RESEARCH AND DEVELOPMENT DISSERTATION

A MULTI-CRITERIA DECISION-MAKING APPROACH TO SELECTING DRONES FOR HEALTHCARE DELIVERY SERVICES

IN PARTNERSHIP WITH APIAN AND INTERACTION MAGIC

AUTHOR:

JAMIE BELL-THOMAS

EMAIL: WS19177@BRISTOL.AC.UK

STUDENT NUMBER: 1820499

University of Bristol
Engineering Design
Faculty of Engineering

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Decleration

> *The accompanying research project report entitled: 'A Multi-Criteria Decision-Making Approach to Selecting Drones for Healthcare Delivery Services' is submitted in the fourth year of study towards an application for the degree of Master of Engineering in Engineering Design at the University of Bristol. The report is based upon independent work by the candidate. All contributions from others have been acknowledged above. The views expressed within the report are those of the author and not of the University of Bristol.*

I hereby declare that the above statements are true.

Signed (author)

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Full Name

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Date

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Executive Summary

This project explores the idea of creating a software based tool that will allow a decision maker to rapidly define micro-AHP structures while having complete control over the hierarchy structure and attribute weightings. This enables users to define multiple models, each with distinct criteria weightings, thereby allowing for the prioritisation of different types of alternatives across different models. This is done with the aim of having the ability to select, from a large batch of delivery drone candidate bids, the optimal model for the delivery at hand on a case-by-case basis. This work is being done for Apian - a medical drone start-up committed to setting up a delivery network powered by an array of autonomous drones. The objective is to offer crucial assistance to the existing supply chain of the National Health Service (NHS).

The conducted literature review provides an in-depth analysis of 8 MCDM methods, including their respective strengths and weaknesses, as well as their areas of application based on case studies. While MCDM methods are generally effective in addressing various tasks, they are limited in their ability to handle dynamic decision problems that involve consistently changing input parameters. Consequently, it was determined that a single MCDM model would not suffice to capture the diverse range of scenarios that decision makers may face. Instead, multiple MCDM models should be defined to suit individual scenarios, making flexibility and ease in creating different iterations of the MCDM model critical design requirements.

Initially, five MCDM frameworks were considered but discarded due to their unsuitability for the problem at hand. After more careful evaluation, AHP was ultimately selected as the best option. TOPSIS was ruled out due to the high dimensionality of the drone data sets, rendering its Euclidean distance algorithm ineffective and PROMETHEE's computational complexity made it less feasible for large-scale comparisons. AHP's pairwise comparison method for deriving criteria weightings is both simple and flexible. More so, all potential drawbacks of this method can be addressed, making it the best option for this particular problem.

Next, the fundamental theory of AHP is considered in order to calculate priority vectors and verify the consistency of pairwise comparison tables. Then, a user interface is developed in *Microsoft Excel*, allowing users to easily define micro-AHP structures and their underlying comparison tables. Detailed information on how the user input is checked for appropriate formatting is provided, and it is determined that an object-oriented approach is the best software design to capture the hierarchy structure. Finally, it is decided that incoming data will be normalised using a 'scale to range' technique.

The proposed framework can create AHP structures and detect formatting errors and inconsistent pairwise comparison tables. In order to test the effectiveness of the models, a database of unique drone candidates is established and a list of scenarios with AHP models is created. When passing the drone candidates through the AHP instances, the optimal candidate is selected each time. This validates the models' effectiveness and confirms the practicality of using this method to select drones for a wide range of delivery tasks. The final validation stage involved variable analysis, which showed a clear correlation between prioritised model weightings and the strengths of the selected drone candidate, further demonstrating the method's efficacy.

The current limitations of the framework are discussed, including the fact that there is an upper limit to the the potential hierarchy size. Additionally, all created models contain an inherent layer of subjectivity, and there is currently no reliable method for verifying that the selected candidate is fully capable of executing the delivery job at hand. Future work was discussed to address the limitations of the current framework, which include increasing the branching factor to extend the hierarchy size and reducing subjectivity by creating a moderately sized 'mock' drone data set through which variable analysis can be applied to fine-tune the model parameters. The selected candidate's ability to perform the delivery job can be verified through job data, which will become available when considering the application of a delivery network, allowing a final check to ensure that the candidate meets the required threshold values before selection.

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Acronyms

AHP Analytic Hierarchy Process

CBR Case-Based Reasoning

CI Consistency Index

CoD Curse of Dimensionality

CR Consistency Ratio

CSV Comma-seperated Variables

DEA Data Envelopment Analysis

ELECTRE Elimination and Choice Translating Reality

HGV Heavy Goods Vehicle

MAUT Multi-Attribute Utility Theory

MCDA Multi-Criteria Decision Analysis

MCDM Multi-Criteria Decision Making

PROMETHEE Preference Ranking Organization Method for Enrichment Evaluations

TOPSIS Technique for Order of Preference by Similarity to Ideal Solution

UI User Interface

VTOL Vertical Take-off and Landing

1. Problem Outline and Objectives

1.1 Problem Introduction and Apian

In July 2022, 54% of pharmacists responding to a survey carried out by The Pharmaceutical Journal [1] said that medicine shortages were now were now putting patient safety at risk. While there are a number of contributing factors to this crisis, one critical component is the surge in demand of standard medicines such as Hormone Replacement therapy (HRT), who's prescription numbers have more than tripled since January 2018, [2] as well as thrombolytic drugs such as alteplase and tenecteplase. Such surges across a wide variety of medicines are resulting in the destabilisation the national pharmaceutical supply chain. Furthermore, the current supply infrastructure is built on petrol powered heavy goods vehicles (HGVs), which will be looked at in more detail in this section.

Apian is a medical drone start-up whose mission is to make people and the planet feel better by building products and platforms that connect the healthcare industry with the drone industry. [3] Integrating a network of delivery drones into the existing infrastructure has the potential to help supply meet demand as well as mitigate emissions and fuel costs. Such a network could also reduce delivery time, tackle road congestion, increase logistical efficiency by having a far wider range of feasible delivery routes as well eliminating duplicate servicing which prevents over stocking subsequently minimising the amount of waste medicine. This could ultimately increase the reliability of the of the whole NHS supply chain.

1.1.1 High Emissions

The CO2 emissions of a standard 40-50 ton HGV operating under the Euro IV Emission standard will be approximately 955g/km. [4] If this class of HGV were to average 200km/day, it would result in in the emission of almost 70 tonnes of CO_2 per annum.

1.1.2 High Fuel Costs

A standard 44 tonne lorry has a consumption of around 8.0mpg. [5] Operating on the same assumption that this class of HGV were to average 200km/day, leads to a consumption of 5670 gallons of fuel per annum. Fuel prices have been at record highs in recent times. The average cost of diesel over the last year was 178.49ppl. [6] The usage and price per unit combined yields a price of around £46,000 per annum.

Although the operating condition of 200km/day is entirely hypothetical, it is very feasible and, in all likeliness, an underestimate as this is only the approximate the distance between London and Birmingham. The true purpose of the basic calculations shown above is to demonstrate in no uncertain terms that a delivery network comprised of a fleet of HGVs will not only lead to frighteningly high levels of emissions but also incur unacceptable fuel costs. This combined with the fact that the current supply chain is failing to keep up with demand points to one inescapable fact – this system cannot be sustained alone.

1.2 Objectives

1.2.1 Group Objectives

As a group, the objective is to come together and understand the critical components in the application of large-scale drone delivery network. This will include the sizing and locations of medicine storage warehouses, upstream and downstream supply chain modelling, drone pad design and locations, autonomous loading and unloading systems, endpoint distribution and drone selection. These individual research areas need to be married together to form the network subsystems: Flight Services, Network Solution Design and Integrated Drone Landing Station which will subsequently combine to form a holistic drone network service system. The distribution of these research areas and how they combine to form the network subsystems can be seen in Figure 1.1.

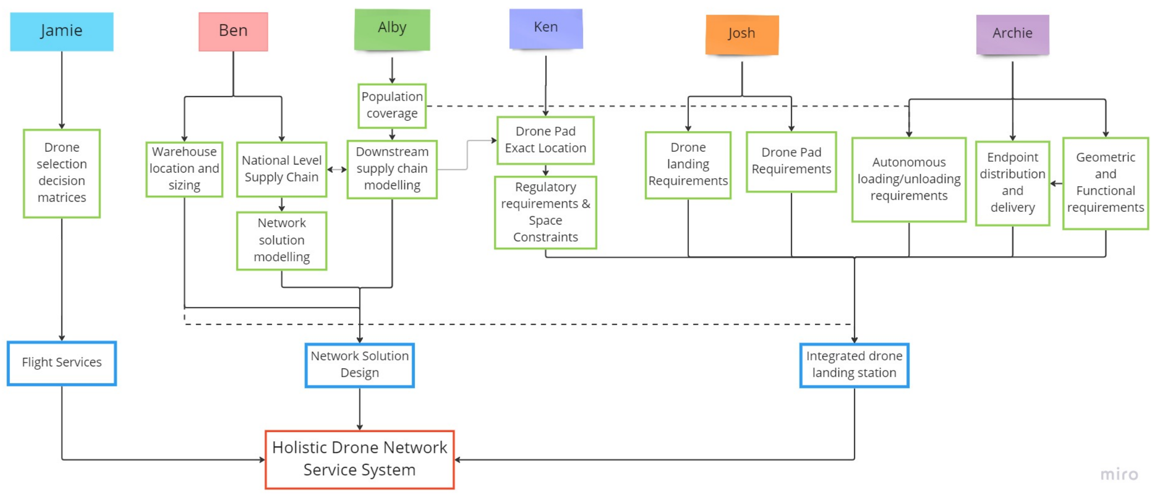


FIGURE 1.1: Individual Objectives of Each Group Member Within the Project

1.2.2 Individual Objectives

The objective for this report is focused on the Fight Services Module, or more specifically, deriving the drone selection decision matrices that will determine which drone candidate will be selected for a given delivery job. Any model created will need to have a high degree of flexibility so that a diverse spectrum of job types can be considered while still selecting the optimal candidate for each. The first step is dividing the objective into specific tasks. These tasks will provide a rough road map for the progression of this project.

Task 1 – Research into Multi-criteria Decision Making

Conduct a thorough literature review on all the major multi-criteria decision methods. In this review, the strengths and weaknesses of each method should be critically evaluated as well as determining in which applications each method performs to the highest degree as defined in academic literature. From this initial review a vague idea of how this framework will be developed so it can encompass a wide variety of delivery scenarios should be established.

Task 2 – Methodology Down-selection

Based on the information gathered from the literature review, the methodologies should be down-selected considering their applicability and usefulness within the context of the project. This stage should examine the types of data each methodology is capable of handling, their levels of complexity, ease of implementation, and adaptability.

Task 3 – Methodology Refinement, Expansion and Implementation

After selecting a methodology, it is necessary to establish the underlying theory supporting the chosen approach. The theory should be further developed into a software-based model capable of assessing drone candidates against a diverse range of delivery scenarios and generate rankings based of each drone model's specifications.

Task 4 – Model Validation via Drone Case Studies

To test/verify the effectiveness of different models, drone 'case studies' should be devised. These can either be based on real-world drone models or can be hypothetical. However, each model should have distinct strengths and weaknesses. Along side this, a range of delivery scenarios should be devised. Ideally, the most suitable drone model will be selected in each of the devised scenarios.

2. Literature Review

Literature Review Methodology This review only examined scholarly literature. To identify the most informative pieces of literature, a search for each of the subject matters was performed through the titles, abstracts and key words of the following literature databases: Springer, ResearchGate, ScienceDirect and IEEE Xplore. This insured the authenticity of the information being gathered. The review is divided into distinct sections, each section discusses the findings related to a single MCDM method.

2.1 Introduction

Multi Criteria Decision Analysis (MCDA), also known as Multi-Criteria Decision Making (MCDM), is a research field that involves the analysis of different possibilities in a given situation to identify the optimal alternative by assessing the relative strengths and weaknesses of each option. This section examines several common MCDA methods, providing a brief introduction to each, exploring a wide variety of real-world applications, including cases where they have been used in conjunction with other MCDM methods to reach a more desirable outcome. Finally, based on the literature reviewed, the strengths, weaknesses, and broad areas of application for each method are determined.

2.2 MAUT

In Multi-Attribute Utility Theory (MAUT), the evaluation of an alternative is defined as the weighted sum of its performance on each attribute, where the weights are determined by the decision maker's preferences or priorities. The evaluation can be represented mathematically as a utility function, which assigns a numerical value to each alternative based on its performance on each attribute and the weights assigned to each attribute. [7] MAUT was first proposed in detail by Keeney and Raiffa. [8] It can be said to be an extension of multiple-attribute value theory (MAVT), however it has a more rigorous methodology when incorporating risk preferences and uncertainty into decision methods. [9]. It has become a very common practice to use MAUT to assist in the decision analysis in real-world problems. In 2022, Uduak Akpan and Risako Morimoto used MAUT to examine how rural roads in Akwa Ibom State, Nigeria may be prioritised for upgrade to maximize access to key socio-economic facilities. Where the roads being prioritised were the alternatives and the decision criteria were the social, economic, demographic, financial, and political effects. [10] In 2019, Meho Saša Kovačević *et al* used MAUT to categorise the condition of railway embankments. The attributes were the current conditions of embankments. These were obtained using a combination of ground penetrating radar (GPR) surveys, visual inspection, and previous maintenance activities. These then supported the decision making process for maintenance planning by categorising 181km of railway embankments in Croatia. [11] Finally, in 2010, Paul Kailiponi used MAUT to provide a framework through which objective trade-offs can be analysed to make optimal evacuation decisions. Examples of objectives in this scenario include: minimise the number of casualties, minimise economic losses and minimise panic and disorder. The Evacuation Responsiveness by Government Organizations (ERGO) sought to put together a model for evacuations in the event of a storm surge and it identifies feature levels (attributes) where evacuation actions were to be taken by emergency managers. The model developed allowed emergency managers to weigh the respective attributes appropriately when preparing to make decisions in emergency situations. [12]

It is also common practice to combine two or more MCDM methods with the aim of making up for the short comings of a given method. MAUT features prominently in several of these combined methods. In 2007, Popi Konidari and Dimitrios Mavrakis utilised several techniques in an integrated multi-criteria analysis method to evaluate climate change mitigation policy instruments. They used an Analytical Hierarchy Process (AHP) to define criteria coefficients followed by a combination of MAUT and a Simple Multi-Attribute Ranking Technique (SMART) process to assign grades to each of the instruments. [13]

MAUT is an expected utility theory that can decide the best course of action in a given problem by assigning a utility value to every possible consequence and calculating the best possible utility. [13]

The decisive advantage of MAUT is that it takes uncertainty into account and produces a utility for each policy, something not often quantified in MCDM methods. It is a very robust method that can incorporate the preferences of each consequence at every step in the decision tree, potentially creating very accurate results. [14] However, to produce such accurate results, a very high amount of data is required at each step in order to accurately convey the agents preferences to the decision maker. A high amount of precision is also required when providing the weightings of each consequence, which depending on the depth of a consequence within the decision tree can not only require significant assumptions but also be very subjective. As a result of its distinctive strength in handling uncertainty MAUT has seen heavy application in economic, financial, agricultural and management problems. [14]

2.3 ELECTRE

Elimination and Choice Translating Reality (ELECTRE) is a family of outranking MCDM methods. Many iterations of this method exist. The first iteration, ELECTRE I was, was initially published by Bernard Roy in 1968. [15] Since then, many new and improved versions have appeared (Iv,II,III,IV,IS,TRI-B,TRI-C...). Each version slightly varies in both its operation and the types of problems they can be used on.

