambda(V_n) = \frac{\beta}{\theta} (\frac{V_n}{\theta})^{\beta-1} \tag{14}$$

### 3.5.2 Criterion 2: Total repair cost

This section will elaborate on how the total repair cost criterion performance rating is calculated. The total repair cost consists of the total cost of the immediate repair action at $t_0$ and the cost of the deferred repair actions at $t_{D_s} = [t_{D_1}, t_{D_2}, ..., t_{D_S}]$, as can be seen in Equation 15. For deferred costs, an inflation factor is added to each deferred maintenance cost depending on the aircraft operating time until the deferred slot. The yearly inflation rate is assumed to be 3%. Such inflation rate has been used before in literature to determine aircraft maintenance costs [23]. In Equation 15, the units of the aircraft operating time until the deferred slot $t_D$ are FC. Therefore, $t_D$ is divided over the aircraft yearly utilization to get the operating time in number of years instead of FC, to be able to apply the yearly inflation rate. If the exact aircraft utilization value is not available for a given scenario, an average value calculated from historical fleet data is assumed.

$$\text{TotalCost} = \text{ImmediateCost}_{t_0} + d \sum_{s=1}^{S} (\text{DeferredCost}_{t_{D_s}} * (1+i)^{\frac{t_{D_s}}{u*365}}) \tag{15}$$

where:

| | | |
|---|---|---|
| $\text{ImmediateCost}_{t_0}$ | = | Direct and indirect maintenance costs of repair actions at $t_0$ |
| $\text{DeferredCost}_{t_{D_s}}$ | = | Direct and indirect maintenance costs of repair actions at $t_{D_s}$ |
| $i$ | = | 0.03 [Yearly inflation rate] |
| $t_{D_s}$ | = | Operating time until deferred maintenance slot [FC] |
| $u$ | = | Aircraft Utilization [FC/day] |
| $d$ | = | $\begin{cases} 1, & \text{if there are deferred maintenance tasks} \\ 0, & \text{if there are only immediate maintenance tasks} \end{cases}$ |
| $S$ | = | Total number of deferred maintenance slots |

Both immediate and deferred repair costs are composed of two main elements, Direct Maintenance Cost (DMC) and Indirect Maintenance Cost (IMC). The approach to calculate DMC is shown in Equation 16. The DMC is composed of the total labor costs and the materials & equipment cost for the required repair, which are scenario and airline-specific. The total labour cost is dependent on the number of man-hours necessary to complete the repair. The approach proposed to calculate the IMC is shown in Equation 17. Downtime is the main driver of the IMC. It refers to the time the aircraft is out of operations due to maintenance. The required man-hours used to calculate the labour cost in the DMC equation differs from the aircraft downtime. For example, in a scenario where a required number of man-hours is required to complete a given repair, extra personnel can be allocated to the repair which reduces the downtime.

$$DMC = MMH \cdot LR + MMC + SC + LC \tag{16}$$

where:

| | | |
|---|---|---|
| $DMC$ | = | Direct Maintenance Cost |
| $MMH$ | = | Maintenance Man-Hours (Including repair and installation hours if applicable) |
| $LR$ | = | Labour Rate |
| $MMC$ | = | Material & Machining costs for perm repair (if applicable) |
| $SC$ | = | Spare part cost (if applicable) |
| $LC$ | = | Lease costs (if applicable) |

$$IMC = \text{HangarRate} * \text{Downtime}/t_{shift} + (\text{TowCost} + \text{HangarInOutCost}) * \text{HangarVisits} \tag{17}$$

where:

| | | |
|---|---|---|
| HangarRate | = | Costs for parking in the maintenance hangar per shift |
| $t_{shift}$ | = | Hours per hangar shift |
| Downtime | = | Aircraft time out of operations in hours (including repair, installation and waiting times) |
| TowCost | = | Cost of towing aicraft to hangar |
| HangarInOutCost | = | Cost of taxiing in and out of the hangar |
| HangarVisits | = | Number of hangar visits |

#### 3.5.3 Criterion 3: Aircraft availability

The third criterion considered in the DSS aims to maximise aircraft availability during high season months. Non-routine structural damages occurrence is characterised by its lumpy or intermittent nature. Its prediction is difficult which complicates the objective of maximising the aircraft availability avoiding unnecessary downtime due to, for example, lack of hangar availability or unavailability of spare parts and equipment. In practice, non-routine temporary repairs are scheduled in a demand-driven manner due to the described random nature of externally-induced aircraft damages and the need for an immediate repair action. Therefore, no direct relation is found between the schedule of non-routine temporary repairs and the seasonality of the airline industry. In contrast, a relation can be found between airline seasonality and the scheduling of non-routine permanent repairs. This is because non-routine permanent repairs which follow an immediate temporary repair are deferred and, therefore, have more flexibility in terms of scheduling. This flexibility drives non-routine permanent repairs to be scheduled preferably during the airline's low season. This way, aircraft availability can be maximised during high season months when the aircraft utilisation is higher, thus reducing downtime costs.

This concept is the motivation for calculating the performance ratings of the availability criterion of the DSS. The rating is calculated using fleet operational historical data and, therefore, is airline and fleet specific. Each month will receive a rating proportional to the amount of historical non-routine permanent repairs that were scheduled in that month compared with the rest of the months of the year. This, as explained in the last paragraph, is assumed to be a good indicator of the most preferable months to undergo maintenance in terms of maximisation of aircraft availability.

### 3.5.4 Criterion 4: Part life

The fourth criterion aims to maximise the aircraft part life of the aircraft structural part. Maximising this part life is important as it will contribute to long-term cost reductions [3]. The damage repair information including the time limits of the repairs is retrieved from the SRM in Step I of the DSS. After a temporary repair, the damaged structure should undergo permanent maintenance (repair or replace) within those specified time limits. The time limits are given in FC. FH and CD. The limit that is met first will drive the constraint. These limits are maximum values, which means that the permanent maintenance can be performed anytime as far as it is before the limit. The different repair options generated using the BDT undergo maintenance at different moments. Although every option is compliant with the airworthiness repair and replace limits, the closer to the limit the repair or replace is performed the longer the aircraft part life. The rating of this criterion is determined using FC as the metric. The ratings are calculated as the difference in flight cycles between the final repair action and the damage event $t_{D_s} - t_0$.

## 3.6 Dynamic framework

As stated in the research objective, the DSS should adapt to the dynamic operational environment. Therefore, the initial DSS output is updated when operational conditions change, following the approach proposed in Figure 5. The yellow rectangles correspond to the execution of a repair action, the blue rectangles show the moment in which the DSS model is run and, the purple rectangles indicate time updates. After the damage, the DSS model showed in Figure 2 is run for the first time. The output of the DSS is a selected repair option including, if applicable, an immediate repair action at $t_0$ and a deferred repair action at $t_D$. Structural aircraft damages need to be repaired when found due to regulations and, thus, an immediate repair action at $t_0$ is required. If the immediate repair action is permanent, the selected repair is executed and the solution is reached. However, the immediate repair action can also be temporary. A temporary repair option at $t_0$ will also include a deferred permanent repair action at a selected time-slot $t_D$. As can be seen in Figure 5, if the operational conditions change before the execution of the deferred option at $t_D$, the DSS will be rerun and a new deferred repair option recommendation will be generated. Depending on the scenario, the updated recommendation can be the same. The DSS model Steps I and IV showed in Figure 2 are only applicable to the first time the model is run as indicated in Figure 5. When running the model for a dynamic update of the decision recommendation only Steps II, III, V, and VI are run. Step I does not need to be run again, as the damage information and repair limits are constant for each individual damage scenario. The criteria weights are also assumed to remain constant through the decision in order to achieve consistency of priorities and company policy preferences. Therefore, Step IV is also skipped after the first run.

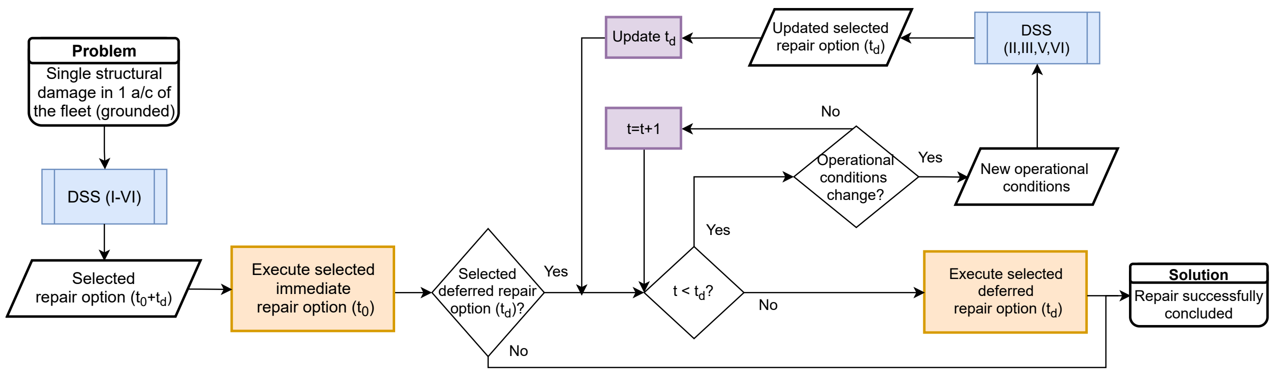


Figure 5: DSS dynamic approach

The dynamic decision-making approach refers to a single structural damage in one aircraft of the fleet. In practice, in the time from $t_0$ to $t_{D_s}$ the same or other aircraft of the fleet can experience other damages, possibly simultaneous. These aircraft damages scenarios will then compete for limited resources. To approach this challenge, a heuristic approach is used to prioritise the recommended repair options. Imagine the following situation: two aircraft of the fleet experience an unexpected damage. Both aircraft get recommended a deferred repair option at the same timeslot $t_{D_1}$. However, $t_{D_1}$ only has a capacity for one aircraft which means that only one of the competing aircraft can be allocated to this timeslot. The recommendation for the other aircraft needs to be at another deferred time slot $t_{D_2}$. Maximisation of the sum of ranking scores of both aircraft is used to decide which timeslot is recommended to each aircraft. In the example, the ranking score of AC 1 at $t_{D_1}$ plus the ranking score of AC 2 at $t_{D_2}$ is compared to the ranking score of AC 2 at $t_{D_1}$ plus the ranking score of AC 1 at $t_{D_2}$. The highest sum drives the recommended options. This heuristic algorithm can be extended to any real-life dynamic scenario with a different number of damaged aircraft and different capacity constraints. An example of such a scenario is shown in the results section.

# 4 Case study

To validate whether the proposed DSS method improves the situational awareness of the operational maintenance decision-maker, the tool is evaluated using a real-world case study corresponding to a B777 fleet of a major European airline. Specifically, the scenario of an unexpected structural outboard flap failure of a B777 is considered. First, assuming a static scenario and then, assuming a dynamic scenario with competing resources. The coming section explains the data considered and the main assumptions taken. Then, the decision-making process that occurred in the real-life scenario is described.

## 4.1 Fleet historical data and main assumptions

A historical database of the failure events of a B777 fleet leading to non-routine maintenance is used to determine the data-driven criteria performance ratings described in Section 3.5. The used database contains failure data leading to non-routine tasks of a B777 fleet spanning 14 calendar years since fleet introduction. Before the analysis, the database was processed and assumptions were made. The main assumptions include:

- Entry to service data of the fleet was extracted from an external source[1]. This data was essential for determining the start of the observation period for each aircraft tail which was used in the reliability analysis. It is assumed that all the aircraft structures are in a as-good-as-new state when they first start operations after being delivered to the airline.
- To calculate the time of occurrence of a failure event the repair date is used. The repair date is assumed to be equal to the date of occurrence of the structural damage, as this information is not available in the dataset and structural damages are typically repaired (temporarily or permanently) immediately before resuming operations.
- The observation period is time truncated as the data is only collected from the start of the fleet operations until the $31^{st}$ of December 2015. The exact time of the next failure after the end day of observations is unknown. This generates right-censored data, which is defined as the time from the last recorded failure until the end of the time truncated observation.
- Aircraft utilization of the fleet is assumed to be 1.48 FC/day which is the average value for one aircraft of the fleet. This value was found by analysing the individual aircraft utilization of each tail number of the fleet over the observation period. The period considered to calculate this number includes some time in which the aircraft is not operating, for example, due to routine and non-routine maintenance. Therefore, this value is an underestimation and the actual aircraft utilization during operating time is higher. This value is used as it represents reality better when used to determine costs over a determined range of time.
- The repair time is assumed to be negligible. This is a valid assumption that is often taken in aircraft maintenance reliability analysis. It is acceptable because the time to perform a non-routine repair is considerably small when compared to the structure's interarrival times $X_n$ which are the times between repairs in FC.
- A superimposed system is assumed for the reliability analysis. This means that all the aircraft of the fleet are assumed to be identical units. This is a reasonable assumption, given that only one aircraft type of the considered airline is analysed.

## 4.2 Real-world repair decision-making

The decision taken in real life regarding the non-routine repair of the outboard flap damage considered in the case study is summarised in Table 5. It can be noticed that the non-routine aircraft maintenance decision-making approach taken in real life is unstructured. Although operational conditions did not change throughout the 44 days, the repair decision was changed 3 times and 3 different options were considered at different points in time, with one of them being considered and rejected twice. The dynamic update of preferences did not follow a clear quantitative approach based on analysis and comparison between different options. Additionally, there was not a clear reason when to reconsider a taken decision. Although the exact total time spent on

[1] https://www.planespotters.net/airlines

decision-making in this real-life scenario is unknown, a substantial amount of labour-hours were required to arrive at a final repair decision [9]. This time can be reduced significantly using a structured decision-making approach.

Table 5: Real-world decision-making steps iteration

| **Timeline** | **Repair Option Immediate** | **Action** |
|---|---|---|
| Day 0 | | Damage found |
| Day 1 | Temporary at 0 FC + Permanent at 30 FC | Option considered and selected.<br>Temporary action executed. |
| Day 2 | Lease at 30 FC + Permanent at 40 FC | Option considered |
| Day 3 | Lease at 30 FC + Permanent at 40 FC | Option rejected |
| Day 15 | Permanent at 30 FC | Option cancelled |
| Day 16 | Exchange at 40 FC<br>Lease at 30 FC + Permanent at 40 FC<br>Perrmanent at 40 FC | Option considered<br>Option considered<br>Option considered and selected |
| Day 31 | Exchange at 40 FC | Option considered and selected |
| Day 34 | Exchange at 40FC | Permanent repair start execution |
| Day 44 | Donor aircraft receives repaired part | Permanent repair finished |

# 5 Results

This section will present the results of applying the proposed DSS to the case study described in Section 4.

## 5.1 Step I Collect damage information

Information of the specific temporary or permanent non-routine tasks necessary to bring the component back to operations is retrieved in this stage. This information, together with necessary airworthiness limits, is retrieved in the SRM documentation given that the damage location and its severity are known. In this specific case study, a temporary repair of the structure is possible according to the SRM. However, if the structure is repaired temporarily, it should then be repaired or replaced permanently within 400 FC.

## 5.2 Step II Identify maintenance timeslots

A-checks of this particular fleet are scheduled every 200 FC, while C-checks are scheduled every 1500 FC. At the moment of the outboard failure flap considered, the aircraft did 170 FC since its last A-check and 1200 FC since its last C-check. Furthermore, the deferred maintenance timeslots generated by DSS need to be within the 400 FC inspection limits found in Step I. Furthermore, from the maintenance schedule, another opportunity to perform maintenance in the aircraft is found at 40 FC. With this data, the model generates the possible timeslots, which can be visualised in the timeline presented in Figure 6.

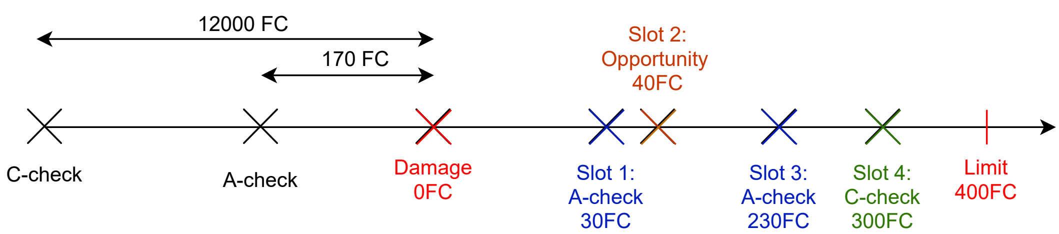


Figure 6: Identified maintenance timeslots for case study

## 5.3 Step III Generate a list of repair options

The next step is to generate a list of possible options for the given scenario. As four deferred maintenance timeslots were identified in Step II, the blue rectangle in the BDT is run 4 times. The resulting list of feasible options can be seen in Table 6. It is interesting to notice that the proposed BDT generates the repair options in a structured and exhaustive way. This leads to 1) identification of all possible repair options at $t_0$ and 2) the generation of repair options that were not even considered in the real-life scenario (such as options F, G, H, and I), increasing the overall situational awareness of the planners regarding the operational maintenance situation.

Table 6: List of repair options for case study

| Repair Option | 0FC | 30FC | 40FC | 230FC | 300FC |
|---|---|---|---|---|---|
| A (1+2) | Temporary | Permanent | | | |
| B (1+4) | Temporary | Exchange | | | |
| C (1+5) | Temporary | Lease | | | |
| D (1+2) | Temporary | | Permanent | | |
| E (1+4) | Temporary | | Exchange | | |
| F (1+2) | Temporary | | | Permanent | |
| G (1+3) | Temporary | | | Spare | |
| H (1+2) | Temporary | | | | Permanent |
| I (1+3) | Temporary | | | | Spare |

## 5.4 Step IV Generate criteria weights

Aircraft maintenance expert opinions were gathered through a questionnaire. The questionnaire was used to make an informed decision on the relative importance of decision criteria used in the tool and estimate an insightful criteria weights vector. The questionnaire was filled in by 10 industry and academia experts, with an average experience in the sector of 10 years. The sample size of 10 is considered significant to drive insightful conclusions, as the optimal number of expert opinions according to literature is between 5 to 10 [34]. More information about the questionnaire can be found in Appendix 1. Figure 7 shows the resulting credal ranking based on the questionnaire answers. The numbers in Figure 7 indicate the confidence level $P(c_i > c_j)$. For example, the availability criterion is more important than the reliability criterion with a confidence level of 0.83. It can be noticed that the lower confidence level is 0.6 between the part life and cost criterion. This indicates that the superiority relation between this pair of criteria is less certain than the relation between other pairs of criteria. The criteria in Figure 7 are visually ordered by importance from top to bottom, top being the most important and bottom being the least important. Therefore, the results show that maximisation of aircraft availability is considered by industry experts as the most important decision criteria, followed by part reliability. On the other hand, the direct repair cost is considered the least important criterion when taking operational maintenance decisions. The final criteria weights vector generated using the Bayesian BWM are shown in Table 7.

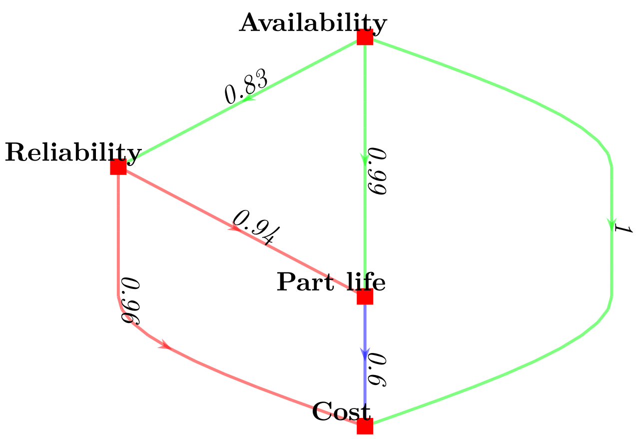


Figure 7: Credal ranking for decision criteria.

Table 7: Bayesian BWM aggregated criteria weight vector

| Criteria | Reliability | Repair Cost | Availability | Part life |
|---|---|---|---|---|
| $w^{agg}$ | 0.2802 | 0.1809 | 0.3460 | 0.1929 |

In Figure 8 a boxplot of the individual experts' criteria weights is shown. It is interesting to notice that every criterion has been selected at least once as the most important criterion by the individual experts. This validates the relevance of the chosen criteria and the existence of different individual preferences when accounting for competing criteria in an operational maintenance scenario. This boxplot also gives maximum and minimum values for each criteria weight that can be used to perform a sensitivity analysis.

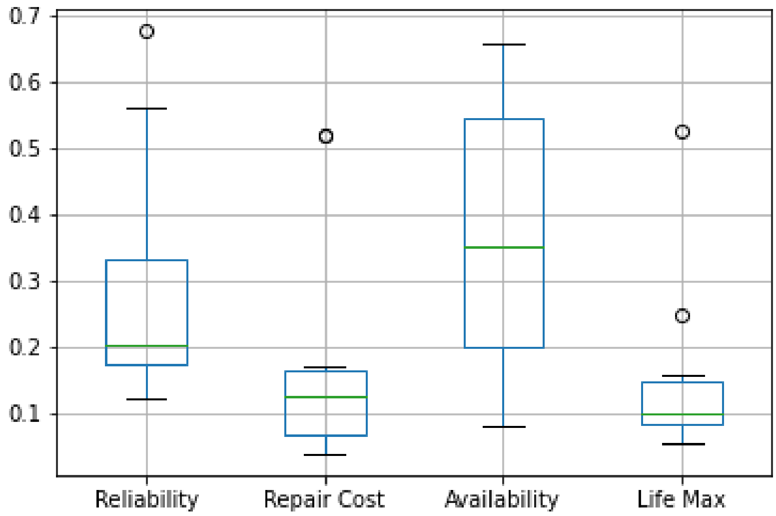


Figure 8: Boxplot of criteria relative importance weights

## 5.5 Step V Generate performance ratings

The individual criteria performance ratings for each option are calculated following the approach explained in Section 3.5. The repair cost and part life criteria can be calculated straightforwardly following the indicated approach. Specific cost data cannot be shared due to confidentiality reasons. For the other two criteria, namely reliability and availability, an analysis of the historical database is required in order to compute the performance ratings for each option. Results following from that analysis are shown in this section.

### 5.5.1 Reliability

Each part of the aircraft follows a different failure pattern. In this case study, the historical dataset is filtered for outboard flap failures and the interarrival times between repairs for each aircraft tail are retrieved. The total number of flap failure events in the clean database is 44. Two sets of data are generated: one including right-censored data and another one excluding it. Censored data in reliability analysis refers to data for which the exact failure time is unknown. There can be both left-censored and right-censored data. Right-censored data refers to failures occurring after the observation period and left-censored data refers to failures occurring before the observation period. In this case study, only right-censored data is applicable, as the observation starts at the beginning of fleet operations and ends at an arbitrary date ($31^{st}$ of December 2015). Therefore, if the last failure event of a flap was for example on the $31^{st}$ of December 2014, it is known that this flap has survived for at least one year, but it is unknown how much longer it survived. This data is called right-censored data.

Once the failure event data is generated, twelve different distributions are fitted into the data. The best-fitting distribution is selected using a goodness-of-fit-test. The distributions are fitted to two datasets: one including right-censored data and another one excluding it. When the right-censored data is included in the reliability analysis, the best fitting distribution for flap failures corresponds to the exponential distribution. This distribution indicates a random and constant failure rate. This makes sense as the failure mode used in this study is externally-induced structural damages, which are normally characterised by their stochastic nature. However, in practice right-censored data is rarely used for reliability analysis, as considering the failures without right-censored data gives a more conservative solution which is preferred by airlines. Therefore, right censored data is not further considered in this study.

