A RISK-VALUE-BASED METHODOLOGY FOR ENTERPRISE-LEVEL DECISION-MAKING

A Dissertation
Presented to
The Academic Faculty

By

Frederic Burgaud

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Aerospace Engineering

Georgia Institute of Technology

August 2017

A RISK-VALUE-BASED METHODOLOGY FOR ENTERPRISE-LEVEL DECISION-MAKING

Approved by:

Dr. Dimitri N. Mavris
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Daniel P. Schrage
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Elena Garcia
School of Aerospace Engineering
Georgia Institute of Technology

Dr. Jonathan E. Clarke
Scheller College of Business
Georgia Institute of Technology

Dr. David Goldsman
School of Industrial and Systems
Engineering
Georgia Institute of Technology

Date Approved: July 28, 2017

There are no useless efforts. Sisyphus was building muscles.

Roger Caillois

ACKNOWLEDGEMENTS

I would like to start by thanking my advisor, Dr. Dimitri Mavris, for all his guidance, advice, and support along my doctoral life in Georgia Tech. I am also grateful for giving me the opportunity to pursue my MBA, go on an internship, and start my current job although I had just passed the proposal stage. Thanks to him I was able to combine my student and career objectives. I would also like to thank my other committee members. I am grateful to Dr. Schrage for his precious advice and point of view on my research. I want to thank Dr. Elena Garcia for reviewing my thesis, and for her lead on the projects I worked on as a Graduate Research Assistant. I would also like to thank Dr. David Goldsman for giving me precious feedback on my dissertation, in particular about the statistical aspects of it. I will also acknowledge Dr. Jonathan Clarke for being part of my committee, verifying the soundness of my financial studies, and bringing ideas that are not commonly found in aerospace.

In addition to my committee members, I would also like to acknowledge the friends who shared parts of my student life at Georgia Tech. Christopher Frank for introducing me to the field of suborbital vehicle design, and for encouraging a collaboration that ultimately led to the research I am presenting in this dissertation. Jean-Guillaume Durand, for being a patient desk neighbor and involving me in various research areas. Antoine Genton, Adrien Ciclet, and Sebastien Mamessier, for helping me spend the necessary time on my PhD to explore all of its aspects.

I need to particularly thank Krithika Iyer for all the support she gave me and for sharing my life during the hectic last years of my doctoral life.

Finally, I thank my whole family for their unconditional support despite the distance and the complications it represents.

TABLE OF CONTENTS

LIST OF TABLES

xiv

LIST OF FIGURES

SUMMARY

Despite its long lasting existence, aerospace remains a non-commoditized field. To sustain their market domination, the major companies need to commit to large capital investments and constant innovation, in spite of multiple sources of risk and uncertainty, and significant chances of failure. This makes aerospace programs particularly risky. However, successful programs more than compensate the costs of disappointing ones. In order to maximize the chances of a favorable outcome, a business-driven, multi-objective, and multi-risk approach is needed to ensure success, with particular attention to financial aspects. Additionally, aerospace programs involve multiple divisions within a company. Besides vehicle design, finance, sales, and production are crucial disciplines with decision power and influence on the outcome of the program. They are also tightly coupled, and the interdependencies existing between these disciplines should be exploited to unlock as much program-level value potential as possible. An enterprise-level approach should, therefore, be used. Finally, suborbital tourism programs are well suited as a case study for this research. Indeed, they are usually small companies starting their projects from scratch. Using a full enterprise-level analysis is thus necessary, but also more easily feasible than for larger groups. These motivations lead to the formulation of the research objective: *to establish a methodology that enables informed enterprise-level decision-making under uncertainty and provides higher-value compromise solutions*.

The research objective can be decomposed into two main directions of study. First, current approaches are usually limited to the design aspect of the program and do not provide the optimization of other disciplines. This ultimately results in a de-facto sequential optimization, where principal-agent problems arise. Instead, a holistic implementation is proposed, which will enable an integrated enterprise-level optimization. The second part of this problem deals with decision-making with multiple objectives and multiple risks. Current methods of design under uncertainty are insufficient for this problem. First, they

do not provide compelling results when several metrics are targeted. Additionally, variance does not properly fit the definition of risk, as it captures both the upside and downside uncertainty. Instead, the deviation of the Conditional Value at Risk (called here downside deviation) is used as a measure of value risk. Furthermore, objectives are categorized and aggregated into risk and value scores to facilitate convergence, visualization, and decision-making. As suborbital vehicles are complex non-linear systems, with many infeasible concepts and computationally expensive M&S environments, a time-efficient way to estimate the downside deviation needs to be used. As such, a new uncertainty propagation structure is used that involves regression and classification neural networks, as well as a Second-Order Third-Moment (SOTM) technique to compute statistical moments.

The proposed process elements are combined, and integrated into a method following a modified Integrated Product and Process Development (IPPD) approach, using five main steps: establishing value, generating alternatives, evaluating alternatives, and making decisions. A new M&S environment is implemented and involves a design framework to which several business disciplines are added.

A bottom-up approach is used to study the four research questions of this dissertation. At the lowest level of the implementation, an enhanced financial analysis is evaluated. Common financial valuation methods used in aerospace have heavy limitations: all of them rely on a very arbitrary discount rate despite its critical impact on the final value of the NPV. The proposed method provides detailed analysis capabilities and helps capture more value by enabling the optimization of the company's capital structure. A sensitivity analysis also verifies the importance of the added factors in the proposed method.

The second implementation step is to time-efficiently evaluate downside deviation. As such, regression and classification neural networks are implemented to estimate the base costs of the vehicle and speed up the vehicle sizing process. Business analyses are already time-efficient and therefore maintained. These neural networks ultimately show good validation prediction root-mean-square error (RMSE), which confirms their accuracy. The

SOTM method is also checked and shows a downside deviation prediction accuracy equivalent to a 750-point Monte Carlo method. From a computation time standpoint, the use of neural networks is required for a reasonable convergence time, and the SOTM used jointly with neural networks results in an optimization time below 1 hour.

The proposed approach for making risk/value trade-offs in the presence of multiple risks and objectives is then tested. First, the importance of using downside deviation is demonstrated by showing the risk estimation error made when using the standard deviation rather than the actual downside deviation. Additionally, the use of risk and value scores also helps decision-making from a qualitative and quantitative point of view. Indeed, it facilitates visualization by supplying a two-dimensional Pareto frontier, while still being able to color it to observe program features and cluster patterns. Furthermore, the problem with risk and value scores provides more optimal solutions, compared to the non-aggregated case, unless very large errors in weightings are committed. Finally, the proposed method provides good capabilities for identifying, ranking, and selecting optimal concepts.

The last research question presents the following interrogation: does an enterprise-level approach help improve the optimality of the overall program, and does it result in significantly different decision-making? Two elements of the enterprise-level approach are tested: the integrated optimization, and the use of additional enterprise-level objectives. In both cases, the resulting Pareto frontiers are significantly dominating their counterparts, demonstrating the usefulness of the enterprise-level approach from a quantitative point of view. It also shows that the enterprise-level approach results in significantly different decisions, and should, therefore, be applied early in the design process.

Hence, the method provided the capabilities sought in the research objective. This research resulted in contributions in the financial analysis of aerospace programs, in design under multiple sources of uncertainty with multiple objectives, and in design optimization by proposing the adoption of an enterprise-level approach.

CHAPTER 1

MOTIVATION

Despite its long-lasting existence, aerospace remains a non-commoditized field. The industry is dominated by only a few companies and countries, ferociously defending their strong historical position. This supremacy is directly observed through the importation and exportation of goods across the world, as seen in Figure 1.1. Historically, few players participated in the global competition; Europe, the United States, and the Soviet Union have been key knowledge holders of aerospace sciences and engineering. More recently, new entrants such as Canada, Brazil, China or India have joined the race, but they have mostly been shy opponents against the established companies, because of the considerable barriers to entry. In order to maintain a consistent growth, aerospace markets have considerably evolved over the years, starting from military aviation and commercial aviation, to space, and soon space tourism or flying cars. Regardless of the field, aerospace programs require extensive investment, and it is then necessary to support decision makers as much as possible to maximize the chances of a positive outcome. In order to best formulate this problem, this chapter presents why assisting key executives is necessary, and how it should be achieved. Section 1.1 highlights how the aerospace sector carries a significant risk, yet provides great profit opportunities. Section 1.2 explains what areas strategic decision makers should be supported with. Section 1.3 shows the need for a multidisciplinary enterprise-level approach within a company, early in the design process, in order to capture more potential value from an aerospace program. It will more particularly be illustrated with the example of suborbital tourism - the commercial activity of taking people for a short flight to an altitude of at least 100 km, at the edge of the atmosphere and space. Section 1.4 justifies such a choice by providing additional motivations, specific to
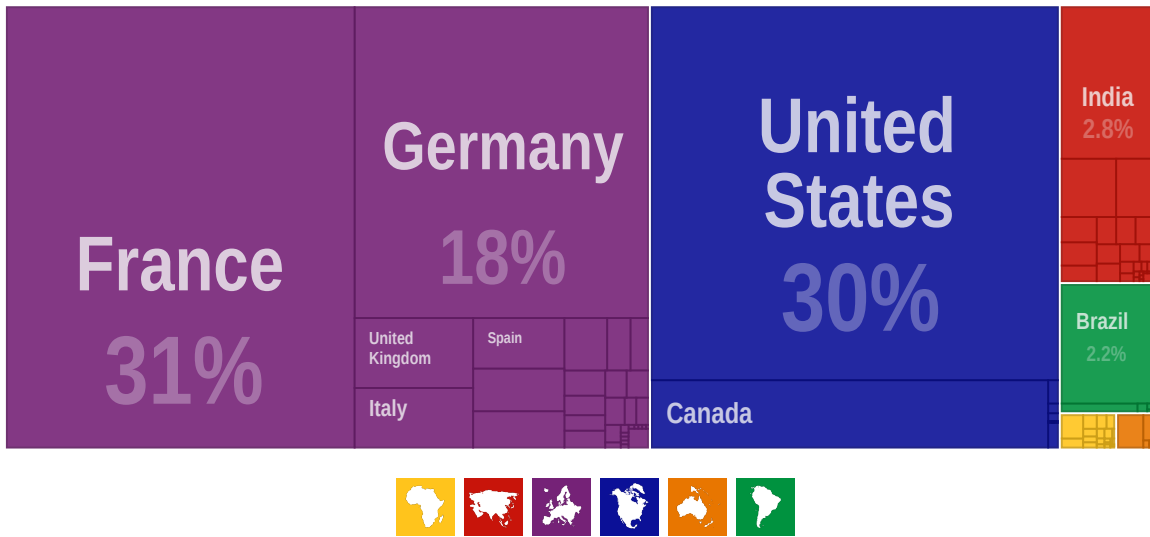
Figure 1.1: Country-wise breakdown of the exports of planes, helicopters and spacecraft [1]

the field of suborbital tourism. Finally, section 1.5 summarizes this chapter and concludes by establishing the research objectives of this thesis.

1.1   Aerospace: a risky yet profitable field

Aerospace programs are considered to be some of the most costly and risky projects among businesses [2, 3]. A lot of money has to be committed to the development of a single vehicle while consenting to the burden of a late payback period [3] - approximately ten years for commercial aviation. Moreover, such projects are also exposed to a broad range of significant risks such as oil price volatility, competition, and a slowing economy. For suborbital tourism, for example, it naturally entails significant risks because of its novelty and complexity. Finally, technologies are continuously advancing, at a fast pace, which requires a significant commitment to remain ahead of the competition. However, it will be shown in this section that despite this notable riskiness, the aerospace field also provides great profit potential and opportunities.

(a) Concorde [4]   (b) A340 [5]   (c) Space Shuttle [6]

(d) A380 [7]   (e) XCOR Lynx [8]

Figure 1.2: Examples of costly aerospace programs

1.1.1 A history of financially unsuccessful programs

As previously indicated, aerospace programs are risky. This is illustrated by various precedents of financially unsuccessful aerospace programs. Examples of the Concorde, the A340, the Space Shuttle, the A380 or the XCOR Lynx show the economic failure of great engineering programs due to an uncontrolled exposure to such risks.

- **The Concorde:** The Concorde is the first supersonic commercial jet ever produced. Jointly designed by Aéropostale (which will later become the Airbus Group), and British Aircraft Corporation (BAC, later BAe - British Aerospace) in the late 1960s, it initially showed decent success among customer airlines, with almost 100 orders and options. Unfortunately for the manufacturers, change in public opinion due to concerns over the sonic-boom later translated in regulations ruling out supersonic flights over land in countries such as the US, India, and Malaysia. Later, the successive oil shocks further reduced the attractiveness of the Concorde, leading most customers to cancel their orders, and leaving Air France and British Airways as the only operators of the aircraft. Only 20 planes were produced; a huge commercial fail-

ure compared to the announced demand for 350 jets by 1980, predicted in a two-page advertisement of the 29 May 1967 issue of Aviation Week & Space Technology [9]. Safety issues, after the 2000 crash in Paris [10], combined with excessive life-cycle costs, sounded the death knell of the Concorde operations [11].

- **The Space Shuttle:** The Space Shuttle was a partially reusable manned spacecraft developed and by the U.S. National Aeronautics and Space Agency - NASA. It started its first flight in 1981 and its first operations in 1982. Missions included launching various types of satellites and probes, carrying out experiments in orbit, or performing maintenance operations on space stations. The spacecraft was designed as reusable in a hope to reduce costs of space exploration. In order to secure funding from Congress, the shuttle was, during early design phases, described as a space vehicle that would be launched weekly. However, this assumption proved unrealistic, and while the shuttle reached a maximum of 9 launches per year in the mid-80s [12], it averaged 4 launches per year over its life-cycle. This lower-than-expected utilization, combined with enormous maintenance costs, led the Space Shuttle program to become a financial sinkhole. NASA claims that the Space Shuttle cost $450 million per flight [13]. Yet, even this massive figure is disputed [14, 15], with some estimates reaching over a billion dollars per flight, totaling as much as $170 billion for the 135 missions performed in 30 years of operation [16]. Hindered by complex operations and maintenance, enormous costs, and targeted by public criticism, the Space Shuttle last flew on July 21st, 2011.

- **The Airbus A340:** The A340 is a four-engine passenger jet designed by the Airbus Group in the early 1980s. It was jointly developed with the two-engine A330. Orders of A340 never reached its awaited potential. With the entry of the Boeing 777 in the competitive market, the substantial relaxation of the ETOPS regulations, and the consistent increase in jet fuel price, four-engine aircraft lost interest from airlines,

along with the A340 [17]. The A340 totaled 377 deliveries when the last A340 was handed to its operator, in 2012.

- **The Airbus A380:** The A380 is an aircraft developed by the Airbus Group in the early 2000s. It can transport up to 853 people, although it approximately seats approximately 544 passengers in a typical configuration, making it the largest passenger jet in the world, as of 2016. While it is difficult to judge its economic outcome as it has only been in production for about ten years, its success remains, at the moment, a question mark. The program has been plagued since the beginning by delays in development due to the complexity of managing projects between the different participating countries. Development costs overruns also jeopardized the profitability of the airplane, as they grew to about 14 billion from a planned 8.8 billion initially [18]. In 2012, cracks were discovered in the airplane wing rib brackets [19]. This incident contributed to further costs, in order to fix the existing planes and provide an appropriate solution for the new ones, as well as potential lost sales due to its tarnished reputation. Finally, the lack of orders can also be interpreted as the failure of the hub-and-spoke strategy that Airbus promoted, while Boeing decided to push its point-to-point 777s and 787s. The A380, as of 2016, only collected a bit over 300 orders, almost half of them being from Emirates and none of them from a North-American airline. While the program is often considered as a commercial failure at the moment [20, 21], Airbus is considering a re-engined version of the aircraft, the A380neo, that would raise its profitability and maybe spur additional demand. Moreover, the development of the A380 gave Airbus the capability to position itself on the Very Large Aircraft (VLA) market, previously monopolized by Boeing. If the demand pattern shifts in the future, Airbus will have a ready product and will be able to capture the prospective customers.

- **The XCOR Lynx:** Previous cited projects were all large programs. It is also important to note that small aerospace programs entail risks as well. The XCOR Lynx space plane is an example of such small aerospace projects that eventually failed. The Lynx was a suborbital vehicle concept being developed by XCOR Aerospace. The design of the vehicle was a space plane that would operate using horizontal take-off and landing. The concept started development in 2003. Although first commercial flights were planned for 2010, complications in development forced the board to push back the inauguration date consistently. Meanwhile, the co-founders left the company in 2015 [22]. Excessive delays in development, combined with difficulties getting funding, led the company to refocus their research on different projects in 2016, lay off 20 employees out of 60 [23], and put the XCOR in hibernation, which portends the end of the project [24].

This subsection, through historical examples, demonstrates the high riskiness of complex aerospace programs. Many programs, for different reasons, ended with poor financial performance. **The strong presence and the consequences of such risks make it crucial to handle risk carefully, in particular from a financial perspective.** The next subsection details the multiple sources of risk and uncertainty existing in the field of aerospace.

1.1.2 A sector exposed to a broad range of uncertainty and risk sources

Through concrete examples, the previous subsection showed that the underlying risk of undertaking aerospace programs was real, and frequently enough observed to require considering it with great care when embarking on this type of adventure. When pondering risk, one should analyze its two main components: severity and likelihood. While the high investment costs increase the severity of failure, its likelihood is amplified because of the wide range of sources of uncertainty affecting aerospace programs. The previous examples emphasized the effect on some sources of uncertainty on the smooth progress of some ma-

6
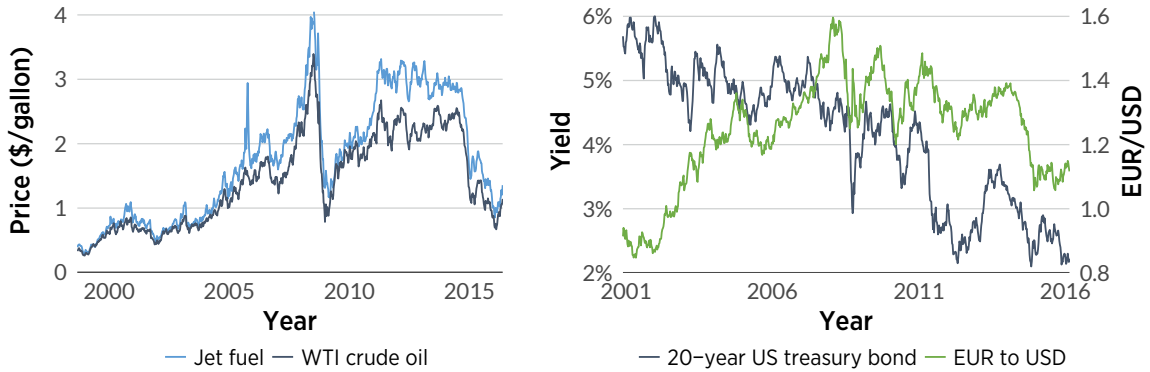
(a) Oil and jet fuel price variations [25, 26]   (b) U.S. bonds and EUR/USD rate variations [27, 28]

Figure 1.3: Volatility of factors affecting aerospace programs

jor programs. The main sources of uncertainty and risk affecting the proper execution of projects are:

- **Jet fuel price:** In order to transport their cargo from their origin to their destination, airplanes need to burn large amounts of jet fuel. With the price of crude oil progressively rising (Figure 1.3a), jet fuel became the airlines' main expense. Therefore, any variation in jet fuel prices has a significant impact on the profitability of an airplane. While there have been several oil price peaks in the past, sudden drops in prices can happen as well; e.g., in late 2014, amid concerns over abnormally high oil inventories and the refusal of OPEC to reduce and balance production, the market price of crude oil plummeted [29].

- **Exchange rates:** Whether they have operations outside their home countries or not, aerospace companies might naturally get exposed to exchange rate risk. Companies such as Airbus, Bombardier, Safran, or Rolls-Royce have revenues in USD while having costs in their home currencies (EUR, CAD or GBP). As exchange rates between these currencies naturally vary (Figure 1.3b), these firms face additional net income volatility.

- **Interest rates:** Interest rates are the rates at which a company or government has to pay when it is issuing debt. Interest rates significantly affect companies as it de-

7

fines their funding capabilities, their profitability, and the rate of return they require from their projects. Interest rates are volatile (Figure 1.3b), are affected by the global economy, and affect the economy in return. US treasury bond rates increased substantially in the 70s, with a peak around 1980. They have since been progressively decreasing, along with a slowing economy.

- **Regulations:** Regulations can substantially affect the outcome of a project, as they act as hard constraints. Many types of regulations can change the design strategy of manufacturers: emissions, noise, safety, etc. In the example of the Concorde, the aircraft was denied supersonic over-fly of numerous countries, including the United States [30], which considerably reduced the number of routes it could fly and the market it could target. To address some of these issues, Frank et al., for example, studies the problem of designing under evolving requirements [31].

- **Delays in development:** Delays in development have particularly affected the aircraft manufacturers. Programs such as the Airbus A380 [32], the Boeing 787 [33], and the Airbus A400M [34] have come to production with several years delay compared to the original schedule, and large cost overruns. Delays in production have other side-effects, such as demand losses, orders cancellations, contractual penalties, degraded reputation, and delayed cash flows. Delays in development are also widespread for suborbital vehicle companies. In section 1.1.1, the example of the XCOR Lynx was given. In this case, the repeated delays in the program led to its failure. More companies are also concerned with such issues. Even the big players Virgin Galactic [35, 36] and Blue Origin [37] were not spared, and delayed their first commercial space flights by several years.

- **Demand:** In most of the previously cited examples, demand was less than initially hoped for, which was a major contributor to the failure of these projects. Given the substantial investment consented by manufacturers, a large enough demand must

8

be captured to ensure profitability, through the amortization of fixed costs. Many factors can lead to demand variability: a shift in public opinion, lower-than-expected performance, slowing economy, or any of the above sources of uncertainty.

- **Safety / Flight risk:** Flight safety is a great concern in aerospace. Incidents can have a great impact on companies suffering them. The crash of the Concorde in 2000 was decisive in the early retirement of the aircraft. Suborbital companies suffer even more from such events, as their relatively smaller financial power does not necessarily allow them to withstand their consequences. The crash of Armadillo Aerospace's STIG-B rocket was a major setback for the company, which ultimately led to their hibernation and takeover by another space company [38]. The crash of Virgin Galactic's SpaceShipTwo [39] induced major delays in the development process [36], although they were able to recover. Overall, safety should be estimated and be a primary design consideration.

- **Financial distress, mergers, and bankruptcies:** After an unsuccessful or a series of unsuccessful projects, a company may become afflicted with unbearable debt and other liabilities. If the organization decides that it is suffocated by an excessive financial pressure, it can consider discontinuing its operations by different means. First, a company can file for bankruptcy. It can then be liquidated or taken over. In the United States, Chapter 11 of the bankruptcy code enables a company under its protection to continue its operations while it is being reorganized. In the aerospace sector, although airlines, mostly, have been subject to bankruptcy (successive bankruptcies and mergers for legacy carriers, amid intensifying competition and market consolidation), manufacturers can be impacted as well, as their orders may not be fulfilled. The second available way out is to be acquired or merge with another company that will pay its debt off, restructure it, and restore its financial health. The merger be-

tween McDonnell Douglas and Boeing, when Boeing took over McDonnell Douglas' operations, is an example [40].

The exposure to those numerous sources of uncertainties has consequences. Some of them were already mentioned, such as the reduced value of the proposed product, the incurred cost overruns, or even bankruptcy. Some other consequences are also worth noting:

- Because of the volatility of the EUR/USD rate, European companies such as Safran and Airbus have to hold hedge books. Safran held in 2015 a $20.8 billion hedge book in 2015 [41], and Airbus a $93.1 billion one [42]. Airbus' hedging policy is displayed in Figure 1.4a.

- During its 2015 yearly earnings report, Boeing provided weak financial guidance for 2016, as it predicted a decrease in deliveries compared to 2015 [43]. The stock price plummeted, and the market capitalization of the company dropped by 9%; more than $8 billion of destroyed value. The fall could arguably be due, in part, to the recently weak value of the euro, which gives a competitive advantage to the Airbus Group.

- Volatility of jet fuel prices can have both positive and negative outcomes for the airlines. With the sudden drop in oil prices, U.S. airlines are making record profits [44] (Figure 1.4b). While the fuel costs had become the largest expense for airlines in the late 2000s and were a great financial burden on their income statement, the recent plummet significantly alleviated their operating costs and helped them reach unprecedented net incomes. To reduce their exposure to oil price variations, airlines can also hedge their jet fuel purchases. However, this a double-edged sword and the companies that profited the most from the decrease were those which did not hedge, such as American Airlines.

As a conclusion of this subsection, it can be observed that **a broad range of uncertainty sources makes the business environment for aerospace programs particularly**

(a) Airbus' 2015 hedging policy [42]   (b) U.S. airlines fuel costs and net incomes [45, 46]
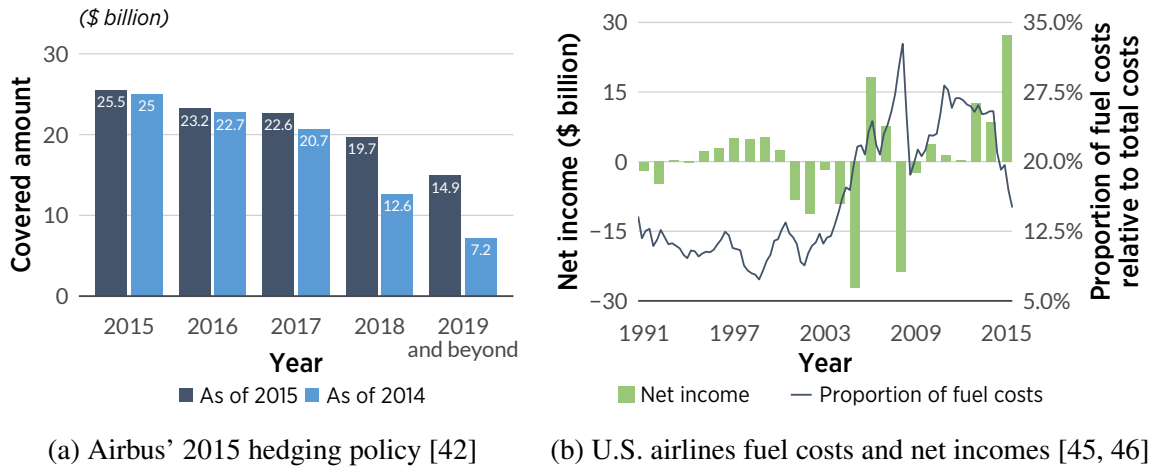
Figure 1.4: Financial consequences of the economic uncertainty

unpredictable. In order to make sound decisions in this context, these sources of uncertainty must be identified, assessed, and managed.

1.1.3   Great opportunities

The previous preceding subsections emphasized the prominence of risk in aerospace programs. While one may think that such risk could scare investors away, aerospace companies keep developing expensive new models regardless. This stems from the high-risk high-reward aspect of those. If a program is successful, it will be worth the risk that was taken. This subsection shows the rich opportunity environment for two aerospace markets of interest: commercial aviation and suborbital tourism.

The commercial aviation market

Commercial aviation is now a very financially attractive sector for the manufacturers. It shows strong growth and very positive outlooks for the next two decades. According to Boeing, the global fleet will double in the next 20 years [47] (Figure 1.5b). This will lead to the production of more than 38,000 new airplanes. As the main actors of this market, Airbus and Boeing will share most of the $5 trillion revenue generated by the demand for new aircraft [48]. Although the competition between the two companies is harsh, the lack

11

(a) Commercial aviation stock prices [49–52] (b) Forecast demand for aircraft [47, 53, 54]
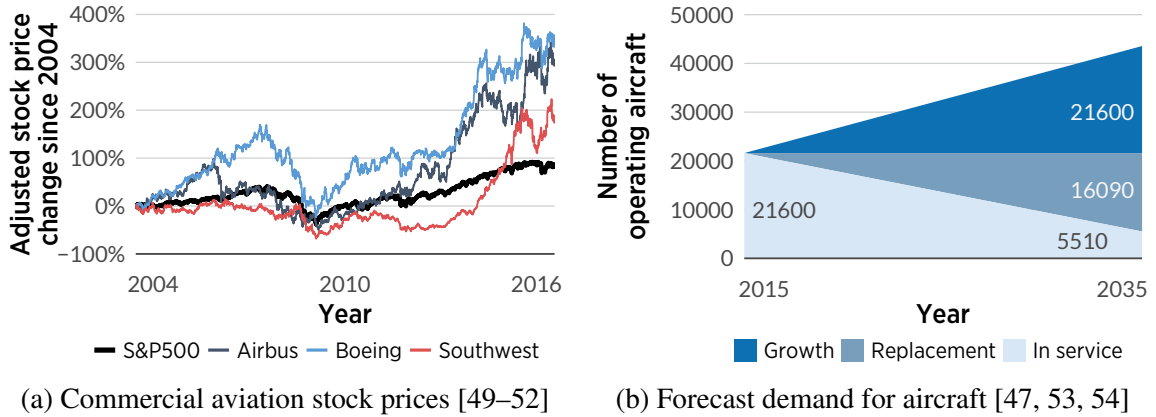
Figure 1.5: Commercial aviation market

of variety in the competition still enables them to capture high profit margins and generate large amounts of cash flow for their respective companies. In the meanwhile, airlines have much more trouble making significant profits.

In spite of the climate of uncertainty, enduring the unpredictable environment has resulted in great profits for manufacturers. Airbus and Boeing have consistently outperformed the US equity market's flagship index: the Standard & Poor's 500 (S&P 500, Figure 1.5a). Even Southwest Airlines, one of the most prolific airlines in America, is beaten by the two aircraft makers. Despite delays in recent civil aviation programs, the two companies are in excellent financial health, have earnings that regularly exceed analysts' expectations, and display stock prices nearing their all-time highs. This could be credited to the history and culture of the aircraft makers of making bold technological and strategic decisions. In order to make the best out of their strong positions, aircraft makers carefully evaluate their opportunities, in order to refrain from taking unnecessary risks and to avoid missing the best opportunities. Such decisions have to be supported by an environment that weighs the value of opportunity against the cost and burden of risk and uncertainty.

The suborbital tourism market

The field of suborbital tourism, due to its novelty and complexity, entails significant risks as well, in terms of costs, profitability, and safety. While this high riskiness represents too
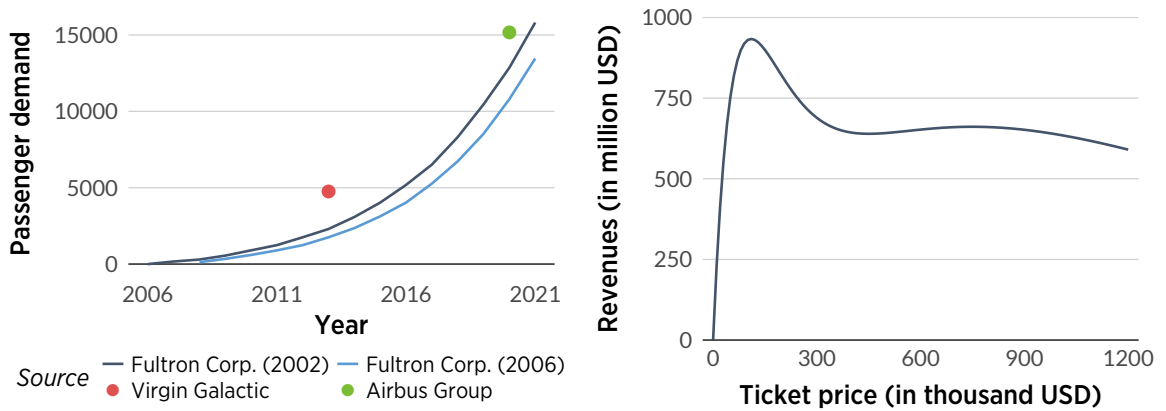
(a) Forecast annual demand for suborbital flights [55–57]

(b) Potential annual revenue per ticket price [58]

Figure 1.6: Commercial aviation market

great barriers to entry for most investors, the space tourism market remains attractive due to the high revenue potential of this sector (Figure 1.6b). Moreover, strong growth is forecast by numerous organizations (Figure 1.6a), which can enable a blue-ocean strategy from space companies. Indeed, the first-to-market would naturally acquire a strong competitive advantage over those who did not move as early. With such a strategy, Burgaud et al. [59] prove that by choosing the appropriate architecture and business parameters, manufacturing and operating a suborbital vehicle can be profitable. Finally, it is important to note that any company that would gain knowledge in the suborbital field would be able later to leverage their core competencies and consider new markets, such as super/hypersonic travel, or satellite launch. As a conclusion, the presence of large uncertainty, combined with great reward potential, makes the suborbital tourism market a high-risk-high-return opportunity for involved companies.

1.1.4 Assertion 1

In this section, it was demonstrated with a particular focus on commercial aviation and suborbital tourism that aerospace programs had a high-risk, high-return aspect, which made them attractive for participants. Yet, the severity of such a failure requires every effort to better the odds of a favorable outcome. Moreover, aerospace companies face uncertainties

that can only be addressed using business-related metrics and analyses, and not simply design variables. Finally, as many cases of failure are related to finance, there should be particular and meticulous attention to the financial side of the programs. These observations lead to the formulation of the following assertion:

> **ASSERTION 1:** *Because large aerospace programs are extremely risky and characterized by various sources of uncertainty, decision makers need to be supported by a business-driven stochastic framework in order to ensure success, with particular attention to financial aspects.*

1.2 Supporting strategic decision makers

The previous section, section 1.1, establishes the assertion that decision makers need to be supported by a business-driven framework to face the highly uncertain environment they are dealing with. This section aims at defining how these strategic decision makers should be supported in order to maximize their chances of success.

1.2.1 Developing a strategy

The importance of a sound strategy

Strategy has a significant impact on the profits of a company. According to Porter [60, 61] strategic positioning enables a company to differentiate from the others and ensures a sustainable competitive advantage. It differs from operational effectiveness, which is simply performing similar activities as rivals, at a lower cost. Instead, a strategy is the creation of a "unique and valuable position". It also requires trade-offs: one cannot outperform rivals for every product, on every aspect. It should focus on creating a "fit" between the company's activities.

The importance of strategy in the company's profits is validated by the literature as well. A company's profitability is mainly determined by two factors: firm effects and industry effects. Industry effects are attributed to the economic structure of the industry in which the
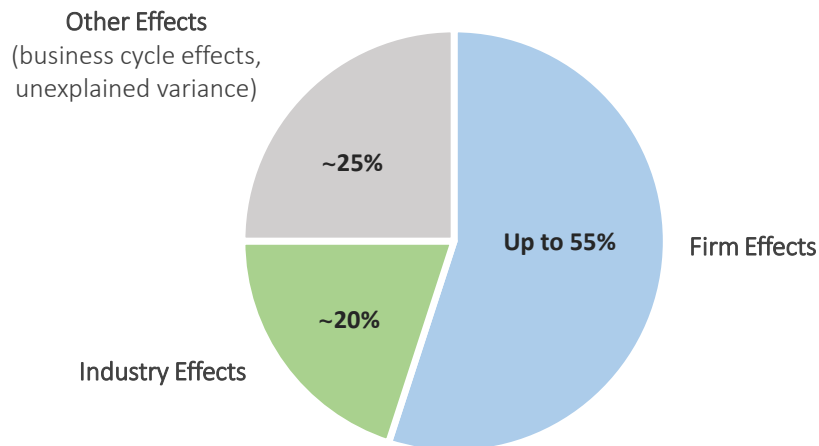
Figure 1.7: Breakdown of industry, firm, and other effects in firm performance [65]

company competes, whereas the firm effects stem from the actions that deciding managers take. Several studies have demonstrated, empirically, that firm effects result in a much greater impact on performance than industry effects [62–64]. Overall, it was estimated that up to 55% of a company's profits were attributed to firm effects, while only 20% came from industry effects, the remaining 25% coming from other effects (Figure 1.7). Therefore, it is crucial for strategic executives to follow a thorough analytic process when developing their strategy.

Steps in strategy development

In order to develop the best possible strategy, Rothaermel [65] developed a holistic framework, the strategy AFI framework (for Analysis Formulation Implementation), that guides strategic executives from initial thoughts to implementation (Figure 1.8). It follows a five steps process:

- **Introduction:** As part of the introductory phase, a manager should start by understanding what strategy exactly is, what it is not, and why it is important for his or her company. He or she should also determine who are the stake holders and what their

Figure 1.8: The AFI Strategy Framework [65]

interests are. Similarly, the firm's vision, mission, and values should be defined. The introduction phase is, somehow, also part of the analysis process.

- **Analysis:** The analysis part encompasses all the examination, search and studies that are required to understand the company and its environment better. It usually includes an internal and an external analysis, that jointly help determine the strength of a company, the competitive environment and the overall external context. It is further detailed in subsection 1.2.1.

- **Business strategy formulation:** This step of the methodology defines how the firm should position itself and compete. For example, should it be through a product differentiation or a cost leadership? What level of innovation should the firm adopt? Overall, it defines the strategy to follow within the industry and businesses the firm is already in.

16

- **Corporate strategy formulation:** In this step of the strategy AFI framework, the objective is to determine where the firm should compete, in terms of markets, industry, or country. It defines if the company should operate as a single business entity, or if it should develop and grow through a related diversification strategy, for example.

- **Strategy implementation:** This final step aims at defining how the company should organize itself in order to apply the formulated strategy. It could, for example, establish the type of governance it wants to adopt in order to ensure proper execution of the said strategy.

All the previous steps are essential in order to achieve superior and sustainable performance. Yet, design mostly concerns the analysis step. In order to build on the existing design process, and complement it with a more business-oriented framework, the analysis step should be focused on. Moreover, as the step just preceding the strategy formulation stage, the strategy analysis is its enabler, and needs, again, particular emphasis. Therefore, **to facilitate their strategy formulation, decision makers need to be supported in their strategic analysis step by using business-oriented parameters and information.**

The strategy analysis step

In order to formulate a proper strategy, decision makers have to perform various analyses that provide a better insight of the competitive environment and the company itself. Rothaermel [65], as well as other authors, detail the external and internal analyses necessary to the strategic analysis process. These analyses should also be included, to some extent, in the decision-making process along with the aircraft performance. The three steps of strategy analysis consist of:

- **Vision, mission and values definition:** The first step of the strategy consists in defining the vision (what does the company want to accomplish), the mission (how to accomplish it) and the values (what are the ethical limits to respect) of the company.

17

Figure 1.9: PESTEL analysis framework [65]

For design problems, this step results in the definition of the company's priorities regarding performance and profitability, as well as other identified criteria.

- **External analysis:** the external analysis consists in examining the critical external factors that impact the company's results. This includes a study of the industry, as well as the global environment. Several approaches exist in order to produce a proper external analysis. A first way to proceed is to conduct a PESTEL analysis (an analysis of Political, Economic, Sociocultural, Technological, Ecological, and Legal factors, see Figure 1.9) [65].

    - **Political factors:** Political factors regroup the effect of the different activities and decisions of the government, which can compel companies to make certain choices.

    - **Economic factors:** Economic factors regroup all the macroeconomic factors that somehow affect the worldwide or local economy. For example, GDP growth rates, treasury bond rates, unemployment rates or foreign exchange rates are economic factors.

    - **Sociocultural factors:** Sociocultural factors consist of the set of social norms, values, and ideas that are commonly accepted within the local or global com-

munity. In the example of the Concorde, it was established that the social norm had shifted and that people were more concerned with the noise pollution of supersonic flight than it was excited about traveling at unprecedented speeds.

– **Technological factors:** Technological factors account for the emergence and availability of new technologies in the marketplace, which should be considered either as a threat from other competitors and substitutes or as an opportunity to differentiate by integrating it into the company's products.

– **Ecological factors:** Ecological factors are related to the evolution of the global ecological environment health, and the consequences of businesses and industries on it. Accounting for these factors enables a sustainable economic growth, more respectful of nature and communities.

– **Legal factors:** Legal factors regroup the evolving regulatory environment, which constrains companies on their way to dealing business. For example, the Committee on Aviation Environmental Protection (CAEP), part of the International Civil Aviation Organization (ICAO) issues standards, such as the CAEP/8, in order to reduce the Nitrogen Oxide (NOx) emissions in the future [66].

A different type of analysis, more competition-centric, is Porter's Five Forces framework [67, 68] (Figure 1.10). It enables the evaluation of the competitive landscape within a given industry, along with its profit potential, and helps understand where the competitive advantage and bargaining power lie in. It is comprised of the following 5 forces:

– **Rivalry among existing competitors:** The rivalry of existing competitors measure the competition intensity between the various industry contestants. The intensity of competition within the industry depends on the industry structure itself (how many competitors, what size, etc.), on the growth potential within
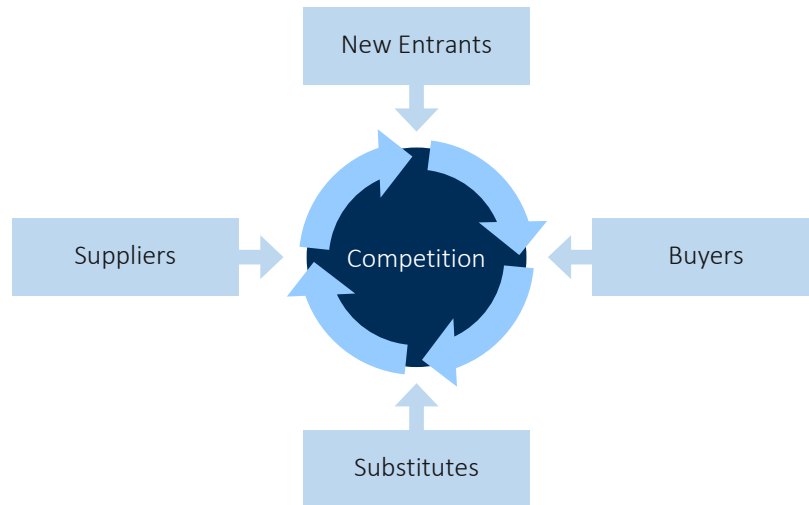
Figure 1.10: Porter's Five Forces [67]

this industry, and on the strategies of the different competitors. For aircraft manufacturing, the industry is qualified as a duopoly, and although some product segments are ferociously fought for (e.g. 737 vs. A320), Airbus and Boeing try to differentiate their product offerings.

– **Bargaining power of buyers:** The bargaining power of the market the industry is targeting. In the case of airplane makers, they are the airlines. The low number of manufacturers, combined with the large number of potential airlines, gives the airlines a relatively low bargaining power, despite their ability to get significant discounts when buying large lots of airplanes.

– **Bargaining power of suppliers:** The bargaining power of the companies preceding the firm in the supply chain. For aircraft manufacturers, again, suppliers have little bargaining power. Indeed, they are not a very concentrated industry, and they depend heavily on Airbus and Boeing in their income statement. One exception to these weak suppliers are the engine manufacturers, which compensate the strength of Airbus and Boeing by a somewhat consolidated industry.

– **Threat of new entrants:** The threat of new entrants describes the likelihood and consequences of the entrance of a potential new competitor in the compet-
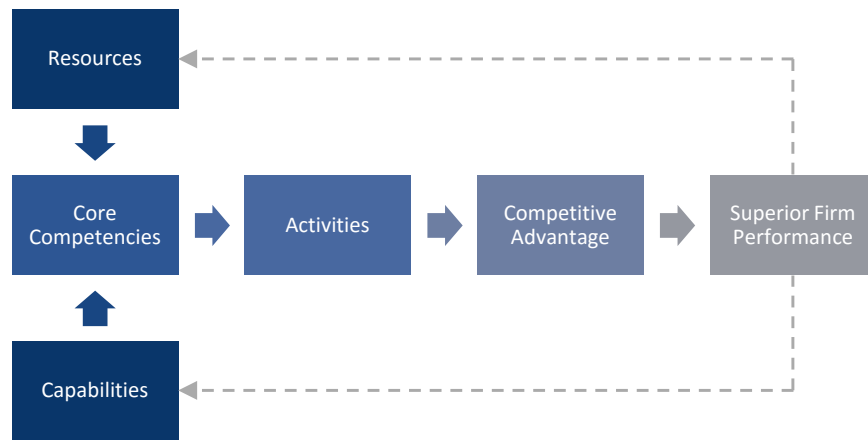
Figure 1.11: How resources, capabilities and core competencies lead to superior firm performance [65]

itive field. For Airbus and Boeing, this risk is represented by the attempts, although not very successful yet, of other manufacturers such as Bombardier [69] or COMAC [70] to enter the prolific short-to-medium haul single-aisle jet business, and propose an alternative to the current A320 and 737 planes.

– **Threat of substitutes:** The threat of substitutes stems from alternative products and services. For commercial aviation, typical substitutes are the train in Europe or Asia [71, 72], and car or bus companies such as Megabus or Greyhound in the United States [73]. These substitutes provide differentiated offerings, by being either more affordable, faster, or more convenient (city center to city center service for example)

- **Internal analysis:** The internal analysis consists in studying the company itself (its resources, capabilities, core competencies and activities). It should consider the essential functions of the value chain of the company or considered program. Figure 1.11 shows how resources, capabilities and core competencies relate.

    – **Resources:** Resources are all the assets, tangible or intangible, that a company can use for its strategy and operations. It can be building, human resources, intellectual property, etc.

21
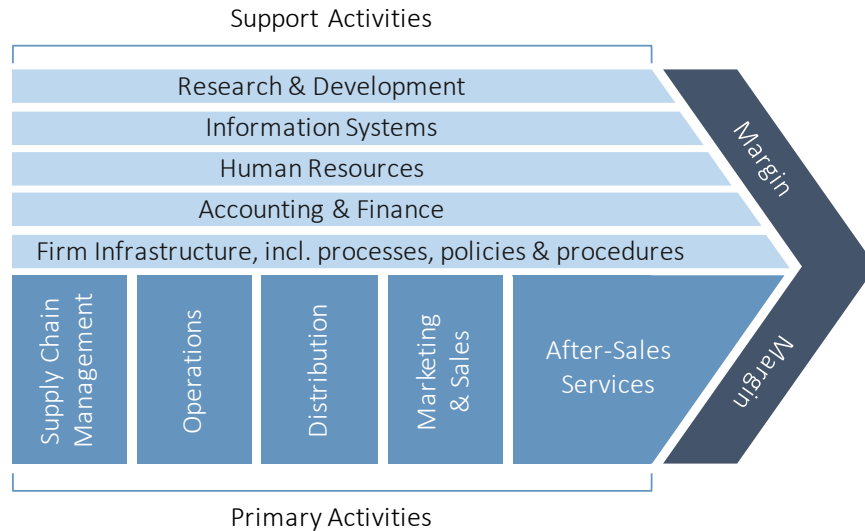
Figure 1.12: Porter's generic value chain [65, 74]

- **Capabilities:** Capabilities are the set of technical and managerial skills a company has available in order to be applied to the execution of the strategy and operations. For aerospace programs, learning about the capabilities of the company could be learning about its design capabilities: what kind of performance, at what price, can be attained?

- **Core competencies:** Core competencies are some of the company's unique strength, that are profoundly intrinsic to the company, and enables it to differentiate its products from others. Core competencies are formed by the combination of capabilities and resources a firm has.

Another important framework for the internal analysis is Porter's Value Chain [74, 75]. It represents the set of activities that are performed by the company in order to create value, and therefore margins. Porter's Value Chain groups the different activities of the value chain in two categories: primary activities, which directly transform the product and infuse added value, and support activities, such as R&D, which add value indirectly to the product. For aerospace programs, when linking this problem to design aspects, some important parts of the value chain, for example,

are the design division, but also the sales division, the production division, and the finance division. These disciplines, in particular, should be studied to contribute to the internal analysis.

While other kinds of analysis frameworks exist (Mintzberg's 5Ps of strategy [76], 4Ps, 5Cs [77]), they are all merely differing in terms of approach structure, but integrate internal and external analyses to some extent. For a research oriented purpose, it would be hard to incorporate every aspect of internal and external analyses. However, the main ones should be accounted for, while the others should be kept in mind. Having a comprehensive approach is important, as it might make the difference between a successful project and one that could have been, had some important shifts or trend in the environment not been disregarded. Overall, it must be retained that **strategic decisions must be supported using elements from internal and external analysis,** such as market studies, financial forecasts, and various other supporting business metrics and visualizations.

1.2.2   The information executives need

In order to support decision makers in proceeding to these analyses, some specific categories of information have to be provided. The first step to help strategic executives is to provide them with the information they need. In its article in Strategy & Leadership [78], Mark McNeilly states:

> *"There are three basic steps to strategic decision making: getting the right information, making a good decision, and implementing that decision. Failure in any of these steps could result in 'the company car' going off the road."*

Often, studies focus on the decision-making itself. Only considering that step would result in an overly simplified problem. It is, therefore, important to begin by determining the required information that will help strategic decision makers. Various approaches are available in the literature about information and decision-making. Calvasina et al. [79]
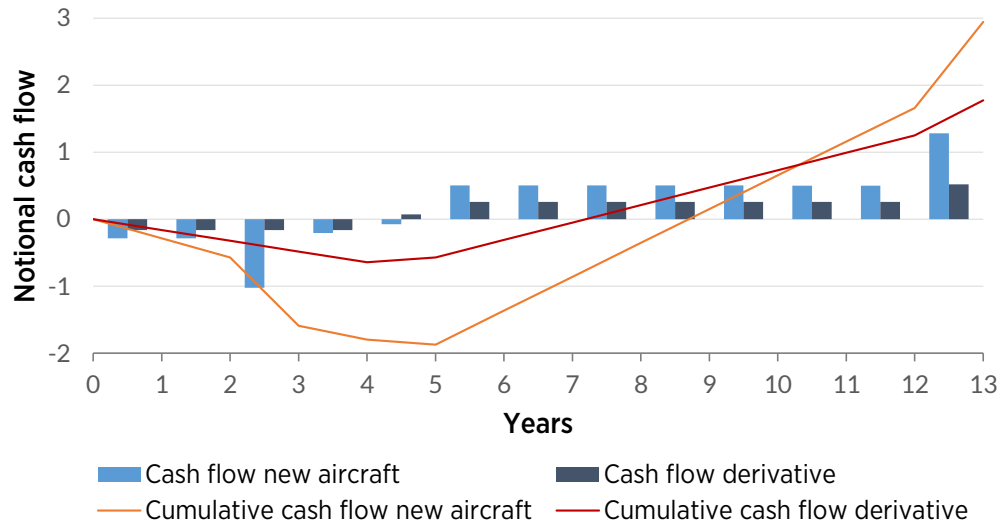
Figure 1.13: Example of cash flow forecasts for two types of projects [81]

talks about information for decision-making in a production environment, and mostly focuses on Enterprise Resource Planning (ERP) systems, and the type of information they should carry. Frishammar [80] carries out a more general study, and observes, for four different test companies, and for different executive positions, what level of information they use (soft or hard), and what way it was obtained (solicited, unsolicited, directed, undirected, etc.). He also observes the prevalence of different information sources in the decision process of the companies of interest (internal vs. external, technical publications vs. newspapers, etc.). More interestingly, McNeilly [78] describes what type of information is necessary. He isolates three main categories of information, or knowledge: competition-related, company-related, and market-related. This goes back to the necessary internal (company-related knowledge) and external (competition-related and market-related knowledge) analyses, which are required for a proper strategy development.

Drucker [82] further details the critical types of information for executives, in what is considered as a management must-read.

- **Foundation information:** Also called the "fundamentals". This is somehow the routine analysis of the company, with most of the fundamental information. Most often,

it includes cash flows and liquidity projections. Fig 1.13 shows an example of data visualization for typical aircraft development projects. It shows notional projected cash flows for a derivative and a new project, according to Schrage [81].

- **Productivity/profitability information:** initially focusing on the productivity of key resources, it is now more popular to talk about *total-factor productivity*. An Economic Value Added (EVA) analysis is one of the ways to proceed. In other terms, it is important to determine if a business has higher returns than its cost of capital. Benchmarking can also be valuable information to provide executives with.

- **Competence information:** it is important to measure the company's core competencies. Most importantly, especially for design, every business or organization needs one core competence: innovation. For a company such as an aircraft manufacturer, innovation could be measured by the number of technologies developed.

- **Resource allocation information:** in general, the most important resources to allocate are capital and people. Capital-wise, the objective is to find the investments that show the best ratio between opportunity and risk.

1.2.3   A diversified set of potential strategies

In order to assist top executives in their strategy development, the program formulation methodology should include elements participating to the external and internal components of a strategy analysis, such as market studies, financial forecasts, as well as metrics related to potential strategies to be followed. A broad range of strategies exist, some common ones being:

- **Maximizing profits:** This is the strategy classically assumed for aircraft design research. In that case, the manufacturer seeks maximum profits, represented by the widely spread metric that is the Net Present Value (NPV).

- **Reducing costs / increasing margins:** While a manufacturer may want to make significant profits, it may not want to have razor-thin margins to do so (which can make the company vulnerable to uncertainty). Therefore, the company may want to have large enough margin. As an example, this differentiates Walmart (with very thin margins) and tech or pharmaceutical companies, which take substantial margins on their sales.

- **Growth strategy**: Before looking for short-term profits and margins, a company may want to grow, increase its market share, and push the question of profitability back. For example, a company such as Amazon has been growing in terms of revenues at a staggering 20.5% rate in the past four years, with a simple 0.15% net profit margin, on average [83]. They only became profitable in late 2015. Airbus is another example. The company has been known to practice aggressive pricing to capture as much market share as possible. A former Airbus executive admitted to "pricing for market share" in order to grow their presence on the market [84]. The evolution of Airbus' and Boeing's market shares as well as their average consented discounts can be observed in Figure 1.14.

- **Blue ocean strategy:** This strategy consists in disrupting the market through significant improvements in both value and costs, or even creating entirely new markets [85]. Either way, this strategy, if successful, creates new norms, and provides the innovative company with large amounts of market share. For aerospace programs, suborbital tourism would constitute such a strategy. The main disadvantage of blue ocean strategy is the subsequent high rate of failure. Many companies would like to revolutionize the markets and the world, but could end up falling in the red ocean of harsh competition [86].

- **Triple bottom line strategy:** This strategy incorporates the notions of sustainability, corporate social responsibility, and business ethics in the company's objectives. In

26

simpler words, it does recommend to seek profits, but not at the expense of the people and the planet. It is an economic, ecologic and social strategy [87]. Developing cleaner planes, less noisy, and paying employees well would contribute towards such a strategy.

- **High-performance strategy:** Some companies might want to maintain a public perception of always providing a high-end product. In that case, performance would be an overweighed objective and strategy. For commercial aviation, performance could mean cost per available seat mile from an airline's point of view, or aircraft speed/trip time for passengers, for example. For suborbital vehicles, objectives linked to such a strategy could be the time in weightlessness, maximum flight altitude, or space available for passengers.

- **Innovation strategy:** Although this strategy overlaps with the previous one, its objectives differ slightly. A company may want to allocate a lot of money to its research and development. One of the reasons could be that it can bring additional value to other products of its family. For example, after the new technologies developed for the 787, Boeing reused some of them for its 737 MAX, and its future 777X. Another reason for putting particular focus on the R&D is if the company is a government agency, such as NASA, which is trying to create new, unconventional concepts that could bring disruptive innovation later on.

- **Risk-averse strategy:** Finally, a company should decide if it is risk-averse, risk-seeking or risk-neutral. Depending on its position on this aspect, it will favor some projects over the others.

Given the variety of possible strategies, **it is important to develop a large multi-objective environment in order to account for the multiple available strategies**. Other metrics can be included as well, in order to support decision makers when they are facing difficult choices.
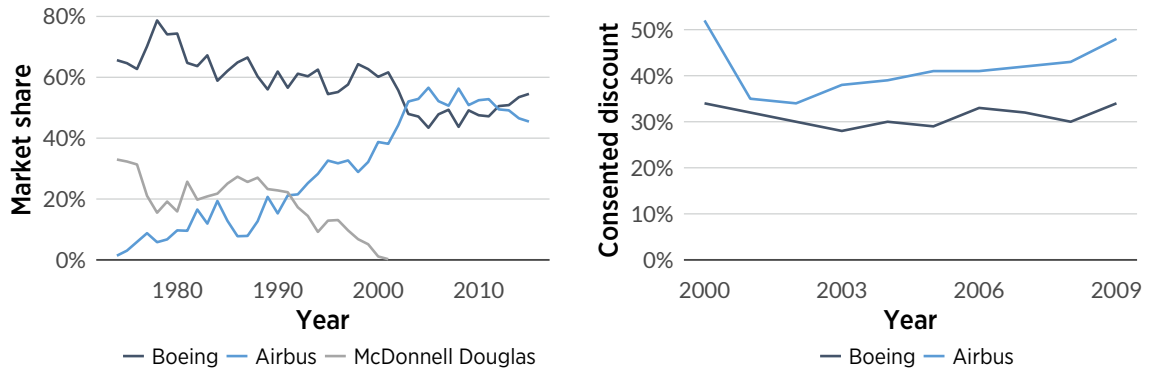
(a) Aircraft manufacturers market shares [88, 89]   (b) Average discounts applied by aircraft manu-
facturers [90]

Figure 1.14: Commercial aviation market

1.2.4   Assertion 2

Overall, this section aimed at demonstrating three ideas: 1) the importance of strategy in the company's performance, and therefore the need to support decision maker in their strategy development process, 2) the need to support the strategic analysis process, through analyses that can contribute to external and internal analyses, 3) the type of information executives need is business-oriented, and goes beyond the simple framework of design, 4) there are multiple potential strategies, and therefore, potential objectives. These observations, put together, lead to the following assertion:

> ***ASSERTION 2:*** *Key decision makers must be assisted in their strategy formulation by a large multi-objective environment supported by additional business metrics and analyses.*

1.3   A need to adopt an enterprise-wide approach during early design phases

1.3.1   Multiple divisions are involved in a program development

The difficulty of making good decisions does not only stem from the aleatory aspect of the performance of a vehicle or the health of the market. The multiplicity of business divisions involved in the full life-cycle of a vehicle program complicates the task of top managers.

28

In order to build the vehicle development program, a manufacturer does not only need its R&D division, but also its marketing and sales department and its financial group. These divisions determine the program budgeting and perform some financial analyses and optimizations. Then, strategic executives make final decisions for the project. Figure 1.15 illustrates a common company structure. As designs and corporate structures become more and more complex, high executives need further assistance in the management of the different divisions.

Moreover, the related business units should not only be accounted for and managed, they should also pursue a common objective. Indeed, for best effectiveness, decision makers need to align business divisions' goals with their company-level objectives, as interdependencies between these disciplines can be exploited. Obstacles arise as each division has its own concurrent objectives, and therefore, cross-functional trade-offs have to be made. This is a problem commonly known as the *principal-agent problem* [91, 92]. The principal-agent problem is a concept in political science and economy where a principal hires an agent to work and perform on his behalf. However, the agent will act in his self-interest, which is influenced by the different incentives the principal can provide, and the constraints he can put on him. Yet, the incentives have to be tailored well to the objectives of the principal. Otherwise, the agent's decisions will deviate from the hoped for optimum. This deviation is called the agency cost.

An analogy can be made in the field of design: Cayley's design paradigm [94, 95]. Sir George Cayley (1773-1857) was one of the pioneers of aerospace engineering. His approach was to proceed to a functional decomposition of the airplane into components dedicated to a particular purpose. Then, each component was to be optimized according to the role it had in the aircraft. While this approach helps structure the design problem, it inhibits the full potential of the studied concept. Indeed, the sum of individually optimal components does not result in an optimal assembled system.
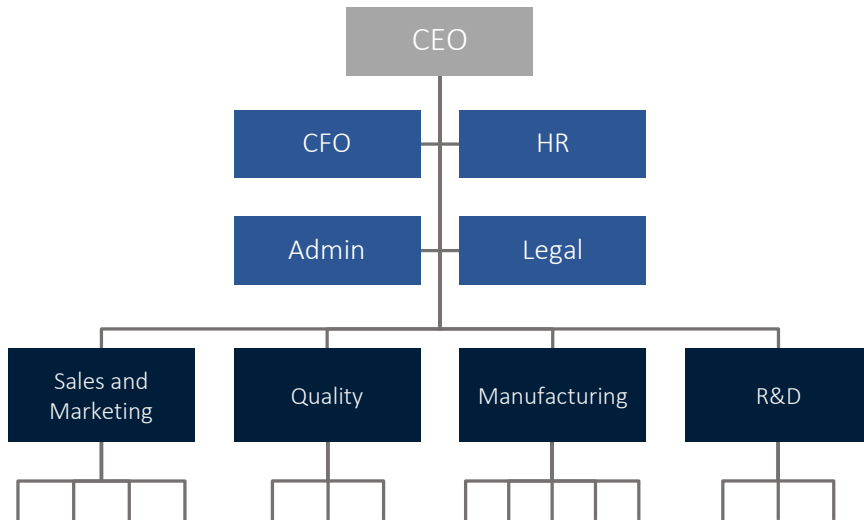
Figure 1.15: A common single business company structure [93]

The situation for a full aerospace program is similar. If only design were to be optimized, it would result in a sub-optimal concept, as other disciplines also have a significant impact on the overall performance of the company. **Design is only one part of the value chain, and other parts should also be optimized, with respect to a program-level objective, instead of their usual local objectives.** As a summary, this subsection demonstrates that **it is necessary to adopt an enterprise-wide collaboration approach to avoid suboptimal programs.**

1.3.2 Pursuing the paradigm shift

A lot of the drawbacks of aerospace problems are associated with the amount of investment to commit, and to their "moonshot" project nature; a multi-billion dollar gamble, where a manufacturer places its whole bank account on the table, along with its future, makes an aircraft, and waits to see a positive or negative outcome. A significant part of the issue is due to the "design-for-performance" character of previous programs. More recently, cost has become one of the main factors of decision in projects, because of the increasing awareness. Authors, such as Mavris et al. [96, 97], have defended a *design-for-affordability* approach, which places more emphasis on economic considerations, instead of simply ver-
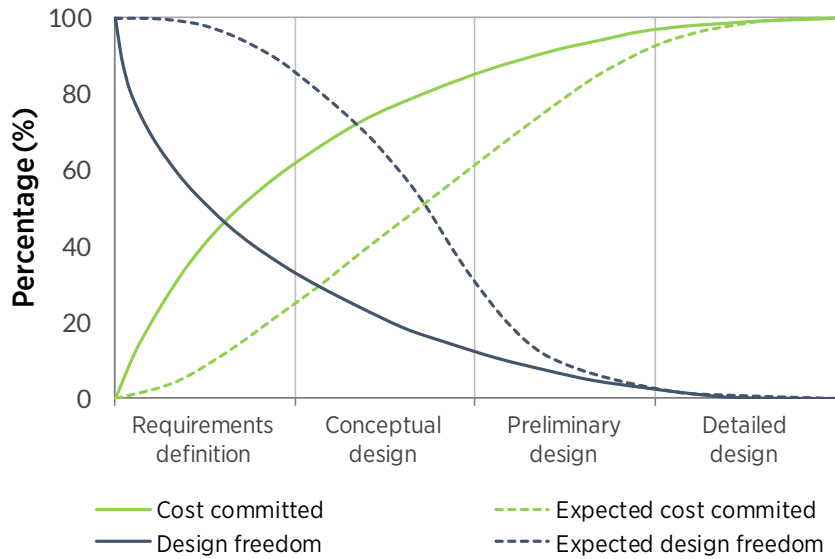
Figure 1.16: Expected impact of the paradigm shift [96]

ifying mission capability requirements. In order to enable design-for-affordability, they first study key characteristics of knowledge acquisition, cost commitment and design freedom for a design-for-performance project. They realize that a lot of the design features get chosen upon and locked in at early phases of design, which result in the commitment of most of the project budget, and a substantially reduced design flexibility. Any variation in environment would not allow any notable modification in design to compensate, unless a significant amount of capital is added to the project, resulting in large cost overruns.

