UNIVERSITY OF SOUTHAMPTON

FACULTY OF ENGINEERING AND THE ENVIRONMENT

Academic Unit of Aeronautics Astronautics and Computational Engineering

Development and Application of a Value Driven Design Assessment Framework to an Unmanned Air System Design

by

Evangelos Papageorgiou

Thesis for the Degree of Doctor of Philosophy

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ABSTRACT

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DEVELOPMENT AND APPLICATION OF A VALUE DRIVEN DESIGN ASSESSMENT FRAMEWORK TO AN UNMANNED AIR SYSTEM DESIGN

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The work presented in this thesis concerns the development of a value driven engineering design assessment framework and its application to the conceptual design of an Unmanned Air System (UAS) to be utilised in a defence application. This research demonstrates the implementation of the value driven design philosophy in this framework, identifying value enhancing designs, with value not converted to monetary worth and as perceived by all stakeholders involved. A *multi-criteria* and *multi-stakeholder* decision making analysis is adopted to address their preferences as well as to study their interacting strategic choices. The ultimate objective of this framework is to convert engineering design to a decision making analysis with multiple conflicting objectives of multiple stakeholders considered.

This framework is capable of providing a product definition and estimation of all performance and cost related attributes for the conceptual phase. However, instead of pertaining to a single aircraft concept, a broad range of combinations of UAS configurations and geometries is generated by systematically searching alternative concepts and design configurations through a novel parameterization of the aircraft geometric topologies.

Value, related to the designed system's capabilities or performance and lifecycle cost, is used to compare different alternatives in the decision making of engineering design through the appropriate value model. Following a value-focused approach, a novel multi-attribute value model is introduced for objectively capturing the stakeholder's preferences and expectations. Furthermore, a more sophisticated multi-attribute utility model, based on standard Multi-attribute Utility Theory, is employed in the evaluation.

Game Theory as an optimization tool is used to develop a novel hybrid cooperative/non-cooperative non-zero sum, complete information game among all involved stakeholders as players. This game successfully addresses the stakeholders' preferences in a functional outcome-focused way, resolving the high indeterminacy of the alternative designs through a cooperative game. At the same time, their strategic interactions are captured in a process-focused non-cooperative game. Hence, the optimal design is identified through the simultaneous employment of the Nash bargaining solution and the Nash equilibrium.

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DECLARATION OF AUTHORSHIP

I, Evangelos Papageorgiou

declare that the thesis entitled

Development and Application of a Value Driven Design Assessment Framework to an Unmanned Air System Design

and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
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Nomenclature and Abbreviations

AR: Aspect Ratio

AEW: Airborne Early Warning

AGILE: Analytic Gaussian Intersection of Lethality Engagement

AHP: Analytic Hierarchy Process

C_D: Total Drag

C_{Di}: Lift Induced Drag

C_{Do}: Profile Drag

C_L: Wing Lift Coefficient

C_{la}: Aerofoil Lift Coefficient

C_{L_a}: Wing Lift Coefficient

C_m: Pitching Moment Coefficient

C_n: Yawing Moment Coefficient

CAB: Consistently Aligned Beliefs

CG: Centre of Gravity

CKR: Common Knowledge of Rationality

CODA: Concept Design Analysis

CPF: Cost plus Fee

D-Level: Depot Level

DAPCA: Development and Production Costs for Aircraft

DATUM: Design Analysis Tool for Unit Cost Modelling

DoE: Design of Experiments

FFP: Firm Fixed Price

GPS: Global Positioning System

HTOL: Horizontal Take-off Landing

I-Level: Intermediate Level

INCOSE: International Council on Systems Engineering

INS: Inertial Navigation System

K_i: Scaling Factor of i^{th} Attribute

LiPo: Lithium-ion Polymer

MAUT: Multi-Attribute Utility Theory

MCDA: Multi-Criteria Decision Analysis

MCS: Monte Carlo Simulation

MDO: Multidisciplinary Design Optimisation

MoD: Ministry of Defence

MTTF: Mean Time to Failure

MTOW: Maximum Take-off Weight

MTTF: Mean Time to Failure

MTTR: Mean Time to Replacement

NBS: Nash bargaining Solution

NPV: Net Present Value

O-Level: Organisational Level

QFD: Quality Function Deployment

RBR: Repair by Replacement

RCM: Reliability-centred maintenance

RCS: Radar Cross Section

RPM: Revolutions per Minute

SAR: Search and Rescue

SE: Systems Engineering

SULSA: Southampton University Laser Sintered Aircraft

TRL: Technology Readiness Level

U: Utility Function

UAS: Unmanned Air System

UAV: Unmanned Air Vehicle

V: Value Function

VDD: Value Driven Design

VTOL: Vertical Take-off and Landing

Λ: Wing Sweep Angle

X_i: ith Attribute

$\bar{X}_{np}$: Neutral Point Longitudinal Position

1. Introduction

"Several person-years of effort developing, modifying, and verifying an elaborate simulation model that outputs the possible levels of several indicators of interest … and perhaps a week with the implications of the alternatives and then (the decision maker) chooses an alternative."

R.L. Keeney and H. Raiffa, Decision with Multiple Objectives, 1976, [1]

The application of multidisciplinary skills in engineering design requires an integrated approach to be successful. Following the systems engineering approach, designers consider each system to be comprised of other subsystems and components, all with a clear role to perform and all dominated by more than one requirement set at the system level, entangling the design task. The generic engineering design process according to Wiese [2] needs to be *'systematic'*, in the way the potential solutions are proposed and evaluated, '*iterative'*, using both simulation and prototyping to assess the solutions proposed, and '*multidisciplinary'*, since several disciplines are needed to encompass all important considerations.

All essential aspects of all lifecycle stages need to be addressed to study the designed system, its elements and their interactions with the wider environment. Starting from the development and production to the final stage of disposal, appropriate features of the designed system are employed in the evaluation of any proposed solution. Thus, the multi-disciplinary engineering design needs to be performed at the full system level and evaluated at the highest system level, addressing all important complexities, changes in technology, following a whole lifecycle approach. Furthermore, the possibility of an optimal arrangement being significantly different to the current or commonly used should also be taken into account.

The work presented in this thesis concerns the development of a value driven engineering design assessment framework, with value not converted to monetary worth, and its application to the conceptual design of a small Unmanned Air System (UAS) for defence use. This framework, through the use of appropriate models, estimates all associated variables and parameters required for the product definition. The designer assesses the "value" of proposed system solutions in an objective way, based only on the needs and preferences of the stakeholders involved. The value assessment relies on both performance and financial needs analysis, to capture all significant priorities and performance criteria. The design generation, following the value driven approach, is carried out more efficiently by relaxing all constraints and exploring the design space extensively; while the multidisciplinary design optimisation applied within this framework addresses all significant for the conceptual design phase complexities of the system and identifies the optimum solution. Therefore, the ultimate objective of this framework is to convert engineering design to a decision making analysis with multiple conflicting objectives of multiple stakeholders considered.

1.1 Motivation for research

In general, design is either *customer driven/market pulled*, when customer requirements and needs drive the technology to design the products that address those needs, or *technology pushed*, when a breakthrough in a certain technology allows for significant improvements in the performance of products, Verganti [3]. One example of the first design philosophy is the Toyota's Design Quality Innovation Division, incorporating customer feedback in automobile design. Typical examples of the second type are the introduction of colour television, the electronic calculator or the Xerox copier.

Design has its etymological origin to the Latin *de+signare*, meaning distinguishing with a sign. One way to achieve this distinction is to relate to the value, usefulness, of the solution that is offered to the stakeholders of the designed system. Following the *Value Driven Design* (VDD) approach, the product value is related to the appropriate product characteristics. The design is distinguished/developed based on the full analysis of all their needs; yet the process of blending these needs through VDD is hard to comprehend and for this reason sometimes not easily accepted. Collopy [4] points out that 'the commercial aircraft industry if left to its own, will naturally tend towards monopoly and technological lethargy', and although currently in the duopoly (Boeing and Airbus) stage, the application of value driven push strategy in the military aircraft design could address its inefficiencies, improving the design process.

The proposed work seeks to develop a value pushed/driven engineering design assessment framework that will propose alternative solutions and assess their "value", relying on both performance and financial needs analysis. This framework will be applied to the conceptual design of a small UAS for defence use. The value assessment can be performed not only at the early abstract design stage but also at any stage of the design process, as the design concept gets more refined and its uncertainties are addressed.

1.2 Research hypotheses

This research aims to add new knowledge by developing a VDD Framework and applying it to the Conceptual Design of a defence system, namely a Small Unmanned Air System. As will be presented, the full application of a VDD framework has been limited up to now to the design of civil aerospace systems, with value mostly related or easily converted to monetary worth; for military systems however, not all objectives/needs can be easily monetized. This VDD framework will identify the value enhancing designs, value perceived by the stakeholders and not translated to economic terms. The research hypotheses are the following:

Hypothesis 1: A VDD framework, when applied to the design of a defence system, can address all the non-economic and economic values of the stakeholders involved with the designed system, to identify the value-enhancing design(s).

Hypothesis 2: Design exploration can be performed more efficiently, after relaxing most performance or cost related constraints and extensively searching the design space in a systematic way.

Hypothesis 3: Multidisciplinary design optimisation can be applied within this framework to address most system complexities associated with the conceptual design phase.

1.3 Proposed research – Objectives

This research aims to develop an implementation of the value driven design philosophy in a framework where all needs of the major stakeholders of the designed defence system are addressed and used in the evaluation of the proposed product solutions, with value not translated to monetary worth. This VDD framework will be applied to the test case of conceptual design of a UAS for a defence application. In this VDD implementation process, also presented in Figure 1-1, the following objectives will be addressed:

- Identification of the needs of all stakeholders involved with the designed system during its whole lifecycle.
- Development of multi-attribute and multi-stakeholder value models, based on all identified stakeholders' performance and financial needs, to assess the value of any proposed solution with appropriate design attributes as their inputs. MAUT supported by AHP will be employed to capture the preferences and risk attitudes of stakeholders involved with the designed product, while Game Theory will be utilised to address the multiple stakeholders' preferences.
- Selection of a wide range of different system configurations, associated technologies, design variables and other stakeholders' choices to widely search the design space.
- Definition of the designed system with appropriate models in a terminology and language relevant to the designer for quick and efficient conceptual design space exploration, easily amended and replaceable for higher accuracy during the later phases of engineering design.
- Development of predictive models to assess all design attributes and especially:
    - Unit acquisition cost modelling that is based on system geometry and material/labour rates.
    - Mission scenarios' definition to run simulations and obtain first estimates of lifecycle cost and performance/capabilities.
- Integration of all models in the design tool.

- Trade/parametric studies to identify the optimal solutions as well as the corresponding optimal ranges of all design variables.

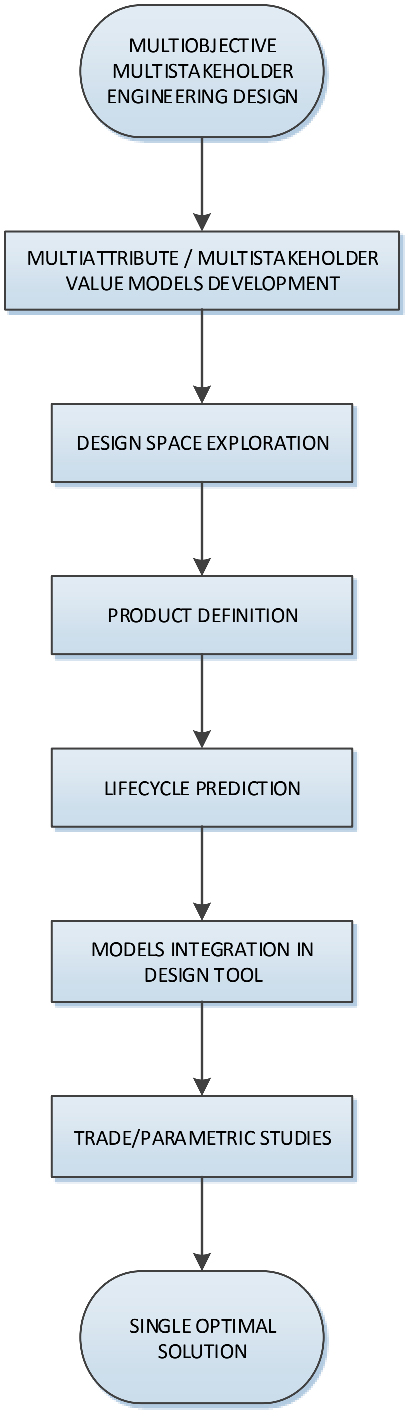


Figure 1-1 General VDD Implementation Process

1.4 Document organisation

The objectives set in the previous section are addressed in the following chapters. The foundation for the development of the proposed VDD framework is presented in the next two chapters, while the rest of the document is organised based on the general VDD implementation process of Figure 1-1. More specifically, the next chapter describes the general engineering design process, translating needs and functional requirements to design parameters. Systems Engineering (SE) and the VDD framework to obtain the best design are also introduced in this chapter. The methods used to assess lifecycle cost, as one the most crucial design attributes of all engineering design problems, are also presented, while the performance related design attributes, originating from the mission requirements and needs of the stakeholders for the specific design, are introduced in the fourth chapter. The basics of the Multi-Criteria Decision Analysis (MCDA), as appropriate tools for the development of multi-attribute value models, are presented in the third chapter. Thus, Multi-Attribute Utility Theory (MAUT), Analytic Hierarchy Process (AHP), Net Present Value (NPV), Cost Effectiveness and Cost/Benefits Analyses, Group Decision Making for aggregating the preferences of many individuals, as well as the employment of Game Theory in Engineering Design are presented. In the fourth chapter, the VDD implementation process starts with a basic general UAS, employed as the test case of the application of the proposed VDD framework. Hence, a representative configuration/category is selected and the complete objectives/attributes hierarchy, reflecting the user's priorities and needs, is structured in this chapter. In the fifth chapter, multi-attribute non-financialised value models, utilised for evaluating any given design alternative based on the single stakeholder priorities/preferences in the Multidisciplinary Design Optimization (MDO), are developed as the next step of the VDD implementation process. In the sixth chapter, Game Theory as an optimization tool is applied to incorporate the preferences of more stakeholders in a Multi-Stakeholder value modelling. In the seventh chapter, appropriate product definition models are developed to perform design sizing within an extensive and systematic UAS design generation. The eighth chapter introduces the predictive models for the estimation of the total lifecycle cost, including the costs of developing and building the aircraft, maintenance, replacements for aircraft losses and the cost related to combat damage. Next, in the ninth chapter, the integration of all models in the VDD framework for the automated optimisation is presented. The results obtained with the automated design space search, through the use of Designs of Experiments (DoE) and MDO, allow for comparison and evaluation of different designs based on their attributes. Finally, the last chapter is dedicated to the primary conclusions, contributions to the current state of knowledge, and future work recommendations concerning the application of the multi-objective, multi-stakeholder optimization approach in value driven engineering design.

2. Engineering Design Background

"…The first step of the engineer in trying to satisfy these wants is, therefore, that of translating as nearly as possible these wants into the physical characteristics of the thing manufactured to satisfy these wants."

Walter A. Shewhart

Economic Control of Duality of Manufactured Products, 1931

In this chapter, engineering design background is presented as the foundation for the development of the VDD framework. Starting from the identification of needs and requirements, engineering design methodologies and tools are introduced to facilitate trade and optimisation studies. Furthermore, beyond the performance related inputs of the objective function which are dependent upon the specific system that is designed, cost engineering is also introduced as the scientific analysis to obtain an accurate estimate of the total lifecycle cost or other cost related characteristics of the product.

Complex engineering design can be divided into three phases, as Raymer [5] describes:

a. *Conceptual design*, requirements are set, technologies are defined, trade-offs between the design features are explored, while the goal is to obtain the general description of a viable and most preferable solution.

b. *Preliminary design*, during this phase the configuration is 'frozen', the exact definition is obtained, basic components are designed and further accuracy is obtained.

c. *Detailed design* phase, where all actual pieces to be built are designed, along with the design of manufacturing processes and appropriate tools.

In the conceptual design phase, the widest possible design space is explored and ultimately the most preferred designs between all alternatives, based on their evaluation against technical and economic criteria, are selected for further analysis. A set of objectives usually comprised of elements, from several operational, technical, economic, safety and other relevant factors is taken into account to derive the evaluation criteria used in the evaluation stage of the proposed solutions. To achieve the objectivity of this evaluation, these criteria should be independent of information, other data available or the proposed solution, but should reflect only the priorities, needs or values of persons involved. Engineering design is all about decision making, aiming towards the identification of the most feasible design based on the customer needs/requirements.

2.1 Engineering Design Process

Engineering design has been studied thoroughly both from academia and industry. Several applications, all aiming to systematize and accelerate the design process, have been introduced by Hubka and Eder [6], Pugh [7], Pahl and Beitz [8], Otto and Wood [9], Eggert [10], Ulrich and Eppinger [11] and Ullman [12]. The iterative engineering design process of Figure 2-1, as a decision making process, involves the generation of several potential design solutions with different characteristics, evaluated against the primary objectives.

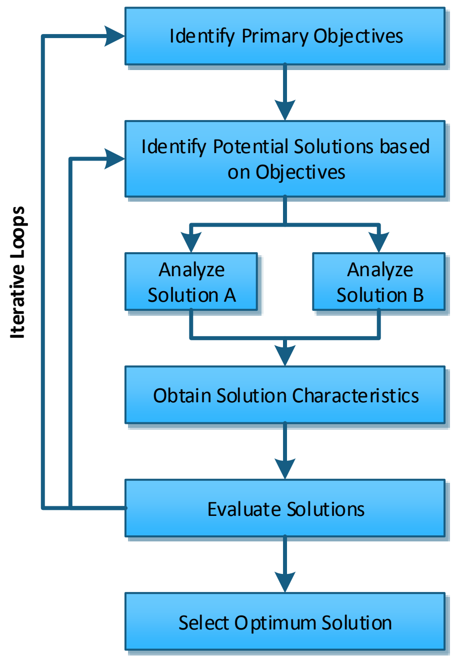


Figure 2-1 Engineering Design Process

Hazelrigg [13] describes engineering design as the generation of all possible designs and the selection of the best one. There are, however, two inherent difficulties: Firstly, the number of all potential designs that can be generated is theoretically infinite, proportional to the number and range of the design variables, the configurations employed, and other design parameter choices the designer has to make; and secondly, the selection of the optimum solution must rely on some commonly used metric, for the evaluation to be objective. Additionally, little technical information and data, other than some broad and vague needs to be satisfied by the concept configuration, size and shape, is available in the conceptual design phase. Cross [14] presents the applicable strategies for product design, starting with the clarification of the design objectives up to the generation and evaluation of the alternatives.

Engineering design formalized the synthesis of the design problems across different disciplines, starting from the early 1960s and by the mid-1980s evolved to more computable and automated methods, as Antonnson and Cagan [15] point out. The generation of the design point can follow a multidisciplinary design spiral, that is a sequential, iterative methodology originally developed for ship designs [16]. For an air system, Keane and Nair's [17] design spiral is illustrated in Figure 2-2, as the design process evolves from concept to detail.

Figure 2-2 Aircraft Design Spiral [17]

Only the most basic of engineering disciplines, configurations and capabilities are circumscribed in the conceptual design, evaluating a number of configurations, while sensitivity analysis is performed through the variation of design parameters. Major parameters are selected in the concept phase, while the most promising design candidates are promoted to base configurations of the design project for further evaluation.

Engineering design is a highly knowledge intensive process and as such the advances in computational tools have allowed geometry manipulation and meshing, access to various databases and management of computing resources during the automated optimisation. However, the use of different type tools makes the linking of them a rather challenging job, to achieve their integration in the design process and therefore the exploration of the widest possible design space over many possible configurations, as Keane and Scanlan [18] describe.

2.2 Stakeholder's objectives – Product's attributes

The first step in the engineering design process is to define the needs of all associated stakeholders. The identification and structuring of objectives will articulate the values of the user and will direct the collection of information and decision making, performed during the generation and evaluation of potential alternative solutions respectively, as Keeney [19] underlines.

According to Freeman [20], stakeholders are 'any group or individual who can affect or is affected by the achievement of the firm's objectives'. In the engineering design a stakeholder has interests/stakes in, is influenced by, or could influence any part of the whole lifecycle of the designed product from the initial steps of the conceptual design up to its disposal. For every stakeholder/organisation, further analysis and questionnaires are employed to define the requirements/objectives that should be addressed. The objectives of the stakeholders should cover the complete lifecycle of the designed product, from the identification of an opportunity for the design of a product, the preliminary concept phase, the full concept definition, the product realization, the product and service support up to its disposal.

There are no universal definitions of the terms, objectives and attributes but according to Keeney and Raiffa [1], each of these objectives in the decision making process corresponds to an area of concern of the stakeholders. Since high level objectives tend to be rather abstract, these are further refined by utilising lower-level objectives, representing the goals to be pursued within the engineering design process. Hence, by subdividing the objectives into lower level objectives, a non-unique objectives' hierarchy is constructed up to the level where all aspects of the higher objective are accounted while the elimination of any of the lower level objectives would alter the selection of the design alternative (the so-called *test of importance*). The generation of the appropriate objectives is based on relevant literature, analytical studies and causal empiricism [21]. Examining how objectives of similar problems have been handled in the past, the modelling of the problem and surveys focusing on the needs and requirements of the stakeholders/decision makers will indicate the appropriate objectives.

For each objective, one or more attributes are associated, indicating the degree to which alternatives satisfy the objective. It is therefore imperative, to identify several attributes, that should be both *comprehensive* with respect to the objective and *measurable*. A *comprehensive* attribute provides the decision maker with the knowledge of the extent that the associated objective is achieved. The attribute is also *measurable*, if for each alternative a probability distribution over the attribute levels is generated and the decision maker's preferences are assessed. The non-unique full set of these should be *complete*, covering the overall objective, *operational*, *decomposable*, *non-redundant*, and *minimal* [1]. The set is *complete* if it indicates the degree to which the objective is met, *operational*, if it serves the purpose of the evaluation, *decomposable*, if the set can be broken down into subsets, *non-redundant*, no attributes are overlapping the same objective and *minimal*, the number of attributes should be as small as possible. This set of attributes will be the scalar input of the objective function, created ad hoc and reflecting the decision makers' attitude towards value trade-offs and uncertainty related choices.

2.3 Cost Engineering

In all engineering design problems, beyond the performance related attributes which are dependent upon the specific system that is designed, the total lifecycle cost or other cost related characteristics of the product are critical components of the objective function employed in the optimization. Hence, for any engineering design problem and irrespective of the designed system, the need for a reliable and detailed cost assessment needs to be addressed through the use of a model suitable for the abstraction of the conceptual and emerging design phase. Quite often, cost assessment has been used within a traditional design-to-cost [22] or a design for cost context [23], when cost is the governing criterion. Cost engineering is defined by Humphreys [24] as 'the application of scientific and engineering principles and techniques to problems of cost estimation, cost control, business planning and management science'. Nevertheless, within a multi-attribute analysis, the total lifecycle cost of the designed product, among the other attributes, has to be accurately modelled. Asiedu and Gu [25] divided lifecycle cost into the following categories:

- Research and development cost.
- Production and construction cost.
- Operations and maintenance cost.
- Retirement and disposal cost.

2.3.1 Acquisition Cost

Curran *et al.* [26] provide a very thorough review of aerospace lifecycle cost modelling relevant to the engineering process and integrating the cost models into the decision making process. Ultimately, they address its genetic nature, historically inherited by certain design attributes and manufacturing processes, as well as causal nature, relative to the design definition and manufacturing processes, of cost modelling methods. The techniques used in modelling the acquisition cost, consisted of the first two of the above lifecycle cost categories, are the following:

- Bottom-up method through the aggregation of cost estimates of the individual components.
- Top down method, when the total cost estimate is broken down to individual components.
- Parametric costing method, when cost drivers are identified and used in appropriate cost estimating relationships, obtained usually through regression analysis.
- Analogous costing method, adjusting the cost of similar components/projects.

- Feature-based cost modelling, when design features are used as relational drivers of cost, such features are geometric characteristics, other attributes, physical properties, manufacturing processes and activities (activity-based costing), all incurring cost to the product.
- Fuzzy logic cost modelling tools are also used when industrial uncertainty needs to be addressed, with algorithms for the prediction or control of a system, based on qualitative expressions linking linguistic variables [27].
- Neural networks are employed, based on the concept of a system learning, to predict the effect on cost given some product-related attributes, [28], requiring a large historic data set to be robust, therefore not applicable to novel designs.

In contrast, Bode [29] acknowledges only two basic methods, the Generative costing method, when cost is composed by the key constituents and the Variant-Based cost estimation, when costs of similar products are used. The generative approach uses the emerging product definition to estimate manufacturing process costs and is divided in manufacturing feature-based, when the product is defined as a set of predefined features, and feature-recognised, when the product model is expressed in terms of manufacturing features, this method is appropriate for novel designs as Scanlan *et al.* [30] point out. Its disadvantages are that it requires a detailed design definition, not available in the conceptual design phase, a deep knowledge of the manufacturing processes involved and that it is computationally expensive. The analogous cost estimating method requires a high degree of expert judgement in the selection and adjustment of costs of similar products to the one that is being designed [25].

Parametric cost modelling is applied when a high volume of historic data is available [31]. As Scanlan *et al.* [30] discuss, parametric cost modelling has been extensively used for military products, relying on historical data. This method however, could potentially lead to errors, if not normalized appropriately, or if used for new manufacturing processes and has very limited resolution for subtle changes of the product. It is also less effective when applied for novel designs or low-volume and high lead time products, in which case the generative approach is considered more appropriate.

Newnes *et al.* [32] evaluated the different approaches and presented the cost estimating systems advantages and disadvantages in particular for the cost modelling of low-volume, infrequent products, suggesting a multi-level hybrid approach using bottom-up and parametric methods. Tammineni *et al.* [33] introduced an object–oriented product data structure, supporting multiple levels of abstraction, statistical modelling and decision support constructs, using varying levels of cost modelling. A special form of feature-based costing is the activity-based cost model, mostly suitable for accurate estimation of production or manufacturing costs, when the cost of each manufacturing operation is assessed and added up to the unit cost [34]. The major disadvantage of this method is that it requires re-modelling, whenever any change in the manufacturing process takes place. Langmaak *et al.* [35] presented a hybrid approach through the interaction between an activity-based cost model and a parametric scalable cost model, depending on the number of units produced, the geometry and other design variables, the operation times used for cost estimation are scaled.

Cost modelling, as an activity based on data mining and analysis, requires access to databases and extraction of useful information to provide a realistic cost estimate. The methodology for data mining is a process of exploring data to identify and validate patterns and/or systematic relationships between variables, defined in [36], [37] and [38]. Rush *et al.* [39], among many authors, point out that 70-80% of the total lifecycle cost is committed at the concept design phase, while making a wrong decision at this stage could be extremely costly further down the development process. Therefore, the accuracy of cost modelling during this phase is extremely important. All cost models in aerospace engineering are very knowledge intensive to capture and manage the cost knowledge from several disciplines, Rush [40]. The growing awareness of knowledge management for cost-estimating purposes, as underlined by Tammineni *et al.* [33], led to an explosion of costing tools and identified the need for representing costing product information in a hierarchical way. The DATUM (Design Analysis Tool for Unit Cost Modelling) project sponsored by Rolls-Royce plc led to the Vanguard Studio (previously called DecisionPro) software as a novel costing tool [33], employed in a hybrid scheme a combination of tree (hierarchy) and object-oriented knowledge representation paradigms. With Vanguard, the complex problem is broken up into multiple tree objects, while costs of manufacturing features are saved in libraries to be reused. According to Tammineni *et al.* [33], each manufacturing cost model is a composition of material and process models, modelling uncertainty through the use of appropriate statistical distributions and sensitivity analysis is done through the use of Monte Carlo simulation (MCS) and correlations. The knowledge based engineering approach used in capturing, structuring and formalizing of manufacturing cost knowledge, is also advocated by Curran *et al.* [41] through the integration of Genetic Causal principle in developing a lean manufacturing cost contingency methodology from the earliest stages of the development cycle. Moreover, in most cost estimating methods, apart from the geometry and material and manufacturing processes, all cost rates are based on historical data collected from similar product/processes [42]. Alternatively, cost could be calculated not based on static modelling, but by determining the resource requirements from manufacturing system dynamic modelling through Discrete Event Simulation, as presented by Jinks [43].

2.3.2 Through-life cost

Technical support as one of the main components of through-life cost, includes all activities for maintaining the product ready for use, as in the case of aircraft flightworthiness, and is a major contributor into the operational readiness, as well as into the related to these activities cost. A general maintenance program includes:

- Aircraft daily/routine inspections and preparation for flight, Organisational Level (O-Level).
- Scheduled maintenance, based on time intervals, flight hours and life-limited components' replacement. Depending on the level of the maintenance, it is performed at an Intermediate Level (I-Level) onsite of operations or at a Depot Level (D-Level) in a repair facility.
- Unscheduled maintenance generated by failures and findings during inspections and could be either I-Level or D-Level, depending on the severity of failure and the required maintenance.

2.3.2.1 Reliability Centred Maintenance

All of the above maintenance activities generate costs that can be variable, depending on the utilisation of the aircraft, fixed, independent of the utilisation and periodic, if performed at specific time intervals. During the conceptual design phase, the variable maintenance costs can be used to distinguish the different designs. In the maintenance cost model and especially for military aircraft, maintenance and operations performed, are linked and should be treated as one process, with reliability central to all deliberations. Reliability is defined as "*the probability a system will perform its intended function for a specified period of time under a given set of conditions*", Lewis [44]. In order to maintain the reliability of a sophisticated system at an acceptable level, the system's design for redundancy, or system components of high reliability or both would have to be considered. Generally, not only the probability of failure but also the number of failures and the time required to be repaired are considered; therefore, the two reliability parameters of availability and maintainability are introduced. Availability is the probability that a system will be available for use at a given time, i.e. the fraction of time the system is operational to the total time [44]. Maintainability, on the other hand, is the probability to be repaired and operational within a certain time interval, provided that maintenance is performed according to predefined specifications [45], i.e. how fast a system can be repaired following its failure.

The cost of achieving greater reliability and the associated benefits of improved reliability in reduction of support costs and increased availability for military equipment, was studied by Alexander [46], based on historic data of previous programs; indicating that reliability improvements are possible, and that in most cases unit production cost did not rise, since the bulk of the cost effects were in nonrecurring investments. The approaches for obtaining better reliability levels are through the use of improved technology, additional resources toward reliability in design and development, trading-off performance for reliability, and through the use of higher quality and time/experience for detection and analysis of reliability problems. In most engineering design problems, the discrete points of cost-reliability data available need to be fitted into a cost vs. reliability curve, usually done with a least squares conventional method for the values of constants calculation as in [47]. Hence, cost can be adjusted based on the value of reliability, as performed by Chang *et al.* [48] who created a model for the reliability-corrected cost estimating relationships based on a satellites' cost database, allowing for reliability to be included as an additional parameter in a parametric cost estimation.

Maintenance and inspections programs are cost related activities and as such, they should be adjusted in terms of inspection intervals at the optimal level. Reliability-centred maintenance (RCM) was first introduced in the 1970s [49], and is described by Nowlan and Rausand [50], [51]. Rosqvist *et al.* [52] applied the RCM methodology in a value driven maintenance approach. Macke [53] optimised maintenance intervals using cost-benefit criteria for deteriorating structures. Wolde and Ghobbar [54] created a model that adjusts the inspection intervals, depending on the actual reliability of the system for optimum cost and availability for a railway carriage maintenance company. The policy of maintenance can be predefined as preventive, corrective or as a selective maintenance operation, i.e. an optimal decision-making maintenance activity for complex systems, with the objective being to select the maintenance scheme that minimizes losses and cost. The problem of reliability optimization and selective optimal maintenance policy has been studied by several authors, such as Bartholomew *et al.* [55], Kuo and Zuo [56], Chern [57], Kuo *et al.* [58], Irfan *et al.* [59] and many others.

For lifecycle maintenance cost modelling, statistical distributions are employed to model the behaviour of components in several analytical methodologies and for different systems, as done by Edwards *et al.* [60], Ghobbar *et al.* [61], Kong and Frangopol [62], Frangopol and Liu [63] and Guarnieri *et al.* [64]. It is however, the complexity of the systems modelled that necessitates the use of simulation for the adequate study of availability and maintainability. As Duffuaa and Andijani [65], [66] describe, simulation allows us to study the interactions of maintenance parameters with other technical and engineering parameters and between them, to successfully model uncertainty. Simulation has been applied in different cases, such as Hill *et al.* [67], Keeney [68], Cobb [69], Matilla and Raivio [70], Upadhya and Srinivasan [71], [72], [73], in modelling military operations, logistics aircraft and weapons failures and maintenance. Discrete Event Monte Carlo Simulation (MCS) is used with different probability distributions for modelling the failure times, due to lack of reliability, the survivability related battle damage, and maintainability related repair times.

MCS is a simulation method that computes, with the desired precision, the probability of failure from the joint probability distribution of the random variables and is relatively easy to implement. A suitable probability distribution is chosen to model the specific parameter, such as uniform, discrete, triangular, normal, lognormal, gamma, Weibull, beta, Bernoulli, binomial, Poisson or a custom distribution. The MCS method generates a random input from the aforementioned distributions and computes the reliability or survivability related lifecycle parameter, such as the maintenance lifecycle cost and the uncertainty involved, by performing this sampling multiple times.

2.3.2.2 Survivability Assessment

Apart from the reliability related failures, the aircraft failures and losses due to battle damage of a military aircraft are an additional aspect related to the lifecycle cost and aircraft's operational availability and success. Survivability is defined as the capability of an aircraft to avoid or withstand a man-made hostile environment, [74], [75]. There are two aspects of survivability, susceptibility, related to the probability of the aircraft being detected and hit by the enemy and vulnerability, related to the probability of the aircraft withstanding the battle damage. As described by Gundlach [76], there is a kill chain, associated with potential battle damage, first the aircraft must be detected, then once detected, to be targeted and hit and finally once hit, to be destroyed.

Ball [74] analysed the failures of fixed wing and rotary wing aircraft based on historic data of World War II and the Korean War and presented in detail a general treatment of survivability. Emerson [77] developed simulation models for combat damage assessment of airbases during wartime. Upadhya and Srinivasan [71],[72],[78],[79] studied the weapon system availability due to combat damage, performing simulation, and obtained ready to use estimates for availability of weapon systems, aircraft and weapons, [80]. Sonawane and Mahulikar [81] studied the aircraft susceptibility to infrared missiles and developed a model with respect to aircraft speed, showing that aircraft speed can be a rather effective countermeasure against threats. An aircraft vulnerability model was presented by Jun *et al.* [82], assessing the effects of redundant technology to the aircraft vulnerability and validating this engineering practice. In an agent-based modelling and DoE of UAV survivability by McMindes [83], speed and stealth were identified as the factors with the greatest impact on UAV survivability. Stoneking *et al.* [84] studied Multiple UAS collaborative dynamic sensor management and its operational advantages for improving situational awareness and UAS survivability in a single collective mission. Several combat survivability enhancement options for an unmanned aircraft were examined by Tham [85], suggesting that there is little room for enhancement, if combat survivability is not included in the design. However, as Coniglio [86] points out, most aircraft combat survivability data originated from World War II and the Vietnam War and although valuable, needs to be updated with respect to the current threats and technologies, to successfully define the survivability related design criteria.

In generic survivability simulation analysis, the aircraft system is represented as a system composed of various subsystems, i.e. structures, propulsion, etc., and battle damage results in the aircraft being either attrited or repaired. Several missions can be generally considered: Reconnaissance, Enemy Air Defence Suppression, Counter-Air/Interception, Ground Attack, Interdiction, Close Air Support and Battle Damage Assessment, while the undertaken missions and sorties are simulated at the specified interval. Values such as ranges of missions and sorties, probabilities of an aircraft or a specific aircraft's system to be hit as well as the probabilities for the aircraft to be lost, are obtained from historic data, such as the tables presented by Upadhya and Srinivasan [80]. Alternatively they can be computed with survivability analysis software, such as AGILE (Analytic Gaussian Intersection of Lethality Engagement) [87], predicting the vulnerability of the aircraft target through the use of Gaussian components, representing uncertainty and reducing or avoiding the need for MCS methods. In order to achieve a higher accuracy of the survivability related cost estimates, Thokala [88] developed a hybrid approach, combining survivability software computed parameters with aircraft performance data, through the use of parametric relationships in an aircraft design optimisation study.

Concerning the detection of aircraft, when operating in a hostile environment, there are several design parameters affecting its detectability characteristics:

- Radar cross section (RCS), since the radar-range is a function of the RCS [76].
- Acoustic signature is also important during surveillance missions, therefore acoustic characteristics should be studied [89].
- Heat sources, such as the aircraft engine, increase its heat signature and therefore its probability of infrared detection [81].
- Visual detection of reconnaissance aircraft from ground observers was studied by Dugas [90], and it is the design parameters of aircraft effective size, such as wing span, overall length, total area that greatly affect visual detection, [76].

Traditionally, combat survivability of the inexpensive and expendable UAS has been a low priority; nowadays as their complexity increases, a combat UAS loss is equivalent to both operational and serious investment losses. It is therefore imperative that survivability analysis and appropriate design criteria are incorporated in the aircraft design from the conceptual design phase, increasing protection/shielding of all vulnerable and critical components and systems, designing for redundancy, structural strength and damage reduction.

2.4 Value Driven Design

The method of Multidisciplinary Design Optimisation (MDO) was systematically launched in the 1960's in an attempt to perform engineering design optimisations with multiple attributes across different functional areas. Sobieski of NASA Langley Research Centre defines MDO as a '*methodology for design of complex engineering systems that are governed by mutually interacting physical phenomena and made up of distinct interacting subsystems*', explaining that for such systems '*in their design, everything influences everything*', [91]. MDO studies the application of numerical optimization techniques to the multidisciplinary engineering design. Since no single mathematical model can be solved for the optimum solution, different models in each discipline are created and solved separately, with their numerical results being forwarded to the next model, until convergence is achieved, providing the optimum solution to the multi-disciplinary problem. To reduce the high number of required calculations, a single approximate model is usually formed by fitting some mathematical surface to the large number of design variables. Several algorithms and MDO methods are applied in engineering design, and the choice of the appropriate method is dependent upon the specific goal. Martins *et al.* [92] provide a survey and classification of the most common architectures/methodologies used to solve the MDO problem. In general, the MDO problem is nothing more than a standard constrained problem of finding the values of the design variables that, subject to some constraints, optimize a particular objective function. The objective function, used to identify the best design alternative, could be a weight, drag or cost to be minimised, a performance related design attribute to be maximized or some other function to be optimised.

In the 1990's Hazelrigg [93] presented the systems engineering approach as a tool for rational decision making in the design process. According to the International Council on Systems Engineering (INCOSE) Systems Engineering Handbook [94], Systems Engineering (SE) is a '*discipline that concentrates on the design and application of the whole (system) as distinct from the parts, through an iterative process of top-down synthesis, development and operation of a system that satisfies in a near optimal manner the full range of requirements for it*'. SE is still currently the dominant integrating framework for engineering design.

During the previous few decades as systems became more elaborate, the fulfilment of engineering design requirements has experienced serious delays and cost overruns. In the U.S. Department of Defence, where a large number of programs are executed, a significant increase has been observed in delays, from 33% in the 1970's to 63% now and in cost, from 50% in the 1970's to 78%, which are mostly due to inefficiencies in the application of SE methodology, as Collopy and Hollingsworth [95] discuss. In the late 1990's Collopy introduced a value based optimisation process, breaking the system to subsystems and components, as proposed by SE, and flowing down the system objective function to the subsystems and components objective functions. For each component, a composition function would be a function that accepts as arguments the vector of the component's attributes and converts them to system extensive attributes, which would then be inputs into the system's value model; thus, a value score would be assigned to rank this specific component design. The objective function/value model would be a scalar function of all appropriate extensive attributes, while the task is to create the design that yields the highest score at the system level. Under VDD, SE is used not only to flow down the objective functions to each component but to monitor the achieved values of component attributes and system attributes, identifying any components with low value scores and keeping the system in balance. The difference between the more traditional approach of SE and VDD is that instead of requirements it flows objective functions down to components. Consequently, Collopy and Hollingsworth [95] proposed VDD as the framework that removes all requirements set by SE and focuses on the pursuit of value throughout the engineering design process.

As presented in Figure 2-3, in the VDD of a UAS, operating in a multiple fleets/multiple agents mode, the objective functions are flowed down from the system of systems level to system, sub-system and parts. The component/subsystem values are optimised and aggregated in forward design to provide the desired range of system attributes.

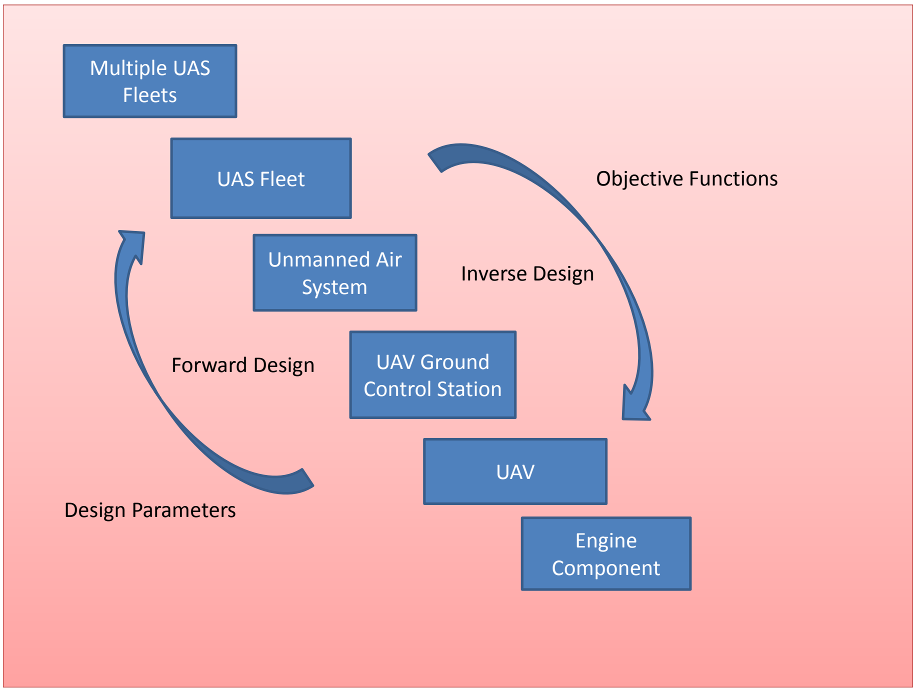


Figure 2-3 Value Driven Design Philosophy

In the VDD framework, one way of defining the value model would be through the use of Net Present Value (NPV), presented in the following section of 3.3. The discounted cash flow (to adjust to present value) generated by an asset over time would assess the net monetary worth for making the investment.

This objective function, to be maximised, can be used as a value model in the comparison of different design options, [95]. The application of Surplus Value theory through the use of the NPV, has been demonstrated with the VDD framework implementation to an aircraft propulsion system by Cheung *et al.* [96]. In a similar way, Castagne *et al.* [97] employed the Surplus Value theory in the aircraft fuselage panels VDD framework through the utilisation of an objective function which related manufacturer's cost and profit with airline's direct operating cost and revenue, adjusting with a discount rate. A value model, scoring engine designs based on their properties, to support the U.S. Air Force Versatile Affordable Advanced Turbine Engine (VAATE) was also developed by Collopy [98]. Keller and Collopy [99] used this philosophy to construct a top level value model to a spacecraft launch system, that employs economic analysis of all parties involved with spacecraft launch and operation. Eres *et al.* [100] applied the VDD methodology in conceptual engineering design, mapping customer needs to engineering characteristics through the use of Concept Design Analysis (CODA) [101], and by using an overall 'design metric' as the governing value score in optimisation studies.

With the employment of Surplus Value Theory, the systems' performance is converted to a straightforward monetary worth. However, monetization can be a rather challenging process, as discussed by Collopy [102]. This may be more appropriate for the design of civil aviation systems, since profit is the driving factor, while less tangible aspects of value, such as environmental friendliness, customer loyalty and contribution to society, are more difficult to monetise. Ross *et al.* [103], applying a series of Value-Centric Design Methodologies in the evaluation of two case studies, a telecommunication mission and a deep-space observation mission, demonstrated than no method is fully complete in capturing value. Instead, as they point out, the perspectives/perceptions of value need to be aligned with the method selected for pursuing VDD. In the case of defence systems, to capture all tangible and intangible concerns, value is not always easily expressed in monetary units, to use a monetised objective function. It is simply the means of ranking the order of relative preference between sets of consequences, consisted of benefits and costs, by assigning a number to each of them. Monetary worth represented by lifecycle cost is meaningful and understandable to the stakeholders of the designed defence system. Nevertheless, the monetisation of operations' related objectives/attributes, such as the ease of flying, the survivability related detectability or the target identification probability of a UAS, might prove problematic to capture the stakeholders' preferences. Value of a defence system, monetised or non-monetised, should always represent a measure of desirability, usefulness and preference of the stakeholders involved, and is related to its operational capabilities and lifecycle cost. This statement is sufficient in this research, since value is used only in a relative sense to compare different alternatives in the decision making process of engineering design. In view of the above, the most appropriate multi-criteria decision analyses for the value driven design of a defence system will be reviewed in the next chapter.

General VDD Framework

The aircraft concept VDD framework suggested by Collopy and Hollingsworth [95] is shown in Figure 2-4. The chosen design variables are varied to generate feasible design points in the *Define phase* of the cycle. Next, values for the extensive attributes are calculated in the *Analyse phase*. These attributes, in the case of an aircraft could be specific fuel consumption, range, endurance, acquisition cost, lifecycle cost etc. They can satisfy or not the requirements in the traditional way of engineering design, providing feasible and infeasible design points respectively and the process will stop, or they will be inputs to the value model to obtain a value index for the specific design point, during the *Evaluate phase*. The process carries on, in the *Search phase* through some optimisation algorithm, or simply by obtaining more design points. The general VDD framework includes the following steps:

1. Identify stakeholders and their objectives.
2. Establish the appropriate extensive system attributes, which should be comprehensive with respect to the corresponding objectives, measurable, while their full set should be complete, operational, decomposable, non-redundant and minimal, [1].
3. Build the Value Model/Objective function with inputs the system attributes, using the most appropriate multiple criteria decision tool.
4. Build the system/subsystem/component models that would generate the system attributes.

5. Perform the design optimization and trade studies, using the value model/objective function as the criterion for maximisation.

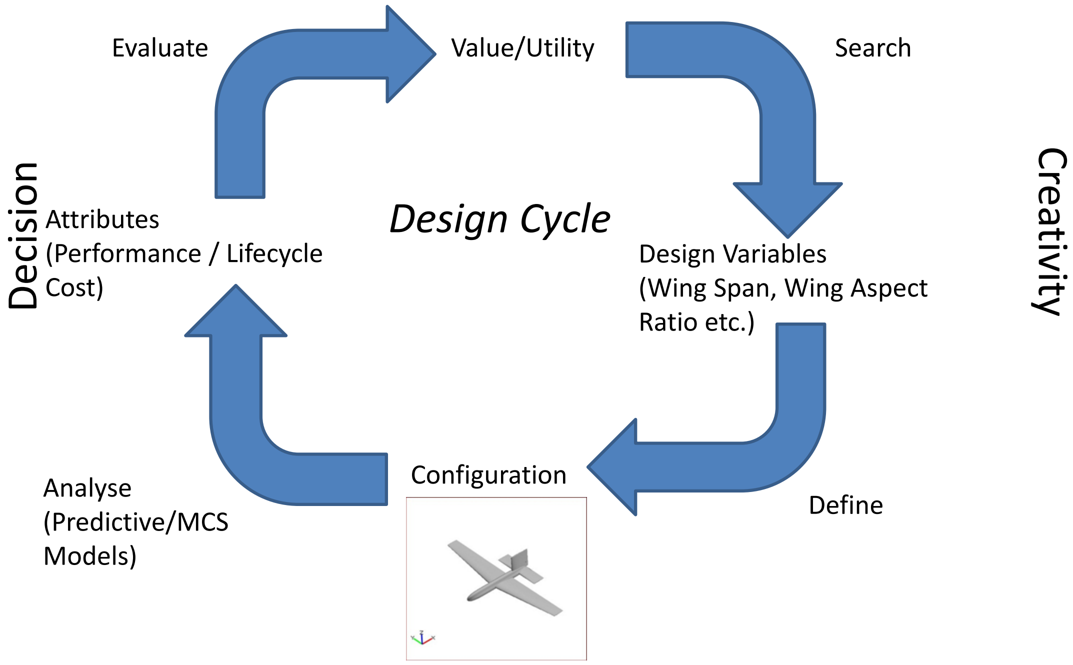


Figure 2-4 The Aircraft Value Driven Design Cycle

As already discussed, MDO is performed with the use of requirements that need to be fulfilled in the SE approach or the use of an objective function scoring each design option and identifying the best design. In the VDD framework, the identification of all stakeholders, involved with the designed system, and their needs is the basis to establish the objectives and the associated design attributes. Following the VDD approach, no constraints or requirements are placed in these design attributes and no design alternatives are excluded from the optimization due to their design attributes' values.

For example and similar to Fig. 11 presented by Collopy and Hollingsworth [95], when two objectives are taken into account, the attribute space for the UAS conceptual design can be plotted in two dimensions. For the attributes of *total UAS program cost* and *operational surveillance time*, Figure 2-5 is obtained. In this figure, following the SE approach, two requirements can be set. The Total

Program Cost has to be lower than a certain value, say £600,000, and the endurance when flying at design speed has to be larger than another value, say 1hr. The feasible UAS design space could also be defined as the space above the curve, shaded in green. With the systems engineering approach, any design inside the feasible design space that fulfils both requirements can be chosen. When the VDD approach is followed and based on the objective function, the optimal design could be the one in the yellow square. This UAS design would be the optimal design based on the objective function, although it exceeds the SE requirement of total UAS program cost of £600,000.