The histogram of the fitted distributions for the dataset not including right-censored data can be seen in Figure 9. The Probability Density Function (PDF) fit is shown in the left plot and the Cumulative Distribution

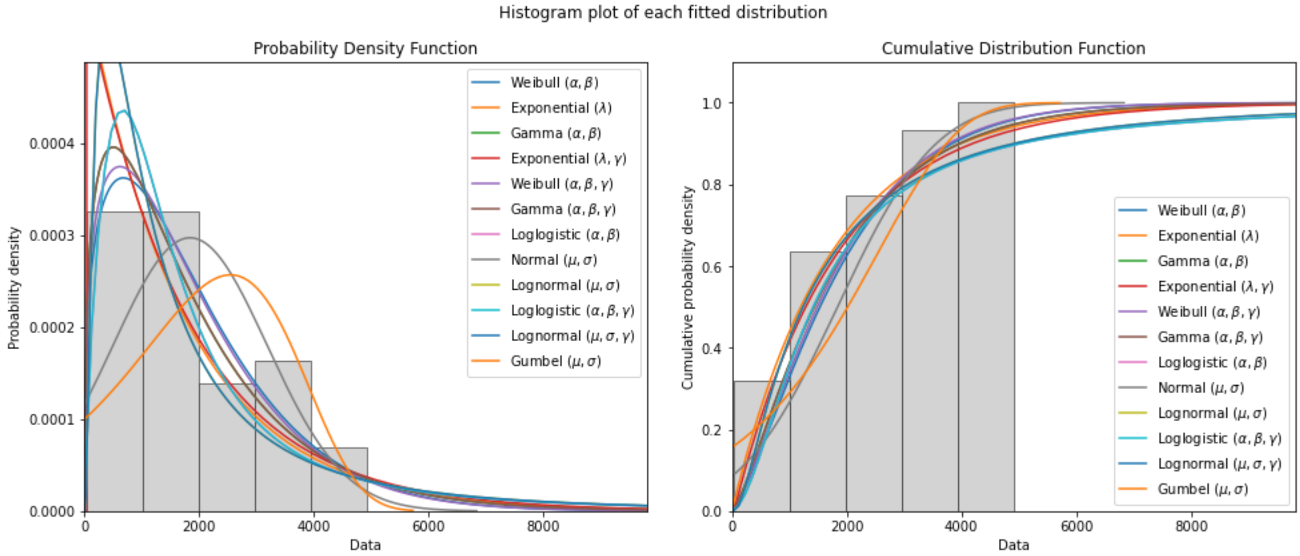


Figure 9: Histogram of the fitted distributions to the flap failure event data

Function (CDF) in the right plot. The different distributions are ordered in the legend from top to bottom based on a goodness-of-fit test. The top distribution is the best fit and the bottom distribution is the worst fit. It can be observed that in this dataset the best fitting distribution becomes the Weibull distribution, which will be selected for this case study. The probability plot showed in Figure 10 indicated how well the Weibull CDF models the failure data (black dots). It is observed that only around 30 % of flaps fail before 1000 FC and that failures occurring between 1000 FC and 5000 FC are more common. The parameters of the Weibull distribution are estimated using the Maximum Likelihood Estimator (MLE) method. The resulting parameters can be seen in Table 8, including the confidence levels. The Weibull distribution has a beta parameter larger than 1, which indicates an increasing failure rate over time. This makes sense as it indicates deteriorating behaviour. As explained before, by deleting right-censored data, a more conservative assumption is to be expected. This deteriorating behaviour ($\beta > 1$) is maintained when considering both the lower and the higher confidence interval of the parameter estimation in Table 8. Once the distribution and its parameters have been estimated, the survival probabilities for the performance criteria rating can be calculated as explained in Section 3.5. It is assumed that the virtual age of the flap at the last repair event before the damage $V_{n-1}$ is its real age at that moment in FC. This is assumed as the specific repair history of the case study's damaged structure is unknown.

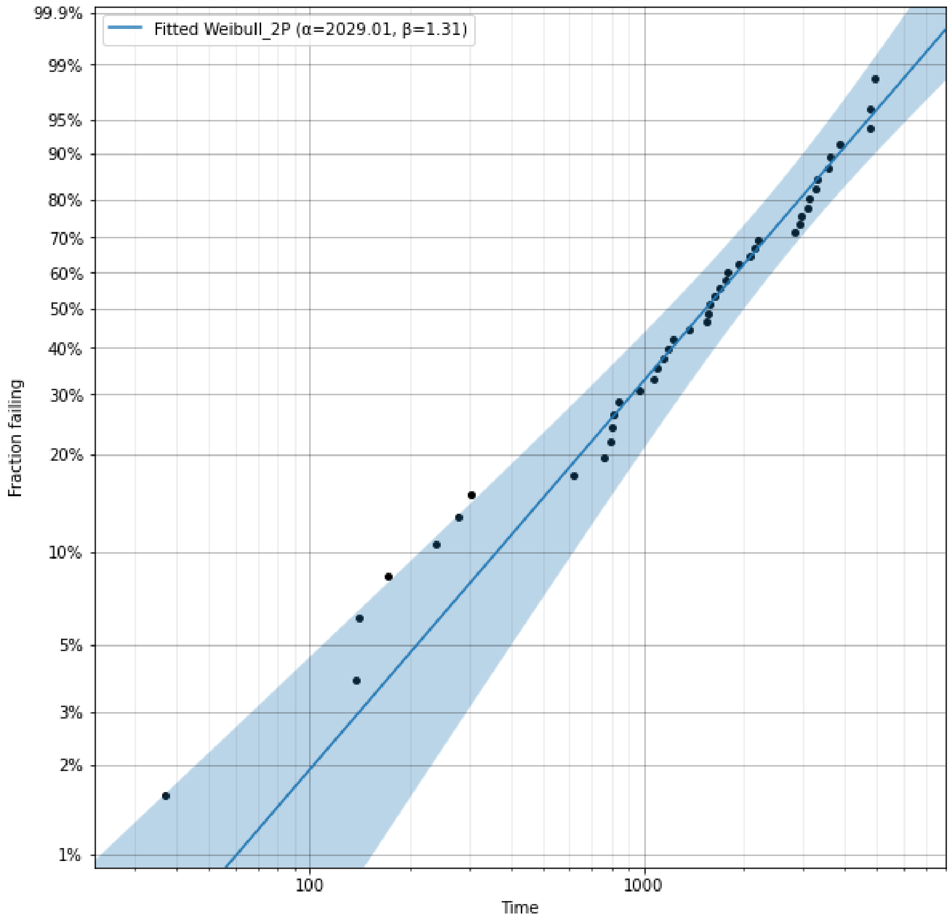


Figure 10: Probability plot of fitted Weibull distribution

Table 8: Weibull distribution parameter estimation for flap failures using MLE

| Reliability Parameter | Point Estimate for Flap | Standard Error | Lower CI | Higher CI |
|---|---|---|---|---|
| $\beta$ | 1.31 | 0.16 | 1.03009 | 1.6659 |
| $\theta$ | 2029.01 | 247.95 | 1596.86 | 2578.11 |

### 5.5.2 Availability

A seasonal rating is created by analysing the permanent repairs schedule pattern in the considered fleet. This rating can be seen in Figure 11. The values in the figure consider every year of observed operations and have been normalised due to confidentiality reasons. A similar seasonal pattern is observed for each year of operations. It can be observed that April is the month in which more non-routine permanent repairs have been scheduled, followed by November. On the other hand, August, followed by July and December, are the months which experience the least amount of scheduled non-routine permanent tasks. This validates the assumption made regarding the benefits of scheduling non-routine permanent repairs during low season months, to maximise aircraft availability during high season months. Using the historical data each month receives an individual rating which is used to generate the availability criterion performance ratings for each repair option.

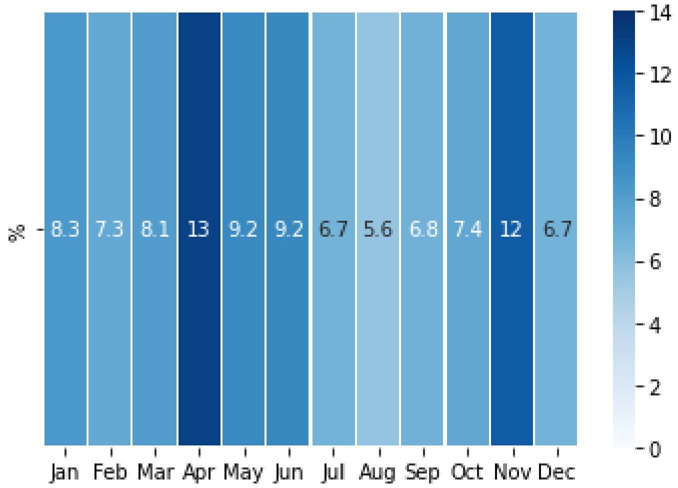


Figure 11: Non-routine permanent repairs distribution per month

### 5.6 Step VI Rank decision options

After evaluation of each criterion for each repair option, the MCDM matrix is generated and shown in Equation 18. The values in this matrix are normalised using min-max normalisation. Options rated a 1.0 are the most beneficial for the given criteria while options rated a 0.0 are the least beneficial. WSM is applied to the matrix and the final ranking of the repair options is shown in Figure 12. This represents the DSS recommendation, which is presented to the decision-maker. The decision-maker can then make an informed decision considering the overall scenario and input the final selected repair option in the system. In this case, the recommended option is option F, which consists of a temporary repair at 0 FC followed by a permanent repair on the original damaged part during the A-check timeslot at 230 FC. It is important to notice that although this preferred option is operationally possible and compliant with airworthiness requirements, the option was never considered in real life as seen in the real-world repair decision-making shown in Section 4.2.

Running the DSS to arrive at the first initial recommendation takes 2 minutes including the calculation of the standard criteria weight vector. This computational time can be reduced significantly when fewer decision-makers are involved in the decision, as the Bayesian BWM aggregated weight vector computation drives 90 % of the computational time. The criteria weights only need to be calculated once for a given fleet and airline, as different decisions should keep a consistent approach regarding criteria importance. In addition, a few extra minutes are required to account for providing the user inputs. Depending on the scenario a few additional labour-hours may be required to gather the necessary data such as, for example, checking whether a spare or lease part are available. The DSS provides clear instructions to the user about the required input data for an exhaustive option identification and evaluation. In real-life industry practices, this decision-making process is unstructured and can take up to several days.

If the operational conditions do not change until the selected repair option is executed, the DSS support will finish here. If operational conditions change, the dynamic algorithm presented in Section 3.6 is used to update the recommendation as shown in the next section.

$$
\begin{array}{c c}
 & \begin{array}{cccc} \text{Reliability} & \text{Repair Cost} & \text{Availability} & \text{Part Life} \end{array} \\
w_j & \begin{array}{cccc} 0.2802 & 0.1809 & 0.3460 & 0.1929 \end{array} \\
\begin{array}{c} n_{Aj} \\ n_{Bj} \\ n_{Cj} \\ n_{Dj} \\ n_{Ej} \\ n_{Fj} \\ n_{Gj} \\ n_{Hj} \\ n_{Ij} \end{array} &
\begin{bmatrix}
1.0 & 1.0 & 0.0 & 0.0 \\
0.5812 & 1.0 & 0.0 & 0.0 \\
0.8876 & 0.2758 & 0.0 & 0.0 \\
0.9768 & 0.9995 & 0.4347 & 0.0370 \\
0.5587 & 0.9995 & 0.4347 & 0.0370 \\
0.1916 & 0.9900 & 1.0 & 0.7407 \\
0.7485 & 0.0085 & 1.0 & 0.7407 \\
0.0 & 0.9865 & 0.6231 & 1.0 \\
0.5487 & 0.0 & 0.6231 & 1.0
\end{bmatrix}
\end{array}
\tag{18}
$$

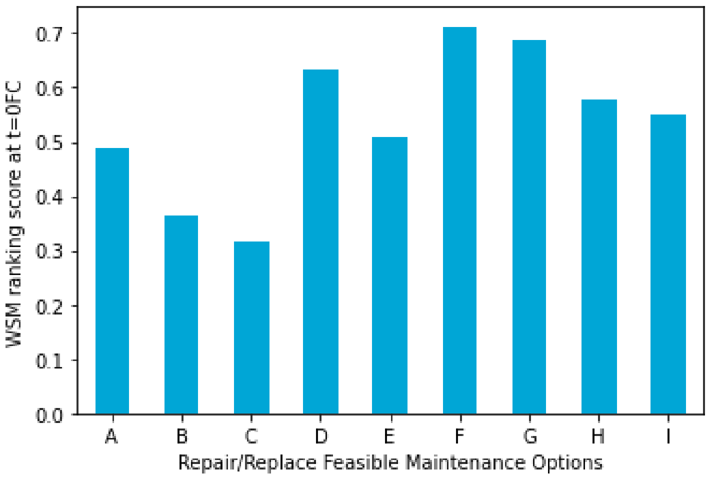


Figure 12: Ranking of repair/replace maintenance options at $t_0$ for flap failure scenario in August

### 5.7 Dynamic scenario

If the operational conditions do not change the recommended option remains constant until the selected option is executed. However, if operational conditions change at least 2 FC before the execution of the selected option, the DSS runs again and updates its recommendation. The threshold of 2 FC is selected for this scenario as it corresponds to approximately 1 day of operations. Changing the planned maintenance action within this threshold will cause major disruptions and, therefore, the DSS will not reconsider the selected option when operational conditions change within this threshold unless the selected repair option becomes unavailable as a consequence of the operational changes. In the real-life scenario presented in Table 5, the operational conditions did not change throughout the 44 days between the damage discovery and the final repair action execution. The selected and executed permanent repair option corresponded to exchanging a flap from a donor aircraft at the deferred timeslot at 40 FC. Then, the donor aircraft received the permanently repaired original damaged part at a later timeslot on day 44. It is unknown whether the operational conditions change after the 40 FC timeslot for this case study. This is because options after 40 FC were not considered in real life. To show how the proposed DSS adapts dynamically to a changing environment with competing resources a dynamic scenario is modelled and analysed in this section.

The dynamic scenario and its results are presented in Table 9. It is assumed that at 100 FC another aircraft of the fleet experiences a flap damage and that the decision-maker selected the recommended option for execution after the first recommendation. All the repair options presented in the table include an initial temporary repair option at $t_0$ for Aircraft 1 and at $t_{100}$ for Aircraft 2. The damage on Aircraft 2 triggers the DSS to run at $t_{100}$ for the second time for the damage on Aircraft 1 and for the first time for the damage in Aircraft 2. Steps I-VI of the DSS are run again, with exception of Step IV as the generated criteria weights remain constant for the given case study. It is assumed that the maintenance hangar only has the capacity to accommodate the non-routine tasks of one aircraft at each timeslot (30 FC, 40 FC, 230 FC, and 300 FC).

For the second run of Aircraft 1, it can be noticed that the list of repair options decreased from 9 to 3 options. Options A, B, C, D, and E are not available as they correspond to slots before 100 FC. Furthermore, Option G is also unavailable as more time is needed for the spare part to be available. For the first run of Aircraft 2, three options are available: J, K, and L. Two main assumptions are taken to arrive at these options: 1) it is assumed that the flap failure on Aircraft 2 has higher severity and, therefore, it must be permanently repaired or replaced after a temporary repair within 300 FC, in contrast with the 400 FC of Aircraft 1, and 2) it is assumed that the same timeslots are available for the maintenance of Aircraft 2 as for the maintenance of Aircraft 1.

After the repair options were identified, the performance ratings and the ranking score are generated for both aircraft. It is important to mention that the min-max normalisation of the performance ratings has been done globally for all the options at $t_{100}$, including Aircraft 1 and Aircraft 2. The final ranking scores can be seen in Table 9. The yellow boxes indicate the recommended option at each DSS run. It can be observed that for both aircraft the option corresponding to a permanent repair on the original structure at 230 FC (Option F and J) is the highest-ranked option. As the capacity at 230 FC slot is one, the heuristic approach explained in Section 3.6 is applied. Repair J is selected as the recommended option for Aircraft 2, while repair H is selected for aircraft 1. These options are selected because they achieve the maximum sum of scores.

Table 9: Dynamic approach of the DSS applied to case study

| | | | AC1 Flap failure at $t_0$ | | | | AC2 Flap Damage at $t_{100}$ | |
|---|---|---|---|---|---|---|---|---|
| | | | Run 1 at $t_0$ | | Run 2 at $t_{100}$ | | Run 1 at $t_{100}$ | |
| Timeslot | Capacity | Repair Type | Options | Ranking | Options | Ranking | Options | Ranking |
| 30 FC | 1 | Perm | A | 0.4886 | - | - | - | - |
| | | Exchange | B | 0.365 | - | - | - | - |
| | | Lease | C | 0.3152 | - | - | - | - |
| | | Spare | No | | - | - | - | - |
| 40 FC | 1 | Perm | D | 0.6321 | - | - | - | - |
| | | Exchange | E | 0.5088 | - | - | - | - |
| | | Lease | No | - | - | - | - | - |
| | | Spare | No | - | - | - | - | - |
| 230 FC | 1 | Perm | F | 0.7127 | F | 0.5168 | J | 0.7474 |
| | | Exchange | No | - | No | - | No | - |
| | | Lease | No | - | No | - | No | - |
| | | Spare | G | 0.687 | No | - | No | - |
| 300 FC | 1 | Perm | H | 0.5777 | H | 0.4094 | K | 0.563 |
| | | Exchange | No | - | No | - | No | - |
| | | Lease | No | - | No | - | No | - |
| | | Spare | I | 0.5486 | I | 0.1807 | L | 0.421 |

# 6 Criteria weights sensitivity analysis

A sensitivity analysis is presented in this section to assess the impact of criteria weights changes on the DSS recommendation. For this, the DSS is run for 10 different weight scenarios. Each scenario corresponds to the individual preferences of one of the 10 experts whose opinions were used to generate the aggregated criteria weight vector used in former sections. Each decision-maker has their own preferences which can differ significantly from each other. These individual preferences are realistic limits of extreme criteria values. The criteria weight vectors for each expert have been generated using the BWM and can be seen in Table 10. It can be noticed that 5 of the decision-makers prioritise the availability criterion as the most important criteria (DM 2, DM 4, DM 6, DM 8, and DM 10). From the other 5 experts, 2 prioritise the reliability criterion (DM 1 and DM 7), 2 prioritise the repair costs criterion (DM 5 and DM 9) and 1 prioritise the part life criterion (DM 3).

The influence of individual preferences in the final DSS recommendation can be seen in Table 11. It can be observed that the Repair Option F (Temporary at 0 FC + Permanent at 230 FC), which was the option recommended in the baseline scenario presented in previous sections, is recommended to 5 out of the 10 individual decision-makers (DM2, DM5, DM8, DM9, and DM10). Furthermore, Option G (Temporary at 0FC + Spare at 230 FC) is recommended to DM 4 and DM 6, Option D (Temporary at 0 FC + Permanent at 40 FC) is recommended to DM 1 and DM 7 and Option I (Temporary at 0FC + Spare at 300 FC) is recommended to DM 3. Although Option G was only recommended to two decision-makers, it is the second recommended option for 5 of the decision-makers (DM 1, DM 2, DM 3, DM 8, and DM 10), with ranking scores sometimes very close to the first recommended option. Despite this, when summing all the individual ranking scores for each option, F continues to be the option with the highest ranking. Therefore, it can be concluded that the recommended repair Option F in the baseline scenario represents well the group overall preference. It can also be concluded that option D becomes the preferred option for decision-makers that prioritise reliability, Option I is recommended for decision-makers with a preference for Part Life criterion, and Option F is recommended for decision-makers that prioritise the repair costs criterion. For decision-makers that prioritise the availability criterion, either Option F or G is recommended depending on their other preferences with respect to the other three criteria.

Table 10: Individual criteria weight vectors

| Expert | Reliability | Repair Costs | Availability | Part Life |
|---|---|---|---|---|
| DM1 | 0.56 | 0.11 | 0.26 | 0.07 |
| DM2 | 0.12 | 0.17 | 0.66 | 0.05 |
| DM3 | 0.21 | 0.06 | 0.21 | 0.52 |
| DM4 | 0.36 | 0.04 | 0.44 | 0.16 |
| DM5 | 0.20 | 0.51 | 0.20 | 0.09 |
| DM6 | 0.16 | 0.07 | 0.65 | 0.12 |
| DM7 | 0.67 | 0.14 | 0.08 | 0.11 |
| DM8 | 0.23 | 0.14 | 0.55 | 0.08 |
| DM9 | 0.20 | 0.51 | 0.20 | 0.09 |
| DM10 | 0.06 | 0.15 | 0.54 | 0.25 |

Table 11: Ranking WSM scores for Repair Options A to I using 10 different criteria weight settings representing individual decision-makers' preferences.

| Scenario | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| DM 1 | 0.672 | 0.437 | 0.528 | 0.774 | 0.54 | 0.528 | 0.731 | 0.34 | 0.538 |
| DM 2 | 0.291 | 0.24 | 0.155 | 0.576 | 0.525 | 0.887 | 0.788 | 0.629 | 0.528 |
| DM 3 | 0.268 | 0.181 | 0.201 | 0.373 | 0.286 | 0.696 | 0.751 | 0.714 | 0.767 |
| DM 4 | 0.403 | 0.25 | 0.335 | 0.592 | 0.439 | 0.663 | 0.83 | 0.468 | 0.632 |
| DM 5 | 0.714 | 0.632 | 0.317 | 0.798 | 0.716 | 0.813 | 0.414 | 0.723 | 0.319 |
| DM 6 | 0.233 | 0.164 | 0.165 | 0.515 | 0.447 | 0.836 | 0.861 | 0.589 | 0.613 |
| DM 7 | 0.815 | 0.531 | 0.639 | 0.836 | 0.554 | 0.423 | 0.666 | 0.291 | 0.527 |
| DM 8 | 0.375 | 0.277 | 0.247 | 0.61 | 0.512 | 0.789 | 0.781 | 0.558 | 0.548 |
| DM 9 | 0.714 | 0.632 | 0.317 | 0.798 | 0.716 | 0.813 | 0.414 | 0.723 | 0.319 |
| DM 10 | 0.215 | 0.187 | 0.099 | 0.456 | 0.428 | 0.881 | 0.771 | 0.73 | 0.619 |
| Sum | 5.189 | 3.896 | 3.318 | 6.96 | 5.672 | 8.042 | 7.694 | 6.343 | 5.959 |
| Baseline | 0.489 | 0.365 | 0.315 | 0.632 | 0.509 | 0.713 | 0.687 | 0.578 | 0.549 |

The sensitivity analysis results emphasize the importance of correctly assessing the criteria weights, as they can significantly impact the DSS recommendation. The use of the Bayesian BWM approach in the DSS to generate an aggregated criteria weight vector is beneficial, as existing literature indicates that it leads to more reliable criteria comparisons when compared to other preference elicitation methods [25] [18].

# 7 Conclusions and future work

A novel hybrid multi-criteria Decision Support System (DSS) for operational aircraft maintenance planning after an unexpected externally-induced structural damage is presented in this paper. The research objective is to improve the situational awareness of the non-routine maintenance planners by providing a fast, systematic, and dynamic framework for decision-making after a structural failure event and it is fully met in this research. In the event of an unexpected structural damage, the DSS provides the planner within minutes with 1) a complete list of feasible repair decision options, 2) a ranking of these decision options, and 3) a systematic approach for dynamic decision iteration.

The main steps of the DSS model for generating the mentioned outputs are: Step I) collect information about damage severity and the required repair limits, Step II) identify the time slots in which non-routine maintenance can be planned, Step III) generate a complete list of feasible repair options using a Boolean Decision Tree (BDT), Step IV) generate standard criteria weights using the Bayesian Best-Worst Method (BWM) and expert judgement, Step V) evaluate the performance of the repair options with respect to the decision criteria, Step VI) generate a ranking of decision options using the Weighted Sum Method (WSM), and Step VII) update the recommendation when the operational scenario changes. Following these steps the three levels of decision-making situational awareness are improved: Level 1) the perception of elements in the current situation was improved in Steps I and II, Level 2) the comprehension of the current situation was improved mostly in Step III and IV, and Level 3) the projection of future status was improved in Steps V and VI. As a result of using the DSS, the planner can make an informed final decision on the selection of a repair option.

Several advantages of using the DSS in a real-life Boeing-777 flap damage scenario were identified. First, the results show that the DSS provides an informed repair option recommendation to the planner in a few minutes, including both the DSS processing time and the input of the required data. In contrast, current real-life decision-making practices can take in the order of hours to days to evaluate similar decision-making problems due to their unstructured approach followed. Second, the DSS lead to the identification of feasible repair options that were not considered in real life but had a more beneficial ranking score than the repair option executed in real life. This emphasizes the advantages of having a systematic and exhaustive approach for identifying all the possible repair options. Third, the ability of the DSS to adapt to changes in operational conditions and update the recommended repair option dynamically was proven to be beneficial. It was shown that when the operational scenario in the case study changed, the initially recommended option was not the most optimal solution anymore and that re-prioritisation considering the full scenario was beneficial. Finally, through sensitivity analysis, it was concluded that the use of the Bayesian BWM to generate standard criteria weights was beneficial. This was concluded because the criteria weights were found to have a great influence on the final recommendation of the DSS. The Bayesian BWM leads to more reliable criteria comparisons when compared to other methods and therefore represents more reliably the preferences of the decision-makers.

Recommendations for future work are proposed in three different areas. The first recommendation area refers to further tool validation. In this research, the potential of the proposed DSS has been demonstrated by applying the methodology to a real-life case study. To further validate the achieved conclusions, it is recommended to implement the DSS in a wider range of real-life case studies addressing failures in different structures and different operational scenarios. The second recommendation area addresses improvements on the used data sources. Certain data was either unknown or limited for some steps of the DSS. Improving these data sources for future research would reduce the number of assumptions taken and improve results reliability. It is recommended to gather the following data: 1) information about reasons behind each decision taken in the real-life case studies to be able to make better comparisons of the improved decision-making process, 2) information about the exact airline maintenance schedule and estimated hangar availability, and 3) historical repair costs information of the failure events used for the reliability analysis which can be used to compare provided airline costs with historical values and create better estimates. Finally, the third recommendations area refers to tool extensions. The current DSS version assumes that a skilled workforce is available whenever the hangar is available. However, in practice, different types of repair need different skilled professionals and their availability is crucial when selecting a repair option. Therefore, integrating skill type availability constraints into the tool should be addressed in future research.

To conclude, this research developed and evaluated the use of a multi-criteria dynamic and data-driven DSS after an unexpected structural damage event. This research set a strong basis for future research in the area of operational aircraft maintenance decision-making.