Each member of the ELECTRE family focuses on one of the main problematic types. ELECTRE I, Iv, and IS methods are appropriate for addressing what is known as the "choice problematic" or "problematic α." This type of problem involves identifying the smallest group of the most favorable alternatives. ELECTRE II, III, and IV were designed to create an arrangement of alternatives, ranging from the best to the worst. This is known as the "ranking problematic" or "problematic γ". ELECTRE TRI-B and TRI-C are used for the "sorting problematic" or "problematic β" in which the goal is to divide the alternatives into pre-established groups. [16] This shows the ELECTRE family is well equipped to deal with a wide array of problem types.

ELECTRE is commonly used in water management. In 1992, Roy, Slowinski, and Treichel developed a methodology for addressing a decision-making problem related to water supply systems (WSSs) in Poland. In the initial stage of the analysis, they employed ELECTRE III to establish a priority order of water users who should be linked to a WSS, based on seven socio-economic criteria. [17]. It has also seen a lot of use in the business management sector. In 2007, De Almeida employed an ELECTRE I decision model to evaluate and select outsourcing contracts. The criteria for this model are utility functions that consider cost, delivery time, and dependability, while also accounting for uncertainties in some of the information. This approach was realised through the final selection of a group of six alternative contracts. [18]. ELECTRE has also seen usage in transportation problems and economics. This is due to ELECTRE's ability to handle uncertainty, similar to MAUT. However, the outranking nature of this method simply offers absolute rankings of alternatives and fails to identifies particular strengths and weaknesses within an alternative. [14]

2.4 CBR

Case-based Reasoning (CBR) is a memory based, data driven, reasoning process in the domain of cognitive science and artificial intelligence. These reasoners solve incoming, unseen, problems by referring to seen and solved cases in an external database that describes similar problem-solving experiences and adapts their solutions to fit the needs of the current problem. [19]

In 2001, at the 4th International Conference on Case-Based Reasoning, The Auguste Project was reported. [20] This is a collaboration among case-based reasoning researchers at the University Alzheimer Center. Clinicians at the university proposed using CBR to aid in the planning of the ongoing care or Alzheimer's Disease (AD) patients. This method allows clinicians to look at previous cases to learn which interventions are effective in specific cases and to document their clinical findings in current cases, both successes and failures in order to train the next generation of AD health care professionals. In 2000, reasearch was conducted to see if CBR could be used in failure analysis in production facilities. The results reported very high levels of accuracy even in exceptional cases therefore concluding CBR is a viable approach for the identification of failure mechanisms. [21]

CBR is quite a general methodology. This means that new hybrid learning techniques can be created using CBR and one or more other techniques. In 2006, Se-Hak Chun and Yoon-Joo Park proposed a new regression CBR (RCBR) which uses regression analysis to apply weightings to to the features (known as regression coefficients). Traditional CBR is then used to select the nearest neighbours (most similar cases) to a given problem. This hybrid technique was used in financial forecasting. [22] Hyunchul Ahn and Kyoung-jae Kim took a similar approach in 2009, in that they applied weightings to the features. However, they used genetic algorithms (GAs) to both optimise their weightings *and* the instance selection for comparison when CBR is being carried out, in order to discard noise and only consider relevant cases. This method proved to be more far more effective than traditional CBR in predicting effective corporate bankruptcy. [23]

This leads, to the first drawback of CBR and how it can be combated. CBR is very sensitive to inconsistent, incorrect, invalid or special data and on certain occasions it can be that referencing previously seen cases does not lead to the most accurate response. However by combining CBR with an optimisation tool (such as regression or GAs in the examples above) can mitigate the noise by prioritising specific predictor variables. However the issue of inconsistent cases can be mitigated by creating a large enough data set meaning that CBR is one of the few MCDM methods which improves in accuracy over time. Furthermore these data sets require little to no maintenance. For these reasons this method is heavily utilised in industries that have large stockpiles of data such as the medical, insurance, financial and engineering sectors.

2.5 DEA

Data Envelopment Analysis (DEA) is primarily used to evaluate decision-making units (DMUs) that are comparable, meaning they operate on similar products or services, in order to determine their relative efficiency when no appropriate weightings are available to aggregate inputs and outputs. The goal is to identify the most efficient DMUs and to provide insights into how less efficient DMUs can improve their performance. This is done by comparing the inputs used to produce a certain level of outputs. [24] This is a non-parametric, statistical method. There are a wide variety of methodologies under the umbrella of DEA. The initial method was CCR (C^2R) which simply evaluates the relative efficiency of different DMUs. This was later refined into the BCC (BC^2), which separated technical and scale efficiency into two separate metrics. Other measurements such as most productive scale size (MPSS) and returns to scale (RTS) can be evaluated. However they are derived from most fundamental methods of DEA, C^2R and BC^2. [25]

In 2015, Gökşen *et al* utilised DEA to determine the performance levels of various faculties in Dokuz Eylul University in Turkey. [26] In this paper both C^2R and BC^2 models were employed to compute the global technical efficiency (GTE) and the local pure technical efficiency (LPTE) respectively. A scale efficiency was also computed by dividing the C^2R value by the BC^2 value. The inputs were the area of land used, the number of academic staff and the number of administrative staff for each faculty and the outputs were the number of publications produced and graduate students. While this report was very good at highlighting the the positive and negative data within the university by considering multiple inputs and outputs as well as indicating where improvements need to me made within these departments, it put on display two key limitations of this technique. Firstly, 8 of the 26 faculties had a perfect score of 100%, these results are impossible to interpret beyond simply labelling these departments as 'efficient'. No comparison can be offered between these data points and no unique solution to the most efficient department exists. The second point, which was identified in the conclusion of the report, the data used in this study was only taken from the year 2012. The authors believed that if more data was provided the results would be more representative of the true state of the university. This is to say, as with most data-driven approaches such as CBR, that this method is only as good as data supplied.

2.6 PROMETHEE

Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) is a family of MCDM methods, similar to ELECTRE, that rank alternatives based on a set of criteria. Since its inception, several iterations of PROMETHEE have been developed, each adjusting the method by which alternatives are ranked. PROMETHEE I and PROMETHEE II were introduced in 1982 by Brans. [27] PROMETHEE I aims to partially rank alternatives by considering the number of outranking relationships an alternative has, i.e., how many alternatives it beats. On the other hand, PROMETHEE II seeks to fully rank alternatives based on both the number of outranking relationships and the weights of alternatives. Since this inception, many more iterations of this method have been developed (III,IV,V,VI,GAIA,GDSS,III-PH,TRI...). [28] Each new iteration expands on the previous so it can cater to more specific problem types or data sets.

Abu-Taleb and Mareschal published a paper on hydrology and water management in 1995, which addressed water resource issues in the Middle East. They employed PROMETHEE II and V as a method to evaluate and select from a range of viable water resource development alternatives. This allowed for the efficient allocation of limited funds to various development projects and programs. [29] In 1998, Babic and Plazibat used a combination of the Analytical Hierarchy Process (AHP) and PROMETHEE to evaluate the level of business efficiency achieved by different enterprises. They ranked the enterprises based on this analysis. PROMETHEE was used for the final ranking and AHP was used to determine the weightings of criteria. [30].

This leads to one of the most significant disadvantages in the PROMETHEE family - there is no given method to prescribe criteria weightings, even though these weightings are a critical component of the method. This often leads to PROMETHEE existing in a hybrid integration with other MCDM methods. However, PROMETHEE performs well in both the fields of user friendliness and simplicity, being preferable to both ELECTRE III and AHP. [31] PROMETHEE is often used in environmental management, hydrology and water management, business and financial management, transportation, manufacturing, energy management, and agriculture. [14]

It is important to note that the PROMETHEE family contains a large number of MCDM methods, each with their own applications, strengths and drawbacks. This review only scratches the surface of the potential of this method. Unfortunately, a full review is outside the scope of this report. However, Behzadian *et al* carried out a comprehensive literature review on this family of MCDMs. [28]

2.7 AHP

Analytic Hierarchy Process (AHP), developed by Saaty in 1977 [32], is one of the most widely used used MCDM tools. AHP is a method used to break down complex decisions with multiple criteria into manageable parts. The process includes three steps: constructing a hierarchy, analyzing priorities, and checking consistency. In the first step, decision makers organize the criteria into different levels of a hierarchy. Next, they compare each group at the same level in a pairwise fashion, using their own expertise and knowledge. Finally, they verify the consistency of their assessments to ensure the results are reliable. [33]

In 2023, Bart MacCarthy proposed a model to evaluate the international location of a manufacturing plant using the AHP. [34] The proposed hierarchy for selecting the best country to locate a manufacturing plant consists of five levels. The first level is the overall objective. The second level includes the principal factors that influence the performance capability of an alternative, such as cost, product quality, and time to market. At the third level, the major determinants of the principal factors of international location decisions are considered. The fourth level compares the sub-factors of each major determinant. The final level is the location alternatives of the manufacturing plants (decision options) that will be passed into the network. This report goes on to shows the exact break down of layers two, three and four, showing the incredible detail that can be considered in this method. However in 2012, Pourghasemi *et al* [35] produced landslide susceptibility maps of susceptible areas in Iran by using both fuzzy logic and (AHP) models. The decision criteria included:

slope degree, plan curvature, altitude, land use, distance from rivers, distance from roads, distance from faults, and slope length. The catalogue of landslides that had already occurred was divided into a 70/30 split for training and validation purposes respectively. The verification data set concluded that fuzzy logic outperformed AHP with an accuracy of 89.7% compared to 81.1%. Fuzzy logic is more adept at dealing with and outputting partial truths and degrees of membership as can be seen in Section 2.8. In this scenario, determining the level of landslide susceptibility through binary classification is not very appropriate, and it is better to use an MCDM method that can deal in uncertainty, as revealed by the results.

AHP and MAUT share similarities in their approach to assigning numerical values to options for comparison. However, AHP is more intuitive, allowing decision makers to quickly establish a hierarchy and weightings through a pairwise method. In contrast, MAUT relies on complex mathematical sums to determine the utilities of different options. Additionally, AHP is less computationally expensive and can be more easily scaled to handle larger problems. [14] However, AHP has certain limitations such as the inability to facilitate probabilities. Additionally, its subjective nature may lead to inconsistencies in judgment and ranking of criteria, ultimately resulting in rank reversal if left unchecked. [36] AHP is often used in performance based problems such as resource management, strategy and planning.

2.8 Fuzzy Theory

Fuzzy theory, also known as fuzzy logic is a way to model logical reasoning where the truth of a statement is not binary. As opposed to classifying variables as a single output value, this theory uses membership curves inferred from expert opinions to create convert a the inputted crisp variable (a single value) to a fuzzy variable which shows a probability of the crisp input throughout each of the classifications. [37]

In 2012, Vasu Murthy *et al* compared various standard PID controller designs to a fuzzy-based intelligent controller for temperature process control of an Industrial furnace system, due to conventional PID controllers' poor performance with non-linear processes, such as temperature regulation. Four conventional PID designs were analyzed, all of which performed relatively poorly. A fuzzy logic controller was also tested, which solved the issue of overshooting but under-performed compared to all PID designs with respect to settling time and introduced a steady-state error. Finally, a Fuzzy-PID controller was examined, incorporating a Fuzzy Inference structure into the proportional, integral and derivative gains, which suppressed the steady-state error seen in the fuzzy logic controller while maintaining an incredibly smooth response. The paper concluded that a fuzzy-based PID controller is a superior choice for controlling non-linear processes. [38]

Fuzzy Theory's main strength is its ability to tackle problems referring to imprecise, uncertain and incomplete data. This is how it was able to outperform the traditional linear techniques seen in PIDs as well as one of the most commonly used MDCMs (AHP) a seen in Section 2.7. However this methodology can require a large amount of simulations and/or a high volume of expert data before remotely accurate membership curves can be curves can be generated. This in turn makes this method computationally expensive, meaning one should tread lightly when choosing this method, ensuring it is only chosen when the data set at hand demands it. [14] One final drawback is that fuzzy logic, by its very nature, has no clear cut-offs between the different membership grades. This can make it difficult to interpret ambiguous results where no clear classification emerges.

2.9 TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method aims to determine an alternative that is nearest to the ideal solution while being farthest away from the negative ideal solution within a multi-dimensional computing space. [39] It was developed my Hwang and Koon [40] and one of it's most attractive features is the limited subjective input required from decision makers, with the only decision needing to be made is the importance weighting for each criteria. TOPSIS is one of the simplest MDCM algorithms to implement. Simply normalise each set criteria, determine what your ideal point (s^+) would be by considering strongest performance on each criterion across the range of alternatives, then determine your negative ideal point (s^-) by considering the weakest performance on each criterion. From here, once weightings have been applied, calculate the Euclidean Distance from each alternative to s^+ and s^-. Finally calculate the distance to the negative ideal divided by the sum of the distance to the negative ideal and the distance to the ideal. This ratio is the fitness of a given alternative. [41]

The simplicity and versatility of TOPSIS has lead to its use in a variety of real world scenarios. In 2012, Bulgurcu utilised TOPSIS model to measure and compare the financial performance of thirteen technology firms trading in Istanbul Stock Exchange. [42] Companies were evaluated according to ten financial ratios, including: Total Debt Ratio, Debt Equity Ratio, Current Assets Turnover and Working Capital Turnover. By normalising each performance criterion and plotting each alternative in a multi-dimensional space, the overall performance of each firm on an annual basis was evaluated and the alternatives ranked.

This method is often used in the hybrid fuzzy AHP-TOPSIS method. This combination offers a solution to the aforementioned shortcoming in the TOPSIS method - the weighting generation for each criterion. The pairwise comparison structure found in the AHP method offers users a stable platform where the criteria weightings can be calculated and the consistency of the decision makers inputs can be verified. These weightings can subsequently be fed into a TOPSIS model to generate a ranking for alternatives. In 2014, Taylan *et al* utilised this method to evaluate different construction projects and their overall risks under incomplete and uncertain situations. [43] In 2021, Ekmekcioğlu *et al* used a hybrid fuzzy AHP-TOPSIS model to produce district-based vulnerability, hazard, and flood risk maps for Istanbul. [44] Finally, in 2012 Choudhary and Shankar used a similar framework for evaluation and selection of optimal locations for thermal power plants in India where alternatives were ranked based on social, technical, economical, environmental, and political (STEEP) considerations. [45]

The greatest strength of this method, and where is exceeds other MCDM methods is in it's simplicity. It is easy to understand and implement. Furthermore, the number of steps required in creating a TOPSIS model is independent of the number of decision criteria and alternatives in the problem at hand. This simplicity is also the reason this method often serves as a source of verification to solutions produced by other MCDM methods as-well as a stand-alone MCDM tool. [14] However, TOPSIS is unable to capture correlations between criteria. [46] When the number of dimensions is high, computing fitness scores can give rise to a phenomena called the curse of dimensionality, where different Euclidean Distances can converge as the number of dimensions in the problem space rises.