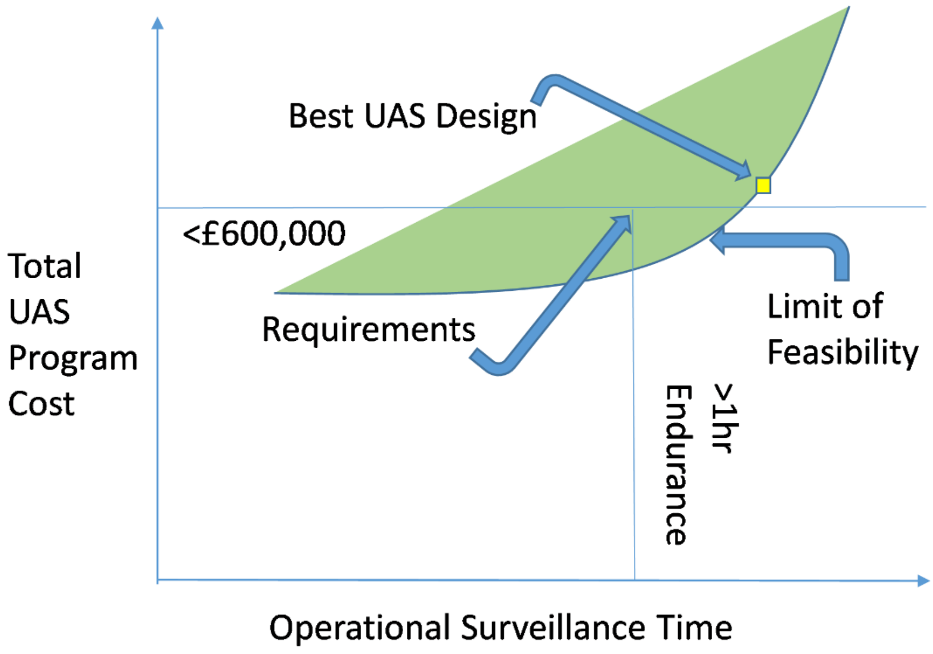


Figure 2-5 VDD Optimization vs. SE Requirements

The challenge lies mostly in the appropriate value model formulation, utilised in the upper left corner of the VDD framework of Figure 2-4 during the optimization and trade studies. This value model will have to include all information necessary, address all stakeholders' needs, expose any uncertainties during the whole design and development program and communicate value scores of all designed components, identifying those low value scored components that require further study and improvement, as in Figure 2-6. Appropriate system/subsystem/ component models are also built to define the design alternatives and generate the attributes, in the lower part of the VDD cycle. Hence, trade studies and optimization are performed based on the selected design variables and their ranges, with the value model as the optimization criterion.

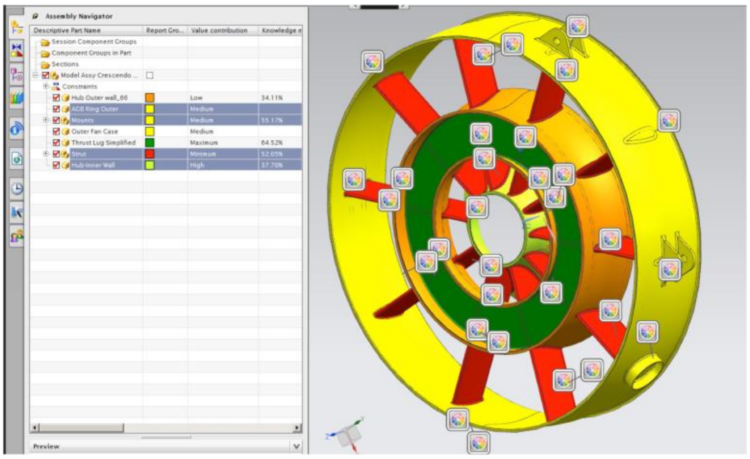


Figure 2-6 Component Colour Value Visualisation by Bertoni *et al.* [104]

2.5 Chapter Summary

The engineering design foundation of the proposed VDD framework and cost engineering, as the scientific analysis estimating total lifecycle cost of the designed product, were presented in this chapter. The basic aim of engineering design is to identify and improve the designs that satisfy customer needs, a process that gets more difficult as the system to be designed gets more complex. In the engineering design process, as the needs and requirements during the conceptual design phase are very broad and abstract, the generation of the different design solutions offers the opportunity to explore the widest possible design space and have a major impact on the following phases of the system development. The application of methodology and engineering design tools, facilitating trade-off and optimisation studies, are imperative to address the complexity of the design and the involvement of several disciplines. The search for the best design is performed either by fulfilling design attributes' requirements or obtaining the highest score of a value objective function. The SE methodology still dominates engineering programs, experiencing however serious delays and cost overruns in several engineering programs. Typical examples include the commercial airliner Boeing 787 with delays and an overrun of $2.5 billion; the Airbus A380, two years late and overspent by over €2 billion;

and the NASA Ares I Launch System with an overrun of $12 billion, [95]. The proposed VDD framework will use the appropriate value model, based on all stakeholders' needs, as the criterion to perform the design optimization. Instead of fulfilling requirements concerning the design attributes, such as the system's performance or total lifecycle cost, no design alternative will be excluded from the optimization due to their design attributes' values. Furthermore, the multidisciplinary engineering design approach will be adopted to address the complexity of the designed system and generate the design candidates in the concept phase.

3. Multi-Criteria Decision Analysis

“The greatest possible good for the greatest possible number … is self-contradictory. In general one function will have no maximum where the other function has one.”

John Von Neumann, Oscar Morgenstern, Theory of Games and Economic Behaviour, 1953, [105]

In the field of decision science, several approaches are employed to support multi-criteria decision making. These value centric methodologies are employed to evaluate a series of alternatives using a number of attributes when the corresponding objectives are pursued. The maximization of value is fundamental to any decision making problem solving; hence, system performance contributes *pari passu* with lifecycle cost in the creation of the value model. The most significant approaches in Multi-Criteria Decision Analysis (MCDA) include ELECTRE (Roy [106]), multi-attribute utility theory (MAUT) (Fishburn [107], Keeney and Raiffa [1]), simple multi-attribute rating technique (SMART) (Edwards [108], Edwards and Barron [109]), Analytic Hierarchy Process (AHP) (Saaty [110]), technique for order preference by similarity to ideal solution (TOPSIS) (Yoon and Hwang [111]) and simple additive weighting (SAW) (Kirkwood and Corner [112]). Collopy [102], surveying some of these MCDA techniques used in the development of the value model for engineering design, concluded that it is the user’s point of view, adopted in value modelling, that defines the selection of the most appropriate tools. Hence, the most appropriate tools of MCDA for capturing the preferences of stakeholders, involved with the designed defence system, with objectives not always translated to monetary worth will be introduced in this chapter. These MCDA tools will be employed to develop the multi-attribute and multi-stakeholder value models.

3.1 Multi-attribute Utility Theory

Value is a general term capturing both utility, representing degree of desire or aversion, and worth, representing monetary value [102]. Value, unless depicted by a single objective, is always related with trade-offs; dealing with problems of multiple objectives, there is not a single "best" alternative to be chosen and an objective is traded off with another. The maximization of value is fundamental to any problem solving. Utility is defined as the degree of desire or aversion towards a consequence, assessing satisfaction. Utility and multi-attribute utility theory [107] [1] are the foundations of the analytical methods for measuring preferences of consequences with one and more dimensions, respectively. Utility is related with the stakeholder's attitude towards uncertainty, assessed through the establishment of indifference between a *Certainty option* of receiving x and the lottery/risky option of getting the best consequence x^* with a probability π and the worst x_o with a probability $(1\text{-}\pi)$ expressed below:

$$x \sim \langle x^*, \pi, x_o \rangle \qquad 3\text{-}1$$

$\sim$ stands for indifference between the two options.

The development of the multi-attribute utility models is based on two assumptions, preferential independence and utility independence. The preferential independence is assumed or verified, implying that preferential ranking between two pairs of two attributes is independent from the levels of the other attributes. Moreover, the utility independence is also assumed or verified, concerning the intensity of preferences, i.e. that the indifference between a lottery and a certainty equivalent for any attribute is independent of the levels of the other attributes. If both assumptions hold, then the model of the multi-attribute utility for *n* attributes is a multiplicative one:

$$K\,U(X) + 1 = \prod_{i=1}^{n} [K\,K_i\,U(X_i) + 1] \qquad 3\text{-}2$$

The scaling constants K_i are assessed using two approaches, the trade-off and the direct rating approaches, as described by Keeney and Raiffa [1] and Dyer and Sarin [113] respectively. The simplest form of multi-attribute utility function is the additive utility function. This form is obtained from equation 3-2, when the sum of the weighting factors $K_1, K_2, \dots K_n$ is found to be equal to 1 and the factor K is equal to 0. Then, the attributes are additive independent, meaning that the stakeholder's preferences over lotteries depend only on their marginal probability distributions and not on their joint probability distribution, while the utility function has the form:

$$U(X) = \sum_{i=1}^{n} K_i \, U(X_i) \qquad \text{3-3}$$

In practice, since an additive model is a special case of the multiplicative model, preferential independence and utility independence is verified or assumed, and if, during the assessment of K_i scaling factors, their sum is found equal to 1, then that implies that $K = 0$ reducing the model to an additive one, [1]. Otherwise, the additional constant K is evaluated iteratively as in Keeney and Raiffa [1].

Among the various multiple criteria decision making approaches, the multi-attribute utility theory has a prominent place, mainly due to its comprehensive theoretical structure. It has been used as a standard technique in several applications in research and real-world problems, such as the airline industry [114], nuclear energy [115], earthquake projects [116] and farming systems [117]. MAUT has been incorporated in the multi-attribute trade-space exploration (MATE) paradigm for generating a multitude of system designs and identifying the optimal ones, [118], [119], [120] and [121]. It was also applied in establishing the requirements' specification of commercial aircraft [122], in evaluating space system designs for the telecommunications and deep-space observation missions [103], and the development of satellite value models [123].

The limitations of MAUT lie in the fact that:

- The goodness of design alternatives is measured through an abstract utility index, which is the reason why Collopy [102] recommends transforming the results back to some certain equivalent monetary value, through the use of a utility-worth function.
- It is inappropriate when more than one individual is considered due to Arrow's Impossibility Theorem, Arrow [124]. As Keeney and Raiffa [1] discuss, in general there is no averaging method used in the aggregation of the individuals' preferences that does not explicitly deal with the interpersonal comparison of preferences.

Utility functions capture the stakeholder's risk attitude by answering the following question: "What is the achievement of one objective that they are indifferent to accept between the certainty option of this achievement and the lottery/risky option of having either the best or worst achievement of this objective?" Simple value functions, as special cases of utility functions, ignore the stakeholder's risk attitude and represent the worth they give under certainty to achieve a certain value of an attribute, since no lottery to certain equivalent utility comparison is involved. According to Keeney and Raiffa [1], their development is based on a different fundamental question: "How much achievement of one objective is the stakeholder willing to give up in order to improve the achievement of another objective by some fixed amount?". Value functions focus on the problem of trading off the achievement of one objective to improve another objective, capturing the stakeholder's preferences. Uncertainty, although present, is ignored and the trade-off issue is addressed through the subjective judgment of the decision maker. For the multi-attribute case, the preferential independence among the attributes is assumed or verified. It refers to the case, when the preferences over any subset of attributes are independent of its compliment. Hence, the multi-attribute value model for *n* attributes has the additive form:

$$V(X_1, X_2, \ldots, X_n) = \sum_{i=1}^{n} K_i \, V(X_i) \tag{3-4}$$

The scaling constants K_i are obtained as in the utility model, while the individual value functions of the attributes $V(X_i)$ are estimated independently with a direct value estimation technique, using three distinctive approaches, the direct rating, direct midpoint assessment and direct ordered metric, [107]. The main deficiencies of this model are that it fails to capture the stakeholder's attitude towards uncertainty and, due to its additive form, no overlapping is assumed among the objectives. Multi-attribute value models have been employed when the stakeholder's risk attitude is ignored, as in the value assessment of various commercial aircraft designs [125]. They were also used in conjunction with bio-economic modelling to study production strategies and the use of soil nutrient resources [126], and with AHP and a fuzzy set based approach in the nuclear spent fuel management [127]. Value functions were combined with utility modelling, eliciting values (through linear value functions) at lower-levels of the objectives hierarchy and assessing risk attitudes at higher levels [128].

3.2 Analytic Hierarchy Process

The analytic hierarchy process (AHP), established by Saaty [110], is a decision analysis technique that applies hierarchical decomposition of a high level objective to lower level sub-objectives to derive a set of ratio-scaled value measures for a number of alternatives, based on the judgments of a group of experts/decision makers.

AHP is a systematic approach to decision making, designed for the selection of the best from a given set of alternatives, when evaluated with respect to several criteria by making pairwise comparison judgments, [129]. Experience of experts as decision makers is used to identify properties and establish the corresponding selection criteria for tradeoffs between these properties, to perform the decision making. As in any decision making process, the most creative task of this approach is the selection of objectives and sub-objectives to be included in the hierarchic structure, as already discussed in 2.2, with enough detail to capture the full problem but at the same time avoiding redundancy by including just the necessary elements. Rationality in the AHP is defined, according to Saaty *et al.* [129], as follows:

1. Focusing on the goal of solving the problem;
2. Knowing enough about a problem to develop a thorough structure of relations and influences;
3. Having enough knowledge and access to knowledge and experience of others to assess the priority of influence and dominance (importance, preference) in the hierarchy;
4. Allowing for differences in opinion with the ability to develop the best compromise.

AHP uses pairwise comparisons between all possible pairs of criteria and alternatives to establish an objective weighting and to form an assessment model for evaluation of different alternatives, due to the fact that humans cannot comprehend the relations among more than a handful of objects. Moreover, through the eigenvalue/eigenvector approach, it measures the consistency of these comparisons, assessing the validity of the answers given. AHP is capable of synthesizing the different opinions in group discussions and decision making, based on consensus, voting or compromising, forming the geometric means of the judgments of individuals and combining results from individual models, as presented by Dyer and Forman [130]. They also comment that when AHP is used in a group setting, it can accommodate both tangible and intangible characteristics and can allow discussion.

However, AHP lacks the theoretical axiomatic foundation of utility theory, as described by Dyer [131], which AHP advocates dispute that it is not required for a decision-making method [103]. In AHP, the weighting factors at a higher level of hierarchy are assessed independent of the priorities (i.e. evaluations of the alternatives) obtained at a lower level; this could result in the phenomenon called *Rank Reversal* [131], [132]. This phenomenon, exhibited by almost all ordinal aggregation methods, happens when the ranking between the dominating alternatives changes when other dominated alternatives are introduced [132]. Dyer [131] suggests that the decision maker should know the ranges over which the attributes vary, based on the alternatives under consideration, to perform the higher level AHP comparison. Saaty [110] also proposes to avoid rank reversal by using absolute measurement for rating the alternatives. Another disadvantage of AHP is the construction of its matrix which is based on the ambiguous question: 'How much better/more *important is attribute/alternative* A_i *than* A_j*?*', assuming the existence of a ratio scale preference, rather than derive the preference through the use of a set of axioms, as done in Utility Theory, [131]. It is, however, a useful tool to define the problem, consider a large number of attributes, communicate value, identify differences and similarities between various stakeholders' points of view and aggregate them [133], [134], [135], [136], [137], [138]. Nevertheless, it is the synthesis of MAUT with AHP that provides significant benefits in the preferences' assessment, as suggested by Dyer [131], and has been successfully demonstrated in several applications, [139], [140], [141], [142], [143], [144], [145].

3.3 Net Present Value (NPV) Cost-Effectiveness and Cost-Benefit Analyses

The Net Present Value method quantifies the monetary value of a system and consequently it is often used in financial appraisals of physical assets. Value is interpreted as cash flow, i.e. revenue minus costs over some lifecycle time. The cash flow generated by an asset over a period of time is assessed to justify or not the net monetary worth for making the appropriate investment in this asset. A discount is applied to adjust future cash flows to present value. The objective function translates everything to a monetary value, allowing for comparison of different designs, even with different attributes in commensurable units, [95]. In general, the corresponding objective function is of the following form, [146]:

$$NPV = D_o + \int_{t_j}^{t_k} \frac{D(t)}{(1+r(t))^t} dt \qquad \text{3-5 a}$$

$$\text{or } D_o + \sum_{t=t_j}^{t=t_k} \frac{D(t)}{(1+r(t))^t} \qquad \text{3-5 b}$$

$$\text{or } D_o + \sum_{t=t_j}^{t=t_k} \frac{D(t)}{(1+r)^t} \qquad \text{3-5 c}$$

Where D_0 is the initial investment, $D(t)$ the net cash flow during the whole duration, $r(t)$ is the discount rate at time t and $[t_j, t_k]$ represents the time interval over which the NPV is calculated, such as the lifecycle of the product. The simplest form is the rightmost, where constant discount rate and discrete time steps are assumed. The basic advantages/disadvantages of NPV as a financial value model, already briefly discussed in 2.4, are the following:

- The process of converting all design attributes to monetary worth/return is rather challenging but, if accomplished, makes the monetary value straightforward and meaningful to the decision makers, unlike the abstract value of utility. Especially for defence and space systems, several attempts have been made to develop a monetized value model, as in [123]. However, in the application of NPV, intangible and more difficult to monetise aspects of value can often be ignored, assuming that the stakeholders perceive value only coming from monetary return.

- The stakeholder's risk attitude can be incorporated in the financial value model of NPV through the employment of risk premium, as discussed by Collopy [102]. Nevertheless, in most cases it is ignored and risk neutrality is assumed. By making no adjustment for risk premium in a financial value model, the expected utility is equated with NPV.
- Finally, NPV does not account for any uncertainties in the assumed values of cash flow, assuming specific values of market demand curves, inflation/deflation and investment returns.

The application of the NPV has been demonstrated by Dragos *et al.* [147] for the evaluation of a spacecraft, by Nickel [148] in the evaluation of a Transportation domain project, by Castagne *et al.* [97] within a aircraft fuselage panels VDD framework, by Cheung *et al.* [96] for the design of a propulsion system and in the value modelling of a space system by [99].

Similar to NPV, the methodologies of Cost-Effectiveness and Cost-Benefit, are used for cases when each action/alternative can be described in terms of cost and a set of benefit measures, $B_1, B_2, B_3, \dots, B_n$, usually in incommensurable units. In the cost effectiveness analysis, the benefits are not combined to a single composite benefit measure, whilst in the cost-benefit analysis some conversion factors, $w_1, w_2, \dots, w_n$ are used to combine them into a composite benefit measure; however, both analyses identify the Pareto set of dominant alternatives. In most cases, the Cost-Benefit Analysis aims in monetising everything, and not just revenue as done with the application of Net Present Value, to provide a single monetary value, [148].

3.4 Group Decision Making

The preferences of an individual decision maker are elicited through multi-attribute utility theory, evaluating the entire set of alternatives by developing and adding up appropriate utility functions for all attributes. However, in most cases, several individuals constitute the decision group and an appropriate aggregation method of the individual preferences is required to obtain the group's objective function, while the conflict between those preferences is a common situation. In engineering design, the designer should assess and articulate the preferences of all experts/individuals, instead of being the 'benevolent dictator', making decisions affecting other people.

MCDA methods provide useful tools to deal with interpersonal preferential conflicts, all aiming to achieve group members' consensus. AHP is well equipped for group decision making, as discussed by Dyer [130], through consensus, voting/compromising, computing the geometric or arithmetic mean of individuals' judgments, or any other way of averaging the individual results. Several applications of this aggregation are presented in literature, such as the computation of the arithmetic mean of the individuals' preferences after being normalized appropriately measuring the group members' satisfaction over the proposed ranking of the alternatives by Matsatsinis *et al.* [149], integrating the individuals' aspirations into the utility theory, Feng *et al.* [150], or computing their geometric mean, Kim *et al.* [151]. Quite often the preferential differences among different alternatives and priorities are also considered/weighted to obtain the group utility values, as in Huang [152]. AHP is used to support multiple stakeholders' decision making, Alvarez *et al.* [135]; the geometric mean calculated by AHP is also used in group decision making Lai *et al.* [134] and Sohn *et al.* [141]; while fuzzy AHP techniques are employed in the geometric means computation by Carnero [153]. In an ordinal ranking and in the presence of strategic voting, the individuals' preferences can also be aggregated to an overall ranking as in Hurley *et al.* [154]. Quite often the individuals' preferential differences among different alternatives and priorities are also considered/weighted to obtain the group utility values, Huang *et al.* [152].

Dijkstra [155] presented a method for the extraction of group weighting factors from the AHP pairwise comparison matrices of the group members, while simultaneously minimizing the inconsistencies introduced in the group preferences synthesizing. To justify the importance of the inconsistencies' assessment, Dijkstra argues than any reasonable synthesization method of the individuals' preferences, as represented in the AHP matrices, should be characterized by the requirement that *the synthesis of consistent judgements ought to be consistent too.* In general, as discussed in 3.1, any averaging method, used in the aggregation of the individuals' preferences, has to explicitly deal with the interpersonal comparison of preferences.

3.5 Game Theory in Engineering Design

In engineering design, several decisions have to be taken into account concerning the whole lifecycle of the designed system, including the design, manufacturing, use, maintenance, repair and disposal stages. These decisions are made by *N* different stakeholders (*N*>1), involved with the designed system at some stage of its lifecycle, each seeking to better promote their own interests, as depicted in their corresponding utility function $U_i,\ i = 1, \dots, N$. Therefore, Game Theory can be employed to study engineering design as a game between the *N* stakeholders/players, each aiming to better promote their interests, through the maximization of their own objective function and all affected by the others' choices.

John Von Neumann is considered to be the founder of the Theory of Games [105] with his proposed Maximin Solution in a zero sum game, i.e. the strategy of each player minimizing the highest loss or maximizing the lowest gain, irrespectively of what the other players do. However, the keystone was set by John Nash with the Nash-equilibrium solution of a non-zero sum, non-cooperative game [156] and the Pareto optimal Nash bargaining solution (NBS) of a non-zero sum, cooperative game [157].

Nash-equilibrium constitutes the set of all players' strategic choices and their corresponding payoffs, if each player has chosen a strategy and no player can benefit by changing his/her strategy while the other players keep theirs unchanged. Game Theory as an optimisation tool, modelling decision interactions among rational players as non-cooperative games, has been applied in numerous engineering design cases such as the engineering asset management between maintenance chain participants in a negotiation model, Trappey *et al.* [158], between engineering disciplinary teams for collaborative decision making, Xiao *et al.* [159], and the design of an aero-structural aircraft wing shape optimisation, with the design space split into two supplementary subspaces assigned to two virtual players of an adapted non-cooperative game, Desideri [160]. The selection of players can vary from actual persons, agents to aircraft components evaluated when different disciplines are involved, Runyan *et al.* [161], considering different disciplines/technologies as players, Habbal *et al.* [162], and based on gene expression programming in multi-objective MDO problems, Xiao *et al.* [163]. Players could also be fictitious, each having control of one design variable in a particle swarm optimisation, Annamdas *et al.* [164], or even objective functions in a multi-objective optimal engineering design, Gonzalez *et al.* [165] and Hu *et al.* [166]. Finally, a hybrid-game strategy for multi-objective design optimization was proposed by Lee *et al.* [167], employing Nash equilibrium as a fast companion optimizer to guide the slower multi-objective evolutionary optimizer, capturing the Pareto non-dominated front.

Nash-equilibrium of games between non-cooperative players does not guarantee the property of Pareto Optimality. Nevertheless, if players cooperate through a bargaining process, they are rewarded with a solution that belongs to the Pareto optimal set. The problem of indeterminacy of the Pareto front was solved by Nash [157] through the determination of an axiomatic-based definite solution among all the Pareto optimal candidates, representing the anticipations the players would agree upon as fair bargains. It is based on the criterion of maximization of the product of utilities' distances from the disagreement points for the bargaining problem between two players reaching a binding agreement. Harsanyi and Selten [168] generalized the bargaining problem for two or more players of not equal relative/bargaining authorities. The NBS has been applied in many cases modelled by cooperative games such as the design and management of microwave access networks, Jiao *et al.* [169], the design of semi-decentralized controllers in a multi-agent team cooperation approach, Semsar-Kazerooni *et al.* [170], bandwidth allocation in networks, Yaiche *et al.* [171], Ma *et al.* [172], collaborative product development, Arsenyan *et al.* [173], and the design of water distribution networks, Beygi *et al.* [174].

3.6 Chapter Summary

In this chapter, basic methodologies of multiple criteria decision analysis were presented, suitable for capturing the preferences of multiple stakeholders with multiple objectives concerning the designed system and not always translated to monetary worth. These decision analysis methods focusing on the identification of value, reflecting all stakeholders' requirements and needs, can be used within the contexts of SE and VDD frameworks to develop the appropriate single and multiple stakeholders' multi-attribute value models. After all, the biggest VDD design framework challenge lies mostly in the value model formulation. The value model has to include all information necessary and address any uncertainties, mostly related to the maturity of the information and data that are used. This will not only create a comprehensive model that provides truthful and justified value score outputs for all design alternatives but will also expose those uncertainties to the decision making stakeholders.

4. Value Driven Design Framework

"The purposes to be served in the plural – a series of compromises of various considerations, such as speed, safety, economy and so on."

D. K. Price, The Scientific Estate, 1968, [175]

Traditionally, engineering design has been using '*Carpet Plots'*, plots of a certain objective function versus two independent variables or even the use of several carpet plots, for more than two variables, as in Figure 4-1. Nowadays, in the design of complex systems, made up of many subsystems governed by physical laws with many disciplines involved, there is a large number of independent variables and a system merit to be optimised, maximised or minimised, in the presence or absence, for VDD, of design attributes' requirements.

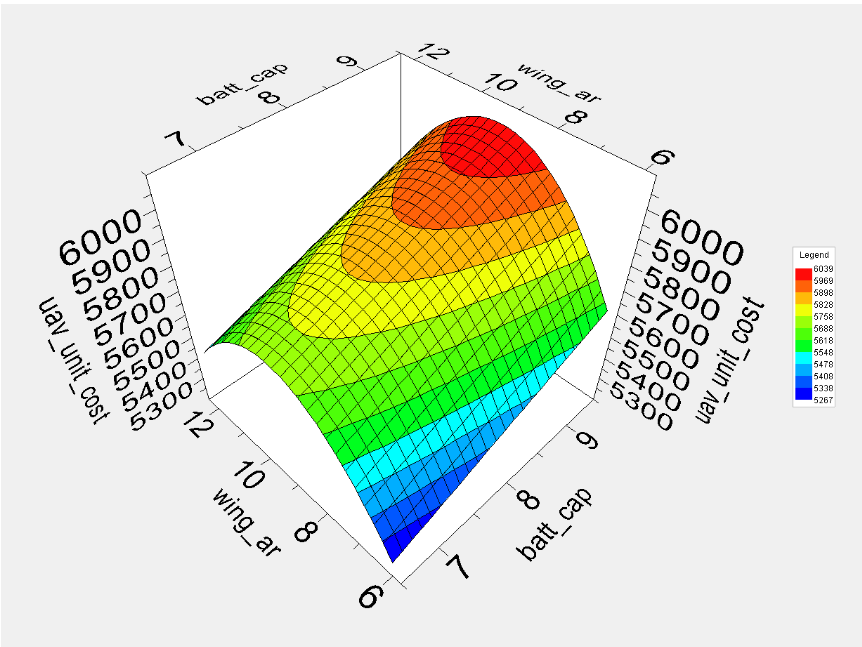


Figure 4-1 Example of a Surface Plot

However, before defining the system's merit, it is imperative to select first the mission and the category of the system that will be designed. This selection will identify the stakeholders involved, their needs/requirements, and the corresponding design attributes, as inputs to the system's objective function to perform the design optimization and trade studies. It will also govern the development of the appropriate product definition and lifecycle prediction models. Hence, the conceptual design of a small military UAS for surveillance and reconnaissance was chosen for the application of the general VDD framework of Figure 2-4. In this framework and following the iterative engineering design procedure, the design variables are selected among all design parameters depending on the needs of the stakeholders, in the *Search* phase of the cycle, numerous design points are generated in the *Define* phase, based on variation of selected design variables and choices. The corresponding values of design attributes, based on the stakeholders' objectives, are computed in the *Analyse* phase, providing an array of parameters, reflecting performance, economic and other concerns, all measured in incommensurable units. The fulfilment of all involved stakeholders' needs is quantified through the estimation of their corresponding figures of merit as single measures of value in the *Evaluate* phase; finally the iterative process continues through a selected optimization algorithm or simply by generating more design points.

4.1 Unmanned Air Systems

Since the beginning of aviation history, the missions and roles of Unmanned Air Vehicles (UAV) have been continuously expanding, with Nikola Tesla describing a fleet of unmanned aerial combat vehicles in 1915 [176], and the earliest attempt by A. M. Low's 'Aerial Target' in 1916 [177]. For the military, the missions of UAV range from surveillance and reconnaissance to weapons deployment, while they are used in numerous civilian, commercial and government applications such as search and rescue (SAR), surveillance, monitoring, customs control, fighting crime and agriculture, to name a few. The U.S. Department of Defence defines UAVs as "powered, aerial vehicles that do not carry a human operator, use aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely, can be expendable or recoverable, and can carry a lethal or nonlethal payload", [178].

Figure 4-2 X45 J-UCAV [179]

It is evident that the only difference between an unmanned and a manned air system is whether the operator is within the air vehicle or not. This difference is an obvious advantage of UAS, in terms of the operator's safety and comfort, and simultaneously a disadvantage, because of the systems required for the UAS to be remotely operated and controlled. As Frampton [180] points out unmanned systems have progressively been fitted with more instrumentation and sensor systems, to make more data of vehicle systems available to the operator, to the same or even higher level than a manned aircraft.

The automated decision making capabilities of UAS will increase, as technology moves forward, reducing control and increasing their autonomy. On the other hand, due to the advantages of UAS to manned aircraft, their use will be expanding with roles such as extended duration reconnaissance and surveillance flights, flying in contaminated environments, in hostile environments, or in covert roles due to lower detectability, [181].

In general, the costs of a UAV smaller than the corresponding manned aircraft and used in the same role, should also be lower. The overall difference in manufacturing cost, depending upon the mission requirements, may be of the order of 20–40% of manned aircraft cost for the UAV cost and 40–80% for both UAV and control station, [182]. Operating cost is expected to be also lower, since maintenance and fuel costs are lower; fuel consumption and labour costs are significantly reduced proportional to the weight/size. It is hard to compare the

UAS operators' costs with the aircrew costs, since all training and keeping the UAS pilots flightworthy need to be taken into account. Moreover, to obtain an accurate estimate of their total cost, their multi agent mode of operation as part of a system should be taken into consideration; a system that is comprised of ground control station, ground crew, remote pilots and sensor operators, communication links and often operated as a fleet of air vehicles. Nevertheless, for the purpose of conceptual design within a VDD framework with various design candidates evaluated, the above issues should be addressed as long as they provide the means to compare the candidate design options.

Figure 4-3 Predator Medium Altitude Long Range UAV [179]

UAS Composition

In general, the UAS is made up of the following systems:

- The *air vehicle*, whose performance and size is determined by the missions it will be involved, being the scope of this value driven conceptual design framework.
- The *payload* it will carry, ranging from a small camera of a few hundred grams or even less to a more sophisticated heavier video system or even high-power radar of a significant weight.
- The *navigation system,* such as an inertial navigation system (INS) or a global positioning system (GPS) for an autonomous flight.
- *Communication system,* for establishing communication and transferring data (uplink and downlink).

- Other *interfaces,* for the proper operation of the systems, if not in a stand-alone operation.
- Equipment for *launching, recovering* and *retrieval* that could be required depending on the aircraft configuration, i.e. bungee, access to runway, etc.
- *Support equipment,* for the performance of maintenance (tools, manuals), transport to the scene of operations and other relevant equipment, etc.
- Finally the *ground communications station,* as the centre of operations and the man-machine interface.

4.2 UAS Stakeholders and Objectives

During the conceptual design phase, once the requirements and technologies available are defined based on the stakeholders needs and the selected "technology readiness level" (TRL), defined by [183], trade-offs between design features are explored to identify the general description of the most preferred and acceptable solution. For the design of a UAS, the needs of the stakeholders, the units to be produced, any cost related requirements/constraints as well as the general system, such as political and regulatory, where the whole program development will take place from the initial design up to its disposal, need to be all identified.

Concerning defence contracting, Adams [184] identifies a military industrial complex of interests, which he calls "iron triangle" of defence policies, consisted of legislature, government and industry. With respect to military aircraft, the corresponding "iron triangle" of blending interests should be addressed in the engineering design, as presented in Collopy [4]; that is, the aircraft manufacturers, the Ministry of Defence (MoD) chiefs and finally, the government and legislature representatives of the regions where the aircraft and its components will be built. Military wants to perform operations successfully, industry to generally maximize profits by maximizing revenue and government/legislature representatives to support the military, contribute to the economy and strengthen the national image.

For brevity, the two most typical stakeholders, the user and the manufacturer, were included in the current analysis. The user whose priorities and needs include not only the mission capabilities of the designed system, but also the technical and logistic support required for its whole lifecycle. Hence, it was assumed that the multiple objectives reflecting the user's priorities and needs would cover the interests of the two vertices of the "iron triangle", the military and the government. Moreover, concerning the manufacturer, a cost plus fee (CPF) contract type was selected as opposed to firm fixed price (FFP), since this contract type generates more desirable results, sharing the risk between industry and government, [76]. Thus, the manufacturer's profit should be a percentage of the Total UAS Program Cost and the corresponding objective/payoff function was modelled as a linear function of this cost. Nevertheless, it would be possible to assume a firm fixed price (FFP) contract type or even a hybrid model and develop the appropriate manufacturer's objective functions for these cases.

The missions related to the user's objectives define appropriate aircraft attributes, listed below:

1. *Payload* varying from a mini camera of 100-200 grams to well over 1000 kg and in volume from a few cubic centimetres to above one cubic meter, with a significant impact on its identification capabilities.
2. *Endurance* and *range*, limited by its fuel or battery capacity, from below one hour for close-range surveillance UAS, to over twenty four hours endurance for a long-range surveillance system.
3. *Operating range*, limited by fuel/battery capacity, or communication links.
4. *Speed range*, with ranges from 0-100 kts for a close range surveillance role, 0-150 kts for naval multiple roles, 80-500 kts for long-range surveillance and airborne early warning (AEW) systems and 100 kts to 1Mach for interception/interdiction roles, [182].
5. *Environmental considerations* based on the environment that the UAS will operate, defined by altitude, temperature, humidity, salinity, wind conditions, possible night operations, noise considerations, due to applicable regulations and detectability issues if operating in a hostile environment.

6. *Operational flexibility*, performing multiple tasks with the minimum time to respond.
7. Operators' and maintenance personnel *workload* considerations, related both to cost and personnel discomfort.
8. *Maintenance* and *reliability* issues, in terms of scheduled, unscheduled inspections and repairs that need to be performed, resulting in labour costs and parts required as well as *operational fleet availability*.
9. *Launching* and *recovery system*.
10. *Safety issues*, for a system operating in a civilian environment and *Survivability issues*, when operating in a hostile environment.
11. *Total Lifecycle System Cost* related to both procurement and maintenance costs.

The identification of objectives and criteria/subcriteria is usually done with appropriate questionnaires answered by the stakeholders. For the UAS conceptual design, the objectives reflecting the user's priorities and needs with their corresponding attributes are assumed to have been identified and structured in the objectives/attributes hierarchy presented in Figure 4-4. Other needs/objectives or different attributes could be incorporated in this user's objectives/attributes hierarchy. For instance, the target identification probability, measured by some payload attribute, or in the objective of minimizing detectability, apart from visual detection measured by the total UAS surface area, the acoustic signature of the aircraft could also be added. The specific hierarchy will be utilised in the employment of the user's multi-attribute value model for the application of the VDD framework in the conceptual design of the UAS for surveillance and reconnaissance. These attributes, as already explained in 2.2, were chosen to be comprehensive, in terms of the corresponding objective, operational, i.e. useful for the purpose they were chosen, decomposable, allowing the objective to be broken down into parts of smaller dimensionality, non-redundant, avoiding double counting and finally minimal, keeping the set as small as possible.

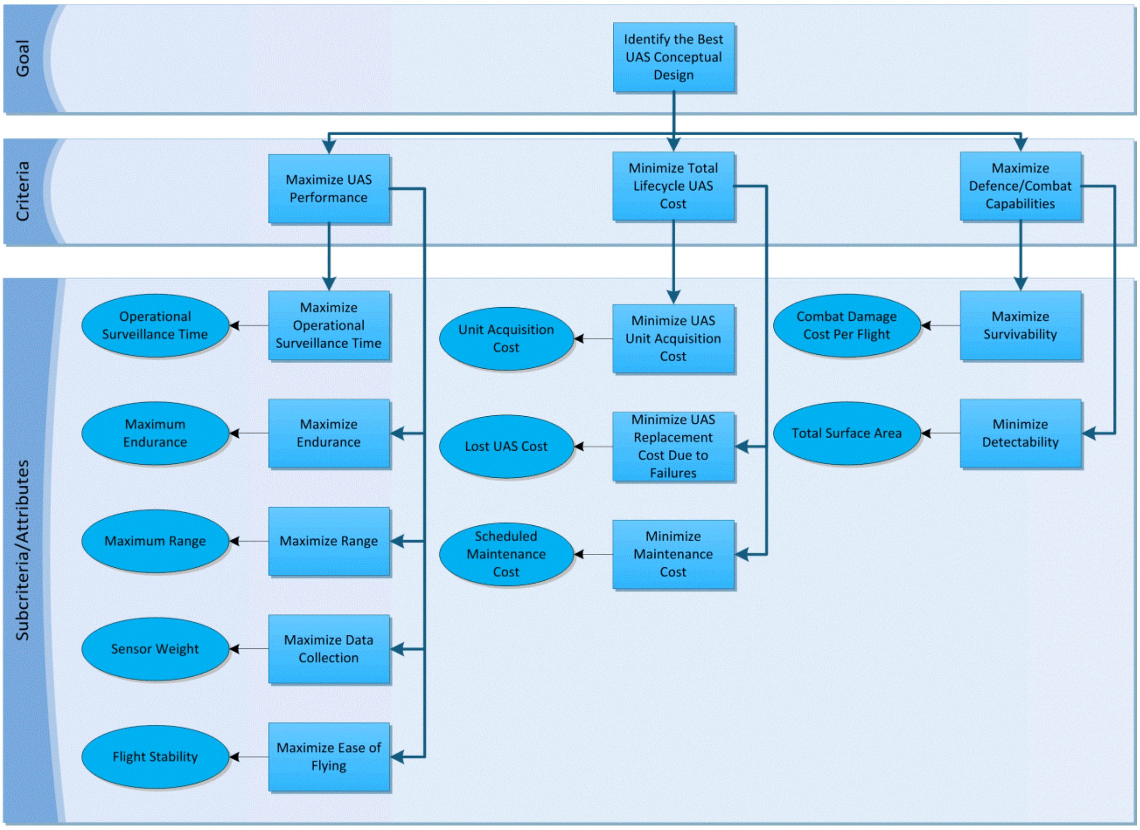


Figure 4-4 UAS User's Objectives/Attributes Hierarchy

For the VDD framework application in the UAS conceptual design, a specific UAS category was selected by the Defence Science and Technology Laboratory (DSTL), as the funding agency of this research. This UAS category would be that of a Mini-UAV with total weight under 5 kg, carried, assembled and deployed by no more than two persons, no undercarriage, fitted with a camera for surveillance and reconnaissance, similar to the Desert Hawk which was designed by Lockheed Martin and is in extensive military use, Figure 4-5.

Figure 4-5 Desert Hawk

In the selected UAS category, several considerations and compromises were noticed, to achieve certain requirements:

- Wing span, such that it allows it to be easily assembled/disassembled and backpacked and still achieve endurance at operational speed of approximately one hour.
- Wing loading should be kept low, for flying at low speeds, making it sensitive in turbulence and with limited ability of flying in strong wings.
- Easily handled and senso-centric flying.
- Minimum (stall) speed high enough (around 14 m/sec) for assisted take-off.
- Electrically driven propulsion for lower detectability and cost, but endurance is greatly affected.
- The structure should be able to withstand hard landings, due to the absence of an undercarriage.
- Major compromise between identification capability, i.e. payload and battery weight, i.e. endurance while total weight is also kept low enough for hand launching.

Based on the above considerations and several choices made by the Defence Science and Technology Laboratory (DSTL), the designed UAS of the Horizontal Take off Landing (HTOL) Close-Range Mini-UAV's category with a defence surveillance/reconnaissance role has the basic characteristics of Table 4-1.

Table 4-1 Basic Specifications

Total Weight Estimate (kg)	3
Design Speed (m/sec)	17
Maximum Speed (m/sec)	25
Landing Speed (m/sec)	15
Propulsion	Electrically Driven Propeller
Landing Gear	No
Endurance (hrs.)	1
Range (km)	50
Wingspan (m)	1.5
Payload weight (kg)	<1
Payload dimensions (cm)	5-10 width/depth – 25 length

4.3 UAS Value Driven Design

The design of an Unmanned Air System follows the process of any other aircraft design with the addition of special considerations, and the following steps:

- Stakeholders' needs identification, selection of the system category, identification/selection of airframe configurations, such as

Horizontal Take-Off and Landing (HTOL), Vertical Take-Off and Landing (VTOL) and other fundamental selections, 'tailplane aft', 'tailplane forward', 'tailless' etc. Identification of all design standards, attributes, all regulatory aspects monitoring the manufacture and operation of UAS.

- The sizing methodology is applied, similar to a manned aircraft design, to achieve the required performance, [76]. To limit the number of design variables to a manageable number for a fast optimization, significant amount of data and UAS design parameters are set to reasonable choices during the conceptual phase, although they too could vary, if desired. This sizing methodology includes the following and is presented in detail in Chapters, 7 and 8:
    - Geometry parametric definition, by means of basic design variables.
    - Structural analysis based on a weight convergence procedure, as the weight is calculated in the weights and balance calculations.
    - Aerodynamic analysis to identify the aerodynamic forces applied, maximum lift, profile drag, drag due to lift.
    - Propulsive thrust required and basic propulsive properties are obtained, calculating fuel/energy consumption and associated ranges and endurances at various speeds, altitudes and thrust required.
    - The mass properties of the various components are calculated during the weight and balance evaluation.
    - Stability analysis, dependent upon the nature of the aircraft configuration.
    - Additionally to the manned aircraft design the UAS conceptual design addresses the electronic flight control system, ground and on board, communications, command and control, sensor or other types of payload, [182].
- The operations analysis studies and provides figures with a relative accuracy, for:
    - Production and acquisition costs of all systems involved.

    - Operational cost based on the missions involved during the lifecycle of the UAS.
    - Reliability/Maintainability estimates based on the customer requirements/needs and all associated support issues.
    - Survivability analysis to assess the UAS stealth capabilities, as well as its ability to survive in a hostile environment.
- All of the above capture the essence of the UAS's desirability and are included in the user's objective function and are employed in the optimisation process; while the number of design variables is kept as low as possible, selecting those with the greatest impact.

4.4 Chapter Summary

The general VDD framework and the methodology for its application to the test case of the conceptual design of a small military UAS for surveillance and reconnaissance, along with the basics of the Unmanned Air Systems technologies were presented in this chapter. The expanding role of UAS for both military and civilian uses and the missions they are involved, was underlined. The absence of pilot on board generates new capabilities for the UAS with less risk, due to their advantages to the manned aircraft; but at the same time, a multi-system integration, performance and cost assessment is required in engineering design. The user's hierarchy of appropriate objectives/attributes, originating from the stakeholders involved and the mission requirements, was also presented. Moreover, the aircraft category with the corresponding specifications was selected as the basis for the VDD framework application.

5. Multi-Attribute Value Modelling

"*If a player can always arrange such fortuitous alternatives in the order of his preferences, then it is possible to assign to each alternative a number or numerical utility expressing the degree of the player's preference for that alternative.*"

Arthur H. Copeland, 1945, [185]

In the formulation of the VDD framework, two distinctive features are involved, the complexity/uncertainty analysis required to develop and validate the design generative model, and the preference analysis, capturing the values of the stakeholders in the value model. As Keeney and Raiffa [1] point out, the engineering design practice is clearly in favour of the alternatives' generation modelling and against the preferences/value modelling.

The relative worth of any future design is summarised not by a single number but an array of numbers, reflecting usually economic, performance, environmental, social, intangible and other concerns; all measured in incommensurable units and some probabilistically dependent entailing a stochastic analysis. Therefore, plugging these numbers into an objective formula is just not possible. Once the objectives and their associated attributes have been identified and evaluated, simple hypothetical questions are employed to address the preferences of the stakeholders. These questions have to be as realistic as possible, comprehensible and precise to assess their preferences and risk attitudes related to any types of uncertainties. They are posed to experts/individuals, representing the stakeholders, with experience to evaluate the selection criteria and the trade-offs between them. For the user of the designed system, these experts are usually involved with the operation and technical/logistic support of the designed system. Furthermore, to accelerate preference modelling and justify the gross imbalance between time spent in the design generation and time spent in the preference analysis, observation of revealed preferences from previous choices can be used to prescribe the stakeholders' preferences.

In light of the above, the development of appropriate multi-attribute value models capturing the preferences of a single stakeholder of a defence system, as the first of the objectives of the VDD implementation process set in section 1.3, will be presented in the following sections. For the VDD of a defence system, the multi-attribute value and utility models, presented in section 3.1, and the cost effectiveness based model are considered as the most appropriate. They can be easily aligned with the different perceptions of value, related to the designed system's performance and combat/defence capabilities as well as lifecycle cost. These models will be used for the evaluation of the design alternatives, based on the hierarchy of the user's objectives/attributes, as in Figure 4-4. Concerning the manufacturer as the other major stakeholder discussed in 4.2 and to simplify the analysis, the corresponding objective/payoff function is modelled as a single attribute value model that is a linear function of the Total UAS Program Cost, based on the assumption of a CPF contract type (i.e. manufacturer's profit is a percentage of the Total UAS Program Cost). This payoff function should be maximized to maximize the manufacturer's profit and satisfaction. However, a firm fixed price (FFP) contract type or even the proposed multi-attribute value models could also be utilised, if desired, in the manufacturer's objective function.

5.1 Cost Effectiveness

The quantification of value of a design into a single, monetary metric requires all direct costs and benefits to be converted into a monetary value. In the design of a defence system, all design attributes associated with the stakeholders' tangible and intangible objectives have to be monetised. The conversion of the performance and defence related attributes to monetary value and subtracting costs from benefits, as suggested by Net Present Value, is a very challenging process. As a demonstration of the cost effectiveness analysis presented in 3.3, each design alternative is described by a value of cost and an array of benefit measures. Thus, following the Systems Engineering approach, the UAS design alternatives which do not exceed a cost constraint and subject to that, maximise a portfolio of joint benefits, can be identified, in a process traditionally described as *design to cost*. Alternatively, the identification of design alternatives that achieve some minimum level of performance characteristics, so-called *aspiration levels*, and minimise cost could also be done, *designing for cost*.

A Cost Effectiveness model provides the Pareto front of all designs that are superior in all attributes to the other dominated designs. It identifies also the optimum design that minimises acquisition or through life cost, while it achieves a certain level of performance measure. For instance, minimum endurance at design speed set to one hour, based on similar aircrafts, could be selected as an aspiration level for the benefit measures. Another optimum design would be the design maximising some performance measure while cost is kept below a certain aspiration level.

5.2 Multi-attribute Value Modelling

Traditionally, the values of an ideal attribute level g_I, at which further improvement in the attribute is either not possible or of no additional value to the stakeholder, and the critical attribute level g_C, as the worst value achieved or at which further degradation makes the design worthless, are used in conjunction with some value equation, such as Cook's value equation [186], to assess the value of a design with respect to this attribute. While most value functions use the *a posteriori* assignment of values to specific attributes levels, such as the best and worst obtained values, in this case the assignment of the neutral reference points can be done from the stakeholder *a priori*, before the design space exploration and subject to the technology readiness level assumed.

The assignment of average levels of expectations with respect to the attributes by the stakeholder is the basis of this novel *multi-attribute value model*, used both for the scaling constants K_i and value functions V_i assessments. Thus, as Keeney [19] advocates, the alternative-focused process of selecting the best from what is readily available (i.e. a final set of design alternatives) is converted to a value-focused process of identifying needs, attributes and values of these attributes that give the stakeholder a 'neutral' response, i.e. a 50% satisfaction level, utilized by Eres *et al.* [100] in the Concept Design Analysis (CODA) methodology.

The major advantage of this value model is that it is an efficient and operational way to evaluate each design point during the conceptual design phase, when only basic needs and vague requirements are known and the set of design alternatives is not finalized, with the minimum interaction with the stakeholder. Moreover, the objectivity of the evaluation is maintained by capturing the stakeholder's preferences, with criteria independent of information, other available data or the proposed alternative solutions. For the multi-attribute case, first *preferential independence* is assumed or verified, i.e. whether the preferential ranking between two pairs of two attributes is independent of the other attributes, to obtain the multi-attribute additive value model described by equation 3-4.

