Comparing Multi Criteria Weighted Decision Methods for Simultaneous Operational Aircraft Maintenance Processes

by

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Preface

This report contains the results of the work done in the course of a Master of Science thesis. The thesis was conducted at the Air Transport and Operations department of the faculty of Aerospace Engineering at Delft University of Technology. It is the final part of the MSc. Aerospace Engineering degree, with a specialization in Air Transport and Operations of the Delft University of Technology.
I would like to express my gratitude to W.J.C. Verhagen and V.S. Dhanisetty for providing me with more insight on the scientific as well as the operational backgrounds and for their support to be able to conduct this research.

I. A. Ruchser
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Research Paper

COMPARING MULTI CRITERIA WEIGHTED DECISION MAKING METHODS FOR SIMULTANEOUS OPERATIONAL AIRCRAFT MAINTENANCE PROCESSES

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During the operation of a commercial aircraft damages require immediate attention. Typically, there are several alternatives to choose from, all resulting in a different consequence. The most beneficial choice is however not always apparent immediately. To avoid subjectivity and take a traceable decision quickly in an operational environment, the use of multi criteria decision systems (MCDM) was investigated. In doing so, this research contributes to the state of the art by considering alternative evaluation for multiple simultaneous operational occurrences. Additionally, by performing a comparative analysis of several MCDM methods in terms of applicability, suitability and robustness. Using the criteria survivability, time and cost, different scenarios have been evaluated. In order to assess whether one theory is superior for this operational approach, three methods have been identified as potentially appropriate; WSM, TOPSIS and VIKOR. They were applied to a variety of different scenarios and the results were compared. It resulted that for single occurrences the outcome only varies for very extreme weight settings. In a multiple damage occurrences scenario, i.e. several aircraft competing for limited resources, differences have been found. While TOPSIS and VIKOR generate a similar recommendation, WSM yields different results. Furthermore, it was found that VIKOR is not suited for the used heuristic approach, as it results in an ambiguous performance score of several solutions relative to each other. Additionally, VIKOR proved to be the most sensitive method, making its use in an operational environment questionable, as small changes easily lead to a different recommendation. Looking at the frequent use of a DSS in an operational environment as opposed to a strategic one, which is typically evaluated using MCDM, it was concluded that WSM is the best choice. This is due its ease of implementation, its robustness and its simplicity.

Keywords: MCDM, WSM, TOPSIS, VIKOR, operational decision-making, aircraft maintenance

Nomenclature

A/C	Aircraft
ATA	Air Transport Association
AHP	Analytical hierarchy process
AOG	Aircraft on ground
C	Cancellation
DSS	Decision support system
ELECTRE	Elimination et choix traduisant la realité
FC	Flight cycles
GDSS	Group decision support system
KPI	Key performance index
MADA	Multiple attribute decision analysis
MADM	Multiple attribute decision method
MAUT	Multi attribute utility theory
MAVT	Multi attribute value theory
MCDA	Multiple criteria decision analysis
MODA	Multiple objective decision analysis
MODM	Multiple objective decision method
MRO	Maintenance, repair and overhaul
NHPP	Non-homogeneous Poisson process
PR	Permanent repair
PROMETHEE	Preference ranking organization for enrichment evaluation
TAT	Turnaround time
TPA	Temporary repair followed by permanent repair at A-Check
TPC	Temporary repair followed by permanent repair at C-Check
TOPSIS	Technique for order of preference by similarity to ideal solution
VIKOR	VlseKriterijuska optimizacija i komoromisno resenje
WPM	Weighted product model
WSM	Weighted sum model

I. Introduction

A. Background

Aircraft have to undergo frequent maintenance activities. Based on the amount of time that has passed and/ or the amount of flight cycles that have been flown, parts have to be inspected or exchanged. Furthermore, if a component breaks or another damage occurs, it often has to be repaired immediately, to allow the operator to continue flying. Even though some of these events can be planned (planned replacements), the majority of the demand for aircraft spare parts can be classified as lumpy (high in variability and infrequent) [1], which can make predictions difficult. While there are many approaches to predict damages and allow to implement a pro-active maintenance strategy, some are not, such as impact damage for example and have thus to be treated differently. Given the fact that an aircraft on the ground (AOG) does not make money, these situations of grounded aircraft have to be avoided or at least minimized. The best strategy for this is to accurately predict when a damage will occur and how long a repair will last. Since a high accuracy prediction for impact damages might not be possible, the consequent reactive approach should be optimized as much as possible. That means tailoring the reaction such that a decision between different options can be found as quickly, as clearly and as unambiguous as possible. By making a trade-off between survivability, repair time and associated cost, the best decision in the interest of the user (usually the operator) can be found.

Kumar et al. [2] describe that every decision making problem consists of four main elements: Firstly, one or more objectives, often based on a subjective opinion/desire, usually this is the person taking the decision. Secondly, different alternatives which are the possible options to choose from. Thirdly, criteria that influence the outcome and can be assigned a certain importance/ weight. Lastly, the final outcome scenarios.

Looking at this definition, it can be seen that in a conventional decision process the decision maker is able to take quite a subjective influence on the final outcome. This becomes especially evident in the second and the last element of the model. In fact, research shows that especially experts tend to go with their intuition, often because the data is not available or not presented in the right format or quality. This becomes even more evident by looking at several experiments such as the famous Linda experiment by Gigerenzer et al. [3] and other work. [4], [5], [6], [7]

All these examples show that subjective decision making does not always lead to the optimum result. Using computer assisted simulations or tools can therefore often lead to a more objective picture of a situation. A lot of research has been done already on different techniques and approaches to solve this. However, it is not always clear which methods are superior to others in specific situations.

B. Relevance

The goal of this report is to provide a strategy and a tool that can support the decision finding process when comparing potential damage resolutions. A damage can be repaired permanently immediately or temporarily. If the latter is chosen, a permanent repair needs to follow at a later, more suitable instant of time. If neither option is possible, the flight can also be cancelled and the decision left for a later moment. Using multi criteria decision making theory (MCDM) the best decision in terms of cost, survivability and time can be identified. There are however many different MCDM approaches available in literature, which is why three selected techniques will be evaluated and compared. With this approach the work will be building up upon the work done by Dhanisetty et al. [8]. The aim is to consider damage events that are dependent instead of independent and observe the magnitude of the impact of this more realistic scenario, namely several simultaneous occurrences as well as the effect of different MCDM methods on the outcome.

MCDM is applied for many different situations and industries, varying from energy management, over finance to sustainability and supplier selection. However, the problems presented were typically one-time decisions on a strategic level. The search through various search engines and databases did in fact not give many results regarding the research work done for operational decision making. Even less so, when searching for application of decision theory to real world applications and scenarios. While many authors verify their findings using real data, this data is often selected or drawn from a static, already known environment, as it is typically historic data rather than live data. This can quickly lead to unintentional bias in the findings.

In this article two gaps in literature are addressed; firstly the first mentioned methodological scaling to a multiple occurrence scenario and secondly the application of real operational data to an operational setting in a way that results can be obtained quickly. Additionally, it will be investigated which MCDM techniques are most suited for this approach (Section III). This results in the following research question:

"How can demand fulfillment be prioritized, using MCDM methods, given that the option set is limited and multiple simultaneous impact damage occurrences may have to be fulfilled?"

C. Structure

Based on the background and the scientific relevance laid out in this section, the research is structured as follows[a]. A more thorough literature review is provided, in Section II. Additionally, a complete literature study can be found in Appendix A. In Section III the readers can familiarize themselves with the overall approach, the theory used, as well as the assumptions made. In Section IV the results are presented. A thorough discussion follows in Section V including some limitations and further research potential. The key findings are summarized in the final element of this article (Section VI).

II. Literature Background

Decisions are found in every single aspect of daily life, some of which are easy to take, others require a more thorough analysis. Therefore, next to decision making theories itself, various different methodologies and approaches have been researched and evaluated.

A. Decision Theory

Literature offers a broad bandwidth of definitions, processes and decision models of which a few are described hereafter.

MacCrimmon et al. divide decision theory into two branches, normative decision making and descriptive decision making [9]. While normative decision making, also referred to as decision analysis, tries to find the best solution to a given problem, descriptive decision theory looks at the behavior that decision making agents display under certain conditions. In order to be able to justify the need for a decision tool, and also to understand the decision maker,

[a]Please note: This report contains many appendices. Relevant details, data tables and intermittent results that are not mentioned in the article, as well as a thorough literature review can be found there.

descriptive decision theory is the basis. Once this part has been understood, a well founded and justified decision support can be established.

Broekhuizen et al. [10] summarize that every decision problem has three properties, no matter the objective. Firstly, there is at least one or more criteria. Secondly, this criteria can be quantitative, qualitative or a combination of both. Thirdly, the criteria and the underlying weight or performance parameters can be deterministic or stochastic. Thus, regardless of the potential effects and impact of the decision, all decisions are made following the same high level process. This process starts with an ‘intelligence’ (investigation) phase, followed by a ‘choice’ phase and ends with a ‘review’ phase, in which a learning effect can occur as defined by Simon [11] and elaborated on by Arduin et al. [12].

When a decision is being made, different alternatives are evaluated in order to arrive at the best outcome. In real life however, several criteria or alternatives have an effect on different levels, which ultimately influences the final and best decision. This is commonly in literature referred to as multiple criteria decision making problems or multiple decision making analysis. A multiple criteria problem can possibly lead to more than one optimal or even no optimal solution. Therefore, a distinction between single and multiple criteria problems is essential.

Having only one criterion, like cost for example, will render a straight forward optimization approach, using only one objective function, which can be solved using optimization techniques such as discrete optimization, linear or non-linear programming [13], [14]. This approach is more straight forward (in terms of the decision making process) and will therefore not be covered more extensively in this review. From this point onward, when referring to a decision making problem, a multiple criteria decision making problem is assumed.

Research shows that especially experts tend to go with their intuition, often because the data is not available or not presented in the right format or quality. Several studies have been conducted to investigate the way people take decisions, confirming the above stated and illustrating how time, mood and other factors can influence decisions. [15], [3], [4], [5], [6] The outcome of these experiments clearly illustrates the need for a less subjective approach when complex decisions are involved.

B. Decision support systems (DSS)

In order to prevent or at least minimize the subjectivity introduced above (Subsection A), systematic approaches or even mathematical and computer based models can be used [16], [13]. For this, a new approach was developed in the 80’s, the decision support systems (DSS) [17]. This does not completely eliminate the subjectivity as criteria and input weights to the model are still decided upon subjectively [18], but supports the decision maker to take a decision which is both justified and based upon documented reasoning. Accordingly decisions cannot only be traced, but also be repeated or carried out independently of the individual decision maker, which often also results in a reduced decision making time. Dhanisetty et al. [8] give an illustrative example of this by finding that up to 50% of decision time can be saved by applying a decision support system (DSS) in form of a weighted sum approach to an operational maintenance process decision.

Different ways are used in literature to define and classify decision support systems. Häettenschwieler et al. [19] make a differentiation between active, passive and cooperative DSS. Other research groups look at the purpose and the medium of the DSS [20], [21]. More detail on this can be found in Appendix A. Based on classifications of DSS in literature different elements of a DSS can be distinguished as introduced in Subsection C. The consequent development of a DSS is looked at in Subsection D followed by an overview over the three different groups of underlying theory of DSS (Subsection E).

C. Elements of DSS

Some researchers looked into the elements a decision support tool consists of.

Finlay et al. [22] take the well known split of a DSS into a logical model and a data model from Alter et al. [21] and Sprague et al. [23] a step further and add the presentation element, displaying the computer/ user interface. A DSS can thus be said to be using different kinds of data as an input, which is analyzed and then, using a certain logical model, displayed to the user through an interface [24]. The first part of the model is the data model, which is the input. In this element all the required information (such as criteria, alternatives, weights and objectives) are gathered and assorted in the required structure. The second element is the logic model. There are a vast number of logical approaches for decision making processes available. The most important ones are discussed later on in this section. Depending on the objective of the decision finding (one-time only versus operational use for example) this logical model is then applied by the user once or more frequently. In case of a simple algorithm this means to initiate the program, while in case of a more sophisticated tool there could be a start button that initiates the algorithm in the background. Finally, the system will deliver/ display a result to the user, which can then be verified and implemented. This final verification step is however not further discussed in the above mentioned literature.

Serifi et al. [25] slightly deviate from this classification and distinguish between external and internal data. The logical element is split up into a model management and a knowledge management part. Further than that, their findings are similar to the ones of Finlay’s research group.

D. Development and implementation of DSS

When using a decision support tool, the high level process remains the same as the one mentioned above in Part A.

Applying a (often model based) decision support tool, Sabaei et al. [26], Fulop [20] and Marques et al. [16] further detail the decision process with the following eight steps (Figure 1), rendering a more objective conclusion:

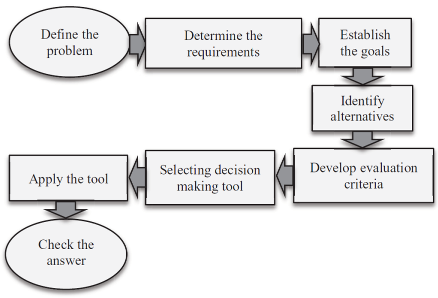

Fig. 1. Decision making steps [26].

The first step is to define the problem itself. This step is straightforward. This is followed by the second step, namely determining the requirements that come into play with respect to the defined problem. Mathematically expressed, the requirements act as constraints. Thirdly, the goals of the decision have to be evaluated. Is there one or more objectives? This could typically be minimizing cost or/ and time for example. Unlike the requirements, goals are not hard constraints, they should rather be seen like desired directions. Once this baseline has been established, the different alternatives have to be identified. This means thus that all possible outcomes or scenarios that do not violate the constraints, often referred to as a set of choices [27] are found. Usually, none of the alternatives in MCDM is the perfect one, thus a trade-off needs to be made among them [26]. In order to make this trade-off, evaluation criteria have to be established in the next step. An example criteria for minimizing cost could be for example the cost in euros. Baker et al. as well as Sabaei et al. state that well defined criteria need to have the following characteristics [13], [26]:

- Allow for distinction between alternatives
- Cover all goals
- Non-redundant
- Few in numbers
- Operational and meaningful
- Be comparable across different units/ metrics

Once all these parameters have been established, a method and/or tool (decision model) is selected. This is usually the most difficult task, as there are many different techniques available. Based on the purpose and the objective, different options can be considered. Having chosen a tool, a best alternative can be established. As there is often more than one alternative, it is referred to as a best, instead of the best solution [14].

Finally, the outcome alternative (outcome scenarios) is assessed against the requirements, with the goals in mind, and a final solution confirmed.

E. Theoretical approaches to a DSS

The modeling approaches chosen to develop such a decision support tool vary, depending on the problem statements. Different grouping of decision theory approaches have been defined in literature. Sanayei et al. [28] distinguish up to six different categories, namely multiple attribute decision making, multiple-objective decision making, mathematical programming, probabilistic approaches, intelligent approaches and hybrid approaches. The first two are rather similar, a more detailed distinction will be made in the following subsection. Probabilistic approaches by themselves are either straightforward or employ one method of one of the other categories. Hybrid approaches are simply a combination of different methods. This leaves generally speaking three larger categories: artificial intelligence/ simulation techniques (intelligent), MCDM (multiple criteria decision methods) techniques and mathematical programming.

F. Conventional multiple criteria decision (MCDM) methods

Mardani et al. [29] conclude from their literature review that MCDM techniques are the most common and well researched decision making approaches. This is a logical conclusion as they are not only the theories that have been established for the longest time, but tend to have a simpler and more straightforward underlying theory and applicability. Additionally from the conducted research, it has been found that this group of methods is the most suitable for this master thesis, keeping in mind the identified gap in literature, as well as the required short computing time for an operational environment.

When reading papers dedicated to dedicated to multiple criteria decision making, commonly abbreviated as MCDM, one often comes across two more definitions, multiple attribute decision making (MADM) and multiple objective decision making (MODM). The three definitions are not always clearly distinguished and often used interchangeably in literature

In MADM one looks at the given existing alternatives and aims to choose the best among them. This implies naturally that there is a finite number of alternatives to choose from. In MADM one can again differentiate between non-compensatory methods and compensatory methods. Examples of the non-compensatory method are the dominance method (eliminating the dominated alternatives with respect to all criteria, generally yielding more than one solution), the maxmin method (choosing the alternative with the strongest weak attribute) and the maxmax method (choosing the alternative with the strongest attribute). The premise for the latter two is that all attributes are comparable. More sophisticated methods are the scoring methods (e.g. AHP, MAUT etc.) and the compromising methods (e.g. TOPSIS) [30].

MODM on the other hand looks at the objectives first and assumes an infinite solution space. This is the type of problems that can be found for example in aerodynamic or structural designs.

In the investigated literature the abbreviations MCDM, MDMA, MODM and MODA are used interchangeably and with different definitions, depending on the author. For the remainder of this report the abbreviation MDMA will refer to multiple decision making **analysis** (problem analysis) while MCDM will be defined as multiple criteria decision **method(s)** (solution theories). MODM and MODA will be treated likewise.

Hobbs et al. [31] argue that that depending on the method chosen, the obtained best solution may differ. This is due to different methods having different underlying principles and focus. Understanding the objective of the chosen approach is therefore essential to be able to interpret results in a meaningful way. Apart from being aware of advantages, disadvantages and assumptions made, results should be verified by using different methods with a similar input. This output of results should then be evaluated taking into account the differences between the theories.

Balalit et al. [32] make a distinction between three different kind of multiple criteria decision method (MCDM) approaches; the selection problems, thus choosing the best alternative from a given set, the ranking problems, putting a set of alternatives in a certain order, and finally the sorting problems which assigns alternatives to different sub groups. Cavallaro et al. [33] additionally identify descriptive problems, treating problems where no data but only a description exists as a different case.

Another distinction commonly made in literature is the classification into value measurement models, outranking models and goal aspiration models [33], [34].

- **Value measurement models** assign scores to different alternatives, by evaluating criteria. Based on the best score, the preferred alternative is selected. Examples that were considered are WSM, WPM, AHP, MAUT and MAVT.

- **Outranking models** are often referred to as ‘French School’, as the founder of them was B.Roy. These methods rate alternatives as being “at least as good”, through pairwise comparisons. Examples considered are ELECTRE and PROMETHEE.

- **Goal aspiration models** define optimal or desired values for all criteria. The method assesses then the alternative that is closest to this solution. Examples discussed are VIKOR and TOPSIS.

With an eye on the objective of a quick and adaptable decision support tool, the above mentioned methods and their applications have been studied carefully and their respective properties compared in Table B-1 in Appendix B. Furthermore, for a more detailed description of the other MCDM approaches, the reader is referred to the literature study of this thesis in Appendix A.

Three suited methods have been chosen; WSM, VIKOR and TOPSIS. While AHP would have been suited as well at a first glance as well, its closeness to WSM make its investigation for now redundant for the objective of this research. A short overview of these three methods can be found below.

WSM: The weighted sum model (WSM), is the most common and simplest way of evaluating a MCDM problem [35]. It is very simple and straightforward to apply. This means, for a large number of criteria and/or alternatives little computational power is required in order to quickly compare several alternatives. According to research done by Triantaphyllou [35], [36], for single dimensional problems, the WSM appears to be the most effective and reliable model. However, WSM is a highly subjective way of comparing, as weights are assigned lacking a certain scheme. Extreme care has to be taken when choosing the weights, as indirectly, due to the linear addition of weighted criteria, the assigned weights directly represent subjective preferences. Marlar and Arora investigate the effect of determining the weights when using a WSM approach and come to the conclusion that *"it can be difficult to discern between setting weights to compensate for differences in objective-function magnitudes and setting weights to indicate the relative importance of an objective as is done with the rating methods"* [37]. Furthermore, WSM can only be applied if, firstly, the criteria are of quantitative nature and secondly if the problem is one dimensional (e.g. cost, time etc.). The latter is due to the additive utility assumption, which will be violated if WSM is applied to a multi-dimensional problem. [35]

VIKOR: VlseKriterijuska Optimizacija I Komoromisno Resenje or short VIKOR is based upon the principle of eliminating the units of criterion function by linear normalization. A translation of the methods name is 'multi-criteria optimization and compromise solution' [38]. Obricovic et al. [38], who first introduced the method based on the work done by Yu [39] describe it as "a compromise solution, providing a maximum 'group utility' for the 'majority' and a minimum of an individual regret for the 'opponent'". In order to assess the stability of the weights, the VIKOR method has been extended later on by Obricovic and Tzeng [40]. The extension adds a way of determining the stability interval of the weights, as well as a procedure to make a trade-off if the decision maker does not agree with the values. Generally speaking, the method is often used as basis for a discussion rather than for a final decision [41].

A large advantage of the VIKOR method is that it does not only give the best alternative, but also results, in a relatively simple way in a complete ranking of all alternatives. Furthermore, the method allows for non-commensurable criteria to be evaluated. Another advantage is that the last steps of the extended VIKOR method allow the decision maker to deal with decisions where preferences are not known in the beginning of the decision process [40]. Sanayei et al. [28] used the VIKOR method for a theoretical example of supplier selection, combining it with a fuzzy approach.

TOPSIS: The technique for order of preference by similarity to ideal solution (TOPSIS), has many similarities with VIKOR, as both belong to the group of goal aspiration methods. It was introduced in 1981 by Hwang and Yoon [42]. Similarly to VIKOR it eliminates the units of criterion function, but does this by vector normalization [38]. TOPSIS is, unlike VIKOR, based upon two points of reference. The best alternative is thus not only closest to the ideal solution, but also the furthest away from the negative solution [43].

In their review Socorro García-Cascalesa et al. [44] list four main advantages of TOPSIS:

- Understandability and rationality
- Straightforward computation process
- The best mathematical alternative can be pursued in a simple mathematical form
- The criteria weights are incorporated in the comparison process

Another advantage is the fact that limited subjective input is required from the decision maker (unlike for the outranking methods) [45]. Velasquez and Hester [46] confirm the above stated observations and add that the overall process is rather simple. This is why it is often used to confirm the findings of another approach. They add however, that the euclidean distance does not take into account the correlation of attributes. Even though this method considers the distances from the ideal and anti-ideal solution, it does not consider their relative importance [38]. Another drawback, as with many other methods, is the issue of rank reversal [44], [47]. As the method does not take uncertainty into account, it is often used in combination with fuzzy set theory (Cavallaro [48], Kaya and Kahramann [49]). Velasquez and Hester's [46] review finds and confirms what the results on search engines confirm, that TOPSIS is used in a broad variety of different fields.

III. Method

A. Procedure

In Section I two major limitations to the current state of the art in literature were identified. Firstly the methodological scaling to a multiple occurrence scenario of a decision support system and secondly the application and analysis of MCDM theory in terms of applicability, suitability and robustness to an operational setting. In order to structure this, four questions were formulated:

1. When looking at cost (minimize), time (minimize) and survivability (maximize), should a single damage in the fuselage be permanently repaired, be temporarily repaired or be ignored?
2. How does the result of the above change if there is more than one simultaneous occurrence and not enough resources?
3. Is there a significant change in the results from the questions above if another underlying MCDM theory is used?
4. Are there other influencing factors such as seasonality?

As a first step the data provided was evaluated. Then it was cleaned and missing data entries were completed if possible and eliminated otherwise. A more detailed description of this damage occurrence data can be found in Subsection III B. To start the process, the requirements (suitability) were identified. These are the restriction of such a tool in an operational setting, thus easy to use, quick to use and straightforward. Then the goals of a general operator and the ways of the support a decision support can deliver were identified to be: smooth operations, cheap operations and safe operations. Additionally, a set of different alternatives was selected, which is presentable of a real life scenario. Based on the previously established requirements and goals the input parameters for the decision criteria cost, time and survivability were first chosen and their input then determined from literature and data. By importing the xls data into Matlab, the scenarios were evaluated one by one using different MCDM theories. Finally, the output was evaluated and verified by varying the inputs and the applied weights.

After this was completed for the single occurrence case, it was followed by evaluating the change of decision if there were several aircraft, as this has an impact on the repair time as well as the cost. Several constraints were considered. One of the pursued approaches was limited hangar capacity, enforcing a sub-optimal resolution for at least one aircraft, thus for example cancelling a flight. Alternatively, aircraft could be repaired at a later moment. This was done to discover whether or not a different result per model might result. The survivability is naturally independent of the amount of simultaneous occurrences, provided the assumption that the repair will also under higher workload be of the same quality.

Two approaches have been chosen here. The first was one was a greedy approach, selecting the best option at that moment, and then moving on to evaluating the remaining aircraft. The second approach was to define all possible combinations of all occurrences, to compute the total criteria of the specific combination and evaluate these combinations. The latter is a more global approach and only possible for a small number of simultaneous occurrences, due to the options being at least of magnitude $n!$, where n is the amount of occurrences considered. This number increases quickly if options diverge even more.

