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RPAS Design: An MDO Approach
PhD Dissertation

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RPAS DESIGN: AN MDO APPROACH

ABSTRACT

Unmanned aircraft and, particularly, RPAS (Remotely Piloted Aircraft Systems) are nowadays experiencing great growth both in the military and civil industries. This is due to the fact that removing the need to be manned has enabled the improvement of their endurance, range, and overall performance while, at the same time, reducing the risk to which human lives were exposed. In addition, RPAS can be made much smaller. This decrease of mass and size increases the variety of missions they can perform. However, the design process to manufacture such aircraft is often long and costly, which prevents small companies from undertaking it.

Multidisciplinary Design Optimization (MDO) is an engineering field whose focus is to solve highly complex problems by the means of optimization techniques. It has been used in the design of commercial aircraft for a long time, but integrating the various engineering disciplines that take part in designing an RPAS within an MDO to simplify the design process is a challenge. In addition, there is an ample variety of architectures for MDO projects and, the reasons to choose a particular one, have to be discussed on a case by case basis. During the last years, distributed architectures have become widespread, given that they can take advantage of parallel computing (even with graphical platforms) and reduce computing time. Adapting the formulation of a problem to a particular

architecture is a slow and ponderous task that, in many cases, must be repeated several times to find out which is the architecture that provides the best results. Therefore, a new architecture has been developed: GPPA (Generic Parameter Penalty Architecture), which is able to behave like a number of different architectures by modifying three parameters.

Usage of MDO techniques in aerospace engineering is not new. These techniques have been applied to numerous and somehow complicated aeronautical problems, but never before as the sole element in charge of the preliminary design of a full RPAS, including multiple subdisciplines and the ability to contemplate unconstrained aerodynamic configurations. That is the reason why a new MDO methodology for the quick, efficient, and robust design of RPAS has been developed. This methodology takes into account the various subdisciplines of aeronautical design, such as aerodynamics, structural calculus, propulsion, economy, etc. It provides the environment to generate, from the RPAS' objective performance, a design that is suitable for the flight conditions of the aircraft and its mission. It also generates the RPAS' geometry, structure, and position of all its elements to establish the foundations from which more precise (and slow) methods such as FEM/VEM can further evolve the design.

RPAS DESIGN: AN MDO APPROACH

RESUMEN

En la actualidad las aeronaves no tripuladas y, más concretamente, los RPAS (sistemas aéreos pilotados a distancia) están experimentando un gran crecimiento tanto a nivel militar como civil, ya que la eliminación de la necesidad de estar tripulados permite la mejora de su autonomía y actuaciones, y elimina gran cantidad de riesgos para la vida humana. Además, permite la reducción de su tamaño en gran medida. Esta disminución en masa y tamaño aumenta así mismo la variedad de misiones que son capaces de realizar. Sin embargo, el diseño de estas aeronaves suele ser largo y costoso, lo que dificulta que pequeñas empresas puedan acometerlo.

La optimización de diseño multidisciplinar (MDO por sus siglas en inglés), es una rama de la ingeniería dedicada a resolver problemas altamente complejos mediante técnicas de optimización que se emplea en el diseño de aviones comerciales desde hace tiempo. Integrar las diversas ramas de la ingeniería que intervienen en el diseño de un RPAS en una estructura MDO que simplifique el proceso de diseño es un desafío. Además, actualmente hay una amplia variedad de arquitecturas para el desarrollo de proyectos MDO, y la motivación para emplear una u otra arquitectura varía según las necesidades del problema concreto. En los últimos años las arquitecturas distribuidas se han vuelto mucho más comunes, ya que permiten el cálculo en paralelo (incluso con plataformas gráficas), reduciendo

los tiempos de proceso. Adaptar la formulación de un problema a una determinada arquitectura es un proceso pesado que, en ocasiones, debe repetirse varias veces con el fin de comprobar cuál es la arquitectura que mejor funciona para dicho problema. Por ello se ha desarrollado una nueva arquitectura, la GPPA (Generic Parameter Penalty Architecture), capaz de comportarse como multitud de arquitecturas distintas con la variación de tres parámetros.

La utilización de técnicas MDO en la ingeniería aeroespacial no es nueva. Estas arquitecturas han sido aplicadas a multitud de problemas aeronáuticos con relativa complejidad, pero nunca como el único responsable del diseño preliminar de un RPAS en su totalidad con variedad de subdisciplinas y la posibilidad de emplear configuraciones aerodinámicas sin restricciones. Por ello también se ha desarrollado una nueva metodología de diseño MDO rápida, eficaz y robusta, para RPAS de tamaño reducido. Esta metodología ha tenido en cuenta las diversas ramas del diseño aeronáutico (como son la aerodinámica, el cálculo estructural, la propulsión, etc.). Esta metodología permite, en función de unas actuaciones objetivo, generar un diseño adaptado a las condiciones de vuelo de la aeronave y su misión, proporcionando la geometría del RPAS, su estructura, y la disposición de todos los elementos de la aeronave, sentando la base para continuar con el diseño mediante modelos más precisos, aunque más lentos, como los FEM.

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Dissertation Overview

Chapter 1: This is the introduction to the thesis. It presents the evolution of RPAS and the current state of the art both in MDO and in RPAS design methodologies.

Chapter 2 introduces the Generic Parameter Penalty Architecture (GPPA): a new, flexible MDO architecture, oriented towards the solution of engineering problems that present different levels of complexity.

Chapter 3 introduces the RPAS Advanced MDO Platform (RAMP). A new MDO environment aimed at the design of small RPAS.

Chapters 4-7 present RAMP's main analysis models: aerodynamics, structure, economy and pricing, propulsion, and performance.

Chapter 8 presents an application case of RAMP to a real-world mission. Chapter 8 does so by limiting RAMP's configuration availability to just classical. This provides the opportunity to compare its results to most commercially available RPAS, while Chapter 9 unleashes RAMP's full capabilities to also consider Blended Wing Body (BWB) and Canard configurations.

Chapter 9 presents results for the various tests and hypothesis that are presented in the thesis, while Chapter 10 serves to give shape to the conclusions of the thesis and the future lines of research.

INDEX

Abstract	i
Resumen	iii
Acknowledgments	v
Dissertation Overview	vii
Index	ix
1. Introduction and State of the Art	1
1.1. Origins[1–7]	2
1.2. Economy	5
1.3. Current challenges and situation	6
1.3.1. Military/combat operations	6
1.3.2. Observation, reconnaissance and mapping	7
1.3.3. Atmospheric survey/scientific missions	7
1.3.4. Load delivery	7
1.3.5. Small vs large RPAS	8
1.3.6. Regulations	9
1.3.7. Air traffic management (ATM)	9
1.3.8. Human interface and control	10
1.4. Multidisciplinary design optimization	10
1.5. Trends and conclusions	20
1.6. Objectives and motivation	20
2. GENERIC PARAMETER PENALTY ARCHITECTURE	25
2.1. Nomenclature	25
2.2. Introduction	26
2.3. Generic Parameter Penalty Architecture	28
2.4. MDO Architectures for Comparison	32

2.4.1. Monolithic Architecture	32
2.4.1.1. All at Once	32
2.4.2. Distributed Architectures	33
2.4.2.1. Collaborative Optimization	33
2.4.2.2. Analytical Target Cascading	34
2.5. Tests Problems	35
2.5.1. Simple analytical problem	37
2.5.2. Golinski's speed reducer	38
2.5.3. Propane combustion in air	42
3. RAMP: RPAS Advanced MDO Platform	45
3.1. Introduction	45
3.2. Mission definition and additional requirements	46
3.3. Modules	49
3.3.1. Main	49
3.3.2. Discipline optimization	50
3.3.3. Results output	50
3.3.4. RPAS	50
3.3.5. Objective functions	51
3.3.6. Consistency	53
3.3.7. Variable mutation	54
3.3.8. Airfoil Database	54
3.3.9. Common Functions	55
3.3.10. Aerodynamics	55
3.3.11. Structure	55
3.3.12. Propulsion and Integral Performance	55
3.3.13. Economic Analysis/Pricing	56
3.4. RAMP's workflow and overall operation	56

4. Subdiscipline: Aerodynamics	59
4.1. Nomenclature	59
4.2. Introduction	61
4.3. Aerodynamic Model	63
4.4. Definition of the RPAS	65
4.5. Airfoil characterization	67
4.6. Modeling of lift and lift distributions of the wing	69
4.6.1. Considerations for the canard configuration	74
4.6.2. Considerations for the blended wing body configuration	75
4.7. Estimation of drag polar	75
4.7.1. Considerations for the canard configuration	82
4.7.2. Considerations for the blended wing body configuration	82
4.8. Validation of the model	83
5. Subdiscipline: Structure	87
5.1. Nomenclature	87
5.2. Introduction	88
5.3. Structure generation and mutation	88
5.3.1. Material generation	89
5.4. Mass/center of gravity calculation	91
5.4.1. Center of gravity of the full RPAS	92
5.4.2. Body	92
5.4.3. Wing	93
5.4.4. Horizontal and vertical stabilizing surfaces	93
5.5. Force and moment	94
5.5.1. Body	95
5.5.1.1. Forces	95
5.5.1.2. Bending moment	99

5.5.1.3. Torsion	101
5.5.2. Wing	102
5.5.2.1. Forces	102
5.5.2.2. Bending moment	104
5.5.2.3. Torsion	106
5.5.3. Horizontal stabilizer	108
5.5.3.1. Forces	108
5.5.3.2. Bending Moment	109
5.5.3.3. Torsion	110
5.5.4. Vertical stabilizer	111
5.5.4.1. Forces	111
5.5.4.2. Moments	111
5.5.4.3. Torsion	112
5.6. Stress	116
5.6.1. Body	116
5.6.2. Wing and stabilizers	116
5.6.3. Calculation of stress	116
5.6.3.1. Shear stress from torque	116
5.6.3.2. Buckling critical load	117
5.6.3.3. Compound stress	117
6. Subdiscipline: Propulsion and Performance	119
6.1. Nomenclature	119
6.2. Introduction	120
6.3. Powerplant generation	121
6.4. Propeller's performance	122
6.4.1. Propeller's efficiency	122
6.4.2. Limitations	123

6.4.3. Feasible solutions	124
6.5. Integral Performances Estimation	126
6.5.1. Piston engine	127
6.5.2. Electric engine	127
7. Subdiscipline: Pricing Analysis	131
7.1. Introduction	131
7.2. Data gathering	134
7.3. Factor Analysis	137
7.4. Price as a function of other variables	143
8. RAMP Benchmark Model	147
8.1. Introduction	147
8.2. Objective mission	148
8.3. RAMP set-up	150
8.3.1. GPPA parameters	150
8.3.2. Aerodynamic configurations	150
8.4. RPAS seed	151
8.4.1. Body	151
8.4.2. Pod	151
8.4.3. Wing	152
8.4.4. Horizontal stabilizer	152
8.4.5. Vertical stabilizer	153
8.4.6. Payload, instruments, engine and batteries/fuel	153
8.4.6.1. Payload	153
8.4.6.2. Engine	154
8.4.6.3. Batteries/fuel	155
8.4.7. Relative positions	155
8.4.8. RPAS seed parameter values	156

9. Results	159
9.1. Introduction	159
9.2. GPPA	160
9.3. Aerodynamics	165
9.4. RAMP Tests	175
9.4.1. Configuration evolution	175
9.4.1.1. CIC	175
9.4.1.2. CaC	179
9.4.2. Objective functions	184
9.4.3. Key parameters	190
10. Conclusions	197
10.1. Introduction	197
10.2. GPPA	197
10.3. Aerodynamics	199
10.4. Economy	200
10.5. RAMP	202
10.6. Overall research	204
Appendix A: Airfoils	207
Appendix B: Engines and Batteries	211
List of acronyms	215
List of figures	217
List of tables	220
References	221

1

INTRODUCTION AND STATE OF THE ART

Remotely Piloted Aircraft Systems (RPAS) are a type of vehicles whose main difference with traditional aircraft is the absence of a crew on board, id. est. they are unmanned. This allows them to face more demanding missions and flight conditions, as well as using more innovative configurations and geometries. A manned aircraft would not be able to take advantage of them in order to ensure the safety of its crew and/or passengers. All these reasons have favored RPAS to steadily spread in the world market during the last years.

1.1. Origins^[1–7]

Aircraft origins go back to Wright brothers' first flight in December of 1903. Ever since then aeronautics have not stopped growing and serving as a tool for humankind. However, it is not until more recent years that replacing manned aircraft with RPAS has been seriously considered. In any case, manned and unmanned aircraft have followed a parallel path.

In 1895, Nikola Tesla performed a remote-control demonstration with a small boat, for which he registered control system patents. Later on, he suggested the idea of remotely controlling a small aerial vehicle [6]. This idea, however, would still take some years to be put in practice.

The first RPAS was developed shortly after the first manned flight. In 1915, inventors Elmer Sperry and Peter Cooper Hewitt developed the first remotely controlled flying vehicle: the Curtis Flying Boat. All throughout World War I several efforts were made (mostly by the US Army) to develop some kind of radio-controlled bomb. With this aim, Glen Curtis' Aerial Torpedo for the US Navy or Charles Kettering's Flying Bomb for the US Army were developed. These inventions, however, did not make it to the battlefield, among other reasons, because of their low effectiveness.

Investment towards military development of RPAS was increased in between World Wars, even though a few projects, like Kettering's bomb, were shut down without result. During this time, the strongest efforts were put into developing

aerial targets for naval combat simulations because they had been shown to be extremely vulnerable to aerial attacks.

The first flight that was fully piloted in every step took place in 1921. An F-5L with a radio-control system was the chosen aircraft. Similarly, the Royal Aircraft Establishment flew the RAE 1921 Target for 39 minutes, which was also aimed at the development of aerial targets for training. A year later, the Larynx started its development. It was a single-seater that could be used as an anti-ship guided weapon and made its maiden flight in 1927.

Slowly, various prototypes arose both from the US and the UK. While the latter started using the Queen Bee as a target from 1933 (an adaptation from a De Havilland Tiger Moth), the US reached an agreement with actor Reginal Denny to be supplied radio-control drones used as a target. Mr. Denny had been selling radio-control models at his store, Reginal Denny Hobby Shops, since 1934.

Until the start of World War II, where UAVs were already commonly used as aerial targets, when investment was aimed back at stalled projects from the 20's. These projects consisted in developing remotely controlled guided bombs. By March 1942, the US Navy had successfully tested an aircraft that had been remotely piloted from a different plane on the bombing of USS Aaron Ward. Later they would also test BG-1 and BG-2.

On the other hand, Germans had been developing the V-1 Buzzbomb since 1939, which was aimed at bombing allied territories. Its control system was

inaccurate, and it was used for carpet bombing. They had already developed targets such as the Argus As292, whose manufacturing plant had been bombed by US RPAS without much success. These missions were named Aphrodite.

The end of World War II brought the Cold War. It was distinguished by multiple skirmishes during manned reconnaissance missions along enemy borders. This situation brought over hesitation about such missions and renewed interest about unmanned missions which, by the end of the previous war, had not produced a satisfactory outcome.

Then, at the start of the 50's, the first truly successful reconnaissance RPAS appeared: Ryan Aeronautical Company's Firefly 147A. This aircraft was an adaptation of Firebees that were used as a training target, and are still used through the version AQM-34N. At the end of that decade the first unmanned combat helicopter also appears: the QH-50.

Vietnam's War is, however, the first time that the US massively used UAVs, in up to 3400 reconnaissance, propaganda, and counter-intelligence missions. Ever since then, unmanned aircraft have become a regular in the following military conflicts where the US have been involved, and also an increasingly used tool nowadays. Even though military conflicts have been the engine that has pushed RPAS forward, the increasingly available and cheaper technology have made them more and more available and used in civil environments.

1.2. Economy

RPAS related industry and economic impact in world economy and politics is greater and greater [8–10]. Reports such as Teal Group's [11] highlight the growing investment, both military (not exempted from polemics[12]) and civil, in this industry. Moreover, economical distribution, where the military receive the larger share, is progressively leveling. Estimations suggest that the market will be 14% civil, and the average for the decade will approach 11%. Current world budget is estimated to be around \$6400 million, and it is expected to grow up to \$11500 million.

Even though these numbers point to an important growth of the market, they imply a softening of last decade's tendency. As an example, US DoD's investment grew from \$300 million to \$3300 million in 2010[8].

Current economical surveys mostly talk about the US [13], and particularly about the states that share most investment (California, Washington, Texas, Florida and Arizona). The US represents slightly more than half of the budget [14].

These numbers show that the civil sector is the one that will suffer the largest growth. Amazon, Google and Facebook have already started to use RPAS in huge amounts to offer their services [15–17].

The aperture of the civil market and the measurable reduction of costs is common when new technologies make it to the general society, as their global

interest and market growth increase. RPAS' market, in particular, is similar to many other new technologies market, such as cellphones or domestic appliances. A few years ago, only a few units were available. Mostly prototypes and very expensive models. Nowadays, almost anyone can afford to acquire a small recreational RPAS in most western countries where some have similar prices to cellphones.

1.3. Current challenges and situation

Initial development and application of RPAS shaped the beginnings of unmanned aircraft in the beginning (one must not forget, however, that one of the main suppliers of the US Army was a recreational models company). However, technological advances and the reduction of their price have made possible the reduction of the cost of RPAS, increasing their reliability and, therefore, using them in a number of new missions. This is a key factor in their international development [18].

1.3.1. Military/combat operations

Inherited from their origins, and the source of the largest investment, RPAS have been used as a substitute of manned aircraft in combat missions (as Unmanned Combat Air Systems), reconnaissance, or practice targets. Their importance can be observed in the change that the US' strategy [19] experienced. Now it is mandatory to prove that an RPAS is unable to perform a particular

mission before using a manned aircraft. These RPAS are used as well in joint operations with satellites [20].

1.3.2. Observation, reconnaissance and mapping

The logical evolution of RPAS includes equipping it with a visible-spectrum camera and any additional technology currently available (IR, thermal, radar, etc.) that can be adapted to a small platform and be used for topography and land mapping [21,22], wildlife [23] and crop monitoring [24,25], border control, etc. In this kind of missions, RPAS provide a key advantage: being unmanned, their endurance increases, and so does the maximum time-length and range of the mission.

1.3.3. Atmospheric survey/scientific missions

In the same way RPAS can carry a vision system, they can be equipped with a number of measuring systems and sensors, which provides a very useful platform for scientific missions, such as atmospheric surveys [26].

Earth observation missions can also be included in this section, since they help study and understand the evolution of, for instance, ecosystems and geographic accidents, demography, etc.

1.3.4. Load delivery

Companies such as Amazon are currently considering and developing RPAS to help them deliver packages [27]. Even though this use seems obvious attending

to beginning of aviation as a mail transportation system, in this case, massive amounts of RPAS represent a game changer from a safety standpoint. That is the reason why some legislation conflicts have arisen with the Federal Aviation Administration. The main regulatory agencies, such as OACI or the FAA have to work against the clock to stay up to date and ensure that RPAS are used in a positive and safe manner.

1.3.5. Small vs large RPAS

Another key factor, when dealing with RPAS, is their comparatively reduced weight and size in comparison to conventional aircraft. Distributions of size and other parameters in RPAS have been studied before [28]. Removing the pilot from the cockpit (and the cockpit itself), together with the progressive advance of technology have made possible manufacturing miniature planes. The wingspan of these RPAS may be no longer than a few centimeters, and perform missions that, before, had not even been considered. As an example, we could mention urban flight or espionage missions.

RPAS in general and, particularly, micro-sized RPAS, fly at low-Reynolds number. This opens the door to a new world of different aerodynamic configurations, that require further study, but may greatly increase current levels of aerodynamic efficiency [29,30], and even further improve current levels of range and endurance.

1.3.6. Regulations

As stated before, the quick spread of RPAS in the civil market has motivated that organizations such as OACI, EASA, or the FAA feel obligated to take a stand in the subject, as well as provide regulation for the manufacturing, commercialization and operation of RPAS [31], and their safety requirements [32].

In this line and, with a wide variety of guidance, navigation and control systems of unmanned aircraft, OACI claims that it may rule only on RPAS [33]. This leaves other variants of unmanned aircraft, such as self-guided, or automatic piloted aircraft, out of their regulation. In any case, it is clear that the operation of RPAS needs to be integrated within the current airspace, which is a challenge that OACI is undertaking [34], and will require a gradual and studied integration [35,36].

The first attempts at a standardization and regulation of RPAS came from the military world as a set of rules aimed at the certification of military RPAS: the STANAG 4671 [37].

1.3.7. Air traffic management (ATM)

The access to the use of RPAS by the main public, both for recreational and non-recreational purposes, suggests that the volume of flying aircraft will quickly grow. The current model of air traffic management, though reliable and safe, cannot be scaled up in a practical manner, since it would entail a parallel increase in airplane-related accidents that would not be admissible by the population. In

addition, swarms of RPAS may rend current ATM systems unable to face the air traffic demand. That is why Eurocontrol, among others [38], is also developing, studying [39] and implementing new systems that may adapt to this new theater of operations and, even better, improve its safety even more.

1.3.8. Human interface and control

RPAS handling has been shown to be a very stressing task [40–44] that presents work conditions not found in conventional aircraft. In addition, the opportunity to use new flight configurations, where a single pilot may control various RPAS [45], have created an environment that favors the study of new instruments [46] and human interfaces so that the pilot interacts with the aircraft [47]. Not to forget the option to use an autopilot [48–50] and/or combining it with automatic self-response systems [51].

1.4. Multidisciplinary design optimization

Multidisciplinary design optimization (MDO) is a discipline that has experienced a fast and deep evolution during the last years, and it is still evolving even from a philosophical point of view [52]. It lifted off in the 60's, when industrial and structural design started interacting with various disciplines [53] and Schmit [54] and Haftka [55] proposed initial formulations. In its origin, gradient algorithms were used as the state of the art in computer optimization given their simplicity and low computational requirements. However, with the evolution of electronics, the available processing capacity has increased, leading to the

emergence of much more complex algorithms, such as evolutionary [56], and also new versions of the original gradient methods.

In addition, the mathematical evolution of optimization models enabled processes to focus on any problem by applying new techniques such as robust optimization [57] or games theory [58].

Finally, the rise of finite and volume element model (FEM and VEM) analysis led to putting together more complex and richer environments for optimization and multidisciplinary design [59,60]. These models are mostly used on wing design [61,62] or fine tuning of already set aerodynamic configurations, either conventional [63] or non-conventional [64]. Along with them, a series of Computer Aided Design (CAD) tools appeared, but they did not involve any optimization [65–68], as well as diverse parametrization methodologies [69]. These design tools represent another evolution of classical design manuals such as Egbert Torenbeek's or similar works [70–73]. An intermediate approach between manuals and FEM/VEM analysis is the use of meta-models [74], but even flight simulators have been used [75]. There are some versions which implement optimization at some level, also with the intent to finely tune an already set configuration [76].

MDO has a wide variety of engineering-related applications; many of them related to fluid dynamics, such as wind turbine design [77,78], energy generation systems [79], windfarms [80] or, more particularly related to the subject of this thesis, aerospace engineering [81,82]. For instance, there are works related to the

design of space launchers [83–91], vehicles [92–94] and satellites[95], thermal and power analysis [81], rotorcraft [96], wings[61,67,69,97–108], fuselage [109,110], and complete subsonic [111–113], supersonic [114–116] and even hypersonic [117] aircraft. There are also works that focus on aircraft family design [118] or RPAS design [119], as well as those who address MDO as a solution for the management of every aircraft-related process during the life-cycle of the plane [120].

As it was stated before, there has been an intense development of MDO from a mathematical perspective as well [121]. These studies enable to better stretch the limits of the formulation and behavior of models, achieving better results in a smaller time and with lesser processing capacity requirements.

This way, we can find several works exclusively related to the mathematical side of optimization. In this segment of the bibliography, just the behavioral aspects and properties of the models and algorithms are studied. As representatives of such approach, [122] provides several adaptive hybrid functions to create surrogate models; [123] presents Large-Scale System Theory MDO methods for aircraft; [124] studies Analytical Target Cascading (ATC) and ways structure the hierarchy of the formulation; in [125] sensitivity of Concurrent SubSpace Optimization (CSSO) and its use with neural networks are addressed; [126] compares distributed multidisciplinary and All at Once (AAO) Monte Carlo uncertainty analysis; uncertainty is also addressed in [127] through the sparse grid technique, and [128] presents a new model of estimation; [129] proposes a method

for analysis of the solution subspace by using graphs to successfully reduce the amount of processing required; in [130] a new decomposition algorithm is introduced, and its mathematical properties are developed; another decomposition method is studied in [131]; [132] studies the algebraic properties of complex sets as a base for MDO; finally [133] studies the interactions between particles in Particle Swarm Optimization (PSO) through statistics, and its conditions for convergence.

Several more documents relate mathematical analysis and application. Various address aeronautics, such as [134], where ATC is studied and applied to a wing optimization, or [98] where several algorithms and architectures are studied with the same intent; [135] studies Genetic Algorithm (GA) uncertainty to optimize the shape of wing and horizontal tail plane (HTP) of an airplane, while [136] studies them together with the Kriging method to design a supersonic business jet; [137] uses game theory to develop new algorithms and also for wing optimization, as well as [138], where the succession of a cooperative strategy followed by a competitive one are employed. In [139] a mixed model for fuselage optimization is developed from game theory; and [140] studies uncertainty of random-fuzzy continuous discrete variables (RFCDV) and applies them to the design of a pressure vessel. Other works, such as [141], step into robust formulation of PSO applied to the hydrodynamic calculations of a ship fin; or fitness inheritance techniques in PSO in [142] to be compared with Sequential Quadratic Programming (SQP) and the Method of Centers (MOC).

Other works, still with a predominantly mathematical approach, apply the models to non-aeronautical subjects. Among these, we can name [143] and [144]. Whereas the first work addresses the optimization with an ATC decomposition-based algorithm, the second one analyzes different models to add modifications to CAD models. Another model [145] introduces ensemble of surrogates into ATC black-box problems with implicit constraints, applying it to a machining problem in a lathe. And last but not least, there are various works with the same scope, but different approach, such as [146], that relates the efficiency of quasi-separable problems to their decomposed versions in an AAO environment; [147] presents a new method where the feasible subspace is modified by using Multi-objective Robust Collaborative Optimization (MORCO), Non-dominated Sorting Genetic Algorithm (NSGA-II), and Linear Physical Programming (LPP). Both methods are applied then to a changing gear problem as a benchmark. Finally, [148] addresses Bi-Level Integrated System Collaborative Optimization (BLISCO) as a new model made by mixing BLISS and CO architectures which, through improvement has become Enhanced Collaborative Optimization (ECO) [149,150], Bayesian Collaborative Sampling (BCS)[151], and Enhanced Design Space Decrease Collaborative Optimization (EDSDCO) [152].

The reasons to choose an architecture will depend on the particular problem to solve but, during the last years, distributed architectures have become more common [121], among other reasons, because they thrive on parallel computing, which reduces the processing time.

On the other hand, most of the bibliography leaves aside the purest mathematical elaboration and focuses on presenting new algorithms or methods and/or studying their behavior under different conditions. As it happened with the works presented before, the type of example provided differs from work to work.

Several documents address aeronautic problems. In [153,154], the truss-braced wings are studied with a monolithic architecture; [155] analyzes the pareto frontiers of an aircraft design; [156] applies the gradient Method of Moving Asymptotes (MMA) to a cost and weight model in order to study fuselages; [157] is one of the few works where the optimization of a complete aircraft is addressed, in this case a GA, together with some engineer taking decisions to design it; [158] optimizes a wing with a discipline Multidisciplinary Feasible (MDF) analysis and CO, increasing the feasible subspace to find better solutions, just in the same way as it is done in [159]; a wing is also studied together with the uncertainty of the model in [160] by using a gradient method called SNOPT; the same surface is employed in a robust study of a Hierarchical Asynchronous Parallel Multi-Objective Evolutionary Algorithms (HAPMOEA) algorithm in [161]; [162] studies the effects of uncertainty on the solution of the optimization system and applies it to the design of the nose of a plane with a Monte Carlo (MC) algorithm; the design of a jet plane is undertaken with both a BLISS and CSSO algorithms in [163] by continuously updating sensitivity values while the calculations are being made; [164] presents a program for aerodynamic shape optimization with gradient methods; this kind of algorithm is also used in [165] for the design of a supersonic

nozzle. Here, optimization is used as much as CFD analysis and application of theory (method of characteristics); in [166], an MDO preliminary designing tool is presented. Such tool uses databases to help an operator designing an aircraft; finally, [167] uses an Agent-Based Modeling/Simulation (ABM/S) optimizer to study the design of aircraft systems. On the other hand, in [168] the aerodynamic and performance design of a full aircraft is undertaken with CO. There are, as well, several cases where no example of application is provided; [169] introduces a way to couple aeroelasticity and flight control and applies it to the calculations of a turning maneuver by using an Airbus' solver LAGRANGE. In [170], an MDO advisory system, coupled to an optimization configurator for a Process Integration and Design Optimization (PIDO) system is presented; [171] introduces a platform that automatically creates and performs aeroelastic and mass calculations with a FEM model; in [172], a system for aircraft systems integration is explained and ,additionally, [173] provides a tool to manually generate RPAS configurations from a database and estimate their performance; also, in [174], a similar tool is developed, aimed at calculating manufacturing costs. Even though the last four works do not perform any kind of optimization, this type of tools are part of more complex MDO structures, such as the one in [175], which consists of different and progressively detailed optimization loops for more; or [176], where Reverse Iteration of Structural Model (RISM) is proposed as a technique to be used with surrogate models to solve faster, and with enough precision, aircraft designing problems; in [177] the authors present pyOpt, a framework for optimization mostly

employing SQP, SLSQP and MMA, but with several other algorithms available; and [178], another MDO framework linked to CAD solvers. In most methods there is also the choice to allow the model to study unfeasible solutions. These are not to be chosen in the end, but may connect various feasible regions of the solution subspace and ease the optimization process with different levels of precision [179–185]. Another work studies the influence of the system design variables with a satellite optimization as the benchmark case [186]. Finally, some studies, [187,188], address the current state of the art in MDO at predesign stage and space launchers. Both conclude that gradient and evolutionary algorithms are the trend nowadays, and that those are used together with sensitivity and robust techniques.

Similar works exist, but not applied to aeronautic matters, such as the development of a carrier ship family by using PSO [189]; marketing and manufacturing, as well as design, in [190], by using ATC. This architecture is the same used in [191], where a quadratic penalty function (QEPF) model is developed with promising results. Finally, in [192], a moving least squares (MLSM) response surfaced based approximate optimization method is studied. On the other hand, [193] studies the inclusion of airworthiness requirements into MDO, while [194] does so with emissions.

There is also a different trend of research, where the models are tested with different model problems, or several algorithms or architectures [195] are tested with the same problem. This kind of benchmark usually compares new versions of

widely used algorithms and solutions to well-known problems [196–198], new MDO frameworks under various similar circumstances [199], or even MDO derived methodologies such as Natural Domain Modeling for Optimization (NDMO) [200]. Among these we can find [201], where ATC and Augmented Lagrangian Coordination (ALC) are compared; the study of ALC in [202]; the same way that MDF, CO, and Individual Discipline Feasible (IDF) methods are compared in [203]; or algorithms from game theory and evolutionary ones in [204]; [205] compares different formulations of PSO, and [206] studies its use with CO; [207] develops Improved Collaborative Optimization (ICO) from Classic Collaborative Optimization (CCO); in [208], a new formulation for Sequential Quadratic Programming (SQP) is presented and used with approximated coupled models; [209] develops a mixed model from MDF and CSSO, also addressed in [210]. In this case the model is tested with the gear changing problem and the design of a satellite. Finally, two analyses of algorithms applied to several problems are [211] and [212]. In the first case, a Tabu Search Monte Carlo (TSMC) algorithm is developed and tested with orbit calculation, batteries designing, and stock options; the second work studies the behavior of three different algorithms: GPS, LT-MADS and OrthoMADS, when used with a styrene production problem, a plane range calculation, and well placement.