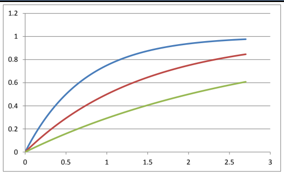
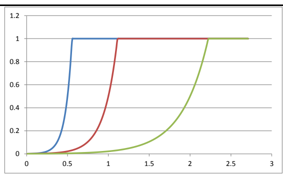
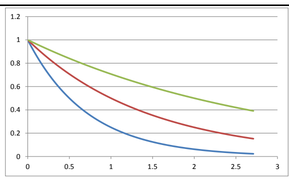
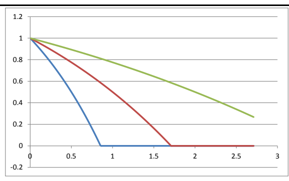
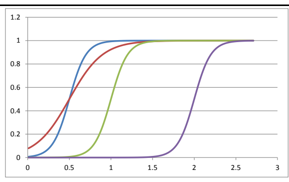
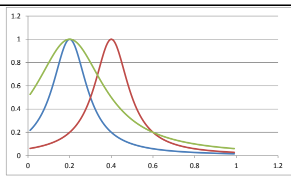
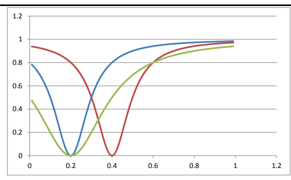
5.2.1 Value Functions

Value functions, as special cases of utility functions, represent the worth the stakeholder gives to achieve a certain value of an attribute under certainty. They could be considered as a way of normalizing attributes of incommensurable units to a common scale of value, by knowing how much they evaluate the specific outcome.

Before the design space exploration starts and subject to the technology readiness level assumed, average levels of expectations with respect to all attributes are provided *a priori* by the stakeholder as neutral points, representing the 50% satisfaction level. Next, the relationship type for each attribute is defined, *maximizing*, if more is better (for performance attributes), *minimizing*, if less is better (for cost related attributes) or *optimizing*, if a specific attribute value is better. The preferences of the stakeholder are qualitatively assessed in terms of the marginal evaluation with respect to each attribute; in the language of classical economics, how much the stakeholder is willing to sacrifice in terms of other attributes for a positive change of this attribute as its value changes, reflected in the slope of the value functions; adjusting attributes as concave, convex or sigmoidal functions. A convex value function reflects the preferences of a stakeholder who is willing to sacrifice more and more in terms of other attributes for the same positive increment as this attribute's values increase. A concave value function is selected if the stakeholder is willing to sacrifice less and less in terms of other attributes for the same positive increment as this attribute's values increase. A sigmoidal shape is selected for mixed preferences, i.e. if the stakeholder is willing to sacrifice more and more in terms of other attributes for the same positive increment of this attribute up to the neutral point/inflection point and less and less beyond that.

Depending on the previous selections, the appropriate, ready to use, value function is generated from all available, presented in Table 5-1. In the equations of this Table, X is the input attribute value for any design, n is the assigned neutral point of the design attribute, while V_{in} and V_f are the initial and final values of the value functions (set accordingly, depending on their type). In the corresponding figures, the pairs of design attribute X and value V of the value function are plotted on the x (horizontal) and y (vertical) axes, respectively.

Table 5-1 Value Functions

Mathematical Formulation	Figure	Stakeholder's Qualitative Preferences
$V_f\left(1-\exp\left(\ln\left(\frac{2\,V_f-1}{2\,V_f}\right)\frac{X}{n}\right)\right)$		Maximizing, decreasing marginal evaluation
$V_{in}\,\exp\left(\ln\left(\frac{1}{2\,V_{in}}\right)\frac{X}{n}\right)$		Maximizing, increasing marginal evaluation
$2\,V_{in}-\exp\left(\ln\left(2\,V_{in}-\frac{1}{2}\right)\frac{X}{n}\right)$		Minimizing, decreasing marginal evaluation
$\left(V_{in}-V_f\right)\,\exp\left(\ln\left(\frac{1}{2}\right)\frac{X}{n}\right)+V_f$		Minimizing, increasing marginal evaluation
$V_{in}+(V_f-V_{in})/(1+\exp\left(\frac{n-X}{\mathrm{Slope}}\right))$ Slope: Curve Steepness		Maximizing or minimizing, mixed/sigmoidal (increasing/decreasing) marginal evaluation
$\left(\frac{1}{1+\left(\frac{X-n}{\tau}\right)^2}\right)$ τ: Attribute tolerance		Optimizing, aiming towards specific attribute value
$1-\left(\frac{1}{1+\left(\frac{X-n}{\tau}\right)^2}\right)$		Optimizing, avoiding specific attribute value

5.2.2 Assessment of Weighting Factors

Engineering design with multiple objectives involved entails trade-offs, and the scaling constants represent the 'weighting importance' of each objective/attribute within the set/subset it belongs. For their assessment, AHP was employed to perform pairwise comparisons between the attributes and not only provide the values of the scaling factors, but also assess the consistency of the answers provided by the stakeholder.

AHP was chosen among the several multi-criteria techniques due to its ability to incorporate a large number of both qualitative and quantitative criteria in the decision making process, allowing for a hierarchy to be built in line with the VDD. Thus, based on the eigenvalue/eigenvector theory, an AHP matrix is constructed with each element, representing the relative importance of the corresponding row attribute with respect to the column attribute. The normalised eigenvector column obtained represents the weighting factors, while the consistency ratio assesses the consistency of the model, based on the pairwise comparisons and should be kept below *0.10* (i.e. *10%*), as suggested by Saaty [110].

However, the construction of the AHP matrix is based on the ambiguous question: '*How much better/more important is attribute/alternative A_i than A_j?*', assessing the ratio scaled strength of preference. It has been found that this unjustifiable selection of the specific numerical scale converting the linguistic response to the above question to ratio scaled numerical values, greatly affects the identification of optimal design. These AHP numerical scales convert the *stimuli*/psychological perception of strength of preference increments among various attributes to a *response*/numerical value through the use of an arbitrary relation, namely:

- The integer scale, assuming a logarithmic relation between stimuli and response, was based on the individual's perception of the relation between just distinguishable masses, p, following presumably an arithmetic progression related to the logarithm of the stimuli, s, with constants a and b depending on the specific individual's perception:

$$p_n = a\, ln(s_n) + b \tag{5-1}$$

  This relation was used by Saaty [187] to obtain the integer sequence $1,2,3,\dots,9$ of the integer scale in AHP.

- The balanced scale assumes an even distribution of attribute weights, Salo and Hamalainen [188], i.e. that the weights deduced from the pairwise comparison between two attributes should be evenly distributed when using this scale, obtaining the following scale: $1, \frac{11}{9},\ 1.5, \frac{13}{7}, \frac{7}{3}, 3, 4, \frac{17}{3}, 9$.
- The power scale assumes a geometric relation between stimuli/psychological perception of strength of preference increments among various attributes and response/numerical values of the form:

$$p = s^{\beta} \tag{5-2}$$

Where β some positive constant, Lootsma [189]. Hence, for a $1-9$ numerical scale and nine increments, the power scale sequence is: $1, 1.316, 1.732, 2.28, 3, 3.948, 5.196, 6.84, 9$.

Hence, as presented in Table 5-2, the selections of integer and power scales with five degree preference scheme quantify exactly the same linguistic responses to different numerical values. For instance the verbal response: '*A_i is much more important to attribute A_j*' is converted to a numerical value of 7 with integer scale and to a value of 5.2 with power scale, with the integer scale favouring more the most important to the stakeholder attributes and weighing less the least important ones.

Table 5-2 AHP Numerical Scales

Definition	Integer Scale	Power Scale	Explanation
Equal importance	1	1	Two factors contribute equally
Somewhat more important	3	1.73	Slightly favour one over the other
Much more important	5	3	Strongly favour one over the other
Very much more important	7	5.2	Very strongly favour one over the other
Absolute more important	9	9	Highest possible validity of favouring one over the other

Due to the absence of justified criteria for choosing a particular scale, converting the linguistic answer/stimuli to a numerical value/response, the distribution of weights and level of consistency, obtained by different scales used in AHP, can be studied to select the best one. The distributions of weights for the integer, balanced and power scale were obtained with all possible combinations of weighting scales and are presented (in this order) in Figure 5-1, for a nine degree preference scheme between just three attributes, similar to Fig. 1 in Elliot [190]. The coordinates of each point in these figures represent a possible combination of weights (w_1, w_2) for the two attributes, obtained through the use of the specific numerical scale. The third attribute's weight w_3 is computed simply by subtracting the sum of weights of the other two from one, since the sum of their weights is always equal to unity. Thus, the three scales can be compared in terms of the number of distributed points and existence of sparse regions, in order to select the scale with the highest number of points and the least sparse regions.

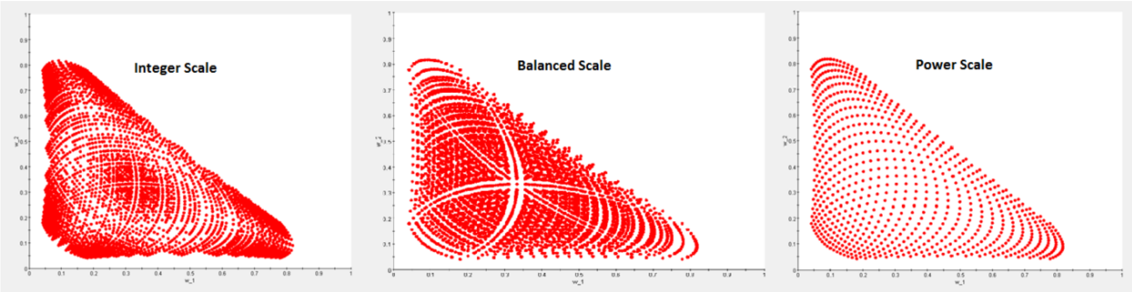


Figure 5-1 Weights Distribution of AHP Numerical Scales

Elliot [190], comparing these numerical scales, identifies the power scale as the most preferable scale; however in Figure 5-1 the following are noticed:

- The integer scale gives a high number of points in the most extreme values of weights as expected, considering the distribution of values of the integer scale: 1, 2, 3, 4, 5, 6, 7, 8, 9, that weighs more the most important to the stakeholder attributes and less the least important ones, as compared to the distribution of values of the balanced scale: 1, 11/9, 4/3, 13/7, 7/3, 3, 4, 17/3, 9 and the distribution of values of the power scale: 1, 1.316, 1.732, 2.28, 3, 3.948, 5.196, 6.84, 9. Therefore, the balanced and power scales are more evenly distributed than the integer scale.

- Comparing the sparse regions and clustering obtained with these scales; the power scale fails to cover a larger area in the graph than the integer and balanced scales which produce a definitely higher number of points and less clustering. This observation is not in agreement with the larger sparse regions and clustering of the weights in integer and balanced scales noticed in the corresponding Figure 1 of Elliot [190].

Furthermore, it was found in MDO that exactly the same verbal responses/preferences provided by the stakeholder, when converted to numerical weights through different AHP scales produced different optimal design alternatives. For instance, in the UAS conceptual design with identical user's preferences, through the use of integer scale a V-shape tail, push propeller, conventional fuselage with a wing span 1.5m aircraft was identified as optimal; while through the power scale, an aircraft of T-shape tail, tractor propeller, conventional fuselage with a wing span of 1.25m was the optimal solution, Figure 5-2.

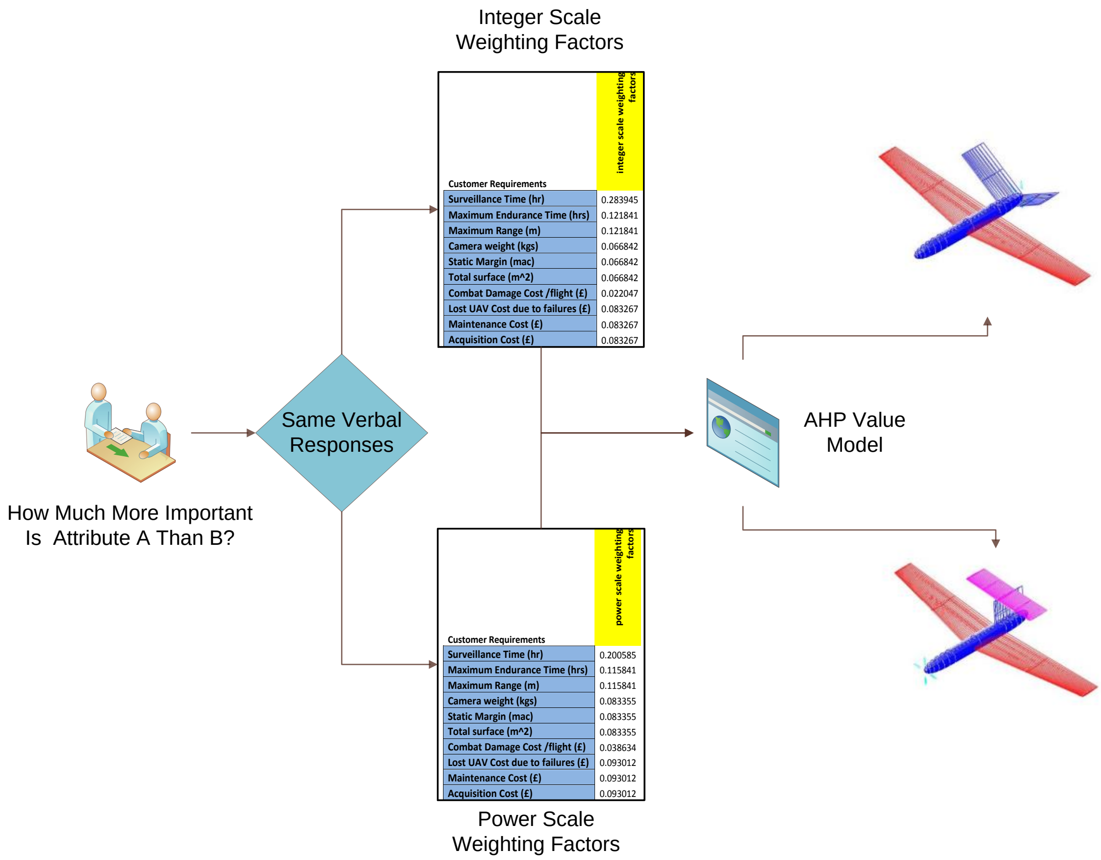


Figure 5-2 AHP Numerical Scales Comparison

The problem of converting verbal preference responses between attributes to numerical values through the use of some unjustifiable scale in AHP for the calculation of weighting factors can be tackled if the stakeholder is forced to compare specific value differences of these attributes, instead of performing pairwise comparisons between abstract attributes. The theory of measurable multi-attribute value functions, presented by Dyer [113], is employed to assess the strength of preferences (value differences) between alternatives instead of abstract attributes. For this purpose, the assumption of weak difference independence is required, i.e. that the order of preference differences between pairs of each attribute is independent of the levels of the other attributes.

The attribute neutral points, already used for the value functions assessment, are again utilized in a direct rating approach to compute the scaling constants by assessing the relative importance of:

- The preference difference between a design with attribute x_i at the neutral point, $x_i^{1/2}$, and all other attributes $\bar{x}_i$ at their worst value, $\bar{x}_i^o$, and the design with attribute x_i at *0* (value of *0* or *1*, depending on the form of value function) and all other attributes $\bar{x}_i$ at their worst value, $\bar{x}_i^o$.

- And the preference difference between a design with attribute x_j at the neutral point, $x_j^{1/2}$, and all other attributes $\bar{x}_j$ at their worst value, $\bar{x}_j^o$, and the design with attribute x_j at *0* (value of *0* or *1*, depending on the form of value function) and all other attributes $\bar{x}_j$ at their worst value, $\bar{x}_j^o$.

Through the relative importance assessment of changes to the neutral point value of any two attributes, the use of any numerical scale can be avoided. This comparison is represented by equation, used to assess the ratio of the weighting factors:

$$\frac{\boldsymbol{K_i}\,(\boldsymbol{U_i}(\boldsymbol{x_i^{0.5}}) - \boldsymbol{U_i}(0))}{\boldsymbol{K_j}\,(\boldsymbol{U_j}(\boldsymbol{x_j^{0.5}}) - \boldsymbol{U_j}(0))} = \frac{\boldsymbol{K_i}}{\boldsymbol{K_j}} = \boldsymbol{c_{ij}} \qquad \text{5-3}$$

In the AHP matrix, as presented in Table 5-3 for the UAS conceptual VDD, instead of comparing abstract attributes, each cell is the ratio of relative importance/preference of a change from *0* to the neutral point value of the row attribute to the change from *0* to the neutral point value of the column attribute. Following the methodology of AHP, several pairwise comparisons are performed, not only to compute the values of the weighting factors, but also assess the consistency of the answers provided by the stakeholder.

Table 5-3 AHP Value Model Weighting Factors Assessment

User Needs/Attributes	Operational Surveillance Time (hrs.)	Maximum Endurance Time (hrs.)	Maximum Range (m)	Data Collection (Camera weight / kg)	Ease of Flying (Static Margin / %mac)	Detectability (Total Aircraft Surface / m^2)	Survivability (Combat Damage cost per flight / £)	Lost UAV Cost (£)	Maintenance Cost (£)	Acquisition Cost (£)	Nth Root of Product of Values	Normalised Eigenvector	[Judgements] x [Eigenvector]	[Judgements] x [Eigenvector] / [Normalised Eigenvector]
Operational Surveillance Time (hrs.)	1	1.333	1.333	2.000	2.000	4.000	4.000	2.000	2.000	1.333	1.898041	17.64%	1.7767	10.07
Maximum Endurance Time (hrs.)	0.75	1.000	1.000	1.333	1.333	2.000	4.000	1.333	1.333	1.333	1.381289	12.84%	1.292	10.06
Maximum Range (m)	0.750	1.000	1.000	1.333	1.333	2.000	4.000	1.333	1.333	1.333	1.381289	12.84%	1.292	10.06
Data Collection (Camera weight / kg)	0.500	0.750	0.750	1.000	1.000	1.333	2.000	1.333	1.333	0.800	1.006475	9.36%	0.9416	10.06
Ease of Flying (Static Margin / %mac)	0.500	0.750	0.750	1.000	1.000	1.333	2.000	1.333	1.333	0.800	1.006475	9.36%	0.9416	10.06
Detectability (Total Aircraft Surface / m^2)	0.250	0.500	0.500	0.750	0.750	1.000	1.333	0.667	0.667	0.500	0.633538	5.89%	0.594	10.09
Survivability (Combat Damage cost per flight / £)	0.250	0.250	0.250	0.500	0.500	0.750	1.000	0.500	0.500	0.333	0.435275	4.05%	0.4081	10.08
Lost UAV Cost (£)	0.500	0.750	0.750	0.750	0.750	1.500	2.000	1.000	1.000	0.800	0.907701	8.44%	0.8484	10.05
Maintenance Cost (£)	0.500	0.750	0.750	0.750	0.750	1.500	2.000	1.000	1.000	0.800	0.907701	8.44%	0.8484	10.05
Acquisition Cost (£)	0.750	0.750	0.750	1.250	1.250	2.000	3.000	1.250	1.250	1.000	1.199769	11.15%	1.1205	10.05
											10.75755	1	MEAN	10.09
													CONSISTENCY INDEX	0.01
													RANDOM CI	0.55
													CONSISTENCY RATIO	1.72%

This *multi-attribute value model* is based on the qualitative assessment of the stakeholder's preferences and the quantitative assignment of neutral point values of attributes. It allows for the objective and operational evaluation of all design alternatives, independent of information, with the minimum interaction with the stakeholder. The assignment of neutral values of attributes by the stakeholder, before the design starts, is the basis of this value model, utilised in a novel way for both the value functions generation and the weighting factors' assessment. The generated value functions capture the stakeholder's preferences by focusing on the trade-offs between the different objectives. For each design point generated, the values of the aforementioned attributes are converted to value indices, depending on the generated value function, and using the weighting factors obtained from AHP a multi-attribute single value is computed. The deficiency introduced by the unjustifiable selection of numerical scale used in AHP is solved through the synthesis of AHP with the multi-attribute value functions. Moreover, as engineering design progresses and more information from simulation and prototyping becomes available, the stakeholder's preferences, in terms of values of attribute neutral points and the AHP-assessed weighting factors, may be updated. Nevertheless, the individual value functions of the attributes are all assumed to be identical, depending on the stakeholder's selections described in 5.2.1, while, the overall objective function is not appropriate for capturing the stakeholder's risk attitude towards uncertainty and the additive linear value model assumes no overlapping among the objectives.

5.3 Multi-Attribute Utility Model

In the single attribute and deterministic case, the decision maker chooses among several alternative designs, $D_1, D_2, \dots, D_m$ each described with a single attribute $X_1, X_2, \dots, X_m$ as optimum the design with the optimal value of attribute (maximum, minimum or optimum). However, due to various uncertainties, each of these attributes is described by a series of consequences with probabilities assigned to each of them; therefore the theory of expected utility is employed to identify the alternative with the maximum value of expected utility. Utility functions provide the necessary information concerning the attitude of the stakeholder to risk, associated with uncertainties. Moreover, multi-attribute utility theory is the most appropriate tool for dealing with problems, such as the UAS VDD, with more than one attributes required to address the multiple objectives.

The assessment of utility functions and weighting/scaling factors for the multi-attribute case, as already described in 3.1, is based on the stakeholder's attitude towards uncertainty and is assessed through the indifference between *Certainty options* and *Lottery/risky option*s. The process of creating the utility model involves an analyst/interrogator interacting with the decision maker, who has to respond to a series of questions. The analyst has to make sure that the decision maker understands the attributes/consequences, their domain and the trade-off between them. All questions posed to the decision maker should follow the convergence technique, described by Keeney and Raiffa [1], starting with an initial estimate either of the probability π or the value of the certainty option x, until indifference is achieved.

First, *preferential independence* assumption needs to be verified or assumed, i.e. that the preferential ranking between two pairs of two attributes is independent of the other attributes. For example, if the indifference of the user between a higher acquisition cost with a greater endurance UAS and one with lower cost and lower acquisition cost is independent of the surveillance capabilities of the two design alternatives.

Next, *utility independence*, concerning the intensity of preferences, needs to be also checked or assumed. Utility independence states that the indifference between a lottery and a certainty equivalent for any attribute is independent of the levels of the other attributes or that the shape of the utility function of any attribute does not depend on the values of the other attributes. If that holds, then the model of the multi-attribute utility is the multiplicative one of equation 3-2.

In practice, this is done by obtaining the utility functions of, say attribute y at different levels of its complement $\bar{y}$. If there is no dependence between the responses of the stakeholder to the certainty equivalent/lottery comparisons in y and the values of $\bar{y}$, then utility independence is concluded. For utility modelling in UAS VDD, utility independence and not additive independence is checked or assumed, since the additive model is a special and more restrictive case of the multiplicative model. In many cases, additive independence is assumed to have a much simpler to derive and compute form of multi-attribute additive utility model, such as the one presented by Carnero [153]. However preferential independence implies an additive value function, but not an additive utility function. The simplest form of multi-attribute additive utility function is appropriate only if the attributes are additive independent, i.e. that the stakeholder's preferences over lotteries depend only on their marginal probability distributions and not on their joint probability distribution. Nevertheless, the multiplicative utility model allows to verify through the calculation of the scaling factors K_i, if the additive independence assumption holds, [1]. If their sum is found to be equal to *1*, then that implies that $K = 0$ and the model is reduced to an additive one. Otherwise, the additional constant K is generated through an iterative process as in Keeney and Raiffa [1].

5.3.1 Assessment of Utility Functions

Having established as appropriate the assumptions of preferential independence and utility independence, the first task is to determine the utility functions of all attributes. They are assessed on a 0 to 1 scale, using the techniques described by Keeney and Raiffa [1]. For each attribute a range is chosen, depending on the values obtained during the design alternatives generation. For attributes to be maximised, the maximum value is assigned a utility of 1 and the minimum value a utility of 0. For cost related attributes to be minimised, the maximum value is assigned a utility of 0 and the minimum value a utility of 1. For attributes with an optimum value, such as ease of flying assessed by the attribute of neutral point position in the aircraft, the optimum value is assigned a utility of 1 and two other critical values are assigned a utility of 0.

Next, certainty equivalents for a number of 50-50 lotteries are obtained, in order to fix the utilities of several particular points on the utility function. The 50-50 lotteries involve the best x^* and worst x_o value of the attribute and the corresponding certainty equivalent x, which has a utility of 1/2:

$$u(x) = \frac{1}{2}u(x^*) + \frac{1}{2}u(x_o) \qquad 5\text{-}4$$

Similarly, the points of utility of 0.25 and 0.75 are fixed, as certainty equivalents to the 50-50 lottery of worst point x_o and point of 0.5 utility, and best point x^* and point of 0.5 utility, respectively.

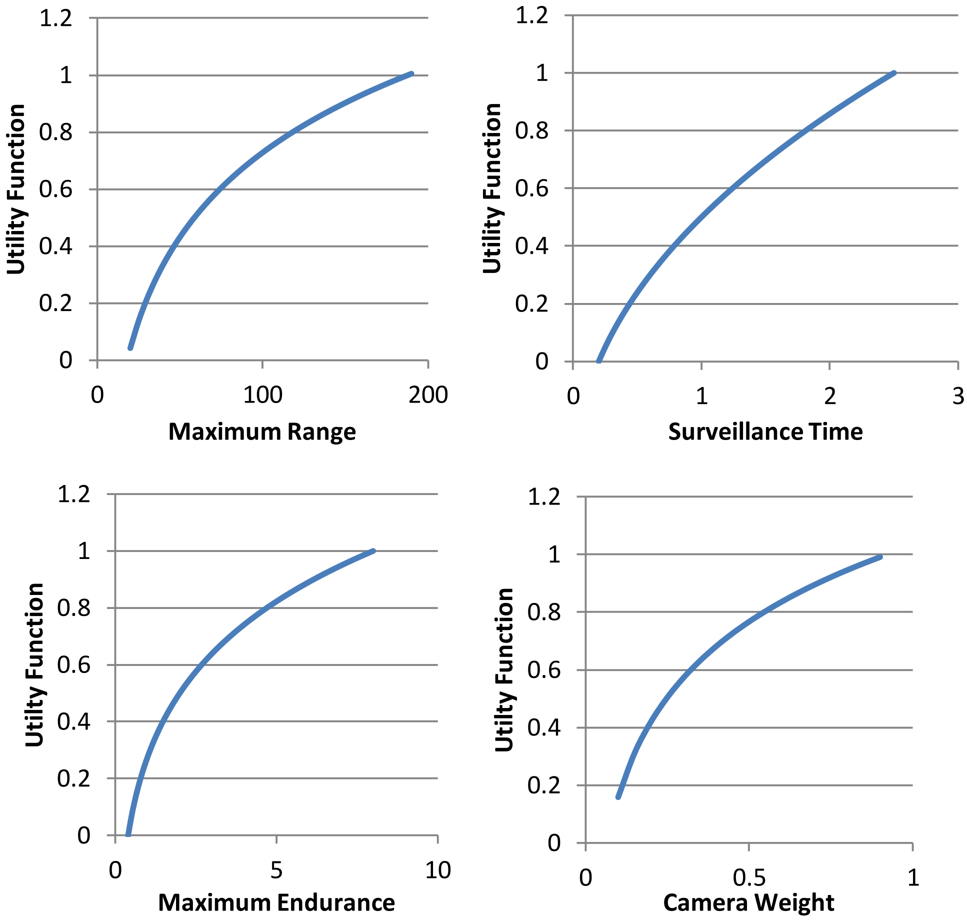
After some qualitative and quantitative characteristics of the utility functions have been determined, parametric families of utility functions that possess the relevant characteristics are selected, and their parameters are computed fitting the data to this specific parametric model. For this purpose, non-linear regression analysis is used to compute the values of the parameters β by minimizing the sum of squares of the residuals/errors between the predicted values of the model $f(x_i, \beta)$ and the data y_i:

$$S = \sum_{i=1}^{m} (y_i - f(x_i, \beta))^2 \qquad 5\text{-}5$$

In Excel using the Solver add-in, these estimates are obtained along with an assessment of the goodness of curve fitting, based on the R^2 *coefficient of determination*, indicating how well the data points fit the statistical model. The stakeholder inputs best, worst and certainty equivalent to lottery values, as already described, for all attributes. Some commonly used utility functions are selected from the stakeholder to be curve fitted, and the validity of the model is assessed based on the values of R^2 obtained. The utility functions used have the following forms [191], [1]:

$$U(x) = a + b\,x^c \quad U(x) = a + b\,e^{(-c\,x)} \quad U(x) = a + b\ln(c\,x) \qquad 5\text{-}6$$

Utility functions of the UAS attributes, consistent with these assessments are presented below, where the pairs of design attribute X and value U of the utility function are plotted on the x (horizontal) and y (vertical) axes, respectively:



Utility Function
Maximum Range
Utility Function
Surveillance Time
Utility Function
Maximum Endurance
Utility Function
Camera Weight

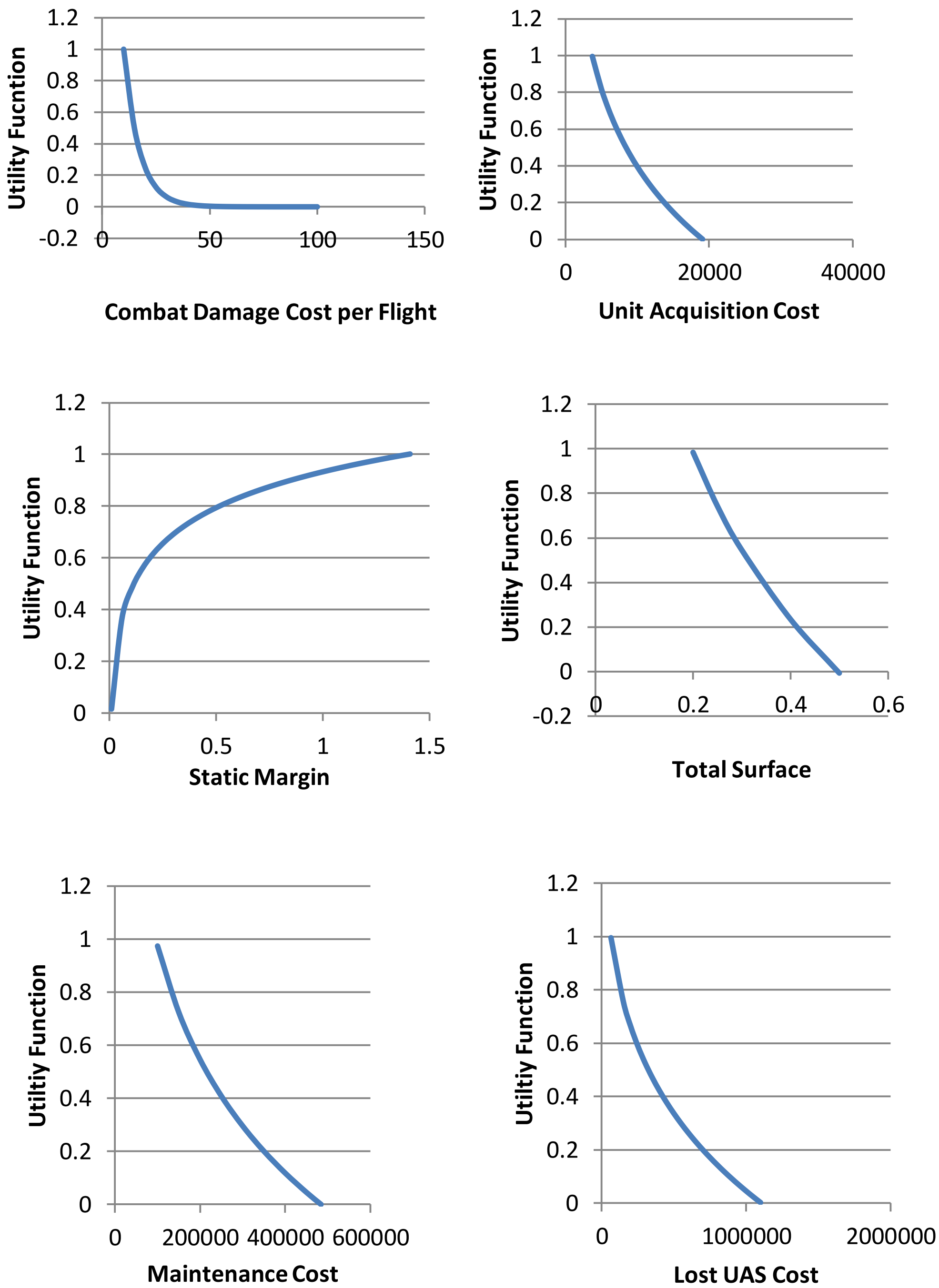


Figure 5-3 Utility Functions

5.3.2 Assessing the Weighting Factors

In the multiplicative utility model of equation 3-2, there are eleven scaling factors to be evaluated, $K_1, K_2, \ldots, K_{10}$ and K for the UAS conceptual VDD.

Therefore, eleven independent equations are required to be solved, generated from certainty, probabilistic considerations, or both.

All attributes are ranked in terms of desirability, producing a ranking of the weighting factors, as in Keeney and Raiffa [1]. The AHP table obtained in the Multi-attribute Value Modelling for the weighting factors calculation of the value functions is used for this purpose. The relative values of the scaling factors are obtained with the trade-off method, since the stakeholder has to trade off some value of one attribute to improve the other to its best value. Hence, they are asked to compare attributes, providing a certainty (since no lottery is involved in this question) scaling between the scaling factors:

$$\frac{K_i}{K_j} = c_{ij} \qquad \text{5-7}$$

The question is posed $(n-1)$ times, for the n attributes, to create $(n-1)$ similar independent equations, and therefore to scale the factors K_i between them. To obtain the necessary n_{th} equation required for computing all weighting factors, a probabilistic (involving a lottery/certainty equivalent) scaling is used to assess the K_1 highest weighting factor, as described in [1].

In the multiplicative model, if the sum of the weighting factors $K_1, K_2, \dots K_n$ is found to be equal to 1 then the factor K of the multiplicative utility equation 3-2 is 0 and the utility model is converted to an additive. If the sum of these weighting factors is greater than 1 the multi-attribute utility model is indeed multiplicative, and K is obtained by solving iteratively the following equation for roots between -1 and 0:

$$1 + K = \prod_{i=1}^{10} (1 + K_i\, K) \qquad \text{5-8}$$

AHP based Weighting Factors Assessment

Keeney and Raiffa [1] suggest to create for the n attributes, n independent equations, to obtain the values of the K_i factors. They argue that more independent equations would introduce inconsistencies, but they still acknowledge that the desire is to have the decision maker, answering the above question, to reflect on the inconsistencies and if necessary, change some responses to imply a consistent set of preferences. Indeed, one of the most important obstacles to overcome and obtain a valid/consistent utility/value model is the open-mindedness and willingness of the stakeholder to think hard about consequences in order to correctly assess preferences, through the questions posed. The decision maker/stakeholder has to be interested and enthusiastic, while there is always a possibility of providing even unintentionally inaccurate answers concerning their preferences. Therefore, getting more valid estimates of the weighting factors and measuring the consistency of answers is advantageous, and thus the following approach was followed in the assessment of the scaling factors, based on the synthesis of MAUT and AHP.

In the utility model, instead of using the trade-off approach described above, the direct rating approach described by Dyer and Sarin [113] was used for the assessment of the scaling factors. A matrix similar to the AHP matrix used for the weighting factors calculation of the value model, is created. In this matrix, the attributes are set in rows and columns after been ranked in terms of desirability. Each element x_{ij} represents the ratio of the relative importance of a change from the worst to the best value of row attribute to the change from the worst to the best value of the column attribute, expressed in the following equation:

$$\frac{K_i\ (U_i(x_i^*) - U_i(x_i^o))}{K_j\ (U_j(x_j^*) - U_j(x_j^o))} = \frac{K_i}{K_j} = c_{ij} \qquad 5\text{-}9$$

In this matrix, this equation is created, based on the combination of $\binom{n}{2}$ with $\binom{n}{2} = \frac{n\ (n-1)}{2}$ times for the n attributes, in order not only to solve for the values K_i, but also to assess how good these values are that provide an estimation of the actual matrix A. These values do not represent the precise values of the K_i/K_j, but are mere estimates of these ratios given by an expert representing the stakeholder. Hence, according to Saaty [110], the small perturbations of the eigenvalues from the value n of the matrix created assess the error due to inconsistency of the answers given by the expert, showing the measure of consistency of the matrix. The highest weighting factor K_i and the K factor of the multiplicative utility model are obtained as described above in the Keeney and Raiffa method. Hence, the following matrix is constructed:

Table 5-4 AHP Utility Weighting Factors Assessment

Attributes	Max Operational Surveillance Time	Max Endurance Time	Max Range	Min UAV Acquisition Cost	Max Data Collection	Max Ease of Flying	Max Reliability/Lost UAV Cost	Min Maintenance	Min Detectability	Max Survivability	Nth Root of Product of Values/Eigenvector	Utility Independence Scaling Factor	[Judgements] x [Eigenvector]	[Judgements] x [Eigenvector] / [Eigenvector]
Max Operational Surveillance Time	1.00	1.33	1.33	1.33	2.00	2.00	2.00	2.00	4.00	4.00	1.90	**0.18**	19.12	10.07
Max Endurance Time	0.75	1.00	1.00	1.33	1.33	1.33	1.33	1.33	2.00	4.00	1.38	**0.13**	13.91	10.07
Max Range	0.75	1.00	1.00	1.33	1.33	1.33	1.33	1.33	2.00	4.00	1.38	**0.13**	13.91	10.07
Min UAV Acquisition Cost	0.75	0.75	0.75	1.00	1.33	1.33	1.33	1.33	2.00	4.00	1.27	**0.12**	12.80	10.10
Max Data Collection	0.50	0.75	0.75	0.75	1.00	1.00	1.33	1.33	1.33	2.00	1.00	**0.09**	10.06	10.06
Max Ease of Flying	0.50	0.75	0.75	0.75	1.00	1.00	1.33	1.33	1.33	2.00	1.00	**0.09**	10.06	10.06
Max Reliability/Lost UAV Cost	0.50	0.75	0.75	0.75	0.75	0.75	1.00	1.00	1.33	2.00	0.89	**0.08**	8.96	10.06
Min Maintenance	0.50	0.75	0.75	0.75	0.75	0.75	1.00	1.00	1.33	2.00	0.89	**0.08**	8.96	10.06
Min Detectability	0.25	0.50	0.50	0.50	0.75	0.75	0.75	0.75	1.00	1.33	0.65	**0.06**	6.54	10.08
Max Survivability	0.25	0.25	0.25	0.25	0.50	0.50	0.50	0.50	0.75	1.00	0.42	**0.04**	4.28	10.13
												1.02	MAX EIGENVALUE	10.13
											Scaling Factors Geometric Mean=	**0.09**	CONSISTENCY INDEX	0.01
													RANDOM CI	0.55
													CONSISTENCY RATIO	0.03

The structured approach of pairwise comparison of AHP is used to correlate the attributes between them and the computation of the weighting factors is done with a much higher accuracy, while the consistency ratio assesses the consistency of the responses given by the stakeholder, who is forced to think harder for the answers provided. As discussed by Saaty [110], the consistency of a judgment depends on the homogeneity of the elements compared (in this case the attributes), the sparseness of the elements, because humans cannot simultaneously conceptualize the relations of more than one objects, and above all the knowledge and care of the decision maker. Instead of relying on $n-1$ equations for the weighting factors assessment of n attributes, getting $n \cdot (n-1)/2$ redundant equations means essentially averaging the answers given for each scaling factor, gaining in accuracy. Nevertheless, the deficiency of this method is the workload involved, since more interaction with the stakeholder is required to obtain these equations.

For comparison of the two methods, the values of the relative scaling factors were also obtained for a single case, by scaling all factors with the most important weighting factor K_1, creating only the $(n-1)$ necessary equations. These values are presented below and significant differences are noticed:

Table 5-5 Weighting Factors Comparison

Keeney-Raiffa Method									
k1	k2	k3	k4	k5	k6	k7	k8	k9	k10
0.18	0.135	0.135	0.135	0.09	0.09	0.09	0.09	0.045	0.045
AHP Method									
0.18	0.131	0.131	0.120	0.095	0.095	0.085	0.085	0.062	0.040

The utility model, created in Excel, was used for the UAS user's interrogation and calculation of the value of the total multi-attribute utility. The value of the multi-attribute utility is calculated once the values of the attributes are input to the model, as presented below:

Table 5-6 Utility Model

Attributes	Attribute Value	Attribute Utility	Utility Independence K_i Scaling Factors	K factor
Max Operational Surveillance Time	1.376	0.630	0.180	-0.049
Max Endurance Time	2.034	0.598	0.131	
Max Range	91.567	0.684	0.131	
Max Data Collection	0.150	0.336	0.095	
Max Ease of Flying	0.145	0.768	0.095	
Min Detectability	0.410	0.929	0.062	
Max Survivability	21.733	0.637	0.040	
Max Reliability/Lost UAV Cost	179351.970	0.799	0.085	
Min Maintenance	114142.000	1.000	0.085	
Min UAV Acquisition Cost	5978.399	0.596	0.120	
		Utility Independence Total Utility	**0.682**	

5.4 MAUT Implementation – Independence Conditions

In the implementation of MAUT for the development of the multi-attribute value/utility models, there is a certain procedure to be followed to create the utility models required for the evaluation of all design alternatives. This procedure involves the interaction between an analyst and the experts/individuals representing the stakeholder and is divided into the following steps , according to the guidelines described by Keeney and Raiffa [1]:

1. Preparing for assessment and familiarization, i.e. verifying/identifying the objectives/attributes of Figure 4-4, clarifying that the goal is to assess the stakeholder's preferences and that there are no objectively correct preferences. Additionally, the analyst has to verify that it is fully comprehended that they need to think deeply, since all judgmental inputs have implications in the evaluation.
2. Verifying, instead of assuming, the validity of the independence conditions, i.e. preferential and weak difference independence for the multi-attribute value model and preferential and utility independence for the multi-attribute utility model, as discussed in 3.1 and 5.2.2 and elaborated below.
3. Identifying through interrogation the appropriate qualitative characteristics of the utility and value functions, such as monotonicity, marginal evaluation, risk attitudes etc.
4. As discussed in 5.2.1and 5.3.1, specifying quantitative restrictions, i.e. fixing pairs of values of attributes and corresponding values of utility and the value of each attribute neutral point for the multi-attribute utility and value models, respectively.
5. Choosing the most suitable utility functions for the multi-attribute utility model and checking for consistency of these selections.

Concerning the check for validity of the independence conditions between the multiple objectives of the UAS user, the specific attributes were divided in three natural groups of attributes (related to the objectives/attributes' hierarchy, Figure 4-4) to facilitate this process:

- *Performance related attributes*: maximum range, maximum endurance, operational surveillance time, sensor weight and flying stability/static margin.
- *Cost related attributes*: Acquisition unit cost, Lifecycle Maintenance cost and Lifecycle UAS replacement cost.

- *Survivability related attributes*: Combat damage cost, total surface area (detectability related).

Preferential independence condition is first checked between the three natural attribute groups and then within the same natural attribute group. Between natural attribute groups, levels of attributes of different natural groups (X_1, X_2), (X_1', X_2') are obtained for indifference or preference of the experts, and if indifference or preference holds for different levels of attributes $\overline{(X_1, X_2)}$ of the third natural group:

$$(X_1, X_2) \sim (X_1', X_2'),\ \forall\, \overline{(X_1, X_2)},\ \ (X_1, X_2) \succ (X_1', X_2'),\ \forall\, \overline{(X_1, X_2)} \qquad 5\text{-}10$$

Then, it may be assumed that there is the additive value model between the natural attribute groups:

$$V(Performance,\ Lifecycle\ Cost,\ Survivability) = K_p\, V_p + K_{lc}\, V_{lc} + K_s\, V_s \qquad 5\text{-}11$$

Next, the preferential independence condition within the same natural attributes groups is checked by identifying levels of attributes of the same natural group for indifference or preference and verifying if the indifference or preference holds for other levels of the other attributes of the same natural group:

$$(X_1, X_2) \sim (X_1', X_2'), \forall \overline{(X_1, X_2)} \qquad 5\text{-}12$$

In this case, the corresponding value model will be:

$$V(Natural\ Attribute\ Group) = \sum_{i=1}^{n} K_i\, V_i(X_i) \qquad 5\text{-}13$$

Once it is determined that these preference independence conditions hold, it may be concluded that the user's value model is an additive one. Similarly, the process is repeated to verify weak difference independence and utility independence conditions for the multi-attribute value and utility models respectively.

5.5 Chapter Summary

The multi-attribute value/utility models, used to assess the value/utility of any given design alternative based on the qualitative and quantitative preferences of a single stakeholder of a defence system, were presented in this chapter. Two main value models were created, a novel additive value model which assumes no uncertainties and a multi-attribute utility model, assessing the risk attitude of the stakeholder. The utility model is far more complicated and elaborate, requiring extensive interaction with the stakeholder, who has to think hard about consequences in order to correctly assess their preferences, through the questions posed, to obtain the utility functions. On the other hand, the value model is much more straightforward and suitable for capturing needs and preferences in the conceptual design phase, rather than selecting from a finalized set of design alternatives; however, it fails to capture the stakeholder's attitude towards uncertainty. In the calculation of the scaling/weighting factors, the arbitrary use of AHP numerical scales was also avoided, obtaining higher accuracy in the assessment of the stakeholder's preferences.

6. Multi-Stakeholder Value Modelling

"All the world's a stage, and all the men and women merely players."

William Shakespeare, As You Like It

The first step of engineering design, as described in 2.2, is the identification of all stakeholders with interests/stakes in any part of the whole lifecycle of the designed product. As already discussed in 3.1, one of the major limitations of MAUT, summarised through Arrow's General Possibility Theory [124], is its inability to aggregate the preferences of more than one stakeholder. Despite the methods of integrating multiple stakeholders' preferences into a common value/utility function provided by Keeney and Raiffa [1], they too acknowledge that "*no procedure can combine several individual's rankings of alternatives to obtain an (aggregated) ranking that will simultaneously satisfy these five assumptions*" of Arrow's Impossibility Theorem.

In this analysis heretofore the user has been identified as one major stakeholder whose preferences are to be elicited and used in the evaluation of all design alternatives. However, the objectives of other than the user stakeholders with different interests/stakes should be taken into account in the engineering design, based on the assumption that the whole lifecycle of the designed system is not a zero-sum game, where each participant's gain (or loss) of utility is exactly balanced by the other participants' loss (or gain) of utility. Hence, in the VDD implementation and following the development of appropriate multi-attribute/single attribute value models for all stakeholders, Game Theory has to be employed for multi-stakeholder value modelling. Although, it would be possible to employ any kind of value model, such as a financial value model, the multi-attribute utility functions presented in the previous chapter, as models of rational behaviour, will be utilised by Game Theory to address the preferences of multiple stakeholders. Value driven engineering design is modelled through Game Theory as a non-zero sum game between the major stakeholders of the designed system. Consequently, in this game that can be extended if desired to include more stakeholders, the decisions of the stakeholders/players concerning the whole lifecycle of the designed system aim to promote their interests through the maximization of their corresponding objective/utility functions, while being affected by the other players' choices. Moreover, since a group of experts/individuals is usually involved with the operation and technical/logistic support of the designed system during all different stages of its lifecycle, the integration of all these experts' preferences is a *sine qua non* of the user's value modelling. Thus, a synthesization averaging method based on AHP is introduced to deal with the interpersonal preferential conflicts between individuals representing a stakeholder and all having the same objectives but different quantitative preferences.

6.1 Aggregation of Individual Preferences

For the purposes of engineering design, a group of knowledgeable experts/individuals involved during the whole lifecycle of the designed system constitutes a group of decision makers whose preferences need to be incorporated into the user's objective function. In most cases the selection of the averaging method used in the aggregation of the individuals' preferences is rather arbitrary, as already discussed in 3.4. Moreover, during the conceptual engineering design phase the set of alternatives is not finalized for the group ranking of the alternatives to be obtained, identifying the optimal design among all candidates. The aggregation of individual preferences aims mostly in synthesizing the judgments/preferences of group members in value modelling, rather than averaging the individuals' rankings of a final set of design alternatives.

AHP comparison matrices provide not only an objective weighting to assess the set of alternatives, but also a measurement of consistency of the redundant answers provided by each individual with the computed consistency ratio. In the group value model, the judgments of *n* experts need to be synthesized to obtain the group weighting factors through a group AHP comparison matrix, satisfying the requirement that the *synthesis of consistent judgments ought to be consistent as well*.

As discussed by Dijkstra [155], for the simplest case of two experts with AHP comparison matrices: $A = (a_{ij})$, $B = (b_{ij})$, the synthesis matrix will be defined as $C = \sum(A, B) \coloneqq (\sigma(a_{ij}, b_{ij}))$, while the synthesizing function $\sigma: \mathbb{R}_+ \times \mathbb{R}_+ \to \mathbb{R}_+$,with $\mathbb{R}_+$the set of positive real numbers, should have the following properties:

- It should be continuous.
- $\sigma(a,a) = a$.
- $c_{ij} \in [\min(a_{ij}, b_{ij}), \max(a_{ij}, b_{ij})]$.
- If A, B are consistent matrices, as AHP consistency is defined, $a_{ik} \cdot a_{kj} = a_{ij}$, then the synthesis matrix C should be consistent too: $\sigma(a_{ik}, b_{ik})\, \sigma(a_{kj}, b_{kj}) = \sigma(a_{ij}, b_{ij})$.