2.10 Review Summary

Table 2.1 summarises the advantages, benefits, and areas of application for each of the MCDM methods that have been reviewed in this section. Generally speaking over the history of MCDM, outranking methods such as ELECTRE and PROMETHEE have been surpassed by value measurement approaches such as AHP and MAUT. In recent times, with the advances in technology making these algorithms more accessible, seeing a combination of methods employed in a solution has become a common occurrence allowing for shortcomings of deficiencies that may be found in certain methods to be addressed. Throughout this review MCDM methods have demonstrated remarkable effectiveness in addressing static decision problems by enabling the evaluation and comparison of multiple conflicting criteria to determine the best solution. However, these methods are not as effective in handling dynamic decision problems that involve a changing decision-making environment. The inflexibility of MCDM methods hampers their ability to adapt to new information, which may result in sub-optimal or even erroneous decisions. Therefore, to effectively tackle the inherently dynamic nature of decisions involved in drone allocation, a designated priority of the developed architecture must be its adaptability to a change in input parameters. The purpose of this is to enable rapid definition of multiple MCDM models, facilitating consideration of a wide spectrum of decision-making scenarios. This wide field of consideration would mitigate the inflexible nature of the reviewed MCDM methods.

2.11 Summary Table

	Stregnths	Weaknesses	Areas of application
MAUT	Can factor in probabilities. Can factor in preferences.	Accurate results require a lot user input. Probabilities can be difficult to obtain. Preferences are very subjective.	Economic, financial, agricultural and management problems.
ELECTRE	Many iterations of this method exist, making it adept at solve a wide variety of problems. Ability to factor in uncertainty	Cannot identify particular strengths and weaknesses of an alternative	Water management, economics and transportation problems.
CBR	Being data-drive, the accuracy of this method increases over time. Requires no maintenance. Adaptable to changes in environment.	Sensitive to inconsistent, incorrect, invalid or special data. Accurate results demand a large dataset.	Businesses, vehicle insurance and design engineering.
DEA	Capable of handling multiple inputs and outputs. Can analyse efficiency.	All inputs and outputs must be known. Cannot handle inaccurate data.	Economics, agricultural and business problems.
PROMETHEE	Simple to use. Many iterations of this method exist, making it adept at solve a wide variety of problems.	No clear methodology by which criteria weightings are assigned.	Environmental management, financial management, and transportation
AHP	Not data intensive. Easy to use. Adjustable to different problem sizes.	Inconsistencies may arise between judgment and ranking criteria when there is interdependence between the alternatives and the criteria being used.	Performance-based problems, resource management, planning and strategy
Fuzzy Theory	Allows for imprecise or insufficient data.	Difficult to implement, can require numerous iterations and lots of professional inputs.	Engineering, economics and environmental management.
TOPSIS	Simple methodology. Easy to programme. Number of steps is independent of the number of criteria and alternatives.	Euclidian Distance does not consider correlation between criteria. Consistency of weightings can be difficult to maintain.	Logistics, engineering, manufacturing, business and marketing, resources management.

TABLE 2.1: Summary of MCDM Methods

2.12 Initial Considerations

When determining which MCDM method is most appropriate for the task at hand, a few candidates can be dismissed immediately. CBR is a data-driven approach that finds solutions to problems by looking to previously seen instances for situations that had similar conditions and drawing inspiration from past solutions. Here there are no past situations or data stockpiles to examine meaning it would not be appropriate in this instance. DEA can instantly be discounted as it is a method that evaluates the efficiency of comparable DMUs, making it redundant in this scenario. Fuzzy Theory is a mathematical framework that specialises in handling subjective and vague inputs. While it does have potential for application in decision making, the crisp nature of the data set in this project means it is not suitable for the task at hand.

3. Research Methodology

3.1 Determining the Appropriate MCDM Framework

The decision for which MCDM is most appropriate is entirely dependent on the problem at hand. For this let's refer back to Section 1.2.2. The objective of this project is to create a tool that allows Apian to create a flexible MCDM framework so that multiple job scenarios can be considered. Section 2.10 then provided a more comprehensive objective, which was to create an architecture capable of rapidly defining multiple MCDM models so that criteria importance can be altered in such a way that each model is tailored for a specific job type. Each model needs to take a set of drone specifications and return a fitness score defining how appropriate that drone model would be for the job in question. The drone data sheet received from Apian has 17 distinct parameters on it. The value of each of these parameters need to be converted into a format that can be processed by an MCDM framework. For example, discrete categorical qualitative variable inputs need to be expressed as continual inputs that can be multiplied by their respective weightings.

Three MDCM methods were discarded immediately in Section 2.12 due to their unsuitability. This leaves five candidates, all of which sit in the discrete alternative multi-attribute decision making family. The first two are the outranking methods, ELECTRE and PROMETHEE, the third is the pairwise comparison method AHP, the fourth is the utility function method, MAUT and the fifth is the distance based method, TOPSIS. These remaining methods can be examined in greater detail. In this instance it is easier to start with the chosen methodology and then explain why the remaining candidates were rejected. For reasons that are explained at the end of this subsection, the chosen framework is AHP.

3.1.1 Framework Candidate 1: ELECTRE

The first and most clear rejection was ELECTRE. As the problem at hand is a ranking problematic/ problematic γ, One of ELECTRE II,III or IV would be used. Let's consider ELECTRE II. In the context of this problem, it is an unnecessarily complicated method. The user, who would most likely have no experience with MCDM methods, would need to determine threshold values for each criterion and derive a matrix of concordance and discordance indices to evaluate each alternatives performance in that criterion. Any program based on ELECTRE would be difficult to understand and very time consuming for a user to complete. This lack of transparency which makes it difficult to understand for decision makers who are not familiar with the method makes it an inappropriate framework for this project. There is also no prescribed technique to allocate criteria weightings. [47]

3.1.2 Framework Candidate 2: MAUT

The second method to be dismissed was MAUT. While MAUT is a very powerful MCDM method, it specialises in outcome probability and user preferences however the problem at hand is deterministic. This alone isn't enough to be grounds for dismissal as MAUT frameworks can be applied successfully in deterministic problems and the utility function that would need to be derived could help deal with the variety of parameter types being inputted into the model. However these utility functions is what makes MAUT infeasible. Seperate utility functions need to be derived based of each stated user preference. [48] The lack of flexibility and potential complexity in this process would make creating multiple MCDM models a challenging task. Furthermore, this method has no prescribed technique to allocate criteria weightings. To summarise, while this method could produce accurate results, the lack of a probabilistic element means that using this method would be needlessly over-complicating this process.

3.1.3 Framework Candidate 3: PROMETHEE

For a complete ordering of alternatives, PROMETHEE II would need to be used. [49] As was the case with MAUT and ELECTRE, there is no prescribed technique to allocate criteria weightings. These are assumed knowledge in this method. Apart from this, this method it is a very strong candidate for this project. PROMETHEE has it's own built in system of normalisation for criteria values based on whether they are beneficial or non-beneficial (whether they want to be maximised or minimised). Each alternative is compared to every other alternative across all criteria with respective weightings being applied. The resulting comparisons are captured by an aggregated preference function, which is used to determine the preference degree of each alternative with respect to the others. These preference degrees are then combined to calculate the net preference flow for each alternative, which reflects the degree to which it is preferred over the other alternatives. Finally, the alternative with the highest net preference flow is considered to be the most preferred and is assigned the highest rank. It is a simple methodology that would be easy to implement. The only potential shortcoming is the fact that each alternative needs to be directly to compared to all other alternatives over all the criteria, which could lead to high level of computational complexity with respect to number of alternatives. This is examined below in a scenario where there are 10 decision criteria

Number of alternatives (A)	3	4	5	6	7
Number of comparisons per alternative	2	3	4	5	6
Number of alternative comparisons	6	12	20	30	42
Number of criteria (N)			10		
Number of calculations (n_c)	60	120	200	300	420

TABLE 3.1: Number of calculations in the PROMETHEE II method at a micro scale

From this data it can be deduced the following equation can be deduced:

$$n_c = N \cdot A(A-1) = O(n^2) \tag{3.1}$$

Equation 3.1 shows that the number of calculations has an order of n^2 time complexity with respect to the number of alternatives, meaning this algorithm will be very slow and difficult to run with high volumes of alternative data. Despite being well documented as an effective and accurate MCDM method, the scale of Apian's future operations is unknown. Should the number of drone operators bidding on jobs rise significantly, the situation could arise where each job required hundreds of thousands of calculations are required per job as Table 3.2 shows. By not choosing PROMETHEE II in favour of a computationally less complex framework, this project should be future-proofed against a rapid up-scaling in Apian's operations.

Number of alternatives (A)	10	20	50	100	150	200	500
Number of criteria (N)				17			
Number of calculations (n_c)	1530	6460	41650	168300	379950	676600	4241500

TABLE 3.2: Number of calculations in the PROMETHEE II method at a macro scale

3.1.4 Framework Candidate 4: TOPSIS

TOPSIS is a relatively simple MCDM tool, so much so that the full methodology has already been defined in section 2.9. To summarise, each alternative's fitness score is a function of its Euclidean Distance from the ideal and negative ideal point, which are determined by collecting the best and worse values from each criterion within the set of alternatives. The Euclidean Distance is the straight line distance between two points in multi-dimensional space and is calculated by the square root of the sum of the squared differences between the corresponding coordinates of the two points. For example:

$$\begin{aligned}
\mathbf{P}_1 &= (i_1, j_1, k_1, ..., z_1) \\
\mathbf{P}_2 &= (i_2, j_2, k_2, ..., z_2) \\
\mathbf{P}_{1\to 2} &= \sqrt{(i_1 - i_2)^2 + (j_1 - j_2)^2 + (k_1 - k_2)^2 + ... + (z_1 - z_2)^2}
\end{aligned}$$

As was the case with all the previous framework candidates, there is no prescribed technique to allocate criteria weightings, this would have to be done via an external process.

PROMETHEE struggled as the number of alternatives (data points) increase due to the time complexity. TOPSIS however, is a much simpler algorithm. It's complexity is analysed below. In a sample space of N criteria, each alternative requires $3N$ calculations to determine the Euclidean Distance to s^+ (N subtractions, N squares, $(N-1)$ additions and 1 square root). A further $3N$ calculations to determine the Euclidean Distance to s^- and finally a single calculation is required to determine the fitness score. This means each alternative that is added requires an additional $(6N+1)$ calculations. Expressing the number of calculations as a function of number of alternatives and number of criteria as was done in Equation 3.1 gives:

$$n_c = A \cdot (6N+1) = O(n) \tag{3.2}$$

Equation 3.2 shows TOPSIS has a time complexity of $O(n)$ with respect to the number of alternatives and the number of criteria. This is a moderate growth rate of complexity and should pose no issues for large scale calculations, as Table 3.3 shows.

Number of alternatives (A)	2	5	10	20	50	100	150	200	500
Number of criteria (N)	17								
Number of calculations (n_c)	206	515	1030	2060	5150	10300	15450	20600	51500

TABLE 3.3: Number of calculations in the TOPSIS method at a macro scale

The main concern with using TOPSIS is that, by having up to 17 decision criteria, the set of alternatives being compared is quite a high dimensional data set. This will give rise to a phenomenon called the Curse of Dimensionality (CoD). As the number of dimensions increases, the volume of the sample space increases exponentially as a result of this, the fixed size input will cover a dwindling fraction of the input space. As a result of this the distance between data points becomes more uniform. This makes it more difficult to differentiate between alternatives which leads to incorrect rankings, decreasing the accuracy of the algorithm. This phenomenon can often be difficult to visualise. To put it into context, it a high dimensional hypercube with side length $2r$ were placed into the a high dimensional space and it was inscribed with a hypersphere with radius r, almost all of the volume inside the hypercube would sit outside the hypersphere in this high dimensional space. [50] This shows, that in high dimensional Euclidean Space, the accuracy of the TOPSIS algorithm can be severely compromised.

3.1.5 Framework Candidate 5: AHP

AHP stands apart from the previously mentioned methodologies as it is fundamentally, a criteria weighting evaluation method. This is a critical characteristic that no other framework has. It is also the only method that offers a structured approach to decision-making. It does this by breaking down a universal set of criteria into smaller decision constellations, where the decision makers complete simple pairwise comparisons to express their preferences. These criteria preferences are then expressed as weightings. This creates engagement with the decision maker by allowing them to provide input on the weights used in the analysis. The data structure of criteria and sub-criteria is shown in Figure 3.1

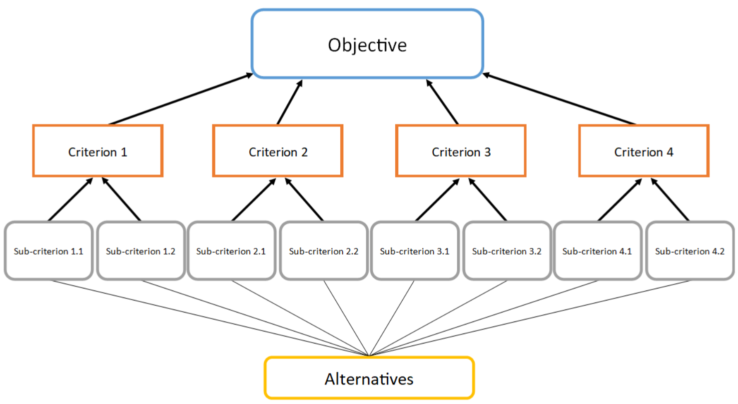


FIGURE 3.1: AHP criteria and sub-criteria structure

Each grouping of criteria require their own pairwise comparison table to determine their respective weightings. The set of comparisons required to complete the weightings in Figure 3.1 can be seen in Figure 3.2. Once weightings have been determined, alternative sub-criteria scores are passed into the network, where the respective weightings are applied. A singular score is produced for each alternative, which represents its overall performance across the selected decision criteria.

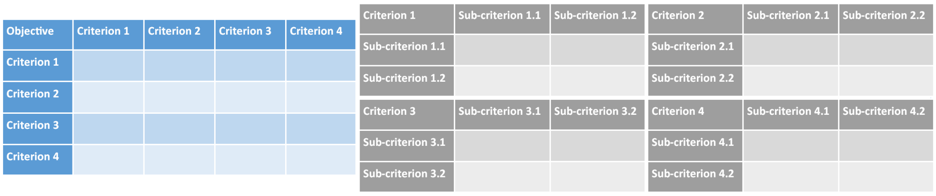


FIGURE 3.2: AHP criteria and sub-criteria pairwise comparison structure for Figure 3.1

Furthermore, this data structure allows means users can rapidly define a variety of MCDM models with different sets of sub-criteria and weightings. This offers flexibility to the user, allowing the decision maker to create and select tailored MCDM models that prioritise an appropriate set of sub-criteria for a task at hand. To bring some context to that statement, should Apian receive a job request that requires the urgent delivery of a specific item, for example a blood sample, a model that significantly prioritises drone speed as opposed to payload capacity could be created so that faster drones would be favoured in the decision making process.