The last work presented here does not fit into any of the previous categories, since [213] addresses the expression of MDO problems from a graphical point of

view, and introduces the Extended Design Structure Matrix (XDSM) as a tool to express, in two dimensions, the increasing complexity of MDO formulation and architectures.

With regard to particular MDO frameworks, there are multiple solutions available [59]. Some approaches focus on a generic environment where integrating analysis and optimization modules [214]; or a problem-like formulation [215]; NASA has been an important developer of MDO studies [216] and frameworks, such as MDAO [217], a modular and flexible environment aimed at aerospace optimization; Onera's ARTEMIS manages multilevel/multifidelity MDO applied at the design of commercial airplanes [218], which has been studied before [219,220]; SORCER takes advantage of multi-platform computing [221]; NeoCASS [222] focuses on structural and aeroelastic optimization; while the Air Force's Research Laboratory for Multidisciplinary Science and Technology Center (MSTC) has developed a framework aimed at the design of Efficient Supersonic Air-Vehicle Exploration (ESAVE) [223]. The project AGILE [224], which is aimed at a 40% increase in solving speed in aircraft design MDO problems, also deserves be noted. There is, as well, an implementation of a modified ECO architecture to design unmanned aircraft [225] with morphing wing. MDO approach at the design of There are also Matlab based suites, such as [226,227]. Other frameworks implement an AAO-like architecture with several disciplinary modules [228]. On a side note, there are also tools dedicated to the analysis of MDO and distributed design frameworks and their performance [229,230].

1.5. Trends and conclusions

The current state of the art of MDO is wide and diverse. There are many different approaches to optimization, but some trends can be extracted from the studied bibliography:

- ATC, evolutionary (GA, PSO) and gradient algorithms, together with CO derivatives, are the most used methods in aeronautics and with the best results.
- Sensitivity and uncertainty studies help to better take advantage of the underlying mathematical foundations of the formulation. These methodologies follow the same current as the use of robust optimization since it is now not enough with obtaining an optimal solution, but one that may withstand limited changes to design variables.
- The classic formulation of a problem is not usual. Using combinations of different techniques usually provides better results.
- Most of the tools and frameworks developed for aeronautical design consist of a core optimizer and several CAD/FEM/VEM/Kriging modules that feed said core with analysis results.
- There is not a single work where the complete change of aerodynamic configuration is considered. The most extreme cases contemplate just some variation in the configuration of the vertical stabilizing surface, and the geometry of the wings.

1.6. Objectives and motivation

In view of the conclusions presented in the previous section, and the analysis undertaken along this chapter of the state of the art, the research has been focused on the two main following objectives:

- **To develop a generalized MDO architecture that can be used with diverse problems and, in particular, to design RPAS.**

The motivation behind this objective is grounded on the fact that the literature is filled with different architectures. Most new architectures present only small variations from the source. A generalization of current architectures would shift the paradigm under which architectures are studied. Currently they are considered as independent tools to solve a problem. A generalization would help study them as a whole to better understand what differences each of them. This would also facilitate the conception and study of new architectures that fall within a subspace of architectures not considered before.

- **To develop an MDO environment for small RPAS design. This environment shall be capable of performing the quick preliminary design of small RPAS and be strongly multidisciplinary.**

This objective is motivated by the fact that current approaches have very particular characteristics:

- They tend to include no more than two disciplines (chosen from aerodynamics, structural calculus and propulsion).

- They tend to rely on either very time and resources consuming CFD, or extremely simplistic surrogate models for each discipline.

The motivation for this environment to be aimed at small RPAS is justified by current trends on small RPAS design. While medium size and big military-grade RPAS tend to follow the design models that are used to design manned aircraft, small RPAS tend to follow the not so systematic approach that is used with RC models.

In addition to the two previous main objectives, the research pretends to achieve the following secondary objectives, which support and strengthen the main objectives:

- **To study the feasibility of using simple but reliable manual-like aerodynamic models with small RPAS.**

In order to create a quick MDO environment for the design of small RPAS, it is necessary to avoid the use of time consuming CFDs. The alternatives are mostly aimed at the design of commercial aircraft. This leads to the need of making sure that using them with small RPAS will not provide wrong information to the MDO environment.

- **To consider multiple aerodynamic configurations within the MDO environment.**

This is motivated by the fact that the aerodynamic configurations are considered separately when using MDO. In other words, when designing of

optimizing the design of an aircraft, each configuration is approached with a different model. If the MDO environment allowed the design to fluidly evolve from, let us say, a canard configuration to a classical configuration, the end result would be better than any result that considered each configuration separately. A designing concept where each configuration is isolated from the others includes constraints that unnecessarily limit the optimality of the end result and will leave intermediate configurations out of consideration.

- **To study the influence of RPAS design parameters on their market price.**

There are well established models to estimate the manufacturing price of commercial and military aircraft, and there is broad information regarding the market price of most commercial aircrafts and most important military aircraft programs. However, given the particularities of the RPAS market, coming up with an estimation of the market price of a particular aircraft is, to say the least, difficult. Mostly when addressing medium size and small professional-grade RPAS. A deep study of the market price of these types of RPAS and how it relates to their characteristics will serve to the creation of a comprehensive MDO environment.

- **In addition, as a transversal requirement, the constraints of the model shall be limited to high level requirements and physical feasibility of the design.**

In complex multidisciplinary designs, high-level constraints and disciplinary interactions usually produce lower-level constraints that are necessary to

reduce the complexity of the decision making process. In long designing processes, these constraints may become outdated and produce suboptimal results. By keeping the constraints to a minimum, we will ensure that the solution that the MDO environment provides will not be limited by unnecessary constraint.

2

GENERIC PARAMETER PENALTY ARCHITECTURE

Part of the content of this section has been previously published (with small modifications) as a research article in the journal Structural and Multidisciplinary Optimization with the title “Generic Parameter Penalty Architecture”, DOI: 10.1007/s00158-018-1979-2. The original source [231] can be found at:

<https://doi.org/10.1007%2Fs00158-018-1979-2>

2.1. Nomenclature

c	- Vector of design constraints	C_{gi}	- Coefficients related to gearbox constraints and requirements
c^c	- Vector of consistency constraints	D	- Euclidean distance used as error measure
C_{Ai}, C_{Bi}	- Coefficients related to gearbox constraints and requirements	f	- Objective function
C_{fi}	- Coefficients related to the volume of the gearbox	J	- Consistency constraints

K_i	- Coefficients representing empirical data	y	- Vector of coupling variables
N	- Number of disciplines	α	- Generic Parameter Penalty Architecture (GPPA)
p	- Pressure during the combustion of propane		parameter of the main objective function
R	- Air to fuel ratio	β	- GPPA parameter of discipline objective functions
R_i	- Discipline constraints in residual form	ϕ	- Weight parameter
x	- Vector of design variables	γ	- GPPA parameter of constraints
Subscript			
arch	- Architecture	0	- Shared among disciplines
i	- Index referred to discipline i		
j	- Index		
ref	- Reference solution		
Superscripts			
$^{\wedge}$	- Copy of a variable for use in a discipline	-	- State variable
		*	- Function at its optimal value

2.2. Introduction

Multidisciplinary Design Optimization (MDO) is an engineering discipline that uses mathematic models to optimize and obtain solutions for engineering problems. It has experienced a fast and deep evolution during the last years and it is widely used in aerospace engineering, particularly in aircraft design.

As stated in Chapter 1, there is a trend of works discussing the design of aeronautical structures by the means of MDO[135,137–142]. Similarly, another group addresses the mathematical side of optimization [122,124,125,129,130,132,133]. Finally, part of the literature focuses on the comparison of optimization models by optimizing different physical/mathematical problems, or by testing several algorithms with the same problem. These benchmarking studies tend to compare

new versions of widespread algorithms under similar circumstances [201,203,204,207–209,211,212].

From the literature analysis that was presented in Chapter 1 we inferred that ATC, evolutionary (GA, PSO) and gradient algorithms, together with CO, are the most used methods and with the best results. In addition, sensitivity and uncertainty studies help to better take advantage of the underlying mathematical foundations of the formulation. This methodology follows the same current as the use of robust optimization. Obtaining an optimal solution is not enough anymore: the solution must withstand limited changes in the variables. Therefore, classical formulation of a problem is no longer a choice. Using combinations of different techniques usually provides better results. In that direction, most of the tools and frameworks developed for aeronautical design consist of a core optimizer and several Computer Aided Design (CAD), Finite Element Method (FEM) or Virtual Element Method (VEM) modules that feed such core with analysis results.

Our aim is to develop an MDO model for Remotely Piloted Aircraft Systems (RPAS) design. This model will provide the full design of the aircraft from an objective performance and study the whole configuration of the aircraft: propulsion, structure, aerodynamics [232], equipment, econometrics, etc.

In this chapter we present a new architecture, called Generic Parameter Penalty Architecture (GPPA), which drives the optimization in our model, and compare its performance to that of several common architectures. This

comparison will be performed by subjecting three benchmark problems to an optimization driven by distributed architectures: GPPA, CO, ATC and the monolithic All at Once (AAO).

2.3. Generic Parameter Penalty Architecture

In MDO distributed architectures there are two levels where optimization is undertaken. There is a system level optimization, and a subdiscipline optimization. In each one of them, a different objective function is used. The system level optimization must necessarily pursue a global objective, which could be minimizing either the global objective function or the inconsistency between subdisciplines. On the other hand, each subdiscipline will aim at obtaining results regarding the objective that is not carried out by the system level optimization. In addition, one of the levels will also address the partial objective of each one of the subdisciplines.

There are a number of architectures with different approaches, including sensitivity analysis, surrogate models, or variable budgets, but most of them adopt the previous task distribution of optimization objectives. That is the reason why we are introducing here GPPA. A new architecture concept that did not exist before. In GPPA, the distribution of the three previously mentioned tasks (global objective, subdiscipline objective, and consistency) is undertaken by both the system level and the subdiscipline optimization. This distribution of the system level and subdiscipline optimization is controlled by three parameters (α , β , γ) that

define the load on each level. Additionally, there is a fourth parameter, ϕ , which is used as a penalty parameter to address the consistency of the disciplines' solutions and takes a different value for each of them, in a similar way to ATC.

The general formulation for a GPPA MDO problem is as follows (formulation convention as from [121]):

$$\begin{aligned} \text{minimize} \quad & f_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) + \sum_{i=1}^N \beta_i f_i(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) + \\ & \sum_{i=1}^N \gamma_i \Phi_i J_i \left(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}) \right) \end{aligned} \quad (2.1)$$

with respect to $x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}$

subject to

$$c_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \geq 0 \quad (2.2)$$

$$c_i(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \geq 0 \quad \text{for } i = 1, \dots, N \quad (2.3)$$

$$c_i^c = \hat{y}_i - y_i = 0 \quad \text{for } i = 1, \dots, N \quad (2.4)$$

$$J_i = \left\| \hat{x}_{0i} - x_0 \right\|_2^2 + \left\| \hat{x}_i - x_i \right\|_2^2 + \left\| \hat{y}_i - y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}) \right\|_2^2 \quad \text{for } i = 1, \dots, N \quad (2.5)$$

Whereas each discipline i subproblem is:

$$\begin{aligned} \text{minimize} \quad & (1 - \alpha) f_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) + (1 - \beta_i) f_i(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) + \\ & \sum_{i=1}^N (1 - \gamma_i) \Phi_i J_i \left(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}) \right) \end{aligned} \quad (2.6)$$

with respect to $x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}$

subject to

$$c_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \geq 0 \quad (2.7)$$

$$c_i(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \geq 0 \quad \text{for } i = 1, \dots, N \quad (2.8)$$

$$c_i^c = \hat{y}_i - y_i = 0 \quad \text{for } i = 1, \dots, N \quad (2.9)$$

$$J_i = \|\hat{x}_{0i} - x_0\|_2^2 + \|\hat{x}_i - x_i\|_2^2 + \left\| \hat{y}_i - y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}) \right\|_2^2 \text{ for } i = 1, \dots, N \quad (2.10)$$

The vector of consistency constraints, c^c , comprises each consistency constraint in residual form. On the other hand, J is the sum of the squared residues of all the consistency constraints of the problem.

As the equations above show, both problems adopt the same shape, but the system level optimization will support a load of α, β, γ (with $\alpha, \beta, \gamma \leq 1$), whereas each subdiscipline will do so with a factor of $1-\alpha, 1-\beta, 1-\gamma$. In cases where α, β , or γ have extreme values of 0 or 1 the model can take forms similar to those of already existing architectures, as well as architectures that may not provide a consistent or optimal solution at all.

The parameter α manages the distribution of the main objective function load between the high-level problem and the subdisciplines. Each β_i distributes the load of each subdiscipline's objective function, while the γ_i do so with the consistency constraints and each ϕ_i establishes a weight factor for them.

Following the convention introduced by Martins and Lambe [213], Figure 1 shows GPPA's XDSM.

Figure 1: GPPA's Extended design structure matrix (XDSM) as per [213].

2.4. MDO Architectures for Comparison

A wide variety of approaches can be used to tackle an optimization problem. To study the performance of our model, we will compare it to three common approaches widely used in the field. These methodologies are the monolithic AAO, and the distributed CO and ATC. Formulation is taken from [121]:

2.4.1. Monolithic Architecture

In monolithic architectures all the disciplines are solved at once, or in succession, only once. After every variable has been calculated the solution is evaluated to measure its optimality. The next iteration will evaluate one or several candidates depending on the optimization methodology and algorithm.

2.4.1.1. All at Once

The general formulation for an AAO MDO problem is as follows:

$$\text{minimize} \quad f_0(x, y) + \sum_{i=1}^N f_i(x_0, x_i, y_i) \quad (2.11)$$

$$\text{with respect to} \quad x, \hat{y}, y, \bar{y}$$

subject to

$$c_0(x, y) \geq 0 \quad (2.12)$$

$$c_i(x_0, x_i, y_i) \geq 0 \quad \text{for } i = 1, \dots, N \quad (2.13)$$

$$c_i^c = \hat{y}_i - y_i = 0 \quad \text{for } i = 1, \dots, N \quad (2.14)$$

$$R_i(x_0, x_i, \hat{y}_{j \neq i}, \bar{y}, y_i) = 0 \quad \text{for } i = 1, \dots, N \quad (2.15)$$

The function to minimize includes the system level objective, f_0 , as well as the objective of every subdiscipline, f_i . This problem is subject to subdiscipline, c_i , and interdisciplinary, c_0 , consistency constraints. Each R_i represents a discipline constraint in residual form. These constraints are both consistency and design constraints. Using both R_i in addition as c^c and c may seem redundant, but it is consistent with the various shapes that the constraints in the problem adopt.

2.4.2. Distributed Architectures

In distributed architectures there is a system level optimization, as well as discipline level optimization. Each step of the optimization process requires for the subdisciplines to achieve an optimum solution before evaluating the optimality of the system level solution. To be able to obtain such intermediate solutions, the model admits a limited level of elasticity between the shared variables of each subdiscipline. In order to achieve consistency, such elasticity is included in the objective function with a weighting factor. Doing so with the system level function, or with the subdiscipline function, is a characteristic of each discipline.

2.4.2.1. Collaborative Optimization

In collaborative optimization the consistency is held in the subdiscipline optimization, whereas the system-level optimization is in charge of the global objective.

The system level problem is:

$$\text{minimize} \quad f_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \quad (2.16)$$

$$\text{with respect to} \quad x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}$$

subject to

$$c_0(x_0, \hat{x}_1, \dots, \hat{x}_N, \hat{y}) \geq 0 \quad (2.17)$$

$$J_i^* = \|\hat{x}_{0i} - x_0\|_2^2 + \|\hat{x}_i - x_i\|_2^2 + \|\hat{y}_i - y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i})\|_2^2 \text{ for } i = 1, \dots, N \quad (2.18)$$

J_i^* is J_i at its optimal value. It is obtained by performing the subdiscipline analyses.

Whereas each discipline i subproblem is:

$$\text{minimize} \quad J_i(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i})) \quad (2.19)$$

$$\text{with respect to} \quad \hat{x}_{0i}, x_i$$

$$\text{subject to} \quad c_0(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i})) \geq 0 \quad (2.20)$$

2.4.2.2. Analytical Target Cascading

In Analytical Target Cascading the consistency is held in the system-level optimization and the subdiscipline optimization, which is also in charge of the global and disciplinary objectives. In addition, the consistency weights are modified as the optimization evolves in order to improve the convergence rate.

The system level problem is:

$$\text{minimize} \quad f_0(x, \hat{y}) + \sum_{i=1}^N \Phi_i(\hat{x}_{0i} - x_0, \hat{y}_i - y_i(x_0, x_i, \hat{y})) + \Phi_0(c_0(x, \hat{y})) \quad (2.21)$$

$$\text{with respect to} \quad (x_0, \hat{y})$$

Whereas each discipline i subproblem is:

$$\begin{aligned} \text{minimize} \quad & f_0(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}), \hat{y}_{j \neq i}) + \\ & f_i(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}), \hat{y}_{j \neq i}) + \\ & \Phi_i(\hat{y}_i - y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}), \hat{x}_{0i} - x_i) + \\ & \Phi_0(c_0(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i}), \hat{y}_{j \neq i})) \end{aligned} \quad (2.22)$$

$$\text{with respect to} \quad \hat{x}_{0i}, x_i$$

$$\text{subject to} \quad c_0(\hat{x}_{0i}, x_i, y_i(\hat{x}_{0i}, x_i, \hat{y}_{j \neq i})) \geq 0$$

2.5. Tests Problems

Three different problems were selected for the architectures comparison. All of them can be found at NASA's MDO Test Suite [233]. NASA's MDO Test Suite problems have been widely used as a benchmark for numerous MDO formulations, architectures, and algorithms. The three chosen problems consist in a simple analytical problem, a speed reducer, and the study of propane in air, and have been useful before when comparing MDO architectures [152,183,191,195,203]. By using these three problems as benchmark, we are able to compare the performance of the architectures with increasingly more complex problems.

All three problems presented here were solved by using both the benchmarking architectures and GPPA. In all cases, a simple version of Evolutionary Algorithms (EA) was used. Gradient-based algorithms tend to have problems with non-continuous functions and multi-modal problems [234]. Since GPPA will be used as the core architecture of the MDO framework for RPAS design, the use of evolutionary algorithms is advisable. Therefore, they were used in the benchmarking as well. EA consist on a population of candidate solutions (vectors with values for each variable in the problem) that are evaluated by the objective function to assess their fitness. Among the candidates, the best one was selected by comparing objective functions: the best candidate's objective function will present the lowest value. Then, a new population is generated by creating mutated copies from it. The mutation consists on randomly modifying the value of each variable in the solution vector, thus creating different new candidates. In this case we measured the mutation of the variables through a parameter called *Mutation Rate* which defines the percentage of change that each variable can experience in a single mutation. We initially set this parameter to 1%, but it was automatically reduced during the optimization when no improvement in the solution had been achieved for a predetermined number of steps. This value was particular for each architecture and problem and was obtained through fine tuning.

2.5.1. Simple analytical problem

The first problem analyzed has been used before [203,208] for the analysis of multiple architectures and benchmarking, and previously presented and used in [235] to analyze CSSO.

Formulation

$$\text{minimize} \quad f = x_1^2 + x_2 + y_1 + e^{-y_2} \quad (2.23)$$

subject to:

$$1 - \frac{y_1}{3.16} \leq 0 \quad \frac{y_2}{24} - 1 \leq 0 \quad (2.24)$$

$$-10 \leq x_1 \leq 10 \quad 0 \leq x_2 \leq 10 \quad (2.25)$$

$$0 \leq x_3 \leq 10 \quad (2.26)$$

Disciplines

Discipline 1 is defined by the following expression:

$$y_1 = x_1^2 + x_2 + x_3 - 0.2y_2 \quad (2.27)$$

And discipline 2:

$$y_2 = \sqrt{y_1} + x_1 + x_3 \quad (2.28)$$

The optimal solution of this problem corresponds to an objective function with a value of 3.18339 and variables $(x_1, x_2, x_3) = (1.9776, 0, 0)$ [203].

2.5.2. Golinski's speed reducer

The speed reducer was first proposed by Golinski [236]. It consists of two connected gears, their respective shafts, and a box housing all the parts. The objective of the problem is minimizing the volume and, therefore, the mass of the system while satisfying several restrictions. It was, originally, a single level problem, but has been modified ever since to become a three-level MDO problem [198], which is the version analyzed here. An analysis of solutions proposed by various authors can be found in [148,196,209], and has been used before as a benchmark problem [152]. This problem has seven variables, five of which are shown in Figure 2. The remaining two variables define the number of teeth of the model, x_3 , and the size of the teeth of the gears, x_4 . These two variables do not appear in Figure 2. Coefficients C_{f1} - C_{f6} derive from the calculation of the volume of the gearbox. On the other hand, coefficients C_{g1} - C_{25} , C_{g245} , C_{Ai} and C_{Bi} are originated from the imposition of mechanical and physical constraints on the gearbox as follows: g_1 and g_2 establish the upper bound on the bending and contact stress of the gear tooth respectively. Then, g_3 and g_4 provide upper bounds on the transverse deflection of shafts 1 and 2, while g_5 and g_6 do so on the stress of the shafts. Finally, g_7 - g_{25} and g_{245} establish dimensional restrictions and requirements from experience.

Single level formulation

$$\begin{aligned} \text{minimize} \quad & f = C_{f1}x_1x_2^2(C_{f2}x_3^2 + C_{f3}x_3 - C_{f4}) - C_{f5}(x_6^2 + x_7^2)x_1 + \\ & C_{f6}(x_6^3 + x_7^3) + C_{f1}(x_4x_6^2 + x_5x_7^2) \end{aligned} \quad (2.29)$$

subject to:

$$2.6 \leq x_1 \leq 3.6 \quad 0.7 \leq x_2 \leq 0.8 \quad (2.30)$$

$$17 \leq x_3 \leq 28 \quad 7.3 \leq x_4 \leq 8.3 \quad (2.31)$$

$$7.3 \leq x_5 \leq 8.3 \quad 2.9 \leq x_6 \leq 3.9 \quad (2.32)$$

$$5.0 \leq x_7 \leq 5.5 \quad (2.33)$$

where

$$C_{f1} = 0.7854 \quad C_{f2} = 3.3333 \quad (2.34)$$

$$C_{f3} = 14.9334 \quad C_{f4} = 43.0934 \quad (2.35)$$

$$C_{f5} = 1.5079 \quad C_{f6} = 7.477 \quad (2.36)$$

Figure 2: Speed reducer schematics with physical measurements.

Multilevel formulation

Following Azarm and Li's formulation [198,237], the global problem:

$$\begin{aligned} \text{minimize} \quad & f_g = C_{f1}x_1x_2^2(C_{f2}x_3^2 + C_{f3}x_3 - C_{f4}) - C_{f5}x_1(x_6^2 + x_7^2) + \\ & C_{f6}(x_6^3 + x_7^3) + C_{f1}(x_4x_6^2 + x_5x_7^2) \end{aligned} \quad (2.37)$$

$$\text{subject to:} \quad \frac{C_{g7}}{x_2x_3} \geq 1.0$$

The low level subproblem 1:

$$\text{minimize} \quad f_1 = C_{f1}x_1x_2^2(C_{f2}x_3^2 + C_{f3}x_3 - C_{f4}) \quad (2.38)$$

subject to:

$$x_1 \geq \frac{C_{g1}}{x_2^2x_3} \quad x_1 \geq \frac{C_{g2}}{x_2^2x_3^2} \quad x_1 \geq C_{g8}x_2 \quad (2.39)$$

$$x_1 \geq C_{g10} \quad x_1 \geq C_{g9}x_2 \quad x_1 \geq C_{g11} \quad (2.40)$$

The low level subproblem 2:

$$\text{minimize} \quad f_2 = -C_{f5}x_1^*x_6^2 + C_{f6}x_6^3 + C_{f1}x_4x_6^2 \quad (2.41)$$

subject to:

$$x_6 \geq \left(\frac{1}{C_{g5}C_B} \sqrt{\frac{C_{A12}^2x_4^2}{x_2^2x_3^2} + C_{A1}} \right)^{\frac{1}{3}} \quad x_6 \geq \left(\frac{C_{g3}x_4^3}{x_2x_3} \right)^{\frac{1}{4}} \quad (2.42)$$

$$x_6 \geq C_{g20} \quad x_6 \leq C_{g21} \quad x_7 \leq \frac{x_4 - C_{g245}}{C_{g24}} \quad (2.43)$$

The low level subproblem 3:

$$\text{minimize} \quad f_3 = -C_{f5}x_1^*x_7^2 + C_{f6}x_7^3 + C_{f1}x_5x_7^2 \quad (2.44)$$

subject to:

$$x_7 \geq \left(\frac{1}{C_{g6}C_B} \sqrt{\frac{C_{A12}^2x_5^2}{x_2^2x_3^2} + C_{A2}} \right)^{\frac{1}{3}} \quad x_7 \geq \left(\frac{C_{g4}x_5^3}{x_2x_3} \right)^{\frac{1}{4}} \quad (2.45)$$

$$x_7 \geq C_{g22} \quad x_7 \leq C_{g23} \quad x_7 \leq \frac{x_5 - C_{g245}}{C_{g25}} \quad (2.46)$$

where

$$C_{g1} = 27.0 \quad C_{g2} = 397.5 \quad C_{g3} = 1.93 \quad (2.47)$$

$$C_{g4} = 1.93 \quad C_{g5} = 1100.0 \quad C_{g6} = 850.0 \quad (2.48)$$

$$C_{g7} = 40.0 \quad C_{g8} = 5.0 \quad C_{g9} = 12.0 \quad (2.49)$$

$$C_{g10} = 2.6 \quad C_{g11} = 3.6 \quad C_{g12} = 0.7 \quad (2.50)$$

$$C_{g13} = 0.8 \quad C_{g14} = 17 \quad C_{g15} = 28 \quad (2.51)$$

$$C_{g16} = 7.3 \quad C_{g17} = 8.3 \quad C_{g18} = 7.3 \quad (2.52)$$

$$C_{g19} = 8.3 \quad C_{g20} = 2.9 \quad C_{g21} = 3.9 \quad (2.53)$$

$$C_{g22} = 5.0 \quad C_{g23} = 5.5 \quad C_{g24} = 1.5 \quad (2.54)$$

$$C_{g25} = 1.1 \quad C_{g245} = 1.9 \quad C_{A12} = 745.0 \quad (2.55)$$

$$C_{A1} = 1.69 \cdot 10^7 \quad C_{A2} = 1.575 \cdot 10^8 \quad (2.56)$$

$$C_B = 0.1 \quad (2.57)$$

The optimal solution of this problem corresponds to an objective function with a value of 2996.232157 and variables $(x_1, x_2, x_3, x_4, x_5, x_6, x_7,) = (3.5, 0.7, 17, 7.3, 7.8, 3.35021468, 5.28668325)$ [196].

2.5.3. Propane combustion in air

Also from NASA's MDO Test Suite [233], the third problem addresses propane combustion in air. The problem presents ten variables, which represent the number of moles of each product at the end of the reaction, x_1 - x_{10} . There is an additional variable, x_{11} , which represents the sum of every product. This problem has previously been addressed in [183,203,216,238]

Formulation

$$\text{minimize } f = f_2 + f_6 + f_7 + f_9 \quad (2.58)$$

subject to:

$$f_2 \geq 0 \quad f_6 \geq 0 \quad f_7 \geq 0 \quad f_9 \geq 0 \quad (2.59)$$

$$x_1 \geq 0 \quad x_3 \geq 0 \quad x_6 \geq 0 \quad x_7 \geq 0 \quad (2.60)$$

where

$$f_2 = 2x_1 + x_2 + x_4 + x_7 + x_8 + x_9 + 2x_{10} - R \quad (2.61)$$

$$f_6 = K_6 x_2^{\frac{1}{2}} x_4^{\frac{1}{2}} - x_1^{\frac{1}{2}} x_6 \left(\frac{p}{x_{11}} \right)^{\frac{1}{2}} \quad (2.62)$$

$$f_7 = K_7 x_1^{\frac{1}{2}} x_2^{\frac{1}{2}} - x_4^{\frac{1}{2}} x_7 \left(\frac{p}{x_{11}} \right)^{\frac{1}{2}} \quad (2.63)$$

$$f_9 = K_9 x_1^{\frac{1}{2}} x_3^{\frac{1}{2}} - x_4^{\frac{1}{2}} x_9 \left(\frac{p}{x_{11}} \right)^{\frac{1}{2}} \quad (2.64)$$

Disciplines

Discipline 1 is defined by the following expressions:

$$f_1 = x_1 + x_4 - 3 = 0 \quad f_5 = K_5 x_2 x_4 - x_1 x_5 = 0 \quad (2.65)$$

Discipline 2:

$$f_8 = K_8 x_1 - x_4 x_8 \left(\frac{p}{x_{11}} \right) = 0 \quad f_{10} = K_{10} x_1^2 - x_4^2 x_{10} \left(\frac{p}{x_{11}} \right) = 0 \quad (2.66)$$

With regard to discipline 3:

$$f_3 = 2x_2 + 2x_5 + x_6 + x_7 - 8 = 0 \quad (2.67)$$

$$f_4 = 2x_3 + x_9 - 4R = 0 \quad f_{11} = x_{11} - \sum_{j=1}^{10} x_j = 0 \quad (2.68)$$

Finally, the coefficients receive the following values:

$$K_5 = K_6 = K_7 = K_9 = 1 \quad (2.69)$$

$$K_8 = K_{10} = 0.1 \quad (2.70)$$

$$p = 40, R = 10 \quad (2.71)$$

The optimal solution of this problem corresponds to an objective function with a value of 0 and variables [183]:

$$(x_1, x_2, x_3, x_4, x_5, x_6) = (1.3789, 1.3729, 18.4268, 1.6211, 1.6141, 1.0948)$$

$$(x_7, x_8, x_9, x_{10}, x_{11}) = (0.9312, 0.0632, 3.14638, 0.0537, 29.7031)$$

3

RAMP: RPAS ADVANCED MDO PLATFORM

3.1. Introduction

RAMP (RPAS Advanced MDO Platform) is a new design platform aimed at the early stages of conception of small RPAS. Once mission and additional requirements are defined, RAMP will generate a random RPAS that will progressively evolve until its design is optimum for the mission parameters. RAMP is a direct application of GPPA, the architecture presented in Chapter 2. RAMP puts into practice some of the design philosophy from classical design manuals [70,71,239] and more recent works [240–242]. Similar efforts have been undertaken

at developing this kind of MDO environment. Amongst which the one developed by Albuquerque et al stands out [225]. In Albuquerque's model, ECO is used to design UAVs with morphing wings. The model includes several disciplines, such as aerodynamics, propulsion, and weight calculation. Even though the aim of the reference and RAMP may be similar, the following chapters will show that RAMP undertakes the design in a more ambitious way: RAMP's architecture is GPPA, which is very flexible in its application and shape, it can adopt ECO's shape and performance, or it can be set so that it acts as a completely different architecture. RAMP's take on aerodynamics is much more detailed, and RAMP performs not only weight estimation, but also structure definition and estimation, price estimation, payload and C₃ arrangement and, most importantly, open aerodynamic and propulsion system configurations.