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# II

## Literature Study

previously graded under AE4020

# 1
# Introduction

Maintenance is considered a key strategic element influencing companies' competitiveness and profitability [6]. In the airline industry, this is evident as aircraft maintenance plays a crucial role in the direct operating cost of an aircraft, representing approximately 10% to 20 % of the total cost according to Papakostas et al. [77].

Dynamic decision-making processes in operational maintenance situations is a topic that has not been extensively investigated in literature. Current industry practices assume the maintenance scenario as static and rely on the decision-maker situation awareness and knowledge to analyse the situation and provide a fast solution. This solution is rarely reviewed when constraints change, except if the changes invalidates the selected option. The creation of a dynamic decision support system could lead to shorter time responses, improvements on the situation awareness and reductions of cost.

The research at hand has the objective to improve the situational awareness of the aircraft maintenance decision maker by developing a decision support tool that identifies and evaluates decision alternatives dynamically in the con-text of short-term operational aircraft maintenance (up to A-checks) characterised by a changing and complex environment. The steps involved in the decision making have been determined and can be seen in Figure 1.1. This report presents a critical review of the state-of-the-art regarding short-term decision-making during operational aircraft maintenance activities. Every identified step of the decision-making process is reviewed. The report is intended to provide a solid, high-quality starting point for a subsequent Master thesis research. The literature studied has been chosen to give an extensive historical perspective as well as an good overview of up-to-date developments in the research area.

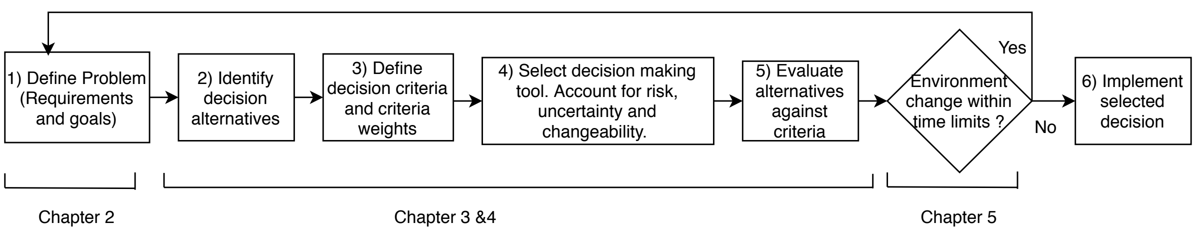


Figure 1.1: Flowchart of decision-making problem and report structure.

The report is structured as follows. Chapter 2 will define the problem and provide background information on aircraft maintenance and decision-making. Chapter 3 presents a literature review about decision support systems. Multi-criteria decision-making methods will be reviewed in Chapter 4. Chapter 5 refers to how can the risky and dynamic environment be considered in the decision-making process. Specific research questions which add value to the research field investigated will be defined in chapter 6, together with a research methodology proposal and a project planning. Finally, in Chapter 7 the literature study conclusion and recommendations can be found.

# 2

# Background information and problem definition

This chapter defines the project objective by defining the considered problem. Section 2.1 presents an introduction to aircraft maintenance. Then, section 2.2 describes the process of human decision making in an operational maintenance context. In section 2.3 the current practices in aircraft operational maintenance decision-making are described. Finally, the project objective is defined in section 2.4.

## 2.1. Introduction to aircraft maintenance

Maintenance is defined by the European standard EN13306 [40] as the "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function". The main goal of aircraft maintenance is to ensure aircraft airworthiness while minimizing costs [43].

In the early ages of aircraft maintenance, corrective maintenance was the prevalent approach taken. Maintenance was undertaken when a fault was detected. Preventive maintenance started to be considered in the 1930's with the introduction of Hard-Time (HT) limits for components with limited life-time. In the 1940's, after the second world war, reliability analysis and statistics started to be considered in aircraft maintenance. On-condition maintenance started then to be explored and the Hard-Times (HT), used during the 1930's, were extended. [71].

With the introduction of the Boeing 747 on 1968, the MSG-1 (Maintenance Steering Group) guidelines were introduced by the FAA for the development of a minimum scheduled maintenance program. In the 1970's the guidelines were generalised to other types of aircraft with the introduction of MSG-2 [4] . Nowadays, the guidelines from the task-oriented MSG-3 philosophy are followed. MSG-3 has been reviewed several times since its introduction. The philosophy uses a top down approach which considers system failure modes from a system level. [43]. MSG-3 approach is used to create the Maintenance Review Board Report (MRBR), which contains the minimum necessary scheduled maintenance tasks and intervals. After approval, the MRBR become the framework around which the operators create their own scheduled maintenance programs [4].

Scheduled maintenance programs refer to preventive maintenance. Big improvements have been achieved in long-term maintenance schedules in the past years, with the exploration of innovative prediction techniques such as structural health-monitoring [93]. Maintenance activities (scheduled and unscheduled) are performed as part of heavy or line maintenance. Heavy maintenance is performed in a hangar and requires the aircraft to be out of service for a considerable amount of time, while line maintenance is performed during turnaround time (TAT). During line maintenance operations a daily check is performed before the first flight or when an aircraft is on ground for 4 or more hours. In addition, transit checks are performed at every stop when the aircraft is in transit as described in [61].

Despite the efforts, unexpected failures are inevitable and continue to occur due to their stochastic nature.

This draws the need for corrective maintenance as can be seen in Figure 2.1. Corrective maintenance can be either deferred to a later scheduled-check or immediate, incurring extra costs and sometimes leading to a disruption on the flight schedule. This decision is made by considering the Manufacturer Minimum Equipment List (MMEL). If the aircraft does not comply with the MMEL, the corrective tasks need to be solved immediately [77]. Unscheduled tasks during line maintenance require quick response time and real-time rescheduling decisions that aim to minimise the unexpected failure consequences.

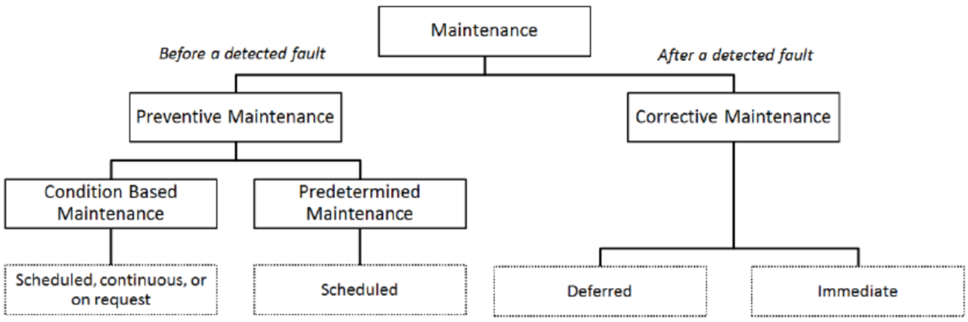


Figure 2.1: Aircraft maintenance types [40]

## 2.2. The process of decision-making

Decision-making was defined by Wickens, Gordon, and Liu [106] as the task in which "(a) a person must select one choice from a number of choices, (b) there is some amount of information available with respect to the choices, (c) the time frame is relatively long (longer than a second), and (d) the choice is associated with uncertainty; that is, it is not clear which is the best choice". Subsection 2.2.1 will describe the process of human decision-making with a focus on operational aircraft maintenance decisions. Then, the influence of situational awareness during decision-making will be described in subsection 2.2.2.

### 2.2.1. Human decision-making in operational maintenance

Human decision making has been subject of many studies in very diverse domains, ranging from philosophy to medicine. Traditional theories of human decision-making focus on normative aspects of valid judgments. Human decision-making is, by nature, subjective and dependent on the individual decision-maker. Making a decision can be compared to climbing a mountain, as explained by Buchanan, Henig, and Henig [19]. The mountain can be climbed following different paths, which represent the decision alternatives. Each climber will take its own decisions based on objective information, such as aerial photographs but also subjective information, such as their personal goals, past experiences or the opinions of other climbers. Subjective Expected Utility (SEU) theory is the most used normative theory. SEU has been used to explain decisions under uncertainty as it allows for subjective evaluation of the decision variables by considering probabilities [80].

During maintenance operations, fast decisions need to be taken daily. Little research has been done in the influence of human decision making on the effectiveness of operational maintenance decisions. C.E. Zsambok [112] described the characteristics of real-life problems such as the operational aircraft maintenance. The problems are difficult to define and the goals can be changing or even competing. Decisions are usually taken by a group of people via collaboration. Furthermore, the environment is characterised by dynamic environmental cues, uncertainty, risk and high time stress.

Traditional normative standards are difficult to apply in complex dynamic environments such as operational maintenance as they do not represent the real human behaviour. Normative theories assume complete information and unlimited time to take a decision, which is rarely the case in real-life. Naturalistic theories are more realistic in real-life decision-making. In Figure 2.2, Peter D. Elgin [36] presents an integrated model of several naturalistic theories. These theories show the influence of time-stress in the decision-making process, which affects the decision-maker's strategy and the decision outcome. When time pressure is high the decision-making process is mostly skill-based and intuitive, while when more time is available the decision-maker tends to take a more analytical and knowledge-based decisions.

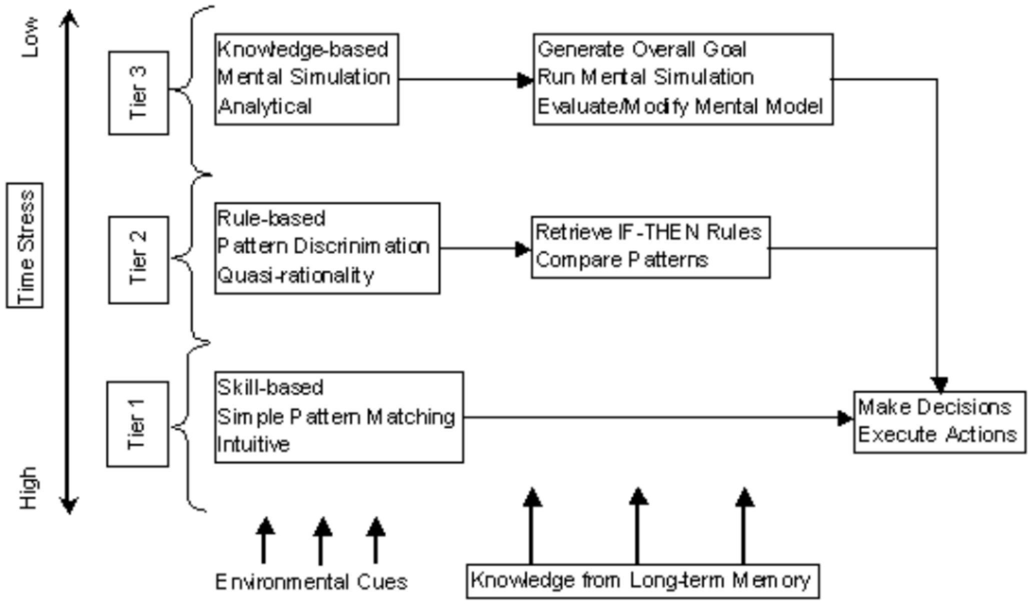


Figure 2.2: Naturalistic decision-making model: the influence of time-stress [36]

### 2.2.2. Influence of situational awareness on decision-making

Situational Awareness (SA) refers to the perception and understanding of a situation and its environment by a decision-maker, and the ability to project its future status 2.3. SA plays a key role in decision-making in dynamic and complex environments, being a critical element for taking a successful decision. The influence of situational awareness in short-term decision making in aviation has been widely studied in literature with a strong focus on crew decisions [75, 30].

The role of situational awareness in decision-making processes can be seen in Figure 2.3. SA does involve big amounts of data knowledge, an advance level of the situation understanding and projection of future consequences of decisions [38]. Endsley [38] describes 3 levels of situational awareness. Level 1 corresponds to the personal perception of the decision-maker of the state of the environment. Level 2 refers to the actual understanding of the perceived perception. Finally, level 3 refers to the ability of making prognostics of projections about the future consequences of decisions.

In the context of operational aircraft maintenance decision making, human situation awareness is a predominant factor influencing the decisions outcome. A big amount of information is available before the decision-making process such as costs, resources availability, flight schedule and airline maintenance program. However, current practices to obtain information before decision-making, lack completeness of data and are incapable to interconnect the available information. The load of information is too big for a human decision-maker to consider and compare simultaneously. Furthermore, this information is continuously changing, which makes it difficult for the decision-maker to consider changes to dynamically adapt his decisions. Maintenance decisions need to be taken by considering high load of information and risks.

The decision support systems used nowadays are reactive and focus on minimizing the consequence of failures [1][34]. The dynamic environment and big amounts of heterogeneous data, drives the necessity of context driven decision support systems [51].

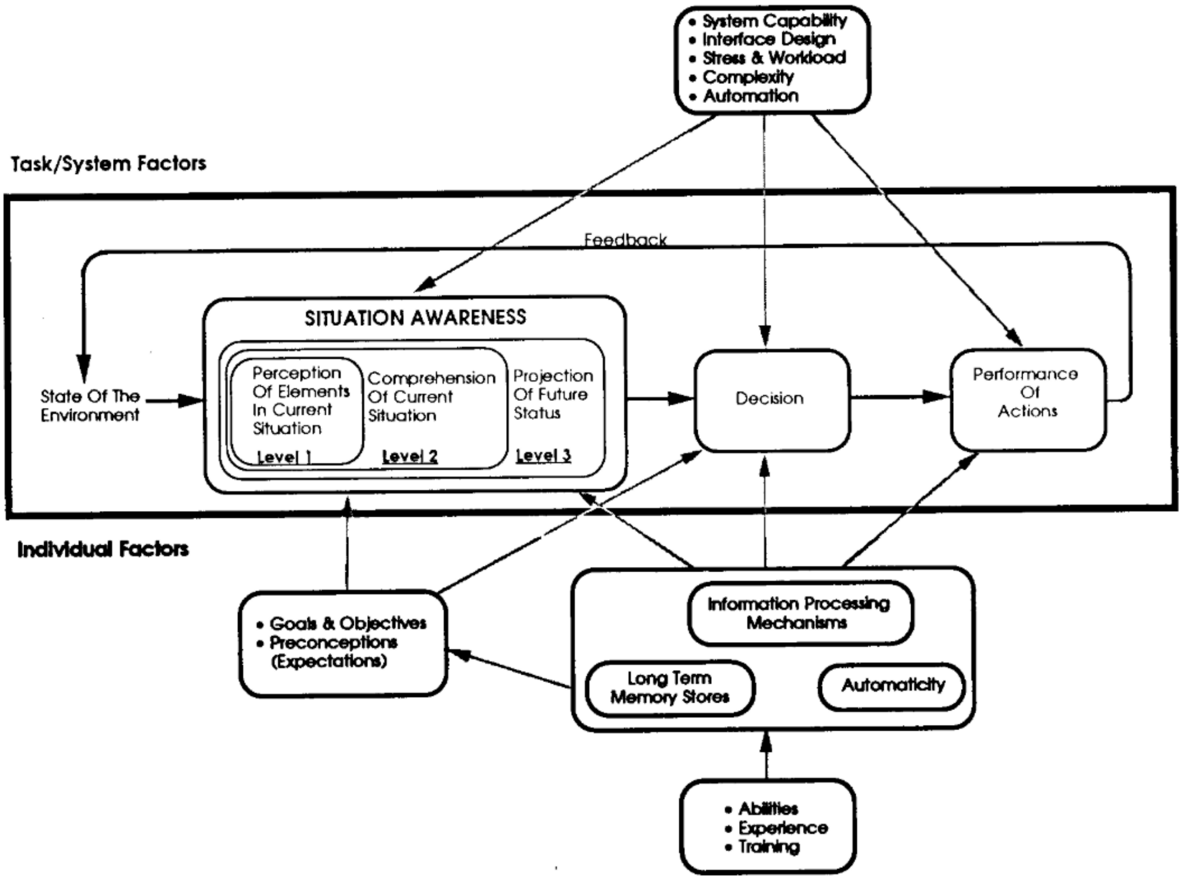


Figure 2.3: Situational awareness in dynamic decision-making [38]

## 2.3. Current practices in aircraft maintenance decision-making

Diverse planning & scheduling problems in the airline industry have been solved in literature by using Operations Research methods. There are four main areas of optimization that have been largely explored: flight scheduling, fleet assignment, aircraft maintenance routing and crew scheduling. After the fleet assignment is finalised, the Aircraft Maintenance Routing problem studies the integration of the maintenance checks required by the authorities in the schedule [66]. The Aircraft Maintenance Routing problem has been widely explored in literature in the past decades [11, 37, 96].

Lots of tools for strategic long-term planning & scheduling have been developed in the Maintenance Repair & Overhaul (MRO) industry in the past decade such as AMOS, Trax, IFS Maintenix, Ramco, Rusada or Swift MRO. These solutions provide extensive decision support in a well-developed user interface by considering reliability data and operational constraints [77].

Despite the mentioned developments, operational disruptions to the determined schedule are common in daily aircraft operations. Multiple studies aim to solve the aircraft 'Disruption recovery problem' in literature [27], by trying to minimize the consequences of the disruptions. The early efforts to study the airline recovery problem, such as the research done by Teodorović and Guberinić in 1984 [94], ignored maintenance constraints. Most recent studies show a trend to integrate multiple interrelated constraints, such as maintenance or crew constraints, in order to provide more insightful results at expenses of increased computational time [111].

In real-life maintenance operations, the initial plan experiences disruptions due to inevitable unplanned failures. After the occurrence of an unplanned failure, a corrective maintenance diagnostic or troubleshooting needs to be performed to understand the scope of the problem and develop different solution scenarios or alternatives. An effective solution needs to be provided in a short time span in order to repair the failure within specified airworthiness requirements and by minimising the possible consequences (cost, downtime, cancellations, etc). In this stage, decision-making plays a key role.

Current industry practices, as concluded in the research performed by V.S.V. Dhanisetty [32] remark the lack of an structured decision-making approach and insufficient gathering of information in operational maintenance decisions. The incompleteness of the information directly affects the decision-maker situational awareness having an impact in its ability to make correlations and identify risks and therefore has a big impact performance of the decisions. The lack of using a structured approach for decision making drives an incomplete set of decision alternatives generated by the decision-maker when the fault occurs. Furthermore, the maintenance scenario nowadays is considered static despite the dynamic nature of the maintenance environment. Considering the risks and dynamically adapting the decisions to the operational conditions is hardly used in real life. The repair decision is taken at the moment of failure and different options are uniquely considered when the chosen alternative is no longer possible. Finally, the human nature of the decision-maker drives his inability to process big amounts of changing, correlated and contradicting data and constraints simultaneously. This leads to loses of time or selection of no-optimal solutions. These reasons set a need for a decision-support tool at operational maintenance level.

## 2.4. Project objective

A literature and industry gap in the context of aircraft structures operational maintenance was found in the past sections: the lack of a systematic and dynamic decision-making process considering environment characteristics and minimising individual subjectivity. The proposed research objective aims to bridge this gap and can be formulated as follows:

> “To improve the situational awareness of the aircraft maintenance decision maker by developing a decision support tool that identifies and evaluates decision alternatives dynamically in the context of short-term operational aircraft maintenance (up to A-checks) characterised by a changing and complex environment”

The project focus on operational decisions, as opposed to strategic long-term decisions support tools which are popular in literature. Operational decisions are taken daily and the available time to take the decision is limited. Therefore, the minimisation of computational time of the decision support tool becomes essential. Furthermore, operational decisions are usually taken by staff with lower industry knowledge and situational awareness than strategic decisions. This sets the need for the tool to minimise human workload, be understandable and easy to use, in order to achieve its implementation on the daily routine of the decision-makers. Finally, the tool should be able to cope with risk, competing goals, uncertainty and changing environment cues.

# 3

# Decision Support Systems (DSS)

Decision Support System (DSS) was defined for first time by Gorry and Morton [46] as a computer-based tool or framework that helps decision-makers with solving ill-structured problems interactively. The general steps of a decision support system can be seen in Figure 3.1. The process is iterative and can go backwards when new information is discovered. First, the problem needs to be defined, considering both the initial conditions of the environment and the desired final state. Requirements and goals to solve the problem need to be determined. The process of identification of decision alternatives is further discussed in section 3.2, while the decision criteria definition and weighting process is described in section 3.3. The generated alternatives are evaluated against the criteria, following a decision-making tool of choice. Multiple modelling approaches for DSS exist, which will be discussed and compared in section 3.4. Finally, the solution provided by the DSS needs to be validated in order to ensure compliance with the problem definition. The opportunities and challenges of decision support systems will be discussed in section 3.5.

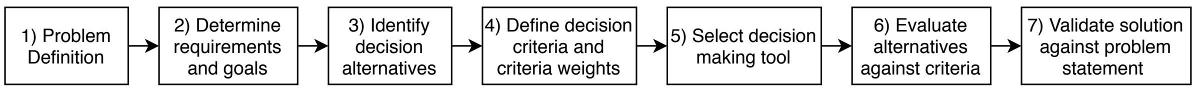


Figure 3.1: Decision support system steps [8]

## 3.1. Decision support systems structure

The general structure of a decision support system is presented in Figure 3.2 [78]. It can be noted the interaction of the decision-maker with the system via computer technologies, which is a central characteristic of DSS and the person that takes the final decisions. The level of interaction of the decision-maker with the system can vary per DSS. In the context of this research, the interaction should be limited and easy to understand by the decision-maker as decisions need to be taken fasts and operational maintenance decision-makers do not usually have enough knowledge to handle high-level human-machine interactions.

A decision support system has three inputs: 1) a data base, 2) a knowledge base and 3) a model base [78]. The data base contains any data relevant to the decision. In the context of the research of this report, this would be the environment characteristics, dimension of the structure failure and repair time-limits among others. The knowledge base contains any information that helps evaluating criteria or alternative as well as validating the solutions. Finally, the model base contains information related to the selected modelling method. After processing has been performed guided by the decision-maker, the DSS will recommend a decision, make prognostics and give explanations and advice to the decision-maker. The decision-maker will then take a final decision. Some decision support systems, as the shown in Figure 3.2, use output and input feedback loops to dynamically improve the system. These feedback loops will be of interest in the research context treated in this report.

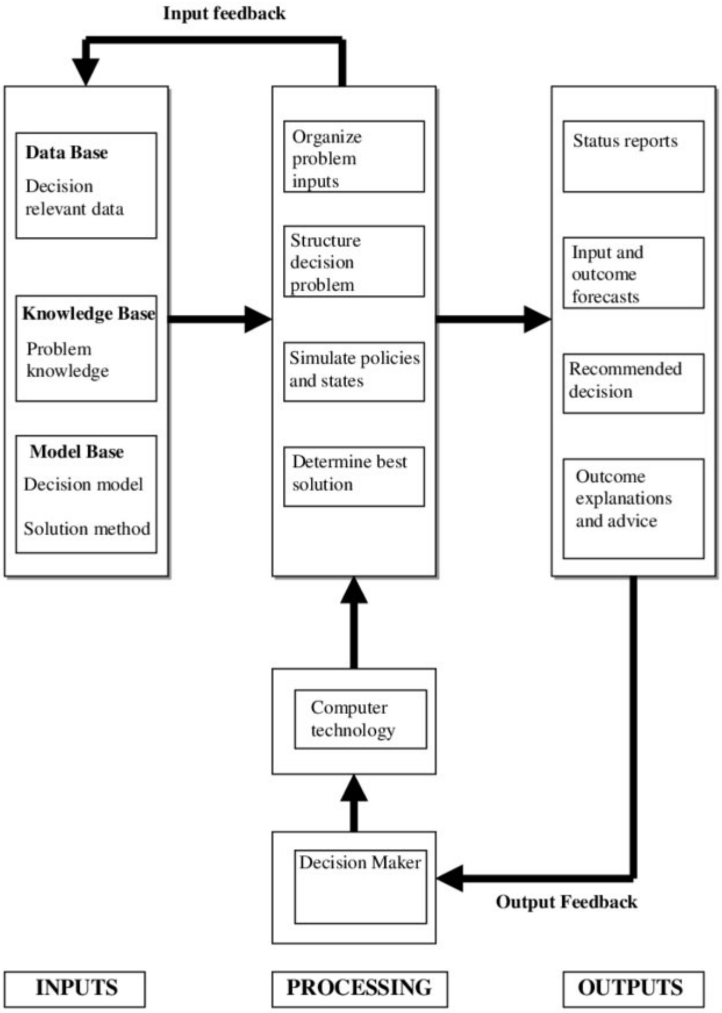


Figure 3.2: DSS structure [78]

## 3.2. Maintenance alternatives identification

In the context of aviation decision-making studies, decision alternatives are usually given or obvious, for example, in Chen and Ren [25], where the decision on the use of different fuel types is made. In this example, a finite number of fuel choices is known beforehand. In operational maintenance decision-making problem treated in this report, the repair options are finite: temporary repair, permanent repair, part lease, part purchase, etc. However, the combination of the different possibilities to create the final decision alternatives is not obvious. Therefore, an approach to determine the alternatives needs to be chosen. For this, different methods will be explained in subsection 3.2.1 and the most suitable one for the project at hand will be selected in subsection 3.2.2. In practice brainstorming is used to generate the decision alternatives in an operational maintenance environment. The decision alternatives generation for the environment considered in this study needs to be complete, easy and fast.