There is no fixed or maximum value to the depth of a decision tree in AHP as seen in Section 2.7, a tree of 5 levels is possible should the underlying decision criteria be diverse enough. In the problem, as all the sub-criteria are related, a tree depth of no more than 2 should be considered. The maximum number of computations would occur when each parent criteria points has only a single sub-criteria attached to it. In this instance:

$$n_c = 2A(N+1) = O(n) \tag{3.3}$$

Equation 3.3 shows AHP has a time complexity of $O(n)$ with respect to the number of alternatives and the number of criteria. As was the case with TOPSIS, this poses no issues for large scale calculations. However, there is a further consideration with AHP. The user must define their preferences via a pairwise comparison. This is a function of number or criteria (N).

$$\text{Number of comparisons} = \frac{N(N-1)}{2} = O(n^2) \tag{3.4}$$

Equation 3.4 [33] shows that the time complexity with respect to the number of criteria is in fact $O(n^2)$. Furthermore, this methodology has no flexibility on the types of data it receives. AHP relies firmly on receiving continual, normalised data to ensure that sub-criteria that have inherently large values do not dominate the decision making process. This means external processes of data handling are required in this framework.

3.1.6 Framework Selection Justification

To justify the selection of AHP, the strengths and weaknesses of each strong candidate need to be highlighted in clear fashion. This is done in Table 3.4.

	Weighting generation?	Complexity w.r to A	Complexity w.r to N	Method of normalising data?	CoD?
PROMETHEE	✗	$O(n^2)$	$O(n)$	✓	✗
TOPSIS	✗	$O(n)$	$O(n)$	✗	✓
AHP	✓	$O(n)$	$O(n^2)$	✗	✗

TABLE 3.4: Summary of strong framework candidates

The complexity of the PROMETHEE method with respect to the number of alternatives (A) rules out this method for reasons highlighted in Section 3.1.3, and TOPSIS cannot be considered due to the high dimensional nature of the data potentially compromising the algorithm's effectiveness. This only leaves AHP. As highlighted by Table 3.4, there are still two drawbacks that need to be addressed before modelling can begin. The first is the high level of complexity with respect to the number of criteria (N). This is mitigated by the context of the problem. The number of criteria in this instance relates to the drone specifications and therefore has an upper limit of 17. This many criteria in a single comparison table corresponds to 153 comparisons. While this is a very large number of user inputs, it can be mitigated further by effectively using the hierarchy structure to divide the sub-criteria into groupings. This effect is shown in Table 3.5, the parent criteria columns are highlighted.

Number of groupings	1		2			3				4				
Number of Criteria	18	1	9	9	2	6	6	6	3	5	5	4	4	4
Number of comparisons	153	0	36	36	1	15	15	15	3	10	10	6	6	6
Total number of comparisons	153		73			48				38				

TABLE 3.5: Effect of AHP structure on the number of pairwise comparisons

The second drawback is that the drone data needs to be processed and normalised before being passed into the network. The main problem with this is that there is no one method that can be applied to all the criteria as the data is a combination numerical (both beneficial and non-beneficial) and non-numerical. The first step must be to assign discrete linguistic values, distinct numerical values that reflect their worth in an equivalent manor to the normalised continual data so these criteria can be passed through an AHP network. Once all criteria values are numerical, the second step is to normalise incoming data in each category so all values are between either 0 and 1. This ensures that criteria that have inherently larger values do not dominate the the formation of the final fitness score. This step is where the clarification between beneficial and non-beneficial data needs to be realised. For beneficial data, a high normalised score reflects a larger absolute criteria value whereas for non-beneficial data, a high normalised score reflects a smaller absolute criteria value, in other words, in these criteria, a lower value is desired. While the specific methodology to achieve this requires some additional consideration, it is very achievable.

3.2 AHP Methodology

Section 2.7 covered a preliminary introduction to AHP, looking at some of its strengths, weaknesses and how it holds up against other MCDM models in real world applications. Section 3.1.5 then looked at AHP in more detail, showing how sub-criteria can be arranged to form an AHP network and how the pairwise comparisons should be performed in that network. Finally, Section 3.1.6 covered the key shortcomings of AHP and highlighted work that would need to take place to mitigate said shortcomings. This section covers how weightings are calculated from a pairwise comparison table and how the consistency of a decision makers comparisons are verified.

There are four main methods by which one can derive relative weightings according to a hierarchical system: the eigenvalue method, the geometric mean method, the linear programming method and the lambda-max method. However, the eigenvalue method is the only one suited to handling crisp inputs to derive priority vectors, with the remaining approaches being used to handle fuzzy variables. As the drone specifications are crisp inputs - this is the method that has been considered. [51]

3.2.1 Creating and Completing a Pairwise Comparison Table

The pairwise comparison tables - examples of which can be seen in Figure 3.2 are the bedrock of AHP from which all weightings are calculated. The first step is to compare the n attributes in a pairwise manner to form a pairwise comparison matrix as seen below:

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & a_{2,3} & \cdots & a_{2,n} \\ a_{3,1} & a_{3,2} & a_{3,3} & \cdots & a_{3,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & a_{n,3} & \cdots & a_{n,n} \end{bmatrix}$$

Furthermore, when comparing attribute i with attribute j, this matrix must satisfy three properties:

$$a_{i,j} > 0 \tag{3.5}$$

$$a_{i,i} = 1 \tag{3.6}$$

$$a_{i,j} = \frac{1}{a_{j,i}} \tag{3.7}$$

To be perfectly consistent, the matrix should also align with the following relationships:

$$a_{i,j}a_{j,k} = a_{i,k} \tag{3.8}$$

$$a_{i,j} = \frac{w_i}{w_j} \tag{3.9}$$

Where w_i and w_j are the weightings for attributes i and j respectively. While relationships 3.8 and 3.9 are desirable, they are not required. Consistency does not have to be absolute. Instead it is governed by a critical value which must not be exceeded. This is explained in more detail in Section 3.2.3.

When it comes to allocating attribute pairwise scores, it is critical that a consistent set of importance definitions are used to avoid inconsistent comparisons. For this reason, AHP comes with a fundamental linguistic scale from which all attribute comparisons must be made. This can be seen in Table 3.6

Intensity of Importance	**Definition**	**Explanation**
1	Equal Importance	Two attributes contribute equally to the objective
2	Slight Importance	
3	Moderate Importance	Experience and judgment slightly favour one attribute over the other
4	Moderate Plus Importance	
5	Strong Importance	Experience and judgment strongly favour one attribute over the other
6	Strong Plus Importance	
7	Very Strong or Demonstrated Importance	An attribute is favoured very strongly over another. Its dominance is displayed in practice
8	Very, Very Strong Importance	
9	Extreme Importance	Evidence favouring one attribute over another is of the highest possible order of affirmation
Reciprocals of above	If attribute i has an assigned importance relative to attribute j then attribute j will have the reciprocal of this importance when compared to i	Ensures a certain level of rationality in the decision making.

TABLE 3.6: Linguistic Definitions of Importance Intensities in AHP [32]

3.2.2 Calculating Attribute Weightings

One of the essential steps in AHP is to obtain the weightings or priorities of the criteria or alternatives from the positive reciprocal pairwise comparison matrix, which reflects the decision-makers' judgments about the relative importance of each element. However, the complexity and size of the pairwise comparison matrix can make analysis difficult, especially when dealing with numerous criteria or alternatives. To overcome this challenge, AHP employs the eigenvector method to analyse the pairwise comparison matrix and determine the weightings or priorities of the criteria or alternatives. The eigenvector method utilises mathematical concepts such as eigenvalues and eigenvectors to identify the most significant features of the matrix. However, the reason why eigenvalues and eigenvectors are used isn't entirely clear at first glance. The creator of AHP, Thomas L. Saaty, wrote a separate piece of literature in 2001 explaining why principal eigenvectors are necessary when determining attribute weightings. [52]

The weightings for each attribute are stored in a priority vector. This is what needs to be determined. The ranking in this vector must incorporate the level of intensity or cardinal preference, as indicated by the ratios of the numerical values in the positive reciprocal pairwise comparison matrix. Ultimately it comes down to a single definition - a priority vector must remain invariant under the hierarchic composition principle. In other words, to preserve the strength of preferences, when applied to an attribute preference matrix, a priority vector must be able to reproduce itself on a ratio scale, as it is these ratios that maintain consistency in the users decision making process. Furthermore, the priority vector must remain invariant when multiplied by some constant k. From this information, the following relationship can be defined:

$$\mathbf{A}x = kx \tag{3.10}$$

Saaty then goes on to prove the following theorem:

"For a given positive matrix $\mathbf{A}$, the only positive vector x and only positive constant k that satisfy $Ax = kx$, is a vector x that is a positive multiple of the Perron vector (principal eigenvector) of $\mathbf{A}$, and the only such k is the Perron value (principal eigenvalue) of $\mathbf{A}$."

The principal eigenvalue is the largest eigenvalue of a square matrix and it is denoted by λ_{max} and plays a key role in checking the consistency of the users preference allocations. This value is paired with the principal eigenvector. This is the non-standardised priority vector. The final step in deriving the final priority vector is to normalise the principal eigenvector. This is done quite simply by dividing each element in the vector by the sum of all elements. An example of how the priority vector of a 3x3 pairwise comparison matrix is calculated can be found in Section A.1 of the Appendix.

3.2.3 Checking Matrix Consistency

The consistency of a pairwise matrix is measured by the consistency ration (CR), which in turn is a function of the consistency index (CI) and a random index (RI). The CI, as defined by Saaty, measures the inconsistency of a positive reciprocal pairwise comparison matrix.

$$\text{CI} = \frac{\lambda_{\text{max}} - n}{n - 1} \tag{3.11}$$

Where λ_{max} is the principal eigenvalue for square pairwise comparison matrix of size n. If the matrix is perfectly consistent, then λ_{max} is equivalent to the size of the matrix and the CI is zero. As inconsistency between comparisons increases, so does the principal eigenvalue and therefore consistency index, which is a measure of the degree of inconsistency in the decision makers comparisons.

The CR measures the degree of which the decision-makers deviate from a consistent set of judgments. It is defined as the ratio of the CI to the mean CI from a large sample of randomly generated matrices.

$$\text{CR} = \frac{\text{CI}}{\text{Mean Random CI}}$$

However, it isn't feasible to average the the CI of hundreds of randomly generated pairwise comparison tables every time a CR is calculated. For this reason, Saaty developed a third metric - the random index. This index is a list of reference values correlating the Mean Random CI for different size pairwise comparison tables using the method given above. Table 3.7 shows these values.

	n									
	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

TABLE 3.7: RI vales for n = 1-10

This leads to the final equation when calculating the CR:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3.12}$$

Saaty claimed that for a pairwise comparison table to be regarded as consistent, the CR should be less than 0.1 although a CR between 0.1 and 0.2 is considered tolerable. [53]

3.3 Modelling an AHP Production Tool in Python.

There are two key stages when it comes to creating such a tool. The first is devising an intuitive user interface (UI) through which decision makers can define their own hierarchy structure and complete all necessary pairwise comparisons. This UI needs to be simple to use and must be able to enforce Properties 3.5, 3.6 and 3.7. The second is to design a program that can read in the UI output, interpret the hierarchy structure, calculate weightings, check consistency and return a data structure in such a format that attribute scores can be passed through it to compute a fitness score. Furthermore this process needs to be repeatable, so that the only change necessary when creating a new model is altering values in the UI so multiple AHP models can be created with ease.

3.3.1 Building a User Interface

A good starting point for developing a UI is *Microsoft Excel*. It is highly adaptable, easy to understand and simple to use. There is a clear downside to using it and that is, it puts a limit on the size and depth of the tree. This limit was set at a depth of 2 and a width of 5 meaning a hierarchy can have, at most 5 sub-criteria groupings each pointing to a single parent criteria which in turn feed directly into the objective. An explination for these dimensions can be found in Table 3.11

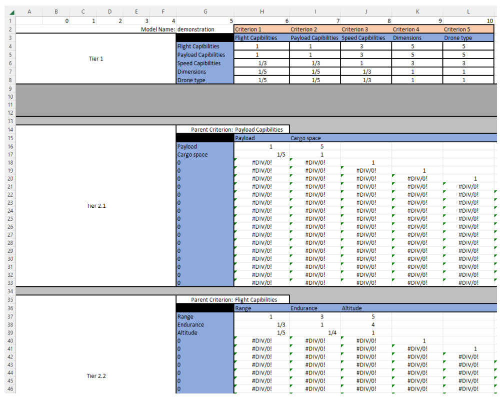


FIGURE 3.3: Snippet from the *Microsoft Excel* UI

Figure 3.3 shows a section of the proposed UI. This program uses the Data Validation Lists for large portion of the inputs. These lists only allow users to input values from a predetermined list. This ensures that pool of attributes points to one of the parent criteria defined in Tier 1. It also guarantees that Properties 3.5 and 3.6 are enforced as users can only enter values that are defined in Table 3.6. Furthermore, formatting equations are used in the bottom left hand values on of all the pairwise comparison tables. This not only saves saves the user alot of time, it also also enforces Property 3.7. An additional downside of using *Microsoft Excel* is that it creates a scope for errors in the format of the users input. For example, a user could fill in Tier 2.4 before they've filled in 2.3, or an attribute grouping may not be assigned a parent criterion. This means that an additional program needs to be created to vet the formatting of the user input, to ensure it is fit to pass into the AHP production program. It is important that if a formatting mistake is discovered an informative and comprehensive error message is returned so it can be rectified with ease.

3.3.2 Vetting User Input Format

As mentioned in the previous section, using *Microsoft Excel* grants the users a lot of flexibility with the format of their input. For this reason the format of the user input needs to be scrutinised before being passed into the AHP production tool. By enforcing a rigid formatting structure all errors associated with the interpreting of the user input should be removed and if a formatting error is encountered, the user can be informed and the program can be terminated prematurely and in a controlled manner. To be passed into AHP model there are 5 key rounds of formatting checks that the user input must pass

1. Valid model name must be present and in the correct location.
2. Each sub-criteria grouping must point to a distinct parent criteria. Sub-criteria groupings must also be completed sequentially.
3. Each parent criteria and sub-criteria can only appear exactly once.
4. Parent criteria and sub-criteria must be inputted sequentially (from left to right) in their respective pairwise comparison table.
5. All criteria and sub-criteria comparison tables must be complete.

The format tests are run in that order. If an error is encountered, the user is informed of the error and the program halts. If all these tests are passed, the input is ready to be passed into the AHP production tool. Comprehensive pseudo-code for these processes can be found in Section A.2 of the Appendix.

3.3.3 AHP Production Dataflow

The final piece of this tool is to determine how the hierarchy structure defined in Section 3.3.1 can be interpreted in code and the calculations seen in Sections 3.2.2 and 3.2.3 can be applied. The difficulty of this challenge lies with the former. The fundamental unit of an AHP instance is attribute clustering (a tier of sub-tier of the network). Each of these units share an underlying structure - a list of attributes and a pairwise comparison table from which a priority vector and CR can be calculated. Python supports three main programming paradigms: functional, procedure orientated, and object oriented. [54]. When the problem is viewed in this way, it is clear that an object oriented programming paradigm is the appropriate choice. Section 3.3.3 demonstrates why.