Lastly, different MCDM theories were applied and the results compared. While the methods don't have an impact on the criteria themselves, the relative weighting and thus the result might change. This was done to give a feeling for the robustness of the obtained results.

These steps can be summarized in the following adaption of the process suggested in Figure 1, resulting in Figure 2.

In order to bound the problem and contain it to the scope, several assumptions were made. These assumptions are listed in the following.

Data[b]

- Damage time data entries are treated as the actual occurrence, since the actual time of the incidence is unknown
- Data before 2011 is irrelevant as it is incomplete and has very little entries
- Incomplete data can be ignored without changing the conclusions that can be drawn from the remaining data

Input

- The repair costs found in literature and obtained by employees are representative and constant for all incidences (Subsection IV A)
- The repair time found in literature and obtained by employees is representative and constant for all incidences (Subsection IV A)
- All costs are known beforehand
- Time required is known beforehand
- The desired weights are known

[b] A detailed explanation of the evaluated data set is provided in Subsection III B

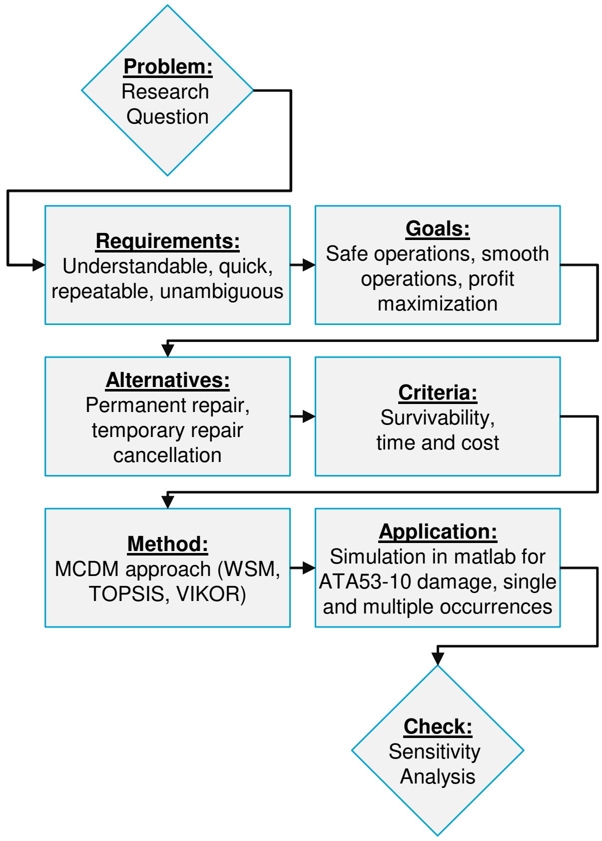

Fig. 2. Application of DSS development schema to the research question, adapted from [26].

- Five simultaneous occurrences are representative for the situation at hand
- Effect of conversion from dollar to euros is negligible
- Repairs during larger checks (i.e. C-check is larger than A-Check, which is larger than an immediate (unscheduled) repair) are more cost efficient
- Quality of repair is independant of time and place

Method and Theory

- Impacts on the fuselage can be modeled using a Weibull process, assuming that age of the aircraft has no influence on the degradation of the overall system
- The determined survivability function does indeed reflect realistic scenarios
- Aircraft is 'as good as new' after a planned repair

B. Damage Occurrence Data

1. Raw Data

In order to apply and test the above explained MCDM and the potentially varying effect on the outcome real life maintenance data was used. The data set was obtained from a large European operator via the faculty of Aerospace Engineering.

The data set consisted of a large consolidation of the damage report history of 100 different tail registrations. It contained entries from 2005 up until 2015. These entries included (amongst others that are less relevant for this study) the following with respect to an incident: ATA chapter, sub-ATA chapter, details on exact location, description, repair date, validation date, hangar location, type of repair, type of inspection, flight hours, flight cycles, A/C registration and A/C type.

2. Data Evaluation

It was decided to look specifically at ATA chapter 53, which represents the fuselage of the aircraft. It resulted that a lot of sub-ATA chapters were missing. These entries were completed from keyword as well as damage report descriptions and station numbers (ambiguous entries were treated in that order). In order to obtain a correct dataset, entries with multiple sub-ATA chapter references in the keywords were duplicated, rendering a total of 2567 data points. However, closer analysis showed that several data entries were incomplete, especially older entries as can be seen in Figure 3.

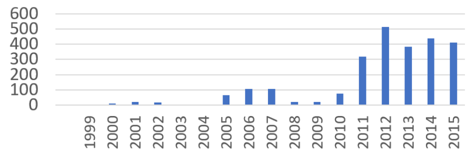

Fig. 3. Before 2011 there are only very few data entries, rendering the data quality questionable.

Therefore, the data was cleaned according to the following criteria:

- Only data between 2011 and 2015
- No data without a recoverable sub-ATA chapter entry
- No shop registrations
- Only data with entry in the type of repair section

Additionally to these restrictions, a more detailed data analysis showed that only for sub-ATA chapter 10 (which represents the nose section of the fuselage) sufficient data was available to draw valid conclusions. Therefore, only this part of the aircraft will be considered from here on. As this part of the aircraft is on the front of the aircraft, it makes sense that this is the area with the largest amount of entries. The total amount of data points considered was thus reduced to 617 data points. The second largest amount of data entries was observed at sub-ATA 30, which is located next to the wheel, also a logical observation, given the amount of particles that fly around during landing and take-off. Unfortunately, the amount and quality of the data of this area was not sufficient to allow for a proper analysis. From the analysis of the results, even the data points concerning sub-ATA 10 were too few to determine a clear survivability distribution. Upscaling the data by a factor ten might help reduce this. Ideally, the distributions per aircraft start converging at a realistic number of data points.

C. Seasonality

Typically a large amount of aircraft maintenance activities is planned in winter, as more aircraft are grounded. This is due to less tourism during the winter months, compared to the summer, when most people go on vacation. Seasonality is an interesting factor to consider in this research, as time might be more relevant in summer, while in winter hangars are fuller in winter and survivability (to avoid downtime in summer) might be of larger interest in winter. This might have a significant impact on the results.

However, looking at the data (see Figure 4 below) there is no indication of any seasonality in the repairs done over the year. Neither on a quarterly nor on a monthly basis. While there are some variances, they can with a maximum variation of +/- 10% be disregarded. Looking at the individual data revealed that these fluctuations are rather coincidental (small data size N) and large deviations from the general trend on individual level. This becomes more obvious from a detailed heatmap which can be found in Appendix E-3.

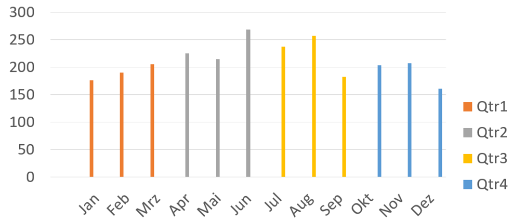

Fig. 4. Damage reports are relatively even distributed over the year.

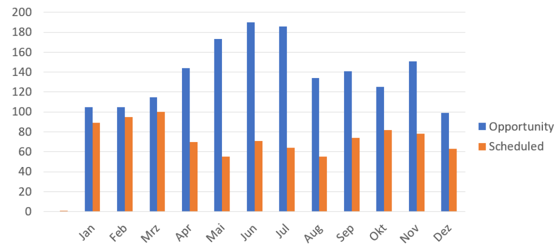

Fig. 5. Seasonality can be seen in the planning of maintenance activities.

Figure 5 shows that there is seasonality in planned versus opportunity repair, which reflects the above stated winter maintenance activities. As hangar capacity is a constant variable in this research this can be neglected. Nevertheless, this would be an interesting factor to pick up in follow-up research to investigate the impact this seasonality has on hangar availability and consequently on the decision made.

D. Theory

In order to evaluate the survivability of a certain repair, a Weibull distribution was used, which will be shortly explained. During the literature research many papers and articles have been read and evaluated. The relevant theory and equations are provided in the following.

1. Weibull distribution

In order to determine the survivability or reliability of a repairable, different methods and approaches exist. One of them is the Weibull process [50]. In literature this method is also referred to as power law process, power law NHPP, Weibull restoration process, NHPP with Weibull intensity function, or Weibull Poisson process. Weckmann et al. describe in their paper why it is one of the most appropriate probability theories for repairable aircraft components [51]. While the fuselage is not really a repairable component, modeling it as such is a valid due to some underlying wear-out behaviour. This means that through a permanent repair it can be returned to a 'good as new' state. The reliability of a repairable component can be modeled as follows from Equation 1 as a function of total component lifetime t and using the following parameters:

β	-	Weibull shape parameter
η	-	Weibull scale parameter
λ	-	intensity function

$$u(t) = \lambda \cdot \beta \cdot t^{\beta - 1} \text{ with } \beta, \lambda > 0 \tag{1}$$

A shape parameter $\beta > 1$ indicates that the system is deteriorating over time. For values $\beta < 1$ the system is becoming more reliable over time. The scale parameter η stretches or contracts the failure curve over the component's lifetime [52]. There are two ways to determine these parameters. The first is to apply estimates to Equation 1 and derive the values from failure data. The second way is a graphical method, using logarithmic drawing paper. As this method does not differ significantly in accuracy, the second method has been chosen. The procedure can be found in Appendix C.

2. Time

Repair time is a numerical input found from literature (Subsection IV A). No equations were used to determine the input of the time criterion.

3. Cost

Similar to the data concerning time, there was no information on cost available. This was therefore treated similar to the case of the time parameters and retrieved from literature and the operator that also provided the data. Also here some inputs vary in reality per occurrence and will further be elaborated during the sensitivity analysis.

Equations 2 and 3 were used to determine the cost. Machine and material cost vary widely in literature. Furthermore, an efficiency factor applies if the permanent repair is done during an A-Check or a C-check reflecting a cost reduction. This cost reduction is due to efficiency, staff, material and time being already available on site as opposed to a spontaneous (unplanned) permanent repair [53]. This factor becomes larger for a C-Check. The inputs are summarized in Tables 4 and 5 in Section IV.

$$\begin{aligned} total\ cost\ of\ permanent\ repair = repair\ time \cdot men \\ \cdot hourly\ wage\ + material\ cost +\ machinery\ cost \\ + delay\ time \cdot cost/delayed\ hour \end{aligned} \tag{2}$$

$$\begin{aligned} total\ cost\ of\ temporary\ repair = repair\ time \cdot men \\ \cdot hourly\ wage\ + material\ cost +\ machinery\ cost \\ + delay\ time \cdot cost/delayed\ hour \\ + cost\ of\ permanent\ repair \cdot efficiency\ factor \end{aligned} \tag{3}$$

4. WSM

In WSM problems are categorized as follows. If there are n criteria in order to evaluate m alternatives, then each of the criteria is assigned a weight w, where w becomes larger as the criterion is more important. The best alternative A_i will then be the one that returns the highest score, applying Equation 4. a_{ij} represents the actual value of the alternative in terms of the j-th criterion and is multiplied with the corresponding defined weight w. The governing assumption is an additive utility assumption [35].

$$A_i^{WSM_{score}} = \sum_{j=1}^{n} a_{i,j} w_j \qquad \text{for} \quad i = 1, 2, 3, ..., m \tag{4}$$

5. TOPSIS

Applying the method consists of seven steps [42]:

1. Establishing the performance matrix, sometimes referred to as decision matrix X
2. Normalization of the performance matrix:
$$\overline{x_{i,j}} = \frac{x_{i,j}}{\sqrt{\sum_{j=1}^{n} x_{i,j}^2}} \tag{5}$$
3. Calculation of the weighted performance matrix v, using weight vector w:
$$v_{i,j} = x_{i,j} \cdot w_j \tag{6}$$
4. Determination of positive and negative ideal solutions:
$$V_j^+ = \max_i [v_j] \tag{7}$$
$$V_j^- = \min_i [v_j] \tag{8}$$
5. Calculation of the relative distance to the previously established ideal solution and anti-ideal solution:
$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{i,j} - v_j^+\right)^2} \tag{9}$$
$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{i,j} - v_j^-\right)^2} \tag{10}$$
6. Final ranking of the solutions according to preferred order of performance score P:
$$P_i = \frac{S_i^-}{S_i^- + S_i^+} \tag{11}$$

6. VIKOR

Obricovic et al. [38], who first introduced the method based on the work done by Yu [39] describe it as "a compromise solution, providing a maximum 'group utility' for the 'majority' and a minimum of an individual regret for the 'opponent'". By determining the ideal alternative using all $i = 1, 2, 3, ..., n$ of the given criteria weighted by weights w_i, a rating is established for each alternative a_j.

Obricovic [38] defines the following steps:

1. Determination of the best f_i^* and the worst values f_i^- of all criterion functions

2. Computation of value S_j and R_j, where S and R are expressed by Equations 12 and 13 respectively:

$$S_j = \sum_{i=n} w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \quad (12)$$

$$R_j = \max_i [w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-}] \quad (13)$$

3. Computation of Q_j using Equation 14 and v as a factor of utility (the majority of criteria or the maximum group utility), and with $S^* = \min_j S_j$ as well as $S^- = \max_j S_j$ and likewise for R_x^x, thus resulting in Equation 14:

$$Q_j = v \frac{S_j - S^*}{S^- - S^*} + (1 - v) \frac{R_j - R^*}{R^- - R^*} \quad (14)$$

4. Ranking of alternatives with respect to Q (minimum), R and S (resulting in three different rankings)

5. Proposal of alternative a" that ranks best in Q, given the following two conditions:

   - C1: "Acceptable advantage":

   $$Q(a") - Q(a') \geqslant \frac{1}{J - 1} \quad (15)$$

   - C2: "Acceptable stability in decision making" Alternative a" should at least also be best ranked in either R or S. The solution is considered stable if the value v if "ruling by majority" (v larger than 0.5), "voting by consensus" (v = 0.5) or "considering veto" (v smaller 0.5). V is affected by the overall decision making strategy.

   The author proposes a compromise solution of a" and a' if the the second condition is not satisfied and a combination of the solutions $a", a', ..., a^m$ until the first condition is satisfied.

In order to assess the stability of the weights, the VIKOR method has been extended later on by Obricovic and Tzeng [40]. The extension adds a way of determining the stability interval of the weights, as well as a procedure to make a trade-off if the decision maker does not agree with the values.

IV. Results

In this section the results of the analysis are presented. Investigated scenarios for all three MCDM methods can be found in Table 1. In the beginning of the section the input parameters are determined. This is followed by the results of a single scenario analysis, using three different weight settings. The same weight settings have been used to evaluate two multiple scenarios. First using a greedy heuristic method, followed by a global approach.

Table 1. Three scenarios were evaluated using different MCDM techniques. Each scenario was considered using three different weight settings.

Scenario	WSM	TOPSIS	VIKOR
Single occurrence for different initial flight cycles	✓	✓	✓
5 multiple occurrences with limited options - Heuristic Approach	✓	✓	✓
5 multiple occurrences with limited options - Global Optimization	✓	✓	*X*

A. Input Parameters Survivability, Time and Cost

1. Survivability

The survivability for a temporary repair as well as a permanent (as good as new) repair had to be determined from the data as no other information was available. this was done based on initial flight cycles, thus the amount of flight cycles since the last maintenance opportunity. More details can be found in Appendix C.

The assumption that if an occurrence was labeled an opportunity repair, thus not planned, the damage occurred close to the time of the repair was necessary. This is because the actual date of occurrence or when a repair was found was not presented in the data set. By looking at single aircraft and the target region ATA 53, sub-ATA 10, the amount of flight cycles between opportunity repairs was determined. Planned activities were neglected here as they would falsify the obtained interval. This of course results in a much lower occurrence rate than what would be the case in reality and has to be judged with care. Improving the accuracy of these intervals would increase the quality of the results and is worth investigating as a follow-up study.

Using the intervals the Weibull parameters β and η were determined for three aircraft (shown in Table 2). The aircraft were selected as they had the largest amount of data entries, counteracting the limitation mentioned above to some extend.

Table 2. Three different sets of Weibull parameters were determined from damage occurrence data.

Registration	Sample size N	Shape parameter β	Scale parameter η
Aircraft 1	10	0.48	120
Aircraft 2	10	0.68	120
Aircraft 3	6	1.8	5.2

The results in Table 2, especially for aircraft 3, do not correspond to expected impact damage behaviour (which is a random process), so need to be used and interpreted with care. A graphical visualization of this can be found in Appendix C.

2. Time

As the data did not contain any information on time of repair, delay or turnaround time, standard values from IATA or from literature were used. Furthermore, a delay time for repairs that take longer than the planned turn around time of the aircraft was considered. Using the times in the Table 3 for the concerning scenarios the results were generated. One has to keep in mind that some of these times vary per occurrence thus some damages in reality take longer to repair than others. This factor will be considered later in this article (Section V) as part of the sensitivity analysis.

Table 3. Input times.

Parameter	Value	Source
Temporary repair time	60 minutes	employee[c]
Permanent repair time	180 minutes	employee[c]
Next A-Check Opportunity	200 flight cycles	N/A
Next C-Check Opportunity	400 flight cycles	N/A

Additional A-Check and C-Check moments were introduced artificially, as the nature of the next planned repair is not defined in the data. Usually a C-Check are conducted around every 1000 to 1500 flight cycles [52]. However, 400 flight cycles between the last maintenance moment and the next C-Check were chosen to increase the quality of the survivability data input, as it diverges with very large flight cycles.

3. Cost

Similar to the input data for the time criteria, no information on cost was available. This was therefore treated similar to the case of the time parameters and resulted in Tables 4 and 5 below. Also here some inputs vary in reality per occurrence and will further be elaborated upon the discussion section (Section V).

Using Equations 2 and 3 with the input from Table 3 resulted in different inputs for the Matlab model. The inputs are summarized in Tables 4 and 5. An efficiency factor applies if the permanent repair is done during an A-Check or a C-check reflecting a cost reduction. This cost reduction is due to efficiency, staff, material and time being already available on site as opposed to a spontaneous permanent repair [53].

Table 4. Used input values for cost of a permanent repair.

Parameter	Value	Source
Man hours	3 hrs	from repair time and TAT
Hourly wage	$50	[54], [55]
Material cost	$200 (variable)	employee[c]
Machinery cost	$100 (variable)	employee[c]

Cook et al. [56] define some soft as well as some hard cost corresponding to every delay in intervals per minute. The soft cost are indirect factors such as loss of market share due to passengers choosing a different airline. Hard cost are the costs directly related to a delay such as re-booking, compensation or overnight stays for example. In Figure 6 the used values are shown in intervals of 10

[c]These values were determined from an employee source for typical component repairs. While the cost for the fuselage nose section might deviate from this value, sensitivity analysis showed that even a 100% deviation has no impact on the results.

Table 5. Used input values for cost of a temporary repair.

Parameter	Value	Source
Man hours	0.5 hrs	from repair time and TAT
Hourly wage	$50	[54], [55]
Material cost	$100 (variable)	employee[c]
Machinery cost	$100 (variable)	employee[c]

minutes. Assuming an aircraft of about 300 seats (wide body aircraft) with a load factor of about 80% this results in 240 passengers per flight [57].

Delay [min]	Soft cost [$]	Hard cost [$]	Total cost [$]	Delay [min]	Soft cost [$]	Hard cost [$]	Total cost [$]
10	0.454	0	0.454	310	392.968	20	412.968
20	1.985	0	1.985	320	407.782	20	427.782
30	5.127	0	5.127	330	422.596	20	442.596
40	10.399	0	10.399	340	437.410	20	457.410
50	18.078	0	18.078	350	452.224	20	472.224
60	28.048	10	38.048	360	467.039	40	507.039
70	39.878	10	49.878	370	481.853	40	521.853
80	53.035	10	63.035	380	496.667	40	536.667
90	67.056	10	77.056	390	511.481	40	551.481
100	81.870	10	91.870	400	526.295	40	566.295
110	96.684	10	106.684	410	541.109	40	581.109
120	111.499	15	126.499	420	555.924	40	595.924
130	126.313	15	141.313	430	570.738	40	610.738
140	141.127	15	156.127	440	585.552	40	625.552
150	155.941	15	170.941	450	600.366	40	640.366
160	170.755	15	185.755	460	615.180	40	655.180
170	185.569	15	200.569	470	629.994	40	669.994
180	200.384	15	215.384	480	644.809	250	894.809
190	215.198	15	230.198	490	659.623	250	909.623
200	230.012	15	245.012	500	674.437	250	924.437
210	244.826	15	259.826	510	689.251	250	939.251
220	259.640	15	274.640	520	704.065	250	954.065
230	274.454	15	289.454	530	718.879	250	968.879
240	289.269	20	309.269	540	733.694	250	983.694
250	304.083	20	324.083	550	748.508	250	998.508
260	318.897	20	338.897	560	763.322	250	1013.322
270	333.711	20	353.711	570	778.136	250	1028.136
280	348.525	20	368.525	580	792.950	250	1042.950
290	363.339	20	383.339	590	807.764	250	1057.764
300	378.154	20	398.154	600	822.579	250	1072.579

Fig. 6. Delay cost per passenger in intervals of ten minutes [58] adapted from [56].

Furthermore, a cancellation cost of around €114500 for a double aisle Boeing was determined from literature [59], [60], [61]. The delay time for a cancelled flight was decided to correspond at least to three times the delay time in case of a permanent repair and last at least 6 hours, as a disruption like that cannot directly be quantified in time. This ensures that this option is the least favorable as flight cancellations are to be avoided as much as possible. The latter is a general business rule that has been learned during several internships at major European operators.

B. Results of the Single Occurrence Scenario

Using the three different MCDM theories with the above discussed input data for a certain input of weights some exemplary results were generated.

The input matrix was determined using the equations from Section III. Thus an i by j matrix displaying i different resolution options/ alternatives (four in this case) and j different criteria (probability of failure, cost and time). These inputs are summarized in Table 6. The failure input is dependent on the amount of flight cycles until the next planned A-Check or C-Check. The significantly larger cost for an immediate repair result from the large cost of delay as introduced in the previous section (Section III).

Table 6. Input values for the MCDM models.

Options	Probability of failure	Total delay	Total Cost
Temporary repair and permanent repair at A-Check (TPA)	Flight cycle dependent	0.5 hrs	$1860
Temporary repair and permanent repair at C-Check (TPC)	Flight cycle dependent	0.5 hrs	$1680
Permanent repair (PR)	Flight cycle dependent	3 hrs	$52050
Cancellation (C)	0.99	9 hrs	$114500

Three scenarios for the weights were considered:

1. All weights are equal
2. One weight is zero
3. One weight (survivability) is significantly larger than the other two

The first case was selected to obtain a neutral picture. The second scenario should show the difference in number of criteria. The last scenario was chosen to visualize the impact of decreasing survivability over time better, as this criteria is the only one being impacted by the amount of initial flight cycles, thus varying per occurrence.

Applying the different weight combinations led to the recommendations shown in Table 7. It can be seen that **TPA is the best** option, unless the weights are significantly unbalanced with respect to survivability. This applies to each of the explored theories.

Table 7. Outcomes for different weights for single occurrences.

Scenario	I	II	III
Weights for Survivability	1	1	30
Weights for Time	1	0	1
Weights for Cost	1	1	1
Result WSM	TPA	TPA	PR
Result TOPSIS	TPA	TPA	PR
Result VIKOR	TPA	TPA	PR

Naturally, the input values have the deciding effect on the results and the best resulting method. Plotting the results over initial flight values between zero, thus a damage immediately after the last maintenance event until 200 (right before the next A-Check), results in the three graphs below (Figures 7 - 9. Here the first use case $weights = [1, 1, 1,]$ (for $weights = [survivability, time, cost]$) is depicted. The graphs for the other two use cases ($weights = [1, 0, 1,]$ and $weights = [30, 1, 1,]$), can be found in Appendix E-1.

The values on the y-axis represent the respective rankings that resulted from each method. Keeping in mind that probability of failure, time and cost should be minimized, the smallest value should be considered to be the best. For WSM that means taking the smallest performance value. Looking at TOPSIS, one can see that the method is able to take minimization into account by interchanging the ideal and the anti-ideal solution. However it will the assign a maximum performance value to the best solution. To be able to compare the graphs, the values have been multiplied with negative 1. While for VIKOR the return values are the minimum distances to the optimum solution, the smallest value is the best. However, as the criteria are to be minimized, the maximum values should be considered here. Just like for TOPSIS, the results have been multiplied be negative 1, to allow for a better visual comparison in the graph.

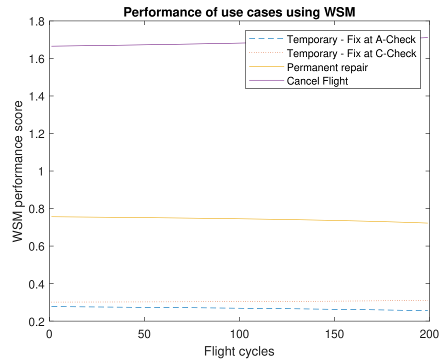

Fig. 7. WSM ranking over 200 flight cycles after last maintenance opportunity. Due to minimization small performance scores are preferred.