### 3.2.1. Methods for generating decision alternatives

The decision alternatives generation for the environment considered in this study needs to be complete, easy and fast. In practice, brainstorming is used to generate the decision alternatives in an operational maintenance environment. However, this lacks a systematic approach. In this section, two methods commonly used in literature to solve similar problems than the one presented in this study will be further discussed: Decision Trees and Bayesian Networks.

### Decision Trees

Decision trees are a very popular tool in decision-making and machine learning, as they represent a sequential decision-making process in a visual way. This method has been used in literature by Dhanisetty [31] to generate decision alternatives in an operational maintenance environment as the one considered in this study. A decision tree can have one or more different types of nodes as can be see in the example shown in Figure 3.3. The diamonds represent utility nodes while the ovals represent probabilistic nodes and the rectangles Boolean decision nodes. When a decision-tree has one or more probabilistic nodes they are called probabilistic decision trees, and otherwise, they are called deterministic decision trees. The different branches of a BDT lead to different decision alternatives [10].

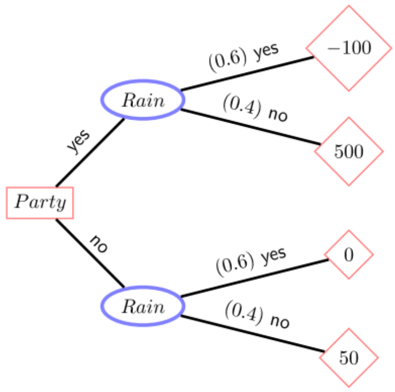


Figure 3.3: Boolean decision tree example [10]

### Bayesian Networks

A Bayesian Networks (BN) is a machine learning graphical method very popular in decision-making. It is used to represent joint probability distributions (JPDs) in a compact and intuitive way via a Directed Acyclic Graph (DAG) [7]. Its popularity comes from its combination of a probability approach, a visual method and an efficient tool. In Figure 3.4 a typical example of a Bayesian network is shown, with its corresponding JPDs [7]. The arrows shown in the diagram represent the causal relationships between variables. BNs have not yet been used for alternatives generation in operational aircraft maintenance decision-making.

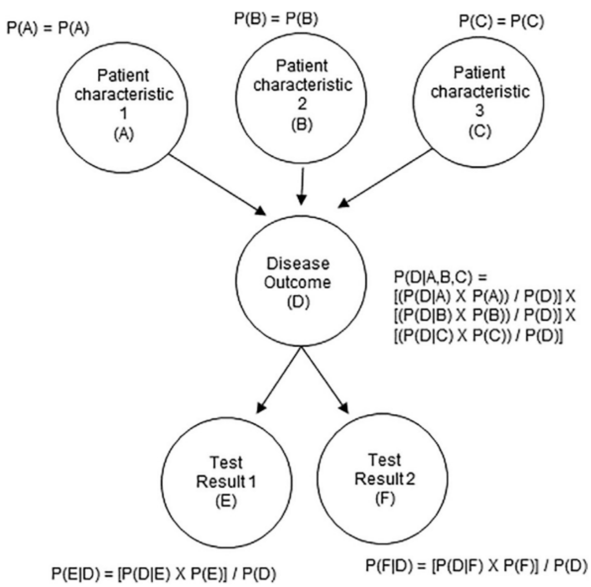


Figure 3.4: Bayesian network example developed by Arora et al. [7]

### 3.2.2. Discussion

Several advantages and disadvantages of decision trees and Bayesian networks have been gathered in Table 3.1 [7] [76]. This section will select the most suitable method for decision alternatives generation for the problem at hand.

Table 3.1: Decision trees and Bayesian networks comparison [7] [76]

| Method | Advantages | Disadvantages |
| --- | --- | --- |
| Bayesian Networks | -Casual structure represented explicitly<br>-Able to learn from data, expert opinions or both<br>-Able to model 'what-if' scenarios<br>-Able to model different outcomes in the same model<br>-Used in decision models | -Specialised knowledge necessary to understand the model<br>-Not possible to model cyclical relationships<br>-Computationally expensive<br>-Available probability or expert opinions data necessary |
| Decision trees | -Easy to understand by the decision-makers<br>-Can accept both categorical and numerical values<br>-Can model a high degree of non-linearity | -Prone to over-fitting<br>-Difficult to classify multiple output classes |

Bayesian Networks, although being a very promising technique for decision alternative generation, it is not suitable for the problem at hand due to the lack of data to generate probabilities. Furthermore, BN are not well-suited for the considered operational environment because of the need of specialised knowledge to understand the model and because of being computationally expensive.

Boolean Decision Tree (BDT) is selected in this project against Bayesian Networks as they are easier to understand and interpret by the maintenance decision-makers, while having a short computational time and not being data-intensive. These characteristics are of great importance in an operational environment, as established in chapter 2. Furthermore, BDT accepts both categorical and numerical predictor values. This is essential in order to generate repair alternatives by considering operational and technical constraints which can be both numerical or categorical [76]. Although BDT can be prone to over-fitting, this disadvantage can be overcome by introducing a pruning method.

## 3.3. Decision criteria identification

Once the decision alternatives have been identified, decision-criteria need to be selected, to measure the performance of each alternative. Bouyssou [17] describes three properties of consistent list of criteria as follows:

1. Complete: This implies that if the judgement of two alternatives a and b for all criteria is the same, then the selection of one alternative over the other is indifferent.
2. Monotonic: This implies that if alternative i is preferred over alternative j, then any alternative k, judged similar or better than alternative i on every criterion, should also be preferred over alternative j.
3. Non-redundant: The criteria do not include any unnecessary criterion.

The selection of criteria is, therefore, important to construct a useful decision-making tool. Shafiee [90] determined a list of criteria that can be useful when taking maintenance strategy decision, which can be seen below:

- Quantitative

  - **Economic**: Spare parts cost, Manpower costs, Personnel training costs, ect.
  - **Technical**: MTBF, MTTR, spare machine availability, time efficiency, lead time, spare part availability, current reliability level, risk level of the system, etc.
  - **Social**: Employees' performance, labour wage level, etc.
  - **Environmental**: Resource availability, raw material consumption, cost of cleaning the waste, toxic emissions, energy consumption, etc.

- Qualitative
  - **Economic**: Customer satisfaction, severity of failure, accessibility, etc.
  - **Technical**: Repairability, technical complexity, type of system, etc.
  - **Social**: Personnel safety, personnel training, government regulations, etc.
  - **Environmental**: type of waste, environment protection, holding environmental standards, etc.

In the context of operational decisions in aircraft maintenance, V.S.V Dhanisetty [32] considers downtime, survivability and cost as criteria in his model while N. Papakostas [77] considers Remaining Useful Life (RUL), cost, operational risk and flight delay. When dealing with complex multiple criteria problems in maintenance, sensitivity analysis is necessary to accurately assess the importance of criteria [97]. Furthermore, establishing criteria weights is crucial for the outcome of the decision-tool.

## 3.4. Decision-Making modelling approaches

There are multiple modelling approaches in literature for different support systems. The problem in hand is complex and have different, sometimes conflicting objectives. The most common modelling approaches for this type of problems are grouped by Doumpos and Grigoroudis [33] in two categories: 1) multi-criteria decision-making and 2) computational intelligence. This section will briefly discuss the different types of modelling approaches and their applicability to the given problem. Hybrids models in which different methods are combined are very common in literature [91]. While hybrid methods are able to profit from advantages of various methods, the effectiveness of each individual method can be decreased when combined [87]. It needs to be noted that different model combinations will not be discussed in this review in order to simplify the classification process, but they might be selected as final modelling approach.

### 3.4.1. Multi-Criteria Decision-Making (MCDM)

Multi-criteria Decision-Making (MCDM) are also referred to in literature as Multi-Criteria Decision-Analysis (MCDA). MCDM methods were divided by Sabaei, Erkoyuncu, and Roy [86] in two categories: Multi-Attribute Decision-Making (MADM) and Multi-Objective Optimization (MOO). Sabaei, Erkoyuncu, and Roy [86] compared the characteristics of both categories, which have been gathered in Table 3.2.

Table 3.2: MADM & MODM comparison [86]

| MCDM Type | Criteria | Alternatives | Constraints | DM's interaction |
|---|---|---|---|---|
| MODM | Goals | Infinite | Clear | High |
| MADM | Attributes | Finite | Not clear | Low |

Keeping in mind the characteristics of each category, the following subsections will explain them more in-depth and determine their suitability for the problem at hand.

#### Multi-objective decision-making

Mathematical programming approaches, studied in the area of Operations Research (OP), are used to solve multi-objective decision-making problems. Multi-objective mathematical programming methods solve optimization problems in which k objective functions $f(\mathbf{x})$ need to be maximised or minimised while complying with a set of m inequality constraints $g(\mathbf{x})$. The general problem formulation is defined in Equation 3.1. In Equation 3.1 $\mathbf{x}$ refers to the decision vector, while X refers to the feasible set of constrained decisions [33].

$$\begin{aligned} &\text{minimize} && f(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_k(\mathbf{x}))^T \\ &\text{subject to} && \mathbf{x} \in X = [\mathbf{x} \in R^n | g_i(\mathbf{x}) \leq 0,\ i = 1, \ldots, m] \end{aligned} \tag{3.1}$$

Mathematical programming consists of different modelling approaches, whose suitability is dependent on the problem at hand. The most common approaches are: Linear Programming (LP), Non-Linear Programming (NLP), Goal Programming (GP), Integer Programming (IP) and Mixed-Integer Programming (MIP). From these methods, goal programming is the only approach able to consider multiple objective functions simultaneously, which is of special interest for the topic of this research [48]. The other mentioned methods will not be considered further as they are not suitable for the problem at hand, being unable to consider multiple objectives. The main advantage of GP is to be able to handle infinite alternatives, therefore being suitable for large-scale problems. In the research at hand, the alternatives are finite. Furthermore, GP is unable to handle weighting of coefficients [22]. For these reasons, this method will also not be further researched in this report.

**Multi-attribute decision-making**

MADM is a popular research branch of decision-making [72]. Multi-attribute decision-making methods are able to evaluate decision alternatives dependent on diverse and conflicting criteria, modelling trade-offs explicitly. These methods are therefore of special interest for operational maintenance decision-making. There exist multiple modelling approaches for MADM, each with their advantages and disadvantages. Some of the most popular methods are: AHP, WSM, ELECTRE, TOPSIS, PROMETHEE and VIKOR.

MADM methods are more suitable for the problem at hand than MODM, as they are able to handle problems with finite repair options [86]. Furthermore, MADM approaches are easier to understand by the decision-makers than multiple-objective optimization methods, requiring less interaction. Therefore, this approach is selected and will be further explored in chapter 4, where a comparison between different MADM methods will be performed in order to select the most suitable method to tackle the considered problem.

### 3.4.2. Computational Intelligence (CI)

Computational intelligence (CI) can be considered a sub-field of Artificial Intelligence (AI) and a super-set of Machine Learning (ML). Duch [35] defined CI as the field of science that aims to use intelligent systems to solve difficult problems requiring intelligence, and for which no effective computational algorithm is available. It gathers promising methods which are applicable to the problem at hand in this report. Doumpos and Grigoroudis [33] distinguished four main paradigms of CI that will be discussed in this review: 1) Artificial neural networks, 2) metaheuristics and 3) intelligent agents. The applicability and limitations of these methods for the given project will be explained.

**Artificial Neural Networks (ANNs)**

Artificial Neural Network (ANN) systems are inspired by biological networks of interconnected neurons [64]. ANNs are desired to possess qualities similar to those of a human brain: ability to learn and generalise, parallelism, low consumption of energy, fault tolerance, ease to adapt and intrinsic ability to process contextual information [56]. The usual structure of an artificial neural network consists of three neuron layers in a feed-forward network, as can be seen in Figure 3.5 [95].

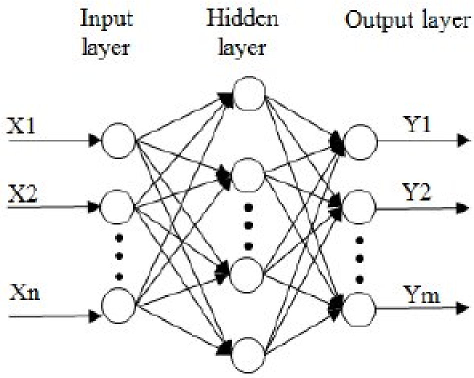


Figure 3.5: The basic structure of ANNs [95]

ANNs have been used to solve diverse problems such as clustering, pattern recognition or forecasting. It is a field of special interest in decision-making or optimization problems, such as the problem considered in this report, due to its ability to learn from representative data, which can potentially reveal unknown relationships between the data and help the decision-maker achieve better decisions over time. Although ANNs are promising for solving complex real-life problems, there are some disadvantages that make this method unsuitable for the treated problem. When using small training data-sets, the performance of ANNs is negatively affected [50]. Therefore, big amounts of data are required to create a reliable system, which is currently unavailable in this project. Furthermore, large computational time required to train the data in ANNs, which is unsuitable for applications in an operational environment in which fast decision-making is key [50].

**Metaheuristics**

Metaheuristics is a rapid evolving field of CI, that was first introduced by Glover [44] in 1986. Metaheuristics are described by Blum and Roli [16] as guiding strategies of the search process which aim is to investigate the search space to find near-optimal solutions for complex real-life problems. Their success in the decision-making community is due to the complex nature of decision-problems [33]. Metaheuristic can be divided in single solution-based algorithms and population-based algorithms as can be seen in Figure 3.6 [9]. Single solution-based algorithms are non-nature inspired algorithms in which one randomly generated solution is used to find the near-optimal solution, such as tabu search algorithm. Meanwhile, population-based algorithms are nature-inspired, such as genetic algorithms or ant colonies.

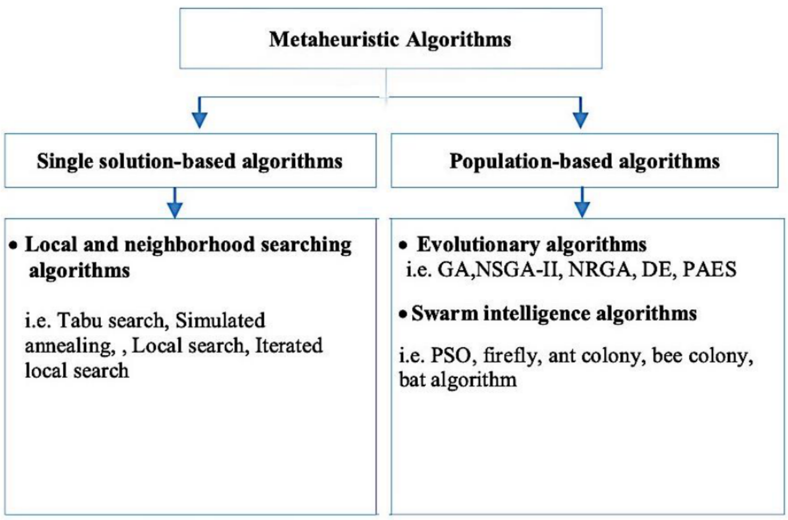


Figure 3.6: Meta-heuristics algorithms classification [9]

Metaheuristic approaches have been of special interest for computationally intensive optimization decision-making problems because of their ability to search efficiently in big solution spaces while making a small amount of assumptions [33]. These methods have been used in decision-making in combination with MCDM to increase the robustness of the outcomes, such as in the study performed by Eppe, De Smet, and Stützle [39]. However, they will not be further researched in the project at hand due to the need of extensive data which is unavailable.

**Agent-based modelling**

Agent-based modelling (ABM) is a novel modelling approach that deals with distributed, autonomous and intelligent systems. An agent is an entity with different internal states which can interact with other agents and the environment. The intelligent agents act depending on a set of stochastic or deterministic rules [53]. ABM permits flexibility in assumptions and it generates outcomes both at individual and population levels. In the context of decision-making agent-based models are of special interest because of its ability to account for behavioural diversity of the decision-makers [105].

The main advantage of using ABM is its ability to capture emergent phenomena, using a bottom up approach [12]. Furthermore, it is suitable for dynamic and uncertain environments. Although these characteristics could be useful for decision-making in an operational aircraft maintenance environment, there is still some scepticism from the decision-making community on this method [104]. This could be minimised by involving the decision-maker in the modelling process. However, this possibility is not available in this project. Furthermore, in order to create a ABM model suitable and realistic for the problem would be too computationally heavy and require big amounts of data which are currently unavailable due to the current real-life undocumented repair maintenance decision process. The outcome of an ABM model is highly influenced by the quality of the input data and unit behaviour definitions, potentially leading to sub-optimal solutions when modelled with bad quality or scarce data [12]. Therefore, although ABM is a promising modelling approach it will not be researched further for the scope of this project.

## 3.5. The opportunities and challenges of DSS

The expected benefits of introducing a decision support tool providing a structured decision-making approach for operational short-term operational decisions in maintenance are listed below:

- Decision time savings
- Better management control on the quality of decision-making: easier to reproduce and document
- More consistent and objective decision-making process
- Contribute with the digitization trend of e-maintenance
- Reduced workload and improved decision-maker's situational awareness
- Possibility of improved efficiency, higher aircraft utilization and lower costs by considering complete data sets and risks at an early stage.
- Prevention of possible human errors and flight delays

There are some limitations to decision support systems which are important to keep in mind. One of the main challenges of DSS was identified by Karacapilidis and Gupta [59] as the difficulty to considerate the tacit knowledge and constructive feedback that comes from group collaboration and personal experience during decision-making. Finally, the creation of customized systems that adapt to individual decision makers preferences is difficult to implement. Another limitation is the creation of a, sometimes inaccurate, feeling of objectivity. The integration of intelligent DSS have the potential to overcome some of these limitations.

It must be noted that the modelling approaches used in DSS generate a simplified version of the real-life problem environment. As such, an optimal solution generated by a DSS will be an optimal solution in the simplified environment, but it will not necessarily represent the optimal solution for the actual problem in hand [48]. Therefore, sensitivity analysis is necessary to determine the model´s most critical parameters and ensure results quality and valid approximations.

# 4

# Multi-Attribute Decision-Making

MCDM methods, specifically multi-attribute decision-making, was determined as the most suitable modelling approach for the problem at hand in chapter 3. This chapter will start describing the state-of-the-art of MCDM in section 4.1. Then, the most common methods for MADM will be described in section 4.2. A comparison of the methods and selection of the most suitable ones is presented in section 4.3. In section 4.4 different normalization techniques used in the selected MADM methods will be discussed.

## 4.1. State-of-the-art of MCDM

An increasing interest trend on MCDM methods can be seen in Figure 4.1, as the number of articles related to the topic are increasing over the years. In 2018, there was a peak on articles related to air transport, explained by the special editorial topic in the Journal of Air Transport Management: 'Multiple Criteria Decision Making in Air Transport Management' [82].

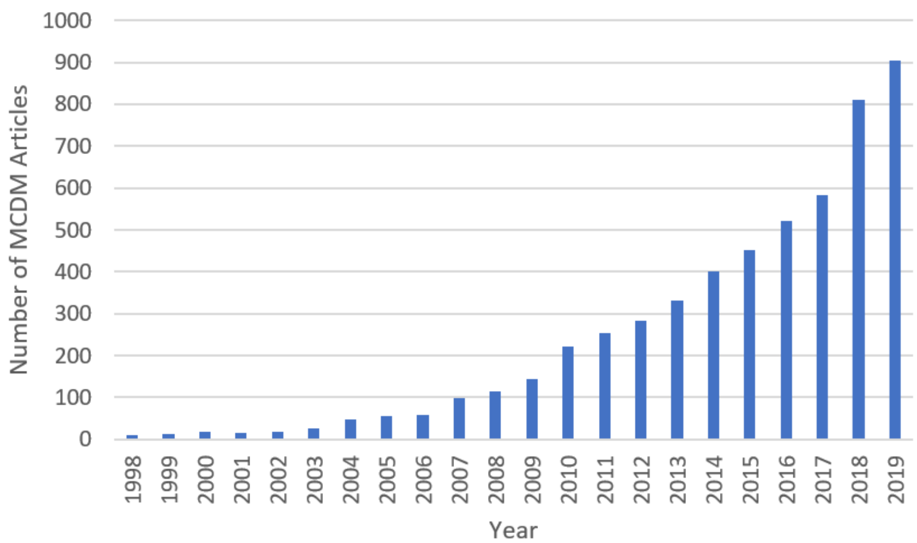


Figure 4.1: Article publications about MCDM in the past years (source: scopus)

MCDM methods have proven efficacy in diverse industries in the past decades, for example in energy management [63] [28] or in supply chain management [58]. Using the most recent MCDM papers in literature, a keyword co-occurrence network has been created in Figure 4.2. The goal of the network is to show the most popular and recurrent topics in the research field. The method that appeared the most was AHP, followed by TOPSIS and VIKOR. Furthermore, the area in which MCDM methods were applied the most was found to be supplier selection and supply chain management. A high interest on fuzzy sets and dealing with risk and uncertainty was observed. Finally, the use of linguistic variables, which are represented by words instead of numbers, is common [109].

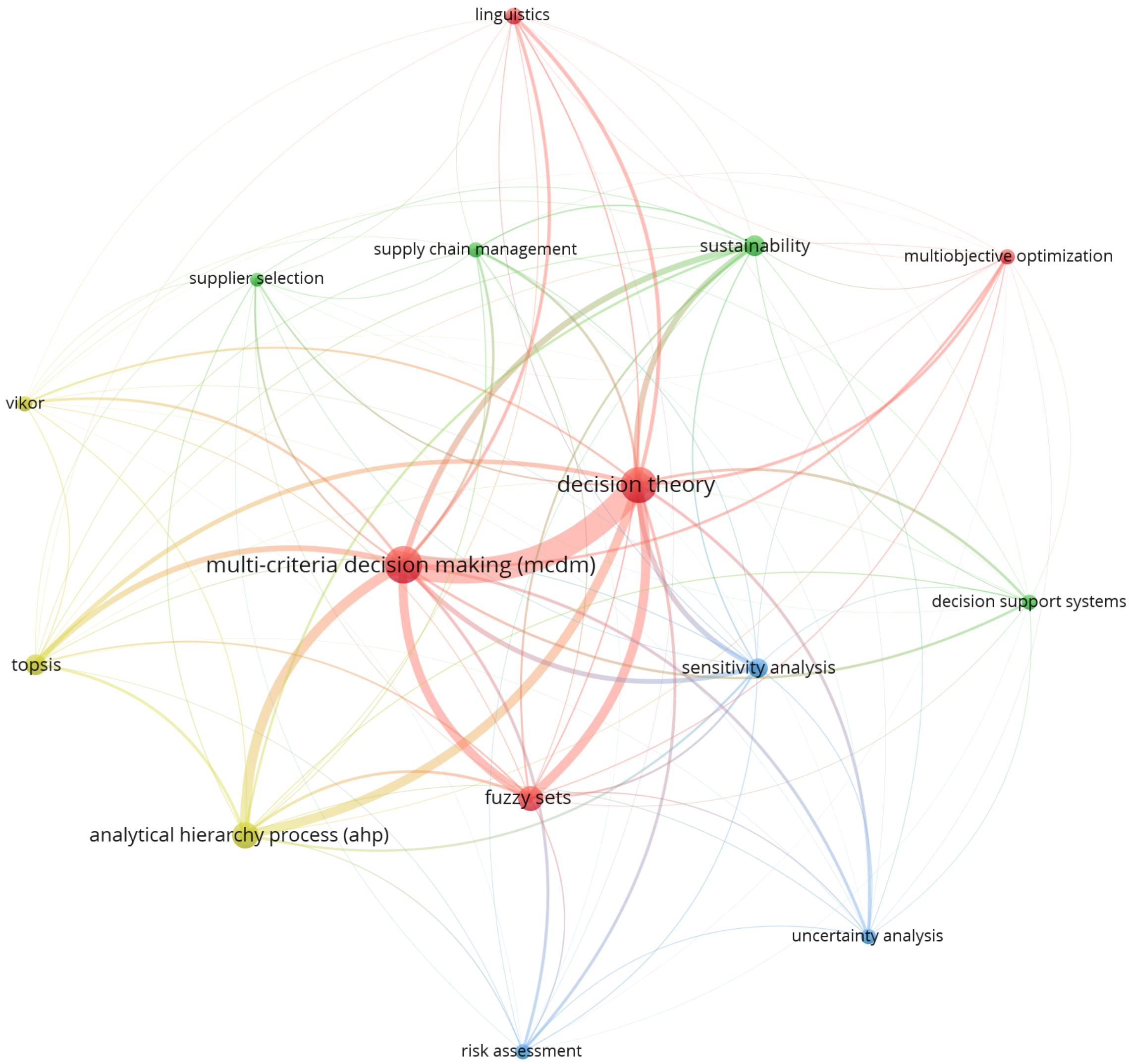


Figure 4.2: Keywords co-occurrence network in the 2,000 most recent MCDM papers in literature (Created with VOSviewer and scopus data).