Object oriented programming paradigms

An object in Python is essentially an instance of a class that comprises both data members and method functions. A class is simply a template by which objects are created. Each object has its own set of data and methods according to the blueprint defined in the class initialisation. A simple class and object can be seen below.

```
class Book:
    def __init__(self,release,author,title):
        # Initial parameters inherent to the class
        self.release = release
        self.author = author
        self.title = title
    def years_since_published(self)
        # Additional values calculated via a method
        self.years_since_published = 2023 - self.release
        return self.years_since_published
great_gatsby = Book(1925,"F. Scott Fitzgerald","The Great Gatsby")
print(great_gatsby.author)
print(great_gatsby.years_since_published())

>> F. Scott Fitzgerald
>> 98
```

This style of coding can be quickly redeployed to effectively encapsulate similar groupings of data. This is perfect in this application. The inherent data sets are the associated (sub-)criteria and the pairwise comparison table and there are be three methods, one to calculate a priority vector, another determines the whether the pairwise table is consistent and the third expresses the weightings as a dictionary where each weighting is linked to its respective (sub-)criteria. The proposed architecture can be seen in Figure 3.4 in an equivalent format to Figure 3.1 and the complete code for the definition of the AHPTier class can be found in Section A.3 of the Appendix.

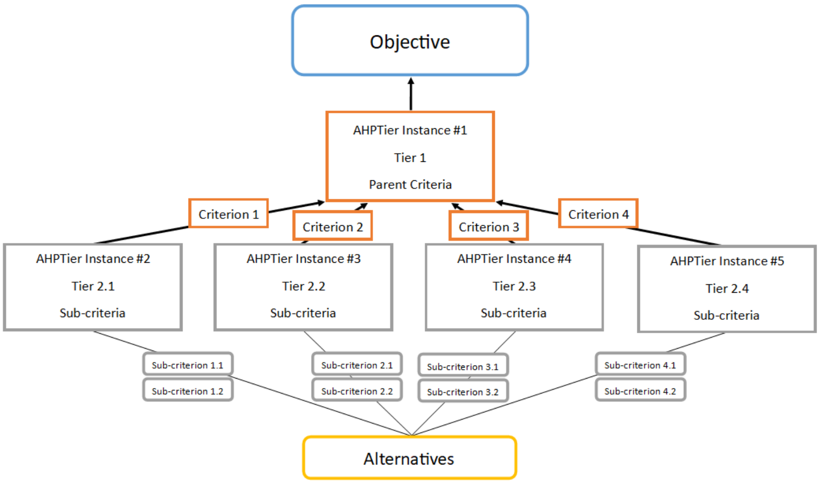


FIGURE 3.4: AHP criteria and sub-criteria class instance structure

Instances of the AHPTier class are iteratively created for each sub-criteria grouping in the user input. Once the consistency of each instance has been verified, the weightings for each are exported to a global sub-criteria weightings dictionary. A dictionary consists of a collection of key-value pairs. Here, each key is a parent criterion and each value is the weightings dictionary created by class. This ensures that output scores of each sub-criteria grouping is directed to the correct parent criterion for the final calculation of fitness scores. The parent criteria weightings dictionary and the global sub-criteria weightings dictionary are then exported as a single PKL file. This file will allow the model to be loaded and deployed at a later date in a separate script to calculate match scores for candidate drone models.
Also exported is an output log file. This is where all the underlying processes that have taken place are displayed. Should an error occur with the formatting or consistency checks, the error message will be shown in this log file. The final resource this model generates is a comma-separated values (CSV) file that presents the sub-criteria employed in the model as column headers in the top row. This CSV file is utilised as the input location for drone data when the scores are calculated. Collectively the PKL, log file and input CSV are exported to a unique folder in the working directory. The file name is be the same as the model name. Detailed pseudo-code for this process can be found in Section A.4 of the Appendix.

3.4 Normalisation of Drone Parameters

As mentioned in Section 3.1.6, AHP replies on normalised data so that sub-criteria that have inherently large values do not dominate the decision making process. Drone parameters have three types of variables: numerical beneficial, numerical non-beneficial, and non-numerical. Normalisation values are between 0 and 1. For beneficial data, higher raw values correspond to higher normalised values, and for non-beneficial data, lower raw values correspond to higher normalised values. Non-numerical values are assigned values on a case-by-case basis based on each outcome's desirability, while numerical data uses a 'scaling to range' method.

Numerical Data 'Scaling to range' means that all values are represented as a portion of the range of the data set. In this case, a data set contains the values in a specific criterion for each drone alternative. In this way the best value in a group of alternatives receives a score of 1 and the worst receives a score of 0. If the parameter is non-beneficial, the normalised data is simply inverted by subtracting it from 1. Primitive examples of this normalisation can be found in Tables 3.8 and 3.9.

Non-numerical data This is done on a case-by-case basis for each relevant drone parameters, of which there are two: Propulsion type and VTOL capabilities. The allocated normalised values are shown in Table 3.10 and the reasoning for these values can be found in Table 3.11.

Equation: $a_{\text{norm}} = \frac{a - a_{\text{min}}}{a_{\text{max}} - a_{\text{min}}}$

a	a_{norm}
1 (a_{min})	$\frac{0}{4} = 0$
3	$\frac{2}{4} = 0.5$
5 (a_{max})	$\frac{4}{4} = 1$
4	$\frac{3}{4} = 0.75$
2	$\frac{1}{4} = 0.25$

TABLE 3.8: Beneficial data normalisation

Equation: $a_{\text{norm}} = 1 - \frac{a - a_{\text{min}}}{a_{\text{max}} - a_{\text{min}}}$

a	a_{norm}
1 (a_{min})	$1 - \frac{0}{4} = 1$
3	$1 - \frac{2}{4} = 0.5$
5 (a_{max})	$1 - \frac{4}{4} = 0$
4	$1 - \frac{3}{4} = 0.25$
2	$1 - \frac{1}{4} = 0.75$

TABLE 3.9: Non-beneficial data normalisation

Parameter	Parameter Value	Normalised Value
Propulsion Type	Electric	1
	Hybrid	0.5
	Other	0
VTOL Capabilities	True	1
	False	0

TABLE 3.10: Normalised values for non-numeric drone parameters

Pseudo-code showing how this method would be applied to an input drone data set can be found in Section A.5 of the Appendix.

3.5 Methodology Assumptions

MCDM is a field that acknowledges the complexity and subjectivity inherent in decision-making processes and does not rely on strict assumptions. Rather, it aims to provide a flexible framework that allows decision-makers to evaluate alternatives based on multiple criteria while taking into account their specific preferences. While MCDM methods generally do not rely on many assumptions, the few that have been made in this methodology are listed in Table 3.11.

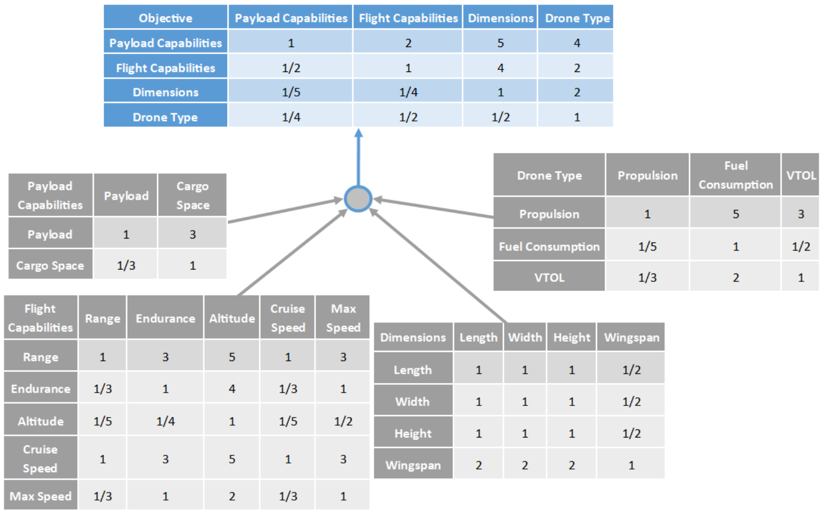
Assumption	Justification
AHP structures have a maximum width of 5	There are 17 drone parameters, a width of five averages at 3.4 attributes per sub-criteria grouping. Fewer slightly larger comparison tables are favourable compared to lots of small ones as if reduces the potential for inconsistencies and makes the results more interpretable.
AHP structures have a maximum depth of 2	As all decision criteria are in the category of drone parameters, two layers is sufficient to categorise the data. Each parameter grouping is summarised by a single parent criteria.
Electric drone models are more desirable	Section \ref{sec:emissions} demonstrated how environmentally unsustainable the current supply chain is. Petrol powered drone models would be adding to this problem and is therefore undesirable.
VTOL models are preferable	Drone models with VTOL capabilities are more flexible as they do not require runway facilities.
There will be no more than 10 attributes per grouping	$n = 10$ is the upper limit on the RI, furthermore if over half of the sub-criteria are in a single grouping , the AHP structure will be very inefficient as model attribute weightings would become very similar defeating the purpose of this study.

TABLE 3.11: Methodology assumptions

4. Results and Discussion

4.1 Model Output

To verify the model runs as expected and produces a usable output, a stratified sample of pairwise comparison tables were created to form a rigorous test set, specifically designed to assess the model's performance and validate its efficacy. These attribute comparisons were designed to emulate a prototypical delivery job scenario, in order to thoroughly test and benchmark the model's performance within the relevant context. The proposed hierarchical structure for the drone attributes is shown in Figure 4.1.



Objective	Payload Capabilities	Flight Capabilities	Dimensions	Drone Type
Payload Capabilities	1	2	5	4
Flight Capabilities	1/2	1	4	2
Dimensions	1/5	1/4	1	2
Drone Type	1/4	1/2	1/2	1

Payload Capabilities	Payload	Cargo Space
Payload	1	3
Cargo Space	1/3	1

Drone Type	Propulsion	Fuel Consumption	VTOL
Propulsion	1	5	3
Fuel Consumption	1/5	1	1/2
VTOL	1/3	2	1

Flight Capabilities	Range	Endurance	Altitude	Cruise Speed	Max Speed
Range	1	3	5	1	3
Endurance	1/3	1	4	1/3	1
Altitude	1/5	1/4	1	1/5	1/2
Cruise Speed	1	3	5	1	3
Max Speed	1/3	1	2	1/3	1

Dimensions	Length	Width	Height	Wingspan
Length	1	1	1	1/2
Width	1	1	1	1/2
Height	1	1	1	1/2
Wingspan	2	2	2	1

FIGURE 4.1: Pairwise structure for a typical delivery job

This hierarchy structure was translated to the UI and the AHP model creation script was applied to it. This script first applies the checks described in Section 3.3.2. Once these checks have been passed, it proceeds onto the calculations and subsequent consistency checks that are described in Section 3.3.3. As the UI had sound formatting and consistent comparisons, the model was created with no errors. Figure 4.2 shows all the outputs of the model creation script.

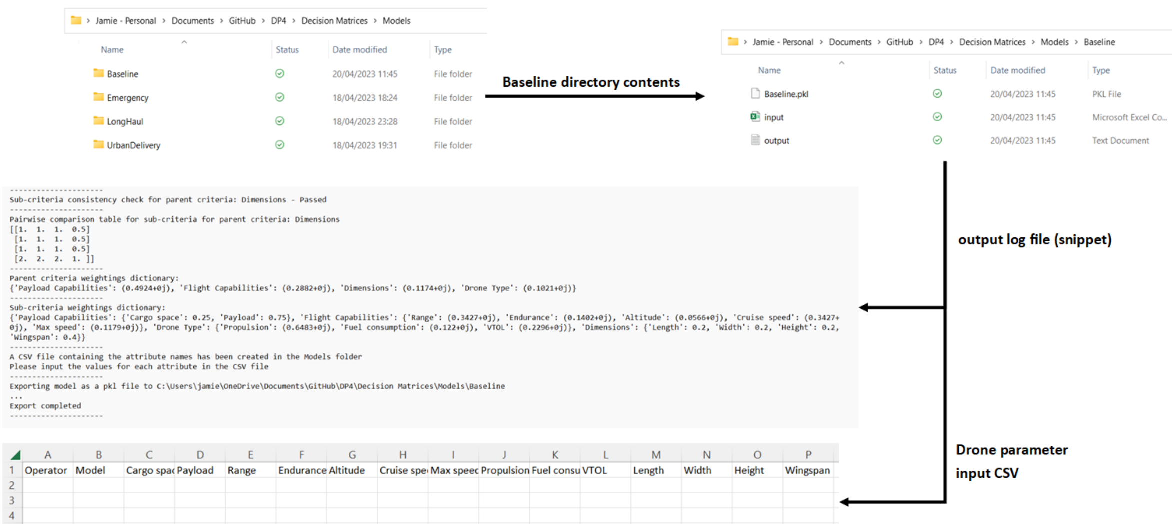


FIGURE 4.2: Model creation - outputs

Now that an AHP model has been established, it can be used to compare drone candidates. The relevant parameters for each candidate should be entered into *input.csv* (the generated CSV file). The output of the score calculations can be seen in Section 4.3. The complete weightings for the baseline model are in Tables 4.1 to 4.5.

Payload Capabilities	Flight Capabilities	Dimensions	Drone Type
0.4924	0.2882	0.1174	0.1021

TABLE 4.1: Parent Criteria Weightings

Payload	Cargo space
0.75	0.25

TABLE 4.2: Payload Capabilities Weightings

Range	Endurance	Altitude	Cruise Speed	Max Speed
0.3427	0.1402	0.0566	0.3427	0.1179

TABLE 4.3: Flight Capabilities Weightings

Length	Width	Height	Wingspan
0.2	0.2	0.2	0.4

TABLE 4.4: Dimensions Weightings

Propulsion	Fuel Consumption	VTOL
0.6483	0.1220	0.2296

TABLE 4.5: Drone Type Weightings

The obtained weightings corroborate the model's efficacy by aligning with the pairwise comparisons, thus affirming the model's ability to accurately capture and quantify the relative preferences of the evaluated criteria. Another, less effective observation is that all weightings are positive and each grouping sums to 1. This is in accordance with the normalisation of the weightings and will ensure accurate probabilistic interpretations of each alternative and facilitate meaningful, comparisons in the decision making process.
When tested, formatting errors and inconsistent decision matrices were also detected successfully with specific error messages being returned to the log file. Sample output messages for both successful and a variety of unsuccessful model creations can be found in Section A.6 of the Appendix.

4.2 Model Validation Strategy

The objective of this project is to create a tool that will allow for the creation of multiple MCDM models in which criteria importance can be altered in such a way that each model is tailored for a specific job type. To assess whether this goal has been achieved, three things need to happen.

1. A variety of delivery scenarios need to be devised that demand the prioritisation of different drone attributes.
2. Pairwise comparison tables and the subsequent priority vectors need to be derived for each of these scenarios.
3. A mock database of potential drone candidates needs to be constructed.

Once these tasks have been complete, normalised drone data can be passed through each of the scenario models and produce fitness scores for each of the candidates. These scores can be used to assess this tool's ability to create models that prioritise different attributes.

4.2.1 Delivery Scenarios

Four realistic and distinct examples will be used.

Scenario 1 - An emergency delivery of an organ or other perishable object.

In this scenario, speed and wind resistive capabilities are key to ensure that payload is delivered as quickly as possible. Furthermore, attributes that increase maneuverability and add delivery flexibility such as VTOL capabilities and drone dimensions should be considered. Some standard features such as payload capacity are less important in this instance and other more niche criteria such as propulsion mechanism can be discounted entirely.

Scenario 2 - A long haul, large scale delivery of COVID-19 vaccinations.