Instead, design-for-affordability should delay any design freeze to later phases of design, while acquiring knowledge at early stages, as illustrated in Figure 1.16. This improvement is only enabled through a profound paradigm shift of the design process. Hence, it should deviate from a deterministic, performance-based process, to a parametric, high-fidelity, physics-based, cost-oriented, stochastic process. The parametric environment will help acquire more information at the beginning of the design project while preserving design freedom, which delays any budget commitment.

Based on these considerations, it can be established that such a method should be taken inspiration from. Yet, although it provides a shift towards a less performance-oriented design, this approach remains design-centric.

1.3.3 Assertion 3

In the light of the previous sections, it can be stated that other disciplines such as sales or finance should also be accounted for, and their interdependencies considered. Nonetheless, this paradigm shift can be extended to the aforementioned proposed process. Indeed, **it is necessary to acquire information and knowledge during conceptual design in order to delay cost commitment and preserve design freedom.** Since an enterprise-level approach is a complex task, it is also important to perform it during early phases of design, as it might become even more intricate later on. Hence, the following assertion can be formulated:

> *ASSERTION 3: Business disciplines need to be modeled in an enterprise-level environment during conceptual design in order to ensure collaboration between the company's businesses and to avoid sub-optimal solutions.*

1.4 A case study: suborbital vehicles

While the methodology detailed in this dissertation aims to be applicable to complex aerospace programs in general, it is applied to suborbital vehicles as a case study. This section discusses some additional aspects of interest carried by the suborbital vehicles industry which further motivate this research. Two main traits of this domain are treated: 1) the consequences of the novelty of the suborbital tourism industry are described (subsection 1.4.1); 2) how the limited size of companies dealing with suborbital tourism facilitates a company-wide planning (subsection 1.4.2).

(a) Mercury-Redstone rocket   (b) North American F-15 space plane

Figure 1.17: First manned suborbital vehicles

1.4.1 A short market history

Although research on manned suborbital flights is not new, with manned flights as early as the 1960s, with the successes of the Mercury rocket and F-15 plane (Figure 1.17), suborbital space travel for entertainment and tourism has only seen significant interest in the recent decades and remains quite novel. The first non-governmental suborbital flight happened in 2004 when pilot Mike Melvill of Scaled Composites reached first the 100-kilometer threshold separating the Earth's atmosphere and space in his SpaceShipOne space plane. Yet, at this time, no suborbital space flight with commercial passengers has ever been performed, as involved companies consistently delay their maiden public flight.

The novelty of this field is not without consequences. The main one is the absence of historical data, which makes it very complicated for manufacturers to develop new spacecraft. One of the readily observable symptoms is the complete lack of a standard architecture manufacturers bet on. As such, four major architectures can be isolated: regular rockets, space planes with conventional or vertical take-off and landing, space planes with jets, and space planes launched from a carrier aircraft.

As a result of the scarcity in historical data, design teams cannot simply build on previous projects or use any past experience. Instead, they have to start from scratch and develop a whole new vehicle. **It is, therefore, necessary to implement detailed simulations and**

analyses, which will be able to forecast the costs and performance of systems that have never been designed before. It is also required to establish careful planning of the different steps of the program.

The recent interest in this market also results in uncertainty in regulations. Indeed, due to the variety of developed products, rapidly advancing technologies, and newness of such activities, the regulatory frameworks for such vehicles are still being discussed, and yet to be established. This brings further uncertainty to the problem and illustrates the high risk endemic to this domain. Suborbital tourism, due to its novelty and complexity, entails significant risks, in terms of costs, profitability, and safety. Following the crash of SpaceShipTwo in 2014, the National Transportation Safety Board issued a press release, emphasizing the importance of flight safety:

> *"Manned commercial spaceflight is a new frontier, with many unknown risks and hazards. In such an environment, safety margins around known hazards must be rigorously established and, where possible, expanded. For commercial spaceflight to successfully mature, we must meticulously seek out and mitigate known hazards, as a prerequisite to identifying and mitigating new hazards"* [98].

Hence, because it is very recent, commercial suborbital tourism should be even more concerned with risks than regular aerospace programs. **Overall, the novelty of this industry brings further risks, and further requires the adoption of detailed analyses, to make up for the lack of knowledge and historical data.**

1.4.2   Small candidate companies

As noted in the previous subsection, the suborbital flight industry is very recent. Being in the introduction stage of its life-cycle, this industry is primarily made of relatively small companies, as often observed during this phase. Hence, Table 1.1 shows the numbers of

Table 1.1: Size of main aircraft manufacturing or suborbital tourism companies

Company	Number of employees
Companies with suborbital vehicles projects	
Airbus Defense and Space	38,000
Armadillo Aerospace	7
Blue Origin	600
Copenhagen Suborbitals	58
Scaled Composites	200
The Spaceship Company	250
XCOR Aerospace	100
Main airplane manufacturers	
Airbus Group	138,000
Boeing Co.	149,000

employees for the main companies involved in such projects and compares it with the main aircraft manufacturers. Except for Airbus Defense and Space, which decided to participate in the commercial suborbital flight race despite its large-firm status, all companies are actually relatively small; only up to 600 employees for Blue Origin. This is even more considerable when compared to the size of aircraft manufacturers, which typically manage over 100,000 employees.

While the reduced scale of the major players in the field might look like a weakness and disadvantage, it also represents a great opportunity. Indeed, small size companies benefit from much fewer operational and management constraints. As a consequence, smaller companies enjoy greater flexibility and collaboration between their divisions. **Hence, the reduced size of the firms forming this industry facilitates the adoption of an enterprise-level vision for the development of suborbital vehicles.**

1.4.3 Assertion 4

In this section, some of the specific motivations and needs in the suborbital tourism industry were detailed. First, it was established that due to the newness of this market, historical data was scarce, and risk was more significant than for mature fields. As a result, there is an additional need for the adoption of detailed analyses, to make up for the lack of knowledge and historical data. Moreover, it is even more critical to carefully quantify and handle uncertainty and risk than with regular aerospace problems. While these needs are additional constraints to address, the reduced size of suborbital vehicle companies makes them ideal for the adoption of an enterprise-level vision and approach, as it is simpler to ensure interdisciplinary collaboration with a limited number of employees. Accounting for these observations, assertion 4 can be formulated as:

> **ASSERTION 4:** *The suborbital vehicle industry is recent and characterized by a lack of historical data and standards. As a consequence, there is a need for a detailed analytical approach, with a strong emphasis on risk/uncertainty and finance.*

1.5 Summary of motivations and research objectives

This section starts by summarizing the motivation and its outcomes: observations and assertions. Put together, these lead to the establishment of research focuses, and a research objective that aims at fulfilling the previously formulated requirements.

1.5.1 Main research focus areas

In this chapter, the objective was to demonstrate why strategic decision makers needed support, how they should be assisted, what kind of analyses and information would help them, and when in the design process this support should be provided.

Section 1.1 started by stating the riskiness of aerospace programs. These programs are particularly risky, for two reasons: 1) the amount of investment to be committed is very

large, and the payback period is long, making the consequences of failure particularly severe; 2) multiple examples have shown, in the past, that failure was likely, even with great engineering products, because of the probable cost overruns, lower-than-expected demand, and other potential mishaps. This high probability of things not going as planned stems from the multiplicity of the sources of uncertainty, which, together, create an unpredictable, turbulent environment that aerospace companies have to cope with and overcome. **In order to make sound decision in these circumstances, these sources of uncertainty must be identified, assessed, and managed.** Yet, competing is such a harsh context is rewarded through the high potential returns that can be expected from successful projects. This competitive landscape requires executives to be assisted in order to maximize their chances of favorable outcomes when undertaking large programs. However, **these numerous sources of uncertainties cannot be addressed only through design improvements, and therefore key decision makers need to be supported by a business-driven stochastic framework in order to ensure success, with particular attention to financial aspects,** as many programs came short from an economic performance standpoint.

Section 1.2 explained how decision makers could be assisted. First, the importance of strategy on the company's performance was reviewed. This demonstrated the necessity to support executives in the development of their strategy, and more particularly in their strategic analysis step. Overall, decision makers need not only performance figures, but also business-oriented information. Finally, multiple strategies can be thought of, and a proper analysis should be able to include the appropriate metrics and objectives. It was then concluded that **key decision makers must be assisted in their strategy formulation by a large multi-objective environment supported by additional business metrics and analyses.**

Section 1.3 demonstrated first that, because of the many divisions involved in such large scale programs, it is necessary to have a multidisciplinary, enterprise-level approach. If a company's divisions only follow their local objectives, a principal-agent problem will

occur. Such a problem qualifies a situation when a principal hires agents to act on his behalf, but agents seek their own interest. In such a case, the analogy can be made with Cayley's design paradigm, who suggested to optimize all subcomponents of a system individually. Yet, such a practice results in a suboptimal system, as an assembly of optimal subcomponents does not make an optimal assembled system. Therefore, interdependencies between R&D and the main divisions of the company sharing the same value chain path should be considered in order to capture more value and increase the chances of success. Finally, to follow the paradigm shift proposed by Mavris et al. [96], this enterprise-level approach should be performed parametrically during early phases of design, in order to acquire knowledge soon and to maintain design flexibility. These observations resulted in the assertion that **business disciplines need to be modeled in an enterprise-level environment during conceptual design in order to ensure collaboration between the company's businesses and to avoid sub-optimal solutions.**

Section 1.4 presented some particular characteristics of suborbital vehicle programs and companies. Due to the lack of historical data, there is a specific need for a program-wide analytical approach. Additionally, the companies developing such vehicles tend to be fairly small in comparison to those working on large aerospace programs. While this is a disadvantage from some points of view, it also represents an opportunity as it facilitates the adoption of an enterprise-wide vision. Given these additional motivations, it appears that the topic of this thesis would be well suited to the study of suborbital vehicle programs. **Therefore, the rest of this dissertation will be applied to the field of suborbital vehicle design.** However, it is important to note that, as shown previously, the research presented next has sufficient motivations for other areas such as commercial aviation as well.

The previous reflection leads to the emergence of two research focuses. One of the central problematics arising from this study is the need to make the most out of every project, because of the high risk entailed. This results in the necessity to capture more

value from the development programs, not only through design, but also through the other disciplines on the value chain path, by adopting an enterprise-level approach.

> **RESEARCH FOCUS 1:** *To develop an enterprise-level methodology to capture more value from programs.*

The other research focus is a by-product of the first one. Because there is a broad range of available strategies, a lot of objectives have to be accounted for. Further, these objectives are probabilistic, because of the stochastic nature of aerospace programs. Yet, decision makers need to be able to perform risk and return trade-offs and to assess the robustness of programs. To do so, a methodology is required that supports decisions when dealing with large, multi-objective, and uncertain trade spaces.

> **RESEARCH FOCUS 2:** *To support decisions in large, multi-objective, and uncertain trade spaces.*

1.5.2 Establishment of the research objective

Based on the aforementioned research focuses, the characteristics, benefits, and capabilities of this new methodology are described below:

- In order to capture more value from programs, the proposed methodology should model jointly design techniques and main business disciplines, at a conceptual level. Such an environment should also be capable of identifying and ranking optimal designs and business variables. Therefore, it should enable the observation of the effect of the chosen dominant strategy on the program selection.

- Aerospace programs are characterized by the presence of significant sources of uncertainty. These must be identified, assessed, and managed. Moreover, these uncertainties affect concepts in different manners. The proposed methodology should be able to determine the main contributors to uncertainty on the objective functions of

various programs. It should also be able to determine the effect of variations in market conditions on the selected optimal design. Finally, it should have the ability to measure the robustness of the different programs to these environmental variables.

- The methodology should be able to determine the impact of risk aversion on the optimal program selection. Depending on the context, and scenario adopted, the overall study may result in a single optimum valid regardless of risk aversion, or in a trade-off leading to radically different selections.

- The methodology should be capable of determining which variables, whether they are design-related or business-related, are the strongest contributors to performance. Similarly, it should also be able to assess which are the strongest risk mitigation factors.

In order to develop these capabilities and address these issues, the research presented in this document will be pursued in accordance with the following research objective:

> **RESEARCH OBJECTIVE:** *To establish a methodology that enables informed enterprise-level decision-making under uncertainty and provides higher-value compromise solutions.*
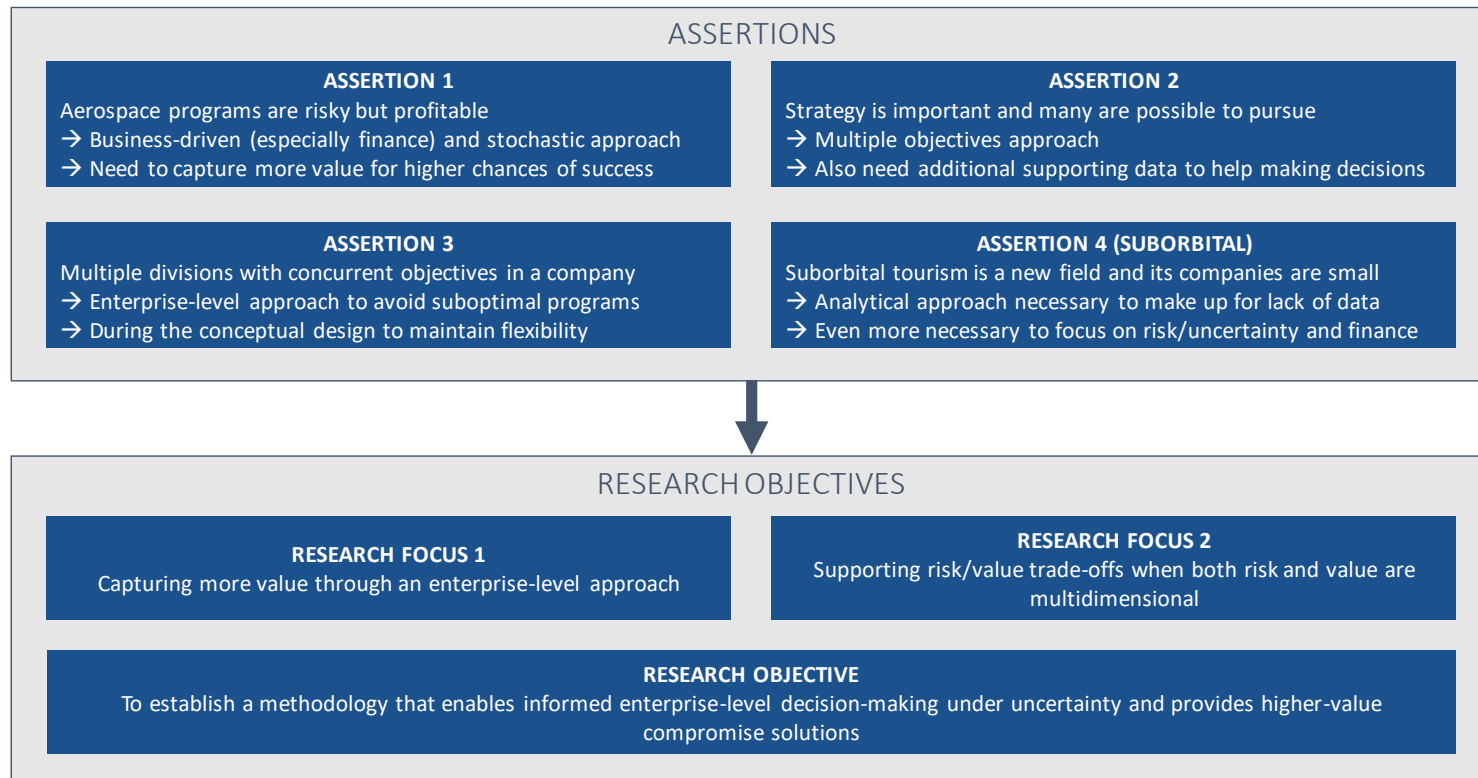
Figure 1.18: Simplified summary of the research objective establishment

CHAPTER 2

PROBLEM DEFINITION

This chapter builds on chapter 1, and follows the research objective and focuses that were established. It studies the literature's state-of-the-art techniques and methodologies linked to the proposed line of research, and either determines the best methods for a given purpose, or identifies gaps that have to be bridged. These gaps will result in the formulation of *research questions*, which will have to be addressed and answered in order to fulfill the research objective. Through a thorough study of various new fields to the topic, hypotheses are made, as a tentative answer to the research question, and will have to be verified or rejected in the next step of this research. This chapter articulates around the two research focuses. As such, section 2.1 discusses of the means **to develop an enterprise-level methodology to capture more value from programs.** Section 2.2 studies how **to support decisions in large, multi-objective, and uncertain trade spaces.**

2.1 Adopting an enterprise-level approach to capture additional value

In order to fulfill the research objective, it is necessary to provide a methodology that captures more value from aerospace programs by accounting for business disciplines or features alongside design and exploits their interdependencies.

2.1.1 Gap identification

This subsection identifies the main methods used to perform design, in the field of aerospace. To determine potential shortcomings in current approaches, the literature is consulted and techniques are grouped by similarities in their procedures and objectives. Two main classes of methods have been identified. The first one is the classic design approach: design-for-performance methods, where the only goal is to fulfill mission-driven

requirements. The second one is called Value-Centric Design (VCD) or Value-Driven Design (VDD) and promotes the use of a cost-oriented value metric as an objective of the design process. These two main categories group most of the design approaches. Some more minor yet promising categories are also studied in this subsection. Overall, these methods involve more exploitation of interdependencies between business disciplines and design, although not to a sufficient extent. This subsection is articulated around the analysis of these different categories.

Design for performance

Design for performance is the classic approach used in aircraft design. In that case, an aircraft has to be designed under mission constraints and other performance requirements. This process can be followed at any step of design. During conceptual design, a standard procedure is to use a sizing and synthesis process, such as the one given as an example in Figure 2.1 by Mattingly [99]. In this process, two main analyses are performed: 1) a mission analysis, which will simulate the mission performed by the airplane, and determine various fuel fractions and other mission-related metrics, 2) a constraint analysis, which will determine the minimum characteristics the airplane should have in order to perform according to given requirements, at different phases of the mission. These two analyses are coupled, and an iterative process must take place. Once convergence is reached, the calculation returns the characteristics of the sized aircraft. The sizing and synthesis element only represents the analysis part of design. This process has to be repeated with various inputs, following an optimization process.

Multiple applications of design for performance exist. Any optimization of the design of an aircraft (derivative or new, conventional or unconventional), or of its subsystems, as long as it does not involve costs and economics, can be categorized as design for performance. Among many other cases, some examples are:
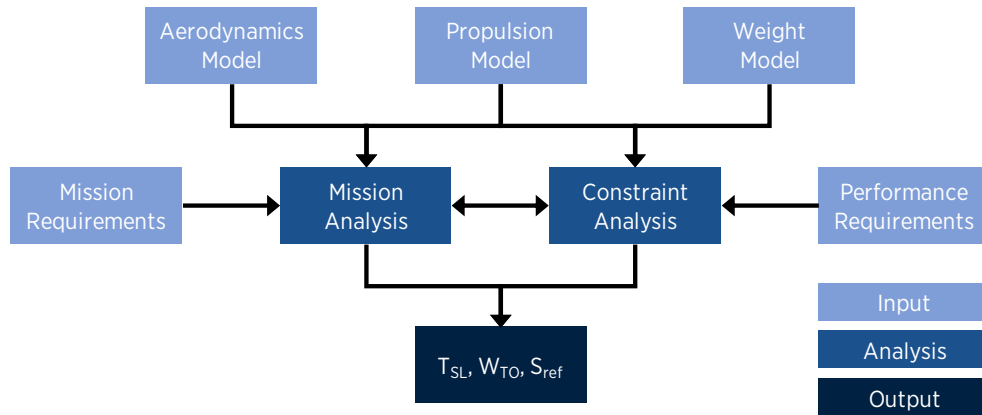
Figure 2.1: Mattingly's sizing and synthesis process [99]

- Martins et al. [100] carry out the high-fidelity aerostructural design optimization of a supersonic business jet. They use as an objective function an aggregate of aerodynamic drag and weight of the aircraft. Another example of supersonic jet design for performance is given by Alonso et al. [101]. In that case, the supersonic jet is optimized with range and noise levels as objective functions, which results in a Pareto frontier, and trade-offs to make between these two objectives.

- Mukhopadhyay et al. [102] conducts the analysis, design, and optimization of a blended-wing-body aircraft's fuselage. It intends to minimize the fuselage weight for such an airplane while keeping some constraints on the maximum allowable stresses, and on buckling. Similarly Hansen and Horst [103] proceeds to the multilevel optimization of a blended-wing-body aircraft. Using different levels of optimization, with the inner loops providing more detailed structural analyses, the structural weight of the plane is minimized.

- More classically, Wrenn [104] uses such a multilevel optimization technique, to perform the multidisciplinary optimization of a civil aircraft wing, with block fuel weight as an objective. Other examples of design-for-performance methods applied to conventional aircraft exist, but the trend has been moving towards more inclusion of costs in the design process.

- In the field of suborbital transportation, Marti and Nesrin Sarigul-Klijn [105] present an overview of all possible methods for launch and recovery of manned suborbital vehicles along with qualitative economic considerations. However, there is a lack of a quantitative, systematic, and rigorous methodology to compare and optimize suborbital vehicles. Others [106–109] do not even include any economic information and only focus on vehicle performance. Generally speaking, the literature is essentially articulated around a design-for performance approach, for suborbital vehicles studies. Design methods for suborbital vehicles are surveyed in further detail in Chapter 3.

Overall, the design-for-performance studies were the first step towards a better optimization approach. These methods often used the empty weight of an aircraft as a proxy for its desirability and performance, and they assumed that profits would be optimized accordingly. While this approach was a significant improvement as a first implementation of computerized optimization techniques, these remain too simple nowadays, as the economic characteristics of an aircraft are its most important attributes, and computer power has increased sufficiently to allow for more sophisticated analyses.

Value-Centric / Value-Driven Design

Value-Driven Design (VDD), also known as Value-Centric Design (VCD), originates from a growing concern and awareness of cost and economics issues in aerospace. After decades of unsuccessful programs, cost overruns, and unfulfilled promises of financial glory and affluence, researchers realized that designers had to see further than the mere performance of a system. They should rather envision it as a commercial product, with all the financial responsibilities it entails. Authors, such as Mavris et al. [96, 110], advocated shifting from a design-for-performance perspective, to design for affordability. Affordability would then be the new key objective and represents a compromise between the value of the aircraft and the cost or investment required. In [110] for example, Mavris et al. attempts to minimize

the $/RPM (dollar per Revenue Passenger Mile), or in other words, the minimum yield an airline should manage to gain per RPM in order to be profitable. However, this measure remains closer to an aircraft performance characteristic, as it targets a profitability metric for the airline, rather than for the manufacturer, although the manufacturer is designing the plane and, therefore, making the decisions. Nonetheless, these efforts participated in paving the way towards a more financially-oriented design perspective. Overall, VDD and VDC promote the creation of tradeoffs between value -an aggregate metric identifying what is the value according to identified stakeholders- and cost, rather than trying to minimize cost for given requirements. Collopy [111], of the Value-Driven Design Institute, summarizes well the history and principles of VDD. Many different applications of VDD are found in the literature. Some of them are the following:

- Value-Centric Design (VDC), which is in fact very similar to VDD (and is said to be a mere alias for VDD), is mostly used in space-related applications, where several examples can be found [112–115]. Ross [116] conducts multi-attribute trade studies to analyze various space systems architectures and design, using VCD. He simulates different life-cycle costs and performance metrics, in order to compute a utility value, and select the best system. Brown[117], followed by Brown and Eremenko [118], use value-centric design to proceed to the evaluation of fractionated space systems, where, instead of having one monolithic system, the space system is decomposed into several modules communicating wirelessly. Several authors have also used value-centric design to work on the DARPA System F6 program [119–121], which is a demonstration project for fractionated spacecraft, where a cluster of independently orbiting modules interacts wirelessly. It enables some capabilities that could not be achieved without using a larger satellite, in a conventional configuration.

- One of the primary objectives promoted in Value-Driven design (most often by Collopy) is called *surplus value*. Surplus value is introduced by Collopy [122] and represents the value-potential of a particular system when all manufacturing and oper-

ating costs are discounted. For an aircraft, it would be the difference between the discounted revenues generated through the operation of the aircraft, and the various costs of operation, costs of manufacturing the airframe, and costs of manufacturing the engines. In other words, the value-potential of the aircraft before the airframe and engine manufacturers took their share of the profits. Surplus Value SV is expressed in Equation 2.1, where P_R is the reservation price, $C_{M,A}$ the cost of manufacturing the airframes, and $C_{M,E}$ the cost of manufacturing the engines.

$$SV = P_R - C_{M,A} - C_{M,E} \qquad (2.1)$$

Collopy [123] uses surplus value in its methodology of distributed optimal design, consisting in the local optimization of subcomponents rather than the overall system all at once. To do so, he defines local objectives for components based on the partial derivatives of the system-level objective with respect to component attributes. This approach provides a good way to reduce dimensionality for large systems' optimization problems, but makes the bold assumption that system-level constraints will be enforced and that there is no interaction between components. Moreover, local objectives are approximated using polynomial series expansion, which makes them inaccurate. Collopy [124] also used surplus value to evaluate propulsion system technologies, and help optimize aircraft engine cycles. Cheung et al. [125] give another example of surplus value use. They use surplus value to evaluate designs of commercial aircraft engines, and see the impact of some design parameters and technologies on the surplus value.

- When a financial metric is not used for value, authors might use an aggregate function, in order to model the value of a system. Curran et al. [126] use a complex, thorough aggregate function incorporating multiple aspects, such as costs, utilization, emissions, or passenger comfort and convenience. Ross et al. [127] detail different

methods used in Value-Centric Design - the Net Present Value (NPV), the Multi-Attribute Utility Theory (MAUT) and the Cost-Benefit Analysis - and compare the results of their application to the valuation and optimization of telecommunication satellites.

- Other applications can also be found in the literature. Willcox and Wakayama [128, 129] use a value-driven approach to perform the simultaneous optimization of a family of aircraft, and to estimate the value of commonality within this family. Peoples and Willcox [130, 131] proceed to a more in-depth life-cycle costs and revenues analysis for a blended-wing-body aircraft with uncertain market demand, in order to perform the valuation of the aircraft development program. Markish and Willcox [132] carries out a similar type of study. Castagne et al. [133] perform a value-driven optimization of aircraft fuselage panels, using semi-empirical cost functions, and objectives such as minimum weight, minimum cost, and maximum manufacturer profit.

Through these diverse examples, it could be observed the essence of Value-Driven Design: optimizing a system for its value (often, its economic value). However, one of the main disadvantages lies in the fact that, while VDD does not disallow a broader scope, the focus is usually in one metric, whether it is the NPV or the surplus value. Moreover, analyses were rarely placed in the point of view of the manufacturer, in which case the objective was simply to maximize the program's profit, maybe missing the real goals of the company. Finally, the non-design objectives are disregarded and not optimized for, which does not, therefore, take advantage of their interdependencies, and limits the value potential of the system or program by not exploiting it.

Other promising approaches

While the previous paragraphs provided the main categories of design approaches, some other more minor but interesting approaches exist.

- **Design-for-manufacturing:** Design-for-manufacturing, which is sometimes called Manufacturing-Influenced Design (or MInD), is a category of design frameworks and approaches which jointly perform the classic design analyses (mission analysis, constraint analysis, sizing, etc.) and a manufacturing process analysis, for the structural elements of the airframe. Additionally, some sets of manufacturing variables can also be optimized, such as the types of machines, their numbers and layout, as well as the production planning, under constraints of inventory, production capability, etc. Various examples of such applications can be found in the literature [134–138]. This approach enables a better alignment between design and manufacturing, and exploits the interdependencies between the two disciplines. Indeed, design can affect the manufacturing process, and manufacturing constraints can affect the design space, ultimately having an interaction impact on the enterprise-level objective. While this type of methodologies is oriented towards the right progress direction, it limits itself to manufacturing as an extra discipline to align, and does not consider other important ones. Furthermore, this type of methods is more related to preliminary design, rather than conceptual design as required in the research objective.

- **Competition analysis:** While methods including a competitive analysis are not very different from VDD per se, these approaches bring more business-informed analyses, and are worth noting in this subsection. Briceno and Mavris [139, 140], followed by Briceno [141], conduct a game-theoretical study of the aeroengines' competitive landscape, and the optimization of the design of such engines under such market conditions. Morrison et al. [142] perform a game theoretical analysis to determine airframe manufacturer strategies in different scenarios, assuming manufacturers are seeking maximal NPV. Justin et al. [143] provide a framework to estimate the value of an airplane, and to determine the market share of airframe manufacturers given certain scenarios.

- **"Design-for-costs":** While this is not the most common approach, some authors maintain costs in their objectives, in opposition to the concepts of affordability and VDD. Bower et al. [144] perform trade studies and the optimization of an aircraft design for a particular route network, with emissions and operating costs as their considered objectives. Frank et al. [31] address the problem of evolving requirements in the design of unconventional aerospace vehicles. However, they focus on minimizing the life-cycle costs of the program and do not consider other financial metrics such as the NPV and Internal Rate of Return (IRR).

Summary

As seen in this subsection, there are two main visions of design: design-for-performance and value-driven design. It can be noticed that, although the literature is attempting a more cost/profit-oriented approach, it tends to overly focus on one financial aspect of the problem (most often, the NPV) and fails to integrate other figures of interest, which are essential to strategic decision makers. In particular, a financial analysis cannot be limited to the NPV only. Other factors, such as market share, margins, or technology acquisition can be just as relevant objectives as value and performance. Yoffie [84], for example, quotes a former Airbus executive admitting to pricing for market share. Furthermore, VDD only promotes the addition of an evaluation module, which does not provide any basis for exploiting the interdependencies existing between disciplines. **Supplementary disciplines should be present in the M&S environments, as well as the levers to optimize them, in order to capture more value from aerospace programs.** In other words, VDD's value module is passive, while active disciplines should also be present. While this is partially the case for examples such as design-for-manufacturing, this approach only incorporates one particular supplementary business discipline and does not belong to conceptual design but preliminary design. Figure 2.2 and Table 2.1 compare the structure and attributes of the

(a) Design for performance (b) Value-Driven Design (c) Design for manufacturing
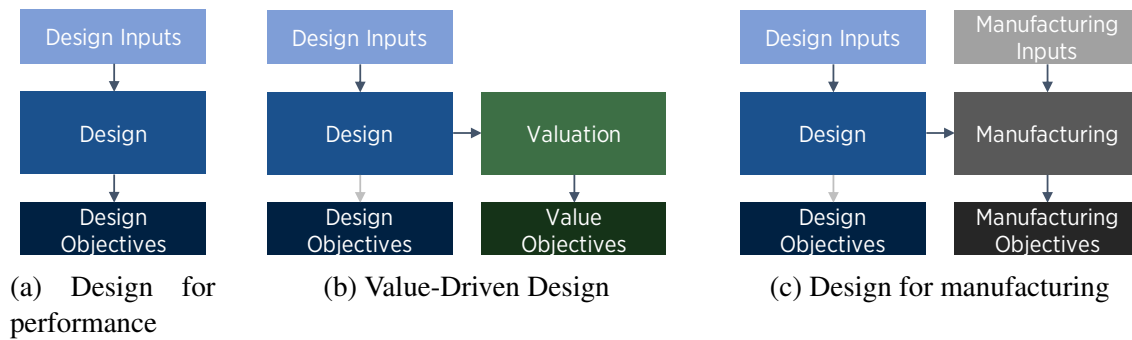
Figure 2.2: Comparison of the analysis structure of the main design approaches

various previously described methods and applications, and highlight the gaps in today's literature. Three shortcomings can be identified:

- Current design approaches do not exploit well the interdependencies between enterprise-level disciplines.

- The range of business objectives used is too narrow, which can limit strategic flexibility.

- Overall, current approaches remain more at the system level than the enterprise level, which automatically limits the value potential of the program of interest.

Based on these observations, a first research question is formulated:

> **RESEARCH QUESTION 1:** *Does the adoption of an enterprise-level optimization approach during conceptual design help executives capture more value from aerospace programs and lead to significantly different decision-making?*

Table 2.1: Comparison of the main design methodologies' characteristics

	Design Optimization	Valuation	Analyzes beyond design	Exploits interdependencies	Multiple business objectives	Support business data
Traditional design-for-performance						
Alonso et. Al. [101]	●					
Martins et al. [100]	●					
Mukhopadhyay et al. [102]	●					
Value-Driven/Value-Centric Design						
Peoples et al. [131]	●	●	◔			
Cheung et al. [125]	●	●	◔			
Collopy and Horton [124]		●	◔			
Collopy [123]	●	●	◔	◔		
Ross et al. [127]	●	●	◔		◐	
Saleh et al. [113]		●	◐		◐	◐
Others						
Design-for-costs - [144]	●		◔		◔	
Design-for-costs - [31]	●		◔		◔	
Competition analysis - [141]	●	●	◔			◔
Design for manufacturing - [134]	●	◐	◐	◔	◔	◐
Design for manufacturing - [138]	●	◐	◐	◔	◔	◐

2.1.2   Problem decomposition

In order to answer the first research question best, it is necessary to decompose the effects of an enterprise-level approach into three categories:

- **Additional business-oriented objectives.** In the previous subsection, the types of objectives adopted in classic aircraft design approaches were detailed. It was shown that this list of objectives was limited, and should include more business-related targets. As a result, it should be verified whether having a more exhaustive set of objectives can have a positive impact on the overall enterprise-level target value. To do so is relatively straightforward, as such targets should be added to a program-wide approach.

- **Additional business disciplines and their inputs.** An enterprise-level approach would bring more non-design disciplines, as well as their corresponding inputs. It is now important to measure whether the addition of such business disciplines has a significant enough impact on the company-level objective. To verify this, a new framework including such disciplines needs to be developed.

- **Exploiting interdependencies between disciplines by aligning them towards a common enterprise-level objective.** An enterprise-level approach should capture the interdependencies between disciplines. The aim of the research question is to determine the significance of using the interdependencies instead of not using them. In order to resolve this question, an environment that aligns disciplines towards a common objective should be provided. However, it was demonstrated in subsection 2.1.1 that such an alignment was not performed yet in the aerospace engineering's literature. As several ways to proceed could be envisioned, the following question is raised: **how can business disciplines be aligned in conceptual design?** The rest of this section aims at defining an approach that will enable the exploitation of interdependencies that exist between the division disciplines of a company.

2.1.3   Exploiting interdependencies between disciplines

This section aims at providing the basis to establish a possible answer to research question 1.1. It starts by summarizing the different methods used in aircraft design that exploit the interdependencies between disciplines by providing an alignment of these disciplines towards a global objective, rather than a local one. As the limitations in current approaches in aircraft design are made evident, an analogy between discipline alignment and supply chain integration is made. Based on these observations, a hypothesis is then formulated, along with a proposed experiment to verified or reject the hypothesis.

Alignment methods in aircraft design

While subsection 2.1.1 already partially addressed this question, the focus was then more on demonstrating a lack of methods providing business disciplines alignment. This subsection summarizes the different approaches adopted to provide (or not) some alignment of disciplines, and to categorize them into distinct groups. Three main categories of methods exist, regarding alignment: no alignment at all, partial alignment, and indirect alignment.

- **No alignment.** This is the category most applications belong to. Only design variables are considered. Potential additional disciplines or analyses are passive (they are limited to computing an output, given non-controllable inputs). The maximum value that can be attained is fairly limited as well, as only one discipline is optimized. Moreover, as other disciplines are not optimized yet, they will still have to be optimized later in the process. Therefore, the requirement of question 1 to proceed to alignment during conceptual design is not met. Furthermore, it also means that **this approach leads to *sequential optimization*,** which results in suboptimal designs, as it is explained in subsection 2.1.3. Many examples from this category can be found in the literature [90, 100, 101, 131, 145].

- **Partial alignment.** Through the naming *partial alignment*, it is implied that the methodology limited itself in the potential business disciplines it could align. Most often, only one specific discipline besides design is implemented, simulated and aligned. While this still provides good foundations for further alignment, this is not thorough enough when trying to get the maximum value as a stakeholder. Moreover, some of these disciplines do not occur during conceptual design, but later in the design process; during preliminary design for example. An example of partial alignment is design-for-manufacturing [134–138].

- **Indirect alignment.** Alignment is not always achieved using one common objective for every module. Local objectives which are correlated with the primary high-level objectives can be employed. For instance, Collopy [123] uses a distributed optimization technique in order to perform the design optimization of aerospace systems. He partitions the system into components, and determines which are their *extensive attributes*: the attributes affecting the overall system's value. Once these attributes are known, he determines their effect on the full system through the computation of a Jacobian matrix. Finally, components are individually optimized, by relating the subsystem's design variable to its extensive attributes (through any modeling and simulation of this component), which are then translated into the overall system's objectives, using first-order Taylor series expansion, and the previously computed Jacobian matrix. This approach provides a good way to reduce dimensionality for large systems' optimization problems, but makes the bold assumption that system-level constraints will be enforced and that there is no interaction between components. Moreover, local objectives are approximated using polynomial series expansion, which makes them inaccurate.
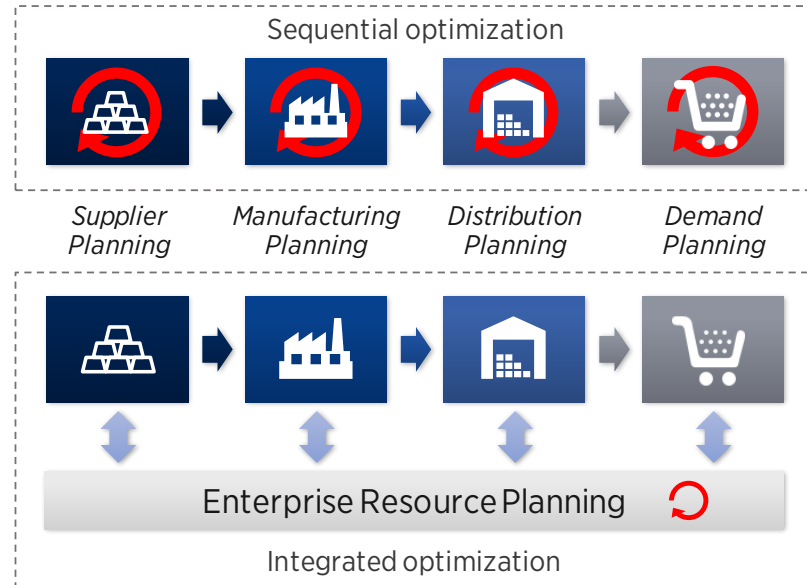
Figure 2.3: Comparison between sequential and integrated optimization [146]

Sequential and integrated optimization

As previously stated, it is complex to exploit company disciplines interdependencies by aligning them towards a single objective for a given program. It was also established that current techniques used in aerospace design do not provide a compelling basis for the alignment of disciplines. In order to broaden the scope of available practices, this section introduces the notion of sequential and integrated optimization, in the context of supply chain optimization. The comparison between the two approaches is presented in Figure 2.3.

In sequential optimization, each layer of the supply chain is optimized after the previous one with local objectives. This results in the aforementioned principal-agent problem, where the resulting optimized solution differs from the true optimum. There are two aspects of the principal-agent problem when sequential optimization is used: higher induced volatility, and suboptimal operating conditions, both increasing the supply chain costs and reducing profits.

Higher volatility is characterized by the bullwhip effect [147]. This phenomenon is illustrated in Figure 2.4. It generates large disturbances in a supply chain when small
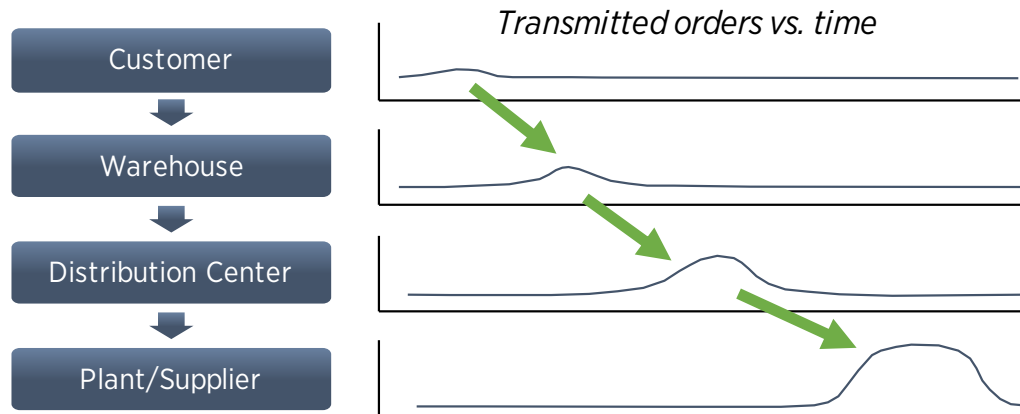
Figure 2.4: Bullwhip effect under sequential optimization

changes in demand occur. It happens because of the lack of information available for each manager at each step of the supply chain. Each manager ignores what happens upstream and downstream. They have to satisfy local objectives (as a symptom of the principal-agent problem) and tend to overreact to changes, which results in the amplification of the effect going down the supply chain, destabilizing the system. On the other hand, a more integrated approach can mitigate this issue. Integrated optimization (sometimes called global optimization [146], but called *integrated* in the rest of this document to avoid confusion with the opposite of local optimization) refers to an approach where all disciplines are integrated into a holistic optimization environment. The bullwhip effect is effectively damped in the presence of information sharing and collaboration between entities of the supply chain [148, 149], using, for example, an Enterprise Resource Planning (ERP) structure, which enables the adoption of an enterprise-level vision.

Sequential optimization is also detrimental, from a supply chain standpoint, because each element of the chain does not perform regular operations optimally (suboptimal production quantities, retail prices, inventories, etc.), because of the principal-agent problem. This has been demonstrated on multiple occasions when comparing the efficiency of decentralized (sequential) and centralized (integrated) supply chains. The adoption of a cen-

tralized approach enables the increase of the chain's total profits, and/or the reduction of its costs. Spengler [150] estimates a 16% total earnings improvement on a notional supplier-retailer chain. Cachon [151] predicts up to 13% cost reduction under certain conditions. Chen [152] predicts up to 13% higher profits on a dual-channel supply-chains.

Sequential optimization has consequences in design as well. It was established that Cayley's design paradigm (the individual optimization of independent components) produced suboptimal designs [94]. This case can be seen as an example of sequential optimization inside design. Alexandrov and Hussaini [153] assesses the performance of sequential optimization on the aerostructural design of a wing. An aerodynamics discipline first optimizes the geometry of the wing to minimize drag, then passes the resulting loads to a structure discipline which minimizes weight. The computed "optimal" wing has an 11% higher drag than Prandtl's analytical solution [154]. Durand et al. [155] compare sequential and integrated optimization for the design of robotic swarms. Two aspects of the robotic swarm are optimized; 1) the composition of the swarm; 2) the individual characteristics of each type of robot in the swarm. Sequential optimization sequentially optimizes these aspects, while integrated optimization jointly does so. The results show an average 16% improvement of mapping time with the integrated optimization approach compared to sequential optimization. While Multidisciplinary Design Optimization (MDO) addresses these issues at a design level, MDO was usually applied to design only, as shown in these two examples. **Not integrating the business disciplines would result in the same problem: sequential optimization, and sub-optimal results.**

The analogy can be made between the disciplines of an aerospace program, and the elements of a supply chain, or disciplines within design. Based on these observations, it can be inferred that an integrated optimization of aerospace programs would provide the alignment capabilities sought in research question 1. It can be concluded that a holistic, enterprise-wide, integrated approach can help aligning the different disciplines, exploit interdependencies between disciplines, and capture additional potential value for the overall

program that otherwise would have been missed if only optimizing the vehicle design, or using sequential optimization.

2.1.4 Hypothesis 1

This section studied the question of whether the adoption of an enterprise-wide optimization method, consisting of additional business disciplines, inputs and objectives, as well as an integrated framework exploiting their interdependencies, could help capture more value. The literature was reviewed, and main categories of aerospace design methods concerning the inclusion of business disciplines and exploitation of interdependencies were identified. It was concluded that no current approach was providing the required alignment and business disciplines during conceptual design, which resulted in research question 1: *does the adoption of an enterprise-level optimization approach during conceptual design help executives capture more value from aerospace programs and lead to significantly different decision-making?* This research question naturally brought another: how to align disciplines and exploit their interdependencies? Subsection 2.1.3, therefore, summarized the main ways to align disciplines. As no real method fulfills the established requirements, an analogy was made with supply chain optimization, and the concepts of sequential and integrated optimization were introduced. Given the exposed benefits of integrated optimization, it was then concluded that a holistic, integrated and enterprise-level approach was necessary.
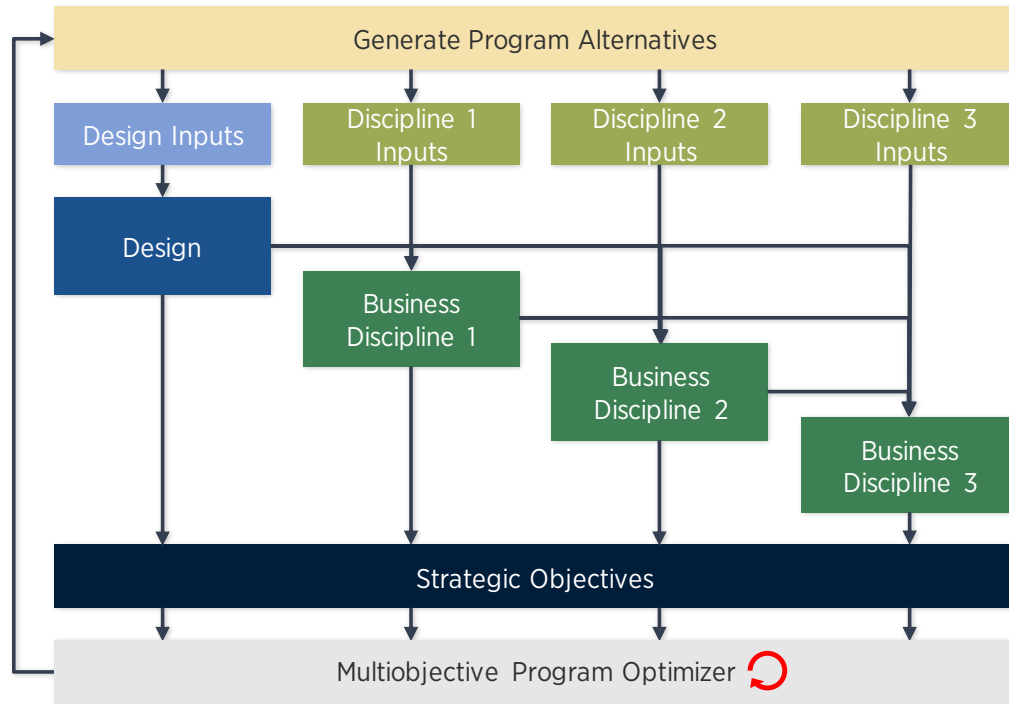
Figure 2.5: Proposed design structure

The proposed answer to research question 1 is, therefore, a combination of the conclusions of sections 2.1.2 and 2.1.3. It results in the enterprise-level development framework displayed in Figure 2.5. The proposed structure integrates several key features which are required to solve research question 1:

- **Implement a vehicle design framework.** The vehicle design framework is the central part of the structure, and its start point. Creating this framework can be achieved using any type of previously studied design environment.

- **Integrate key additional business disciplines.** Additional business disciplines should be modeled and incorporated into the overall environment. Those methods can range from pricing, to finance, or production.

- **Include a wide variety of strategic objectives to target.** Including many strategic objectives will allow greater flexibility on the business strategy analyzed by the

decision maker. This feature is enabled by the inclusion of the additional business variables.

- **Align disciplines through the addition of main discipline drivers.** The alignment of disciplines in the model is permitted if several key enablers are present. First, it is necessary to add main inputs for the business disciplines. These inputs help adjust and direct the disciplines towards optimal company-level objectives. Both enterprise-level and vehicle-level inputs must also be generated. Finally, an enterprise-level, multi-objective and integrated optimization method is implemented, in order to find the optimal disciplines' inputs for the defined objectives.

This proposed holistic enterprise-level process and structure is believed to give decision makers the ability to exploit interdependencies between the business divisions' disciplines by aligning them towards the right strategic objectives using an integrated optimization approach, which should, in turn, result in additional value captured from the considered programs. Therefore, hypothesis 1 is formulated as follows:

HYPOTHESIS 1: IF a holistic business-driven framework is developed that integrates enterprise-level disciplines and their inputs in conceptual design AND IF enterprise-level strategic objectives are implemented and targeted THEN more value from aerospace programs can be captured and significantly different decisions are made.

2.1.5   Experiment 1

In order to verify hypothesis 1, an experiment must be carried out. Four scenarios are implemented, with increasing capabilities: 1) one with no business disciplines, and only two objectives targeted, as the baseline case; 2) one with business disciplines, two objectives, and sequential optimization; 3) one with business disciplines, two objectives, and integrated optimization; 4) one with business disciplines, multiple objectives, and inte-

Table 2.2: Study cases for Experiment 1, and their purpose

Case	Business disciplines	Strategic objectives	Optimization method	Purpose
Case 1	No	Two	N/A	Baseline case
Case 2	Yes	Two	Sequential	Business disciplines impact
Case 3	Yes	Two	Integrated	Integrated optimization impact
Case 4	Yes	Multiple	Integrated	Strategic objectives impact

grated optimization, as the complete case. The details of the four experiments are present in Table 2.2. The impact of each incrementally added feature is then assessed.

Using the aforementioned scenarios, several characteristics of the produced results are analyzed:

- **The optimality of solutions.** One key point of the experiment is to check if the integrated optimization provides better results than the sequential one and the design-only method. This aspect will be analyzed through the use of Pareto Frontiers, or average TOPSIS scores, for example.

- **The difference in optimal inputs.** The other main verification point is to compare the difference between the inputs of each scenario's optimal solutions and measure if they significantly differ. This will show if different approaches result in significantly different decisions. Notable differences in decisions due to the use of an enterprise-level approach justify the application of this method early, to avoid costly redesigns.

Hypothesis 1 will be considered verified if it checks the following verification criteria:

> **VERIFICATION CRITERION 1.1:** *The approach with multiple strategic objectives Pareto-dominates the one with only two objectives.*

> **VERIFICATION CRITERION 1.2:** *The approach with additional business disciplines Pareto-dominates the one without them.*

> ***VERIFICATION CRITERION 1.3:*** *Integrated optimization Pareto-dominates sequential optimization.*

> ***VERIFICATION CRITERION 1.4:*** *Optima from the enterprise-level approach significantly differs from the baseline case.*

2.2 Risk/value trade-offs in uncertain multi-objective environments

Another essential aspect of the research objective deals with the problem of making risk/value trade-offs in large uncertain multi-objective environments. With this goal in mind, this section is articulated around four main subsections. Subsection 2.2.1 explains the required characteristics of the candidate method in order to fulfill the research objective. Subsection 2.2.4 reviews current approaches to risk/value trade-offs in aircraft design and identifies a gap in these methods. This leads to the formulation of a research question. In order to find inspiration in different fields, Subsection 2.2.5 surveys financial approaches to optimization under uncertainty. After making these observations, a hypothetical answer to the research question is established. Subsection 2.2.9, finally, proposes an experiment which will be used to verify the research question.

2.2.1 Required characteristics

The objective of this section is to find a method that helps executives make risk/value trade-offs in large uncertain multi-objective environments for aerospace programs. The sought method should provide certain capabilities and features, which are described in the following:

- **Provide a probabilistic design environment.** The implemented modeling and simulation environment should be able to provide probabilistic outputs, which involves the implementation of an uncertainty quantification method.

- **Deal with several sources of risk.** There are various types of risk in an aerospace program, such as risk on safety, or financial risk. These should be accounted for in the decision-making process.

- **Handle multiple uncertain objectives.** Multiple strategic objectives can be considered. These objectives can all be affected by uncertainty. The proposed method should, therefore, be able to handle this type of contexts.

- **Enable easy but relevant risk/value trade-offs.** Executives charged with making the risk/value trade-offs may or may not have in-depth knowledge of the particular implementation of the method. Therefore, an easy-to-use way of making these trade-offs should be provided. These compromises should be sound too. This requires an appropriate definition of risk and value. Additionally, decision makers should be provided with a set of alternatives for further comparison and selection.

In this subsection, the literature is reviewed in order to find a compelling method which fulfills the research objective. It is shown that none matches the previously stated requirements, which outlines a gap in the literature, and leads to the formulation of research question 2. To get to this result, this subsection is decomposed into three parts. First, the various definitions of risk are discussed, in order to understand the underlying scope of the word risk. Following the identification of the most important aspects of risk, a review of the various meanings of risk in the aerospace literature is performed, highlighting some of the limitations of current approaches. More limitations are also found through the review of main current approaches to design under uncertainty. In order to have a more original view of risk-based methods, the antepenultimate part of this subsection studies how risk/value trade-offs are performed in the field of finance. As a conclusion, the final part summarizes the strengths, weaknesses, and shortcomings of both approaches, highlights the gap, and formulates research question 2.

2.2.2 Multi-objective optimization

As the problem formulated by research question 2 is fundamentally multi-objective, multi-risk, it is important to review the different types of multi-objective optimization approaches. Two categories of methods exist: 1) a-priori optimization; 2) a-posteriori optimization. This subsection describes these techniques, details their advantages and disadvantages, and compares them.

A-priori optimization

A-priori optimization consists in the optimization of objective functions while knowing decision makers' preferences before performing the optimization algorithm. Most cases include the implementation of an aggregate function, enabling the transformation from a multi-objective problem to a single-objective one. A list of the major approaches to a-priori multi-objective optimization is the following:

- **Linear aggregate function.** When using a linear aggregate function, a linear combination of the multiple objective functions is used in order to define a new objective function. Each objective is weighted according to the preferences of decision-makers. Equation 2.2 expresses the aggregate function f to be used as a new objective function, as a function of the initial objective functions f_i, and the weights w_i respectively given to these objectives by decision makers. The main advantage of this method is its simplicity of implementation.

$$f(x) = \sum_i w_i f_i(x) \quad where \quad \sum_i w_i = 1 \tag{2.2}$$

  The main disadvantage of this form of aggregate functions is that objectives might be difficult to compare, due to their potentially different dimensions, which makes it complicated for decision makers to define weights.

- **Scaled aggregate functions.** In order to reduce some of the drawbacks of linear aggregate functions, where it becomes complicated to define weights, scaled aggregate functions normalize the multiple objective functions used in the aggregate. Vanderplaats [156] gives a common expression for such a scaled aggregate, as shown in Equation 2.3, where w_i are the weights associated to the objective functions f_i, f_i^* is the target value for objective i, and f_i^- is the worst computed value of objective function f_i.

$$f(x) = \sqrt{\sum_i \left[w_i \frac{f_i(x) - f_i^*}{f_i^- - f_i^*} \right]^2} \quad where \quad \sum_i w_i = 1 \qquad (2.3)$$

Mavris et al. [157] provide another formulation and define an Overall Evaluation Criterion (OEC), which uses a linear combination of normalized objectives. Equation 2.4 shows the general expression of the OEC, where w_i are the weights associated with the objective functions f_i, and f_i^{ref} represents a reference value for the objective function f_i; frequently, the value of objective i for the baseline case is used as a reference value.

$$f(x) = \sum_i w_i \left[\frac{f_i(x)}{f_i^{ref}} \right] \quad where \quad \sum_i w_i = 1 \qquad (2.4)$$

This type of aggregate function carries the same disadvantages as the other aggregates: it relies on arbitrary weights pre-established by decision makers. However, weights are more meaningful than with simple linear aggregates.

- **Multi Attribute Utility Theory (MAUT).** MAUT was introduced by the field of economics and enabled the aggregation of various financial or non-financial objectives. Ross et al. [127] provide the expression of MAUT's aggregate utility $U(\hat{X})$ in

66

Equation 2.5, where w_i is the weight of objective i, and $U(X_i)$ is the utility associated to objective i.

$$U(\hat{X}) = \frac{[\prod_i K w_i U(X_i) + 1] - 1}{K} \quad where \quad K = -1 + \prod_i [K w_i + 1] \quad (2.5)$$

This technique has the advantage to be well suited for problems involving economics and financial information but introduces a more complicated aggregate function. Moreover, MAUT is considered more of a Multi-Criteria Decision-Making technique than a value to be optimized.

- **Lexicographic ordering.** In this approach, no aggregate function is established. Instead, decision makers prioritize their objectives, which are sequentially prioritized. While the main advantage of this approach is that it does not require a precise weighting between objectives, it excessively favors one objective over all the other ones, which gives it a behavior similar to single-objective optimization, therefore limiting the interest of such an approach.

A-priori optimization techniques usually involve the creation of a new objective function integrating the importance of the various considered objectives whose weights are set by decision makers prior to performing the optimization. They are interesting as a way to simplify problems but result in a single optimum, which limits possibilities for decision makers to trade the objectives off and further compare and select among optima.

A-posteriori optimization

The principle of a-posteriori optimization is to come up with a set of non-dominated solutions, and to let decision makers analyze and select which of these optima suits them best. The non-domination criterion is defined following partial ordering space rules [156]:

- A weakly dominates B if A is better in some attributes and equal in others.

- C strongly dominates B if C is better in all attributes.

- A and C are incomparable if A is better than C in some attributes but worse in others.

Hence, multi-objective optimization results in the identification of this set of incomparable, non-dominated optima, which is called a Pareto frontier. Figure 2.6 shows a notional Pareto frontier when the objective is to minimize two objectives.
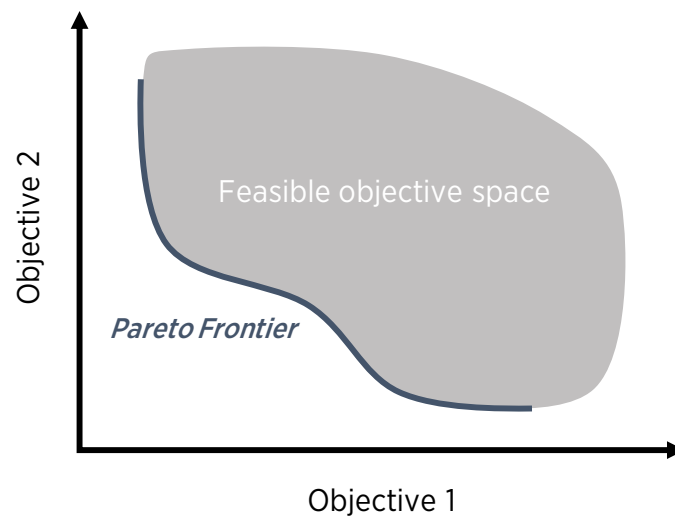
Figure 2.6: Notional Pareto frontier

A-posteriori optimization has many advantages. First, decision makers do not have to establish a set of weights to aggregate objectives, as for a-priori optimization. This makes this method much less arbitrary. Additionally, it also helps analysts better understand the trade-offs to be made, which can be hard before knowing the solution. However, multi-objective optimization tends to become computationally expensive when the number of objectives is high, or to result in scarce Pareto frontiers. Moreover, it is also more complicated to select a Pareto frontier point when the dimensionality of the problem is more than three, as it becomes difficult to represent a larger number of dimensions.

Table 2.3: Characteristics of main multi-objective optimization techniques

	Objectivity	Simplicity	Good with many objectives
Linear aggregate		●	◐
Overall Evaluation Criterion	◔	●	●
Multi Attribute Utility	◔	◐	●
Lexicographic ordering		●	◐
A-posteriori optimization	●	◐	◔

Summary

In this subsection, the different techniques of multi-objective optimization were described. Their principal features are summarized in Table 2.3. Two major categories exist: a-priori optimization and a-posteriori optimization. While a-priori optimization usually relies on an aggregate objective function, making it a simple yet arbitrary approach, a-posteriori optimization maintains all objective functions and comes up with a set of non-dominated solutions. However, when the number of objectives becomes high, this method becomes computationally expensive, results in scarce Pareto frontiers, and loses some of the comparison and selection capabilities as the Pareto frontier is hard to visualize. Additionally, a-priori optimization does not allow decision makers to further compare and select concepts after optimization. Hence, while both categories are compelling, these techniques cannot be used directly in the context of large multi-objective optimization sought in this research.

2.2.3   Risk and design under uncertainty

Definitions of risk

As the concept of risk is an important part of this dissertation, it is necessary to have a thorough understanding of the true meaning of the word risk. There are several definitions of risk depending on the source, and depending on the context. Through the analysis of

a few definitions, this part determines the main attributes of risk. The most complete and generic definition of risk can be found in the *Oxford English Dictionary* [158]:

> *"(Exposure to) the possibility of loss, injury, or other adverse or unwelcome circumstance; a chance or situation involving such a possibility."*

First, according to this definition, risk contains the notion of **stochasticity**, and **likelihood** of particular events, as shown in the word *"possibility"*. The second main aspect of risk is the **detrimental** effect of the event that is associated to risk, as seen in "loss", "injury", "adverse", "unwelcome". Other definitions from the *American Heritage Dictionary* [159] (*"the possibility of suffering harm or loss; danger."*) or the *Merriam-Webster Collegiate Dictionary* [160] (*"possibility of loss or injury"*) support similar meanings.

Additionally, another important word in the *Oxford English Dictionary*'s definition, *"exposure"*, shows that risk contains the notion of a dependence of some element to the outcome of certain events. This can be interpreted as risk carrying two similar attributes: **sensitivity** and **severity**.

The notion of **uncertainty** can be found again in another definition of the *American Heritage Dictionary* [159] (*"A factor, thing, element, or course involving uncertain danger; a hazard"*) and the *Oxford English Dictionary* [158] (*"the probability of an error; the mean weighted loss incurred by a decision taken or estimate made in the face of uncertainty"*). Interestingly, most alternative definitions of risk relate to the fields of insurance and finance. They similarly carry the notions of likelihood (*"the chance of nonpayment of a debt"* [159], *"the danger or probability of loss to an insurer"* [159], *"the chance of loss or the perils to the subject matter of an insurance contract; also : the degree of probability of such loss"* [160], *"the chance that an investment (such as a stock or commodity) will lose value"* [160]), severity (*"the amount that an insurance company stands to lose"* [159]), and stochasticity (*"the variability of returns from an investment"* [159]).