RAMP is composed of a main module (called "Main") that controls the workflow of the environment. This module is connected to a number of secondary modules that are called when needed. Figure 3 presents a scheme of RAMP's structure and organization.

3.2. Mission definition and additional requirements

The objective mission of the RPAS to be designed is managed by RAMP's Main module. The mission is defined by assigning values to objective variables.

Endurance and range are key parameters for any aircraft operation. Whereas in commercial aircraft range is the most important parameter of these two, in the

RPAS field, the endurance is the key factor for observation and monitoring missions. Therefore, the following parameters are used:

- Endurance required for the mission.
- Range required for the mission.

The weight and dimensions of an RPAS determine its portability and limit some of the missions it can perform. For instance, RPAS for tactical observation need to be man-portable, which is limited by the weight that a person can carry, as well as its size. Larger RPAS may be limited to being carried by a particular vehicle, or have to be disassembled every time they are used. These objective values are considered to be achieved if the size or weight of the RPAS are below the limit values. That is the reason why the following parameters are used to define the mission:

- RPAS' MTOW (Maximum Take Off Weight).
- RPAS' maximum wingspan.
- RPAS' maximum length.

Missions almost always require some payload. Whether they are a camera, atmospheric measurement tools, or even antennas, at least part of them must fit within the fuselage. These are not objective values, but requirements that are enforced during the optimization. In addition, the price of the payload is used to

estimate the full manufacturing and components price of the RPAS. That is the reason why the following parameters are used to define the mission:

- Payload length.
- Payload width.
- Payload mass.
- Payload price.
- Payload power requirements.

The command, control, and communication subsystem (C_3) of the RPAS is addressed in a manner similar to that of the payload. It must fit the fuselage, and its price and weight are taken into account for further calculations. That is the reason why the following parameters are used to define the mission:

- C_3 price.
- C_3 length.
- C_3 width.
- C_3 mass.
- C_3 power requirements.

Finally, the RPAS must be able to cover distances within a limited time, and fly at a particular altitude in order to perform its mission with the selected payload. That is the reason why the following parameters are used to define the mission:

- RPAS' minimum speed.
- RPAS' flight altitude.

The last two requirements could easily be removed, and RAMP would then look for the optimal values for them.

Additionally, a maximum manufacturing price, or minimum market price can be defined if the design is aimed at commercial purposes.

3.3. Modules

RAMP is a modular environment. Each analysis module follows particular theories and experimental data to provide results, but they can be exchanged by different models without the need to modify any other modules. Some are dedicated to the generation of geometry and aircraft elements, in a similar way to [243], while others are focused on the analysis of said elements.

3.3.1. Main

The module Main is where the mission is defined, and it manages the workflow through the rest of the modules. It manages the discipline optimizations and performs the main objective optimization and serves as the front end of the environment. It also generates new RPAS and triggers the mutation of the variables

every loop. It is also connected to the RPAS module, from where that controls all the discipline analysis.

3.3.2. Discipline optimization

This module performs the optimization of each subdiscipline through two functions. The first function generates a number of mutated RPAS, whereas the second function chooses the one with the highest objective function.

3.3.3. Results output

The Results output module is in charge of writing the current state of the optimization into an external report. This includes the best solution for the optimization problem so far. That way, if any problem arose, the optimization can take place from the same point where it stopped. It also provides the end result RPAS.

3.3.4. RPAS

Even though the module Main controls the events and workflow of the optimization, the RPAS module is the core of the environment. It is connected to all the subdisciplinary modules and structured to ease the functions of the main module. In the RPAS module all the variables and functions for disciplinary analysis are established.

3.3.5. Objective functions

This module calculates all the objective functions, both global and disciplinary, by following the structure defined by GPPA and its parameters α, β , and γ .

The challenge when choosing objective functions is being able to represent the problem's objectives in such a manner that the decrease of the objective function is always a positive result, while at the same time representing the subdiscipline with high fidelity.

The discipline objective functions (OF) are the following:

- Structure:

The objective of the structure is ensuring that it can withstand the stress to which the RPAS is exposed.

$$OF_{Structure} = \sum \max(0, StructureStress - StructureResistance) \quad (3.1)$$

- Economy:

The objective of this subdiscipline is achieving the highest possible proficiency ratio. It aims at being able to sell the RPAS at the highest price, whereas the manufacturing and components price should be as low as possible.

$$OF_{Economy} = \frac{Manufacturing\&ComponentsPrice}{MarketPrice} \quad (3.2)$$

- Aerodynamics:

$$OF_{Aerodynamics} = C_D \quad (3.3)$$

It could be argued that the inverse of the aerodynamic efficiency would be a more appropriate objective function. However, the purpose of MDO is reducing, as much as possible, the value of the objective function. Using the drag coefficient as the objective function is then suitable.

- Propulsion:

The Propulsion discipline ensures that the power that is required during the flight is provided by the plane. Other than that, the objective function's value is zero. The power can have either thermal or electrical sources depending on the engine type that a particular instance of the RPAS presents.

$$OF_{Propulsion} = \max(0, V_{RPAS} \cdot D_{RPAS} - W_{Engine}) \quad (3.4)$$

- Equipment position:

The objective of this discipline is ensuring that all the equipment and elements within the fuselage do not intersect each other or the fuselage itself. An alternative way to treat this objective, is setting it as a consistency requirement. However, given that the position of the engine also affects the push/pull configuration of the RPAS, it has been addressed as a separate discipline. For this, a mutation function was developed to only change the variables associated to this subdiscipline.

$$OF = \sum IntersectingVolume_{PL,I,Eng,Fuel/Batt} \quad (3.5)$$

3.3.6. Consistency

This module calculates the level of inconsistency of the problem, and feeds it to the Objective Functions module. It ensures that the problem is physically feasible and makes sure that considerations and requirements that have not been specifically addressed by a subdiscipline are still considered in the problem. It has been divided in several requirements:

- Battery consistency:

The objective of this consistency is ensuring that the batteries are capable of feeding the engine for the duration of the mission.

$$Cons_{Batt} = \max (0, W_{Eng}t_{mission} - Energy_{batt}) \quad (3.6)$$

- Stabilizing surfaces

Gusts have not been included in the model, as neither has been maneuverability. The approach that has been taken consists on ensuring a ratio between the vertical and horizontal stabilizing surfaces' (VSS and HSS respectively) volume coefficients. This ratio is based on typical volumetric ratios necessary to guarantee the stability of similar aircraft under gusts.

$$Cons_{VTP} = VolCoef_{HSS}/10 - VOLCoef_{VSS}. \quad (3.7)$$

3.3.7. Variable mutation

Every cycle of the optimization a number of mutated RPAS are generated. They are a copy of an original seed RPAS (which was the best solution in the previous cycle) with small changes in some of their variables. The variables that experience change depend on the subdiscipline that is going through optimization, and the amount of change they experience depends on the Mutation Rate. The Variable Mutation module contains functions that change a subdiscipline's associated variables when triggered a random amount.

The change experienced by each variable every cycle is as follows:

$$NewValue = OriginalValue.random(1 - MutationRate, 1 + MutationRate) \quad (3.8)$$

3.3.8. Airfoil Database

Even though it is used mostly by the Aerodynamic Analysis, the Airfoil database is a separate module with information about various airfoils: E387, FX63-137, S822, S834, SD2030, SH3055, E420. Its relationship with the Aerodynamics module is explained on Chapter 4. Particular parameters, such as the position of the aerodynamic center, or the lift-curve slope, were obtained [244–246], and are shown in Annex A as a function of the Reynolds number.

3.3.9. Common Functions

The Common Functions module contains a series of equations that are used by various modules, such as the International Standard Atmosphere (ISA), or functions to calculate the airfoil chord at a particular length of the wing.

3.3.10. Aerodynamics

This module performs a detailed analysis of the aerodynamic behavior of the RPAS. It is divided in Lift Estimation and Drag Polar Estimation. A detailed exposition of this subdiscipline can be found on Chapter 4.

3.3.11. Structure

The Structure module is in charge of generating the RPAS' structure and perform an analysis of its behavior and performance. It is divided in Structure Generation and Structure Analysis. A detailed exposition of this subdiscipline can be found on Chapter 5.

3.3.12. Propulsion and Integral Performance

This module generates the propulsion system of the RPAS and performs analysis of its performance. It is capable to generate both On the other hand, together with the information produced by the Aerodynamics module, it estimates the general performance of the RPAS, i.e. its endurance and performance. A detailed exposition of this subdiscipline can be found on Chapter 6.

3.3.13. Economic Analysis/Pricing

This module estimates the market price of the RPAS, as well as its manufacturing price. A detailed exposition of this subdiscipline can be found on Chapter 7.

3.4. RAMP's workflow and overall operation

Once all the modules have been introduced, this section will explain how RAMP works.

The first step is to tell RAMP what the mission requirements are. This is done by introducing the requirements as numbers in RAMP's Objective functions module. As explained before, this module contains the variables that define the requirements for each subdiscipline and the global objective. Optionally, a seed RPAS configuration can be set up. This is the RPAS that RAMP uses as a baseline for the optimization. Its definition will be explained in more detail in Chapter 8. After this, RAMP starts its operation, which is fully automatic.

During operation, RAMP's purpose is to improve the seed RPAS in steps until an optimal solution has been achieved. How good an RPAS is depends on the objective functions. These functions evaluate the dimensions, parameters (in other words, all the variables) that define an RPAS and assess their fitness to each discipline (see section 3.3.5).

RAMP's operation is as follows:

For each subdiscipline RAMP performs a series of operations:

1. RAMP evaluates the initial seed and calculates scores for each objective function.
2. From the initial seed, a number of RPAS are generated by mutating the original seed.
3. RAMP evaluates each new RPAS by calculating scores for each objective function.
4. RAMP chooses the best RPAS as a new seed. The best RPAS is that with the lowest score in the relevant objective function.

Depending on the MDO architecture, the relationships between the subdisciplines may change. In our case, RAMP has GPPA as a built-in architecture (see Chapter 2), but other architectures could be used as well.

As it operates, RAMP saves the RPAS configurations that are chosen and their performance values (endurance, range, aerodynamic parameters) at every step of the optimization in an external folder. RAMP also saves the values of the objective functions in a different folder.

Once the convergence requirements have been achieved, RAMP stops its operation.

Figure 3: RAMP Schematic organization.

4

SUBDISCIPLINE: AERODYNAMICS

Parts of the content of this chapter has been previously published (with some modifications) as a research article in the journal *Advances in Engineering Software* with the title “*Development and validation of software for rapid performance estimation of small RPAS*”, DOI: 10.1016/j.advengsoft.2017.03.010. The original source [232] can be found at: <https://doi.org/10.1016/j.advengsoft.2017.03.010>

4.1. Nomenclature

A	- Aspect ratio	Err	- Error
b	- Wingspan	f	- Diederitch's lift distribution function
C	- Coefficient	h	- Height
c	- Chord	HTP	- Horizontal tailplane
C _{ci}	- Circumferential length of the wing-fuselage intersection	i _n	- Angle of incidence
C ₁ -C ₄	- Diederitch's method coefficients	K	- Factor for calculating the lift on the wing plus body
D	- Drag	k	- Ratio of βCl_α to 2π
d _i	- Diameter	l	- Length

L	- Lift	y	- Spanwise coordinate from the airplane centerline
MAC	- Mean aerodynamic chord	α	- Angle of attack
max	- Maximum	α_{0l}	- Zero-lift angle per unit of twist
min	- Minimum	δ	- Increment of wing vortex-induced drag from additional lift
N	- Number	β	- Prandtl's compressibility correction
q	- Dynamic pressure	Δ	- Increment
R	- Range	ϵ	- Twist
Re	- Reynolds number	η	- Non-dimensional length
SMC	- Standard mean chord	Λ	- Sweepback angle
S	- Surface	λ	- Slenderness
t	- Time	ν	- Kinematic viscosity of air
V,v	- Flight speed	ρ	- Density of air
Vol.	- Volume	ϕ	- Shape factor
VTP	- Vertical tailplane		
W	- Weight		
$W_{\frac{1}{2}p}$	- Half wing perimeter		
x	- Coordinate measure from the MAC leading edge		

Subscripts

a	- Additional lift distribution	lam	- laminar
ac	- Aerodynamic center	L,l	- Lift
airf	- airfoil	loit	- Loiter
att	- Attached	m	- Moment
b	- Basic lift distribution	man	- Manufacturer
cg	- Center of gravity	max	- Maximum
char	- Characteristic	min	- Minutes
corr	- Correction	mod	- Model
cp	- Center of pressure	n	- Nacelle
cr	- Cruise	p	- Point
det	- Detachment	prof	- Profile
del	- Delivered	r	- Root
D	- Drag	req	- Required
eff	- Effective	t	- Tip
f	- Fuselage	tot	- Total
fi	- Final	tur	- Turbulent
fn	- Fuselage nose	u	- Undercarriage
F	- Friction	V	- Vertical stabilizer
h	- Horizontal stabilizer	vor	- Vortex
i	- Initial	W	- Wing
int	- Interference	Wf	- Wing- fuselage
j	- Number index		

x	- Axis parallel to the chord of the airfoil	0, l ₀ , L ₀	- Zero lift
α	- lift-curve	$\frac{1}{2}$	- Point $\frac{1}{2}$ of the chord
		$\frac{1}{4}$	- Point $\frac{1}{4}$ of the chord

4.2. Introduction

As it has been discussed in the Introduction chapter of this dissertation, Remotely Piloted Aircraft Systems (RPAS) are increasingly more present in every aspect of society [247]. Their unique suitability for a great number of different tasks and the possibility of being easily designed and manufactured without deploying an extended multidisciplinary team or employing great resources have enabled small businesses and amateurs to build and commercialize a wide range of platforms. These possibilities greatly differ from the usual methodology and resources required to build a traditional civil or military transport aircraft.

There is, however, literature that studies the design of RPAS from a broader perspective, such as [71], that discusses the implications of the different subsystems present in the RPAS without deepening into detail in equations or values for parameters that could be found in classical hand-book style methods such as [70,239]. This can easily be explained if we take into consideration the already stated extraordinary differences both in shape and flight regimes that can be found among the RPAS. The current trend consists mostly in extensive Finite Element Models (FEM) analysis with different degrees of detail for high-end and detailed design, as well as vortex-lattice methods for lighter analysis. Additionally, optimization methodologies have also been used for detailed calculation [248].

More recently, mixed approaches employing experimental data have arisen [249]. Code implementations of classical hand-book style methods, such as [250] are less and less used in favor of more complex and detailed models and environments for designing [251,252] that better take into account the different interrelations between disciplines, taking advantage of Multidisciplinary Design Optimization (MDO). There are as well a number of works aimed at studying the aerodynamic stability by mixing experimental or precomputed Computational Fluid Dynamics (CFD) data and analytical modelling [253,254].

Our objective in the long run is developing a fully working MDO software environment for RPAS design, principally aimed at low Reynolds number flight conditions. This environment will consist on several discipline modules that will be controlled and managed by an MDO main module, as we saw in Chapter 4. Among such modules, there is one for aerodynamic analysis and integral performances estimation of RPAS, which is the subject of this chapter. Therefore, we will first introduce the aerodynamic facet of it, where we describe its structure, how the RPAS is defined in order to be studied, and the performed, aerodynamic estimations to obtain the lift and drag polar of the aircraft. Then, we will address the mathematical model for range and endurance used by the integral performances estimator, to be followed by a detailed aerodynamic analysis of two existing RPAS, the Kahu UAV and a Greek UAV designed for reconnaissance; as well as performance estimations for ten additional UAV for comparison and model validation purposes. The conclusions and future work to be developed in this

subdiscipline are discussed in Chapter 9. Similar works with an emphasis in different subsystems, such as the powertrain, exist in the literature [255].

As we mentioned, to validate this aerodynamic and integral performances estimation software model, we gathered information about the flight conditions and geometry of ten different RPAS, mostly with low Reynolds numbers flight conditions, as well as the endurance advertised by their manufacturers in order to compare it with that obtained with our own model. With regard to the Kahu and the Greek RPAS, they have been studied previously by Shafer et al. [253], and Spyridon et al. [256], and the results that have been presented regarding the behavior of their drag polar, aerodynamic efficiency, pitching moment and lift coefficient will be used as a baseline to compare and validate our results, which will ultimately validate the aerodynamic and integral performance estimation model presented here.

4.3. Aerodynamic Model

This chapter presents a new performances estimation model that implements the philosophy of hand-book style methods and adapts it to micro and small RPAS flight regimes by integrating surrogate models of the behavior of the wings based on experimental data [245,257]. This model enables the designer to estimate the lift, drag polar and performance of a given model from the flight conditions and geometry of the RPAS. The software currently admits fixed-wing aircraft with

classical configuration, where the only wing of the RPAS is closer to its nose than its stabilizing surfaces.

As it is shown in Figure 4, an aerodynamic module receives geometrical data from the analyzed RPAS. This information includes all the dimensions of the aerodynamic surfaces and fuselage, as well as any other element that may be in contact with the air. The aerodynamic module will then gather information about the airfoils referenced in the RPAS data. With these two sources of information it will first calculate the lift distributions and moment coefficients of the aircraft. Obtaining the drag of the aircraft is the next step, which will provide a three-component polar.

The performance module will afterwards take information about the kind of the RPAS propulsion system, and obtain its detailed characteristics from the propulsion database. This includes efficiency, battery power and mass, etc. Together with the drag polar of the RPAS and its flight conditions, the model will finally provide an estimate on the integral performances of the RPAS.

Figure 4: Flowchart of the Aerodynamic model

4.4. Definition of the RPAS

There are in the literature tools and models aimed at the generation of geometrical meshes for CFD analysis [258]. The present aerodynamic and performances estimation software model requires the RPAS to be defined following a simple parametrical architecture. Each one of the elements forming the aircraft is defined as wing, body, or stabilizing surfaces, as well as with a different group of key dimensions, commonly used in the aerospace field, depending on the particular element. This responds to the different predominant behavior and, consequently, treatment that they refer.

Figure 5 shows an example of input file. In this file the parameters are grouped by element of the RPAS. The main fuselage is defined by its width and height at two points, as well as its length, and the length of its nose and afterbody. This block of the data also includes the position of the center of gravity of the full RPAS, and parameters to define an additional pod for extra payload or equipment. There is an additional parameter, “noFus”, accounting for connection beams in between the fuselage and stabilizing surfaces. The following block defines the wing. It is divided in several sections, with higher value subscripts corresponding to outer sections. A value of zero in this fields will be interpreted as if the section did not exist. Parameters *ct* and *cr* correspond to the tip and root chord of each section of the wing; *yfb* and *cfc* account for the position of deflectable surfaces and their chord extension divided by the chord of the wing respectively; *wngsba* represents the sweep angle of each section of the wing; *xcma14* the length from the

tip of the nose of the RPAS to the $\frac{1}{4}$ chord line of the wing; *awing* stands for the angle between the zero-lift line of the airfoil at the root of the wing with the middle line of the fuselage; *hw* is the height of the airfoil at the root of the wing with the middle line of the fuselage. Similar parameters are used for the stabilizing surfaces, which are indicated with the character *h* or *v* depending on whether they are horizontal or vertical. Horizontal stabilizers are considered to be symmetrical along the length of the RPAS regarding spam. Vertical stabilizers can be of three kinds: classical, V shaped, and Y shaped; this is accounted for with the parameter *tailtype*. The geometry of V shaped stabilizers, as well as the V part of Y shaped stabilizers is projected on the vertical and horizontal axis, by the means of the dihedral, and treated as horizontal or vertical surfaces then. There are two additional blocks of information that define the engine and the mass of the batteries or fuel loaded on the aircraft, as well as the flight conditions and mass of the RPAS. Different parameters can be used, such as wing slenderness or aspect ratio. The software will calculate all the required parameters from the ones provided. In case that there is any conflict between two given parameters, or incomplete information, the program will rise a warning. Lengths are expressed in meters, angles in radians, and weights in kg. Air density is expressed in kg/m^3 .

```

#RPAS data input file
#RPAS geometry
#body parameters
D1h   =    0.35
D1v   =    0.35
D2h   =    0.35
D2v   =    0.35
lfn   =    0.37
afterbody= 0.29
lf     =    2.12
xcg   =    1.52
noFus  =    0
lpod  =    0
hpod  =    0
bpod  =    0
zpod  =    0

#wing parameters
airfoil = "E387"
ct1     =    0
ct2     =    0.38
cr1     =    0
cr2     =    0.38
b1      =    0
b2      =    2.32
yfb     =    0.5
cfc     =    0.30
dihedral = 0
wngsba1 = 0
wngsba2 = 0
xcma14  =    1.52
torsion  =    0
awing   =    0
hw      =    0.35

#htp parameters
airfoilhtp = "E387"
crh        =    0.45
cth        =    0.45
hh         =    0.50
bh         =    1.31
xench     =    3.25
htpswp    =    0
cdhch     =    0.30

#vtp parameters
tailtype  = "Y"
airfoilvtp = "E387"
crv       =    0.45
ctv       =    0.07
bv        =    0.22
cdvcv     =    0.33
vtpswp    =    0.17
xencv     =    3.50
dihedralv =    0.79

#RPAS propulsion
engtype   = "electric"
fuelbatms =    0.5

#RPAS flying conditions
V         =    15
rho       =    1.225
RPASmass =    6

```

Figure 5: Program input file sample.

4.5. Airfoil characterization

The behavior of airfoils at high Reynolds numbers has been thoroughly studied. This has led to the development of a number of models that accurately estimate such behavior from parameters such as the relative thickness of the airfoil. However, at low Reynold numbers, their behavior is more difficult to predict and CFD are usually the used resource. On the other hand, CFD estimations can be time consuming and, within an environment aimed at the preliminary design of an aircraft as a whole, they could render impractical.

Therefore, in this approach, relevant airfoil performance at low Reynolds numbers has been extracted from experimental research, and included in an airfoil database, from which the aerodynamic model obtains the required data for each airfoil. This database is made of results from wind-tunnel tests for different airfoils at low Reynolds numbers [245]. These values include the maximum lift coefficient of the airfoil, cl_{max} ; the lift-curve slope of the airfoil, cl_α ; the longitudinal position of the aerodynamic center of the airfoil, x_{ac} ; the aerodynamic pitching moment of the airfoil about the aerodynamic center of it, cm_{ac} ; as well as the zero-lift angle of the airfoil. Originally, the database contains $cl-\alpha$ and $cm_{ac}-\alpha$ curves. The maximum lift coefficient of the airfoil is a value that can be obtained as the maximum cl present on each $cl-\alpha$ curve. The lift-curve slope can also be calculated in a very straightforward manner by picking two points of the linear part of the curve and dividing the variation of cl by the variation of α :

$$cl_\alpha = \frac{cl_2 - cl_1}{\alpha_2 - \alpha_1} \quad (4.1)$$

To obtain the position of the aerodynamic center we calculate the pitching moment with values from two points and, since the pitching moment at the aerodynamic center must be equal independently of the point where it is calculated from [70]:

$$cm_{ac} = \left(cm_{\frac{1}{4}} \right)_{pj} - cl_{pj} \frac{\Delta x}{c} = cte. \rightarrow \left(cm_{\frac{1}{4}} \right)_{p1} - cl_1 \frac{\Delta x}{c} = \left(cm_{\frac{1}{4}} \right)_{p2} - cl_2 \frac{\Delta x}{c} \rightarrow$$

$$\frac{\Delta x}{c} = \frac{\left(cm_{\frac{1}{4}} \right)_{p1} - \left(cm_{\frac{1}{4}} \right)_{p2}}{cl_1 - cl_2} \rightarrow x_{ac} = 0.25 - \frac{\Delta x}{c} \quad (4.2)$$

Annex A contains multiple graphs showing the evolution of various aerodynamic parameters with the Reynolds number of all the airfoils included in the database.

4.6. Modeling of lift and lift distributions of the wing

There are a number of methods to estimate the aerodynamics of an aircraft with various degrees of precision. Classical manual models, such as the ones gathered and developed by Torenbeek [70] provide results with a similar accuracy to those of vortex lattice methods (VLM) with a fraction of their calculations. Such accuracy is more than enough for the preliminary sizing of aircraft, which is the design stage here addressed. The speed with which the performances estimation of each RPAS is performed is a key parameter for the MDO environment that this aerodynamic model forms part of. We aim at obtaining a full analysis of each aircraft in 1-2 seconds with a commercial computer, which is a mark that could not be achieved should the calculations were slightly more complex. Torenbeek [70] provides several alternatives for the estimation of the various aerodynamic values that define the behavior of aircraft at high Reynolds numbers. These have been implemented in our model and, even though they were not initially developed for low Reynolds numbers, the results presented in subsequent sections validate their use as a part of this model.

First, the flight conditions of the airplane provide the cruise or endurance lift coefficient:

$$C_L = W / (\frac{1}{2} \rho V^2 S_W) \quad (4.3)$$

$$\beta = \sqrt{1 - M^2} \quad (4.4)$$

where $M = \frac{V}{a}$, is the Mach number of the RPAS. Here β is retained given that, even though the model is aimed at low speed flight conditions, we intend to make it available for high speeds as well in the future.

The wing lift-curve slope is obtained from the MAC airfoil aerodynamic values, as explained in Datcom [250]:

$$C_{LW\alpha} = \frac{1}{\beta} \frac{2\pi}{\frac{2}{\beta A} + \sqrt{\frac{1}{k^2 \cos^2 \Lambda_\beta} + \left(\frac{2}{\beta A}\right)^2}} \quad (4.5)$$

where $k = \frac{\beta c_{l\alpha MAC}}{2\pi}$, and $\tan \Lambda_\beta = \frac{\tan \Lambda_1}{\beta}$

The lift distribution along the wing can be divided in a basic, c_{lb} , and an additional, c_{la} , lift distributions so that $c_l = c_{la} + c_{lb} = \frac{SMC}{c(y)} \left(C_L + \epsilon_t \frac{b}{W \frac{1}{2} p} \frac{SMC}{c(y)} C_L L_b \right) L_a$ by using Diederich's following formulas [259]:

$$L_a = C_1 \frac{c}{SMC} + C_2 \frac{4}{\pi} \sqrt{1 - \eta^2} + C_3 f \quad (4.6)$$

$$L_b = \beta W \frac{1}{2} p \left(L_a C_4 \cos \Lambda_\beta \left(\frac{\epsilon}{\epsilon_t} + \alpha_{ol} \right) \right) \quad (4.7)$$

where $\alpha_{ol} = - \int_0^1 \frac{\epsilon}{\epsilon_t} L_a d\eta$, $\eta = \frac{y}{b}$ is the adimensional length of the wing, and

C_1, C_2, C_3, C_4 are Diederitch's factors for additional lift distribution estimation and f is Diederitch's lift distribution function (Figure 6).

Figure 6: Diederich's lift distribution function (left) and factors for additional lift distribution (right) [259].

Once the lift distributions along the wing are known, we can calculate the pitching moment of the wing, $C_{mac W}$:

$$c_{m ac W} = \frac{2}{S_{WMAC}} \int_0^{\frac{b}{2}} c_{mac}(y) c(y) dy - \frac{2}{S_{WMAC}} \int_0^{\frac{b}{2}} c_{lb}(y) c(y) \tan \Lambda_{ac} y dy \quad (4.8)$$

The first term is the contribution of each airfoil section along the wing, which can be obtained from the airfoil database, whereas the second term represents the contribution of the basic lift distribution.

And the pitching moment of the wing, $x_{ac\ W}$, by integrating its position in each airfoil section along the wing:

$$x_{ac\ W} = \frac{2}{b\ c_L} \int_0^{\frac{b}{2}} (x_{ac}(x) + y \tan \Lambda_{ba}) cl(x) dy \quad (4.9)$$

These values, with a correction from Munk's theory [260] will provide the pitching moment of the wing-fuselage, $C_{mac\ Wf}$:

$$C_{mac\ Wf} = C_{mac\ W} + \Delta C_{mac} \quad (4.10)$$

$$\Delta C_{mac} = -1.8 \left(1 - \frac{2.5b_f}{l_f} \right) \frac{\pi di_f h_f l_f}{4 S_W MAC} \frac{C_{L0}}{C_{L\alpha\ Wf}} \quad (4.11)$$

where ΔC_{mac} accounts for the influence of the fuselage.

And the pitching moment of the wing, $x_{ac\ Wf}$:

$$x_{ac\ Wf} = x_{ac\ W} + \Delta x_{ac1} + \Delta x_{ac2} \quad (4.12)$$

$$\Delta x_{ac1} = -\frac{1.8}{C_{L\alpha\ Wf}} \frac{b_f h_f l_f n}{S_W}; \Delta x_{ac2} = \frac{0.273}{1+\lambda} \frac{di_f SMC(b-di_f)}{CMA^2(b+2.15di_f)} \tan \Lambda_{\frac{1}{4}} \quad (4.13)$$

where Δx_{ac1} and Δx_{ac2} represent, respectively, the forward shift of the aerodynamic center due to the fuselage before and behind the wing [261]; and the lift loss where the lift carryover is concentrated [250].

Now, the wing incidence in relation to the fuselage line can be obtained by optimizing the incidence for minimum drag during cruise, since this is the most common condition for the aircraft during flight. A zero deflection of the elevator is therefore imposed. Also, in this flight conditions, the total pitching moment at

the aerodynamic center of the RPAS is zero, which enables us to write the incidence of the wing following the next equation:

$$i_{nW} = \frac{C_{LWf}^* - \Delta_z C_L}{K_{II} C_{LW\alpha}} + \frac{K_I}{K_{II}} \alpha_{0l} \epsilon_t + \alpha_{l0r} \quad (4.14)$$

where $C_{LWf}^* = \left(C_{L0} - \frac{MAC}{l_h} C_{mac} \right) / \left(1 + \frac{x_{cg} - x_{ac}}{l_h} \right)$, $K_I = \left(1 + 2.15 \frac{b_f}{b} \right) \frac{S_{net}}{S_W} + \frac{\pi}{2 C_{LW\alpha}} \frac{b_f^2}{S_W}$ and $K_{II} = \left(1 + 0.7 \frac{b_f}{b} \right) \frac{S_{net}}{S_W}$ are approximations of a method for calculation of K_I and K_{II} [262] for fuselages with near-circular cross sections; α_{l0r} is the zero-lift angle of the root airfoil, which can be obtained from the airfoil database.

Now the lift-curve slope of the wing-fuselage will be [262]:

$$C_{L\alpha Wf} = C_{L\alpha W} K_I \quad (4.15)$$

Equations 4.16.a-4.19.a can be found in [70], and are used to estimate the angle of attack of the fuselage and the incidence of the horizontal tail-plane in symmetrical cruise flight.

The lift-curve slope of the whole aircraft:

$$C_{L\alpha Wf} = C_{L\alpha Wf} + C_{L\alpha h} \left(1 - \frac{d\epsilon_h}{d\alpha} \right) \frac{S_h}{S_W} \frac{q_h}{q} \quad (4.16.a)$$

The previous equation can be used to obtain the angle of attack relative to the fuselage datum line:

$$\alpha_{Lof} = - \frac{C_{L0}}{C_{L\alpha}} \quad (4.17.a)$$

Finally, the effect of the horizontal stabilizing surfaces can be calculated attending to the previously imposed condition of symmetrical cruise flight, where longitudinal equilibrium must be held:

$$C_{Lh} \frac{S_h}{S_w} \frac{q_h}{q} = \frac{MAC}{l_h} \left(c_{mac} + C_L \frac{(x_{cg} - x_{ac})}{MAC} \right) \rightarrow C_{Lh} = \frac{S_w}{S_h} \frac{q}{q_h} \frac{MAC}{l_h} \left(c_{mac} + C_L \frac{(x_{cg} - x_{ac})}{MAC} \right) \quad (4.18.a)$$

And so, the incidence of the tail relative to the wing zero-lift line:

$$i_{nh} = \left(C_{mac} w_f + C_{L0} \frac{(x_{cg} - x_{ac})}{MAC} \right) / \left(C_{Lh} \alpha \frac{S_h l_h}{S_w MAC} \frac{q_h}{q_w} \right) + \frac{\delta \epsilon_h}{\delta \alpha} \frac{C_{L0}}{C_{LW\alpha}} - \frac{C_{L0}}{C_{L\alpha}} \quad (4.19.a)$$

4.6.1. Considerations for the canard configuration

Equations 4.16.b-4.19.b are a modification of Equations 4.16.a-4.19.a for canard configuration. In this configuration the wind flow goes through the horizontal stabilizer before reaching the wing.