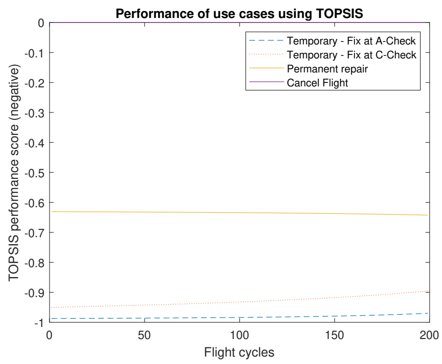

Fig. 8. TOPSIS ranking over 200 flight cycles after last maintenance opportunity. Due to minimization small performance scores are preferred.

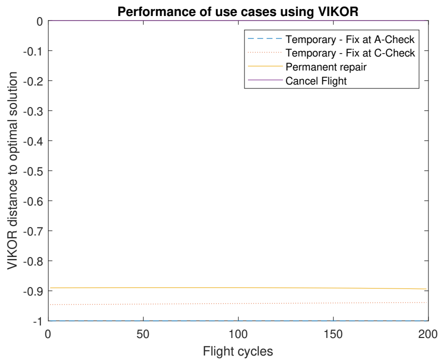

Fig. 9. VIKOR ranking over 200 flight cycles after last maintenance opportunity. Due to minimization small performance scores are preferred.

C. Results of the Multiple Occurrences Scenario

1. Greedy Heuristic Approach

Extending the simulation created for the scenarios above allows to compare situation of different occurrences at the same time. Thus several aircraft requiring a repair action/ decision. Two different options have been considered, using a greedy heuristic evaluation strategy and using again a MCDM approach to evaluate the best decision.

Resulting from the observations of the single occurrence case, the order of preference does not change with increasing initial flight cycles. Thus, a certain amount of aircraft will compete for the same resolution. However, as can be seen in the graphs above (Part B of this section), not all lines in the graph are straight, implying that the preference is more or less pronounced, depending on the initial flight cycles. Ranking these values per solution option against each other, allows determining which occurrence will draw the most or least value of a certain decision.

Again the three use cases (input weights as in Table 7) were evaluated and the first method suggested in Section III of simply filling up the available space applied. It was assumed that for the two best options temporary repair followed by permanent repair at next A-Check, and temporary repair followed by permanent repair at next C-Check only one spot would be available. Furthermore, that one flight would have to be cancelled. While the latter doesn't usually reflect the practical world, this approach allows more insight into differences in the results. Looking at the best and the worst option, evaluation for VIKOR is not possible, as the method considers the distance to the theoretical optimal solution. Thus, if an optimal solution exists, that distance will be zero. This results in the 'performance score' for all five occurrences to be exactly zero, thus they are all on rank 1.

In Tables 8 - 10 the actual ranking values are shown for the third use case. The third use case was chosen because the values differ more, whereas in even weights the results of TOPSIS only yields small differences, with differences too small to visualize in a table due to rounding effects. The respective best values for each alternative are printed in bold. Using an heuristic greedy approach the recommended resolutions were found by taking the best option that was still available for each case. For a better visualization, the resulting recommendations are highlighted in yellow. For the results generated by VIKOR, a similar approach was used. But since the ranking is the same for all TPAs, the best value for TPC was chosen first. Then the two best for the third best option (PR). This led to two options being possible for the best and the worst options for the decision maker to choose from.

Table 8. Suggested prioritization of 5 occurrences for use case III ($weights = [30, 1, 1,]$), using WSM.

Occurrence	TPA	TPC	PR	C
O_1	6.5913	7.3705	**7.9292**	**10.1091**
O_2	6.3912	7.3496	7.9431	10.3154
O_3	6.3110	7.3423	7.9511	10.3056
O_4	6.1240	7.3278	7.9707	10.5775
O_5	**5.8234**	**7.3109**	8.0086	10.8572
Opportunities avail.	1	1	2	1

Table 9. Suggested prioritization of 5 occurrences for use case III ($weights = [30, 1, 1,]$), using TOPSIS.

Occurrence	TPA	TPC	PR	C
O_1	0.9995	**0.6664**	**0.6148**	**0**
O_2	0.9996	0.6484	0.5937	**0**
O_3	0.9996	0.6420	0.5860	**0**
O_4	0.9997	0.6284	0.5693	**0**
O_5	**0.9997**	0.6093	0.5459	**0**
Opportunities avail.	1	1	2	1

Table 10. Suggested prioritization of 5 occurrences for use case III ($weights = [30, 1, 1,]$), using VIKOR.

Occurrence	TPA	TPC	PR	C
O_1	**1**	**0.6570**	**0.6144**	**0**
O_2	**1**	0.6439	0.5930	**0**
O_3	**1**	0.6390	0.5853	**0**
O_4	**1**	0.6282	0.5689	**0**
O_5	**1**	0.6123	0.5462	**0**
Opportunities avail.	1	1	2	1

2. Global Optimization

In order to verify the results obtained by using the local optimization approach described in Part B of this section, a more global approached was used to compare. For all five occurrences with the same input, all possible orders of resolution were considered. This means a total of $n!$, where n is the number of occurrences. The total of all three of the criteria for each sequence was calculated and inserted into the MCDM tools, using the same weight combinations as before. For the third use case (i.e. $weights = [30, 1, 1,]$) the following two sequences were found to be best (Table 11):

Table 11. Suggested prioritization of 5 occurrences for use case III ($weights = [30, 1, 1,]$) using a global approach.

Occurrence	Flight cycles	WSM	TOPSIS	VIKOR
1	20	Cancel	Cancel	Cancel
2	80	PR	PR	PR
3	100	TPC	TPC	TPC
4	140	TPC	TPC	TPC
5	190	TPA	TPA	TPA

V. Discussion

A. Discussion of the Single Occurrence Scenario

Assuming that the input values are representative, it seems that for all flight cycles the most beneficial is a **temporary repair**, followed by a **permanent repair at the following A-check**. Interesting to notice here is that with increasing initial flight cycles the temporary repairs score stronger. This makes sense, as with increasing flight cycles, the remaining flight cycles to the next planned maintenance opportunity become less. Therefore, the probability of failure of a temporary repair until then decreases, which is considered beneficial. Another factor that might play into this observation is the small number of cases as well as criteria considered. By just looking at cost, time and survivability, the amount of criteria is smaller than the number of options. This naturally results in one option being the best. It would be interesting to introduce additional criteria or options to see if the results changes. This could be limited hangar capacity, aircraft age or network dependency. Depending on the weights and how large or small different options score on these criteria the outcome might vary more. If several aircraft have almost the same input for one criterion, the results will become more sensitive and respond quicker to a small change in any other input parameter. This can to some extent already be observed by varying survivability.

Furthermore, it can be seen that with regard towards the MCDM methods, the tendency (preference) and ranking is the same for all three methods. This can be easily explained by the fact that the problem is so straight forward and the difference between the different criteria is large enough that all methods give the same output. Noteworthy however is the proportional differences in the spacing. This suggests that due to the way the different procedures reach a ranking (linear versus quadratic distances for example) a difference results. An observation that becomes especially apparent when looking at the VIKOR graph. VIKOR directly considers the distance to the theoretical optimal solution. Thus, if an optimal solution exists, that distance will be zero validating the observation that with the given input the solution is unambiguous.

B. Discussion of the Multiple Occurrences Scenario

As can be seen from Part A, the ranking of all methods results in the same recommendation. Taking the overall best ranking and assigning aircraft to the best options until capacity is reached and then moving on to the second best option, again until capacity is reached is not affected by the use of a different method. The results of the ranking (the lowest initial flight cycles scoring better on a permanent repair) makes sense. Temporary repairs are cheaper and faster, but the survivability is lower, the longer the aircraft is not fixed permanently. Thus, with increasing initial flight cycles, the preference for a permanent repair should be less favorable. Interestingly it can be noticed, that using a heuristic approach, actually does yield different results (see yellow marked recommendations in Tables 8 - 10) per method. While this might come surprising at first, it can be easily explained by the fact that TOPSIS and VIKOR are using a square root approach to calculate the respective distances to the ideal. For WSM a linear approach is used. What can be observed here, is in fact the same observation as for the single occurrence, namely the difference in proportional spacing and slope of the different options. Even by using this relatively straight forward approach, VIKOR however does not yield unambiguous results. It is interesting to see however, that the results are very similar to the TOPSIS results. This reflects the similarity of the methods, as both of them belong to the group of goals aspiration models and follow the same underlying principle. Nevertheless, it can be concluded at this point that VIKOR in its original form is not the best method to evaluate this situation.

In the second approach, two large differences can be seen, as compared to the results of the heuristic approach discussed above. Firstly, both methods yield the same sequence. Secondly, the resulting sequence differ from the found sequences above. As a short note; VIKOR is not further discussed at this point, due to the above mentioned conclusions.

The first phenomenon can be explained by the fact, that for looking at the overall situation, total cost and delay have been assumed to be independent of flight cycles, which is the only thing distinguishing the different occurrences from each other. Therefore, the result is again very similar to the one of the single occurrence scenario, as only one variable is varying. The change in sequence is caused by the same reasons. Varying the other criteria as well would result in different sequences. However, as no values are known for this, it could not be done in a realistic way. Randomly changing all inputs would not add any value content-wise since this would only result in a theoretical comparison of both methods, which has been discussed plenty of times in literature already. Additionally, it should be added that this approach is not favorable for a larger number of simultaneous occurrences, as the computational time increases quickly with increasing options. For a more global picture, an agent-based or mathematical programming approach would be more suited.

C. General Observations

In order to assess the robustness of the found results, two aspects were evaluated. The first one is the investigation of the effect of varying the weights to an extreme until a change results occurs. The second one is observing how results behave if input values (namely the three criteria) are changed.

The most interesting weight to investigate is obviously the survivability, as it is, unlike the other two inputs, varying per occurrence, thus aircraft dependent. Looking at the results in Table 7, it is clear that a change must occur at a certain weight setting. For PR (yellow) to become the best, it needs to intersect TPC (red), followed by an intersection (thus outperforming) of TPA (blue). The minimum required weight for the survivability for this to happen can be seen in Table 12. It can be noted that these 'boundary' weights differ per method.

A visualization of the above sensitivity analysis can be found in Figures 10 - 12. From the graphs it becomes quickly evident that WSM is the most robust, while VIKOR is the quickest affected by a change in weights, thus the most sensitive. This makes sense, when looking at the theory of all three approaches. In the theory of WSM the weights are used as is. For TOPSIS they are introduced before square root operations, enhancing the effect.

Table 12. Minimum weight w_i required in $weights = [w_i, 1, 1,]$ to introduce a change in performance results for WSM, TOPSIS and VIKOR.

	PR better than TPC	PR better TPA
WSM	20	30
TOPSIS	4	22
VIKOR	3	5

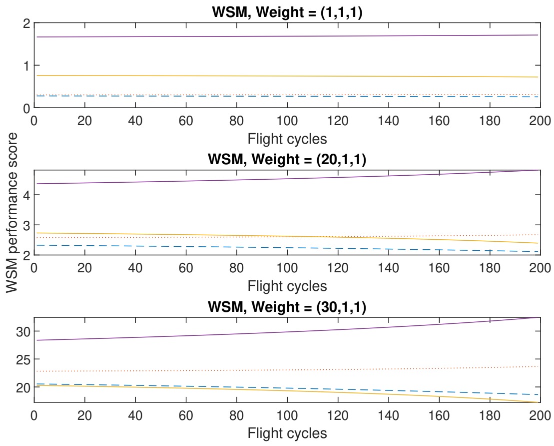

Fig. 10. Results for WSM by varying the weights[d].

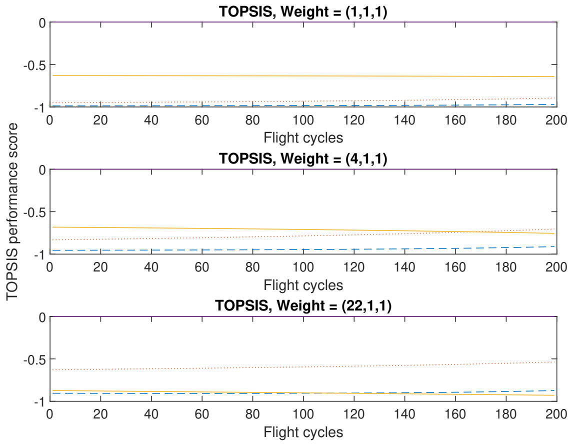

Fig. 11. Results for TOPSIS by varying the weights[e].

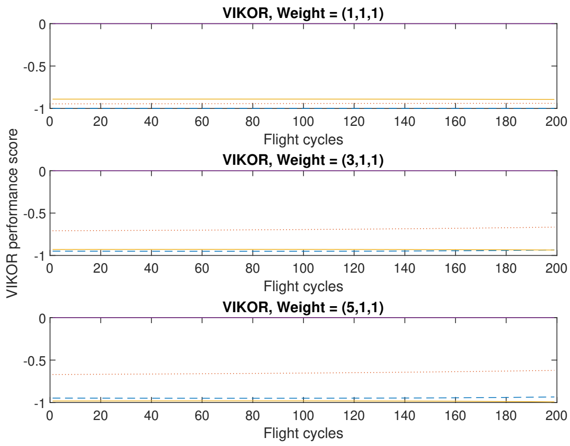

Fig. 12. Results for VIKOR by varying the weights[f].

Using VIKOR the performance is bound by the outer values. However, R as well as S are multiplied by the weight, which also enhances slight changes (see Equations 13 and 12). Taking into account the subjectivity with which weights are selected, WSM might be the more appropriate approach to resolve this and introduce some stability in the operational process.

The same procedure was also done for time and cost. However, as the case $weights = [1, 0, 1]$ has already been explored, and the resulting recommendations are already unambiguously leaning towards the alternative with the most favorable input time, increasing the time weight doesn't reveal any further insights.

Looking at cost, it can be seen that due to an efficiency factor, TPC is favorable over TPA in terms of cost. However, the difference is so small (when keeping other values constant), that increasing the weight for cost the two options converge, while PR approaches C further. This shows how much larger and significant operational cost are, compared to actual material and labor on an aircraft. In order to achieve significant cost savings, delay time should be minimized. This depends on different factors however, such as maintenance availability, exact type of damage or hangar distance (if required).

The second aspect that determines the outcome of the simulation are the inputs. Given the fact that survivability has the largest impact on changes in the results, it is interesting to look at the Weibull parameters. Several values have been assessed.

While the first part of this discussion, varying the weights, can easily be adapted by the operator and changed if needed, the actual input is dictated by the outside, and therefore more rigid to change, even though perhaps of larger influence on the results. In order to gain advantage from such an analysis, a thorough understanding of the weights is therefore even more important than of the effect of the input parameters.

Looking at survivability it was found that for the weight setting of the third use case ($weights = [30, 1, 1]$) significant changes occur for $\beta > 2.5$ and $900 < \eta < 1500$. These values have been found by choosing a $\beta > 1$ as it more accurately represents the situation at hand. While impact damages occur at a constant rate, the more the system wears out, the more critical an additional damage is. Consequently, η had to be found such, that overall drop in survivability reassembles the original values. If chosen too large, a

[d,e,f] The legend was omitted due to legibility reasons. Please refer to any other graphs or the text, as the legends are coherent throughout this report.

temporary repair results to be more reliable than a permanent repair. If chosen too small, the reliability goes to zero immediately. Neither of these two scenarios is arealistic one. A graphical analysis of different Weibull parameters is provided in Appendix E-2.

When varying the time input, for consistency the associated delay cost were kept as before. Repair time for a permanent fix were set equal to the one of a temporary repair. Naturally, this does not have an impact on the results, as the difference in cost is still much higher. This time the standard case $weights = [1, 1, 1]$ was considered. While WSM and TOPSIS remain stable, starting at around 160 initial flight hours, a reversal in second and third rank is observed in the VIKOR generated results (Figure 13).

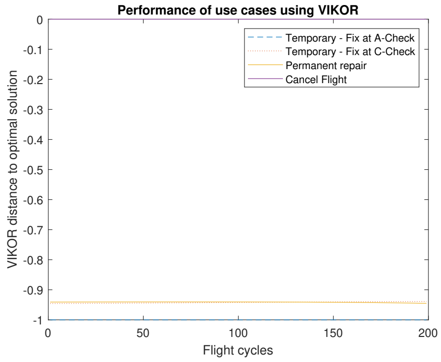

Fig. 13. Using VIKOR and a constant time input, PR becomes slightly more favorable than TPC at around $FC = 160$.

This shows again the sensitivity of this method. This reversal is due to the dominating survivability of a permanent repair compared to a temporary repair which is now not counteracted by a larger repair time. Increasing the weight for time counteracts this as the time punishment for the cancellation moves further away from the rest of the options. This lessens the impact of the superior survivability of the permanent repair due to the normalization of the inputs.

Lastly, the effect of cost was investigated. Multiplying the pure repair cost by as much as a factor of hundred has, as mentioned before, no impact on the results. While the options do move slightly more towards each other, with especially the cancellation option becoming less bad, the results remains the same for all three methods. This is because the actual maintenance cost are very low compared to the disruption cost due to a delayed flight (see Section III). The largest assumption taken here is the amount of passengers, which has a tremendous effect on the outcome. Two major conclusions can be drawn at this point: Firstly, for larger aircraft a fast temporary repair is more attractive as delay cost are influenced by passenger cost. Guidelines concerning a decision as to whether or not to decide for a temporary repair should therefore always take the aircraft type/ available seats into account, especially, when the aircraft is supposed to fly a second flight leg the same day which might be impacted by a potential delay as well. Looking solely at the current B777 fleet, the fuller the aircraft, the larger the impact. For a delay of four hours, one passenger will cost the operator more, than one maintainer for the entire repair at that point. Therefore, amount of passengers should perhaps become a more direct metric when evaluating such a decision. Total amount of delayed passenger minutes might thus be a better criterion than delay time. It captures the two aforementioned aspects and additionally introduces customer satisfaction into the evaluation. A point that, in such a competitive industry as the travel industry, is increasingly important for operators.

Secondly, for every flight a delay point should be established, at which cancellation cost becomes actually lower than delay cost. Currently, the simulation does not recommend cancellation even at that point as punishment factor p was introduced in the delay time due to cancellation. Therefore, only once the delay cost are factor higher than the cancellation cost, a cancellation will result is in a more preferable solution. This reflects the decisions that have been observed during various internships in the industry, as cancellation is always the least favorable option.

D. Limitations and Further Research Potential

To constrain the research to a feasible scope some boundaries were set and are explained in the following. An extension of these boundaries leads to potential future research and is described thereafter.

1. Data

The data set that was used to generate the survivability data has very few data points and many errors were found. This has a direct implication on the outcome. Especially since the survivability is the only thing varying per input flight cycle, while the other two criteria time and cost are independent of the last and next planned maintenance opportunity. Additionally, the other inputs used to compute the cost and the delay time are based on literature. This may however vary, or not even be known by the maintenance team at the time of the decision.

2. Approach

For the chosen approach the option to fix the damage at a later stage is not considered. However, when looking at the fuselage, a small dent might not have to be repaired right away. This can then result in a bundling of repairs at a later stage, decreasing overall cost and potential disruptions and consequentially changing the final result.

In this paper three MCDM approaches were chosen and applied to a limited amount of criteria. In real life, more parameters, such as network routing, quality of repair or urgency of repair might arise and play an important role in the decision process.

Lastly, when looking at the survivability curves, it can be seen that their quality diminishes with an increasing amount of flight cycles. Therefore, small deviations at very high initial flight cycles should not be blindly followed.

3. Further Research

The article at hand looks specifically at the nose section of the fuselage (ATA 53-10). It would be interesting to take it a step further and look at the entire fuselage, as well as other parts of the aircraft that can be repaired into an 'as good as new' state. Furthermore, by increasing the sample size and quality of the damage data, the survivability data can be increased, rendering more representative results. Ideally, they are also valid for higher initial flight cycles. While the observed results are interesting, a proper validation process has not been possible. It would therefore be very insightful to compare the output of the tool to actual maintenance decisions in real life. Concluding, it would be interesting to look into a mathematical programming or machine learning approach that can be implemented in a more complex tool. Such an approach could take into account future fleet routing as well as maintenance planning and thus generate different, globally potentially even more beneficial results.

VI. Conclusions

A. Conclusion and Recommendations

In the conducted analysis three main areas have been addressed to answer the question **"How can demand fulfillment be prioritized, using MCDM methods, given that the option set is limited and multiple simultaneous impact damage occurrences may have to be fulfilled?"** The question was divided into four sub questions:

1. When looking at cost (minimize), time (minimize) and survivability (maximize), should a single damage in the fuselage be permanently repaired, be temporarily repaired or be ignored?
2. How does the result of the above change if there is more than one simultaneous occurrence and not enough resources?
3. Is there a significant change in the results from the questions above if another underlying MCDM theory is used?
4. Are there other influencing factors such as seasonality?

Several conclusions were drawn by answering these questions. A short overview can be found in Appendix F. Firstly it was seen that for a single occurrence problem with no conflict, a straight forward solution exists. This is an interesting observation as this means that in practice a simple analysis, which is much easier to do than a rather complex procedure as the TOPSIS method for example, will yield the same best solution. It can therefore be said that for single occurrences, with a limited amount of criteria, a simple, straight forward and easy to understand method, such as the weighted sum approach is sufficient. Only for extreme weight ratios on the survivability the methods show a different sensitivity, with VIKOR being the most sensitive and WSM the most robust method. This indicates how crucial a proper understanding of the influence of the weights is.

Secondly, it was discovered that for a multiple occurrences scenario VIKOR is not well suited, as it does not yield an unambiguous recommendation, due to the way the best and the worst values are defined.

Thirdly, through a sensitivity analysis it was concluded that survivability has the largest influence on the simulation, as it comparably varies the most. Delay has very little direct impact on the results. While cost are a big factor, maintenance cost are significantly small compared to disruption cost. Therefore, the underlying wear-out behavior assumption of the considered ATA-chapter needs to be kept in mind. Furthermore, instead of delay time, total delay passenger minutes should be used as a criterion.

Lastly, it was observed from aircraft damage occurrence data that seasonality does not have an impact on damages on the fuselage. While there is a clear difference between the amount of planned (more pronounced in winter) and unplanned (more in summer) maintenance events, the overall number of events does not show any seasonality.

B. Recommendations

Apart from addressing the before mentioned limitations and further research potential (Section **??**), there are other additional steps that can be taken to take this research a step further.

In order to use a decision support system to evaluate a difficult maintenance decision appropriate standard weights should be used. Processes like the AHP are can be useful for determining such weight settings. While the method does not matter in particular, the WSM method is recommended due to its robustness and simplicity. Evaluating more data and establishing an initial flight cycle setting per situation might be helpful to the decision maker. This would mean a range of a number of initial flight cycles and delayed passenger minutes after which a temporary repair is more beneficial, automatically evaluated by the simulation. Consequently allowing to limit the complexity of the tool. This requires however, that all this data is available at the point of decision.

Looking further into the future, a more sophisticated global approach should be used. While WSM is simple to understand, it is very limited in its capability of assessing indirect factors such as network effects, maintenance schedules, hangar capacity, damage type etc. Ideally, all the maintenance as well as operator and airport data would be evaluated by a complex machine learning algorithm using for example agent based modeling allowing for a higher automation of such a decision. Lastly, the before mentioned further research suggestions should be investigated, as they can potentially add additional value to an airline operator.

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Appendices

Appendix A

Literature Review

In the following the reader can find a completed literature review on MCDM methods. This literature review has already been graded. It is thus not part of the thesis and serves solely as background information.

A study of decision support systems in an operational environment using MCDM methods

Literature Review

I. Ruchser

TU Delft

A study of decision support systems in an operational environment using MCDM methods

Literature Review

by

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Preface

This report contains the results of a literature study in preparation for a Master of Science thesis. The thesis will be conducted as a collaboration between Delft University of Technology and KLM Royal Dutch Airlines. It is part of the MSc. Aerospace Engineering degree, with a specialization in Air Transport and Operations of the Delft University of Technology.

The aim of this report is to gain a deeper understanding of decision support systems, with a particular focus on multiple criteria decision methods (MCDM). The purpose of the study is to identify existing gaps in literature while at the same time developing a system at KLM that will increase the current service level towards their component pool customers.

I would like to express my gratitude to Wim Verhagen (TU Delft), Thomas Knappers (KLM) and Sterre Koppenol (KLM) for providing me with more insight on the scientific as well as the operational backgrounds and for their support to be able to conduct this review.