Finally, risk can be seen as the impact of a particular source of uncertainty (*"an insurance hazard from a specified cause or source <war risk>"* [159]).

As seen in this part, the risk is a complex concept, which carries multiple attributes or aspects:

- Result of uncertain events

- Detrimental, unfavorable, harmful

- Combination of likelihood and severity

- Comprises the notion of volatility or deviation from regular course of events

- Can be from a specific source of uncertainty

With multiple constituents enumerated in general definitions, risk can be a fairly ambivalent concept, but these aspects should be implemented when trying to quantify it, and the method that has to be developed has to capture the essence of risk as described.

As these aspects of risk are identified, it is then interesting to see how risk is defined and used in aerospace vehicles' design. In NASA's *Probabilistic Risk Assessment Procedures Guide for NASA Managers and Practitioners* [161], the main risk characteristics can be found: likelihood, severity, and separation of sources of risk (*"Determining risk generally amounts to answering the following questions: 1. What can go wrong? 2. How likely is it? 3. What are the associated consequences?"*). Overall, the most utilized measure of risk is the probability of an adverse outcome occurring, in particular with performance risk, which is the probability of not attaining a given performance level [96, 97, 162], but also with a broader meaning of the exposure to risk [163]. Frank et al. [164] use severity and likelihood of uncertainty factors to define risk, while the sensitivity of objectives to uncertainty factors can be another utilized method [131], as well as the full characterization of the probabilistic distribution of objective functions depending on uncertain inputs [165].

While current aerospace approaches seem to cover most of the constituents of risk, several shortcomings can still be noticed. One of the requirements stated at the beginning of this section is that in order to follow the research objective, the sought methodology

should handle several sources of risk. Additionally, it is suggested that several risk scenarios should be analyzed. Yet, current implementations do not seem to have a very multi-objective approach to risk, as it is only a single variable. As a consequence, each approach only uses one of the listed aspects of risk at a time.

The reviewed approaches also do not really account for risk as a measure of the volatility of the objective value, as in the financial definition of risk. However, this aspect is treated in the context of design under uncertainty. The following part reviews the main methods belonging to this field, and identifies additional gaps in current work.

Main approaches to design under uncertainty

Research Focus 2 does not only consider risk but more particularly deals with optimal risk-value trade-offs. In order to help decision makers be aware of the uncertainty of projects, and to help them consider their risks against the potential benefits they could profit from by undertaking them, it is first important to review the major ways to design under uncertainty. German [166] identifies three main techniques to account for variability in design: 1) robust design defines a new objective function to be optimized, that accounts for the variance of the initial objective function; 2) robust design Pareto frontiers generate a Pareto frontier that uses two objectives: the objective function and its variance; 3) reliability-based design optimization minimizes the objective functions while ensuring that certain constraints are not violated more than a given probability.

- **Robust design.** Robust design defines a new objective function to be optimized, which also accounts for the variance of the initial objective function. Various versions of the new aggregate function can be found in the literature. German [166] suggests the sum of the initial objective function and its variance, as presented in Equation 2.6, where μ_Y is the mean value of the objective function, σ_Y is its the standard deviation, and y_T is the targeted value. Such an aggregate function is nonetheless not very meaningful as it groups two variables that are not necessarily comparable in size and

(a) Robust design   (b) Reliability-Based Design Optimization
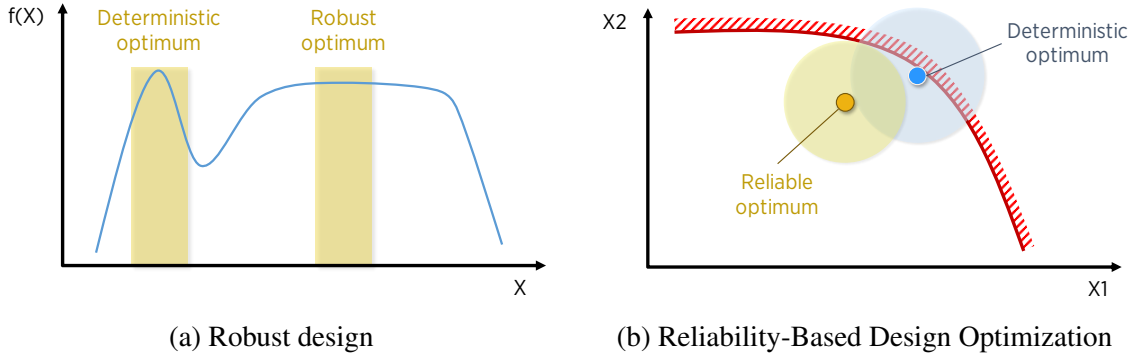
Figure 2.7: Methods of design under uncertainty

importance.

$$\min \quad (\mu_Y - y_T)^2 + \sigma_Y^2 \tag{2.6}$$

Other authors [167, 168] minimize the average of the initial objective function in the neighborhood B_δ of input variables x (Equation 2.7). An example is $B_\delta = \{y|y_i \in [x_i - \delta_i, x_i + \delta_i]\}$. Other variations exist by replacing the simple average by a weighted average, or by minimizing the objective function, subject to a variation constraint in the local neighborhood of the input variables (Figure 2.7a). This approach is promising but only accounts for variability through the expected value of the objective function. Two designs with equal mean objective functions but different variances would be deemed equal. It seems necessary to account for the negative impact of variance in the decision-making process, but this method does not allow it.

$$\min \quad f_{\text{eff}}(x) = \frac{1}{|B_\delta|} \int_{y \in B_\delta} f(y) dy \tag{2.7}$$

- **Robust design Pareto frontiers.** Robust design Pareto frontier techniques [166] aim at determining the set of non-dominated solutions with respect to both the objective function and its variance or standard deviation. The advantage of this method is to enable "a posteriori" decision making. Hence, decision makers can analyze the non-dominated solutions, and based on their judgment, select the alternative that suits

them best. However, such a method works well for single objective problems (one objective and one variance, resulting in a two-dimensional Pareto frontier), but is difficult to exploit in multi-objective problems, with potentially multiple measures of risk as well.

- **Reliability-Based Design Optimization.** Reliability-Based Design Optimization (RBDO) minimizes the objective function while ensuring that certain constraints g_i are not be violated more often than a given probability R_i as displayed in Equation 2.8 [166] and Figure 2.7b. In this equation, f is the objective function and ϵ the set of uncertain variables. Various methods to estimate this probability exist, such as the worst case analysis method [169], the corner space evaluation method [170], and the variation patterns formulation [171]. RBDO can handle multiple uncertain variables, using for example joint probability distribution models [172–175]. However, this method is insufficient as it only ensures reliability. It is limited to the implementation of a set of constraints accounting for uncertainty, and uncertainty does not affect the objective function. Moreover, as long as the probability to exceed the constraint is not too high, the alternative is deemed reliable. It does not try to limit the severity of this excess, for example.

$$
\begin{aligned}
&\min && f(x) \\
&\text{subject to} && P\left(g_i(x, \epsilon) \le 0\right) \le R_i
\end{aligned}
\tag{2.8}
$$

- **Others.** Other authors have adopted less conventional approaches to uncertainty. For example, Frank et al. [31] consider the time dimension of uncertainty in design. Indeed, uncertainty over requirements and some potential market conditions evolve with time, and there is, therefore, an optimal trade-off between potential gains and the safety of waiting, that can lead to support in go/no go decisions. Burgaud et al. [176] relate volatility and profitability, by introducing a systematic way to com-

74

pute a Risk-Adjusted Discount Rate (RADR), used to calculate the NPV as a measure of profitability. In these conditions, higher volatility or higher risk aversion increase the RADR, which in turn reduces the NPV, resulting in the selection of safer concepts when decision makers are risk averse, yet not limiting the potential of a risky but profitable project. However, this application only uses the variance as a measure of risk, and does not account for the multidimensionality of risk.

In this part, the main methods of design under uncertainty were reviewed. First, classic robust design techniques try to jointly minimize the objective function and its variance, by using an aggregate function of the two. Robust design Pareto frontiers, similarly, try to minimize these two objectives, in a multi-objective optimization process, resulting in a two-dimensional Pareto frontier. These two techniques remain limited, in particular when multiple objectives are targeted. Additionally, they both use the variance as a measure of risk. However, while the variance measures well the volatility of objectives, it gives equal importance to the downside and upside deviations. Yet, risk, as previously established, relates to harmful situations. Hence, a decision maker will be more concerned about having lower than expected performance, than extraordinarily high. **Therefore, a measure of the downside deviation is necessary in order to measure uncertainty risk.** RBDO does not use variance, but remains limited as well as reliability is used as a constraint rather than an actual objective. It also only integrates risk as a probability, but not its other aspects. Overall, these three methods, while being promising, only implement different parts of the concept of risk, while excluding others. **A method encompassing all aspects of risk is required.** Finally, the aforementioned methods are compelling, but an "a posteriori" approach to handle uncertainty in a multidisciplinary environment is missing. With current techniques, executives are unable to make risk/value trade-offs. Therefore, a different approach must be developed.

2.2.4 Gap identification

In this subsection, the literature was reviewed to understand how to deal with risk/value trade-offs. As value was already extensively discussed in section 2.1, the definition of risk was studied. Hence, it was established that there were four essential aspects to address about risk: 1) risk describes unfavorable, detrimental or harmful consequences of uncertain events; 2) it is a combination of likelihood and severity of such incidents; 3) risk can also be seen as volatility of targeted objectives; 4) various sources and types of risk have to be accounted for. While aerospace applications have frequently utilized risk in their studies, there were some shortcomings to these approaches:

- Current approaches miss the ambivalence of risk and focus on one aspect of risk (risk as a probability, or risk as volatility, etc.). A method encompassing all aspects of risk is required.

- Most applications only include one type of risk, and there is no method dealing with multidimensional risk (e.g. financial risk, performance risk, safety risk should be jointly minimized).

- When targeting uncertainty, variance is usually the go-to metric. However, variance gives equal importance to the downside and the upside deviation. Risk should give more importance to the detrimental variations, and therefore, a measure of downside deviation is required.

More over, the review of current methods of design under uncertainty also showed that current techniques are not easily suitable for the design of systems with many uncertain objectives. Ultimately, these approaches fall short when being used in the context of multi-objective risk/value optimization. A technique helping consider more uncertain objectives and types of risks is required. Current approaches need to be adapted to provide a way to

handle the risk/value trade-off in a multi-objective environment. Hence, research question 2 is formulated as follows:

> **RESEARCH QUESTION 2:** *How to facilitate sound risk/value decision-making in a multi-objective multi-risk enterprise-level environment during conceptual design?*

The following subsections describe various literature surveys and proposed implementation, to lead to the formulation of a hypothesis to answer research question 2. First, financial approaches to risk and uncertainty are described, in order to get from another field new techniques that could help respond to the research question. Based on this review, these techniques are adapted to match the requirements to answer research question 2. A calculation process is proposed, in order to come up with a multi-objective optimization structure enabling risk/value decision-making. As this process requires the quantification of value uncertainty, the uncertainty propagation process is then described. Finally, the suggested decision support environment proposed to assist decision-makers when making risk/value trade-offs is described. Together, these elements enable the formulation of a hypothesis answer to research question 2.

2.2.5 Financial approaches to risk and uncertainty

The financial theory provides solid foundations for accounting for risk in the valuation of financial assets, such as bonds, stocks, or options, as well as projects or companies. In this subsection, the various methods used in finance will be described and analyzed, as a source of inspiration for potential applications to aircraft design techniques and decision-making. The main ways to account for uncertainty and risk in finance are the following:

- **Net Present Value.** The Net Present Value, also commonly known as the NPV, is a powerful financial tool. The NPV expresses the value of an expected income stream determined as of the date of valuation. The key principle of the NPV is the notion of *time value of money*, which expresses the greater value of present money than

future one. This is due to diverse factors, such as inflation, opportunity costs, or the riskiness of an investment, which induces investors to give higher preference and value to present streams of money. Indeed, money received early can be invested and increase in value later on. The NPV is the sum of the discounted free cash flows, and can be computed as presented in Equation 2.9, where FCF_i are the free cash flows at period i, N is the number of periods the free cash flows are spanning on, and d is the discount rate applied to these free cash flows.

$$NPV = \sum_{i=1}^{N} \frac{FCF_i}{(1+d)^i} \tag{2.9}$$

The power of the NPV does not only stem from the time value of money it integrates. A form of cost of risk is built in the NPV, through the discount rate d. A higher discount rate will represent the greater underlying risk of a project, which in turn will discount future cash flows to a greater extent. This results in a lower value for riskier financial products, projects or companies.

Various theories exist in order to determine the appropriate discount rate for a given risk. Nobel prizes Sharpe [177] and Lintner [178] developed the widely used Capital Asset Pricing Model (CAPM) that relates the market exposure of a company (its risk) with the returns r_e it should produce. The CAPM method is presented in Equation 2.10, where the coefficient "beta" β of the describes the company's market exposure, r_f is the risk-free rate (the rate of return of risk-free investments; usually, U.S. treasury bonds are considered risk-free), $E\left[r_m - r_f\right]$ is the market risk premium, which represents how much more returns investors are expecting from the market compared to risk-free investments due to its riskiness.

$$r_e = r_f + \beta\, E\left[r_m - r_f\right] \tag{2.10}$$

The required rate of return on equity r_e can be used as a discount factor for the NPV calculations within companies consisting only of equity, and provides a good way to account for company-specific risk. Another commonly used discount factor is the Weighted Average Cost of Capital (WACC), which is further described later in this document.

While the CAPM and WACC methods provide good way to account for company-specific risk, they do not allow to account for project-specific risk. Using these methods, two projects with different uncertainties within the same company would be discount in the same fashion. One way to resolve this issue is to use a Risk-Adjusted Discount Rate (RADR). The RADR can account for project-specific risk by including an additional term in its computation [179]. Most techniques to compute the RADR, however, are arbitrary and depend on the subjective judgment of the financial analyst (*"This project sounds risky, it should be a $WACC + 2\%$ discount rate"*). Burgaud et al. [176] suggests a more objective way to compute the RADR, by calculating it as a function of the standard deviation of the IRR of a project. The probability distribution of the IRR is determined by using a modeling and simulation environment which enables the calculation of the life-cycle revenues and costs of an aerospace program. Such a method makes the RADR based on the results of simulation, rather than a gut-feeling estimation. Although the NPV is a compelling tool for valuation, the method sought in research question 2 should be able to handle risk for multiple uncertain outputs. Unfortunately, the NPV approach is not suitable to determine other measures than the valuation and profitability of a company.

- **Modern Portfolio Theory.** The Modern Portfolio Theory (MPT) was developed in 1952 by Nobel prize Harry Markowitz, in "Portfolio Selection" [180]. The MPT is a mean-variance analysis of various financial assets. Markowitz states that an investor should maximize the expected returns of his investment, and minimize its variance. To do so, he suggests the construction of portfolios, which can be designed in a way
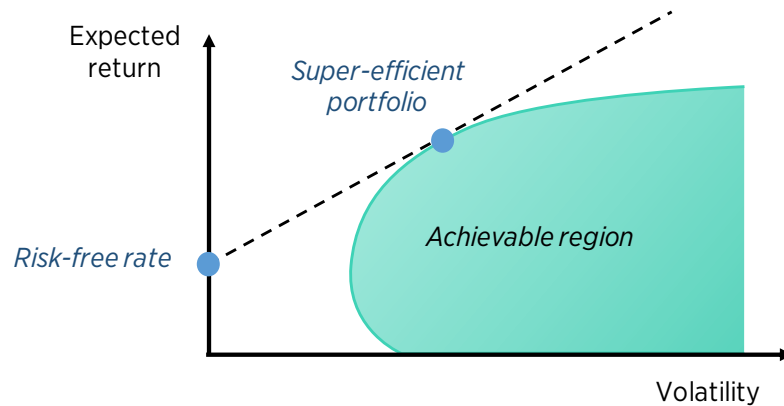
Figure 2.8: Portfolio selection

that maximizes returns for a given conceded risk. The set of optimal expected returns is called the *efficient frontier*. Used as is, it is simply the equivalent of the robust design Pareto frontiers. However, it is possible to leverage the characteristics of financial markets to identify even better portfolios. Given a risk-free asset, it is possible to determine a portfolio that is at the tangent point of a line passing by the risk-free asset, and the efficient frontier (see Figure 2.8). This portfolio is called the *super-efficient portfolio*. The tangent line is known as the Capital Market Line (CML), and represents combinations of the risk-free asset and super-efficient portfolio. The CML Pareto dominates the other portfolios, and therefore, any portfolio should be designed so as to be on the CML. While the MPT is extremely influential in the field of finance, the CML cannot be used for non-financial applications. As for the mean-variance analysis, it is simply a different name for robust design Pareto frontiers.

- **Post-Modern Portfolio Theory.** The Post-Modern Portfolio Theory (PMPT) originated from the work of Sortino et al. [181, 182] and was then used in the literature multiple times [183–186]. The central assertion of the PMPT is that risk should not be evaluated using a two-sided measure such as the variance, because only the downside part of uncertainty is unfavorable. Hence, instead of the variance, it uses a metric

80

called the *downside deviation,* which is the standard deviation of the returns falling under a defined threshold called the minimum acceptable return (MAR). Doing so, it accounts for the fact that investors are generally more concerned with losses than unexpected gains. Once the downside risk is known, the investor trades expected returns against the downside deviation. Although this approach is promising and shows that better risk measures than the standard deviation are available, it requires decision makers to know what is their particular MAR. While this is fairly intuitive for investment, it might become more complicated for potentially aggregated objective functions.
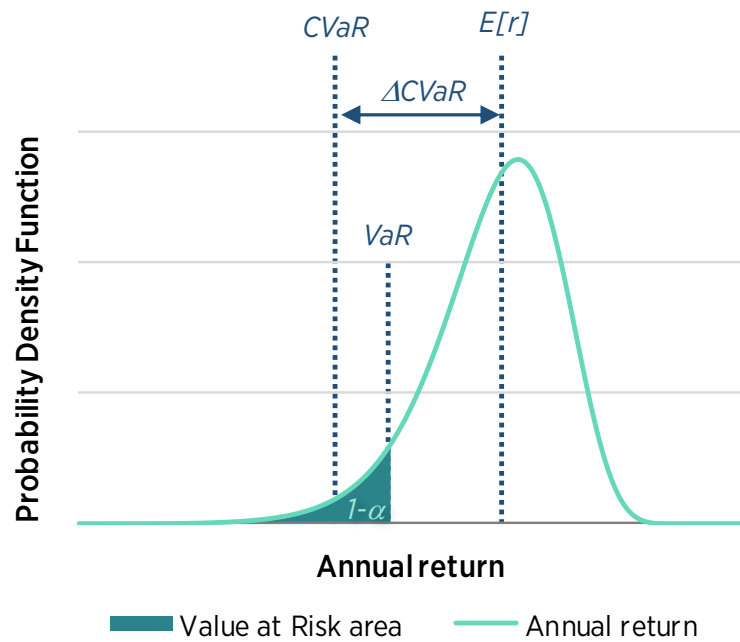
Figure 2.9: Value at Risk and Conditional Value at Risk

- **Value at Risk and Conditional Value at Risk.** The Value at Risk (VaR) and Conditional Value at Risk (CVaR) are other ways to deal with losses risk. Jorion [187] defines the VaR as *"the maximum loss over a target horizon such that there is a low, prespecified probability that the actual loss will be larger."* In more mathematical terms, if α is the probability not to incur such larger loss, and X is the returns'

random variable, $VaR_\alpha(X)$ is the $(1 - \alpha)$-quantile of the returns' probability distribution, and is computed as in Equation 2.11 [187, 188], where f is the probability distribution function of the random returns.

$$VaR_\alpha(X) = \sup \left\{ x \middle| P(X < x) \leq 1 - \alpha \right\} = \sup \left\{ x \middle| \int_{-\infty}^{x} f(x)dx \leq 1 - \alpha \right\}$$
(2.11)

The VaR is a simple way to measure of potential loss under normal market conditions for an investment, or, for design purposes, the lowest potential performance under normal conditions. Yet, VaR has limitations, as, for example, it does not account for any loss that is grater than its value. To overcome this issue, the Conditional Value at Risk (CVaR) was introduced, and used in various portfolio optimization applications [189–191]. The CVaR measures the expected loss an investment can incur, if this loss is larger than the VaR, for continuous functions, as shown in Equation 2.12.

$$CVaR_\alpha(X) = \mathrm{E}\left[X \mid X \leq VaR_\alpha(X)\right] = \int_{-\infty}^{VaR_\alpha(X)} \frac{xf(x)}{1 - \alpha}dx$$
(2.12)

The CVaR is believed to have superior mathematical properties compared to the VaR [192, 193]. It also results in more conservative estimates because it has more emphasis on the worst-case scenarios. CVaR deviation (ΔCVaR) can be used to replace standard deviation as a measure of downside deviation, and can be computed as shown in Equation 2.13.

$$\Delta CVaR_\alpha(X) = \left| CVaR_\alpha(X) - \mathrm{E}[X] \right|$$
(2.13)

The VaR and CVaR only have interest when the distribution of interest is not symmetric. Otherwise, they are proportional to the standard deviation, and as a consequence return the same optimum. Therefore, a first-order uncertainty quantification cannot

be used anymore. A second-order one has to be used to be able to compute the skewness of the distribution. Hence, estimating such variables is more computationally expensive than estimating the variance.

The financial theory evolved from the use of simple variance as a measure of risk, to metrics measuring the downside risk, such as the Post-Modern Portfolio Theory, the VaR, and CVaR. The main drawback of these methods is that they only consider two objectives: the expected returns and a measure of their deviation. They are also limited to one type of risk: the risk of making a loss. However, while many of the techniques presented in this part are hard to apply to non-financial issues, the VaR and CVaR look like promising techniques to be implemented in external fields.

2.2.6 Proposed multi-objective multi-risk environment and process

In order to provide a hypothetical answer to research question 2, and after reviewing multiple techniques, a new process is proposed. First, the objectives pursued by the optimization process have to be defined. After reviewing multi-objective techniques, it was observed that a-priori optimization techniques did not enable decision makers to properly do risk/value trade-offs by comparing and selecting alternatives, as only one optimum was generated. However, it was shown that a-posteriori optimization was not suitable when too many objectives are used.

In order to bridge these shortcomings, an intermediate approach is used. Hence, it is proposed to separate objectives into two categories: risk objectives and value objectives. After doing so, two aggregate functions based on Multi Attribute Utility (for its good fit when using a mix of financial and non-financial objectives) are formulated, around these two categories, enabling the calculation of a *risk score* and a *value score*. Doing so, the multi-objective multi-risk problem is reformulated as shown in Equation 2.14, where the objective is to minimize the risk score $R(x)$ while maximizing the value score $V(x)$, by finding the optimum set of inputs x; V_i is the i-th function component of value, with weight

$w_{v,i}$, while R_j is the j-th function component of risk, with weight $w_{r,j}$; finally, g and h are the inequality and equality constraints applied to the problem.

$$\min_{x} \quad [-V(x), R(x)]$$

$$\text{where} \quad V(x) = \frac{\left[\prod_{i} K_v w_{v,i} V_i(x) + 1\right] - 1}{K_v} \quad and \quad K_v = -1 + \prod_{i} [K_v w_{v,i} + 1]$$

$$R(x) = \frac{\left[\prod_{j} K_r w_{r,j} R_j(x) + 1\right] - 1}{K_r} \quad and \quad K_r = -1 + \prod_{j} [K_r w_{r,j} + 1]$$

$$\text{subject to} \quad g(x) \leq 0$$

$$h(x) = 0$$

$$\tag{2.14}$$

The advantages of such an approach are multiple. Although it concedes to have some a-priori aggregation and objective weight estimation, it maintains the ability to make risk/value trade-offs, by using a two-objective optimization process. As a consequence, a two-dimensional Pareto frontier is generated, which facilitates visualization and avoids the scarce Pareto frontier that would result from a high-dimension set of objectives.

It is interesting to describe in more depth the selection of risk objectives. Indeed, one of the limitations previously stated was that only one measure of risk was usually selected. Hence, several general types of risk can be thought of, although one can add context specific cases as well. In the context of this research, where the objective is to have a relatively finance-oriented approach while keeping design as another key aspect, several types of relevant risk are identified:

- **Financial risk.** As previously said, finance is a key part of this research. As a consequence, it is important to know the risk taken from a financial point of view. This can involve the cost committed to the program, or chances of financial distress.

84

- **Performance risk.** Depending on the realization of some uncertain factors, the overall vehicle performance or program performance can vary, as measured by the probability distribution of value. This represents a risk for the company as value can be lower than expected.

- **Operational risk.** This research deals with the design of vehicles. A major concern for such products is to maintain safe operation of the vehicle.

- **Stakeholder preference risk.** Because of the use of aggregation when defining value, stakeholders need to weigh the value objectives. However, fixing these weights can be complicated, and it is unsure whether they reflect the real stakeholder preferences. As a consequence, it is necessary to estimate the impacts of these weights on value.

Additionally, all types of risks should not be treated equally. Depending on whether risk describes extreme yet unlikely events or small but unavoidable ones, the approach to quantifying risk should not be the same. Yao et al. [194] suggest what approach to follow, depending on the chance of the event happening and the consequences it can have on the system, as shown in Table 2.4. Hence, small perturbations leading to uncertainty in performance require riskiness to be estimated using robustness, as the variability of objectives needs to be assessed. On the other hand, large unlikely events necessitate the measure of reliability. Indeed, such events are usually punctual, and it is more meaningful to measure risk through probabilities, or a combination of likelihood times severity.

Table 2.4: Selection the type of risk [194]

Impact of event	Uncertain event	
	Small perturbation	Extreme event
Performance loss	Robust design optimization	Reliability is not an issue
Catastrophe	No engineering applications	Reliability-based design optimization

While this mapping between type of risk and evaluation method was initially meant as a criterion for selection of the whole optimization method, it can be used in order to pick the appropriate risk metric individually. Moreover, further differentiation can be made based on the knowledge of the risk generating uncertain factors. Figure 2.10 describes the proposed mapping of risk types with their respective risk metrics. Hence, four cases can be enumerated: 1) robustness with known uncertainty; 2) robustness with unknown uncertainty; 3) reliability with known uncertainty; 4) reliability with unknown uncertainty.
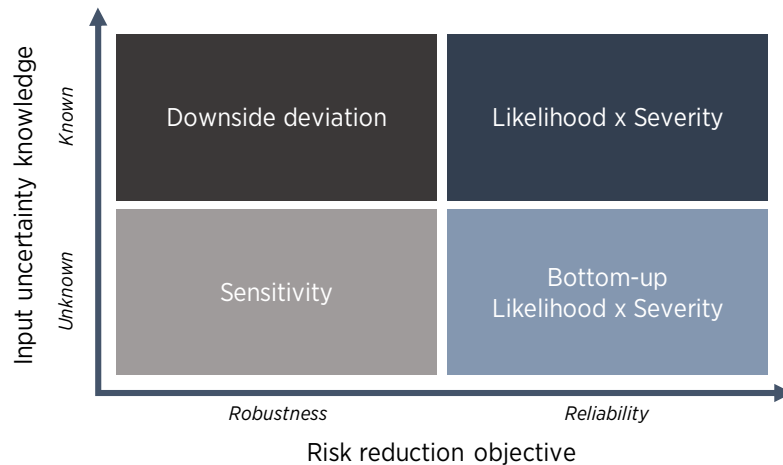
Figure 2.10: Mapping between risk type and risk evaluation metric

These four cases respectively get associated with an appropriate type of risk evaluation metric:

- **Robustness with known uncertainty.** This is the typical robust design case. Uncertain inputs propagate through the model of a system, resulting in uncertain outputs. This uncertainty can then be evaluated, and variance is usually calculated. As it was pointed out previously in this dissertation, variance is a poor measure of risk, and the downside deviation should be computed instead. Hence, the ΔCVaR of one or several outputs is suggested as a measure of downside deviation, as it focuses on the detrimental impact of variability, and does combine the probabilistic and severity aspects of risk, to some extent. Performance risk, for example, could be evaluated with this approach

- **Robustness with unknown uncertainty.** When the uncertainty of certain random factors is not well known, it is then not possible to propagate it through the modeling and simulation environment. This prevents computation of the downside deviation. However, it is still possible to determine to what extent outputs get impacted by potential variations of these factors. To do so, it is recommended to compute the sensitivity of the quantity of interest to these uncertain inputs. Stakeholders' weightings of objectives in the computation of value are uncertain, but their exact probabilistic distribution is unknown. As such, sensitivity to these objectives should be estimated.

- **Reliability with known uncertainty.** This case is close to the reliability-based design optimization scenario, with a punctual event likely to happen once only. However, in RBDO, reliability is used as a constraint, and is only expressed through a probability. The proposed approach suggests using a multiplication of likelihood and severity of the potential event, in order to form a risk factor.

- **Reliability with unknown uncertainty.** In this case, decision makers cannot depend on a known probability in order to determine reliability. They should then, somehow,

rely on some expert judgment, and use a bottom-up approach from subsystems to the overall system in order to gi an estimation of the top-level risk. Doing so, a risk factor is established, although it must be understood as an ordinal value, rather than a cardinal one. Hence, it can be used for comparative purpose, but not to have a precise measure of risk.

In this subsection, various modifications to current approaches regarding computation of risk and the overall optimization problem formulation are proposed, in order to formulate a multi-objective multi-risk optimization process. The major steps of this process are described in Figure 2.11, and are the following:

In order to enable decision-makers to easily make risk/value trade-offs, a new uncertainty propagation structure is set up, as shown in Figure 2.11. Because of the high number of uncertain objectives, Multi-Attribute Utility (MAU) functions are created. The following process is performed:

1. **Target value and risk objectives are identified.** Decision-makers define their quantities of interest, and classify them as risk or value.

2. **Risks are mapped to risk metrics.** As shown previously, different types of risk functions should be depending on the type of risk and uncertainty represented.

3. **Objectives are prioritized by decision makers.** Using expert judgment and the company's strategic vision, executives associate an importance weight to each objective.

4. **Uncertain inputs are modeled.** All different uncertain inputs are assigned a probability distribution.

5. **Uncertain inputs are evaluated by the M&S environment.** The M&S returns uncertain outputs for each evaluated program.
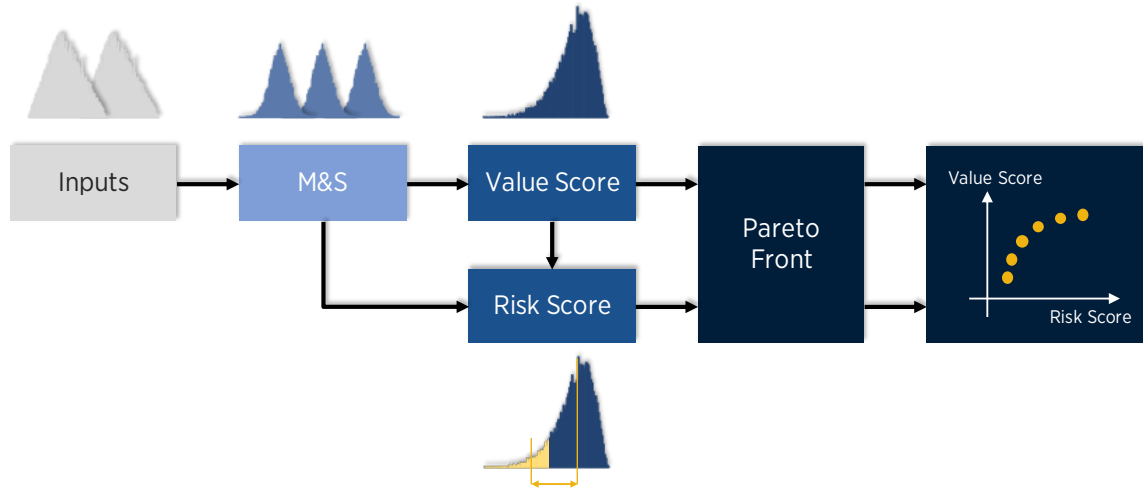
Figure 2.11: Proposed multi-objective multi-risk environment and process

6. **Value objectives are aggregated using a Multi-Attribute Utility.** Using an MAU function, value objectives are aggregated into a value score.

7. **Risk objectives are aggregated using a Multi-Attribute Utility.** Using an MAU function, risk objectives are aggregated into a risk score. The ΔCVaR of the value score can also be required to compute the risk score.

8. **A Pareto frontier is created.** A Pareto frontier is computed, using the value and risk scores as only two dimensions. Because of its low dimensionality, the produced Pareto front can be easily used by decision makers for further trade studies.

The proposed process is believed to be essential to help top managers make risk/value trade-offs in a large multi-objective environment. In order to operate correctly, this process needs an uncertainty quantification and propagation method. In the next subsection, uncertainty propagation techniques are reviewed, leading to a proposed implementation.

2.2.7   Uncertainty propagation structure

In this section, the objective is to help decision makers make informed risk/value trade-offs. To do so, a multi-objective multi-risk optimization environment was proposed in

the previous subsection. In order to be able to provide proper estimations of risk, this environment requires the implementation of an uncertainty propagation and quantification process.

While many uncertainty propagation techniques exist, it is important to remind the context and the constraints applied to the selection of a technique to be used in this research. Complex aerospace systems, and in particular suborbital vehicles, are characterized by the following features:

- **Highly non-linear system.** Complex vehicles are characterized by highly non-linear behavior. Therefore, their integration within an enterprise-level environment is arguably at least as non-linear. The selected technique must be able to handle such aspects.

- **Many infeasible configurations.** Because they are extremely intricate systems, complex aerospace vehicles are difficult to design. As a result, many generated configurations might not be feasible, resulting in the modeling and simulation not to converge. Hence, the proposed uncertainty propagation structure should be robust to such situations.

- **Need at least third central statistical moment.** The uncertainty propagation method should be able to estimate the ΔCVaR. However, when limiting the estimation to the second statistical moment, the approximation is limited to a normal distribution. In this situation, the ΔCVaR is proportional to the variance, which cancels all interest of using a non-symmetric metric to estimate risk. In order to exploit the asymmetry of output distributions, at least the third central statistical moment (proportional to the skewness) needs to be estimated. Moreover, as the evaluation environment is non-linear, there are high chances that results are skewed, which therefore requires a sufficiently precise method to ensure satisfactory accuracy.

- **Multiple case studies.** Decision makers might want to perform several studies in order to know the optimal configuration in different scenarios, which requires fast enough approaches to allow for such studies.

- **Computationally expensive modeling and simulation environment.** As a result of the complexity of the studied system, the modeling and simulation environments developed to design such systems usually require significant execution time. Additionally, in order to propagate uncertainty, replication is needed, making the approach slower than a regular deterministic one. Finally, as such uncertainty propagation has to be used in the context of multi-objective optimization, computation time is further increased. Therefore, the adopted technique needs to be fast enough to allow for proper convergence of the algorithm, within a reasonable time frame.

Given these requirements, the following research question is formulated:

> **RESEARCH QUESTION 2.1:** *How to time-efficiently estimate the downside deviation of value of complex aerospace system programs, in the context of multi-objective optimization?*

Uncertainty propagation method

In order to estimate the downside deviation of value, uncertainty propagation methods have to be implemented. This part reviews the main techniques in use, compares them, and selects the approach that answers research question 2.1 best.

DeLaurentis and Mavris [195] suggest, for example, to pick either from a brute force Monte Carlo sampling used on the M&S environment, the use of surrogate modeling combined with Monte Carlo methods, or the use of Fast Probability Integration directly on the M&S. While these are compelling possibilities for particular applications, other practices exist as well. In order to propagate the different sources of uncertainty through the model, the following methods are available:

91

- **Monte Carlo methods.** Sample the input variables according to their probability distributions, and compute the corresponding outputs. A large sample will result in an approximation of the probability distribution of the outputs. The Monte Carlo methods can be very accurate, and provide the exact output distributions, but require very large samples to do so.

- **Surrogate modeling then Monte Carlo.** In this method, the random inputs are first sampled using a Design of Experiment. The responses are evaluated for the sampled values of the inputs. A surrogate model is then fit, to model their impact. Finally, the inputs are sampled again, using a Monte Carlo method, and evaluated using the surrogate model. The use of a surrogate reduces the need for a large number of function calls, which can be advantageous when the simulation environment is expensive. Polynomial chaos/stochastic collocation is an example of an effective surrogate modeling method for uncertainty quantification [196]. Because the objective functions can be very non-linear and discontinuous, and because there are discrete input variables, a surrogate modeling technique does not seem to be the best solution for this situation.

- **Fast Probability Integration (FPI).** Fast Probability Integration is a set of techniques associated to RBDO, with significant work from Rackwitz and Fiessler [197], and Chen and Lind [198]. FPI methods facilitate the evaluation of the multiple integral used to compute the probability of violating a constraint, by simplifying input variable distributions and the constraint function. The objective of FPI is to find a Most Probable Point (MPP), and the distance from this point to the constraint in the input variable space, using Taylor series to approximate the constraint function. The probability of violating the constraint is then a simple quantile calculation on a normal distribution. Several aerospace applications use FPI [172, 199–201]. FPI is interesting because it makes the computation of multivariate integrals much faster,

compared to Monte Carlo methods, especially to compute low-probability quantiles. However, FPI mostly targets RBDO and not the more general propagation of uncertainty.

- **Fuzzy set theory.** Fuzzy set theory is a mathematical paradigm introduced in 1965 by Zadeh [202] and in 1969 by Goguen [203], where previously deterministic models and problem formulation become uncertain, due to the variability of some of their parameters, or the lack of consensus over their value. To do so, it makes the use of membership functions taking values from 0 to 1, which represent the degree of membership of a parameter to a particular set, as a function of its value. Through a collection of simple algebraic rules, fuzzy set theory enables to propagate uncertainty easily, and estimate, for example, to what degree a linear constraint is violated, fuzzy classification of a system (when it is unsure whether a system is from one category or another, from a definition standpoint), or other useful applications [204, 205]. Applications of fuzzy set theory to aerospace problems range from fuzzy classification [206, 207], to uncertainty propagation in presence of ambiguity and subjectivity [208, 209], and decision making with uncertain preferences [207, 210, 211]. By simplifying problems, fuzzy set theory enables faster analysis of uncertain problems with vagueness. However, the main advantage of fuzzy set theory is when there is a non-binary membership to categories, and therefore, for classification problems.

- **Interval analysis.** The goal of interval analysis is to determine the lower and upper bound of values an output variable can take, in presence of uncertain input [212–214]. To do so, inputs are represented by intervals as well. Interval analysis was initially created to estimate the loss of accuracy due to measurement or rounding-off error; now, it can be used for various topic, where the objective is to simply know the range of variation of variables. As for fuzzy set theory, interval analysis uses a specific set of rules, call interval arithmetic, which facilitates the computation of

93

output intervals. Equations 2.15, 2.16, 2.17, and 2.18 respectively show the interval arithmetic operations for additions, subtraction, multiplications and divisions as an example, where $X = [X_1, X_2]$ and $Y = [Y_1, Y_2]$ are the intervals used for operations.

$$X + Y = [X_1 + Y_1, X_2 + Y_2] \tag{2.15}$$

$$X + Y = [X_1 - Y_1, X_2 - Y_2] \tag{2.16}$$

$$
\begin{aligned}
X \cdot Y = &[\min\left(X_1 \cdot Y_1, X_1 \cdot Y_2, X_2 \cdot Y_1, X_2 \cdot Y_2\right), \\
&\max\left(X_1 \cdot Y_1, X_1 \cdot Y_2, X_2 \cdot Y_1, X_2 \cdot Y_2\right)]
\end{aligned}
\tag{2.17}
$$

$$X \div Y = [X_1, X_2] \cdot [1/Y_2, 1/Y_1] \tag{2.18}$$

Interval analysis has been extensively used in aerospace applications with emphasis on reliability [215–219]. Interval analysis is a computationally efficient, but too simplistic approach for this problem. Moreover, in presence of several input intervals, output intervals tend to grow excessively, making them less meaningful and harder to exploit for decision making. Finally, interval analysis is not suitable for highly non-linear systems such as complex aerospace systems or suborbital vehicles.

- **Method of moments.** The method of moments is a statistical method introduced in 1894 by Karl Pearson [220] aiming at approximating a probability distribution function (frequency curve in the document) by estimating its statistical moments. While various approaches enable to compute statistical moments, Taylor-series-based approaches allow a fast estimation of these, in particular in the context of highly non-linear, computationally expensive codes. Two specific implementations are described

in the following: First Order Second Moment (FOSM) and Second Order Third Moment (SOTM) methods.

First Order Second Moment (FOSM). FOSM methods use the properties of first-order Taylor series to give an approximation of uncertain variables, as shown in Equation 2.19, where y is the variable of interest, σ_y is its standard deviation, x_i the given uncertain variables, and σ_{x_i} are their standard deviations.

$$\sigma_y = \sqrt{\sum_i \left(\frac{\partial y}{\partial x_i}\right)^2 \sigma_{x_i}^2} \tag{2.19}$$

FOSM has been widely used for aerospace applications where only simple approximations of variance were needed [199, 210, 221–223]. Such a method is usually computationally inexpensive, but only returns the variance of the distribution, and makes the assumptions that outputs are normally distributed, and that there are no interaction factors. Although this method might have the lowest computational cost of all, this approach is mostly good for regular robust design, where only the variance is necessary. Indeed, it does not have the capability to compute the skewness of the distribution, which is necessary for the calculation of a downside deviation.

Second Order Third Moment (SOTM) methods are an extension from FOSM, where second-order Taylor series terms are included to improve the accuracy of measurement. In particular, it includes cross derivatives, which enables to account for interaction terms. Examples illustrate this method [224, 225], but it is mostly useful for improved accuracy rather than additional capabilities.

Second Order Third Moment (SOTM). SOTM methods were designed for problems requiring higher order moments than just mean and variance, as in the case of non-normal distributions. They use additional Taylor series terms, which increases the accuracy of statistical estimators and to estimate the response's skewness. These higher order terms also modify the expression of the standard deviation. Standard

deviation and skewness $\gamma_{y,1}$ of y are respectively given in Equation 2.20 and Equation 2.21 [226], in case of normal inputs.

$$\sigma_y = \sqrt{\sum_{i=1}^{N} \left(\frac{\partial y}{\partial x_i}\right)^2 \sigma_{x_i}^2 + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \left(\frac{\partial^2 y}{\partial x_i \partial x_j}\right)^2 \sigma_{x_i}^2 \sigma_{x_j}^2} \tag{2.20}$$

$$\gamma_{y,1} = \frac{\sum_{i=1}^{N} 3 \left(\frac{\partial y}{\partial x_i}\right)^2 \left(\frac{\partial^2 y}{\partial x_i^2}\right) \sigma_{x_i}^4 + \sum_{i=1}^{N} \sum_{j=1}^{N} 6 \left(\frac{\partial y}{\partial x_i}\right) \left(\frac{\partial y}{\partial x_j}\right) \left(\frac{\partial^2 y}{\partial x_i \partial x_j}\right) \sigma_{x_i} \sigma_{x_j}}{\sigma_y^3} \tag{2.21}$$

For generic distributions with independent uncertain inputs, SOTM uses the following equations, where the mean μ_y, the variance σ_y^2, and the skewness γ_y of the output distribution is given as a function of the value $y = f\left(x = (\mu_{x_1}, ..., \mu_{x_N})\right)$ of the output evaluated at the mean of the inputs x_i, and the mean μ_{x_i}, variance $\sigma_{x_i}^2$, skewness γ_{x_i}, and excess kurtosis ϵ_{x_i} of the input distributions [227].

$$\mu_y = y + \frac{1}{2} \sum_{i=1}^{N} \left(\frac{\partial^2 y}{\partial x_i^2}\right) \sigma_{x_i}^2 \tag{2.22}$$

$$\begin{aligned}
\sigma_y^2 = &\sum_{i=1}^{N} \left(\frac{\partial y}{\partial x_i}\right)^2 \sigma_{x_i}^2 + \sum_{i=1}^{N} \left(\frac{\partial y}{\partial x_i}\right) \left(\frac{\partial^2 y}{\partial x_i^2}\right) \sigma_{x_i}^3 \gamma_{x_i} \\
&+ \frac{1}{4} \sum_{i=1}^{N} \left(\frac{\partial^2 y}{\partial x_i^2}\right)^2 \sigma_{x_i}^4 (\epsilon_{x_i} + 2) + \sum_{i<j} \left(\frac{\partial^2 y}{\partial x_i \partial x_j}\right)^2 \sigma_{x_i}^2 \sigma_{x_j}^2
\end{aligned} \tag{2.23}$$

$$\begin{aligned}
\gamma_y = \frac{1}{\sigma_y^3} \Bigg[&\sum_{i=1}^{N} \left(\frac{\partial y}{\partial x_i}\right)^3 \sigma_{x_i}^3 \gamma_{x_i} + \sum_{i=1}^{N} \left(\frac{\partial y}{\partial x_i}\right)^2 \left(\frac{\partial^2 y}{\partial x_i^2}\right) \sigma_{x_i}^4 (\epsilon_{x_i} + 2) \\
&+ \sum_{i<j} \left(\frac{\partial y}{\partial x_i}\right) \left(\frac{\partial y}{\partial x_j}\right) \left(\frac{\partial^2 y}{\partial x_i \partial x_j}\right) \sigma_{x_i}^2 \sigma_{x_j}^2 \Bigg]
\end{aligned} \tag{2.24}$$

SOTM methods are illustrated in several engineering applications, mostly in the field of structural reliability [228–230]. Because of the estimation of the third statistical moment, SOTM methods enable not only an increase in accuracy, but also an increase in capabilities and in the possible range of probability density functions to fit. Because of the presence of a skewness terms, non-normal distributions can be modeled, which enables to differentiate systems with same variances which would have different downside deviations.

In this section, various uncertainty propagation methods were reviewed. Table 2.5 compares the characteristics of such methods. The most common one, the Monte Carlo method, is the most accurate if large enough samples are created. However, in the context of multi-objective optimization, with computationally expensive M&S environment, and knowing that decision makers might want to optimize multiple times in order to try several case studies, such method is not feasible. Simplified methods enable faster computation, although they do not always provide the necessary capabilities. Even when they do, as for SOTM methods, it still requires too much computational time. Rather than using direct optimization on the actual M&S environment, the use of a surrogate model enables to reduce computational time, and is particularly interesting when decision-makers perform multiple optimizations, as most of the cost comes from the training of such model. Yet, using Monte Carlo on it might still be too computationally expensive when trying to assess tail statistics, as required for the ΔCVaR. As a result, it is proposed to use a combination of a surrogate model and an SOTM method, in order to reduce computational time while maintaining the capability of estimating the output's skewness.

In order to implement such a structure, a particular type of surrogate model, suitable for this problem, needs to be selected. Hence, next subsection reviews the main types of surrogate models.

Table 2.5: Comparison of uncertainty propagation methods

	Speed	Accuracy	Downside deviation	Facilitates multiple studies
Monte Carlo		●	●	
Surrogate + MC	◗	◕	●	◕
FPI	◗	◗		
Fuzzy set theory	◗	◔		
Interval analysis	◕			
Method of moments				
FOSM	◗	◔		
SOSM	◔	◗		
SOTM	◔	◕	●	

Surrogate modeling

Previously in this subsection, it was decided to use a surrogate-model-based approach in order to propagate uncertainty through a M&S environment efficiently. However, different types of surrogate models with different characteristics exist, and it is important to review them in order to select the one that suits this problem best.

- **Polynomial response surface model.** The simplest kind of surrogate model is the polynomial response surface, represented by multivariate polynomial equation, as shown in Equation 2.25, where $f(x)$ is the response of the model to inputs $x = (x_i)_i$, with coefficients β_i. x_i are the system inputs or integer power of the system inputs.

$$f(x) = \sum_i \beta_i x_i \tag{2.25}$$

In order to find the least squares estimator for such coefficients (estimators that will minimize the sum of squared error of the model), linear regression is used. As such, the regression coefficients vector β are expressed as in Equation 2.26, where X is a matrix listing the sampled inputs used to train the regression model, and Y is the vector of outputs.

$$\beta = (X^T X)^{-1} X^T Y \tag{2.26}$$

Polynomial response surfaces are simple, and can be very accurate when knowing the terms of a model. However, in this research, the M&S environment is very non-linear, and therefore cannot be efficiently fitted with a polynomial model.

- **Radial basis functions (RBF).** Surrogate models can also use radial basis functions in order to approximate the response of a model. To do so, part or all points of the sample are associated a radial function; i.e. a function whose value depends on the distance to this points. As a consequence, the RBF $f(x)$ is expressed as in Equation 2.27, where w_i are the weight associated to the functions, ϕ is the radial function, and x_i are the points radial functions are associated to.

$$f(x) = \sum_i w_i \phi(\|x - x_i\|) \tag{2.27}$$

RBF networks have the ability to fit non-linear responses due to their structure; however, they need the response to be smooth enough for satisfactory fit [231]. This is a major problem for the problem studied in this research, as the considered variables include discrete or categorical ones, potentially resulting in non-continuous behavior.

- **Kriging.** Kriging, also called Gaussian process regression, is a regression technique using Gaussian processes as constituents. The particularity of this model is that it predicts not only the model's response but also the epistemic uncertainty due to the lack of knowledge between sample points. The farther away a point of the design
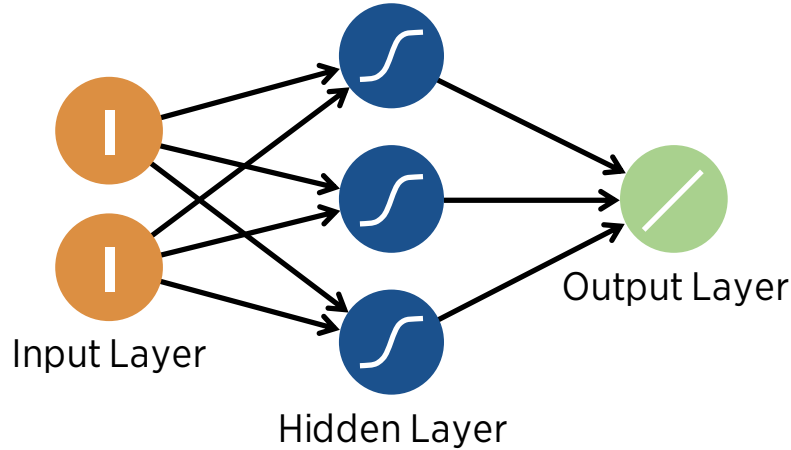
Figure 2.12: One-hidden-layer neural network

space is from the sample points, the greater the error is. Because of its design, Kriging fits non-linear models well and has interesting capabilities. While Kriging is a useful type of regression process, it becomes excessively expensive to train in the presence of a large number of data points.

- **Artificial neural network.** Artificial neural networks are a machine learning technique whose heuristic is inspired by biological brains. Most common implementations are feed-forward neural networks, where information is simply computed sequentially, without feedback processes. Figure 2.12 represents a one-hidden-layer artificial neural network. Neural networks consist of several layers of nodes, each of these nodes being connected to each node of the previous layer. An activation function is used in order with compute the value associated to each node. Most common activation functions are sigmoid (Equation 2.28), hyperbolic tangent (Equation 2.29) and linear (Equation 2.30), where the value $a_i^{(j)}$ of node i in layer j is a linear combination z of the values of upstream layer nodes, as shown in Equation 2.31, with $w_{k,i}^{(j-1)}$ being the weight given to node k of layer $j-1$, and $b^{(j-1)}$ is a constant offset from layer $j-1$.

$$a_i^{(j)} = \frac{1}{1 + e^{-z}} \tag{2.28}$$

$$a_i^{(j)} = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{2.29}$$

$$a_i^{(j)} = z \tag{2.30}$$

$$where \quad z = b^{(j-1)} + \sum_k w_{k,i}^{(j-1)} a_k^{(j-1)} \tag{2.31}$$

The first layer in the network consists of the inputs variables, while the output nodes predict the value of objectives. When neural networks are used for regression purposes, the activation function for the output layer is usually linear. Neural networks are powerful regression tools, which can fit highly non-linear functions, with potentially discrete or categorical input variables. Yet, neural networks are complex tools, which sometimes have a *"black-box"* behavior. There is also little theory over the best structure for the network regarding the number of hidden layers, the number of hidden nodes, or the distribution of residuals. Despite this inherent complexity, artificial neural networks can be very efficient models with impressive predictivity.

The primary surrogate modeling techniques presented here show different features, and different capabilities, as shown in Table 2.6. The simplistic polynomial response surface is good when it is known that the response is polynomial or close in behavior. However, in the case of complex systems as for suborbital vehicle programs, this type of models is not sufficient. As for RBF and Kriging, they bring more compelling capabilities, but also have some limitations. Despite their complexity, artificial neural nets can handle highly non-linear systems, discrete and categorical inputs, and lots of data points. For their great

Table 2.6: Comparison of surrogate modeling methods

	Non-linear	Discrete and categorical variables	Scalable
Polynomial response surface			◗
Radial basis functions	●		●
Kriging	●		
Artificial neural networks	●	●	●

characteristics, ANNs are selected as a regression method. In the next subsection, the different elements of the uncertainty propagation process are put together, and the structure is described.

Proposed process

Previous parts dealt with common uncertainty propagation and surrogate modeling techniques. It was established that these methods could not be used as is, and needed to be implemented in a larger uncertainty propagation frame, in order to handle a complex, highly non-linear M&S environment with many infeasible concepts, provide satisfactory predictivity, compute downside deviation, and be fast enough to be able to deliver these capabilities in the context of several multi-objective optimization scenarios.

In addition to these methods, a classification process is necessary. Indeed, as a surrogate model is used to replace all or part of the disciplines, it becomes unknown whether a particular set of inputs would result in the convergence of the design process or not. Yet, only feasible converged concepts should be accepted. Hence, at the beginning of the process, a classification step is implemented. While many classification techniques exist (logistic regression, k-nearest neighbor, clustering, etc.), an artificial neural network is used for this step as well, as this method is already in use for regression. Moreover, it has, again, good

predictivity performance with highly non-linear systems. **The classification module does not have to do with the uncertainty propagation process. It is made necessary for the overall alternative evaluation process, in order to detect infeasible concepts.**

Finally, the surrogate modeling technique does not have to be applied to the whole M&S environment. Indeed, some analyses have rapid execution times, and do not need to be replaced. Limiting the number of disciplines replaced by surrogate models can help improve the accuracy of predictions, as some error is generated for each of these surrogates. On the other hand, some analyses can be very slow, such as the design discipline. In that case, replacement can be beneficial. Overall, it is necessary to assess which modules are the bottlenecks in the M&S framework, and to replace them adequately.

Following these observations and remarks, a series of steps have to be followed in order to implement the uncertainty propagation process:

- **Identify and define uncertain factors.** In order to propagate uncertainty, the sources of uncertainty must be selected, and their probabilistic distributions must be defined (type of distribution, mean, variance, additional parameters, etc.)

- **Identify computationally expensive disciplines.** Some disciplines might have long execution times (design, usually), while some might be very fast. As only the slow steps should be replaced, it is important to analyze each step's execution time, and to identify those with lengthy computations.

- **Train classification network.** In order to ensure feasibility of the evaluated concepts, a classification network must be used. This requires to train it before integrating it into the M&S environment. To do so, design and business inputs must be sampled along with potential external factors subject to uncertainty or modifications (in case of scenario studies for example), and the feasibility of each alternative assessed. Using a standard backpropagation algorithm, the neural network is trained to minimize cross-entropy.

- **Train regression network.** The outputs of disciplines subject to replacement by surrogate models have to be predicted, requiring to train regression networks. Reusing the same sample as for classification, but reduced to feasible alternatives, the responses of disciplines of interest are predicted. A standard backpropagation algorithm minimizing mean squared error (MSE) is used.

- **Regression on ΔCVaR as function of mean, variance, and skewness.** The value of the ΔCVaR might not have a closed form equation. Therefore, a non-parametric regression can help accurately predict its value as a function of the mean, variance and skewness of the output distribution.

Once these steps performed, the uncertainty propagation process is ready, and uses the following steps, as shown in Figure 2.13:

- Assess feasibility of the design using the classification network.

- Uncertain factors are sampled to allow for calculation of Jacobian and Hessian matrices, which are necessary for the second-order estimates of the mean, variance, and skewness.

- Evaluate each of these uncertain factors alternatives using the M&S environment where costly disciplines have been replaced by regression neural networks.

- Evaluate mean, variance, and skewness through SOTM equations.

- Compute the ΔCVaR based on the three statistical moments.

This subsection attempted to answer research question 2.1, by defining a process that would efficiently estimate the downside deviation of value of complex aerospace system programs, in the context of multi-objective optimization. Using the structure proposed in this part is believed to be a solution to this research question. As a consequence, hypothesis 2.1 is formulated as such:
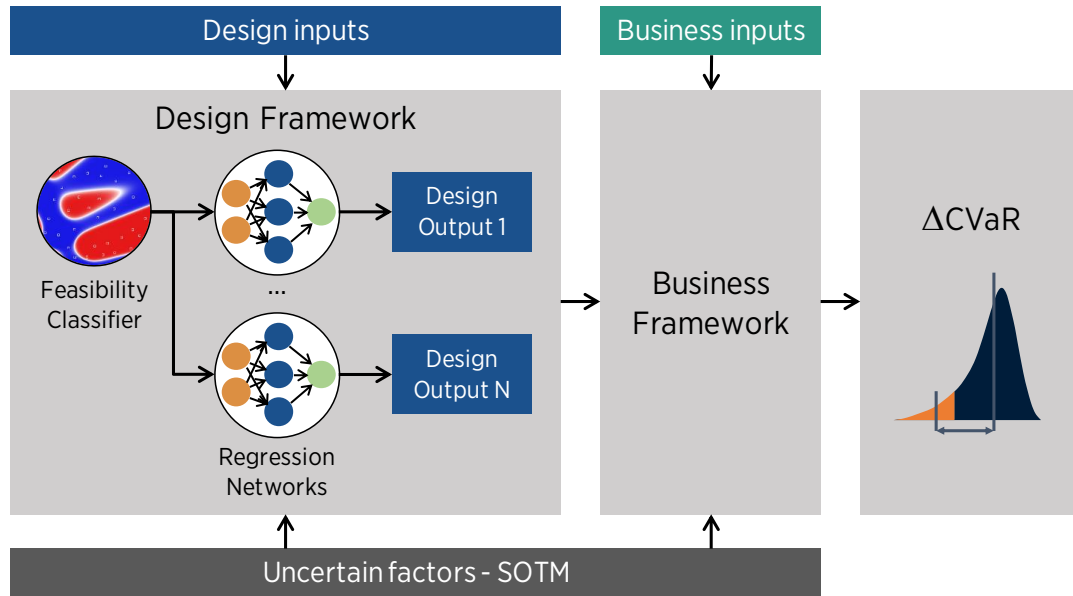
Figure 2.13: Uncertainty propagation process with surrogate modeling

> **HYPOTHESIS 2.1:** *IF a process using SOTM uncertainty propagation on classification and regression networks is implemented THEN the downside deviation of value of complex aerospace system programs can be estimated in a timely manner, in the context of multi-objective optimization.*

In order to verify hypothesis 2.1, an experiment must be carried out. Each main element of the research question must be checked:

- **Capable of computing the ΔCVaR.** The proposed process is implemented with the goal to compute the downside deviation, and should, therefore, be able to do so.

- **Usable in multi-objective optimization.** In order to be usable in the context of multi-objective optimization, the process must be fully automated, and provide the downside deviation with sufficient accuracy. It must also be capable of propagating uncertainty while providing all other objectives of the M&S environment. As such, the M&S program should be operated just as if no alteration had been made, also requiring sufficient accuracy of the regression networks.

105

- **Time-efficient.** The proposed process should be efficient. In particular, it should be fast enough so that it can enable proper convergence of multi-objective optimization algorithms within a reasonable time frame.

Considering these aspects, the following verification criteria are created:

VERIFICATION CRITERION 2.2.1: The proposed process provides a measure of the ΔCVaR of value with at most 10% mean squared error.

VERIFICATION CRITERION 2.2.2: The multi-objective optimization process is completely automated.

VERIFICATION CRITERION 2.2.3: The regression networks' mean squared error is at most 10%.

VERIFICATION CRITERION 2.2.4: The classification network's misclassification error is at most 10%.

VERIFICATION CRITERION 2.2.5: A multi-objective optimization converges in at most 10 minutes.

2.2.8   Decision support environment

In order to best answer research question 2, a decision support environment is also developed. Several features need to be implemented in order to fulfill the requirements established in subsection 2.2.1:

- **Rapid trade-offs enabled.** Because of its integrative structure, the decision support environment allows for very quick analysis, trade-offs, and decision-making. Depending on the user's preferences, the Pareto frontier is calculated and visualized.

- **Exhaustive description of each program.** The environment does not only provide the Pareto frontier of optimal programs, but it also displays a more in-depth description of the selected program (vehicle-level and program-level parameters) by simply selecting a point on the Pareto frontier.

- **Supplementary graphs and analyses.** In addition to the results of the calculations from the M&S, the decision support environment provides supplementary analyses and plots, such as cash flow projections, life-cycle costs breakdown, etc.) These extra analyses help the decision makers understanding the selected program in further details.

Hypothesis 2

In this subsection, the three main parts of the proposed implementation to answer research question 2 were described. Part 2.2.7 described the structure of the overall calculation, from uncertainty propagation to MAU functions and resulting Pareto frontiers, using the value score and risk score as its two dimensions. Part 2.2.7 described the uncertainty propagation techniques used to analyze the uncertain outputs of the modeling and simulation environment, and defined that a second-order uncertainty propagation model was the most appropriate one. Finally, part 2.2.8 described the proposed decision support environment which is used to assist decision-makers when trading risk against value. Put together, these parts lead to the formulation of hypothesis 2:

> *HYPOTHESIS 2: IF uncertain strategic objectives are combined into risk and value scores using stochastic Multi-Attribute Utility functions AND IF and if an SOTM uncertainty propagation technique is used to efficiently estimate downside deviation AND IF an integrated trade-off environment facilitating programs ranking and visualization is used THEN strategic leaders can easily make sound risk/value trade-offs in an uncertain multi-objective enterprise-level environment in conceptual design.*

2.2.9   Experiment 2

In order to verify the hypothesis to research question 2, experiment 2 is created. The experiment consists in using the uncertainty propagation framework and the decision support

environment to make decisions, as well as verifying the main aspects of the research question:

- **Uncertain.** Does the decision-making process include uncertainty? The developed environment should be able to propagate uncertainty, and provide accurate enough measures of the uncertainty of the various outputs. To verify this property, a few programs can be evaluated using the second-order model, and compared to the reference represented by the Monte Carlo process. Although the Monte Carlo process would be too expensive to use in the context of optimization, it is here acceptable to have a longer computational time to provide validation data for the uncertainty propagation process.