In aviation, where decisions are dependent on multiple different criteria, MCDM are of special interest. The criteria can be both qualitative and quantitative and are sometime are interconnected or contradictory. Dožić [34] performed a state-of-the-art analysis of the use of MCDM methods within the aerospace industry. The study analysed 166 papers published between 2000 and 2018, where the trend of an increase of papers per year could be observed. Only 3 out of those 166 papers referred to maintenance and none of them referred to decision-making in operational maintenance. Dožić [34] study also sets the strong tendency of using fuzzy logic while considering MCDM in aviation. Fuzzy logic is useful to help taking decisions in uncertain situations, such as unscheduled maintenance. Although MCDM methods are good for prioritization of decisions, their main disadvantage is their incapability for setting causal relationship between the different optimisation objectives as mentioned by Jahangoshai Rezaee and Yousefi [55].

In the context of operational aircraft maintenance decision-making, two papers have been found in literature which refer to this topic. V.S.V Dhanisetty [32] proposed a MCDM method to aid the maintainer during operational decision-making. V.S.V Dhanisetty uses a deterministic Boolean Decision Tree (BDT) to determine decision alternatives, which are then ranked using Weighted Sum Method (WSM). In this model, weights are free to set by the maintainer and risk to dynamically adapt the decision was not taken into consideration. The main findings of this study set a necessity for a systematic approach in decision-making, as such approach does not exist in current industry practices and can lead to an improvement in time and efficiency. The second study which focus on operational maintenance decision-making was performed by N. Papakostas [77] as an optimization problem with the aim of maximizing aircraft fleet operability and minimize maintenance costs. This framework considers risk and the possible consequences when ranking decision alternatives. However, the dynamic environment is also not considered in this study, setting a literature gap in this field.

MCDM can be divided in MADM and MOO methods, which were discussed in chapter 3. MADM was found to be the most suitable modelling approach for the problem considered in this report, as they are easy to understand by the decision-makers and can handle finite decision alternatives. MADM methods will be further discussed in the next section.

## 4.2. Different MADM methods

Multiple MADM methods are available and have been used in literature. The different methods were divided by Tscheikner-Gratl et al. [98] in three types explained in Table 4.1. The three types of methods are: 1) value measurement; 2) goal, aspiration and reference level and 3) outranking [98].

Table 4.1: Types of MCDM models [98]

| MADM Type | Explanation | Methods |
|---|---|---|
| Value measurement | Criteria weights are assigned depending on its importance and alternatives are assigned a numerical score. | WSM, AHP |
| Goal, aspiration and reference level | Measure the the ability of alternatives to reach a specific goal | TOPSIS, VIKOR |
| Outranking | Alternatives are compared pairwise for all criteria | ELECTRE, PROMETHEE |

In the category of goal, aspiration and reference level methods, the most common used methods are TOPSIS and VIKOR. These techniques consist of an aggregated function that measures how close an alternative is to the most ideal or least ideal solution. The use of VIKOR is recommended by Mei-Tai Chu [26] in the case of a large number of decision-makers involved, else TOPSIS is preferred. As in the study at hand multiple decision-makers are not considered only TOPSIS will be further analysed [2]. The rest of methods classified in Table 4.1 will be further discussed below.

### 4.2.1. Weighted Sum Method (WSM)

The Weighted Sum Method (WSM) is the simplest and most used MADM approach in literature. For a problem with $m$ alternatives and $n$ decision criteria, Equation 4.1 [108] [20] is used in WSM. The weight coefficients of the criteria $w_j$, have values between 0 and 1, which add up to 1. A higher weight coefficient indicates a bigger importance of the considered criterion. Using Equation 4.1 [108] [20] the best alternative can be found, which correspond to the alternative which achieved the highest score.

$$A_i^{WSMscore} = \sum_{j=1}^{n} w_j a_{ij}, \quad i = 1,2,...,m; \qquad with \sum_{j=1}^{n} w_j = 1, \quad w_j \in (0,1) \tag{4.1}$$

WSM presents benefits in the considered operational setting as it is easy to understand and implement by the decision-makers. However, this method has some drawbacks, such as the inability to produce criteria weights. The decision-maker need to select criteria weights which can affect highly the results. For the context of this project this method will not be further considered because the decision-maker's subjectivity minimisation by generating standard criteria weights is of interest.

### 4.2.2. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a method that aims to select an alternative which is the closest to an optimal solution and the farthest from a sub-optimal solution. Behzadian et al. [13] defined the main steps of a TOPSIS model, which are shown in Figure 4.3.

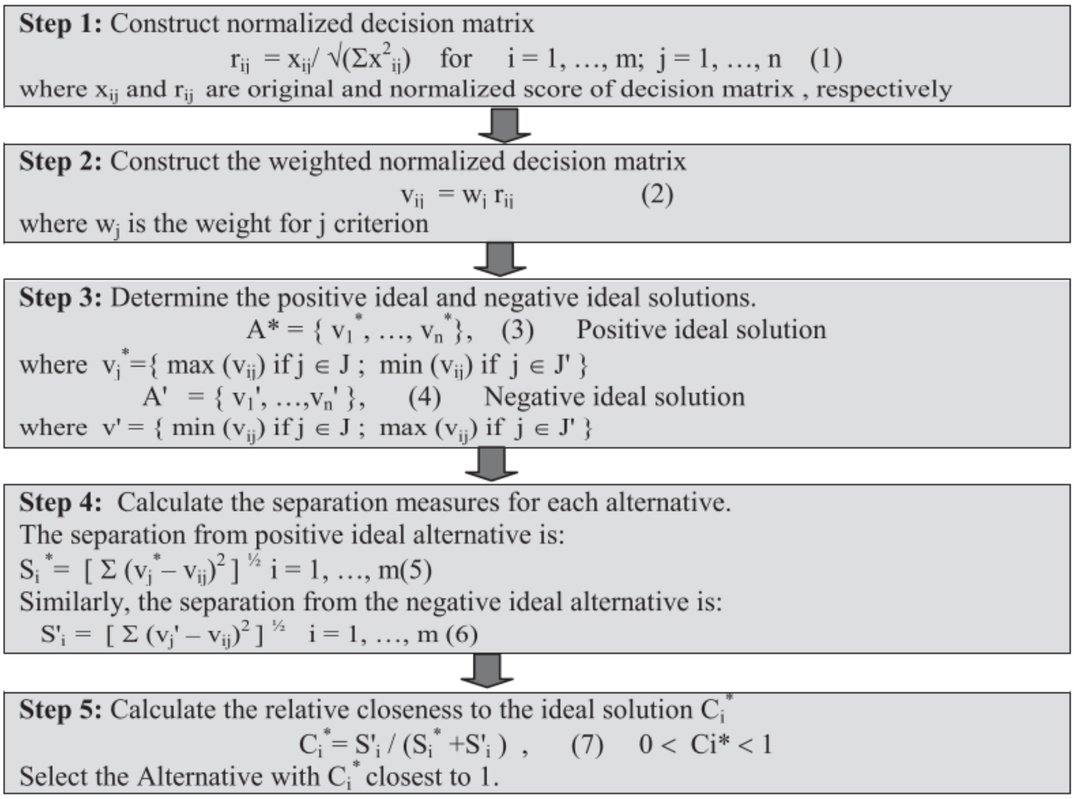


Figure 4.3: TOPSIS steps defined by Behzadian et al. [13]

The popularity of TOPSIS comes from its ease to be used and programmed. Its main disadvantages are that another method needs to be used in order to obtain criteria weights and that it is difficult to consider correlations between criteria. In order to deal with these disadvantages, Xu et al. [107] proposed an improved TOPSIS method, in which a weighting method considering both human subjectivity and data variance is implemented together with a new R-cluster based evaluation system.

### 4.2.3. Analytic Hierarchy Process (AHP)

Analytical hierarchy process has been widely used in decision support literature, since it was first proposed by Saaty [85] in 1987. The method consists in two phases defined by Bertolini, Braglia, and Carmignani [15]: 1) the definition of the hierarchy tree and 2) the numerical evaluation phase. During the first phase, three levels of tree hierarchy are defined: the goal, the criteria and the alternatives. An example of the structure of the tree is shown in Figure 4.4 [102].

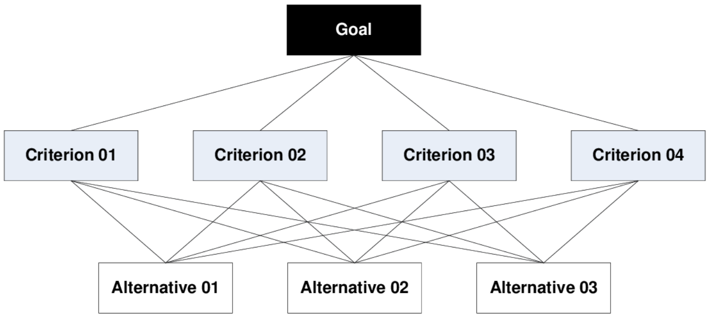


Figure 4.4: Hierarchy tree for AHP example [102]

The second phase consists on a numerical evaluation, using pair-wise comparisons and creating a $n$ by $n$ comparison matrix A which can be seen in Equation 4.2 [65], in which $b_{ij}$ corresponds to the relative important of criteria i compared to criteria j. The comparisons follow a bottom-up approach: starting by the alternatives and ending with the goal. The decision-makers are not fully replaced but their judgements are taken into account throughout the process [15]. Table 4.2 created by Saaty [85] shows the scale of relative importance to convert linguistic meaning into numbers, which is used during the pairwise comparisons. This method is used both for weighting the different criteria as for ranking the decision alternatives.

$$B = \begin{pmatrix} 1 & b_{12} & ... & b_{1n} \\ b_{12} & 1 & ... & b_{2n} \\ \vdots & \dots & \ddots & \dots \\ b_{n1} & b_{n2} & \cdots & 1 \end{pmatrix} \tag{4.2}$$

Table 4.2: AHP scale of relative importance determined by Saaty [85]

| Intensity of importance | Definition | Explanation |
|---|---|---|
| 1 | Equal importance | Two activities contribute equally to the objective |
| 3 | Moderate importance of one over another | Experience and judgement moderately favour one activity over the other |
| 5 | Essential or strong importance | Experience and judgement strongly favour one activity over the other |
| 7 | Demonstrated importance | An activity is strongly favoured and its dominance demonstrated in practice |
| 9 | Absolute importance | The evidence favouring one activity over another is of the highest possible order of affirmation |
| 2,4,6,8 | Intermediate values | When compromise is needed |
| 1/1,1/2,1/3... | Reciprocals | If activity i has one of the above numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i |

The pair-wise comparison matrices need to be consistent. The consistency ratio in Equation 4.3 is typically used to assess the consistency of the pairwise matrix. An acceptable value of CR is equal or below 0.1. If the value of the CR is higher, this indicates that the pair-wise judgements have not been consistent [79] [65]. The consistency ratio CR was introduced by [85] and is the ratio between consistency index CI and the random consistency index RI. The CI can be calculated with Equation 4.4, in which $\lambda_{max}$ corresponds to the maximum eigenvalue of the comparison matrix and $n$ corresponds to the number of criteria. In Table 4.3, the average value of the random consistency index RI for different matrix dimensions can be found [65] [85].

$$CR = \frac{CI}{RI} \tag{4.3}$$

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{4.4}$$

Table 4.3: Average random consistency index values depending on comparison matrix dimension [65] [85]

| **Dimension of comparison matrix n** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| **Average random consistency index RI** | 0 | 0 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 |

One of the main advantages of AHP is its easy and straightforward implementation and methodology [81]. This is of special interest in the context of operational decisions, as it is important that the decision-makers understand the concepts underlying the decision support system. Furthermore, it provides a clear method not only for raking alternatives but also weighting criteria. However, inconsistencies due to compensation between bad scores or good scores in different criteria can exist. It is therefore important to perform a good sensitivity analysis to ensure the validity of results. Furthermore, although it has overall a good scalability it may become computationally intensive for big amounts of criteria and alternatives. This is not the case in this project, as the number of criteria and alternatives is moderately low.

### 4.2.4. Elimination and Choice Expressing Reality (ELECTRE)

ELECTRE is a popular family of outranking multi-attribute decision-making methods, which was introduced by Roy [84] in 1968. Different versions of ELECTRE methods have been introduced throughout the years, from ELECTRE I to ELECTRE IV, all of them with the same basis and small modifications. ELECTRE methods are based on pair-wise comparisons and use the concepts of concordance (positive arguments) or discordance (negative arguments) to outrank alternatives [42]. Şenel, Şenel, and Aydemir [89] gathered the main steps of ELECTRE methods as follows:

Step 1: Construction of the decision matrix

Step 2: Construction of the normalised decision matrix

Step 3: Construction of the weighted matrix

Step 4: Determination of the relation between concordance and discordance sets

Step 5: Construction of concordance and discordance matrices

Step 6: Determination of concordance and discordance dominance matrices

Step 7: Determination of aggregate dominance matrix

Step 8: Rank the of alternatives by checking the highest scores on the aggregate dominance matrix

One of the main advantages of ELECTRE methods is that small variations on alternative performance against criteria will not modify significantly the ranking of alternatives [42]. Furthermore, it accepts both qualitative and quantitative data. ELECTRE III is the most used method of the ELECTRE family in literature and it considers the fuzzy nature of the decision maker, which is of special interest for the project at hand. The main disadvantage of ELECTRE methods are their subjectivity, low robustness and that their limitation of use to problems where the importance of criteria can be quantified [98]. Finally, another disadvantage is that the final ranking can lead to more than one best alternative. This method will not be used as it is more difficult to understand by decision-makers than other formerly discussed methods, which is undesirable in the operational environment considered.

### 4.2.5. Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)

PROMETHEE is a family of outranking methods first introduced by Brans [18] in 1982. Different methods are available, ranging from PROMETHEE I to VI, each of them presenting small adaptations from each other. PROMETHEE II allows for a complete ranking of alternatives, in contrast with PROMETHEE I that allows a partial ranking. The main steps of these PROMETHEE II, which is the most suitable for the considered project, have been gathered by Behzadian et al. [14] in Figure 4.5.

**Step 1**. Determination of deviations based on pair-wise comparisons

$$d_j(a,b) = g_j(a) - g_j(b) \qquad (1)$$

Where $d_j(a,b)$ denotes the difference between the evaluations of $a$ and $b$ on each criterion.

**Step 2**: Application of the preference function

$$P_j(a,b) = F_j[d_j(a,b)] \qquad j=1,\ldots,k \qquad (2)$$

Where $P_j(a,b)$ denotes the preference of alternative $a$ with regard to alternative $b$ on each criterion, as a function of $d_j(a,b)$.

**Step 3**: Calculation of an overall or global preference index

$$\forall a,b \in A, \qquad \pi(a,b) = \sum_{j=1}^{k} P_j(a,b) w_j \qquad (3)$$

Where $\pi(a,b)$ of $a$ over $b$ (from 0 to 1) is defined as the weighted sum $p(a,b)$ of for each criterion, and $w_j$ is the weight associated with $j$th criterion.

**Step 4**: Calculation of outranking flows/ The PROMETHEE I partial ranking

$$\phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a,x) \qquad (4) \qquad \text{and} \qquad \phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x,a) \qquad (5)$$

Where $\phi^+(a)$ and $\phi^-(a)$ denote the positive outranking flow and negative outranking flow for each alternative, respectively.

**Step 5**: Calculation of net outranking flow/ The PROMETHEE II complete ranking

$$\phi(a) = \phi^+(a) - \phi^-(a) \qquad (6)$$

Where $\phi(a)$ denotes the net outranking flow for each alternative.

Figure 4.5: Main steps of PROMETHEE II method identified by Behzadian et al. [14]

PROMETHEE methods are simple to use. Their main advantage over other methods is that it solely requires evaluation of each alternative on each criterion [99]. The main disadvantage of PROMETHEE methods is that they do not provide guidelines for weights determination [99]. Furthermore, they have a non-compensatory nature and, therefore, it is necessary to attentively validate the ranking solutions.

## 4.3. Discussion

In this section the methods that will be used in the thesis research will be selected by making a comparison table. Advantages and disadvantages of the main methods discussed in section 4.2 have been gathered in 4.4 [103].

Table 4.4: MCDM methods analysis [22][103]

| Method | Advantages | Disadvantages |
|---|---|---|
| WSM | - Easy to understand<br>- No data intensive. | -Not clear weight assignment method |
| AHP | -Easy to use<br>- Scalable<br>-Adjustable to fit different sized problems due to its hierarchy structure<br>- No data intensive. | -Problems due to interdependence between criteria and alternatives<br>-Can lead to inconsistencies between judgment and ranking criteria<br>- rank reversal |
| ELECTRE | -Takes uncertainty and vagueness into account. | -Its process and outcome can be difficult to explain in layman's terms<br>-outranking causes the strengths and weaknesses of the alternatives to not be directly identified |
| PROMETHEE | -Simple to use<br>-Does not require criteria proportionality assumption | -Not clear weight assignment method |
| TOPSIS | -Simple process.<br>-Easy to use and program.<br>-The number of steps is the same regardless of the number of criteria | -It does not consider the correlation of attributes<br>-Difficult to weight<br>-Difficult to keep judgement consistency |

AHP is a consistent and structured method of proven quality. It is able to use both qualitative and quantitative criteria. The main disadvantage of the method is that it may become time consuming and complex when analysing a big number of alternatives and criteria. Furthermore, it may lead to a loss of information due to the possible compensation between bad and good scores in different criteria [98]. The main advantage of ELECTRE over AHP is the consideration of uncertainty. However, this advantage diminishes when using Fuzzy AHP. Furthermore, ELECTRE is difficult to understand by the decision-maker. PROMETHEE and WSM are characterised by its easy use. However, these methods will not be considered as they fail in providing a clear weight assignment method.

Despite its few disadvantages, AHP is selected as the most suitable method for the operational maintenance decision-making problem considered. The method is the most suitable because of its proven quality and ease to use, especially important in an operational environment. Furthermore, the use of pair-wise comparisons is of special interest for the field, as it helps establishing criteria weights which can be useful to improve the maintenance planner situational awareness, decreasing his/her workload. TOPSIS has been used in literature to validate the solutions of other MCDM methods, due to its simple process [103]. Therefore, TOPSIS would be selected in order to verify the results given by AHP.

## 4.4. Data normalization in MADM

Selecting a normalisation technique is the first step in the development of a MADM model [100]. Normalization techniques are used in order to create a comparable unit for alternative ratings. Jahan and Edwards performed a state-of-the-art review on the topic, identifying 31 different normalisation methods and proving the big influence of the used normalisation technique in the ranking performance of different MADM methods. Vafaei, Ribeiro, and Camarinha-Matos [100] gathered the 5 most common techniques which will be analysed further. These techniques and their formulas can be seen in Table 4.5. Each method presents two formulas, one beneficial and one no-beneficial. For beneficial attributes or criteria high values will correspond to high normalised values, while high values of no-beneficial criteria will generate low normalised values.

Table 4.5: MCDM normalization techniques grouped by Vafaei, Ribeiro, and Camarinha-Matos [100]

| **Normalization Technique** | | **Formulas** | **Notes** |
|---|---|---|---|
| Linear scale transformation (max) [23] | Beneficial | $n_{ij} = \frac{r_{ij}}{r_{max}}$ | Best for AHP in combination with linear scale transformation (sum) |
| | No beneficial | $n_{ij} = 1 - \frac{r_{ij}}{r_{max}}$ | |
| Linear scale transformation (max-min) [23] | Beneficial | $n_{ij} = \frac{r_{ij} - r_{min}}{r_{max} - r_{min}}$ | Used in combination with linear scale transformation (sum) in AHP |
| | No-beneficial | $n_{ij} = \frac{r_{max} - r_{ij}}{r_{max} - r_{min}}$ | |
| Linear scale transformation (sum) [23] | Beneficial | $n_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$ | Worst for AHP |
| | No-beneficial | $n_{ij} = \frac{1/r_{ij}}{\sum_{i=1}^{m} 1/r_{ij}}$ | |
| Vector normalisation [23] | Beneficial | $n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$ | Best for GRA, TOPSIS and PROMETHEE |
| | No-beneficial | $n_{ij} = 1 - \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}}$ | |
| Logarithmic normalisation [54] | Beneficial | $n_{ij} = \frac{ln(r_{ij})}{ln(\prod_{i=1}^{m} r_{ij})}$ | Not suitable for AHP |
| | No-beneficial | $n_{ij} = \frac{1 - \frac{ln(r_{ij})}{ln(\prod_{i=1}^{m} r_{ij})}}{m-1}$ | |
| Fuzzification [83] | Every case | Using membership function | Used to compare fuzzy sets ratings |

Vafaei, Ribeiro, and Camarinha-Matos [101] compared normalisation techniques in AHP using Pearson and Spearman correlation and draw conclusions on the most suitable normalization techniques for the method. Logarithmic normalisation was found to not be suitable for AHP, as it can lead to zero or infinite normalized values which are not suitable to continue the AHP process. Furthermore, Vafaei, Ribeiro, and Camarinha-Matos concluded that Linear scale transformation (max and max-min) and vector normalization techniques need to be used in combination with linear scale transformation (sum) in order to ensure that the sum of the columns of the pair-wise comparison matrix used in AHP is equal to 1, which is a requirement for the method. The best normalisation technique was linear scale transformation (max) combined with linear scale transformation (sum), while the worst technique was the linear scale transformation (sum) alone [101].

In another study, Chatterjee and Chakraborty [24] showed that vector normalisation technique achieved the best performance in PROMETHEE, GRA and TOPSIS using as metric the mean $r_s$ value. Furthermore, TOPSIS is the method which is the most sensitive to the use of different normalisation techniques. Vafaei, Ribeiro, and Camarinha-Matos [100] found using Pearson and Spearman correlations as metric that vector optimization is the best technique for TOPSIS, while logarithmic normalisation is the worst.

# 5

# Robust and dynamic decision-making

The operational aircraft maintenance environment characteristics were described in chapter 2. This chapter will deal with how to account for two of these characteristics during the repair decision-making process. The challenges which will be dealt with are the following: 1) imperfect or uncertain information and risks during decision-making in section 5.1 and 2) dynamic situation development in section 5.2.

## 5.1. Accounting for uncertainty and risks: robust decision-making

Uncertainty during decision-making can be defined as limited knowledge about present, past or future events [69]. Mosadeghi et al. [74] divides the type of uncertainty in multi-criteria decision-making problems in two categories: the decision-maker preferences and knowledge and the model uncertainty. The model uncertainty will not be considered as it is out of the scope of this report. The next sections will deal with different methods to account for uncertainty and risks in the context of the problem considered in this report, in order to achieve a robust decision support system.

### 5.1.1. Risk as a criterion in AHP

AHP was decided in section 4.3 to be the most suitable modelling approach for the problem considered in this report. Millet and Wedley [73] discussed different approaches to model risk in AHP. From the different approaches, considering risk as a decision-criterion is the most suitable in the considered problem. This is of special interest when there is information available about how the decision-maker judges the risk itself and no clear information is available about the risk's effects on the outcomes [73]. In the study at hand, the risk ratings can be generated by calculating probabilities of occurrence using available repair historical data.

### 5.1.2. Risk modelling using scenario-based reasoning

Another way to consider risks in the problem at hand is using scenario-based reasoning. Most aircraft maintenance literature regarding risk assessment in literature focus on evaluating the past to try to predict the future. Scenario analysis is a promising forecasting technique that can contribute to risk assessment based on the assumption that the future does not necessarily depend on the past. It focuses on Level 3 Situational Awareness, the projection of future status [41]. In the context of short-term repair maintenance context, there is a literature gap in implementing scenario analysis to account for risks.

Figure 5.1 shows how considering scenarios in decision-making can contribute in making more robust decisions. The goal of robustness is not to select an alternative that is optimal for one scenario, but the alternative which perform the best in the majority of scenarios [70]. It is important to construct comparable and consistent scenarios. These scenarios will not only improve the situational awareness of the decision-makers but also help in exploring possible consequences of decisions [29].

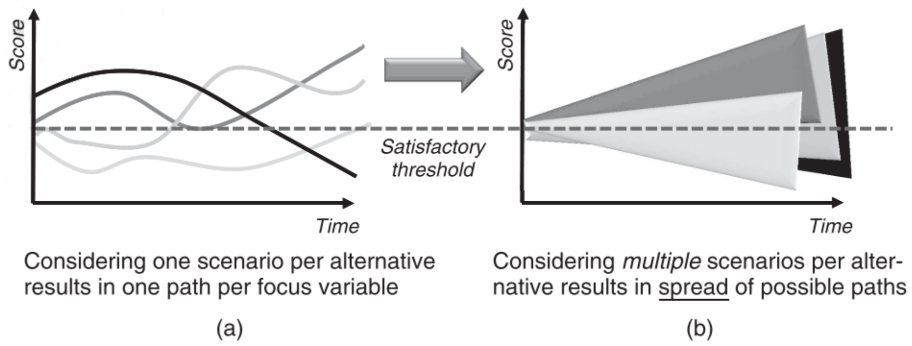


Figure 5.1: Scenario-based robust decision-making [29]

Comes, Wijngaards, and Schultmann [29] defined a method to integrate decision-based reasoning with multi-criteria decision-making methods. Their study proposed a scenario construction process which consists in two steps: 1) Creation of top-down DAGS (directed acyclic graphs) and 2) Generate a bottom-up attribute tree with expert opinions. The decision map generated by following these steps is visualised in Figure 5.2.