The functional equation representing consistency can also be written as:

$$\sigma(x_1, y_1)\, \sigma(x_2, y_2) = \sigma(x_1 x_2, y_1 y_2) \qquad \text{6-1}$$

Taking logarithms of this equation and defining that $\tilde{\sigma} \coloneqq \log(\sigma)$, $\tilde{x}_i \coloneqq \log(x_i)$, $\tilde{y}_i \coloneqq \log(y_i)$, the functional *Cauchy equation* is obtained:

$$\tilde{\sigma}(\tilde{x}_1, \tilde{y}_1) + \tilde{\sigma}(\tilde{x}_2, \tilde{y}_2) = \tilde{\sigma}(\tilde{x}_1 + \tilde{x}_2, \tilde{y}_1 + \tilde{y}_2) \qquad \text{6-2}$$

The Cauchy equation has solutions of the form $\tilde{\sigma}(\tilde{x}, \tilde{y}) = \theta_1 \tilde{x} + \theta_2 \tilde{y}$, for real θ_1, θ_2 i.e. $\tilde{\sigma}(\tilde{x}, \tilde{y}) = \log(\sigma(x,y)) = \theta_1 \log(x) + \theta_2 \log(y) = \log(x^{\theta_1} y^{\theta_2})$. Therefore, for two experts/individuals each cell of the group AHP comparison matrix is obtained from the corresponding cells of the individual AHP matrices $\sigma(x,y) = x^{\theta_1} y^{\theta_2}$ or in terms of the original variables and for $\theta \in [0,1]$:

$$\sigma(a,b) = a^{\theta} b^{1-\theta} \qquad \text{6-3}$$

In this equation θ is set to ½ for experts of equal power or appropriately set, reflecting power and experience/competence between them. This equation can be analogously extended for an arbitrary number n of experts of not equal power/authority, with $\theta_1 + \theta_2 + \cdots + \theta_n = 1$:

$$\sigma(a_1, a_2, \dots, a_n) = a_1^{\theta_1} a_2^{\theta_2} \dots a_n^{\theta_n} \qquad \text{6-4}$$

In the UAS VDD to incorporate the preferences of the individuals/experts into the user's value model and based on equation 6-4, once the AHP matrices of judgments between the design attributes of all group members are obtained, a new synthesized AHP matrix is generated with cells equal to the geometric means of the corresponding cells of the experts' judgment matrices. In this AHP group matrix, presented graphically below, the group weighting factors of the user's multi-attribute utility model are computed while consistency is maintained. Finally, the individual preferences in terms of the attributes' neutral points are also synthesized in the group value model by computing their arithmetic mean.

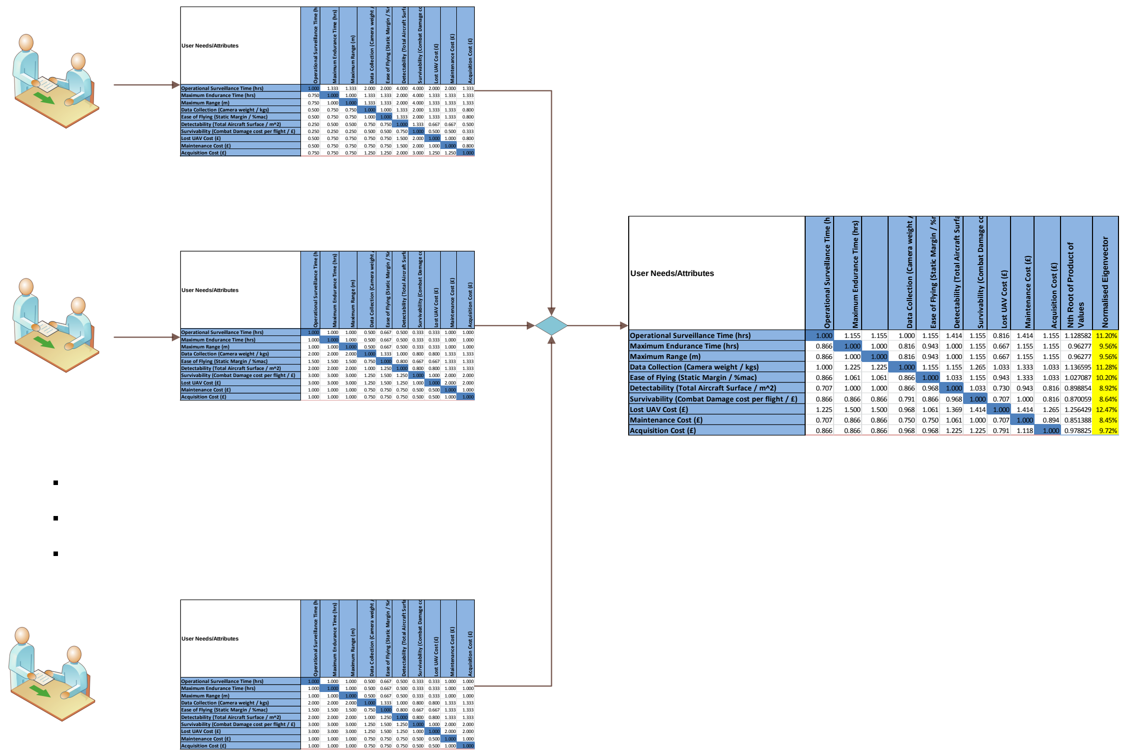


Figure 6-1 Group Decision AHP

6.2 Game Theory in Value Modelling

Several stakeholders can be selected as players in the application of Game Theory in engineering design. Based on the analysis in section 4.2, the user and the manufacturer of the designed system are chosen as the two players participating in this game. Nevertheless, the game can be easily extended to include more stakeholders/players, such as part suppliers, public/local communities etc. Furthermore, different models of Game Theory could be developed, considering as players the designed system's components, disciplines or even technologies, as already discussed in 3.5. For the user, the group multi-attribute value function already presented is considered as the objective/payoff function. Concerning the manufacturer, the cost plus fee contract type was assumed and the objective/payoff function is modelled as a linear function of the Total Program Cost for entire lifecycle of the designed product. The basic and often debatable assumptions of Game Theory for these stakeholders as players of the game [192], are the following:

- The players are instrumentally rational, i.e. they act only according to their preferences as modelled by their objective functions.
- They share Common Knowledge of Rationality (CKR); an endless chain of beliefs, concerning their rationality, is created: each player is rational (0^{th} order of rationality), each player knows that each player is rational (1^{st} order of rationality), each player knows that each player knows that each player is rational (2^{nd} order), and so on.
- They have Common Priors or Consistently Aligned Beliefs (CAB), i.e. given the same information the rational players should draw the same conclusions.
- They share common knowledge of the game rules, i.e. they know all possible alternatives/acts of the game and the utility functions of all players. It is therefore, a game of perfect/complete information.

In the pursuit of values articulated by the stakeholders' objectives, each of them is forced to select particular strategies and make decisions, based on their incentives. Some of these incentives are determined purely by the player's payoff function in the game and are independent of any other information or expectations the player may have about the other players' likely strategies. Some other incentives may also depend on their information and the aforementioned expectations. Harsanyi [193] designates the former incentives as *structural incentives* and the latter as *strategic.*

Engineering design is modelled as a game of *complete information*, with the players knowing each other's payoff functions, i.e. knowing each other's *structural incentives.* In this game however, each stakeholder may also have *strategic incentives*, which are not only dependent on their payoff function but also on their expectations on the other players' most likely strategies based on their information about the other players' *structural incentives*. Thus, the optimal design alternative selection process has to be modelled on the one hand as an axiomatic based cooperative game, using only the players' *structural incentives*; on the other hand, the process of strategic interactions among the players has to be encompassed in a non-cooperative game, with all the players' *strategic incentives* included in the design process.

In this game, the optimal design alternative is selected as the solution giving the amount of satisfaction every rational stakeholder anticipates and agrees upon as fair bargain. This binding agreement, satisfying the rational expectations of gain of all stakeholders, would be the outcome of a bargaining process modelled by Game Theory as a cooperative *2* players' non-zero sum game. The bargaining problem is solved in an axiomatic way with the Nash bargaining solution (NBS) [157], which is the one and only definite solution among all the Pareto optimal candidates all rational players would accept.

Additionally, each of the stakeholders/players is forced to select a particular strategy, based on their *strategic incentives*, i.e. to make some important decisions in isolation, influencing the delivery of value to all. Such decisions could be:

- For the manufacturer, the use of improved technology, the improvement of reliability through design and development, the use of higher quality assurance processes for detection and analysis of reliability problems, the employment of a new manufacturing process etc.
- For the user, trading-off performance for reliability, such as some compromise in maximum speed to improve reliability related failure rates, or applying different (more or less demanding) maintenance policies.

These important decisions could be considered as strategic choices, all aiming to promote the stakeholder's objectives, through the maximization of the corresponding objective/payoff function, but more importantly being dependent on the information and expectations the players may have about the other players' likely strategies. Thus, the process of interaction of these stakeholders' strategic choices and their corresponding payoffs is studied as a *2* players' non-zero sum, non-cooperative game, solved through Nash equilibrium, [156]. Nash equilibrium, as a solution to this problem, constitutes the set of all stakeholders' strategic choices and their corresponding payoffs when no player can benefit by changing his/her strategy while the other players keep theirs unchanged. In case indeterminacy arises and multiple Nash equilibria are obtained, Nash's product of the payoff/utility functions suggested by Harsanyi [193], is the sole criterion used for the selection of the specific Nash equilibrium as the solution of the non-cooperative game.

Hence, the following novel hybrid game, modelling successfully the interactions between the stakeholders' preferences and their strategic choices, is created to accurately evaluate the alternative designs. This hybrid cooperative/non-cooperative game is formed in two levels:

1. For all combinations of strategic choices of the stakeholders, the corresponding cooperative game is employed to identify the NBS, as the design alternative from all generated design alternatives that guarantees the Pareto optimality property and acceptance by all rational players.
2. Among all bargaining solutions obtained in the first level, the non-cooperative game identifies through Nash equilibrium the design alternative as the overall optimal solution of the game along with the combination of strategic choices, selected by the stakeholders to better promote their objectives.

This simultaneous employment of the two players' cooperative non-zero sum games and two players' non-cooperative non-zero sum game, used in the multi-stakeholder value modelling of engineering design, is presented in detail in the following sections. This novel hybrid game is considered the most effective way of:

- Addressing the stakeholders' preferences, i.e. their *structural incentives*, and defining for all cooperative games the most desirable outcomes in an axiomatic way.
- Modelling the strategic interactions among the players, i.e. their *strategic incentives*, and yielding to a single, optimal and well-defined solution, identified as both Nash equilibrium and Nash bargaining solution.

6.3 Cooperative Non-zero Sum Bargaining Game

Nash's bargaining model is used to identify the optimum design from the Pareto front of the design alternatives' set. In general, each design alternative is characterized by a utility vector $\vec{u} := (u_1, u_2, u_3, \dots, u_n)$, with the *n* utility/payoff functions of the *n* stakeholders. The NBS [157], defined as a^*, achieves a unique bargaining solution satisfying the following axioms of:

- Individual rationality, no stakeholder will agree to a solution with a payoff lower than the one guaranteed under disagreement.
- Pareto optimality, that the agreement between the stakeholders is reached when there is no other feasible solution such that one stakeholder can improve the payoff without decreasing the other stakeholder's payoff.
- Independence of irrelevant alternatives, if the set of design alternatives is reduced but still includes the NBS and the disagreement alternative, the solution will not change.
- Independence of linear transformations, if one stakeholder's payoff function is linearly transformed, the new NBS is the image of the previous one under the same transformation.
- Symmetry, identical stakeholders receive identical payoffs. The NBS does not change if we rename the original stakeholders, i.e. if, for example, we replace each utility vector $\vec{u} := (u_1, u_2, u_3, \dots, u_n)$ with the utility vector $\vec{v} := (u_2, u_1, u_3, \dots, u_n)$.

In general the a^* NBS is obtained by solving the following maximization problem:

$$\begin{aligned}&\big(u_1(a^*) - u_1(\bar{a})\big)\big(u_2(a^*) - u(\bar{a})\big) \dots \big(u_n(a^*) - u(\bar{a})\big) \\ &\qquad = max_{a\epsilon A}[\big(u_1(a) - u_1(\bar{a})\big)\big(u_2(a) - u_2(\bar{a})\big) \dots \big(u_n(a^*) - u(\bar{a})\big)]\end{aligned} \tag{6-5}$$

In this equation $\bar{a}$ is the disagreement point, if no agreement is reached. In the UAS VDD, the disagreement values of payoff functions were all assumed to be 0.

An equivalence relation between two design alternatives described by the two utility vectors for *n* stakeholders: $\vec{u} := (u_1, u_2, u_3, \dots, u_n)$ and $\vec{v} := (v_1, v_2, v_3, \dots, v_n)$ written as: $\vec{u} \sim \vec{v}$, exists if the two alternatives are equally reasonable to select. Then, according to Theorem 4.2 [194], for a scale-invariant and symmetric equivalent relation (Axioms 4, 5 of NBS), each of the design alternatives is equivalent to:

$$(u_1, u_2, u_3, \dots, u_n) \sim (u_1 u_2 u_3 \dots u_n, 1, 1, \dots, 1) \quad 6\text{-}6$$

Hence based on the aforementioned theorem, the quality of each design alternative is uniquely determined by the Nash's product of utilities, while alternatives with the same product of utilities are equivalent. Therefore, in the UAS value driven conceptual design, the product of the user's and manufacturer's utilities was utilized as the sole criterion to determine the quality of each design alternative. For presentation purposes and based on some specific stakeholders' preferences, the values of the user's and manufacturer's utility/payoff functions are plotted for the set of all generated UAS alternatives in Figure 6-2.

For simplicity, the two stakeholders were assumed to be equal in bargaining skills and relative authorities. The problem of indeterminacy of the Pareto front is resolved through the introduction of the above criterion, obtaining a definite Pareto-efficient solution as the one with the maximum value of user's and manufacturer's payoff functions' product. Thus, from the Pareto front in Figure 6-2, a single UAS may be identified as the NBS. In this cooperative game, more players could be added of not equal relative authorities γ to obtain the generalized Nash bargaining solution for *n* players: $\left(v_1(a^*) - v_1(\bar{a})\right)^{\gamma_1}\left(v_2(a^*) - v_2(\bar{a})\right)^{\gamma_2} \dots (v_n(a^*) - v_n(\bar{a}))^{\gamma_n})$, [168].

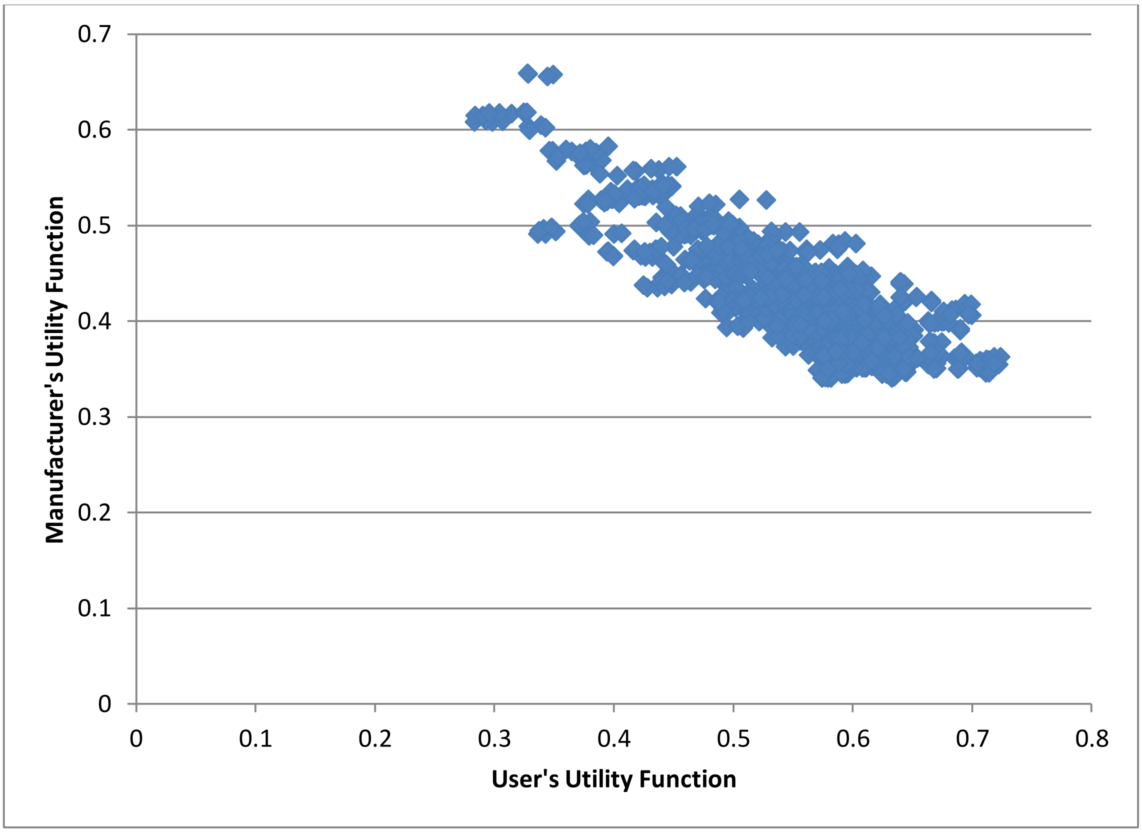


Figure 6-2 Utility/Payoff Functions Plot

6.4 Non-cooperative Non-zero Sum Game

Concerning the user's and manufacturer's strategic choices, modelled in a two players' non-zero sum, non-cooperative static game, the available list is rather long, different performance requirements, assumed constant in the design space exploration, improvement or not of technology, different quality control processes, and so on.

The above strategic choices define the non-cooperative game to be played by the players, based on all possible combinations between the strategic decisions made by them. The selection of the specific strategic choice for any of the two stakeholders is based on their *strategic incentives*; it depends not only on the value of the payoff function but also the expectations the player has concerning the other player's most likely strategy.

In Table 6-1, a general non-cooperative game between the two major stakeholders is presented with indicative payoff values shown for all combinations of strategies. In each cell of the table, the values of the user's and manufacturer's utility/payoff functions are presented. The + and – signs represent the best move for each player in response to each move of the other player. For example, the – sign next to the value of 0.7 of the user's payoff function means that the user's strategy 1 is the best choice for the user (as opposed to 0.5), if the manufacturer selects strategy 1. In a similar manner, the + sign next to the value of 0.5 of the manufacturer's payoff function means that strategy 2 is the best response of the manufacturer (as opposed to 0.4), if the user selects strategy 1. The cell that includes both + and – signs constitutes a Nash equilibrium and a potential solution of the game, since it represents the optimal strategic choice of both players. This selection does not maximize the objective function of each individual player (user and manufacturer), but represents the optimal strategic choice in response to the other player's strategic choice, justified through the successive elimination of strictly dominated strategies, applied for the specific stakeholders' preferences reflected in the values of the utility functions, as follows:

- Independent of the manufacturer's selected strategy, the common knowledge of rationality of the players means that the rational user will always select strategy 1, since it is strictly dominating strategy 2 (irrespective of what the manufacturer does, i.e. 0^{th} order of CKR).

- The manufacturer knowing that the user is rational, i.e. that the user will select strategy 1, will prefer strategy 2, since the value of his utility function is higher (guaranteeing a higher profit, i.e. 1^{st} order of CKR).

Table 6-1 General User - Manufacturer Non-Cooperative Game

User's / Manufacturer's Strategies			**User's Strategy 1**			**User's Strategy 2**		
Manufacturer's Strategy 1		Manufacturer's Payoff: 0.4 User's Payoff: 0.7	-		+	Manufacturer's Payoff: 0.5 User's Payoff: 0.5		
Manufacturer's Strategy 2	+	Manufacturer's Payoff: 0.5 User's Payoff: 0.8	-	Nash Equilibrium		Manufacturer's Payoff: 0.4 User's Payoff: 0.6		

As already discussed, if more than one Nash equilibrium is obtained, the indeterminacy is avoided using Nash's product of the payoff/utility functions,

$\pi^k = \prod_{i=1}^{n=2} u_i^k$, proposed by Harsanyi [193], as the criterion for the selection of the specific Nash equilibrium as solution of the non-cooperative game. This coinciding Nash equilibrium/NBS is the single, well-defined, optimal solution of the hybrid game in the multi-stakeholder value modelling of engineering design.

6.5 Chapter Summary

Game Theory has set the goal to prove that all social activities can be modelled as games with solutions predicted using only the assumption of instrumental rationality of the players involved. In this chapter, a multi-stakeholder value model was developed for the evaluation of engineering design solutions, taking into account the objectives of multiple stakeholders, to successfully identify the optimal solution. A novel hybrid game modelling the interactions between the two major stakeholders, the user and the manufacturer, was introduced under the assumptions of players' instrumental rationality, CKR, CAB and common knowledge of the game rules. Despite many objections expressed concerning the validity of these assumptions [192], Game Theory successfully employs the expected utility theory as the only acceptable exemplar of rational behaviour; it is used in this context to address the preferences of more than one stakeholder. Furthermore, a consistent aggregation of the preferences of individuals representing a stakeholder of the designed system was presented, through the synthesization of their corresponding AHP matrices of judgments between the design attributes and the development of a group value model.

7. Design Alternatives Generation

"Scientists investigate that which already is; engineers create that which has never been."

Albert Einstein

In the pursuit of application of the VDD philosophy, advocating the absence of any objectives' requirements, the widest possible design space should be explored. A large number of different concepts and configurations would generate, through the variation of appropriate design variables, a multitude of design alternatives, to be evaluated in the evaluation phase of the VDD cycle. Ultimately, the evaluation/optimization would produce the set of superior designs of different configurations and parameter values, depending on the stakeholders' needs, to be further evaluated during the later stages of engineering design. Moreover, technology availability, depending upon the "technology readiness level" TRL [195] involved in the risk assessment of the program, would permit or prohibit the addition of other more 'advanced' configurations. In view of the above and according to the objectives set in the VDD implementation process in section 1.3, the design space exploration process and appropriate product definition models for the UAS VDD are introduced in this chapter.

7.1 Aircraft Geometric Topologies

To perform a wider exploration of the design space, as advocated by the VDD philosophy, the aircraft geometries are generated by parameterizing geometric topologies in a novel way, as proposed by Sobester [196]. Hence, instead of performing a single concept design optimization, a broad range of UAS configurations is obtained and evaluated.

This novel hierarchical coding of different topological designs of aircraft is based on fundamental design selections:

1. Starting from the fundamental requirement of having a wing to provide lift.
2. Follows the existence (or not) of a fuselage, resulting in an aircraft with a fuselage or a flying wing.
3. Next, the type of fuselage is defined, i.e. a conventional (“monolithic”) fuselage or a twin boom fuselage aircraft is obtained.
4. The existence (or not) of a horizontal stabilizer, distinguishing the type of stabilizer, is the next fundamental selection.
5. The longitudinal position of the stabilizer (forward or aft).
6. Its vertical position, relative to the fuselage (‘conventional’ horizontal tail or T-shape tail).
7. The existence and number of vertical fins.
8. The position of the propeller (forward or aft)
9. And finally the selection (or not) of all moving control surfaces generate more aircraft geometries.

The sequence of these fundamental design selections is presented in Figure 7-1:

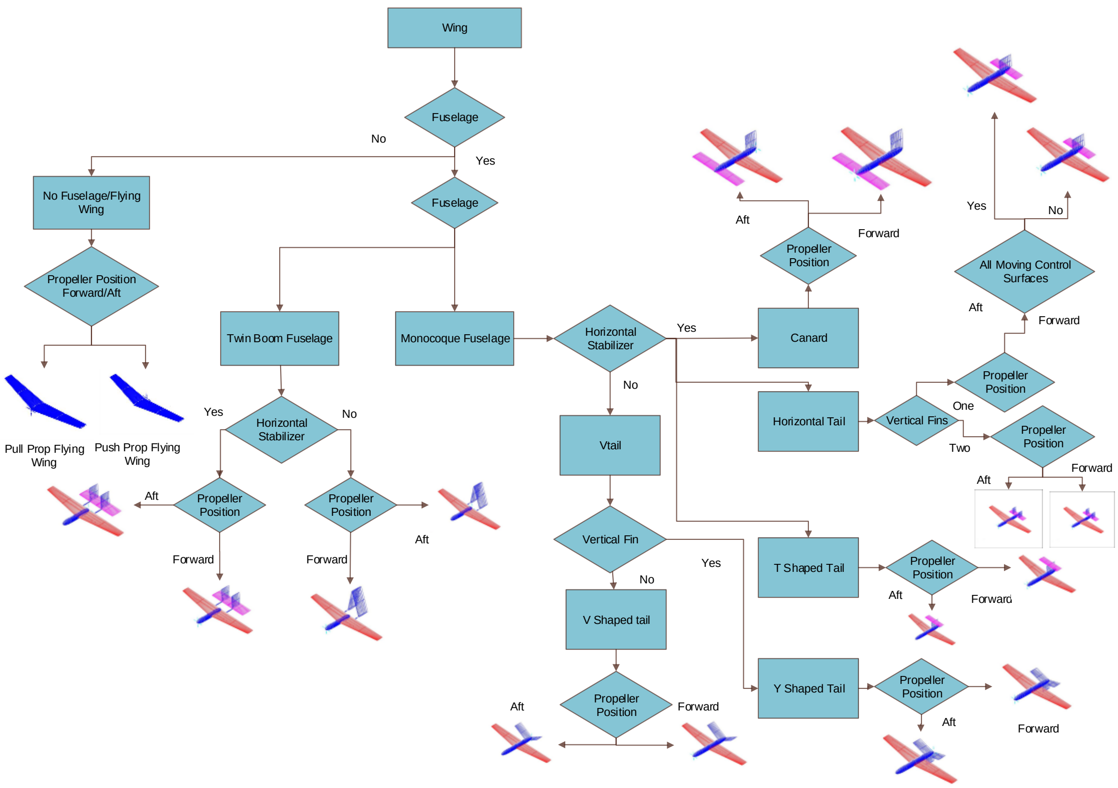


Figure 7-1 Aircraft Geometric Topologies

Hence, a multitude of basic aircraft geometries (34 in total for the specific selections, presented in Appendix B.1) is generated, described by a hierarchical coding composed as a series of 0's and 1's, depending on the selections made. In the generation of these geometries, several issues were taken into account and certain configurations were excluded. For example, no V-shape tail was included for the twin boom fuselage, to avoid torque issues, and only the horizontal stabilizer and the inverted V-shape tail were the available options for this configuration. Although the above selections aimed mostly at generating aircraft geometries for the low cost UAS test case, more fundamental selections could be added in the sequence, e.g. a single or twin engine option or a blended wing body with a partial fuselage option, to obtain more alternative design configurations.

This hierarchical coding is input into the appropriate design models defining the aircraft and estimating its relevant attributes. For example, an aircraft with monolithic fuselage, horizontal tail, one vertical fin, a pusher propeller and no all moving control surfaces would be coded as *111110110*, a flying wing with a pusher propeller as *100000010* and an aircraft with a twin boom fuselage, inverted V-shape tail, pull propeller as *110011000*. This nine digit representation of a large number of aircraft geometric topologies allows for the shape definition to be input in the design models, which are then scaled through the use of appropriate design variables, such as wing span, wing aspect ratio (AR), horizontal tail aspect ratio (AR) etc. By employing a large number of different UAS configurations, the designer considers numerous advantages and disadvantages of each design choice, identifying a different optimal design depending on the stakeholders' preferences and priorities.

7.2 UAS Conceptual Design Generation

The conceptual design generation and analysis, presented in Figure 7-2, having as inputs the selected UAS design variables and outputs the attributes defined in the objectives/attributes hierarchy of Figure 4-4, is done in the following four steps:

- *Aircraft sizing.* Structural analysis, to define basic structural components, such as wing spars and tail booms (if fitted). Drag calculations that drive the engine performance and propulsion requirements. Weight and balance calculations and aerodynamic analysis are also performed.

- The *acquisition cost* analysis model uses as inputs the design parameters, product definition and geometry, along with the material and labour cost rates, to calculate the unit and total fleet acquisition cost.
- The *operational simulation* analysis model, using as inputs the design parameters and according to the chosen maintenance policy, calculates the maintenance lifecycle cost and the losses due to reliability related failures.
- The *simulation survivability analysis* model provides estimates of the combat damage cost and associated UAS losses based on the design parameters, mission/sorties and battle damage rates.

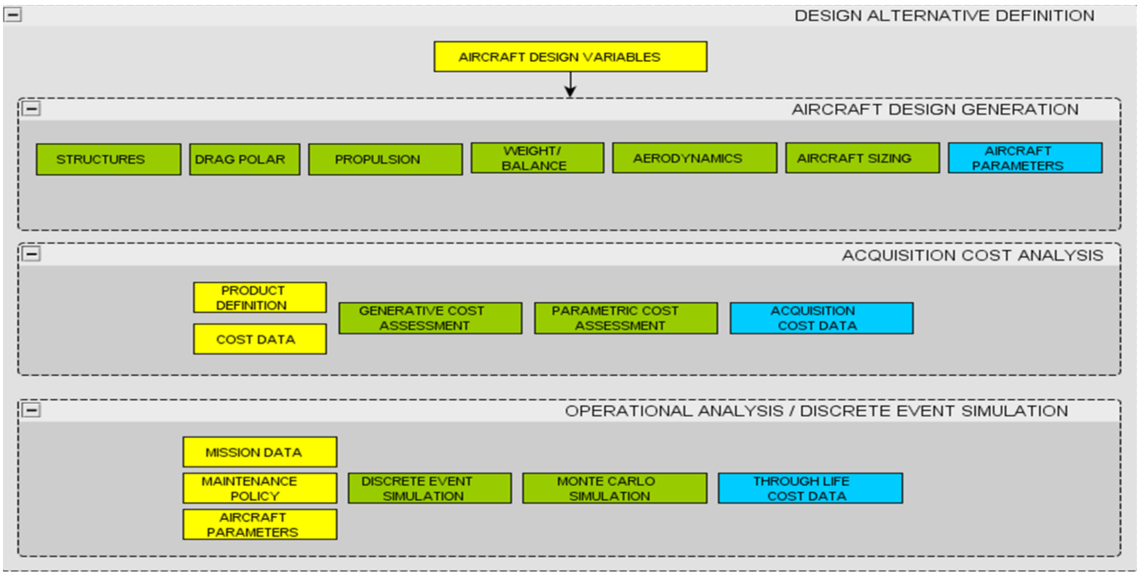


Figure 7-2 UAS Conceptual Design Generation

7.3 Aircraft Sizing Model

The aircraft sizing model is built with Excel spreadsheets. It should be noted that the same models are used for all configurations, allowing for their easy amendment or replacement for higher accuracy, if desired. The following design variables are inputs to these models:

1. *Wing AR.*

2. *Wing taper ratio*.
3. *Wing span*.
4. Wing position in terms of the location of the *front bulkhead*, which is the most forward point of the fuselage where the nose is attached, using as reference point ($x = 0$) the longitudinal position of the wing main spar.
5. Horizontal *tail AR*.
6. *Fin AR*.
7. *Canard AR.*
8. *Battery Capacity*, as the driving factor for endurance and range.
9. *Component Reliability,* used in the lifecycle cost models for the scheduled maintenance cost and reliability associated cost calculations, when the critical components Repair by Replacement (RBR) policy is performed.
10. *UAS Replacement Time Interval* used in the lifecycle cost models for calculating the lifecycle cost, when the whole aircraft instead of individual components replacement policy is selected.

To limit the number of design variables to a reasonable number, many design parameters were defined and fixed, as presented in Appendix B.2 UAS Parameters. However, these too could be added as extra design variables to explore further the design space, such as:

1. *Wing sweep*, which for the case of the low sweep, no twist flying wing, was chosen to be 15^0 and for all other configurations 0^0.
2. *Wing twist*, with all configurations having 2^0 and the flying wing zero twist, as explained in the following paragraph.
3. *Total weight estimate* (based on the chosen category) is initially set to 3 Kg, which in the loop iteration changes to converge to the calculated weight.
4. *Payload dimensions* and *weight*, based on a camera selection such as the GOPRO Hero3.
5. *Aerofoil* selection, as described below.
6. *Design/Operational speed*, *Landing speed* and *Maximum speed*.

The models are placed in a series, according to the design spiral approach. The process iterates using the initial weight estimate until it converges, calculating UAS weight and the other parameters.

For all configurations other than the flying wing, the same aerofoils were selected: for the main wing the NACA 23015 and the horizontal tail, fin etc. the NACA 0012. For the flying wing, the wing sweep is necessary to move the aerodynamic centre aft enough, to create the stabilizing increased moment of lift when angle of attack is increased (pitch down). The use of wing sweepback and twist provide the pitch stability, however to avoid large sweep and twist, for ease of manufacturing, a reflexed shape aerofoil was selected such as the FAUVEL 14%, (thickness to chord ratio) in order to have positive pitching down moment coefficient during all flight conditions. This aerofoil with a positive pitching moment about the aerodynamic centre, having its trailing edge lifted slightly, provides natural stability. In all configurations, no undercarriage and flaps are present. For the calculations in the following sections, all data used in regression analysis and the corresponding formulae are presented in Appendix B.3 Regression Data / Formulae.

7.3.1 Sizing Model

The sizing model 'blends' all inputs and outputs from the following models into a single spreadsheet that contains all design parameters, variables and attributes to be used further in the analysis. Based on the values of the selected design variables and fixed parameters, the geometry of all basic UAS components is generated. The process is concluded by iterating through the loop the weight, until convergence is achieved and the final values of all design parameters are obtained.

For the wing geometry, the values of design variables, wing span b, wing aspect ratio AR and wing taper ratio λ, are used to compute the mean aerodynamic chord $\tilde{c}_W$ as $\frac{b}{AR}$, wing root chord $c_{Wr} = \frac{2\,\tilde{c}_W}{(1+\lambda)}$, wing tip chord $c_{Wt} = \frac{2\,\tilde{c}_W}{(1+1/\lambda)}$, wing total area $S_W = \frac{b^2}{AR}$, while the wing thickness to chord ratio and actual wing thickness are obtained based on the specific airfoil selected as described in the previous section (i.e. thickness ratio 15% or 14%), and the wing mean aerodynamic chord. Concerning the flying wing, the wing span b is computed based on the payload dimensions requirements, to be accommodated inside the wing rather than placed partially out of the wing. For the fuselage, a fineness ratio of 8 is assumed for the monolithic fuselage and 5 for the twin boom fuselage, as suggested by Raymer [5], and is kept constant in the optimizations. The fuselage height and width are computed based on the payload's dimensions, to be accommodated inside the fuselage. The fuselage length is calculated as the product of the fuselage fineness ratio and the fuselage width/height. A nose is also assumed of spherical shape with radius equal to the fuselage width/height.

In the tail/fin calculations, the tail volume coefficients, C_{h_tail}, C_{fin} are kept constant at a value of 0.6 for the horizontal tail and 0.04 for the fin, as suggested by Table 6.4 [5], and adjusted for the different configurations, i.e. if all moving tail, reduced by 10% and if T-shape tail, reduced by 5%. With these values of horizontal tail/fin volume coefficients, the mean aerodynamic chord $\tilde{c}_W$, the wing span b, the wing area S_W and the moment arms, L_{h_tail}, L_{fin} set to 60% or 47.5% of the fuselage length for a front-mounted or aft-mounted propeller [5] respectively, the tail is sized using the formulae 6.28 and 6.29 [5], to obtain the horizontal tail and fin areas:

$$S_{h\_tail} = \frac{C_{h\_tail}\,\tilde{c}_W S_W}{L_{h\_tail}}$$

$$S_{fin} = \frac{C_{V\_tail}\,b\,S_W}{L_{fin}} \qquad 7\text{-}1$$

With the horizontal tail and fin aspect ratios as inputs and the horizontal tail and fin areas computed above, the horizontal tail and fin spans are calculated as $b_{h\_tail} = \sqrt{S_{h\_tail}\,AR_{h\_tail}}$, $b_{fin} = \sqrt{S_{fin}\,AR_{fin}}$. Then, the corresponding horizontal tail and fin chords are S_{h_tail}/b_{h_tail} and S_{fin}/b_{fin}. The horizontal tail and fin spars' longitudinal position are found by subtracting from the most forward point of the fuselage the fuselage length and adding to that the horizontal tail/fin chord. The thickness to chord ratio of the horizontal tail and fin are obtained from the selected airfoil, as discussed in the previous section. The boom length is equal to the distance between the tail position and the end of the fuselage (based on the fuselage length for the twin boom configuration).

For the V-shape and Y-shape tail configurations, the tails are assumed to consist of an equivalent horizontal tail and an equivalent vertical fin, sized as the horizontal tail and fin above. For the canard configurations, an average value for the canard volume coefficient C_{can} of 0.75 [197] and a moment arm L_{can} equal to 40% of the fuselage length [5], are assumed to compute the canard area S_{can}:

$$S_{can} = \frac{C_{can}\ \tilde{c}_W S_W}{L_{can}} \tag{7-2}$$

Thus, the canard span is computed based on the canard aspect ratio AR_{can}, as $b_{can} = \sqrt{S_{can}\ AR_{can}}$ and the canard chord as S_{can}/b_{can}.

Many of the fixed UAS parameters could be converted to design variables to perform further parametric and trade studies; however, at this stage, they were kept constant to accelerate the optimization. For example, the fuselage fineness ratio could be considered as an additional design variable or the tail volume vs. boom length trade-off could be explored based on the values of tail volume coefficient, to study their effect on value index.

7.3.2 Structural Calculations

In the structural model, structural analysis of the wing is performed. Based on wing AR, wing span, wing taper ratio and the estimated UAS weight, the wing spars are calculated, in terms of weight, outer diameter (for an assumed thickness 10% of the outer diameter). The weight used in these calculations is replaced by the weight obtained in the weights and balance model, and iterated until convergence is achieved.

The chord along the wing span is calculated as the average between the elliptical chord C_{ell} and trapezoidal chord C_{trap}, according to the Schrenk method [198]. Thus the centre of gravity along the wing span is obtained from equation 7-3, with y_i the lateral positions on the wing where the chords are computed:

$$CG\%\text{Semispan Location} = \frac{\sum(C_{ell} + C_{trap})\, 1/2\, y_i}{\sum(C_{ell} + C_{trap})_i} \qquad 7\text{-}3$$

Next the total load applied on each wing, based on the weight of the UAS, W_{UAS} and a maximum load factor of 6, is calculated and the corresponding moment M applied at the span wise centre of gravity position, with b the wing span, will be:

$$M = \frac{6\, W_{UAS}}{2} (CG\%\text{semispan location}) b/2 \qquad 7\text{-}4$$

The diameter of the wing spar is obtained assuming a maximum stress applied σ_{max} equal to 600MPa for carbon fibre material and solving for the section modulus of the wing spar W in equation 7-5. Finally, the wing spar cross sectional area and weight are obtained, since for a circular tube the section modulus is found with equation 7-6, based on its inner and outer diameters, d_1 and d_2.

$$W = \frac{M}{\sigma_{max}} \qquad 7\text{-}5$$

$$W = \frac{\pi(d_2^4 - d_1^4)}{32 d_2} \qquad 7\text{-}6$$

In the structural model, depending on the aircraft configuration, the tail booms' (if fitted) weight and dimensions are also calculated based on wing span, wing mean chord and front bulkhead position. The total load P applied on the boom is found with equation 7-7, also a maximum deflection angle of the boom of 10^0 and a maximum horizontal tail lift coefficient C_{Lmaxh_tail} of 1.5 are assumed.

$$P = 1/2\, \rho\, V_{max}^2\, S_{h\_tail}\, C_{Lmaxh\_tail} \qquad 7\text{-}7$$

In this equation ρ is the air density, S_{h_tail} the horizontal tail area, calculated based on a tail volume coefficient of 0.6, as in Table 6.4 of [5] and V_{max} the maximum speed of the UAS. The angle of deflection for a cantilever beam is:

$$\varphi_B = \frac{PL^2}{2EI} \tag{7-8}$$

Where P the load applied, L is the length of the booms, E the Young's Modulus for carbon fabric. Solving equation 7-8 for the moment of inertia I, the boom dimensions and weight are then calculated, assuming a cylindrical tube with a thickness of 10%.

7.3.3 Drag Calculations

The drag model calculates, using drag polar methods, the total drag (profile drag and lift induced drag) at the three pre-defined speeds, design, landing and maximum speed according to the parametric formulae/equations, which are valid for low subsonic Mach numbers ($M < 0.6$) as presented in [199]. The corresponding drag polar coefficients for other speeds are obtained through interpolation, based on these three flight conditions.

In the drag calculations, the variables are the UAS geometric code and the wing AR, wingspan, wing taper ratio, horizontal tail AR, fin AR, canard AR and front bulkhead location. The total drag is equal to the sum of profile drag and induced drag due to lift of wing/body:

$$\begin{aligned} C_D = {} & C_{DoWB} + C_{DoV\_tail} + C_{Doh\_tail} + C_{Dofin} + C_{DoCan} + C_{DoY\_tail} + C_{Dobooms} \\ & + C_{Donac/eng} + C_{DiWB} \end{aligned} \tag{7-9}$$

The profile drag for wing body C_{DoWB} is calculated for all individual components using equation 7-10, [199]:

$$\begin{aligned} C_{DoWB} = {} & \Bigg\{ C_{fW}\left[1 + L\left(\frac{t}{c}\right) + 100\left(\frac{t}{c}\right)^4\right] R_{LS}\frac{S_{Wet,e}}{S_{REF}} \\ & + C_{fb}\left[1 + \frac{60}{\left(\frac{l_b}{d}\right)^3} + 0.0025\frac{l_b}{d}\right]\frac{S_{s,e}}{S_{REF}}\Bigg\} R_{WB} + C_{Db}\frac{S_B}{S_{REF}} \end{aligned} \tag{7-10}$$

Where C_{fw} is the flat plate skin friction coefficient of the wing, which is a function of skin roughness, Mach number and Reynolds number, calculated based on the reference length/wing mean aerodynamic chord through regression (based on the figures 3.1, 3.2 of [199]). Additionally, t/c is the thickness ratio of the wing, L is an airfoil location parameter, assumed 2 for $(\frac{t}{c})_{max}$ located at a distance smaller than $0.3c$, $S_{Wet,e}$ the wetted area of the wing, S_{REF} the wing projected planform area, R_{LS} a lifting surface correction factor, function of Mach number, assumed based on Figure 3.3 of [199] to be 1.07. The C_{fb} is the turbulent flat plate skin friction coefficient for the body, a function of Mach number, Reynolds number and reference length/fuselage length. The term l_b /d is the fuselage fineness ratio (fuselage length to diameter/width), $S_{s,e}$ the exposed wetted area of the fuselage, R_{WB}, the wing-body interference correlation factor, obtained from Figure 3.5 of [199], assumed to be 1. Finally the C_{Db} is the fuselage base drag coefficient, based on maximum fuselage frontal area.

For the calculation of zero lift drag coefficient of the horizontal tail, fin, canard, V-shape and Y-shape tails, $(C_{Do})_P$ the equation 7-11 is used, [199]:

$$(C_{Do})_P = C_{fP}[1 + L\,\frac{t}{c} + 100\left(\frac{t}{c}\right)^4]_P\, R_{LS,P}\,\frac{S_{Wet,p,e}}{S_{REF}} \qquad \text{7-11}$$

The coefficients in this equation are computed in a similar manner as those in equation 7-10, with C_{fP} the flat plate skin friction coefficient of the specific surface, L the airfoil location parameter and t/c the thickness ratio of the surface. The Reynolds number for the specific surface, based on its chord, is used to calculate C_{fP}. $S_{Wet,p,,e}$ is the wetted area of the surface, S_{REF} the projected total wing planform area and $R_{LS,P}$ the lifting surface correction factor. This method is also applied for the V-shape and Y-shape tails.

The zero lift drag coefficient of the nacelles/engines $C_{D_{o_{nac/eng}}}$ for an aft-mounted propeller configuration and the zero lift drag coefficient of the tail booms (if fitted) are computed similarly with the fuselage zero lift drag coefficient from equation 7-10. For a forward-mounted propeller configuration, the following equation is used with the value of C_{D_π} taken from table 2.2, [199] as 0.06 and A_π the maximum frontal area of the nacelles/engines:

$$C_{D_{o_{nac/eng}}} = \frac{1}{S_{REF}}\sum C_{D_\pi}A_\pi \qquad \text{7-12}$$

For the calculation of the induced drag of wing/body $C_{Di\mathrm{WingBody}}$ equation 7-13 is used:

$$C_{DiWB} = C_{DL,W} + [C_D(a)]_B \frac{S_B}{S_{REF}} \qquad 7\text{-}13$$

In this equation $C_{DL,W}$ is the drag due to lift of the wing obtained from equation 7-14, $[C_D\ (a)]_B$ is the body drag due to angle of attack, obtained from equation 7-15, where S_B the fuselage reference area and S_{REF} the wing reference area.

$$C_{DL,W} = \frac{C_L^2}{\pi\, A\, e} + C_L\, \theta\, C_{la}\, v + (\theta\, C_{la})^2 w \qquad 7\text{-}14$$

$$[C_D(a)]_B = 2\, a^2 \frac{S_b}{(S_B)_{REF}} + n\, C_{dc} \frac{S_p}{(S_B)_{REF}}\, a^3 \qquad 7\text{-}15$$

In the above equations C_L is the wing lift coefficient, C_{la} the aerofoil lift coefficient, θ the wing twist, v and w drag factors, obtained based on the wing twist, e is the span efficiency factor, a the angle of attack in radians, S_b the fuselage base area, $(S_B)_{REF}$ the fuselage frontal area, S_P the fuselage planform area and n the ratio of drag of a finite cylinder to the drag of an infinite cylinder, obtained through regression based on the fuselage fineness ratio. C_{dc} an experimental drag coefficient assumed to be 1.2 for small products of Mach number and sine of angles of attack.

Based on the above computations, the drag is calculated in three flight conditions, landing, design and maximum speed, at various values of lift coefficient and through regression the corresponding coefficients are obtained of the general drag polar equation, 7-15:

$$C_D = K_1 + K_2\, C_L + K_3\, {C_L}^2 \qquad 7\text{-}16$$

For other flight conditions, the corresponding values of coefficients of the drag polar K_1, K_2, K_3 are calculated through interpolation, as a function of speed, with equation 7-17, enabling to compute drag at any flight speed v.

$$K = a + b\,v + c\,v^2 \qquad 7\text{-}17$$

7.3.4 Performance Calculations

In the performance model, electric propulsion parameters are obtained, having as inputs the weight, wing span, wing AR, battery capacity, the maximum, design and landing speeds and finally drag polar coefficients *a, b, c* (from the drag model) for calculating the drag polar coefficients at any flight speed.

The drag/thrust required is computed at all flight speeds and the power required is found in equation 7-18 from drag D and speed v:

$$P_{req} = D\,v \qquad 7\text{-}18$$

Following the approach described in Traub [200], the power supplied by the battery will be:

$$P_{batt} = V\,I \qquad 7\text{-}19$$

In the above equation 7-19, V is the battery voltage and I the current. For electric propulsion, due to the Peukert effect [201], the greater the current drawn from the battery, the less effective the battery capacity is and the smaller the current, the greater the effectiveness of the battery (in time to discharge). Hence, using equation 7 of [200] the battery power P_{batt} is written as:

$$P_{batt} = V\,\frac{C}{Rt}\left(\frac{Rt}{t}\right)^{\frac{1}{n}} \qquad 7\text{-}20$$

Here, C is the battery capacity, Rt the hour rating of the battery, i.e. the discharge time over which the battery capacity was determined (typically 1hr for small rechargeable battery packs) and n the battery discharge parameter dependent on the battery type and temperature (typical value for Lithium-Polymer LiPo batteries is 1.3).

The battery power output, reduced by the losses of the propulsion system reflected in the total efficiency factor n_{tot} (typically assumed 0.5 [200]), will be equal to the power required due to drag, combining the two equations 7-18 and 7-20. Thus, the electric propulsion is sized to achieve the maximum speed (of 25m/sec) the maximum current is calculated. In this model, the endurance of the UAS is calculated at all flight speeds using the same approach by solving for the time *t* of equation 7-20, as in 7-21:

$$t = Rt^{1-n}\left(\frac{n_{tot}\ V\ C}{D\ v}\right)^{n} \qquad 7\text{-}21$$

In case that a minimum endurance is assumed as a parameter to size the battery, instead of having the battery capacity as a design variable, this model can also calculate the battery capacity required (say for 1hr endurance) by solving the above equation for the battery capacity *C.* Then the endurance for all flight speeds, using this battery capacity is computed.

Additionally, the maximum endurance and maximum range for the corresponding flight speeds (since when flying for maximum endurance with propeller driven propulsion $C_{D_i} = 3C_{D_o}$ and for maximum range $C_{D_o} = C_{D_i}$) is computed. The endurances and ranges in the three flight conditions, landing, design and maximum speeds are calculated using the above equation 7-21.

In this model, data for Lithium-ion Polymer (LiPo) batteries, electronic speed controllers and electric motors are used to perform regression analysis by plotting these data and obtaining appropriate relationships. Hence, the battery weight is calculated based on the battery capacity through regression (after plotting battery weights and prices versus capacity of several LiPo batteries). Similarly, through regression, the motor power, weight, RPM and dimensions are calculated from the maximum current (at maximum speed). The electronic speed controller weight is also obtained based on maximum current.

For the propeller sizing, the propeller diameter is calculated using the statistical equation 10.23 of [5], provided that it is lower than the maximum allowable propeller diameter for maximum blade tip speed, assumed 200m/sec. Choosing first the number of propeller blades (in this case 2, 3 or 4) the propeller diameter is found as a function of power P with equation 7-22:

$$D = K_P \sqrt[4]{P} \qquad 7\text{-}22$$

In this equation the coefficient K_P is adjusted based on the number of blades selected. Additionally the propeller pitch is computed based on the propeller diameter, after regression analysis.