- **Easy-to-use and multi-objective.** How easy is it to make decisions using the designed environment, while considering many objectives? On of the key requirements of this section is to be able to make decision in large, uncertain multi-objective environments. A verification test involving multiple (and more than 3) objectives should be carried out.

- **Enables trade-offs.** Is the process resulting in enough potential solutions to permit trade-offs? The proposed process should result in enough candidate points to create a Pareto frontier from which decision makers can trade risk and value.

- **Sound/relevant.** Is decision-making based on most of the crucial program information? Does the supporting environment enable their visualization? In order for executives and designers to make sound decisions, they cannot only rely on the simple aggregate scores of the selected programs. They also need additional analyses and visualizations which will help them get better understanding of the individual programs. Such analyses can include cash flow projections, life-cycle costs breakdowns, visualization of the Pareto frontier with additional categorical information

(type of propellant, number of passengers, etc.), or probability distributions of the output variables.

If the decision support environment includes all these features, hypothesis 2 will be deemed verified. The verification of these characteristics is carried out through the formulation of five verification criteria:

> ***VERIFICATION CRITERION 2.1:*** *Selecting a program with more than 3 objectives takes less than 15 minutes using the decision support tool.*

> ***VERIFICATION CRITERION 2.2:*** *Multiple program and vehicle analyses or visualizations are integrated.*

> ***VERIFICATION CRITERION 2.3:*** *Decision makers can choose among multiple optima.*

> ***VERIFICATION CRITERION 2.4:*** *Downside uncertainty is taken into account in the decision-making process.*

> ***VERIFICATION CRITERION 2.5:*** *The optimization process can handle more than one risk and one value objectives.*

Upon verification of these verification criteria, the hypothetical answer to research question 2 will be deemed checked.

CHAPTER 3

PROPOSED APPROACH

This research aims at establishing a business-driven methodology that enables strategic executives to make sound risk/value trade-offs at a conceptual level in an uncertain multi-objective environment and to capture more value from aerospace development programs. The adopted approach follows the generic top-down design decision support process, shown in Figure 3.1.

Establish the need	Treated in chapter 1
Define the problem	Treated in chapter 2
Establish value	Step 1 - Described in section 3.2
Generate alternatives	Step 2 - Described in section 3.3
Evaluate alternatives	Step 3 - Described in section 3.4
Make decisions	Step 4 - Described in section 3.5
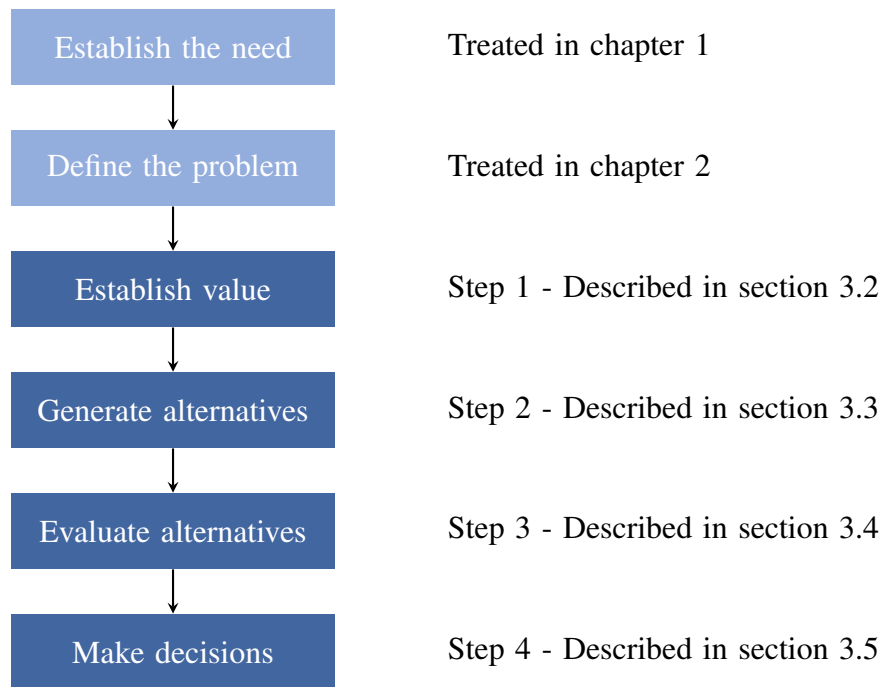
Figure 3.1: Proposed approach

The first two steps of this approach were already addressed in the motivation and problem definition chapters. Chapter 1 established a need, which was formalized through the statement of three key assertions, plus one assertion specific to suborbital vehicle programs:

1. Because large aerospace programs are extremely risky and characterized by various sources of uncertainty, decision makers need to be supported by a business-driven stochastic framework in order to ensure success, with particular attention to financial aspects.

2. Key decision makers must be assisted in their strategy formulation by a large multi-objective environment supported by additional business metrics and analyses.

3. Business disciplines need to be modeled in an enterprise-level environment during conceptual design in order to ensure collaboration between the company's businesses and to avoid sub-optimal solutions.

4. The suborbital vehicle industry is recent and characterized by a lack of historical data and standards. As a consequence, there is a need for a detailed analytical approach, with a strong emphasis on risk/uncertainty and finance.

These assertions identified key capabilities decision makers need in order to maximize their success when considering new aerospace programs. These assertions led to the formulation of the research objective: *To establish a methodology that enables informed enterprise-level decision-making under uncertainty and provides higher-value compromise solutions.* Chapter 2 identified shortcomings in current methods, which could not provide the required capabilities to fulfill the research objective. Once the problem identified, three research questions were expressed:

1. Does the adoption of an enterprise-level optimization approach during conceptual design help executives capture more value from aerospace programs and lead to significantly different decision-making?

2. How to facilitate sound risk/value decision-making in a multi-objective multi-risk enterprise-level environment during conceptual design?

3. How to time-efficiently estimate the downside deviation of value of complex aerospace system programs, in the context of multi-objective optimization?

Given these research questions, hypothetical answers were formulated, and experiments were designed in order to provide a formal way to verify the hypotheses. This chapter proposes a methodology to address the previously established research questions. In order to develop the methodology, a testbed is required. Therefore, a case study is formulated and implemented, as an instantiation of the proposed methodology: the optimization of a suborbital vehicle program, where the company designs and operates the vehicle. This methodology follows the last four steps of the generic top-down design decision support process and adapts them to provide the required features. Hence, this chapter is articulated around the description of the stages of the method. Section 3.2 explains the first step, which is the selection of the evaluation criteria, and constraints of interest. Section 3.3 presents step 2 and describes the definition of the design space for the optimization of aerospace programs. Section 3.4 describes step 3; it presents the modeling and simulation environment which was developed and used in this research. Additionally, surrogate models are used to speed up M&S computation are trained. Section 3.5, finally, details step 4, and how the decision making process is carried out. The following sections describe the each step of the methodology in a generic way, then its particular implementation for the case study. Before describing the methodology's stages, a brief description of the study case is provided in section 3.1.

3.1 Study case

In order to demonstrate the capabilities of the method to be established, the methodology is applied to various scenarios of suborbital vehicle programs, as motivated by Chapter 1. These scenarios should provide a quantitative way to measure profitability, as well as the availability of multiple other potential objectives, whether they are financial or not. They should also be exposed to significant sources of uncertainty. Finally, they should provide a

Figure 3.2: Modeled value chain for suborbital vehicle programs

sufficiently large decision space, that will require from strategic executives to make trade-offs. All scenarios involve a notional company in charge of developing, manufacturing and operating a suborbital vehicle, as represented by its value chain in Figure 3.2. The scenarios start with an initial design phase, when the company sees substantial costs and no revenue, followed by a production and operation phase. The project life cycle is set to 20 years. The designed vehicle has to carry a given number of passengers and their pilots (if any) to suborbital space: around 100 km depending on regulations and requirements. Decision makers have to select a vehicle architecture, design parameters, as well as production quantities, ticket pricing, and financial metrics, in order to optimize their objectives of interest. Production and prices can be changed a few times during the life-cycle of the program. Additionally, as suborbital tourism is not an established field, no standard architecture emerged from the feasible ones. Hence, several architectures have to be considered. These architectures do not have the same design inputs, and therefore, an appropriate design space structure needs to be adopted.

Scenario variations can include differences in external factors (more or less uncertainty, more or less average demand, stable or increasing demand, external funding or not, cost of fuel, regulations, risk-free interest rate, etc.), stakeholder preferences in terms of risk and value scores and/or risk aversion factor, and targeted objectives.

3.2 Step 1: Selection of the decision criteria

This first step aims at defining the list of decision criteria of the optimization, which will be used to evaluate and rank alternatives, as well as the constraints restraining the problem. The main decision criteria are the risk score and value score, which are used as objective functions in the optimization process. They are aggregates of various attributes of the program which characterizes its value or quality, and risk. As a consequence, indirectly, the variables used for the computation of such scores are decision criteria as well. As stated in subsection 1.2.3, these decision criteria should be representative of the set of main strategies a company could be trying to pursue. Therefore, the modeling and simulation environment later described has to be able to produce such outputs. These could include data about the vehicle's performance, the program profitability, or even environmental aspects. The overall strategy can be a mix of each of the identified strategies, and therefore, these variables are accordingly weighted in the creation of the risk and value scores.

Similarly, the components of the risk score are multiple and based on the main sources of risk that a complex aerospace program can face, such as performance risk, value risk, financial risk, operational risk, or stakeholders uncertainty. These types of risk should be treated as described in subsection 2.2.6 and mapped to a relevant risk evaluation metric.

Constraints also have to be set up to limit the set of programs to those producing acceptable outcomes according to various criteria. Constraints may stem, for example, from regulations, customer requirements, or from stakeholders' requirements in general. These could apply to levels of safety, volume per passenger, allowable acceleration, etc.

Before studying the particular implementation of step 1 to suborbital vehicles in subsection 3.2.2, it is useful to remind the reader of common financial techniques to assist in capital budgeting and assess profitability. Hence, subsection 3.2.1 describes some of the most popular financial metrics.

3.2.1 Popular financial metrics

The financial techniques presented in this section are used for different steps of the methodology. First, it is important to remind the reader of the main financial techniques used to determine the profitability of a project. Whereas subsection 2.2.5 reviewed financial techniques to trade risk and return, this subsection reviews profitability metrics. A few parameters regularly come up in most capital budgeting studies: the NPV, the IRR, the payback period, the gross margin and the net profit margin.

- **Net Present Value (NPV).** The NPV was already described earlier in this document (section 2.2.5). It is the method most frequently used by managers to perform project valuation and make investment decisions. Even Warren Buffet, the famous investor, uses it to evaluate the companies he has interest in [232].

- **Internal Rate of Return (IRR).** The Internal Rate of Return or IRR is a fundamental alternative (and complement) to the NPV. It approximates the rate of growth a project is predicted to generate. On a calculation point of view, the IRR is the value of the discount rate that cancels the NPV. There is great interest in the use of the IRR. The main benefit is that it does not depend on any interest rate for its calculation, making it a much more objective measure than the NPV. It is also intuitive, accounts for time value of money, and provides managers with a normalized figure to compare different projects. There are however several shortcomings to the IRR. In particular, it is possible to find multiple values of the IRR for one single project for some non-conventional cash flows. The fact that the IRR is a relative value can be problematic too. Is a project that costs $10 and returns $20 in one year (100% IRR) better than a project that costs $10,000 and returns $12,000 in one year (20% IRR)?

- **Payback Period.** The payback period is the number of periods it takes to cover an investment. In other words, how long does it take before making profits? The simplicity to understand this criterion is its main advantage. It is also straightforward

to compute. However, it is presenting some significant limitations. In particular, it does not account for the time value of money, and it ignores the cash flows occurring after the cutoff date.

- Other techniques such as the EVA, Market Value Added (MVA), discounted payback, and Modified Internal Rate of Return (MIRR) can also be considered, but are not as common as the previously presented methods.

It is interesting to observe the most commonly used financial parameters when trying to make investment decisions. As time went by, the most frequently used tools have evolved. While the payback period was highly popular in the 60s and 70s [233, 234], companies have increased their interest in NPV in more recent years, and NPV has become the most used figure for capital budgeting [235, 236].

Two other metrics, unrelated to capital budgeting but used to measure the financial performance of a company, are used in this section: gross margin and net profit margin. These measures are useful, in order to differentiate companies such as Walmart, generating large profits, at the expense of margins, and companies such as Apple, producing great profits as well, but with lower revenue and higher margins.

- **Gross margin.** Gross margin expresses the company's gross profits in relative value. The gross profits are the difference between the company's total sales revenue and its Cost Of Good Sold (COGS). The gross margin represents how much money remains after selling a product or service and incurring its direct costs. Gross margin can be expressed as in Equation 3.1.

$$Gross\ margin = \frac{Gross\ profits}{Revenue} = \frac{Revenue - COGS}{Revenue} \tag{3.1}$$

- **Net profit margin.** Net profit margin expresses the company's net profits in relative value, where the net profits are the revenues, minus COGS, operating expenses, interest, and taxes. In other words, the net profit margins represent what percentage of

revenues remains and is converted into profits after all costs are deducted. Net profit margin can be expressed as in Equation 3.2.

$$Net\ profit\ margin = \frac{Net\ profits}{Revenue} \tag{3.2}$$

This subsection aimed at defining some of the most commonly utilized financial metrics, which are also used in the next subsection. The particular application of step 1 to the studied scenarios is presented in the following subsections. Subsection 3.2.2 defines the value and risk variables of interest for suborbital vehicle programs, as well as the limiting constraints.

3.2.2 Case study implementation

This subsection details the different decision criteria and constraints used for the suborbital vehicle program scenario. As just mentioned, the decision criteria need to be related to the list of identified potential strategies. Table 3.1 lists the output variables associated with each strategy which are used in the creation of value scores. This scenario allows the study of strategies such as profit maximization, margin maximization, demand maximization, product differentiation through performance and comfort, or even triple bottom line objectives, for example by providing the pilots with a higher wage.

Table 3.1: Decision criteria per strategy for suborbital tourism programs

Strategy	Associated variables
Maximize profits	Program NPV
Increase margins	Gross margin, net profit margin, program IRR
Growth/Demand	Total demand
Product differentiation	Weightlessness time, volume per passenger
Triple bottom line	Pilot salaries

Risk also needs to be taken into account to compute a risk score. As suggested before, four primary sources of risk are considered: value risk (lower value than expected), financial risk, operational risk, and uncertainty over decision makers' preferences. These risks are then mapped to a risk evaluation metric, following the method proposed in subsection 2.2.6. Hence, Table 3.2 describes these sources of risks and provides their risk evaluation metrics. Value risk is represented a downside deviation measure: the ΔCVaR of the value score. Financial risk measures the risk of financial distress for the company. As financial distress is a punctual event, it is measured as a Likelihood x Severity approach. In the case of this study, severity can be seen as the potential amount invested lost due to distress, while likelihood is simply the probability of distress. As such, the financial risk level R_F can be computed as in Equation 3.3, where P$[FD]$ is the probability of financial distress (computation is given in subsection 3.4.8), and the sunk cost is defined as the minimum of cumulative cash flow.

$$R_F = P[FD].SunkCost \tag{3.3}$$

Table 3.2: Risk type and risk evaluation metrics used in the risk score

Value risk	Risk type	Small perturbations, known distribution
	Metric type	Downside deviation
	Metric used	ΔCVaR of value score
Financial risk	Risk type	Punctual event, known distribution
	Metric type	Likelihood x Severity
	Metric used	P[Financial distress] x sunk cost
Operational risk	Risk type	Punctual event, unknown distribution
	Metric type	Bottom-up Likelihood x Severity
	Metric used	Operational risk level (see section 3.4.4)
Preference risk	Risk type	Small perturbations, unknown distribution
	Metric type	Sensitivity
	Metric used	Sensitivity of value score to value weights

Operational risk aims at measuring the risk of incidents during flight. As likelihood and severity are not directly known, the operational risk level is calculated following a bottom-up approach, starting from subsystems. The calculation of this risk is further detailed in section 3.4.

Finally, preference risk, translating the uncertainty over stakeholders' preferences, is also measured. As it is more of a vague uncertainty, with no known distribution, this risk is measured through sensitivity analysis. Hence, the sensitivity $S_{w_{v,i}}^{V}$ of value V to the weight $w_{v,i}$ of i-th function component of value is given in Equation 3.4, where ΔV is the change in value when subject to a change $\Delta w_{v,i}$ in the i-th weight, and V_{ref} is a reference value for

the value score, constant for all sensitivity calculations.

$$S_{w_{v,i}}^{V} = \lim_{dx \to 0} \frac{dV/V_{ref}}{dw_{v,i}/w_{v,i}} \simeq \frac{\Delta V/V_{ref}}{\Delta w_{v,i}/w_{v,i}} \quad \text{where} \quad \Delta w_{v,i} \ll 1 \tag{3.4}$$

It should be noticed that as the sum of weights should be one, other weights are impacted and should be rebalanced. It is assumed that these weights evolve proportionally to their own value. As a consequence, the variations $\Delta w_{v,j}$ of other weights $w_{v,j}$ is given in Equation 3.5.

$$\Delta w_{v,j} = \left[\frac{-\Delta w_{v,i}}{\sum_{k \neq i} w_{v,k}} \right] w_{v,j} \tag{3.5}$$

Constraints are also to be modeled. Because of the breadth of the proposed model, various types of constraints can be accounted for, as presented in Table 3.3. Performance constraints will ensure that the spacecraft goes high enough (100 km, the limit of space) and provides enough weightlessness time to make the product attractive. Although weightlessness time is also an objective, the constraint ensures sufficient weightlessness experience for passengers even when decision makers do not put any weight on this decision criteria. The volume per passenger also enforces adequate comfort and user experience. Finally, as investors do not have unlimited means, the sunk cost of the program, which corresponds somehow to the amount of debt and equity used to fund the company in charge of the program, is limited to a large, but acceptable amount of money.

Table 3.3: Constraints and their values for suborbital tourism programs

Constrained variable	Constraint value
Weightlessness time	3 min
Altitude	100 km
Volume per passenger	1.5 m^3
Total cabin length	10 m
Sunk cost	$4 billion

3.3   Step 2: Input space definition

Defining the design space means here defining the complete set of feasible alternatives that can be used for further analysis and optimization. While a large number of concepts can be thought of, the process described in subsection 3.3.1 helps structure the non-trivial design space where multiple architectures are considered, each holding a different set of input variables. In this section, required features of the alternative generation method are first listed. A quick survey of existing alternative generation techniques is then provided to identify the method most adapted to this problem. Finally, the particular implementation is given.

3.3.1   Alternative generation

Required method features

This subsection is based on one observation: an environment is needed that enables the easy generation of feasible and relevant program alternatives. To achieve such capabilities, the proposed solution needs to encompass several key features. The required critical characteristics of the suggested method are listed as follows:

- **Generate alternatives at a program level.** The most important feature that the proposed method should include is the ability to generate alternatives both at a program level and vehicle level. While the generation of alternatives at a vehicle level is already fairly common, the proposed approach should be able to include this additional layer, which entails the ability to include a few subfeatures:

  - **Allow for multiple vehicle types, with different sets of sizing parameters.** The design space of feasible programs comprises many different potential vehicle architectures. The challenge to produce a design space with such capabilities resides in the difference between the sets of sizing parameters for different architectures. This results in complex design spaces, and a method capable of generating them is required.

  - **Consider additional business-related features.** Programs do involve not only design studies, but also various business disciplines. The proposed method should be able to consider them and generate program alternatives with different sets of business-related variables. This implies departing from methods aiming at generating combinations of physical attributes, to methods generating physical and intangible attributes.

- **Be quick and simple to use.** As top executives, probably involved in different aspects of the project, and not necessarily familiar with the intricacies of the various model implementations used for the decision-support process, decision makers need to be provided with a method which is simple to use and does not require extensive prior knowledge of the underlying techniques. Additionally, their time is precious, and therefore, any proposed method should be fast to execute.

Current alternative generation methods

To determine if a particular method can fulfill the aforementioned requirements, an extensive literature search on alternative generation is performed. The main techniques are analyzed and evaluated according to the formulated specifications. The detailed description of each method is provided in appendix A. Many techniques are meant to supply a designer or a team of designers with a quick process to generate a few alternatives, based on brainstorming and use of historical solutions. 6-3-5 method [237], design catalogs [238, 239], chi-matrix [240, 241], TRIZ [242, 243], and A-design [244] are examples of this type of approach. They do not provide exhaustive lists of alternatives and hard to automate. Decision trees [245], as they provide a more structured process, are easier to automate. However, each branch of the tree must be defined, which limits the number of alternatives it can generate. Morphological matrices [246, 247] and IRMA [248] provide both exhaustiveness and easiness to automate. They can however only perform single-level alternative generation. M-IRMA [249, 250], an evolution of IRMA, incorporates enables some multi-level mapping of subcomponents, while keeping the advantages of the morphological matrices and IRMA.

Based on these observations (summarized in Table 3.4), it appears that the M-IRMA method seems to be the closest to the expected capabilities of the required alternative generation process. The process should, for example, contain a system decomposition, a constraint check, and a multi-level structure. Yet, the M-IRMA is not completely suitable because it is too complex, and the scoring process can be nonobjective for non-mature systems, as little knowledge has been acquired and it is hard to rate alternatives before evaluating them. Moreover, it was designed for MAST, rather than complex aerospace programs. For example, in order to adequately define an aerospace program, some vehicle alternatives should be available. Such alternatives should also have their own morphological matrices of alternatives to define their sub-level design spaces, but M-IRMA does not

Table 3.4: Comparison of existing alternative generation methods

	Exhaustive	Easy to automate	Objective	Multi-level
6-3-5 Method	◔	◔	◑	
Design catalog	◑	◔	◕	
Chi-matrix	◑	◔	◕	
TRIZ	◔	◔	◑	
Decision tree	◑	◑	◑	◔
A-design	◑	◔	◕	
Morphological matrix	●	●	●	
IRMA	●	◑	◕	
M-IRMA	●	◔	◕	◑

allow for such structure. This method should then be adapted and enhanced in order to fulfill the formulated specifications.

Proposed method

Previously in this subsection, Subsection 3.3.1 the different methods currently in use for the generation of alternatives were shown. They were evaluated according to several criteria to determine which method could fulfill the previously established requirements to generate program alternatives. However, no method was suitable for aerospace programs. Yet, the M-IRMA technique was promising and can be adapted and improved to satisfy the formulated specifications. This subsection proposes a process that will provide the necessary capabilities. This process follows four key steps: 1) bi-level decomposition of the program and vehicle; 2) creation of a morphological matrix tree structure; 3) compatibility check
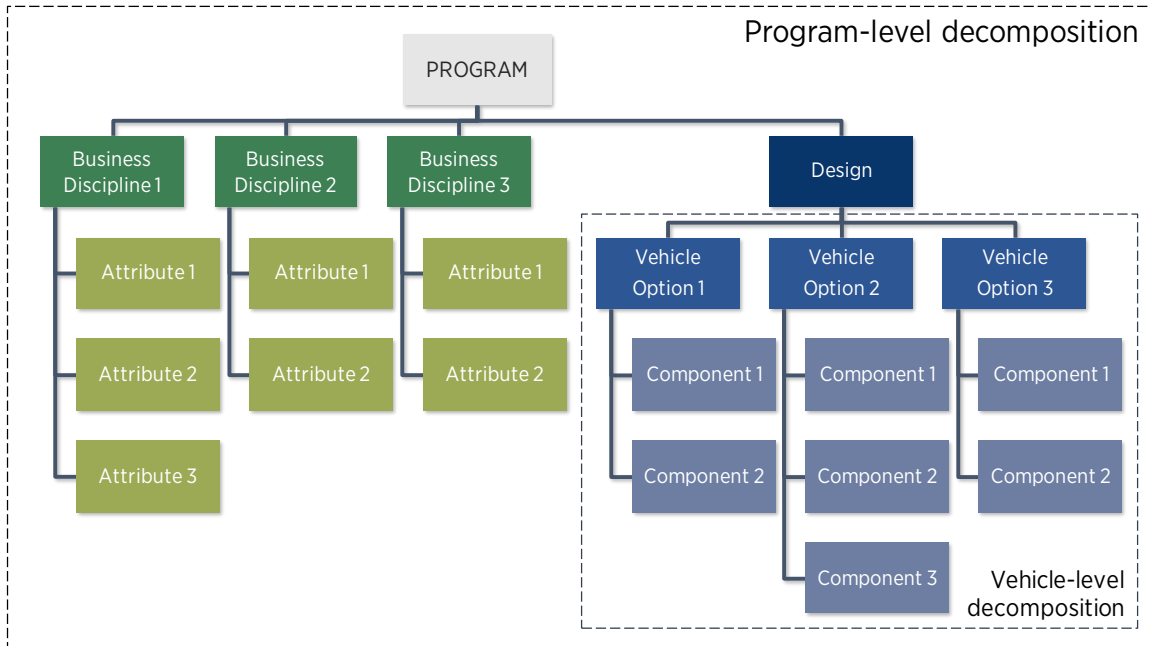
Figure 3.3: Program-level and vehicle-level decomposition

and filtering; 4) generate alternatives based on the setup structure. These steps are detailed in greater details as follows:

1. **Bi-level decomposition.** To appropriately define an aerospace program, a two-level decomposition should be performed initially. The program is first broken down into enterprise-level features, which describe various tangible and intangible features of the program. In this case, the program is decomposed into non-design business disciplines, which themselves carry a series of attributes, but also the design discipline which contains various vehicle options. The second decomposition in this process is the vehicle-level one. Each vehicle option is further broken down into design features and components, as it is usually done for the regular morphological analysis. Figure 3.3 illustrates the two levels of decomposition considered in this step.
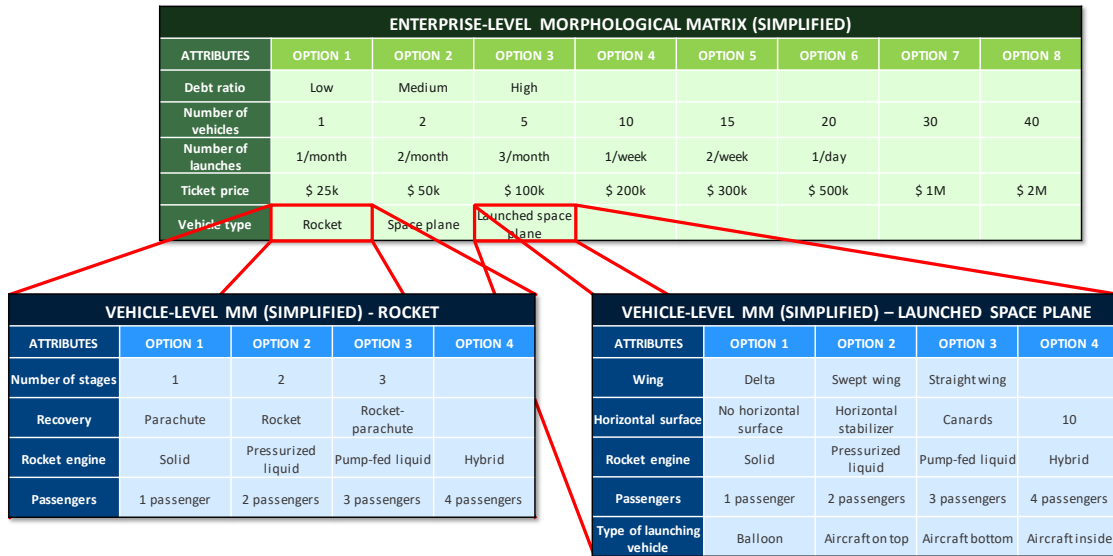
Figure 3.4: Example tree of morphological matrices

2. **Tree of morphological matrices.** The objective of this part of the method is to start defining the contours of the design space for aerospace programs. To do so, it is necessary to have a multi-dimensional structure, unlike the one-dimensional morphological matrices or IRMA. A different structure is then proposed, and based on step 1's two-level decomposition of the program. The idea of this step is to create a two-level tree of morphological matrices. The first level is a program-level morphological matrix. It contains the options for the various non-design business features, as well as the considered vehicle options. The second level includes the vehicle-level morphological matrices. Each type of vehicle is linked to its own vehicle-level morphological matrix, which contains options for various components and features of the aircraft. Because of this kind of structure and branching, it enables considering different types of vehicles, with different components, and therefore different morphological matrices. Figure 3.4 shows a simplified example of morphological matrix tree, for a suborbital vehicle program, where a suborbital spacecraft is designed then operated. Program-level features include characteristics such as ticket pricing, number of vehicles to be assembled, but also the type of spacecraft (rocket, independent

space plane, launched space plane, etc.) Each type of spacecraft is linked to its specific vehicle-level morphological matrix, as they may not be characterized by the same components. For example, it is essential to determine what type of vehicle would carry a launched space plane, while it is not applicable for a rocket.

3. **Compatibility check and filtering.** To end up with an appropriate number of feasible relevant alternatives, two modules are used to reduce their amount: a compatibility check and filtering process. Compatibility is verified and enforced using a compatibility matrix, to downselect feasible alternatives. Such a matrix is simply a binary array, which determines, pair-wise, if an option is compatible with another. Feasible alternatives only contain options that are compatible with each other.

4. **Generate alternatives.** Once the option compatibility is enforced and the tree of morphological matrices is filtered, it becomes relatively easy to generate all feasible alternatives, using a computer script. The successful accomplishment of this step ends the alternative generation process, and all the generated alternatives can then be used for further evaluation and analysis.

This subsection aimed at defining the alternative generation process for aerospace vehicle programs. As no existing process was suitable for an enterprise-level approach, a new method was implemented, combining the feature of several promising existing methods. The overall process followed is summarized in Figure 3.5. The process starts with a two-level decomposition of the program: at a program level and a vehicle level. A tree of morphological matrices is then created in order to account for all potential options for the different identified attributes. Finally, a compatibility check and a filtering of the various options ensure the feasibility of alternatives and limit the size of the design space.
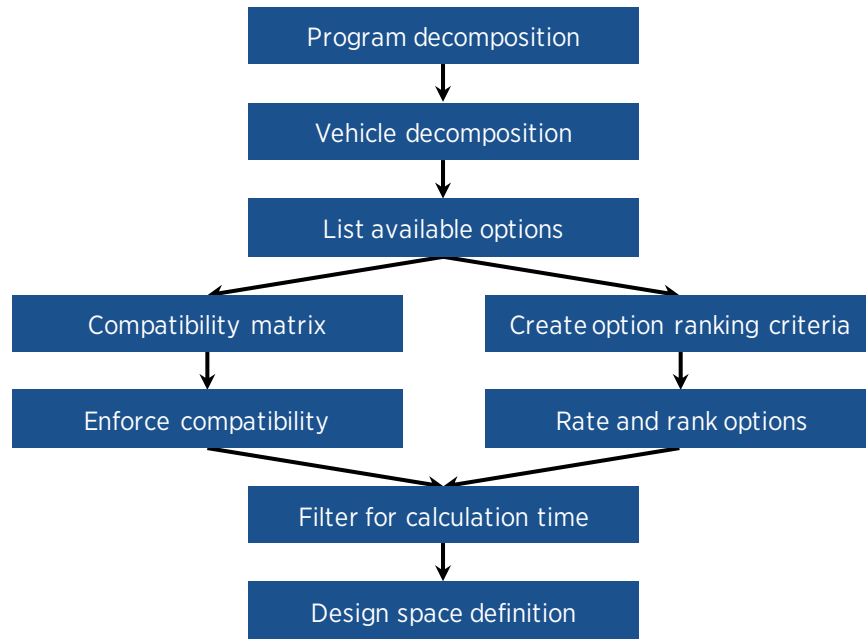
Figure 3.5: Design space definition process

Through this process, the design space can be defined and explored efficiently. The newly created design space serves then as an input to the modeling and simulation environments which are developed to evaluate the different alternatives. It is also used for the training of surrogate models, which are utilized in the next step.

3.3.2 Modeling uncertainty

Modeling uncertainty is another important part of step 2. Indeed, while uncertain factors are not optimization variables and therefore not controllable by decision makers, they remain valuable inputs of the M&S environment. Therefore, it is important to model them as well as possible.

The primary sources of uncertainty presented in motivation should be represented: interest rates, demand, development costs, stakeholders' preferences, and regulations, among others. The inputs associated with these factors need to be represented by probabilistic distributions to propagate this uncertainty through the M&S environment. Different types of probability distributions can be thought of: normal variables are commonly used and

have good mathematical properties but are unbounded, which can lead to absurd results; triangular distributions are commonly used when input distributions are not well defined; beta distributions are also fairly common as they can look similar to a normal one while remaining bounded. As most quantities represented here are bounded and sometimes non-negative, this approach proposes to use triangular or beta distributions to represent the uncertain inputs.

In addition to regular random inputs, some time-dependent uncertain variables need to be modeled as well. Indeed, this research focuses on the enterprise-level optimization of complex aerospace programs, and therefore involve a temporal aspect. While most uncertain variables can be modeled easily, time-dependent variables need a slightly more sophisticated approach.

Modeling time-dependent uncertain variables

Diverse macroeconomic parameters of are used in the evaluation of operational and financial performance of a program or vehicle. Such parameters include oil prices, interest rates, and market demand. Some general techniques exist to model the time evolution of random variables. Time series [251] are a common way to model stochastic processes in terms of the previously realized values, but are more suited for short-term forecasting and simulation. Brownian motion is also common but also has a too high dimensionality for this problem. Binomial lattice is a discrete version of Brownian motion which helps reduce the number of cases necessary to describe the probability distribution. Finally, scenario-based models [252–258] provides a small set of expected scenarios for each random variable. It does not require a lot of dimensions to be described but is a bit simplistic. Some specific methods also exist for particular variables. Oil prices can be either described by time series [259, 260], the price of future contracts [261], or more advanced economic models [262]. Interest rates also have specific models, such as the Vasicek model or the Ho-Lee model [263].

Table 3.5 evaluates the general forecasting techniques based on several key characteristics: simplicity to implement and use, objectivity and predictivity, relevance for long-term prediction and, finally, dimensionality.

Table 3.5: Comparison of general forecasting techniques

	Simple	Objective	Long-term	Low dimensionality
Time series	◔	●	◔	◔
Binomial lattice	◕	◕	●	◕
Brownian motion	◕	●	●	◔
Scenario-based	●	◔	●	●

Proposed implementation of time-dependent uncertain variables

While scenario-based methods are attractive because of their simplicity and low dimensionality, they lack objectivity in predicting the probability distributions of the variables to forecast. Binomial lattice and Brownian motion are better, but dimensionality remains high as multiple uncertain variables might be considered. Therefore, these methods cannot be directly applied as they are.

To model time-dependent uncertain inputs, a hybrid approach is adopted. Using a Brownian motion or binomial lattice method proper to the considered uncertain input, multiple variable paths are simulated, based on uncertainty scenarios. This leads to a probabilistic distribution of the variable over time. This distribution is fitted using two uncertain parameters: the initial value of this variable and its growth rate. Doing so, objective scenarios are generated, while maintaining reasonable dimensionality.
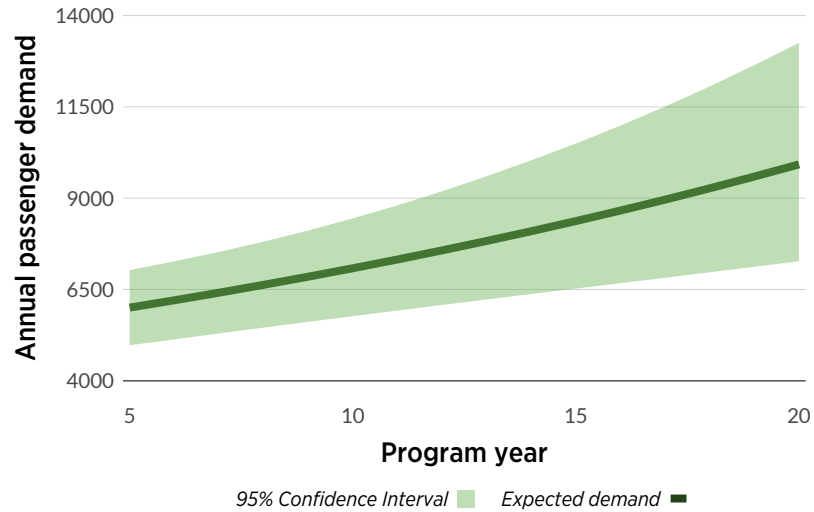
Figure 3.6: Notional uncertain variations of demand

Figure 3.6 shows a notional representation of the uncertain evolution of demand over time, where the bold line represents the average scenario, and the semitransparent area is a confidence interval of variation.

3.3.3 Case study implementation

The previous two subsections proposed a general approach to use to define the input space of aerospace programs. In this subsection, the proposed method is applied to the case study, with two main parts: generating alternatives and modeling uncertain inputs.

First, a morphological matrix tree is created, as mentioned in subsection 3.3.1. To come up with this tree, an enterprise-level decomposition first needs to be carried out. This functional decomposition is based on the main value-chain components listed in section 3.1. Four main functions are identified:

- **Design.** The company is in charge of developing a spacecraft for suborbital flights. Hence, a design phase needs to be carried out to size the vehicle and evaluate its performance.

- **Production.** The company needs to produce the vehicle after completion of the design phase. It also needs to control how many of such spacecraft need to be produced over time.

- **Operation.** The company's business model involves the operation of the vehicle. As such, it needs to define how frequently the vehicle must be used, and the price of the tickets sold to customers.

- **Finance.** While finance is only a support activity of the value chain, one of the main objectives targeted in this research is profitability. Therefore, finance is included in order to assess it. Moreover, it is shown in section 3.4 that finance is also a critical contributor to profitability and therefore is required.

Using this functional decomposition, the enterprise-level morphological matrix is established, as shown in Table 3.6.

Table 3.6: Enterprise-level morphological matrix

Attributes	Range	Option 1	Option 2	Option 3	Option 4
Debt ratio	[0; 1]	Low	Medium	High	
FY 5-10					
# Vehicles	[1; 15]	1	3	10	20
Ticket price (USD)	[25k; 1.2M]	25k	100k	300k	1.2M
# Launch (/year)	[12; 104]	12	24	52	104
FY 11-15					
# Vehicles	[1; 15]	1	3	10	20
Ticket price (USD)	[25k; 1.2M]	25k	100k	300k	1.2M
# Launch (/year)	[12; 104]	12	24	52	104
FY 16-20					
# Vehicles	[1; 15]	1	3	10	20
Ticket price (USD)	[25k; 1.2M]	25k	100k	300k	1.2M
# Launch (/year)	[12; 104]	12	24	52	104
Vehicle type	-	Rocket	Rocket-plane	RP + jets	Launched RP

Four primary enterprise-level functions help populate this enterprise-level morphological matrix: design is in charge of the vehicle and its type, finance deals with the debt ratio, production defines the number of vehicles in operation, and on the operational side, the ticket price and the number of launches for year are set. These three last variables are set for periods of 5 years, as demand may evolve. This increases the size of the design space but gives the opportunity to be more flexible.

| (a) Architecture 1 | (b) Architectures 2 and 4 | (c) Architecture 3 |
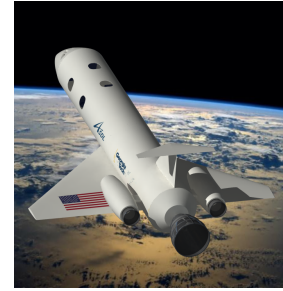
Figure 3.7: Notional representation of considered architectures [210]

Four main categories of vehicles are possible and serve as branches in the morphological matrix tree [210]. They are represented in Figure 3.7. The four considered architectures are the following:

- **Architecture 1 - Conventional rocket.** This architecture consists of a wingless, standard rocket, with vertical take-off and landing.

- **Architecture 2 - Rocket-plane.** In this architecture, a rocket-powered plane is considered. It consists therefore in a fuselage and wing, with the option to either perform horizontal or vertical take-off. Landing is performed horizontally, using the plane as a glider.

- **Architecture 3 - Rocket-plane with jets.** In this configuration, the rocket-plane has additional jet engines. It allows it to take-off horizontally with its jet engines and to fly up to a given altitude when rocket engines are then used. It lands horizontally, using the jet engines a second time, or gliding.

- **Architecture 4 - Launched rocket-plane.** This architecture involves the use of an additional plane, which carries the rocket plane up to a given altitude where it is launched. It uses only a rocket engine, and lands by gliding.

As these architecture involve different subsystems and missions, different morphological matrices need to be used for each of them. To do so, a physical and functional decompo-

sition of each architecture has to be made. In the rest of this subsection, the decomposition process leading to the morphological matrices of each architecture is detailed.

Architecture 1

To come up with each architecture's morphological matrix, a functional decomposition of the mission is performed, along with a system decomposition to identify the principal subsystems. For the standard rocket architecture, three main mission functions are identified:

- **Take-off.** The first phase of the mission is take-off. However, this architecture makes it necessary to perform vertical take-off.

- **Landing.** Similarly, landing must be vertical and rocket-engine-powered for architecture 1.

- **Piloting.** The mission also requires piloting. Zero, one or two pilots can be considered to control the suborbital vehicle.

After mission's functional decomposition, the vehicle needs to be decomposed into subsystems. Two subsystems can be identified for the conventional rocket architecture:

- **Rocket engine.** This is the only engine that propels the rocket. Various factors can change, such as the type of propellant, the nozzle expansion ratio, or pressure inside the engine chamber.

- **Fuselage.** Apart from the rocket engine, architecture 1 only consists of a fuselage. The dimensions of this fuselage and the number of passengers in the cabin are potential variations for the morphological matrix.

Following this decomposition, a morphological matrix of alternatives can be established for architecture 1, as shown in Table 3.7. This leads to a set of 10 design variables.

135

Table 3.7: Architecture 1's morphological matrix

Attributes	Range	Option 1	Option 2	Option 3	Option 4
Mission					
# Pilots	[0; 2]	0	1	2	
Rocket engine					
Propellant	-	Solid	Liquid	Hybrid	
Chamber pressure (MPa)	[2; 12]	2	4	8	12
Nozzle expansion ratio	[2; 100]	2	10	25	100
Thrust (kN)	[50; 700]	50	100	300	700
Fuselage and cabin					
Seat pitch (m)	[0.8; 10]	0.8	2	5	10
Fuselage base diameter (m)	[0; 1]	0	0.25	0.5	1
Front fuselage length (m)	[1; 5]	1	2	3	5
Aft fuselage length (m)	[0.1; 1]	0.1	0.3	0.6	1
# Passengers	[1; 8]	1	3	5	8

Architecture 2

The process illustrated with architecture 1 is applied to architecture 2 as well. The functional decomposition is similar, and includes three main elements:

- **Take-off.** Unlike architecture 1, architecture 2 brings more take-off options. Indeed, the rocket plane can either take-off horizontally or vertically. This gives the opportunity to bring these alternatives in the morphological matrix.

- **Landing.** Landing with rocket-planes is done by performing a gliding approach.

- **Piloting.** As for architecture 1, the rocket-planes can host zero, one, or two pilots to control the vehicle during the mission.

Architecture 2 is also decomposed into subcomponents. Four main subsystems can be identified:

- **Rocket engine.** As for architecture 1, the rocket-plane has a rocket engine, with similar attributes and variables.

- **Fuselage.** Similarly, the fuselage is described the same way as for architecture 1.

- **Wing.** Additionally, architecture 2 comes with a wing. This gives the opportunity to generate alternatives in terms of size and shape.

- **Empennage.** Architecture 2 also makes use of an empennage for flight stability.

Following this decomposition, the morphological matrix for architecture 2 is created. Table 3.8 provides the list of alternatives for this configuration. This leads to a set of 20 design variables.

Table 3.8: Architecture 2's morphological matrix

Attributes	Range	Option 1	Option 2	Option 3	Option 4
Mission					
# Pilots	$[0; 2]$	0	1	2	
Take-off	-	Horizontal	Vertical		
Rocket engine					
Propellant	-	Solid	Liquid	Hybrid	
Chamber pressure (MPa)	$[2; 12]$	2	4	8	12
Nozzle expansion ratio	$[2; 100]$	2	10	25	100
Thrust (kN)	$[50; 700]$	50	100	300	700
Fuselage and cabin					
Seat pitch (m)	$[0.8; 10]$	0.8	2	5	10
Fuselage base diameter (m)	$[0; 1]$	0	0.25	0.5	1
Front fuselage length (m)	$[1; 5]$	1	2	3	5
Aft fuselage length (m)	$[0.1; 1]$	0.1	0.3	0.6	1
# Passengers	$[1; 8]$	1	3	5	8
Wing					
Surface (m^2)	$[10; 100]$	10	25	50	100
Aspect ratio	$[1; 6]$	1	2	4	6
Taper ratio	$[0; 1]$	0	0.25	0.5	1
Thickness-to-chord ratio	$[0.08; 0.14]$	0.08	0.1	0.12	0.14
Sweep angle (°)	$[30; 80]$	30	45	65	80
Empennage					
Horizontal tail aspect ratio	$[1; 2]$	1	1.25	1.5	2
Horizontal tail sweep angle (°)	$[30; 60]$	30	40	50	60
Vertical tail aspect ratio	$[1; 2]$	1	1.25	1.5	2
Vertical tail sweep angle (°)	$[30; 60]$	30	40	50	60

Architecture 3

The decomposition process is applied again, to architecture 3. As architecture 3 is equipped with jet engines, it gives it a different mission profile and set of subsystems.

- **Take-off.** In architecture 3, there is only one take-off option: horizontal.

- **Transition.** Architecture 3 makes use of its jet engines to take-off and climb to an altitude to be set, where it switches to its rocket engine.

- **Landing.** There are two landing options with architecture 3. It can either exploit its jet engines to perform landing or simply glide down to the runway.

- **Piloting.** As with other architectures, there can be zero, one, or two pilots flying the rocket-plane.

The list of subsystems for architecture 3 is similar as that of architecture 2, with additional jet engines.

- **Rocket engine.** Same as other architectures.

- **Jet engines.** Architecture 3 has additional jet engines. The number of jet engine and the high-level design variables of these jet engines constitute a set of alternatives.

- **Fuselage.** Same as other architectures.

- **Wing.** Same as architecture 2.

- **Empennage.** Same as architecture 2.

This decomposition leads to the morphological matrix presented in Table 3.9. This table is used to generate a set of 26 design variables.

Table 3.9: Architecture 3's morphological matrix

Attributes	Range	Option 1	Option 2	Option 3	Option 4
Mission					
# Pilots	[0; 2]	0	1	2	
Landing	-	Gliding	With jets		
Transition altitude (km)	[5; 18]	5	8	12	18
Rocket engine					
Propellant	-	Solid	Liquid	Hybrid	
Chamber pressure (MPa)	[2; 12]	2	4	8	12
Nozzle expansion ratio	[2; 100]	2	10	25	100
Thrust (kN)	[50; 700]	50	100	300	700
Jet engines					
# Engines	[1; 4]	1	2	3	4
Bypass ratio	[0; 1]	0	0.25	0.5	1
Turbine Inlet Temperature (K)	[1500; 2500]	1500	1800	2200	2500
Thrust (kN)	[5; 100]	5	20	50	100
Afterburners	-	No	Yes		
Fuselage and cabin					
Seat pitch (m)	[0.8; 10]	0.8	2	5	10
Fuselage base diameter (m)	[0; 1]	0	0.25	0.5	1
Front fuselage length (m)	[1; 5]	1	2	3	5
Aft fuselage length (m)	[0.1; 1]	0.1	0.3	0.6	1
# Passengers	[1; 8]	1	3	5	8
Wing					
Surface (m^2)	[10; 100]	10	25	50	100
Aspect ratio	[1; 6]	1	2	4	6
Taper ratio	[0; 1]	0	0.25	0.5	1
Thickness-to-chord ratio	[0.08; 0.14]	0.08	0.1	0.12	0.14
Sweep angle (°)	[30; 80]	30	45	65	80
Empennage					
Horizontal tail aspect ratio	[1; 2]	1	1.25	1.5	2
Horizontal tail sweep angle (°)	[30; 60]	30	40	50	60
Vertical tail aspect ratio	[1; 2]	1	1.25	1.5	2
Vertical tail sweep angle (°)	[30; 60]	30	40	50	60

Architecture 4

For the last architecture, the functional and physical decomposition is performed again. To start with functional decomposition, there are four main functions related to architecture 4:

- **Take-off.** Architecture 4 takes-off by being carried by another vehicle.

- **Launch.** As architecture 4 is launched, various launch altitudes can be considered.

- **Landing.** Architecture 4 lands by gliding.

- **Piloting.** As with other architectures, there can be zero, one, or two pilots flying the rocket-plane.

The subsystems present in architecture 4 are the same as in architecture 2.

- **Rocket engine.** Same as other architectures.

- **Fuselage.** Same as other architectures.

- **Wing.** Same as architectures 2 and 3.

- **Empennage.** Same as architectures 2 and 3.

This decomposition results in the creation of Table 3.10 which represents architecture 4's morphological matrix. With this matrix, 20 design variables are considered.

Table 3.10: Architecture 4's morphological matrix

Attributes	Range	Option 1	Option 2	Option 3	Option 4
Mission					
# Pilots	[0; 2]	0	1	2	
Launch altitude (km)	[5; 18]	5	8	12	18
Rocket engine					
Propellant	-	Solid	Liquid	Hybrid	
Chamber pressure (MPa)	[2; 12]	2	4	8	12
Nozzle expansion ratio	[2; 100]	2	10	25	100
Thrust (kN)	[50; 700]	50	100	300	700
Fuselage and cabin					
Seat pitch (m)	[0.8; 10]	0.8	2	5	10
Fuselage base diameter (m)	[0; 1]	0	0.25	0.5	1
Front fuselage length (m)	[1; 5]	1	2	3	5
Aft fuselage length (m)	[0.1; 1]	0.1	0.3	0.6	1
# Passengers	[1; 8]	1	3	5	8
Wing					
Surface (m^2)	[10; 100]	10	25	50	100
Aspect ratio	[1; 6]	1	2	4	6
Taper ratio	[0; 1]	0	0.25	0.5	1
Thickness-to-chord ratio	[0.08; 0.14]	0.08	0.1	0.12	0.14
Sweep angle (°)	[30; 80]	30	45	65	80
Empennage					
Horizontal tail aspect ratio	[1; 2]	1	1.25	1.5	2
Horizontal tail sweep angle (°)	[30; 60]	30	40	50	60
Vertical tail aspect ratio	[1; 2]	1	1.25	1.5	2
Vertical tail sweep angle (°)	[30; 60]	30	40	50	60

Uncertain inputs

Morphological matrices are now set and define the potential set of inputs and alternatives available to the decision maker. However, some other inputs affect designs and their performance: uncertain factors. Other inputs previously considered were under control of analysts, when uncertain factors are uncontrollable yet observable. They are therefore an important part of the input space. Uncertain factors' distributions are set later in this research, as they depend on the studied scenario. However, the same uncertain factors are considered in all following chapters: target altitude, allowable load factor, average demand, demand growth, risk-free interest rate, development cost overruns

1. **Target altitude.** Whether from customer requirement or regulations, the targeted maximum altitude of the flight is uncertain, although most likely 100 km. Variations in this threshold altitude affect the performance of the design and its economic viability.

2. **Allowable load factor.** During the mission, the vehicle is subject to significant load factors. However, it can be unsafe for operations and for passengers to be exposed to excessively high accelerations. Hence, regulations might limit the allowable level. However, the newness of the suborbital market makes it prone to regulatory uncertainty, and therefore, the allowable load factor is undetermined.

3. **Average demand.** As no company has successfully established consistent suborbital operations yet, the average demand for this market is not known yet, and therefore subject to uncertainty.

4. **Demand growth.** Similarly, the rate of growth of demand is uncertain as well.

5. **Risk-free interest rate.** Interest rate levels naturally vary with time and can be modeled as previously described in this section.

6. **Development costs overrun.** There is a high amount of uncertainty over the total amount of development costs, as seen historically. Hence, this model also includes variation of such factor.

These uncertain factors are represented by probability distributions and are further detailed in the next chapters. As objectives, inputs, and other external factors are defined, a modeling and simulation environment is then used to link these elements. Next two sections describe the process to come up with this M&S model.

3.4   Step 3: Evaluate alternatives

Last two sections defined the objectives of interest, the considered control variables to optimize them, and the uncertain factors that affected the system. The next step is to provide a modeling and simulation environment that processes these elements and estimates the objectives' values accordingly. Subsection 3.4.1 lists the required features of the M&S framework to be selected. Subsection 3.4.2 reviews the existing M&S frameworks for suborbital vehicles. As no adequate solution is found, a new M&S environment is created and its architecture is given in subsection 3.4.3. Each of the main modules of the M&S environment is described in subsections 3.4.4 to 3.4.8. However, as such environment have slow execution times, a surrogate modeling phase is necessary, before evaluating alternatives with optimization in mind. As such, subsection 3.4.9 provides the proposed surrogate modeling process. Finally, subsection 3.4.10 describes the M&S environment after incorporation of surrogate models.

3.4.1   Required characteristics

A method is needed that evaluate alternatives, in order to assess their risk and value within an optimization algorithm. To do so, a modeling and simulation environment must be developed to provide the required enterprise-level capabilities as indicated in chapter 2's

specifications. Therefore, the modeling and simulation environment should have the following features:

- **Incorporates a conceptual design module.** While the main focus of this research is not on the design discipline, it is still important to include it in the simulation environment, as the other disciplines can only exist because of a previously performed design process. Moreover, it was also stated in assertion 3 that the alignment of disciplines had to be carried out during the conceptual design phase. Therefore, the included design module should implement a conceptual-level technique.

- **Includes various business analyses, inputs and outputs.** In order to be able to exploit interdependencies between the enterprise-level disciplines, additional business analyses, inputs, and outputs must be included in the M&S. The additional analyses should be selected as those providing the ability to calculate the identified decision criteria, or having an influence in their calculation.

- **Can be used in a multi-objective optimization process.** It is important that the M&S environment can be used in a multi-objective optimization process. Indeed, once the evaluation method is implemented, it is employed in an optimization process in order to find the best programs under certain conditions. This involves several important features:

  - **Integrated.** There should only be one modeling and simulation environment. The user should not have to pass information from one to another, or run several M&S environments. This is necessary to make the methodology easy enough to use, convenient, useful, and able to be used by an optimization process. This also implies that the environment should be completely automated in the evaluation of aerospace programs.

  - **Fast.** Decision makers have limited time, and so do their projects. Therefore, the computation time of the evaluation of a single program should be short

enough so that it can be reused as many times as necessary in the context of an optimization process. Indeed, the presence of uncertainty propagation techniques further increase the computation time of the model and make it necessary to be fast enough. To increase computational speed, surrogate modeling techniques are used as suggested in chapter 2.

- **Available to the author.** This last feature is of lesser importance, but all codes integrated into the M&S are available to the author and do not require any particular investment in uncommon software licenses.

With these required features in mind, the following subsection presents the particular modeling and simulation implementation to evaluate suborbital vehicle programs.

3.4.2   Existing modeling and simulation environments for suborbital vehicles

In order to evaluate the set of identified alternatives, a modeling and simulation environment needs to be developed. It has to model a company developing, producing, and operating suborbital vehicles. As such, the literature is briefly reviewed to come up with the best basis for the computation framework for the design of suborbital vehicles. Several key features are required:

- This study focuses on conceptual design. As such, only methods adapted to that level of design (optimization of high-level system characteristics) can be chosen. For example, the framework cannot involve Computational Fluid Dynamics (CFD), which requires a detailed geometry and involves too many variables.

- Suborbital vehicles lack historical data. Therefore, empirical models cannot be used. Physics-based models have to be used instead.

- The framework must be able to be integrated into an optimization environment.

- This study emphasizes profitability. Life-cycle costs and revenues must, therefore, be modeled.

- A framework specific to suborbital vehicles is preferred.

- Ultimately, the developed M&S environment needs to allow for an enterprise-level approach.

Most existing design frameworks that could be used to evaluate the performance of suborbital vehicles do not model life-cycle cost such as TSSP [106], ASTOS [264], HAVOC [265], and the ones developed by Stanley [266], Sarigul [105], and Olds [267]. RASAC [268] provides cost components, but they are simplistic, and the flexibility in design is limited. Finally, while Mattingly [99] and FLOPS/ALCCA [269] model cost components, they are more specific to aircraft design and cannot be used to model all suborbital vehicle configurations. Table 3.11 compares the various design frameworks just cited in this paragraph, in terms of features critical to this research: execution speed, conceptual-level design, in-depth cost modeling, enterprise-level approach, and adaptability to suborbital vehicle programs.

3.4.3 Proposed modeling and simulation structure for suborbital vehicles

It appears that the framework developed by Frank et al. [164] is the most suitable one for this research. It is the one providing the most in-depth cost analysis for such vehicles, while enabling various architectures to be considered. In addition, it also evaluates the vehicle's operational risk. However, while this model is a good base for the design and cost aspects, it fails to assess profitability aspects. Indeed, developing more expensive vehicles may result in increased revenue. In that case, the current model would not capture this effect and would return a sub-optimal concept, or maybe even give the opposite conclusion. Moreover, this implementation is very design-centric, rather than enterprise-level as required. Indeed, this M&S framework does not provide any information in terms of revenues, cash

Table 3.11: Comparison of aerospace vehicle design frameworks

	Fast	Conceptual level	Cost modeling	Enterprise level	Suitable for suborbital
Sarigul [105]		◐			●
TSSP [106]	●				◐
Mattingly [99]	●	◐	◐		
FLOPS/ALCCA [269]	●	◐	◐	◐	
ASTOS [264]	◔				●
RASAC [268]	●	●	◐		◐
Stanley [266]	●	●			●
Olds [267]		◐			◐
HAVOC [265]	●	◐			
Braun [270]		◐	◐		◐
Frank [164]		●	◕		●

flows or other financial metrics, neither does it model demand, production or the actual operation of the vehicle. Finally, the costs provided are only totals, and no time dimension is considered. Therefore, a new model fulfilling the given specifications must be developed to have an enterprise-level view of the full life-cycle of the suborbital vehicle program. Figure 3.8 summarizes the proposed modeling and simulation environment. Frank et al.'s M&S framework is integrated into a larger, higher-level simulation environment. It is leveraged by adding various business analyses, business inputs, and business outputs, in order to provide it with the capability to exploit interdependencies between disciplines.

The design framework incorporates five main disciplines: weight estimation, aerodynamics, trajectory and propulsion control, safety, and base costs. The spacecraft sizing is performed using an iterative process between historical, empirical weight equations, aero-
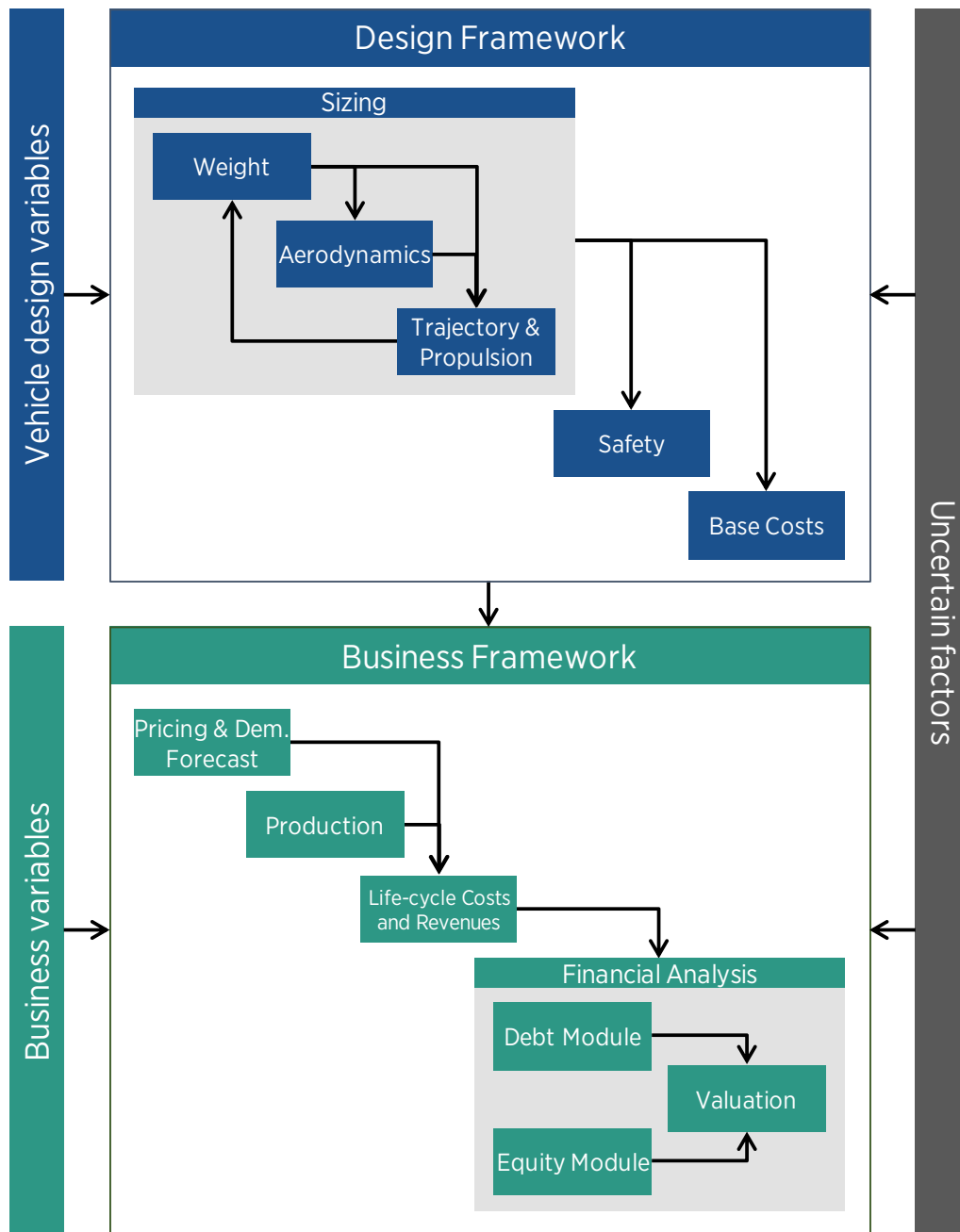
Figure 3.8: Proposed enterprise-level modeling and simulation structure for suborbital vehicle programs

dynamics analysis, and a trajectory and engine optimization. Operational risk level and base costs can then be estimated. The considered five disciplines are the following:

- **Weights.** Determines weight and dimensions of subcomponents based on component-level empirical models.

- **Aerodynamics.** Determines the aerodynamic coefficients of the vehicle using a semi-empirical approach developed by Roskam [271].

- **Trajectory and propulsion.** Determines the best trajectory and propulsion characteristics for a given vehicle and propulsion system using the Energy-State Approximation method.

- **Base Costs.** Determines total RDT&E, operating and manufacturing costs of the vehicle using Suborb-TransCost [272].