I. Ruchser
Schiphol-Oost, October 1, 2019

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List of Abbreviations & Symbols

ABS	Agent based system
AHP	Analytical hierarchy process
AOG	Aircraft on ground
CP	Compromise programming
CS	Component Services
DSS	Decision support system
ELECTRE	Elimination et choix traduisant la realité
FIFO	First in first
GDSS	Group decisionsupport system
GP	Goal programming
KLM	Koninklijke Luchtvaart Maatschappij N. V. (Royal Dutch Airlines)
KLM E & M	KLM Engineering & Maintenance
KPI	Key performance index
LP	Linear programming
MADA	Multiple attribute decision analysis
MADM	Multiple attribute decision method
MAS	Multi agent system
MAUT	Multi attribute utility theory
MAVT	Multi attribute value theory
MCDA	Multiple criteria decision analysis
MCDM	Multiple criteria decision method
MODA	Multiple objective decision analysis
MODM	Multiple objective decision method
MILP	Mixed integer linear programming
MRO	Maintenance, Repair and Overhaul
PROMETHEE	Preference ranking organization for enrichment evaluation
SE	Serviceable
SL	Service level
TAT	Turnaround time
TOPSIS	Technique for order of preference by similarity to ideal solution
US	Unserviceable
VIKOR	VlseKriterijuska optimizacija i komoromisno resenje
WPM	Weighted product model
WSM	Weighted sum model

Summary

In this literature the theory and research available in the area of decision making theory was evaluated. This was done to be able to develop a resource allocation tool for the spare part component pool of KLM Engineering & Maintenance.

Three different fields of decision theory have been identified. These are mathematical programming, artificial intelligence and multiple criteria decision methods (MCDM). While MCDM and mathematical programming have been researched for several decades, the research on artificial intelligence is still relatively novel. However, for the project at hand and the given thesis framework, MCDM was found to be the most suitable option. MCDM is simple to understand and to track, which makes it more attractive for a self-managed application within a company.

Within MCDM three different classes of MCDMs can be distinguished. Firstly, value measurement models, which assign scores to different alternatives, by evaluating criteria. Based on the best score, the preferred alternative is selected. Examples discussed are WSM, WPM, AHP, MAUT and MAVT. The second group discussed are goal aspiration models. Goal aspiration models typically define optimal or desired values for all criteria. The method assesses then the alternative which is closest to this solution. Examples discussed are VIKOR and TOPSIS. Lastly outranking models were considered. This type of MCDM is often referred to as 'French School'. These methods rate alternatives as being "at least as good" through pairwise comparisons. Examples discussed are ELECTRE and PROMETHEE.

Three literature gaps in the research of the application of multiple criteria decision theory were identified. The first one is the lack of the application of multiple criteria decision theory in operational environments in general. MCDM models are commonly used and researched for strategic decisions. The second topic is the application of MCDM in operational environments, using real and live data. Even though authors do use real data to verify their results, the data is previously known, and more importantly, pre-selected. Thus, exceptions and limitations as well as faulty data points are not considered in literature.

The third topic which has not yet been fully investigated is the applicability of artificial intelligence in operational supply allocation problems. As machine learning is still very new in the scientific area compared to the other two approaches, a lot of research can still be done there. However, due to the complex nature of its structure and its unsuitability for this particular application this technique is not thoroughly discussed in this review.

Taking the above into account, two research questions were formulated to describe the first two gaps:

- ***Which decision support (system/ theory) is suitable for an operational environment?***
- ***What impact does the implementation of a decision support system in a real environment have?***

1 Introduction

KLM Engineering & Maintenance is part of the Air France Group. As aircraft maintenance organization they provide aircraft maintenance, repair and overhaul (MRO) services to airlines of the group as well as external customers. One of their industry branches is the provision of an aircraft spare part pool for participating airlines and other customers.

Aircraft have to undergo frequent maintenance activities. Based on the amount of time that has passed/ and or the amount of flight hours that have been flown, parts have to be inspected or exchanged. Additionally, if a component breaks, it often has to be replaced immediately, to allow the operator to continue flying. Even though some of these events can be planned (planned replacements), the majority of the demand for aircraft spare parts can be classified as lumpy (high in variability and infrequent) [73], which makes predictions difficult. Given the fact that an aircraft on the ground (AOG) does not make money, these situations of grounded aircraft have to be avoided.

Especially for smaller operators it would be very costly to maintain a complete spare part inventory for only a few aircraft. Therefore larger companies such as KLM Engineering & Maintenance, more specifically the department of Component Services, offer a spare part pooling service, providing these smaller customers with the parts they need, when required. The cycle at KLM Engineering & Maintenance is described in an eight, as illustrated in Figure 1.1 on the next page. The customer sends a request to Component Services who sends a serviceable item to the customer. In return a broken (unserviceable) part (US) is sent back to the provider and consequently will be sent out internally or externally for repair to the vendor or repair shop. Eventually the repaired part will returned into the inventory as serviceable item into the warehouse of Component Services. However, as more inventory always represents an increase of cost, it is minimized. This minimization (optimization) of inventory occasionally results in a stock-out, thus more customers requiring a certain part at once, but not sufficient stock being available in the warehouse at that particular moment. In this case, a decision has to be taken in order to maximize the overall service level towards the customer, taking into account various criteria. Currently, this is being done by individual best judgement practices. An approach that is subjective and neither documented nor traceable. To improve this decision making process, a decision support tool will be developed for KLM Engineering & Maintenance which will indicate the best choice in such situations. Such a tool should, ideally, also be able to tell when to ship a part to the customer, and when it is better to wait due to anticipation of another, more important request. The part of the process loop of the business process of Component Services that will be affected by this tool is indicated by the blue outline in Figure 1.1.

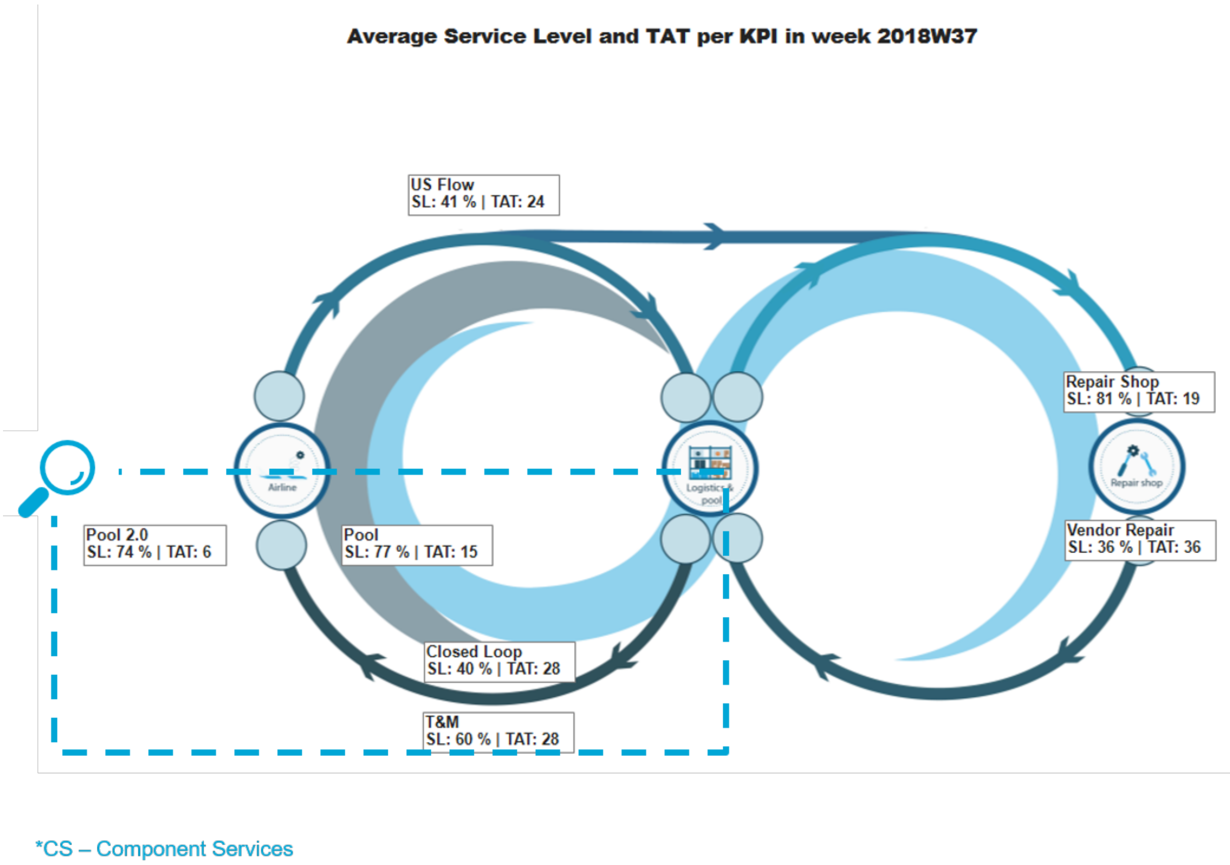

Figure 1.1: Business process of Component Services (area of research project indicated in blue). (Source: KLM E & M)

In order to be able to develop a state of the art decision support system, a thorough review of existing methods and decision theory has been conducted. This literature review aims to gain a further understanding of the available decision support systems and methods which are applicable to the problem at hand. The main objectives are to gain an overview over the already existing research and methods, their workings, underlying theory as well as inherent advantages and disadvantages. From this analysis still uncovered or neglected areas of research are identified. Based on the research done as well as the identified gaps a novel approach for the above described problem can be developed.

The literature study was conducted using several search engines and databases, namely Google Scholar, Scopus, Research Gate, IEEE and Elsevier. By applying search terms such as "decision making", "decision theory", "supply chain", "operational decision making", "multiple criteria decision making", "aircraft spare part pooling" and all their respective possible combinations a broad variety of papers has been found and evaluated. The majority of the articles encountered does not date back further than 2000. However, since the foundation of many multiple criteria decision making methods has been laid long before that, many older papers were studied as well, in order to gain a better understanding of the theory behind the method. It was noted that the majority of the papers found were published in either *European Journal of Operational Research, International Journal of Operations Research, Journal of Multi-Criteria Decision Analysis* or some industry specific journals. Much of the research done on decision theory are the fields of energy management, sustainability, supplier selection and water management, all being very current and result-promising problems.

From the analysis of these papers it could be noted that there is no research on order allocation in specific, but also more generally speaking, not many papers deal with operational decision making, which will be the framework of the resulting thesis work.

The outline of this literature review is as follows. Chapter 2 starts out with a general overview of decision making. Later in the chapter a more detailed picture of decision support systems is provided and an overview of the three main areas of decision theory is given. However, as the main focus of the research lays in multiple criteria decision methods, a selection of the most well-known methods is discussed in detail in Chapter 3. This is done by discussing the common applications and their strong points as well as their drawbacks. The findings are consolidated in an matrix to provide the reader with an overall picture. The identified research gap is presented in Chapter 4 in terms of application to industry field and purpose. Finally, the resulting findings are contemplated and summarized in the conclusion in Chapter 5.

2

Decision making

Decisions are found in every single aspect of daily life, some of which are easy to take, others require a more thorough analysis. This chapter discusses the underlying principle of decision making in Section 2.1, and guides the reader through the different kind of support systems that exist to assist in a decision making process in Section 2.2.

2.1. Decision theory

According to a study done by the Roberts Wesleyan College in 2015 [47], the average person faces about 35,000 decisions a day. These decisions start with the simple choice of what to eat, over more impacting choices as to which car to buy, up until important business decisions with great impact and potential consequences [37]
.

Literature offers a broad bandwidth of definitions, processes and decision models of which a few are described hereafter.

MacCrimmon et al. divide decision theory into two branches, normative decision making and descriptive decision making [54]. While normative decision making, also referred to as decision analysis tries to find the best solution to a given problem, descriptive decision theory looks at the behavior that decision making agents display under certain conditions. In order to be able to justify the need for a decision tool, and also to understand the decision maker, descriptive decision theory is the basis. Once this part has been understood, a well founded and justified decision support can be established.

Broekhuizen et al. [16] summarize that every decision problem has three properties, no matter the objective. Firstly, there is at least one or more criteria. Secondly, this criteria can be quantitative, qualitative or a combination of both. Thirdly, the criteria and the underlying weight or performance parameters can be deterministic or stochastic. Thus, regardless of the potential effects and impact of the decision, all decisions are made, following the same high level process. This process starts with an 'intelligence' (investigation) phase, followed by a 'choice' phase and ends with a 'review' phase, in which a learning effect can occur as defined by Simon [4] and elaborated on by Arduin et al. [87].

When a decision is being made, different alternatives are evaluated in order to arrive at the best outcome. In real life however, several criteria or alternatives have an effect on different levels, which ultimately influences the final and best decision. This is commonly in literature referred to as multiple criteria decision making problems or multiple decision making analysis. A multiple criteria problem can possibly lead to more than one optimal or even no optimal solution. Therefore, a distinction between single and multiple criteria problems is essential.

Having only one criterion, like cost for example, will render a straight forward optimization approach, using only one objective function, which can be solved using optimization techniques such as discrete optimization, linear or non-linear programming [5],[45]. This approach is more straight forward (in terms of the decision making process) and will therefore not be covered more extensively in this review. From this point onward, when referring to a decision making problem, a multiple criteria decision making problem is assumed.

Kumar et al. [52] describe that every decision making problem consists of four main elements: Firstly, one or more objectives, often based on a subjective opinion/desire, usually this is the person taking the decision. Secondly, different alternatives which are the possible options to choose from. Thirdly, criteria that influence the outcome and can be assigned a certain importance/ weight. Lastly, the final outcome scenarios.

Looking at this definition, it can be seen that in a conventional decision process the decision maker is able to take quite an subjective influence on the final outcome. This becomes especially evident in the second and the last element of the model. In fact, research shows that especially experts tend to go with their intuition, often because the data is not available or not presented in the right format or quality.

Several studies have been conducted to investigate the way people take decisions, confirming the above stated. Worth mentioning at this point is the heavily debated experiment conducted by Tversky and Kahneman in 1989 . The set up is as follows:

After being provided with a personality description of a fictitious character, the subjects were asked to decide which of two alternatives was the more likely one [23]:

> Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.
>
> (a) Linda is a bank teller.
>
> (b) Linda is a bank teller and is active in the feminist movement.
>
> Tversky and Kahneman (1983) report that in this version of the experiment, 85 percent of respondents indicated that (b) is more likely than (a), thereby violating the conjunction rule.

This experiment (and other, similar experiments conducted by psychologists) was heavily criticized by the economists Charness et al. [23], arguing that subjects were answering these decisions in isolation. Their further investigations showed that group decisions and decisions with a monetary incentive yielded better results than isolated, theoretical experiments such as the Linda experiment. As impacting decisions are always group decisions they argue further, the Linda experiment does not reflect reality. Gigerenzer et al [40] (also economists) take this claim a step further by stating that these kind of experiments do not represent how people react to natural stimuli.

However, keeping in mind the assignment at hand, experiments like the one above still nicely reflect the subjectivity of decision making, and show the need for a systematic approach. Especially when complex decisions are involved a structured tool should be used to ensure that the best decision is made.

Other experiments show how individuals can be influenced by formulation of statements, room atmosphere and mood [62], [97], [63].

Danziger et al. [26] found in their research that the amount of positive decisions of a judge decline throughout the day, with a small peak after lunch. This is an indication as that willpower per day is limited Danziger further concludes. Thus, depending on the amount of decisions made already, the outcome may vary.

Looking at the results of these studies and the clear proof of the subjectivity of decision makers, further emphasizes the need for a different strategy for complex structures.

2.2. Decision support systems (DSS)

In order to prevent or at least minimize the subjectivity introduced in Section 2.1, systematic approaches or even mathematical and computer based models can be used [58], [5]. For this, a new approach was developed in the 80's, the decision support systems (DSS) [1]. This does not completely eliminate the subjectivity as criteria and input weights to the model are still decided upon subjectively [74], but supports the decision maker to take a decision which is both, justified and based upon documented reasoning. Accordingly decisions cannot only be traced, but also be repeated or carried out independently of the individual decision maker, which often also results in a reduced decision making time. Dhanisetty et al. [27] give an illustrative example of this by finding that up to 50% of decision time can be saved by applying a decision support system (DSS) in form of a weighted sum approach to an operational maintenance process decision. In the following some classifications of DSS in literature are discussed (Subsection 2.2.1). Based on this different elements of a DSS are displayed in Subsection 2.2.2. The development of a DSS is looked at in Subsection 2.2.3 followed by an overview over the three different groups of underlying theory of DSS (Subsection 2.2.4).

2.2.1. Classification of DSS

Different ways are used in literature to define and classify decision support systems.

Häettenschwieler et al. [61] make a differentiation between active, passive and cooperative DSS:

- **Passive decision support system:** Supports the decision making process, without suggesting a solution. For example a evaluation matrix (the user uses the information to get to the decision themselves)
- **Active decision support system:** This system is able to actively suggest solutions. Example is a model or optimization algorithm
- **Cooperative decision support system:** User and computer model find a solution through an iterative process.

Other classifications, perhaps a bit more detailed than the one by Häettenschwieler and his research group, look at the purpose and the medium of the DSS. So the following overview can be given:

- **Communication driven**: Through the possibilities provided by online tools, group decision support systems (GDSS) have evolved into communication driven DSS. They are used to take decisions within a group and to facilitate the sharing of information. Usually in the form of meetings or discussions. Typical support systems are chats, messengers or schedules.
- **Data driven:** Help the user to get specific answers to a specific question, for example the evaluation of a large dataset. This can be in the form of a databases with a query and retrieving tool, or in form of a higher level analysis model.
- **Document driven:** This is a more recent development, becoming more relevant with the era of the internet and increased use of computers. It is used to structure, search and retrieve documents, catalogues or product descriptions.
- **Knowledge driven:** Theses systems are more advanced systems that can recognize problems and suggest actions based on the accumulated knowledge in a certain domain.
- **Model driven:** Model driven systems the most advanced systems that actively manipulate data. Examples range from simpler tools like statistical analysis tools to more complex optimization or financial analysis models.

2.2.2. Elements of DSS

Some researchers also looked into the elements a decision support tool consists of.

Finlay et al. [35] take the well known split of a DSS into a logical model and a data model from Alter et al. [3] and Sprague et al. [90] a step further and add the presentation element, representing the computer/ user interface. A DSS can thus be said to be using different kinds of data as an input, which is analyzed and then, using a certain logical model displayed to the user through an interface [69]. This is illustrated in Figure 2.1. The first part of the model is the data model, which is the input. In this element all the required information (such as criteria, alternatives, weights and objectives) are gathered and assorted in the required structure. The second element is the logic model. There are a vast number of logical approaches for decision making processes available. The most important ones are discussed later on in this chapter. Depending on the objective of the decision finding (one-time only versus operational use for example) this logical model is then applied by the user once or more often. In case of a simple algorithm this will mean to initiate the program, while in case of a more sophisticated tool there could be a start button that initiates the algorithm in the background. Finally, the system will deliver/ display a result to the user, which can then be verified and implemented. This final verification step is however not further discussed in the above mentioned literature.

Serifi et al. [109] slightly deviate from this classification and distinguish between external and internal data. The logical element is split up into a model management and a knowledge management part. Further than that, their findings are similar to the ones of Finlay's research group.

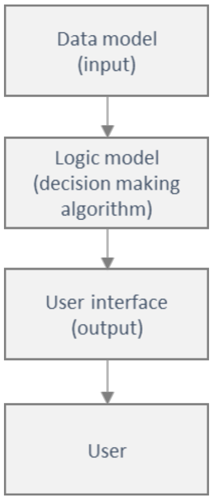

Figure 2.1: The fundamental structure of a decision support system.

2.2.3. Development and implementation of DSS

When using a decision support tool, the high level process remains the same as the one mentioned in Section 2.1.

Applying a (often model based) decision support tool, Sabaei et al. [82], Fulop [38] and Marques et al. [58] further detail the decision process with the following eight steps (Figure 2.2), rendering a more objective conclusion:

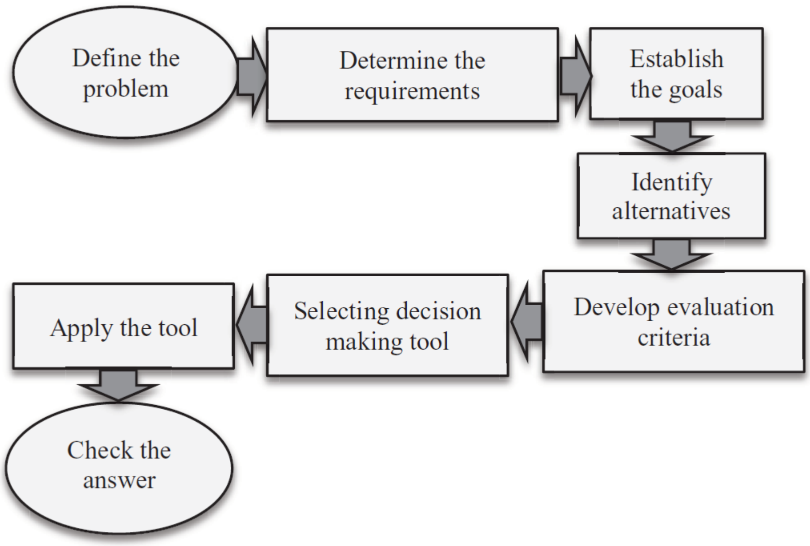

Figure 2.2: Decision making steps [82].

The first step is to define the problem itself. This step is straightforward. This is followed by the second step, namely determining the requirements that come into play with respect to the defined problem. Mathematically expressed, the requirements act as constraints. Thirdly, the goals of the decision have to be evaluated. Is there one or more objectives? This could typically be minimizing cost or/ and time for example. Unlike the requirements, goals are not hard constraints, they should rather be seen like desired directions. Once this baseline has been established, the different alternatives have to be identified. This means thus that all possible outcomes or scenarios that do not violate the constraints, often referred to as a set of choices [10] are found. Usually, none of the alternatives in MCDM is the perfect one, thus a trade-off needs to be made among them [82]. In order to make this trade-off, evaluation criteria have to be established in the next step. An example criteria for minimizing cost could be for example the cost in euros. Baker et al. as well as Sabaei et al. state that well defined criteria need to have the following characteristics [5],[82]:

- Allow for distinction between alternatives
- Cover all goals
- Non-redundant
- Few in numbers
- Operational and meaningful
- Be comparable across different units/ metrics

Once all these parameters have been established, a method and/or tool (decision model) is selected. This is usually the most difficult task, as there are many different techniques available. Based on the purpose and the objective, different options can be considered. The most common ones are covered in detail in Sections 3.2 - 3.10. Having chosen a tool, a best alternative can be established. As there is often more than one alternative, it is referred to as a best, instead of the best solution [45].

Finally, the outcome alternative (outcome scenarios) is assessed against the requirements, with the goals in mind, and a final solution confirmed.

2.2.4. Theoretical approaches to a DSS

The modelling approaches chosen to develop such a decision support tool vary, depending on the problem statements. Different grouping of decision theory approaches have been defined in literature. Sanayei et al. [84] distinguish up to six different categories, namely multiple attribute decision making, multiple-objective decision making, mathematical programming, probabilistic approaches, intelligent approaches and hybrid approaches. The first two are rather similar, for a closed distinction the reader is referred to the following subsection. Probabilistic approaches by themselves are either straightforward or employ one method of one of the other categories. Hybrid approaches are simply a combination of different methods. This leaves generally speaking three larger categories: artificial intelligence/ simulation techniques (intelligent), MCDM (multiple criteria decision methods) techniques and mathematical programming. In Figure 2.3 some examples are indicated. Even though a lot of different combinations are possible (hybrid approaches), these three groups of approaches will be investigated separately in the next sections.

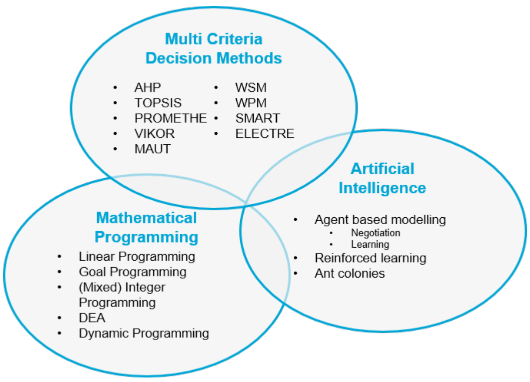

Figure 2.3: Theoretical approaches to a DSS.

Conventional multiple criteria decision methods

Mardani et al. [55] conclude from their literature review that MCDM techniques are the most common and well researched decision making approaches. This is a logical conclusion as they are not only the theories that have been established for the longest time, but tend to have a simpler and more straightforward underlying theory and applicability.

When reading papers dedicated to dedicated to multiple criteria decision making, commonly abbreviated as MCDM, one often comes across two more definitions, multiple attribute decision making (MADM) and multiple objective decision making (MODM). As the three definitions are not always clearly distinguished and often used interchangeably in literature, Figure 2.4 aims to clarify their interrelation as most commomly found and used.