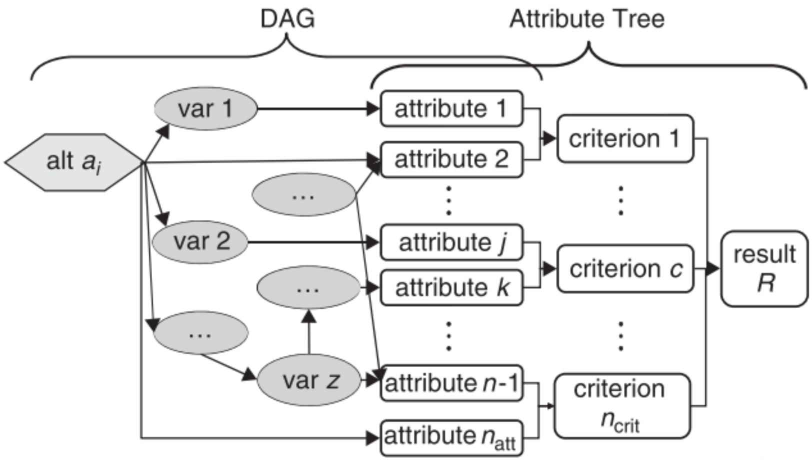


Figure 5.2: Decision map for scenario generation developed by Comes, Wijngaards, and Schultmann [29]

The main advantages of scenario-based MCDM is the ability to create a robust decision support system accounting for risk. Furthermore, it can improve the decision-maker situational awareness. The main disadvantage of the method is the possible need of extensive expert judgement data. Scenario-based MCDM will be further considered in this research as the possible advantages of this method outrank its disadvantage.

### 5.1.3. Fuzzy set theory and evidential reasoning

Fuzzy set theory is part of computational intelligence and has been extensively used to deal with uncertainty in real-life decision-making problems [67]. Fuzzy set theory was introduced by Zadeh [110] in 1965. A fuzzy set is characterised by a membership function which associates each point of the fuzzy set with a real number between 0 and 1 [110]. Fuzzy numbers are commonly used in decision-making modelling approaches. Lima Junior, Osiro, and Carpinetti [67] defines a fuzzy number as a special type of fuzzy set whose membership function complies with normality conditions.

The triangular membership function is the most used in decision-making as it is the most intuitive. A fuzzy number $\tilde{A} = (a, b, c)$ is triangular if its membership function is given by Equation 5.1 [5]. Other types of membership function also exist, such as the trapezoidal, sigmoid or gaussian [60].

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & x < a; \\ \frac{x-a}{b-a} & a \le x \le b; \\ \frac{c-x}{c-b} & b \le x \le c; \\ 0 & x > c \end{cases} \tag{5.1}$$

The use of fuzzy numbers provides a suitable method for the problem at hand, thanks to their ability to handle both qualitative and quantitative imprecise information and deal with the vagueness of ill-structured problems [67]. However, the use of fuzzy sets can be complex to understand for the decision maker.

Evidential Reasoning (ER) has also been used in maintenance literature to address uncertainties, as an alternative to fuzzy models [90]. Evidential Reasoning approach aim to fit both qualitative and quantitative data under uncertainty. The ER rule is based on Dempster-Shafer evidence theory [3]. Evidential reasoning approach is able to consider the decision-maker preferences using the theory of belief functions or degree [92]. This approach has usually better acceptance by the decision-makers, as they are no longer expected to provide objective or certain assessments of criteria but to use their intuition and experience to make judgements [92].

Irungu, Akumu, and Munda concluded that for problems in which big expert opinion datasets are not available, evidential reasoning approaches tend to give better results than fuzzy methods due to its flexibility. Furthermore, ER methods are easier to understand by the decision-maker than fuzzy methods, as has been discussed before. Therefore, the suitability of a ER-AHP methods, such as the developed by Hong-tao et al. [49], will be further considered in this research. The use of both an hybrid fuzzy and ER approach is also not yet discarded.

## 5.2. Accounting for environment changes: dynamic decision-making

The operational maintenance environment is constantly evolving. In a certain time in the future after a decision has been taken, the inputs of a DSS about the past, present or future could change, changing as well the decision alternatives and its ranking. If this is detected within suitable time-limits, the performance of the DSS can be highly improved by considering the decision-process as dynamic and adapting or changing the taken decisions. This section will introduce several dynamic decision approaches in literature, which are able to account for the environment changing nature of the problem at hand.

Jassbi, Ribeiro, and Varela [57] proposes a dynamic decision-making model which can be seen in Figure 5.3. The model merges three decision matrices (past, present and future) to generate a ranking for the decision alternatives. Different methods to perform this aggregation are available in literature and further research needs to be performed in order to choose a suitable one. Meanwhile, Campanella and Ribeiro [21] developed a similar framework, but only considering historical and present data. In both methods a literature gap is observed gap in using different aggregation techniques within the context of the frameworks to assess the robustness of the generated solutions.

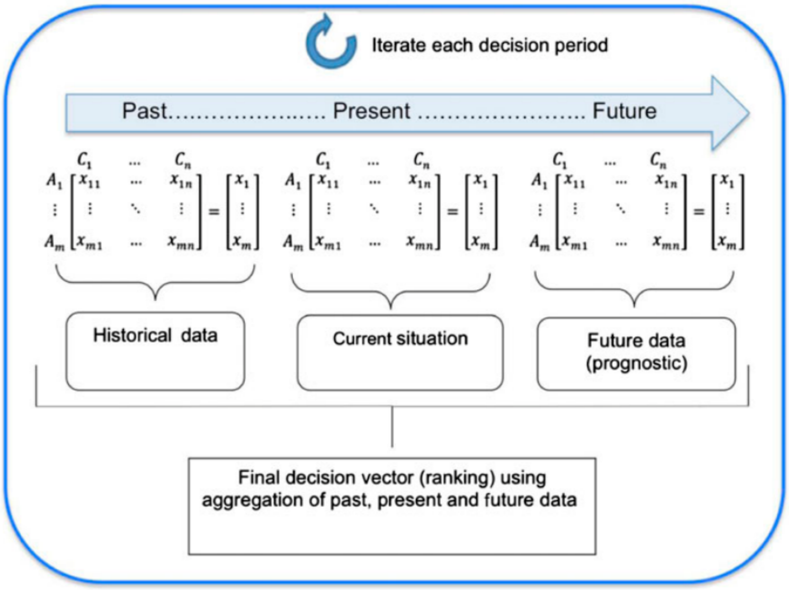


Figure 5.3: Dynamic multi-criteria decision-making framework by Jassbi, Ribeiro, and Varela [57]

González-Prida et al. [45] developed a method for a dynamic analytical hierarchy process. As AHP was selected as the modelling approach for this project, this method is of interest. However, the main disadvantage is that this method has not been validated by its author. This disadvantage can also become an opportunity to add value to literature by validating this method via a case study. This is however out of the scope for this project, due to time constraints.

Finally, scenario analysis can also be used to create a dynamic decision-making approach. In Table 5.1, the proposed implementation of scenarios for dynamic decision support can be seen. "A" stands a for alternative, "C" for criteria and "W" for weight in Table 5.1. The sources of uncertainty in the maintenance scenario need to be identified and defined in order to create the different possible scenarios. Examples of uncertainties would be the occurrence of a new failure in the same or different aircraft, change in available resources, unexpected delay on flight performed by the considered aircraft, etc. The scenarios and influence on the ranking would be explored beforehand. Time limits will be generated for each scenario and if a scenario occurs at any time within its time-limit the decision ranking will be updated and a new decision will be taken. This approach, although innovative, presents a difficult implementation as the time limits for each scenario are difficult to predict or generate. Furthermore, it has never been used in literature before in the context of maintenance decision-making. Therefore, this method will not be further researched.

Table 5.1: Decision model using scenario analysis

| | **Scenario 1** | | | | **...** | **Scenario x** | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **W_{1,1}** | **...** | **...** | **W_{n,1}** | **...** | **W_{1,x}** | **...** | **...** | **W_{n,x}** |
| | **C_{1}** | **...** | **...** | **C_{n}** | **...** | **C_{1}** | **...** | **...** | **C_{n}** |
| **A_{1}** | $a_{11,1}$ | ... | ... | $a_{1n,1}$ | ... | $a_{11,x}$ | ... | ... | $a_{1n,x}$ |
| **.** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **.** | ... | ... | | ... | ... | ... | ... | ... | |
| **.** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **A_{m}** | $a_{m1,1}$ | ... | ... | $a_{mn,1}$ | ... | $a_{m1,x}$ | ... | ... | $a_{mn,x}$ |

# 6
# Research Plan

This section presents a research proposal to improve the situational awareness of the maintenance decision maker by developing a decision support tool that identifies and evaluates decision alternatives dynamically in the context of short-term operational aircraft maintenance (up to A-checks) characterised by a changing and complex environment. This will be achieved by a hybrid model consisting of multi-criteria decision-making, scenario analysis and boolean trees methods. The project plan consists of: a description of the project contribution, definition of research questions, project methodology, experimental set-up, a prediction of the results, relevance of the project and a project planning. The research adds value to the body of knowledge by creating a systematic, robust and dynamic framework for maintenance repair decision-making. The dynamic consideration of repair options is the main novelty of the presented research proposal.

## 6.1. Contribution and novelty of the project

There is a gap in literature in decision support tools for dynamic environments such as operational aircraft maintenance where the human-machine interaction is essential [62].The proposed research aims to add value to the body of knowledge by creating a systematic, complete, robust and dynamic decision-making framework for aircraft repairs in operational maintenance. Current industry practices lack a structured and complete approach for decision-making and consider the repair scenario as static. This means that the decisions are rarely re-considered when the environment or constraints change. Furthermore, the unstructured decision-making process leads to an insufficient use of available information and incomplete set of decision alternatives.

The use of MCDM methods is selected due to its ability to evaluate decision alternatives dependent on diverse and conflicting criteria in an structured way. Specifically, AHP and TOPSIS have been found to be the most suitable methods for aircraft maintenance repair decision-making. In order to ensure a complete decision alternatives identification, BDT is selected as the most suitable method. Finally, different methods such as scenario analysis or fuzzy logic will be explored and implemented with the aim to create a robust and dynamic tool that account for the environment characteristics.

The novelty of the project consists in the consideration of risk and changing nature of the problem, creating a robust tool able to dynamically adapt decisions. Furthermore, the project addition to the body of knowledge consists on the creation of a systematic decision-making tool which satisfies operational constraints for aircraft structures maintenance. Current industry practices and literature lack a consistent and systematic analysis of the situation before taking a maintenance decision and the decision-making process is static [32] [77].

## 6.2. Research questions

The following research questions and sub-questions need to be answered in order to achieve the research objective defined in chapter 2.

1. How can decision trees, MCDM and scenario analysis methods be combined in a fast (in the order of

minutes), systematic, robust and dynamic decision support tool for operational maintenance affecting aircraft structural damage decisions (up to A-checks) to help improving the situational awareness of the maintenance decision-maker?

(a) How can a complete set of decision alternatives be generated using a deterministic decision tree?
(b) Which operational constraints need to be included in the model in order to ensure feasibility of the generated decision alternatives and how can these be added to the framework?
(c) Which criteria are suitable to evaluate the generated options?
(d) How can the importance weight of the different criteria be modelled using Analytic Hierarchy Process (AHP)?
(e) How can the selected evaluation criteria be normalised using historical data in order to be represented through a similar rating to make comparisons possible?
(f) How can decision alternatives be quantitatively evaluated and ranked using AHP?
(g) How can decision alternatives be ranked using TOPSIS and what are the advantages of ranking the alternatives using TOPSIS in comparison with AHP?
(h) Can the implementation of fuzzy logic or evidential reasoning in AHP or TOPSIS benefit the decision-making tool and is it a realistic goal to implement it in this project? If so, how can this be implemented in the tool?
(i) What are the main uncertainties and risks in the maintenance scenario and how can they be used to formulate different possible future scenarios to achieve robust decision-making? How can this be implemented in the tool?
(j) Which modelling framework for making the tool dynamic is the most appropriate for the project and how can it be implemented?

2. What conclusions can be drawn from the developed decision support tool compared to the initial proof of concept and to the tool developed by Dhanisetty, Verhagen, and Curran [32]?

(a) What performance indicators are most suitable to assess and compare the decision support tool?
(b) What is the difference in performance between AHP+TOPSIS Multi-Criteria Decision-Making method compared with the Weighted Sum Method (WSM) used by Dhanisetty, Verhagen, and Curran [32]?
(c) What is the influence of implementing risk assessment through scenario analysis in the model compared to the initial model and to the model created by Dhanisetty, Verhagen, and Curran [32]?
(d) What are the limitations and challenges for the implementation of the developed decision support tool in real-life operations?

## 6.3. Methodology

To meet the project objective a decision-making framework will be developed using MCDM (AHP+TOPSIS), BDT and scenario analysis, as determined in former chapters. Multi-phase programming will be used, first creating a baseline model and then an extended version. An evolutionary fashion will be always used, first creating a simple model and developing it further to make it as similar as possible to the problem. Scenario analysis techniques to dynamically adapt decisions will be included in the extended model and responds to research question 1i.

1. Creation of baseline model

Step 1: **Evaluation of structural damage**: When a damage occurs in an aircraft structure, the damage is quantified and time limits for the required repair are established. The severity of the damage is quantified using the Structural Repair Manual (SRM) and the Original Aircraft Manufacturers (OAM) documents.

Step 2: **Identification of all feasible repair decision alternatives**: This step aims to answer research question 1a and 1b. A complete set of decision alternatives will be generated using a boolean decision tree (BDT). The tree will be prunned. Necessary inputs for the BDT are operational conditions (flight schedule, flight planning, maintenance shop, etc) and the availability of purchase/lease/exchange of the damaged structure from external stakeholders.

Step 3: **Criteria identification and weighting**: This step aims to answer research questions 1c and 1d. The considered criteria will be cost, downtime, reliability and risk. These criteria are chosen due to popularity in literature and availability of data. The relative importance of criteria will be determined in the form of criteria weights using pair-wise comparisons (AHP).

Step 4: **Criteria rating**: This step aims to answer research questions 1e. The selected criteria (cost, downtime, reliability and risk) will be normalised and rated. Historical damage, cost and downtime data from a European airline will be used to create the criteria ratings. Risk ratings can be generated by calculating probabilities of occurrence using available repair historical data.

Step 5: **Ranking of decision alternatives**: This step aims to answer research questions 1f, 1g and 1h. Quantifiable evaluation of the criteria is performed in order to rank the alternatives. This is first done using AHP and then TOPSIS. The aim of using both MCDM methods is to assure consistent results. If the answer to research sub-question 1h is positive, fuzzy theory will be also implemented in this step.

Step 6: **Take final decision**: After the alternatives have been ranked, the maintenance decision-maker can select the most suitable solution.

2. Creation of extended model

Step 1: **Creation of future scenarios**: This step aims to answer research questions 1i. The sources of uncertainty in the maintenance scenario need to be identified and defined in order to create the different possible scenarios. Each scenario will have a time-limit. Outside of the time-limit the occurrence of the scenario will be neglected. The inputs to estimate the time limits are expert opinions, historical data and maintenance documentation.

Step 2: **Implement scenario-based approach to improve robustness**: This step aims to answer research questions 1i. A scenario-based approach will be implemented in order to account for the risky nature of the environment and achieve robust decision-making.

Step 3: **Implement dynamic framework**: This step aims to answer research questions 1j. It consist in re-evaluate final decision in a dynamic approach to consider the changing nature of the environment

A methodology flowchart showing the inputs, outputs and processes of the final model can be seen in Figure 6.1. The model starts when a structural damage is found by the MRO organisation and finishes when the final decision regarding the repair of the damage is taken.

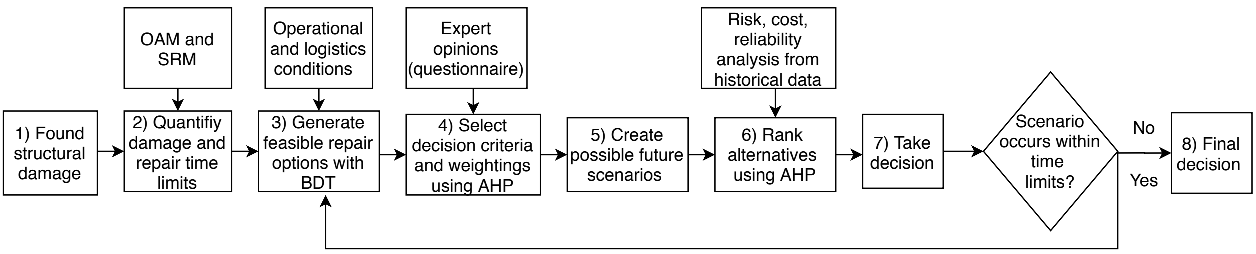


Figure 6.1: Methodology flowchart

## 6.4. Experimental set-up

Several experiments are required in order to gather data necessary to answer the research questions. This section will discuss their set-up and limitations. The proposed experiments are a computer model and a questionnaire, which are explained respectively in subsection 6.4.1 and subsection 6.4.2.

### 6.4.1. Computer model set-up

The computer model will be built based on preceding work done by V.S.V. Dhanisetty during his PhD research at TU Delft, in the topic of 'Impact damage repair decision-making for composite structures'. The model aims to answer research question 1 and 2, by developing a decision-making tool and meeting the research objective. V.S.V. Dhanisetty's model will be modified and extended to account dynamically for maintenance risks given the dynamic nature of the repair scenario through simulations. The program of choice will be Matlab, as it is a robust and consistent programming language. Furthermore, proceeding implementations in this field were also performed using Matlab. The model will have data limitations, as data availability on maintenance decisions is scarce. It will be run on a HP ZBook 15 G2 with a Intel Core i7-4710MQ CPU @ 2.50 GHz processor, therefore simulation runs will last in the order of minutes.

### 6.4.2. Questionnaire set-up

Determining criteria weights using AHP requires pairwise comparisons between the different selected criteria. Due to the limited data available, a questionnaire will be handed to experts in which the relative importance of the selected criteria will be asked. Using this data, a realistic estimation of the criteria weights can be reached. The limitation is that in maintenance, decisions are case-dependent and therefore there is no absolute correct decision. Furthermore, the respondents of the questionnaires need to reach a suitable sample size of at least 30 [88]. The questionnaire will be generated using Google Forms. Google Forms is selected due to its ability to automatically gather the data in an excel sheet, which can be directly imported to Matlab.

## 6.5. Results

This section will outline the predicted outcome of the model created following the methodology explained in section 6.3. Furthermore, the relevance and impact of the work will be described. Verification and validation of the model are also discussed in this section and are used to achieve high quality and credible results.

### 6.5.1. Project results and relevance

The results expected after implementation of the methodology explained in section 6.3 and experiments in section 6.4 are a complete list of repair decision alternatives in the case of a maintenance repair operational decision and a ranked list of those alternatives for different future scenarios. Two ranked lists are expected, one ranked using AHP and another one using TOPSIS. It is expected that the results from both models are comparable to each other, and also comparable to the model developed by [32]. This means, the ranked options are estimated to have the same order, regardless of the used method. Results after scenario analysis and dynamic framework implementation are predicted to change and, in the long-run, lead to more suitable option selection which will decrease cost and increase time savings. The dynamic consideration of repair options is the novelty of the presented research proposal.

The relevance of the project is two-folded. First, it will introduce a systematic decision-making framework which can be used by the repair maintenance decision-making in Maintenance, Repair & Overhaul (MRO) organizations to improve their situational awareness and decrease the work-load. Second, the introduction of a robust and dynamic decision-making in comparison with current static assumptions will, in the long-run, lead to a decrease in costs and increase in time savings.

### 6.5.2. Project verification

Verification is performed to assure the model matches the conceptual model specifications and assumptions [47]. The model will be programmed using block-based programming. This method is of special interest in order to help debugging the program during the development phase and minimising possible coding errors. As part of the verification data model errors, logic model errors, project management errors and experiment errors will be looked for and corrected as they are the most common errors in computer simulation models [47]. Furthermore, the model will be tested for a diverse set of input variables (very big or very small values) in order to test its correctness. Finally, the model outcomes will be compared to the outcome of similar studies in literature such us the model performed by Dhanisetty, Verhagen, and Curran [32].

### 6.5.3. Project validation

Validation is performed to assure the created model provides a result which answers the research question at hand. Validation of the model will be performed by means of a case study related to a damaged Boeing 777 outboard flap. The case study tests the model in a real-life operational setting. Repair data and a timeline of a specific Boeing 777 outboard flap failure is provided by a European airline. Case specific cost, downtime and failure rate data are also provided by the European airline. The case study can then be solved using the extended model. Differences between the real-life case and the simulated results about the decision outcome, computational speed, cost savings and decisions alternatives completeness can then be drawn to validate the model. One limitation of the real-case scenario is the lack of data of future scenarios, as the taken decisions were static and therefore future possible events were neglected. Furthermore, the model will be run in two set-ups: One using TOPSIS and the other AHP. Comparison of the different or similar results provided by both methods will also contribute to the validation.

## 6.6. Project planning

After the research goal, the methodology, experimental set-up and expected results have been determined. It is essential to determine a project planning as it helps keeping an organised overview of the project steps, deliverables and milestones. It is of special interest in long projects, such as a master thesis research, in order to not lose track of the progress. It needs to be noted that the planning presented in this section is an initial estimation and that the project planning should be updated after the mid-term review to account for any unexpected change.

A project gantt chart has been generated and can be seen in Appendix A. The gantt chart presents a realistic planning and contains iterations and interlinking of activities. The tasks have been divided in 4 work packages. After the kick-off meeting, 'WP1: finish literature Study' starts. WP1 ends with the delivery of the literature study report. 'WP2: Baseline MCDM model (proof of concept)' can then start. After the baseline model, the mid-term review will take place. Then, both WP3 and WP4 can start simultaneously. WP3 refers to the extended model while WP4 is related to the real-life case study. After completion of both WP3 and WP4, the green-light meeting will happen, followed by the thesis defence few weeks later. The project timeline has been estimated, considering the nominal thesis duration of the aerospace engineering Master thesis at TU Delft. Holidays are also accounted for in the planning.

# 7
# Conclusion and recommendations

The purpose of this report was to present a literature review which sets a solid base to start a master thesis research. The literature study on the context of maintenance repair decision-making sets the necessity of a dynamic and structured decision-making framework to aid maintenance decision-makers. Current industry practices assume the maintenance scenario as static and rely on the decision-maker situation awareness and knowledge to analyse the situation and provide a solution. The decisions are rarely re-considered when the environment or constraints change. Furthermore, the unstructured decision-making process leads to an insufficient use of available information and incomplete set of decision alternatives. [32].

The project goal was defined aiming to bridge the literature and industry gap found during the literature study. The project goal is to improve the situational awareness of the maintenance decision maker by developing a decision support tool that identifies and evaluates decision alternatives dynamically in the context of short-term operational aircraft maintenance (up to A-checks) characterised by a changing and complex environment. The research adds value to the body of knowledge by creating a systematic and dynamic framework for maintenance repair decision-making which does not solely rely on human judgement.

Several research questions were created, necessary to achieve the project goal. A methodology for the decision-making framework was developed. First, the structural damage in consideration is evaluated. Second, all feasible repair decision alternatives are generated using a Boolean Decision Tree. Then, important decision criteria are chosen and weighted using pair-wise comparisons in AHP. A questionnaire is developed to gather data for the pair-wise comparisons. Then, the criteria is rated and the decision alternatives can be evaluated. The ranking of alternatives is performed with AHP and TOPSIS, generating two different rankings. The results from both models are predicted to give similar outcomes. Once the baseline model is working, scenario analysis and a dynamic framework are implemented in order to create dynamic and robust decision-making approach. Results after this implementation are predicted to change and, in the long-run, lead to more suitable option selection which will decrease cost and increase time savings. The dynamic and robust consideration of repair options is the novelty of the presented research proposal. The model is verified and validated to ensure high quality and credible results. A real-life case study is used for validation. The model and experiments present data limitations, as real-life data on maintenance decisions is scarce. The project is planned to last from the kick-off review on the twentieth of may 2020 until the thesis defence planned on the 12 of January 2021.

A recommendation (if the required data is available) would be to explore the possibility of using machine learning algorithms (Bayesian networks and attribute relevance analysis) in order to, for example, evaluate which components are more susceptible to fail. This information could be used in order to improve the AHP generated weights, by using conditional probabilities. This approach was taken by Lima et al. [68] and it has the potential to improve the decision tool.

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# III

## Supporting Work

# 1

# Questionnaire for criteria weight determination

This appendix elaborates on the questionnaire used to gather maintenance experts' opinions. An overview of the questionnaire is presented in section 1.1. The global and individual criteria weights that follow from the analysis of the questionnaire responses are presented in section 1.2.