- **Safety.** Determines the operational risk level of the vehicle accounting for both the failure severity and occurrence of each subsystem.

In addition to the design framework, a newly built, business-oriented framework is integrated. It is meant to overcome the shortcomings of the design framework used alone, and contains four additional disciplines:

- **Pricing and demand forecast.** The modeled company needs to set the ticket price for its spacecraft's suborbital flights and the impact it has on global demand for space tourism.

- **Production.** The production of the spacecraft to be operated need to be modeled. In particular, the time distribution of produced vehicles needs to be defined.

- **Life-cycle costs and revenues.** This step aims at providing a time distribution of revenues and costs during the entire life-cycle of the program, based on the previous

results in terms of costs, demand, pricing, and production. It allows for the computation of free cash flows.

- **Financial analysis.** The financial analysis module aims at providing various metrics about profitability (NPV, IRR, payback period, etc.) and financial risk, as well as the required return on capital for the company. It mainly consists in a cost of debt and a cost of equity modules, as explained in subsection 3.4.8. This structure enables a more objective evaluation of the NPV, and provides additional but required capabilities, such as the ability to estimate the financial risk and to account for the costs of financial distress.

The following subsections aim at describing in greater detail the different non-design modules of the M&S environment. A quick summary of design disciplines was provided earlier in this subsection, and a complete description should be found in the work of Frank et al. [164] As risk is tightly related to this research, a brief explanation of the operational risk level calculation is still given in subsection 3.4.4. Other subsections describe non-design modules. Hence, subsection 3.4.5 presents how demand and pricing are correlated and simulated, subsection 3.4.6 describes the production model, subsection 3.4.7 deals with the time distribution of revenues and costs for the spacecraft program, and subsection 3.4.8, finally, describes the financial analysis implementation.

3.4.4   Safety

The safety module computes the operational risk level. Safety is defined as the "freedom from those conditions which can cause injury or death to personnel, damage to or loss of equipment or property" [273]. Hence, a vehicle's safety is achieved by estimating and limiting the operational risk level. The algorithm that computes the operational risk level uses a modified Fault Tree Analysis (FTA) with three levels of system decomposition; from the selected architecture to subcomponent features. A bottom-up approach is then used, by summing the product of the failure likelihood and severity for each component.

Five main features impacting the safety of suborbital vehicles are considered, with the following failure occurrence rates: rocket propulsion (75.95%), jet propulsion (1.27%), launch method (7.38%), landing method (10.44%), and number of pilots (4.96%) [105, 274, 275]. The severity of failure is evaluated for each subsystem using a coefficient γ, which varies from 0 to 10, 0 being the safest and 10 the riskiest. This coefficient comes from the aggregation of two factors: a baseline value that depends on the discrete parameters and a variable term that depends on the continuous parameters, which are estimated by Frank et al. [164]

It can be seen in this subsection that, as the overall probability of the vehicle to incur damage or distress is not known, a bottom-up approach is used to compute the overall operational risk level, starting from subcomponents. Each component has a likelihood and severity of failure, and the overall risk is a weighted aggregate of the risks of the individual subcomponents.

3.4.5   Pricing and demand forecast

The pricing and demand forecast module aims at predicting the annual passenger demand based on the proposed ticket price. To do so, demand is forecast using the customers' willingness to pay for a given ticket price, as measured by a study of the Tauri group [58]. Figure 3.9 describes the evolution of the annual demand for space tourism and highlights the most common range of prices predicted by suborbital spacecraft companies. It can be observed that demand goes down in a decreasing exponential fashion, as ticket price goes up.
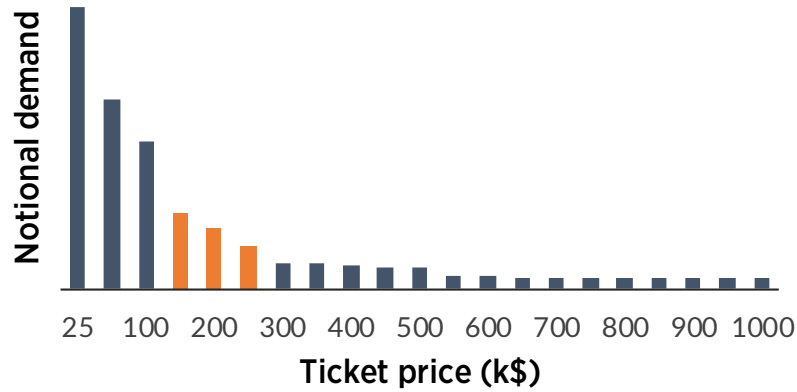
Figure 3.9: Annual suborbital tourism demand and most common prices [58]

Using the given data points, it is then possible to fit a regression model enabling a continuous distribution of demand as a function of the ticket price. This is particularly useful in the context of optimization, as the ticket price will be one of the input business variables, and should be continuous. The regression model providing best results is a double exponential one. Equation 3.6 expresses $Demand$ as a function of the ticket price P.

$$Demand = 18513 \exp\left(-0.01149P\right) + 1856.3 \exp\left(-0.001286P\right) \quad (3.6)$$

It is worth noting that in order to come up with Equation 3.6, as the demand curve was only providing notional demand, this curve was scaled so as to result in a 7,500 annual passenger demand for a ticket price of $100,000, or half the predicted demand for 2021 in Futron Corporation's studies [55, 56].

This demand function can be used to compute the potential annual revenue as in Equation 3.7, where R_p is the potential annual revenue at a given ticket price P.

$$R_p = DemandP = \left[18513 \exp\left(-0.01149P\right) + 1856.3 \exp\left(-0.001286P\right)\right]P \quad (3.7)$$
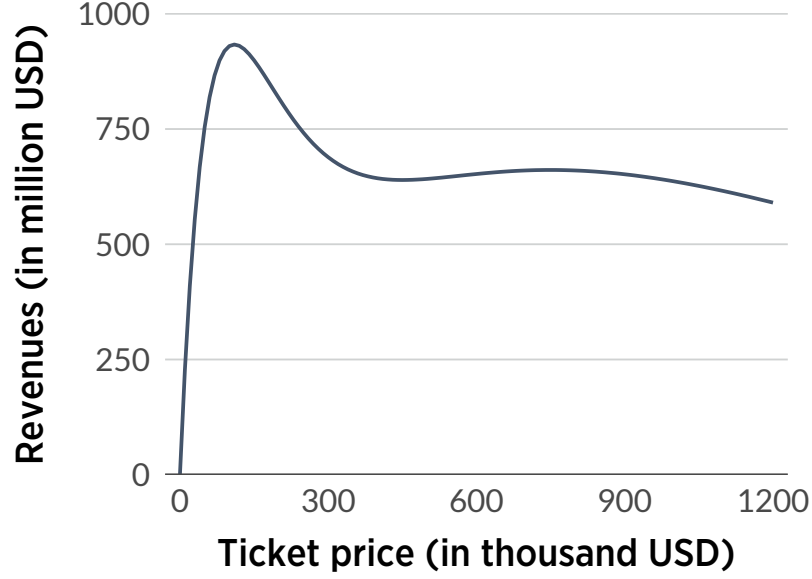
Figure 3.10: Potential annual revenue per ticket price

Figure 3.10 shows the annual revenue as a function of the ticket price. It allows identifying two potential target segments: a low-price, high-frequency segment, with a price range between \$120,000 and \$250,000, and a high-price, low-frequency one, with ticket prices in excess of \$800,000. It will be shown later in this research that optimal ticket prices will vary between these two areas, depending on the designed spacecraft, and its costs.

3.4.6 Production and fleet capacity

The production module aims at modeling the the number of vehicles produced over time and the fleet capacity. Production is modeled as a constant rate manufacturing, with a production limit of 5 spacecraft per year, and can start at year 6. Hence, $Prod_i$, the number of spacecraft produced at period i is given in Equation 3.8, where $N_{v,p}$ is the total number of vehicles to be manufactured during the five-year period p.

$$Prod_i = \begin{cases} 0 & i < 6 \\ \min\left(N_{v,p} - \sum_{j=1}^{i-1} Prod_j - \sum_{q=1}^{p-1} N_{v,q}, 5\right) & i \in [5p+1, 5p+5], p \in \{1, 2, 3\} \end{cases}$$

(3.8)

The production module also manages the total capacity in terms of number of flights per year, and number of passengers per year. Indeed, it is necessary to know how many spacecraft are available at a given time period to know if it can fulfill passenger demand. Annual passenger capacity Cap_i at period i can be computed using Equation 3.9, where N_v is the number of available vehicles at period i, N_f is the number of flights per year per vehicle, and N_{pax} is the passenger capacity of the spacecraft.

$$Cap_i = N_{v,i} N_f N_{pax} \qquad (3.9)$$

The number of available spacecraft is not only defined by production. In the last four years of the program, a quarter of the maximum capacity is lost every year, to model the retirement of spacecraft. Before retirement, and after production, capacity remains constant during the program. The number $N_{v,i}$ of spacecraft available at period i is given by Equation 3.10.

$$N_{v,i} = \begin{cases} \sum_{j=1}^{i} Prod_i & i < 18 \\ N_{v,tot} - \frac{i-17}{4} N_{v,tot} & i \geq 18 \end{cases} \qquad (3.10)$$

3.4.7 Life-cycle costs and revenues

This part aims at defining a time distribution for costs and revenues, in order to compute the program's Free Cash Flows (FCF). A company's free cash flow is the cash it can generate after deducting all operating costs, and investment into new assets. First, it is important to note that free cash flows do not include interest and depreciation. Free cash flows FCF can be expressed as in Equation 3.11, where $EBIT$ are the Earnings Before Interest and Taxes, $Capex$ is the amount of capital expenditure, and ΔWC is the change in net working

155

capital during the period.

$$FCF = EBIT(1 - \tau) + Depreciation - Capex - \Delta WC \qquad (3.11)$$

The $EBIT$ is the profit a company makes before paying taxes and its creditors. It is given in Equation 3.12, where R is the amount of sales revenue, $COGS$ is the Cost Of Goods Sold, and $SG\&A$ are the Sales, General and Administrative (SG&A) costs, and are assumed to be 20% of revenues, as it is a common value for this expense [276].

$$EBIT = R - COGS - SG\&A - Depreciation \qquad (3.12)$$

The net working capital represents the cash a company needs to perform its regular operations. Hence, ΔWC is the change in current assets or liabilities, excluding cash and notes payable, and is given in Equation 3.13. ΔWC is assumed to be zero in this research, as the balance sheet of assets and liabilities is not modeled.

$$\Delta WC = \Delta\big(Current\ assets\big) - \Delta\big(Current\ liabilities\big) \qquad (3.13)$$

To compute the free cash flows, revenues and costs have to be calculated for each time period of the program. The computation of total costs is performed using Frank et al.'s framework [164], as previously indicated. These costs belong to four categories: RDT&E, manufacturing, operating, and carrier aircraft costs. Yet, the design framework does not provide the time distribution of these costs. Therefore, this module aims at defining this distribution for each of them.

- **RDT&E costs.** Research, Development, Testing and Evaluation costs. They account for the overall development of the spacecraft. In the design framework, they are only computed as a total value. To find a time distribution, inspiration is taken from AL-CCA (Aircraft Life-Cycle Costs Analysis). Hence, the suggested time distribution is

fairly proportional as that of ALCCA for commercial jets. The leads to the following assumptions:

1. The program development period lasts six years.

2. RDT&E costs are distributed as in Table 3.12, during this period.

Table 3.12: Time distribution of RDT&E costs

Year	1	2	3	4	5	6
Value	5%	20%	20%	20%	20%	15%

Using Table 3.12, costs can easily be computed as the total RDT&E costs provided by the costs module in the design framework, times the percentage of the cost associated with the year RDT&E costs are applied to.

- **Manufacturing costs.** These costs are related to the production of the spacecraft. The design framework computes an average manufacturing cost per spacecraft. As for RDT&E costs, ALCCA is used to find a time distribution of costs. After observing ALCCA's behavior with production costs, it is assumed that 40% of the manufacturing cost of a single vehicle is charged the year preceding the end of its production, and 60% is charged the year it is delivered. This results in Equation 3.14, which computes the manufacturing costs $C_{M,i}$ for period i, where c_M is the average manufacturing cost per vehicle.

$$C_{M,i} = 0.6c_M Prod_i + 0.4c_M Prod_{i+1} \qquad (3.14)$$

- **Operating costs.** Operating costs include all the costs related to the operation of the spacecraft, direct or indirect, including SG&A costs. The design framework provides them as a cost per flight. Hence, it is easy to compute the annual operating costs, as

the sum of operating costs for each vehicle and flight. Operating costs $C_{O,i}$ at period i can be computed using Equation 3.15, where c_O is the average operating cost for a single flight on a single spacecraft.

$$C_{O,i} = c_O N_{v,i} N_f \qquad (3.15)$$

- **Carrier aircraft costs.** Carrier aircraft costs treat the costs related to the purchase and operation of a carrier aircraft used to launch the spacecraft. This type of cost is only computed for the launched spaceplane architecture, as other architectures are autonomous. Hence, the cost $C_{CA,i}$ of carrier aircraft at period i can be expressed by Equation 3.16, where $c_{CA,P}$ is the unit purchase cost for a carrier aircraft, and $c_{CA,O}$ is the average operating cost per flight of one carrier aircraft.

$$C_{CA,i} = c_{CA,P} Prod_i + c_{CA,O} N_{v,i} N_f \qquad (3.16)$$

Once the four types of costs are known, they can be used to compute the total costs incurred by the company. The total costs C_i at period i are simply the sum of these four types of costs, and are given in Equation 3.17, where $C_{RDTE,i}$ is the capital spent in RDT&E at period i.

$$C_i = C_{RDTE,i} + C_{M,i} + C_{O,i} + C_{CA,i} \qquad (3.17)$$

Costs are not the only element to be computed for the calculation of free cash flows. Revenues must be known as well. As seen in part 3.4.5, potential annual revenues are exclusively a function of the ticket price. Yet, the actual revenues perceived by the company also depend on its capacity in terms of annual passengers it can send to suborbital altitudes.

Therefore, revenues R_i earned by the company at period i are given in Equation 3.18.

$$R_i = \left[\min(Cap_i, Demand)\right] P \tag{3.18}$$

Knowing the revenues and costs for each period, it is then possible to compute the free cash flows, as explained in Equation 3.11. As explained before, it is assumed that the change in net working capital is zero. Moreover, the capital expenditures are also considered to be null (RDT&E is usually considered to be an expense rather than an investment in assets). Finally, as everything is assumed to be expenses, there is no depreciation. The expression of free cash flows FCF_i at period i therefore simplify to Equation 3.19, where τ_i is the corporate tax rate applied at period i.

$$FCF_i = (R_i - C_i)(1 - \tau_i) \tag{3.19}$$

It is worth noting that the corporate tax rate, around 35% in the United States, actually depends on the period. For example, if a company makes net losses, it will not receive 35% of its losses back. Instead, a 0% rate is applied. However, a company incurring losses can proceed to a loss carryforward, which enables it to reduce it tax liability for one of the next 7 years. In order to take into account this feature, Equation 3.20 is formulated, where LCF_{i-1} is the amount of loss carried forward from period $i - 1$.

$$\tau_i = \max\left[0.35\frac{R_i - C_i - LCF_{i-1}}{R_i - C_i}, 0\right] \tag{3.20}$$

This equation simply computes the effective tax rate a company pays if there is a loss carryforward, by computing the actual taxable income, and makes sure this rate does not go below 0%. The loss carryforward amount evolves at each period, depending on the company's losses or profits. A loss will increase the amount of loss carryforward, while a profit

will decrease it. Eq 3.21 gives the expression of the loss carryforward LCF_i at period i.

$$LCF_i = LCF_{i-1} - \min(R_i - C_i, LCF_{i-1}) \tag{3.21}$$

In this part, the way to compute life-cycle costs and revenues based on the results of Frank et al.'s design framework and the suborbital tourism demand curve was explained, as well as the way to compute free cash flows and effective tax rates. These free cash flows are later used in the financial analysis module, which assesses the program's profitability. As a conclusion of this part, Figure 3.11 represents the time distribution of costs and revenues, per category, for an example suborbital vehicle program.
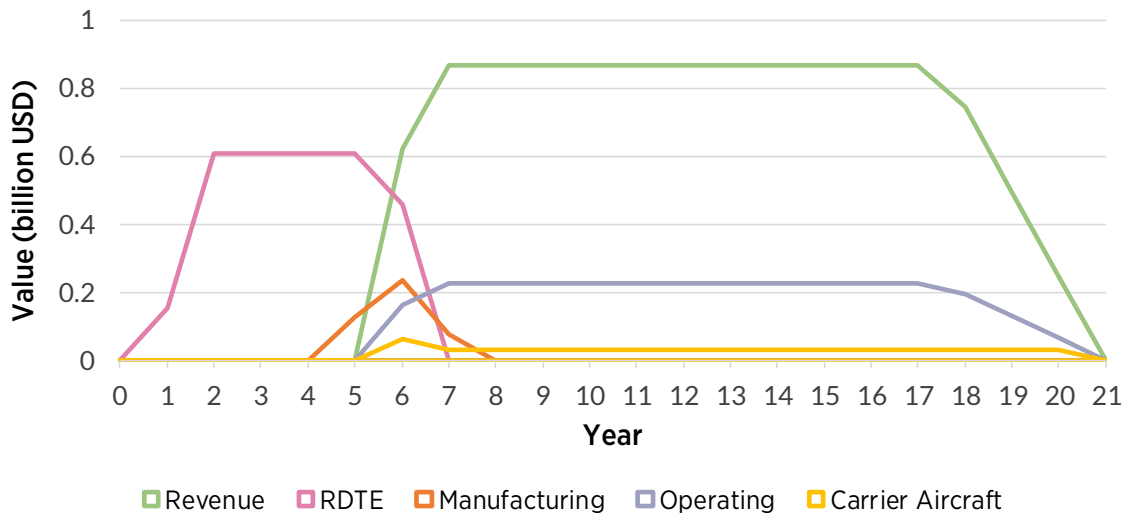
Figure 3.11: Costs and revenues variations with time for a suborbital vehicle program

3.4.8   Financial analysis

This part explains the various calculations and modules involved in the financial analysis process. Before proposing any implementation, a review of financial analysis methods used for aerospace problems is carried out. One of the most important and most commonly used methods is the Net Present Value. The NPV was previously presented, in part 2.2.5 and subsection 3.2.1. It is important to remind and outline, again, the importance of the
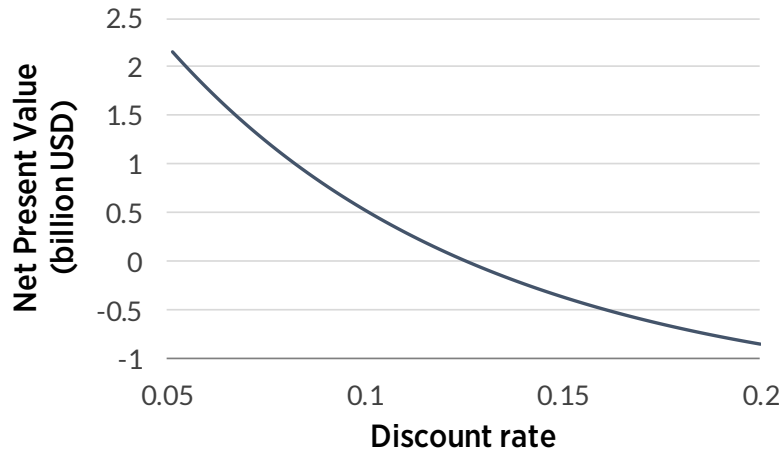
Figure 3.12: Influence of the discount rate on the Net Present Value

discount rate in financial analyses. The discount rate is the factor defining how quickly future cash flows are discounted to define the value of an investment, project, asset or company (Equation 2.9). This variable can be estimated using various techniques (CAPM, WACC, RADR, etc.) Whichever technique is chosen, however, it is important to choose the discount rate wisely. Indeed, the NPV is highly sensitive to the discount rate, and any small variation can result in great differences in valuation. Figure 3.12 shows the variations in NPV as a function of the discount rate applied, for a suborbital vehicle program. An acceptable value for the discount rate, around 10% (the WACC is giving similar values), results in a $500 million NPV for the program. Such a result means that the project is profitable and can be pursued. At discount rate values over 12.5%, the NPV becomes negative, which means that the project is deemed not to be profitable enough, and will not be carried out. Hence, it is crucial to accurately define the discount rate, in order to avoid making erroneous decisions. Therefore, an implementation that computes the discount rate as objectively as possible is needed.

One of the parameters affecting the discount rate is the leverage of a company. The leverage, or debt-to-equity ratio, is expressed in Equation 3.22, where D is the amount of debt carried by the company, and E is the dollar value of the equity it is constituted of. In other words, the leverage expresses the origin of funding within a company, and
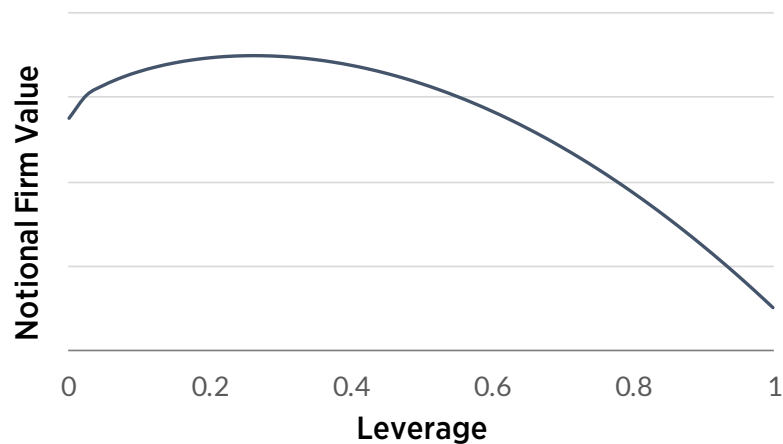
Figure 3.13: Impact of leverage on a project's or company's value

how debt-funded it is.

$$Leverage = D/E \tag{3.22}$$

The value of a project is affected by leverage in two antagonist ways. On the one hand, debt has usually lower required returns than equity. Therefore, a company taking on more debt does not need as high returns from its projects. Subsequently, the discount rate decreases and the value of projects increase. On the other hand, as leverage increases, the cost of debt increases because the creditors become more concerned over the ability of the company to repay their debt. Moreover, the company is taking more risks and becomes more exposed to bankruptcy or other financial risks, which are translated into expected costs of financial distress. Hence, Figure 3.13 shows the impact of leverage on the value of a company or project. At first, the value increases, but then, financial pressure of excessive leverage makes additional debt unattractive. These two opposite behaviors uncover potential financial trade-offs: debt against equity. These trade-offs need to be accounted for in the proposed method used for financial analyses. Not integrating them would result in suboptimal programs.

Another important point to remind is that step 1, in part 3.2.2, identified a list of variables included in the calculation of the risk and value scores. One of the decision criteria is financial risk. Hence, the financial analysis module should be able to output a measure of such risk.

The last necessary feature of the implemented method comes from a particular characteristic of suborbital tourism companies. Companies developing products which will provide such services include SpaceX, Virgin Galactic, and Blue Origin. These companies are exclusively private. This attribute of space tourism companies reduces the availability of information and data. In particular, market data such as the stock price variation, which is required to compute the famous "Beta" coefficient, is not available for such companies. Yet, any proposed method should be able to be applied to such enterprises.

As a summary of the last paragraphs, four requirements for the proposed financial analysis implementation are identified.

1. The implemented method should provide an objective measure of the discount rate.

2. The implemented method should enable financial trade-offs.

3. The implemented method should provide a measure of financial risk.

4. The implemented method should apply to private and public companies.

Implementation of financial analysis in aerospace applications

As requirements for the implementation are identified, it is possible to review existing financial analyses in aerospace applications. The thoroughness of financial analyses in aerospace applications is fairly minimal. They are usually limited to the calculation of the NPV (although some authors include measures of the IRR and ROI [148]). For the calculation of the NPV, two levels of implementation can be identified: 1) based on a fixed, arbitrary discount rate; 2) based on a fixed discount rate equal to the WACC, arbitrary or calculated.

- **Fixed, arbitrary discount rate.** The use of a fixed, arbitrary discount rate is arguably the most common practice for the valuation of aerospace programs. Many different authors have been using such an approach. Within this category of discount rate selection, many authors do not provide any reason for the value they pick. Markish and Wilcox [145] uses a 15% discount rate for the valuation of a Blended Wing Body (BWB) development program, without justification. Similarly, Peoples and Wilcox [131], rather than selecting an appropriate discount rate, provide valuations of a BWB with 12% and 20% discount rates. Castagne et al. [133], uses without further explanation a 17% discount rate for the optimization of fuselage panels. The second way of selecting an arbitrary discount rate is based on experience. Collopy and Horton [124] use a 7% discount rate for the value modeling of technologies, claiming it is a common rate used for government projects. Later, Keller and Collopy [277] apply a similar discount rate for the valuation of space systems. Ross et al. [127] uses a fixed 10% discount rate, based on experience, and mentions this is a relatively standard rate for space systems. Miller and Clarke [278] use an 18% discount rate to calculate the NPV of commercial jet programs, based on the experience of the manufacturer. These various examples lead to several observations. The discount rates used by various authors are arbitrary and based on no justification, or simply historical practices which might have been arbitrarily selected as well. Moreover, there is no apparent consensus on the right value of the discount rate to use. Such an approach is not objective enough for the requirements of the sought financial analysis implementation. It does not enable financial trade-offs either, nor does it provide a measure of financial risk.

- **Fixed discount rate using the WACC, arbitrary or calculated.** The Weighted Average Cost of Capital (WACC) is one of the most commonly used discount rates in valuation. Yet, it is less frequently used in the literature, compared to arbitrary discount rates. Several authors suggest the use of the WACC as a discount rate for

164

(a) Fixed, arbitrary discount rate

(b) Fixed discount rate using an arbitrary WACC

(c) Fixed discount rate using a calculated WACC
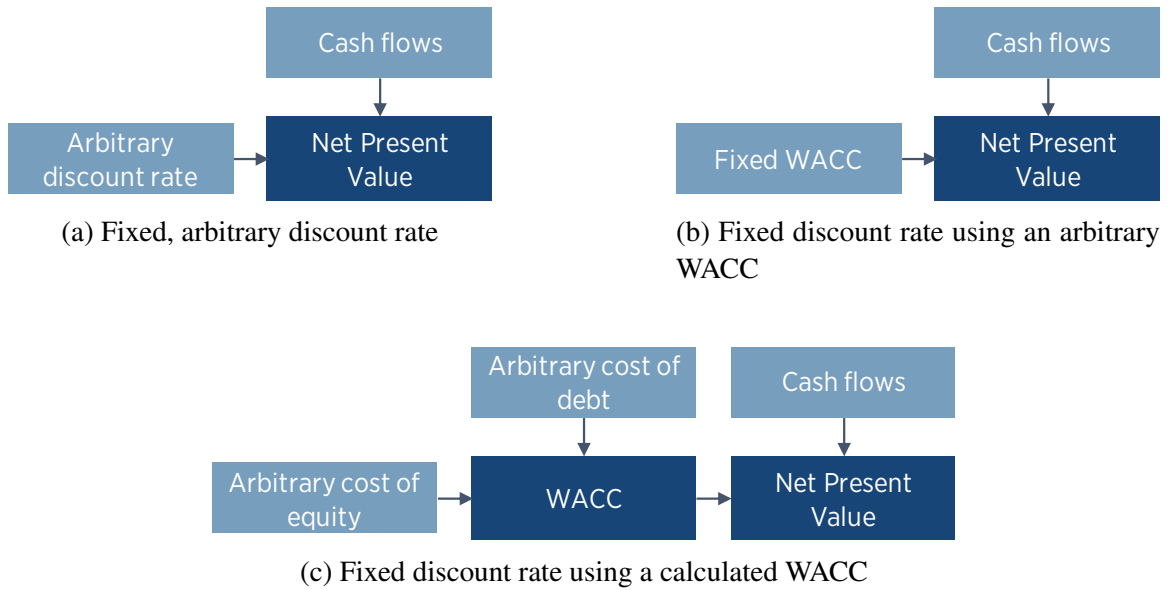
Figure 3.14: Current implementations of financial analyses in aerospace engineering

aerospace applications. Brooker [279] estimates the WACC is a robust estimate of the discount rate. Justin et al. [143] also uses the WACC to compare the value of aircraft in order to do a competitive analysis of the commercial jet market. However, the utilized WACC is fixed, and its computation is not provided. Gibson and Morrell [236], and later Gibson [280], also promote the use of the WACC and describes how to find the cost of debt and equity used for its computation. While the use of the WACC is an improvement compared to the arbitrary discount rate, using a fixed WACC remains a method with shortcomings. First, a completely fixed WACC does not account for the potential variations of the debt or equity of a company, and therefore does not allow financial trade-offs, and is not very objective. If the WACC is not given but calculated from fixed costs of debt and equity, the WACC does depend on debt and equity, but financial trade-offs are still not enabled. Indeed, using such fixed parameters result in an optimal NPV for a company made of 100% debt, which is an absurd result. Hence, an approach with fixed costs of debt and equity is not sufficient to fulfill the aforementioned specifications.

Current implementations of financial analyses in aerospace engineering are minimalist. Figure 3.14 summarizes the different types of implementations (the case with fixed discount rate using the WACC is separated in two subcases, whether the WACC is arbitrary or calculated). Although the computation of a WACC using market parameters improves the objectivity of the choice of discount rate, compared to a fixed, arbitrary one, this approach is not sufficient to fulfill the previously established requirements. First, the use of fixed cost of debt and cost of equity results in absurd financial trade-offs. Therefore, a method is needed that computes more accurately these costs, as a function of leverage. Additionally, current methods do not provide measures of financial risk, are hardly applicable to public companies (which cannot have access to a measure of cost of equity using the CAPM), and do not use objective values of the discount rate. A new implementation of financial analysis, adapted to aerospace programs (both commercial aviation and suborbital travel) and fulfilling the formulated specifications, must be developed. This conclusion leads to the statement of research question 3:

> **RESEARCH QUESTION 3:** *How can the current implementations of financial analyses for aerospace programs be improved in order to be more objective and accurate, support risk/value decision-making, and enable optimal financial trade-offs?*

The rest of this part is dedicated to finding a hypothetical solution to research question 3 and describes the proposed approach. To answer this research question, and provide the required capabilities, an extended financial framework is proposed. Figure 3.15 presents a flowchart of the calculation process to compute the Net Present Value, as well as the other available outputs. This new method can provide more objective measures of the discount rate, enables financial trade-offs, measures financial risk, and can be applied to both public and private companies. In order to provide the process with these capabilities, the calculation of the cost of debt and cost of equity is refined. Hence, the new computation structure is articulated around the calculation of these two parameters: a debt module and

an equity module are in charge of estimating their values, as well as other related variables of interest. Each of these two costs is necessary to the calculation of the WACC, which is used as discount rate for the NPV. The framework uses as inputs the free cash flows computed in the life-cycle costs and revenues module, as well market data, and the capital structure of the company (value of debt and equity of the company). It provides the NPV of the aerospace program, the probability of financial distress of the company, and the credit rating of the firm's debt, which can be useful additional information for decision makers, who might want to maintain an investment grade debt.
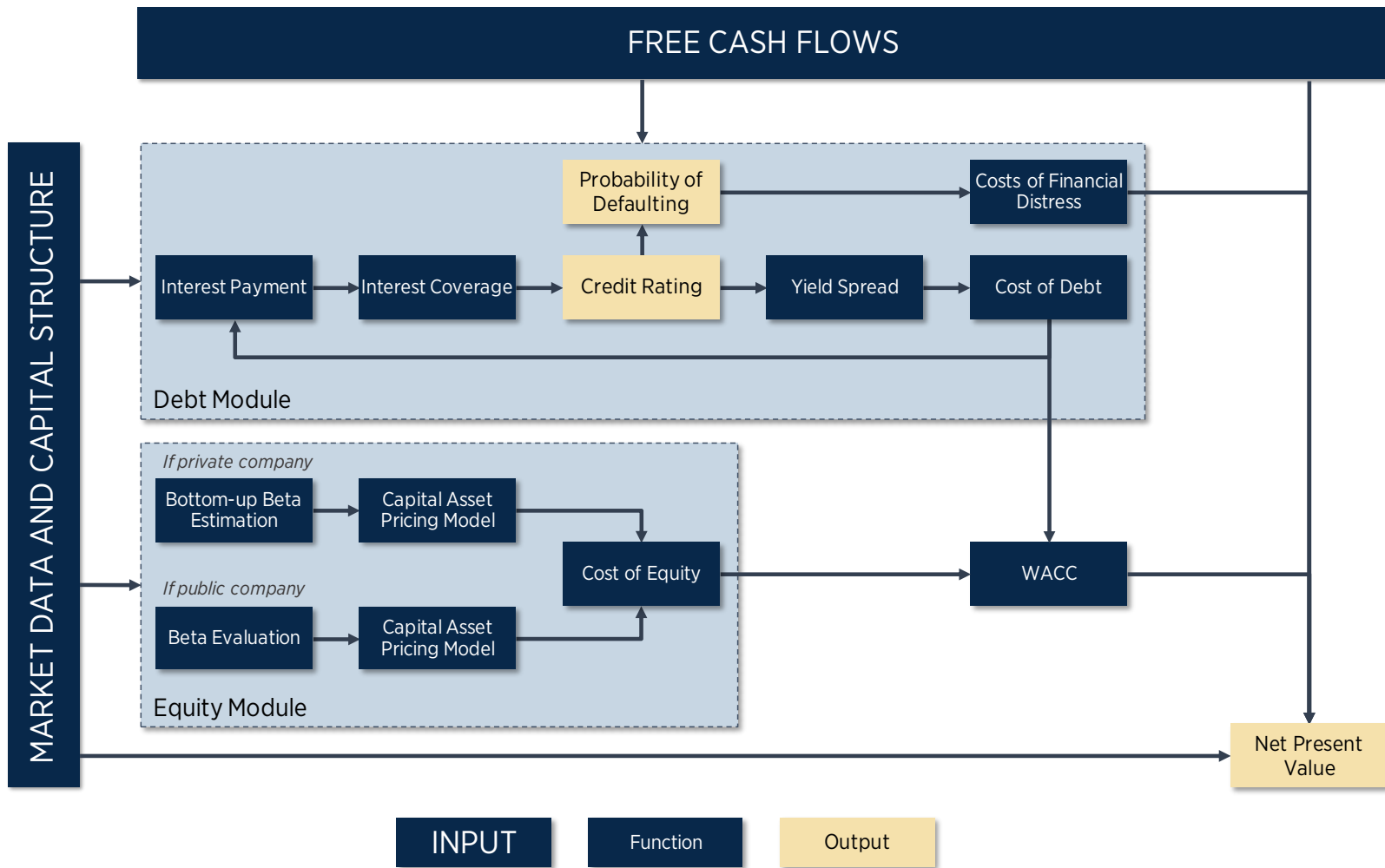
Figure 3.15: Net Present Value's computation process

The debt and equity modules are detailed in the following paragraphs, as well as the calculation of the WACC.

WACC and capital structure

The capital structure of a company impacts the returns the market is expecting, also called cost of capital or $WACC$. In other words, the WACC depends on the proportion of debt and equity used to fund the firm. It can be computed using Equation 3.23, where E is the market value of equity, D the market value of debt, r_e the cost of equity, r_d the cost of debt, and τ the corporate tax rate.

$$WACC = \frac{E}{D+E}r_e + \frac{D}{D+E}r_d(1-\tau) \tag{3.23}$$

As for the free cash flows, while the corporate tax rate can seem to simply be the 35% U.S. corporate tax rate, the *effective* corporate tax rate paid by the company has to be used. For example, a company making zero profits on a specific period will not pay any tax for this period. Companies also have various ways and tools to decrease the amount of tax they pay. As previously mentioned, the calculation of the WACC also involves the costs of debt and equity. These parameters are not set, and the actions of a company can affect them. Their objective computation is thus important, and the next two paragraphs describe each of their respective modules.

Equity module

The equity module aims at computing the value of the cost of equity r_e. The most common way to compute the cost of equity is to use the Capital Asset Pricing Model (CAPM) as suggested in Equation 2.10. This calculation requires to know the market risk premium $E[r_m - r_f]$, the risk-free rate r_f, and the "beta" coefficient β. The two first ones can be determined using historical data. The risk-free rate is usually supposed to be the yield

of long-term U.S. treasury bonds, as it is assumed that USA's Federal Reserve System will never default. The market risk premium can be evaluated using the historical average difference between the market returns (represented by the variations in value of the S&P 500) and the risk-free rate, over the past few decades. While these parameters are market-related, and therefore available to anybody, the beta coefficient is company-specific. The beta coefficient β_A of a public company A can be evaluated using Equation 3.24, where r_M are the daily market returns, and r_A are the daily returns of firm A's stock price.

$$\beta_A = \frac{Cov(r_A, r_M)}{Var(r_M)} \tag{3.24}$$

While this parameter can easily be computed for a public company (a company quoted on a stock exchange), it is not possible to calculate it if the variations in stock price are not known. Therefore, another approach is necessary for private companies, such as suborbital tourism ones. A way to overcome this issue is to use the *bottom-up betas* method [281]. If the beta coefficient is not known, it is possible to estimate it by analogy to other companies. To do so, beta coefficients of similar companies are collected. As leverage increases the cost of equity, these collected beta coefficients are first unlevered, using Equation 3.25, where β_U is the unlevered beta, calculated from β_L, the collected levered betas.

$$\beta_L = \beta_U \left(1 + (1 - \tau)\frac{D}{E} \right) \tag{3.25}$$

The unlevered beta of the firm is then estimated to be the average unlevered beta of the equivalent companies. Finally, the actual beta coefficient of the firm is computed levering it, using Equation 3.25 again. This beta coefficient can then be used to compute the cost of debt as for regular public companies, using Equation 2.10. Hence, this method does provide a way to handle private companies. Yet, it can still be challenging to find the beta coefficient of equivalent companies if all similar companies are public as well. This might lead to analogies with less similar companies, and therefore less accurate measures of beta.

Debt module

This module's first goal is to compute the cost of debt r_d. Additionally, it also deals with other interesting metrics, such as the probability of defaulting, or the firm's credit rating. The main way to determine the cost of debt is to exploit the ratings given to the company by the big credit rating agencies: Standard and Poor's [282], Moody's [283], and Fitch Ratings [284]. Using these ratings, it is then possible to determine the expected yield spread for the corporate bonds (Table 3.13), which is a penalty applied to companies' bond yield reflecting their relative riskiness. Fairly intuitively, the better the credit rating, the lower the yield spread. This yield spread Δr is then added to the yield of the U.S. treasury bonds' yield [285], often considered as a representation of the risk-free rate r_f (Equation 3.26 [286]).

$$r_d = r_f + \Delta r \tag{3.26}$$

Table 3.13: Yields spread based on credit ratings on November 2015 [285]

Credit rating	AAA	AA	A	BBB	BB	B
Default spread	0.76%	0.95%	1.20%	2.18%	3.88%	6.20%

While this approach is a good way to estimate the current cost of debt for a rated company, it has two main disadvantages. First, if the company is not rated, the cost of debt cannot be computed. Furthermore, if the company changes its capital structure (which is one of the required features), its credit rating could change. Therefore, a systematic method computing the firm's credit rating is developed. To do so, Damodaran [287] relates the credit rating of a company to its Interest Coverage Ratio (ICR) (Table 3.14).

Table 3.14: Relation between ICR, credit rating and default spread for <$5 billion companies [288]

If interest coverage ratio is			
Greater than	**$\leq$ to**	**Rating**	**Spread**
12.5	100000	Aaa/AAA	0.75%
9.5	12.499999	Aa2/AA	1.00%
7.5	9.499999	A1/A+	1.10%
6	7.499999	A2/A	1.25%
4.5	5.999999	A3/A-	1.75%
4	4.499999	Baa2/BBB	2.25%
3.5	3.999999	Ba1/BB+	3.25%
3	3.499999	Ba2/BB	4.25%
2.5	2.999999	B1/B+	5.50%
2	2.499999	B2/B	6.50%
1.5	1.999999	B3/B-	7.50%
1.25	1.499999	Caa/CCC	9.00%
0.8	1.249999	Ca2/CC	12.00%
0.5	0.799999	C2/C	16.00%
-100000	0.499999	D2/D	20.00%

The ICR of a firm measures how easy it is for the company to pay off its debt every period, based on its earnings. A small coverage ratio indicates that the company has meager margins after reimbursing its debt, and therefore is under heavy financial pressure. This translates into bad credit ratings, and high yield spread. Reversely, a high ICR means that interest expenses are a low share of the companies profit, and therefore, the company is perceived as safe by creditors, who give them low yield spreads. The Interest Coverage Ratio ICR can be computed according to Equation 3.27, where $EBIT$ are the Earnings
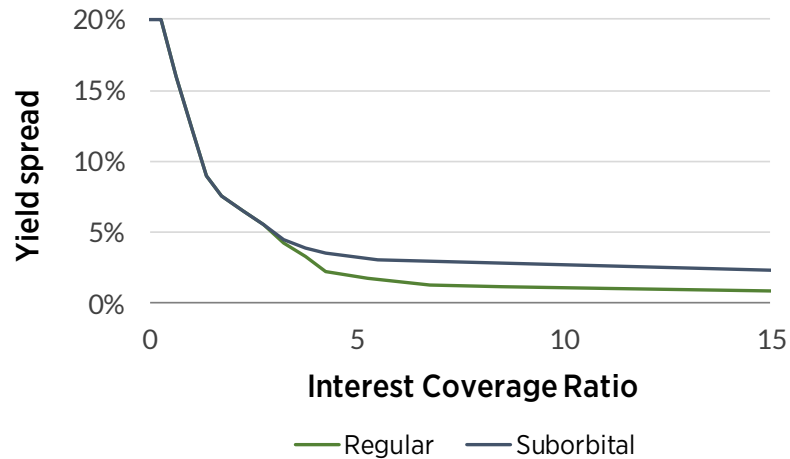
Figure 3.16: Yield spread for regular and suborbital tourism companies

Before Interest and Taxes of the company, and $Interest\ Expense$ is the amount paid to the creditors by the company every period.

$$ICR = \frac{EBIT}{Interest\ Expense} \tag{3.27}$$

Using Equation 3.27, the ICR can be known, and translated into a credit rating and default spread, which is used to compute the cost of debt. For the implementation of this method to suborbital vehicle programs, the values of yield spread as a function of the ICR are slightly modified (Figure 3.16). Indeed, as suborbital tourism remains a completely new field, creditors might not agree to loan money for a low rate. In this case, the assumption is made that the best credit rating the company can get is BBB. Moreover, the distribution of yield spread is also smoothed, by using a linear interpolation between the middle points of each category.

To compute the interest expense, Equation 3.28 is used. It is assumed that the capital structure of the company does not change during the program time period, and therefore, this expense remains constant with time.

$$Interest\ Expense = Dr_d \tag{3.28}$$

The company's EBIT is assumed to be the average profit the company makers during the program time period, as shown in Equation 3.29, where N is the number of years the program is spanning on.

$$EBIT = \frac{1}{N} \sum_{i=1}^{N} R_i - C_i \qquad (3.29)$$

Merging Equation 3.27, 3.28 and 3.29, the expression of the ICR for the proposed implementation is obtained, as shown in Equation 3.30.

$$ICR = \frac{\sum_{i=1}^{N} R_i - C_i}{NDr_d} \qquad (3.30)$$

However, it can be observed that the ICR not only depends on the amount of debt carried by the firm but also on its cost of debt. Hence, there is a circular reference in the calculation of the cost of debt, which leads to an iterative process. To start this process, an initial value of the cost of debt is guessed. The ICR is then calculated, which enables to estimate a new value of the credit rating and yield spread, and therefore, of the cost of debt. This algorithm is repeated until convergence of the variables.

The last point to be treated in the debt module is the probability of defaulting or financial distress. After the cost of debt has converged, such probability can be inferred from historical data, by categorizing companies with respect to their credit rating. Hence, companies with good credit rating have low chances to default. Reversely, companies with high debt pressure might end up defaulting, or file for bankruptcy. This aspect can be recognized in the historical default probabilities, as provided in Table 3.15.

Table 3.15: Cumulative probability of default and bond rating (1971 - 2001) [289]

Rating	5 years	10 years
Investment-grade		
AAA	0.03%	0.03%
AA	0.18%	0.25%
A+	0.19%	0.40%
A	0.20%	0.56%
A-	1.35%	2.42%
BBB	2.50%	4.27%
High-yield		
BB	9.27%	16.89%
B+	16.15%	24.82%
B	24.04%	32.75%
B-	31.10%	42.12%
CCC	39.15%	51.38%
CC	48.22%	60.40%
C+	59.36%	69.41%
C	69.65%	77.44%
C-	80.00%	87.16%

Hence, the credit rating of the company can be mapped to a probability of defaulting. The same type of linear smoothing/interpolation as the one used to define the default yield is used with the default probability. The probability of defaulting is used as a measure of financial risk, which fulfills the associated requirement.

The last three paragraphs proposed a more in-depth financial analysis and its application to aerospace programs. The thorough calculation of the costs of debt and equity allows the computation of the NPV to be more objective, as such parameters are estimated using market and company data, rather than judgment or the perpetuation of historical practices. The modifications in the calculation of the costs of debt and equity enable them to be computed not only for public companies, but also private companies with missing market data. Through the estimation of a credit rating, a probability of default can be assessed and used as a measure of risk. Finally, because of the impact of leverage on the cost of equity, and the influence of the ICR on the cost of debt, excessive debt becomes penalized, which can lead to relevant financial trade-offs, between debt and equity. Hence, the proposed method is believed to be a possible answer to research question 3, which results in the formulation of hypothesis 3:

> **HYPOTHESIS 3:** *IF a more comprehensive approach to financial analysis of aerospace programs is developed based on financial modeling of cost of debt, cost of equity and costs of financial distress THEN the current implementation can be improved in order to be more objective and accurate, support risk/value decision-making, and enable optimal financial trade-offs.*

In order to test the validity of hypothesis 3, an experiment is set up, and verification criteria are defined. The main features to be tested for in order to accept hypothesis 3 as an answer to research question 3 are the higher objectivity and accuracy of the method, the enabled financial trade-offs, and the measure of financial risk.

- **Higher accuracy and objectivity.** A model including additional terms having a large impact on its outcome will be more accurate than a model that did not consider these terms. Borgonovo and Peccati [290] use a differential sensitivity analysis to determine and rank the importance of parameters involved in the NPV and IRR equations. Other authors [291–295] also used different types of sensitivity analysis to determine

176

parameter importance in more general cases. Therefore, such a sensitivity analysis can prove the usefulness of the aforementioned additional terms.

- **Enables financial trade-offs.** Models with fixed costs of debt and equity result in an absurd 100%-debt optimum. Can this model find a compromise between debt and equity? Does this compromise results in a higher NPV than the solutions provided by current approaches? If it does, this feature will be considered verified.

- **Support risk/value decision-making.** Can the model provide financial information that could support decision making? In particular, can the model estimate the financial risk the company is taking? It is crucial for the overall methodology to be able to output various sources of risk. The model should be able to compute a company's probability of financial distress, given a selected program, and deduct the financial risk.

In order to verify the aforementioned specifications, four verification criteria are formulated. Checking these criteria will lead to the verification of hypothesis 3.

> ***VERIFICATION CRITERION 3.1:*** *The additional terms modeled have at least 10% of the contribution of the discount rate.*

> ***VERIFICATION CRITERION 3.2:*** *The capital structure resulting in maximum NPV is not 100% debt or 100% equity.*

> ***VERIFICATION CRITERION 3.3:*** *This approach results in significantly higher NPV than current ones.*

> ***VERIFICATION CRITERION 3.4:*** *The model produces a measure of financial risk and multiple financial metrics.*

3.4.9 Surrogate modeling on computationally expensive disciplines

Execution time analysis

The last subsections presented the major elements of the considered modeling and simulation environment for the enterprise-level analysis of suborbital vehicle programs. However, detailed environment can prove difficult to run in a reasonable amount of time when used in the context of multi-objective optimization or uncertainty propagation. To reduce computational time and make these processes feasible, surrogate modeling is used. However, only parts of the environment need to be replaced by surrogates. To identify disciplines subject to replacement, a computation time analysis can be performed. Disciplines with high calculation time are usually good candidates for replacement, as they represent the bottlenecks of the process.

Such an execution time assessment is performed for this research's case study. To have a good statistical significance, 100 data points are evaluated using the suborbital vehicle M&S process. The average computational times of each discipline are presented in Figure 3.17. These are the average execution time for **one** data point analysis. Therefore, coupled disciplines, which need iteration are multiply counted, such as trajectory, weight, and aerodynamics. However, this gives a better estimate of their real cost in the process.
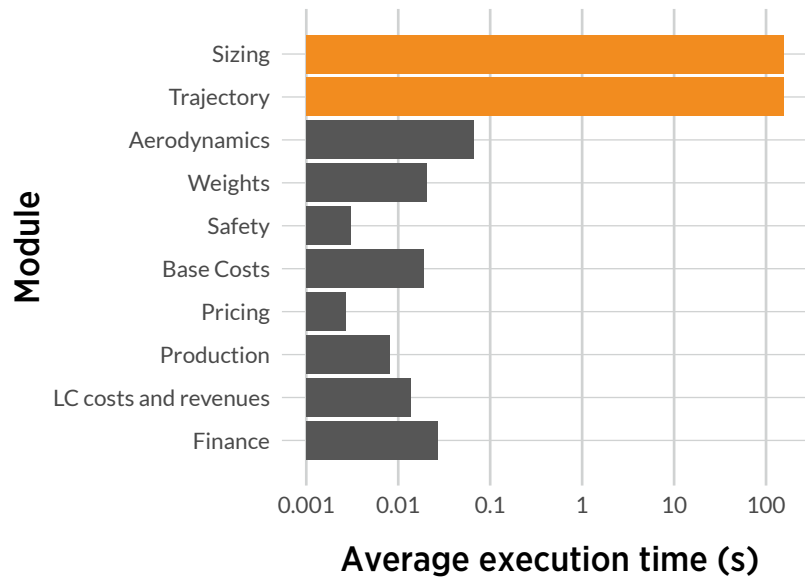
Figure 3.17: Average execution time for architecture 3

The result of this analysis identifies the bottleneck in the process: the trajectory and propulsion module is excessively lengthy, as shown in orange on Figure 3.17. Indeed, it takes on average almost 150 seconds to optimize the vehicle's trajectory, while all other disciplines require below 0.1 seconds to produce results. Moreover, while other modules are based on analytical equations and are therefore potentially usable in vector calculations to further speed the process up, trajectory optimization can only treat one concept at a time. This results in a very long sizing process, which does not permit multi-objective multi-risk optimization. Hence, the sizing module seems to be a good candidate for surrogate modeling. However, due to the numerous outputs of this analysis, it is in this case simpler to replace the whole design framework by a surrogate model that estimates operational risk and base costs. On the other hand, the business framework is computationally efficient and does not require replacement. Keeping part of the original analysis reduces the complexity of data to be fitted, and therefore enhances the predictivity capabilities of the models.

Surrogate modeling process

The surrogate models must predict two aspects of the model. As suborbital vehicles are complex systems, not all concepts are feasible. Hence, the surrogate model needs to be able to predict feasibility, through classification. The surrogate also needs to be able to estimate the responses of the model given certain design criteria and environment variables.

| Simulating | → | Cleaning | → | Feature scaling | → | NN fitting | → | Check model validity |
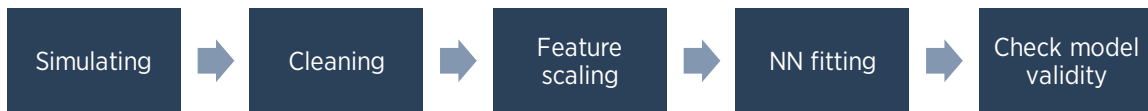
Figure 3.18: Typical neural network training process

In order to develop each of these surrogate models, a five-step process is followed.

- **Sampling and simulating.** Using the M&S environment, data is simulated using a Designs of Experiment (DoE) in order to provide inputs for the models to learn.

- **Cleaning.** Data is cleaned, by removing outliers, errors, and verifying data integrity.

- **Feature scaling.** Data is scaled to a 0-1 range in order to improve the models' learning performance.

- **Model fitting.** Using the cleaned, scaled data, a learning algorithm is used to generate the models. In this research, neural networks are used because of their strong capability of fitting non-linear data. Regularization is also used in order to ensure good fit of new data.

- **Model validity check.** Data validity is checked to detect lack of fit, or overfitting. Analyzing the distribution of residuals, using test sets, or looking at learning curves can help test if the fit is right.

The rest of this subsection describes in more detail the process followed to train the classification and regression neural networks used to replace the suborbital vehicle design framework.

Sampling and simulating data points

In order to train the surrogate models, a certain number of data points are required. Hence, it is necessary to sample the design space and to evaluate this input data to have an estimation of their responses. Figure 3.19 summarizes the sampling and simulation process. This process is individually followed for each of the four architectures, as their input spaces greatly differ.
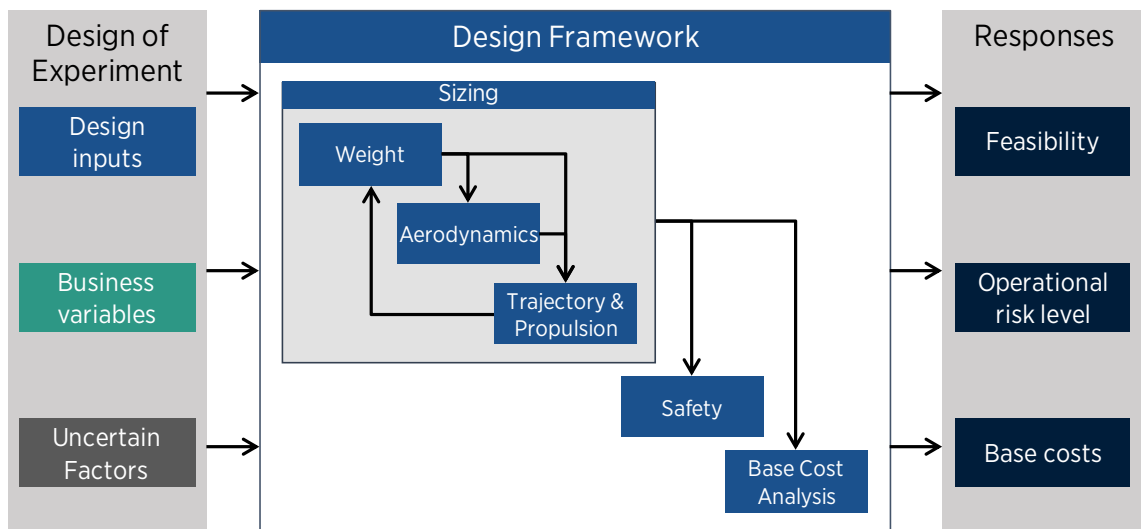
Figure 3.19: Sampling and simulating data before training neural networks

It is important to not only sample input variables, but also business variables used for costs (number of vehicles operated, number of flights per year), and uncertain inputs. Indeed, while decision makers have no control over these uncertain inputs, it is necessary to model the impact of their variations on the considered responses.

Several methods can be used to sample the input space. Due to its size and complexity, DoEs such as full factorial or Box-Behnken are not suitable. Instead, space filling DoEs

are recommended. As such, a Latin hypercube design is used. The M&S environment then evaluates the response of the sampled points. The analysis needs to evaluate six responses:

- **Feasibility.** A concept's feasibility is checked if the sizing process converges. Indeed, some configurations lead to divergent sizing, with dimensions and weight increasing toward infinity, which indicates no feasible solution can be found.

- **Operational risk level.** For feasible concepts, the safety module can compute the operational risk level based on mission and subcomponent parameters.

- **Base costs.** For feasible concepts, the base cost analysis module estimates four base costs. Research, Development, Test, and Evaluation (RDT&E) costs, operating costs, manufacturing costs, and carrier aircraft costs.

In the next steps, the generated data is processed in order to be used as an input to the neural net training method.

Cleaning

Once data is generated, it is important to clean it. Indeed, there can be unwanted results which might interfere with the training process, and lead to reduced predictivity of the model. Common results to be cleaned out are NaNs (Not a Number), infinite results, and outliers. One has to be cautious when removing outliers, as they may actually be the proper response of the system. To detect outlier candidates, several techniques exist:

- **Cook's distance.** When using linear regression, Cook's distance can be used to detect outliers. Cook's distance measures the influence that each point has on the ordinary least squares regression parameters. Data points with high impact (and therefore high Cook's distance) are potential outliers. Cook's distance D_i of point i is given in Equation 3.31, where $\hat{y}_{j(i)}$ is the regression's prediction of point j's response, when not including point i, $\hat{y}_j$ is the prediction with all points, p is the

number of regression parameters, and s^2 is the estimated variance from the fit [296].

$$D_i = \sum_j \frac{\left(\hat{y}_{j(i)} - \hat{y}_j\right)^2}{ps^2} \tag{3.31}$$

Cook's distance is, in other words, a normalized measure of the variation in response prediction depending on the presence or not of point i. Another technique to compute the influence of a data point is the analysis of leverage. These methods are interesting, but only apply to linear regression, and is therefore not applicable to this research, as regression is performed by neural networks.

- **Univariate statistical methods.** These methods attempt to identify outliers by using a one-dimensional metric. In this method, the objective is to identify points that deviate too much from the overall distribution of points, and are therefore deemed unlikely. The most common approach is to approximate the quantity of interest to a normal distribution, and to categorize as outliers points outside a confidence interval determined by a given confidence level. Hence, the set $\text{out}(\alpha, \mu, \sigma^2)$ of outliers is given by Equation 3.32, where α is the considered confidence level, μ is the distribution's mean, σ^2 is its variance, and $z_{1-\alpha/2}$ is the $1 - \frac{\alpha}{2}$-th quantile of the standard normal distribution [297].

$$\text{out}(\alpha, \mu, \sigma^2) = \left\{ x : |x - \mu| > z_{1-\alpha/2}\sigma \right\} \tag{3.32}$$

- **Multivariate statistical methods.** Multivariate methods are an extension of univariate ones. In multivariate methods, several metrics are considered rather than one, and a multivariate normal distribution is assumed. In order to find outliers, the Mahalanobis distance M_x of a point x can be used, as shown in Equation 3.33, where μ is the the mean vector of the data set, S is its covariance matrix, and x_i is the i-th

element of vector x [297].

$$M_x = \sqrt{(x - \mu)^T S^{-1}(x - \mu)} \quad \text{where} \quad S = \frac{1}{n-1}\sum_i (x_i - \mu)(x_i - \mu)^T \quad (3.33)$$

- **Other methods.** More sophisticated methods can also be used to model the probabilistic distribution of a set of data points. The likelihood of each of these points can then be estimated; points with low likelihood being potential outliers. Such techniques include Isolation Forest, Support Vector Machine, or Kernel Density Estimation.

Several methods can be used for outlier detection. However, the considered system is too non-linear to consider multivariate methods, and while more complex methods could capture non-linearity, they are too complex and out of the scope of this research. Therefore, a univariate method is used for detection and removal of outliers. As data can greatly vary, a high confidence level is required. Points exceeding this level are removed from the dataset.

As for NaNs and infinite responses, they are classified as infeasible concepts. All infeasible concepts are removed from the dataset used for regression of operational risk level and base costs.

Feature scaling

After data is cleaned, data is further prepared using feature scaling. Indeed, not all inputs and outputs are on the same scale, feature scaling standardizes the range of these variables. This is useful as feature scaling is believed to improve convergence of the surrogate modeling training algorithms. Usually, the objective is to bring all or most values to a $[0; 1]$ or $[-1; 1]$ range. Two main feature scaling approaches can be used:

- **Unity-based normalization.** Unity-based normalization ensures a $[0; 1]$ scale for variables, by normalizing the data by its range. This normalization is given in Equation 3.34, where the normalized value X_{norm} of metric X is function of its minimum

184

and maximum values.

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (3.34)$$

- **Standardization.** Standardization focuses on centering the mean of a metric on 0, and results in most point being within the $[-1; 1]$ range, with standard deviation equal to 1. Standardization's formula is given in Equation 3.35, where the standardized metric X_{stand} is a function of the initial distribution X, its mean μ, and its standard deviation σ.

$$X_{stand} = \frac{X - \mu}{\sigma} \quad (3.35)$$

Both methods can be applied to this problem, and the unity-based normalization is selected for this research.

Neural network fitting

The two previous step prepared the data before training classification and regression neural networks. Before running the algorithm, it is useful to split the data set in three sets of points: a training set, a validation set, and a test set. These three sets have the following purposes:

- **Training set.** The training set is the set of point the training algorithm is run on. The objective of the algorithm is to minimize the RMSE (Root Mean Squared Error) of the fitted model, in terms of training set error.

- **Validation set.** The validation set enables to determine the predictivity of the trained model with different points than those used to train it. The validation set can be used when selecting the best model parameters or model structure. The RMSE of different alternatives of models can be compared, and the one with the lowest validation RMSE is then selected. For example, if a neural network's predictivity is not satis-

185

factory, one can try different numbers of hidden layers and hidden nodes and pick the structure with highest validation RMSE.

- **Test set.** The test set is used to determine predictivity with points other than the training and validation ones. Indeed, as the validation set can be used to select some model characteristics, the model is somehow biased to fit the validation set better. Therefore, the test set ensures that the selected models are also valid for a different set.

Most of the data set is used for training. A common breakdown is 70% of points in the training set, 20% in the validation set and the remaining 10% in the test set. This distribution is adopted in this research. Once these sets are defined, the training algorithm can be run on the training set. A standard backpropagation algorithm is used to train the neural networks. A classification neural network is created to model feasibility, while regression networks are used for operational risk level, RDT&E costs, operating costs, manufacturing costs, and carrier aircraft costs. Only networks with between one and two hidden layers are considered. Several alternative structures are tested in order to find the model with best predictions. Additionally, replication is used for each structure, as the outcome of the training process is not deterministic. Finally, the models with highest validation RMSE are selected.