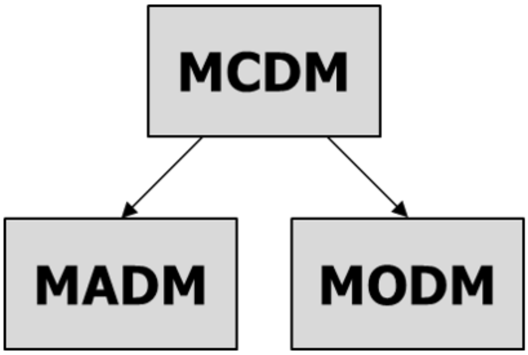

Figure 2.4: MADM and MODM are subsets of MCDM.

MADM and MODM are both sub groups of MCDM [52].

In MADM one looks at the given existing alternatives and aims to choose the best among them. This implies naturally that there is a finite number of alternatives to choose from. In MADM on can again differentiate between non-compensatory methods and compensatory methods. Examples of the non-compensatory method are the dominance method (eliminating the dominated alternatives with respect to all criteria, generally yielding more than one solution), the maxmin method (choosing the alternative with the strongest weak attribute) and the maxmax method (choosing the alternative with the strongest attribute). The premise for the latter two is that all attributes are comparable. More sophisticated methods are the scoring methods (e.g. AHP, MAUT etc.) and the compromising methods (e.g. TOPSIS) [89], which will be covered in detail later in Chapter 3.

MODM on the other hand looks at the objectives first and assumes an infinite solution space. This is the type of problems that can be found for example in aerodynamic or structural designs.

In the investigated literature the abbreviations MCDM, MDMA, MODM and MODA are used interchangeably and with different definitions, depending on the author. For the remainder of this report the abbreviation MDMA will refer to multiple decision making **analysis** (problem analysis) while and MCDM will be defined as multiple criteria decision **method(s)** (solution theories). MODM and MODA will be treated likewise.

Mathematical programming

Mathematical programming has many applications and is commonly better known as an optimization tool rather than a decision making approach. However, when a decision has to be made, one or several objectives are desired to be maximized, or minimized, which turns most optimization problems also in a decision making problem and vice versa.

Linear programming Linear programming (LP) deals with the most basic forms of optimization. A typical example often referred to is cost minimization or benefit maximization when producing/ selling batches of different products or product versions. Using LP the optimal batch size can be determined. This approach is rather straight forward and used for optimization rather than multiple criteria decisions, as it can only deal with one objective at the time and requires linear constraints [45]. Furthermore, given its linear nature, it is not of relevance for this research and only mentioned for completeness.

Non-linear programming Non-linear programming is an extension of LP which, as the name already says, is bound by non-linear constraints or tries to optimize a non-linear objective function. As can be seen here already, this method is not suitable either, as the problem at hand deals with discrete integer solutions rather than a function. Furthermore, as will be discussed at the end of this part, this method is of high computational complexity, rendering it unsuitable for an operational environment [12],[45].

Dynamic programming The main characteristic of dynamic programming is the splitting of the problem into smaller sub-problems and solving them step-wise. By remembering the previous results, the best solution can be found eventually [45]. The typical structure of these problems, like optimizing a route or optimizing packaging for example, does not resemble the structure that is required for the problem at hand. After studying the work that has been done in the field of dynamic programming it has been decided that this method is not suited for the problem at hand, as it cannot be split up into sub problems as required to comply with the theory.

Goal programming: According to the state of the art review by Tamiz et al. in 2008 [92], goal programming (GP) is one of the most common mathematical programming approaches to decision making, and as

Romero claims [75] even the oldest approach to general computer based decision making approaches. The beginnings started in the 50, introduced by Charnes and Cooper [92] who then further refined the approach up until the late 70's [22]. The underlying logic of this method is to determine the alternative with the shortest distance to the goal or objective. Looking at the mathematical formulation, it can even be considered the larger generalization of the aforementioned methods. Even though this method is able to handle large data sets, it is mainly used to find the best alternative, rather than rank a finite set of decision options. Drawbacks of this method are its Pareto inefficiency, as defined by Tamiz et al. [92]:

> " *In any multiple objective problem, a solution is said to be pareto inefficient (or dominated) if the achieved level of any one objective can be improved without worsening the achieved level of any other objective*".

Another drawback that has been identified is incommensurability. Therefore this method is often combined with other methods such as AHP.

Other variants and further developments of GP are multiple-objective programming (MOP) which identifies extreme efficient points by moving from one efficient point to the adjacent efficient point or compromise programming (CP), which has a similar underlying logic. They all follow a similar theory and structure. Therefore at this point they will not be further discussed in detail.

Evaluation: Gershon and Duckstein [93], [28] draw the line of difference between MCDM, or decision analysis as they refer to it and mathematical programming by the nature of the problem. As they state

> *"Either a continuous set of alternatives (mathematical programming) or a discrete set (decision analysis) must be evaluated; such a criterion for classifying the techniques is advocated [...].It is particularly desirable because it arises from two characteristics of the decision process. First, the analyst responsible for implementing the solution technique will probably be trained in one of these areas and will slant his selection toward that group. Second, the nature of the problem will probably be such that it will lead to a solution by a technique from one of these groups, but not both of them."*

However, even though their work is frequently referred to in state of the art literature, their statement is based on the classification by MacCrimmon in 1973 [53] and therefore outdated on this part. Current literature reviews show that a mathematical programming can also be applied to discrete decision sets and MCDM methods to problems of continuous nature. What can be said however, is that mathematical programming techniques tend to be applied for routing and network problems, problems of quantitative structure only. This is based in the nature of the underlying theory of being able to "remember" the previous result and go back if the new result proofs to be worse, rendering a rather computationally intensive approach. Given the assignment at hand these techniques are not considered adequate, as an operational tool which is able to continuously reevaluate the current output based on new data input has to be developed. This statement is also supported by Sanayei et al. [84], who find in their review that generally speaking *"mathematical programming is too complex for practical use"* [(and the understanding thereof) and is] *"to be used by an operating manager"*. Additionally, the problem at hand can be classified at least as NP-hard. An NP hard problem is a problem that can, as of now, only be verified in polynomial time. Finding the best solution however will take much longer. Given the operational nature of the assignment, the computational time required by a mathematical approach would be to large for a model to find a solution within the required time.

Artificial intelligence

One large part of artificial intelligence is agent based modelling or in general multiple agent systems (MAS). While most investigated literature uses these terms interchangeability, there is quite some discussion within the scientific community about the definition behind the two expressions. Wellman [105] dedicated almost an entire article to the proper definition of this issue. As he defines it one has to distinguish between agent based systems (ABS), which according to him are systems containing humans and artificial ABS or artificial MAS, where MAS is the more general term and does not require the presence of a human character within the system. For the definition of the word itself, this might be of relevance. However, for a thorough literature research, this should be ignored, given the fact that all keywords are used interchangeably.

As computers become faster and programming skills and knowledge advance there are more possibilities to completely model and simulate different scenarios, we now require systems to ".. *decide for themselves what they need to do in order to achieve the objectives that we delegate to them*" as Wooldridge et al. fittingly put it into words [106]. One of these simulation techniques is simulating events by assigning properties of the real world to agents or intelligent agents as they are called. This is a relatively new approach to a vast variety of disciplines and problems, which range from air traffic simulations over design problems to crowd simulations.

Agent based modelling is thus a broad discipline with a range of techniques and theories. Weiss et al. [104] give the reader a nice introduction to the underlying principles of the approach. As to the problem to be researched, negotiation, the process of coming to a mutual agreement, is especially of interest as it is considered the fundamental part of agent interaction, as stated by Jennings et al. [49]. Therefore, the focus of this paragraph will heavily lay on negotiation theory.

While theoretically in classical decision theory there can be several agents thus several parties of conflicting interest, they don't interact during the decision making process, but act independently. In MAS agents can actively react upon another agents decision and adapt or even completely change their strategy, thus act strategically. This approach is referred to as game theory, which is the underlying theory of decision making using MAS [104].

Even though all agents have a self interest, they need to come to an agreement with each other and try to find the best solution through communication. This is done by the manners of interacting, negotiating and communicating, just like real people would do. There are two underlying concepts that should be mentioned at this point, namely bargaining and auctioning, which both are a form of negotiation [17], [11]. However, when referring to other authors, bidding and bargaining are defined as being both a process of negotiation, while auctioning should be distinguished from the two [91]. As the majority of the evaluated literature however sticks to the first definition, in the following bargaining and auctioning will be explained as the two most common forms of negotiation as defined by Bulling and Bichler [17], [11].

Bargaining: Bargaining between agents can occur in cooperative and in non-cooperative settings. In cooperative settings negotiation axioms have to be set. Non-cooperative settings typically require several rounds of negotiation. These pairwise negotiations of course still have to converge at some point, a task Chen et al. [25] struggled with during their first research within decision making for supply chains. There are several bargaining strategies, some are limited by time, other are constructed in such a way that negotiation ends when both parties are satisfied only constrained by a discount factor, which then again of course has an effect on the outcome [71], [85], [33]. It becomes especially complex when human behaviour is modelled, as humans don't act rationally like agents. Fatima and Rahwan [32] propose heuristics on how to deal with human actions and how to predict the counteroffer that will be generated during a negotiation.

Auctioning: During auctioning several agents, instead of dealing with each other pairwise, give an offer at the same time. The advantage of this approach is that the optimum is found on a more global level, but of course, on the other hand making the negotiation process more complex, as all participants have to react to each other simultaneously [104]. Welsh et al. [102] developed an approach to deal with task allocation within supply chains. Their approach however only considered a homogeneous set of bidders, which does not represent reality.

No matter which of the two approaches is chosen, a negotiation protocol needs to be developed. In order to do so, all criteria and objectives have to be determined and weighted accordingly. A process that is in its foundation the same as the for any other DSS.

Evaluation: Applying agent based modelling, specifically negotiation theory, to the problem at hand would be a promising approach. Especially since agent based modelling is, compared to the other two approach methods discussed in this chapter, relatively new and many new developments are currently being pushed forward. The (relative) newness of this area also becomes clear from the many terms that are not (yet) clearly defined in literature and vary per author and article, as a lot of new research is currently being published on the domain. A large gap in literature using an agent based approach in decision making has already been identified by Bulling in 2014 [17], but still, especially with respect to operative decision making, not yet been filled.

However, implementing a MAS requires accurate modelling of the entire environment. Due to the time constraints of this assignment this approach will not further be pursued.

3
Multiple criteria decision methods (MCDM)

As has been already touched upon in the previous chapter (Chapter 2), multiple criteria decision methods are the most commonly applied approaches to decision making problems in industry. In this Chapter, after a short classification of multiple criteria decision methods (Section 3.1), the most relevant methods and their respective approaches will be discussed (Sections 3.2 - 3.10), followed by an evaluation and comparison in Section 3.11.

3.1. Classification of multiple criteria decision methods (MCDM)

Hobbs et al. [46] argue that that depending on the method chosen, the obtained best solution may differ. This is due to different methods having different underlying principles and focus. Understanding the objective of the chosen approach is therefore essential to be able to interpret results in a meaningful way. Apart from being aware of advantages, disadvantages and assumptions made, results should be verified by using different methods with a similar input. This output of results should then be evaluated taking into account the differences between the theories.

Balalit et al. [6] make a distinction between three different kind of multiple criteria decision method (MCDM) approaches; the selection problems, thus choosing the best alternative from a given set, the ranking problems, putting a set of alternatives in a certain order, and finally the sorting problems which assigns alternatives to different sub groups. Cavallaro et al. [19] additionally identify descriptive problems, treating problems where no data but only a description exists as a different case.

Another distinction commonly made in literature is the classification into value measurement models, outranking models and goal aspiration models [19], [8].

- **Value measurement models** assign scores to different alternatives, by evaluating criteria. Based on the best score, the preferred alternative is selected. Examples discussed in this chapter are WSM, WPM, AHP, MAUT and MAVT.
- **Outranking models** are often referred to as 'French School', as the founder of them was B.Roy. These methods rate alternatives as being "at least as as good", through pairwise comparisons. Examples discussed are ELECTRE and PROMETHEE.
- **Goal aspiration models** define optimal or desired values for all criteria. The method assesses then the alternative which is closest to this solution. Examples discussed are VIKOR and TOPSIS.

3.2. WSM - Weighted sum model

The weighted sum model (WSM), is the most common and simplest way of evaluating a MCDM problem [95].

In WSM problems are categorized as follows. If there are n criteria in order to evaluate m alternatives, then each of the criteria is assigned a weight w, where w becomes larger as the criterion is more important. The best alternative A_i will then be the one that returns the highest score, applying formula 3.1. a_{ij} represents the actual value of the alternative in terms of the j-th criterion and is multiplied with the corresponding defined weight w. The governing assumption is an additive utility assumption [95].

$$A_i^{WSM_{score}} = \sum_{j=1}^{n} a_{i,j} w_j \qquad for \quad i = 1,2,3,...,m \tag{3.1}$$

Advantages and limitations

This method is very simple and straightforward to apply. This means, for a large number of criteria and/or alternatives little computational power is required in order to quickly compare several alternatives. According to research done by Triantaphyllou [95],[96], for single dimensional problems, the WSM appears to be the most effective and reliable model. However, WSM is a highly subjective way of comparing, as weights w_i are assigned, lacking a certain scheme. Extreme care has to be taken when choosing the weights, as indirectly, due to the linear addition of weighted criteria, the assigned weights directly represent subjective preferences. Marlar and Arora investigate the effect of determining the weights when using a WSM approach and come to the conclusion that *"it can be difficult to discern between setting weights to compensate for differences in objective-function magnitudes and setting weights to indicate the relative importance of an objective as is done with the rating methods"* [57]. Thus, ensuring a well represented weight determination and also knowing the effect of the chosen criteria is essential. However the WSM method does not offer an approach to this. Furthermore, WSM can only be applied if, firstly, the criteria are of quantitative nature and secondly if the problem is one dimensional (e.g. cost, time etc.). The latter is due to the additive utility assumption, which will be violated if WSM is applied to a multi-dimensional problem [95].

3.3. WMP - Weighted product model

The weighted product model (WPM) is very similar to the afore mentioned WSM (Section 3.2). But instead of computing a sum, the product is determined in order to tackle the issue of the one-dimensional restriction [36].

Again a a set of m alternatives exists, characterized by n criteria C_j. These criteria are assigned a weight w_j for the j-th criteria.

However, instead of adding the factors, the ratios of each criterion are compared pairwise and raised to the power of weight w_j. Applying equation 3.2 leads to a direct comparison between alternatives A_K and A_L.

$$R(A_K/A_L) = \prod_{j=1}^{n} (a_{K_j}/a_{L_j})^{w_j} \qquad for \quad i = 1,2,3,...,m \tag{3.2}$$

A result of $R(A_K/A_L) \geq 1$ indicates that alternative A_K should be favored. The best alternative is found by comparing all alternatives and identifying the one that is better or at least equal to the other alternatives [96].

An alternative, simplified method to this approach is shown below in Equation 3.3:

The actual value $a_{i,j}$ of the i-th alternative is then multiplied by w_j.

$$A_i^{WSM_{score}} = \prod_{j=1}^{n} a_{i,j} w_j \qquad for \tag{3.3}$$

Advantages and limitations

The first version of the WPM approach allows for the evaluation of multi-dimensional problems, as the units can be eliminated by normalizing the actual values a_{n_j} [96]. The second version that was presented in Equation 3.3, is more straight forward and thus easier to compute. However, it does not offer the option of a dimensionless analysis. Being similar to the WSM, also its advantages and disadvantages are resembling. By computing the product however, unfavorable solutions are punished more heavily than in the WSM approach [21]. Looking at the equations above, one can quickly see that in case of zero or varying signs (negative and positive) in one of the criteria the method will simply not work as intended.

3.4. AHP - Analytic hierarchy process

The analytic hierarchy process (AHP) is a decision making process that is especially suited for decisions that involve a finite number of attributes/criteria and alternatives. One of the advantages of this method is, that it allows the decision maker to compare qualitative and quantitative criteria directly. Due to its pairwise comparison approach has been used as basis for many other decision making models [30]. The model has first been introduced to the scientific community by Saaty in the 80's [80]. Belton and Gear introduced an

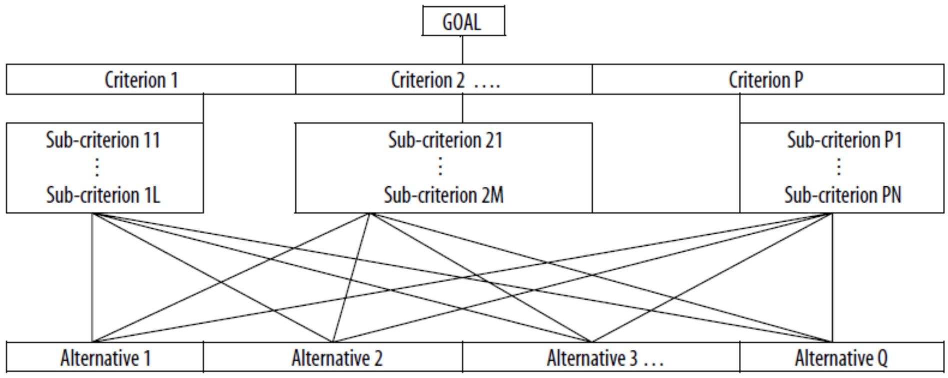

Figure 3.1: Hierarchic structure of the AHP method [10].

Table 3.1: Values to assign when comparing pairwise.

Value	Definition	Explanation
1	Equal importance	Two activities contribute equally to objective
2	Weak or slight	-
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	-
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	-
7	Very strong or demonstrated importance	An activity is favored very strongly over another, its dominance is demonstrated in practice
8	Very, very strong	-
9	Extreme importance	The evidence favoring one activity

additional step to the method, called the revised-AHP, in order to tackle problems with rank reversal. Saaty adapted this version and named it the ideal mode AHP. According to Triantaphyllou, who has been publishing many papers in the field of challenges and short-comings of different MCDM methods, especially the AHP, the ideal mode AHP is the most commonly applied and accepted as most reliable version of AHP [30].

In order to determine a best alternative using AHP, again the weights w_j and the real value $a_{i,j}$ have to be determined. Unlike in the WSM and the WPM approach, the AHP process allows for criteria to be of qualitative as well as of quantitative nature [42]. It hereby considers criteria as well as sub criteria, an impression is given in Figure 3.1.

The basic structure can be compared to a family tree, with the goal on top, defining the criteria, from which the sub-criteria and eventually the alternatives follow. Using pairwise comparisons of each criterion and Table 3.1 as adapted from [81], the criteria are set into relation to each other. In literature one often finds the table only with the values that do not have an explanation (odd numbers). This is due to fact that the table has been developed taking into account different psychological and research based factors. A result based on the findings that humans are not able to simultaneously compare more than seven objects or distinguish between numbers with small differences [30], [44]. For completeness the "in between values" (even numbers) are shown as well. The outcome of this evaluation will be a matrix.

The same steps are followed for every criterion, checking the different alternatives pairwise against each other. From every criterion a matrix of size n x n will thus result. In order to determine the importance of each criterion, the right principal eigenvector of each matrix is determined, also called the reciprocal matrix.

This results in a m x n matrix (still assuming m alternatives and n criteria).

The best alternative will then be as shown in Equation 3.4 below:

$$A^*_{AHP} = \sum_{j=1}^{n} a_{i,j} w_j \qquad for \quad i = 1,2,3,...,m \tag{3.4}$$

Advantages and limitations

AHP is a commonly applied method in the field of decision making for real world problems [99]. Looking at Equation 3.4 the relationship with the WSM becomes clear quickly. This explains why for few criteria the WSM method is probably the better option, as a detailed analysis of the relative importance becomes redundant [96]. But it could also be an explanation of its frequent use; even though the procedure of pairwise comparison can be tedious work at first, it is a well structured and straight forward approach.

The weaknesses most frequently mentioned in literature of AHP are with respect towards rank-reversal, transitivity of criteria and the used measurement scale. Rank reversal is a phenomenon that occurs in some approaches, when adding an additional, irrelevant or non-best alternative to the problem changes the final best solution. Gass [39] argues that even though AHP is prone to rank reversal, this should not be considered a particular drawback, as no one using the model would ever use a MDCM in such a way in real life as any real life decision making problem starts with a predefined set of alternatives. Admittedly, rank reversal is an issue most MCDM approaches have to overcome, however in the context of AHP, this phenomenon is discussed most intensively. noteworthy here is however that AHP is also onw of the most discussed methods in literature, which might naturally contribute to this observation. An extensive list of arguments and research dealing with this can be found in the work done by Socorro Garcia-Cascales [88]. The bottom line is however, that this not a problem unique to AHP and has to be kept in mind for most MCDMs.

3.5. MAVT - Multi attribute value theory

Multi attribute value theory (MAVT), is a decision making model, which tries to capture the desirability of different objectives in so called value functions. The method was introduced by Fishburn as well as Keeney and Raiffa in the late 70's [36], [51]. The idea of the value concept was already touched upon by Bernoulli in 1945 [9]. He explains that an object might have the same price for everyone, but not the same utility. So is a thousand ducats much more valuable to a poor man than to a rich man, as utility is always dependent on the surrounding circumstances. The MAVT methodology follows the four steps below as summarized by Herwijnen [98]:

1. Definition of all possible alternatives (finite set)
2. Definition of all criteria
3. Assignment of value to all criteria
4. Using a value function U on all criteria and consequent ranking of the alternatives

Important to note here is the assumption of mutual independence of preference for each criterion.

Advantages and limitations

Even though MAVT assumes certainty, the method is often combined with other models and approaches to introduce probabilistic events. Estévez et al [31] give an detailed example of combining MAVT with info gap theory, compensating for this limitation. MAVT is able to deal with quantitative as well as qualitative criteria, rendering it more widely applicable. The large amount of data required for this method forces the user to spend a lot of time on the problem, resulting in a thorough understanding of the decision and implications. The compensatory nature of the method has advantages as well as drawbacks, depending on the overall decision strategy and problem at hand. When considering a health of environmental hazard, this should be kept in mind and the method should be not be used or at least employ some threshold. Constructing the utility function U is quite time intensive and especially complex problems often require experts for its set up. This is especially true if there are many criteria that vary largely in scale and characteristics. [98].

3.6. MAUT - Multi attribute utility theory

Multi attribute utility theory (MAUT), is the addition of uncertainty to the previously discussed MAVT method [83]. It was first introduced by von Winterfeldt and Edwards in 1986 [101]. Sometimes MAUT is called the strong and MAVT the weak form of decision making [98]. This method gives the user the possibility to aggregate and quantify different conflicting criteria. By modeling the preferences in a function, all criteria can be aggregated. However, these preferences should be independent of each other [2]. Multi attribute value theory is a compensatory method, meaning a strong performance of one criterion will to compensate for another criterion's weak performance. MAUT belongs to the group of value measurement methods as it allocates a certain utility to every available alternative and determines thus the largest utility. Dyer et al. [29] distinguishe three different kinds of MAUT:

- **Additive decomposition**: Firstly the additive multi-attribute preference model which assumes mutual preference independence. This version is appropriate for decision analysis under certainty. However, it requires explicit trade-off between the criteria. It becomes thus quickly quite work intensive if a larger number of criteria are considered[98]. This form assumes an additivity of the criteria x_i with weights k_i and gives the utility function u_i as described in Equation 3.5:

$$u(x_1,...,x_n) = \sum_{i=n}^{n} k_i u_i(x_i) \tag{3.5}$$

  where the sum of $k_i = 1$.

- **Multiplicative decomposition**: This form of MAUT is very similar to the above mentioned additive decomposition form. Instead of adding the criteria and weights, there is a multiplication resulting in Equation 3.6:

$$u(x_1,...,x_n) = \prod_{i=n}^{n} k_i u_i(x_i) \tag{3.6}$$

- **Multilinear decomposition**: The third form of MAUT (also called polynomial or multiplicative additive), is expressed by Equation 3.7:

$$u(x_1,...,x_n) = \prod_{j\in j} k_j \sum_{j\in j} u_k(x_k) \tag{3.7}$$

  where J is the set of subsets of 1,...,n and for k_i holds $k_1 + ... + k_i + k_{1i} = 1$.

Additive utility function is the strongest form, as it assumes additive independence allowing for a complete decomposition of the problem. The latter two forms require only (mutual) utility independence, which is weaker than additive independence [59].

Advantages and limitations

The advantages of MAUT that are predominantly found in literature are its ability to take uncertainty into account. According to Velasquez et al. [99], MAUT is one of the most frequently used and combined with other methods at the moment. It's application is spread out broadly over the fields of watermanagement, energy management, agricultural problems, economics and finance. Velasquez et al. [99] further cite many researcher applying the method to real world situations, especially when a certain risk is involved. Being a very accurate method, the model requires a lot of input data, consequently a lot of data processing, rendering the approach more time consuming and difficult. As input is required at every step of the process, operational implementation of a pure MAUT tool is challenging. To deal with these shortcomings, as well as the shortcomings of other methods (especially inability of many methods to deal with uncertainty) MAUT is often combined with other methods. Dyer et al. [29] even goes as far as stating that goal programming can be used for approximation of MAUT.