7.3.5 Weights and Centre of Gravity Calculations

In the weights and balance model, the total, propulsion, structural and equipment weights along with the CG are calculated by estimating the weights of all individual components and the moments they produce. In this model, the UAS configuration along with the other inputs, such as wing AR, wing span etc. are used.

Based on geometric properties (fuselage width, depth, length) and the fuselage density, the fuselage weight is computed. The weights of wing, tail, canard etc. are calculated with weight estimating relationships based on their calculated geometry, while the weights of wing spar and booms are inputs from the structural model. For the avionics, standard weights are used for the servos, receiver, autopilot and camera. For the motor, electronic speed controller, battery and propeller their weights are calculated from a weight estimating relationship based on regression analysis from existing data, as presented in Appendix B.3.

7.3.6 Stability Calculations

Following a similar approach in this model, the UAS configuration and the same design variables and parameters as inputs are linked to the previous models. Based on the aerofoil chosen and the configuration, the longitudinal stability, in terms of the most basic aerodynamic coefficients, is assessed. The lift coefficient slopes C_{L_a} of the wing, horizontal tail, fin etc. are calculated using the semi-empirical equation 12.6 of [5]:

$$C_{L_a} = \frac{2\pi A}{2 + \left(4 + \frac{A^2\beta^2}{\eta^2}\left(1 + \frac{tan^2\Lambda_{maxt}}{\beta^2}\right)\right)^{1/2}} \qquad 7\text{-}23$$

In the above equation, A is the corresponding aspect ratio, $\beta^2 = 1 - M^2$ with M the Mach number, $\eta = C_{l_a}/(\frac{2\pi}{\beta})$ with $C_{l_a}$the airfoil lift coefficient and Λ_{maxt} the sweep at the chord location where the airfoil is the thickest (for the wing, equal to the constant sweep Λ, and for the other unswept surfaces set to 0).

The fuselage contribution to pitching moment coefficient due to lift slope $\frac{dC_m}{dC_L}$, as in [202], is found according to 7-24:

$$\frac{dC_m}{dC_L} = \frac{k_f w_f^2 L_f}{S_W c_W C_{L_{aW}}} \tag{7-24}$$

In this equation, k_f is a coefficient dependent of the position of quarter wing chord in the fuselage, calculated through regression, w_f the width of the fuselage, L_f the length of the fuselage, S_w the wing area, c_w the wing mean aerodynamic chord and C_{LaW} the wing lift coefficient slope.

Additionally, this model evaluates the lateral stability, as in [203], that is yawing moment coefficient slope C_{n_ψ} due to several components: the fuselage, the fin and the propeller. For the fuselage contribution, the empirical formula of [203] is used:

$$(C_{n\Psi})_{fus} = \frac{0.96K_\beta}{57.3}\left(\frac{S_s}{S_W}\right)\left(\frac{L_f}{b}\right)\left(\frac{h_1}{h_2}\right)^{1/2}\left(\frac{w_2}{w_1}\right)^{1/2} \tag{7-25}$$

In this equation, the coefficient k_β is obtained through regression analysis from data of figure 8-4, [203], S_s the projected fuselage area, S_W the wing area, L_f the fuselage length, b the wing span, the h and w refer to the depth/height and width dimensions of the fuselage (in this case the ratios are assumed to be one, cylindrical fuselage).

For the contributions of the vertical areas, the formula 8-12, [203] is used:

$$C_{n_\psi} = -\left(\frac{dC_L}{d\psi}\right)_v \psi \frac{S_v}{S_w}\frac{l_v}{b}\frac{q_v}{q} \tag{7-26}$$

In this equation, the first term is assumed to be approximately equal to the slope of the lift coefficient of the vertical area (fin, equivalent fin for v-tail, y-tail), S_v the vertical area, S_w the wing area, l_v the distance between the centre of gravity and the aerodynamic centre of the vertical tail, b the wing span.

For the propeller contribution the equation 8-7 of [203] is used in 7-27, providing a stabilizing moment for a pusher propeller and destabilizing for a tractor one. N is the number of the propellers, D the propeller diameter, the derivative in the parenthesis depends on the number of propeller blades and for a two blade propeller is 0.00165, S_w the wing area and b the wing span:

$$C_{n\psi} = \frac{\pi D^2 l_p \left(\frac{dC_{Yp}}{d\psi}\right) N}{4 S_w b} \qquad \text{7-27}$$

The downwash effect of the wing on the horizontal tail is computed, as described by Raymer [5], and the downwash of the canard on the wing, [204], is found using data from figure 16.12 of [5], after obtaining through regression the appropriate formula, according to the reverse flow theory, [205]. Hence the static margin is calculated, using the equation 16.9 of Raymer [5]:

$$\bar{X}_{np} = \frac{C_{La}\bar{X}_{acW} - C_{ma,fuselage} + n_h \frac{S_h}{S_W} C_{Lah} \frac{\partial a_h}{\partial a} \bar{X}_{ach}}{C_{La} + n_h \frac{S_h}{S_w} C_{Lah} \frac{\partial a_h}{\partial a}} \qquad \text{7-28}$$

In this equation, C_{La} is the wing lift coefficient slope, the X_{acW} is the position of the aerodynamic centre, assumed to be 0.25, the pitching moment coefficient slope due to the fuselage $C_{ma,fuselage}$ as found in equation 7-24, n_h is the ratio of the dynamic pressure of the tail to the free-stream dynamic pressure, usually taken 0.9, the term S_h is the tail area, S_w the wing area, C_{Lah} the tail lift coefficient slope. The derivative term is calculated based on the downwash effect of the wing to the tail (and for the canard, the canard downwash on the wing, up to the tips of the canard), $1 - \frac{\partial \varepsilon}{\partial \alpha}$.

7.3.7 Validation of Aircraft Sizing Models

As a very basic validation of the presented aircraft sizing models, they were used to compute the design parameters of an existing UAS. Southampton University Laser Sintered Aircraft (SULSA) is an unmanned air vehicle whose entire structure was 3D printed as a demonstrator of the laser sintering process flexibility for rapid prototyping, that would otherwise involve the traditional, slower and more costly manufacturing techniques. This process allowed for its full development from concept to flight within days.

Figure 7-3 SULSA Launched from a Royal Navy Warship[206]

The specific UAV was chosen to check the validity of the sizing models, as its configuration is among the chosen ones, i.e. a monolithic/conventional fuselage, aft V-tail and push propeller configuration; and since its design parameters are within the range of those chosen for this research. The design variables were set according to those of SULSA, as follows:

Wing Span: *1.2* m, wing AR: *6*, wing taper ratio: *0.5*(SULSA elliptical wing), wing sweep angle: *0°*, wing twist: *2°*, horizontal tail AR (equivalent for v-tail): *4*, fin AR (equivalent for v-tail): *1.9*, battery capacity: *6* Ahr (not available for SULSA) and front bulkhead position (wing position relative to the fuselage nose): *0.4* m.

Performing the sizing of the UAS with the above design variables, the design parameters were obtained, as presented below along with the corresponding SULSA values. The values of the SULSA design parameters were either physically measured or obtained from the appropriate models used for its design.

Table 7-1 UAV-SULSA Design Parameters

	Aircraft Sizing Calculated Parameters	**SULSA**
Electric Propulsion Efficiency	0.5	0.6

	Aircraft Sizing Calculated Parameters	SULSA
Installed Power (Kw)	0.052	-
Wing Chord (m)	0.2	0.2
Limit Load Factor	3.8	3.8
Fuselage Depth/Width (m)	0.085	0.100
Fuselage Length (m)	0.679	0.960
Nose Length (m)	0.106	0.100
VTAIL Span (m)	0.808	0.716
VTAIL Chord (m)	0.136	0.164 (root chord)
VTAIL Dihedral Angle	35°	43°
Motor Length (m)	0.042	0.055
Propeller Diameter (m)	0.267	0.270
MTOW (kg)	2.526	2.556
Structure Weight (kg)	1.051	1.430
Equipment Weight (kg)	0.82	0.31(avionics only)
Propulsion Weight (kg)	0.655	0.720
CG Longitudinal Position (m)	0.0097	0.001
Max Speed Range (km)	44.81	46.92
Max Speed Endurance (hrs.)	0.622	0.650

It can be seen that there is a relatively close agreement between most of the calculated design parameters and those of SULSA. Hence, a very basic validation of the aircraft sizing models used throughout this research may be assumed. However, the following should be pointed out:

- Concerning the fuselage, the fuselage width/depth defined by the payload carried (camera dimensions) are very close to those of SULSA, yet the calculations assumed a fineness ratio (length to width/depth) of 8 and gave a fuselage length of 0.68 m as opposed to the SULSA measured fuselage length of 0.96 m.
- For the performance and battery related calculations, the SULSA battery capacity was not available but the battery power was known, therefore a reasonable value for battery capacity of 6Ahr was assumed, which based on the calculated values of range and endurance, is considered as an acceptable choice.
- In the sizing of the V-tail, a difference is noticed between the values of the V-tail calculated parameters and the SULSA values, as a result of the assumed fuselage length and the assumed values of tail volume coefficient, used for the calculation of the equivalent horizontal tail and fin areas and thus the sizing of the V-tail.
- In the weight calculations, a payload/camera was assumed; while in the SULSA no payload was included, giving a difference in equipment weight. A significant difference in the structural weight, between the calculated 1.051 kg and the SULSA of 1.43 may be noticed, and for the SULSA propulsion weight, a motor weight of 0.24 kg and battery weight of 0.48 kg was assumed. However, the computed total weight is very close to the total weight of SULSA.

7.4 Chapter Summary

In this chapter, appropriate product definition models for the UAS conceptual design were presented. A novel approach for parameterizing aircraft geometric topologies was also introduced to enable the systematic search of a large number of alternative concepts and design configurations within the UAS design generation. The aircraft sizing models provide accurate assessment of all attributes, such as endurance at design speed, maximum range and static margin stability, associated with the performance related objectives. The number of design variables of the aircraft sizing models was limited to a reasonable number for a fast generation of UAS alternatives and parameters' calculation.

8. Lifecycle Operations Analysis

"The more observations are made, the less will the conclusions be liable to error, provided they admit of being repeated under the same circumstances."

Thomas Simpson, 1710-1761

Following the VDD implementation process, predictive models are developed to assess the total lifecycle cost and performance related attributes of the designed system. The lifecycle operations analysis should provide estimates of all total lifecycle cost and defence/combat related attributes, based on the stakeholders' objectives, presented in Figure 4-4, to be used in the evaluation of the design alternatives. For the lifecycle operations analysis, Vanguard [207] was chosen as the most appropriate tool for design modelling, since it combines all basic quantitative methods of spreadsheets with mathematical applications to produce an advanced modelling system. Its capability of representing complex models in a hierarchical tree layout overcomes one of the spreadsheets' limitations, enabling not only to work more efficiently but also to communicate/present ideas in a clearer way. Uncertainties, related to probabilities which the English philosopher, Thomas Hobbes describes as *"the very guide to life"* are modelled in Vanguard through Monte Carlo simulation to quantify and manage risks associated with them, while Sensitivity Analysis and Optimisation can be performed very efficiently.

8.1 UAS Acquisition Cost Model

During the conceptual design stage of value driven UAS design, the traditional methods for cost estimation such as bottom-up, analogous, activity-based and parametric were chosen as more appropriate for acquisition cost integration into the design process. For this purpose, the parametric representation of the design was well suited for the fast and automated exploration of the design space and as input into the lifecycle cost models and the optimisation study.

The acquisition cost model uses explicit aircraft design parameters, the specific configuration, weights, geometry, material type and systems data, along with the assumed wrap rates for all manufacturing processes. The UAS geometry includes the basic parts geometry, i.e. wing, fuselage and empennage design parameters: wing span, root chord, tip chord, sweep, thickness-to-chord ratios, fuselage, length, width, depth, fuselage and nose skin volume, as calculated in the weight model, nose length, horizontal tail area, fin area, v-tail area, boom length and diameter, canard area, etc. Weight parameters are also inputs, such as total weight, structure weight and propulsion weight. All design variables are inputs into this model from the aircraft sizing model, while the UAS design parameters and manufacturing parameters kept constant in MDO are presented in Appendix B.2. The acquisition cost model was created in Vanguard, due to its hierarchical structure and its analysis capabilities (See Figure 8-1); however, these cost models were also created as Excel spreadsheets.

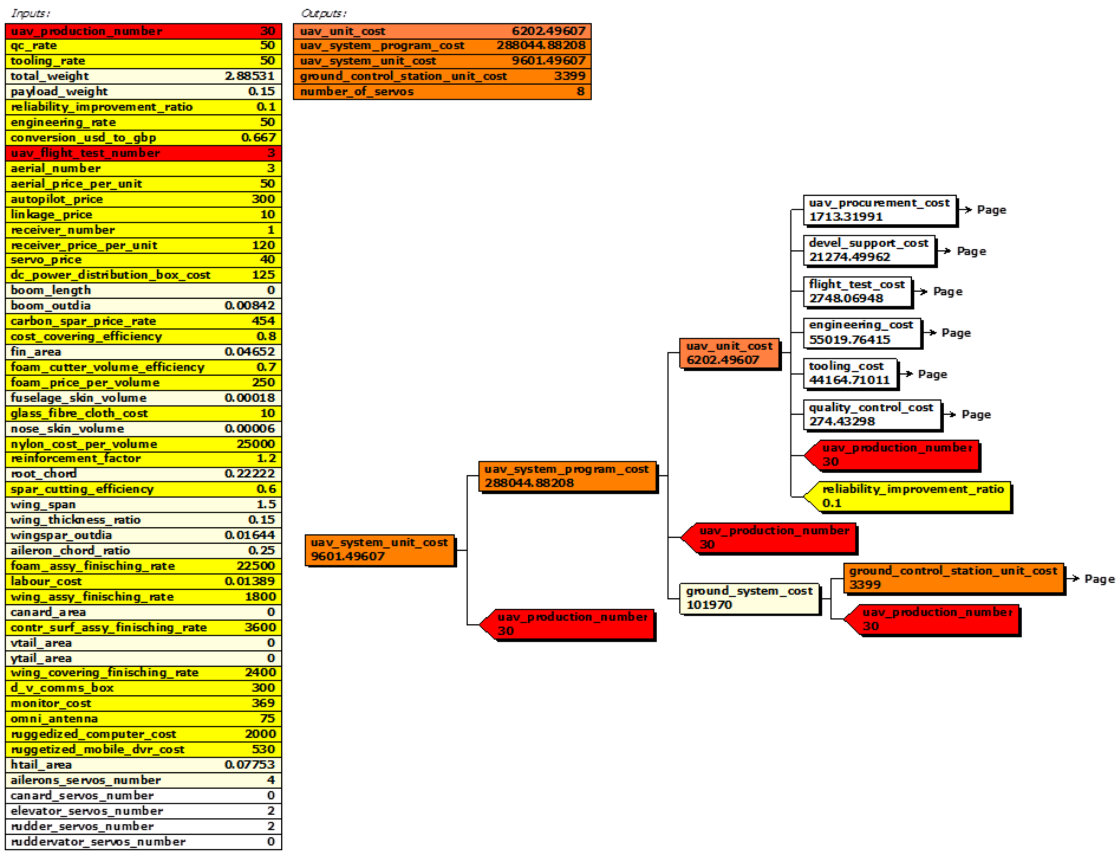


Figure 8-1 Vanguard Acquisition Cost Model

The same acquisition cost model is used for all aircraft configurations, varying the appropriate design parameters.

1. The costs incurring during airframe manufacturing processes are modelled using the activity-based approach, with the computed geometry of the aircraft defining the material cost and manufacturing labour cost. The cost of the airframe is calculated as the sum into cost of wing, fuselage, appropriate empennage, depending on the specific configuration, booms, etc. Hence, the UAS manufacturing cost is computed by adding the following material and labour costs, assuming standard manufacturing rates and manufacturing efficiencies:
    - The wing spar, tail booms and ailerons carbon costs are obtained from the carbon unit cost and the calculated geometric parameters of wing span, wing spar diameters, boom length and boom diameters.
    - The wing material costs (i.e. foam, covering, nylon tip, connection and aileron material costs) are computed from the calculated wing volume, wing area and the foam unit cost, nylon unit cost and glass fibre cloth unit cost.
    - The fuselage nylon cost is obtained from the total fuselage volume and the nylon price per volume.
    - The horizontal tail, canard and fin material costs are obtained by multiplying the total wing material costs with the ratio of the corresponding control surfaces' area to the wing area.
    - The manufacturing labour cost is computed based on the geometric parameters, manufacturing production rates and labour costs.

    The total manufacturing cost for the whole UAS fleet is also assessed based on the assumed total number of units produced.
2. For the calculation of development, engineering, tooling, quality control and flight testing costs, the Development and Production Costs for Aircraft (DAPCA) parametric equations, presented in [5] and [76], are used based on the calculated empty weight, maximum speed and wrap rates to compute:

    The development support cost C_{dev_sup}:

$$C_{dev\_sup} = 66\, {W_{UAS}}^{0.63} {v_{\max}}^{1.3} \qquad 8\text{-}1$$

The engineering cost C_{eng}:

$$C_{eng} = 4.86\, {W_{UAS}}^{0.777} {v_{\max}}^{0.894} {UAS_{numb}}^{0.163} EngRt \qquad 8\text{-}2$$

The tooling cost C_{tool}:

$$C_{\text{tool}} = 5.99\, {W_{UAS}}^{0.777} {v_{\max}}^{0.696} {UAS_{numb}}^{0.263} ToolRt \qquad 8\text{-}3$$

The quality control cost C_{qc}:

$$C_{qc} = 0.133\, Man\_hrs\, QC_{rt} \qquad 8\text{-}4$$

The flight testing cost $C_{\text{flight\_test}}$:

$$C_{\text{flight\_test}} = 2498\, {W_{UAS}}^{0.325} {v_{\max}}^{0.822} {UAS_{\text{flight\_test}}}^{1.21} \qquad 8\text{-}5$$

In the above equations, W_{UAS} is the computed UAS weight, $v_{\max}$ the UAS maximum speed, UAS_{numb} the UAS fleet size, $EngRt$ the standard engineering cost rate, $ToolRt$ the standard tooling cost rate, QC_{rt} the standard quality control cost rate, Man_hrs the computed manufacturing hours per UAS, and $UAS_{\text{flight\_test}}$ the number of UAS for flight testing. The above parametric equations provide sufficient accuracy for the requirements of conceptual design and can be replaced during the next stages of design with more accurate calculations.

3. For the cost modelling of propulsion components, the analogous approach is followed through the use of cost data of similar components, parameterized with appropriate design parameters through regression analysis, as presented in Appendix B.3. Hence, the costs of battery, electronic speed controller, motor and propellers based on the calculated design variables of battery capacity, maximum current, motor weight and power and propeller diameter, respectively are assessed.
4. The cost of all avionics' components is kept constant, based on the cost of similar products, presented in Appendix B.2. Depending on the number of required components used in the specific aircraft

configuration (e.g. number of servos varying with configuration), the costs of autopilots, servos, receivers, aerials and other components are summed up, to provide a cost estimate, as in Figure 8-2. For payload, a standard camera is assumed with a cost estimate as input in the cost calculations. Concerning the ground control station cost assessment, the cost is approximated based on the cost of standard military specifications' components and kept constant throughout the design iteration, the focus of this research being mainly on the aircraft design.

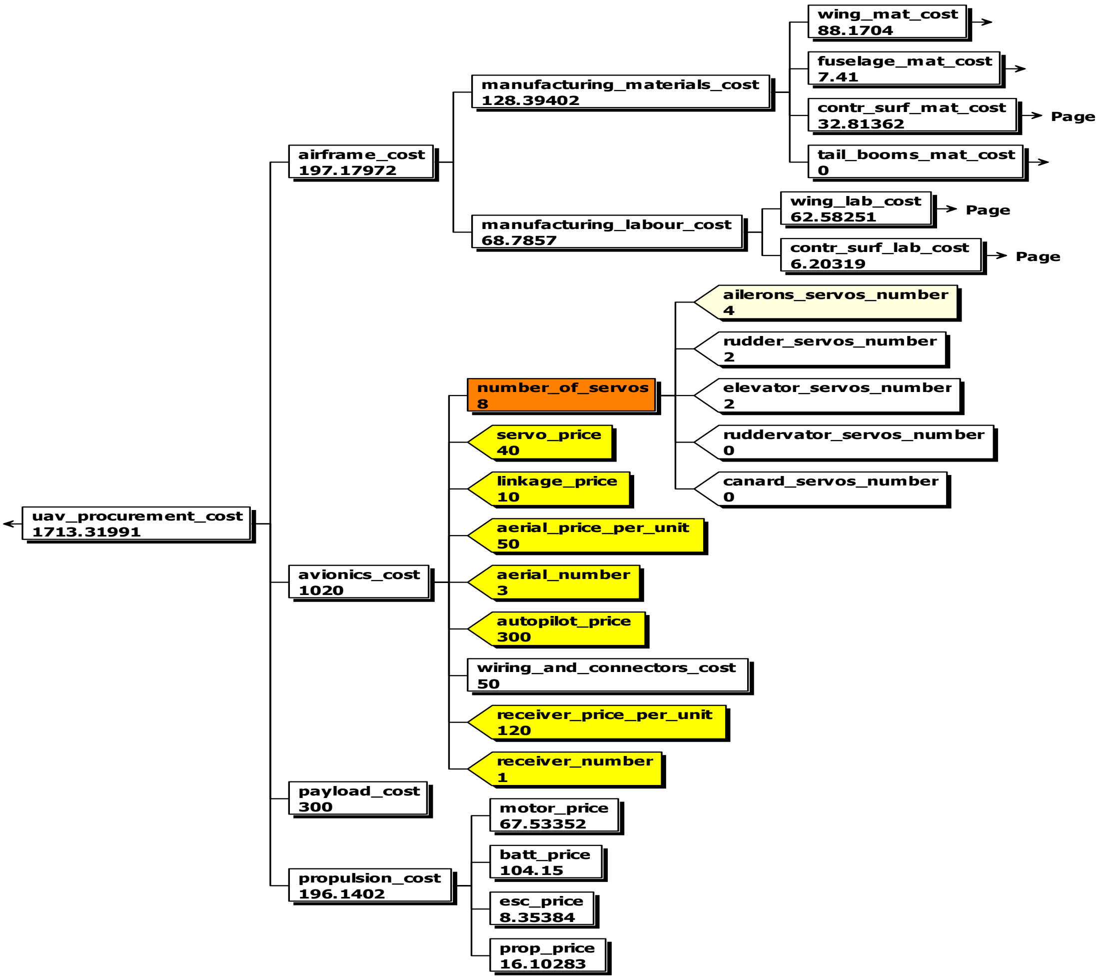


Figure 8-2 UAV Procurement Cost

All the created cost models are aggregated to produce a bottom-up cost estimate, for an assumed initial fleet size of thirty UAS with an extra three aircraft for flight testing. The constant design parameters can be easily amended or added as extra design variables, if desired. Hence, the unit cost, total procurement cost for the whole UAS fleet, total procurement cost for the whole program (including ground control stations and aircraft) and complete UAS system cost (aircraft and ground control station) are computed. In the MDO, as the UAS design variables are varied during the design space exploration, the cost models produce new assessments of unit and fleet acquisition costs as attributes to be used in the multi-criteria analysis of the value models.

Vanguard provides extensive capabilities for sensitivity analysis, to isolate cost drivers, through the variation of design parameters and their effect on total cost. Finally for uncertainty analysis, Monte Carlo simulation provides predictions of cost, replacing uncertain design parameters, such as cost rates with probabilistic distributions to identify their effect on the costs.

8.2 UAS lifecycle cost model

Electric propulsion is assumed throughout this aircraft conceptual design, hence the lifecycle cost modelling is converted to reliability and survivability analysis since power consumption is ignored. The failures due to lack of reliability, the scheduled maintenance performed and the survivability related combat damage are the driving factors defining the lifecycle cost and the operational availability of the UAS fleet.

Maintenance is defined as all actions taken to preserve a system available for use, minimising cost, maintaining/increasing required levels of reliability and addressing all failure causes, [44]. Maintenance can be either preventive or corrective, however for the purposes of this design and since the designed aircraft and its components are all considered of low cost, no repairs and only replacements of critical components and/or whole aircraft were assumed to be performed.

In this section the reliability related lifecycle cost modelling is presented, whilst in the next section the survivability related cost modelling will be discussed. A UAS fleet size was assumed and any aircraft component failure or aircraft battle damage resulted in either an aircraft loss, followed by replacement with a newly acquired aircraft, or an unscheduled Repair by Replacement (RBR) of the failed aircraft component, as presented in the state transition diagram of Figure 8-3.

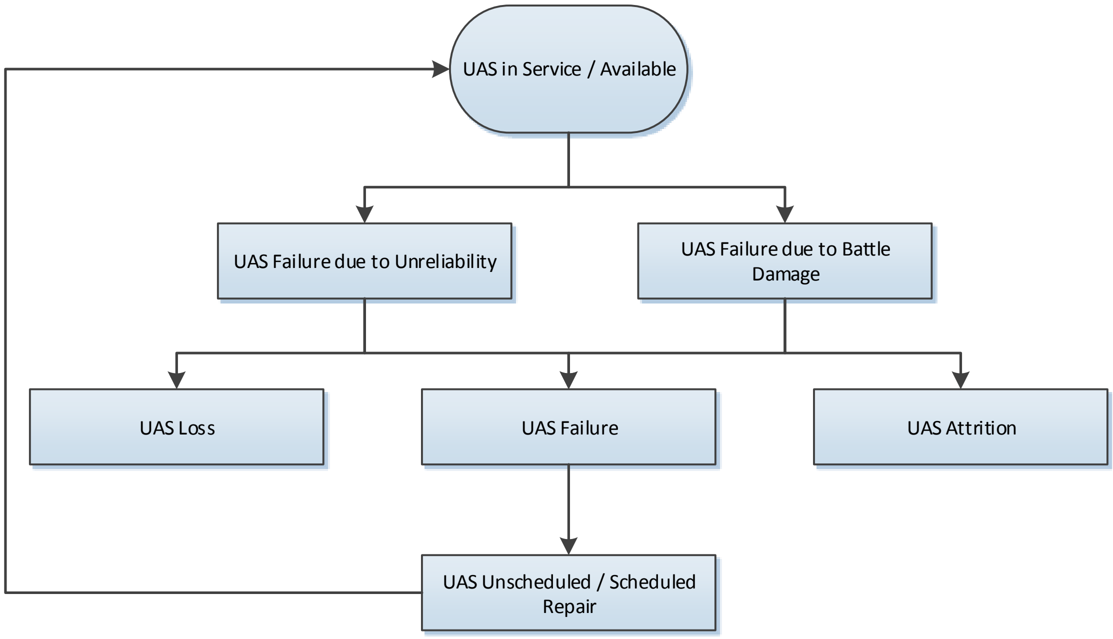


Figure 8-3 UAS State Attrition Diagram

The unexpected failures that occur during the lifecycle of the UAS fleet are due to lack of reliability of the critical subsystems/components of the UAS. The critical aircraft subsystems studied for reliability failures are the motor, battery, propeller, airframe, electronic speed controller, autopilot, receiver, ground control station and the appropriate, depending on the configuration, pairs of servos. Since servos are redundant for every control surface (due to their low reliability), both servos of the same pair have to fail during the same flight to have an aircraft loss. Also, human factor related failures, associated with the operation of the UAS and maintenance performed, are not considered at this stage.

In terms of reliability analysis, since a failure of any of the above subsystems/components would result in an aircraft loss, the UAS is considered as a reliability series system [44], consisted of n critical subsystems/components, with R_i the reliability of the i-th subsystem/component, and its reliability R_{UAS} expressed as:

$$R_{UAS} = \prod_{i=1}^{n} R_i \qquad 8\text{-}6$$

As defined in 2.3.2.1, the reliability R of each component is "*the probability a system will perform its intended function for a specified period of time under* *a given set of conditions*". It is expressed in terms of time *t*, the time-to-system-failure, and the probability density function $f(t)$, which has the physical meaning of the probability that failure takes place at a time between *t* and *t*+Δ*t*:

$$R(t) = \int_t^{\infty} f(t')dt' \tag{8-7}$$

The single most-used parameter to characterize reliability is the *mean time to failure* (MTTF), i.e. the mean time of operation without a failure [45], is written directly in terms of reliability as:

$$MTTF = \int_0^{\infty} R(t)dt \tag{8-8}$$

The time to failure due to unreliability is modelled with a Weibull distribution more than with any other distribution, such as the normal, exponential and lognormal distributions. Weibull distribution is used mainly because it is suitable for model increasing, decreasing and steady failure rates, is mathematically simple and can model most lifetimes, [44]. The probability density function (pdf) of the Weibull distribution is the following:

$$f(t) = \frac{\beta}{\eta}\left[\frac{(t-\gamma)}{\eta}\right]^{\beta-1} e^{-\left[\frac{(t-\gamma)}{\eta}\right]^{\beta}} \tag{8-9}$$

- η, a scale parameter representing the time when there is 0.6321 probability for a component to have failed.
- β, a shape parameter related to the failure rate, i.e. if equal to 1 refers to a constant failure rate throughout the component's life, greater than 1 if the failure rate is increasing and less than 1 for decreasing failure rate, and it is usually taken between 0 and 5.
- γ, a location parameter, representing the time until the first failure, usually assumed as 0, but for a fully repaired component can be set to the time of the repair.

The reliability for the Weibull distribution is:

$$R(t) = e^{-\left(\frac{(t-\gamma)}{\eta}\right)^{\beta}}, t > \gamma \tag{8-10}$$

The Weibull parameters for all critical components are set to appropriate values, kept constant and presented in Appendix B.2, but are changeable and can be converted to design variables, if desired. Hence, the aircraft reliability model of equation 8-6 can be written as:

$$R(t) = \prod_{i=1}^{n} e^{-(\frac{t}{\eta_i})^{\beta_i}} \quad \text{8-11}$$

As far as the mission undertaken by the UAS, a single reconnaissance/surveillance mission at the design speed is assumed with a total annual flight workload of three thousand (3,000) flight hours for the fleet of thirty aircraft and a total program duration of ten years. This was considered a rather realistic scenario for the fleet of the UAS and the missions to be undertaken. During each mission, with duration equal to the computed aircraft's endurance when flying at the design speed, single or multiple failures can occur.

8.2.1 Components Scheduled Replacement Policy

In this policy, all aircraft critical components are replaced at specific time intervals depending on their reliability level, simplifying maintenance and reducing workload especially when performed in the area of operations. Also, the replacements of components are assumed to be performed instantaneously, with no logistic supply related delays due to spares, equipment or crew unavailability.

In the Vanguard lifecycle models, a generic *component reliability* is defined as an additional design variable of the MDO, representing the probability one component lasts until it is scheduled to be replaced, as part of the scheduled maintenance performed in the UAS. For example, a value of 0.99 means that there is 99% probability for a component to survive until it is scheduled to be replaced. For the same UAS component (i.e. with the same Weibull distribution parameters), a component reliability value of 0.99 will give shorter scheduled replacement intervals and higher scheduled maintenance cost but less aircraft losses, while a component reliability value of 0.9 will result in longer scheduled replacement intervals and lower scheduled maintenance cost but higher aircraft losses. Based on the value of this design variable of component reliability and the specific Weibull distribution parameters, the scheduled replacement time

(Mean Time to Replacement – MTTR) is computed for every UAS component, solving for time from equation 8-10, if γ is assumed 0:

$$MTTR = [-\ln[R(t)]]^{\frac{1}{\beta}}\, n \qquad 8\text{-}12$$

Thus, for each component and based only on the value of the design variable of generic *component reliability* and its specific Weibull parameters, a different scheduled replacement time interval is computed, used in the scheduled maintenance cost assessment.

In the Lifecycle MCS, for anyone of the critical subsystems/components (motor, battery, propeller, airframe, electronic speed controller, autopilot, receiver, ground control station and the appropriate, depending on the configuration, servos) and based on its specific Weibull Distribution parameters (Appendix B.2), a failure time is randomly generated. If this number is smaller than the scheduled component's replacement time (computed with equation 8-12) an aircraft loss is counted, otherwise the component is replaced as scheduled. Hence, the following parameters are generated, due to failures of each critical component for the whole UAS program duration:

- Aircraft losses due to failures of the component, reflecting operational success of the UAS fleet, and the associated cost, based on the aircraft unit cost.
- The component's scheduled replacement cost during the whole program duration.

For redundant components, such as the servos, and depending on the specific aircraft configuration, both components have to fail during the same flight of duration equal to the computed operational surveillance time to have an aircraft loss, otherwise the failure is considered as an unscheduled replacement of the failed component. Adding up the above cost estimates of all aircraft's components, total lifecycle cost for the whole aircraft is computed. Through the MCS, estimates of the lifecycle cost due to reliability related aircraft losses, aircraft losses reflecting operational success/availability and maintenance cost due to lifecycle components replacements are obtained, along with the associated uncertainty, as described by statistics parameters of standard deviation, posterior standard deviation, variance, confidence intervals etc.

Due to assumed program duration, all future lifecycle costs are adjusted to present values using a standard discount rate of 7% annually, according to the formula below:

$$\text{Net Present Cost} = \sum_{t=1}^{\substack{\text{program}\\ \text{duration}\\ \text{in years}}} \frac{\text{Cost}(t)}{(1 + \text{discount rate})^{t}} \tag{8-13}$$

8.2.2 UAS Replacement Policy

No component but instead a whole aircraft replacement is performed at specific time intervals expressed in flight hours with this policy. The design parameter of *UAS replacement time interval* is taken as an additional design variable instead of the design variable of component reliability of the previous section, when this policy is applied. No individual critical components scheduled replacements are made; therefore all failures, occurring prior to the aircraft's scheduled replacement, result in either aircraft losses or unscheduled maintenance, depending on whether the failure concerns a non-redundant or redundant component respectively. Applying this policy, the maintenance workload is completely eliminated, but the cost is much higher than in the first policy, as expected.

Lifecycle costs due to lack of reliability related failures and scheduled UAS replacements are computed through MCS as follows: In the lifecycle simulation for each critical subsystem/component, a failure time is randomly generated based on its specific Weibull distribution parameters. If this failure time is smaller than the value of the *UAS replacement time interval* then an aircraft loss is counted, otherwise the aircraft is replaced as scheduled. For redundant components, such as the servos, both components have to fail during the same flight of duration equal to the computed operational surveillance time, to have an aircraft loss. This process carries on until the end of the whole UAS program. Thus, the associated aircraft losses' cost and component's unscheduled replacement cost (if the component is redundant) are computed for the whole duration of the program. Adding up these costs for all aircraft's components, total reliability related cost is computed. Finally, the whole program's scheduled UAS replacement cost is computed and added to the reliability related lifecycle cost, to obtain the whole program UAS cost.

Hence, through the MCS, estimates of cost due to failures, aircraft losses reflecting operational success and scheduled UAS replacements' cost are obtained, along with the associated uncertainty, described by the statistics parameters of standard deviation, posterior standard deviation, variance, confidence intervals etc. Again, as in the components scheduled replacement policy, all lifecycle costs are adjusted using a standard discount rate of 7% annually.

8.2.3 Comparison of Maintenance Policies

Three different replacement/maintenance scenarios were compared to identify their advantages and disadvantages:

- *Critical components replacement policy*, as presented in 8.2.1, in this case the components replacement times, UAS survival rates and lifecycle costs were computed to use a fleet of UAS for a number of annual flight hours over a specific duration.

- *Whole aircraft replacement policy* at specific intervals and no critical component replacement with UAS survival rates and lifecycle costs computed, as described in 8.2.2.

- A combined policy, with UAS replaced at specific time intervals but high failure rate components also replaced at specific time intervals, as part of an RBR policy. In this case propeller, autopilot, electronic speed controller and servos were considered as high failure rate components (i.e. $\beta \leq 500$, as presented in Appendix B.2). The Monte Carlo simulation computed the UAS losses, UAS replaced cost and scheduled replacements costs.

To compare the three scenarios all other design variables were fixed to the mean values from their ranges presented in Appendix B.2, and MCS was performed for different values of required reliability, hence average values of

UAS survival rates and lifecycle maintenance cost estimates were obtained. The reliability analyses for the three scenarios are presented below:

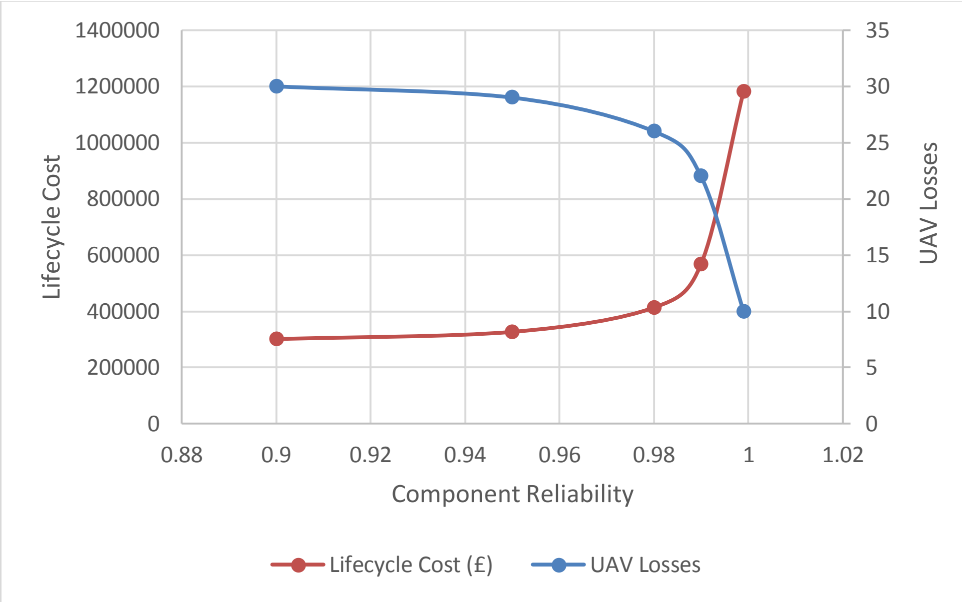


Figure 8-4 Reliability Analysis of Critical Components Replacement Policy

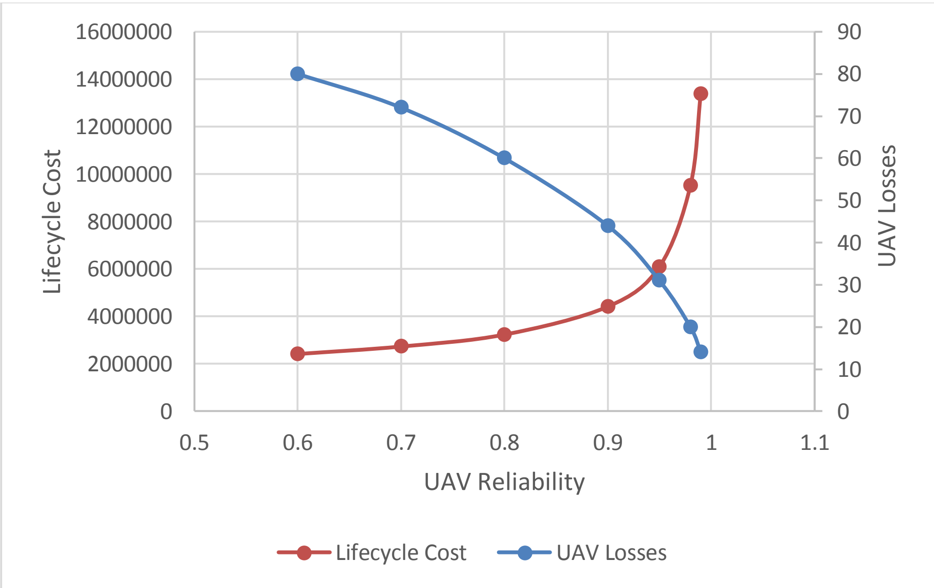


Figure 8-5 Reliability Analysis of UAS Replacement Policy

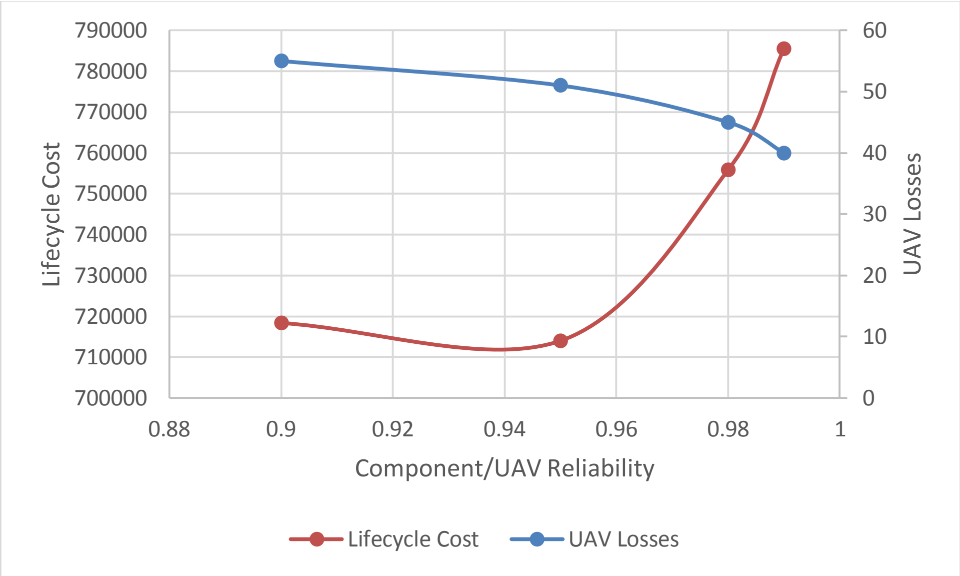


Figure 8-6 Reliability Analysis of Combined UAS and Critical Components Replacement Policy

From these figures when aircraft losses, lifecycle costs and maintenance workload for component replacement are taken into account, the following can be concluded:

- The component replacement policy provides the lowest lifecycle costs and aircraft losses, however maintenance workload is higher.
- UAS replacement policy has the highest lifecycle cost compared to the other policies and aircraft losses slightly lower than the first policy, but maintenance workload is eliminated.
- The combined UAS/components replacement scenario is inferior to the components' replacement policy in terms of both cost and aircraft losses.

Therefore, the *combined UAS/components replacement scenario* was rejected while the *components scheduled replacement policy* and *UAS scheduled replacement policy* were selected to be included in the conceptual value driven UAS design optimization for the lifecycle cost assessment.

8.2.4 Reliability Improvement

As discussed in 2.3.2.1, the improvement of reliability is possible through the use of improved technology, additional resources toward reliability in design and development, trading-off performance for reliability, and through the use of higher quality and time/experience for detection and analysis of reliability problems. To demonstrate the non-cooperative game between the user and the manufacturer of the designed system, the application of a reliability improvement program through the selection of more reliable aircraft components with higher MTTF, modelled by the Weibull distribution parameter η, was chosen as the manufacturer's strategic decision. This decision would result in:

- Less aircraft losses.
- Less scheduled components' replacements, i.e. less maintenance workload.
- Higher acquisition cost, due to more expensive components.
- Scheduled maintenance/replacement costs that would depend on both the cost of the increased reliability and the replacements performed during the whole UAS program.

The cost of a reliability improvement program, as discussed in 2.3.2.1, relies heavily on previous historic data, quantifying the cost-reliability relationship. For most systems, this relationship is not static and generally follows a sigmoidal shape of Figure 8-7:

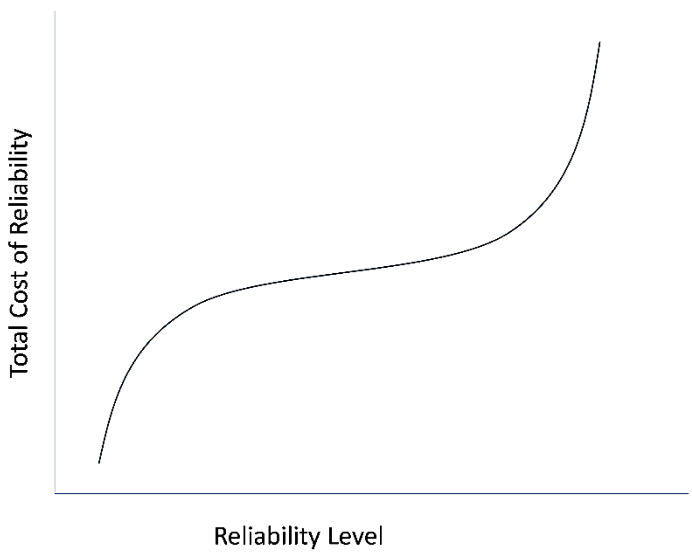


Figure 8-7 Cost - Reliability Curve [46]

The position and shape of the cost-reliability curve during design and development of a system and over time are affected by program choices, technology and experience, while the complexity of the designed system and the subsystems' interactions can move the curve up or down, increasing or decreasing cost. Therefore, instead of choosing an optimal pair of values of reliability and cost on a single curve, a family of curves should be analysed with respect to their necessary resources before selecting the optimum values of reliability and cost. The cost-reliability relationship for several reliability improvement programs was quantified by Alexander [46], exhibiting considerable variability and suggesting that considerable reliability improvement is possible without significant increase of cost, but the greater the improvement the more costly is the necessary investment. Moreover, least squares fit of the cost-reliability data is used to provide an acceptable cost-reliability curve, [47].

The strategic decision concerning the application of a reliability improvement program is made by the stakeholders involved with the designed system, based on their objectives. In general, a reliability improvement program could include the use of improved technology components or additional resources toward reliability in design and development, trading-off performance for reliability and also the use of higher quality assurance processes for detection and analysis of reliability problems. In the UAS conceptual VDD, for the purposes of demonstrating the selection of more reliable components as an additional strategic choice made by the manufacturer, two levels of components' reliability were assumed, a lower original level and an improved one, reflected in their corresponding cost as presented in [46]. This strategic choice of the manufacturer was included in the Game Theory application of value modelling of multiple stakeholders' objectives, elaborated in section 6.2.

Summarizing, the lifecycle cost model created in Vanguard, providing estimates of lifecycle costs due to reliability related UAS losses and due to scheduled and unscheduled replacements of UAS components, is presented below:

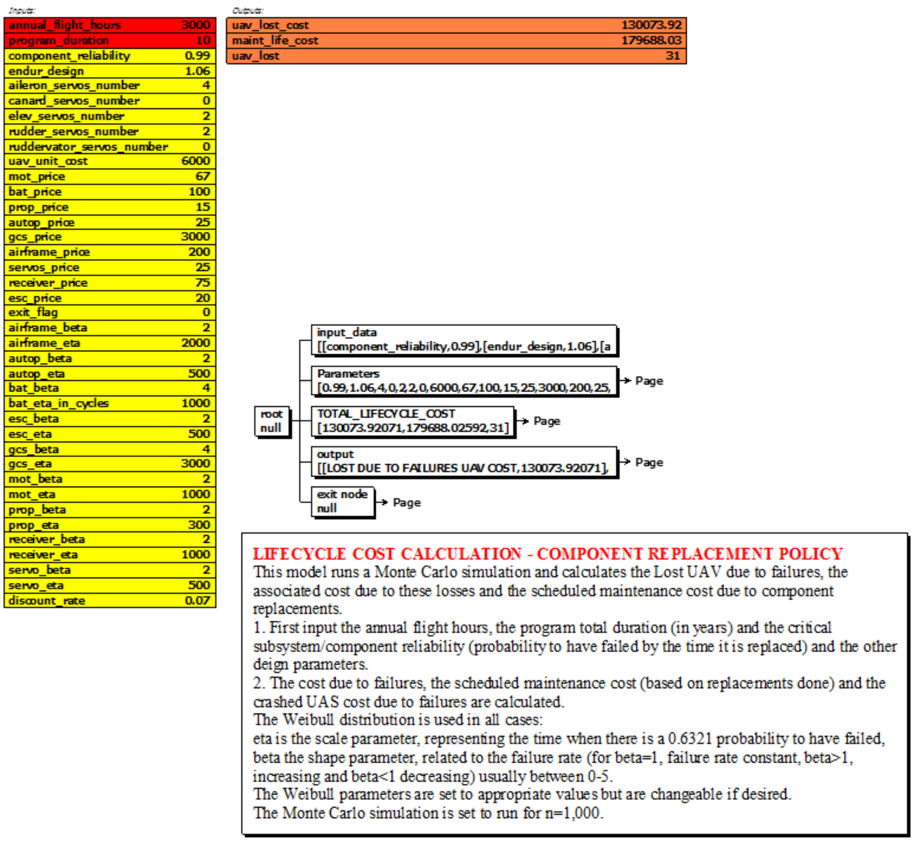


Figure 8-8 Vanguard Lifecycle Cost Model

8.3 UAS Survivability Model

In this section, the basics of the aircraft combat survivability model are presented and used to assess the battle damage. As already discussed in 2.3.2.2, since an aircraft used in military missions has to avoid and withstand hostile environments, it is imperative to assess this capability. Ball [74] identifies susceptibility, i.e. the capability to avoid a damage causing mechanism, measured with a probability of the aircraft to be detected and hit P_H and vulnerability, i.e. the aircraft's capability to withstand the damage, measured with the probability to be killed after been hit $P_{K/H}$. The probability of the aircraft to be killed P_K is the product of these two probabilities and measures the aircraft's survivability:

$$P_K = P_H \, P_{K/H} \tag{8-14}$$

This formula is employed to evaluate the survivability of the aircraft with respect to each critical system of the aircraft, which if been hit could result in loss of the aircraft. The critical systems considered are the airframe, avionics, battery and propulsion. As already described in 2.3.2.2, the values of these probabilities P_H and $P_{K/H}$ depend upon the performance of the aircraft, missions and threat scenarios and are assessed through previous historic data and/or survivability analysis software. In this survivability model, historic data for a reconnaissance/surveillance UAV are used, such as the Tables IV and V in [73], after being adjusted based on the specific aircraft's geometry. All UAS survivability related design parameters kept constant in the survivability simulation are presented in Appendix B.2.