Model validity check

After fitting the neural networks, it is important to ensure that they are giving satisfactory results. To do so, it is important to look at the predictions of these models, at the residuals, and at learning curves, as these analyses give useful insight over predictivity and potential overfitting.
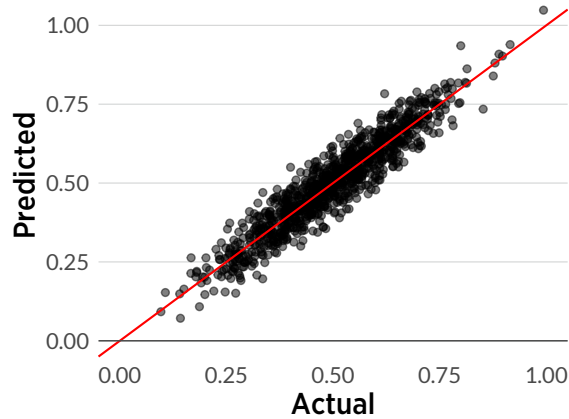
Figure 3.20: Notional actual versus predicted plot

■ **Actual vs. predicted.** The first and most intuitive analysis to make to verify model validity is the comparison of actual and predicted values. Indeed, if the predicted values greatly differ from actual ones, the regression does not manage to capture the essence of the system to be modeled. In that case, the regression model should be changed to fit the response better. Figure 3.20 shows an example of actual versus predicted graph. Fit here is ideal as all points are very close to the first bisector.
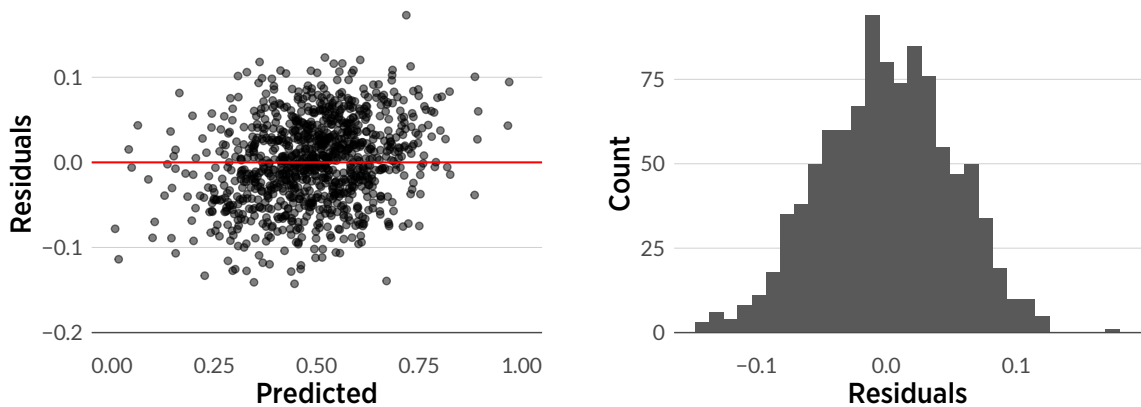
(a) Notional residuals versus predicted plot

(b) Notional distribution of residuals

Figure 3.21: Residuals analysis

■ **Residuals.** Another useful test is to analyze residuals. This can be visualized with the comparison of actual response and residuals, as seen on Figure 3.21a, or by looking at the distribution of residuals, as on Figure 3.21b. When comparing residuals

and actual response, two aspects should be check. First, residuals should be evenly distributed in terms of variance for all values of the actual response. While heteroscedasticity is not an issue, it still indicates better performance of the model for a given range of values to fit, and therefore non-even predictivity. Similarly, residuals should also be centered on zero. While this is not one of the assumptions for neural networks, residuals centered on zero for all values of the response show a more uniform fit. Biased residuals indicate a lack of fit of the model, which may require the inclusion of additional components to improve predictivity. The overall distribution of residuals can be observed as well. It is in general preferable to have normally distributed residuals, although this is not an assumption of neural network regression.

- **Training, validation, and test set RMSE.** Three datasets were used during the training process. The separation of data into three datasets is also useful for checking the resulting neural networks. Indeed, the model should show similar prediction behavior with each of these sets. Excessive differences in predictivity between these sets portend the presence of overfitting: when a model starts fitting noise error rather than the actual average response of the system, resulting in poor prediction performance. Solutions to overfitting include reducing the number of terms in the regression models (or selecting better ones) and the addition of regularization terms. Small overfitting can be acceptable and, ultimately, models with smallest validation RMSE should be selected.
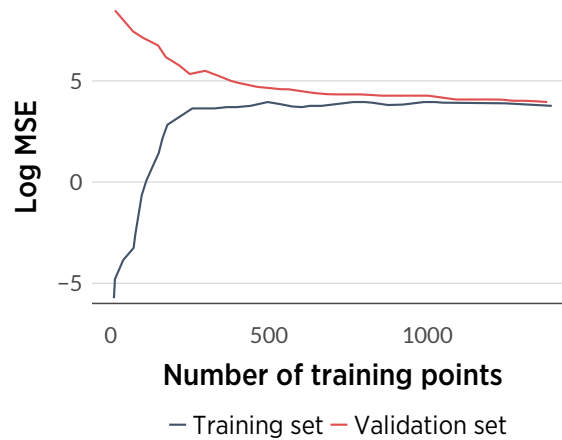
Figure 3.22: Notional learning curves

- **Learning curves** Learning curves are also useful to better understand the model's bias and variance. In machine learning, learning curves represent the evolution of the RMSE of the training, validation, and test sets with the number of data points included in the model. Figure 3.22 shows a notional example of learning curves. At first, the training RMSE is small, as it is easy only to fit a few points. However, the validation RMSE is high because the model does not have sufficient information to predict well all points of the design space. With the addition of points, the training set becomes harder to fit, but the addition of points helps the neural network learn the system, and increases its predictivity on the validation set. With the number of points increasing, validation and training RMSE ultimately converge to an equal value. If the learning curves have not converged yet, and there is still a significant difference between training and validation RMSE, generating supplementary points can help improving the validation RMSE. If it looks like too many points will be required, reducing the number of nodes should be considered. Reversely, if learning curves have already converged for some time, adding hidden nodes can help reduce both the training and validation RMSE.

The aforementioned tests are the main techniques to verify the validity of the trained model. If the checks are conclusive, the created neural networks can then be used in the model, as described in the next section.

3.4.10   Evaluation of the generated alternatives with surrogates

After creating the classification and regression neural networks, these surrogate models can be used instead of the computationally expensive discipline they have to replace. In this research, the initial design framework is replaced by the sequence of neural networks. As such, the process starts with the classification network, which assesses if a concept is feasible or not. This network acts as a gate for concepts and only allows to continue computation for the feasible ones. For feasible concepts, the base costs and operational risk levels are then computed. The other business disciplines can then carry on with the calculation. All disciplines of the business framework remain unchanged, as they are computationally inexpensive. Figure 3.23 illustrates the modified M&S environment, with use of neural networks.
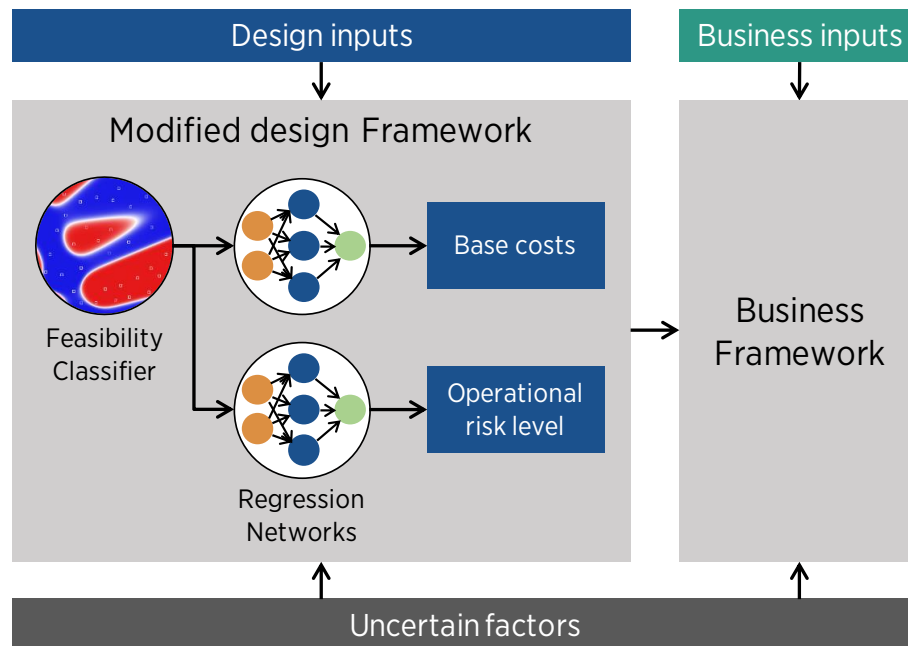
Figure 3.23: Modified modeling and simulation structure

190

3.5 Step 4: Decision-making

The objective of this step is to provide decision makers with a way to select the concept or program that is optimum with respect to their preferences. This includes optimizing the program, as well as selecting the optimum among the set of Pareto optimal points. Hence, subsection 3.5.1 first defines the Multi-Objective Optimization algorithm used in this methodology. Subsection 3.5.2 with the remaining, a-posteriori decision-making to do after the optimization is done, as well as the provided decision support.

3.5.1 Multi-objective optimization

It is first necessary to select an optimization algorithm which is suitable for the type of problem studied in this research. Instead of seeking for one optimum solution, the idea is to generate a set of optimum solutions. For that purpose, the Pareto optimization is based on a partial ordering space instead of a total ordering space. This space has the following rules [166]:

- A "weakly dominates" B if A is better in some attributes and equal in others

- C "strongly dominates" B if C is better in all attributes

- A and C are "incomparable" if A is better than C in some attributes but worse in others

Based on these rules, the subset of all non-dominated points is called the Pareto frontier. Even though this technique does not provide a single optimized point, the visualization of the Pareto frontier allows decision-makers to understand better the trade-offs that must be made. It then helps them formulate a single-objective optimization problem to select their "best" design. This advantage becomes even more important when uncertainty is present in requirement. This technique is harder and more complicated to implement but is promising and has already provided significant benefits to the conceptual design of spacecraft, launch

vehicles, and supersonic aircraft [268, 298–300]. Another important advantage of this approach is its applicability to sub-problem optimization with its capability to only keep non-dominated alternatives without any decisions.

Therefore, the implemented algorithm should have several essential characteristics: being a-posteriori, evolutionary, able to handle non-linear and non-continuous objective functions, and able to find optimal solutions in complex design spaces.

- **A-posteriori.** One of the objectives of this chapter is to provide decision makers with risk/value trade-offs. Step 3 already resulted in the creation of risk and value scores. The selected algorithm should produce the Pareto frontier of these two outputs.

- **Evolutionary.** An evolutionary Multi-Objective Optimization (MOO) is preferred, in order to find global optima and to have better performances than repeated Single-Objective Optimization (SOO) algorithms.

- **Non-linear non-continuous objective functions.** The proposed modeling and simulation environments involve many variables, continuous or discrete, and many highly non-linear analyses. Therefore, the selected algorithm should be able to generate the full Pareto frontier even in these conditions.

- **Complex design spaces.** Similarly, the algorithm should have the capability to handle complex design spaces.

The algorithm to be selected should include all the aforementioned characteristics. A review of existing multi-objective algorithms is carried out to provide a list of algorithms to be selected from. Table 3.16 compares the main existing optimization algorithms and rates them according to the previously established criteria.

The collected algorithm can be grouped into three categories: a-priori optimization, sequential single-objective optimization, and evolutionary multi-objective optimization.

- **A-priori optimization.** Algorithms such as the simple aggregate or the Overall Evaluation Criterion (OEC) are meant for a-priori optimization, and although they can

192

deal with several objectives, they aggregate them into only one and are then using SOO techniques. They are therefore unfit for this research.

- **Sequential single-objective optimization.** These techniques, such as the weighted p-norm, epsilon-constraint, normal boundary intersection, and normal constraint method, transform the multi-objective optimization problem in a series of SOO ones. While this makes them usually fairly easy to implement, they lack predictivity with complex, non-convex output functions. Moreover, for each point to add on the Pareto frontier, a new SOO has to be performed, without being able to leverage the results from previous optimizations, which can become computationally expensive. Hence, such methods are not suitable for the optimization of aerospace programs.

- **Evolutionary multi-objective optimization.** The Non-dominated Sorting Genetic Algorithm (NSGA), NSGA-II, and Strength Pareto Evolutionary Algorithm (SPEA) are examples of evolutionary MOO algorithms. These algorithms progressively evolve, improve, and optimize a population of points altogether. They are much more complex than previously mentioned algorithms but enable robust exploration of Pareto frontiers.

Several types of MOO algorithms were just presented. It was observed that evolutionary MOO algorithms are more suitable for the optimization of aerospace programs than the others. Consequently, such an algorithm is selected. Although all three cited algorithms have interesting properties, the NSGA-II algorithm seems to provide slightly better performance than the two others and is therefore selected as the MOO optimizer used in the proposed approach.

Table 3.16: Comparison of optimization algorithms

	A-posteriori	Evolutionary	Non-linear non-continuous functions	Complex design space
Simple aggregate			●	●
OEC			●	●
Weighted p-norm	◐		●	◔
Epsilon-constraint	◐		●	◔
Normal Boundary Intersection	◐		◐	◐
Normal Constraint Method	◐		◐	◐
NSGA	●	●	●	◕
NSGA-II	●	●	●	●
SPEA	●	●	●	◕

3.5.2 A-posteriori decision-making and decision support

This part deals with the diverse methods and tools used to support decision makers after the MOO. The MOO optimization generated a Pareto frontier of optimal compromises between risk and value. In order to make sound decisions, decision makers can use the support environment proposed in part 2.2.8 as an integrated platform which can provide them with several useful assistance tools.

First, the environment enables executives to visualize the Pareto frontier of programs, select various program concepts on the plot, analyze their characteristics, and compare them.

The second support tool uses Multi-Attribute Decision Making (MADM) techniques. In particular, it uses a TOPSIS method to rank the set of optimal programs, based on the risk-aversion of decision makers. The "Technique for Order Preference by Similarity to Ideal Solution" (TOPSIS) is based on the assumption that the best alternative has the short-

194

est distance to the utopia solution [301, 302]. This approach first defines the utopia and the anti-utopia solutions which are respectively a combination of the best and the worst alternatives for each criterion. Then, the Euclidean distance between each concept and those two points is calculated. The ranking of all alternatives is consequently obtained: from the best (closest to the utopia point) to the worst (farthest to the utopia point). The distance is computed using a utility function as presented in Equation 3.36. The weighting factor w_i represents the importance of the ith criterion and y_i^j the value for this criterion for the jth concept. This value is usually normalized in order to ensure consistent results while comparing small and large numbers such as take-off gross weight and sweep angle. Moreover, if no cardinal information exists, a scale can be created to quantify all objective values. For example, one can evaluate safety on a scale from 1 to 10, 1 being the worst and 10 the best.

$$U(y^j) = \sum_i y_i^j w_i \qquad (3.36)$$

This technique has a few disadvantages. It assumes a monotonic behavior of the evaluation criteria and requires subjective and fixed values for the different weighting factors w_i. Modifying those weighting factors can be analogous to stretching the corresponding axes. However, while providing the advantages of the Pugh Matrix (simplicity and capability to compare a large number of criteria/concepts), the TOPSIS makes up for some of its drawbacks. Indeed, the weighted sum allows decision-makers to define their preferences on specific aspects (cost, performance, etc.). Besides, it uses absolute values rather than a relative comparison with the baseline.

However, in addition to its main advantages, TOPSIS can have several interesting applications. For example, designers can use TOPSIS on a Pareto frontier with all possible weightings. This helps filter the Pareto frontier and only retain the possible selections by TOPSIS, producing a less dense Pareto frontier displaying only relevant concepts. Additionally, this TOPSIS analysis method can help compare two different Pareto frontiers, by

comparing the average TOPSIS score on the weightings value domain. Hence, it is possible to quantify the improvement provided by a Pareto frontier over another one.

3.6 Approach summary

Previous sections of this chapter presented the proposed approach and methodology used in order to answer the research questions. This approach is based on a four-step process. First, decision criteria and constraints are defined. The design space is then defined, and alternatives generated. A modeling and simulation environment must then be developed in order to evaluate alternatives. However, execution time is usually excessive and requires the use of surrogate modeling. A modified M&S environment where computationally expensive disciplines are replaced by surrogate models is therefore created and can be used to evaluate alternatives. Finally, a multi-objective optimization algorithm is used, with the value and risk outputs of the M&S environment as objective functions. The generated Pareto frontier can then be generated and visualized in an integrated trade-off environment, which supports executive in their decision making. This overall process is illustrated by Figure 3.24, which details the interactions between the different steps of the proposed process. The implementation of this approach is believed to prove the claimed capabilities and benefits of this methodology, as well as the expected contributions to research.
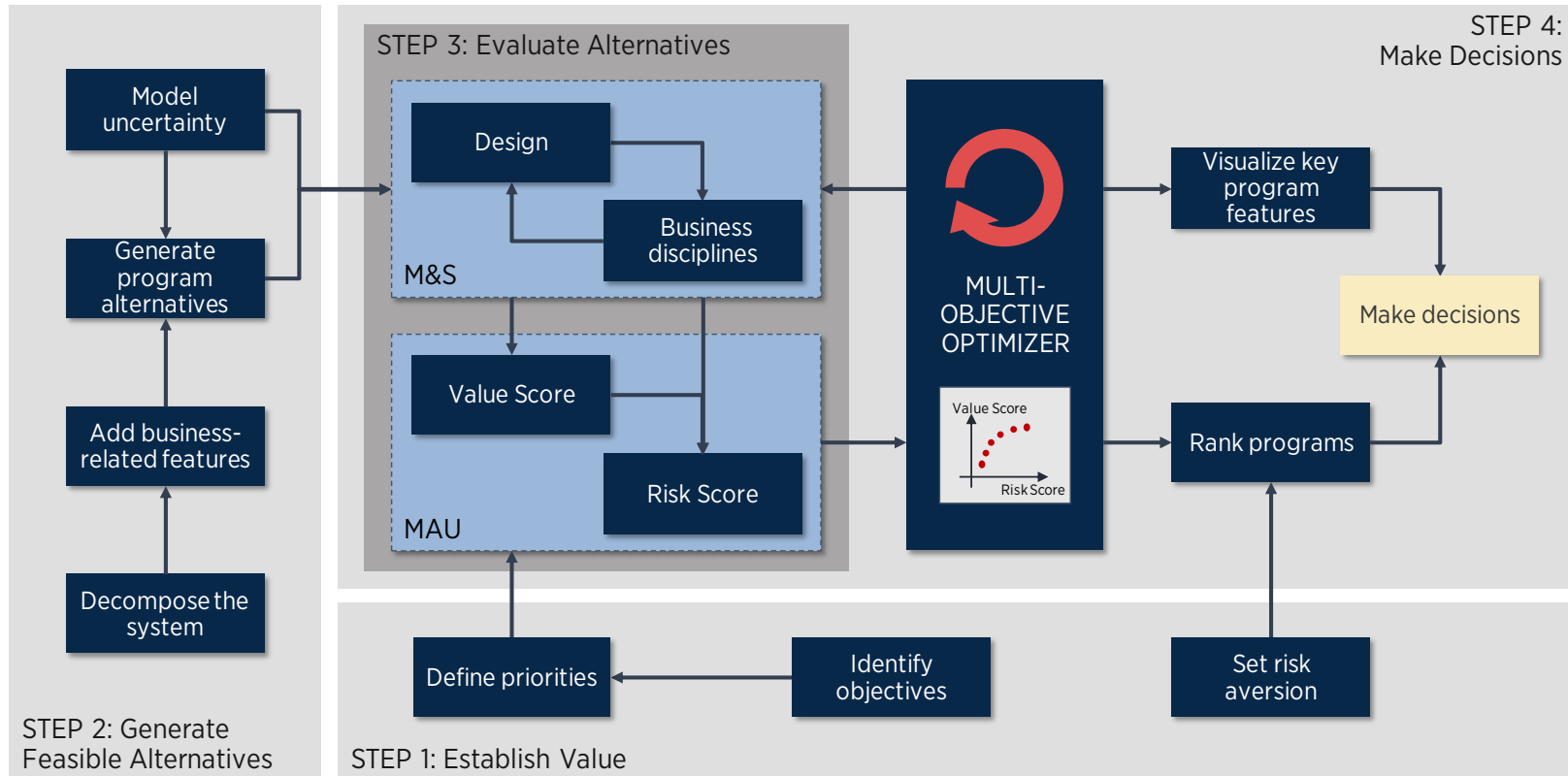
Figure 3.24: Functional breakdown of the proposed methodology

CHAPTER 4

A DETAILED FINANCIAL ANALYSIS

In order to follow a bottom-up resolution approach of research questions, research question 3 must be answered first. Research question 3 deals with the implementation and use of financial analysis in aerospace design methodologies, and raises the following problematic: *"how can the current implementations of financial analyses for aerospace programs be improved in order to be more objective and accurate, support risk/value decision-making, and enable optimal financial trade-offs?"* A thorough study of corporate finance techniques enabled formulating a hypothesis to this question: *"if a more comprehensive approach to financial analysis of aerospace programs is developed based on financial modeling of cost of debt, cost of equity and costs of financial distress, then the current implementation can be improved in order to be more objective and accurate, support risk/value decision-making, and enable optimal financial trade-offs."* Hence, a more in-depth financial analysis is implemented, and the results and observations from this implementation are presented in this chapter in order to confirm or reject hypothesis 3. As such, a study case is built in section 4.1 and used to generate the results presented in this chapter. First, the effect of financial leverage on the modeled financial metrics is studied in section 4.2. This study helps understand how the main financial optimization variable impacts the financial behavior of the company. Following this analysis, section 4.3 studies the sensitivity of the company's profitability as a function of the supplementary finance variables, modeled in this approach but not in other aerospace applications. This demonstrates the importance of including such variables as they have a significant impact on the resulting NPV. Finally, in section 4.4, a broader comparison of the quality and capabilities of the proposed method with other implementations is carried out, in order to summarize the main benefits of the financial analysis developed for this research.

4.1 Study scenario

In this chapter, the objective is to study the importance of a proper financial analysis in aerospace applications. As such, a simple scenario is implemented, where only one arbitrarily-selected vehicle is studied. In this case, demand is assumed to be constant over time as well as the interest rates. Required altitude and maximum load factor requirements are deterministic. Values for these parameters are shown in Table 4.1.

Table 4.1: Scenario factor settings

Factor	Value
Demand at k$100 ticket price	7500 pax/year
Risk-free interest rate	3%
Required altitude	100 km
Maximum load factor	4.5

Variables must also be set at the enterprise level and vehicle level. This scenario involves the use of a six-passenger rocket-plane with jets (architecture 3), only produced once over the life-cycle of the vehicle. As demand does not evolve with time, the number of vehicles operated and the ticket price remain constant. The proportion of debt held by the company is not set and is the main variable studied in this chapter, as it has a major influence on other financial metrics. Table 4.2 shows the values of enterprise-level variable settings for the remainder of the chapter.

Table 4.2: Enterprise-level variable setting

Variable	Value
Debt ratio	$[0; 1]$
FY 5-10	
# Vehicles	1
Ticket price (USD)	1,000,000
# Launch (/year)	104
FY 11-15	
# Vehicles	1
Ticket price (USD)	1,000,000
# Launch (/year)	104
FY 16-20	
# Vehicles	1
Ticket price (USD)	1,000,000
# Launch (/year)	104
Vehicle type	Rocket-plane with jets

After setting company-level variables, main vehicle design characteristics need to be set as well. The considered vehicle's architecture is the third one. It requires setting variables belonging to this particular architecture, as described in chapter 3. The modeled vehicle carries six passengers to suborbital space and is controlled by two pilots. It transitions from its three jet engines to its rocket engines at an altitude of about 14 kilometers, climbs to the required altitude, and lands horizontally with the assistance of its jet engines. A more detailed list of mission and sizing variables is given in Table 4.3.

Table 4.3: Considered vehicle characteristics

Variable	Value
Mission	
# Pilots	2
Landing	Jet-powered horizontal
Transition altitude	14000 m
Rocket engine	
Propellant	Hybrid
Chamber pressure	2 MPa
Nozzle expansion ratio	100
Thrust	69.7 kN
Jet engines	
# Engines	3
Bypass ratio	0.2
Turbine Inlet Temperature	2190 K
Thrust	58 kN
Afterburners	No
Fuselage and cabin	
Seat pitch	1.3 m
Fuselage base diameter	0.5 m
Front fuselage length	1 m
Aft fuselage length	0.42 m
# Passengers	6
Wing	
Surface	24 m^2
Aspect ratio	1
Taper ratio	0
Thickness-to-chord ratio	0.085
Sweep angle	40°
Empennage	
Horizontal tail aspect ratio	0.4
Horizontal tail sweep angle	30°
Vertical tail aspect ratio	0.4
Vertical tail sweep angle	48.5°

4.2 Impact of leverage on financial metrics

The proposed financial module has the advantage of enabling a deep analysis of many financial metrics related to this problem. In particular, it enables the user to model, visualize, and understand the effect of leverage on the financial behavior of suborbital vehicle companies. Indeed, leverage defines the capital structure of the company and has a significant impact at several levels, such as the cost of equity, cost of debt, discount rate, or financial risk. This section is articulated around the main financial analysis parts: the equity module (subsection 4.2.1), the debt module (subsection 4.2.2), and the estimation of the WACC leading to the calculation of the NPV (subsection 4.2.3).
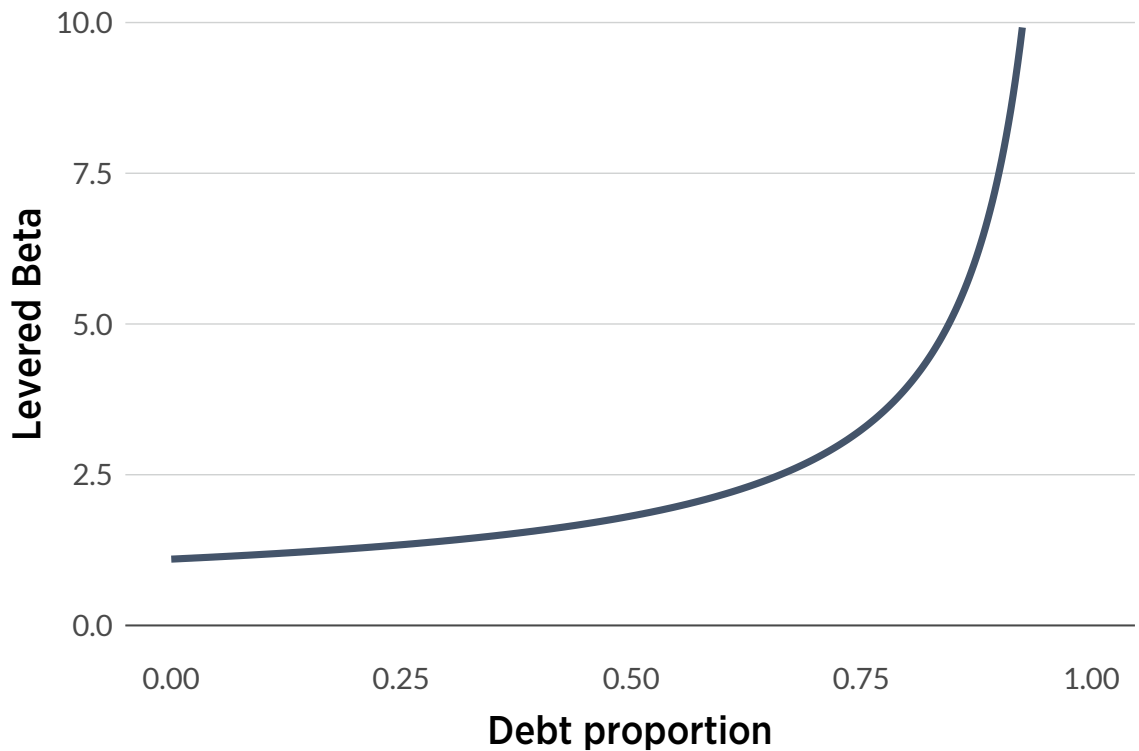
Figure 4.1: Levered Beta as a function of the company's debt proportion

4.2.1 Equity module

The objective of the equity module is to compute the rate of return required by the share-holders, or cost of equity. Suborbital vehicle companies being mostly private, a bottom-up approach is required to estimate its Beta coefficient before this cost can be estimated. By comparison with similar companies, the unlevered beta was found to be around 1.1. This Beta then needs to be levered again to estimate the cost of equity. The levered Beta is a function of the leverage of the company. Figure 4.1 shows the evolution of the suborbital company's Beta coefficient as a function of its debt proportion. The levered Beta starts from its unlevered value of 1.1 and monotonically increases as the amount of debt carried by the company increases. This reflects the increasing equity risk, whose Beta is a proxy of. Eventually, the levered Beta diverges to infinity when the amount of debt becomes too big and the risk too high.
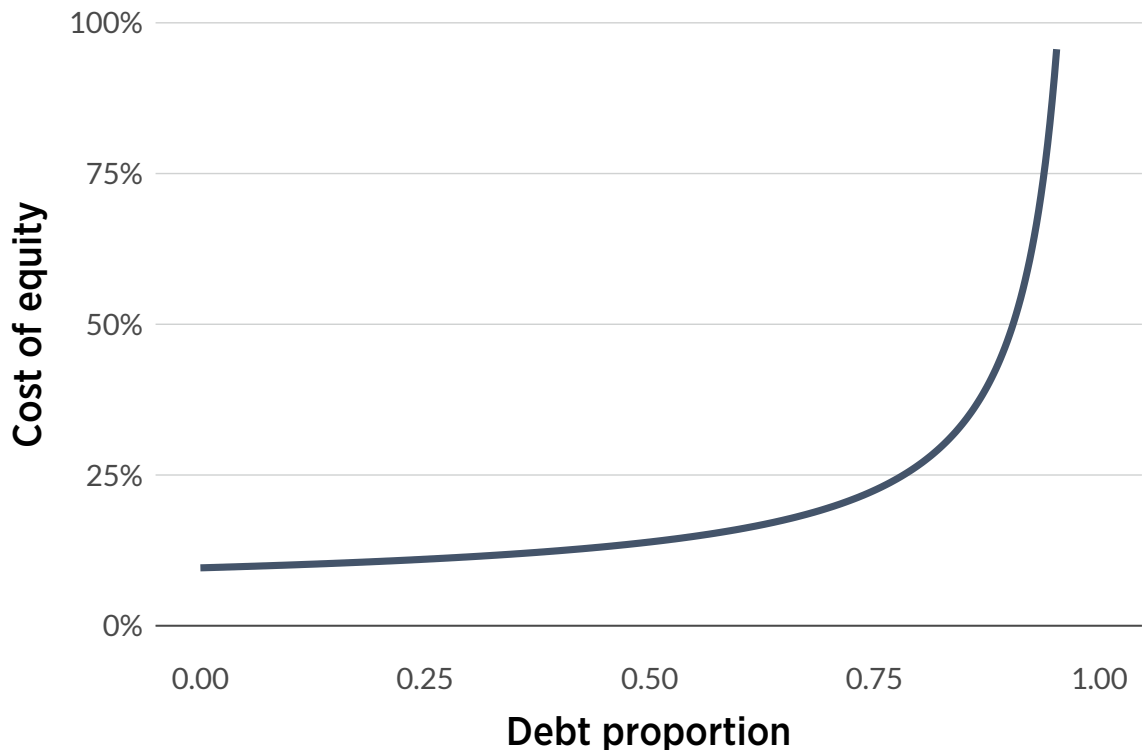
Figure 4.2: Cost of equity as a function of the company's debt proportion

From the levered beta, the cost of equity can be computed using the CAPM method. The evolution of the cost of equity is similar to that of the levered beta and is presented in Figure 4.2. The cost of equity monotonically increases with the debt proportion. As the amount of debt increases, shareholders perceive additional risk for the company and they require greater returns to make up for it. Indeed, when distributing earnings or in the case of a company liquidation, shareholders are the last ones to be paid, which puts them in a riskier position than, for example, debtholders. The cost of equity eventually diverges when the amount of debt becomes too large and stockholders can require returns over 100 % if they deem the risk too significant.

4.2.2 Debt module

The second part of the financial analysis module deals with the company debt and the metrics that are related. The debt module is more complex than the equity one, as there is coupling occurring, requiring an iterative calculation. Indeed, four main elements are coupled: 1) the cost of debt influences the amount of interests the company pays; 2) the interest expense impacts the interest coverage ratio; 3) the company receives a credit rating based on its interest coverage ratio; 4) the cost of debt is a function of the credit rating. The iterative process converges and provides estimations of these four measures, although this was not guaranteed (one could imagine a vicious circle where taking on debt would result in a sharp downgrading, hence a significant increase in cost of debt, resulting in even more interests to be paid, leading to a higher cost of debt, etc.). The implemented system is therefore stable.
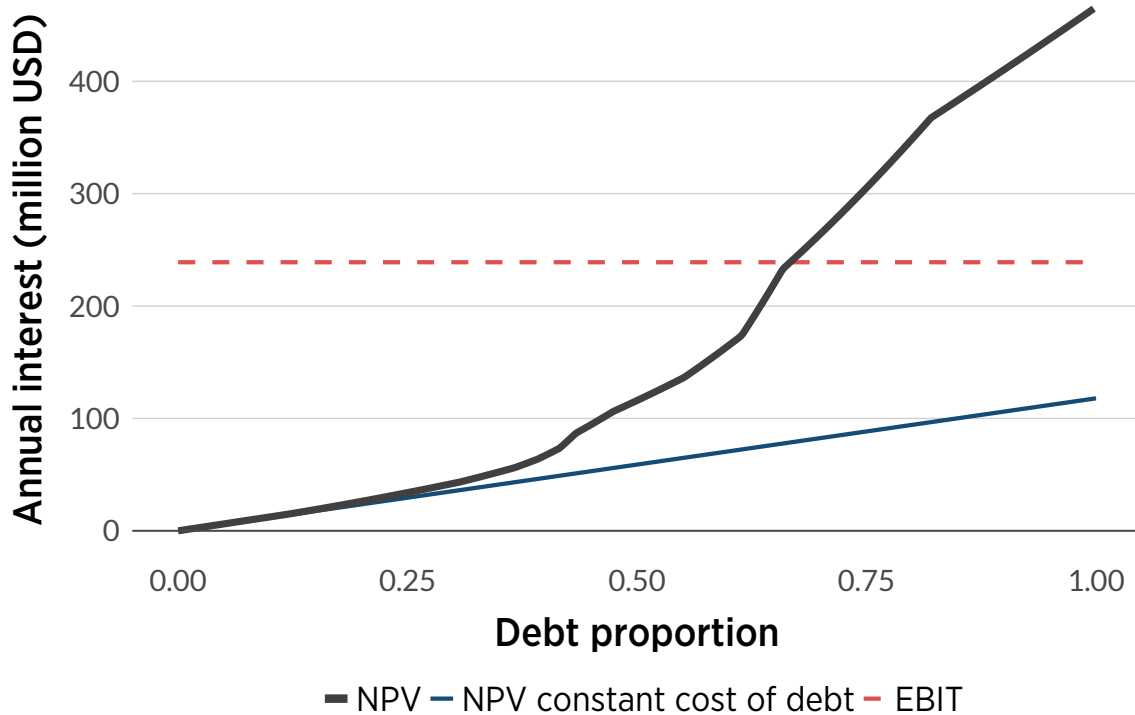
Figure 4.3: Annual interest expense as a function of the company's debt proportion

Interest

The first metric to study is the annual amount the company pays in interest to its debtholders. This quantity is simply the product of the cost of debt with the total debt held by the enterprise. As such, leverage comes into play in two ways: 1) higher leverage increases the total amount of debt the company carries and therefore its interest expense; 2) higher leverage increases cost of debt and therefore its interest expense. This effect can be visualized in Figure 4.3, which shows the annual interest expense paid by the company as a function of its debt proportion. Hence, while the increase in interest expense is relatively linear at first, the slope becomes steeper as the enterprise becomes excessively financed by debt. Eventually, the company pays more interest than its earnings before interest and taxes (EBIT), which would most likely result in dramatic consequences as it is not able to pay for its debt anymore. Figure 4.3 also shows an estimation of the amount of interest to be paid as predicted by methods which assume a constant cost of debt (as it is usually the

case). It can be noted that if the cost of debt had been fixed and were the same as when the company had no leverage, it would pay around $120 million every year in interest, far below the $460 million estimated by this method. This would ultimately result in improper conclusions and financial planning and put the company in a difficult position due to the poor cost of debt estimations. Therefore, this particular observation shows that the method proposed in this thesis is necessary to avoid significant errors in the prediction of annual interest expenses.
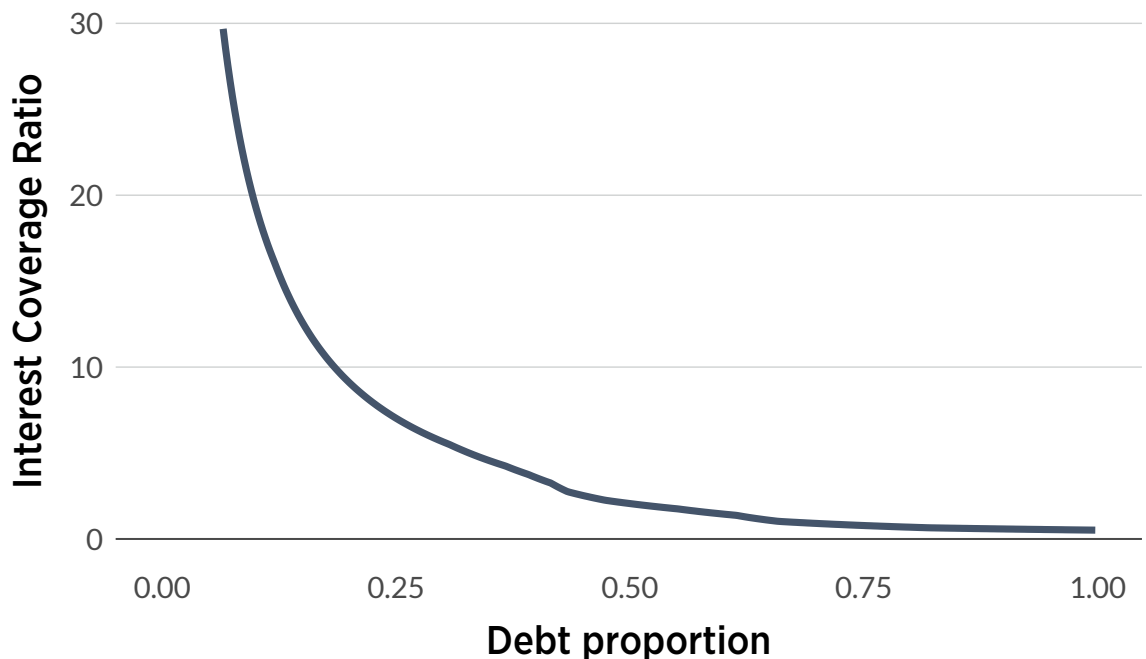
Figure 4.4: Interest coverage ratio as a function of the company's debt proportion

Interest coverage ratio

The interest coverage ratio is the ratio of the average EBIT of the company to the amount of interest it pays. As a consequence, because the average EBIT is fixed, the interest coverage ratio is just inversely proportional to the amount of interest paid. Figure 4.4 shows the evolution of the ICR as a function of the company's debt proportion. The ICR starts from

infinity and decreases as the amount of debt increases. Increases in the cost of debt make the ICR fall faster than an inverse function with high values of leverage.
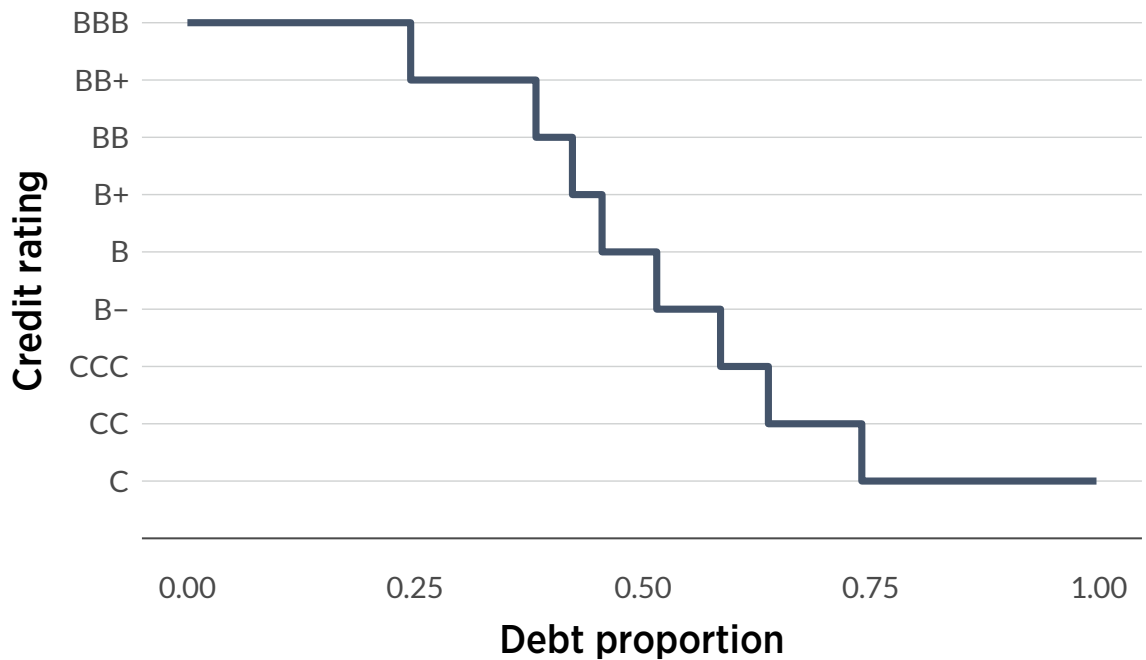
Figure 4.5: Credit rating as a function of the company's debt proportion

Credit rating

Credit rating can also be estimated for the company. Credit rating is interesting in two ways. First, credit rating is useful at giving a grade to a company's debt quality, as to estimate if the company is issuing a reasonable amount of debt. Additionally, credit rating can be used in order to estimate the cost of debt. Indeed, the credit rating of a company reflects the perception the market has of the risk of a business. As such, debtholders will require greater returns from the debt of a company that might default, compared to a company that will most likely pay the interest it owes. In order to estimate the chances of defaulting, creditors can use the interest coverage ratio, which indicates the ability of the company to repay its debt. High ICR results in good credit rating. Figure 4.5 shows the evolution of the scenario company's credit rating with its debt proportion. As the company increases its debt, the credit rating initially remains reasonable, before sharply decreasing after los-

ing its BB+ grade. This observation shows that it is easy to drop in the ratings and that it is of particular importance to have a complete financial analysis process with the best estimations possible in order to avoid making potentially harmful mistakes. Indeed, a reasonable overestimation of the best leverage can result in a significant drop in credit rating, and therefore in NPV.
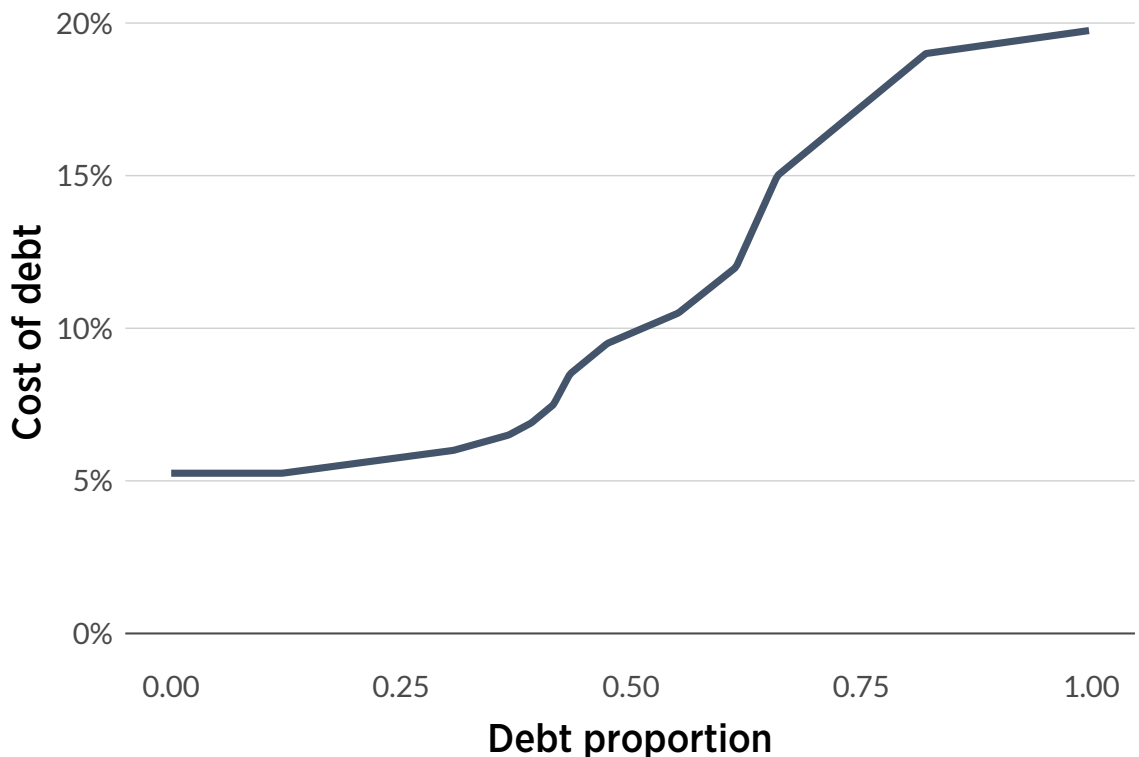
Figure 4.6: Cost of debt as a function of the company's debt proportion

Cost of debt

The aforementioned iterative process enables the calculation of the company's cost of debt. It defines the return debtholders expect from the company's debt, and therefore how much the company does pay. The cost of debt is the output of the debt module and is used in the estimation of the WACC, crucial for the calculation of the NPV. Figure 4.6 shows the resulting cost of debt for the scenario company, as a function of its debt proportion. As the company leverage increases, the cost of debt initially increases slowly. However,

debtholders eventually become more concerned with the amount issued and the ability of the company to pay back, leading the cost of debt to rise due to the higher perceived risk of carrying additional debt. It should be noticed that cost of debt significantly departs from its initial 5.25% value and can reach up to 20% with high levels of leverage. It is therefore important to capture this behavior, which is considerably different from a usual assumption of a constant cost of debt.
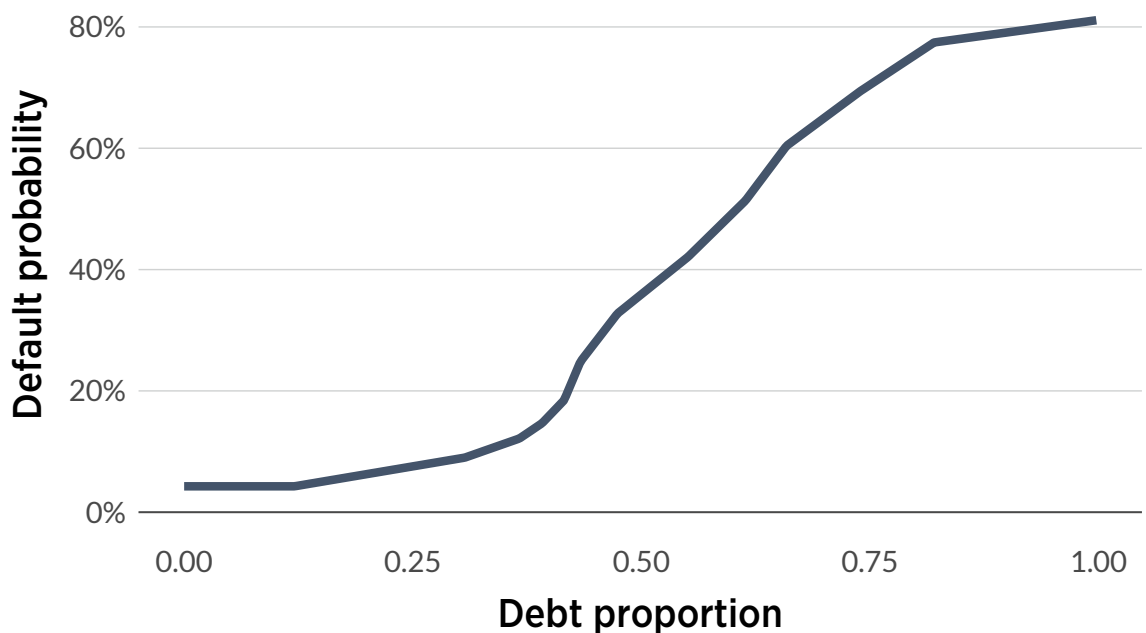
Figure 4.7: Probability of defaulting as a function of the company's debt proportion

Probability of financial distress

The proposed methodology also enables the estimation of the probability of financial distress. Although this probability is not required in the calculation of the NPV, it is useful to measure the financial risk taken by the company. The company's credit rating is used as a proxy for the probability of defaulting. Figure 4.7 shows the probability of the scenario company to default as a function of its debt proportion. Initially, the probability of defaulting is small, and only slowly increases. Eventually, the rate of increase becomes higher,

and the default probability becomes large, up to 80%. While initial probabilities seem low, defaulting can be a particularly harmful event. The risk can therefore be high even with a small probability because the severity is considerable. For example, with 25% of financing coming from debt, the probability of defaulting is 7.5%, compared to 4.3% with debt nearing zero, which makes defaulting 75% more likely. Hence, knowing the probability of financial distress is important as it shows the financial risk that stakeholders are taking and enables to compare the riskiness of different approaches. While the proposed method allows this calculation, typical aerospace approaches do not.
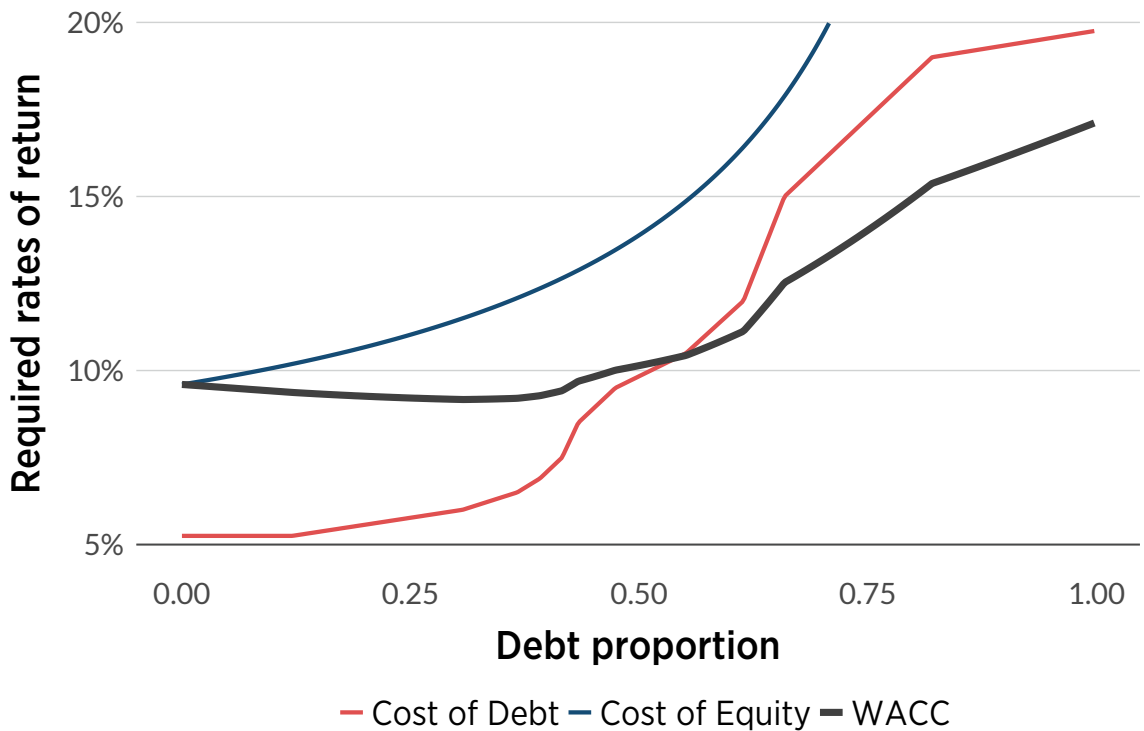
Figure 4.8: WACC, cost of debt, and cost of equity as a function of the company's debt proportion

4.2.3 WACC and NPV optimality

The two previous subsection studied the cost of debt and cost of equity of the company as a function of its leverage. These two variables are then used to compute the WACC.

The WACC is a weighted average of the cost of debt and cost of equity, where the weights are the proportions of debt and equity. Additionally, the cost of debt gets discounted by the effective tax rate, as the interest paid by the company is tax-exempt. The WACC is used as a discount rate in the calculation of the NPV and is therefore a crucial metric to estimate. Figure 4.8 shows the relation between the WACC and the company's debt proportion. The costs of debt and equity are also represented, as they help understand the variations in WACC. At zero debt, the WACC is equal to the cost of equity because the company is fully equity-funded. As debt increases, initially, the WACC decreases as the cost of debt is lower than the cost of equity. Indeed, the addition of cheap debt, helped by the benefits of the tax shield, more than compensates the increase in the cost of equity. However, the eventually faster increase in the cost of debt leads to a change of direction of the WACC, which increases for higher leverage levels. The relation between leverage and WACC results in the presence of a minimum in WACC; for around 31% of debt funding for this scenario. This debt level is also the debt level that maximizes the NPV. Hence, the proposed method enables the identification of an optimal capital structure for the company by finding the optimal trade-off between debt and equity.
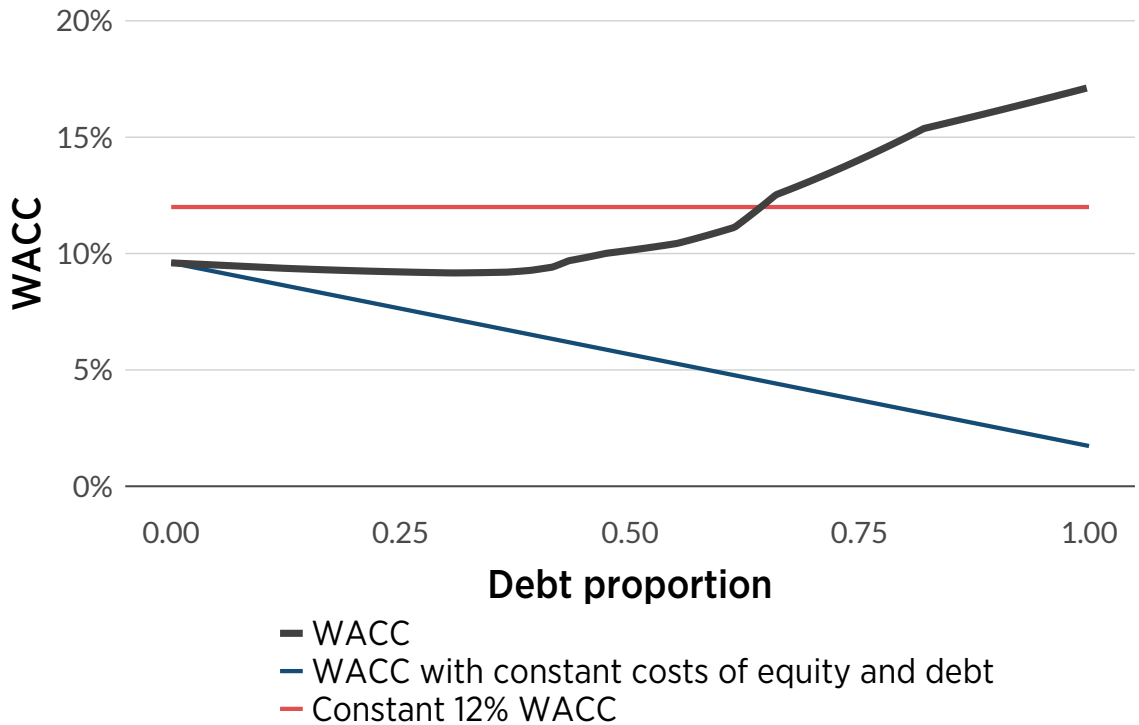
Figure 4.9: Comparison of the WACC for various evaluation methods

Additionally, it is also possible to compare the results of the proposed methods with other approaches that evaluate the WACC. Two different practices are used in aerospace to estimate the WACC: using an arbitrary, constant WACC based on a guess or previous work guesses; or use constant costs of equity and debt. Figure 4.9 displays how the WACC varies with these two methods, compared to the proposed financial analysis. This comparison does not only unveil large differences in estimated WACC value. It also shows differences in capabilities. Indeed, while the proposed approach results into an optimal trade-off between debt and equity, the two other methods are not able to. Indeed, with constant WACC, leverage has no impact on the profitability of the company, and therefore, no optimal capital structure can be identified. With constant costs of debt and equity, the WACC monotonically decreases from the cost of equity to cost of debt (with tax shield) as leverage increases. Hence, this approach always results in a 100% debt structure if the

cost of debt is lower than the cost of equity, and 100% equity otherwise. This is an absurd result, and therefore this second method cannot be used either.
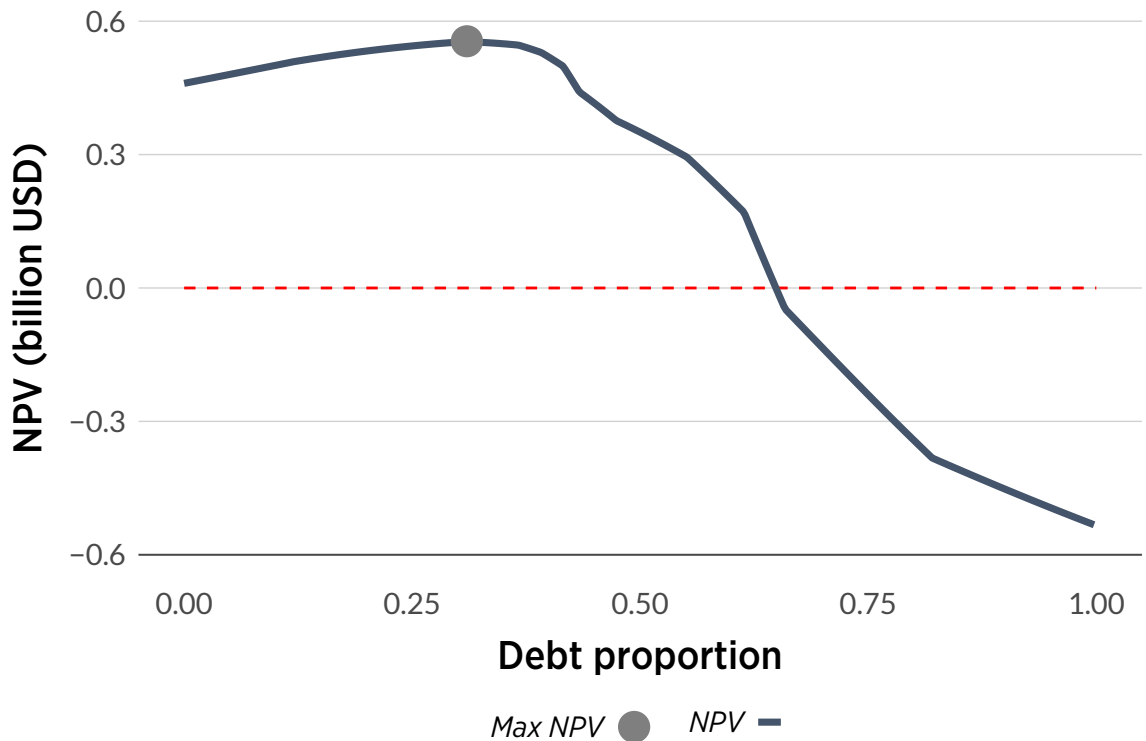
Figure 4.10: Net Present Value as a function of the company's debt proportion

Using the WACC and an estimation of the company's free cash flows, the NPV can then be calculated. Figure 4.10 shows the NPV of the considered suborbital vehicle program as a function of the company's debt proportion. It increases slowly first, reaches a maximum, and eventually plummets as the company's debt quality degrades. Analyzing the NPV enables making several observations. First, it can be seen (again) and verified that the proposed method leads to the identification of an optimum in NPV. Reversely, the other two previously mentioned methods do not provide such optimum, or at least a relevant one. A second observation can be made: the capability to find the optimal trade-off between debt and equity enables to capture additional value. Indeed, the NPV can be raised from $450 million with zero debt, to $540 million with the optimal leverage level; a 20% improvement. Moreover, using the proposed method also saves value by preventing selecting

an inappropriate debt level that would result in value destruction, and could even make a potentially profitable concept unprofitable.

It is important to note that the maximum identified here is only optimal if the sole objective is to maximize the NPV. Other cases can apply, as one can also want to reduce financial risk and therefore debt, which would lead to a different optimal trade-off.

4.3 Importance of in-depth financial modeling

The previous section showed the behavior of intermediate and output variables in the proposed financial analysis. A comparison with the outcome other simpler methods would have led to is also provided. It revealed significant differences between these methods regarding capabilities and results. However, it did not prove that all added parameters were useful to the overall calculation of the NPV. Hence, this section aims at assessing the importance these terms in the evaluation of the NPV.

Indeed, another advantage of the implemented financial analysis is its greater objectivity. Based on more in-depth corporate finance techniques, it involves the incorporation of additional parameters to compute the NPV. Hypothesis 3 states that the inclusion of such parameters increases the objectivity of the valuation module. To verify this aspect of the hypothesis, the relative importance of variables must be determined. Parameters with high impact on the value of the NPV should be included in the computation. Borgonovo and Peccati [290] use a differential sensitivity analysis to estimate and rank the importance of parameters involved in the NPV and IRR equations. Other authors [291–295] also used different types of sensitivity analysis to determine parameter importance in more general cases. Hence, the sensitivity S_x^{NPV} of the NPV in computed, according to Equation 4.1.

$$S_x^{\text{NPV}} = \lim_{dx \to 0} \frac{d\text{NPV}/\text{NPV}_{ref}}{dx/x} \simeq \frac{\Delta\text{NPV}/\text{NPV}_{ref}}{\Delta x/x} \qquad (4.1)$$

In Equation 4.1, x are the studied parameters, and Δx are the small variation applied to them to evaluate the variation ΔNPV in NPV. This sensitivity analysis is performed for 3 cases: 0% debt company, 25% debt, and 50% debt. Indeed, a company with 0% debt will not be sensitive to the variation of the cost of debt, for example. Using different cases enable to assess the sensitivity in various situations, and not miss important factors. Moreover, as the NPV is not an absolute scale, but rather a relative scale, a reference value NPV$_{ref}$ is used in the calculation in order to make sensitivities comparable.