3.7. ELECTRE - Elimination et choix traduisant la realité

Roy [76] first introduced ELimination Et Choix Traduisant la Realité (ELECTRE) or (eliminating and choice expressing reality), in 1968. The method entails *choosing the best action of a given set of actions* as the work of Figueira et al [34] describes it. It is essentially an extension of the previous MARSIAN (method for analysis research and selection of new activities), which has been extended to suit a large number of criteria [79]. Over the past decades the method evolved, generating an entire family of its kind, namely ELECTRE I/IV, ELECTRE IS and ELECTRE TRI [34]. ELECTRE II was introduced shortly after ELECTRE I, allowing for a ranking of alternatives. One of the drawbacks that were found in both methods, was the lack of taking into account uncertain information. Roy [77] addressed this problem in 1978 and developed ELECTRE III which allowed to work with indifferences, thus pseudo criteria, as well as fuzzy alternatives. In order to avoid the relative ranking of criteria as this is not always possible, ELECTRE IV was developed shortly afterwards. ELECTRE TRI is the most recent and also most general version, which was build upon the the groundwork done before [34]. The underlaying principle of ELECTRE is partial aggregation, based upon the assumption that decision makers cannot always make perfectly rational statements as to whether a alternative is perferred or not. It therefore offers the choice between: preference (P), indifference (I), weak preference (Q) and incomparability (R) [19]. This approach makes this method a non-compensatory method, meaning a good performance of one criterion cannot compensate for a bad performance of another criterion. Gökhan et al [44] summarized the procedure as follows:

1. Establishment of a decision matrix of dimension $m \times n$, containing n criteria and m alternatives
2. Normalization of the decision matrix
3. Multiplication of the decision matrix with the weight matrix to obtain the weighted decision matrix
4. Determination of concordance and discordance through pairwise comparison, and consecutive clustering into two sets. Concordance are the criteria that are better than the criterion they are being compared to
5. Calculation of the concordance matrix through addition of the weights
6. Calculation of the discordance matrix by division of the criteria by the sum of all criteria
7. Calculation of advantage identifies the entries in the concordance matrix that are larger than the average
8. Calculation of the net concordance and the discordance then yields a final ranking. Which can however result in more than one best alternative.

Advantages and limitations

ELECTRE is a method that proved useful for problems with more than at least three and not more than five criteria. Up to twelve or thirteen criteria can be considered through an adaption of the method [34]. Being able to deal well with change, ELECTRE is often used to eliminate a first set of alternatives, after which the remaining are evaluated using a different method [6]. Other popular applications are energy related and environmental problems [19], [41].

One of the largest advantages is that this method is able to deal with uncertainties and incomparable criteria.

However, the pairwise ranking can cause the solution to yield more than one best alternative, which leaves the decision maker with more than one final alternative. Mendoza et al. [60] find from their extensive literature review that specifically ELECTRE III, but generally all outranking methods make use of a very subjective approach. They suggest to use other methods for the generation of decisions that need objective results. Furthermore, due to the non-compensatory characteristics, it only yields partial rankings, meaning that some alternatives are rejected due to bad performance on one of the criteria. Additionally it is rather complex to apply which is why Govinda et al. recommend the application of dedicated software [41]. Lastly, it has to be noted that the method does not provide a way of determining the weights, which of course is an essential step in the process.

For the above mentioned reasons, ELECTRE is often used as a hybrid method to determine a pre-selection of options. Using another method the best of this pre-selection is then determined.

3.8. PROMETHEE - Preference ranking organization method for enrichment evaluation

As the name 'preference ranking organization method for enrichment evaluation' (PROMETHEE) already suggests, this method uses an outranking principle to indicate the best alternative. Here, similar to ELECTRE, also a pairwise comparison is used to rank alternatives according to specific criteria [70]. By defining the difference of value between two options with respect to the selected criterion, the decision maker is able to find the best alternative. This distance d_j is defined by Equation 3.8, where C_j is the selected criterion and A_j and A_k the alternatives to be compared.

$$d_j(A_j, A_k) = C_j(A_j) - C_j(A_k) \tag{3.8}$$

A preference function as defined in Equation 3.9 can then be determined.

$$P_j(A_j, A_k) = F(d_j(A_j, A_k)) \tag{3.9}$$

with properties, for minimization problems the difference d_j has to be multiplied by -1:

$$0 \leq P_j \leq 1$$

$$d_j(A_j, A_k) > P_j(A_j, A_k) > 0$$

$$d_j(A_j, A_k) \leq P_j(A_j, A_k) = 0$$

$$d_j(A_j, A_k) > P_j(A_j, A_k) = 0$$

P_j then indicates the preference, where closer to 0 means indifferent and closer to 1 indicates a stronger preference.

Using the found values, an outranking graph is constructed. From this an "entering" and a "leaving" flow is defined [15]. A higher leaving flow and a lower entering flow indicates a better action, which then allows for an ordering of the alternatives. The decision maker can use this pre-ordering to evaluate their decision. However, some actions will remain incomparable. This is why PROMETHEE II has been developed. Using the partial pre-ordering and analysing the "net" flow, a complete ranking is achieved. Brans et al. [15] who first introduced this method, PROMETHEE I, in the late 80's, defined six different types of criteria, with their respective shapes depicted in Figure 3.2:

- **Usual criterion**
- **Quasi criterion**
- **Criterion with linear preference**
- **Level criterion**
- **Criterion with linear preference and indifference area**
- **Gaussian criterion**

These criteria functions can be used to determine the flow. According to Barns these six represent the most commonly found criteria, but are not an exhaustive list. Something that has to be kept in mind when applying the method.

Advantages and limitations

As PROMETHEE is actually based on the outranking methods by Roy [18], it possesses all their advantages, while minimizing the limitations. Based on Brans' original work, PROMETHEE II up to PROMETHEE VI have been developed, each increasing the ranking quality and procedures more. Other extensions of PROMETHEE are PROMETHEE GAIA (visual representation) [14] and PROMETHEE GDDS (group decisions) [56]. Due to broader applicability, mostly PROMETHEE I and II are considered in literature reviews [7]. Even though PROMETHEE II provides the user with a complete ranking, Brans argues that PROMETHEE I is closer to reality. While the team found in their analysis that PROMETHEE delivered more stable results than ELECTRE III, the method is rather complex to grasp [15]. The above mentioned different variants, similarly to ELECTRE variants, are tailored to different applications. This is why PROMETHEE methods have been applied to a broad spectrum of fields, like banking, water management, logistics, energy management to name a few. For a more extensive review, the reader is referred to the work done by Behzadian et al. [7].

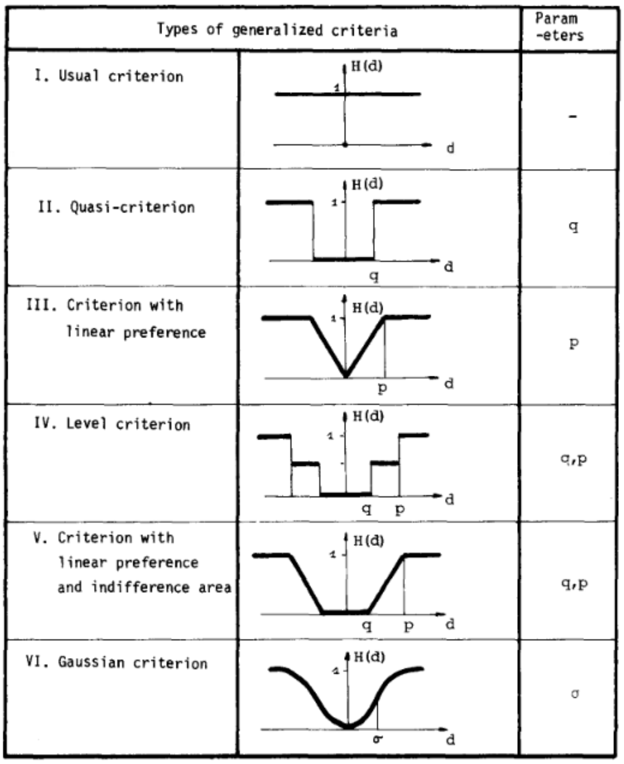

Figure 3.2: The six types of generalized criteria used in PROMETHEE [15].

Alternatives in PROMETHEE I are considered incomparable if one alternative does better on one criterion than another one but worse on another criterion. Given the intrinsic nature of a decision making tool, this renders the practical consideration of an implementation of a solely PROMETHEE I method obsolete [13].

Generally speaking, PROMETHEE also requires additional information, such as weights, and, more importantly value functions for the criteria. Even though the list of required additional information is very well defined and clear, developing such a value function for practical use proofs to be difficult. Furthermore, none of the papers developed by Barns suggest a clear procedure for the determination of the weights [18], [7]. To overcome this weakness, Balali et al. [6] propose AHP for determination of the weights, as an extension to their research on the combination of ELECTRE III and PROMETHE. Especially for operational purposes one has to keep in mind that the method is based upon pairwise comparisons and that rank reversals do occur [7], [13]. Lastly, the non-compensatory characteristic of this method imply a need for careful interpretation of the ranking results.

3.9. VIKOR - VlseKriterijuska optimizacija i komoromisno resenje

VlseKriterijuska Optimizacija I Komoromisno Resenje or short VIKOR is based upon the principle of eliminating the units of criterion function by linear normalization. A translation of the methods name is "multi-criteria optimization and compromise solution" [66]. Obricovic et al. [66], who first introduced the method based on the work done by Yu [107] describe it as "a compromise solution, providing a maximum 'group utility' for the "majority" and a minimum of an individual regret for the 'opponent'". By determining the ideal alternative using all $i = 1, 2, 3, ..., n$ of the given criteria weighted by weights w_i, a rating are established for each alternative a_j.

Obricovic [66] defines the following steps:

1. Determination of the best f_i^* and the worst values f_i^- of all criterion functions

2. Computation of value S_j and R_j, where S and R are be expressed by Equations 3.10 and 3.11 respectively:

$$S_j = \sum_{i=n} w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \tag{3.10}$$

$$R_j = max_i[w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-}] \tag{3.11}$$

3. Computation of Q_j using Equation 3.12 and v as a factor of utility (the majority of criteria or the maximum group utility), and with $S^* = min_j S_j$ as well as $S^- = max_j S_j$ and likewise for R_x^x, thus reasulting in equation 3.12:

$$Q_j = v\frac{S_j - S^*}{S^- - S^*} + (1-v)\frac{R_j - R^*}{R^- - R^*} \tag{3.12}$$

4. Ranking of alternatives with respect to Q (minimum), R and S (resulting in three different rankings)
5. Proposal of alternative a" that ranks best in Q, given the following two conditions:
   - C2: "Acceptable advantage":

$$Q(a") - Q(a') \geqslant \frac{1}{J-1} \tag{3.13}$$

   - C2: "Acceptable stability in decision making" Alternative a" should at least also be best ranked in either R or S. The solution is considered stable if the value v if "ruling by majority" (v larger than 0.5), "voting by consensus" (v = 0.5) or "considering veto" (v smaller 0.5). V is affected by the overall decision making strategy.

   The author proposes a compromise solution of a" and a' if the the second condition is not satisfied and a combination of the solutions $a", a', ..., a^m$ until the first condition is satisfied.

In order to assess the stability of the weights, the VIKOR method has been extended later on by Obricovic and Tzeng [67]. The extension adds a way of determining the stability interval of the weights, as well as a procedure to make a trade-off if the decision maker does not agree with the values.

Advantages and limitations

Using this method, stability intervals can by definition be easily obtained (see above) by only changing one weight at the time. The set up of the method strives to maximize group utility. A large advantage of the VIKOR method is that it does not only give the best alternative, but also results, in a relatively simple way in a complete ranking of all alternatives. Furthermore, the respective rankings for Q, R and S can be established independently, potentially shortening computational time for a larger number of alternatives. Furthermore, the method allows for non-commensurable criteria to be evaluated. Another advantage is that the last steps of the extended VIKOR method allow the decision maker to deal with decisions where preferences are not known in the beginning of the decision process [67]. This at the same time, with the assignment in mind, also imposes a weakness on the method. As the method has to be able to deliver one final ranking, thus is to be used as an operational tool, iteration with additional user input is not desired. Sanayei et al. [84] used the VIKOR method for a theoretical example of supplier selection, combining it with a fuzzy approach. Even though their problem structure is quite similar to the structure for the thesis at hand, their problem is tailored to an perfect example. As they mix up some numbers in the result evaluation, their results are not clear to the reader. They also do not discuss the difficulties that may arise when one of the two conditions is not satisfied. This leaves the reader with the question how to deal with this in case of a discrete set of alternatives where only one can be chosen. In their later paper Obricovic and Tzeng define a variety of characteristics for which the VIKOR method is to be used. The first one being "compromises are acceptable", which delivers an answer to the above mentioned problematic, however also disqualifies the method for the intended purpose. The later is a reason why the method is often used as basis for a discussion rather than for a final decision [24].

3.10. TOPSIS - Technique for order of preference by similarity to ideal solution

The technique for order of preference by similarity to ideal solution (TOPSIS), has many similarities with VIKOR, as both belong to the group of goal aspiration methods (see Section 3.1). It was introduced in 1981 by Hwang and Yoon [48]. Similarly to VIKOR it eliminates the units of criterion function, but does this by vector normalization [66]. TOPSIS is, unlike VIKOR, based upon two points of reference. The best alternative is thus not only closest to the ideal solution, but also furthest away from the negative solution [21].

Applying the method consists of seven steps:

1. Establishing the performance matrix, sometimes referred to as decision matrix
2. Normalization of the performance matrix
3. Calculation of the weighted performance matrix
4. Determination of positive and negative ideal solutions
5. Calculation of separation measures
6. Calculation of the relative distance to the previously established ideal solution
7. Final ranking of the solutions according to preferred order

Advantages and limitations
In their review Socorro García-Cascalesa et al. [88] list four main advantages of TOPSIS:

- Understandability and rationality
- Straightforward computation process
- The best mathematical alternative can be pursued in a simple mathematical form
- The criteria weights are incorporated in the comparison process

Another advantage is the fact that limited subjective input is required from the decision maker (unlike for the outranking methods) [65]. Velasquez and Hester [100] confirm the above stated observations and add that the overall process is rather simple. This is why it is often used to confirm the findings of another approach. They add however, that the euclidean distance does not take into account the correlation of attributes. Even though this method considers the distances from the ideal and anti-ideal solution, it does not consider their relative importance [66]. Another drawback, as with many other methods, is the issue of rank reversal [88], [103]. As the method does not take uncertainty into account, it is often used in combination with fuzzy set theory (Cavallaro [20], Kaya and Kahramann [50]). Velasquez and Hester's [100] review finds and confirms what the results on search engines confirm, that TOPSIS is used in a broad variety of different fields.

3.11. Comparison and considerations

3.11.1. Comparison
Evaluating the in the above sections (Section 3.2 - Section 3.10) described MCDM approaches can be summarized to an overview, crystallizing the advantages and disadvantages of the respective method. This overview can be seen in Table 3.11.1. An additional column has been added to point out characteristics or comments with respect to the method that should be kept in mind when applying it.

From this table it can be quickly seen that the afore mentioned grouping of methods into their respective main objective (value measurement, outranking and goal aspiration) is also strongly reflected in the corresponding strong and weak points. This comes at no surprise however, as the underlying principles are similar.

Table 3.2: Comparison matrix of evaluated MCDM methods.

Theory	Advantages	Disadvantages	Comment/ Applications
WSM	Simple to use Simple to understand	Requires normalization/ or one dimensional units	Simple problems Alternatives are ranked independently Commensurable
WMP	Simple to use Simple to understand Dimensions are eliminated	Requires normalization Extreme features are magnified Criteria cannot be negative or zero	Alternatives are ranked independently Commensurable
AHP	Simple to understand Qualitative and quantitative data Much research done	Rank reversal No uncertainty considered	Often used for criteria selection Pairwise comparison
MAVT	Qualitative and quantitative data Produces robust results	Very complex Requires large amount of data No uncertainty considered Assumes criteria of the same unit Large level of subjectiveness Assumes independence of criteria	Suitable for large amounts of data Commensurable Conversion of criteria into value function
MAUT	Accounts for uncertainty Qualitative and quantitative data	Very complex Requires large amount of data Large level of subjectiveness	Suitable for large amounts of data Conversion of criteria into utility function
ELECTRE	Accounts for uncertaincy Robuster than PROMETHEE	Minimum of three criteria Identification of (dis)advantages difficult	Suited for non-sortable problems Pairwise comparison Non-commensurable Often used to eliminate non-suited alternatives
PROMETHEE	Qualitative evaluating	Weight determination not defined Difficult to take a decision in case of incomparability Identification of (dis)advantages difficult	Suited for non-sortable problems Pairwise comparison Non-comensurable
VIKOR	Accounts for uncertainty	Best solution is not necessarily the best	Used as initial starting point for negotiations
TOPSIS	Consideration of distance to worst alternative	No consideration of relative importance	Compensatory

3.11.2. Considerations

Velasquez et al. [99] state in their review of the field that many researchers tend to combine different DSS, in order to overcome their individual shortcomings. This is especially true for MAUT, having the ability to account for uncertainty and AHP having considerable troubles with rank reversal. Looking at the assignment, one can quickly see, that the evaluation of the criteria and their respective weights, is another decision that has to be made. Unlike the actual purpose of the tool however, these decisions are of tactical of even strategic nature. Therefore the possibility of using a different method to determine the weights of the criteria should be considered in this approach as well.

As discussed by Dhanisetty et al. [27], AHP is not only one of the most commonly used MCDM approaches in literature Due to its pairwise comparisons however, it is particularly suited to select weights, especially when sub-criteria are involved. From the literature review it has been found that in fact the most popular combination studied in papers (in recent papers (work from 2018) but also in older work (beginnings of 2000)), is the research and use of AHP in combination with TOPSIS and/ or fuzzy theory This shows the interesting aspects of this combination. Examples are [94], [72], [64], [108], [43].

Furthermore, it can be noted, that choosing the proper MCDM is actually a decision problem by itself. In literature different rankings, evaluations and applications are discussed. What can be seen from all these comparisons, there is no one size fits all best method. Therefore, Ozernoy et al. [68] and Tecle et al. [93] developed different approaches to choose an appropriate decision technique. Hobbs et al. [46] concluded from an experiment that in fact, in reality decision makers prefer simple, transparent procedures. Another interesting point they found is that often the weights placed upon criteria when developing a decision tool do not reflect the compromises and decisions that are made when the decision is actually taken. This depends rather strongly on the person applying the method. Their experiment is a good example of illustrating that even a tool is not able to make a decision completely objective. Belton and Steward [8] summarize the above mentioned by listing three myths:

1. Myth 1: MCDM will provide the correct answer
2. Myth 2: MCDM provides an objective analysis
3. Myth 3: MCDM is THE solution to the decision making problem

Roy et al. [78] suggest to first think of the type of result the method is supposed to deliver, with respect to the three classifications suggested by Belton [8] (value measurement models, goal aspiration models or outranking models). Even though the article is written for 'one-time' decisions only, their considerations are very valid and should be taken into account [28].

4

Novelty and research contribution

In this review a lot of literature has been discussed and even more reviewed and read. From a glance at the sources used, it can be quickly seen that there is a broad spectrum of articles, research and material readily available in the area of decision making. In this chapter the novelty of the research project will be discussed. The contribution of this work can be split into two sections. Section 4.1 focuses on the novelty of the application of a decision support tool using MCDM in an operational environment. Section 4.2 explores the research gaps concerning the real world applications and implementations of MCDM techniques.

4.1. Decision making in an operational environment

From the analysis done in Chapters 2 and 3 it can be seen that the majority of the decision making methods used is tailored for strategic decisions. The procedures are time consuming and often require iterations throughout the process. Characteristics that are highly undesirable in an operational environment.

In fact, using the researching tools introduced in Chapter 1, it has been concluded that most MCDM techniques are applied to strategic situations or planning. Very common areas of research are water resource management, electricity and energy management and supplier selections. All are decisions that have to be taken once, but not on a daily or even hourly basis. This means in return that the time and the (computational) budget available is much larger than what is desirable or even possible for operational decisions.

In operational environments on the other hand, decisions have to be made more quickly and often by staff that has less knowledge of the underlying theory of the tool. Such a tool has thus, unlike a strategic "one-time use" tool, be verified beforehand, should have a built in sanity check and should be easy to handle. Additionally, for a long-term usage of the tool, it should be possible to adjust the weights in case of adaptions to the overall strategy. Furthermore, it should have a relatively quick run-time, thus not include several iterations that require a large amount of human decisions in the loop. As opposed to strategic decision making, the following unique requirements for operational DSS can thus be summarized:

- Quick computational time
- Clear output, understandable without knowledge of the workings of the tool
- Preferably no human interaction in the iteration process
- Verified tool rather than verified results
- Adaptable inputs for long-term changes of the company

With respect to the literature on supply chain management, the majority of the work done focuses on inventory management and supplier selection.

One of the few researches done on decision making in an operational environment in the field of aircraft maintenance (a field particularly characterized by lumpy demand behaviour, meaning demand is highly varying in quantity as well as order timing) is the work done by Dhanisetty et al. [27]. One of the limitations to their research identified is the fixation of standard weights using a pairwise comparison. The in Chapter 3 proposed AHP method to determine the weights on a tactical and strategic level proceeds exactly with this suggestion, as it is based upon pairwise comparison, meant to provide a standard input to the tool.

This leaves thus the researcher with the question:

- ***Which decision support (system/ theory) is suitable for an operational environment?***

In practice, it has been found that in the case of the problem at hand, basic queuing theory is applied. The FIFO (first in first out) principle is often used. Furthermore, there are some general business rules, which however do not correspond in any way to the current situation and serve as guidelines rather than process steps. I.e single criteria of importance are singled out and situations are ranked only by looking at one or two criteria at the time, lacking a systematic or documented, and thus traceable method behind the process. Lastly, many other operational environments (mainly in the supply chain industries), such as warehouses, production orders, telecommunication firms etc. are using readily developed and customized software that have been developed by large IT-providers. Unfortunately, their work and research is classified and not available to the scientific community.

4.2. Decision making using real data and system implementation

The majority of the research found and discussed in the previous chapters is based on theoretical cases. If real data is used for verification, often simplified examples are taken or strong assumptions are made. In fact, this data is often selected or drawn from a static, already known environment, as it is typically historic data rather than live data. Additionally, no paper was found that actually discussed the implementation of a MCDM method into an system for use on a daily basis.

IT companies and solutions providers do however provide systems and solutions to give users a form of decision support. In their extensive discussion paper on operational decision making Seilonen et al. [86] summarize the following overview of decision support IT systems:

> *Maybe the most essential information systems in manufacturing operations management include Manufacturing Execution Systems (MES) and Enterprise Asset Management Systems (EAM). MES provides functionality to support some selection of different activities in production, inventory and quality operations management. EAM provides functionality to support of maintenance of the physical assets of a company. They are connected to related information and automation systems of a company, e.g. Enterprise Resource Management systems (ERP), Distributed Control Systems (DCS) and Condition- Based Monitoring systems (CBM). ERP provides functionality for business and logistics management of a company, DCS functionality to control and monitor continuous production processes and CBM functionality to monitor the condition of physical equipment. In addition to the previously mentioned systems, companies may also have other related information systems, e.g. Laboratory Information Systems (LIMS), Production Information Systems (PIMS) and Advanced Planning Systems (APS). Sometimes these systems are part of MES or DCS.*".

As these systems are however developed by firms for the purpose of selling a product, the underlying theory is not discussed in literature. The question that can be asked here is as follows:

- ***What impact does the implementation of a decision support system in a real environment have?***

To address this question, using the research project and analyzing the result, this gap in literature will be covered. In fact, this research will apply MCDM not only to an operational supply chain problem, but also be implemented using real data, thus requiring the ability to deal with irregularities of real world applications.

5 Conclusion

A literature study was done to evaluate the theory available and gain knowledge in the area of decision making theory. This was done to be able to develop a resource allocation tool for the component pool of KLM Engineering & Maintenance.

In this literature a broad variety of literature and scientific articles using several search engines and databases, namely Google Scholar, Scopus, Research Gate, IEEE and Elsevier was reviewed. By applying search terms such as "decision making", "decision theory", "supply chain", "operational decision making", "multiple criteria decision making", "aircraft spare part pooling" and all their possible combinations a broad variety of papers has been found and evaluated. The majority of the articles found does not date back further than 2000. However, the foundation of many multiple criteria decision making methods has been laid long before that, many older papers were considered as well, in order to understand the theory behind the method. It was noted that the majority of the papers found were published in either *European Journal of Operational Research, International Journal of Operations Research, Journal of Multi-Criteria Decision Analysis* or some industry specific journals. Much of the research done on decision theory are in the fields of energy management, sustainability, supplier selection and water management, all being very current problems.