The lift-curve slope of the whole aircraft:

$$C_{L\alpha} w_f = C_{L\alpha} w_f \left(1 - \frac{d\epsilon_w}{d\alpha} \right) \frac{q_w}{q} + C_{Lh\alpha} \frac{S_h}{S_w} \quad (4.16.b)$$

The previous equation can be used to obtain the angle of attack relative to the fuselage datum line:

$$\alpha_{Lof} = - \frac{C_{L0}}{C_{L\alpha} \left(1 - \frac{d\epsilon_w}{d\alpha} \right)} \quad (4.17.b)$$

Finally, the effect of the horizontal stabilizing surfaces can be calculated attending to the previously imposed condition of symmetrical cruise flight, where longitudinal equilibrium must be held:

$$C_{Lh} \frac{S_h}{S_w} \frac{l_h}{MAC} = \left(c_{m ac} + C_L \frac{(x_{cg} - x_{ac})}{MAC} \right) \rightarrow C_{Lh} = \frac{S_w}{S_h} \frac{MAC}{l_h} \left(c_{m ac} + C_L \frac{(x_{cg} - x_{ac})}{MAC} \right) \quad (4.18.b)$$

And so, the incidence of the canard:

$$i_{nh} = \left(C_{m ac wf} + C_{L0} \frac{(x_{cg} - x_{ac})}{MAC} \right) / \left(C_{Lh} \alpha \frac{S_h l_h}{S_w MAC} \right) + \frac{\delta \epsilon_h}{\delta \alpha} \frac{C_{L0}}{C_{LW\alpha}} - \frac{C_{L0}}{C_{L\alpha} \left(1 - \frac{d\epsilon_w}{d\alpha} \right)} \quad (4.19.b)$$

4.6.2. Considerations for the blended wing body configuration

Blended wing body aircraft may have canard or classical horizontal stabilizers, as well as have them integrated with the wing in a flying-wing fashion. Depending on whether the stabilizers are positioned before, or after the wing, they will be treated as the former or the latter.

A particularity of BWB aircraft is the non-near-circularity of the cross-section of the fuselage. In this case, Equation 4.11 must be multiplied by the ratio $S_{fus cs} / \frac{\pi}{4} b_f h_f$ [70].

4.7. Estimation of drag polar

The second main step of the model consists in the estimation of the trimmed drag polar of the RPAS. A common approach that has been employed [70,239,240]

consists in adding up the contribution of every element of the aircraft, which already include interactions between elements.

$$C_D = \sum C_{Dj} \quad (4.20)$$

Even though there are different ways to subdivide the drag, here we will use vortex and profile drag. Whereas the first is caused by the generation of trailing vortices, the second is produced by the viscous effect of the boundary layer of the aircraft plus form drag. It greatly depends on the amount of surface exposed to the fluid, and the friction coefficient, which can be calculated from the Reynolds number of the flow. Such number also depends on whether the boundary layer is attached or detached. As to estimations of the friction coefficient, we consider that the boundary layer is completely attached in every element but the surfaces with airfoil shape, such as the stabilizers and the wing, where it is attached up to the point $x_{det} = \frac{Re_{tur}}{Re}$ of the chord, where it detaches. $Re \approx 500,000$ is typically the transition Reynolds number for a flat plate [240].

$$\begin{matrix} C_{F\ lam} = \frac{0.664}{\sqrt{Re}} \\ C_{F\ tur} = \frac{0.0583}{Re^{0.2}} \end{matrix} \rightarrow C_F = \frac{S_{att}}{S_{tot}} C_{F\ lam} + \frac{S_{deat}}{S_{tot}} C_{F\ tur} \quad (4.21)$$

$$C_{F\ airfoil} = \frac{x_{det}}{c_{cr}} C_{F\ lam} + \left(1 - \frac{x_{det}}{c_{tur}}\right) C_{F\ tur} = \frac{x_{det}}{c_{cr}} \frac{0.664}{\sqrt{Re}} + \left(1 - \frac{x_{det}}{c_{tur}}\right) \frac{0.0583}{Re^{0.2}} \quad (4.22)$$

$$C_{F\ body} = C_{F\ lam} = \frac{0.664}{\sqrt{Re}} \quad (4.23)$$

$$\text{where } Re = \frac{V l_{char}}{\nu}$$

Without loss of generality, the profile drag will be directly proportional to the surface of the element that generates it, the friction coefficient, and modified by a shape factor, ϕ , depending on the slenderness of the element, as in:

$$D_{prof} \propto S_{element} C_{F\ element} (1 + \phi_{element}) \quad (4.24)$$

The following paragraphs are a summary of the components used in the drag estimations as taken from [70]. The drag contributions are arranged by element of the RPAS (body, wing, vertical and horizontal stabilizers, etc.). As a standard, each drag coefficient is non-dimensional, and the surface that contributes to each element's drag is divided by the wing surface, given that it is the used surface parameter for the drag calculation as to $D = \frac{1}{2} \rho S_w V^2 C_D$.

The body contributes with the following components to the overall drag: profile drag due to the friction of the skin and the airflow around it, and vortex drag from vortices due to the lift of the fuselage.

The profile drag from the fuselage will take the shape of the general profile drag equation once its parameters have been particularly calculated for the fuselage, and reshaped into a coefficient:

$$C_{D\ prof\ f} = \frac{S_{fus}}{S_w} C_{Ff} (1 + \phi) \quad (4.25)$$

where ϕ is a shape factor that depends on the slenderness of the fuselage, λ [70]:

$$\phi = \frac{2.2}{\lambda^{1.5}} + \frac{3.8}{\lambda^3} \quad (4.26)$$

Vortex drag depends on the angle of attack of the fuselage, α_f , and its volume, V_f :

$$C_{Df\,vor} = 0.15 \alpha_f^2 V_f^{\frac{2}{3}} \quad (4.27)$$

$$\text{where } \alpha_f = \frac{C_L - C_{L0}}{C_{L\alpha}}$$

The wing is one of the elements that contributes the most to the overall drag of the RPAS. In this case, most of it is profile drag. It can be estimated by integrating the drag for each airfoil section along the wing. Since the lift distributions are already known, the drag can be obtained from the c_d/c_l relationship in the airfoil database.

$$C_{DW\,ind} = \frac{2}{s_W} \int_{\frac{b_W}{2}}^1 c_{d\,prof}(\eta) c(\eta) b_f d\eta \quad (4.28)$$

On the other hand, the vortex drag generated by an untwisted wing is [70]:

$$C_{DW\,vor} = \frac{(1+\delta)C_L^2}{\pi A} \quad (4.29)$$

where Garner's $\delta = 46.264 \left(\eta_{cp} - \frac{4}{3}\pi \right)^2$, and $\eta_{cp} = \int_0^1 \frac{c_l c}{c_L c_g} \eta d\eta$, which is the spanwise center of pressure [263].

Then, the drag due to the twist, ϵ , of the wing can be added [264]:

$$C_{DW\epsilon} = 3.7 \cdot 10^{-5} \epsilon^2 \quad (4.30)$$

For a mid-wing fuselage, Torenbeek [70] provides a model based on Lennertz and Marx's results [265,266] that explains the behavior of drag because of the effect of the wing lift carry-over by the fuselage:

$$C_{D\ Wf\ int1} = \frac{0.55\eta_f}{1+\lambda} (2 - \pi\eta_f) \frac{C_{L0}^2}{\pi A} \quad (4.31)$$

$$\text{where } \eta_f = \frac{D_f}{b_w}$$

Also, in the area where the connection of the wing and the fuselage takes place, viscous interference appears, which generates drag because of a thicker boundary layer and a higher local flow velocity [70]. This approach highly depends on the friction coefficient within that area and its extent [267]:

$$C_{D\ W\ int2} = \frac{1}{S_W} 1.5 C_{Ftr} C_{ci} \cos \Lambda_{\frac{1}{2}} \quad (4.32)$$

where C_{ci} is the total circumferential length of the wing-fuselage intersection.

Additionally, the drag must also be corrected depending on the position of the wing in relation to the body, as high wing configurations tend to reduce the drag, and low wings tend to increase it. Torenbeek [70] provides a simple equation to estimate the influence of low and high wings in the drag. We linearized such equation to also take into account intermediate configurations by using the parameter $\frac{h_w}{d_{if}}$, which indicates the height of the wing in relation to the diameter of the fuselage.

$$C_{DW\ corr} = -0.88 \frac{1}{S_W} C_F C_L c_r di_f \frac{h_w}{di_f} \quad (4.33)$$

Given that the RPAS is in a symmetric cruise flight condition, the horizontal stabilizer is trimmed (eq. 4.34), and the drag produced at the horizontal stabilizer can be divided in two components plus a correction to include inter-element interferences.

$$L_{Wf}(x_{Wf} - x_{cg}) + L_h(x_h - x_{cg}) = 0 \quad (4.34)$$

$$L_{Wf} + L_h + W = 0 \quad (4.35)$$

The basic profile drag follows the model of eq. 4.24, where the shape factor takes into account the thickness of the airfoil and the wing sweep:

$$C_{Dh} = 2 \frac{S_h}{S_W} C_F \left\{ 1 + 2.75 \left(\frac{t}{c} \right)_h \cos^2 \Lambda_{\frac{1}{2}h} \right\} \quad (4.36)$$

By adding an Oswald factor of $0.75 \cos^2 \Lambda_h$ Torenbeek [70] accounts for the increase of the drag due to the elevator deflection, which depends mostly on C_{Lh} .

$$C_{Dhi} = 0.33 \frac{S_h}{S_W} \frac{C_{Lh}^2}{\pi A_h \cos^2 \Lambda_h} \quad (4.37)$$

The vortex drag of the horizontal stabilizer is similar to that of the wing:

$$C_{Dh} = 1.02 \frac{C_{Lh}^2 S_h}{\pi A_h} \quad (4.38)$$

where the lift of the horizontal stabilizer can be obtained from the pitching moment equilibrium at the aerodynamic center:

$$C_{Lh} = \frac{C_{mac} + \frac{C_L(x_{cg} - x_{ac})}{MAC}}{\frac{S_h l_h}{S_W MAC}} \quad (4.39)$$

Finally, the wing-horizontal stabilizer interference depends on the downwash behind the wing generated by the lift of the stabilizer:

$$C_{Dh\ int} = \frac{S_h}{S_W} C_{Lh} C_L \left(\frac{d\epsilon}{dC_L} - \frac{2}{\pi A} \right) \quad (4.40)$$

where the downwash gradient in unpowered flight is $\frac{d\epsilon}{dC_L} = 1.75 \frac{C_{LW\alpha}}{\pi A (\lambda r)^{0.25} (1 + |m|)}$ and is greatly influenced by the relative position of wing and tailplane, which defines the flow interaction between both surfaces.

The same approach can be taken with the vertical plane. However, as stated before for the horizontal stabilizer, the RPAS is in a symmetrical cruise and, accordingly, the yaw value of the aircraft is null. Therefore, the vertical stabilizer only produces profile drag, which can be expressed as follows:

$$C_{DV} = 2 \frac{S_V}{S_W} C_F \left\{ 1 + 2.75 \left(\frac{t}{c} \right)_V \cos^2 \Lambda_{\frac{1}{2}V} \right\} \quad (4.42)$$

Some additional terms accounting for attachments and protuberances can be added. Among these, we can find the drag produced by a nacelle (whether it houses fuel, payload, or an engine) and depends on its slenderness and surface:

$$C_{Dn} = \frac{C_F}{S_W} S_n \left(1 + \frac{2.2}{\lambda_{eff}^{1.5}} + \frac{3.8}{\lambda_{eff}^3} \right) \quad (4.41)$$

$$\text{where } \lambda_{eff} = \frac{l_n}{d_{in}}$$

And also the influence of undercarriage or landing gear, that Torenbeek [70] relates to its shape and frontal surface:

$$C_{Du} = K_u * N_u * S_u \quad (4.42)$$

where K_u is a value depending on the shape of the undercarriage and ranges from 0.17 to 1.28 depending on its shape.

These contributions are a combination of terms that are constant, or proportional to the first or second power of the overall C_L of the RPAS which, when added up all together, form a classical balanced polar that takes the form of the following expression:

$$C_D = C_{D0} + C_{D1}C_L + C_{D2}C_L^2 \quad (4.43)$$

4.7.1. Considerations for the canard configuration

In this case, the wing-horizontal stabilizer interference happens because of the downwash behind the stabilizer generated by the lift of the wing:

$$C_{DW \text{ int}} = C_{Lh}C_L \left(\frac{d\epsilon}{dC_{Lh}} - \frac{2}{\pi A} \right) \quad (4.39.b)$$

where the downwash gradient in unpowered flight is $\frac{d\epsilon}{dC_{Lh}} = 1.75 \frac{C_{Lh}\alpha}{\pi A_h (\lambda_h r)^{0.25} (1+|m|)}$

4.7.2. Considerations for the blended wing body configuration

Because of the particularly smooth transition between wing and body in Blended Wing Body aircraft, the interference effects between them tend to be

negligible; and by definition nonexistent in flying wings. We assume that, in this case, equations 4.31 and 4.32 are equal to zero and, therefore, $C_{D\,wf\,int1} = C_{D\,wf\,int2} = 0$.

4.8. Validation of the model

Shafer et al [253] studied different methods and approaches to obtain the basic aerodynamic and performance of the Kahu. Such methods included CFD analysis, flow solvers (USM₃D, Kestrel and Cobalt), potential flow, empirical and handbook methods, as well as a wind tunnel for empirical measurements. Given the ample variety and results provided by the authors, comparing the output of our aerodynamic model to the one obtained in that work can provide an approximation of the accuracy of our model. Therefore, we present in this section the results obtained by Shafer et al and the ones from our new model superimposed. The authors, however, did not include a scale with their graphs, but the angle of attack was mentioned to range between -8 and 30 degrees, and we assumed the minimum drag shown in the figures to be zero. With regard to the vertical axis of the lift curve, matching grids at the point where most of the curves are close to the origin set the figure. Figures 7-10 present a comparison between our results (dark grey) and the multiple methods in the reference (light grey). The methods used in the model use a small-angle approximation. They are applicable within the [-10, 10] degrees range. Out of this range, the small-angle approximation incurs in errors higher than 1%. Therefore, the results presented for the new model

lay within the previous values for the angle of attack. This range is ample enough to estimate the behavior of the aircraft in cruise/loiter conditions, since the angle of attack tends to be small.

Figure 7: Lift coefficient vs angle of attack comparison of Kahu UAV.

Figure 8: Drag coefficient vs angle of attack comparison of Kahu.

Figure 9: Drag polar comparison of Kahu UAV.

Figure 10: Pitch moment vs angle of attack comparison.

The behavior of the lift curve is shown in Figure 7. Our new model closely matches the average of the models in the reference. A similar behavior is shown in Figure 8, where the new model presents average values for positive angles of attack (AOA)

up to 10 degrees, but leans on the upper limit of drag for negative angles of attack. As a result, for C_L with positive value, our model results in a similar drag coefficient to that of most models; as well as a higher drag for negative lifts (Figure 9). With regard to the pitching moment (Figure 10), we obtained a behavior matching the reference's methods, but leaning on the lower limit. On the other hand, in [256], a small reconnaissance UAV capable of carrying photography and video recording equipment is designed. Throughout the design process, an estimate of its drag polar is given (Figure 12), and CFD models are used for detailed aerodynamic analysis in the reference. We studied this UAV with our model in the same way as we did with the Kahu UAV. In Figures 11-14, results from [256] are presented together with the values obtained with our model. Each curve from the reference indicates whether the influence of the aircraft's fan has been taken into (Fan) account or not (No Fan). Figure 11 shows a comparison of lift curves where the new model results in a similar curve with a slightly steeper slope but a slightly smaller lift at zero angle of attack. Figure 12 shows a comparison of drag polars. The new model provides an estimate whose behavior lays in between the various estimates in the reference. In the same way, the estimation of the RPAS' efficiency by the new model lays among the rest of the estimates up to an AOA close to 10 degrees (Figure 13). Regarding the pitching moment in Figure 14, the estimation from the new model is also average amongst the others.

Figure 11: Lift coefficient vs angle of attack comparison.

Figure 12: Drag coefficient vs angle of attack comparison.

Figure 13: Efficiency comparison.

Figure 14: Pitching moment vs angle of attack comparison.

5

SUBDISCIPLINE: STRUCTURE

5.1. Nomenclature

b	- Wingspan	MAC	- Mean aerodynamic chord
bu	- Buckling	m	- Mass
c	- Airfoil chord	n	- Load factor
CFRP	- Carbon fiber reinforced polymer	T	- Thrust
D	- Drag	S	- Surface area
d	- Diameter	M_T	- Torsion moment
E	- Elastic modulus	t	- Thickness
F	- Force	UTS	- Ultimate tensile strength
G	- Shear modulus	V_s	- Structure volume
F	- Force	W	- Weight of the RPAS (unless stated otherwise by the subscript)
g	- Slant height	x	- Longitudinal axe (body axis)
L	- Lift of the wing (unless stated otherwise by a subscript)	y	- Side to side axe (body axis)
l	- Length	Λ	- Sweep angle
M	- Moment	θ	- CFRP orientation angle

ρ - Density

σ - Surface density

Subscripts

ac - Aerodynamic center

b - Body

batt - battery

cg - Center of gravity

e - Engine

eqj - Element j of equipment

f - Fuselage

ft - Fuel tank

h - Horizontal stabilizer

i - Index

le - Leading edge

long - Longitudinal

z - Vertical axe (body axis)

MAC - Mean aerodynamic chord

mr - Mutation rate

p - Propeller

s1-s3 - Aerodynamic surfaces of the RPAS. Horizontal stabilizer, wing, and vertical stabilizer.

trans - Transversal

v - Vertical stabilizer

W - Wing

x - Longitudinal axe

y - Side to side axe

z - Vertical axe

5.2. Introduction

The structural module defines and generates the whole structure of the RPAS.

It defines the shape and materials that it consists of and estimates the forces and moments that each element must resist.

5.3. Structure generation and mutation

Small and micro RPAS support smaller stress levels than their larger counterparts. In addition, the search for simplicity and reduced manufacturing costs points to the use of monocoque solutions with a foam filling. Therefore, RAMP uses this kind of structure.

5.3.1. Structure

The structure of the RPAS is divided in five parts: body, pod, wing, horizontal stabilizer and vertical stabilizer. Each part's structure is divided in skin and filling

foam. The skin is made of a material with a thickness that is selected individually for each part. With regard to the foam, all the volume of the parts that is not filled by payload or other equipment is filled with Expanded Polypropylene (EPP). To generate an initial RPAS, RAMP selects a random thickness for the skin of each structural element (body, wing, horizontal stabilizing surface, and vertical stabilizing surface), and a material from the list of available materials (Table 1). Then, RAMP selects a random density for the foam filling.

5.3.2. Material generation

The available materials for the skin of the RPAS' parts are generic examples of high-modulus CFRP (Carbon Fiber Reinforced Polymer), low carbon steel, PVC, and aluminum 6061 [268,269]. As stated before, the foam filling is made of EPP, a polypropylene foam, which is a thermoplastic polymer [270].

Mechanical values for isotropic materials are used as they are. However, the directionality of the CFRP requires that the orientation and layers of the material are taken into account. The CFRP values in Table 1 take into account both the carbon fiber and the binding polymer. RAMP's CFRP structures can be made of up to five layers of randomly oriented composite. They must be symmetrically oriented. The limitation on the number of layers comes from the expectancy that they will be enough to withstand the loads in small RPAS and thus, reduce the complexity of the model.

In every cycle of the optimization, RAMP will multiply the thickness of the skin by a number within the range $[1 - mr, 1 + mr]$ (see section 3.3.7), this is what we refer to as “mutating the structure”. In the same way, the density of the filling foam is also multiplied by a random number within the same range. Moreover, if the material in two consecutive cycles is CFRP, RAMP will also mutate the orientation of the layers in a similar manner.

Table 1: Material properties [268–270].

Material	Elastic modulus [GPa]	Shear modulus [GPa]	Ultimate tensile strength [MPa]	Density [kg/m ³]
Low Carbon Steel	200	80	540	7800
Aluminum 6061	60	4	450	2700
PVC	3	1	52	1300
CFRP 0°	140	20	1500	1800
CFRP 90°	20	20	20	1800
EPP	$0.0006\rho^2+0.09\rho-0.7115$	$0.0003\rho^2+0.0433\rho-0.3421$	$-1.10^{-5}\rho^2+0.0116\rho-0.0938$	20-200

The calculation of the mechanical properties of a layer of CFRP is as follows [269]:

$$E_i = E_{long} \cos \theta_i + E_{trans} \sin \theta_i \quad (5.1)$$

$$G_i = G_{long} \cos \theta_i + G_{trans} \sin \theta_i \quad (5.2)$$

$$UTS_i = UTS_{long} \cos \theta_i + UTS_{trans} \sin \theta_i \quad (5.3)$$

where θ is the orientation angle of the layer with respect to the desired direction (Figure 15).

The calculation of the properties of a section of any RPAS part are as follows:

$$E_{total} = \frac{\sum_i^5 E_i t_i}{\sum_i^5 t_i} \quad (5.4)$$

$$G_{total} = \frac{\sum_i^5 G_i t_i}{\sum_i^5 t_i} \quad (5.5)$$

$$UTS_{total} = \frac{\sum_i^5 UTS_i t_i}{\sum_i^5 t_i} \quad (5.6)$$

Figure 15: Orientation angle of CFRP layer.

5.4. Mass/center of gravity calculation

Knowing the mass and center of gravity of each element is necessary to calculate the center of gravity of the whole RPAS. The mass of equipment, fuel/batteries, engine and payload are known and were defined in a different module of the model. Here we present the approach taken to estimate the mass and center of gravity of the structure of the aircraft.

5.4.1. Center of gravity of the full RPAS

The center of gravity of the complete aircraft can be estimated by using the following equations:

$$x_{cg} = \frac{\sum_{i=0}^n x_{cg\ i} m_i}{\sum_{i=0}^n m_i} \quad (5.7)$$

$$y_{cg} = \frac{\sum_{i=0}^n y_{cg\ i} m_i}{\sum_{i=0}^n m_i} \quad (5.8)$$

5.4.2. Body

RAMP's body shape definition is a truncated cone with two elliptic paraboloids. One at the front and another one at the back. This gives RAMP enough flexibility to create fuselages that range from the standard cylindrical body of commercial aircraft, to a more uncommon blended wing body configuration when the body blends with the wing.

The surface area of the body is:

$$S_b = \pi g (d_1 + d_2) \quad (5.9)$$

where $g = \sqrt{l_f^2 + (d_1 - d_2)^2}$ is the slant height of the cone.

The structure volume:

$$V_{S_b} = S_b t_b \quad (5.10)$$

And the mass:

$$m_b = V_{S_b} \rho_b \quad (5.11)$$

With regard to its center of gravity, it is assumed to be at half its length:

$$x_{cg\ b} = \frac{l_f}{2} \quad (5.12)$$

5.4.3. Wing

The wing surface comprises both the upper and lower sides of the wing. Therefore, the total surface area that must be used to estimate mass is twice the one used in aerodynamic calculations:

$$V_{S_W} = 2S_W t_W \quad (5.13)$$

And the mass:

$$m_W = V_{S_W} \rho_W \quad (5.14)$$

With regard to its center of gravity, it is assumed to be at the point 1/4 of the MAC of the wing:

$$x_{cg\ W} = 0.25MAC_W + x_{MAC\ W} \quad (5.15)$$

5.4.4. Horizontal and vertical stabilizing surfaces

These elements are treated in the same way as the wing since their geometry is similar.

Their structural volume:

$$V_{S_h} = 2S_h t_h \quad (5.16)$$

$$V_{S_v} = 2S_v t_v \quad (5.17)$$

And mass:

$$m_h = V_{S_h} \rho_h \quad (5.18)$$

$$m_v = V_{S_v} \rho_v \quad (5.19)$$

With regard to their centers of gravity, they are assumed to be at the point 1/4 of their MAC:

$$x_{cg\ h} = 0.25MAC_h + x_{MAC_h} \quad (5.20)$$

$$x_{cg\ v} = 0.25MAC_v + x_{MAC_v} \quad (5.21)$$

5.5. Force and moment

Once the structure has been defined, RAMP calculates the forces and moments that it must withstand. All equations and calculations use body axis as a reference system (Figure 16). The weight of the PL, equipment, etc. are applied at their center of mass. The weight of the RPAS structure is distributed, but modeled as a punctual force when addressing interactions between parts of the RPAS. The same approach has been taken with aerodynamic forces: they are distributed along the parts of the RPAS, but are modeled as punctual loads when addressing interactions between different parts of the RPAS.

The forces and moments that the RPAS supports come from three sources: aerodynamics, gravity, and propulsion. Aerodynamic forces and moments are subdivided in drag and lift. The lift is assumed to affect only the wing and horizontal stabilizer of the aircraft, while the total drag is spread through all the parts of the RPAS. During the calculation of the overall drag, a polar equation is generated for each part. This polar equation takes into account the aerodynamic forces affecting that element (including aerodynamic interactions between elements).

As the structural module is merely a demonstrator to assess RAMP's performance, so far it only takes into account one load case: symmetrical cruise flight. As a future work, to widen RAMP's capabilities, more load cases could be added to the model.

Figure 16: RPAS' body axis used as a reference for the calculation of forces and moments.

The following sections present the forces and moments that each part of the RPAS withstands. They are sorted first by part, then by force, bending moment, and moment of torsion and, finally, by axis.

5.5.1. Body

5.5.1.1. Forces

Depending on the configuration of the RPAS, wing, horizontal stabilizer, and vertical stabilizer can present in different orders when measuring from the nose of the aircraft. Therefore, to address all possible configurations with a simple formulation, we will use s_1 for the closest of these three to the nose of the vehicle,

s3 for the farthest one, and s2 for the remaining one. In addition, depending on the position of the propeller (pulling or pushing), the forces will also present in a different manner.

X axis:

The forces applied to the body in this axis are the drag generated along the body, the force generated by the propeller (whether it is puller or pusher), and the total drag force of the wing and stabilizers at their respective roots. Depending on the horizontal and vertical stabilizers' relative position, the one with the most forward position will adopt the subscript s1, while the other will adopt the subscript s2. If they have the same position along the X axis, then x_{s1} and x_{s2} are equal and the third equation is not necessary.

Classical configuration

- Pulling propeller

$$0 < x < x_{s1} \rightarrow F_{bX} = -T + \frac{D_b}{l_f} x \quad (5.22)$$

$$x_{s1} < x < x_{s2} \rightarrow F_{bX} = -T + \frac{D_b}{l_f} x + D_{s1} \quad (5.23)$$

$$x_{s2} < x < x_{s3} \rightarrow F_{bX} = -T + \frac{D_b}{l_f} x + D_{s1} + D_{s2} \quad (5.24)$$

$$x_{s3} < x \leq l_f \rightarrow F_{bX} = -T + \frac{D_b}{l_f} x + D_{s1} + D_{s2} + D_{s3} \quad (5.25)$$

- Pushing propeller

$$0 < x < x_{s1} \rightarrow F_{bX} = \frac{D_b}{l_f} x \quad (5.26)$$

$$x_{s1} < x < x_{s2} \rightarrow F_{bX} = \frac{D_b}{l_f} x + D_{s1} \quad (5.27)$$

$$x_{s2} < x < x_{s3} \rightarrow F_{bX} = \frac{D_b}{l_f} x + D_{s1} + D_{s2} \quad (5.28)$$

$$x_{s3} < x \leq l_f \rightarrow F_{bX} = \frac{D_b}{l_f} x + D_{s1} + D_{s2} + D_{s3} \quad (5.29)$$

In addition, the drag generated by the pod is transmitted to the body:

$$x_{podcg} - \frac{l_{pod}}{2} < x \leq x_{podcg} + \frac{l_{pod}}{2} \rightarrow F_{bX_{pod}} = \frac{D_{pod}}{l_{pod}} \left(x - \left(x_{podcg} - \frac{l_{pod}}{2} \right) \right) \quad (5.30)$$

Y axis:

In symmetrical cruise flight there are no relevant forces applied on the body of the RPAS along the Y axis.

Z axis:

Lift and gravity are the main forces on this axis. The engine, batteries/fuel, and equipment are assumed to be positioned along the middle line of the fuselage unless otherwise stated. The main importance of these forces is the moment they generate on the Y axis. In the following equations, there are three parameters (F_{s1} , F_{s2} and F_{s3}) that represent the force associated to the aerodynamic surfaces. When F_{si} refers to the wing or the horizontal stabilizer, this force is equal to its weight, multiplied by the load factor, minus the lift force that the surface generates ($F_{si} = nW_{si} - L_{si}$). With regard to the vertical stabilizer, the force is equal to its weight multiplied by the load factor ($F_{si} = nW_{si}$).