Figure 4.11 displays the results of the sensitivity analysis for various parameters. The sensitivity to the WACC or discount rate is large, as previously demonstrated. Indeed, a variation of 1% in the WACC value results in more than 4% variation in NPV. This amount is used as a reference for comparison with the other sensitivities. It should be noted that the sensitivity to the cost of debt is, understandably, much higher when the debt proportion
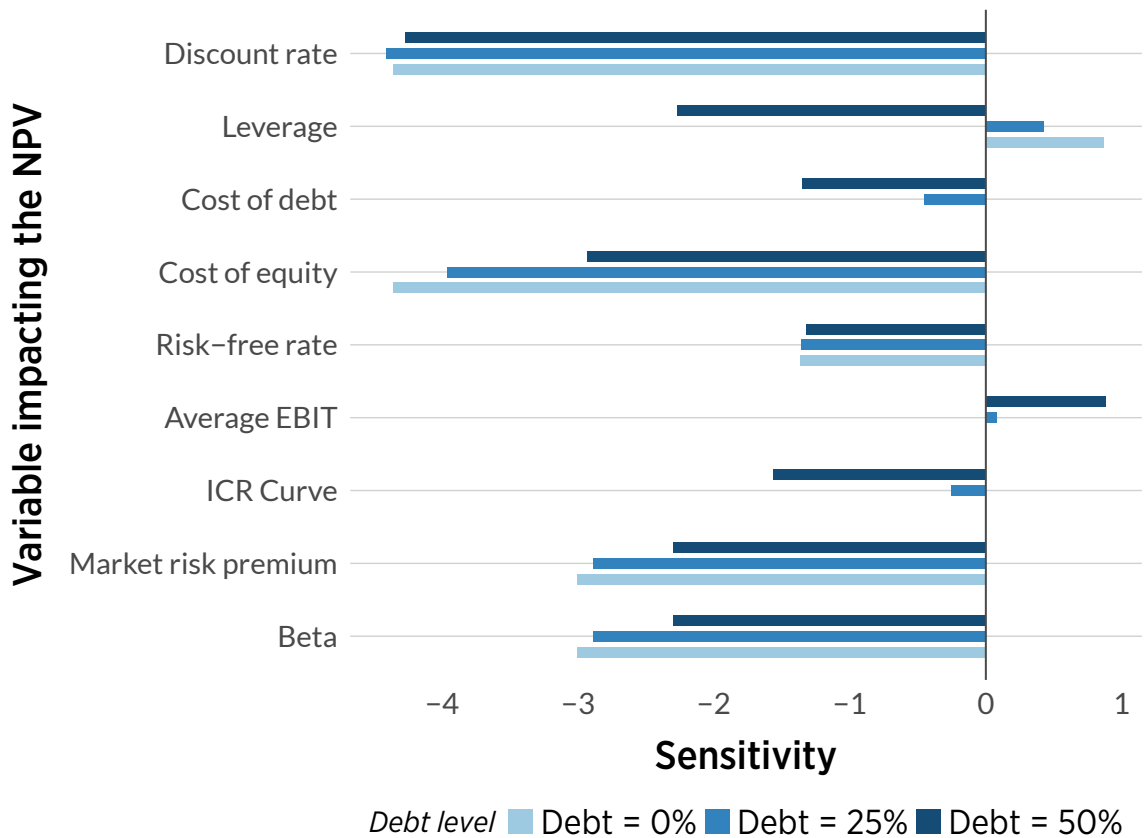
Figure 4.11: Sensitivity analysis of implemented financial parameters

215

increases, as both the amount of debt and the cost of debt increase. Overall, the NPV is sensitive to all parameters. The least impactful, the average EBIT, still results in an 0.88% increase in NPV when raised by 1% at 50% debt (the impact is much lower for lower debt proportions: creditors do not give high importance to the company's earnings as long as it is apparent it will not be in financial distress). Compared to the reference variation, this 0.88 sensitivity is close to 20% of the sensitivity to the discount rate. Hence, even this parameter has a large enough significance and should be included in the model along with the different other additional parameters. Therefore, all parameters included in the proposed method are significant, which proves that they are required for a more objective financial analysis.

4.4 Summary and comparison with different financial approaches

In this chapter, various aspects of the proposed financial module implementation were presented. The primary capabilities the proposed method brings were illustrated in the scenario of a suborbital vehicle company and were benchmarked against conventional approaches to finance for aerospace applications. While the proposed method provides the ability to compute many more financial metrics and is more detailed and objective, other approaches have shown severe limitations. In this section, the benefits of the proposed method are summarized and its main features are compared to those of two typical approaches: 1) using an arbitrary discount rate; 2) using a discount rate computed from arbitrary costs of debt equity.

Hence, the proposed method provides superior performance regarding six crucial features of the financial analysis:

- **Objective estimation of the discount rate.** The method analyzed in this chapter proposes a detailed process that leads to the estimation of the discount rate, crucial in the proper calculation of the NPV. In opposite, the two other methods only use arbitrary values based on guessing.

216

- **Inclusion of crucial parameters.** The proposed financial analysis makes use of multiple yet essential financial parameters, which have a major impact on the outcome of the computation and should therefore be included to provide a reliable estimate. On the other hand, the two other approaches only include a small fraction of these. With an arbitrary discount rate, only one parameter is used; with arbitrary costs of debt and equity, two more parameters are included. Many more should be present in the calculation. As all additional factors have a significant impact on the calculation of the NPV, verification criterion 3.1 is checked (*The additional terms modeled have at least 10% of the contribution of the discount rate*).

- **Evaluation of the financial risk.** The proposed implementation provides a framework to estimate the financial risk stakeholders are incurring. Reversely, other methods do not provide any measurement.

- **Detailed analysis capabilities to support risk/value decision-making.** The method detailed in this section also enables a detailed analysis of multiple financial factors, which helps better understand the financial characteristics of the company and can be used in the decision-making process. Other methods, on the other hand, can only provide the NPV, without being able to compute any lower-level financial factors that could influence decision-making. As such, verification criterion 3.4 is checked (*The model produces a measure of financial risk and multiple financial metrics*).

- **Optimal financial trade-offs.** The proposed process leads to the identification of an optimal trade-off between the amount of debt and equity the company needs to issue to maximize the NPV. With an arbitrary discount rate, no trade-off can be made, while with arbitrary costs of debt and equity, absurd optima are found. As a meaningful optimal capital structure is found, verification criterion 3.2 is checked (*The capital structure resulting in maximum NPV is not 100% debt or 100% equity*).

- **Enables the realization of a significantly greater NPV.** Finally, the proposed approach leads to greater NPVs in two ways: 1) by enabling the identification of a maximum in NPV, and therefore reaching a greater NPV than in the zero-debt case; 2) by avoiding the value destruction that would happen in case of a poor guess of the best leverage level for the company, as it would most likely be the case with the other two methods. In the studied example, 20% greater NPV could be achieved compared to the zero-debt case, which is a significant improvement and hence checks verify criterion 3.3 (*This approach results in significantly higher NPV than current ones*).

Table 4.4 sums up the main features of the three considered financial approaches, and it becomes clear that the proposed financial method overcomes the large limitations of current implementations in aerospace applications.

Table 4.4: Feature comparison of the proposed financial implementation with current aerospace practices

Features	Arbitrary discount rate	Arbitrary costs of debt and equity	Proposed method
Discount rate estimation		◔	●
Financial risk			●
Crucial parameters		◔	●
Detailed analysis capabilities	◔	◔	●
Optimal financial decision-making			●
Greater NPV			●

The objective of this chapter was to verify or reject the hypothesis to research question 3, which states: *"if a more comprehensive approach to financial analysis of aerospace programs is developed based on financial modeling of cost of debt, cost of equity and costs*

of financial distress, then the current implementation can be improved in order to be more objective and accurate, support risk/value decision-making, and enable optimal financial trade-offs.". To do so, verification criteria were tested in this chapter and were all checked, and hypothesis 3 was deemed verified.

CHAPTER 5

EFFICIENTLY ESTIMATE DOWNSIDE DEVIATION

The last chapter dealt with the implementation of a more in-depth financial analysis as compared to regular implementations used in aerospace applications. Hypothesis 3 was found to be a solution to research question 3. Verifying the usefulness, soundness, and validity of the proposed financial module was essential for the overall modeling and simulation process. Hence, with research question 3 answered, the M&S environment is set. The next step is enabled: propagating uncertainty to assess the riskiness of each considered design and program. To do so, a process that efficiently estimates the downside deviation of targeted objectives is required. As such, research question 2.1 was formulated as follows: *"how to time-efficiently estimate the downside deviation of value of complex aerospace system programs, in the context of multi-objective optimization?"* After studying various uncertainty propagation and surrogate modeling techniques, hypothesis 2.1 was formulated in order to answer this question: *"if a process using Second-Order-Third-Moment uncertainty propagation on classification and regression neural networks is implemented then the downside deviation of value of complex aerospace system programs can be estimated in a timely manner, in the context of multi-objective optimization."* Hence, to confirm or reject hypothesis 2.1, a process integrating the main suggested elements is implemented and studied in this chapter. First, a study case is built in section 5.1 and used to produce the results presented in this chapter. Using the specified scenario, classification and regression neural networks are first trained, in section 5.2. The fitting process is detailed, and the predictivity of these networks is verified for each metric to be estimated. Once the neural networks are created, the accuracy of the SOTM method is estimated in the case of suborbital vehicles and the proposed M&S environment, in section 5.3. At this point, the uncertainty propagation process is set and its time-efficiency can be assessed in the context

of multi-objective optimization, as shown in section 5.4. Finally, section 5.5 summarizes the chapter, compares the proposed method to alternatives, reminds the verification criteria, and checks hypothesis 2.1.

5.1 Study scenario

In this chapter, the objective is to study the proposed method used to estimate downside deviation efficiently. As such, an uncertainty scenario is implemented. Unlike the previous chapter, no particular concept is chosen. Indeed, one of the goals is to study the ability of the proposed technique to quickly provide an estimate of downside deviation while using multi-objective optimization. However, as the process of training neural networks is involved, this chapter focuses on architecture 2 (rocket-plane) as an illustration of the proposed process. Results for other architectures can be found in appendix C.

In this chapter, an uncertainty scenario is defined. Five base uncertain variables are defined. To model these uncertain inputs, triangular probability distributions are used. The probability distribution function $f(x)$ of a triangular distribution is defined in Equation 5.1, where a is the lowest possible value the random variable can take, b is its highest possible value, and m is the mode of the distribution.

$$f(x) = \begin{cases} \frac{2(x-a)}{(b-a)(m-a)} & x \in [a, m] \\ \frac{2(b-x)}{(b-a)(b-m)} & x \in [m, b] \\ 0 & elsewhere \end{cases} \qquad (5.1)$$

Triangular variables are particularly used in management science as a way to approximate a random variable when little information is known, but some estimates can be provided. Using a as the best-case estimate, m the most likely estimate, and b the worst-case estimate, the triangular distribution can be built. Triangular distributions are easy to implement and facilitate closed-form statistical calculations. It also has important advantages over normal distributions. Indeed, while normal distributions are frequently used in many

aerospace applications, they have significant limitations. The main disadvantage of the normal distribution is that it is unbounded. This can result in the random variable taking potentially unwanted values, such as negative numbers for a positive metric, or excessively high or low values which can result in an abnormal response of the system – for example if the input gets out of the design range of the neural network. Reversely, as a bounded function, the triangular distribution does not have these drawbacks. Moreover, the normal distribution is completely symmetric. On the other hand, the triangular distribution can introduce skewness in the system, which can sometimes be more realistic.

(a) Required altitude distribution   (b) Maximum load factor distribution
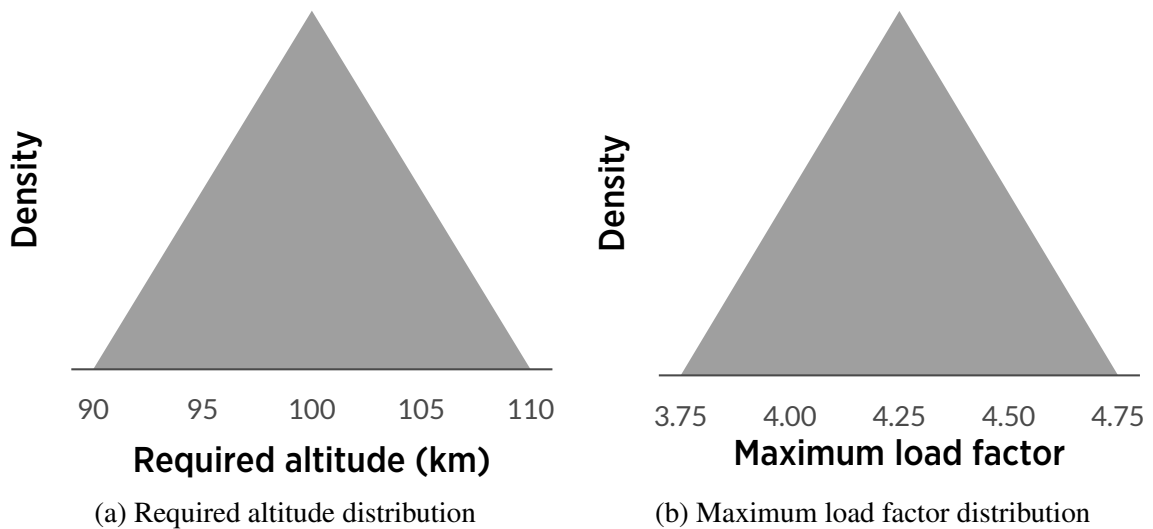
Figure 5.1: Distributions of uncertain regulatory variables

First, uncertainty over regulations-related inputs is defined. Figure 5.1a and Figure 5.1b respectively show the probability distributions of the required flight altitude and the maximum allowable load factor during the flight. The required altitude ranges from 90 km to 110 km, with a most likely estimate at 100 km. The maximum allowable load factor varies from 3.75 to 4.75 with the mode at 4.25.

(a) Initial demand distribution   (b) Demand growth distribution
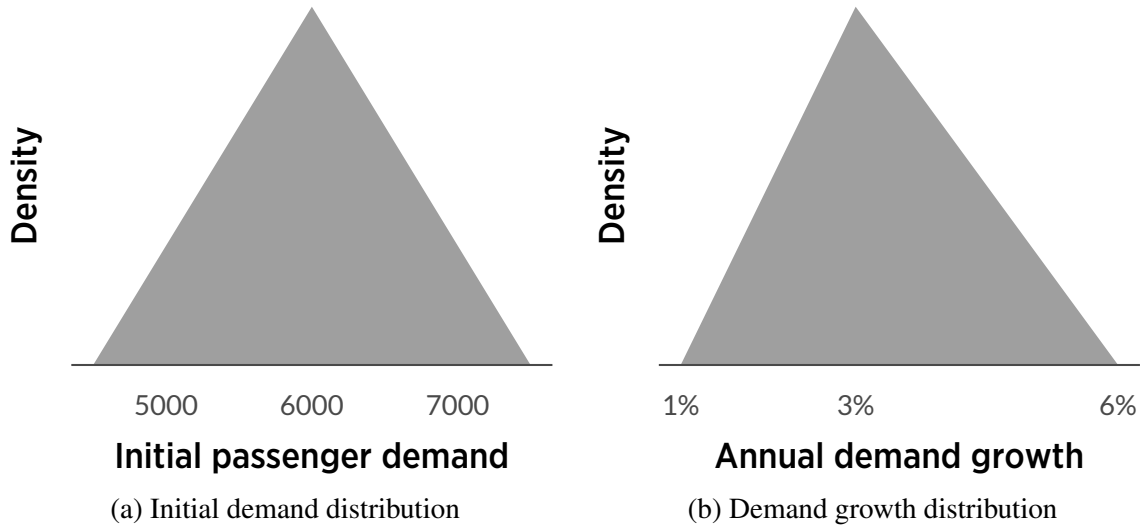
Figure 5.2: Probabilistic distributions of the two demand parameters

Demand is another important uncertain input. Demand is characterized here by an initial demand and a demand growth. Demand $D(t)$ at time t is expressed as shown in Equation 5.2, where D_0 is the initial demand, and g_D is the rate of growth of demand. This equation is only defined for $t \geq 5$, as the spacecraft only starts being operated o year 5 of the program.

$$D(t) = D_0(1 + g_D)^{t-5} \quad \text{for} \quad t \geq 5 \tag{5.2}$$

Demand as a function of time is uncertain because initial demand and demand growth are uncertain as well. Figure 5.2a and Figure 5.2b respectively present the probabilistic distribution of initial demand and demand growth. Initial demand ranges from 4500 passengers to 7500 passengers per year, with a mode at 6000 passengers per year. Demand growth takes values from 1% to 6%, and its most likely value is 3% increase per year.
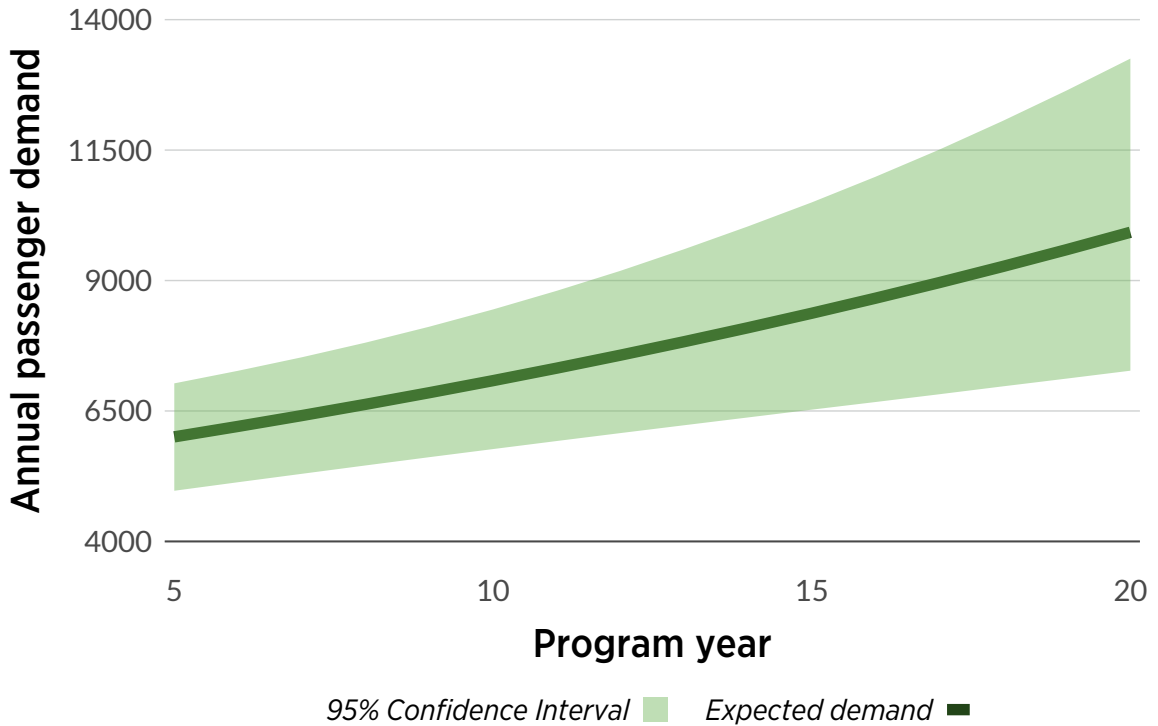
Figure 5.3: Time distribution of demand

With initial demand and demand growth defined in a stochastic way, it is then possible to estimate the probabilistic distribution of demand over time. The distribution of demand each year can be estimated as the product of multiple triangular distributions and is therefore fully determined. Figure 5.3 shows the evolution of demand over the program life cycle. The 95% confidence interval, represented on the graph by a ribbon, approximates the range of values that demand can take over time. In the initial years, uncertainty over demand is relatively small, but uncertainty increases with time, as demand growth is uncertain. In the most likely case, demand grows from 6000 passengers per year to about 10000 passengers per year. In the worst-case scenario, demand remains fairly low and stagnates, while in the best case, demand can more than double and reach over 13000 passengers per year.

Table 5.1: Summary of random inputs used in this chapter

Random input	Low estimate	Most likely estimate	High estimate
Required altitude	90 km	100 km	110 km
Max. load factor	3.75	4.25	4.75
Initial demand	4500 pax.	6000 pax.	7500 pax.
Demand growth	1%	3%	6%

Table 5.1 summarizes the choice of uncertain inputs distributions used in this chapter, based on their low, most likely, and high estimates. Only these three parameters are necessary to fully describe them as they are triangularly distributed. These uncertain inputs are later used in this chapter to be propagated through the M&S environment and assess the downside deviation of the program's Net Present Value, chosen as a representation of value in this scenario.

5.2 Neural network training and verification

To propagate uncertainty through the M&S environment, neural networks are fitted, as described in chapter 2. The proposed five-step process is followed in order to come up with the best neural networks possible. Hence, the first step is to sample the design and uncertain space using a design of experiment, in order to estimate the targeted responses. Data is then cleaned, and outliers are removed. Additionally, feature scaling is used to facilitate convergence of training algorithms. The prepared is then used by the standard backpropagation training algorithm used for fitting the neural networks. The fitted neural networks are analyzed, in order to verify their proper predictivity. The following subsections further detail this steps, with the exception of feature scaling, which is trivial. As such, subsection 5.2.1 describes the sampling process, subsection 5.2.2 gives information about data cleaning and removal of outliers, subsection 5.2.3 details the followed neural

network training process, and, finally, subsection 5.2.4 shows the verification of neural nets generated in the previous step.

5.2.1 Sampling and simulating

The first step of the process consists in sampling the input space and uncertain space to evaluate the response in function of vehicle and environmental variables. The number of vehicles produced and the total number of flights performed during the year also have an impact on the vehicle-level costs. These two variables are therefore also part of the design of experiment. Following the method proposed in chapter 2, each data point of the DOE is inputted in the design part of the M&S environment, and six responses are evaluated: the operational risk of the vehicle, the four base vehicle-level costs (development costs, operating costs, manufacturing costs, and carrier aircraft costs), as well as the feasibility of the concept. To do so, for each architecture, 10000 data points are first sampled and evaluated by the sizing part M&S environment. This initial data set only contains the vehicle and environmental variables, which are necessary to size the spacecraft. As the cost discipline is computationally inexpensive, the feasible data points can be replicated, augmented with the production and operation variables, and their costs can be evaluated. In this case, the feasible data points are replicated 20 times, creating a DOE of 200000 data points.

5.2.2 Cleaning data and removing outliers

After evaluating the response of the data set, data must be cleaned. First, 220 data points resulted in complex number outputs. These 220 points are not removed from the data set, but are categorized as infeasible, and are therefore not used as part of the training of regression neural networks, but are used for the training of classification neural networks. Using outlier detection methods described in chapter 2, 350 data points resulting in extreme values of cost are labeled infeasible and taken off the regression network training data set.

The evaluation process also naturally resulted in many infeasible concepts. The M&S environment marked 138105 sets of inputs as infeasible. Adding outliers and complex responses, a total of 92070 concepts are categorized as infeasible, or about half of the design space. This leaves 107360 feasible concepts (or around 54% of the initial data set) which can be used for the training of regression neural networks. The initial 10000-point data set has to be used for the training of the classification neural network and for the evaluation of the operational risk.

5.2.3   Training neural networks

The three first step of the surrogate modeling process prepared the data to be used for fitting the neural networks. Hence, both the regression and classification neural networks can be trained at this stage. The next two parts describe the training process, detail the selection of the neural network's structure, and provide observation relative to the predictivity of these models, both for classification and regression networks.

Regression neural networks

To train the regression neural networks, the inputs and responses of the 107360 feasible concepts are used. These are fed into a standard backpropagation training algorithm. The data set is split into a training, validation, and test set, respectively with the proportions 70%, 20%, and 10%. The training algorithm attempts to minimize the RMSE of the training set. Two convergence criteria are used:

- The algorithm is deemed to have converged if 2000 iterations are reached.

- The algorithm is stopped if the RMSE of the validation set has not improved since 30 iterations.

To improve the predictivity of the models, two techniques are used: replication and optimization of the neural network structure. Indeed, replication can help improving pre-

dictivity, because neural network training is not a deterministic process, and therefore the goodness of fit can vary. For this application, five replications are used for each considered neural network structure. Additionally, several neural network structures are used. This enables to find the structure that offers the best fit. Single and double hidden layer neural networks are evaluated. In this study, structures with two hidden layers are designed with a given number of nodes in the first hidden layer, and half that number in the second one.

Each of the five responses (operational risk, development costs, manufacturing costs, operating costs, and carrier aircraft costs) requires the training of a separate regression neural network. This part focuses on the analysis of the training process for the prediction of development costs. Other models are also fitted, and their results can be found in appendix.

(a) Validation error with one-hidden-layer neural network

(b) Validation error with two-hidden-layer neural network
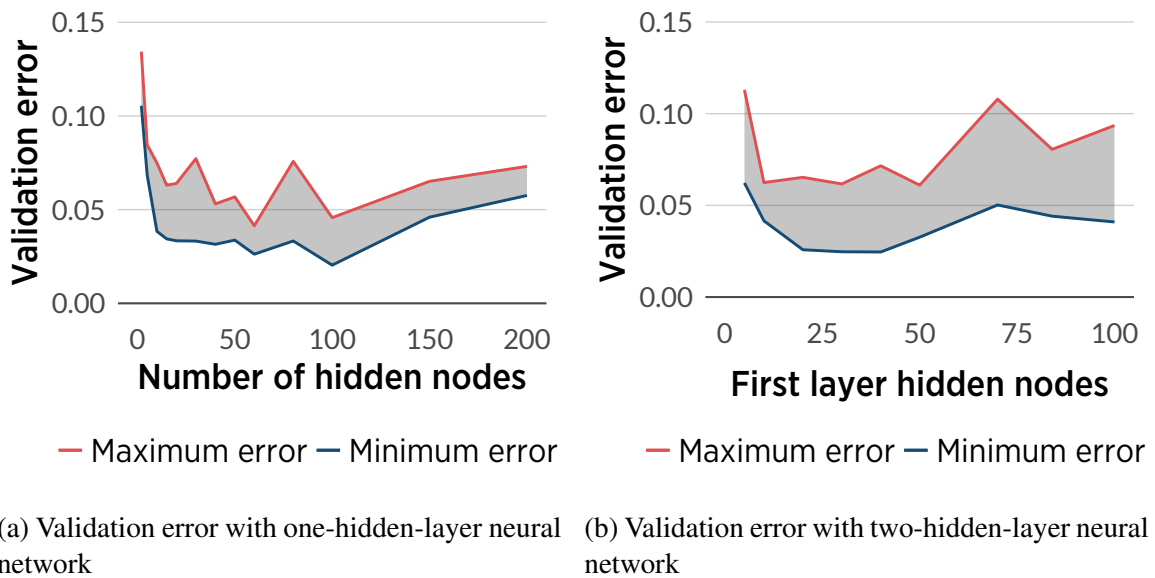
Figure 5.4: Validation set error as a function of the neural network size

Figure 5.4a and Figure 5.4b respectively show the validation set RMSE for single and double hidden layer neural networks, as a function of the network size. Minimum and maximum values of the RMSE found for the five replications are represented. The benefits of replication can be observed, as there is a significant difference between the RMSE values found for a given structure with different replications. Yet, only the minimum RMSE matters for the selection of a model, and it is found that a single-layer neural network

228

with 100 hidden nodes provides the best results, with a validation RMSE of 0.0204 and an R^2 of 0.987. This is, therefore, the neural network selected to estimate development costs for architecture 2.
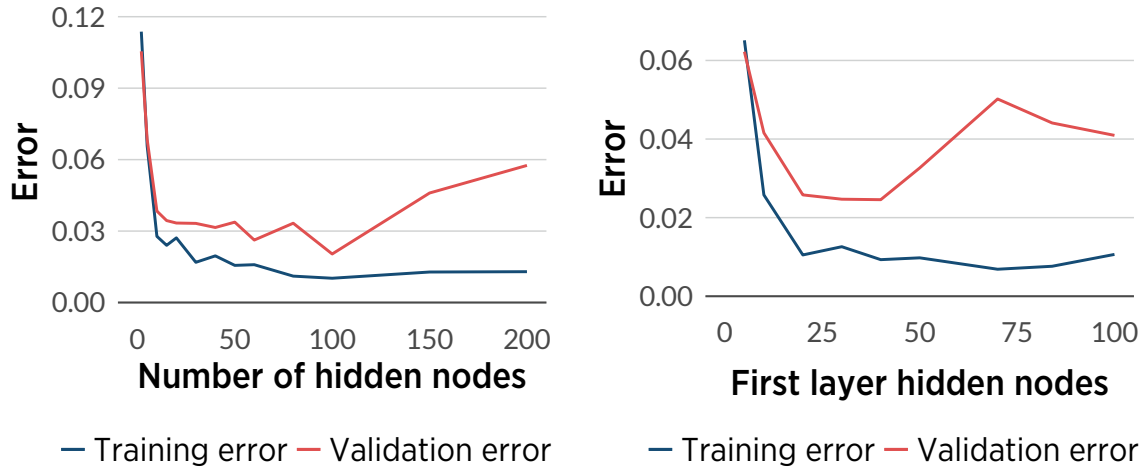
(a) Training and validation error with one-hidden-layer neural network

(b) Training and validation error with two-hidden-layer neural network

Figure 5.5: Training and validation set error as a function of the neural network size

It is also interesting to observe the evolution of the training set RMSE, as it helps understand how the number of hidden layers and hidden nodes affect the predictivity of models. Figure 5.5a and Figure 5.5b respectively represent the training and validation RMSE for single and double hidden layer neural networks. As the number of hidden nodes increase, both validation and training error increase, at first. Indeed, the increasing number of nodes in the model gives it more freedom and the capability to fit well the average response of the model. However, as the number of hidden nodes become too large, the model starts fitting noise, rather than the average behavior. This results in further decrease in training set error, but an inversion of the trend for validation set error. The significant difference between training RMSE and validation RMSE is symptomatic of overfitting. This behavior is not desirable as the model will provide poor predictivity when estimating new data points. With the 100-hidden-node neural network, some overfitting can be observed, but it is here small enough and acceptable because it still provides the best validation RMSE.

With a higher number of hidden nodes, overfitting becomes too large, and the model loses predictive performance.
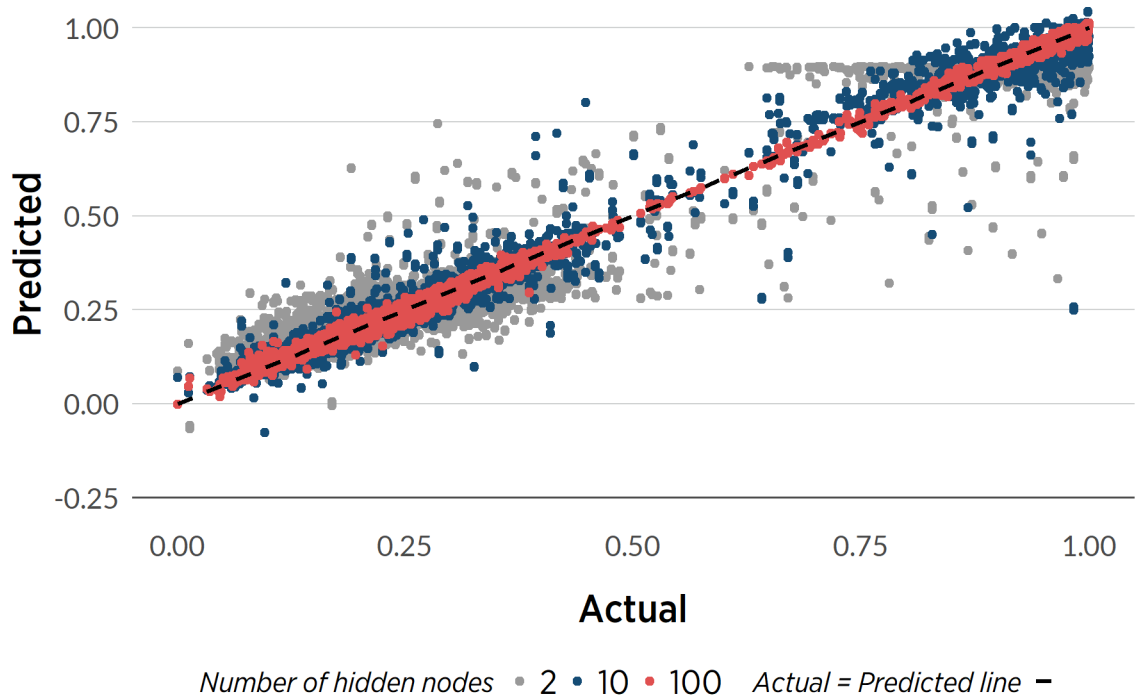
Figure 5.6: Predicted responses as a function of their actual value and the number of hidden nodes

The increase in performance due to the use of a larger number of hidden nodes can be directly visualized using an actual versus predicted plot. Figure 5.6 is a scatter plot representing each point with the actual value of its response and the prediction made by the neural network. Ideally, each point is as close as possible to the first bisector, which represents perfect prediction as the predicted value equals the actual one. Figure 5.6 overlays these results for three different neural network structures: 2 hidden nodes, 10 hidden nodes, and the optimum, 100 hidden nodes. The two-hidden-node neural network shows poor predictivity, with a lot of points far from the actual equals predicted line. As the number of nodes increase, points start aggregating closer to the first bisector, and fewer extreme mispredictions are observed.

Classification neural networks

The same type of process is applied to the classification neural network. Such a type of neural network is used to predict the feasibility of a given concept. In this case, the full 10000-point data set is used. The data set is split into training, validation, and test sets, respectively with the proportions 70%, 20%, and 10%. The training algorithm attempts to minimize the cross entropy of the training set. The same two convergence criteria as with regression neural networks are used:

- The algorithm is deemed to have converged if 2000 iterations are reached.

- The algorithm is stopped if the RMSE of the validation set has not improved since 30 iterations.

To improve the predictivity of the models, ten replications are used for each considered neural network structure. This number is higher than for regression neural networks because the algorithm runs faster for classification, allowing for additional calculations. Single and double hidden layer neural networks are evaluated to find the structure that offers the best fit. In this study, structures with two hidden layers are designed with a given number of nodes in the first hidden layer, and half that number in the second one.

In addition to determining the optimal network structure, an optimal threshold for classification has to be selected. Indeed, classification neural networks result in a continuous value between 0 and 1. Hence, a threshold used to separate positive from negative cases has to be used. This threshold determines the trade-off between recall (also sensitivity or true positive rate) and fall-out (false positive rate).
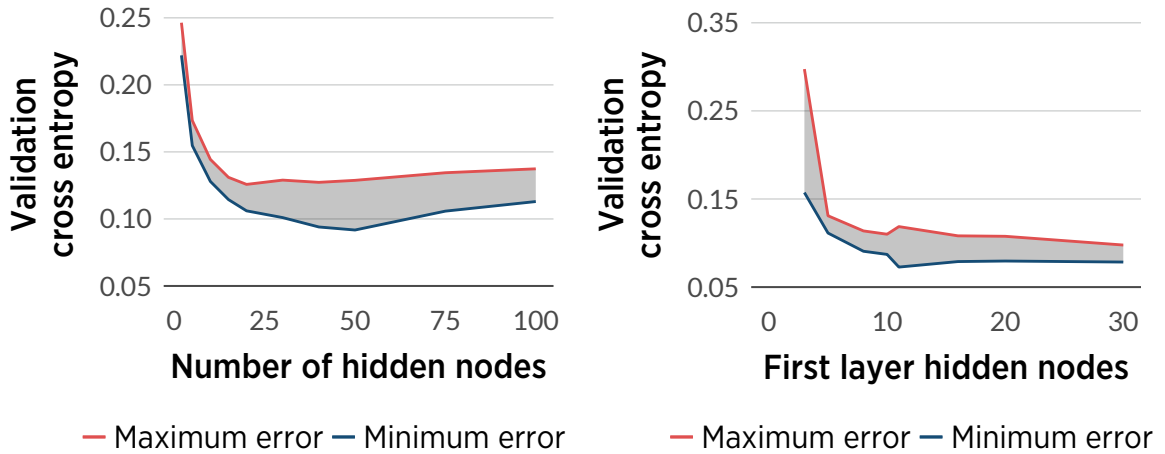
(a) Validation cross entropy with one-hidden-layer neural network

(b) Validation cross entropy with two-hidden-layer neural network

Figure 5.7: Validation set cross entropy as a function of the classification neural network size

As for regression neural networks, the evolution of validation error with the number of hidden nodes is analyzed. Figure 5.7a and Figure 5.7b respectively show the validation set cross entropy for single and double hidden layer neural networks, as a function of the network size. Minimum and maximum values of the cross entropy found for the ten replications are represented. In this case, a two-hidden-layer neural network with 11 nodes on its first hidden layer and 5 nodes on its second is optimal, with a validation cross entropy of 0.073. Hence, this particular neural network is used to represent the feasibility of architecture 2 concepts.

(a) Receiver operating characteristic   (b) Misclassification rate
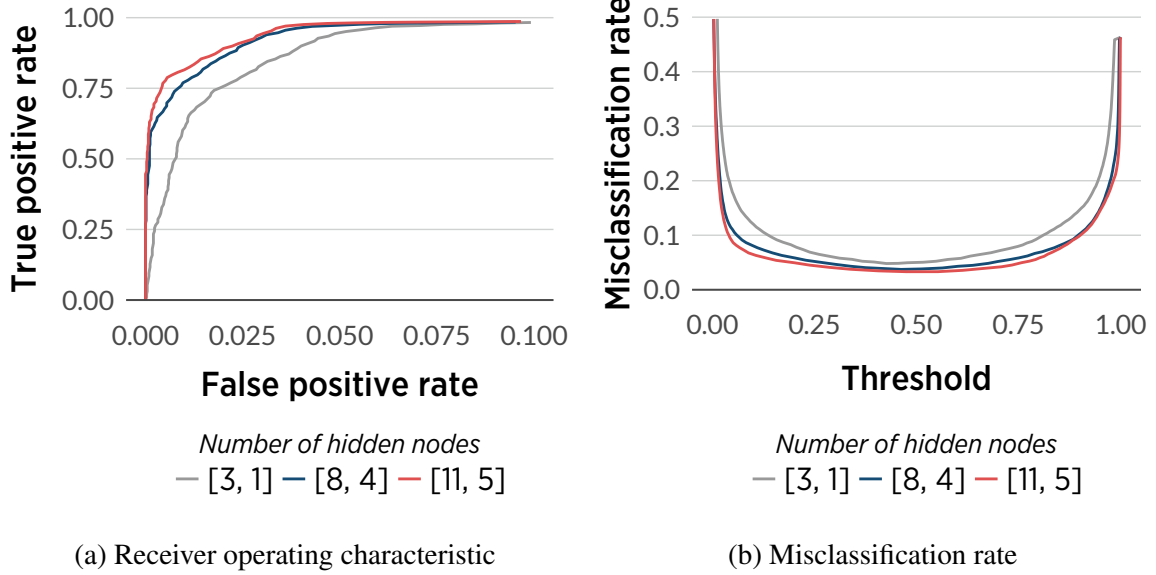
Figure 5.8: Evolution of classifier predictivity with number of hidden nodes

The evolution of classification neural networks predictivity with the number of hidden nodes can also be studied. Figure 5.8a represents the sets of possible combinations of recall and fall-out for three different two-hidden-layer neural networks: 3+1 hidden nodes, 8+4 hidden nodes, and the optimum, 11+5 hidden nodes. The objective is to maximize recall, minimize fall-out, and therefore approach the top left corner of the graph as much as possible. It can be observed that the 11+5 neural network offers much better predictivity than others. Additionally, for all cases, the false positive rate seems fairly low, while it appears a bit harder to increase the true positive rate.

In Figure 5.8b, the misclassification rate is represented for the same three neural networks as a function of the selected classification threshold. Misclassification rate MCR can be estimated as given in Equation 5.3, where FP is the number of false positives, FN the number of false negatives, N_N the number of actual negatives, N_P the number of actual positives, TPR the true positive rate, FPR the false positive rate, and N the total number of data points.

$$MCR = \frac{FP + FN}{N} = \frac{N_N(1 - TPR) + N_P FPR}{N} \tag{5.3}$$

Again, the optimal neural network shows greater predictivity than the two others as its misclassification rate is much lower. Figure 5.8b also helps understand the selection of the classification threshold. With the 11+5 neural network, the minimum misclassification rate is obtained for a 0.5315 threshold, resulting in a 3.25% misclassification rate.

5.2.4 Verification of generated models

The previous step consisted in the training of regression and classification neural networks, and the selection of the structure with the best predictivity. In this step, the selected neural networks are checked, to make sure that they are providing sufficient prediction performance. Both the regression and the classification neural networks are checked. The next two parts are articulated around these two categories.
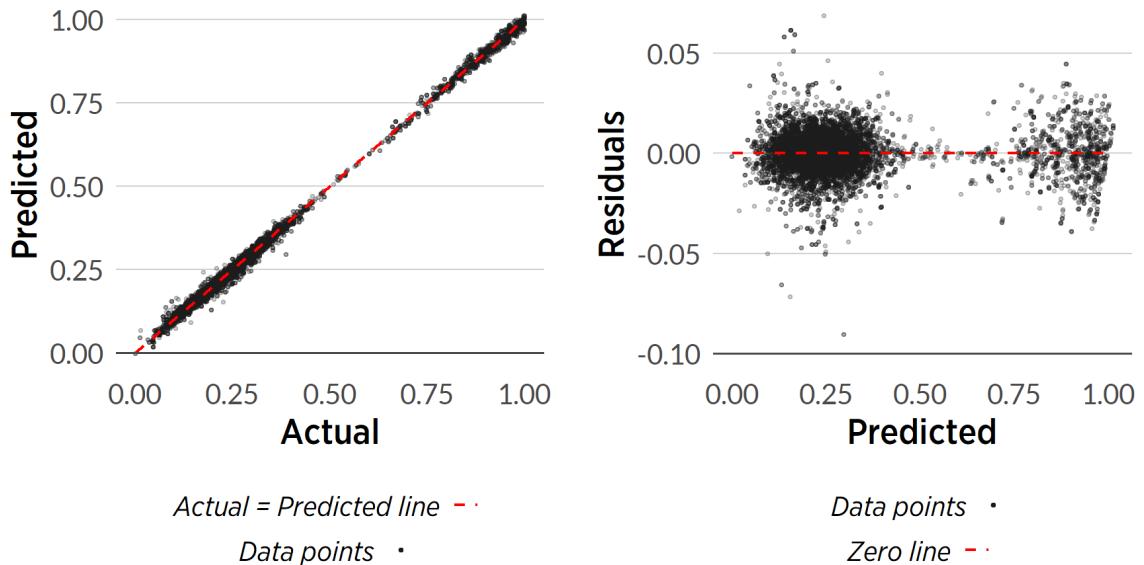
(a) Predictions as a function of actual values   (b) Residuals as a function of predicted values

Figure 5.9: Analysis of the regression model's predictions

Regression neural networks

In this part, regression neural networks are checked. As suggested in chapter 2, several aspects should be checked: the model's predictions against their actual values, the values

of residuals against predicted values, the overall distribution of residuals, and the overall training, validation, and test set RMSE.

In previous subsection, Figure 5.6 compared the predictivity of neural networks with different sizes. In this subsection, Figure 5.9a also represents a scatter plot of predictions as a function of their actual values but focuses on the selected regression neural network for the estimation of development costs. In this graph, two clusters of points can be identified. While clustered responses can be typical of poor input sampling, this is here the result of the presence of multiple discrete and categorical variables in the input set. Overall, the fit looks good and centered around the actual equals predicted line. Only a few points seem to show significant deviation.

Figure 5.9b is a scatter plot of the value of residuals as a function of the predicted values of the surrogate model. As for the previous graph, two clusters of points can be seen. It is, however, important to notice that both clusters seem to provide similar variance for their residuals. This is not a necessary feature for the model, but it is appreciable to have a homogeneous quality of fit across the response space. Additionally, Figure 5.9b shows that residuals are well centered on zero, which indicates that the surrogate model is not biased.

(a) Distribution of residuals   (b) Normal Q-Q plot of the residuals
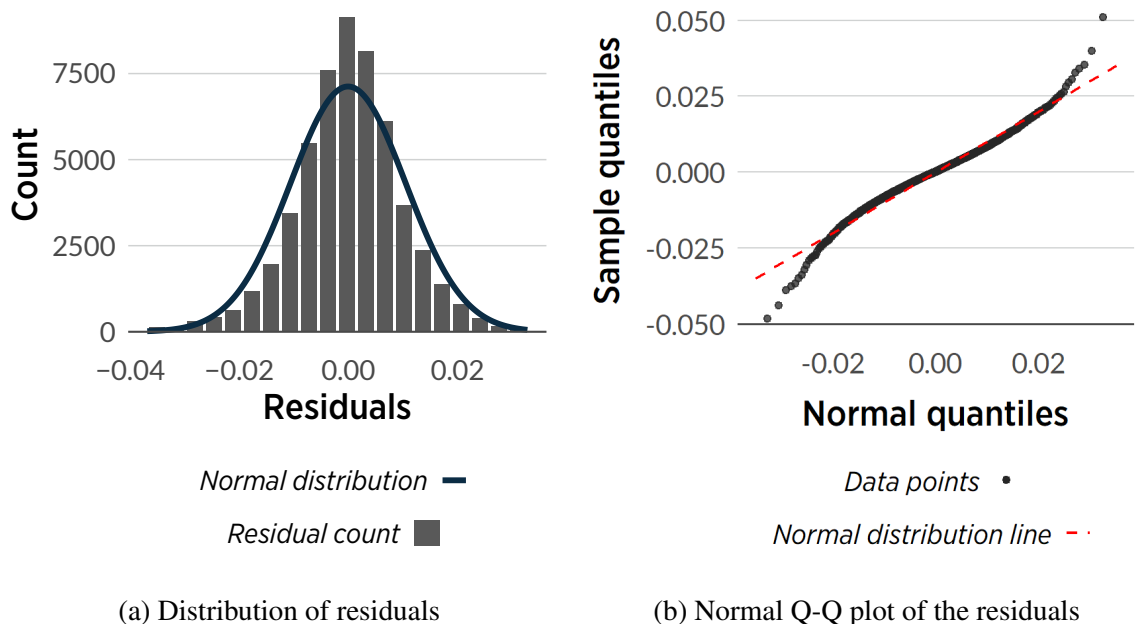
Figure 5.10: Analysis of the distribution of residuals

The overall distribution of residuals can also be analyzed. Figure 5.10a provides a histogram of the values taken by residuals, and compares it to a normal distribution. Normality of residuals is not an assumption of neural networks, but a familiar distribution is a better indication of proper fit than an unusual pattern. The distribution seems close to a normal distribution, although it is more pointy and presents slightly fatter tails: a shape typical of leptokurtic distributions. Figure 5.10b is a quantile-quantile plot (also called Q-Q plot) of the residuals and is used as an assessment of normality. Most of the distribution seems close to a normal one, although the tails are longer.

Overall, the goodness of fit of the selected neural network to estimate development costs seems good. The residuals are evenly distributed, there are only a few significant residuals, and the model is not biased. Residuals are close to being normally distributed, and their variance is low. The overall RMSE is 0.0127, while it is 0.0091 for the training set, 0.0205 for the validation set, and 0.0221 for the test set. The model seems to overfit slightly, but this overfitting remains acceptable as it provided the best validation RMSE.

(a) Training set confusion matrix

(b) Validation set confusion matrix
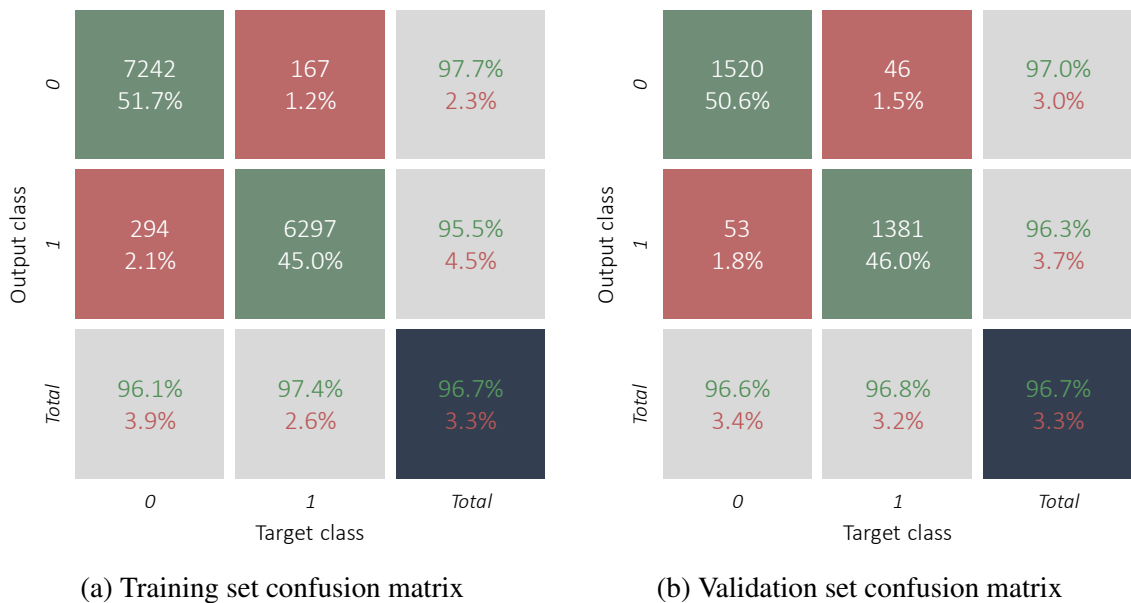
Figure 5.11: Neural net classification predictivity

Classification neural network

The classification neural network is also verified to check the accuracy of feasibility predictions. One way to have a detailed performance summary of the classification net is to use confusion matrices. Figure 5.11a and Figure 5.11b respectively show the confusion matrices of the selected neural network for the training set and for the validation set. It provides the number of points categorized as feasible or infeasible as a function of the actual feasibility. This leads to the evaluation of a true positive rate, true negative rate, false positive rate, and false negative rate. The classification network offers similar performance on the training and validation set. The classification performance of the neural net is similar for these different categories, as all these rates lie between 2% and 4%, with an overall misclassification rate of about 3.3%. Therefore, the accuracy of the selected classification neural network is deemed satisfactory.

5.2.5   Summary of results

In this section, the overall neural network training process was applied and detailed in the case of the prediction of feasibility and development costs for architecture 2. The same process can be repeated for other architectures and other metrics. As such, Table 5.2 summarizes the structure of selected neural networks for each of archtiecture 2's responses. Overall, all responses can be properly fitted with a neural network. Operating costs are a bit harder to predict, but remain within the satisfactory range. Operational risk is very easy to predict as it is modeled as a function of the concept's inputs, and does not depend on the converged vehicle. Other architectures are also represented by these six neural networks, and the results for these are given in appendix C.

Table 5.2: Predictive accuracy of architecture 2 regression neural networks

Response	NN structure	R^2	$RMSE_{train}$	$RMSE_{val}$	$RMSE_{test}$
Development costs	100 nodes	0.987	0.0091	0.0205	0.0221
Manufacturing costs	20+10 nodes	0.992	0.0096	0.0115	0.0112
Operating costs	30+15 nodes	0.983	0.0122	0.0132	0.0163
Carrier aircraft costs	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Operational risk	16+8 nodes	1.000	0.0002	0.0004	0.0004

5.3 Second-Order Third-Moment uncertainty propagation

The previous section dealt with the implementation of regression and classification neural networks, from data simulation, cleaning, and scaling, to network training and verification. The implementation of such neural networks enables the fast evaluation of multiple data points, making possible efficient uncertainty propagation. In this section, the uncertainty propagation method proposed in chapter 2 is implemented, its results are detailed, and the accuracy of the method is verified for further use in optimization scenarios.

To proceed to the verification of the method's accuracy, and in order to benchmark it against other methods, an experiment is designed where the accuracy of each method in predicting various statistical moments and metrics is estimated and compared. Five methods are considered: FOSM, SOSM, SOTM, Monte Carlo with 1000 replications, Monte Carlo with 1 million replications. These five methods are described in the following paragraphs, as they are used as benchmarks for the proposed method.

- **First-Order Second-Moment method.** FOSM represents the most basic approach, often used in applications where the M&S environment is computationally expensive, and the propagation of uncertainty is therefore difficult. It can give a first-order estimate of the mean and variance of the target distribution, which is then approxi-

238

mated by a normal distribution. This method does not provide excellent accuracy but is fast to execute. This method is used as a lower bound for prediction accuracy.

- **Second-Order Second-Moment method.** SOSM is a more accurate version of FOSM. It uses a second-order approximation to estimate the mean and variance of the target distribution, also approximated here as normal.

- **Proposed method (Second-Order Third-Moment).** The proposed method uses SOTM. Unlike SOSM, it also provides an estimate of the skewness of the target distribution, which enables it to be approximated to a distribution with more degrees of freedom and therefore potentially more accuracy. In the context of this research, a *Pearson distribution* is used. The Pearson distribution is a family of distributions that can be described by their mean, variance, skewness, and kurtosis. The density $f(x)$ of Pearson distribution is a solution to the following differential equation (Equation 5.4), where μ_2 is the second statistical moment, γ is the skewness, κ is the kurtosis, and λ is a differential equation parameter.

$$\frac{f'(x)}{f(x)} + \frac{a + x - \lambda}{b_2(x - \lambda)^2 + b_1(x - \lambda) + b_0} = 0$$

$$where \quad b_0 = \frac{4\kappa - 3\gamma^2}{10\kappa - 12\gamma^2 - 18}\,\mu_2$$

$$a = b_1 = |\gamma|\,\sqrt{\mu_2}\frac{\kappa + 3}{10\kappa - 12\gamma^2 - 18}$$

$$b_2 = \frac{2\kappa - 3\gamma^2 - 6}{10\kappa - 12\gamma^2 - 18}$$

(5.4)

As the kurtosis is not estimated, a kurtosis value of 3 is assumed, as it is the kurtosis of a normal distribution. Using this value, Equation 5.4 resolves to a type I Pearson distribution, which is a four-parameter Beta distribution. If the observed skewness of the distribution is zero, the four-parameter Beta distribution simplifies to normal.

- **Monte Carlo method with 100 replications.** This method is used as a benchmark for Monte Carlo methods with a large yet reasonable number of points.

- **Monte Carlo method with 1000000 replications.** This case is used as a reference, in order to find the true values of mean, average, skewness and downside deviation of the distributions. The number of replications is very large, making it very difficult to use in the context of multi-objective optimization.

In order to compute the downside deviation of Pearson distributions, an interpolating model is precalculated, where the downside deviation is expressed as a function of the skewness and standard deviation of the distribution. As such, type I Pearson distributions with various standard deviations and skewnesses are created. For each of these, one million sample points are generated, and the resulting downside deviation is observed.
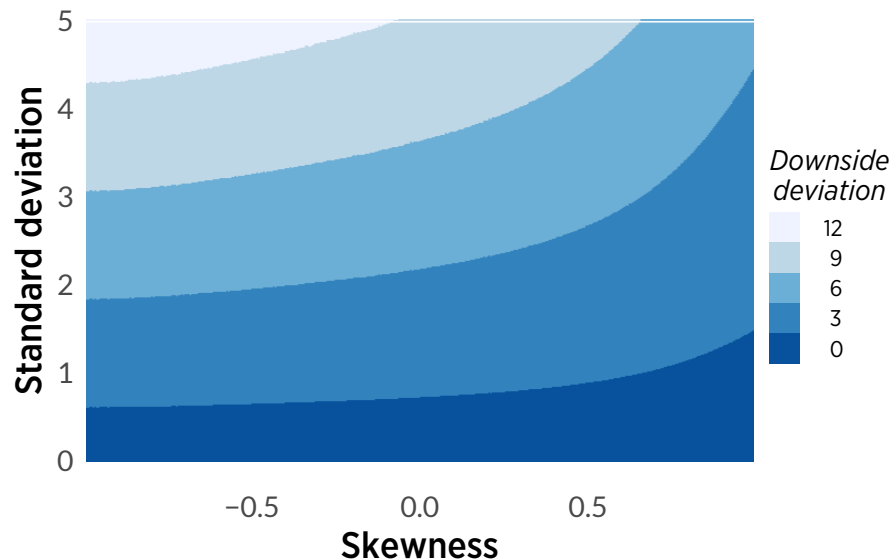
Figure 5.12: Downside deviation as a function of standard deviation and skewness

Figure 5.12 shows the values taken by the downside deviation as a function of the standard deviation and skewness of the distribution. The mean does not have any effect as the deviation is centered on it. It can be observed that as standard deviation increases, the downside deviation increases as well. Additionally, the skewness also has a major

impact on the value of the downside deviation. A distribution more skewed to the right (positive skew) will have a smaller downside deviation than a left-skewed distribution. Hence, there can be significant errors in estimating the downside deviation if not taking skewness into account.

5.3.1 Testing the accuracy of Pearson distribution approximation

Before testing the uncertainty propagation methods, it is possible to test the approximate distribution in order to assess the generated error due to this assumption. To do so, the value of downside deviation resulting from the Pearson distribution, which is given the true mean, variance, and skewness, is compared to the true downside deviation value. Additionally, the downside deviation prediction error of a normal distribution is estimated, in order to assess the benefits of using a distribution with more degrees of freedom.
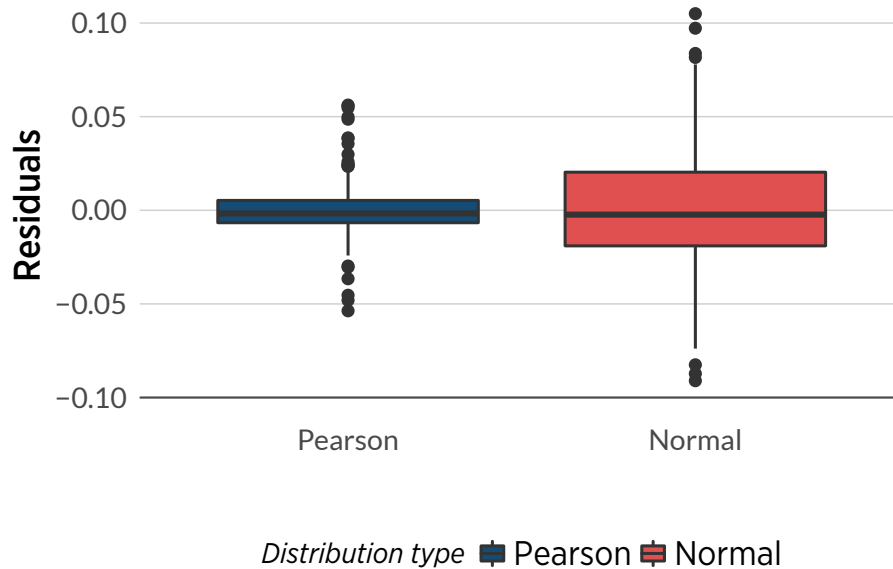
Figure 5.13: Error in downside deviation with Pearson and normal distribution approximation

As such, 250 data points are selected, and uncertainty is propagated to estimate their statistical moments and downside deviation. The prediction error is then calculated. Figure 5.13 is a box plot representing the distribution of residuals for the prediction of down-

241

side deviation when using a Pearson distribution, and when using a normal distribution. Residuals are much more spread out with the normal distribution than the Pearson one, and they are much larger in absolute value. Tab. 5.3 compares several key statistical metrics related to the residuals of these two distributions. As observed in the box plot, Pearson distribution is performing much better than the normal distribution. Although bias is slightly higher for Pearson distribution, the RMSE is almost three times as low as that of the normal distribution. The 5% and 95% quantile of residuals are also much smaller, as well as the range of values residuals can take. While the difference of RMSE can appear small in absolute value rather than relative, it is important to reduce as much as possible all source of error, as these can easily add up, and become much more significant. Additionally, this subsection also shows that approximating the propagated uncertainty to a Pearson distribution does not bring much error to the model and that this approximation is therefore relevant.

Table 5.3: Statistical characteristics of the residuals of Pearson and normal distributions when predicting downside deviation

Distribution	Bias	RMSE	$Q_{0.05}$	$Q_{0.95}$	Range
Normal	0.20%	2.43%	-3.72%	3.82%	16.69%
Pearson	0.28%	0.88%	-1.16%	1.36%	7.06%

5.3.2   Testing the accuracy of SOTM

To test and benchmark the accuracy of the proposed uncertainty propagation method, five methods were mentioned: FOSM, SOSM, SOTM (the proposed method), Monte Carlo with 1000 points, and Monte Carlo with one million points (used as a reference to compute true statistical metrics). These methods are compared by performing, for each of them, the following process:

- 250 data points from the design space of architecture 2 are used as inputs for the experiment, in order to ensure the overall prediction performance of the methods.

- Uncertainty is propagated through the model with the objective to estimate the NPV.

- The RMSE of each method is used as measure of predictivity for the prediction of the mean, standard deviation, skewness, and downside deviation of the NPV.

- The number of Monte Carlo points required to provide similar prediction accuracy is estimated for each method.

This process is implemented and followed, and results regarding prediction accuracy of statistical moments and metrics are obtained.

(a) Mean predictor error

(b) Standard deviation predictor error

(c) Skewness predictor error

(d) Downside deviation predictor error
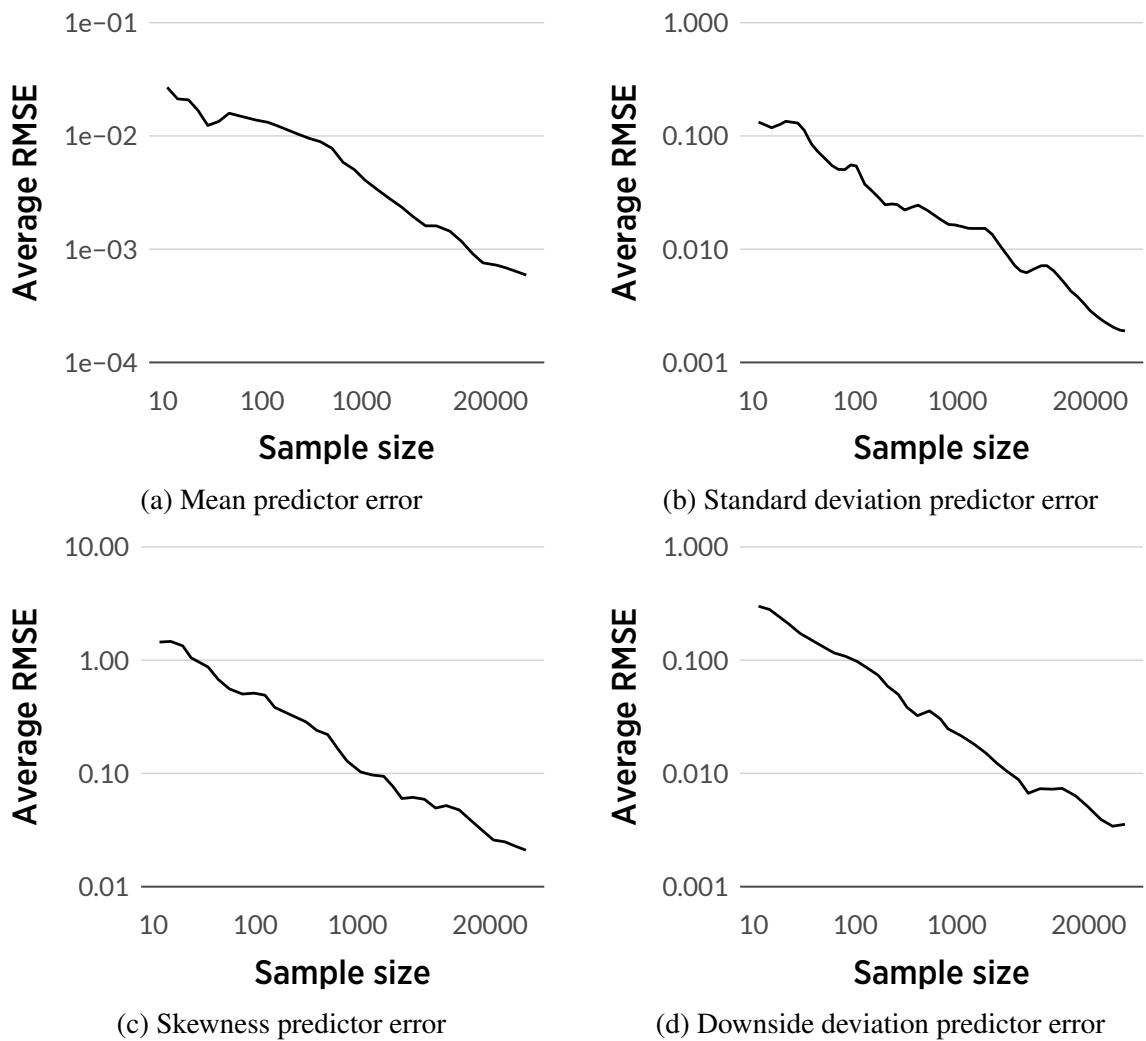
Figure 5.14: Convergence of mean, standard deviation, skewness, and downside deviation predictors, with Monte Carlo sampling

First, predictivity of Monte Carlo methods is analyzed, as a function of the number of sample points used. This analysis permits two things. First, it permits to understand the convergence speed of Monte Carlo methods. This helps determine the required number of sampled points to provide a given prediction accuracy. Additionally, it helps ensure that the reference data used to compute the true values of statistical moments and metrics provides converged measures. As such, the convergence analysis is performed on ten different samples to provide an accurate measure of the average prediction error. Figure 5.14 shows the evolution of the average prediction RMSE of the mean, standard deviation, skewness, and downside deviation, as a function of the number of sample points generated by the Monte Carlo method. The mean, standard deviation, and downside deviation are normalized using their average value, while skewness is normalized according to its range (as its mean is zero). For all statistical measures, there is a very linear evolution of the RMSE of predictors, when applying a log-log transform. The convergence coefficient can then be defined as the regression coefficient of the number of sample points when doing the log regression of prediction RMSE.