Three different fields of decision theory have been identified. These were mathematical programming, artificial intelligence and multiple criteria decision theory (MCDM). Mathematical programming was reviewed, but given the context of the problem it proofed not to be suitable for operational application due to high complexity and long computational times. Artificial intelligence was found to be a very new and emerging topic, which could definitively provide some large benefits in operational decision making due to its inherent nature of adapting to current situations in an intelligent way. The scope of the knowledge required for this kind of application exceeds however the one of the project and the thesis behind it by far. Therefore this field of decision theory was identified as a very interesting gap in literature, but left for future research.

The remaining field of MCDM was investigated in detail. Three different classes of MCDMs can be distinguished:

- **Value measurement models** assign scores to different alternatives, by evaluating criteria. Based on the best score, the preferred alternative is selected. Examples discussed in this chapter are WSM, WPM, AHP, MAUT and MAVT.
- **Outranking models** are often referred to as 'French School', as the founder of them was B.Roy. These methods rate alternatives as being "at least as as good", through pairwise comparisons. Examples discussed are ELECTRE and PROMETHEE.
- **Goal aspiration models** define optimal or desired values for all criteria. The method assesses then the alternative which is closest to this solution. Examples discussed are VIKOR and TOPSIS.

From the analysis a comparison matrix was established. It was noted in this comparison that methods of the same group typically display similar advantages as well as disadvantages, as the underlaying principle is similar. Even though there are many other MCDM theories available, they are not discussed in this article as they mostly represent a variation of one of the best known-theories or are a combination of several ones, so called hybrid approaches.

Furthermore, it has been noted that MCDM techniques are often combined to eliminate the disadvantages of one method. MCDM is applied for many different situations and industries, varying from energy management, over finance to sustainability and supplier selection. However, the problems presented were typically one-time decisions on a strategic level. The search through various search engines and databases did in fact not give many results regarding the research work done for operational decision making. Even less so, when searching for application of decision theory to real world applications. While many authors verify their findings using real data, this data is often selected or drawn from a static, already known environment, as it is typically historic data rather than live data. These observations results in two research questions:

- ***Which decision support (system/ theory) is suitable for an operational environment?***
- ***What impact does the implementation of a decision support system in a real environment have?***

The answer to these questions will be found in the upcoming months at KLM Engineering & Maintenance, within the framework of above mentioned proposed real case scenario.

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Appendix B

MCDM Overview

In the following Table B is provided to give an overview over the different MCDM methods investigated. Relevant characteristics as well as advantages and short comings are summarized.

Table B.1: Comparison matrix of evaluated MCDM methods.

Theory	**Advantages**	**Disadvantages**	**Comment/ Applications**
WSM	Simple to use Simple to understand	Requires normalization/ or one dimensional units	Simple problems Alternatives are ranked independently Commensurable
WMP	Simple to use Simple to understand Dimensions are eliminated	Requires normalization Extreme features are magnified Criteria cannot be negative or zero	Alternatives are ranked independently Commensurable
AHP	Simple to understand Qualitative and quantitative data Much research done	Rank reversal No uncertainty considered	Often used for criteria selection Pairwise comparison
MAVT	Qualitative and quantitative data Produces robust results	Very complex Requires large amount of data No uncertainty considered Assumes criteria of the same unit Large level of subjectiveness Assumes independence of criteria	Suitable for large amounts of data Commensurable Conversion of criteria into value function
MAUT	Accounts for uncertainty Qualitative and quantitative data	Very complex Requires large amount of data Large level of subjectiveness	Suitable for large amounts of data Conversion of criteria into utility function
ELECTRE	Accounts for uncertaincy Robuster than PROMETHEE	Minimum of three criteria Identification of (dis)advantages difficult	Suited for non-sortable problems Pairwise comparison Non-commensurable Often used to eliminate non-suited alternatives
PROMETHEE	Qualitative evaluating	Weight determination not defined Difficult to take a decision in case of incomparability Identification of (dis)advantages difficult	Suited for non-sortable problems Pairwise comparison Non-comensurable
VIKOR	Accounts for uncertainty	Best solution is not necessarily the best	Used as initial starting point for negotiations
TOPSIS	Consideration of distance to worst alternative	No consideration of relative importance	Compensatory

Appendix C

Determination of Weibull Parameters

In order to determine the survivability of the temporary and the permanent repairs, a variety of parameters had to be determined. Assuming a non-homogeneous poisson distribution for temporary repairs, allows to find determine the survivability over time. For this the intensity, scale and shape parameter for the NHP process as well as the input the RP method where determined as stated below.
The weibull process can be modelled as stated in Equation C.1:

$$f(t) = \frac{\beta}{\eta} \cdot (\frac{t}{\eta})^{(\beta-1)} \cdot e^{-(\frac{t}{\eta})^{\beta}} \tag{C.1}$$

where t is the time since the last repair. For this case t has been the amount of flight cycles, as this is more adequate for the problem at hand. (The fuselage is mostly impacted during landings rather than the amount of flight hours). A shape parameter $\beta < 1$ indicates that the system is deteriorating over time. For values $\beta < 1$ the system is becoming more reliable over time. The scale parameter η stretches or contracts the failure curve over the components lifetime.
A special case occurs when assuming a constant intensity function and a homogeneous poisson process. This can be modelled as shown in Equation C.2.

$$f(t) = \frac{e^{t\lambda(t)}(t\lambda(t))^{N}}{N!} \tag{C.2}$$

The constant intensity parameter λ can be determined by using the following relation (Equation C.3):

$$\lambda = \frac{1}{MTBF} \tag{C.3}$$

with MTBF being the mean time between failures. MTBF from N = 200 resulted to be 670,7 flight cycles, which yielded a $\lambda = 0.001491$ MTBF was determined from the data by evaluating the average interval (from the filtered dataset) from a permanent repair until a next event. While this is not completely correct, as the event detection and thus registration in the data is not the same as the actual occurrence. This is due to the fact that the latter is unknown.
The probability for a permanent repair was then found by further manipulating Equation C.1 and finding the expected as well as the variance in time (flight cycles) to failure (Equations C.4 and C.5)

$$E = \theta\Gamma\Big(1 + \frac{1}{\beta}\Big) \tag{C.4}$$

$$\sigma^2 = \theta^2\Big(\Gamma\big(1 + \frac{2}{\beta}\big) - \big(\Gamma(1 + \frac{1}{\beta})\big)^2\Big) \tag{C.5}$$

With E the expected time until failure and σ the associated variance. Taking the limit of Equation C.2 of $t- > \infty$ for $N(t) < \lambda$ the distribution of the renewal process can be found.
Using a graphical method and plotting the provided data onto logarithmic weibull paper [1] resulted in the parameters as shown in Table C.1 below.

Table C.1: Three different sets of Weibull parameters were determined.

Registration	**Sample size N**	**Shape parameter β**	**Scale parameter η**
GSPG	10	0.48	120
GSPH	10	0.68	120
GSPP	6	1.8	5.2

A plotting of the data can be found on the following pages (Graphs C.1 until C.3. The data points are plotted in red, the blue lines where used to determine the parameters.
Using the obtained values and plotting them over a range of flight cycles results in Graphs C.4 until C.6. It can quickly be seen that only the second graph results in remotely useful values, which is why these values have been chosen for the analysis of the survivability.

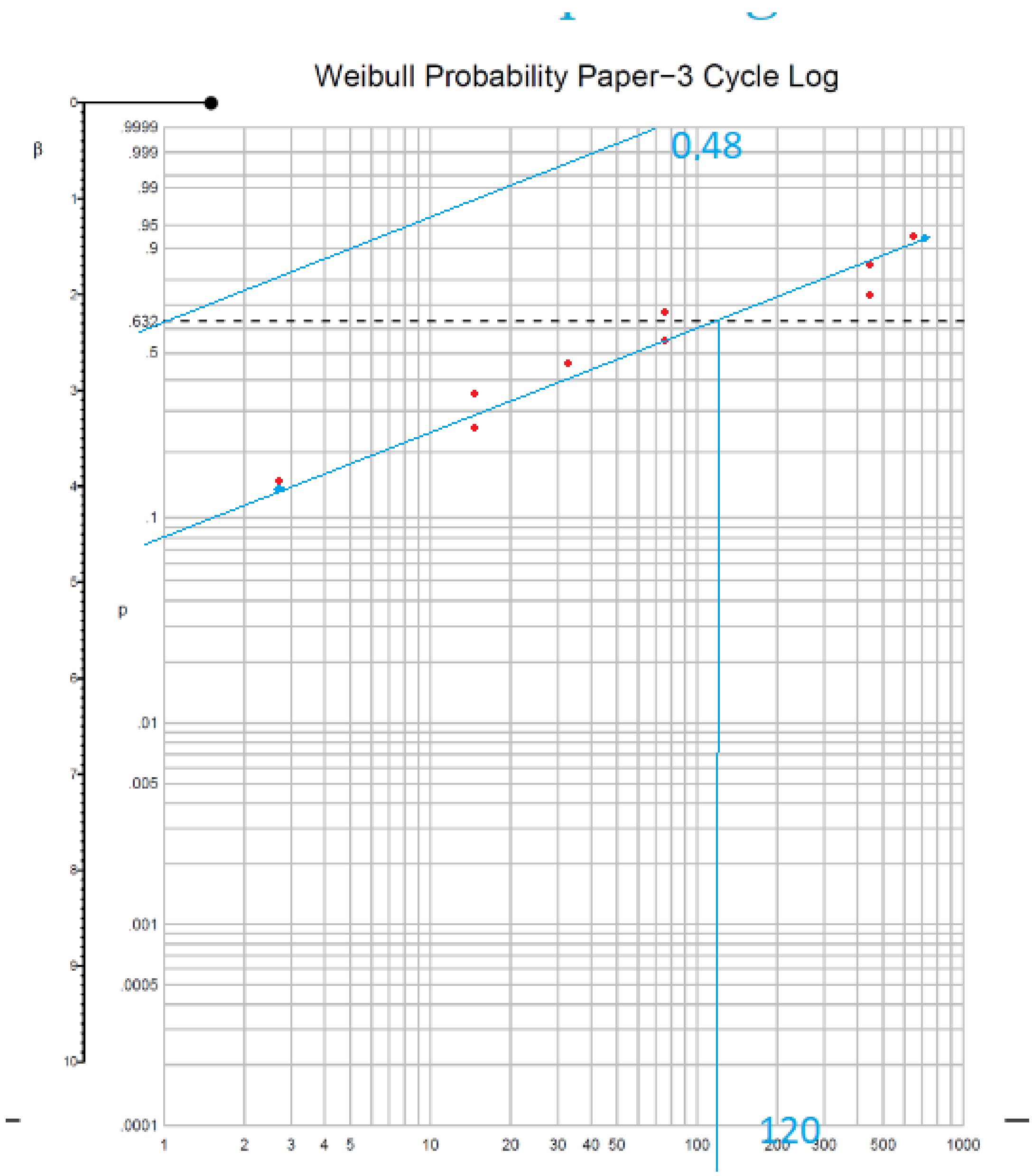

Figure C.1: Failures of A/C 1 on logarithmic paper and resulting weibull shape parameter $\beta = 0.48$ *and scale parameter* $\eta = 120$.

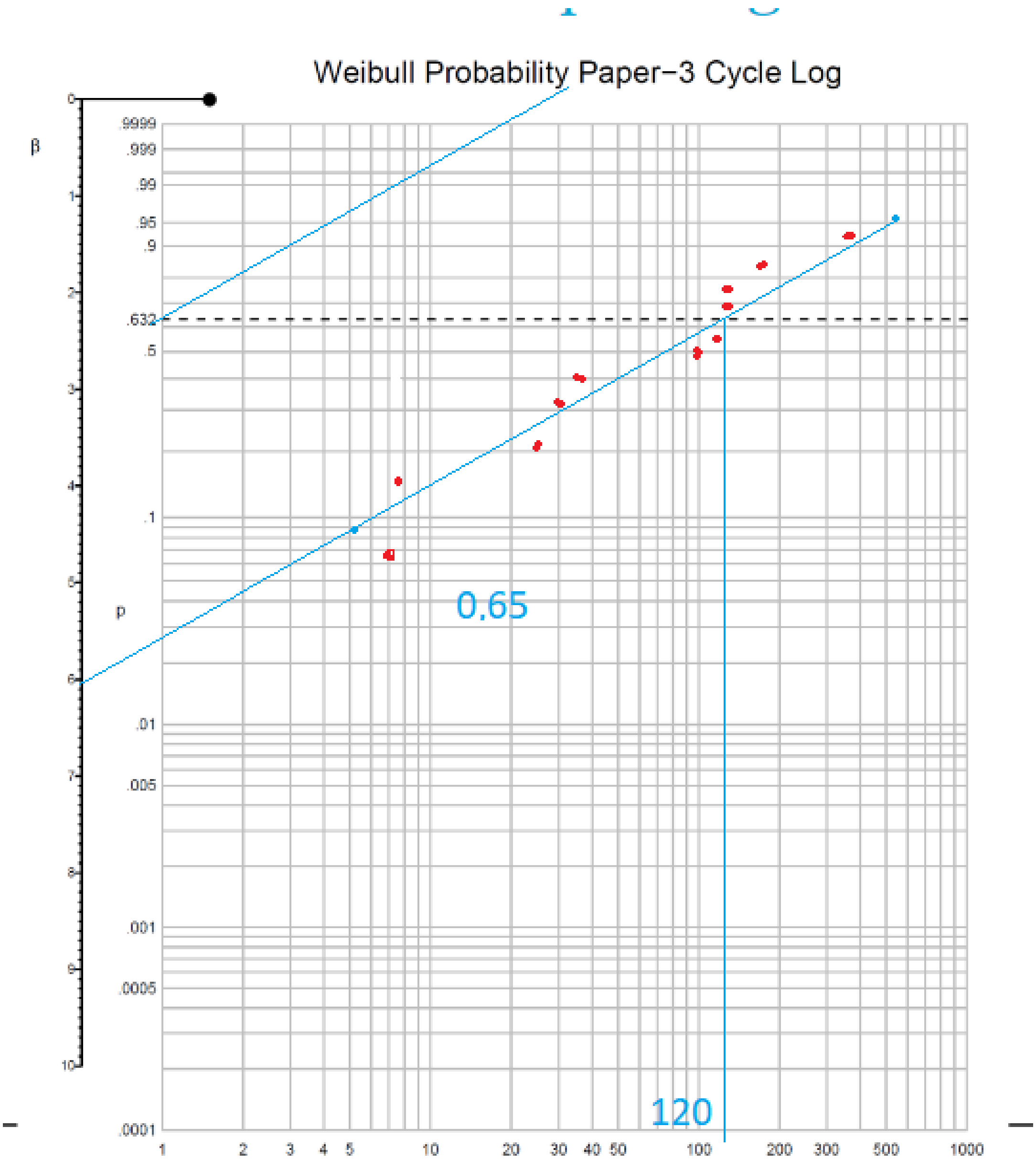

Figure C.2: Failures of A/C 2 on logarithmic paper and resulting weibull shape parameter $\beta = 0.68$ *and scale parameter* $\eta = 120$.

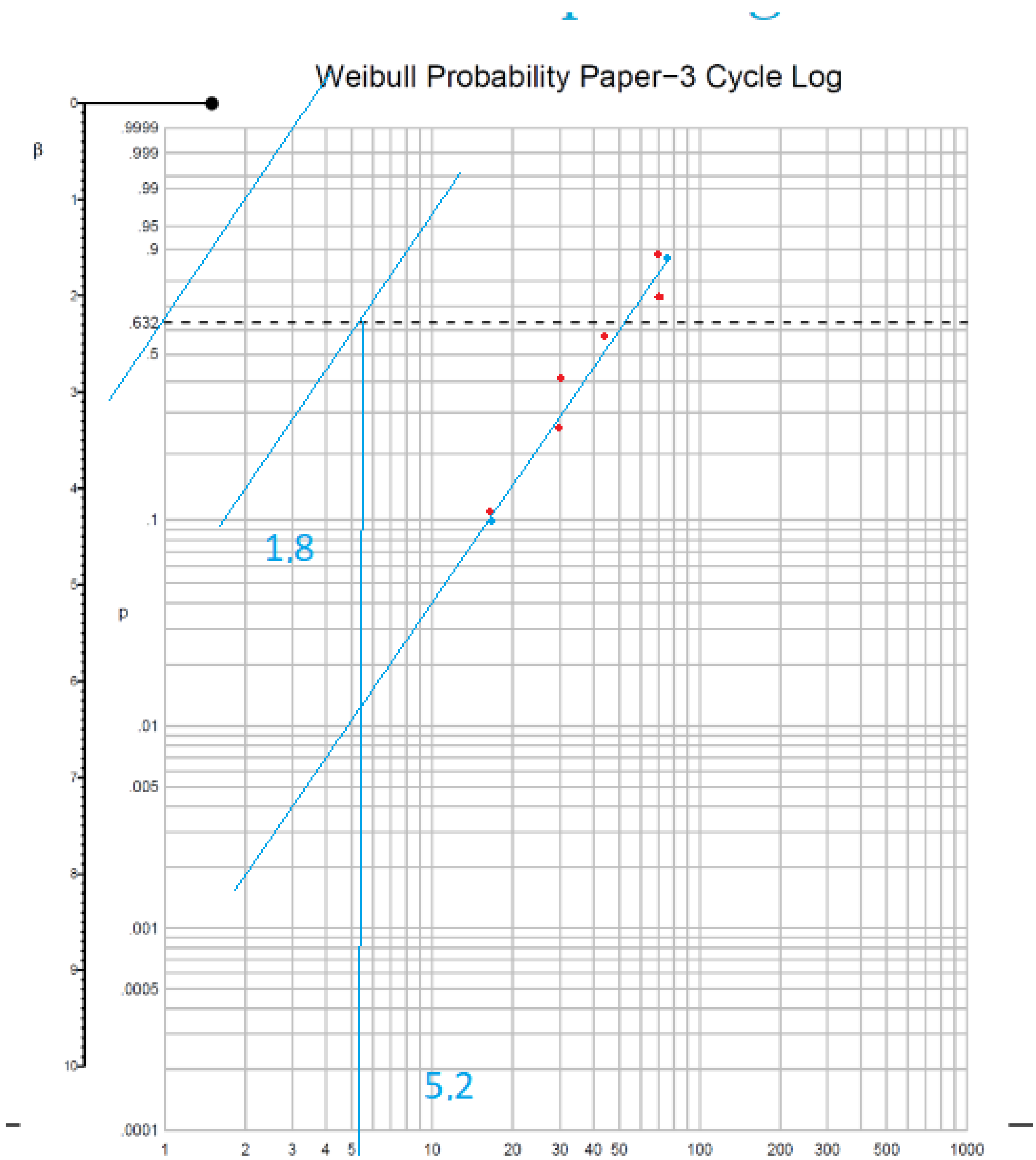

Figure C.3: Failures of A/C 3 on logarithmic paper and resulting weibull shape parameter $\beta = 1.8$ *and scale parameter* $\eta = 5.2$*.*

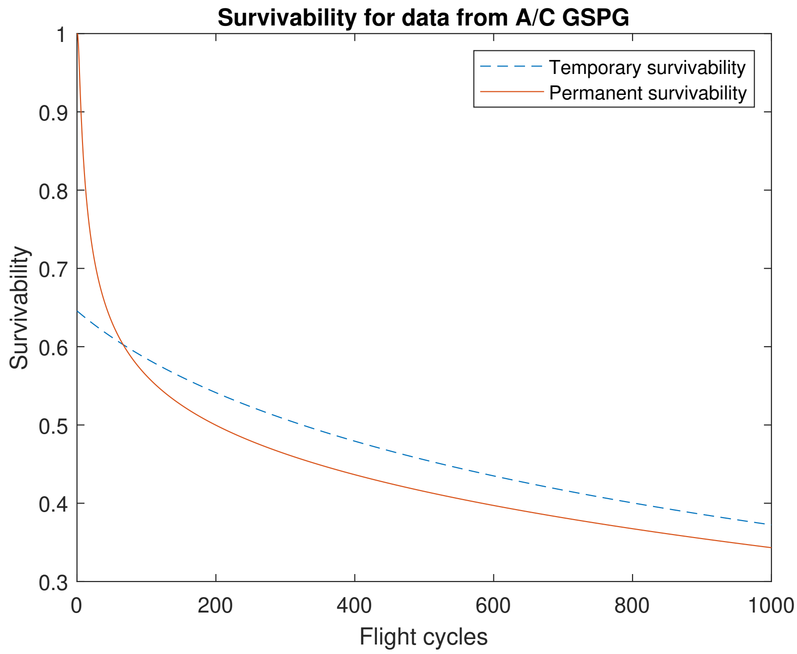

Figure C.4: Survivability of A/C 3 using weibull shape parameter β = 0.48 and scale parameter η = 120.

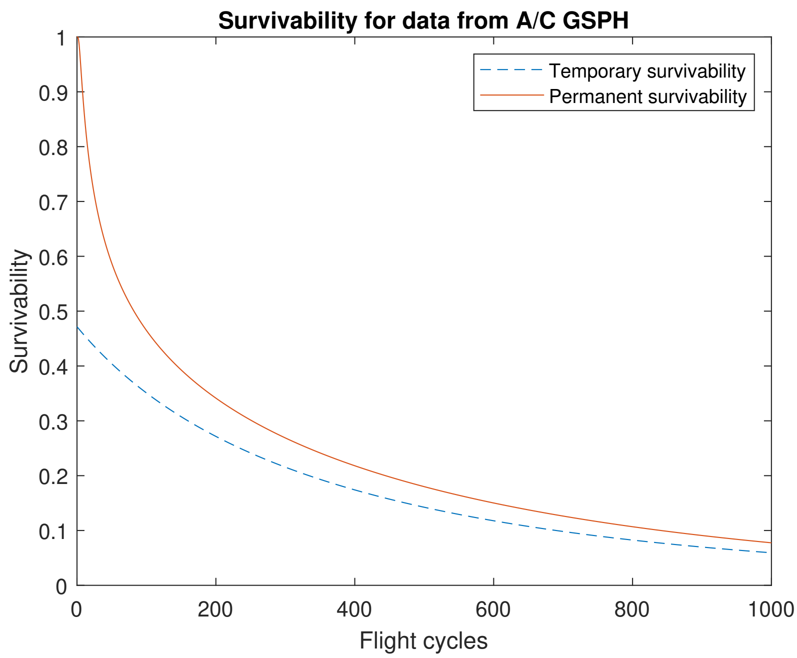

Figure C.5: Survivability of A/C 2 using weibull shape parameter β = 0.68 and scale parameter η = 120.

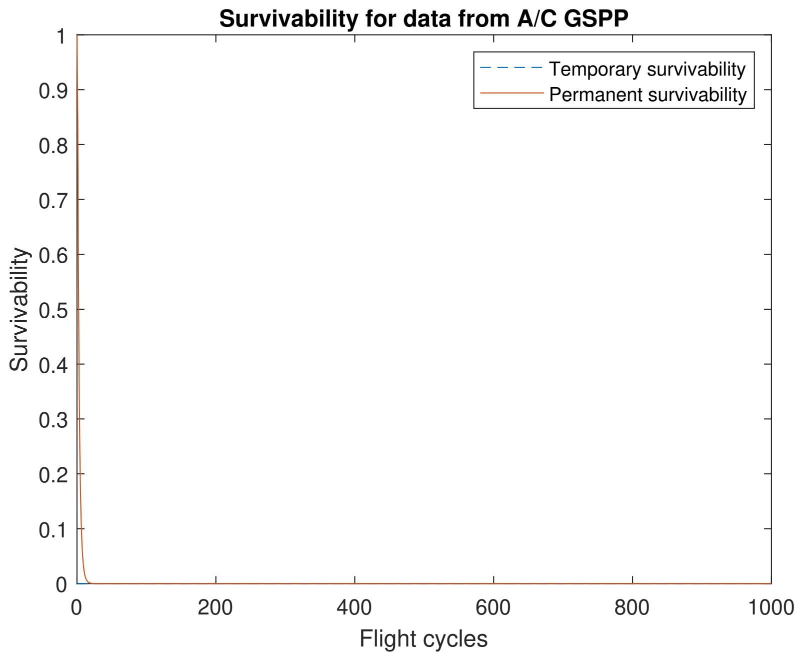

Figure C.6: Survivability of A/C 3 using weibull shape parameter β = 1.8 and scale parameter η = 5.2.