- Pulling propeller

$$0 \leq x < x_e \rightarrow F_{bZ} = nW_P + \frac{nW_b}{l_f} x \quad (5.31)$$

$$x_e < x < x_{eq1} \rightarrow F_{bZ} = nW_P + \frac{nW_b}{l_f} x + W_e \quad (5.32)$$

$$x_{eq1} < x < x_{s1} \rightarrow F_{bZ} = nW_P + \frac{nW_b}{l_f} x + nW_e + \sum_{i=1}^j nW_{eqi} \quad (5.33)$$

$$x_{s1} < x < x_{eqn} \rightarrow F_{bZ} = nW_P + \frac{nW_b}{l_f} x + nW_e + \sum_{i=1}^j nW_{eqi} + F_{s1} \quad (5.34)$$

$$x_{eqn} < x < x_{s2} \rightarrow F_{bZ} = nW_P + \frac{nW_b}{lf}x + nW_e + \sum_{i=1}^j nW_{eqi} + F_{s1} \quad (5.35)$$

$$x_{s2} < x < x_{s3} \rightarrow F_{bZ} = nW_P + \frac{nW_b}{lf}x + nW_e + \sum_{i=1}^j nW_{eqi} + F_{s1} + F_{s2} \quad (5.36)$$

$$x_{s3} < x \leq lf \rightarrow F_{bZ} = nW_P + \frac{nW_b}{lf}x + nW_e + \sum_{i=1}^j nW_{eqi} + F_{s1} + F_{s2} + F_{s3} = P_w + \frac{nW_b}{lf}x + nW_e + \sum_{i=1}^j nW_{eqi} + nW_{s1} + nW_{s2} + nW_{s3} - nW_{RPAS} \quad (5.37)$$

- Pushing propeller

$$0 \leq x < x_{eq1} \rightarrow F_{bZ} = \frac{nW_b}{lf}x \quad (5.38)$$

$$x_{eq1} < x < x_{s1} \rightarrow F_{bZ} = \frac{nW_b}{lf}x + \sum_{i=1}^j nW_{eqi} \quad (5.39)$$

$$x_{s1} < x < x_{eqn} \rightarrow F_{bZ} = \frac{nW_b}{lf}x + \sum_{i=1}^j nW_{eqi} + F_{s1} \quad (5.40)$$

$$x_{eqn} < x < x_{s2} \rightarrow F_{bZ} = \frac{nW_b}{lf}x + \sum_{i=1}^j nW_{eqi} + F_{s2} \quad (5.41)$$

$$x_{s2} < x < x_{s3} \rightarrow F_{bZ} = \frac{nW_b}{lf}x + \sum_{i=1}^j nW_{eqi} + F_{s1} + F_{s2} \quad (5.42)$$

$$x_{s3} < x < x_e \rightarrow F_{bZ} = \frac{nW_b}{lf}x + \sum_{i=1}^j nW_{eqi} + F_{s1} + F_{s2} + F_{s3} \quad (5.43)$$

$$x_e < x \leq lf \rightarrow F_{bZ} = \frac{nW_b}{lf}x + \sum_{i=1}^j nW_{eqi} + F_{s1} + F_{s2} + F_{s3} + nW_e = \frac{nW_b}{lf}x + nW_e + \sum_{i=1}^j nW_{eqi} + nW_{s1} + nW_{s2} + nW_{s3} - W_{RPAS} \quad (5.44)$$

In addition, the weight of the pod is transmitted to the body:

$$x_{podcg} - \frac{l_{pod}}{2} < x \leq x_{podcg} + \frac{l_{pod}}{2} \rightarrow F_{bZ_{pod}} = \frac{nW_{pod}}{lf} \left(x - \left(x_{podcg} - \frac{l_{pod}}{2} \right) \right) \quad (5.45)$$

These weights can also be studied following their distribution along the Z axis:

$$-\frac{h_f}{2} \leq z < z_1 \rightarrow F_{bZ} = \frac{nW_b}{h_f} \left(z + \frac{h_f}{2} \right) \quad (5.46)$$

$$z_1 < z < z_2 \rightarrow F_{bZ} = \frac{nW_b}{h_f} \left(z + \frac{h_f}{2} \right) + nW_1 \quad (5.47)$$

$$z_2 < z < z_3 \rightarrow F_{bZ} = \frac{nW_b}{h_f} \left(z + \frac{h_f}{2} \right) + nW_1 + nW_2 \quad (5.48)$$

$$z_3 < z < z_4 \rightarrow F_{bZ} = \frac{nW_b}{h_f} \left(z + \frac{h_f}{2} \right) + nW_1 + nW_2 + nW_3 \quad (5.49)$$

$$z_4 < z < \frac{h_f}{2} \rightarrow F_{bZ} = \frac{nW_b}{h_f} \left(z + \frac{h_f}{2} \right) + nW_1 + nW_2 + nW_3 + nW_4 \quad (5.50)$$

where W_1, W_2, W_3 and W_4 correspond to $\sum_{i=1}^n W_{eqi} + W_e, W_W - L_W, W_h - L_h$, and W_v depending on their relative heights. Smaller subscript values represent elements with a lower position.

5.5.1.2. Bending moment

X Axis:

As stated before, symmetrical cruise is the only load case that is considered by RAMP at the moment. During symmetrical cruise there is no bending moment that the body structure supports on the X axis. In the future, once additional flight conditions and load cases are included (such as the effect of gusts), the model will have to include the bending moments generated in those cases.

Y Axis:

All the forces that are directed following the Z axis generate a bending moment on the Y axis.

- Pulling propeller

$$0 \leq x < x_e \rightarrow M_{bZ} = nW_p x + \frac{nW_b}{l_f} \frac{x^2}{2} \quad (5.51)$$

$$x_e < x < x_{eq1} \rightarrow M_{bZ} = nW_P x + \frac{nW_b x^2}{lf} + nW_e(x - x_e) \quad (5.52)$$

$$x_{eq1} < x < x_{s1} \rightarrow M_{bZ} = \frac{nW_P x + nW_b x^2}{lf} + nW_e(x - x_e) + \sum_{i=1}^j nW_{eqi}(x - x_i) \quad (5.53)$$

$$x_{s1} < x < x_{eqn} \rightarrow M_{bZ} = nW_P x + \frac{nW_b x^2}{lf} + nW_e(x - x_e) + \sum_{i=1}^j nW_{eqi}(x - x_i) + F_{s1}(x - x_{s1}) \quad (5.54)$$

$$x_{eqn} < x < x_{s2} \rightarrow M_{bZ} = nW_P x + \frac{nW_b x^2}{lf} + nW_e(x - x_e) + \sum_{i=1}^j nW_{eqi}(x - x_i) + F_{s1}(x - x_{s1}) \quad (5.55)$$

$$x_{s2} < x < x_{s3} \rightarrow M_{bZ} = nW_P x + \frac{nW_b x^2}{lf} + nW_e(x - x_e) + \sum_{i=1}^j nW_{eqi}(x - x_i) + F_{s1}(x - x_{s1}) + F_{s2}(x - x_{s2}) \quad (5.56)$$

$$x_{s2} < x \leq lf \rightarrow M_{bZ} = nW_P x + \frac{nW_b x^2}{lf} + nW_e(x - x_e) + \sum_{i=1}^j nW_{eqi}(x - x_i) + F_{s1}(x - x_{s1}) + F_{s2}(x - x_{s2}) + F_{s3}(x - x_{s3}) \quad (5.57)$$

- Pushing propeller

$$0 \leq x < x_{eq1} \rightarrow M_{bZ} = \frac{nW_b x^2}{lf} \quad (5.58)$$

$$x_{eq1} < x < x_{s1} \rightarrow M_{bZ} = \frac{nW_b x^2}{lf} + x \sum_{i=1}^j nW_{eqi}(x - x_i) \quad (5.59)$$

$$x_{s1} < x < x_{eqn} \rightarrow M_{bZ} = \frac{nW_b x^2}{lf} + \sum_{i=1}^j nW_{eqi}(x - x_i) + F_{s1}(x - x_{s1}) \quad (5.60)$$

$$x_{eqn} < x < x_{s2} \rightarrow M_{bZ} = \frac{nW_b x^2}{lf} + \sum_{i=1}^j nW_{eqi}(x - x_i) + F_{s1}(x - x_{s1}) \quad (5.61)$$

$$x_{s2} < x < x_{s3} \rightarrow M_{bZ} = \frac{nW_b x^2}{lf} + \sum_{i=1}^j nW_{eqi}(x - x_i) + F_{s1}(x - x_{s1}) + F_{s2}(x - x_{s2}) \quad (5.62)$$

$$\begin{aligned}
x_{s3} < x < x_e \quad \rightarrow M_{bz} &= \frac{nW_b}{lf} \frac{x^2}{2} + \sum_{i=1}^j nW_{eqi}(x - x_i) + \\
&F_{s1}(x - x_{s1}) + F_{s2}(x - x_{s2}) + F_{s3}(x - x_{s3})
\end{aligned} \tag{5.63}$$

$$\begin{aligned}
x_e < x \leq lf \quad \rightarrow M_{bz} &= \frac{nW_b}{lf} \frac{x^2}{2} + \sum_{i=1}^j nW_{eqi}(x - x_i) + \\
&F_{s1}(x - x_{s1}) + F_{s2}(x - x_{s2}) + F_{s3}(x - x_{s3}) + nW_e(x - x_e)
\end{aligned} \tag{5.64}$$

Z axis:

During a symmetrical cruise there is no moment that the body structure must support along the Z axis.

5.5.1.3. Moment of torsion

X axis:

- Pulling propeller

$$0 \leq x < x_{eq1} \quad \rightarrow M_{TBX} = M_e \tag{5.65}$$

$$x_{eq1} < x < x_{eqn} \rightarrow M_{TBX} = M_e + \sum_{i=1}^{n-1} nW_{eqi}(y - y_i) \tag{5.66}$$

- Pushing propeller

$$0 \leq x < x_{eq1} \quad \rightarrow M_{TBX} = 0 \tag{5.67}$$

$$x_{eq1} < x < x_{eqn} \rightarrow M_{TBX} = \sum_{i=1}^{n-1} nW_{eqi}(y - y_i) \tag{5.68}$$

Y and Z axis:

As stated before, symmetrical cruise is the only load case that is considered by RAMP at the moment. During symmetrical cruise there is no torsion moment that the body structure supports in either axis. In the future, once additional flight

conditions and load cases are included (such as the effect of gusts), the model will have to include the moments of torsion generated in those cases.

Figure 17: Diagram of the forces to which the body is subject.

5.5.2. Wing

We first define a weight surface density for the wing.

$$\sigma_{WW} = \frac{W_W}{S_W} \quad (5.69)$$

5.5.2.1. Forces

X axis:

There are only drag forces in the wing along the X axis (using the body axes):

$$x < x < x: F_{WX} = \int_y^{b_W/2} c_d(y) c(y) dy \quad (5.70)$$

Y axis:

During a symmetrical cruise there are no forces that the wing structure must support along the Y axis.

Z axis:

The mass of the wing and fuel/batteries (if there are any), as well as the lift, are present in this axis.

- In a RPAS with batteries:

$$0 \leq y < y_{cg \text{ batt}} - \frac{l_{batt}}{2} \rightarrow$$

$$F_{WZ} = \sigma_{WW} \int_y^{\frac{b}{2}} c(y) dy - \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) + \frac{W_{batt}}{2} \quad (5.71)$$

$$y_{cg \text{ batt}} - \frac{l_{batt}}{2} \leq y < y_{cg \text{ batt}} + \frac{l_{batt}}{2} \rightarrow$$

$$F_{WZ} = \int_y^{\frac{b_W}{2}} \sigma_{WW} c^{1.2}(y) dy -$$

$$- \frac{1}{2} L \left(1 - \sin \frac{\pi y}{b_W} \right) + \frac{1}{2} \frac{W_{batt}}{l_{batt}} \left(\frac{l_{batt}}{2} + y - y_{cg \text{ batt}} \right) \quad (5.72)$$

$$y_{cg \text{ batt}} + \frac{l_{batt}}{2} \leq y \leq \frac{b_W}{2} \rightarrow$$

$$F_{WZ} = \int_y^{\frac{b_W}{2}} \sigma_{WW} c^{1.2}(y) dy - \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) \quad (5.73)$$

- In a RPAS with liquid fuel:

$$0 \leq y < y_{cg \text{ ft}} - \frac{l_{ft}}{2} \rightarrow$$

$$F_{WZ} = \int_y^{\frac{b_W}{2}} \sigma_{WW} c^{1.2}(y) dy - \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) + \frac{1}{2} W_{fuel} \quad (5.74)$$

$$\begin{aligned}
 y_{cgft} - \frac{l_{ft}}{2} \leq y < y_{cgft} + \frac{l_{ft}}{2} \rightarrow \\
 F_{WZ} = \int_y^{\frac{b_W}{2}} \sigma_{WW} c^{1.2}(y) dy - \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) \\
 + \rho_{fuel} \int_y^{y_{cgft} + \frac{l_{ft}}{2}} c(y) t(y) dy
 \end{aligned} \tag{5.75}$$

$$y_{cgft} + \frac{l_{ft}}{2} \leq y \leq \frac{b_W}{2} \rightarrow F_{WZ} = \int_y^{\frac{b_W}{2}} \sigma_{WW} c^{1.2}(y) dy - \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) \tag{5.76}$$

5.5.2.2. Bending moment

X axis:

Lift and gravity generate forces that result in a bending moment applied along the wing.

- In a RPAS with batteries:

$$\begin{aligned}
 0 \leq y < y_{cg \text{ batt}} - \frac{l_{batt}}{2} \rightarrow \\
 M_{WZ} = \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \sigma_{WW} c^{1.2}(y) dy - \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) dy + \\
 \frac{W_{batt}}{2} (y_{cg \text{ batt}} - y)
 \end{aligned} \tag{5.77}$$

$$\begin{aligned}
 y_{cg \text{ batt}} - \frac{l_{batt}}{2} \leq y < y_{cg \text{ batt}} + \frac{l_{batt}}{2} \rightarrow \\
 M_{WZ} = \sigma_{WW} \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) c(y) dy - \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) dy + \\
 \int_y^{y_{cg \text{ batt}} + \frac{l_{batt}}{2}} \frac{1}{2} \frac{W_{batt}}{l_{batt}} \left(\frac{l_{batt}}{2} + y - y_{cg \text{ batt}} \right) \left(y_{cg \text{ batt}} + \frac{l_{batt}}{2} - y \right) dy
 \end{aligned} \tag{5.78}$$

$$\begin{aligned}
y_{cg batt} + \frac{l_{batt}}{2} \leq y \leq \frac{b_W}{2} \rightarrow \\
M_{WZ} = \sigma_{WW} \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) c(y) dy - \\
- \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) dy
\end{aligned} \tag{5.79}$$

- In a RPAS with liquid fuel:

$$\begin{aligned}
0 \leq y < y_{cgft} - \frac{l_{ft}}{2} \rightarrow M_{WZ} = \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \sigma_{WW} c^{1.2}(y) dy - \\
\int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) dy + \frac{1}{2} W_{fuel} (y_{cgft} - y)
\end{aligned} \tag{5.80}$$

$$\begin{aligned}
y_{cgft} - \frac{l_{ft}}{2} \leq y < y_{cgft} + \frac{l_{ft}}{2} \rightarrow \\
M_{WZ} = \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \sigma_{WW} c^{1.2}(y) dy - \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) dy + \\
\rho_{fuel} \int_y^{y_{cgft} + \frac{l_{ft}}{2}} \left(y_{cgft} + \frac{l_{ft}}{2} - y \right) c(y) t(y) dy
\end{aligned} \tag{5.81}$$

$$\begin{aligned}
y_{cgft} + \frac{l_{ft}}{2} \leq y \leq \frac{b_W}{2} \rightarrow M_{WZ} = \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \sigma_{WW} c^{1.2}(y) dy - \\
- \int_y^{\frac{b_W}{2}} \left(\frac{b_W}{2} - y \right) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_W} \right) dy
\end{aligned} \tag{5.82}$$

Y axis:

There is no bending moment along the Y axis.

Z axis:

The drag to which the wing is exposed generates a moment on the Z axis:

$$M_{WX} = \int_y^{b_W/2} \left(\frac{b_W}{2} - y \right) c_d(y) c(y) dy \tag{5.83}$$

5.5.2.3. Moment of Torsion

There is a torsion moment along the wing following the Y axis. This moment is generated by the lift, fuel/batteries and weight of the wing itself.

- In a RPAS with batteries:

$$\begin{aligned}
 0 \leq y < y_{cgft} - \frac{l_{ft}}{2} \rightarrow \\
 M_{TWY} = - \int_y^{\frac{b_W}{2}} (y \tan \Lambda_{le} + x_{ac}(y) - x_{acW}) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_w} \right) dy - \\
 \int_y^{\frac{b_W}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{4} - x_{acW} \right) \sigma_{WW} c^{1.2}(y) dy - \\
 \left(y_{cg batt} \tan \Lambda_{le} + \frac{c(y_{cg batt})}{2} - x_{acW} \right) \frac{1}{2} W_{batt}
 \end{aligned} \tag{5.84}$$

$$\begin{aligned}
 y_{cgft} - \frac{l_{ft}}{2} \leq y < y_{cgft} + \frac{l_{ft}}{2} \rightarrow \\
 M_{TWY} = - \int_y^{\frac{b_W}{2}} (y \tan \Lambda_{le} + x_{ca}(y) - x_{acW}) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_w} \right) dy - \\
 \int_y^{\frac{b_W}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{4} - x_{acW} \right) \sigma_{WW} c^{1.2}(y) dy - \int_y^{y_{cgft} + \frac{l_{ft}}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{2} - \right. \\
 \left. x_{acW} \right) \frac{1}{2} \frac{W_{batt}}{l_{batt}} \left(\frac{l_{batt}}{2} + y - y_{cg batt} \right) dy
 \end{aligned} \tag{5.85}$$

$$\begin{aligned}
 y_{cgft} + \frac{l_{ft}}{2} \leq y < \frac{b_w}{2} \rightarrow \\
 M_{TWY} = - \int_y^{\frac{b_W}{2}} (y \tan \Lambda_{le} + x_{ca}(y) - x_{acW}) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_w} \right) dy - \\
 \int_y^{\frac{b_W}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{4} - x_{acW} \right) \sigma_{WW} c^{1.2}(y) dy
 \end{aligned} \tag{5.86}$$

- In a RPAS with liquid fuel:

$$\begin{aligned}
 &0 \leq y < y_{cgft} - \frac{l_{ft}}{2} \rightarrow \\
 &M_{TWY} = - \int_y^{\frac{b_W}{2}} (y \tan \Lambda_{le} + x_{ac}(y) - x_{acW}) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_w}\right) dy - \\
 &\int_y^{\frac{b_W}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{4} - x_{acW}\right) \sigma_{WW} c^{1.2}(y) dy - \left(y_{cgft} \tan \Lambda_{le} + \frac{c(y_{cgft})}{2} - \right. \\
 &\left. x_{acW}\right) \frac{1}{2} W_{fuel} \tag{5.87}
 \end{aligned}$$

$$\begin{aligned}
 &y_{cgft} - \frac{l_{ft}}{2} \leq y < y_{cgft} + \frac{l_{ft}}{2} \rightarrow \\
 &M_{TWY} = - \int_y^{\frac{b_W}{2}} (y \tan \Lambda_{le} + x_{ca}(y) - x_{acW}) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_w}\right) dy - \\
 &\int_y^{\frac{b_W}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{4} - x_{acW}\right) \sigma_{WW} c^{1.2}(y) dy - \int_y^{y_{cgft} + \frac{l_{ft}}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{2} - \right. \\
 &\left. x_{acW}\right) \rho_{ft} c(y) t(y) dy \tag{5.88}
 \end{aligned}$$

$$\begin{aligned}
 &y_{cgft} + \frac{l_{ft}}{2} \leq y < \frac{b_w}{2} \rightarrow \\
 &M_{TWY} = - \int_y^{\frac{b_W}{2}} (y \tan \Lambda_{le} + x_{ac}(y) - x_{acW}) \frac{1}{2} nW \left(1 - \sin \frac{\pi y}{b_w}\right) dy - \\
 &\int_y^{\frac{b_W}{2}} \left(y \tan \Lambda_{le} + \frac{c(y)}{4} - x_{acW}\right) \sigma_{WW} c^{1.2}(y) dy \tag{5.89}
 \end{aligned}$$

Figure 18: Diagram of the forces to which the wing is subject.

5.5.3. Horizontal stabilizer

The forces and moments that the horizontal stabilizer supports are very similar to those in the wing.

5.5.3.1. Forces

X axis:

There are only drag forces in the wing along the X axis (using the body axes):

$$F_{hX} = \int_y^{b_h/2} c_{dh}(y)c(y)dy \quad (5.90)$$

Y axis:

During a symmetrical cruise there are no forces that the horizontal stabilizer structure must support along the Y axis.

Z axis:

The mass of the wing and fuel/batteries (if there are any), as well as the lift, are present in this axis.

$$0 \leq y \leq \frac{b_h}{2} \rightarrow F_{hZ} = \sigma_{Wh} \int_y^{\frac{b_h}{2}} c(y) dy - \frac{1}{2} L_h \left(1 - \sin \frac{\pi y}{b_h} \right) \quad (5.91)$$

5.5.3.2. Bending Moment

X axis:

Lift and gravity generate forces that result in a bending moment applied along the stabilizer.

- In a RPAS with batteries:

$$0 \leq y \leq \frac{b_h}{2} \rightarrow$$

$$M_{hZ} = \sigma_{Wh} \int_y^{\frac{b_h}{2}} \left(\frac{b_h}{2} - y \right) c(y) dy - \int_y^{\frac{b_h}{2}} \left(\frac{b_h}{2} - y \right) \frac{1}{2} L_h \left(1 - \sin \frac{\pi y}{b_h} \right) dy \quad (5.92)$$

Y axis:

There is no bending moment along the Y axis.

Z axis:

The drag to which the horizontal stabilizer is exposed generates a moment on the Z axis:

$$M_{hX} = \sigma_{Dh} \int_y^{b_h/2} \left(\frac{b_h}{2} - y \right) c(y) dy \quad (5.93)$$

5.5.3.3. Moment of Torsion

There is a torsion moment along the wing following the Y axis. This moment is generated by the lift and weight of the stabilizer.

$$0 \leq y < \frac{b_h}{2} \rightarrow$$

$$M_{ThY} = - \int_y^{\frac{b_h}{2}} \left(y \tan \Lambda_{le_h} + x_{ac}(y) - x_{ac_h} \right) \frac{1}{2} L \left(1 - \sin \frac{\pi y}{b_h} \right) dy - \int_y^{\frac{b_h}{2}} \left(y \tan \Lambda_{le_h} + \frac{c(y)}{4} - x_{ac_h} \right) \sigma_{Wh} c^{1.2}(y) dy \quad (5.94)$$

Figure 19: Diagram of the forces to which the horizontal stabilizer is subject.

5.5.4. Vertical stabilizer

We first define a weight surface density for the vertical stabilizer.

$$\sigma_{Wv} = \frac{W_v}{S_v} \quad (5.95)$$

5.5.4.1. Forces

X axis:

There are only drag forces in the vertical stabilizer along the X axis (using the body axes):

$$F_{hX} = \int_z^{b_v} c_{dv}(z)c(z)dz \quad (5.96)$$

Y axis:

Gusts are not considered in this model. Therefore, there is no force along the Y axis.

Z axis:

The weight of the stabilizer itself is the only force present in the Z axis.

$$F_{vZ} = \int_z^{b_v} \sigma_{Wz}c^{1.2}(z)dz \quad (5.97)$$

5.5.4.2. Bending Moment

X axis:

As stated before, only the condition of symmetrical cruise is considered in at the moment. Therefore, no bending moments are considered along the vertical stabilizer.

Y axis:

The drag generates a moment along the Y axis.

$$M_{vZ} = - \int_z^{b_v} (b_v - z)c(z)dz \quad (5.98)$$

Z axis:

There is no bending moment along the Z axis.

5.5.4.3. Moment of Torsion

Z axis:

As stated before, only the condition of symmetrical cruise is considered in at the moment. Therefore, no moments of torsion are considered along the vertical stabilizer.

Figure 20: Diagram of the forces to which the vertical stabilizer is subject.

5.5.5. Pod

5.5.5.1. Forces

The pod has the same shape as the body, but it may present different dimensions. Its purpose is to house payload. Therefore, the forces that it withstands are due to any equipment that is inside it instead of inside the body of the RPAS.

X axis:

$$x_{pod_{cg}} - \frac{l_{pod}}{2} < x \leq x_{pod_{cg}} + \frac{l_{pod}}{2} \rightarrow F_{pod_x} = \frac{D_{pod}}{l_{pod}} \left(x - \left(x_{pod_{cg}} - \frac{l_{pod}}{2} \right) \right) \quad (5.99)$$

Y axis:

In symmetrical cruise flight there are no relevant forces applied on the pod of the RPAS along the Y axis.

Z axis:

Lift and gravity are the main forces on this axis. The equipment is assumed to be positioned along the middle line of the pod unless otherwise stated. The main importance of these forces is the moment they generate on the Y axis.

$$x_{pod_{cg}} - \frac{l_{pod}}{2} < x \leq x_{eq1} \rightarrow F_{pod_z} = \frac{nW_{pod}}{l_f} \left(x - \left(x_{pod_{cg}} - \frac{l_{pod}}{2} \right) \right) \quad (5.100)$$

$$x_{eq_{pod1}} < x < x_{pod_{cg}} + \frac{l_{pod}}{2} \rightarrow$$

$$F_{bz} = \frac{nW_{pod}}{l_f} \left(x - \left(x_{pod_{cg}} - \frac{l_{pod}}{2} \right) \right) + \sum_{i=1}^j nW_{eq_{pod}i} \quad (5.101)$$

5.5.5.2. Bending moment

X Axis:

As stated before, symmetrical cruise is the only load case that is considered by RAMP at the moment. During symmetrical cruise there is no bending moment that the pod structure supports on the X axis. In the future, once additional flight conditions and load cases are included (such as the effect of gusts), the model will have to include the bending moments generated in those cases.

Y Axis:

All the forces that are directed following the Z axis generate a bending moment on the Y axis.

- Pulling propeller

$$x_{pod_{cg}} - \frac{l_{pod}}{2} < x \leq x_{eq_{pod}1} \rightarrow M_{podZ} = \frac{nW_{pod}}{lf} \left(\frac{x^2}{2} - \left(x_{pod_{cg}} - \frac{l_{pod}}{2} \right) x \right) \quad (5.102)$$

$$\begin{aligned} x_{eq_{pod}1} < x < x_{pod_{cg}} + \frac{l_{pod}}{2} \rightarrow \\ M_{podZ} &= \frac{nW_{pod}}{lf} \left(\frac{x^2}{2} - \left(x_{pod_{cg}} - \frac{l_{pod}}{2} \right) x \right) + \\ \sum_{i=1}^j nW_{eq_{pod}i} &\left(x - \left(x_{pod_{cg}} - \frac{l_{pod}}{2} \right) \right) \end{aligned} \quad (5.103)$$

Z axis:

During a symmetrical cruise there is no moment that the pod structure must support along the Z axis.

5.5.5.3. Moment of torsion

X, Y and Z axis:

As stated before, symmetrical cruise is the only load case that is considered by RAMP at the moment. During symmetrical cruise there is no torsion moment that the pod structure supports in either axis. In the future, once additional flight conditions and load cases are included (such as the effect of gusts), the model will have to include the moments of torsion generated in those cases.

Figure 21: Diagram of the forces to which the pod is subject.

5.6. Stress

In order to estimate the maximum stresses that a particular structure or element can withstand RAMP calculates its moments of inertia, and then the stress itself [271].

5.6.1. Body

$$I_{hor} = \frac{1}{4}\pi \left(\frac{b}{2}\right) \left(\frac{h}{2}\right)^3 - \frac{1}{4}\pi \left(\frac{b-t}{2}\right) \left(\frac{h-t}{2}\right)^3 \quad (5.104)$$

$$I_{vert} = \frac{1}{4}\pi \left(\frac{h}{2}\right) \left(\frac{b}{2}\right)^3 - \frac{1}{4}\pi \left(\frac{h-t}{2}\right) \left(\frac{b-t}{2}\right)^3 \quad (5.105)$$

$$I_{hv} = 0 \quad (5.106)$$

$$A = \pi \left(\frac{h b}{4} - \left(\frac{h}{2} - t \right) \left(\frac{b}{2} - t \right) \right) \quad (5.107)$$

5.6.2. Wing and stabilizers

$$I_{hor} = \frac{\pi}{8} R^4 - \frac{\pi}{8} e^4 + \frac{t e}{6} l_{bar}^4 + 2 \left(\frac{e}{6} \right)^2 t l_{bar} \quad (5.108)$$

$$I_{ver} = \frac{\pi}{8} R^4 - \frac{\pi}{8} c^4 + \frac{t c}{6} l_{bar}^4 + 2 \left(\frac{c-R}{6} \right)^2 t l_{bar} \quad (5.109)$$

$$I_{hv} = 0 \quad (5.110)$$

$$A = \pi e t + 2 l_{bar} t \quad (5.111)$$

$$\text{where } l_{bar} = \sqrt{c^2 + e^2}$$

5.6.3. Calculation of stress

5.6.3.1. Shear stress from torque

$$\tau_{tor} = \frac{T}{Wp} \quad (5.112)$$

5.6.3.2. Buckling critical load

$$F_{bu} = \frac{\pi^2 EI}{c(y)^2} \quad (5.113)$$

5.6.3.3. Compound stress

$$\tau_{comp} = \frac{N}{A} + \frac{M'_z y}{I_z} + \frac{M'_y z}{I_z} \quad (5.114)$$

$$M'_z = \frac{M_z - \frac{M_y I_{yz}}{I_y}}{1 - \frac{I_{yz}^2}{I_y I_z}} \quad (5.115)$$

$$M'_y = \frac{M_y - \frac{M_z I_{yz}}{I_z}}{1 - \frac{I_{yz}^2}{I_y I_z}} \quad (5.116)$$

6

SUBDISCIPLINE: PROPULSION AND PERFORMANCE

6.1.Nomenclature

AF	- Activity factor	L	- Lift
b	- Number of batteries	n	- RPM
C	- Coefficient	Nb	- Number of blades
C _{ap}	- Battery capacity (Ampere hours)	P	- Power
D	- Drag	R	- Range
Di	- Diameter	Rt	- Battery hour rating (hours)
E	- Endurance	sc	- Specific consumption
i	- Discharge current (Amperes)	Sw	- Wing surface
J	- Advance ratio	t	- Time
		V	- Flight speed

Volt - Output voltage of the battery	ρ - Air density
W - Weight	σ - Solidity
η - Efficiency	

Subscripts

batt - Batteries	L - Lift
D,d - Drag	P - Power
del - Delivered	prop - Propulsion
eng - Engine	0 - Initial
fin - Final	1 - Final
i - Induced	
init - Initial	

6.2. Introduction

This module provides information about the way that the propulsion subsystem of the aircraft is generated and mutated within RAMP. It includes information about two types of engine (electric and piston), and the method to estimate the performance of the propeller. Here, a random engine is chosen together with a propeller. Fuel load and/or batteries are also selected depending on the engine type. Then, together with information from the Aerodynamics module, the RPAS' performances are estimated.

The main components of an electric propulsion subsystem are the engine and batteries. The information presented here has been gathered from two different sources. The batteries belong to Thunder Power RC [272], whereas the engines are T-Motor brushless engines [273]. The RPAS can also have a combustion engine. In such a case, the engine will be chosen from the combustion engine database's information [274].

6.3. Powerplant generation and mutation

Firstly, an engine type is randomly chosen (piston or electric). Then a random engine is selected from RAMP's database (Appendix B). Then, in the case that the engine is electric, a random model and number of batteries will be selected. At this step, RAMP ensures that an integer number of them will provide, at least, the required working voltage for the engine (eq 6.1). If the RPAS incorporates a combustion engine, instead of batteries, a random amount of fuel will be allocated to the deposits. Finally, a propeller will randomly be generated. The propeller is defined by the parameters N_b , AF , CL_i , D_i , P , and n . The model also requires the flight speed, V , and the density of air, ρ . Finally, the model will estimate the propeller's efficiency in the required flight conditions.

$$bV_{batt} = V_{eng} \quad (6.1)$$

RAMP's system to mutate the engine is divided in the mutation of the energy storage system (either fuel weight or capacity of the batteries), and the mutation of the propeller. The mutation of the storage system is performed as with any other parameter of the RPAS (see section 3.3.7). On the other hand, the parameters of the propeller need a particular treatment, as will be explained in section 6.4.2.