For a standard, high volume, long distance delivery, emulating the work done by HGV's, the five main priorities are cargo space, maximum payload mass, range and endurance. In instances such as this, the speed of the drone plays less of an important role and criteria such as propulsion mechanism, dimensions and altitude should only be considered in a minor capacity.

Scenario 3 - A restock of standard pharmaceuticals to a facility in an urban centre.

When delivering to an urban centre, it is a safe assumption that there will be no runway available so VTOL drone models are required. Furthermore, to aid with both noise reduction and align with any urban emissions regulations, an electric motor is preferable to internal combustion engine (ICE). Finally, to maximise maneuverability and remain in line with all local aviation regulations, drone dimensions should be minimised as a priority.

Scenario 4 - Baseline

The model derived in Section 4.1 for a 'typical' delivery will be used as a baseline to which other model results will be compared. This model considers almost all drone attributes and should return the drone that is overall most suited to cargo transportation. Ideally the results from this validation will show that the adjusted weightings offered by the models devised for scenario's 1-3 are enough to change this order so that the more suitable drone will be selected for the job at hand.

Summary of Delivery Scenarios

	Scenario 1 (Emergency)	**Scenario 2 (Large, long-haul deliveries)**	**Scenario 3 (Small-scale urban deliveries)**	**Scenario 4 (Baseline)**
Prioritised Drone Attributes	- Cruise Speed - Max Speed - VTOL	- Payload Capacity - Cargo Volume - Range - Endurance - Cruise Speed	- Dimensions - VTOL - Propulsion type	- Payload Capacity - Range - Cruise Speed

TABLE 4.6: Prioritised sub-criteria for each scenario

Exact weightings for each scenario can be found in Section A.7 of the Appendix

4.2.2 Drone Candidates

Drone 1 - AirLogiX Hammerhead eV20

The Hammerhead eV20 Delivery Drone [55] is an electric tilt-rotor vertical take-off and landing (EVTOL) model. It is a small/medium model and is very light for its size granting it a relatively fast top speed of 84mph. This model trades off speed for range and payload capacity, having a limit of 100km and a 20kg respectively.

FIGURE 4.3: Hammerhead eV20 Delivery Drone

Drone 2 - UAVOS Albatross 2.2

The Albatross 2.2 [56] is a medium altitude long endurance unmanned aircraft and is designed to operate in harsh conditions. It boasts an remarkable range of 2255km at a cruising speed of 90mph. It is large model having a wingspan of 15 metres. Its payload capacity of 250kg making it well suited for cargo delivery. There are some significant drawbacks. Being a fixed wing model means it does not have VTOL capabilities and requires a 770m runway to operate. Additionally, it runs off a petrol engine and consumes fuel at a rate of 13 litres/hour.

FIGURE 4.4: UAVOS Albatross 2.2 Fixed-wing UAV

Drone 3 - Plymouth Rock XV-L

The XV-L [57] is a lithium polymer/ICE hybrid. It is a lightweight, long range, high speed vehicle, with a cruise speed of 70mph and a top speed of 105mph over a range of 793km (with cellular communication modules). On top of this it is a fixed-wing VTOL hybrid, having four upward facing rotors for lift and a single rear propeller for thrust as seen in Figure 4.5. This model is not suitable for large-scale cargo deliveries, having a maximum payload capacity of only 25kg.

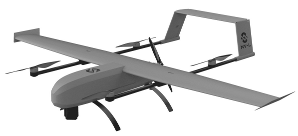


FIGURE 4.5: PLYROTECH XV-L Fixed-wing VTOL Drone

Summary of Drone Candidates

	Hammerhead eV20	Albatross 2.2	XV-L
Drone Summaries	- Short range - EVTOL - Moderately fast - Small payload capacity - Medium/small in size	- Long range - Fast model - Large in size - Fixed wing - ICE - High payload capacity	- Medium/long range - Fast model - Medium/small in size - Hybrid engine - VTOL - Small payload capacity

TABLE 4.7: Summary of candidate drone attributes

4.3 Model Validation Results

Using the scenario descriptions in Section 4.2.1, the AHP linguistic definitions in Table 3.6 and intuition, pairwise comparison tables were defined for each scenario using the tools shown in Section 3.2 and 3.3. Before the models could be tested, a script that can calculate alternative scores had to be created. This work package was split into two distinct sections. The first is the normalisation of the raw drone data in the input CSV in the model directory. The second was passing the normalised data through the calculated AHP models.

For the normalisation of the raw data, the processes laid out in Section 3.4 were applied iteratively to each column of input data.

The computation of alternative scores entailed two distinct sections. The first section involved calculating the weighted normalised scores for each sub-criteria, achieved by multiplying the normalised data of the sub-criteria with the corresponding sub-criteria weightings. The second section was summing the weighted normalised sub-criteria scores for each sub-criteria pool, and subsequently multiplying it by its respective parent criterion weighting. Finally, the resulting weighted criteria values were aggregated to give the final fitness score.

Figures 4.6 shows the parameter inputs for the three drone candidates for the Baseline model. It then shows the output from the normalisation and score calculation script. Each drone attribute column in the output shows the normalised weighted attribute score. The parent criteria columns represents the weighted sum of the attribute columns for each sub-criteria in it grouping. Finally, the alternative score column shows the sum of the parent criteria score columns.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	Operator	Model	Payload	Cargo spac	Range	Endurance	Altitude	Cruise spe	Max speec	Propulsion	Fuel consu	VTOL	Length	Width	Height	Wingspan
2	UAVOS	Albatross 2	250	200	2255	660	23,600	90	130	Petrol	13	n	6.5	15	1.82	15
3	AirLogiX	Hammerhe	20	95	100	60	1,482	56	84	Electric	0	y	2.9	4.7	0.75	4.7
4	Plymouth I	XV-L	25	100	793	420	15000	70	105	Hybrid	12	y	3.4	4.5	0.8	4.5

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	Payload Ca	Flight Capa	Drone Typ	Dimension	Operator	Model	Cargo spac	Payload	Range	Endurance	Altitude	Cruise spe	Max speec	Propulsion	Fuel consu	VTOL	Length	Width	Height	Wingspan	Alternative Score
2	0.4924	0.288229	0	0	UAVOS	Albatross 2	0.25	0.75	0.3427	0.1402	0.0566	0.3427	0.1179	0	0	0	0	0	0	0	0.78062882
3	0	0	0.10209	0.116058	AirLogiX	Hammerhe	0	0	0	0	0	0	0	0.6483	0.122	0.2296	0.2	0.19619	0.2	0.392381	0.218148076
4	0.01389	0.122154	0.057496	0.113042	Plymouth I	XV-L	0.011905	0.016304	0.110205	0.08412	0.034593	0.141112	0.053824	0.32415	0.009385	0.2296	0.172222	0.2	0.190654	0.4	0.306582323

FIGURE 4.6: Input and output of the score calculation script for Baseline model

The CSV of weighted normalised attribute parameters and fitness scores is appended to the model directory. These results can be regenerated at any time if the model parameters are changed or a new set of alternatives need to be considered.

Once these processes had been created, candidate fitness scores can be calculated for each delivery model. Figure 4.7 shows a bar chart of the scores for each drone candidate in each delivery scenario. A step-by-step guide to using this architecture, from inputting attribute comparisons in the UI through to generating alternative scores can be found in Section A.8.

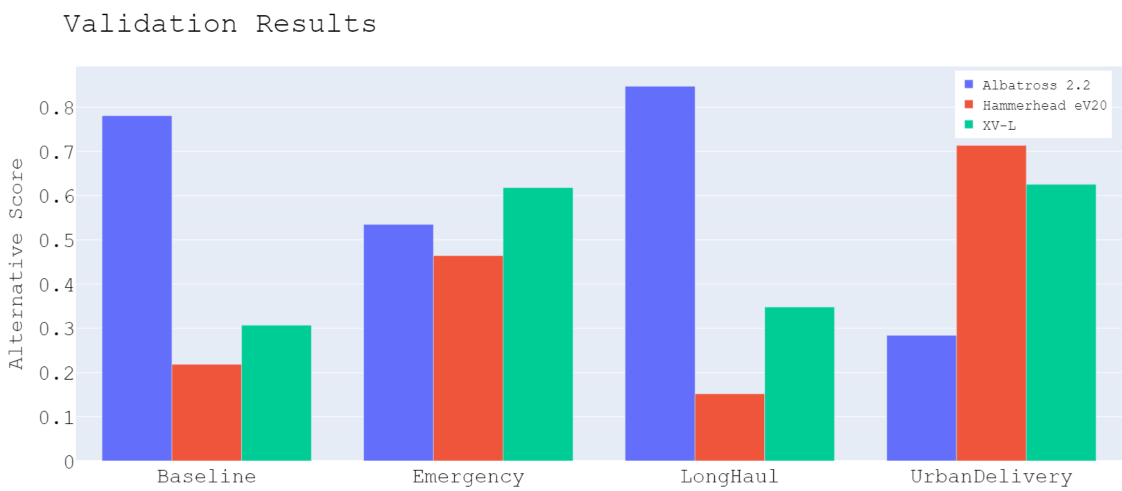


FIGURE 4.7: Match scores for each drone candidate in each scenario

4.3.1 Results Analysis

Baseline Results (Scenario 4) These are the results for a 'typical' delivery. The prioritised attributes were payload capacity, range and cruise speed. Having the highest score in all the heavily weighted attributes, the Albatross 2.2 significantly outperformed the other models.

Emergency Results (Scenario 1) The primary criteria for the emergency response model were: cruise speed, top speed and VTOL capabilities. These were supplemented in a minor capacity by drone dimensions, which is a non-beneficial variable and will therefore sought to be minimised, and range. XV-L was the strongest in candidate in this situation due to its high speeds, VTOL capabilities, small size and moderate range. The XV-L outperformed the Albatross 2.2 in this instance despite it being faster and having a superior range. This was due to its large frame and its lack of VTOL capabilities.

Long Haul Results (Scenario 2) The long haul model is a specialised variant of the Baseline, incorporating prioritised attributes tailored for long-range cargo deliveries, such as maximum cargo volume and endurance. It intentionally omits certain secondary criteria, such as VTOL capabilities. The Albatross 2.2 demonstrates exceptional performance in terms of maximum cargo volume and endurance. Therefore, it is unsurprising that it outperforms other models by an even wider margin than the Baseline model.

Urban Delivery Results (Scenario 3) The urban delivery scenario differs from other scenarios in that it considers traditional drone attributes, such as range, speed, and payload capacity, to a lesser extent. This model strongly favors small drones with VTOL capabilities and electric propulsion systems. As a result, the Hammerhead eV20, which is the only model possessing all these attributes, receives a higher score than the other alternatives, despite its relatively weaker performance in other scenarios. Moreover, the Albatross 2.2, which has consistently scored highly in other scenarios, performs poorly in this scenario, indicating its unsuitability for urban delivery operations.

Summary As mentioned previously, the measurement of the effectiveness of the model will be evaluated by its ability to not only increase the scores of more suitable drone models, but to elevate them to a degree where they achieve a higher ranking on the list of alternatives. compared to the Baseline model. Table 4.8 shows the raw data for the validation results.

	Baseline score	Emergency score	Long haul score	Urban delivery score
Albatross 2.2	0.780629	0.534600	0.847434	0.283700
Hammerhead eV20	0.218148	0.464157	0.151741	0.713476
XV-L	0.306582	0.617997	0.347835	0.625277

TABLE 4.8: Summary of validation results

From these results it is clear to see that the different models have not only caused significant changes in the drone candidate fitness scores but also, as highlighted, in the drone candidate rankings, consistently giving the highest score to the model that is most suitable for the job at hand. From these findings it wouldn't be unreasonable to assume that this modelling methodology is functioning as expected. However, this will be assessed in more detail in Section 4.3.2

4.3.2 Model Variation Analysis

In order to gain further insights into the generated models, a model variation analysis was conducted on each of the established non-baseline AHP instances. The analysis assesses the impact of changes in parent criteria weightings on candidate fitness scores, with the aim of linking changes in criteria weightings and drone candidates attributes to the final ranking of alternatives. Prior to conducting the analysis, it is important to note that it will solely focus on the direct manipulation of criteria weightings, rather than the underlying pairwise comparison tables or sub-criteria weightings. Analysing individual attribute comparisons would introduce an excessively high level of dimensionality to the analysis, rendering it computationally infeasible and exceedingly challenging to visualise.

There is an additional assumption that must be made. This assumption arises from the fact that all weightings in any priority vector must sum to 1, making it impossible to study the effect the variation of a single weighting. So, it was determined that the collective difference in the weightings of analysis variables between the original model and the modified model would be uniformly redistributed across the remaining criteria. For instance, in a model with three criteria, if one weighting was increased by 0.1, the weightings of the other two would subsequently be decreased by 0.05 each as a balanced adjustment.

The first model considered was the 'UrbanDelivery' model. This example exhibited the most distinct results, with alternative rankings that are inverted compared to the baseline model. Figure 4.8 shows how collective variations in the two primary criteria weightings, dimensions and drone type (which account for 71.64% of the total criteria weighting in the original model), influence the candidate selection of the model. The first observation that can be drawn from this heat map is that when, collectively, the drone type and dimension weightings no longer account for the majority of the weighting, the superior speed, range and payload capabilities of the Albatross 2.2 cause it to become the dominant candidate. Furthermore, this graphic demonstrates that that when the weightings of just the drone type criterion, which the XV-L doesn't score as well in due to its hybrid engine, is redistributed to the

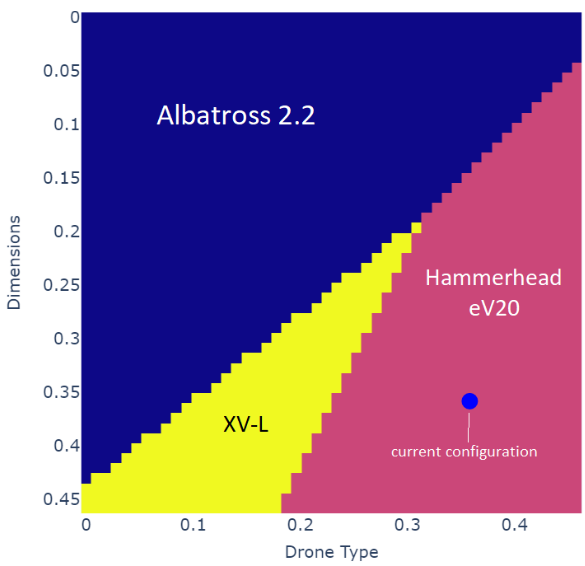


FIGURE 4.8: Variation of primary criteria weightings of the 'UrbanDelivery' model

speed, range and payload capabilities, while maintaining a high priority on drone dimensions the XV-L, which has a high performance in most of these areas becomes the preferred candidate.

An equivalent analysis was applied to the emergency model, where the primary weightings were speed capabilities and drone type, accounting for 77.65% of the candidate fitness score. These are supplemented by dimensions and range capabilities. Figure 4.9 shows these results. The behaviour displayed on this graphic is simple to explain. When balance of weighting is shifted significantly toward speed capabilities, the Albatross, being the fastest model, will dominate and when the balance is shifted toward VTOL capabilities and propulsion type, the Hammerhead, due to its purely electric propulsion system, will dominate. The XV-L, once again, acts as the middle ground between this alternatives by striking a clear balance between between the two completing criteria. The unplotted space in the bottom right hand corner of Figure 4.9 refers to space where the redistribution of criteria weighting has resulted in a criteria weighting being less than zero. In such instances, weightings would have to be redistributed asymetrically therefore these instances of the model were removed from the analysis.