Appendix D

Verification and Validation

D.1 Verification

In order to verify the code some procedures have to be followed. The modelling was completely done in Matlab and the data analysis in Microsoft Excel. All codes were tested using a uni-code test approach. This means that the code was divided into the smallest blocks possible, to ensure it does not only run without resulting in an error, but also produce the desired results. Troubleshooting the code with negative, zero or very large input values ensures that no errors result once all the blocks come together. By step for step adding the blocks together and repeating the troubleshooting process, it was successfully verified that the code runs as intended, without producing undesired or questionable results.
As mentioned before, the different methods as well as the survivability were first coded independently. These independent codes were then tested with example values found online, to ensure that there where no bugs or misinterpretations. The survivability function was verified using the data of the work done by [2]. WSM, TOPSIS, and VIKOR were verified using the data found in the research by [3] as well as the web blog of tutorials on MCDM models applied by [4]. By playing around with minimization as well as maximization it was ensured that these objectives were translated correctly into the code (minimization of cost and time, maximization of survivability).

D.2 Validation

While verification ensures that a model produces the output that is desired, a validation process has to be done to check whether this output is actually appropriate and suited towards the problem at hand. This is usually done by comparing the model to a real situation and looking at similarities and differences of the real and the simulated result.
As a first step of validation, simple, obvious use cases were generated (input matrices with one clear winning or losing option) and plotted graphically to ensure the validity of the code. An example can be seen below in Figure D.1. Here it can be seen clearly, that for five randomly generated flight cycles since the last maintenance event, at damage occurrence different scenarios are the best. The input used was as follows in Table D.1. From this it can be seen, that for 5 moments in time the inputs vary exactly the way one would expect them to. For case 5, the values (as to be expected, are significantly different as the matrix input variables are different. This has been done for all methods.
While this is a first step to validate the output/ advice the model produces, a proper validation would need

Table D.1: Input matrix for validation.

	Case 1	**Case 2**	**Case 3**	**Case 4**	**Case 5**
Flight cycles	71	166	116	109	180
Criteria 1	121	537	826	666	random
Criteria 2	666	121	537	826	random
Criteria 3	826	666	121	537	random
Criteria 4	537	826	666	121	random

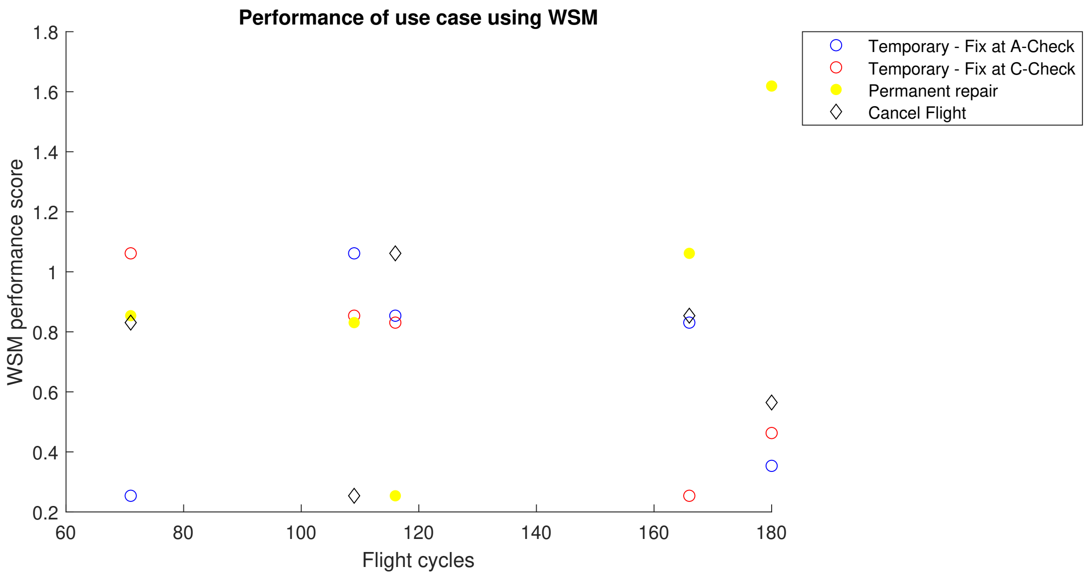

Figure D.1: Validation of WSM code.

to be tested in a real operational environment. Or at least on real, complete historical data. Unfortunately, this opportunity is not provided at this point in time and the appropriate data not available. Therefore, the results should be considered carefully, with the mentioned limitations as well as potential additional interference and considerations in mind.

Appendix E

Results

E.1 Single Occurrences

In the following the plotted results for all weight cases are presented. It can be seen that the results change proportionally in relation to each other, depending on the weights, but not in their under laying nature.

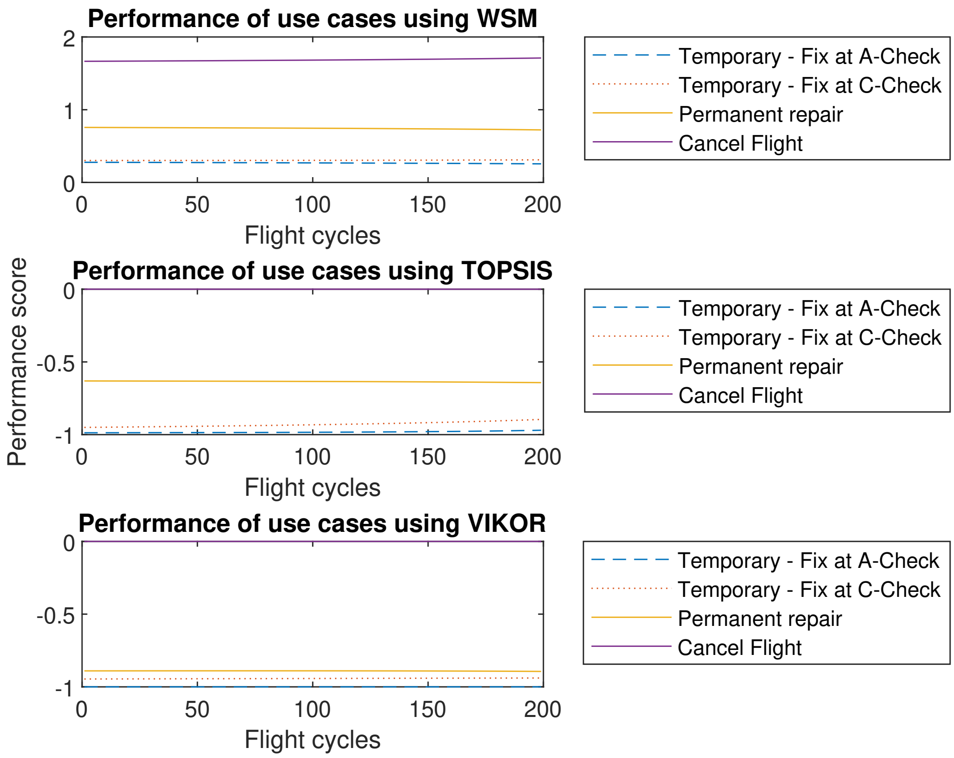

Figure E.1: Use case I - Performance ranking using WSM, TOPSIS and VIKOR using weights = [1, 1, 1].

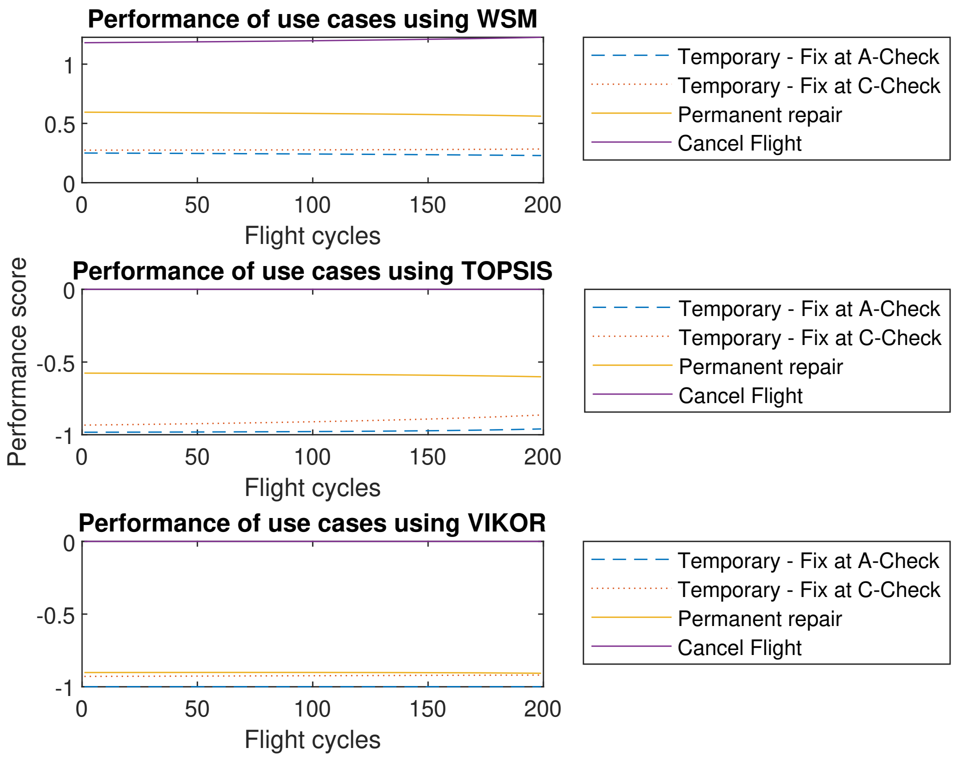

Figure E.2: Use case II - Performance ranking using WSM, TOPSIS and VIKOR using weights = [1, 0, 1].

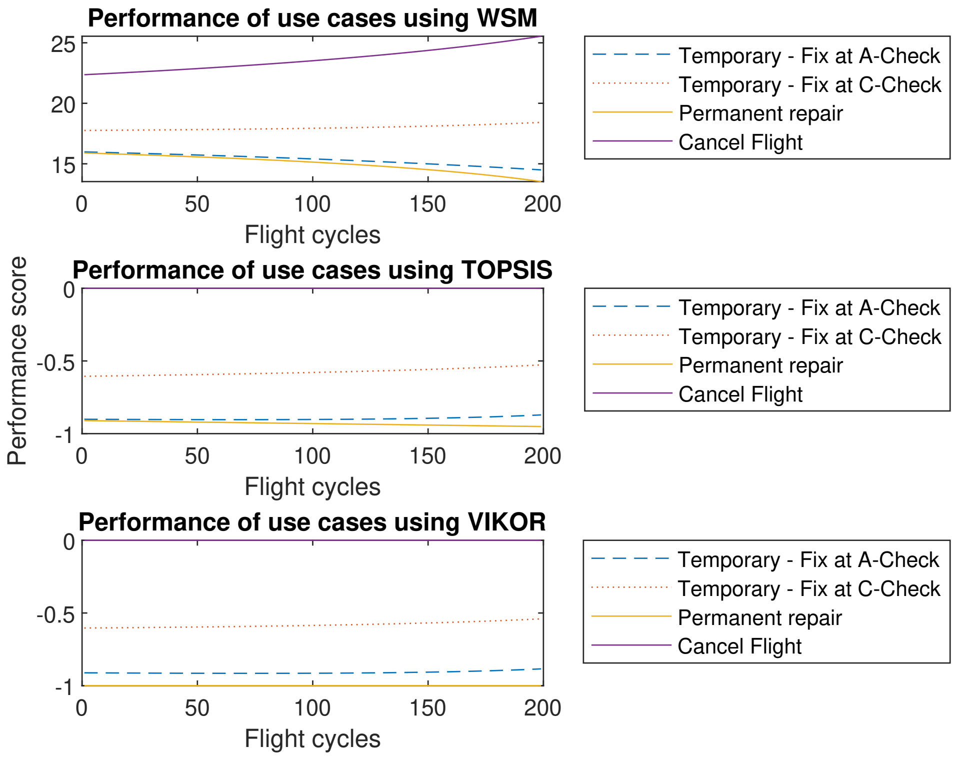

Figure E.3: Use case III - Performance ranking using WSM, TOPSIS and VIKOR using weights = [30, 1, 1].

E.2 Varying Survivability Input Parameters

As it can be observed that survivability has a large impact on the results the following set of β and η values has been investigated (Table E.1). Aircraft 4 is a fictional aircraft to investigate different parameters. In Figures E.4 - E.7 the results can be seen.

Table E.1: Four different sets of Weibull parameters were used to observe the change in results.

Registration	Sample size N	Shape parameter β	Scale parameter η
Aircraft 1	10	0.48	120
Aircraft 2	10	0.68	120
Aircraft 3	6	1.8	5.2
Aircraft 4	N/A	2.5	1000

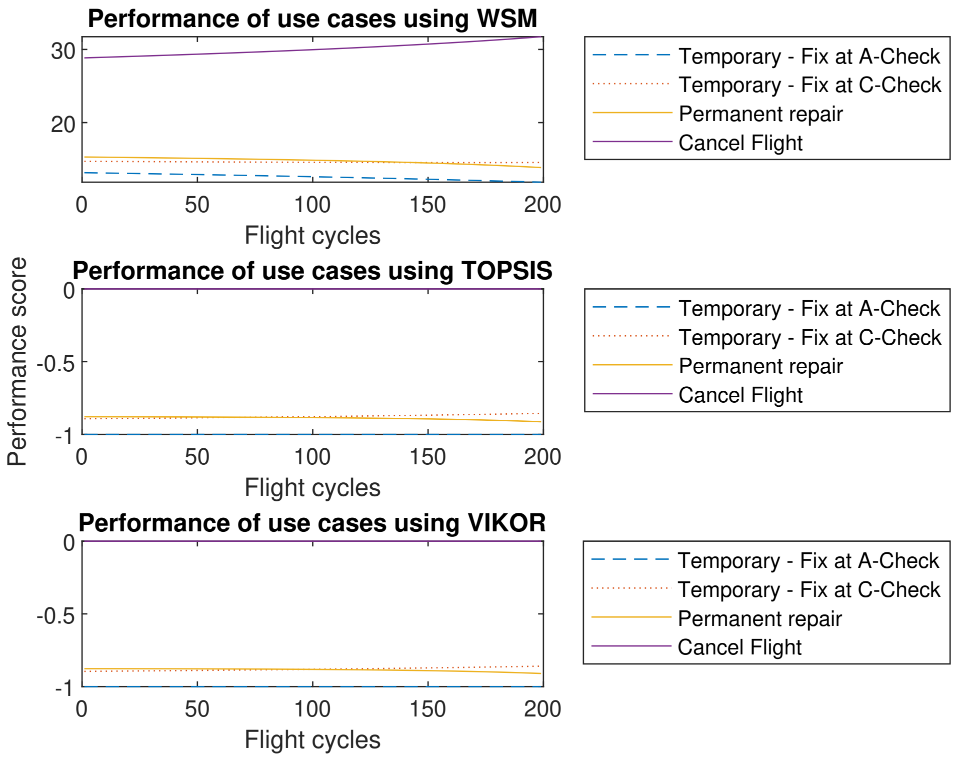

Figure E.4: Use case III - Performance ranking of WSM, TOPSIS and VIKOR using weights = [30, 1, 1], $\beta = 0.48$ *and* $\eta = 120$.

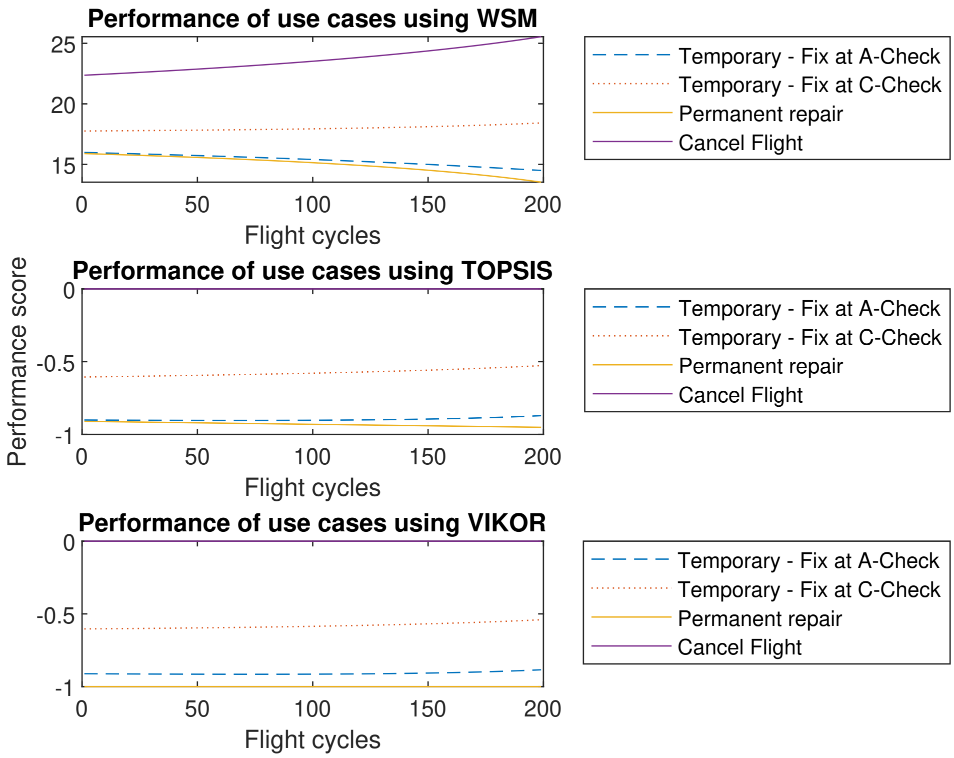

Figure E.5: Use case III - Performance ranking of WSM, TOPSIS and VIKOR using weights = [30, 1, 1], $\beta = 0.68$ *and* $\eta = 120$.

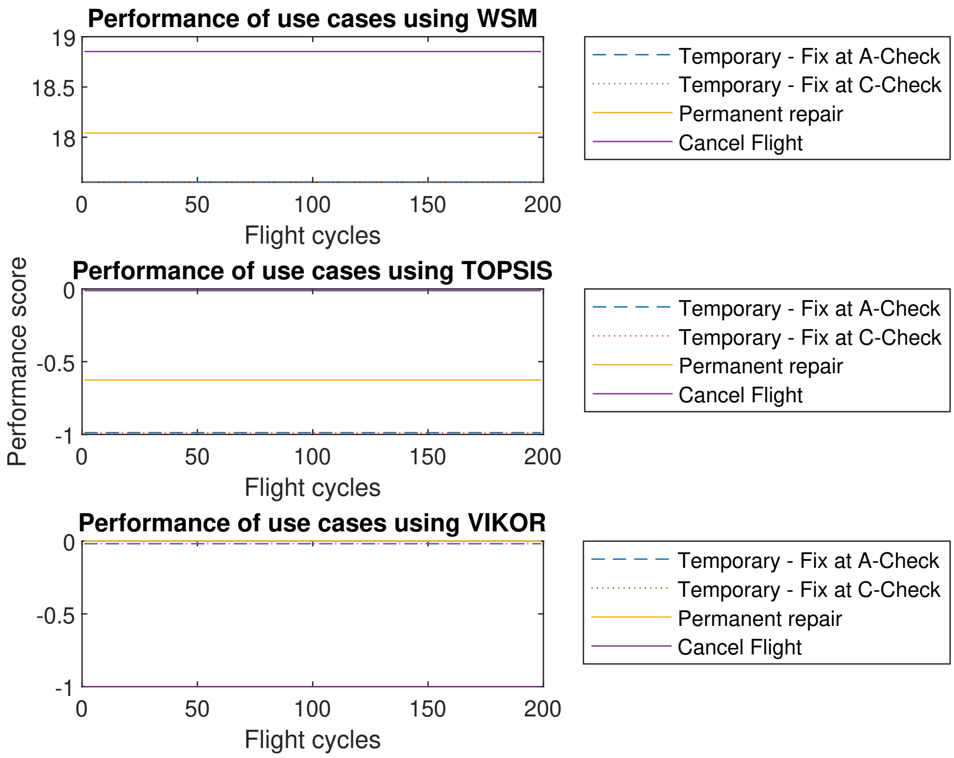

Figure E.6: Use case III - Performance ranking of WSM, TOPSIS and VIKOR using weights = [30, 1, 1], $\beta = 1.2$ *and* $\eta = 5.2$.

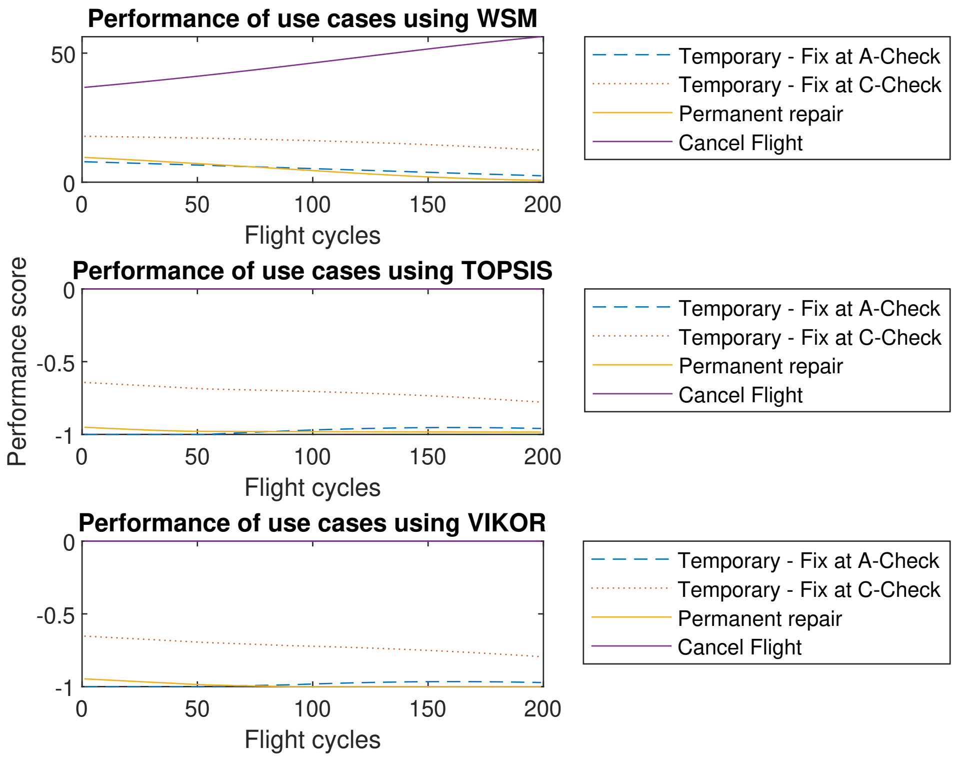

Figure E.7: Use case III - Performance ranking of WSM, TOPSIS and VIKOR using weights = [30, 1, 1], β = 2.5 *and* η = 1000.

E.3 Seasonality

In the following figure (Figure E.8) an overview of the quarterly incidence distribution is given. As mentioned in the Discussion Section, there is no dominating seasonality in the data on quarterly level.

Row Labels	<20.04.1999	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Grand Total
<20.04.1999																			
Qtr1		0%	18%	11%	30%	8%	11%	4%	24%	18%	23%	10%	12%	19%	20%	32%	24%	27%	23%
Qtr2		33%	27%	21%	20%	67%	22%	11%	36%	33%	27%	14%	12%	35%	27%	28%	25%	32%	28%
Qtr3		67%	18%	32%	30%	8%	22%	45%	20%	43%	18%	38%	8%	24%	33%	24%	25%	22%	27%
Qtr4		0%	36%	36%	20%	17%	44%	40%	19%	6%	32%	38%	68%	22%	20%	16%	25%	19%	23%
Grand Total		**6**	**11**	**28**	**20**	**12**	**9**	**75**	**103**	**88**	**22**	**21**	**85**	**303**	**553**	**386**	**426**	**377**	**2525**

Figure E.8: Quarterly distribution of damage incidents.

Appendix F

Conclusion

An overview over the analyzed scenarios and the drawn conclusions is provided in Figure F.1.

	WSM	TOPSIS	VIKOR	General findings
Single occurrence	• Clear recommendation • Easy implementation	• Steep slope of graphs -> change for higher FC	• For 200 different initial flight cycles • For all methods	• Straight forward evaluation • Doesn't require complex evaluation
Multiple occurrences – heuristics	• Clear recommendation • Easy implementation	• Different recommendation than WSM • Evaluates worst	• Not suited, ambiguous results	• Results differ per method
Multiple occurrences – global opt.	• Clear recommendation	• Clear recommendation	• Not suited, ambiguous results	• Approach not suited for situation
Sensitivity Analysis	• Very robust • Able to account for uncertain survivability	• Sensitive • Survivability has large impact	• Very sensitive • Survivability has large impact	• Use delay/ pax • Weights method dependent

- **For the problem at hand WSM and TOPSIS have similar advantages. WSM is less complex, easier to understand and more robust towards survivability function**
- **TOPSIS superior for more evenly tied cases, as it also takes account anti-ideal solution. Survivability needs to be verified carefully and weights well understood to take advantage of this property.**

Figure F.1: Overview of conclusions per scenario and method.

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