6.4. Propeller's performance

6.4.1. Propeller's efficiency

To estimate the efficiency of the propeller, an algorithm developed by Glauert [275] and refined by Ohad Gur [276] is used:

First, the two-dimensional drag coefficient of the propeller must be estimated.

$$\bar{C}_d = -0.136 \left(C_{Li} \frac{C_P}{J} \right)^2 + 0.116 \left(C_{Li} \frac{C_P}{J} \right) + 0.00627 \quad (6.2)$$

Then, its activity factor:

$$\sigma = \frac{128 N_b A F}{100\,000 \pi} \quad (6.3)$$

Continuing with the same method, the next step consists in performing calculations in an iterative way with equations 6.4-6.8 until the end result converges to the guess. This process will provide the efficiency of the propeller in the flight condition. The initial guess is $\eta_1=1$.

$$\eta_2 = 1 - \frac{4}{\pi^3} \frac{\eta_1}{J} C_P \quad (6.4)$$

$$\tan \varphi_1 = \frac{J}{\pi \eta_1 \eta_2} \quad (6.5)$$

$$f(\varphi_1) = \frac{1}{8 \cos \varphi_1} (2 + 5 \tan^2 \varphi_1) - \frac{3}{16} \tan^4 \varphi_1 \log \frac{1 - \cos \varphi_1}{1 + \cos \varphi_1} \quad (6.6)$$

$$\eta_3 = 1 - \frac{\pi^4}{8} \frac{\eta_2^2}{C_P} \sigma \bar{C}_d f(\varphi_1) \quad (6.7)$$

$$\eta_1 = 1 - \frac{2}{\pi} C_P \eta_2 \eta_3 \left(\frac{\eta_1}{J} \right)^3 \quad (6.8)$$

Once the final value of η_1 is close enough to the guess (we have established $\left| \frac{\eta_{1\text{fin}}}{\eta_{1\text{init}}} - 1 \right| \leq 0.001$), the value of the efficiency of the propeller can be estimated as:

$$\eta_{prop} = \eta_1 \eta_2 \eta_3 \quad (6.9)$$

6.4.2. Limitations

We have experimentally found that the iteration of the method diverges when the values of the parameters exceed particular thresholds. These values are interdependent of the values of the rest of the variables. The mathematical equations establishing such relationships are 6.4-6.8, plus $\eta_1 \leq 1$. A set of initial propellers from which to choose seems more appropriate than using trial and error every time that a new optimization is performed. Additionally, the suitability of the parameters also depends on the flight conditions. Therefore, we have created a database of suitable solutions by exploring the subspace of feasible propellers. This database consists of 503.328 points for which the algorithm converges, which represents approximately a 1% of the tested points. The ranges of values that we have explored for the parameters are the following:

$$Nb \in [2,5] ; AF \in [1,220] ; CLi \in [0.15,0.75] ; Di \in (0,2] m ; V \in [1,250] m/s ; n \in [0,70000] rpm ; P \in (0,1000] hPa ; \rho \in [0.3,1.225] kg/m^3$$

These are initial points for the convergence of the model. When RAMP mutates the RPAS, the propulsion system's values may move away from the initial point if a more optimal solution is found. However, in this search for optimality, RAMP may generate a propulsion system for which the previously presented algorithm does not converge. In such a case, RAMP will search for a point from the database that is the closest (Cartesian distance) to the new point, from which the optimization may continue.

6.4.3. Feasible solutions

As stated before, we tested propeller's performance algorithm with a subspace of points that fully swept the parameter ranges defined in section 6.4.2. The points for which the algorithm converged define the subspace of propellers that RAMP can use as a starting point for the model. In addition, such propeller configurations are completely independent of the rest of the parameters that RAMP uses to define a RPAS. The points for which the propeller's performance algorithm converged are presented in Figures 22 and 23 for illustrative purposes. Figure 22 shows points for which the algorithm converged. Each plot shows the point distribution depending on different variables. Figure 23 shows various 4D representations of the points. The efficiency of the propeller is shown at each point through a color gradient (panel D).

Figure 22: Distributions of feasible solutions as a function of the variables of the model for propeller performance analysis. Each point marks a combination of variables for which the model converged.

Figure 23: Color distributions of propeller efficiency as a function of the variables of the model.

6.5. Integral Performances Estimation

Part of the content of this section has been previously published (with some modifications) as a research article in the journal *Advances in Engineering Software* with the title “*Development and validation of software for rapid performance estimation of small RPAS*”, DOI: 10.1016/j.advengsoft.2017.03.010. The original source [232] can be found at: <https://doi.org/10.1016/j.advengsoft.2017.03.010>

The last step to calculate the range and endurance of an RPAS is developing equations to obtain such results from the flight conditions and the polar that we

calculated before. Such model is based on the well-known Breguet equations [70] for endurance and range, and are present in literature both for propeller driven aircraft and for turbofan/turboprop engines. Only the equations for propeller driven aircraft are used here, since the segment of RPAS addressed in this document are powered by either piston or electric engines.

6.5.1. Piston engine

The equations for range and endurance have the following expressions [70]:

$$R = \frac{\eta}{sc} \frac{L}{D} \int_{W_1}^{W_0} \frac{dW}{W} = \frac{\eta}{sc} \frac{L}{D} \ln \frac{W_i}{W_{fi}} \quad (6.10)$$

$$E = \int_{W_1}^{W_0} \frac{dW}{c_P} = \frac{\eta}{sc} \frac{C_L^{\frac{3}{2}}}{C_D} \sqrt{2\rho S_W} \left(\frac{1}{\sqrt{W_{fi}}} - \frac{1}{\sqrt{W_i}} \right) \quad (6.11)$$

6.5.2. Electric engine

A great amount of the commercially and non-commercially available RPAS is powered with electrical batteries and, since Breguet equations are based on the change of weight of the aircraft during the flight, they cannot be used with electrical RPAS. There is an alternative way to obtain similar equations, which takes into consideration the discharge process of the battery. Nevertheless, the existing model [277] obtains the equations for a two terms polar, whereas we develop here the equations for a three terms polar.

We must clarify that, whereas the existing model optimizes such equations to calculate the maximum range and endurance that an aircraft can deliver, and the associated flight speed, we are aiming to obtain the range and endurance

delivered at a generic speed, which may not be the most appropriate for endurance or range flight. There is no need to obtain the equations to estimate the optimum flight conditions of the aircraft for maximum range or endurance. Once these equations are introduced in the MDO model, the optimization process itself will lead to a solution where the flight conditions are optimum for the desired objective (range, endurance, etc.). Should the solution of any step of the optimization be capable of achieving the desired range or endurance, the design will not be optimum from another point of view (e.g. mass, size, structure) and the optimization will continue. In addition, the optimum flight conditions do not necessarily have to be the ones that maximize range or endurance, and so, the model must be capable of estimating the performances of the RPAS under any flight condition.

From the balance equilibrium in steady cruise flight:

$$\begin{aligned} W=L=\frac{1}{2}\rho V^2 S_W C_L \quad (4) \quad \begin{cases} C_L = \frac{2W}{\rho V^2 S_W} \\ D = \frac{1}{2}\rho V^2 S_W C_D \end{cases} \rightarrow D = \frac{1}{2}\rho V^2 S_W (C_{D0} + C_{D1} C_L + C_{D2} C_L^2) \\ D = \frac{1}{2}\rho V^2 S_W \left(C_{D0} + C_{D1} \left(\frac{2W}{\rho V^2 S_W} \right) + C_{D2} \left(\frac{2W}{\rho V^2 S_W} \right)^2 \right) \end{aligned} \quad (6.12)$$

Therefore, the power required from the engine can be written as:

$$P_{req} = D V = \frac{1}{2}\rho V^3 S_W C_{D0} + C_{D1} V W + \frac{C_{D2} 2W^2}{\rho V S_W} \quad (6.13)$$

The time it takes for the battery to discharge, according to [277], is:

$$t = \frac{Rt}{in} \left(\frac{Cap}{Rt} \right)^n \quad (6.14)$$

And the power that it must deliver:

$$P_{del} = V_{olt} i \quad (6.15)$$

Given that the battery must deliver the power required by the aircraft to keep its steady flight:

$$\left(\frac{Rt}{t} \right)^{\frac{1}{n}} \left(\frac{Cap}{Rt} \right) = \frac{1}{\eta_{tot} V} \left(\frac{1}{2} \rho V^3 S_W C_{D0} + C_{D1} V W + \frac{C_{D2} 2 W^2}{\rho V S_W} \right) \quad (6.16)$$

Which, solving for the time, provides:

$$E = t = (Rt)^{1-n} \left(\frac{\eta_{tot} Cap V}{\frac{1}{2} \rho V^3 S_W C_{D0} + C_{D1} W V + C_{D1} 2 \frac{W^2}{\rho V S_W}} \right)^n \quad (6.17)$$

And, multiplying by the speed, V, that the aircraft maintained, we obtain the range:

$$R = V t = V (Rt)^{1-n} \left(\frac{\eta_{tot} Cap V}{\frac{1}{2} \rho V^3 S_W C_{D0} + C_{D1} W V + C_{D1} 2 \frac{W^2}{\rho V S_W}} \right)^n \quad (6.18)$$

7

SUBDISCIPLINE: PRICING ANALYSIS

7.1. Introduction

Companies like Airbus or Boeing employ multinational and very specialized teams of designers to make reality the design of one aircraft. This process is very demanding, given that the full design of an aircraft must undertake a certification process previously defined by national and international aviation authorities, such as the European Aviation Safety Agency (EASA) or the American Federal Aviation Administration (FAA). A similar trend is developing with Remotely Piloted Aircraft Systems (RPAS), also referred to as UAV, UAS or drones. EASA intends to ease the

certification process and accessibility for small RPAS [278,279], as well as ease the certification requirements for the lightest categories of aircraft, which would enable virtually everyone to design, build, and commercialize their own RPAS; still with the need to maintain the level of standards required by the international organizations [31].

Our aim in this chapter is to develop a design methodology that takes advantage of Multidisciplinary Design Optimization (MDO) and the high process capacity of standard computers to provide small companies with a powerful environment to design RPAS, for which we have already developed an aerodynamics module (see Chapter 4) [232]. For that, it is necessary to know how market price relates to other parameters of the RPAS.

Price is a key variable in the development of a product, as preliminary pricing and potential profitability may determine the decision of whether undertaking or not the development of the product, more so in the case of a fast-evolving market such as that of UAS. The objective of this chapter is developing a pricing model for RPAS that can be used as an additional discipline within an MDO environment. Pricing and costs of commercial aircraft has been studied before [280,281], most often using their weight as the main if not only variable, while parts number and complexity have also been used to estimate production and manufacturing costs of substructures of aircraft [282] and also from a conceptual point of view [283]. Recently, genetic-causal models have been used to estimate life-cycle costs of aircraft [281,284,285]; and statistical models for commercial transportation aircraft

have also been developed [286,287]. On the other hand, very detailed bottom-up methodologies have been used to estimate accurate final costs of planes [283], but they generally require a frozen-almost-final configuration and are not suitable for preliminary analysis. Costs of RPAS operation has also been studied before [288,289], but a preliminary pricing model and analysis of RPAS has yet to be published, which is why we address it here.

To study the price of RPAS in the market, both civil and military, we used Factor Analysis (FA) and regressions. FA is a statistical method that has been used in many fields to describe interrelationships between variables referred to as factors [290]. It is used to try and describe the behavior of a group of variables from a more reduced number of variables. In practical terms, it studies the covariance of a group of variables and selects a smaller group of variables that contribute the most to the covariance of the group. These variables, which are sorted in groups or “factors”, can help understand what variables define the outcome or characteristics of a subject. In this research, we intend to use FA to understand what factors or parameters of the RPAS can be used to define the RPAS market. FA’s aeronautical applications include the analysis of aircraft accidents [291], score predictors in the selection of pilots [292], and the market of UAV itself [293].

Finally, we performed a FA including the variables *Price* and *Year*; and a linear regression to analyze the relationship of the Price with the rest of variables.

7.2. Data gathering

We gathered data of 67 RPAS from Jane's all the World's Aircraft: Unmanned [294], which included the following variables: wing span (lb , m), overall length ($lfus$, m), maximum take-off/launching weight ($MTOW$, kg), payload (PL , kg), maximum level speed ($MSpeed$, m/s), ceiling ($hmax$, m), range ($Rang$, m), endurance (End , h). Additionally, when not available in the reference, we obtained the price ($Price$, \$) of the RPAS by comparing information regarding amount of RPAS and budget in commercial transactions from a number of sources [295–326] as well as the year that the RPAS were sold for that price ($Year$). This information is generally scarce, and more so when addressing military related UAV. As stated before, most times only the overall cost of a transaction involving RPAS, ground control systems and additional equipment is known. In such cases we divided the overall amount of the transaction by the estimated number of RPAS involved, given that all the additional elements included in the transaction are usually required to operate the RPAS to their full potential.

After our literature research, we managed to find enough data to fill all the values for lb , $MTOW$, $Year$, and $Price$; while the variables $lfus$, PL , $MSpeed$, $hmax$, $Rang$, and End were missing a 7.4%, 10.4%, 5.9%, 10.4%, 11.9% and 2.9% of entries respectively. A 32.8% of the RPAS were missing, at least, one value.

To perform a statistical and FA of the dataset, it is necessary to analyze the data to know what the best way to impute the missing values is. If the missing data

follows particular patterns, the missing values should be inputted taking that into account or even entries of the dataset with missing values could be discarded. A first step is testing whether the data is missing completely at random or not. In such case, it could be inputted by using a random number generator with the variance and mean values of the data distribution as defining parameters. Little's MCAR (Missing Completely at Random) test [327] checks whether this hypothesis is true. When used with our sample, it failed to reject the null hypothesis (that the samples are not MCAR), which means that our sample's missing values probably follow a trend or pattern. If the variable PL is removed from the sample, Little's MCAR test does reject the null hypothesis. This points to the PL as the culprit governing the missing values. Such a result seems reasonable, since it is closely related to the MTOW, and heavier RPAS are more likely to belong to the military, for which the data is scarcer.

Figure 24 (left) shows the amount of entries (elements) in the database that are missing values and what variables those values belong to. The red squares mark the missing values, while the white squares mean that the value for a variable in the database exists. The right panel of Figure 24 shows the number of entries in the database that are missing particular amounts of values. Analyzing the patterns of these missing values also showed that they are not monotonic. In other words, the variables for which data is missing cannot be sorted in a way that the missing values for each variable are also missing for the previous variable. The existence of

such patterns would ease the imputation of the missing values, since they could be used to impute the data [328].

Markov Chain Monte Carlo (MCMC) Multiple Imputation (MI) is a method that is commonly used to impute missing data. On one hand, MI is the standard method to replace missing data [329]. On the other hand, MCMC can reliably recreate a data distribution with the characteristics of the original distribution, even when the database is incomplete, better than non-MCMC methods [330]. Using MCMC-MI, which is indicated for no monotonic MCAR distributions [330], with all variables resulted in PL values that were not physically reasonable. For instance, an RPAS cannot carry a *PL* heavier than its MTOW. Therefore, it was necessary to impute PL separately. Given that the *PL* missing values showed a clear trend, we deemed appropriate to impute them with a polynomial. A 3rd degree polynomial ($y = x^3 10^9 - 3x^2 10^{-5} + 0.2421x - 0.9612$, where x is the MTOW of the RPAS; $R^2 = 0.9575$) was used for this task, given that polynomials of lower degree did not provide a value of $R^2 > 0.9$, while those of greater degree did not provide a meaningful improvement ($R < 0.97$). On the other hand, the imputation of the rest of the missing values with MCMC-MI was performed in SPSS [331], a statistics software package that provides this imputation method in an easy and convenient manner.

Figure 24: Number of elements that are missing values (left) for particular variables (red), and number of elements missing particular percentages of values (right).

7.3. Factor Analysis

In order to know whether a FA can be carried out with a dataset, a Kaiser-Meyer-Olkin [331] test must be performed (eq. 1). It measures the proportion of variance that may be common for several variables. Values higher than 0.5 or (0.6, depending on the author) are considered suitable to perform FA. When this test was performed on the data, it resulted in a value of 0.791, which indicates that a FA is suitable. At the same time, Bartlett's test of sphericity [331] is used to test if the variables in the data set are related. Values of significance lower than 0.05 suggest so. When applied to our data set, Bartlett's test of sphericity throws a significance lower than 0.001. This last value also suggests that a FA will properly explain the relationships between the different variables.

$$KMO_j = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} u_{ij}} \quad (7.1)$$

where r_{ij} are the elements of the correlation matrix, and u_{ij} are the elements of the partial correlation matrix of the dataset.

The next step is extracting the factors, or groups of variables, that explain the behavior of all the variables in our dataset. This is called “principal factors extraction”. The aim is to explain the variations that exist within our dataset, by using the least possible number of variables. This variables (factors) will be new, and will be made of percentages of the variables in the dataset. Each consecutive variable (from the dataset) that is extracted (added to the factor) explains a smaller fraction of the variables than the one that was extracted before. This way, the factors change until all variables have been extracted. Then, from all the progressively more complex factors that were created, one is chosen. Table 2 shows communalities in each variable of the model. The extraction value of each variable represents the proportion of each variable’s variance that can be explained by the model. In this method the initial communalities are set as 1,0. Results show that more than 67% of the covariance of each variable can be explained by the model (each extraction value is higher than 0.67). In some cases (*MTOW*, *lb*, *lfus*, *Year*), the model explains more than a 90% of it (the extraction value is higher than 0.9).

The sedimentation graph (Figure 25) is used to study the number of factors to use. The eigenvalue of the factor represents the amount of information that it adds to the model. When using a sedimentation graph to study the factors that are going to be used, the ones before and after the main drop in the graph are selected.

Table 2: Variable communalities and extraction values.

	Initial	Extraction
lb	1,000	0,918
lfus	1,000	0,901
MTOW	1,000	0,956
PL	1,000	0,831
hmax	1,000	0,863
MSpeed	1,000	0,699
Rang	1,000	0,864
End	1,000	0,676
Year	1,000	0,973
Price	1,000	0,791

This is because their eigenvalues are in a similar order of magnitude, and it is higher than that of the factors after the drop. Adding the factors after the drop to the model would not noticeably improve its information and would complicate it [332]. In Figure 25, the drop is present after factors 1 and 2. However, a second drop can be observed after the third factor. In addition, only components with eigenvalues greater than 1 are usually extracted. In this case the third factor's eigenvalue is very close to the unit (Table 3) and it would add almost a 10% of explained variance to the model, so we decided to include it as well. The three selected factors are the non-rotated factors that can be found on Table 5.

Once the factors were chosen, they were rotated to increase the correlation of the factors with the variables of the model. We will use an example to explain the meaning of this rotation: If the factors were reference axis and the variables were points in a 2D plot, rotating the factors would be the same as rotating the axis of the plot so that the points show a stronger correlation with the factors. Rotating

the factors helps understand the association of variables and factors. Table 4 shows the amount of variance that can be explained by the three chosen factors once they have been rotated. When the factors are rotated, the amount of each variable that is associated with each factor changes.

Figure 25: Sedimentation graph.

The total amount of covariance that the rotated factors explain does not change, but it is redistributed among them. This is the same as saying that the RPAS database can be equally characterized both by the non-rotated factors and by the rotated factors. But, using the analogy of the 2D plot from before, because the rotation of the factors is the same as a rotation of the reference axis, the points in the rotated reference will have different coordinates. Because the factors are artificial variables that are built from other variables, the amount of each original

variable contained in each factor changes after the rotation. The total amount of the original variables that the factors explain remains the same.

The exact composition of each factor before and after the rotation can be found in Table 5. The non-rotated Factor 1 is highly correlated with all the physical variables, which would suggest that this factor is related to the technical facet of the RPAS. However, once rotated, the correlation with the Range and Year drops, which makes this factor end up as a representative of the size of the RPAS. Factor 2 was mostly correlated with the Price or the RPAS, but the rotation made it be dominated by the Range and have a number of bridge variables as well. Finally, Factor 3 was clearly dominated by the Price before the rotation, and more so afterwards. Some variables also act as bridge variables between factors. Clear cases of this behavior are *PL*, *hmax*, *MSpeed* and *End*, which act as bridges between Factors 1 and 2. The reason behind these changes is that rotation tends to maximize the differences between factors. Therefore, variables that are highly correlated will tend to stay together, while more independent variables will isolate at a particular factor. This seems to be the case with the Range and Price, which were clearly shifted to Factors 2 and 3. The variables that were clearly related to the overall size of the RPAS stayed together.

Table 3: Amount of variance explained by each factor and their eigenvalues.

Factor	Eigenvalue	% of variance	Cumulative %
1	6,373	63,733	63,733
2	1,133	11,335	75,068
3	0,965	9,652	84,720
4	0,564	5,643	90,363
5	0,343	3,428	93,791
6	0,276	2,764	96,555
7	0,173	1,725	98,280
8	0,125	1,251	99,532
9	0,031	0,307	99,839
10	0,016	0,161	100,000

Table 4: Amount of variance explained by each rotated factor and eigenvalues.

Factor	Eigenvalue	% of variance	Cumulative %
1	4,211	42,110	42,110
2	3,204	32,036	74,146
3	1,057	10,574	84,720

Table 5: Association of each factor to the variables.

	Non-rotated Factor			Rotated Factor		
	1	2	3	1	2	3
lb	0,955	-0,064	0,034	0,947	0,238	0,045
Ifus	0,926	0,070	0,028	0,919	0,103	-0,094
MTOW	0,920	-0,170	0,161	0,791	0,430	0,146
PL	0,880	0,344	-0,252	0,733	0,569	0,041
hmax	0,878	0,244	-0,003	0,692	0,661	-0,053
MSpeed	0,830	-0,071	-0,072	0,639	0,524	-0,127
Rang	0,776	0,302	-0,412	0,095	0,882	0,063
End	0,719	-0,365	0,163	0,559	0,766	-0,039
Year	0,633	-0,371	0,503	0,314	0,740	-0,172
Price	-0,058	0,742	0,648	0,011	-0,056	0,985

These correlations suggest that the dataset of aircraft can be characterized by just three mostly independent variables. One of them (Factor 1) would represent the size of the RPAS, another one (Factor 2) would represent their range, while the third one (Factor 3) would measure their price.

7.4. Price as a function of other variables

The final intent of RAMP's Pricing Analysis subdiscipline or module is being able to accurately estimate the market price of an RPAS. In order to do so, we studied the price as a function of the rest of the variables of the dataset. The results of each step to obtain a regression to estimate the price of the RPAS are shown in the residual plots of Figure 26. A residual is the difference between the predicted value of the variable (*Price*) and its real value, and they are calculated by comparing the real price of the RPAS in our dataset with the estimations from the regression.

The initial step was calculating a preliminary linear regression including every variable of the model with *Price* as the predicted variable. This regression showed heteroscedasticity (Figure 26, panel A). This means that, when the linear regression was used to predict the price of the RPAS in the sample, the variability of the result was not homogeneous throughout the sample. The heteroscedasticity can be seen in the cone-like shape of Figure 26 (panel A). The predictions of the linear regression also showed X-axis unbalance (the points are concentrated on one side of the axis), which suggests non-linear relationships between the variables; as well as outliers that do not follow the same trends as the rest of RPAS. A log-transformation of the predicted variable removed most of the heteroscedasticity and some of the X-axis unbalance (Figure 26, panel B). Further log-transformation of some of the predicting variables (*MTOW*, *MPL* and *Rang*) was needed to completely remove the heteroscedasticity and X-axis unbalance. Additionally, four outliers were removed. Two of them showed outlier behavior in

two partial residue plots (*MSpeed* and *hmax*), and the other two in one partial plot (*MSpeed*). The removal of these four outliers notably reduced the standard deviation of all but three variables (*Price*, *Year* and *End*) (Figure 26, panel C).

The linear regression initially performed had a $R^2 = 0,562$; whereas a step by step linear regression including all variables and their log-transformed versions resulted in an $R^2 = 0,643$ that used *MTOW*, *Year*, *Radius*, $\text{Log}(hmax)$, $\text{Log}(End)$, *hmax*, *MSpeed*, *lb*, *PL* and $\text{Log}(MTOW)$ as predictors.

A look at univariate plots of each variable with $\text{Log}(Price)$ showed that there is, at least, one solution with better estimates. *lb*'s best correlation is achieved with a logarithmic function; *hmax*'s is a linear function; *PL*'s is a second-degree polynomial; *lfus*' is a logarithmic function; *MSpeed*'s is a linear function; *End*'s is a second-degree polynomial; *MTOW*'s is a logarithm, as well as *Range*'s; while the highest value of R^2 for *Year* is 0.0716 for an exponential function, which is negligible. We tested, therefore, a combination of the previous functions:

$$\begin{aligned} \text{Ln}(Price) = & \beta_0 + \beta_1 \cdot \text{Ln}(lb) + \beta_2 \cdot \text{Ceiling} + \beta_3 \cdot \text{MPL} + \beta_4 \cdot \text{MPL}^2 + \\ & \beta_5 \cdot \text{Ln}(lfus) + \beta_6 \cdot \text{MaxSpeed} + \beta_7 \cdot \text{Endurance} + \beta_8 \cdot \text{Endurance}^2 + \\ & \beta_9 \cdot \text{Ln}(MTOW) + \beta_{10} \cdot \text{Ln}(Range) \end{aligned} \quad (7.2)$$

An SPSS analysis of this non-linear regression resulted in the following values:

$$\begin{aligned} \beta_0 = 10,631; \beta_1 = -0,232; \beta_2 = 0; \beta_3 = 0,005; \beta_4 = -6,105 \cdot 10^{-6}; \beta_5 = \\ 0,702; \beta_6 = -0,007; \beta_7 = 0,045; \beta_8 = -0,001; \beta_9 = 0,582; \beta_{10} = 0,001. \end{aligned}$$

This combination of values (which removes $hmax$ from the regression) has a value of $R^2=0,655$, which is higher than that obtained with the original linear regression. A comparison of the predicted *Price* and residue for each of the RPAS in the dataset can be seen in Figure 26 (panel C).

The conclusions that can be drawn from these values are presented in Chapter 10.

Figure 26: Residual plots of the initial regression (Panel A), log-transformed regression (Panel B), and final non-linear regression (Panel C).

8

RAMP BENCHMARK MODEL

8.1. Introduction

This research's primary objective is to develop a model and framework to generate the preliminary design of an RPAS. That objective was materialized through RAMP. Once RAMP was structured and all its physical/disciplinary models were implemented it was necessary to assess its performance. The objective of this chapter is to define the tests that RAMP underwent and the values of the

parameters of the RPAS that was used as a seed for the optimization. RAMP's benchmarking consisted of several runs and a comparison of the results that were obtained. Therefore, a scientific mission that could typically be performed by small RPAS was defined. The main objective of these tests is to ensure that the resulting RPAS designs have physically feasible configurations, and to compare them to commercially available RPAS that may be suitable to perform the same mission.

The ample majority of RPAS that are commercially available, and from which we gathered data, have an endurance of approximately two hours (Chap. 4). However, the aim of this research is focused on smaller RPAS. For that reason, the selected mission's duration is 60 minutes.

In this chapter we present the objective mission, GPPA configuration, and seed RPAS that were used to perform RAMP's benchmarking.

8.2. Objective mission

Climate change is an ongoing phenomena that affects the lives of millions of people all around the world [333]. It has been demonstrated that human impact is the greatest driver in Global Warming [334]. Climate change aside, atmospheric contamination and pollution negatively impact health and quality of life, and have become a major environmental and public health challenge [335]. In order to monitor and assess the impact of atmospheric contamination it is necessary to perform atmospheric measurements. They can be carried out in multiple ways: from sounding rockets, airplanes, hot air balloons, etc. Small RPAS can perform

them in the countryside without the need for a formal runway, or in urban areas, where they can maneuver more easily than manned aircraft. During an atmospheric sounding missions, particles are gathered in the sensors of the vehicle. Then, after their recovery, particles can be analyzed to study the composition of the atmosphere.

The mission consists in obtaining a sample of suspended particles in the atmosphere at 1000 m of altitude during 60 minutes. The particles must be collected on a sheet of filter paper suitable for performing paper-spray [336]. This will make possible performing a detailed analysis of the air contents by an unexperienced researcher or operator[336]. The RPAS must also be man-portable and also be able to perform its mission with high severity wind. This mission definition translates into the following requirements:

- The RPAS shall be able to transport a 0.1 kg payload.
- The RPAS shall be able to perform its mission at 1000 m (3280 ft.) altitude.
- The RPAS shall have an air intake through which air suspended particles will enter the fuselage to be collected by the filter paper.
- The RPAS shall have a fuselage length and a wingspan shorter than 1m
- The RPAS shall weigh less than 15 kg.
- The RPAS shall be capable of flying at 45kts (23.15 m/s) to be able to maintain its position even with severe wind.
- The RPAS shall have an endurance of 60 min.

Therefore, the global objective function will be:

$$OF = \min(0, \text{abs}(E - 2400)) + \min(0, \text{abs}(MTOW - 15000)) + \min(0, \text{abs}(V - 45)) + \min(0, \text{abs}(l_f - 100)) + \min(0, \text{abs}(b_w - 100)) \quad (8.1)$$

The payload requirement does not translate into an element in the global objective function because the weight is already included in the payload of the RPAS in the model. In a similar manner, the altitude requirement is included in the model as the flight altitude already.

8.3. RAMP set-up

8.3.1. GPPA parameters

A look at the results (section 9.2) of the experiments that were carried out with GPPA (chapter 2.1) will show that GPPA05 was the most promising architecture among the studied. It was thus used as the configuration for RAMP's benchmarking.

8.3.2. Aerodynamic configurations

For the first test set, RAMP was limited to providing solutions with only classical aerodynamic configurations. This is, the wing is closer to the nose of the aircraft than the horizontal stabilizer. To ensure that this configuration is kept during the optimization, every cycle, after mutating the horizontal stabilizer's position, if it is closer to the nose of the RPAS than the wing, it is moved back to the wing's position.

The second test released the previous limitation. This way, RAMP can provide solutions with any kind of configuration: BWB, Canard, Classical, or a combination.

8.4. RPAS seed

This section presents the geometry and measurements that were used to establish the seed for the optimization.

8.4.1. Body

The body of the RPAS is defined by its diameter, b_d ; nose length, b_{nl} ; afterbody length, b_{aftl} ; and total length, b_l .

Figure 27: Body dimensions.

8.4.2. Pod

The pod is an additional body-like structure that can house equipment and payload. It is attached to the body. It is defined in a similar manner to the body of the aircraft, by its diameter, Pod_d , and total length, Pod_l ; the afterbody measures a 10% of the total length. The afterbody's size could have been independent of the pod's total length. However, this restraint has been included for simplicity. The

pod's nose is half the pod's diameter in length, so that it is shaped as a spherical cap.

Figure 28: Pod dimensions.

8.4.3. Wing

The wing is defined by its inner-half span, b_{W1} ; fullspan, b_W ; root chord, c_{rW1} ;

inner-half taper ratio, $\lambda_{W1} = \frac{c_{tW1}}{c_{rW1}} = \frac{c_{rW2}}{c_{rW1}}$; outer-half taper ratio, $\lambda_{W22} = \frac{c_{tW2}}{c_{rW2}} =$

$\frac{c_{tW2}}{c_{tW1}}$; inner-half leading edge sweep angle, Λ_{leW1} ; outer-half leading edge sweep

angle, Λ_{leW2} ; and dihedral, T_W .

8.4.4. Horizontal stabilizer

The horizontal stabilizer is defined by its span, b_h ; root chord, c_{rh} ; taper ratio, λ_h ;

leading edge sweep angle, Λ_{leh} ; and dihedral, T_h .

8.4.5. Vertical stabilizer

The vertical stabilizer is defined by its span, b_v ; root chord, c_{rv} ; and taper ratio,

$$\lambda_v = \frac{c_{tv}}{c_{rv}}.$$

Figure 29: Wing dimensions.

8.4.6. Payload, instruments, engine and batteries/fuel

8.4.6.1. Payload

The payload is modelled as a 5 cm in width, 10 cm in length rectangular prism that weighs 0.1kg. It requires a small slit of 1 cm² to make the atmospheric air pass through it in order to capture particles in suspension.

Figure 30: Dimensions of the horizontal stabilizer.

Figure 31: Dimensions of the vertical stabilizer.

8.4.6.2. Engine

Once the engine has been chosen, its volume is estimated from its weight and the density of aluminum. Then, the size of the engine is estimated by defining it as a rectangular prism whose length is 1.5 times its width.

8.4.6.3. Batteries/fuel

RAMP's mutation module provides the fuel/batteries mass of the RPAS. Then, depending on which one the RPAS has, the volume of the batteries or the fuel deposits is estimated from the density of Li^+ ion batteries or gasoline. Finally, the batteries or fuel deposits are shaped as a rectangular prism whose length is three times its width.