## 1.1. Questionnaire

The relative importance of the decision criteria strongly depends on the underlying business model and stakeholder perspective (airline, MRO provider, etc.). To tackle this a questionnaire is created to gather expert opinions in the research case study to generate a standard criteria weight vector using a Bayesian BWM approach. The questionnaire has 13 questions it is created using Google Forms. Google Forms is selected due to its ability to automatically gather the data in an excel sheet, which can be directly imported to Python. Before presenting the maintenance experts with the questions, some information was provided about the DSS research objective and a summary of the proposed methodology. Furthermore, a brief explanation of the meaning of each of the decision criteria was presented to ensure meaningful answers. In total, 10 maintenance experts filled out the questionnaire which is a significant number to draw meaningful conclusions. The questions answered by the maintenance experts are presented below:

- Question 1: Name
- Question 2: Area of expertise and years of experience in aircraft maintenance
- Question 3: Which criterion is the most important in your opinion? (BEST)
  - A) Minimization of Repair Cost
  - B)Maximization of Aircraft Part Reliability
  - C)Maximization of Aircraft Utilization
  - D)Maximization of Part life.
- Question 4: Which criterion is the least important in your opinion? (WORST)
  - A) Minimization of Repair Cost
  - B)Maximization of Aircraft Part Reliability
  - C)Maximization of Aircraft Utilization
  - D)Maximization of Part life.
- Question 5: Compare your BEST criteria to A(Minimization of Repair Cost)
  - 1 : Equally Important (If your BEST criterion is A, select this option)

- 3: Moderated importance of BEST criteria over A
- 5: Strong importance of your BEST criteria over A
- 7: Demonstrated importance of BEST criteria over A
- 9:Absolute importance of your BEST criteria over A

- Question 6: Compare your BEST criteria to criteria B(Maximization of Aircraft Part Reliability)
  - 1 : Equally Important (If your BEST criterion is B, select this option)
  - 3: Moderated importance of BEST criteria over B
  - 5: Strong importance of your BEST criteria over B
  - 7: Demonstrated importance of BEST criteria over B
  - 9:Absolute importance of your BEST criteria over B
- Question 7: Compare your BEST criteria to criteria C(Maximization of Aircraft Utilization)
  - 1 : Equally Important (If your BEST criterion is C, select this option)
  - 3: Moderated importance of BEST criteria over C
  - 5: Strong importance of your BEST criteria over C
  - 7: Demonstrated importance of BEST criteria over C
  - 9:Absolute importance of your BEST criteria over C
- Question 8: Compare your BEST criteria to criteria D (Maximization of Part Life)
  - 1 : Equally Important (If your BEST criterion is D, select this option)
  - 3: Moderated importance of BEST criteria over D
  - 5: Strong importance of your BEST criteria over D
  - 7: Demonstrated importance of BEST criteria over D
  - 9:Absolute importance of your BEST criteria over D
- Question 9: Compare criteria A (Minimization of Repair Cost) to your WORST Criteria
  - 1 : Equally Important (If A is your WORST criterion, select this option)
  - 3: Moderated importance of criteria A over your WORST criteria
  - 5: Strong importance of criteria A over your WORST criteria
  - 7: Demonstrated importance of criteria A over your WORST criteria
  - 9:Absolute importance of criteria A over your WORST criteria
- Question 10: Compare criteria B (Maximization of Aircraft Part Reliability) to your WORST Criteria
  - 1 : Equally Important (If B is your WORST criterion, select this option)
  - 3: Moderated importance of criteria B over your WORST criteria
  - 5: Strong importance of criteria B over your WORST criteria
  - 7: Demonstrated importance of criteria B over your WORST criteria
  - 9:Absolute importance of criteria B over your WORST criteria
- Question 11: Compare criteria C (Maximization of Aircraft Utilization) to your WORST Criteria
  - 1 : Equally Important (If C is your WORST criterion, select this option)
  - 3: Moderated importance of criteria C over your WORST criteria
  - 5: Strong importance of criteria C over your WORST criteria
  - 7: Demonstrated importance of criteria C over your WORST criteria

  - 9:Absolute importance of criteria C over your WORST criteria

- Question 12: Compare criteria D (Maximization of Part Life) to your WORST Criteria
  - 1 : Equally Important (If D is your WORST criterion, select this option)
  - 3: Moderated importance of criteria D over your WORST criteria
  - 5: Strong importance of criteria D over your WORST criteria
  - 7: Demonstrated importance of criteria D over your WORST criteria
  - 9:Absolute importance of criteria C over your WORST criteria

- Question 13: Are there any other criteria you consider of importance when taking operational maintenance decisions that have not been mentioned?

## 1.2. Analysis of questionnaire responses

The individual experts' answers to this questionnaire are the required inputs for the Bayesian BWM. Using these answers the standard the aggregated weight vector presented in the research paper is generated and can be seen in Table 1.1. The individual expert preferences can be seen in Table 1.2. The years of experience in aircraft maintenance of each of the experts can also be seen in Table 1.2. These individual preferences are considered to be extreme values and are set the basis to perform a sensitivity analysis of the tool.

Table 1.1: Bayesian BWM aggregated criteria weight vector

| **Criteria** | **Reliability** | **Repair Cost** | **Availability** | **Part life** |
|---|---|---|---|---|
| $w^{agg}$ | 0.2802 | 0.1809 | 0.3460 | 0.1929 |

Table 1.2: Individual criteria weights vectors using the BWM developed by [6]

| **Expert** | **Years of experience** | **Reliability** | **Repair Costs** | **Availability** | **Part Life** |
|---|---|---|---|---|---|
| DM1 | 25 | 0.56 | 0.11 | 0.26 | 0.07 |
| DM2 | 10 | 0.12 | 0.17 | 0.66 | 0.05 |
| DM3 | 5 | 0.21 | 0.06 | 0.21 | 0.52 |
| DM4 | 21 | 0.36 | 0.04 | 0.44 | 0.16 |
| DM5 | 14 | 0.20 | 0.51 | 0.20 | 0.09 |
| DM6 | 12 | 0.16 | 0.07 | 0.65 | 0.12 |
| DM7 | 5 | 0.67 | 0.14 | 0.08 | 0.11 |
| DM8 | 2 | 0.23 | 0.14 | 0.55 | 0.08 |
| DM9 | 4 | 0.20 | 0.51 | 0.20 | 0.09 |
| DM10 | 10 | 0.06 | 0.15 | 0.54 | 0.25 |

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# 2

# Reliability analysis

The historical damage occurrence database used in this research had to be pre-processed and cleaned. First, a general analysis is performed to understand the database and its limitations. This is explained in section 2.1. Cleaned data for two structures (flap and inlet) is presented in section 2.2. Finally, different distributions are fitted into the cleaned databases and the reliability parameters are estimated for each case in section 2.3.

## 2.1. Historical database general analysis

Historical damage occurrence data of a Boeing 777 fleet is used in this research. The database needed to be cleaned and organised before it could be used to perform reliability analysis. The cleaning involved both manual and automated cleaning in Python. Manual cleaning was mostly necessary to find out the correlations between temporary and permanent repairs to be able to identify which repair actions corresponded to the same damage event. This was only possible when reading the damage description provided in the database. Filtering the aircraft part and the failure mode, filling missing data, and eliminating incorrect data entries was done with Python.

After cleaning the database, a general analysis was performed to understand the database and the context of the research. The cleaned fleet contained data from a Boeing-777 airline fleet with 37 aircraft. The data was collected from the start of the fleet operations until the $31^{st}$ of December 2015. The five parts with the highest number of damage occurrences were found to be: 1) the inlet assembly, 2) the fan duct cowl and thrust reverser assembly, 3) the sleeve translating assembly, 4) the flap assembly, and 5) the elevator assembly.

Figure 2.1 shows a heatmap that aims to find correlations between different parameters of the database and the number of unexpected damages occurrences. It can be observed that the relation between the number of damages and the aircraft fleet age is significant. This indicates that the more aged the aircraft fleet becomes the more often damage events happen. The fleet age and the number of occurrences data used in this analysis is scaled per number of aircraft at every time point to be able to get meaningful correlations not based on the influence of aircraft being added to the fleet over time. Finally, in Figure 2.2 the unexpected damages in the fleet over the observation period can be seen. The actual damages are shown as red dots and are aggregated monthly for ease of visualisation. It can be observed that the damage occurrence is lumpy. It is therefore very difficult to predict the occurrence of externally-induced structural damages, as can be seen by the linear regression forecasting attempt show in green. Data before 2012 is limited. This can be due to poor data entering in those years. This can affect the quality of the data and the analysis and it is therefore a limitation of this research.

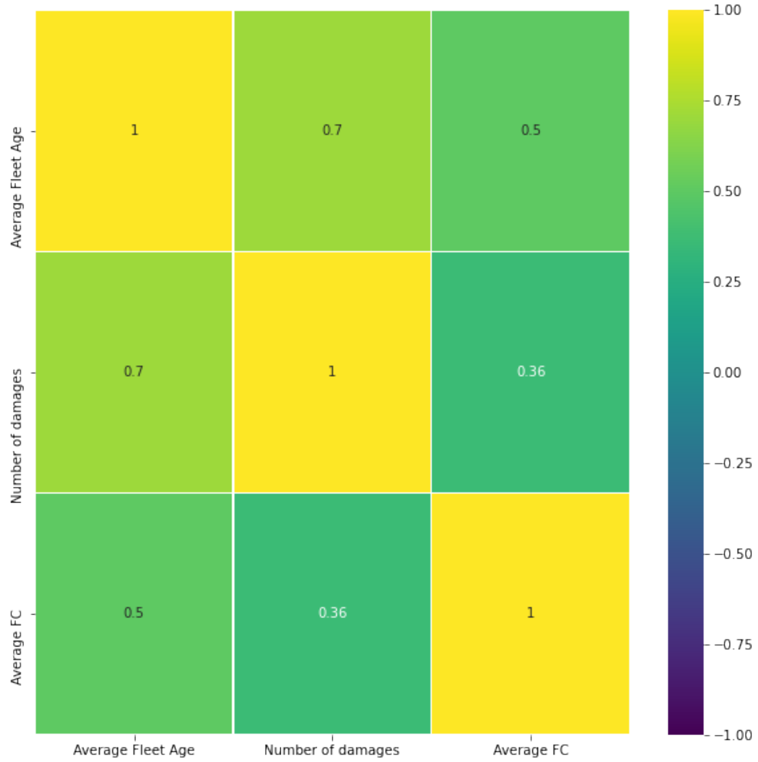


Figure 2.1: Correlation heat-map of the fleet historical data

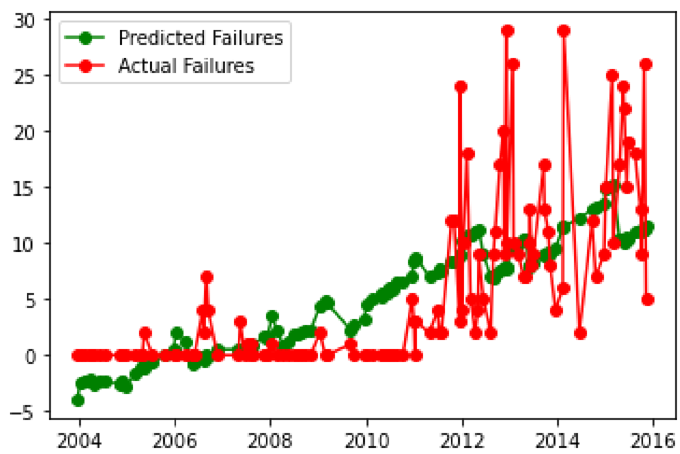


Figure 2.2: Fleet externally-induced structural damages forecast using linear regression

## 2.2. Cleaned database for reliability analysis

After cleaning and understanding the dataset, damage occurrence databases can be generated. Different aircraft structures have different failure patterns and the data of each part should be analysed separately. Databases for flap and inlet externally-induced impact damages were generated in this study. The cleaned database for inlet damages can be found in Table 2.2 and the cleaned database for flap damages can be found in Table 2.1. Right-censored data is also added to these databases. Right-censored data in the context of this research can be defined as the flight cycles between the last permanent repair and the end of the observation time. The failures interarrival times shown in the databases are calculated from the time of last permanent repair until the next damage event.

Table 2.1: Flap structural damage events dataset

| A/C Tail | Start | End (FC) | Failure 1 | Failure 2 | Failure 3 | Failure 4 | Failure 5 | Right-Censored |
|---|---|---|---|---|---|---|---|---|
| A/C 1 | 0 | 8460 | 3591 | 5523 | 5661 | - | - | 2799 |
| A/C 2 | 0 | 8400 | - | - | - | - | - | 8400 |
| A/C 3 | 0 | 8340 | 970 | - | - | - | - | 7370 |
| A/C 4 | 0 | 8160 | 1770 | 5028 | 5081 | 6623 | 7422 | 2508 |
| A/C 5 | 0 | 8100 | 2955 | 2992 | 4365 | - | - | 3709 |
| A/C 6 | 0 | 8040 | 2934 | - | - | - | - | 5106 |
| A/C 7 | 0 | 7980 | 618 | 4233 | 4373 | - | - | 3607 |
| A/C 8 | 0 | 7860 | 4742 | - | - | - | - | 3118 |
| A/C 9 | 0 | 7800 | 675 | - | - | - | - | 7125 |
| A/C 10 | 0 | 7740 | - | - | - | - | - | 7740 |
| A/C 11 | 0 | 7320 | 3293 | - | - | - | - | 4027 |
| A/C 12 | 0 | 7200 | 1688 | - | - | - | - | 5512 |
| A/C 13 | 0 | 7080 | 2844 | - | - | - | - | 4236 |
| A/C 14 | 0 | 6960 | 4923 | - | - | - | - | 2037 |
| A/C 15 | 0 | 6900 | 1553 | 4660 | 4831 | - | - | 1859 |
| A/C 16 | 0 | 6900 | - | - | - | - | - | 6900 |
| A/C 17 | 0 | 6780 | 4762 | - | - | - | - | 1862 |
| A/C 18 | 0 | 6480 | 2158 | - | - | - | - | 4322 |
| A/C 19 | 0 | 6420 | 1149 | - | - | - | - | 5240 |
| A/C 20 | 0 | 6300 | 762 | 2959 | 3264 | 4068 | - | 1813 |
| A/C 21 | 0 | 6240 | 1581 | - | - | - | - | 4659 |
| A/C 22 | 0 | 6180 | - | - | - | - | - | 6180 |
| A/C 23 | 0 | 6120 | - | - | - | - | - | 6120 |
| A/C 24 | 0 | 5940 | - | - | - | - | - | 5940 |
| A/C 25 | 0 | 5580 | - | - | - | - | - | 5580 |
| A/C 26 | 0 | 5520 | 3875 | - | - | - | - | 1645 |
| A/C 27 | 0 | 4860 | 1094 | - | - | - | - | 3738 |
| A/C 28 | 0 | 4740 | - | - | - | - | - | 4740 |
| A/C 29 | 0 | 4740 | 1222 | 3303 | - | - | - | 1122 |
| A/C 30 | 0 | 4740 | 3135 | - | - | - | - | 1605 |
| A/C 31 | 0 | 3660 | - | - | - | - | - | 3660 |
| A/C 32 | 0 | 3420 | 811 | - | - | - | - | 2609 |
| A/C 33 | 0 | 3420 | 239 | 1310 | 3088 | - | - | 1642 |
| A/C 34 | 0 | 3360 | 1184 | - | - | - | - | 2096 |
| A/C 35 | 0 | 2700 | - | - | - | - | - | 2700 |
| A/C 36 | 0 | 2640 | 280 | 1120 | - | - | - | 1800 |
| A/C 37 | 0 | 2700 | 1637 | - | - | - | - | 1063 |

Table 2.2: Inlet structural damage events dataset

| A/C | Start | End | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 | F10 | F11 | Censored |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 8460 | 2875 | 3071 | 3478 | - | - | - | - | - | - | - | - | 8638 |
| 2 | 0 | 8400 | 3137 | 4266 | 5546 | 5793 | - | - | - | - | - | - | - | 9477 |
| 3 | 0 | 8340 | 2401 | - | - | - | - | - | - | - | - | - | - | 8340 |
| 4 | 0 | 8160 | 2950 | 3214 | 3258 | 3339 | 3527 | 3813 | 3891 | 4392 | 5726 | - | - | 9494 |
| 5 | 0 | 8100 | 3151 | 7902 | 8258 | 8538 | 8819 | 9108 | 9163 | - | - | - | - | 11812 |
| 6 | 0 | 8040 | 1765 | 1916 | 2674 | 2999 | 3444 | 4204 | 4929 | - | - | - | - | 7566 |
| 7 | 0 | 7980 | 646 | 675 | 892 | 1308 | 2912 | 2978 | 3106 | - | - | - | - | 7801 |
| 8 | 0 | 7860 | 2789 | 5812 | 6151 | 7128 | - | - | - | - | - | - | - | 10599 |
| 9 | 0 | 7800 | 675 | 892 | 1308 | 2098 | 2240 | 2960 | 3416 | 3986 | 4640 | 4741 | - | 7475 |
| 10 | 0 | 7740 | 4163 | 4951 | - | - | - | - | - | - | - | - | - | 7740 |
| 11 | 0 | 7320 | 1030 | 3505 | 4700 | 4978 | 5041 | - | - | - | - | - | - | 7320 |
| 12 | 0 | 7200 | 838 | 1078 | 2346 | 4918 | 4982 | 4999 | - | - | - | - | - | 7175 |
| 13 | 0 | 7080 | - | - | - | - | - | - | - | - | - | - | - | 7080 |
| 14 | 0 | 6960 | 1694 | 3435 | 3982 | - | - | - | - | - | - | - | - | 6203 |
| 15 | 0 | 6900 | 4486 | 4745 | - | - | - | - | - | - | - | - | - | 6900 |
| 16 | 0 | 6900 | - | - | - | - | - | - | - | - | - | - | - | 6900 |
| 17 | 0 | 6780 | 1821 | - | - | - | - | - | - | - | - | - | - | 6475 |
| 18 | 0 | 6480 | 222 | 4334 | 4460 | - | - | - | - | - | - | - | - | 6480 |
| 19 | 0 | 6420 | 442 | 2270 | 4170 | 5257 | 6200 | 6425 | - | - | - | - | - | 8180 |
| 20 | 0 | 6300 | 1170 | 1266 | 1368 | 1400 | 2281 | 3411 | 3464 | 4149 | 4545 | 4937 | 5339 | 6692 |
| 21 | 0 | 6240 | 1697 | 2913 | 4266 | 4383 | - | - | - | - | - | - | - | 7272 |
| 22 | 0 | 6180 | 2151 | 3201 | 3328 | 3451 | 4330 | - | - | - | - | - | - | 6180 |
| 23 | 0 | 6120 | 903 | 1126 | 1158 | 1474 | 3104 | 4180 | 4262 | - | - | - | - | 6120 |
| 24 | 0 | 5940 | 115 | 240 | 250 | 688 | 1298 | 1439 | 1841 | 4456 | - | - | - | 6128 |
| 25 | 0 | 5580 | 1794 | 2194 | 3877 | - | - | - | - | - | - | - | - | 5580 |
| 26 | 0 | 5520 | 1100 | 1869 | 2801 | 3580 | - | - | - | - | - | - | - | 5520 |
| 27 | 0 | 4860 | 1794 | 3230 | - | - | - | - | - | - | - | - | - | 4860 |
| 28 | 0 | 4740 | 3216 | 3385 | - | - | - | - | - | - | - | - | - | 4740 |
| 29 | 0 | 4740 | 2961 | - | - | - | - | - | - | - | - | - | - | 4740 |
| 30 | 0 | 4740 | 3205 | 6602 | 6954 | 7318 | - | - | - | - | - | - | - | 8297 |
| 31 | 0 | 3660 | - | - | - | - | - | - | - | - | - | - | - | 3660 |
| 32 | 0 | 3420 | 975 | 2338 | 2471 | - | - | - | - | - | - | - | - | 3420 |
| 33 | 0 | 3420 | 1061 | - | - | - | - | - | - | - | - | - | - | 3420 |
| 34 | 0 | 3360 | 762 | - | - | - | - | - | - | - | - | - | - | 3360 |
| 35 | 0 | 2700 | - | - | - | - | - | - | - | - | - | - | - | 2700 |
| 36 | 0 | 2640 | - | - | - | - | - | - | - | - | - | - | - | 2640 |
| 37 | 0 | 2700 | 1374 | - | - | - | - | - | - | - | - | - | - | 2700 |

## 2.3. Distribution fitting and parameter estimation

Given the cleaned damage event occurrence databases presented in the previous section, a reliability analysis can be performed. The data points are fitted to 12 different distributions: Normal, Gumbel, 2 & 3 parameters Weibull, 1 & 2 parameters Exponential, 2 & 3 parameters Lognormal, 2 & 3 parameters Loglogistic, and 2 & 3 parameters Gamma. The best-fitting distribution can be selected using a goodness-of-fit test. The used test is the Bayesian Information Criterion (BIC). The lower the BIC value the best the distribution fits the data. The parameters of each distribution are estimated using the Maximum Likelihood Estimator (MLE). Four analysis are presented in this section: 1) Flap damages without right-censored data, 2) Flap damages including right-censored data, and 3) Inlet damages without right-censored data. Both including and excluding censored data are considered for the flap reliability analysis. In practice, right-censored data is not considered as it gives a more conservative result. The amount of data points available for inlet damage analysis is higher than for flaps. The inlet is the part of the aircraft found to have the greatest number of externally-induced damages. This can have an impact on the analysis, as generally the greater the number of data points available the more reliable the analysis.

### Flap damages without right-censored data - 44 data points

The parameter estimation and goodness-of-fit test for this case are presented in Table 2.3 and their corresponding probability plots are shown in Figure 2.3. The plots are ordered from right to left and from bottom to top, showing the best-fitting distribution in the top left corner and the worst fitting distribution in the down right corner.

Table 2.3: Parameter estimation and goodness-of-fit test for flap failure without right-censored data

| Distribution | Alpha | Beta | Gamma | Mu | Sigma | Lambda | BIC |
|---|---|---|---|---|---|---|---|
| Weibull_2P | 2029.01 | 1.30997 | - | - | - | - | 753.051 |
| Exponential_1P | - | - | - | - | - | 0.000578 | 753.494 |
| Gamma_2P | 1358.35 | 1.36993 | - | - | - | - | 754.298 |
| Exponential_2P | - | - | 36.9999 | - | - | 0.000555 | 755.32 |
| Weibull_3P | 1967.82 | 1.2846 | 8.44962 | - | - | - | 756.787 |
| Gamma_3P | 1358.35 | 1.36993 | 0 | - | - | - | 758.082 |
| Loglogistic_2P | 1416.34 | 1.73585 | - | | | - | 762.959 |
| Normal_2P | - | - | - | 1839.95 | 1342.33 | - | 765.37 |
| Lognormal_2P | - | - | - | 7.12134 | 1.07477 | - | 765.459 |
| Loglogistic_3P | 1416.34 | 1.73585 | 0 | - | - | - | 766.743 |
| Lognormal_3P | - | - | 0 | 7.12134 | 1.07477 | - | 769.243 |
| Gumbel_2P | - | - | - | 2543.27 | 1431.86 | - | 778.265 |

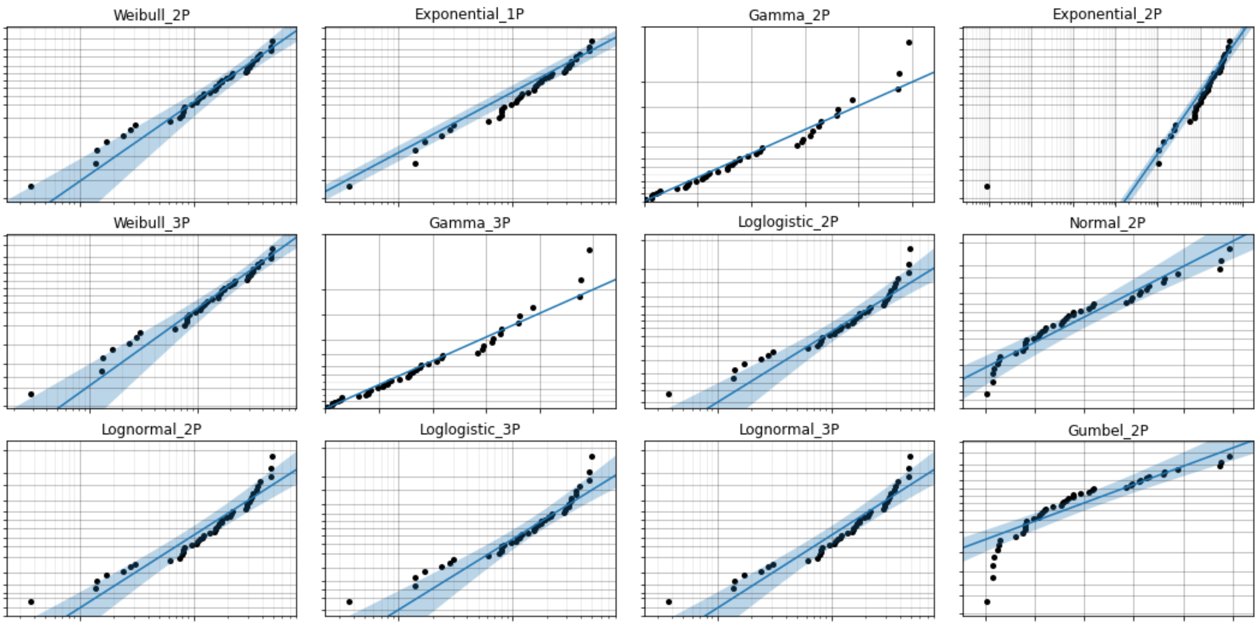


Figure 2.3: Probability plots for each of the twelve fitted distributions on a flap failure time series without right-censored data (y-axis: fraction failing, x-axis: time)

### Flap damages with right-censored data - 44 data points + 37 right-censored

The parameter estimation and goodness-of-fit test for this case are presented in Table 2.4 and their corresponding probability plots are shown in Figure 2.4. The plots are ordered from right to left and from bottom to top, showing the best-fitting distribution in the top left corner and the worst fitting distribution in the down right corner.