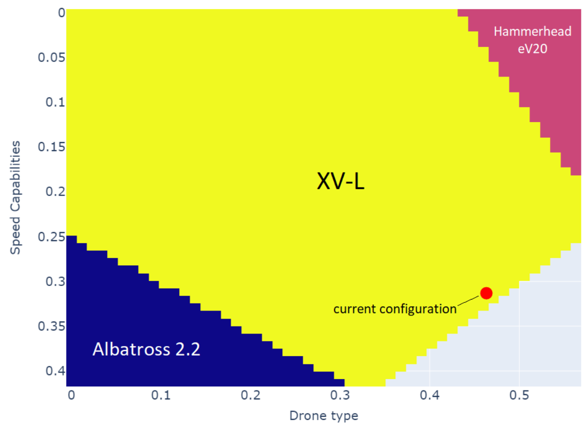


FIGURE 4.9: Variation of primary criteria weightings of the 'Emergency' model

Finally, this analysis was applied to the 'LongHaul' delivery model. The results in Table 4.8 state that the Albatross 2.2 was clearly the most appropriate candidate for this delivery scenario. The primary weightings for this model were payload capabilities and flight capabilities, each accounting for 33.66% of the candidate fitness score. The results can be seen in Figure 4.10

These outcomes confirm the findings presented in Table 4.8, showing that the Albatross 2.2 dominates the solution space. The only way the Albatross 2.2 can be challenged by diminishing the weightings of flight and payload capabilities to a near insignificant extent, which tilts the model weighting towards the secondary criteria - speed capabilities, drone type (VTOL capabilities and propulsion type), and drone dimensions, ultimately defeating the purpose of this model. This adjustment renders the XV-L as the favored candidate, for the reasons seen in the 'Emergency' model. The Hammerhead eV20 does not appear as the selected candidate in this analysis as, at no point, are its primary strengths (VTOL capabilities and drone dimensions) the primary focus of this model, meaning its weak normalised scores in speed, range and payload capabilities permanently hinder its ability to be selected over the other models.

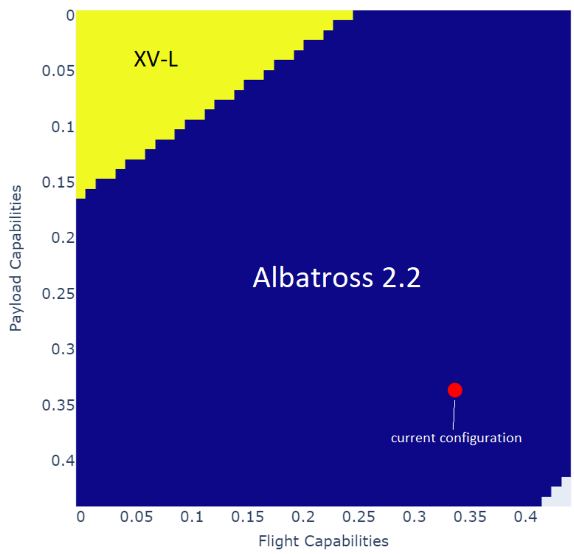


FIGURE 4.10: Variation of primary criteria weightings of the 'LongHaul' model

These studies show that, in certain cases, striking an appropriate balance between competing criteria is vital in ensuring the optimal drone candidate is selected. In addition to this the fact that the behaviour being demonstrated by these plots can easily be explained by simply knowing the the strengths weaknesses and general characteristics of each of the candidate drones validates the work being done by the underlying AHP models in that transitions in criteria weightings are producing the expected changes in drone candidate allocation.

4.4 Discussion

4.4.1 Current model limitations

Limited hierarchy size The current version of this AHP tool puts a limit on the size of the hierarchy that can be constructed, with a maximum tree depth and branching factor of 2 and 5 respectively. This idea was introduced in Section 3.3.1 and formally addressed in Table 3.11. Should the model become more complex in the future and consist of more decision variables, the current hierarchy dimensions may not be sufficient to allow for a comprehensive analysis of all the criteria and sub-criteria that are relevant to the decision problem. The limited branching factor can be addressed with relatively little work by simply expanding the UI so it can facilitate a greater number of parent criteria and sub-criteria comparison tables along with a few minor tweaks in the hierarchy formation code. Unfortunately the current UI format would not be able to facilitate a greater tree depth without making the input process very complicated for a user which in turn would defeat the purpose of using *Microsoft Excel* in the first place. Therefore, should a deeper hierarchy be required, an alternative software for user inputs would need to be considered.

Subjectivity in hierarchy formation The fundamental unit of a hierarchical model is the individual pairwise comparisons between different criteria. These comparisons are subjective meaning so is any model produced in this way. This flaw was briefly introduced in Section 2.7 where it was noted that the subjectivity of the decision making process can lead to can lead to bias and inconsistencies in the judgement of ranking criteria which can potentially lead to undesirable/incorrect alternative rankings. The potential for such an occurrence was demonstrated perfectly in Figure 4.8. Should a different decision-maker have made this model and allocated a lesser importance to drone type and dimensions criteria weightings, an erroneous drone ranking would have been returned.

Selected drone candidate isn't necessarily appropriate The current tool creates models that will match the correct type of drone to a job. Currently however, there is no guarantee that the selected candidate is a feasible solution for the task at hand. For example, in the 'Emergency' model, the XV-L model was deemed the preferable candidate. This drone has a payload capacity of 25kg. This means that if an emergency delivery with a payload greater than 25kg were required, the XV-L model would still be selected, despite its inability to fulfill the request. This situation can lead to significant setbacks delivery process if unsuitable drone models were chosen for deliveries, especially in emergency situations. Fortunately, potential solutions to this issue have been conceived. These will be discussed in greater detail in Section 5.2.

4.4.2 Contribution to Group Objectives

From the group objectives laid out in Figure 1.1, the designing of an MCDM framework to for the selection of drones for deliveries forms the entirety of the flight services module in the design of the delivery network. The framework designed in this report will facilitate the connection between the network solution design module which focuses on the storage locations and supply chain modelling, and the integrated drone landing station module which focuses on endpoint distribution at medical facilities. The proposed MCDM framework offers maximum flexibility to this network, allowing decision makers to define not only general models that can can be used for alternative selection for numerous of delivery routes but also specifically tailored models that can be used for specific and potentially unorthodox routes. As part of the network solution design module, a comprehensive database of nodes should be created. These nodes can represent any point where a drone could pick up or drop-off cargo. The first step in integrating the network solution design module and the flight services module would be to assign two attributes to each node: the location and whether there are runway capabilities onsite. This means when a request is received a comprehensive job package can be assembled, covering the delivery distance, whether or not VTOL capabilities are required as well as the payload capacity requirements. Based off the details in the job package, the appropriate AHP instance structure can be chosen to ensure the ideal candidate is selected.

5. Conclusions and Further Work

5.1 Summary of Work

The objective of this piece of work was to derive a flexible decision making framework that has the ability to rank an incoming pool of drone candidates models over a wide spectrum of job types and select the optimal candidate for each job type. The report began with an extensive examination of leading MCDM methods found in academic literature. This review found that although these methods are effective in ranking alternatives in a static decision-making setting, they are not suitable for ranking alternatives in a dynamic decision-making setting. The project focus was then shifted to developing a tool capable of generating a wide range of MCDM instances, which would enable the consideration of various delivery job scenarios and the subsequent ranking of drone alternatives in each. Furthermore, the ability to define attribute weights flexibly and the ease of creating a model instance were identified as critical features to consider when choosing an MCDM method.

When considering which MCDM method would be most suitable, three candidates were considered in a serious manner. The distance-based method TOPSIS couldn't be considered as the high dimensional nature of the drone data set causes the Euclidean Distances between different points to converge rendering the model less effective. PROMETHEE was also discarded due its high time complexity with respect to the number of alternatives being ranked. This meant that the chosen MCDM method was the Analytical Hierarchy Process (AHP). This method lays out decision criteria in a very informative way and allocates attribute weightings according to user determined pairwise comparisons. By developing a spreadsheet based UI, users could rapidly define micro-AHP structures and their underlying pairwise comparison tables. Python scripts were then developed to translate this input to hierarchical structure of attribute weightings, while verifying the the users preference allocations are consistent. This input format and subsequent code allows decision makers to rapidly define different AHP instances, allowing for any potential job type to be considered when evaluating drone alternatives. The result aligns closely with the objective of this report, but there is one limitation to consider: each AHP model must be defined individually. Therefore, if a new job scenario arises, drone rankings cannot be determined until a necessary AHP instance is created.

The produced framework needed to be validated, this was done by three methods. The first method analysed the weightings produced by from a single baseline model. These weightings aligned with general criteria importance defined in the underlying pairwise comparisons, verifying the models ability to capture and quantify the relative preferences of the decision criteria. The second method utilised hypothetical scenarios and real drone candidates. Once AHP instances had been created for all scenarios, the drone candidates were passed through each instance. The results confirmed that this framework was also capable of determining the ideal drone candidate over a range of distinct delivery scenarios. Variable analysis confirmed that prioritised drone attribute groupings were strongly correlated with the relative strengths of the selected drone model, indicating that the models are behaving as expected. This analysis also demonstrated that the proposed method can be utilised to prioritize any drone attributes and, thus, any possible job scenario.

These validation methods confirm that the current framework effectively serves as a proof of concept, demonstrating that the tool can define various micro-AHP structures for almost any delivery scenario and can select the optimal drone candidate for each situation. Additionally, with some minor modifications, the proposed methodology can be integrated into an autonomous healthcare delivery drone network, linking carrier drones to NHS cargo delivery missions.

5.2 Future Work

Section 4.4.1 highlighted the significant drawbacks of the constructed AHP architecture and some potential strategies to mitigate them. This section covers this in further detail the how these problems can be addressed so that the architecture can be integrated into a drone delivery network.

The limited hierarchy size on its face looks like it could be a big problem, prompting a complete redesign of the UI. However, when the the context of the application is considered, it can be seen that this is not the case. As discussed, increasing the branching factor can be done with relatively little work by simply expanding the parent criteria comparison table and appending the appropriate number of sub-tiers to the bottom of the UI. This expansion is something that will need to take place before integrating this piece of work into the group objective as described in Section 4.4.2, as a greater number of decision variables, coupled with a higher branching factor will lead to a more comprehensive analysis of alternatives and an overall better decision quality. Fortunately, an increase in tree depth will not be necessary as all parameters that go into generating the MCDM instances share something in common - they are *all* drone attributes. This means that the current depth of 2 is enough to effectively categorise the drone parameters. Were there to be another class of decision parameters that contributed to alternative score, then an increase in tree depth would be warranted.

The subjectivity is a flaw inherent to AHP as seen from its first mention in this report in Section 2.7. This is difficult problem to address. Section 4.4.1 looked at how a simple readjustment in criteria weightings could lead to incorrect alternative rankings. Fortunately there are measures to prevent against such things occurring such as model variation analysis using a collection of data from distinctive drone models, as this report did with the Hammerhead eV20, the Albatross 2.2 and the XV-L. By comparing a known, desired result to the obtained results the model weightings and therefore the underlying comparison values can be adjusted so that in a real scenario, the candidate that is most similar to the desired result from the analysis will likely be selected. For this reason, the scripts used to perform the analysis in Section 4.3.2 were formalised so they could quickly and easily be applied to any generated model, utilising whatever drone data is in the input CSV in that model's directory. However this analysis only currently applies to the two principal criteria of the model. It needs to be expanded to cover each combination of parent attributes so that the optimal weighting balance for the scenario model can be struck. Furthermore a larger 'mock' drone database of distinctive candidates will need to be constructed as a control group which will be used in multi variable analysis. Fine-tuning a models weightings so that the optimal candidate from this control group is selected by the model will remove a layer of subjectivity from the decision making process.

The AHP framework currently chooses the optimal candidate based off how well a candidates strengths match to the prioritised attributes of the hierarchy. In doing so it will choose the ideal type of drone for the job at hand. However, due to the lack of job data, there is currently no assurance that the selected candidate is capable of performing the job described by the AHP model. Section 4.4.2 introduces the idea of 'job packages' and how they can be formed. These packages need to be incorporated into the selection process. There are two ways in which this can happen. The first is in the normalisation of drone parameters to replace, where appropriate, the beneficial/non-beneficial data split and instead score a model on its proximity to a job parameter. For example, if maximum payload capacity were considered, the current system scores all models as a proportion of the range of values in the pool of candidates, with the highest value achieving a perfect score of 1. The proposed method would be, if a candidate has a score less than the required capacity as defined in the job package it clearly gets a score of 0, if a candidate has a score equivalent to required capacity, it gets a score of 1 and the greater the capacity is than the required amount, the lower the score it gets. This will further optimise the allocation of drones within the network. The second way job packages will be used in the decision making process is acting as a firm cut-off prior to selection, so instead of selecting the drone with the highest fitness score, it will now be the drone with the highest fitness score that satisfies all the job package requirements (range, payload capacity, VTOL capabilities etc...).

5.3 Final Word

This report has defined an efficient architecture for defining multiple instances of an Analytical Hierarchy Process so that alternatives can be classified over a diverse range of delivery scenarios. This is the first instance of such a tool being developed and will allow Apian, with minimal input outside of the initialisation of models, to efficiently and effectively allocate carrier drones to to a wide array of medical deliveries, helping to quench the increasing demand for the delivery medical supplies and pharmaceuticals in the UK and alleviate the pressure on the current NHS supply chain.

References

[1] Carolyn Wickware. *The Pharmaceutical Journal - Fixing the UK's medicines shortage crisis*. https://pharmaceutical-journal.com/article/feature/fixing-the-uks-medicines-shortage-crisis. 2022.

[2] Bennett Institute for Applied Data Science. *Open Pescribing, British National Formulary, Chapter 6, Section 4 Part 1 - Female sex hormones and their modulators*. https://openprescribing.net/bnf/060401/. 2022.

[3] *Apian Ltd*. https://apian.aero/. 2023.

[4] Stephen Hammond. *Large Goods Vehicles: Exhaust Emissions*. https://www.theyworkforyou.com/wrans/?id=2013-03-01a.144740.h. 2013.

[5] Fraikin Ltd. *What you need to know about: TRUCK OPERATING COSTS*. https://www.fraikin.co.uk/wp-content/uploads/sites/5/2021/05/WYNTK-Truck-Operating-Costs.pdf. 2022.

[6] Sarah Tooze. *Latest petrol and diesel fuel prices*. https://heycar.co.uk/blog/latest-fuel-prices. 2023.

[7] Sylvia J. T. Jansen. "The Multi-attribute Utility Method". In: *The Measurement and Analysis of Housing Preference and Choice*. Dordrecht: Springer Netherlands, 2011, pp. 101–125. ISBN: 978-90-481-8893-2. DOI: 10.1007/978-90-481-8894-9_5. URL: http://link.springer.com/10.1007/978-90-481-8894-9_5.