8.4.7. Relative positions

The position of each of the different elements housed by the fuselage and pod, and the other elements of the aircraft is defined by the XYZ distance of their most forward point to the nose of the airplane, which is the reference point of the RPAS' body axes.

Figure 32: Relative position of the elements of the aircraft

8.4.8. RPAS seed parameter values

For the tests, two equal sets of values were used as a seed RPAS (Figure 33). The only difference between these two sets was the position of the horizontal stabilizer.

The values that were employed in the initial model were the following:

Body

$$b_{lfn} = 0.1 \text{ m}$$

$$b_{aft} = 0.1 \text{ m}$$

$$b_{lf} = 1 \text{ m}$$

$$b_D = 0.1$$

Pod

$$Pod_l = 0.5 \text{ m}$$

$$Pod_x = 0 \text{ m}$$

$$Pod_D = 0.1 \text{ m}$$

$$Pod_z = 0.1 \text{ m}$$

Wing

$$h_W = 0.05 \text{ m}$$

$$\lambda_1 = 0.8$$

$$b_1 = 1 \text{ m}$$

$$\lambda_2 = 0.5$$

$$b_2 = 1 \text{ m}$$

$$x_{enc W} = 0.2 \text{ m}$$

$$\Lambda_{le W1} = 0.3 \text{ rad}$$

$$T_W = 0.3 \text{ rad}$$

$$\Lambda_{le W2} = 0.7 \text{ rad}$$

$$\alpha_0 = 0.1 \text{ rad}$$

$$c_{r1} = 0.4 \text{ m}$$

Horizontal stabilizer

$$b_h = 1 \text{ m}$$

$$T_h = -0.1 \text{ rad}$$

$$h_h = 0 \text{ m}$$

$$c_{rh} = 0.5 \text{ m}$$

$$\lambda_h = 0.8 x_{enc h} = 0.8/0.1$$

Vertical stabilizer

$$b_v = 0.3 \text{ m}$$

$$c_{rv} = 0.5 \text{ m}$$

$$\lambda_v = 0.2$$

$$x_{enc\ v} = 0.6 \text{ m}$$

Figure 33: Classical configuration (left) and canard configuration (right) versions of the seed model.

9

RESULTS

9.1. Introduction

This chapter presents the results that were obtained after performing a series of experiments and tests. The first section shows the results obtained when introducing GPPA, and a comparison of the performance of several of its parameter configurations. The second section reproduces the results of applying the aerodynamic model previously introduced in Chapter 4 to a set of small RPAS. Finally, GPPA is used as an architecture for the full RAMP MDO model. Among all the RPAS optimization that were performed, the three more representative results are presented.

9.2. GPPA

Part of the content of this section has been previously published (with small modifications) as a research article in the journal Structural and Multidisciplinary Optimization with the title “*Generic Parameter Penalty Architecture*”, DOI: 10.1007/s00158-018-1979-2. The original source [231] can be found at:

<https://doi.org/10.1007/978-3-319-799-2>

To measure the fitness of our results we compared the solutions obtained by each of the architectures to the best solution available from the literature. This comparison was performed by calculating the Euclidean distance of the architecture to that of the reference, as in the following equation:

$$D = \sum_{i=0}^n (x_{arch\ i} - x_{ref\ i})^2 \quad (9.1)$$

We studied eight different GPPA architectures with α , β and γ parameters adopting extreme values (either 0 or 1), and a configuration with parameters adopting intermediate values (0.5), which is GPPA05. None of the configurations with $\alpha=0$ (GPPA000, GPPA001, GPPA010 and GPPA 011) converged. On the other hand, GPPA100, GPPA101, GPPA110, GPPA111 and GPPA05 converged. Their parameters are shown in Table 6. The GPPA configurations with $\alpha=0$ are structured in a similar way to already existing architectures, thus, enabling us to assess whether a number of different behaviors can be originated from GPPA. GPPA05 is also interesting because of the objective distribution: both the consistencies and the global objective are equally important in the global function and the discipline functions. Each subdiscipline is also distributed equally between the global function and its disciplinary function.

Each architecture-problem combination was run more than 50 times to ensure that the results were consistently on the same order of magnitude. Figures 34-36 show a single test of each combination for illustrative purposes.

Particularly interesting configurations are GPPA_{101} , which holds a similar structure as ATC; GPPA_{110} , which is structured in a similar way to CO; and GPPA_{111} , which is similar to AAO, since all the optimization is carried out in the main level. For simplicity, all β_i have the same values, as well as the γ_i .

Table 6: GPPA architectures and their associated parameters.

Architecture	α	β_i	γ_i
GPPA₁₀₀	1	0	0
GPPA₁₀₁	1	0	1
GPPA₁₁₀	1	1	0
GPPA₁₁₁	1	1	1
GPPA₀₅	0.5	0.5	0.5

Figure 34 shows the results obtained by using all architectures on the analytical problem (see section 2.5.1). This was the simplest problem that we studied. In this case, AAO achieved the fastest convergence time. However, the best result was obtained by GPPA_{101} , while GPPA_{05} and GPPA_{111} obtained results on the same order of magnitude as AAO, but with longer convergence times. CO and GPPA_{100} had similar convergence behavior.

Figure 35 shows the results for Golinski's speed reducer (see section 2.5.2). This problem presents a higher complexity than the analytical problem, which is reflected on the increased convergence time for ATC (which gave the best results) and GPPA05 (second best results). The benefits of distributed architectures are evident here since AAO fell behind; still with a behavior similar to GPPA101 and GPPA111. Again, the worse results were obtained by CO, together with GPPA100 and joined this time by GPPA110.

Figure 36 shows the results obtained with the combustion of propane test problem (see section 2.5.3). In this problem, the distributed architectures performed much better than AAO. The best results, both in convergence speed and proximity to the optimal solution, were obtained by GPPA101 and GPPA05, followed by CO and ATC which had a much slower convergence speed. They achieved results on the same order of magnitude as GPPA05 and GPPA101. However, CO presented an increasing oscillation of up to one order of magnitude. GPPA111 showed a convergence speed similar to CO and ATC but two to three orders of magnitude farther from the solution. GPPA100 and GPPA110 did not converge and are therefore not shown in Figure 36.

Several architectures showed similar behavior. In the analytical problem this happened on one side to CO and GPPA100, and on the other side to GPPA111, GPPA110, GPPA05 and AAO. In Golinski's speed reducer the similarities were GPPA100, GPPA110 and CO on one hand, and GPPA101 and GPPA111 on the other.

Finally, GPPA₀₅ and GPPA₁₀₁ behaved in a similar manner in the combustion of propane. This behavior is particularly interesting. It suggests that, as expected, the parameters of GPPA define several subgroups of architectures with a similar behavior and different degrees of suitability for each problem. However, these behaviors are not necessarily aligned with that of the reference configurations. GPPA₁₁₀ has a similar structure to CO, but the latter uses an optimum value of J (J^*) at the main level optimization. This may make CO be slower in terms of convergence (as in the analytical problem). In more complicated problems (the combustion of propane), given that GPPA₁₁₀ will use J instead of J^* , the oscillations it suffers (also suffered by CO in smaller amount) prevent it from converging. GPPA₁₁₁ behaved in a similar way to AAO in the analytical problem and Golinski's gearbox. However, its performance was almost three orders of magnitude better than AAO's in the combustion of propane. Even though GPPA₁₁₁ does not perform discipline-level optimization, the inclusion of disciplinary objectives in the main-level optimization may help guiding the optimization. This guidance would be more noticeable in more complex problems. Finally, GPPA₁₀₁ and ATC's main-level are very similar, but ATC's discipline-level function addresses consistency and main objective while GPPA₁₀₁ does not. This may have led to the different behaviors shown in the optimization.

Figure 34: Optimization results of the Analytical Problem. Dashed lines correspond to GPPA, whereas continuous lines correspond to the reference architectures.

Figure 35: Optimization results of Golinski's Speed Reducer. Dashed lines correspond to GPPA, whereas continuous lines correspond to the reference architectures.

Figure 36: Optimization results of the Combustion of Propane. Dashed lines correspond to GPPA, whereas continuous lines correspond to the reference architect.

9.3. Aerodynamics

Part of the content of this section has been previously published (with small modifications) as a paper in the journal *Advances in Engineering Software* with the title “*Development and validation of software for rapid performance estimation of small RPAS*”, DOI: 10.1016/j.advengsoft.2017.03.010. The original source [232] can be found at: <https://doi.org/10.1016/j.advengsoft.2017.03.010>

As stated in Chapter 4, a set of 10 RPAS was used to test the aerodynamic model. These RPAS are aircraft that come from the civil and military worlds, and present various sizes and characteristics (Figures 37-41 and Table 7). After studying every RPAS in the selection (Table 8) with the methodology presented in Chapter 4, we compared the endurance calculated with our model and that provided by the manufacturer (Figure 37).

The model can also provide estimates for range. However, this value cannot be compared since the range published by the manufacturers only regards the communications range and not the range of the aircraft in cruise flight. Therefore,

we will compare only the endurance estimated by the model vs the one provided by the manufacturer.

Figure 37 shows an endurance vs MTOW comparison. The dots represent the data advertised by the manufacturer, whereas the crosses represent the endurance estimated with our model.

Figures 39-41, present a distribution of the error (both in percentage and minutes) of the model vs various characteristic values of the RPAS, such as endurance, Reynolds number at the MAC of the wing, and MTOW. The error is calculated as follows:

$$Err_{\%} = \frac{(E_{mod} - E_{man})}{E_{man}} \quad (9.2)$$

$$Err_{min} = (E_{mod} - E_{man}) \quad (9.3)$$

Figure 39 shows that the RPAS with the worst percentage of error (Evolution) differs 14 minutes from the manufacturer's data. The fact that such small amounts of time result in an error of 30% can be explained by the fact that a relatively small amount of time has an increased impact in small endurances such as that. The endurance estimations for all the other nine RPAS present an error below 12%. Even including the error associated to the estimation of Evolution's endurance, the average error of the model is 8.11%, and a 5.6% excluding it. All the calculations were performed in less than 1.5 seconds per aircraft.

Table 8 presents additional results of the analysis for the ten studied RPAS. The first column shows values for the lift curve slope. This parameter adopts values ranging from 4.623 to 6.266; with the last one being on the same order of magnitude as the theoretical value (2π) [70]. Values for the maximum lift coefficient are close to the maximum of the airfoil used for the estimations (1.35), which is relatively stable with the Reynolds number. In all but one case, the value of the minimum drag is on the order of 2-4 hundredths of the unit. The only exception to this is the Sokol, which is also the only RPAS among the studied that presents a general aircraft-like geometry. The fourth column presents values of the slope of the pitching moment vs. lift curve, and defines the longitudinal static stability of the aircraft. All RPAS but one present a negative value, which implies longitudinal stability, whereas the Evolution is longitudinally unstable. This is also the only RPAS without a horizontal tailplane. The values for the distance between the center of gravity and the tip of the MAC are of the order of centimeters. In every case it has been assumed that the center of gravity matches the $\frac{1}{4}$ point of the MAC [70]. This is a simple and accurate estimation, and more reliable than estimating the weight distribution of each RPAS. The pitching moment that the HTP must produce to balance the aircraft, in the next column, is therefore small. Finally, there is one order of magnitude in between the volume of the HTP and the VTP, which is also reasonable [70].

Figure 37: Endurance comparison between manufacturer's endurance data (dot), and the one obtained with our model (cross) vs MTOW.

Figure 38: Endurance error vs endurance associated to the estimations for each RPAS in minutes (right).

Figure 39: Percentage error vs endurance associated to the endurance estimations for each RPAS.

Figure 40: Percentage error vs MAC Reynolds number for each RPAS.

Figure 41: Percentage error vs MTOW for each RPAS.

Table 7: Key parameters gathered for the ten aircraft studied. Values in cursive show estimated values.

RPAS	MANUFACTURER	MTOW- MLW (kg)	WINGSPAN (m)	OVERALL LENGTH (m)	V (cr/max/loit) (km/h)	MAC (m)	Reynolds number at MAC	ENDURANCE (min)
Kingfisher MKI	BAE	45	4.2	2.12	120-139/185/93	0.388	541 801	120
Sokol	Aviotechnica	16	2.5	1.9	-/140/69	0.38	396 697	120
Cropcam	Micropilot	2.7	2.44	1.22	56/96/42	0.2	127 780	20
RQ-11 Raven	AeroVironment	1.9	1.37	0.9	64/96/43	0.197	127 192	90
YK-7	NRIST	14	2.115	2.05	-/194/96	0.404	584 427	40
DVF 2000	Survey Copter	7.8	3	1.2	60/-/45	0.196	134 169	90
Midge	Cyberflight	1.3	1.8	0.95	-/85/40	0.151	90 690	50
Skylark I LE	Elbit Systems	6.5	2.9	2.2	65/111/49	0.41	304 048	180
Evolution	L3 BAI	2.95	1.14	0.89	48/80/36	0.281	153 883	45
Finder	NRL	26.8	2.62	1.6	129/161/113	0.246	417 387	600

Table 8: Analysis results for the ten aircraft studied.

	$dC_L/d\alpha$	$C_L \text{ max}$	$C_D \text{ min}$	dC_m/dC_L	$\frac{X_{CG} - X_{MAC}}{X_{MAC}}$	HTP pitching moment	Vol. HTP	Vol. VTP
Kingfisher MKI	6.206	1.179	0.023	-1.137	0.097	0.072	1.633	0.018
Sokol	5.990	1.201	0.118	-0.212	0.087	-0.017	0.653	0.089
Cropcam	5.256	1.274	0.020	-0.136	0.050	0.043	0.212	0.020
RQ-11 Raven	5.057	1.204	0.010	-0.039	0.044	0.025	0.245	0.013
YK-7	5.038	1.256	0.044	0.052	0.100	-0.299	0.917	0.144
DVF 2000	6.266	1.284	0.031	-0.692	0.049	0.104	1.112	0.091
Midge	5.485	1.203	0.042	-0.148	0.037	0.017	0.357	0.022
Skylark I LE	4.979	1.292	0.030	-0.221	0.102	0.007	0.472	0.020
Evolution	4.623	1.173	0.038	0.131	0.070	-0.019	0	0.020
Finder	5.645	1.320	0.027	-0.195	0.061	-0.004	0.314	0.023

Additionally, it is important to highlight that manufacturers tend to advertise their aircraft with rounded values of endurance, which could increase or decrease in an unknown way the differences here shown.

The previously presented results (Figures 39-41) show that the error of the model is evenly spread and shows no relation to the selected parameters for its representation (Reynolds number at the MAC, MTOW, and Endurance). A bias on the Error vs Endurance plot (Figure 39) could point out to an error on the endurance equations, whereas a bias on the Error vs MAC Re, or MTOW could possibly mean a tendency of the model to overestimate or underestimate the performance of a RPAS depending on its flight conditions or size. Such results suggest that the model could be used with a wider variety of RPAS. In order to do so, studying the relationships between error and MTOW with a group of RPAS with bigger MTOW would be recommended to test this hypothesis. This has not been addressed in this work since the focus of this research was RPAS with MTOW spanning from 1 to 20 kg.

These results show that we have developed an accurate model that can be used for quick preliminary design in an MDO environment. Also, we would consider that the model is better suited for the design of RPAS with over 0.8 hours of endurance, since the results show that all the results are within a 5% of error, which is considerably below the commonly accepted 15% in preliminary sizing.

9.4. RAMP

This section presents the configurations that RAMP's optimization provided when using the mission presented in Chapter 8 as a baseline. Results from both the classical (ClC) and canard (CaC) seed configurations are provided, as well as their evolution during the optimization.

RAMP provided different final configurations as a result of the optimization process. These final configurations depended mostly on the seed configuration that was used, ClC or CaC. The first part of the results and discussion section will focus on the evolution of the optimization of the aerodynamic configuration, while the second part will address the evolution of the objective and constraints functions during the process, as well as the end result.

9.4.1. Configuration evolution

Here we present three different evolutions of the optimization. One that started with a ClC seed and maintained the configuration during the optimization, and two starting with a CaC seed. One of the CaC seeds maintained the configuration during the process, while the second one evolved into ClC.

9.4.1.1. ClC

The ClC seeded optimization consistently resulted in a similar ClC final result. Figure 42 presents a 3-view superposition of different stages of the optimization

process. Figure 43 shows the evolution of the configuration through the optimization process.

Wing and horizontal stabilizer dihedral do not suffer much change during the process (Figure 42, front view). This behavior suggests that the dihedral angle does not have a strong effect on the aerodynamic performance of the aircraft. Wing and horizontal stabilizer span is reduced, but their sweep angle remains approximately the same. If the seed configuration had not presented sweep angle, a lack of change during the optimization would have been expected. However, the fact that a sweep angle higher than zero is present during the optimization and is meaningful. This behavior suggests that the sweep angle, despite not being necessarily positive towards the overall performance of the RPAS, it is not harmful either. At least not in a relevant order of magnitude.

Overall, the horizontal stabilizer and the wing tend to move in opposite directions, and increase the distance in between them. It is apparent that the horizontal stabilizer moved backwards as much as possible while reducing its surface at the same time. A more backward stabilizer can produce the same moment as a forward one with smaller surface, which will reduce the aerodynamic drag. This is facilitated by a longer body. On the contrary, the vertical stabilizer progressively increased its surface. The model includes an equation to ensure that a particular ratio between the vertical and horizontal stabilizer is maintained. Otherwise, in a model that does not take into account, gusts, lateral stability or maneuvers, the

vertical stabilizer would disappear. The size of the vertical stabilizer is governed by this equation. In a model including a flight-quality related requirement, the vertical stabilizer will likely adopt a more optimal size.

Figure 42: 3-view superposition of the CLC result from the CLC seed. The arrows indicate the evolution of the geometry.

Figure 43: Evolution of the CIC result from the CIC seed.

9.4.1.2. CaC

As stated at the beginning of the chapter, using a CaC seed produced two different results. One of them evolved from the original CaC seed into a ClC RPAS (Figures 44 and 45). This final RPAS was similar to that produced from the ClC seed: The end RPAS presented higher wing aspect ratio than the seed, it had smaller span, wing chords, body and pod than the seed configuration. However, on the contrary to the RPAS that resulted from the ClC seed, the CaC seeded RPAS' dihedral angle of the wing increased during the optimization, as well as its horizontal and vertical stabilizers. This resulted in a configuration where the horizontal stabilizer acts in part as a wing and provides a relevant amount of lift.

Figure 44: 3-view superposition of the ClC result from the CaC seed. The arrows indicate the evolution of the geometry.

Figure 45: Evolution of the CLC result from the CaC seed.

The second solution that originated from a CaC seed can be seen in Figure 46 and 46. In this case the position of wing and horizontal did not change. The horizontal stabilizer remained in front of the wing, increased its span, and its aspect ratio. In fact, it adopted a shape more proper to that of the wing. At the same time, the wing of the aircraft maintained its position. The outer-wing's sweep angle remained the same until the very end, when it increased. This could be a way to move back the center of pressure of the wing and also its center of gravity without increasing the interaction between wing and horizontal stabilizer. Another reason, more in line with the discussion about the sweep angle that was presented in section 9.4.1.1, would be that the sweep angle is not harming for the configuration. During the optimization, when RAMP was comparing RPAS alternatives, the configuration with increased sweep angle would have also presented other changes that would counteract any drawback that this increased sweep angle may pose. As explained before, the size of the vertical stabilizer is governed by the ration of its coefficient volume to that of the horizontal stabilizer. As this configuration has a smaller coefficient of volume for the horizontal stabilizer than the other CaC seeded RPAS, the vertical stabilizer is also smaller.

Figure 46: 3-view superposition of the CaC result from the CaC seed. The arrows indicate the evolution of the geometry.

Figure 47: Evolution of the CaC-result from the CaC seed.

9.4.2. Evolution of the objective functions

The objective functions are the functions that govern the optimization at every step of RAMP's operation. They can be used to assess the optimization's evolution and what discipline, or group of disciplines, is improved at each step. Further information can be found in section 3.3.5 about the discipline objective functions; section 8.2 about the global objective function; and section 3.4 about RAMP's overall workflow and operation.

The evolution during the optimization of the objective functions that were implemented in RAMP is shown in Figures 48-50. These figures present the behavior of the objective functions associated to each of the three RPAS optimizations discussed in section 9.4.1. In the figures, *Global O*, is the main objective function, the one that is related to the mission requirements. On the other hand, *Global F* stands for the main level objective function. This is the function that results from adding each discipline's objective function, the main objective function, Global O, and the consistency function at the main level (see section 2.3, eq. 2.1). The rest of the functions shown in Figures 48-50 are the disciplinary functions at the main level optimization: *Cons* stands for "Consistency function"; *PLPos* for "PL and equipment positioning objective function within the RPAS"; *Struct* stands for "Structure objective function"; *Econ* for "Economy objective function"; *Prop* for "Propulsion objective function"; finally, *Aerod* stands for "Aerodynamic objective function".

GPPA includes a series of weights that multiply the components of the functions. These weights underwent fine tuning in order to make sure that all disciplines and consistency were properly managed by RAMP. The Global Function is shown with the real value that it presented during the optimization (which includes weights). On the other hand, the rest of the functions are shown without weights in order to better represent the real value of the parameters to which they are associated. In all cases, when there is an improvement in one or more of the functions (their value decreases), some of the other functions worsen. This is due to the dependences of the various disciplines involved in the optimization. The discussion refers to all three figures (Figures 48-50) unless otherwise stated.

As expected, the Global Function is higher than its components during the whole process (weights aside). In all three cases its value decreases 2-3 orders of magnitude. This, however, is not very meaningful, since it includes all the other objective functions and their respective weights. Its increase or decrease does not provide a feel of the overall evolution of the optimization other than confirming its progression. On the other hand, the Consistency started off as an irrelevant function but ended up being one of the highest values towards the end of the optimization in two of the three cases (Figures 48 and 49). Coincidentally the ones where the end-configuration was CLC. This behavior suggests that the initial RPAS seed was far from optimal. It was physically feasible, but its performance was not close to the requirements. As the optimization progressed, the RPAS became more

optimal, and the improvement of the configuration was also more difficult. To keep improving the objective functions, some variables started to adopt unfeasible values, which triggered the rise on the *Consistency* value. With regard to the CaC end-configuration, the *Consistency* did not play an important role throughout the optimization, which suggests that the canard configuration gives more flexibility to the variables without going into unfeasible values.

PLPos is never the highest function. The value of this function gives a sense of how crowded the space within the RPAS is. If *PLPos* is high, it means that elements of the C₃, batteries and PL are overlapping each other or the structure of the RPAS. If it is low, then the elements within the RPAS have plenty of space to be housed. Since *PLPos* is low during the whole optimization in all three cases, it is likely that the space within the RPAS is big enough to comfortably house everything, and this is not a limiting factor in the design. If the endurance requirements were low enough, for instance, the size of the RPAS would very likely reduce up to a point where the space inside it would not be enough for the PL. This would increase the value of *PLPos*.

A similar behavior to that of *PLPos* can be seen in the *Structure*. Its value in all three cases is so low that it does not show on the graphs. This simply means that the structure can withstand all the loads that the RPAS undergoes during the mission. For RPAS this size, the usual structural challenge is impact absorption rather than structural strength.

Figure 48: Evolution of the functions during the optimization of the CIC seed (section 9.4.1.1).

Figure 49: Evolution of the functions during the optimization of the CaC seed (CIC result) (section 9.4.1.2).

The same can be said about the *Economy* function: the end value is always lower than 10^{-2} . This means that the estimated commercial price is 100 times the

price of the building materials. This function only takes into consideration the market price and the price of the building materials. In the future, RAMP should take into account the manufacturing costs, as well as operational costs. This will likely drive the value of *Economy* up and pose a more limiting constraint on the design of the RPAS.

Figure 50: Evolution of the functions during the optimization of the CaC seed (CaC result) (section 9.4.1.2).

Some particularities must be taken into account when analyzing the *Propulsion* function: RAMP's Propulsion Module selects a random engine every step of the optimization. Even though the engines are sorted by thrust in RAMP's database, when mutating the propulsion system, the selection of a new engine does not progressively increase the thrust or the power of the engine. If the engine was selected this way, maybe the thrust or power increase would not be enough to

improve the model. This would stop the improvement of the engine at that point, as we experienced during early testing of RAMP. A random selection of engine, even though not optimal, avoids this issue. Because of this engine mutating system, the *Propulsion* function experienced big jumps of several orders of magnitude during the optimization. These jumps can be seen in Figures 48 and 49 around the 17000 and 23000 seconds mark respectively. This behavior was not appreciated on the last case (CaC seed and CaC result), where the value of the *Propulsion* function was low during all the optimization. It is likely that, in this case, an engine powerful enough for the mission was chosen early on in the optimization.

The *Aerodynamic* function suffered small, continuous changes throughout the optimization. These changes happened, in many cases, in an opposite direction to those of the *Consistency* function. This is probably because the *Aerodynamic* function is greatly influenced by the geometry of the RPAS, and this is the main source of geometrical constraints for the *Consistency* function. On the other hand, most of the RPAS parameters and variables have influence on the value of the *Aerodynamic* function. Any small change in any of them will affect its value, which explains why the changes of this function are more progressive and common during the process.

Finally, the *Main Objective* function presented, most of the time, a value close to that of the highest function at the moment. All but one requirements included in this function were easily satisfied from the start of the optimization. The

endurance was the requirement that defined the value of this objective function. This requirement was numerically established in seconds rather than minutes (which is the original requirement) to ensure compliance up to the second. It is likely that using this unit was the culprit that kept the value of the *Main Objective* function high all throughout. However, in early testing, we found out that using minutes instead would prevent this function from having any impact on the evolution of the RPAS, and would remain unfulfilled at the end.

9.4.3. Key parameters

This section studies the evolution of several parameters that can provide some information about the optimization process and how it could be improved in the future. Figures 51-57 present the evolution of key parameters during the optimization. These are Endurance, Range, MTOW, Speed, Pitching moment (that the horizontal stabilizer must counteract) at the center of gravity, Manufacturing price, and Market price. Most parameters had converged to a final value by the moment 25000 seconds (almost 7 h) had passed. Only the pitching moment at the center of mass kept changing at a steady rate in the CaC seeded CaC final result optimization.

Figure 51 shows the endurance of the RPAS, and Figure 52 shows the range of the RPAS at the same speed. Range and endurance are estimated at the same speeds since the baseline mission does not have range requirements. The endurance, in all cases, goes above and below the requirement until it keeps steady

at the objective value. The only remarkable point is that the CIC end-configurations seem to reach the objective value earlier than the CaC result.

Figure 51: Evolution of the endurance during the optimization.

Figure 52: Evolution of the range during the optimization.

The evolution of MTOW (Figure 53) shows an initial drop in the mass of the two models that result in a CIC. However, the MTOW of the model that started off with a CIC, quickly increased early on during the optimization. On the other hand,

this increase in the mass of the RPAS was also accompanied by a reduction in the price of the building materials (Figure 56) and market price (Figure 57). A look at the evolution of the objective functions of this optimization (Figure 48) shows a light improvement of the *Aerodynamic* objective function and the *Global* objective function, as well as a half-order of magnitude improvement at the end of the MTOW's growth.

Figure 53: Evolution of the MTOW during the optimization.

This set of events suggests that small changes on objective functions can greatly affect the design process. We attribute this effect, which is not necessarily positive or negative, to the use of evolutionary algorithms. On the other hand, the two RPAS that started the optimization with a CaC did not suffer major changes to their weight. In all cases the MTOW was considerably below the mission requirement (15 kg). This could explain the small variation it experienced during the whole optimization in two RPAS, and during most of it in the third RPAS.

The flight speed of the RPAS (Figure 54) was mostly stable in all three cases after 10.000 seconds had passed. The CaC seeded, CIC result RPAS experienced an increase of its flight speed at the beginning of the optimization. A steady reduction of the *Global*, *Propulsion* and the *Main* objective functions of the RPAS (Figure 49) can be appreciated at the same time. In this case, an increase of the engine's thrust generated these events.

With regard to the pitching moment generated by the horizontal stabilizer (Figure 55), the CIC seeded RPAS experienced a lower moment than the CaC seeded RPAS most of the time. It is interesting to note that the two aircraft that started with a CaC experienced a "bump" in the moment between 4200 and 10000 s and had similar progressions afterwards. The bumps happen approximately at the same time that both RPAS' endurance experienced an increase, and it is due probably to the growth of the horizontal stabilizer's size in comparison to the wing. In these cases, both RPAS' final configuration presented horizontal stabilizers with a surface comparable to that of the wing, which made them share an important part of the lift. This did not happen in the CIC seeded RPAS, for which the horizontal stabilizer adopted a size more related to a stabilizing surface. Also, the pitching moment's sign is related to the final configuration of the RPAS. An interesting point to note is that the RPAS that ended up with a CaC configuration at the end of the optimization, had a negative pitching moment from the beginning of the process. The two other RPAS had a positive or close to zero pitching moment. In light of these results, it seems that the change of configuration of the

CaC seeded RPAS that ended up with a CIC was the result of the existing pitching moment when the configuration change took place.

Figure 54: Evolution of the flight speed during the optimization.

Figure 55: Evolution of the pitching moment at the center of gravity that the horizontal stabilizer has to counteract during the optimization.

The price of the building materials used to manufacture the RPAS (Figure 56) suffered strong variations in all cases, but the end price was very similar for all

three. It did not suffer major variations after the 10,000 seconds mark. On the other hand, the market price of the RPAS suffered strong variations during the optimization. The final prices are strongly related to the cost of the building materials and the MTOW of the RPAS. There is a higher difference between the different values of market price than the price of the building materials. This may be due to the market price being calculated from a non-linear regression with logarithmic terms. In such an equation, a small change in one of the parameters may trigger a big change in the end result, or even non-feasible results such as negative prices. On a side note, sorting the RPAS by price of building materials or market price provides the same result. The market price's calculation does not depend on the price of the building materials, but it is also strongly related to the MTOW of the RPAS. This suggest that the most relevant variable for the estimation of both the market price and price of building materials is the MTOW.

Figure 56: Evolution of the price of the building materials during the optimization.

Figure 57: Evolution of the estimated market price during the optimization.

10

CONCLUSIONS

10.1. Introduction

This chapter presents the conclusions to each of the different experiments and models that were introduced in previous chapters, as well as to the overall research.

10.2. GPPA

Part of the content of this section has been previously published (with small modifications) as a research article in the journal Structural and Multidisciplinary

Optimization with the title “*Generic Parameter Penalty Architecture*”, DOI: 10.1007/s00158-018-1979-2. The original source [231] can be found at: <https://doi.org/10.1007%2Fs00158-018-1979-2>

GPPA has been proved to be able to tackle very different problems with consistently satisfactory results. In two of the three problems, GPPA achieved the best result among all the architectures; while in the second problem it achieved the second to best solution. GPPA₁₀₁ and GPPA₀₅ have been shown to perform particularly well in all three problems. However, the reason why GPPA₁₀₀ and GPPA₁₁₀ did not achieve convergence with the Combustion of Propane after behaving, at least, as well as CO in the previous problems requires further investigation.

The results confirm the hypothesis that GPPA can be configured to show behavior similar to that of already established architectures. That would remove the need to reformulate each problem to test different architectures or optimization strategies.