Table 2.4: Parameter estimation and goodness-of-fit test for flap failure including right-censored data

| Distribution | Alpha | Beta | Gamma | Mu | Sigma | Lambda | BIC |
|---|---|---|---|---|---|---|---|
| Exponential_1P | - | - | - | - | - | 0.000233 | 837.268 |
| Loglogistic_2P | 3017.69 | 1.217 | - | - | - | - | 838.799 |
| Gamma_3P | 7940.2 | 0.691729 | 36.9999 | - | - | - | 838.826 |
| Weibull_3P | 5091.43 | 0.770349 | 36.9999 | - | - | - | 839.816 |
| Exponential_2P | - | - | 36.9999 | - | - | 0.000215 | 839.985 |
| Lognormal_2P | - | - | - | 8.02342 | 1.48965 | - | 840.32 |
| Weibull_2P | 4331.26 | 0.959324 | - | - | - | - | 841.497 |
| Gamma_2P | 3999.31 | 1.0794 | - | - | - | - | 841.871 |
| Loglogistic_3P | 2904.81 | 1.1581 | 27.9612 | - | - | - | 842.882 |
| Lognormal_3P | - | - | 0 | 8.02342 | 1.48965 | - | 844.726 |
| Normal_2P | - | - | - | 3810.47 | 2894.89 | - | 883.407 |
| Gumbel_2P | - | - | - | 5319.26 | 2850.78 | - | 904.283 |

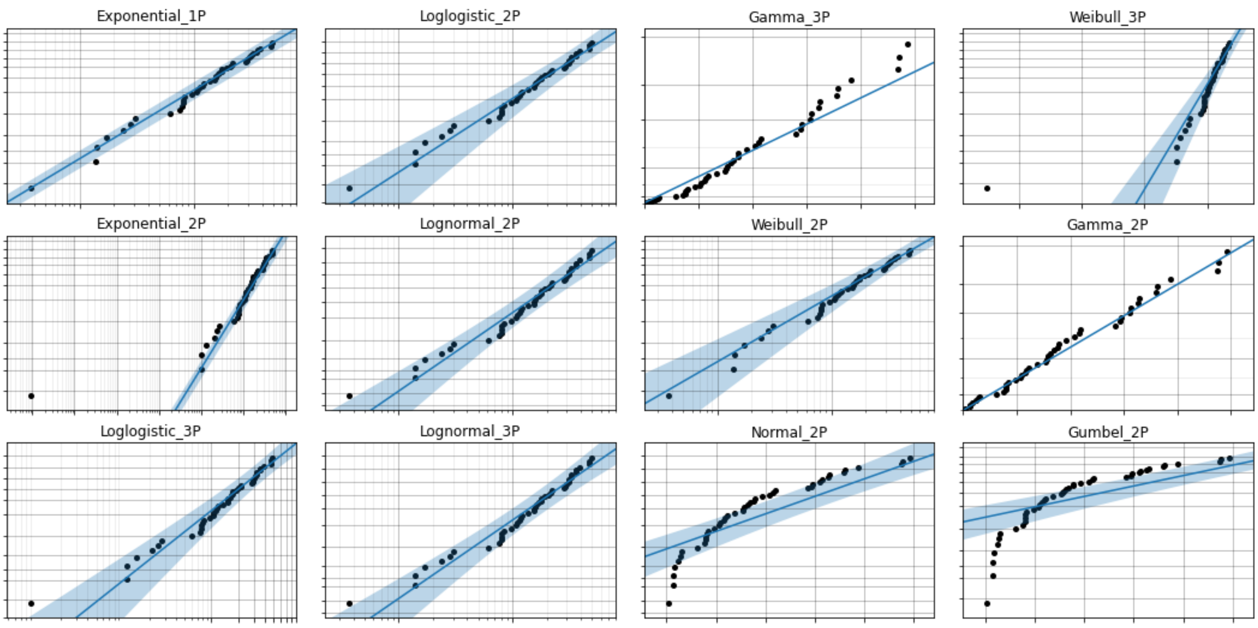


Figure 2.4: Probability plots for each of the twelve fitted distributions on a flap failure time series including right-censored data (y-axis: fraction failing, x-axis: time)

## Inlet damages without right-censored data - 137 data points

The parameter estimation and goodness-of-fit test for this case are presented in Table 2.5 and their corresponding probability plots are shown in Figure 2.5. The plots are ordered from right to left and from bottom to top, showing the best-fitting distribution in the top left corner and the worst fitting distribution in the down right corner. The distributions fit can be seen in Figure 2.6.

Table 2.5: Parameter estimation and goodness-of-fit test for inlet failure without right-censored data

| Distribution | Alpha | Beta | Gamma | Mu | Sigma | Lambda | BIC |
|---|---|---|---|---|---|---|---|
| Exponential_1P | - | - | - | - | - | 0.00101 | 2168.99 |
| Gamma_3P | 1305.82 | 0.760555 | 9.9999 | - | - | - | 2169.41 |
| Weibull_3P | 911.491 | 0.85922 | 9.9999 | - | - | - | 2170.68 |
| Exponential_2P | - | - | 9.9999 | - | - | 0.00102 | 2171.13 |
| Gamma_2P | 1100.91 | 0.899577 | - | - | - | - | 2172.87 |
| Weibull_2P | 938.413 | 0.956332 | - | - | - | - | 2172.9 |
| Lognormal_2P | - | - | - | 6.24815 | 1.29368 | - | 2181.18 |
| Loglogistic_2P | 556.885 | 1.3347 | - | - | - | - | 2185.7 |
| Lognormal_3P | - | - | 0 | 6.24815 | 1.29368 | - | 2186.1 |
| Loglogistic_3P | 547.418 | 1.29949 | 5.6476 | - | - | - | 2190.36 |
| Normal_2P | - | - | - | 990.35 | 1043.35 | - | 2302.98 |
| Gumbel_2P | - | - | - | 1576.95 | 1344.15 | - | 2377.18 |

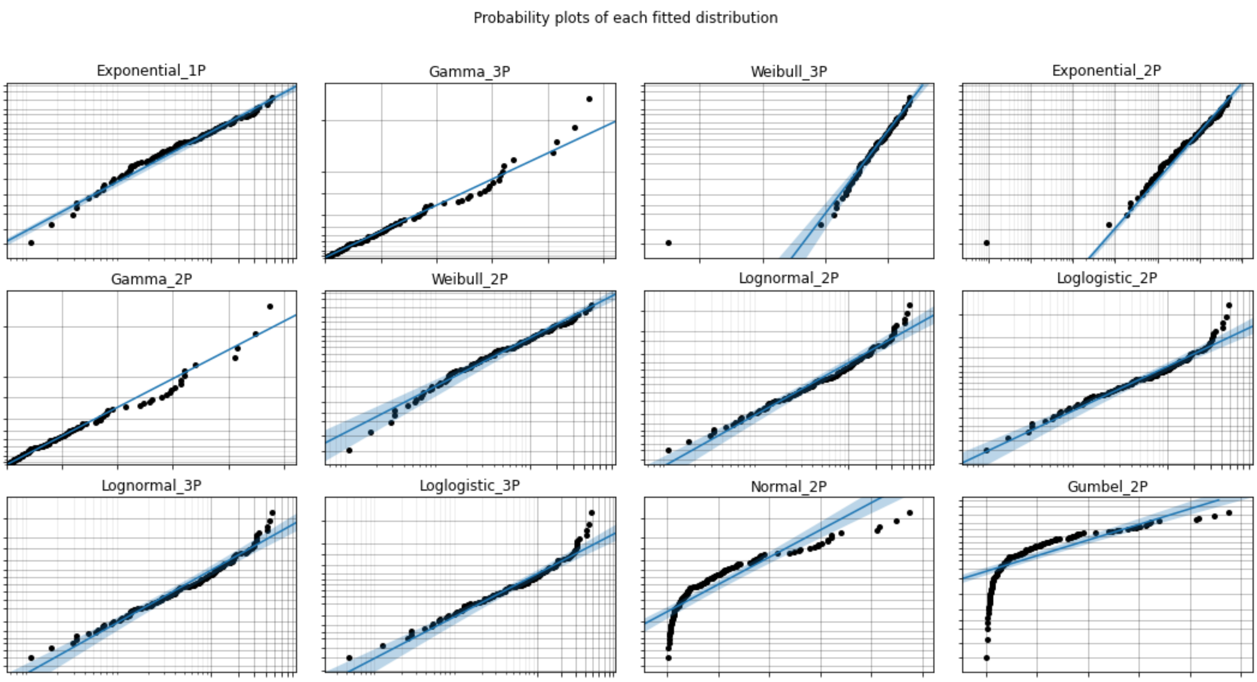


Figure 2.5: Probability plots for each of the twelve fitted distributions on an inlet failure time series without right-censored data (y-axis: fraction failing, x-axis: time)

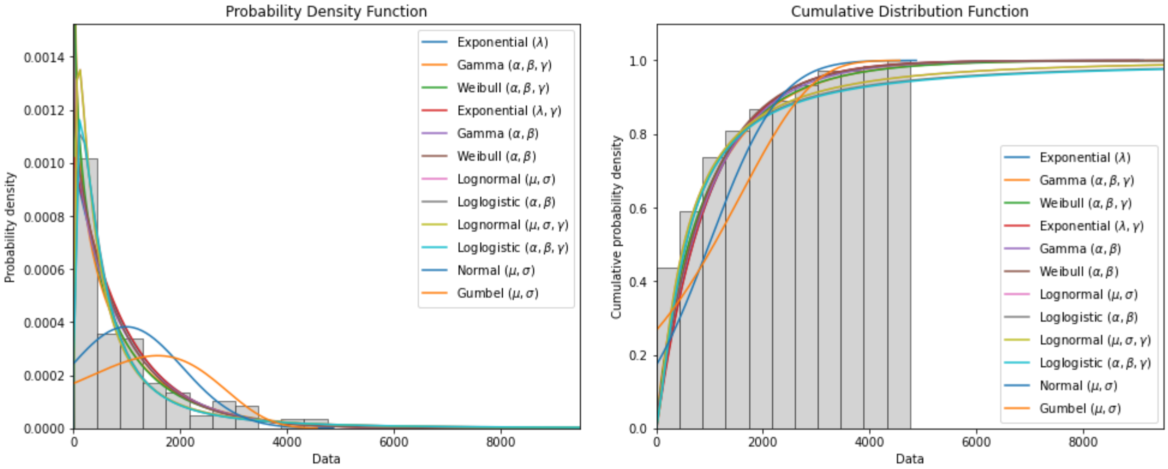


Figure 2.6: Distributions fit to inlet damages event data (without righ-censored data)

# 3

# Sensitivity analysis

In this section, a sensitivity analysis is presented. In section 3.1 a sensitivity analysis of the performance ratings is presented. Then, a sensitivity analysis of the MCDM ranking technique is shown in section 3.2.

## 3.1. Performance ratings

This sensitivity analysis focus on changing input parameters that could change the individual rating of the options with respect to each other. This type of sensitivity analysis is selected as small increases or decreases in the overall estimation of performance ratings would not influence the tool recommendation as the performance ratings are normalised.

### Part reliability performance rating

In Table 3.1 the confidence intervals of the estimated Weibull parameters used in the reliability analysis are shown. These limits are used for performing the sensitivity analysis of the part reliability performance rating. Figure 3.1 shows the influence of these estimated parameters in the DSS ranking. It can be observed that the difference is minimal. This indicates that the standard error of the parameter estimation is acceptable.

Table 3.1: Weibull distribution parameter estimation for flap failures using MLE

| Reliability Parameter | Point Estimate for Flap | Standard Error | Lower CI | Higher CI |
|---|---|---|---|---|
| $\beta$ | 1.31 | 0.16 | 1.03009 | 1.6659 |
| $\theta$ | 2029.01 | 247.95 | 1596.86 | 2578.11 |

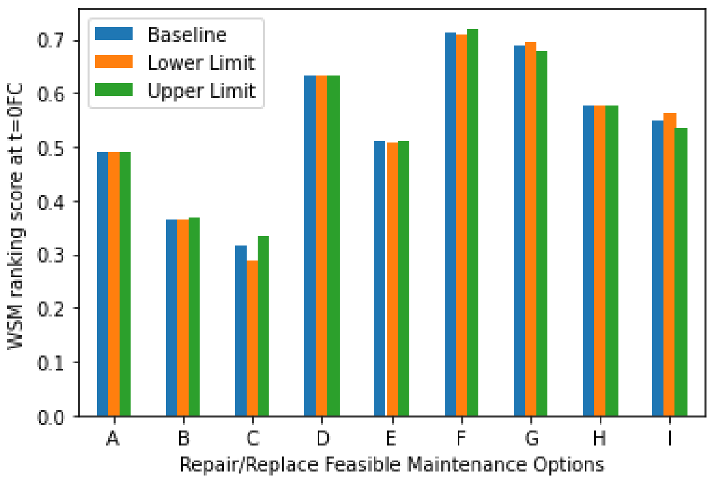


Figure 3.1: Influence of reliability parameters estimation on the DSS recommendation

### Aircraft availability performance rating

Depending on the moment of the year in which the damage is found, the aircraft availability performance rating of the different options changes. It can be seen that this parameter can have a significant influence on the final recommendation. This was expected, as this criterion has the highest criteria weight so it is normal that it is the criteria that influences the DSS recommendation the most.

Table 3.2: Ranking scores for flap failure found at different moments in the year

| Option | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A | 0.7 | 0.71 | 0.6 | 0.82 | 0.62 | 0.66 | 0.62 | 0.49 | 0.49 | 0.49 | 0.75 | 0.49 |
| B | 0.58 | 0.59 | 0.48 | 0.7 | 0.5 | 0.54 | 0.5 | 0.37 | 0.37 | 0.37 | 0.62 | 0.37 |
| C | 0.39 | 0.54 | 0.43 | 0.44 | 0.45 | 0.32 | 0.32 | 0.32 | 0.32 | 0.32 | 0.32 | 0.32 |
| D | 0.57 | 0.82 | 0.82 | 0.61 | 0.63 | 0.49 | 0.49 | 0.63 | 0.65 | 0.74 | 0.49 | 0.7 |
| E | 0.44 | 0.7 | 0.7 | 0.49 | 0.51 | 0.37 | 0.37 | 0.51 | 0.53 | 0.61 | 0.37 | 0.58 |
| F | 0.71 | 0.53 | 0.38 | 0.38 | 0.38 | 0.71 | 0.51 | 0.71 | 0.51 | 0.42 | 0.71 | 0.71 |
| G | 0.69 | 0.5 | 0.36 | 0.36 | 0.36 | 0.69 | 0.49 | 0.69 | 0.49 | 0.4 | 0.69 | 0.69 |
| H | 0.37 | 0.37 | 0.42 | 0.4 | 0.7 | 0.37 | 0.7 | 0.58 | 0.7 | 0.7 | 0.5 | 0.7 |
| I | 0.34 | 0.34 | 0.4 | 0.38 | 0.67 | 0.34 | 0.67 | 0.55 | 0.67 | 0.67 | 0.47 | 0.67 |

## 3.2. MCDM ranking technique

In this section the WSM ranking algorithm is compared to another known MCDM method namely the modified TOPSIS introduced which was introduced by [1]. The purpose of doing this is to check the influence of the ranking method on the overall recommendation of the tool. In Figure 3.2 the repair options identified for the research case study at the moment of failure are shown. The options are ranked using the proposed DSS approach with the WSM (blue line) and with the modified TOPSIS method (orange line). It can be seen that the order of the recommended options does not change. In both cases, the first-ranked option is Option F. The discrimination power of the WSM in this specific example is higher than the discrimination power of the modified TOPSIS method.

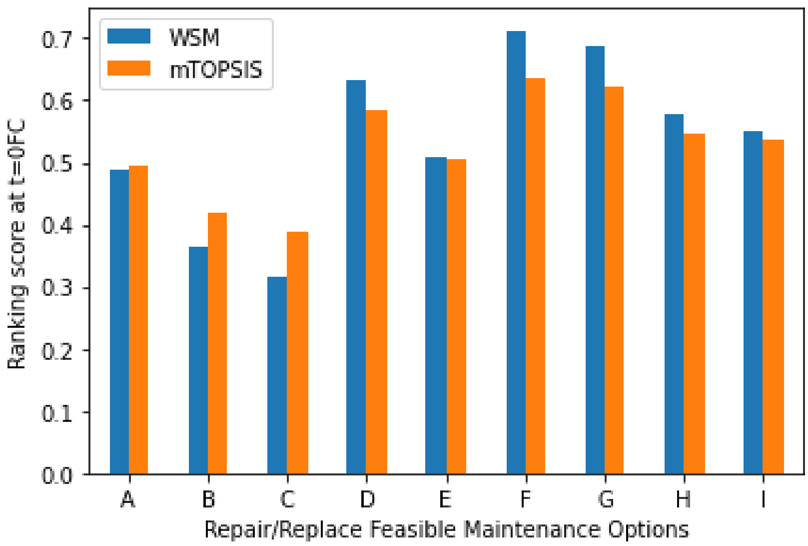


Figure 3.2: Influence of the MCDM ranking method on the DSS final recommendation

# 4

# Verification and validation

This appendix explains the verification and validation of the DSS. In section 4.1 the verification process is covered while the validation is explained in section 4.2.

## 4.1. Verification

Verification of the DSS is performed to assure the model matches the conceptual model specifications and assumptions [3]. The model was programmed in Python. To verify the tool code avoiding any logic model errors unit testing was used, covering verification of all model steps independently.

First, the generation of a criteria weight vector using a Bayesian BWM approach was verified using data from [5]. Then, the MCDM ranking algorithm used to rank the repair options and provide a recommendation was verified using data found in literature [7] and [2]. The generation of criteria ratings was also verified using manually generated scenarios. Finally, to verify the outcome of option identification using a BDT several example scenarios were generated and a possible list of options was found by hand. Then, these scenarios were input in the BDT code and it was verified that the generated list of options was identical to the ones generated manually.

## 4.2. Validation

Validation is performed to assure the created model provides a result which answers the research question at hand. The multi-criteria decision-making developed by [2] is used as a benchmark for the validation as it also deals with operational aircraft maintenance decision-making using a MCDM approach.

In [2] the same outboard flap damage case study was considered. The list of possible repair options identified by [2] is shown in Table 4.1, while the list of options generated by the proposed DSS can be seen in Table 4.2. Comparing this list with the repair options identified in this research it can be observed that all 5 options found by [2] are also found in this research and correspond to repair options A, B, C, D, and E. Four extra repair options are found by the proposed DSS as after repairing the structure temporarily at 0FC the structure only needed to be repaired or replaced permanently within 400 FC according to regulations.

| Maintenance Option | Immediate 0FC Slot | Deferred 30FC Slot | Deferred 40FC Slot |
|---|---|---|---|
| **1** | Temp. repair (original) | Perm. repair (original) | - |
| **2** | Temp. repair (original) | - | Perm. repair (original) |
| **3** | Temp. repair (original) | Perm. replace (exchange) | - |
| **4** | Temp. repair (original) | - | Perm. replace (exchange) |
| **5** | Temp. repair (original) | Temp. replace (lease) | Perm. replace (repaired original) |

Table 4.1: Outboard flap structural damage case study repair options identified in [2]

Table 4.2: Outboard flap structural damage case study repair options identified by the proposed DSS

| Repair Option | 0FC | 30FC | 40FC | 230FC | 300FC |
|---|---|---|---|---|---|
| A | Temporary | Permanent | | | |
| B | Temporary | Exchange | | | |
| C | Temporary | Lease | | | |
| D | Temporary | | Permanent | | |
| E | Temporary | | Exchange | | |
| F | Temporary | | | Permanent | |
| G | Temporary | | | Spare | |
| H | Temporary | | | | Permanent |
| I | Temporary | | | | Spare |

The main differences between [2] and the research performed in this thesis are the following:

- In [2] three decision criteria were considered: Reliability, Cost and Downtime. In this research, downtime is eliminated to avoid redundancy of criteria, as downtime is already considered as the main driver of the indirect maintenance cost. Furthermore, two extra criteria are added in this research that were not considered in [2]. The added criteria are maximisation of aircraft availability and of part life.

- Criteria weights are a user input in the model developed in [2]. In this research, a formal methodology based on pairwise comparisons is proposed to generate meaningful criteria weights.

- To calculate the reliability criteria rating both studies used survivability analysis. In [2] temporary repairs are assumed to be as-bad-as-old and follow a NHPP process and permanent repairs are assumed to be as-good-as-new and follow a HPP process. In contrast, in this research, a GRP process is used assuming minimal repair. This method allows the use of a different repair effectiveness for all the different types of repair considered in the study (temporary, permanent, exchange, spare, and lease). This assumption represents reality better.

- The cost estimations are also improved in this research by 1) considering inflation, 2) considering indirect costs incurred by other aircraft as a consequence of the selected repair option in the given aircraft (in the case of a part exchange).

- The model in [2] is static. The model presented in this research present a dynamic approach to decision-making and updates the recommended repair option if necessary when the operational conditions change.

For validation purposes of the tool output, the proposed DSS had to be adapted to these differences. After doing the required adjustments the DSS scores are the same as the scores achieved in [2]. These results can be seen in Figure 4.1. In comparison, the results achieved by the proposed DSS can be seen in Figure 4.2. The recommended option in the proposed DSS is Option F, which is an option that was not identified by [2]. In contrast, the recommended option by [2] is Option 4, which corresponds to Option E in this research. If the four options not identified by [2] (F, G, H, and I) are disregarded in Figure 4.2, the best-ranked option would be option D (temporary + permanent) instead of E (temporary + exchange). This can be explained by the changes introduced in the criteria evaluation. For example, the cost estimation of the exchange option in the proposed DSS considers the indirect costs incurred by the donor aircraft, which were not considered in [2]. This drives the repair costs of option E to be higher than the costs of option D. This can explain the difference between the recommendation of both DSS.

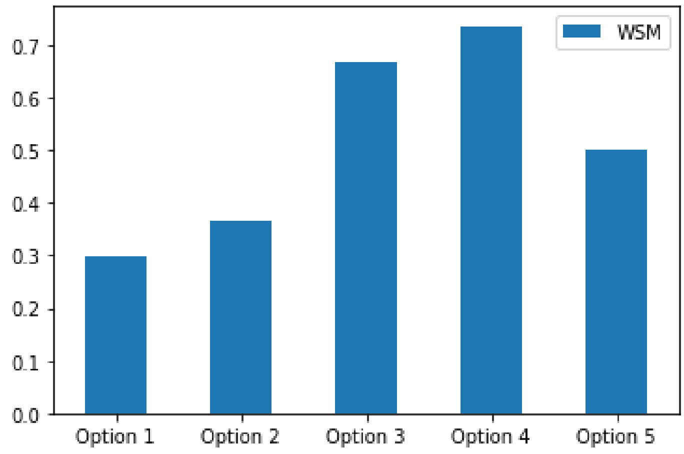


Figure 4.1: Ranking of repair options following the approach followed by [2]

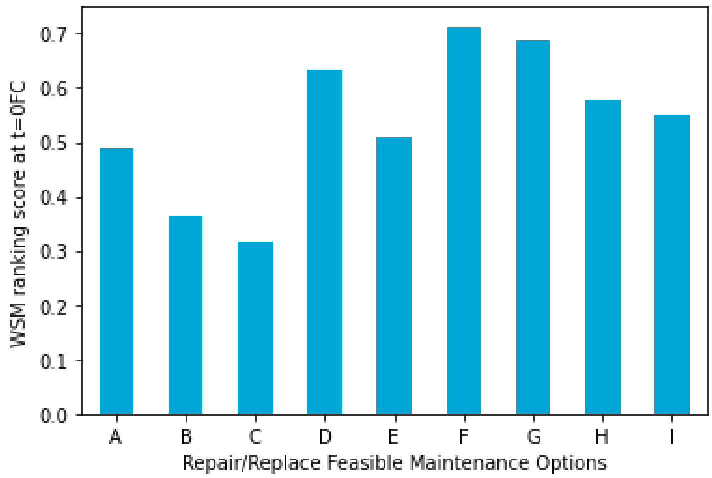


Figure 4.2: Ranking of repair options following the proposed DSS

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