[8] Ralph L. Keeney and Howard Raiffa. *Decisions with Multiple Objectives*. Cambridge University Press, July 1993. ISBN: 9780521438834. DOI: 10.1017/CBO9781139174084. URL: https://www.cambridge.org/core/product/identifier/9781139174084/type/book.

[9] Espen Løken. "Use of multicriteria decision analysis methods for energy planning problems". In: *Renewable and Sustainable Energy Reviews* 11.7 (2007), pp. 1584–1595. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2005.11.005. URL: https://www.sciencedirect.com/science/article/pii/S1364032105001280.

[10] Uduak Akpan and Risako Morimoto. "An application of Multi-Attribute Utility Theory (MAUT) to the prioritization of rural roads to improve rural accessibility in Nigeria". In: *Socio-Economic Planning Sciences* 82 (2022), p. 101256. ISSN: 0038-0121. DOI: https://doi.org/10.1016/j.seps.2022.101256. URL: https://www.sciencedirect.com/science/article/pii/S0038012122000349.

[11] Meho Saša Kovacevic et al. "Categorization of the condition of railway embankments using a multi-attribute utility theory". In: *Applied Sciences (Switzerland)* 9.23 (2019), p. 5089. ISSN: 20763417. DOI: 10.3390/app9235089.

[12] Paul Kailiponi. "Analyzing evacuation decisions using multi-attribute utility theory (MAUT)". In: *Procedia Engineering* 3 (2010), pp. 163–174. ISSN: 1877-7058. DOI: https://doi.org/10.1016/j.proeng.2010.07.016. URL: https://www.sciencedirect.com/science/article/pii/S1877705810004856.

[13] Popi Konidari and Dimitrios Mavrakis. "A multi-criteria evaluation method for climate change mitigation policy instruments". In: *Energy Policy* 35.12 (2007), pp. 6235–6257. ISSN: 03014215. DOI: 10.1016/j.enpol.2007.07.007. URL: https://www.sciencedirect.com/science/article/pii/S0301421507003229.

[14] Mark Velasquez and Patrick Hester. "An analysis of multi-criteria decision making methods". In: *International Journal of Operations Research* 10 (2013), pp. 56–66.

[15] Bernard Roy. "Classement et choix en présence de points de vue multiples". In: *Revue française d'informatique et de recherche opérationnelle* 2.8 (1968), pp. 57–75.

[16] Kannan Govindan and Martin Brandt Jepsen. "ELECTRE: A comprehensive literature review on methodologies and applications". In: *European Journal of Operational Research* 250.1 (2016), pp. 1–29. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2015.07.019. URL: https://www.sciencedirect.com/science/article/pii/S0377221715006529.

[17] Bernard Roy, Roman Slowiński, and Wiktor Treichel. "Multicriteria programming of water supply systems for rural areas 1". In: *JAWRA Journal of the American Water Resources Association* 28.1 (1992), pp. 13–31.

[18] Adiel Teixeira de Almeida. "Multicriteria decision model for outsourcing contracts selection based on utility function and ELECTRE method". In: *Computers & Operations Research* 34.12 (2007), pp. 3569–3574. ISSN: 0305-0548. DOI: https://doi.org/10.1016/j.cor.2006.01.003. URL: https://www.sciencedirect.com/science/article/pii/S0305054806000189.

[19] D B Leake. "Problem Solving and Reasoning: Case-based". In: *International Encyclopedia of the Social & Behavioral Sciences*. Ed. by Neil J Smelser and Paul B Baltes. Oxford: Pergamon, 2001, pp. 12117–12120. ISBN: 978-0-08-043076-8. DOI: https://doi.org/10.1016/B0-08-043076-7/00545-3. URL: https://www.sciencedirect.com/science/article/pii/B0080430767005453.

[20] Cindy Marling and Peter Whitehouse. "Case-Based Reasoning in the Care of Alzheimer's Disease Patients". In: *Case-Based Reasoning Research and Development*. Ed. by David W Aha and Ian Watson. Berlin, Heidelberg: Springer Berlin Heidelberg, 2001, pp. 702–715. ISBN: 978-3-540-44593-7.

[21] T W Liao, Z M Zhang, and C R Mount. "A case-based reasoning system for identifying failure mechanisms". In: *Engineering Applications of Artificial Intelligence* 13.2 (2000), pp. 199–213. ISSN: 0952-1976. DOI: https://doi.org/10.1016/S0952-1976(99)00052-4. URL: https://www.sciencedirect.com/science/article/pii/S0952197699000524.

[22] Se-Hak Chun and Yoon-Joo Park. "A new hybrid data mining technique using a regression case based reasoning: Application to financial forecasting". In: *Expert Systems with Applications* 31.2 (2006), pp. 329–336. ISSN: 0957-4174. DOI: https://doi.org/10.1016/j.eswa.2005.09.053. URL: https://www.sciencedirect.com/science/article/pii/S0957417405002198.

[23] Hyunchul Ahn and Kyoung-jae Kim. "Bankruptcy prediction modeling with hybrid case-based reasoning and genetic algorithms approach". In: *Applied Soft Computing* 9.2 (2009), pp. 599–607. ISSN: 1568-4946. DOI: https://doi.org/10.1016/j.asoc.2008.08.002. URL: https://www.sciencedirect.com/science/article/pii/S1568494608001154.

[24] Wade D Cook and Larry M Seiford. "Data envelopment analysis (DEA) – Thirty years on". In: *European Journal of Operational Research* 192.1 (2009), pp. 1–17. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2008.01.032. URL: https://www.sciencedirect.com/science/article/pii/S0377221708001586.

[25] Quanling Wei. "Data envelopment analysis". In: *Chinese Science Bulletin* 46.16 (2001), pp. 1321–1332. ISSN: 1861-9541. DOI: 10.1007/BF03183382. URL: https://doi.org/10.1007/BF03183382.

[26] Yılmaz Gökşen, Onur Doğan, and Bilge Özkarabacak. "A Data Envelopment Analysis Application for Measuring Efficiency of University Departments". In: *Procedia Economics and Finance* 19 (2015), pp. 226–237. ISSN: 2212-5671. DOI: https://doi.org/10.1016/S2212-5671(15)00024-6. URL: https://www.sciencedirect.com/science/article/pii/S2212567115000246.

[27] Jean-Pierre Brans. *L'ingénierie de la décision: l'élaboration d'instruments d'aide a la décision*. Université Laval, Faculté des sciences de l'administration, 1982.

[28] Majid Behzadian et al. "PROMETHEE: A comprehensive literature review on methodologies and applications". In: *European Journal of Operational Research* 200.1 (2010), pp. 198–215. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2009.01.021. URL: https://www.sciencedirect.com/science/article/pii/S0377221709000071.

[29] Maher F Abu-Taleb and Bertrand Mareschal. "Water resources planning in the Middle East: Application of the PROMETHEE V multicriteria method". In: *European Journal of Operational Research* 81.3 (1995), pp. 500–511. ISSN: 0377-2217. DOI: https://doi.org/10.1016/0377-2217(94)00007-Y. URL: https://www.sciencedirect.com/science/article/pii/037722179400007Y.

[30] Zoran Babic and Neli Plazibat. "Ranking of enterprises based on multicriterial analysis". In: *International Journal of Production Economics* 56-57 (1998), pp. 29–35. ISSN: 0925-5273. DOI: https://doi.org/10.1016/S0925-5273(97)00133-3. URL: https://www.sciencedirect.com/science/article/pii/S0925527397001333.

[31] S Gilliams et al. "Comparing multiple criteria decision methods to extend a geographical information system on afforestation". In: *Computers and Electronics in Agriculture* 49.1 (2005), pp. 142–158. ISSN: 0168-1699. DOI: https://doi.org/10.1016/j.compag.2005.02.011. URL: https://www.sciencedirect.com/science/article/pii/S0168169905000414.

[32] Thomas L Saaty. "What is the Analytic Hierarchy Process?" In: *Mathematical Models for Decision Support*. Ed. by Gautam Mitra et al. Berlin, Heidelberg: Springer Berlin Heidelberg, 1988, pp. 109–121. ISBN: 978-3-642-83555-1.

[33] Omkarprasad S Vaidya and Sushil Kumar. "Analytic hierarchy process: An overview of applications". In: *European Journal of Operational Research* 169.1 (2006), pp. 1–29. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2004.04.028. URL: https://www.sciencedirect.com/science/article/pii/S0377221704003054.

[34] Walailak Atthirawong and Bart MacCarthy. "An Application of the Analytical Hierarchy Process to International Location Decision-Making". In: (2023).

[35] Hamid Reza Pourghasemi, Biswajeet Pradhan, and Candan Gokceoglu. "Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran". In: *Natural Hazards* 63.2 (2012), pp. 965–996. ISSN: 1573-0840. DOI: 10.1007/s11069-012-0217-2. URL: https://doi.org/10.1007/s11069-012-0217-2.

[36] Ying-Ming Wang and Taha M S Elhag. "An approach to avoiding rank reversal in AHP". In: *Decision Support Systems* 42.3 (2006), pp. 1474–1480. ISSN: 0167-9236. DOI: https://doi.org/10.1016/j.dss.2005.12.002. URL: https://www.sciencedirect.com/science/article/pii/S016792360500179X.

[37] L A Zadeh. "Fuzzy logic". In: *Computer* 21.4 (1988), pp. 83–93. DOI: 10.1109/2.53.

[38] B Vasu Murthy, Y V Pavan Kumar, and U V Ratna Kumari. "Fuzzy logic intelligent controlling concepts in industrial furnace temperature process control". In: *2012 IEEE International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)*. 2012, pp. 353–358. DOI: 10.1109/ICACCCT.2012.6320801.

[39] Jason Papathanasiou and Nikolaos Ploskas. "TOPSIS". In: *Multiple Criteria Decision Aid : Methods, Examples and Python Implementations*. Cham: Springer International Publishing, 2018, pp. 1–30. ISBN: 978-3-319-91648-4. DOI: 10.1007/978-3-319-91648-4_1. URL: https://doi.org/10.1007/978-3-319-91648-4_1.

[40] Ching-Lai Hwang and Kwangsun Yoon. "Methods for Multiple Attribute Decision Making". In: *Multiple Attribute Decision Making: Methods and Applications A State-of-the-Art Survey*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1981, pp. 58–191. ISBN: 978-3-642-48318-9. DOI: 10.1007/978-3-642-48318-9_3. URL: https://doi.org/10.1007/978-3-642-48318-9_3.

[41] D.L. Olson. "Comparison of weights in TOPSIS models". In: *Mathematical and Computer Modelling* 40.7 (2004), pp. 721–727. ISSN: 0895-7177. DOI: https://doi.org/10.1016/j.mcm.2004.10.003. URL: https://www.sciencedirect.com/science/article/pii/S089571770400264X.

[42] Berna (Kiran) Bulgurcu. "Application of TOPSIS Technique for Financial Performance Evaluation of Technology Firms in Istanbul Stock Exchange Market". In: *Procedia - Social and Behavioral Sciences* 62 (2012). World Conference on Business, Economics and Management (BEM-2012), May 4–6 2012, Antalya, Turkey, pp. 1033–1040. ISSN: 1877-0428. DOI: https://doi.org/10.1016/j.sbspro.2012.09.176. URL: https://www.sciencedirect.com/science/article/pii/S1877042812036178.

[43] Osman Taylan et al. "Construction projects selection and risk assessment by fuzzy AHP and fuzzy TOPSIS methodologies". In: *Applied Soft Computing* 17 (2014), pp. 105–116. ISSN: 1568-4946. DOI: https://doi.org/10.1016/j.asoc.2014.01.003. URL: https://www.sciencedirect.com/science/article/pii/S1568494614000040.

[44] Ömer Ekmekcioğlu, Kerim Koc, and Mehmet Özger. "Stakeholder perceptions in flood risk assessment: A hybrid fuzzy AHP-TOPSIS approach for Istanbul, Turkey". In: *International Journal of Disaster Risk Reduction* 60 (2021), p. 102327. ISSN: 2212-4209. DOI: https://doi.org/10.1016/j.ijdrr.2021.102327. URL: https://www.sciencedirect.com/science/article/pii/S2212420921002934.

[45] Devendra Choudhary and Ravi Shankar. "A STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: A case study from India". In: *Energy* 42.1 (2012). 8th World Energy System Conference, WESC 2010, pp. 510–521. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2012.03.010. URL: https://www.sciencedirect.com/science/article/pii/S0360544212002010.

[46] Qiang Xu et al. "Improved TOPSIS model and its application in the evaluation of NCAA basketball coaches". In: *Modern Applied Science* 9.2 (2015), p. 259.

[47] I Gede Iwan Sudipa et al. "Implementation of ELECTRE II Algorithm to Analyze Student Constraint Factors in Completing Thesis". In: *2021 6th International Conference on New Media Studies (CONMEDIA)*. 2021, pp. 22–27. DOI: 10.1109/CONMEDIA53104.2021.9617001.

[48] Sung-Kyun Kim and Ohseop Song. "A MAUT approach for selecting a dismantling scenario for the thermal column in KRR-1". In: *Annals of Nuclear Energy* 36.2 (2009), pp. 145–150. ISSN: 0306-4549. DOI: https://doi.org/10.1016/j.anucene.2008.11.034. URL: https://www.sciencedirect.com/science/article/pii/S0306454908003174.

[49] Wim De Keyser and Peter Peeters. "A note on the use of PROMETHEE multicriteria methods". In: *European Journal of Operational Research* 89.3 (1996), pp. 457–461. ISSN: 0377-2217. DOI: https://doi.org/10.1016/0377-2217(94)00307-6. URL: https://www.sciencedirect.com/science/article/pii/0377221794003076.

[50] Pedro Domingos. "A few useful things to know about machine learning". In: *Communications of the ACM* 55.10 (2012), pp. 78–87.

[51] G.H. Tzeng and J.J. Huang. *Multiple Attribute Decision Making: Methods and Applications*. A Chapman & Hall book. Taylor & Francis, 2011. ISBN: 9781439861578. URL: https://books.google.co.uk/books?id=%5C_C7n1ar4f8IC.

[52] Thomas L. Saaty. "Decision-making with the AHP: Why is the principal eigenvector necessary". In: *European Journal of Operational Research* 145.1 (2003), pp. 85–91. ISSN: 0377-2217. DOI: https://doi.org/10.1016/S0377-2217(02)00227-8. URL: https://www.sciencedirect.com/science/article/pii/S0377221702002278.

[53] William C. Wedley. "Consistency prediction for incomplete AHP matrices". In: *Mathematical and Computer Modelling* 17.4 (1993), pp. 151–161. ISSN: 0895-7177. DOI: https://doi.org/10.1016/0895-7177(93)90183-Y. URL: https://www.sciencedirect.com/science/article/pii/089571779390183Y.

[54] Niyazi Ari and Makhamadsulton Ustazhanov. "Matplotlib in python". In: *2014 11th International Conference on Electronics, Computer and Computation (ICECCO)*. 2014, pp. 1–6. DOI: 10.1109/ICECCO.2014.6997585.

[55] AirlogiX. *Hammerhead eV20 Delivery Drone*. https://airlogix.io/hammerhead. 2023.

[56] UAVOS. *Albatross 2.2*. https://www.uavos.com/products/fixed-wing-uavs/albatross-2-2/. 2023.

[57] Plymouth Rock Technology. *XV-L*. https://www.plyrotech.com/products/xv-1/. 2023.