Additional tests should be carried out to assess the performance of further configurations with non-extreme values of α , β and γ ; and also with different values of each β_i and γ_i . Our most immediate interest, however, lays on the study of optimal parameters for optimization and their application to practical problems. In particular, we aim at integrating GPPA within a fully working MDO environment for RPAS design. In this field, a large number of variables are intertwined through a highly nonlinear system, which holds even more complexity than the Propane problem here presented. The trend in the experiments that we

have presented here suggests that GPPA's advantage versus the other architectures increases as the complexity of the problem. This makes GPPA's very promising in the implementation that we are pursuing.

10.3. Aerodynamics

The content of this section has been previously published (with some modifications) as a research article in the journal *Advances in Engineering Software* with the title "*Development and validation of software for rapid performance estimation of small RPAS*", DOI: 10.1016/j.advengsoft.2017.03.010. The original source [232] can be found at: <https://doi.org/10.1016/j.advengsoft.2017.03.010>

An aerodynamic model for RPAS performance estimation has been developed and tested with twelve different commercially available RPAS. Tests with the Kahu and Greek RPAS have shown that the aerodynamic estimations, which are a mixed manual-empirical approach, present results comparable to the most extended and accepted methodologies already employed.

On the other hand, results have shown that such model is accurate and, given its estimation speed, it could effectively be used as part of the core for an MDO environment aimed at small RPAS in preliminary and early stages of the design. The model could certainly be substituted in an MDO environment by a more precise model, including the ones it was compared with in Section 4.8. However, we consider that this would not be an interesting idea. The accuracy of the results, with an average error of 8.11%, show its suitability as a preliminary analysis tool, and its estimation speed in an average computer are very interesting for an optimization process with a number of iterations expected to be over the

thousands. The substitution by a more precise model would considerably slow the optimization process, given that such models take minutes or hours to obtain a solution. Even though the estimations would be more precise in every iteration step, the speed of convergence of an MDO environment depends highly on the optimizer itself. Therefore, the inclusion of a more demanding model, from the computation capacity point of view, would provide a more accurate solution but would also take from tens to thousands of times longer to obtain. Such models are more convenient in a more advanced step of the design process, where a basic configuration has been defined, and the debate is focused on small changes of the geometry.

However, the current variety of allowed configurations is limited. Therefore, we are working on widening the capabilities of the model, and then, integrating it in a full MDO platform, and study its interrelation with other fields, such as structural calculus, or manufacturing engineering.

10.4. Economy

Even though the field of RPAS is very opaque and the information scarce, we could find clear trends and relationships that define it. In particular, the characteristics of RPAS currently available in the market can be explained by three defining factors: size, performance, and price.

These results are not surprising, since the size of a RPAS greatly limits the kind of missions that it can undertake, and the conditions under which it can be

deployed. In a similar manner, performance (range and endurance) define the type of RPAS.

A surprising result, however, is the fact that these two factors are relatively independent. This points out to the versatility of RPAS and the availability of several sizes of RPAS with similar performances. Another conclusion that can be extracted from this result is that the RPAS industry is still not mature. If it was, each kind of mission would be performed by a very particular kind of RPAS given that they would be greatly optimized. This could also be related to the third factor: price. The fact that the price is so independent from the other two factors suggests that the RPAS market behaves like a monopoly or an oligopoly at most, where the price of the product is not completely related to its quality/performance.

With regard to the possibility of explaining the RPAS' price by the other variables, results show that it can be done at some extent. However, there is still a considerable amount of unexplained variance that could be due to socio-political factors and/or the contour conditions of the market itself. The RPAS industry works at large like an oligopoly (mostly the military side of it), which increases the arbitrariness of the RPAS pricing. Still, managing to achieve a predicting regression that, with a $R^2=0.655$ is remarkable. In the future, obtaining more data and considering more variables can prove very valuable towards the improvement of the pricing model. In addition, as the RPAS market expands, it will very likely get closer to a standard perfect competition, which will tie the prices closer to the performances and characteristics of the aircraft.

10.5. RAMP

As the results in the previous chapter show, RAMP is capable to generate and optimize small RPAS that are optimum for a predefined mission. In fact, RAMP has generated different aircraft configurations equally suitable for it. The results that adopted the classical configuration show that RAMP can provide results similar to those generated by the standard methodologies of conceptual design. Moreover, the canard result that was obtained shows that RAMP may be used to explore novel designs that are not currently common. For instance, the sweep angle of the wing may be used to balance its aerodynamic center and displace it to a position closer to the center of gravity of the RPAS. Because of the structure of the model, the use of evolutionary algorithms, and the randomness associated to the initial values of some of the parameters of the seed configuration, each optimization process is dominated by different subsystems. That prevents other subsystems from enduring a similar improvement in their initial conditions. The initial seed of the model was very different from the final results. This may have favored the variability of the final solutions, or biased the optimization towards a particular size or result configuration. Additional tests with different seed-configuration, presenting more variability, would be necessary to assess their influence on the final result. A similar reasoning can be applied to GPPA's driving parameters (α , β and γ). Only the set (0.5, 0.5, 0.5) was used, since it was the most promising amongst the sets that were studied in Chapter 2. However, given the complexity of the problem, maybe other sets of parameters would have led to faster convergences,

or influenced the resulting RPAS in some way. Further experiments are required to assess their influence as well.

The particularities of the propulsion module, where the choice of engine is completely random and does not follow a continuous distribution, makes it difficult to ensure that the engine choice is optimum. It is possible that another engine provides enough thrust with lighter mass, but the optimization could appear to have converged, since it would stay at a particular level (a local optimum) until the new engine is randomly selected. This requires that an alternative engine-selection model is developed, maybe with an engine surrogate model, in order to avoid this scenario.

The values that were obtained for the pitching moment at the center of mass are very high. The culprit of this result could certainly be an excessively big vertical stabilizer. Given that the horizontal stabilizer ended up sharing part of the lift of the RPAS, the vertical stabilizer may have ended up being bigger than necessary. Relating its size to maneuverability instead of to the size of the horizontal stabilizer would, very likely, reduce its size, and thus the values of the moment.

Moreover, the estimations of the price of the building materials of the RPAS should be extended to a full costs model of the company or, at least, the manufacturing and commercialization costs of the RPAS. The intent is for RAMP to be a model with few constraints that can simplify the design process as much as possible. While it does clearly fulfill its objective, a more detailed manufacturing

model implemented instead of the building materials cost estimation would certainly improve the results.

Finally, the overall convergence of the model, which took around 7 hours is short enough to generate a new model in a working day, or 3 in a full 24 h period. While this is considerably shorter than conventional modeling techniques, and short enough to be used by small companies and entrepreneurs, an improvement of some of the processes could reduce the time needed to generate the results. This would allow the design process to be more versatile and even be carried out during a work-meeting.

10.6. Overall research

The main purpose of this research was to develop a new MDO methodology for the quick, efficient, and robust design of RPAS. It should take into account the various subdisciplines of aeronautical design, such as aerodynamics, structural calculus, propulsion, economy, etc. And provide the environment to generate, from the RPAS' objective performance, a suitable design for the flight conditions of the aircraft and its mission.

With these objectives in mind, GPPA has been developed as a new flexible and multipurpose architecture that can be adapted to fit the particular requirements and characteristics of each problem. It serves as the core of RAMP, the new environment that has been created with the purpose of greatly simplifying and speeding up the process to perform preliminary sizing and prototyping of

small RPAS. It takes advantage of new MDO techniques to concentrate all the decisions of the design process and find a solution that is optimum from a global point of view.

In order to provide an adequate level of precision, it was necessary for RAMP's different physical models to be accurate and work properly with the objective RPAS. A new aerodynamics model was developed to mix classical design structure and experimental data to address the flight conditions of small RPAS. Different engine, propeller and performances models have been integrated to be able to estimate the performances of the RPAS. The structural behavior of every main part of the aircraft has been modeled, and the economic prospects of the RPAS commercialization have been statistically estimated from a real distribution.

The model can certainly be improved but, at the moment, it is capable to generate and deliver RPAS models that have similar or better characteristics than commercial aircraft. The challenge, in the future, will be introducing more and more parameters and subsystems in the model, which will both complicate the process and improve the global solution. And ensure that, as technology, aeronautics, and society evolve, the model keeps up with it.

As Pierre Georges Latécoère once said, "All the calculations show it can't work. There's only one thing to do: make it work."

APPENDIX A: AIRFOILS

Figures 59-63 present the behavior of the maximum lift coefficient (Cl_{max}), lift-curve slope (Cl_α), moment coefficient at the aerodynamic center (C_{mac}), position of the aerodynamic center ($X_{c_{mac}}$), and zero-lift angle (α_0) with the Reynolds number of the airfoils included in the Airfoil Database. This information has been derived from that shown on [244-246].

— **E387** — **FX 63-137** — **S822** — **S834** — **SH3055**

Figure 58: Airfoil color-code used in Figures 59-63.

Figure 59: Cl_{max} vs Reynolds number of RAMP's Airfoil Database.

Figure 60: Cl_α vs Reynolds number of RAMP's Airfoil Database.

Figure 61: C_{mac} vs Reynolds number of RAMP's Airfoil Database.

Figure 62: X_{cmac} vs Reynolds number of RAMP's Airfoil Database.

Figure 63: Zero-lift angle vs Reynolds number of RAMP's Airfoil Database.

APPENDIX B: ENGINES AND BATTERIES

Table 9 shows information on the batteries available within the database [272]. Each entry includes the working voltage of the battery, its maximum intensity, as well as its mass and price. Every battery has a capacity of 25 C.

Table 12 shows information on the electrical engines of the database [273]. Each entry includes working voltage, maximum intensity, weight, and price of the engine. Finally, Table 14 presents the piston engines that RAMP includes within its database [274].

Table 9: Batteries database.

<i>Battery</i>	<i>Voltage (V)</i>	<i>Intensity (A)</i>	<i>Mass (kg)</i>	<i>Price (€)</i>
<i>TP380-1SPX25J</i>	3.7	0.38	0.111	7.99
<i>TP380-2SPX25J</i>	7.4	0.38	0.022	10.99
<i>TP380-3SPX25J</i>	11.1	0.38	0.032	14.99
<i>TP500-2SPX25J</i>	7.4	0.5	0.03	11.99
<i>TP500-3SPX25J</i>	11.1	0.5	0.044	17.99
<i>TP750-2SPX25J</i>	7.4	0.75	0.039	13.99
<i>TP750-3SPX25J</i>	11.1	0.75	0.057	19.99
<i>TP910-2SPX25J</i>	7.4	0.91	0.047	14.99
<i>TP910-3SPX25J</i>	11.1	0.91	0.069	19.99
<i>TP1350-2SPX25J</i>	7.4	1.35	0.061	17.99
<i>TP1350-3SPX25J</i>	11.1	1.35	0.094	21.99
<i>TP1350-2SPX25</i>	7.4	1.35	0.064	17.99
<i>TP1350-3SPX25</i>	11.1	1.35	0.095	21.99
<i>TP1350-4SPX25</i>	14.8	1.35	0.126	29.99
<i>TP1350-5SPX25</i>	18.5	1.35	0.157	37.99
<i>TP2200-2SPX25</i>	7.4	2.2	0.107	17.99
<i>TP2200-3SPX25</i>	11.1	2.2	0.151	21.99
<i>TP2200-4SPX25</i>	14.8	2.2	0.197	32.99
<i>TP2800-2SPX25</i>	7.4	2.8	0.123	24.99
<i>TP2800-3SPX25</i>	11.1	2.8	0.181	34.99
<i>TP2800-3SPX25EJ</i>	11.1	2.8	0.181	37.99
<i>TP2800-3SPX25XJ</i>	11.1	2.8	0.181	37.99

Table 10: Batteries database (continuation).

Battery	Voltage (V)	Intensity (A)	Mass (kg)	Price (€)
TP2800-4SPX25	14.8	2.8	0.234	47.99
TP2800-5SPX25	18.5	2.8	0.29	64.99
TP2800-6SPX25	22.2	2.8	0.351	74.99
TP3400-2SPX25	7.4	3.4	0.166	29.99
TP3400-3SPX25	11.1	3.4	0.252	49.99
TP3400-4SPX25	14.9	3.4	0.326	69.99
TP3400-5SPX25	18.5	3.4	0.407	89.99
TP3400-6SPX25	22.2	3.4	0.478	109.99
TP3400-6SPX25L	22.2	3.4	0.488	109.99
TP3400-7SPX25	25.9	3.4	0.546	129.99
TP3400-8SPX25	29.6	3.4	0.611	149.99
TP3400-8SPX25L	29.6	3.4	0.621	149.99
TP4000-2SPX25	7.4	4	0.156	44.99
TP4000-3SPX25	11.1	4	0.269	64.99
TP4000-4SPX25	14.8	4	0.356	84.99
TP4000-5SPX25	18.5	4	0.435	99.99
TP4000-6SPX25	22.2	4	0.526	124.99
TP4000-6SPX25L	22.2	4	0.536	124.99
TP4000-7SPX25	25.9	4	0.614	149.99
TP4000-8SPX25	29.6	4	0.702	174.99
TP4000-8SPX25L	29.6	4	0.712	174.99
TP4000-9SPX25	33.3	4	0.79	199.99
TP4000-10SPX25	37	4	0.877	219.99
TP4000-10SPX25L	37	4	0.887	219.99
TP4400-2SPX25	7.4	4.4	0.205	44.99
TP4400-3SPX25	11.1	4.4	0.306	69.99
TP4400-4SPX25	14.8	4.4	0.406	89.99
TP4400-5SPX25	18.5	4.4	0.505	109.99
TP4400-6SPX25	22.2	4.4	0.601	134.99
TP4400-6SPX25L	22.2	4.4	0.611	134.99
TP4400-7SPX25	25.9	4.4	0.701	159.99
TP4400-8SPX25	29.6	4.4	0.801	189.99
TP4400-8SPX25L	29.6	4.4	0.811	189.99
TP4400-9SPX25	33.3	4.4	0.902	209.99
TP4400-10SPX25	37	4.4	0.994	229.99
TP4400-10SPX25L	37	4.4	1.004	229.99
TP5000-2SPX25	7.4	5	0.237	54.99

Table 11: Batteries database (continuation).

<i>Battery</i>	<i>Voltage (V)</i>	<i>Intensity (A)</i>	<i>Mass (kg)</i>	<i>Price (€)</i>
<i>TP5000-3SPX25</i>	11.1	5	0.349	74.99
<i>TP5000-4SPX25</i>	14.8	5	0.465	99.99
<i>TP5000-5SPX25</i>	18.8	5	0.574	119.99
<i>TP5000-6SPX25</i>	22.2	5	0.695	149.99
<i>TP5000-6SPX25L</i>	22.2	5	0.705	149.99
<i>TP5000-7SPX25</i>	25.9	5	0.813	189.99
<i>TP5000-8SPX25</i>	29.6	5	0.93	209.99
<i>TP5000-8SPX25L</i>	29.6	5	0.94	209.99
<i>TP5000-9SPX25</i>	33.3	5	1.046	239.99
<i>TP5000-10SPX25</i>	37	5	1.162	254.99
<i>TP5000-10SPX25L</i>	37	5	1.172	254.99
<i>TP6000-2SPX25</i>	7.4	6	0.256	44.99
<i>TP6000-3SPX25</i>	11.1	6	0.384	65.99
<i>TP6000-4SPX25</i>	14.8	6	0.49	89.99
<i>TP6000-5SPX25</i>	18.5	6	0.623	109.99
<i>TP6000-6SPX25</i>	22.2	6	0.743	134.99
<i>TP6800-2SPX25</i>	7.4	6.8	0.326	79.99
<i>TP6800-3SPX25</i>	11.1	6.8	0.484	109.99
<i>TP6800-4SPX25</i>	14.8	6.8	0.619	149.99
<i>TP6800-5SPX25</i>	18.5	6.8	0.771	189.99
<i>TP6800-6SPX25</i>	22.2	6.8	0.907	229.99
<i>TP8000-2SPX25</i>	7.4	8	0.35	94.99
<i>TP8000-3SPX25</i>	11.1	8	0.526	134.99
<i>TP8000-4SPX25</i>	14.8	8	0.701	179.99
<i>TP8000-5SPX25</i>	18.5	8	0.859	209.99
<i>TP8000-6SPX25</i>	22.2	8	1.023	249.99

Table 12: Electric engines database.

<i>Engine</i>	<i>Voltage (V)</i>	<i>Intensity (A)</i>	<i>Power (W)</i>	<i>Mass (kg)</i>	<i>Price (€)</i>
<i>MN1804</i>	11.1	8.4	93.24	0.016	25.9
<i>MN1806</i>	11.1	11.1	123.21	0.018	25.9
<i>MD2204</i>	11.1	10.2	113.22	0.023	25.9
<i>MT1306</i>	7.4	6.3	46.62	0.0112	29.9
<i>MN2206</i>	11.1	12.8	142.08	0.03	25.9
<i>MN2212</i>	14.8	10.3	152.44	0.054	46.9
<i>MT2208</i>	14.8	10.1	149.48	0.045	43.9
<i>MT2212</i>	14.8	14.3	149.48	0.055	44.9

Table 13: Electric engines database (continuation).

<i>Engine</i>	<i>Voltage (V)</i>	<i>Intensity (A)</i>	<i>Power (W)</i>	<i>Mass (kg)</i>	<i>Price (€)</i>
MN3110	14.8	14	207.2	0.08	61.9
U3	14.8	19.4	287.12	0.097	109.9
U8	44.4	24.9	1105.56	0.25	279.9
U5	22.2	20	444	0.156	125.9
U8-Pro	44.4	24.9	1105.56	0.25	299.9
U7	25	62	1550	0.255	149.9
U10	56	27	1512	0.4	329.9
U10 Plus	56	31.4	1758	0.5	339.9
U12	48	47.4	2275.2	0.792	349.9
U11	50	56.8	2840	0.73	349.9
MT2814	14.8	23.6	349.28	0.12	65.9
MN4014	22.2	17	377.4	0.149	97.45
4004	24	10.4	249.6	0.052	72.95
4006	24	17.5	420	0.066	74.95

Table 14: Piston engines database.

<i>Engine</i>	<i>Power (W)</i>	<i>Mass (kg)</i>	<i>Price (€)</i>
15LA	298.28	0.138	76.79
35AX	954.5	0.363	145.05
46AX II	1215.491	0.486	127.98
55AX ABL	1252.776	0.525	145.05
65AX	1290.061	0.497	170.65
75AX	1767.309	0.750	213.31
95AX	2132.702	0.745	238.91
120AX	2311.67	0.647	238.91
FS56-a	738.2429	0.461	281.57
FSa-56II	738.2429	0.394	341.30
FS-62V	805.3559	0.486	238.91
FS72-a	879.9258	0.530	324.24
FSa-72II	879.9258	0.530	409.57
FS-95V	1252.776	0.650	255.98
FS155-a	1908.992	0.900	426.63
FT-160	1491.4	1.100	981.26

LIST OF ACRONYMS

AAO	All at Once
ABM/S	Agent-Based Modeling/Simulation
ALC	Augmented Lagrangian Coordination
AOA	Angle of attack
ATC	Analytical Target Cascading
ATM	Air traffic management
BCS	Bayesian Collaborative Campling
BLISCO	Bi-Level Integrated System Collaborative Optimization
BWB	Blended Wing Body
CaC	Canard Configuration
CAD	Computer Aided Design
CCO	Classic Collaborative Optimization
CFD	Computational Fluid Dynamics
CIC	Classical Configuration
CO	Collaborative Optimization
CSSO	Concurrent SubSpace Optimization
EA	Evolutionary Algorithms
EASA	European Aviation Safety Agency
ECO	Enhanced Collaborative Optimization
EDSDCO	Enhanced Design Space Decrease Collaborative Optimization
EPP	Expanded Polypropylene
ESAVE	Efficient Supersonic Air-Vehicle Exploration
FA	Factor Analysis
FAA	Federal Aviation Administration
FEM	Finite Element Model
GA	Genetic Algorithm
GPPA	Generic Parameter Penalty Architecture
GPS	Generalized Pattern Search
HAPMOEA	Hierarchical Asynchronous Parallel Multi-Objective Evolutionary Algorithms
HSS	Horizontal Stabilizing Surfaces
HTP	horizontal tail plane
ICO	Improved Collaborative Optimization
IDF	Individual Discipline Feasible
IR	Infra-Red
ISA	International Standard Atmosphere
LPP	Linear Physical Programming
LT-MADS	Lower-Triangular matrices Mesh Adaptive Direct Search
MADS	Mesh Adaptative Direct Search

MAR	Missing at Random
MTOW	Maximum Take Off Weight
MC	Monte Carlo
MCMC	Markov Chain Monte Carlo
MDF	Multidisciplinary Feasible
MDO	Multidisciplinary Design Optimization
MI	Multiple Imputation
MLSM	Moving Least Squares Method
MMA	Method of Moving Asymptotes
MOC	Method of Centers
MORCO	Multi-objective Robust Collaborative Optimization
MSTC	Air Force's Research Laboratory for Multidisciplinary Science and Technology Center
NDMO	Natural Domain Modeling for Optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm
OF	Objective Functions
PIDO	Process Integration and Design Optimization
PSO	Particle Swarm Optimization
QEPF	Quadratic Penalty Function
RAMP	RPAS Advanced MDO Platform
RFCDV	random-fuzzy continuous discrete variables
RISM	Reverse Iteration of Structural Model
RPAS	Remotely Piloted Aircraft Systems
SQP	Sequential Quadratic Programming
SQP	Sequential Quadratic Programming
TSMC	Tabu Search Monte Carlo
UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle
UCAS	Unmanned Combat Air System
VEM	Volume Element Model
VLM	Vortex Lattice Methods
VSS	Vertical Stabilizing Surfaces
XDSM	Extended Design Structure Matrix

LIST OF FIGURES

FIGURE 1: GPPA'S EXTENDED DESIGN STRUCTURE MATRIX (XDSDM) AS PER [213].	31
FIGURE 2: SPEED REDUCER SCHEMATICS WITH PHYSICAL MEASUREMENTS.	39
FIGURE 3: RAMP SCHEMATIC ORGANIZATION.	58
FIGURE 4: FLOWCHART OF THE AERODYNAMIC MODEL	64
FIGURE 5: PROGRAM INPUT FILE SAMPLE.	67
FIGURE 6: DIEDERICH'S LIFT DISTRIBUTION FUNCTION (LEFT) AND FACTORS FOR ADDITIONAL LIFT DISTRIBUTION (RIGHT) [259].	71
FIGURE 7: LIFT COEFFICIENT VS ANGLE OF ATTACK COMPARISON OF KAHU UAV.	84
FIGURE 8: DRAG COEFFICIENT VS ANGLE OF ATTACK COMPARISON OF KAHU.	84
FIGURE 9: DRAG POLAR COMPARISON OF KAHU UAV.	84
FIGURE 10: PITCH MOMENT VS ANGLE OF ATTACK COMPARISON.	84
FIGURE 11: LIFT COEFFICIENT VS ANGLE OF ATTACK COMPARISON.	86
FIGURE 12: DRAG COEFFICIENT VS ANGLE OF ATTACK COMPARISON.	86
FIGURE 13: EFFICIENCY COMPARISON.....	87
FIGURE 14: PITCHING MOMENT VS ANGLE OF ATTACK COMPARISON.	86
FIGURE 15: ORIENTATION ANGLE OF CFRP LAYER.	91
FIGURE 16: RPAS' BODY AXIS USED AS A REFERENCE FOR THE CALCULATION OF FORCES AND MOMENTS.	95
FIGURE 17: DIAGRAM OF THE FORCES TO WHICH THE BODY IS SUBJECT.	102
FIGURE 18: DIAGRAM OF THE FORCES TO WHICH THE WING IS SUBJECT.	108
FIGURE 19: DIAGRAM OF THE FORCES TO WHICH THE HORIZONTAL STABILIZER IS SUBJECT.	110
FIGURE 20: DIAGRAM OF THE FORCES TO WHICH THE VERTICAL STABILIZER IS SUBJECT.	112
FIGURE 21: DIAGRAM OF THE FORCES TO WHICH THE POD IS SUBJECT.	115
FIGURE 22: DISTRIBUTIONS OF FEASIBLE SOLUTIONS AS A FUNCTION OF THE VARIABLES OF THE MODEL FOR PROPELLER PERFORMANCE ANALYSIS. EACH POINT MARKS A COMBINATION OF VARIABLES FOR WHICH THE MODEL CONVERGED.	125
FIGURE 23: COLOR DISTRIBUTIONS OF PROPELLER EFFICIENCY AS A FUNCTION OF THE VARIABLES OF THE MODEL.	126

FIGURE 24: NUMBER OF ELEMENTS THAT ARE MISSING VALUES (LEFT) FOR PARTICULAR VARIABLES (RED), AND NUMBER OF ELEMENTS MISSING PARTICULAR PERCENTAGES OF VALUES (RIGHT).....	137
FIGURE 25: SEDIMENTATION GRAPH.	140
FIGURE 26: RESIDUAL PLOTS OF THE INITIAL REGRESSION (PANEL A), LOG-TRANSFORMED REGRESSION (PANEL B), AND FINAL NON-LINEAR REGRESSION (PANEL C).....	145
FIGURE 27: BODY DIMENSIONS.....	151
FIGURE 28: POD DIMENSIONS.....	152
FIGURE 29: WING DIMENSIONS.	153
FIGURE 30: DIMENSIONS OF THE HORIZONTAL STABILIZER.	154
FIGURE 31: DIMENSIONS OF THE VERTICAL STABILIZER.	154
FIGURE 32: RELATIVE POSITION OF THE ELEMENTS OF THE AIRCRAFT.....	155
FIGURE 33: CLASSICAL CONFIGURATION (LEFT) AND CANARD CONFIGURATION (RIGHT) VERSIONS OF THE SEED MODEL.....	157
FIGURE 34: OPTIMIZATION RESULTS OF THE ANALYTICAL PROBLEM. DASHED LINES CORRESPOND TO GPPA, WHEREAS CONTINUOUS LINES CORRESPOND TO THE REFERENCE ARCHITECTURES.	164
FIGURE 35: OPTIMIZATION RESULTS OF GOLINSKI’S SPEED REDUCER. DASHED LINES CORRESPOND TO GPPA, WHEREAS CONTINUOUS LINES CORRESPOND TO THE REFERENCE ARCHITECTURES.	164
FIGURE 36: OPTIMIZATION RESULTS OF THE COMBUSTION OF PROPANE. DASHED LINES CORRESPOND TO GPPA, WHEREAS CONTINUOUS LINES CORRESPOND TO THE REFERENCE ARCHITECT.	165
FIGURE 37: ENDURANCE COMPARISON BETWEEN MANUFACTURER’S ENDURANCE DATA (DOT), AND THE ONE OBTAINED WITH OUR MODEL (CROSS) VS MTOW.....	168
FIGURE 38: ENDURANCE ERROR VS ENDURANCE ASSOCIATED TO THE ESTIMATIONS FOR EACH RPAS IN MINUTES (RIGHT)..	168
FIGURE 39: PERCENTAGE ERROR VS ENDURANCE ASSOCIATED TO THE ENDURANCE ESTIMATIONS FOR EACH RPAS.	169
FIGURE 40: PERCENTAGE ERROR VS MAC REYNOLDS NUMBER FOR EACH RPAS.....	169
FIGURE 41: PERCENTAGE ERROR VS MTOW FOR EACH RPAS.	170
FIGURE 42: 3-VIEW SUPERPOSITION OF THE CLC RESULT FROM THE CLC SEED. THE ARROWS INDICATE THE EVOLUTION OF THE GEOMETRY.	176
FIGURE 43: EVOLUTION OF THE CLC RESULT FROM THE CLC SEED.....	177

FIGURE 44: 3-VIEW SUPERPOSITION OF THE CLC RESULT FROM THE CAC SEED.	
THE ARROWS INDICATE THE EVOLUTION OF THE GEOMETRY.	178
FIGURE 45: EVOLUTION OF THE CLC RESULT FROM THE CAC SEED.	179
FIGURE 46: 3-VIEW SUPERPOSITION OF THE CAC RESULT FROM THE CAC SEED.	
THE ARROWS INDICATE THE EVOLUTION OF THE GEOMETRY.	181
FIGURE 47: EVOLUTION OF THE CAC-RESULT FROM THE CAC SEED.	182
FIGURE 48: EVOLUTION OF THE FUNCTIONS DURING THE OPTIMIZATION OF THE CLC SEED (SECTION 9.4.1.1).	186
FIGURE 49: EVOLUTION OF THE FUNCTIONS DURING THE OPTIMIZATION OF THE CAC SEED	
(CLC RESULT) (SECTION 9.4.1.2).	186
FIGURE 50: EVOLUTION OF THE FUNCTIONS DURING THE OPTIMIZATION OF THE CAC SEED	
(CAC RESULT) (SECTION 9.4.1.2).	187
FIGURE 51: EVOLUTION OF THE ENDURANCE DURING THE OPTIMIZATION.	190
FIGURE 52: EVOLUTION OF THE RANGE DURING THE OPTIMIZATION.	190
FIGURE 53: EVOLUTION OF THE MTOW DURING THE OPTIMIZATION.	191
FIGURE 54: EVOLUTION OF THE FLIGHT SPEED DURING THE OPTIMIZATION.	193
FIGURE 55: EVOLUTION OF THE PITCHING MOMENT AT THE CENTER OF GRAVITY THAT	
THE HORIZONTAL STABILIZER HAS TO COUNTERACT DURING THE OPTIMIZATION.	193
FIGURE 56: EVOLUTION OF THE PRICE OF THE BUILDING MATERIALS DURING THE OPTIMIZATION.	194
FIGURE 57: EVOLUTION OF THE ESTIMATED MARKET PRICE DURING THE OPTIMIZATION.	195
FIGURE 58: AIRFOIL COLOR-CODE USED IN FIGURES 58-62.	207
FIGURE 59: CL_{MAX} VS REYNOLDS NUMBER OF RAMP'S AIRFOIL DATABASE.	207
FIGURE 60: CL_A VS REYNOLDS NUMBER OF RAMP'S AIRFOIL DATABASE.	208
FIGURE 61: C_{MAC} VS REYNOLDS NUMBER OF RAMP'S AIRFOIL DATABASE.	208
FIGURE 62: X_{CMAC} VS REYNOLDS NUMBER OF RAMP'S AIRFOIL DATABASE.	209
FIGURE 63: ZERO-LIFT ANGLE VS REYNOLDS NUMBER OF RAMP'S AIRFOIL DATABASE.	209

LIST OF TABLES

TABLE 1: MATERIAL PROPERTIES [265,266].	90
TABLE 2: VARIABLE COMMUNALITIES AND EXTRACTION VALUES.	138
TABLE 3: AMOUNT OF VARIANCE EXPLAINED BY EACH FACTOR AND THEIR EIGENVALUES.	142
TABLE 4: AMOUNT OF VARIANCE EXPLAINED BY EACH ROTATED FACTOR AND EIGENVALUES.....	142
TABLE 5: ASSOCIATION OF EACH FACTOR TO THE VARIABLES.....	142
TABLE 6: GPPA ARCHITECTURES AND THEIR ASSOCIATED PARAMETERS.	161
TABLE 7: KEY PARAMETERS GATHERED FOR THE TEN AIRCRAFT STUDIED. VALUES IN CURSIVE SHOW ESTIMATED VALUES. ...	171
TABLE 8: ANALYSIS RESULTS FOR THE TEN AIRCRAFT STUDIED.	172
TABLE 9: BATTERIES DATABASE.	211
TABLE 10: BATTERIES DATABASE (CONTINUATION).	212
TABLE 11: BATTERIES DATABASE (CONTINUATION).	213
TABLE 12: ELECTRIC ENGINES DATABASE.	213
TABLE 13: ELECTRIC ENGINES DATABASE (CONTINUATION).	214
TABLE 14: PISTON ENGINES DATABASE.	214

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