8.3.1 Survivability Simulation

The simulation scheme for survivability assessment relies on the generation of random numbers from a uniform distribution, in accordance with the simulation described in [73]. First the battle damage rate u_1 for reconnaissance/surveillance mission is generated from a uniform distribution and compared with the standard battle damage rate P_H and if less an aircraft hit is assumed:

$$u_1 < P_H \Rightarrow Aircraft\ has\ been\ hit \qquad 8\text{-}15$$

In this case, the standard battle damage probability P_H of the aircraft is based on historic data from similar aircraft, Table IV [73], performing this type of mission. Additionally, this standard battle damage rate P_H is multiplied with the ratio of the specific UAV's total exposed surface to the lowest possible UAV surface, as calculated from the corresponding values of design variables. The fact that a smaller UAV will have a smaller target dimension and therefore a smaller probability to be spotted and hit, justifies this adjustment and allows for distinguishing between the design alternatives. Aircraft performance such as speed is not taken into account, although a faster aircraft has a lower hit probability, since it was assumed that all aircraft designs would be operating at the same design speed.

The specific system of the aircraft that is hit, is found through a second random number u_2 generation from the uniform distribution, and its comparison with the probabilities P_{h/H_i} that each system is hit, taken from Table V [73].

$$u_2 < P_{h/H_i} \Rightarrow i^{th}\ system\ is\ damaged \tag{8-16}$$

Similarly, the system battle damage is classified as critical, resulting in loss of the aircraft, or non-critical, resulting in the replacement of the specific system. This is based on the comparison of a third randomly generated number u_3 with a value P_{k/H_i} taken from historic data [73]:

$$u_3 < P_{k/H_i} \Rightarrow Aircraft\ Loss \tag{8-17}$$

Otherwise, the system suffers a non-critical damage and is replaced. Running the survivability MCS and based on the previously calculated costs of all systems and aircraft along with the aforementioned survivability parameters, the average battle damage cost per flight and its uncertainty is calculated. Due to lack of information concerning the missions, hostile or non-hostile environments, number of sorties required etc., the attribute computed is combat damage cost per flight and not the whole lifecycle combat damage cost. During the optimization, as the UAV's total exposed surface changes, different values of susceptibility rate and combat damage cost per flight are obtained for the design alternatives. The Vanguard survivability model is presented below:

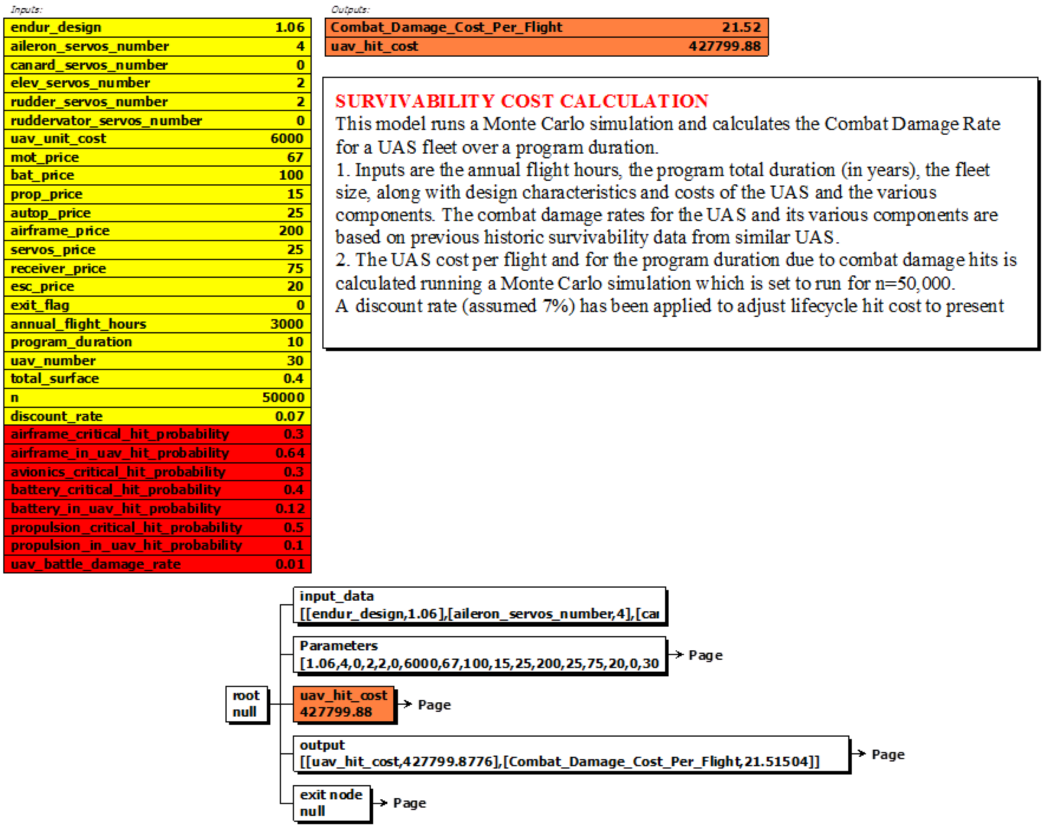


Figure 8-9 Vanguard Survivability Model

8.4 Chapter Summary

In this chapter, the development of all predictive models was presented. These models allow for the operational estimation of total lifecycle cost and defence/combat related attributes, given the design parameters obtained in the previous models. The total lifecycle cost includes the costs of developing and building the aircraft, maintenance, replacements for aircraft losses and an assessment of its combat survivability. The UAS acquisition cost is assessed based purely on the values of the design parameters obtained in the aircraft's sizing model. In the UAS lifecycle cost model, only two design variables, the *component reliability* and the *UAS replacement time interval* for the two different maintenance policies, are utilised to model the reliability of all UAS components and obtain estimates of the reliability related UAS total lifecycle cost. Furthermore, the UAS survivability is assessed and adjusted based on the specific aircraft's geometry. Hence, the design alternatives can be distinguished in terms of their cost related design attributes, using the minimum number of design variables for a fast design space exploration and optimization in the conceptual design phase. These cost models are modular, allowing for easy integration, improvements/replacements in the later stages of design, and automation during the multidisciplinary design optimisation.

9. VDD Models Integration – UAS Conceptual Design Optimization

"Knowledge is of no value unless you put it into practice."

Anton Chekhov

In the previous chapters the development of all necessary components of Multi-Attribute Value Modelling, Multi-Stakeholder Value Modelling, Design Alternatives Generation and Lifecycle Operations Analysis for the VDD implementation was presented. These models are integrated in the VDD framework and the design space exploration and optimization can be performed through the variation of the design variables and based on the stakeholders' preferences.

The full implementation process of the VDD philosophy in the framework for a multi-objective, multi-stakeholder engineering design, also presented in Figure 9-1, aims to address the general objectives set in 1.3 and based on the previous analysis, can be standardised as follows:

1. Identify all stakeholders involved with the designed system during its lifecycle.
2. For all stakeholders, identify their objectives/needs and associated attributes, creating their objectives/attributes hierarchy, as in Figure 4-4.
3. Develop the multi-attribute value models, representing the objective functions of all stakeholders, to be used for evaluating the alternative designs in *Evaluate* phase of the VDD cycle, Figure 2-4, as follows:
    - Prepare for assessment, familiarization of stakeholders.
    - Check for independence conditions.
    - Identify qualitative characteristics.
    - Specify quantitative restrictions.

- Check for consistency of the created value model.
- Synthesize the individual/experts' preferences to obtain the stakeholder's group value model.

Moreover, as engineering design progresses from the conceptual design phase to the preliminary and detailed design phase and more information from simulation and prototyping becomes available, the stakeholder's preferences may be updated in the multi-attribute value models. Thus, quantitative or qualitative characteristics, such as the values of attribute neutral points and the AHP-based weighting factors, may be re-assessed to capture more accurately the evolving stakeholders' preferences and risk attitudes.

4. Select appropriate design variables, stakeholders' strategic choices and their ranges of values, used to define/search the design space in the *Search* phase of VDD cycle, Figure 2-4.
5. Form the appropriate models for the product definition in the *Define* phase of VDD cycle.
6. Develop the predictive/MCS models for the assessment of all attributes in the *Analysis* phase.
7. Integrate all models in the design tool for the multi-objective, multidisciplinary optimization.
8. Perform MDO and trade studies for the user of the system as the only stakeholder.
9. Form the hybrid cooperative/non-cooperative game among all players/stakeholders for a multi-stakeholder optimization. Single optimal solution generated.

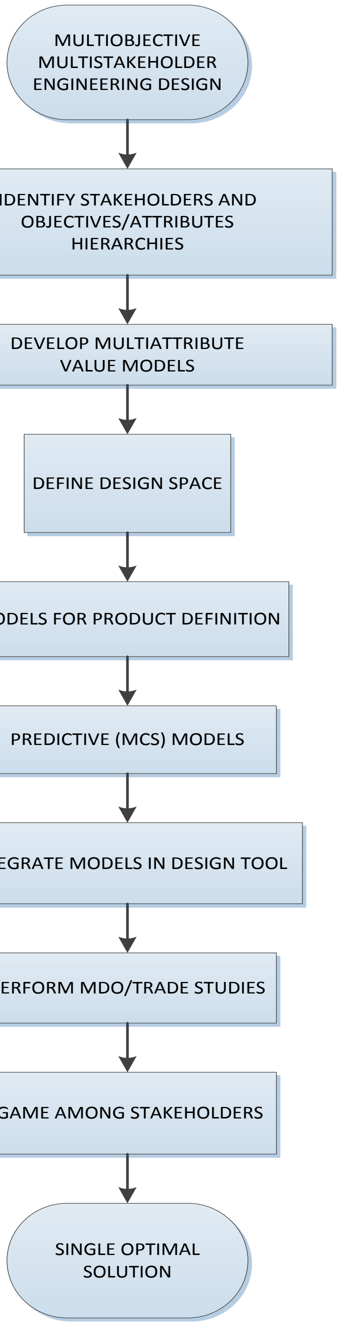


Figure 9-1 VDD Implementation Process

Following the value centred optimization presented by Collopy and Hollingsworth [95], the selected design variables are adjusted to obtain feasible design points in the *Define phase* of the VDD cycle of Figure 2-4. The extensive system attributes are calculated in the *Analyse phase* and are used as inputs into the value model during the *Evaluate phase*. This process carries on, in the *Search phase* through the optimization algorithm or generation of more design points.

This optimization process is shown in detail for the UAS conceptual VDD in Figure 9-2. The first step in this model is the identification of objectives and criteria/subcriteria, usually done with appropriate questionnaires answered by the stakeholders. For the purposes of this analysis, it is assumed that the full set of them has been identified, satisfying the conditions of covering all stakeholders' priorities and being exhaustive, concise, non-redundant and operational with appropriate descriptors and independent/decomposable, [19]. The definition of the design alternatives is the second step in the flow diagram, with the design variables and aircraft geometric topologies as inputs to these models and aircraft performance and cost related parameters computed, while Monte Carlo simulations allow for quantifying uncertainties in the Operations Analysis. The third step involves inputting the aircraft parameters, acquisition cost data and through-life cost data into the value/utility model to assess the value/utility score for each alternative.

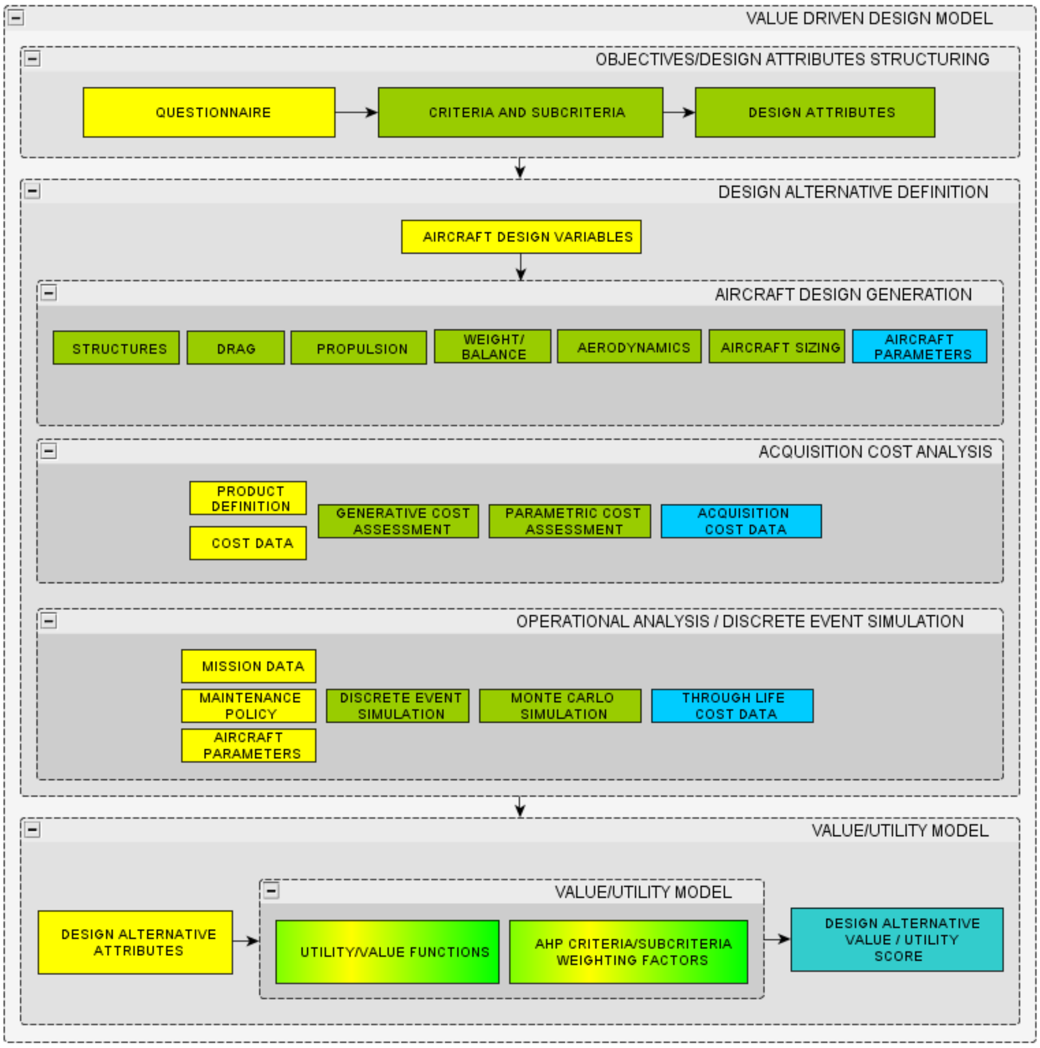


Figure 9-2 Flow Diagram of VDD Model

9.1 Value Driven Design Models Integration

In engineering design, various computational tools are used for analysis, optimisation, performing sensitivity analyses and interpretation of the results from various databases, as well as managing computing resources. However, the use of different type tools makes the job of linking of them and the design process integration required for the exploration of the widest possible design space a rather challenging job. Consequently, Isight [208] was chosen as the integrating design tool of all models because of its ability to execute simulation-based processes in a visual and flexible way, allowing use and control of various software components utilized in the design process. The integration of applications and Isight's ability to automate their execution accelerates the design exploration and evaluation of the alternatives. The design space is explored in a thorough way, without setting any constraints, as advocated by the VDD philosophy. Using the techniques of Design of Experiments (DoE), Optimisation and approximations the design alternatives are evaluated, while post-processing tools perform sensitivity analysis and study trade-offs between design parameters and results.

For the application of the VDD framework in the UAS conceptual VDD, the models for the aircraft design alternatives generation, acquisition cost and operational analyses were created in Excel and Vanguard and were integrated in Isight. The Isight model used for the value driven UAS design is shown below:

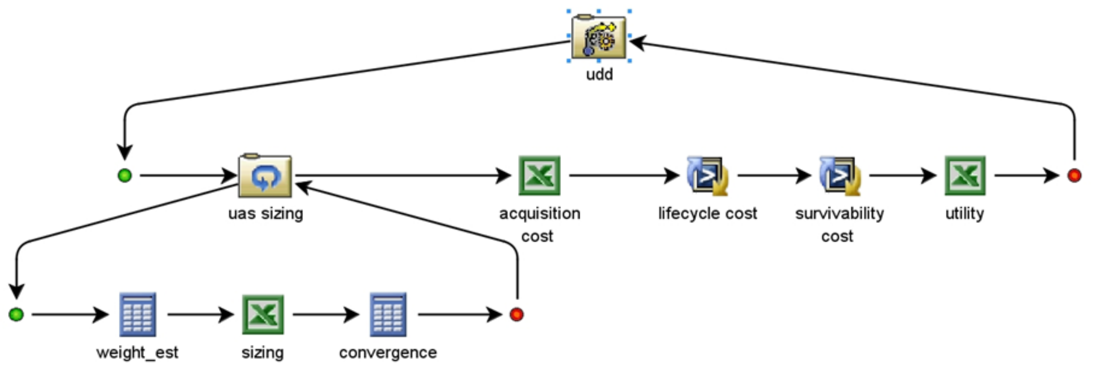


Figure 9-3 Isight VDD Model

This model was used for the automated design space search with the Design of Experiments (DoE) by setting design variables at specified levels. Based on the results obtained from the DoE, the UAS design was also optimised for value and utility, depending on which value model was used and based on the user's preferences. In a traditional Cost Effectiveness Analysis, lifecycle cost and critical design attributes, such as operational surveillance time, maximum endurance and maximum range, were used as the attributes to be optimized while achieving some aspiration level of other attributes, in a *design for cost* or a *design to cost* approach. Approximations of the whole model were possible in Isight by basically employing the response surface methodology, using the previously obtained design points for that, to gain insight as far as the behaviour of the design. Finally, sensitivity analyses allowed for the identification of the most critical design variables, by studying the response estimate of the output for each design parameter.

Alternatively, the hybrid game, described in 6.2, permitted the identification of NBS and Nash equilibrium overall optimal design for the two major stakeholders/players, user and manufacturer. Moreover, to demonstrate the synthesization of preferences of different experts representing the user of the UAS, the AHP matrices of judgments between the design attributes of two individuals, one focusing mostly on the performance capabilities and lifecycle cost and the other focusing on the defence capabilities of the UAS, were used to generate a new synthesized group value model.

9.2 Isight Model Results

Several design variables need to be selected to be varied for multivariable optimisation trade studies but, as Raymer [5] discusses, the workload increases exponentially as the number of the variables goes up. Even with the minimum number of 6 basic design variables suggested by Raymer, to run a full factorial DoE with three levels for each of them, the number of design alternatives is $3^6 = 729$, a number that has to be multiplied by the number of different UAS configurations generated based on the design fundamental selections. Additionally, following the DoE, the designer has to select the optimum method of optimization, relying on many different mathematical techniques, such as the finite difference technique and genetic algorithms. Nevertheless, Isight allows choosing among several different methods of conducting DoE and MDO, while the approximations of the whole model provide the capability of essentially curve fitting the model with a “response surface” that can not only easily identify the optimum design point but provide rough estimates of other design alternatives.

To keep the number of the design variables to a tractable number in the UAS conceptual VDD, the variables selected to be varied were the following along with their corresponding ranges, based on standard values:

- Wing span: $1.25 - 1.75$ m.
- Wing AR: $6 - 12$.
- Wing Position relative to the fuselage: $0.25 - 0.35$ m.

- Wing taper ratio: $0.3 - 0.7$.
- Battery Capacity: $6 - 10$ Ahr.
- Fin AR: $1.2 - 1.8$.
- Horizontal Tail AR: $3 - 5$.
- Canard AR: $5 - 7$.
- General Component Reliability: $0.9 - 0.99$, used in the lifecycle cost assessment models, when the critical components RBR policy is performed.
- UAS Replacement Time Interval: $500 - 1000$ flight hours, used in the lifecycle cost assessment models, when the whole aircraft replacement policy is selected.

The other design parameters were set at reasonable values, such as wing twist 2^o, wing sweep of 15^o for the flying wing, no sweep for other configurations, aerofoils for main wing the NACA 23015 for horizontal tail and fin the NACA 0012, while for flying wing the FAUVEL 14%. However, they too could vary if desired for further MDO to be conducted, as discussed in the Design Alternatives Generation section. Moreover, they could be selected as additional strategic choices, within the Game Theory application of the non-cooperative game in UAS VDD. For instance, the user's potential strategy of performance compromise on a lower maximum speed could be modelled in the Game Theory application. All UAS parameters, fixed and variable, are presented in Appendix B.2.

For the DoE, three levels were chosen for the design variables, i.e. wing AR 6, 9, 12, battery capacity 6.5, 8, 9.5 etc. The DoE's performed were Full Factorial (with 5,832 design points) allowing for all possible interactions to be evaluated, as well as Latin Hypercube for more random combinations' generation, with varying number of experiments. For the optimization, Isight allows several techniques to be implemented. The Hooke-Jeeves Direct Search was selected, since it is suitable for non-linear design spaces and long running simulations. The DoE and MDO results are presented in the following sections, reflecting the specific assessed preferences.

9.2.1 Optimizing for User's Objectives

The design space exploration aimed at maximising a value or utility index, depending on which value model was used and based on the user's assessed preferences; or alternatively optimising some UAS's critical objective, such as operational surveillance time, maximum endurance achieved, data collection capability, unit acquisition cost, lifecycle cost, survivability, detectability by selecting the corresponding design attribute.

It was found that the preferences/priorities of the user, as reflected in the value/utility models, are critical in the identification of the optimal design and can indeed provide different results. Thus, for a user with 'civil' priorities, i.e. balanced between performance (endurance, range) and lifecycle cost (acquisition and through-life), and a 'military' user, focusing mostly on maximizing survivability, minimizing detectability and maximizing data collection capabilities, different aircraft optimal designs were obtained, as graphically presented in Figure 9-4. For the 'civil' user, it was found that the monolithic fuselage, V-shape tail, push propeller with a wing span of $1.5\mathrm{m}$ configuration is dominating, while for the 'military' user, the optimal UAS configuration is the monolithic fuselage, T-shape tail, push propeller with a wing span of $1.25\mathrm{m}$ configuration. Hence, it was verified that the incorporation of the largest possible number of different UAS configurations is essential to the successful MDO based on the user's varying preferences.

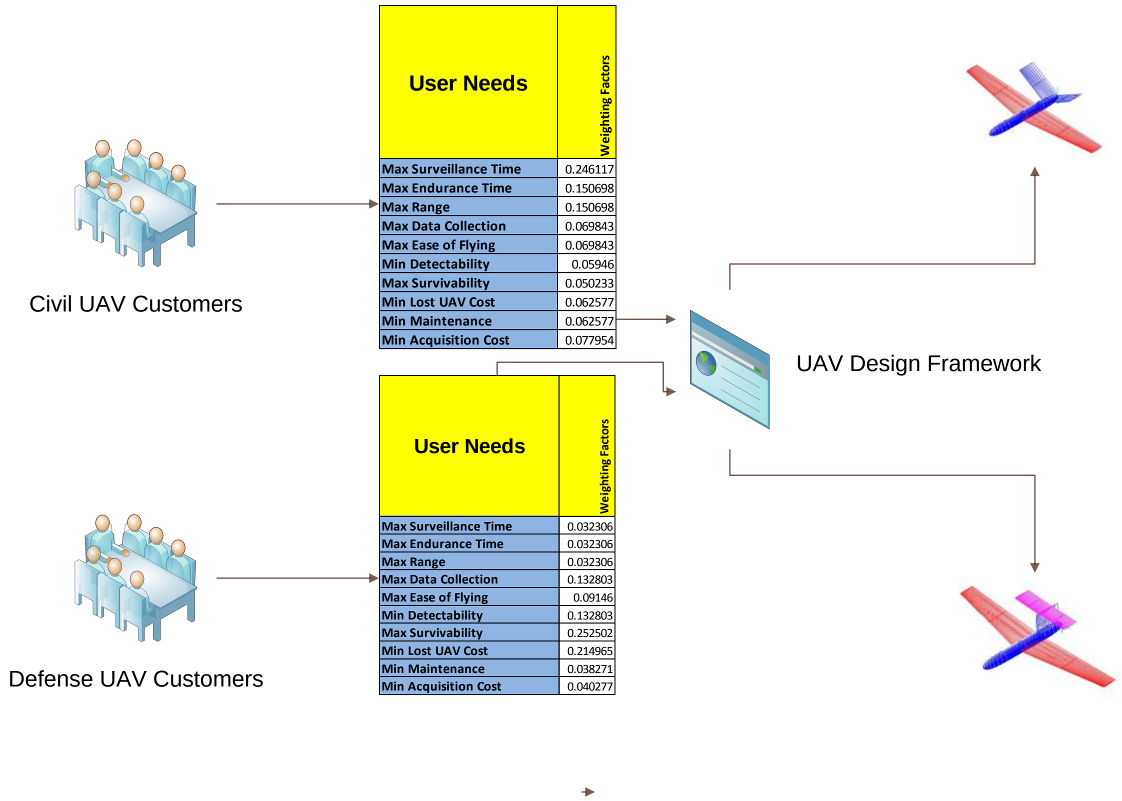


Figure 9-4 Users' Priorities Comparison

The dominant aircraft configurations/geometries maximizing value or utility index or minimizing total cost of UAS can be identified from all configurations included in the MDO (18 configurations, all of them with not all moving control surfaces), presented in increasing order of value index in Figure 9-5. In this figure, the maximum values of value index achieved with all configurations along with the corresponding values of utility index, are plotted. The monolithic fuselage, V-shape tail pusher propeller configuration, followed by the monolithic fuselage, Y-shape tail, pusher propeller configuration and monolithic fuselage, T-shape tail, pusher propeller configuration were dominating in terms of both value and utility indices. It is also noted that, apart from some minor differences, the same trends are observed, and the value model is in close agreement with the utility model. The differences observed in the numerical results of value and utility indices are caused by the different multiplicative utility and additive value models used.

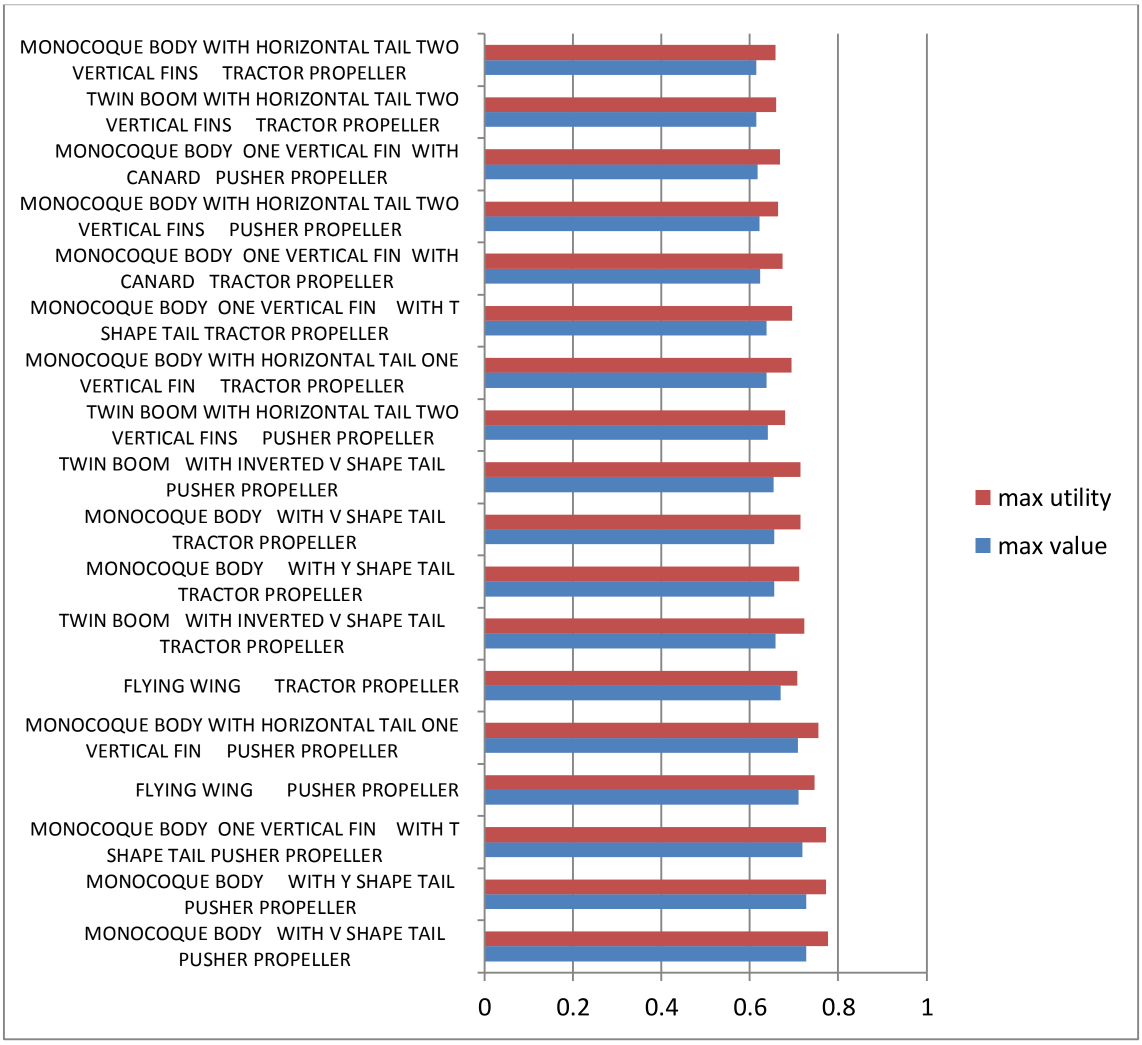


Figure 9-5 Comparison of UAS Configurations based on User's Maximum Value and Utility

Additionally the optimum range of design variables was obtained, with contour plots demonstrating the effect of design variables or other parameters on the response. Once the dominant UAS configuration was identified, contour plots were used to study the design variables' effect on the value index, as in Figure 9-6, and identify their optimal ranges. The corresponding contour plot using the utility model is presented in Figure 9-7, and it may be noticed that it is in close agreement with the value contour plot. Similarly, the corresponding value and utility contour plots for battery capacity and wing AR and battery capacity and component reliability are presented in Figure 9-8, Figure 9-9, Figure 9-10 and Figure 9-11, respectively. A Response Surface Model (RSM) of polynomial form of maximum order of four (i.e. linear, quadratic, cubic and quartic) is constructed for the DoE in Isight. The coefficients of the Response

Surface Models (RSM) obtained and the ANOVA tables are presented in Appendix B.4.

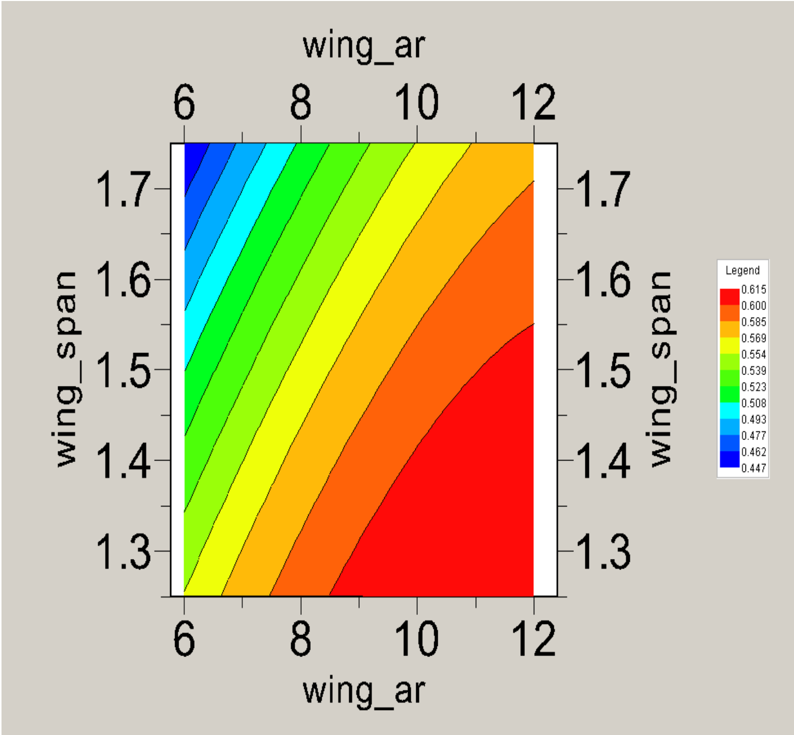


Figure 9-6 Value Index vs. Wing Aspect Ratio and Wing Span Contour Plot

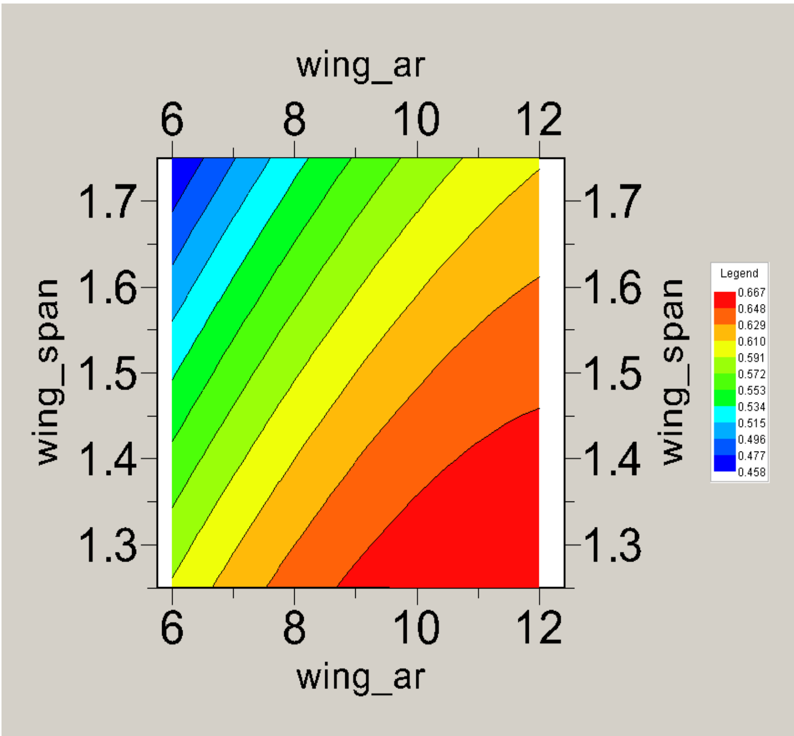


Figure 9-7 Utility Index vs. Wing Aspect Ratio and Wing Span Contour Plot

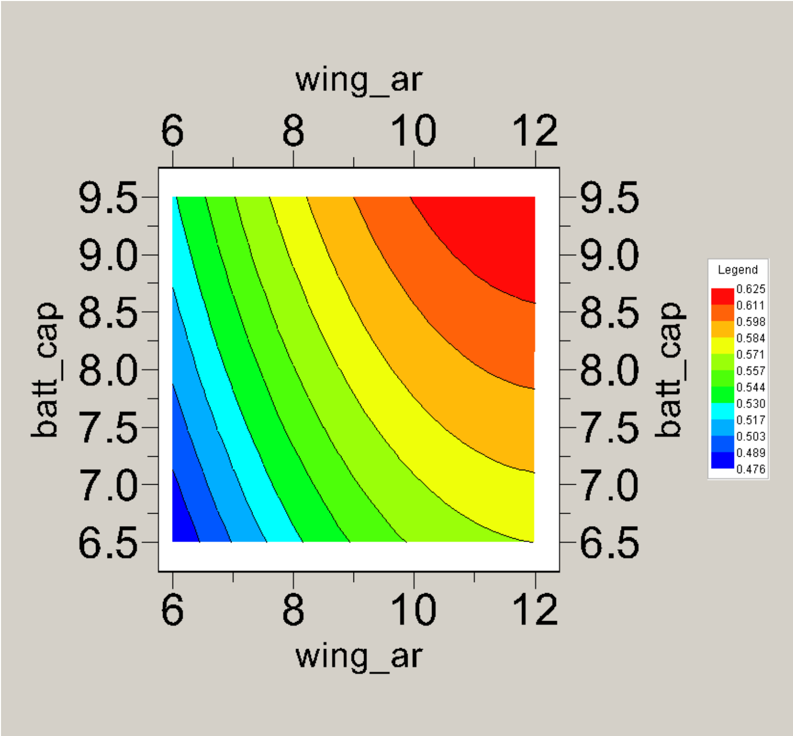


Figure 9-8 Value Index vs. Wing Aspect Ratio and Battery Capacity Contour Plot

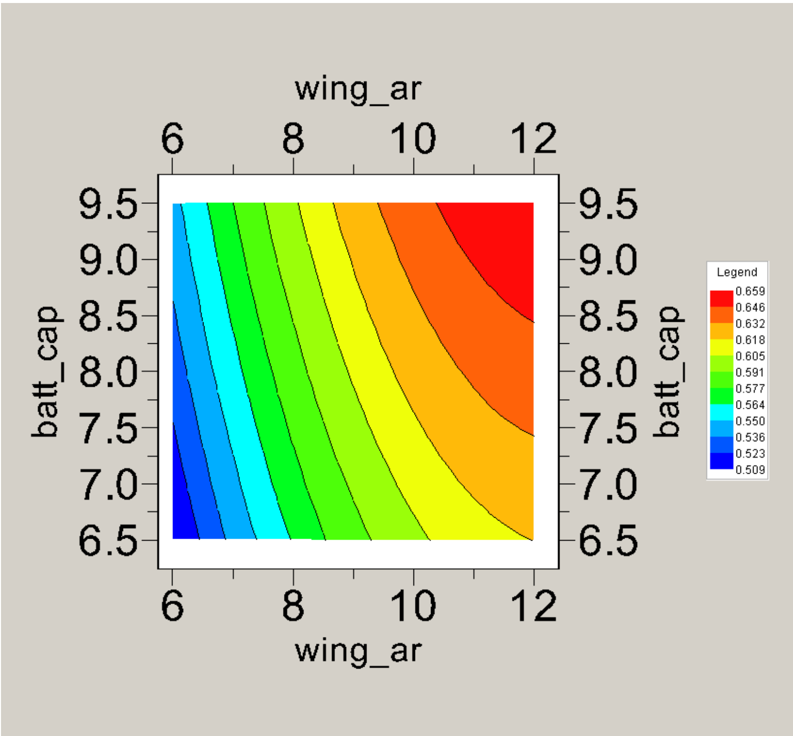


Figure 9-9 Utility Index vs. Wing Aspect Ratio and Battery Capacity Contour Plot

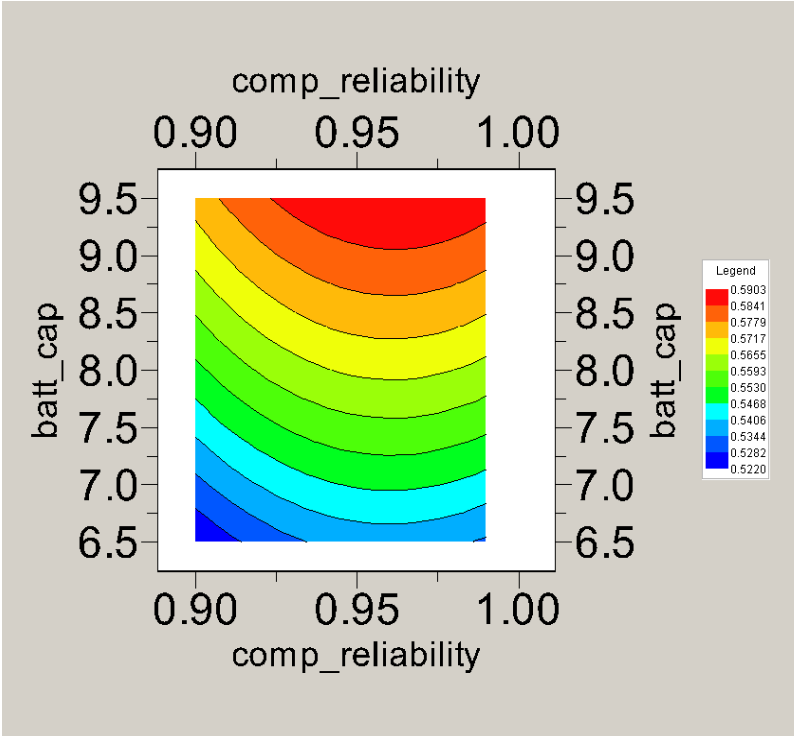


Figure 9-10 Value Index vs. Component Reliability and Battery Capacity Contour Plot

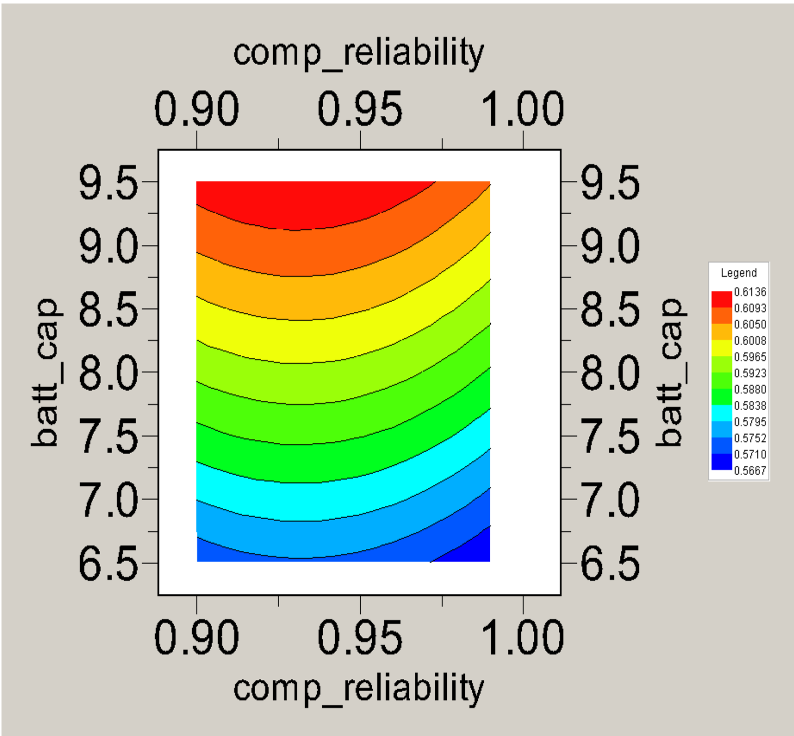


Figure 9-11 Utility Index vs. Component Reliability and Battery Capacity Contour Plot

Both value and utility models point to selecting the same ranges of design variables, which for the specific user's preferences are a high wing AR of $11-12$, a wing span around $1.4\ \mathrm{m}$, a maximum battery capacity as expected of $9.5-10\ \mathrm{Ahr}$, and intermediate scheduled (components') replacement intervals, while for some design variables with small influence, such as fin AR and horizontal tail AR, their optimal ranges are not clear, with the value model suggesting a horizontal tail AR of around 3.5 while the utility model an AR of around 4.5.

Alternatively, MDO was also performed for some critical aircraft attribute. The maximum values of operational surveillance time and minimum values of Total UAS Program Cost achieved with all UAS configurations are plotted in Figure 9-12 and Figure 9-13, respectively. It was found that the twin boom inverted V-shape tail with tractor propeller configuration was the optimal both for maximizing operational surveillance time when flying at design speed and minimizing total lifecycle cost, with wing AR of 12, wing span $1.25\ \mathrm{m}$, fin AR of 1.4 and horizontal tail AR of 3.5. Since UAS weight has a great impact on the operational surveillance time and the Total UAS Program Cost, due to the DAPCA equations, the minimization of the UAS weight with the specific configuration results in both the maximization of operational surveillance time and the minimization of Total UAS Program Cost, as expected. The corresponding contour plots for operational surveillance time and Total UAS Program Cost vs. wing span and wing AR are presented in Figure 9-14 and Figure 9-15.

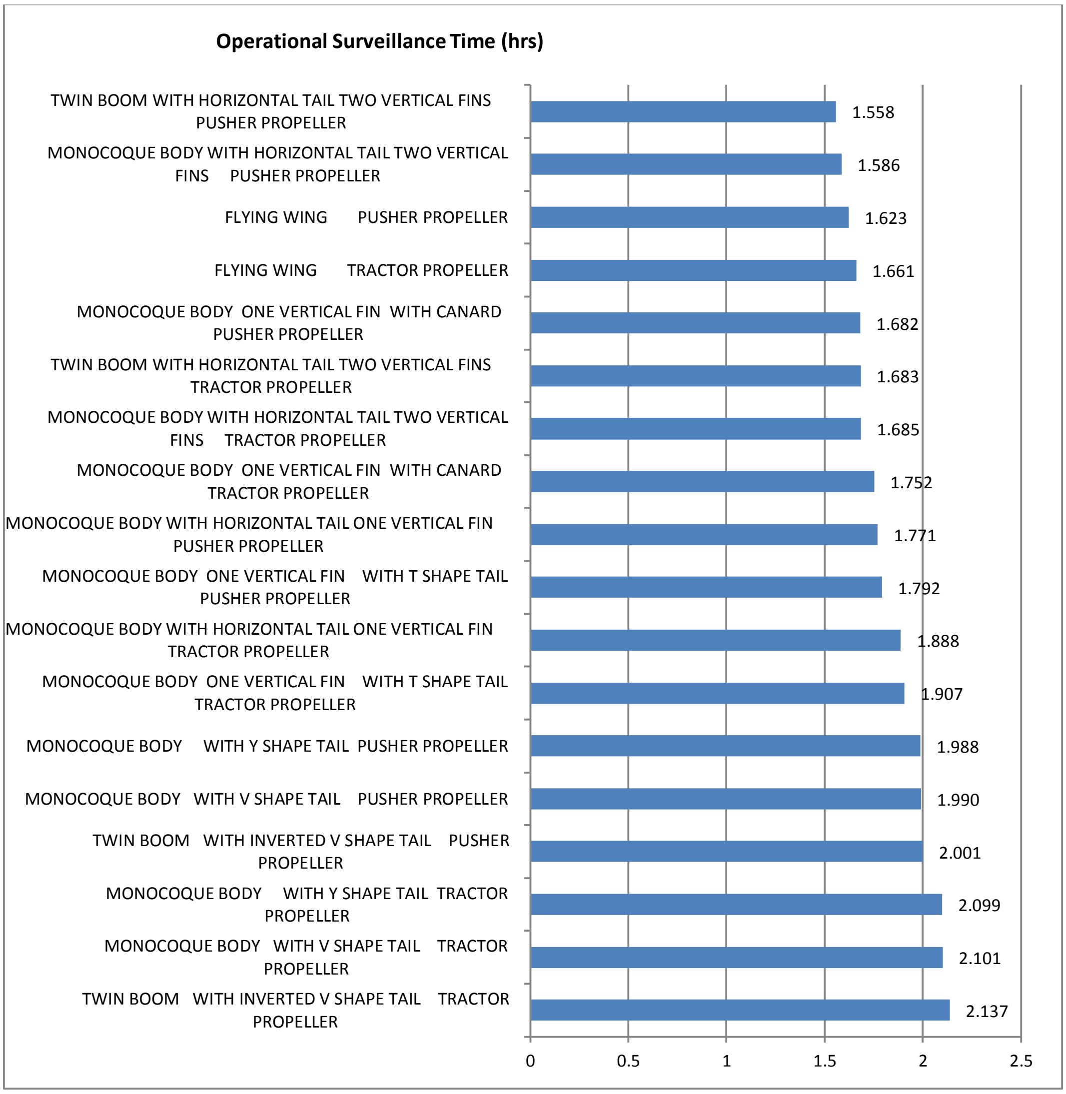


Figure 9-12 Operational Surveillance Time Optimization

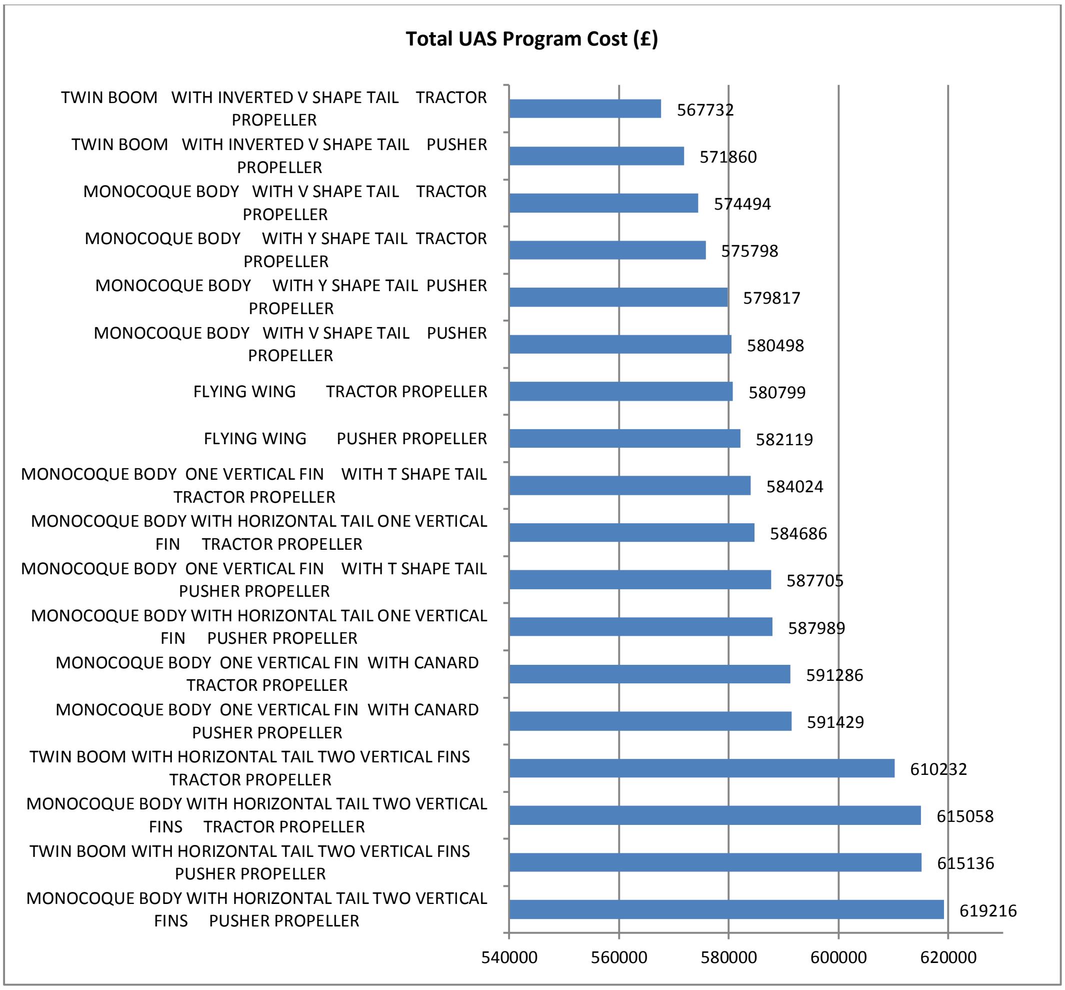


Figure 9-13 Total UAS Program Cost Optimization

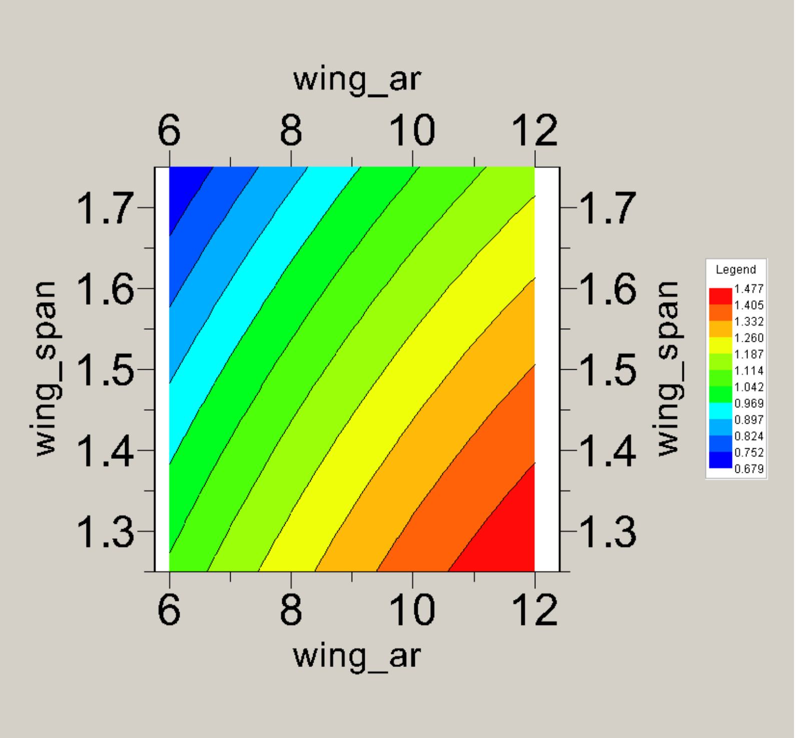


Figure 9-14 Operational Surveillance Time vs. Wing Aspect Ratio and Wing Span Contour Plot

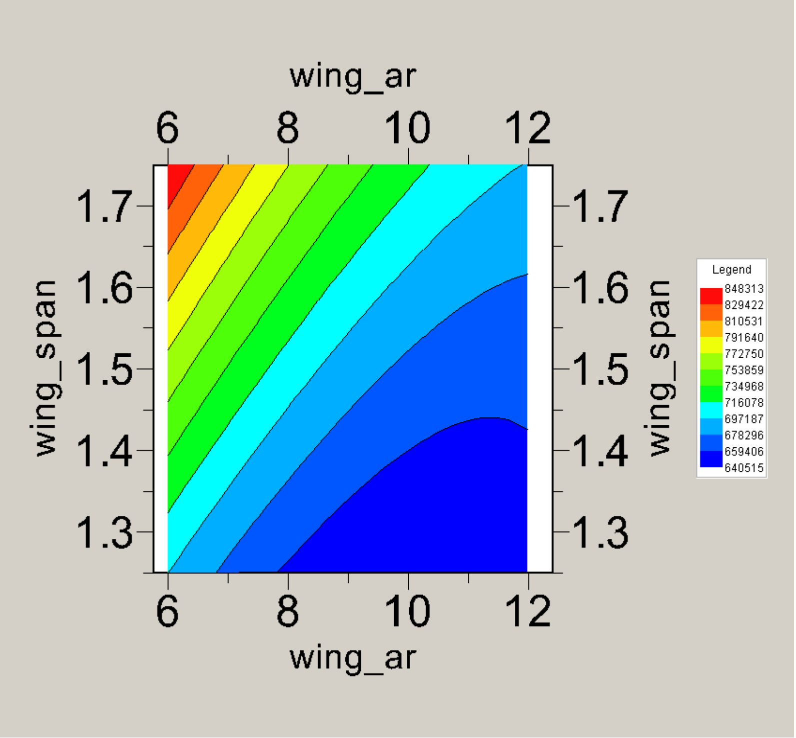


Figure 9-15 Total UAS Program Cost vs. Wing Aspect ratio and Wing Span Contour Plot

The DoE provides estimates of sensitivity analyses of the design variables and their effect on the response, optimised in each case. Based on the Response Surface Model (RSM) for the DoE in Isight, the percentage effect of the design variables on the response, in this case the value index, is presented in Figure 9-16. Thus, the most significant parameters are identified by showing the percent effect, on the response, that has a unit change of each of them, with positive effect shown in blue and negative in red. It may be noticed that the battery capacity, followed by the wing aspect ratio and wing span are the most significant variables.

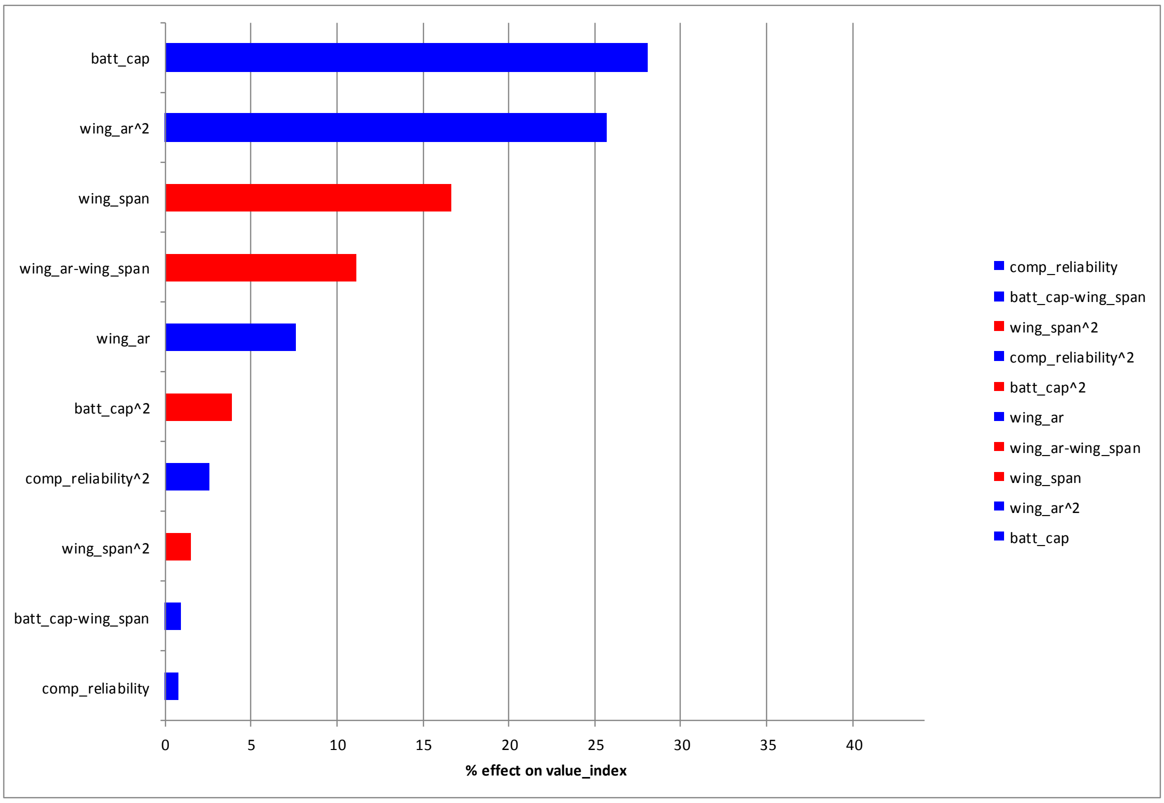


Figure 9-16 Isight Sensitivity Analysis

Finally, once the design space exploration had been concluded, an approximation was created using the Isight Runtime Gateway, by fitting the input/output values to a single mathematical model and exporting them to an

Excel spreadsheet, presented below, to share the approximation information with non-Isight users.

Table 9-1 Isight Approximation

Input Parameters	**Values**	**Minimum**	**Maximum**	**Output Parameters**	**Values**
Battery capacity	6	6	10	Value index	0.538
Canard AR	5.48	5	7		
Comp. reliability	0.962	0.9	0.99		
Fin AR	1.531	1.2	1.8		
Horizontal tail AR	3.759	3	4.931		
Taper Ratio	0.510	0.4	0.593		
Wing AR	6.41	6	12		
Wing Span	1.655	1.2	1.8		
Front bulkhead position	0.2	0.2	0.4		

A Radial Basis Function (RBF) approximation based on the Hardy [209], [210] method was created in Isight (with an adjusted R^2 coefficient of 0.717) and exported to Excel, allowing to compute the value index for any values of the design variables and even obtain approximated surface or contour plots, to study the effect of any two design variables on the response, as in Figure 9-17, plotting value index vs. the design variables of wing span and battery capacity.

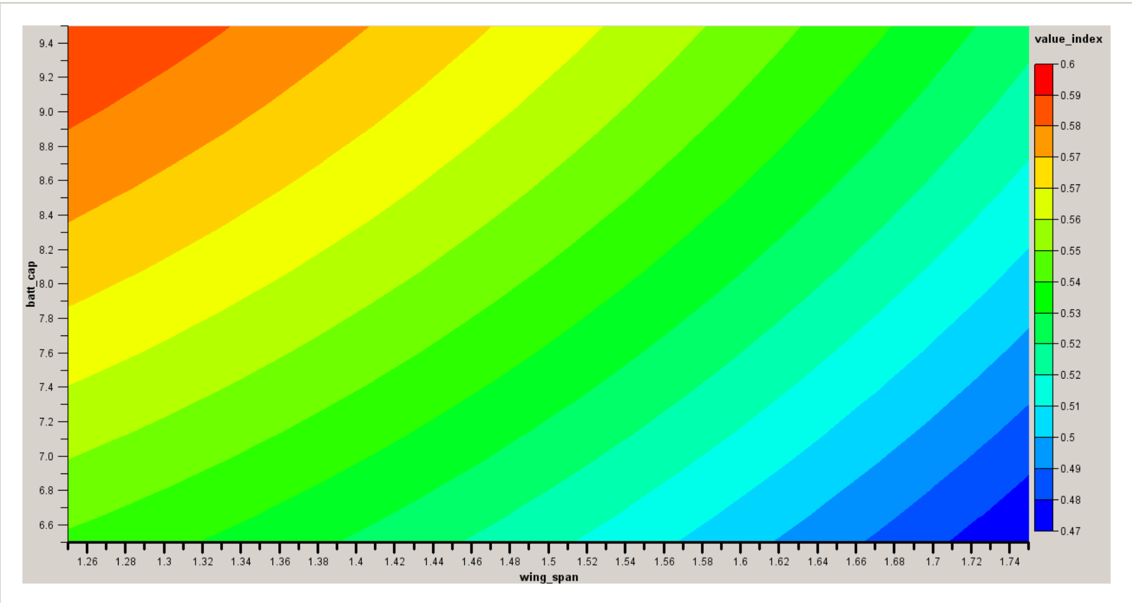


Figure 9-17 Contour Plot of Approximation, Value Index vs. Wing Span and Battery Capacity

Based on the results obtained, the multi-attribute value model was validated, since it provided analogous results with the multi-attribute utility model showing that this easier to apply model can address effectively the user's preferences. Both models identify the same aircraft configurations as dominant in terms of maximizing value or utility index while, in the surface plots, they both capture similar effects of design variables on the response, value or utility.

9.2.2 Optimizing for User's and Manufacturer's Objectives

The preferences of stakeholders other than the user were also implemented through the application of Game Theory as analysed in 6.2. In the UAS VDD the two major stakeholders, user and manufacturer, were involved in a hybrid, cooperative/non-cooperative, non-zero sum, complete information game, modelling the interactions between their preferences and strategic choices, to accurately evaluate the alternative designs in the value driven conceptual design of the UAS. For demonstration purposes, the following strategic choices of the two stakeholders of the UAS VDD, user and manufacturer, were selected:

- As discussed in section 8.2.4, the application by the manufacturer of a reliability improvement program, increasing the Mean Time to Failure (MTTF), modelled by the Weibull parameter n, would result in less aircraft losses, less scheduled components' replacements/less workload, higher acquisition cost and scheduled maintenance/replacement costs that would depend on the cost of the increased reliability as well as the replacements performed during the whole program. In the UAS conceptual design, for the selection of more reliable components as an additional design choice made by the manufacturer, two levels of components' reliability were assumed, a lower original level and an improved one with increased acquisition cost.

- Based on the analysis in 8.2.3, the user's selection between two different scheduled replacement/maintenance scenarios, one critical components replacement policy and one whole designed system replacement policy. These two different scheduled replacement/maintenance scenarios were included in the conceptual value driven UAS design optimization for the lifecycle cost assessment.

In the first scenario, the UAS's critical components average replacement times, survival rates and lifecycle costs were computed, while in the second one the lifecycle cost due to reliability related losses and scheduled UAS replacements.

The first step of the multi-stakeholder optimization process is to perform the design space generation and evaluation of all alternative designs for every possible combination of the stakeholders' strategic choices. For the selected strategic choices of the user and the manufacturer there are four possible combinations:

1. The user performing a scheduled component replacement maintenance policy and the manufacturer using components of lower reliability and cost.
2. The user performing a scheduled component replacement maintenance policy and the manufacturer using components of higher reliability and cost.
3. The user performing a scheduled UAS replacement policy (i.e. no RBR maintenance) and the manufacturer using components of lower reliability and cost.
4. The user performing a scheduled UAS replacement policy (i.e. no RBR maintenance) and the manufacturer using components of higher reliability and cost.

For all the above combinations four independent Isight models, similar to the one presented in Figure 9-3, run in parallel. Each of these Isight models identifies a different NBS, as the one UAS design with the maximum value of the product of utility/payoff functions for the two stakeholders. The user's payoff/utility function was the same as the multi-attribute value function used in 9.2.1. Concerning the manufacturer, the total UAS Program cost after being normalized appropriately was used as the payoff function, since it was assumed that the profit and its associated satisfaction would be a linear function of the total program cost for an assumed CPF contract type. Nevertheless following a similar analysis as the one done for the user's objectives, a multi-attribute utility function could be obtained to model the manufacturer's preferences.

The four NBS's generated as optimum designs from the cooperative non-zero sum, complete information games for all combinations of user's and manufacturer’s strategic choices are used to form the non-cooperative, non-zero sum game and obtain the Nash equilibrium optimum design point, presented in Table 9-2**.**

Table 9-2 UAS User - Manufacturer Non-cooperative Game

User's / Manufacturer's Strategies		**Component Replacement Policy**				**UAS Replacement Policy**		
Original Reliability	+	Manufacturer’s Payoff: 0.418 User’s Payoff: 0.699	-	Nash Equilibrium	+	Manufacturer’s Payoff: 0.524 User’s Payoff: 0.495		
Improved Reliability		Manufacturer’s Payoff: 0.416 User’s Payoff: 0.725	-			Manufacturer’s Payoff: 0.384 User’s Payoff: 0.643		

Through the successive elimination of strictly dominated strategies, described in 6.4, Nash equilibrium is justified as the combination of optimum strategic choices for both players. In this case and based on the achieved values of utility functions, the user will always choose a component scheduled replacement policy from the UAS replacement policy, irrespectively of what the manufacturer selects. Hence, the manufacturer, knowing this fact, will select to maintain the components with the lower reliability levels. Thus, based on the specific preferences, a single Nash equilibrium was obtained, the Component Replacement Maintenance Policy and original reliability of critical components along with the corresponding values of design variables describing the optimum design. The optimal design obtained through the hybrid cooperative/non-cooperative game is a monolithic fuselage, Y-shape tail, pusher propeller, UAS with a wing AR of around 12, wing span of around $1.5\ \mathrm{m}$, battery capacity of $9.5 - 10\ \mathrm{Ahr}$ and large scheduled components replacement intervals.

Having said that, engineering design could also be modelled as a pure cooperative non-zero sum game, solved as a bargaining problem. In this case, no strategic interactions are allowed between the stakeholders and their strategic choices are also considered as design variables. The evaluation of the design alternatives is driven only by their *structural incentives*, i.e. the values of the payoff functions, and the engineering design’s optimal solution is based solely on the criterion of the maximization of their product. Hence, among the four NBS's obtained through the four cooperative games, the NBS with the maximum value of product of utility/payoff functions is selected as the overall solution of the UAS conceptual VDD. For the specific preferences and achieved values of utility functions, that would be the component replacement policy and improved reliability of critical components respectively. This could be justified because the increase of the user's utility function (from 0.699 to 0.725) is much higher that the decrease of the manufacturer's utility function (from 0.418 to 0.416) when a reliability improvement program is applied by the manufacturer, keeping in mind that both stakeholders were assumed of equal bargaining skills and authority in the cooperative model's equation 6-5. The corresponding optimal design would be a monolithic fuselage, Y-shape tail, pusher propeller UAS, with wing AR 12, wing span of around $1.5\ \mathrm{m}$, battery capacity of $9.5-10\ \mathrm{Ahr}$ and large scheduled components replacement intervals. With this pure fully cooperative game modelling, the strategic choices of the stakeholders are mere design parameters, varying to generate more design alternatives and to identify the optimal UAS that maximizes the product of utility functions.

Nevertheless, the designer should focus not only on the articulation of the stakeholders' preferences but also on the strategic interactions between them, based on the information and their expectations concerning the other stakeholders' likely strategies. It is considered more accurate if the game allows the players to make a number of important strategic decisions, such as those already presented, in isolation and purely promoting their *strategic incentives*, instead of simply aiming to maximize their utility functions' product. Therefore, from the designer's perspective in engineering design, the application of Game Theory in the hybrid cooperative/non-cooperative game is capable of modelling both the preferences and the strategic interactions between the players/stakeholders to effectively identify the optimal design.

9.3 Chapter Summary

VDD is based on relaxation of any constraints and thorough search of the design space. In the general sense, this concept is about value-focused thinking for creating more desirable design alternatives and identifying fruitful decision opportunities, tackling the design/decision problem. The standardised VDD implementation process in a framework for a multi-objective, multi-stakeholder engineering design was presented in this chapter. The Design Integration in Isight enables the designer to deal with all associated complexities and focus on value as perceived by the decision makers. The successful design space search and optimization is performed through Isight's automation, based on the major stakeholders' objectives, allowing for post-processing sensitivity analysis and studying trade-offs between design parameters and results. Game Theory is used to create a well-defined hybrid mathematical model, capturing effectively both the conflict and cooperation between the stakeholders, user and manufacturer, through the simultaneous employment of cooperative and non-cooperative, zero-sum, complete information games.

10. Discussion and Conclusions

"To be conscious that you are ignorant is a great step to knowledge."

Benjamin Disraeli

A brief synopsis of the present research work with its primary conclusions and contributions are presented in this chapter. Lessons learned throughout this research are reviewed and key arguments are highlighted. Contributions to the current state of knowledge as well as recommendations for future work are outlined, in an attempt to drive further research into this field.

10.1 Context

The goal of engineering design is the identification and improvement of designs that satisfy customer needs, a process that gets more difficult as the designed system gets more complex. The first step is to distinguish the objectives and their associated criteria/subcriteria, describing the stakeholders' needs. The design of complex aeronautical systems with multiple objectives and multiple disciplines involved entails trade-offs. Despite the advances in computational tools that have transformed engineering design, the inherent complexity of aeronautical design is *prima facie* evident when even the slightest design parameter change has great consequences in lifecycle cost and performance. This growing complexity has had a great impact on program delays and cost overruns and demands the systematic and integrated approach of VDD, as the framework that, after removing all requirements set by SE, focuses on the pursuit of value throughout the engineering design process. The VDD approach should be followed whenever trade-offs between conflicting objectives necessitate decision making, especially during the conceptual design phase when the most critical decisions are made.

In the VDD framework, value represents a measure of preferences of the stakeholders involved, related to the designed system's capabilities or performance and lifecycle cost. This value used in a relative sense to compare different design alternatives, is assessed through the appropriate value model. Typically a single performance or cost related objective, such as lifecycle cost, and the net present (monetized) value of the designed system have been utilized in aeronautical VDD, neglecting other priorities and needs. Instead, in this research a *multi-criteria/objectives* and *multi-stakeholder* decision making analysis is adopted to address the preferences of more than one stakeholder as well as to study their interacting strategic choices effectively.

The challenging design process integration required for the exploration of the widest possible design space was carried out in Isight to achieve the linking of tools of different type for analysis, optimisation and interpretation of the results. Appropriate models were developed to estimate all associated variables and parameters required for the product definition and evaluation. The implemented Isight model was used for the automated design space search with DoE; and subsequently, the design was optimised for maximizing value or utility indices, depending on which value model was used, or some critical aircraft attribute, based on the user's preferences. Game Theory was applied in engineering design for the two major stakeholders through a hybrid cooperative/non-cooperative game that could easily be extended to include more stakeholders/players. Hence, a single overall optimal design point was identified, having the properties of both NBS and Nash equilibrium.

The preferences/priorities of the user, as reflected in the value/utility models, were found to be critical for the identification of the optimal design and could indeed provide different results. Dominant aircraft configurations/geometries and optimal ranges of design variables were identified. Sensitivity analyses were also performed to study the effect of design parameters on the response optimised in each case. Based on the results obtained, the multi-attribute value model was validated, since it provided analogous results with the multi-attribute utility model; showing that, although easier to apply, it can capture effectively the user's preferences especially during the conceptual design phase.

10.1.1 Product Definition – Geometric Topology Modelling

The framework presented in this research is capable of a satisfactory product definition and estimation of all performance and cost related attributes for the conceptual phase. The product definition is input into the lifecycle simulation models, with any design change reflected in performance and lifecycle cost. For the application of the VDD framework in the UAS conceptual design, appropriate design parameters affecting performance and cost were selected for the UAS definition; among them, geometry (i.e. dimensions of the UAS), material type, propulsion, maintenance and aircraft replacement related parameters were included to provide accurate assessment of all attributes. Nonetheless, the number of design variables in the aircraft sizing models was limited to a manageable number to allow through their variation for the fast UAS alternatives' generation and parameters' calculation; while all other parameters were set to reasonable values that could be amended, if desired.

To explore the widest possible design space, a large number of different aircraft geometries were generated by parameterizing aircraft geometric topologies. Based on fundamental design selections, a multitude of basic aircraft geometries, described by a hierarchical coding, was generated. This code representation allowed for the shape definition to be input in the design models, which was then scaled through the use of appropriate design variables. A large number of aircraft configurations were represented: from conventional to flying wing, depending on the type of tail, from the conventional horizontal tail/vertical fin to V-shape tail and Y-shape tail, depending on the position of the propeller etc.

Concerning the sizing models employed in the UAS VDD, much effort was devoted to making use of mostly physics-based analysis methods; however, in certain cases, semi-empirical analysis models were considered as valuable for completing successive design cycles and performing optimizations more rapidly, given the accuracy requirements of the early conceptual aircraft design phase. These models are summarized as follows:

- Basic approximating Schrenk method [198] was used for computing lift distribution.
- In the drag polar estimation, semi-empirical parametric formulae/equations and roughly estimated parameters for a low subsonic airplane during preliminary design, presented in Roskam [199], were used. Based on three flight conditions, landing, flying at design speed and maximum speed, the drag polar in other flying conditions was estimated through interpolation as a function of speed.

- In the performance model, only electric propulsion was studied and standard data for Lithium-ion Polymer (LiPo) batteries, electronic speed controllers and electric motors were utilized to perform regression analysis by plotting these data and obtaining appropriate relationships for other relative parameters. For the propeller sizing, the diameter and pitch were calculated using a statistical equation [5] and regression analysis.
- The weights of aircraft components such as wing, tail, canard, motor, battery, propeller etc. were approximated based on weight estimating relationships and regression analysis, while standard weights were assumed for the servos, receiver, autopilot and payload/camera.
- Semi-empirical equations were also employed in the stability calculations based on the UAS configuration and the design variables. Downwash effect of the wing on the tail and of the canard on the wing were obtained through regression from data for a low subsonic unswept wing, as presented in [5].

A very basic validation of these models was performed by sizing the Southampton University Laser Sintered Aircraft (SULSA) UAV, since its configuration and design parameters were within the chosen ranges of this research. In general, a close agreement was observed between most of the calculated design parameters and those of SULSA. However, these models would have to be replaced to improve accuracy in the later stages of engineering design.

10.1.2 Lifecycle Cost Modelling

Lifecycle operations analysis provided estimates of all total lifecycle cost and defence/combat related attributes, based on the stakeholders' objectives. The parametric representation of the design was input into these models, while Monte Carlo simulation was used to quantify and manage risks associated with them.

The acquisition cost model used explicit aircraft design parameters for calculating manufacturing costs. The DAPCA parametric equations were utilized as the best option to assess development, engineering, tooling, quality control and flight testing costs, since publicly available data for unmanned aircraft design is very limited. For cost modelling of aircraft components, parametric cost estimating relationships were generated through regression analysis, or otherwise the cost of analogous components was used.

In lifecycle cost modelling, reliability and survivability were included to assess aircraft component failures and battle damages resulting in either aircraft losses or unscheduled repairs by replacement (RBR). All maintenance activities were assumed to be either preventive (scheduled) or corrective (unscheduled due to failures) replacements of the designed low cost aircraft and its components. Due to lack of available information, reasonable assumptions concerning the UAS critical components, their reliability, the missions undertaken, the flight workload, the fleet size and program duration were made. The reliability of all aircraft components was modelled with Weibull distribution and Weibull parameters were set to reasonable, constant values. Finally a standard discount rate was applied to all future lifecycle costs to be adjusted to present values.

Three different maintenance policies were modelled, one with all aircraft critical components being replaced at specific time intervals depending on their reliability level, one with whole aircraft replacement at specific time intervals and a combined policy. These maintenance policies were compared and the first two were selected to be included for the lifecycle cost assessment within the multiple stakeholders Game Theory application in UAS VDD. Estimates of the lifecycle cost due to reliability related aircraft losses, operational success reflected in aircraft losses, and maintenance cost due to lifecycle component or whole aircraft replacements were obtained with MCS, along with the associated, uncertainty related, statistics parameters (standard deviation, posterior standard deviation etc.).

The survivability model assessed battle damages in a simulation scheme based on historic data for a similar mission UAV and after been adjusted with respect to the computed, specific aircraft geometric characteristics (aircraft's total surface). Other specific aircraft performance related characteristics, such as maximum speed or manoeuvrability, were not taken into account. Again, due to lack of information concerning the missions, operation in hostile or non-hostile environment, number of sorties required etc., the whole lifecycle combat damage cost was not assessed and only the attribute of expected survivability related cost per flight through MCS was obtained.

All lifecycle cost models are modular, transparent, allowing for improvements/replacements, easy integration and automation in Isight. Vanguard [207] was chosen for lifecycle cost modelling, since it combines the quantitative methods of spreadsheets with superior analysis and communication capabilities, overcoming one of the spreadsheets' limitations. Finally, although the lifecycle cost models provide sufficient accuracy for the conceptual design stage, they could be replaced with more accurate calculations in the later stages of design.

10.1.3 Multi-Objective Value Modelling

Any value model is used to assess the value of any given design alternative based on the qualitative and quantitative preferences of the stakeholder whose preferences are modelled. Two main single stakeholder's value models were developed, a novel additive value model and a multiplicative utility model. Both models employed Multi-Attribute Utility Theory (MAUT), while the Analytic Hierarchy Process (AHP) approach was used to achieve a higher accuracy in the computation of the weighting factors, due to the redundancy of the answers obtained assessing the user's preferences.

The additive value model, ignoring uncertainties and risks related with them, is much more straightforward to apply. It captures more objectively the stakeholder's preferences with criteria independent of information or the set of alternative solutions. Especially during the conceptual design phase, the evaluation process becomes more *value focused*, by identifying *a priori* needs and average levels of expectations of the stakeholder, than the *alternative focused* process of the utility model, with the stakeholder selecting the best from what is already available. It minimizes the interaction with the stakeholder, since ready to use value functions are automatically generated, depending on their preferences. AHP was implemented in the weighting factors' computation to increase the accuracy and to assess the consistency of the answers given. The deficiency of converting verbal preference responses between attributes to numerical values, through the use of an unjustifiable scale in AHP for the calculation of weighting factors, was encountered and tackled. As engineering design progresses and more information is gathered, the stakeholder's qualitative and quantitative preferences may also be updated to capture more accurately their preferences in the value model. Nevertheless, the individual value functions of the attributes are all assumed to be identical, generated from the given set of Table 5-1, and the additive linear value model assumes no overlapping among the objectives.

The multiplicative utility model was created based on standard MAUT, and is more complicated and elaborate to develop. This model is considered more appropriate to be used in the last phases of the design, once the set of design alternatives is finalised, when the generation of the utility functions should be based on this set than on the user's average levels of expectations. Nevertheless, both models allowed through systematic decision making processes to deal effectively with the stakeholder's multiple objectives and their trade-offs. Their advantages/disadvantages are presented below:

Table 10-1 Advantages and Disadvantages of Value/Utility Models

	Multi-Attribute Value Model	Multi-Attribute Utility Model
Advantages	• Easier to apply, less interaction with stakeholder. • Value focused. • More suitable for conceptual design phase. • Capturing stakeholder's preferences.	• Suitable for the last phases of design. • Utility functions assess stakeholder's risk attitude.
Disadvantages	• Value functions all identical. • Additive Model, no objectives overlapping. • Not capturing stakeholder's risk attitude.	• Alternative focused. • More elaborate, requires extensive interaction with user.

In all cases of engineering design, a group of experts/individuals represents the stakeholder's group of decision makers whose preferences are to be combined into the stakeholder's objective function. In the stakeholder's value model, a preferences' synthesization, averaging, AHP-based method was introduced to deal with the interpersonal preferential conflicts between individuals with the same objectives but different quantitative preferences.

10.1.4 Multi-Stakeholder Value Modelling

The objectives of other than the user stakeholders with different interests/stakes were also taken into account in the engineering design. Game Theory was employed to model the value driven engineering design as a non-zero sum game between the two major stakeholders of the defence system, the user and the manufacturer. Their decisions, concerning the system's whole lifecycle, aim to promote their interests through the maximization of their corresponding objective functions and affected by the others' choices.

In game modelling of engineering design, the players' incentives were distinguished to *structural* and *strategic incentives*, depending on whether they were determined purely by their payoff/objective functions or whether they were also dependent on their expectations about the other players' most likely strategies. Thus, the optimal design alternative selection process was modelled as a novel hybrid game consisted of cooperative and non-cooperative games, addressing the stakeholders' structural incentives and modelling the interactions between their strategic choices, respectively.

In the cooperative game, the product of the user's and manufacturer's utilities (both assumed to be equal in bargaining skills and relative authorities) was used as the sole criterion to determine the quality of each design alternative and resolve the indeterminacy of the Pareto front. For the selected strategic choices of the two major stakeholders (maintenance policies and aircraft components' reliability levels) in the UAS conceptual VDD, a non-cooperative game was formed and the optimal strategies were obtained as a Nash equilibrium, based on their *strategic incentives*. Hence, given that the assumptions of Game Theory concerning the players, presented in 6.2, were valid, and that the axioms of section 6.3 were satisfied by the Nash bargaining solutions, the single optimal solution obtained could address effectively both the preferences as well as the strategic interactions between the two stakeholders (and more, if the game is extended). Despite many critiques concerning the validity of these assumptions, in engineering design the designer can successfully address through Game Theory the preferences of more than one rational stakeholder, assuming that their interests are fully and solely described by their utility functions.

10.2 Contributions of Research

In this section, the Value Driven Design Framework is appraised against the overall research goal and the individual objectives set out in the Introduction. This VDD framework was designed to demonstrate the application of the VDD philosophy in the design of a defence system. The value enhancing designs are identified in this framework, with value perceived from multiple non-monetised objectives/attributes of multiple stakeholders involved with the designed system.

10.2.1 Review of Research Hypotheses

The VDD framework is reviewed against the research hypotheses set in Introduction:

Hypothesis 1: *A VDD framework, when applied to the design of a defence system, can address all the non-economic and economic values of the stakeholders involved with the designed system, to identify the value-enhancing design(s).*

The implementation of the VDD framework in this research proved that value driven engineering design is capable of addressing non-economic and economic values of the stakeholders involved with the designed system. The systematic *multi-criteria* and *multi-stakeholder* decision making analysis allowed for dealing with the biggest challenge that is the development of an appropriate value model capable of addressing the different and conflicting preferences of all stakeholders. MAUT supported by AHP was employed to establish comprehensive value models for all stakeholders, while Game Theory addressed their preferences and modelled the interactions of strategic choices among them. Hence, this hypothesis is corroborated.

Hypothesis 2: *Design exploration can be performed more efficiently, after relaxing most performance or cost related constraints and extensively searching the design space in a systematic way.*

After relaxing all performance or cost related constraints set in the traditional Systems Engineering approach, the goal in this research was to explore the widest possible design space, as advocated by the VDD philosophy. The value of all proposed solutions was assessed without setting any design attribute constraints. To search the design space systematically, alternative concepts and design configurations were included through the systematic parameterisation of the aircraft geometric topologies. Beyond the selected design variables to extend even further the design space, strategic choices of the stakeholders were also considered in the Game Theory application as additional, higher level variables, that would normally be assumed constant throughout the MDO.

In the UAS VDD application, the number of design variables of the UAS definition and lifecycle models had to be limited to a reasonable number to allow for the fast generation of UAS alternatives and calculation of lifecycle parameters with all other parameters set to reasonable values. To search more extensively the UAS design space, the workload would increase exponentially as the number of the variables would go up. Despite these limitations, no constraints were placed on the performance or cost related design attributes, hence this hypothesis was verified.

Hypothesis 3: *Multidisciplinary design optimisation can be applied within this framework to address most system complexities associated with the conceptual design phase*.

The MDO applied within this framework addressed many system complexities associated with the requirements of the conceptual design phase for the UAS VDD. However, as already discussed in the Context and the corresponding sections, many assumptions were made in the development of the models used in the product definition and lifecycle modelling. These models are sufficient for the accuracy requirements of the conceptual design phase, but they would have to be improved/replaced for higher accuracy in the later stages of engineering design. Moreover, due to lack of information concerning the missions, UAS fleet, number of sorties etc., the lifecycle models performed a very basic analysis while their validation against some real life UAS lifecycle data was not possible. Hence, this hypothesis was also corroborated.

10.2.2 Research Objectives

As stated in section 1.3, this research aimed to *develop an implementation of the value driven design philosophy in a framework where all needs of the major stakeholders of the designed defence system are addressed and used in the evaluation of the proposed product solutions, with value not only translated to monetary worth*. The objectives of this VDD framework with the research achievements are presented below:

Table 10-2 Research Objectives

Research Objective	Comment
Identification of the needs of all stakeholders involved with the designed system during its whole lifecycle.	For a defence system, the two major stakeholders were identified as the user and the manufacturer of the designed system. The missions related to their objectives were used to define appropriate objectives/attributes hierarchies. The needs of other stakeholders could also be modelled in the multi-objective, multi-stakeholder value modelling and the MDO, if desired.
Development of multi-attribute and multi-stakeholder value models, based on all identified stakeholders' performance and financial needs, to assess the value of the proposed solutions with appropriate design attributes as their inputs.	Appropriate multi-objective value models used to assess the value of any given design alternative were formed using MAUT and AHP; Game Theory was employed to address the needs of all major stakeholders (user, manufacturer).
Selection of a wide range of different system configurations, associated technologies, design variables and other stakeholders' choices to widely search the design space.	A wide range of different UAS alternative concepts and design configurations were included through the selected design variables and hierarchical coding. Concerning the associated technologies, the search was limited to specific choices, such as the electric propulsion. The appropriate models could be extended/amended to include more technologies; however this research focused on demonstrating the application of VDD philosophy in a *multi-objective*, *multi-*

	stakeholder MDO, addressing non-economic and economic values. As future work and with more data available, the design space could be searched more widely by including other technologies, such as internal combustion engine, rotary wing aircraft, other missions etc.
Definition of the designed system with appropriate models in a terminology and language relevant to the designer for quick and efficient conceptual design space exploration, easily amended and replaceable for higher accuracy during the later phases of engineering design.	All models used to size the designed system and assess the lifecycle costs could be easily replaced in Isight design tool for higher accuracy in MDO, during the later phases of engineering design. The system is defined in a terminology and language relevant to the designer with models for system definition built in spreadsheets, and lifecycle cost models in Vanguard to perform the lifecycle simulations and use the hierarchical tree layout for superior presentation.
Unit acquisition costing system, based on system geometry and material/labour rates.	The UAS acquisition cost model was indeed based on explicit design parameters, i.e. the specific configuration, geometry, material type and the assumed wrap rates for all manufacturing processes for calculating manufacturing costs.
Mission scenarios' definition to run simulations and obtain first estimates of lifecycle cost and performance/capabilities.	Discrete event simulation of failures of critical components was the basis of lifecycle modelling with reasonable assumptions concerning the UAS's critical components, their reliability and the missions undertaken. As mission, a single reconnaissance/surveillance mission with a standard annual flight workload was assumed. Given the lack of available data, these estimates

	of UAS lifecycle costs and operational capabilities are considered acceptable for the UAS conceptual VDD. The predictive models could be extended/amended to include alternative mission scenarios.
Integration of all models in the design tool.	All models were integrated in the Isight design tool because of its ability to execute simulation-based processes, accelerating the design space exploration and evaluation of the design alternatives.
Trade/parametric studies to identify the optimal solutions as well as the corresponding optimal ranges of all design variables.	Design of Experiments (DoE), Optimisation, approximations, sensitivity analysis and trade/parametric studies were performed in Isight to identify optimal solutions and optimal ranges of design variables. Hybrid cooperative/non-cooperative game was developed to identify the optimal design based on the major stakeholders' preferences.

10.2.3 Lessons Learnt

- The single performance/cost related objective, or the monetization of certain but not all attributes would definitely neglect some priorities and needs of stakeholders that could be critical in the Multi Objective Optimization. It was found that different optimal designs were obtained, depending on which value model was used, or which single objective was selected for MDO. Thus, only a systematic *multi-criteria* approach, such as the multi-attribute utility theory with its comprehensive theoretical structure, can address all preferences of the stakeholders through their corresponding value models.
- In the development of a value model for a specific stakeholder, the preferences of a number of individuals/experts need to be incorporated frequently. Especially in the conceptual design phase when the set of alternatives is not finalized, instead of averaging the

rankings of a set of design alternatives, a synthesized AHP group value model should be obtained through the aggregation of the preferences of the individuals, all with the same objectives but different quantitative preferences.

- The stakeholders involved during the lifecycle of the designed system have different objective functions, based on their Objectives/Attributes Hierarchies. In general, one objective function will have no maximum where the other function has one and, as discussed, MAUT is inappropriate to aggregate the preferences of more than one stakeholders. Game Theory is an effective way to combine these objective functions in a game among the players. In game modelling of engineering design the players' incentives, modelled by their payoff/objective functions, are included in the design process to address their preferences and strategic interactions through the cooperative and non-cooperative non-zero sum games respectively.
- This research made special effort to explore the widest possible design space by including alternative concepts and design configurations or even considering strategic choices as design variables. However, the design space has to be limited to a certain extent to keep the workload of MDO manageable; thus certain choices have to be made by the designer and a large number of parameters need to be set to reasonable values and kept constant.
- The analysis performed by the lifecycle models is very basic and more information concerning the missions, UAS fleets etc. needs to be available to perform more accurate lifecycle cost assessments, especially in the later design stages.

10.3 Novel Aspects of Research

As stated in the Introduction, this research aimed to add new knowledge by developing a VDD Framework and applying it in the Conceptual Design of a defence system, namely a Small Unmanned Air System. The novel aspects of this research are presented in the next sections.

10.3.1 Aircraft Geometric Topologies Parameterization

In the design space search, a large number of aircraft geometric topologies was parameterised through the introduction of a novel hierarchical coding that was based on fundamental design selections. Basic fundamental design selections were used to generate a multitude of topological aircraft concepts, described by a hierarchical coding composed of 0's and 1's. This representation allowed for the shape definition to be input as an extra variable in the design models, which was then scaled through the use of the appropriate design variables, such as wing span, wing AR, horizontal AR etc. Consequently, the designer considers several aircraft concepts, identifying a different optimal design depending on the user's and other stakeholders' preferences. Based on the results of the MDO, the preferences of the user of the UAS, as reflected in the value/utility models, were found to be critical to the identification of the optimal aircraft configuration:

- For a 'civil' user, focusing mostly on maximizing endurance and minimizing acquisition and lifecycle cost, a monolithic fuselage, V-shape tail, push propeller configuration was the optimal.
- For a 'military' user, interested in maximizing survivability and operational availability (minimizing aircraft losses), the dominant UAS configuration was the monolithic fuselage, T-shape tail, push propeller configuration.

Hence, the incorporation of the largest possible number of different aircraft configurations is essential to the successful MDO. Using the fundamental selections presented in Figure 7-1, a total of 34 different aircraft geometries were generated; however, more alternative design configurations could be added in the UAS design generation.

10.3.2 Multi-Objective Value Model

The *alternative focused* process of having the stakeholder selecting the best from a set of design alternatives was converted to a *value-focused* process of identifying needs and defining average levels of expectations of attributes with the novel multi-objective/attribute value model. Especially during the conceptual design phase when the set of design alternatives is not finalised, the objectivity of the evaluation is maintained by capturing the stakeholder's preferences and expectations with criteria independent of the proposed alternative solutions.

The use of MAUT for value-centric design has been motivated and applied previously, both in industry and in academia, as already discussed in 3.1. However, the novelties introduced with the development of the proposed value model are the following:

- The stakeholder assigns average levels of expectations with respect to the attributes that will give them a 'neutral' response; these neutral points are the basis of this model, used both for the scaling constants K_i and value functions V_i assessments. Based on qualitative characteristics describing the stakeholder's preferences and the neutral values for all attributes provided before the design starts, the ready to use value functions are automatically generated, minimizing the interaction between the stakeholder and the analyst. Thus, different qualitative and quantitative preferences can be incorporated to generate the most appropriate value function in an operational way.
- It was demonstrated in the Assessment of Weighting Factors and Figure 5-2 that, given exactly the same stakeholder's preferences, the employment of different numerical scales, converting verbal preferences to numerical values in AHP, may identify different designs as optimal. To avoid the use of these unjustifiable numerical scales, the attribute neutral points are also employed to compute the scaling factors using the AHP methodology with this multi-attribute value model.
- The aggregation of preferences of individuals, constituting the same stakeholder's group, is also possible through this model, dealing with their interpersonal preferential quantitative conflicts. Instead of averaging the group members' rankings of the set of design alternatives, a synthesized group value model is generated from the individual value models.

This novel multi-attribute value model is less complicated and elaborate than the multi-attribute utility model, since it requires less interaction with the stakeholder to assess their preferences and obtain the value functions. Capturing the stakeholder's preferences and expectations in an objective way, before the design space exploration and independent of information, makes the value model more value focused than the utility model, which is more alternative focused. Both models are characterised by advantages and disadvantages, as already presented in Table 10-1. The value model could be used in all phases of engineering design to define objectively the set of optimal design alternatives, frame and guide engineering design, provided that the stakeholder's preferences are updated based on information from simulation and prototyping. The utility model should be employed as a more thorough approach in the last stages of engineering design, once the list of design alternatives is finalised.

10.3.3 Multi-Stakeholder Engineering Design Game Modelling

Game Theory has been utilised in engineering design as an optimization tool with cooperative or non-cooperative games, modelling decision interactions among stakeholders, system components, disciplines or even technologies as players. Nevertheless, this novel hybrid cooperative/non-cooperative non-zero sum, complete information game is capable of modelling the stakeholders' preferences as well as capturing the interactions between their strategic choices. This hybrid game combines effectively the Nash bargaining solution (NBS), as the axiomatic based outcome of a hidden bargaining process, with the process of strategic interactions between the players in a non-cooperative game.

Game Theory was used to model the interactions and needs of the two major stakeholders, the user and the manufacturer, in engineering design of a defence system through a game played in two levels:

- At the first and lower level, the cooperative non-zero, complete information game uses the Nash bargaining solution (NBS) to identify the single optimal design from the set of all Pareto front design alternatives. This cooperative *outcome focused game* selects the Nash bargaining solution from the set of all potential solutions without involving any explicit bargaining process. The optimal design alternative is determined as the only axiomatic based solution all stakeholders will accept. The main advantage of this functional and elegant approach is that the quality of all design alternatives generated is uniquely determined by the criterion of Nash's product of utilities, resolving the indeterminacy of the Pareto front, to obtain the generalized NBS for *n* players of not equal relative authorities: $\left(v_1(a^*) - v_1(\bar{a})\right)^{\gamma_1} \cdot \left(v_2(a^*) - v_2(\bar{a})\right)^{\gamma_2} \cdot \ldots \cdot (v_n(a^*) - v_n(\bar{a}))^{\gamma_n}$ [168].

- At a higher level, the strategic choices of the stakeholders are considered and placed as additional design variables, constituting the non-cooperative, non-zero, complete information game. These strategic choices are so important that only a non-cooperative *process-focused game* can model the players' strategic interactions. Through this approach, the strategies selected are defined not only by the values of the players' payoff functions but are also dependent of the expectations they have about the other players' most likely strategies.

Thus, the selection of the specific strategies of the stakeholders (user and manufacturer in this case), based on their *strategic incentives*, is generated as the Nash equilibrium, among all NBS obtained in the first step.

In the MDO results of 9.2.2, it was found that the employment of this hybrid game instead of a pure cooperative game identified different optimal strategies. For the specific user's and manufacturer's preferences and achieved values of utility functions, if the strategic choices were considered as mere design variables in a pure cooperative game, the improved reliability of the aircraft components should be selected; while in the hybrid game, the original reliability of the aircraft components should be the optimal strategy for the manufacturer in a Nash equilibrium.

Modelling engineering design through this hybrid game is considered more effective than the pure cooperative or non-cooperative game models, since this novel simultaneous employment of the cooperative and non-cooperative games offers the benefits of both approaches:

- Address the stakeholders' preferences in a functional, outcome-focused way. The high indeterminacy of design alternatives is resolved with equation 6-5, identifying the NBS of the cooperative games.

- At the same time, it models the stakeholders' interactions for some important strategic choices with a process-focused non-cooperative game.

Thus, this game yields a single optimal solution, identified as both Nash equilibrium and Nash bargaining solution, capturing effectively both the conflict and cooperation between the stakeholders through this well-defined hybrid mathematical model.

10.4 Recommendations for Future Work

VDD has been recognised as a key enabler in improving engineering design and abating the deficiencies of the traditional SE approach. In the road map of future work, many different routes have been identified for encouraging research and are discussed in this section. So far, this research regarding the application of VDD philosophy in the design of a defence system has been experimental and employed mostly simplified and approximated models.

The next phase of this research should be the application of this methodology and framework in a project that would address all difficulties and complexities of designing an actual UAS. This application of the VDD framework should concentrate on the following:

- Improvement of the aircraft design and lifecycle cost models or development of other more accurate, to be used in the later stages of design. Isight as the integrating design tool allows for their easy amendment and replacement within the developed VDD framework.
- As discussed in 10.2.2, concerning the research objectives achieved, other technologies should also be explored and included in the design space search, such as other propulsion types (i.e. internal combustion engine, fuel cells), different aircraft types (such as the rotary wing aircraft, lighter than air aircraft). Also, the employment of a wider range of UAS platforms would demand the incorporation of more aircraft geometries or including other design parameters (such as the aerofoil selection) that were kept constant, as design variables in the MDO.
- The main focus of this research has been to present the VDD implementation process, rather than identifying optimal designs based

on the stakeholders' preferences. Thus, the actual preferences of experts/individuals, constituting the stakeholder/user's group of decision makers, should be incorporated in the corresponding value model. They could also provide adequate information and data concerning the whole lifecycle of the designed UAS, in terms of operations and maintenance performed. This data/information should probably demand to revisit and adjust not only the stakeholders' objectives/attributes hierarchies of Figure 4-4, but also all MCS models used in the lifecycle simulation. The simple operational scenario, considered acceptable for the conceptual design phase, could be enriched or even replaced for running more realistic lifecycle simulations.

- Instead of assuming a cost plus fee (CPF) contract type for the manufacturer, other options could be explored. A firm fixed price (FFP) contract type or a hybrid payment method could be modelled in the manufacturer's objective function within the multi-stakeholder value modelling.
- MAUT could be implemented in the development of appropriate value models for all stakeholders, following the approach described in 5.4, to address and synthesize their preferences in a practical manner. Further validation of the multi-objective value model based on the results of multi-objective utility model would also be beneficial.
- Other strategic choices could be explored in the non-cooperative game among the stakeholders to identify the Nash equilibrium through their strategic interactions. For instance, performance requirements set by the user, such as different values of maximum and design speed, would greatly affect not only the operational capabilities of the UAS but also the calculated lifecycle cost (maximum speed is a defining parameter in all DAPCA parametric equations) and could be included as other strategic choices.
- Furthermore, other stakeholders could be included as players in the non-cooperative game, identifying a possibly different Nash equilibrium. Such players in the non-cooperative game could be part suppliers, public/local communities or even competitors of the manufacturer, provided that their strategic choices were first identified and their objective functions were developed and evaluated appropriately.

- In the survivability assessment, a survivability analysis software, such as AGILE (Analytic Gaussian Intersection of Lethality Engagement) [87], predicting the vulnerability of the aircraft target through the use of Gaussian components, could be utilized to reduce or even avoid completely the need for MCS methods using questionable historic survivability data.
- Finally, and most importantly, to capture the complexity of human decision making under uncertainty, biases, emotions and feelings of the individuals as decision makers, apart from rational behaviour, should be incorporated in engineering design. Several experiments and decision making paradoxes have manifested the deficiency of rationality assumption employed by classical decision making and game theory predictions, with humans violating the expected utility theory hypotheses and making irrational choices. After all, the decision making model applied in engineering design should identify the stakeholders' optimal choices, based both on their rationality and their personal intuitive feelings, emotions and behavioural biases.

10.5 Concluding Remarks

The main objective of this research has been the development of a VDD framework which, through automated search, identifies successfully the optimum design, addressing major design uncertainties and all preferences/risk attitudes of all stakeholders involved. The implementation of VDD in a multi-objective and multi-stakeholder engineering design has been manifested and systematized. The extent to which this framework deals with all major design uncertainties depends on the current phase of engineering design. The decision analysis methods used within the context of this framework focused on the identification of the value, reflecting the needs of all stakeholders.

In value modelling, as Collopy [102] successfully points out, one should "*not need to start from scratch. Brilliant thinkers, from Daniel Bernoulli to John Von Neumann to Kenneth Arrow have worked through many of the fundamental issues underlying value models*". Ultimately, the biggest challenge lay mostly in the value model formulation and Utility Theory was used in conjunction with Game Theory as the theoretical axiomatic foundations for addressing the stakeholders' risk and preferences attitudes. Above all, this framework has converted engineering design to a decision making analysis with multiple objectives and multiple stakeholders considered.

Appendices

Appendix A - Publications

A.1 Journal Papers

Papageorgiou, E., Eres, H., Scanlan, J., *Value Driven Conceptual Design of Unmanned Air System for a Defence Application.* Journal of Aerospace Operations, 1-29, (accepted for publication).

Papageorgiou, E., Eres, H., Scanlan, J., *Value Modelling for Multi-Stakeholder and Multi-Objective Optimization in Engineering Design.* Journal of Engineering Design, 1-40, (under review).

A.2 Conference Paper

Papageorgiou, E., Eres, H., Scanlan, J., *Value Driven Conceptual Design of Unmanned Air System for Defence Applications*. In *15th AIAA Aviation Technology, Integration, and Operations Conference, Aviation Forum* 2015, Dallas, US, 22-26 June 2015.

A.3 Poster

Papageorgiou, E., Eres, H., Scanlan, J., *Value Driven Conceptual Design of Unmanned Air System for Defence Applications*. In *2015 Autonomous Systems Underpinning Research (ASUR) Conference*, ARK Conference Centre, Basingstoke, Hampshire, UK, 17 July 2015.

Appendix B Various Data

B.1 Aircraft Configurations

	AIRCRAFT GEOMETRIC TOPOLOGIES
1	MONOLITHIC BODY WITH HORIZONTAL TAIL TWO VERTICAL FINS PUSHER PROPELLER ALL MOVING CONTROL SURFACES
2	MONOLITHIC BODY WITH HORIZONTAL TAIL TWO VERTICAL FINS PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
3	TWIN BOOM WITH HORIZONTAL TAIL TWO VERTICAL FINS PUSHER PROPELLER ALL MOVING CONTROL SURFACES
4	TWIN BOOM WITH HORIZONTAL TAIL TWO VERTICAL FINS PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
5	MONOLITHIC BODY WITH HORIZONTAL TAIL TWO VERTICAL FINS TRACTOR PROPELLER ALL MOVING CONTROL SURFACES
6	MONOLITHIC BODY WITH HORIZONTAL TAIL TWO VERTICAL FINS TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES
7	TWIN BOOM WITH HORIZONTAL TAIL TWO VERTICAL FINS TRACTOR PROPELLER ALL MOVING CONTROL SURFACES
8	TWIN BOOM WITH HORIZONTAL TAIL TWO VERTICAL FINS TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES
9	MONOLITHIC BODY ONE VERTICAL FIN WITH CANARD PUSHER PROPELLER ALL MOVING CONTROL SURFACES
10	MONOLITHIC BODY ONE VERTICAL FIN WITH CANARD PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
11	MONOLITHIC BODY ONE VERTICAL FIN WITH CANARD TRACTOR PROPELLER ALL MOVING CONTROL SURFACES

12	MONOLITHIC BODY ONE VERTICAL FIN WITH CANARD TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES
13	MONOLITHIC BODY WITH HORIZONTAL TAIL ONE VERTICAL FIN PUSHER PROPELLER ALL MOVING CONTROL SURFACES
14	MONOLITHIC BODY WITH HORIZONTAL TAIL ONE VERTICAL FIN PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
15	MONOLITHIC BODY ONE VERTICAL FIN WITH T SHAPE TAIL PUSHER PROPELLER ALL MOVING CONTROL SURFACES
16	MONOLITHIC BODY ONE VERTICAL FIN WITH T SHAPE TAIL PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
17	MONOLITHIC BODY WITH HORIZONTAL TAIL ONE VERTICAL FIN TRACTOR PROPELLER ALL MOVING CONTROL SURFACES
18	MONOLITHIC BODY WITH HORIZONTAL TAIL ONE VERTICAL FIN TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES
19	MONOLITHIC BODY ONE VERTICAL FIN WITH T SHAPE TAIL TRACTOR PROPELLER ALL MOVING CONTROL SURFACES
20	MONOLITHIC BODY ONE VERTICAL FIN WITH T SHAPE TAIL TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES
21	FLYING WING PUSHER PROPELLER
22	FLYING WING TRACTOR PROPELLER
23	MONOLITHIC BODY WITH V SHAPE TAIL PUSHER PROPELLER ALL MOVING CONTROL SURFACES
24	MONOLITHIC BODY WITH V SHAPE TAIL PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
25	MONOLITHIC BODY WITH Y SHAPE TAIL PUSHER PROPELLER ALL MOVING CONTROL SURFACES

26	MONOLITHIC BODY WITH Y SHAPE TAIL PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
27	MONOLITHIC BODY WITH Y SHAPE TAIL TRACTOR PROPELLER ALL MOVING CONTROL SURFACES
28	MONOLITHIC BODY WITH Y SHAPE TAIL TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES
29	MONOLITHIC BODY WITH V SHAPE TAIL TRACTOR PROPELLER ALL MOVING CONTROL SURFACES
30	MONOLITHIC BODY WITH V SHAPE TAIL TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES
31	TWIN BOOM WITH INVERTED V SHAPE TAIL PUSHER PROPELLER ALL MOVING CONTROL SURFACES
32	TWIN BOOM WITH INVERTED V SHAPE TAIL PUSHER PROPELLER NOT ALL MOVING CONTROL SURFACES
33	TWIN BOOM WITH INVERTED V SHAPE TAIL TRACTOR PROPELLER ALL MOVING CONTROL SURFACES
34	TWIN BOOM WITH INVERTED V SHAPE TAIL TRACTOR PROPELLER NOT ALL MOVING CONTROL SURFACES

B.2 UAS Parameters

Design Variables

Design Variable	Range	Units	Note
Wing aspect ratio	6-12		
Wing span	1.25-1.75	m	
Wing taper ratio	0.3-0.7	m	
Battery capacity	6-10	Ahr	

Wing Position relative to the fuselage (from the front bulkhead)	0.25-0.35	m	
Horizontal tail aspect ratio	3-5		
Vertical fin aspect ratio	1.2-1.8		
Canard aspect ratio	5-7		
General component reliability	0.9-0.99		Used in lifecycle cost assessment models, when components are replaced
UAS replacement time interval	500-1000	Flight hours	Used in lifecycle cost assessment models, when no components but whole aircraft is replaced

Constant Parameters

UAS Parameter	Value	(units)	Note
Max speed	25	m/sec	
Landing speed	15	m/sec	
Take-off speed	16.5	m/sec	1.1*landing speed
Design speed	17	m/sec	
Operational speed	17	m/sec	
Payload mass	0.15	kg	Use a GOPRO HERO3 camera, with 5cm depth (150gr) and width
Payload width, depth	**0.05**	**m**	
Payload length	0.25	m	
Maximum Load Factor	6		
Main Spar Location	0	m	
Airfoil Lift Coefficient Slope, C_{l_a}	0.1		
Wing Sweep	0 / 15	Degrees	15° for the flying wing configuration, 0° for other configurations

Wing twist	0 / 2	Degrees	0° for the flying wing configuration, 2° for other configurations
Aerodynamic Efficiency Factor	1.2		
Angle of Incidence of the wing root chord	2	Degrees	
NACA airfoil for all configurations other than flying wing	23015		
Airfoil for the flying wing configuration	FAUVEL 14		
Aileron chord ratio	0.25		
NACA airfoil for horizontal tail, fin, V-shape tail, Y-shape tail, canard	0012		
Fin tailplane volume coefficient	0.04		Table 6.4, Page 160 Typical Values for Volume Coefficient adjusted for different configurations, Raymer [5]
horizontal tailplane volume coefficient	0.6		Use Table 6.4, Page 160, Raymer's Aircraft Design and adjust for different configurations
Canard tailplane volume coefficient	0.75		Set to 0.75(0.6-0.9), Aircraft Design, Ajoy Kumar Kundu
Fineness Ratio	8 / 5		Use 8 for monolithic configurations and 5 for tail boom configurations
Total electric propulsion efficiency	0.5		
Operating altitude	500	ft	

Air density at operating altitude	1.20717	Kg/m^3	
Wing average airfoil ideal lift coefficient	0.3 / 1		0.3 for NACA 23015, 1 for FAUVEL 14%
Wing average airfoil angle of attack for the ideal lift coefficient	1.6 / 8		1.6 for NACA 23015, 8 for FAUVEL 14%
Coefficient of moment with respect to the ac of the airfoil	-0.05 / 0.03		-0.05 for NACA 23015, 0.03 for FAUVEL 14%
Maximum lift coefficient of the clean wing	1.3 / 1.4		1.3 for NACA 23015, 1.4 for FAUVEL 14%
Maximum load factor	6		
Wing spar tube thickness	10	%	
Tail boom tube thickness	10	%	
Ult. carbon fibre maximum strength	600	Mpa	
Ult. carbon fibre density	1700	Kg/m3	
Ult. Carbon fibre Young's modulus	95.0E9	N/m2	
Structural calculations factor of safety	1.66		
Cruising altitude air density (500ft)	1.207	Kg/m3	
Horizontal tail maximum lift coefficient	1.5		

Tail boom maximum deflection angle	5°	degrees	
Wing/fuselage equivalent sand roughness for drag polar calculations **Table 3.1, [199]**	3.00E-3	inch	
Tail boom surface equivalent sand roughness for drag polar calculations **Table 3.1, [199]**	1E-2	inch	
Propeller number of blades	2		
Battery discharge parameter, *n*	1.3		
Battery hour rating, *Rt*	1	hr	
Battery voltage	11.2	V	
Maximum propeller tip speed	200	m/sec	
Fuselage nylon density	900	Kg/m3	
Camera horizontal field-of-view in radians	0.351658	rad	
Camera vertical field-of-view in radians	0.351658	rad	
Camera horizontal number of pixels of the sensor	720		

Camera horizontal number of pixels of the sensor	640		
Camera tilt angle from the flight axis, in radians Pi/2 points straight down, 0 points towards the horizon	1.0471204	rad	
Battery length	0.14	m	
Battery width	0.044	m	

Acquisition Cost Model: Constant Parameters

Design Parameter	Value	Units
UAS fleet size	30	
Number of UAS for flight testing	3	
Camera GOPRO Hero3 price	300	£
Servo price	40	£
Aerial price	50	£
Autopilot price	300	£
Wiring and connectors cost	50	£
Receiver price	120	£
Linkage price	10	£
Cost of carbon spar	454	£/m^2
Spar cutting efficiency	0.6	
Covering efficiency	0.8	
Foam cutter volume efficiency	0.7	
Baseline wing assembly finisching rate	1800	s/m
Foam assembly finisching rate	22500	s/m^3

SLS nylon price per volume	25000	£/m^3
Foam price per volume	250	£/m^3
Wing skin foam price per volume	500	£/m^3
Glass fibre cloth cost	10	£/m^2
Labour cost	50	£/hr
Wing covering finishing rate	2400	s/m^2
Control surface assembly finisching rate	3600	s/m^2
Engineering quality control cost rate	50	£/hr
DC Power Distribution Box 1000W (12V DC-230V Sealey PI1000. For ground control station cost	125	£
Ruggedized Computer Dell Lattitude E6420 XFR. For ground control station cost	2000	£
Digital Watchdog DW-VMAX-TP500G, Ruggetized Mobile DVR. For ground control station cost	533	£
Orion 20rct, 20'' CCTV Monitor. For ground control station cost	369	£
Integrated Data/Video Communications Box (D/V Comms Box). For ground control station cost	300	£
15.4 dB Comet Omni 2.4 GHz Antenna. For ground control station cost	74.67	£

Lifecycle and Survivability Modelling: Constant Parameters

Parameter	Value	Units
Annual flight hours	3000	hr

Program duration	10	years
Airframe Weibull β parameter	2	
Airframe Weibull n parameter	2000	hr
Autopilot Weibull β parameter	2	
Autopilot Weibull n parameter	500	hr
Battery Weibull β parameter	4	
Battery Weibull n parameter	1000	Discharging-charging cycles
Electronic speed controller Weibull β parameter	2	
Electronic speed controller Weibull n parameter	500	hr
Ground control station Weibull β parameter	4	
Ground control station Weibull n parameter	3000	hr
Motor Weibull β parameter	2	
Motor Weibull n parameter	1000	hr
Propeller Weibull β parameter	2	
Propeller Weibull n parameter	300	hr
Receiver Weibull β parameter	2	
Receiver Weibull n parameter	1000	hr
Servo Weibull β parameter	2	
Servo Weibull n parameter	500	hr
Survivability calculations		
UAS battle damage rate	0.01	Probability of UAS been hit
Airframe critical hit probability	0.3	Probability of component hit been critical for UAS
Airframe in UAS hit probability	0.64	Probability of component been hit
Avionics critical hit probability	0.3	Probability of component hit been critical for UAS

Avionics in UAS hit probability		Probability of component been hit
Battery critical hit probability	0.4	Probability of component hit been critical for UAS
Battery in UAS hit probability	0.12	Probability of component been hit
Propulsion critical hit probability		Probability of component hit been critical for UAS
Propulsion in UAS hit probability		Probability of component been hit
Discount rate	0.07	

B.3 Regression Data / Formulae

- For the Drag Polar Method, [199] of 7.3.3:
  - $C_{fWing,}$ the flat plate skin friction coefficient of the wing and the tail/canard surfaces in equation 7-8, which as a function of skin roughness, Mach number and Reynolds number is calculated based on the reference length/wing mean aerodynamic chord, based on the following data from figures 3.1, 3.2 of [199]:

Re	C_f at M=0	C_f at M=0.3
400000	0.00530	0.00526
500000	0.00508	0.00501
600000	0.00490	0.00486
700000	0.00475	0.00470
800000	0.00465	0.00460
900000	0.00453	0.00450
1000000	0.00445	0.00442
2000000	0.00395	0.00390
3000000	0.00370	0.00365
4000000	0.00350	0.00347
5000000	0.00338	0.00335
6000000	0.00328	0.00322

7000000	0.00320	0.00315
8000000	0.00314	0.00310
9000000	0.00308	0.00302
10000000	0.00301	0.00298
100000000	0.00213	0.00210
1000000000	0.00159	0.00155

Hence, the following regression formula is obtained:

$$C_{fWing} = 0.049\ Re^{-0.175}$$

- The w zero lift drag factor in equation 7-11 is obtained using data from fig.3-13, [199]:

AR	w for taper ratio=1	w for taper ratio=0.5
2	0.0009	0.0009
4	0.0015	0.0015
6	0.0019	0.0019
8	0.00211	0.0021
10	0.00221	0.00221
12	0.00223	0.00223
14	0.00222	0.00222

Hence, the following regression formula is obtained for w as a function of the wing aspect ratio:

$$w = 0.0000009722\ AR^3 - 0.0000386\ AR^2 + 0.0005061\ AR + 0.00003429$$

- n, in equation 7-12 is the ratio of drag of a finite cylinder to the drag of an infinite cylinder obtained through regression based on the fuselage fineness ratio. The data from fig. 3.16, [199] is used:

fineness ratio	n
2	0.56
4	0.6
6	0.635
8	0.66

10	0.685
12	0.705
14	0.725
16	0.74
18	0.75
20	0.76
22	0.768
24	0.775
26	0.78
28	0.785

Then, the regression formula is the following:

$$n = 0.000008208\, finess_{ratio}{}^{3} - -0.0007164\, finess_{ratio}{}^{2} + 0.02318\, finess_{ratio} + 0.5175$$

- For the performance calculations of 7.3.4:
  - Using the following data for commercial Lithium-ion Polymer Batteries:

BATTERY	CAPACITY	BATTERY WEIGHT	MAX CURRENT	PACK VOLTAGE	CELLS	CONNECTED	VOLT PER CELL	Price ($)	Price (GBP)
BLACKLINE 3200 35C	3.206	0.288	112	11.100	3	SERIES	3.700		
EPOWER 2500XP 15/25C	2.500	0.192	63	11.100	3	SERIES	3.700		
EPOWER 3700XP 15/25C	3.700	0.285	93	11.100	3	SERIES			
EPOWER 5000XP 15/25C	5.000	0.360	125	11.100	3	SERIES			
EPOWER 1200XPR 15/25C	1.200	0.086	30	11.100	3	SERIES			
FLIGHTPOWER 1800 20C	1.800	0.146	36	11.100	3	SERIES			

FLIGHTPOWER 2100 20C	2.100	0.191	42	11.100	3	SERIES			
FLIGHTPOWER 3300 20C	3.300	0.284	66	11.100	3	SERIES			
G.PLANES ELECTRIFY 5000 20C	5.000	0.366	100	11.100	3	SERIES			
HYPERION HP-LVX 2000 20C	2.000	0.140	40	11.100	3	SERIES			
BLACKLINE 4400 35C	4.400	0.367	154	11.100					
FLIGHTPOWER 3700 20C	3.700	0.298	74	11.100					
POLYQUEST 6000XP 15C	6.000	0.522	90	11.100					
THUNDERPOWER 5000SX 22/50C	5.000	0.366	250						
POLYQUEST 4500	4.500	0.375	90						
LITESTROM 5000VX 20/25C	5.000	0.378	125						
Turnigy 8400 mAh,3S	8.400	0.641	40	11.100	3	SERIES		80.55	120.825
Zippy Flightmax 8000 mAh,3S	8.000	0.644	30	11.100	3	SERIES		48.50	72.750
Turnigy 6400mAh,3S	6.400	0.506	40	11.100				61.95	92.925
Turnigy 6000mAh,3S	6.000	0.481	25					51.94	77.910
Turnigy 5000mAh,3S	5.000	0.570	45					53.76	80.640
Zippy Flightmax 5000mAh,3S	5.000	0.462	45					41.09	61.635
Turnigy 4400mAh, 3S	4.400	0.399	65					53.03	79.545

Turnigy 4000mAh, 3S	4.000	0.375	45					40.01	60.015
Zippy Flightmax 5000maAh,3S 20C	5.000	0.418	20					32.71	49.065
Turnigy nanotech 3850mAh, 3S	3.850	0.349	65					46.38	69.570
Turnigy nanotech 3300mAh, 3S	3.300	0.407	45					33.02	49.530
Turnigy 2650mAh, 3S	2.650	0.337	40					26.53	39.795
Zippy Flightmax 3000mAh,3S	3.000	0.331	40					30.00	45.000
Turnigy 2650mAh, 3S, 20C	2.650	0.309	20					12.77	19.155
Zippy Flightmax 2450 3S, 30C	2.450	0.285	30					17.73	26.595
Turnigy nanotech 2200 3S, 45-90	2.200	0.255	45					20.95	31.425
Turnigy nanotech 1800 3S, 25-50	1.800	0.241	25					16.86	25.290
Turnigy 1500 3S, 20C	1.500	0.215	20					9.65	14.475
Turnigy 1300 3S, 30C	1.300	0.171	30					9.88	14.820
Zippy compact 1500 3S, 35C	1.500	0.148	35					14.46	21.690

The following regression formulae are obtained:

- Battery weight (kg) calculated based on battery capacity (A-h):

$$battery_{weight} = 0.070121 battery\_capacity + 0.072083$$

- Battery price (£) calculated based on battery capacity (A-h):

$$battery\_price = 12.626\ battery\_capacity + 3.1391$$

- Using the following data for commercial off-the-shelf Electronic speed controllers (ESC) appropriate regression formulae are obtained:

ESC Model	Current	Batt Cells	Weight (kg)	Price ($)	Price (GBP)
HobbyKing Reb Brick 10A	10.000	2-3S	0.007	6.070	4.047
Turnigy MultiStar 15A	15.000	2-3S	0.025	7.840	5.227
HobbyKing SS Series 15-18A	15.000	2-3S	0.015	6.500	4.333
Towerpro 18A	18.000	3S	0.020	9.990	6.660
Turnigy MultiStar 20A	20.000	2-4S	0.030	10.070	6.713
HobbyKing Reb Brick 30A	30.000	3S	0.022	8.270	5.513
Turnigy AE-25A	25.000	3S	0.039	10.580	7.053
HobbyKing SS Series 25-30A	25.000	3S	0.040	9.230	6.153
HobbyKing SS Series 35-40A	35.000	3S	0.027	11.310	7.540
Turnigy SuperBrain 40A	40.000	3S	0.045	29.990	19.993
HobbyKing 40A UBEC	40.000	3S	0.036	16.690	11.127
Mystery 40A Brushless	40.000	2-6S	0.030	19.500	13.000
HobbyKing Red Brick 50A	50.000	2-7S	0.040	11.520	7.680
Turnigy Plush 60A	60.000		0.060	34.580	23.053
Turnigy Trust 70A	70.000	2-6S	0.065	28.750	19.167
HobbyKing Red Brick 70A	70.000	2-7S	0.077	18.720	12.480
Birdie 80A	80.000	2-6S	0.086	27.520	18.347
Birdie 90A	90.000	2-6S	0.087	31.200	20.800
Turnigy AE-100A	100.000	2-6S	0.079	40.760	27.173
HobbyKing Red Brick 125A	125.000	2-7S	0.085	30.000	20.000
HobbyKing SS Series 90-100	90.000	2-7S	0.085	24.830	16.553
HobbyKing RedBrick 100A	100.000	2-7S	0.093	30.000	20.000
Birdie 180A	180.000	2-6S	0.104	41.910	27.940

Birdie 190A	190.000	2-6S	0.109	38.430	25.620
HobbyKing RedBrick 200A	200.000	2-7S	0.108	39.600	26.400

- ESC weight (kg) based on current (A):

$$ESC\_weight = 0.0362\ \ln(current) - 0.0851$$

- ESC price (£) based on current (A):

$$ESC\_price = 0.125\ current + 5.9121$$

- Using the following data for commercial off-the-shelf motors and propellers appropriate regression formulae are obtained:

Manufacturer	Model	Diameter (mm)	Length (mm)	Watts	Amps	Weight (Kg)	Load RPM	Motor prices (GBP)	Prop Dia. (in)	Prop Pitch (in)
Graupner	Speed 280	26.92	31.75	12	4.00	0.031	8000		6.00	4.0
Graupner	Speed 280	26.92	31.75	19	3.00	0.031	2000		9.00	7.0
Graupner	Speed 480 Race 7.2	32.77	47.63	67	10.00	0.105	18700		5.00	5.0
Graupner	Speed 280 Race	26.92	31.75	29	4.00	0.040	14500		4.70	2.4
Graupner	Speed 480 7.2	32.77	47.63	80	10.00	0.100	11800		6.00	4.0
Graupner	Speed 700 8.4	42.86	66.68	305	31.00	0.350	7700		10.00	6.0
Graupner	Speed 700 12	42.86	66.68	372	25.00	0.350	5900		12.00	8.0
Graupner	Speed 700 8.4	42.86	66.68	399	32.00	0.350	3350		14.00	7.0
Graupner	Speed 700 9.6	42.86	66.68	390	31.00	0.320	7700		10.00	6.0
Graupner	Speed 480 BB Race 7.2	32.77	47.63	130	16.00	0.105	15500		5.00	5.0
Graupner	Speed 700 9.6	42.86	66.68	402	27.00	0.320	3350		12.00	7.0

Graupner	Speed 700 12	42.86	66.68	496	25.00	0.350	2950		16.00	8.0
Graupner	Speed 280 Race	26.92	31.75	58	5.80	0.040	3630		10.00	7.0
GRAUPNER	O.S. Motor OMA-5020-490	50.00	52.50	1020	90.00	0.350	490	151.200	5.90	3.2
GRAUPNER	HPD 4325-1425 18,5V	43.00	46.50	1000	60.00	0.233	1425	80.400	3.54	2.0
GRAUPNER	O.S. Motor OMA-3825-750	37.50	48.30	584	75.00	0.190	750	103.200	5.11	3.2
GRAUPNER	O.S. Motor OMA-5025-375	50.00	57.50	1295	90.00	0.405	375	168.000	5.91	3.2
GRAUPNER	O.S. Motor OMA-3815-1000	37.00	37.80	504	55.00	0.130	1000	88.800	4.73	2.4
GRAUPNER	O.S. Motor OMA-3820-1200	37.50	43.30	428	75.00	0.155	1200	94.800	4.33	2.0
GRAUPNER COMPACT 850 30 V		65.00	85.00	1800	50.00	0.950			23.60	7.9
GRAUPNER COMPACT 555 18,5 V		49.80	55.50	800	70.00	0.320	660	186.000	15.75	9.8
GRAUPNER INLINE 570 14,8V		36.50	57.00	555	30.00	0.200				

GRAUPNEL INLINE 750 14,8V		36.00	75.00	1200		0.370	1035	165.600		
GRAUPNER COMPACT 630 37V		84.00	63.00	1850	50.00	0.652			23.00	11.0
GRAUPNER COMPACT 555 20 V		49.80	55.50	960	60.00	0.320	510	178.800	15.75	5.9
GRAUPNER COMPACT 345Z 7,4V		35.50	34.50	389	27.00	0.105	1500	70.740	9.85	5.9
GRAUPNER COMPACT 135 7,4V		27.70	13.50	78	7.50	0.019	1720	119.940	8.15	2.0
GRAUPNER COMPACT 345Z 11.1V		35.50	34.50	518	26.00	0.105	900	70.740	9.06	4.7

Propeller	Propeller Diameter (in)	Propeller Diameter (mm)	Propeller Price (£)
APC 10.5X4.5	10.500	266.700	2.633
APC 11.5X6	11.500	292.100	2.280
APC 11.5X4	11.500	292.100	2.647
APC 10X5E	10.000	254.000	1.953

APC 11X5.5E	11.000	279.400	2.107
APC 11X7E	11.000	279.400	2.107
APC 11X6	11.000	279.400	1.907
APC 12X6E	12.000	304.800	2.633
APC 13X7	13.000	330.200	3.260
APC 13X9	13.000	330.200	5.300
APC 13X8	13.000	330.200	3.260
APC 13X6.5E	13.000	330.200	3.260
APC 14X10E	14.000	355.600	3.260
APC 14X8.5E	14.000	355.600	3.260
APC 15X6E	15.000	381.000	4.133
APC 15X4E	15.000	381.000	4.133
APC 16X8E	16.000	406.400	5.000
APC 16X10E	16.000	406.400	5.000
APC 17X8E	17.000	431.800	6.200
APC 17X10E	17.000	431.800	6.200
APC 18X8E	18.000	457.200	7.600
APC 18X10E	18.000	457.200	7.600
APC 18X12E	18.000	457.200	7.600
APC 19X8E	19.000	482.600	8.800
APC 19X12E	19.000	482.600	8.800
APC 20.5X14E	20.500	520.700	10.000
APC 20X10E	20.000	508.000	10.000
APC 21X13E	21.000	533.400	10.000

APC 22X12E	22.000	558.800	13.333
APC 22X10E	22.000	558.800	13.333
APC 24X12E	24.000	609.600	16.667
APC 26X13E	26.000	660.400	23.333
APC 26X15E	26.000	660.400	23.333
APC 27X13E	27.000	685.800	26.667

- Motor power (Watt) based on current (A):
- $motor\_power = 4.9296\ current^{1.2668}$
- Motor weight (kg) based on motor power (Watt):
- $motor\_weight = 0.0003404\ motor\_power + 0.058476$
- Motor RPM based on motor power (Watt):
- $motor\_RPM = 7289.4\ e^{-0.002\ motor\_power}$
- Motor length (mm) based on motor power (Watt):
- $Motor\_length = 0.0189\ motor\_power + 40.445$
- Motor Diameter (mm) based on motor power (Watt):
- $Motor_{diameter} = 0.020929\ motor_{power} + 28.8766$
- Motor price (£) based on motor weight (kg):
- $motor\_price = 191.189\ motor\_weight + 42.504$
- Propeller pitch based on propeller diameter (m):
- $propeller\_pitch = 0.3834\ propeller\_diameter + 1.6112$
- Propeller weight based on propeller diameter (m):

$$propeller\_weight = 110\ propeller\_diameter/0.51$$

- Propeller price (£) based on propeller diameter (m):

$$propeller\_price = 50\ propeller\_diameter$$

- For the weights calculations of 7.3.5, the weights of several UAS components are computed based on the weight parameters of similar components, adjusted with their calculated geometry:
  - Wing box weight (g) based on wing area (m^2):

$$wing\_box\_weight = 187.5\ wing\_area$$

  - Wing skin weight (g) based on wing area (m^2):

$$wing\_skin\_weight = 257.81\ wing\_area$$

  - Wing covers weight (g) based on wing skin weight (g):

$$wing\_cover\_weight = 0.315\ wing\_skin\_weight$$

- Ailerons weight (g) based on wing span (g):

$$aileron\_weight = 22.8806\ wing\_span$$

- Wing connection weight (g) based on wing spar weight (g):

$$wing\_connection\_weight = 150\ wing\_spar\_weight/270$$

- Tail booms connection weight (g) based on tail boom weight (g):

$$tail\_boom\_weight = 150\ tail\_boom\_weight/250$$

- Rudder connection weight (g) based on tail fin weight (g):

$$rudder\_connection\_weight = 50\ tail\_fin\_weight/269$$

- Elevator connection weight (g) based on tail plane weight (g):

$$elevator\_connection\_weight = 50\ tail\_plane\_weight/600$$

- Canard connection weight (g) based on canard weight (g):

$$canard\_connection\_weight = 50\ canard\_weight/600$$

- Motor bulkhead weight (g) based on motor weight (g):

$$motor\_bulkhead\_weight = 300\ motor\_weight/2000$$

- Tail fin, tail plane, canard weight (g) based on tail fin, tail plane, canard area (m^2):

$$tail\_fin/plane/canard\_weight = 2155.7\ tail\_fin/plane/canard\_area + 70$$

- For the stability calculations of 7.3.6:
  - The k_f coefficient in the fuselage contribution to pitching moment coefficient $\frac{dC_m}{dC_L}$ in equation 7-24 is computed based on the % position of the quarter chord in the fuselage, after fitting the following data from http://adg.stanford.edu/aa241/stability/staticstability.html:

wing position	Kf
10.000	0.115
20.000	0.172
30.000	0.344
40.000	0.487
50.000	0.688
60.000	0.888
70.000	1.115

The following regression formula is obtained:

$$k_f = 1.314\ 10^{-4} \left(\bar{x}_{\frac{c}{4}}\right)^2 + 6.539\ 10^{-3}\ \bar{x}_{\frac{c}{4}} + 1.969\ 10^{-2}$$

- In equation 7-25 to compute the yawing moment coefficient slope C_{n_ψ} due to the contribution of the fuselage, the coefficient k_β needs to be computed first. Using the data from figure 8-4, [203]:

$\frac{L_f}{h}$	$\frac{d}{L_f}$	k_β
2.500	0.100	0.173
3.000	0.100	0.149
4.000	0.100	0.120
5.000	0.100	0.080
6.000	0.100	0.051
7.000	0.100	0.038
8.000	0.100	0.024
10.000	0.100	0.002
2.500	0.200	0.200
3.000	0.200	0.175
4.000	0.200	0.140
5.000	0.200	0.120
6.000	0.200	0.070
7.000	0.200	0.065
8.000	0.200	0.055
10.000	0.200	0.035
2.500	0.300	0.230
3.000	0.300	0.210
4.000	0.300	0.170
5.000	0.300	0.140
6.000	0.300	0.115
7.000	0.300	0.095
8.000	0.300	0.075
10.000	0.300	0.065
2.500	0.400	0.260
3.000	0.400	0.235
4.000	0.400	0.210
5.000	0.400	0.170
6.000	0.400	0.140
7.000	0.400	0.125
8.000	0.400	0.115
10.000	0.400	0.095
2.500	0.500	0.285
3.000	0.500	0.265
4.000	0.500	0.230
5.000	0.500	0.200
6.000	0.500	0.175
7.000	0.500	0.155
8.000	0.500	0.140
10.000	0.500	0.125
2.500	0.600	0.325
3.000	0.600	0.300

4.000	0.600	0.270
5.000	0.600	0.230
6.000	0.600	0.205
7.000	0.600	0.180
8.000	0.600	0.170
10.000	0.600	0.155
2.500	0.000	0.355
3.000	0.700	0.330
4.000	0.700	0.290
5.000	0.700	0.260
6.000	0.700	0.230
7.000	0.700	0.220
8.000	0.700	0.205
10.000	0.700	0.180
2.500	0.800	0.380
3.000	0.800	0.360
4.000	0.800	0.325
5.000	0.800	0.285
6.000	0.800	0.260
7.000	0.800	0.245
8.000	0.800	0.225
10.000	0.800	0.215

ANOVA is performed in Excel to obtain the following regression formula for the coefficient k_β with variables the fuselage fineness ratio, $\frac{L_f}{h}$ and the location of the centre of gravity on the body as a percentage of the fuselage length, $\frac{d}{L_f}$:

$$k_\beta = 0.204 - 0.204\,\frac{L_f}{h} + 0.269\,\frac{d}{L_f}$$

- For the downwash of the wing on the horizontal tail and the neutral point calculation, using the data from Fig. 16.12, [5]:

$\frac{d\varepsilon}{d\alpha}$	**Aspect Ratio**	**Taper Ratio, λ**	**$r=L_t/(b/2)$**	**$m=Z_t/(b/2)$**
0.500	6.000	1.000	0.500	0.000
0.450	6.000	1.000	0.500	0.100
0.400	6.000	1.000	0.500	0.200
0.450	6.000	1.000	0.750	0.000
0.400	6.000	1.000	0.750	0.100
0.350	6.000	1.000	0.750	0.200
0.400	6.000	1.000	1.000	0.000

0.370	6.000	1.000	1.000	0.100
0.330	6.000	1.000	1.000	0.200
0.370	6.000	1.000	1.250	0.000
0.350	6.000	1.000	1.250	0.100
0.320	6.000	1.000	1.250	0.200
0.700	6.000	0.330	0.500	0.000
0.600	6.000	0.330	0.500	0.100
0.520	6.000	0.330	0.500	0.200
0.630	6.000	0.330	0.750	0.000
0.520	6.000	0.330	0.750	0.100
0.450	6.000	0.330	0.750	0.200
0.550	6.000	0.330	1.000	0.000
0.470	6.000	0.330	1.000	0.100
0.420	6.000	0.330	1.000	0.200
0.500	6.000	0.330	1.250	0.000
0.430	6.000	0.330	1.250	0.100
0.400	6.000	0.330	1.250	0.200
0.750	6.000	0.200	0.500	0.000
0.650	6.000	0.200	0.500	0.100
0.550	6.000	0.200	0.500	0.200
0.650	6.000	0.200	0.750	0.000
0.570	6.000	0.200	0.750	0.100
0.500	6.000	0.200	0.750	0.200
0.600	6.000	0.200	1.000	0.000
0.500	6.000	0.200	1.000	0.100
0.420	6.000	0.200	1.000	0.200
0.550	6.000	0.200	1.250	0.000

0.450	6.000	0.200	1.250	0.100
0.400	6.000	0.200	1.250	0.200
0.380	9.000	1.000	0.500	0.000
0.350	9.000	1.000	0.500	0.100
0.300	9.000	1.000	0.500	0.200
0.330	9.000	1.000	0.750	0.000
0.300	9.000	1.000	0.750	0.100
0.275	9.000	1.000	0.750	0.200
0.300	9.000	1.000	1.000	0.000
0.250	9.000	1.000	1.000	0.100
0.235	9.000	1.000	1.000	0.200
0.275	9.000	1.000	1.250	0.000
0.250	9.000	1.000	1.250	0.100
0.225	9.000	1.000	1.250	0.200
0.530	9.000	0.330	0.500	0.000
0.450	9.000	0.330	0.500	0.100
0.400	9.000	0.330	0.500	0.200
0.475	9.000	0.330	0.750	0.000
0.425	9.000	0.330	0.750	0.100
0.350	9.000	0.330	0.750	0.200
0.450	9.000	0.330	1.000	0.000
0.400	9.000	0.330	1.000	0.100
0.350	9.000	0.330	1.000	0.200
0.400	9.000	0.330	1.250	0.000
0.350	9.000	0.330	1.250	0.100
0.300	9.000	0.330	1.250	0.200
0.630	9.000	0.200	0.500	0.000
0.500	9.000	0.200	0.500	0.100

0.430	9.000	0.200	0.500	0.200
0.550	9.000	0.200	0.750	0.000
0.450	9.000	0.200	0.750	0.100
0.380	9.000	0.200	0.750	0.200
0.500	9.000	0.200	1.000	0.000
0.400	9.000	0.200	1.000	0.100
0.350	9.000	0.200	1.000	0.200
0.450	9.000	0.200	1.250	0.000
0.380	9.000	0.200	1.250	0.100
0.320	9.000	0.200	1.250	0.200
0.275	12.000	1.000	0.500	0.000
0.250	12.000	1.000	0.500	0.100
0.225	12.000	1.000	0.500	0.200
0.250	12.000	1.000	0.750	0.000
0.220	12.000	1.000	0.750	0.100
0.200	12.000	1.000	0.750	0.200
0.210	12.000	1.000	1.000	0.000
0.200	12.000	1.000	1.000	0.100
0.180	12.000	1.000	1.000	0.200
0.200	12.000	1.000	1.250	0.000
0.185	12.000	1.000	1.250	0.100
0.150	12.000	1.000	1.250	0.200
0.450	12.000	0.330	0.500	0.000
0.375	12.000	0.330	0.500	0.100
0.330	12.000	0.330	0.500	0.200
0.400	12.000	0.330	0.750	0.000
0.340	12.000	0.330	0.750	0.100

0.300	12.000	0.330	0.750	0.200
0.400	12.000	0.330	1.000	0.000
0.300	12.000	0.330	1.000	0.100
0.250	12.000	0.330	1.000	0.200
0.350	12.000	0.330	1.250	0.000
0.300	12.000	0.330	1.250	0.100
0.250	12.000	0.330	1.250	0.200
0.500	12.000	0.200	0.500	0.000
0.400	12.000	0.200	0.500	0.100
0.330	12.000	0.200	0.500	0.200
0.450	12.000	0.200	0.750	0.000
0.350	12.000	0.200	0.750	0.100
0.300	12.000	0.200	0.750	0.200
0.400	12.000	0.200	1.000	0.000
0.350	12.000	0.200	1.000	0.100
0.270	12.000	0.200	1.000	0.200
0.360	12.000	0.200	1.250	0.000
0.300	12.000	0.200	1.250	0.100
0.240	12.000	0.200	1.250	0.200

ANOVA is performed in Excel, to obtain the following regression formula, with $\frac{d\varepsilon}{d\alpha}$ as a function of aspect ratio AR, taper ratio λ, the position of the horizontal tale plane (normalised by the semi-wing span) $r = \frac{L_t}{b/2}$ and the vertical positon of the horizontal tale plane (normalised by the semi-wing span) $m = \frac{Z_t}{b/2}$:

$$\frac{d\varepsilon}{da} = 0.955 - 0.031\,AR - 0.188\,\lambda - 0.156\,r - 0.578\,m$$

For the canard configuration, by the reverse flow theorem [205], the downwash produced from the canard onto the wing (inboard from the canard tips, i.e. on the wing up to a distance equal to the canard span, as suggested by Raymer, [211]) is equal to the downwash produced from the wing to the canard from a reverse flow. Thus it is computed similarly with the above formula based on the values of wing aspect ratio AR, taper ratio λ, the position of the canard (normalised by the semi-wing span) $r = \frac{L_C}{b/2}$ and the vertical positon of the canard (normalised by the semi-wing span) $m = \frac{Z_C}{b/2}$. Also since the distance between the canard and the wing is large (compared to the wing chord) the upwash effect from the canard tip vortices on the wing is ignored. After computing the downwash effect, $\frac{d\varepsilon}{d\alpha}$, the neutral point position is calculated based on equation 7-28.

B.4 Response Surface Model Coefficients

The RSM coefficients for the DOE in Isight using the value model are:

Variable	coefficients	scaled	normalized
constant	-0.78936354		
Wing span	0.373337234	-0.034494104	-12.09084915
Battery capacity	0.044687675	0.026571455	9.313807821
Component reliability	7.797231153	0.006001143	2.103516581
Wing aspect ratio	-0.120497805	0.045012388	15.777711
Configuration code	-4.04E-04	-0.012930027	-4.532223982
Fin aspect ratio	-0.011241581	2.02E-06	7.07E-04
Horizontal tail aspect ratio	0.009881253	-1.60E-04	-0.055981401
Wing span^2	-0.112346883	-0.00702168	-2.461234456
Battery Capacity^2	-0.001419334	-0.003193501	-1.11938371
Component reliability^2	-4.211027142	-0.00852733	-2.98899376
Wing aspect ratio^2	-0.002405477	-0.02164929	-7.588494185
Configuration code^2	1.55E-08	0.026189901	9.180065891

Wing span*battery capacity	8.72E-04	3.27E-04	0.114665751
Wing span*component reliability	0.150526546	0.001693424	0.593577677
Wing span*wing aspect ratio	0.025129201	0.018846901	6.606202644
Wing span*configuration code	-4.80E-05	-0.015621041	-5.475476439
Wing span*fin aspect ratio	-0.002451092	-6.13E-05	-0.021478875
Wing span*horizontal tail aspect ratio	-7.60E-04	-9.50E-05	-0.033285823
Battery capacity*component reliability	0.004118973	2.78E-04	0.097455109
Battery capacity*wing aspect ratio	7.83E-05	3.52E-04	0.123552366
Battery capacity*configuration code	-8.57E-07	-0.001671053	-0.585736499
Battery capacity*fin aspect ratio	-5.18E-06	-7.76E-07	-2.72E-04
Battery capacity*horizontal tail aspect ratio	-1.20E-04	-9.04E-05	-0.031674464
Component reliability-wing aspect ratio	-0.010281436	-0.001387994	-0.486518618
Component reliability*configuration code	9.06E-06	5.30E-04	0.185802579
Component reliability*fin aspect ratio	0.01775392	7.99E-05	0.028003913
Component reliability*horizontal tail aspect ratio	-5.67E-05	-1.28E-06	-4.48E-04
Wing aspect ratio*configuration code	1.32E-05	0.051651714	18.10492279
Wing aspect ratio*fin aspect ratio	1.49E-04	4.47E-05	0.015669863
Wing aspect ratio*horizontal tail aspect ratio	9.15E-05	1.37E-04	0.048095239
Configuration code-fin aspect ratio	-5.14E-07	-6.69E-05	-0.023438764
Configuration code-horizontal tail aspect ratio	-8.73E-07	-5.68E-04	-0.199047866
Fin aspect ratio*horizontal tail aspect ratio	6.68E-04	3.34E-05	0.011705864

The ANOVA table with the results of the statistical analysis of variance, broken down into contributions from each factor when using the value model in the DoE, is:

Variable	DF	SS	V	F	SS'	P(%)
Wing span	2	4.915719547	2.45785977	1571.25505	4.91259102	14.6832236
Configuration code	17	6.935369577	0.40796292	260.801612	6.90877707	20.6496160
Component reliability	2	0.248579209	0.12428960	79.4555776	0.24545068	0.73362655
Wing aspect ratio	2	9.534676041	4.76733802	3047.6531	9.53154751	28.4888041
Horizontal tail aspect ratio	1	2.16E-04	2.16E-04		POOLED	
Fin aspect ratio	1	7.71E-09	7.71E-09		POOLED	
Battery capacity	2	2.740700865	1.37035043	876.03453	2.7375723	8.18231895
e1	5804	9.081908846	0.00156477			
ePooled	2	2.16E-04				
eTotal	5806	9.082124435	0.00156427			27.2624109
Total	5831	33.45716967	0.00573781			100

The RSM coefficients for the DoE in Isight using the utility model are:

Variable	coefficients	scaled	normalized
constant	-0.152166041		
Component reliability	4.466792691	-0.002906033	-1.003000689
Wing span	0.723606378	-0.04723047	-16.30132545

Battery capacity	0.041269982	0.019563309	6.752163572
Wing aspect ratio	-0.17946649	0.051847046	17.89471
Configuration code	-2.17E-04	-0.002705859	-0.933911723
Horizontal tail aspect ratio	0.007663224	-1.95E-04	-0.067324412
Fin aspect ratio	0.023079652	6.85E-05	0.02362824
Component reliability^2	-2.372885959	-0.004805094	-1.658450605
Wing span^2	-0.101788584	-0.006361787	-2.195734054
Battery cap^2	-6.57E-04	-0.001477428	-0.509925663
Wing aspect ratio^2	-0.002485029	-0.022365263	-7.719242116
Configuration code^2	7.99E-09	0.013508512	4.662385434
Component reliability*wing span	-0.045958326	-5.17E-04	-0.178450337
Component reliability*battery capacity	-0.001859629	-1.26E-04	-0.043324211
Component reliability*wing aspect ratio	0.004916782	6.64E-04	0.229094862
Component reliability*configuration code	6.43E-07	3.76E-05	0.012986708
Component reliability*horizontal tail aspect ratio	-1.75E-04	-3.93E-06	-0.001357874
Component reliability*fin aspect ratio	-0.00907965	-4.09E-05	-0.014102051
Wing span*battery capacity	6.42E-04	2.41E-04	0.0831434
Wing span*wing aspect ratio	0.02592441	0.019443308	6.710745977
Wing span*configuration code	-7.00E-05	-0.02275461	-7.853622912
Wing span*horizontal tail aspect ratio	-6.25E-04	-7.82E-05	-0.026979018
Wing span*fin aspect ratio	-0.005865471	-1.47E-04	-0.050610838
Battery capacity*wing aspect ratio	2.57E-04	0.001157382	0.399463647
Battery capacity*configuration code	-1.62E-06	-0.003152098	-1.087928402
Battery capacity*horizontal tail aspect ratio	-5.44E-05	-4.08E-05	-0.014070206
Battery capacity*fin aspect ratio	-5.10E-04	-7.65E-05	-0.026417705
Wing aspect ratio*configuration code	1.73E-05	0.067423388	23.27079492

Wing aspect ratio*horizontal tail aspect ratio	9.92E-05	1.49E-04	0.051367361
Wing aspect ratio* fin aspect ratio	1.36E-04	4.07E-05	0.014045215
Configuration code*horizontal tail aspect ratio	-7.69E-07	-5.00E-04	-0.172690934
Configuration code-fin aspect ratio	-4.94E-07	-6.43E-05	-0.022193644
Horizontal tail aspect ratio*fin aspect ratio	8.58E-04	4.29E-05	0.014807817

The ANOVA table with the results of the statistical analysis of variance, broken down into contributions from each factor when using the utility model in the DoE, is:

Variable	DF	SS	V	F	SS'	P(%)
Wing span	2	9.21768232	4.60884116	1991.39329	9.21305356	21.2662282
Configuration code	17	6.4222747	0.37778086	163.231982	6.38293023	14.7335354
Component reliability	2	0.05814054	0.02907027	12.5607144	0.05351178	0.12351971
Wing aspect ratio	2	12.7242393	6.36211965	2748.9518	12.7196106	29.3603135
Horizontal tail aspect ratio	1	2.92E-04	2.92E-04		POOLED	
Fin aspect ratio	1	2.33E-05	2.33E-05		POOLED	
Battery capacity	2	1.46283346	0.73141673	316.03137	1.4582047	3.36593223
e1	5804	13.4369758	0.00231512			
ePooled	2	3.16E-04				
eTotal	5806	13.4372914	0.00231438			31.150471
Total	5831	43.3224617	0.00742968			100

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