Table 5.4: Convergence metrics of Monte-Carlo-based predictors

Distribution	Mean	Standard deviation	Skewness	Downside deviation
Convergence coefficient	-0.46	-0.51	-0.51	-0.54
Number points s.t. RMSE = 10%	3	35	1000	100
Number points s.t. RMSE = 1%	250	3000	200000	3000

Table 5.4 provides some insight over the convergence an accuracy of Monte Carlo methods. It can be seen that both overall, all metrics have a convergence coefficient close to -0.5, which means that to reduce prediction RMSE by an order of magnitude, the number of sample points must be raised by two orders of magnitude. Convergence is therefore quite slow,

but it is reasonable to believe that the experiment with one million sample points gives a good measure of the true values of statistical metrics. While all metrics converge at similar speeds, they do not have the same start points. Therefore, it is fairly easy to have an accurate measure of the true mean, with around 250 Monte Carlo points necessary. Standard deviation is slightly harder to estimate, while skewness is actually hard to measure, with around 200000 sample points required to have, on average, a 1% prediction RMSE. More surprisingly, providing an accurate measure of the downside deviation requires a significant yet reasonable number of sample points. Indeed, tail-related measurements are usually difficult to provide using Monte Carlo methods. However, the use of bounded input distributions resulted in a bounded output with limited size tails, making it easier for Monte Carlo methods to predict.

(a) Error on mean predictor   (b) Standard deviation prediction error
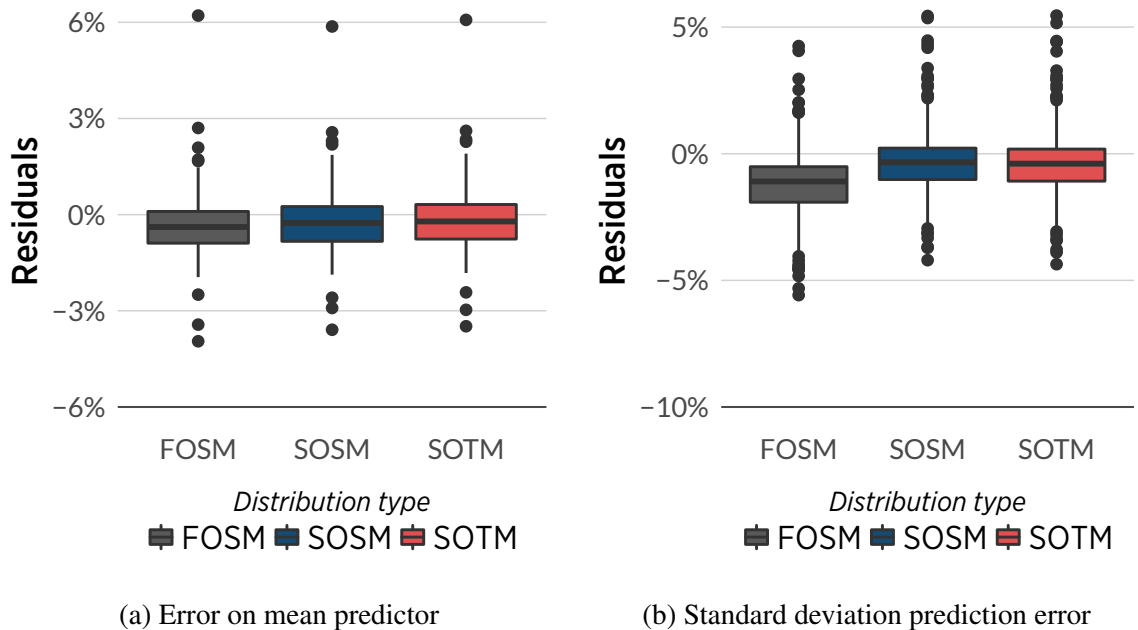
Figure 5.15: Prediction residuals using method-of-moments techniques (mean and variance)

As convergence of Monte Carlo methods has been analyzed, other uncertainty propagation techniques can also be analyzed, and the number of sample points required to provide similar accuracy with Monte Carlo methods can be estimated. To start with, the first

and second statistical moments are propagated through the model, using FOSM, SOSM, and SOTM. Figure 5.15a and Figure 5.15b respectively show a box plot representation of prediction residuals for the mean and standard deviation. There is not a great difference between the three methods of moments in the prediction of the mean, although FOSM has a slightly larger bias. Overall though, predictions are accurate, with RMSEs close to 1%. This observation is similar for the prediction of standard deviation. However, in that case, FOSM bias becomes larger, as well as its RMSE. Indeed, using a second order approach rather than a first order one provides improvements both for the bias and variance of residuals. Finally, SOSM and SOTM have the same results, because they both use a second order estimate of the first two moments.
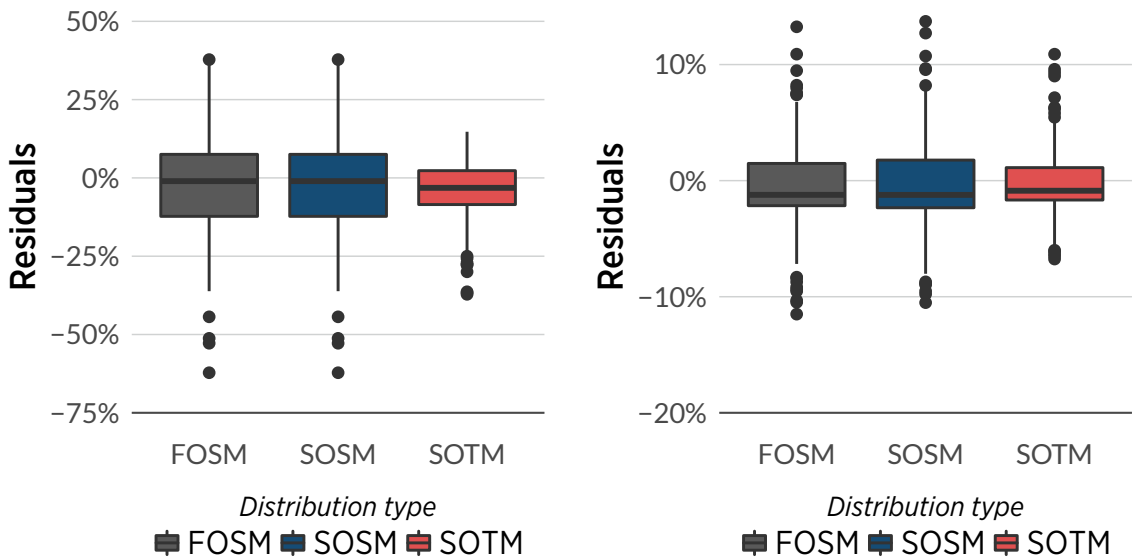
(a) Skewness prediction error   (b) Downside deviation prediction error

Figure 5.16: Prediction residuals using method-of-moments techniques (skewness and downside deviation)

The other two statistical metrics are studied too. As such, Figure 5.16a and Figure 5.16b respectively show the prediction error for the skewness and downside deviation of the output distribution. Unlike the first two statistical moments, these metrics are much harder to predict. FOSM and SOSM do not provide a prediction of skewness, and their prediction

error is therefore significant. The prediction is not very biased in this case, mainly because the average skewness of the considered points is almost centered on zero. Reversely, SOTM has a bit of bias when predicting skewness, but the variance of residuals is much lower, resulting in a smaller RMSE. As for the downside deviation, SOTM overperforms FOSM and SOSM as well. The inclusion of a better estimate of skewness helps provide more accurate measurements by using an approximate distribution with more degrees of freedom: the Pearson distribution. As a result, the downside deviation RMSE of SOTM is 2.76%, compared to 3.78% and 3.89% for SOSM and FOSM - between 27% and 29% improvement in predictivity. While the absolute improvement seems small, the relative one is large. Moreover, even a 1% higher prediction error could mean underestimating or overestimating financial CVaR by dozens of millions of dollars, for example.

To make sure these measures are statistically significant, statistical tests can be performed. While there is no standard test to test the equality of two RMSE, it is possible to test the equality of the variance of residuals. As the biases remain small, the main part of the RMSE comes from the variance. As such, it is possible to use this test as a proxy for testing the equality of two RMSE. In order to test for the equality of two variances, an F-test is performed. Indeed, the ratio of two sample variances is F-distributed, with $n - 1$ and $m - 1$ degrees of freedom, n and m being the size of the two considered samples. As such, the ratio of the variance of the SOTM residuals with the variance of the other residuals is computed. The p-value of this F-statistic is then calculated. This p-value is one-sided, as the objective is to show that the variance of the SOTM residuals is not greater than the others. Table 5.5 shows the result of the F-test when comparing the SOTM to other methods of moments.

Table 5.5: Results of an F-test comparing SOTM with FOSM and SOSM

	FOSM	**SOSM**
F-statistic	0.5495	0.5202
One-sided p-value	1.34e-06	1.55e-07

Both p-values are extremely small, which shows that it is highly unlikely that the variance of the SOTM residuals is greater than the variance of the others. It can be noted that the variance of the SOSM residuals is slightly higher than the variance of the SOTM residuals, but this is compensated by a better bias.

Summary of results can be found in Table 5.6. It can be seen that overall, SOTM provides much better accuracy than FOSM or SOSM in all four considered metrics regarding prediction RMSE. Additionally, the number of Monte Carlo points required to provide equivalent prediction RMSE is indicated. The mean is fairly easy to estimate with Monte Carlo, and SOTM is equivalent to a 250-point Monte Carlo method in terms of predictivity. However, other metrics are harder to predict, and 2500, 1000, and 750 Monte Carlo points are required to provide the same accuracy as the SOTM method for the prediction, respectively, of the standard deviation, skewness, and downside deviation. Hence, SOTM can replace Monte Carlo methods that use a significant amount of sample points, while actually requiring much fewer (SOTM only needs 15 function calls in this scenario with four variables). Hence, SOTM enables a significant gain in computational speed while maintaining good predictivity, or a major gain in accuracy for a given number of function calls.

This section dealt with the analysis of prediction accuracy for several method-of-moments approaches. It was shows that SOTM is a suitable algorithm for estimating the downside deviation, from an accuracy standpoint. In next section, the computational time aspect of this methodology is studied, in order to ensure calculations can be performed in a reasonable time frame and to observe the method's benefits compared to other approaches.

Table 5.6: Summary statistics of considered prediction methods and comparison to Monte Carlo

Method	Bias	RMSE	Equivalent MC points
FOSM			
Mean	-0.35%	1.01%	250
Standard deviation	-1.18%	1.81%	1000
Skewness	-2.68%	16.07%	650
Downside deviation	-1.32%	3.89%	300
SOSM			
Mean	-0.24%	1.01%	250
Standard deviation	-0.27%	1.41%	2500
Skewness	-2.68%	16.07%	650
Downside deviation	-0.38%	3.78%	350
SOTM			
Mean	-0.18%	0.99%	250
Standard deviation	-0.33%	1.44%	2500
Skewness	-4.26%	10.24%	1000
Downside deviation	0.51%	2.76%	750
100-point MC			
Mean	-0.61%	0.60%	100
Standard deviation	-3.15%	3.28%	100
Skewness	-38.47%	39.12%	100
Downside deviation	5.77%	6.22%	100

5.4 Computation time analysis

In the previous section, several methods were compared from a prediction accuracy stand-point. It was shown that SOTM only introduces little prediction error. Another advantage of the SOTM is that it requires only a few function calls, compared to Monte Carlo methods. Tab. 5.7 shows the required number of function calls for each method, assuming that the Jacobian and Hessian matrices are not provided. Additionally, the joint use of SOTM with neural networks makes it even an even faster method, when compared to the direct use of computationally expensive M&S environments.

Table 5.7: Required number of points for method-of-moments techniques with 4 uncertain variables and equivalent number of Monte Carlo points to provide similar prediction accuracy on downside deviation

	FOSM	SOSM	SOTM
Number of sample points	5	15	15
Equivalent MC points	300	350	750

To quantitatively support this argument, this section presents a time analysis of the different considered approaches, in the context of multi-objective optimization. As such, two aspects of the problem must be studied. First, subsection 5.4.1 describes the analysis of convergence of the multi-objective optimization. Knowing the required number of iteration provides an estimate of the required computational time. Then, subsection 5.4.2 estimates the required computational time with other techniques and determines which are reasonably feasible.
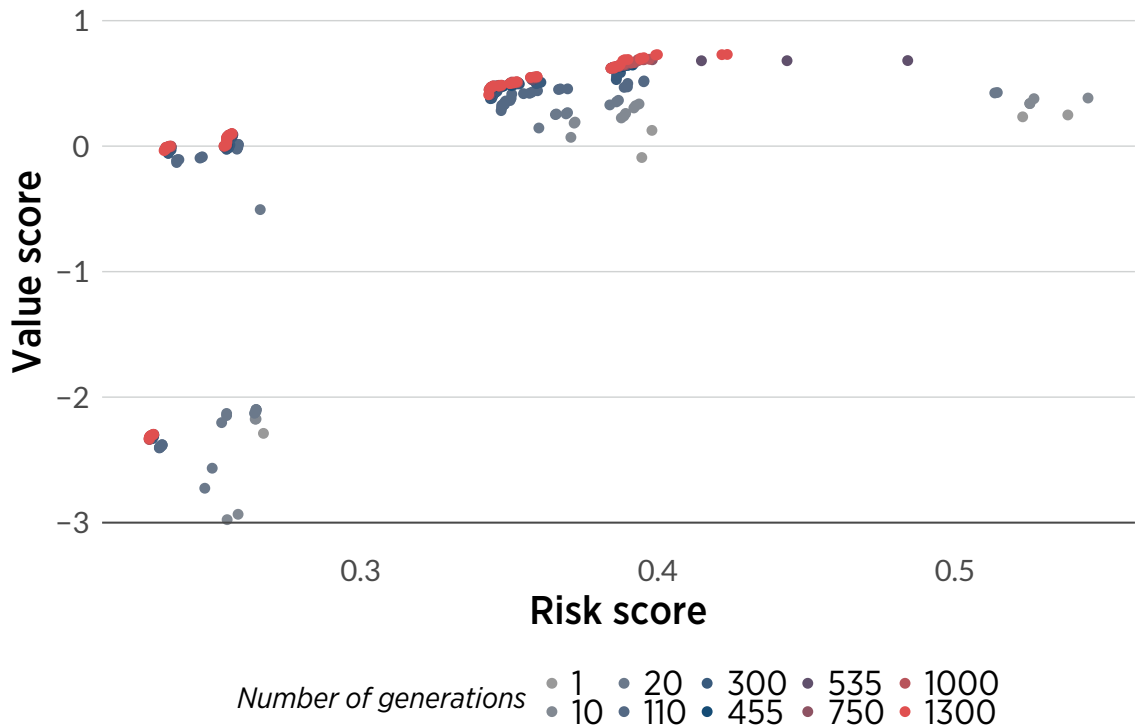
Figure 5.17: Convergence of the Pareto frontier

5.4.1 Convergence analysis

A multi-objective optimization scenario is implemented for architecture 2, and its convergence is analyzed. The optimization algorithm is run for 1300 generations. As suggested in chapter two, two objectives are considered. The first objective is to maximize a value score, defined as a combination of the program NPV, program IRR, and volume per passenger. The second one is to minimize a risk score, which is constituted of the downside deviation of the value score, a financial risk, and operational risk. Figure 5.17 shows the evolution of the Pareto frontier as the number of generations increases. The Pareto frontier improves quickly at first and changes much less after 500 generations.

While Figure 5.17 provides a visual inspection of convergence, a more quantitative ruling can be more objective. In order to measure how close to convergence the current state is, the average TOPSIS score (for all preferences between risk and value) of current Pareto frontier is used, and compared to that of the final state. The average TOPSIS score

ATS is expressed by Equation 5.5, where P_V is the preference for value over risk and is expressed between 0 and 1, and $\text{TS}(y, Y, P_V)$ is the TOPSIS score of y, a vector from the output space, given a preference P_V and a full set of observations Y.

$$\text{ATS} = \int_0^1 \max_y \left[\text{TS}(y, Y, P_V) \right] dP_V \tag{5.5}$$

For a given value preference, a concept is selected for having the best TOPSIS scores. The ATS takes the integral of these best achievable scores. This approach ensures that the overall Pareto frontier matches the optimum one (or at least the set of points selected through TOPSIS for different preferences). Additionally, it provides a simple one-dimensional measure representing the level of convergence of the whole Pareto frontier. To make it even clearer when convergence has been reached, the completion level CL is defined by Equation 5.6 where ATS_I is the initial ATS (at generation1), and ATS_F is its final value (at generation 1300 here). The completion level is a normalization of the average TOPSIS score.

$$\text{CL} = \frac{\text{ATS} - \text{ATS}_I}{\text{ATS}_F - \text{ATS}_I} \tag{5.6}$$

(a) Error on mean predictor   (b) Standard deviation prediction error
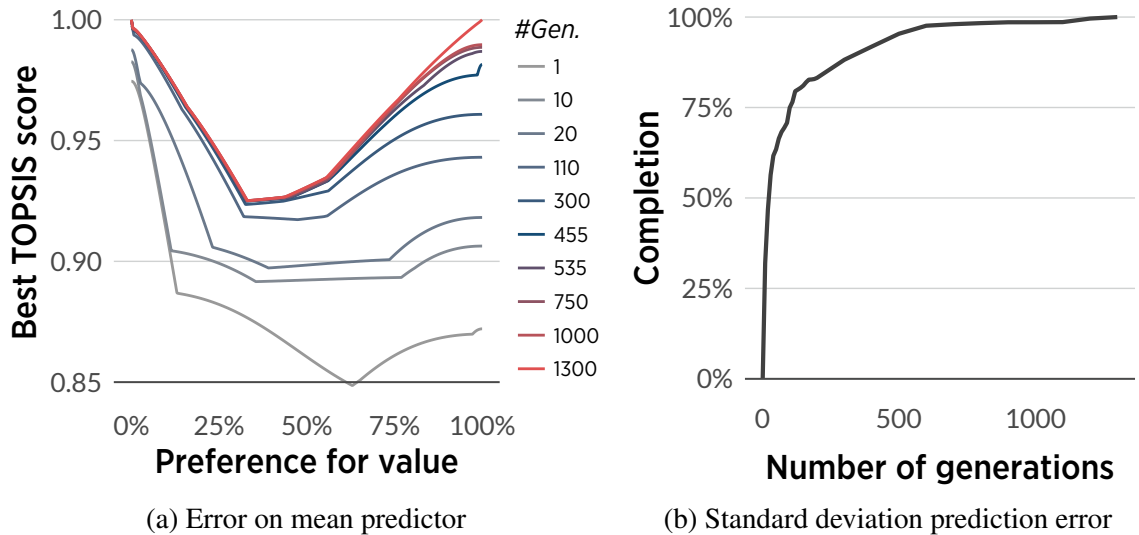
Figure 5.18: Prediction residuals using method-of-moments techniques (mean and variance)

Using these definitions, convergence can be measured. First, Figure 5.18a shows the best achievable TOPSIS score for several numbers of generations as a function of the preference for value. As for the Pareto frontier, it can be seen that the best TOPSIS score for each possible preference is progressively matching that of the converged Pareto frontier. This score does not change much from generation 750 onward. Getting the averages of these TOPSIS scores leads to the estimation of the ATS and completion level. As such, Figure 5.18b shows the level of completion reached as a function of the number of generations. The completion level increases fast, until 600 generations, where it reaches 97.6% completion. At 800 iterations, 98.3% completion is achieved, and completion remains fairly flat after that point. Hence, it can be accepted that 800 generations is a reasonable number of generations to use when being time-concerned. In next subsection, this number is used in order to estimate process time with various uncertainty propagation methods.
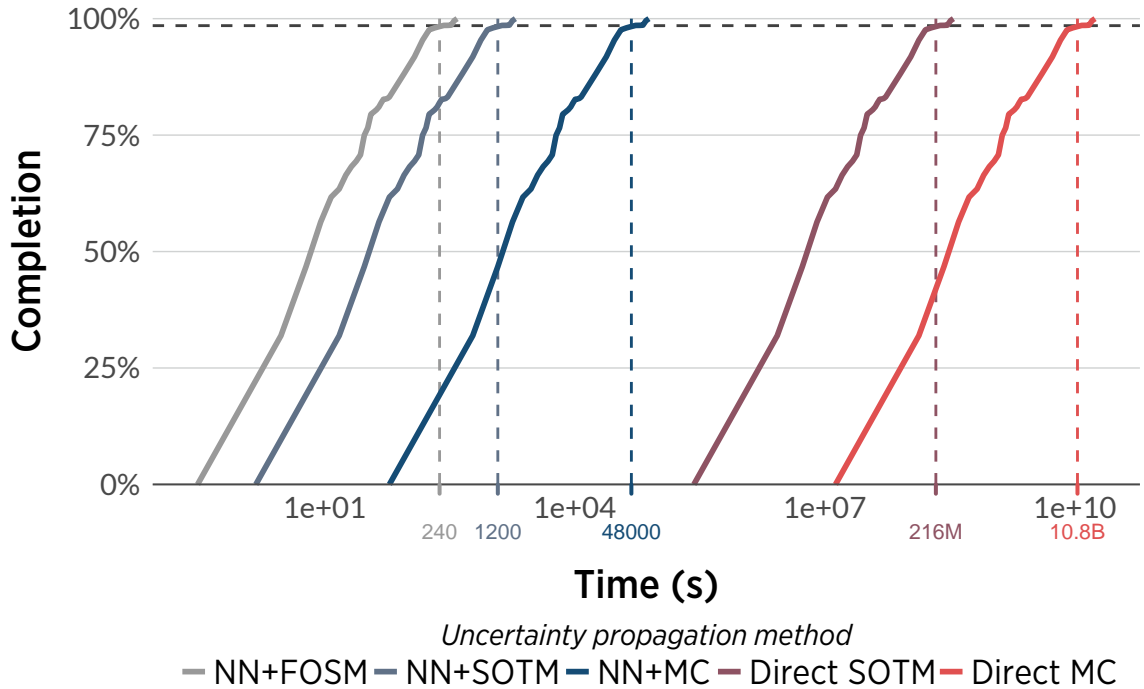
Figure 5.19: Time requirement of convergence for several uncertainty propagation methods

5.4.2   Time analysis

Using the previously established completion curve, other methods can be analyzed as well. In addition to the statistical method used, the presence or absence of neural networks is accounted for as it has a significant impact on computation time. First, the average time per generation is estimated for the different methods. It is then assumed that the convergence of the algorithm in terms of number of generations is not affected by the alternative objective functions. Hence, only the average computation time per generation affects the time outcome. Figure 5.19 represents the completion of several uncertainty propagation methods as a function of time. A logarithmic scale is used to more easily compare the alternatives. Completion is assumed after 800 generations. Two observations are then made. First, the use of neural networks does not only enables a drastic decrease in computation time, but it also enables the optimization process to be run in a reasonable time. Without neural networks, it could take years to converge. Additionally, the method of moments further

reduces to total time by providing a quick yet accurate way to compute the downside deviation of the distribution. Using Monte Carlo method is still feasible but requires long hours, making it complicated when evaluating multiple scenarios. Table 5.8 shows a summary of the time requirements for the considered uncertainty propagation methods. SOTM with neural networks necessitates about 20 minutes when used in the multi-objective optimization scenario of this chapter. FOSM only needs 4 minutes, but at the expense of accuracy.

This section studied the time aspects of the use of uncertainty propagation for the calculation of the downside deviation in the context of multi-objective optimization. The convergence of a multi-objective optimization scenario was studied, to determine a required number of generations. This result enabled the calculation of the total optimization time. It was shown that the use of neural networks is required to provide a converged solution in a reasonable time frame. Moreover, Monte Carlo methods, for the same accuracy, require a much greater computational time than method-of-moments techniques such as the SOTM. As a result from these observations, the importance of using SOTM and neural networks from a time-saving perspective is demonstrated.

Table 5.8: Summary of time analysis

	Number of sample points	Time per generation	Total time
FOSM on neural net	5	0.3 s	4 min
SOSM on neural net	15	1.5 s	20 min
SOTM on neural net	15	1.5 s	20 min
MC on neural net	750	1 min	13.3 h
Direct SOTM	15	3.125 days	6.8 years
Direct MC	750	156.24 days	342.5 years

5.5 Summary and comparison with other methods

In chapter 2, research question 2.1 raised the interrogation of how to time-efficiently estimate downside deviation, knowing that this method would be used with the objective to perform one or several multi-objective optimizations. As specific method exists to estimate downside deviation in the field of aerospace, different methods were surveyed, and hypothesis 2.1 was formulated: *"if a process using Second-Order-Third-Moment uncertainty propagation on classification and regression neural networks is implemented then the downside deviation of value of complex aerospace system programs can be estimated in a timely manner, in the context of multi-objective optimization."* The studies and observations realized in this chapter verify hypothesis 2.1, as explained in this section.

In this chapter, the most important aspects of the uncertainty propagation implementation were discussed. A simplified scenario with uncertainty variables was designed. Using this scenario, neural networks were built, their structure was optimized to improve prediction accuracy, and their residuals were checked to ensure that the fit was adequate. Using these neural networks, several uncertainty propagation techniques were tested: FOSM, SOSM, SOTM and simple Monte Carlo sampling. It was shown that SOTM provides satisfactory prediction accuracy while requiring much fewer sample points than Monte Carlo for an equivalent level of precision when estimating the downside deviation of the output distribution. Finally, The considered methods were compared from a computation time standpoint, and a convergence analysis ruled out Monte Carlo methods and approaches without surrogate modeling because of their excessive time needs.

Table 5.9 summarizes these results, and it appears clear that the proposed method (SOTM with classification and regression neural networks) provides the best solution to the time-efficient estimation of downside deviation. While direct SOTM or even Monte Carlo would be ideal in terms of accuracy, it is completely out of the question from a time stand point. Additionally, using Monte Carlo on neural networks remains lengthy for sim-

ilar accuracy as SOTM. On the other hand, FOSM is faster but loses a bit in accuracy. Finally, usual surrogate modeling methods do not include a feasibility check, unlike the proposed method.

Table 5.9: Comparison of proposed method with main existing approaches

	Direct SOTM	NN+FOSM	NN+MC	Proposed method
Accuracy	●	◗	◗	◖
Speed		●	◖	●
Feasibility check	●			●

Overall, the proposed implementation carries the following features:

- **Usability.** The proposed method leads to a fully integrated and automated process. Multi-objective optimization only needs to be set up and run. This checks verification criterion 2.2.1 (*the multi-objective optimization process is completely automated*).

- **Timeliness.** The proposed process enables decision makers to perform multi-objective optimizations within a reasonable time period. Indeed, about 20 minutes are necessary for the multi-objective optimization to converge. Reversely, methods using Monte Carlo sampling are much lengthier, and those using no surrogate modeling of any kind are not reasonably possible from a time perspective. Due to its time efficiency, the method checks verification criterion 2.2.5 (*a multi-objective optimization converges in at most 1 hour*).

- **Estimation of feasibility.** Unlike other surrogate modeling approaches which are limited to regression predictions, the proposed process also ensures the feasibility of concepts. Without this decision-makers could select a concept that is not feasible, which could lead to serious capability issues and greatly delay the design process.

Additionally, this is also a way to avoid losing one of the features of the original M&S environment.

- **Surrogate modeling accuracy.** Surrogate modeling is performed using neural networks. The proposed process maximizes the goodness of fit by using several techniques such as replication or the optimization of the neural network structure. Overall, the regression neural networks provided a good validation set RMSE, and the classification network had a good misclassification rate, which checks verification criteria 2.2.2 and 2.2.3 (*the regression networks' root mean squared error is at most 10%; the classification network's misclassification error is at most 10%*).

- **Downside deviation prediction accuracy.** The second aspect of this method is the use of a method-of-moments technique (the SOTM) to estimate statistical metrics; downside deviation in particular. The RMSE of this method over a set of 250 points was below 3%, which is equivalent to a 750-point Monte Carlo method and is provides better accuracy than FOSM and SOSM. As such, verification criterion 2.2.4 is checked (*the prediction RMSE of the method-of-moment technique is below 5%.*)

These observations demonstrate that the proposed method is a compelling way to estimate downside deviation in a time-efficient manner. As all verification criteria are checked, hypothesis 2.1 is deemed verified as an answer to research question 2.1.

CHAPTER 6

FACILITATING RISK/VALUE TRADE-OFFS

The previous chapter, chapter 5, dealt with uncertainty propagation with the intent to estimate the downside deviation of a distribution. It was demonstrated that hypothesis 2.1 was an answer to research question 2.1, as a process was proposed that would time-efficiently estimate downside deviation without loss of capabilities from the initial M&S environment. As such, last question was a crucial enabler for this chapter, which deals with carrying out risk/value trade-off, in the presence of multiple objectives and multiple sources of risk. In chapter 2, research question 2 was formulated as the following: *how to facilitate sound risk/value decision-making in a multi-objective multi-risk enterprise-level environment during conceptual design?* After studying multiple ways to approach risk and design under uncertainty, hypothesis 2 was formulated: *if uncertain strategic objectives are combined using a stochastic Multi-Attribute Utility functions and if an SOTM uncertainty propagation technique is used and if an integrated trade-off environment facilitating programs ranking and visualization is used then strategic leaders can easily make sound risk/value trade-offs in a multi-objective multi-risk environment during conceptual design.* Hence, answering research question 2.1 was essential, as downside deviation of value is a major source of risk for programs. This chapter intends to verify or reject hypothesis 2, by carrying out multiple experiments to check its main aspects and verification criteria. First, a study is realized in section 6.1 that demonstrates the difference and importance of choosing the downside deviation of value as a measure of value risk, rather than its variance. Section 6.2, then, shows the usefulness of the use of value and risk scores in reducing objectives dimensionality, facilitating decision-making, and potentially find better trade-offs when time is an issue. Section 6.3 presents the application of this method on various scenarios, where the objective is to identify, rank, and analyze optimal concepts in terms of

vehicle-level and enterprise-level variables. The capabilities of the created trade-off environment and its ability to facilitate risk/value decision-making are also presented. Finally, section 6.4 summarizes the main discussions of this chapter and verifies the hypothesis to the research question.

6.1   Importance of using downside deviation as a measure of value risk

Some of the reasons why downside deviation was a better measure of value risk than standard deviation were given in chapter 2. As risk is meant to measure adverse effects and their probabilities, downside deviation fits the definition of risk better than standard deviation, which is a symmetric measure and considers both upside and downside deviation, and therefore both detrimental and favorable outcomes.

The usefulness of actually using downside deviation as an optimization objective can, however, be questioned. Indeed, when the output is normally distributed, the downside deviation is simply proportional to the standard deviation (-2.0626 for a standard normal distribution). In this particular case, the outcome of an optimization process would be the same. However, output distributions can greatly differ. In particular, in the case of suborbital vehicles, there are a lot of non-linearities and discontinuities that bring skewness to the outputs (actually, a quadratic response to uncertain factors would result in a skewed distribution). Additionally, most real-world problems should preferably use bounded uncertain inputs, such as triangular or Weibull distributions, which usually results in bounded outputs. This can be measured by a lower kurtosis than normal distributions, and a smaller downside deviation.
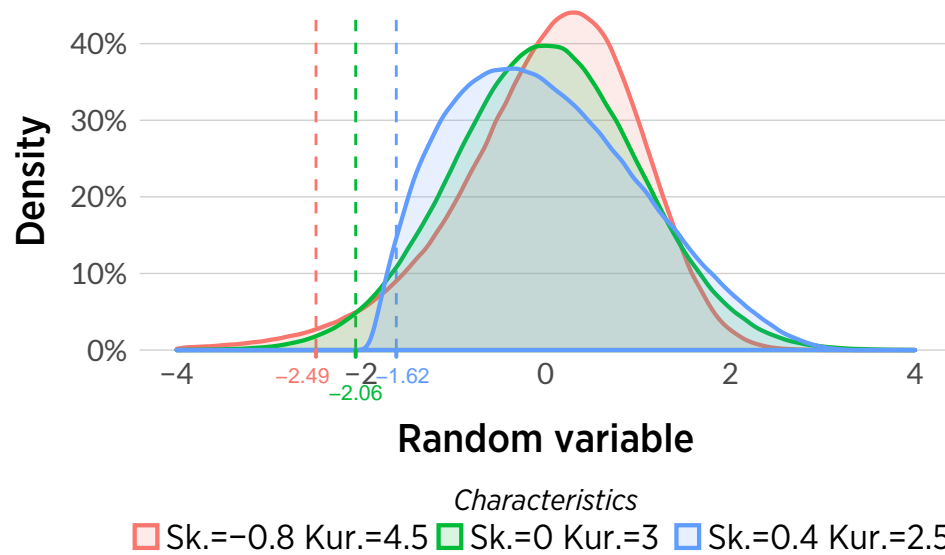
Figure 6.1: Downside deviation for several distributions with the same mean and variance

This difference in downside risk can be illustrated in several ways. Figure 6.1, for example, shows three different distributions that share the same mean and variance. When using standard deviation as an objective, these distributions would be all three treated as if they were the same. However, they have significantly different downside deviations. The green distribution has a null skewness and a kurtosis of 3. It is, therefore, a Gaussian function, and its downside deviation is approximately 2.06. The red distribution is left-skewed and leptokurtic (skewness = -0.8, kurtosis = 4.5). As a consequence, its left tail is longer, resulting in a higher downside deviation: 2.49, or a 20% difference compared to the normal case. Reversely, the blue distribution is right-skewed and platykurtic (skewness = 0.4, kurtosis = 2.5), which leads to a 1.62 downside deviation; a 22% decrease compared to the normally distributed case. Hence, it can be observed with this simple example that the use of variance instead of downside deviation can lead to a significant misrepresentation of the actual value of risk.
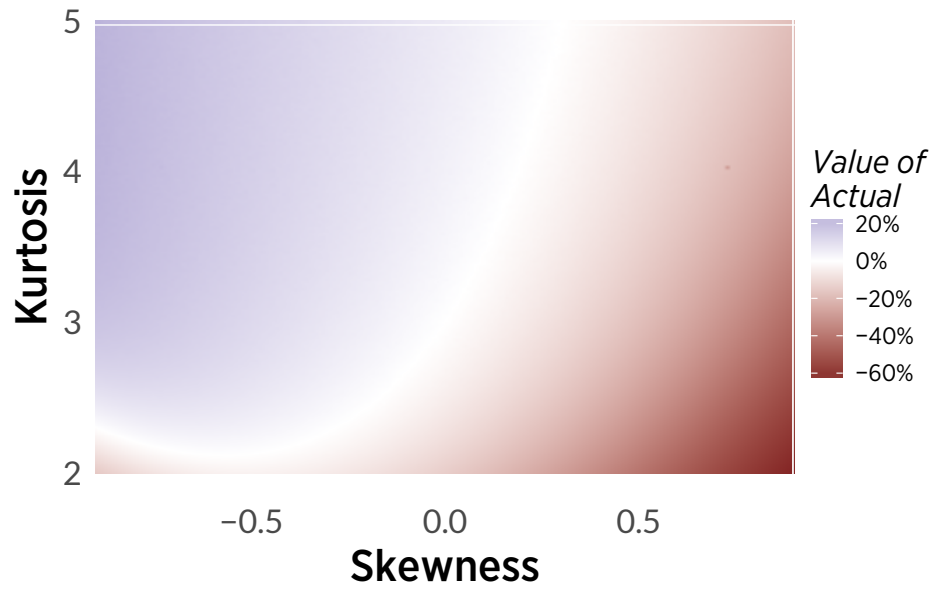
Figure 6.2: Actual downside deviation values relatively to that of a normal distribution

This analysis can be performed for all combinations of skewness and kurtosis to have a mapping of error as a function of these two variables, as shown in Figure 6.2. Figure 6.2 therefore confirms the first observation of Figure 6.1: negatively skewed distributions have higher downside deviations as well as leptokurtic ones. Hence, the color plot shows the error in estimation by giving the actual downside deviation value compared to the standard normal case (-2.0626) as a function of the skewness and kurtosis of the distribution and its kurtosis, for a mean set to zero and a unit standard deviation. This plot shows again that distributions with skewness and kurtosis differing from those of normal distribution can carry significant differences in downside deviation.

6.2 Use of value and risk score to reduce dimensionality

One of the main ideas of hypothesis 2 is to separate objectives in two categories: risk and value. These objectives are then aggregated using a multi-attribute utility function into risk and value scores. One of the main advantages of this aggregation is the reduction in dimensionality when working with multiple objectives. Aggregating objectives has two benefits. First, it is much easier to visualize the Pareto frontier in two dimensions, which facilitates decision making which is then only based on two variables: risk and value. While the multidimensional aspect of risk and value is lost during aggregation, it is still possible, using visualization techniques, to easily determine which are the main contributors to risk and value, and what are the values of the initial objectives within the aggregates (for example by coloring the Pareto frontier as a function of one of these subobjectives).

The other advantage of aggregation is crucial: convergence. While a multi-objective optimization algorithm with two variables requires more computation time than a regular single objective optimization, this additional time remains reasonable. However, as the number of dimensions increases, the optimization problem becomes much more complicated. Indeed, the Pareto frontier increases in dimension as well, which requires a significantly larger population size to be able to properly cover it. Additionally, more iterations are required to come up with a converged solution. This makes it much more complicated to come up with a compelling solution when using all objectives together in the context of a regular multi-objective optimization. To assess this effect, an optimization scenario is set up. As such, architecture 2 must be optimized, with NPV, IRR and seat pitch as value objectives, and financial risk, value risk and operational risk as risk objectives. Two different approaches are considered: one with all objectives kept separate (leading to a 7-dimensional multi-objective optimization: 3 value objectives, 2 risk objectives, and the downside deviations of the two uncertain value objectives), and one with the aggregation between risk score and value score. The two-dimensional approach uses a population of 150 individuals
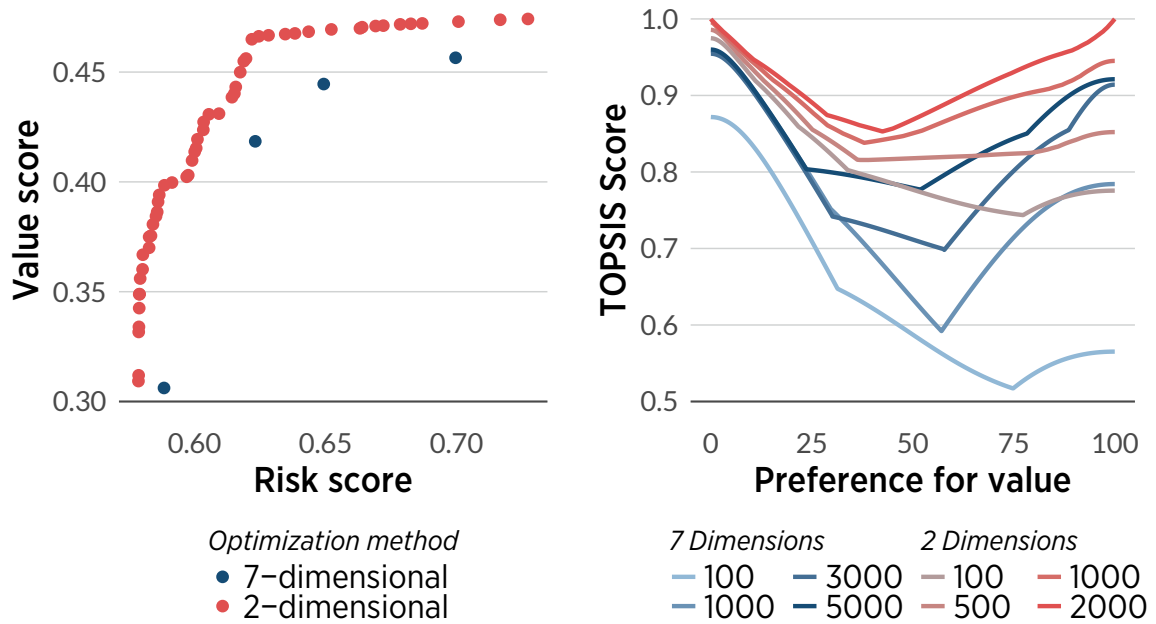
(a) Pareto frontiers in risk and value domain (b) TOPSIS scores by preference for value

Figure 6.3: Convergence of aggregated and independent multi-objective optimizations

and up to 2000 generations. To help the seven-dimensional approach cover more of the Pareto frontier, the population size is set to 1000, and up to 5000 generations are allowed.

Figure 6.3a shows the resulting Pareto frontier for the two considered approaches when converting the non-aggregated optimization to risk and value scores space. Additionally, Figure 6.3b shows a comparison of the evolution of the best resulting TOPSIS scores as a function of the preference for value, for the seven-dimensional and the two-dimensional optimizations, with different numbers of generations. As expected, the results show much better convergence of the optimization where value and risk scores are the targets. Despite a population more than six times larger than for the aggregated case, and a number of iterations 1.5 times larger (i.e. almost 17 times more function calls), the 7-dimensional case underperforms the 2-dimensional one by around 10% in average TOPSIS score. Not only the Pareto frontier is more sparse, but the individuals that compose it are dominated by the 2-dimensional Pareto frontier by a large margin. Hence, the benefits of the aggregation into value and risk score can be observed both from a qualitative point of view, due to

facilitated visualization and reduced number of variables to trade, and from a quantitative point of view, with faster convergence and more optimal solutions.

6.3 Identify, rank, and analyze optimal designs and enterprise-level variables

In this section, the main elements discussed previously are put together, and full-scale optimization scenarios are set. This is useful in showing the capabilities of the model for identifying, ranking and analyzing optimal concepts and their associated optimal business variables. Hence, this section shows how the overall methodology can facilitate decision-making. Subsection 6.3.1 follows and illustrate the different steps of the proposed method for the particular case of a profit-oriented optimization scenario. Subsection 6.3.2 then presents the application of various visualization techniques in order to analyze the solution Pareto frontier. It is then shown in subsection 6.3.3 the results of individual analyses for specific programs and concepts. Finally, subsection 6.3.4 presents a comparison of the profit-oriented scenario solutions with those of a more performance and demand-oriented one.

6.3.1 Proposed method application

One of the objectives of this research was to produce a holistic model that simulates various business disciplines over the life-cycle of the program, in addition to the design model, and that includes additional business-related variables characterizing the program. Such a simulation environment is implemented according to chapter 3 and used to perform a multi-objective optimization of a suborbital tourism program, with profit-oriented objectives. The following parts describe the followed methodology.

Step 1: Selection of the decision criteria

The first step of the methodology is to define the decision criteria. This scenario is profit-oriented, but some more secondary objectives are also possible. As such, the value objec-

265

tives are set as the NPV (with 50% weight), the IRR (with 30% weight), and the volume per passenger (with 20% weight), which is used as a measure of customer experience. The risk objectives are also profit oriented. They are chosen as the downside deviation of the value score (35% weight), the operational risk (35% weight), the financial risk (17.5% weight), and the preference risk (12.5% weight). The objective is to minimize the risk score while maximizing the value score. Table 6.1 summarizes the selection of risk and value scores and weightings.

Table 6.1: Risk and value objectives for the considered scenario

Value objective	Weight	Risk objective	Weight
Net Present Value	50%	Value risk	35%
Internal Rate of Return	30%	Operational risk	35%
Volume per passenger	20%	Financial risk	17.5%
		Preference risk	12.5%

Additionally, constraints are set. In addition to the constraints on required altitude and maximum allowable load factor, it is required that the gross margin of the company is positive. In other words, the value of revenues made must exceed the operating costs. This does not ensure that the program is profitable enough, or even profitable at all, but it filters out all solutions that are not even able to generate any gross profits, as they are deemed not sustainable. The development and manufacturing costs are not included in the calculation of the gross profits, which makes this constraint a fairly loose filter, that really removes the excessively unprofitable alternatives. As profits are set as one of the main objectives, most solutions will anyways be positive. Finally, the infeasible concepts are, of course, off constraints.

Step 2: Design and uncertain spaces definition

Another part of this methodology is to define the design and uncertainty spaces. These bounds of these spaces were described thoroughly in chapters 3 and 5. The same spaces remain in use for this scenario. Hence, four different morphological matrices are used for the four different architectures, while the company-level morphological matrix is shared by all four. The company-level morphological matrix contains business-oriented variables such as the ticket price, number of flights per vehicle per year, and number of vehicles produced. Due to the evolving demand, the period of operation is divided in three (years 5 to 9, year 10 to 14, years 15 to 20), in order to give the opportunity to operate the company in the best conditions in a time-dependent context.

Step 3: Evaluation of alternatives

In order to evaluate alternatives, the M&S environment described in chapter 3 is used, with the regression and classification neural networks used to replace the design framework already created. As each architecture has a different input space, architectures are evaluated using separate sets of neural networks, and therefore separate evaluation functions. The M&S enables to model both the design and the business aspects of the suborbital vehicle programs to be evaluated. The SOTM uncertainty propagation method described in chapters 2 and 5 is used in order to compute the downside deviation of the value score. The evaluation step is incorporated in the multi-objective optimization process used in the following part.

Step 4: Decision-making

In order to select the best alternatives according to the decision criteria, a multi-optimization process is used. Each architecture requires the use of a separate optimization process, as their input spaces differ. Hence, a Pareto frontier is created for each architecture. The overall Pareto frontier is taken as the set of non-dominated solutions among the

(a) Architecture-specific Pareto frontiers

(b) Final Pareto frontier
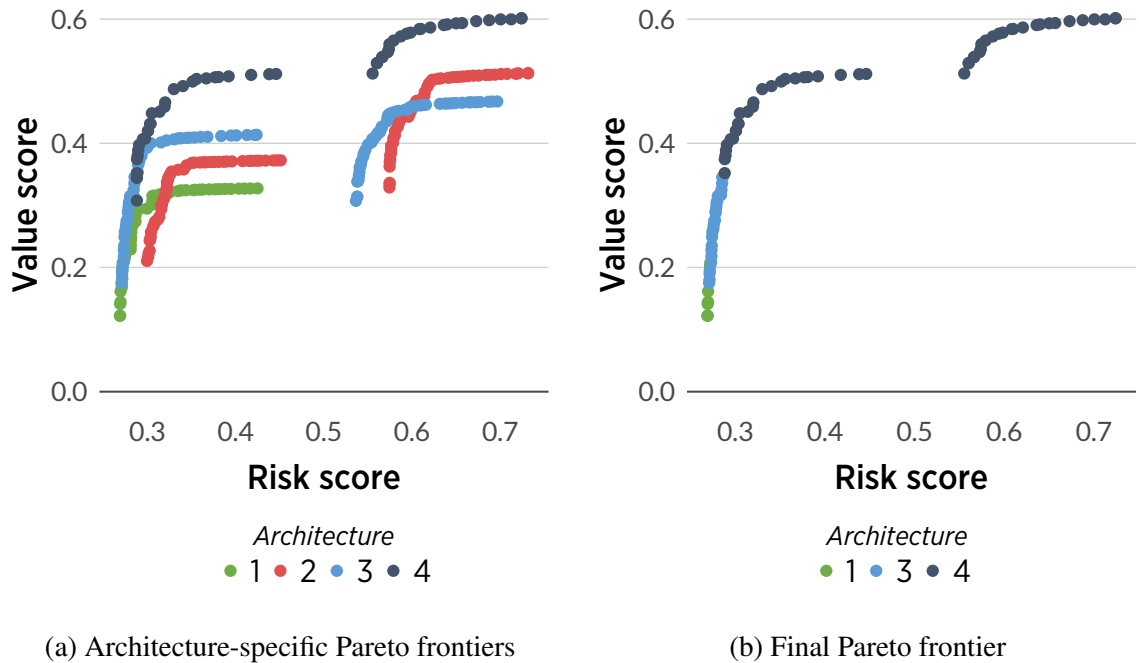
Figure 6.4: Creation of the Pareto frontier

four architecture-specific Pareto frontiers. As such, Figure 6.4a shows the resulting Pareto frontiers for each of the four architectures. Figure 6.4b then shows the set of solutions that get filtered into the final Pareto frontier.

Once the overall Pareto frontier obtained, a set of potential solutions is identified. However, a single solution must be selected. To do so, various analyses must be performed. These analyses can be carried out by decision makers using the developed trade-off environment. This environment helps perform two types of analyses: Pareto frontier analyses and individual analyses. In parallel, a TOPSIS analysis on all possible preferences for risk or value can be performed to downselect a few alternatives and visualize some of their characteristics. Figure 6.5 summarizes the proposed decision-making steps.
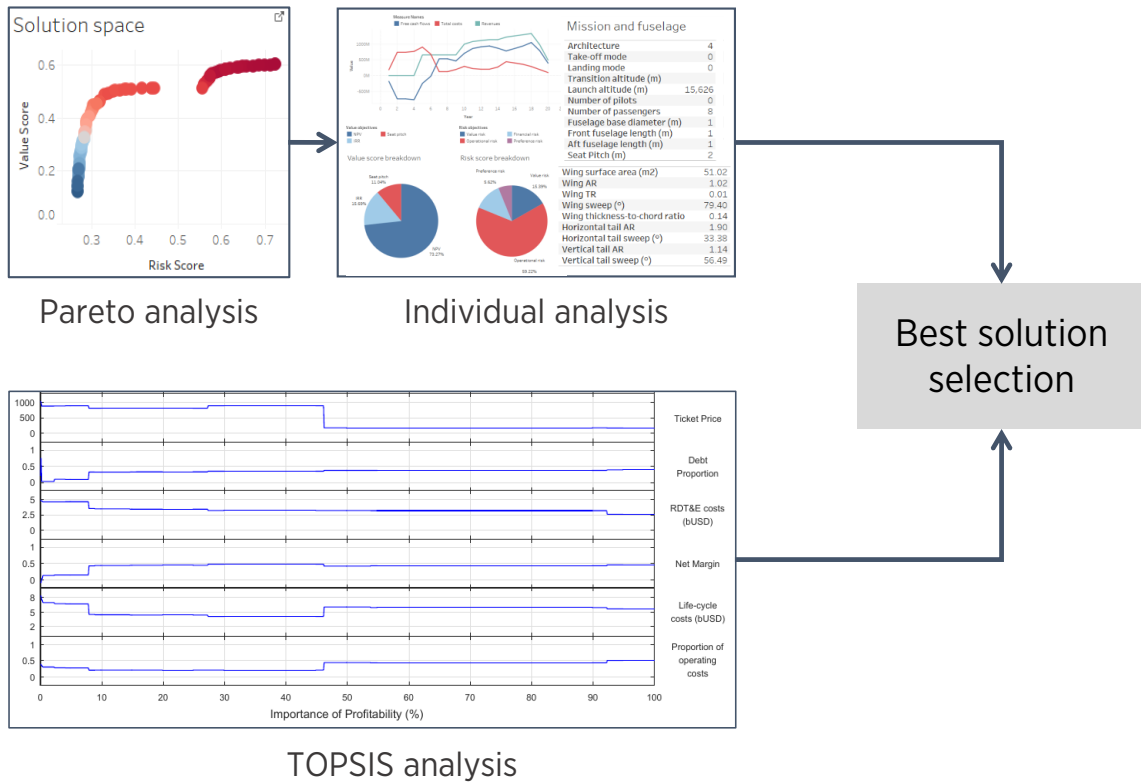
Figure 6.5: Decision-making steps

First, the Pareto frontier can be analyzed in its whole using coloring in the graphical interface. Two aspects of the solutions can be understood by proceeding as such. First, the solution's responses can be observed, such as the different value and risk components or the values of each type of costs. This helps understand some key aspects of the system's performance in terms of risk and value, and therefore what participated to resulting in non-dominated scores. Additionally, the inputs that led to such results can also be studied. Doing so, it is possible to observe qualitatively what the impactful metrics are, and what their effect on the solution's risk and value scores is. In particular, this visualization is particularly interesting for detecting clusters of points that share the same inputs. For example, as seen in the final Pareto frontier, architecture type has a large impact on results, and therefore solutions were all grouped accordingly. Figure 6.6 shows two examples of Pareto analysis visualizations provided by the trade-off environment, with color-

(a) Coloring by architecture type   (b) Coloring by number of pilots
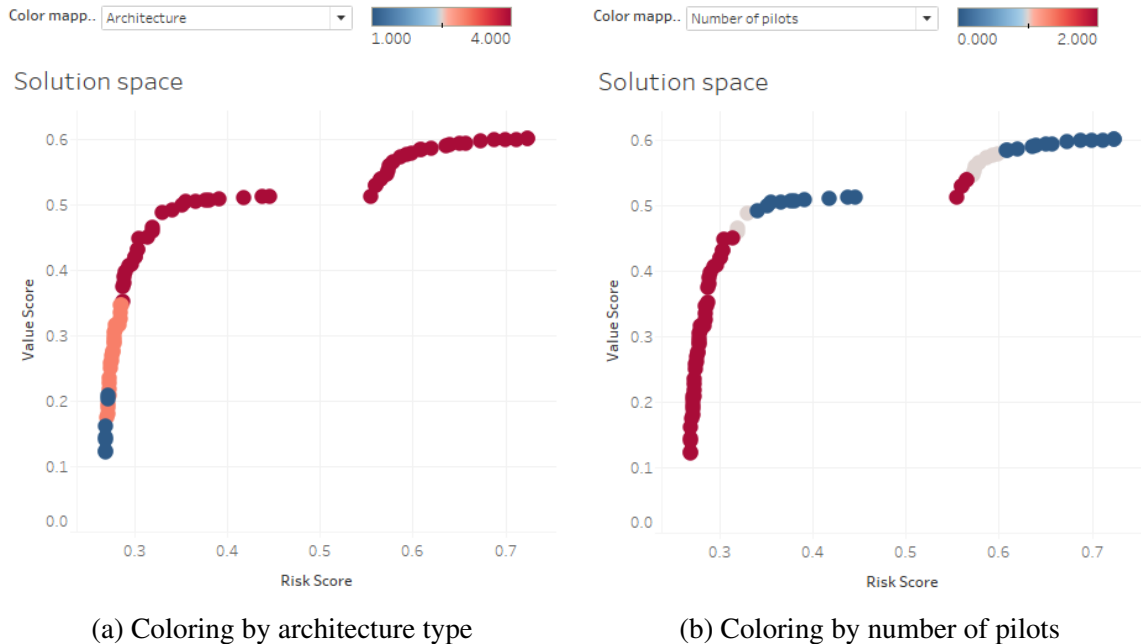
Figure 6.6: Examples of Pareto analysis visualizations

mapping of the Pareto frontier as a function of the architecture type and the number of pilots controlling the vehicle.

The trade-off environment can also provide analysis as the individual solution level. An individual can be selected from the Pareto frontier, in order to study in further details some of its characteristics, such as the time evolution of its revenues, costs, and free cash flows, or breakdowns of the value and risk scores. This helps understand where value and risk come from for a particular program. It also provides a financial forecast, which is an important part of the creation of a business plan for a new company. This also permits to identify when some of the major expenses happen, or when revenues can outweigh costs, for example. Finally, a more exhaustive description of the vehicle's design variables is provided, in order to better understand the geometry of the considered optima. Figure 6.7 gives an example of individual analysis visualization for a program using an architecture 4 vehicle. In the first graph, it can be observed that large costs are incurred in the first five years without revenue. These correspond to the development period, and no vehicles are available yet. Revenue is initially stable, before ramping up at year 10. After year 17,

revenues decrease as vehicles get retired. In the following ones, value and risk breakdowns are provided. Most value comes from profitability as expected. As for risks, a significant portion comes from operational risk (architecture 4 being a bit more unsafe than others due to its launch phase from a carrier aircraft), but also from financial risk as the studied concept uses significant amounts of debt to raise the NPV.

This part described some of the analysis capabilities provided by the trade-off environment in order to facilitate decision-making. In the following subsections, the results for each of these analyses are provided in greater details in order to fully illustrate the capabilities of the proposed method.

6.3.2 Pareto frontier analysis

As a result of the multi-objective optimization of the four considered architectures, four Pareto frontiers are obtained and combined into the overall resulting Pareto frontier. As a consequence, dominant configurations and characteristics can be identified. Because of the presence of many discrete variables, clusters of points are obtained. Figure 6.8 shows the overall Pareto frontier, and details key characteristics of each optimal point. One can notice that not all optimal concepts are profitable and that there is a trade-off between safety and profitability.

- **Architecture type:** main clusters of points can be identified. First, the safest concepts are built around Architecture 1. This makes sense as this take-off mode this the most widely used among all existing space programs, hence benefiting from a long experience and therefore limiting risk. While being the programs with the lowest risk level, these configurations are not profitable enough to justify the conceded investment (unless the company benefits from subsidies to alleviate the financial burden it represents). The second cluster of points contains fairly safe, yet more profitable programs, which make use of architecture 3. They can achieve much greater value than architecture 1. The next group of points consists of two subclusters. The separation

271

Financial forecast

Measure Names
- Free cash flows
- Total costs
- Revenues

Value score breakdown

Seat pitch 15.46%
IRR 14.68%
NPV 69.86%

Value objectives
- NPV
- Seat pitch
- IRR

Risk score breakdown

Preference risk 7.79%
Value risk 26.23%
Financial risk 28.91%
Operational risk 35.23%

Risk objectives
- Value risk
- Financial risk
- Operational risk
- Preference risk
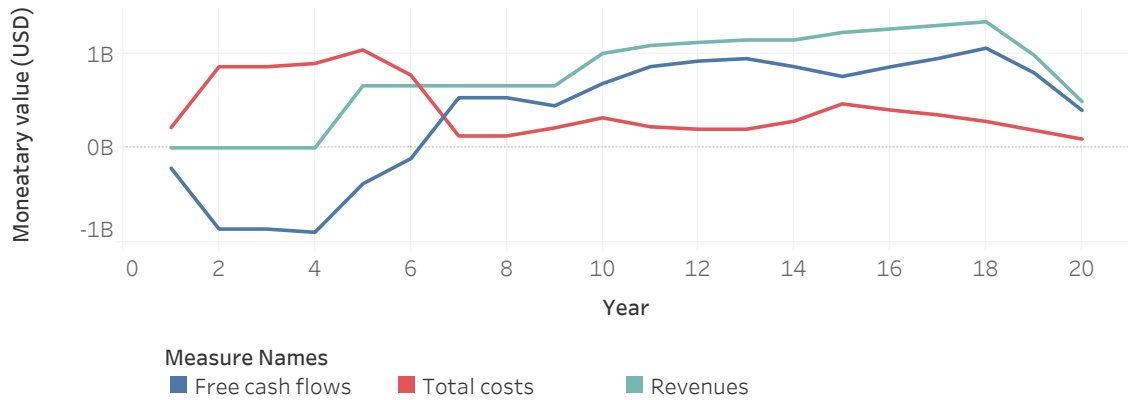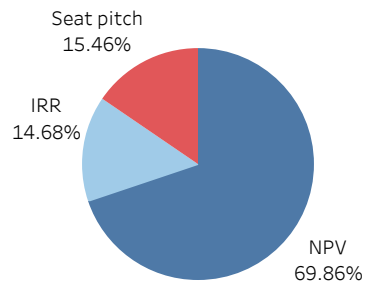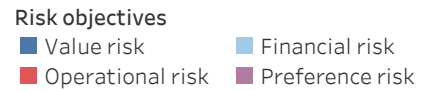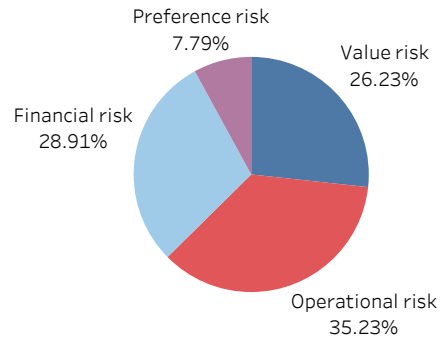
Mission and fuselage

Architecture	4
Take-off mode	0
Landing mode	0
Transition altitude (m)	
Launch altitude (m)	15,624
Number of pilots	0
Number of passengers	8
Fuselage base diameter (m)	1
Front fuselage length (m)	1
Aft fuselage length (m)	1
Seat Pitch (m)	2

Wing and empennage

Wing surface area (m2)	51.11
Wing AR	1.05
Wing TR	0.01
Wing sweep (°)	66.03
Wing thickness-to-chord ratio	0.12
Horizontal tail AR	2.00
Horizontal tail sweep (°)	61.83
Vertical tail AR	1.94
Vertical tail sweep (°)	36.56

Rocket and jet engines

Propellant	3
Thrust (N)	434,060
Chamber pressure (MPa)	2
Nozzle expansion ratio	28
Number of jet engines	
Afterburner	
Jet thrust (N)	
Bypass ratio	
Turbine Inlet Temperature (K)	

Figure 6.7: Individual analysis in the trade-off environment
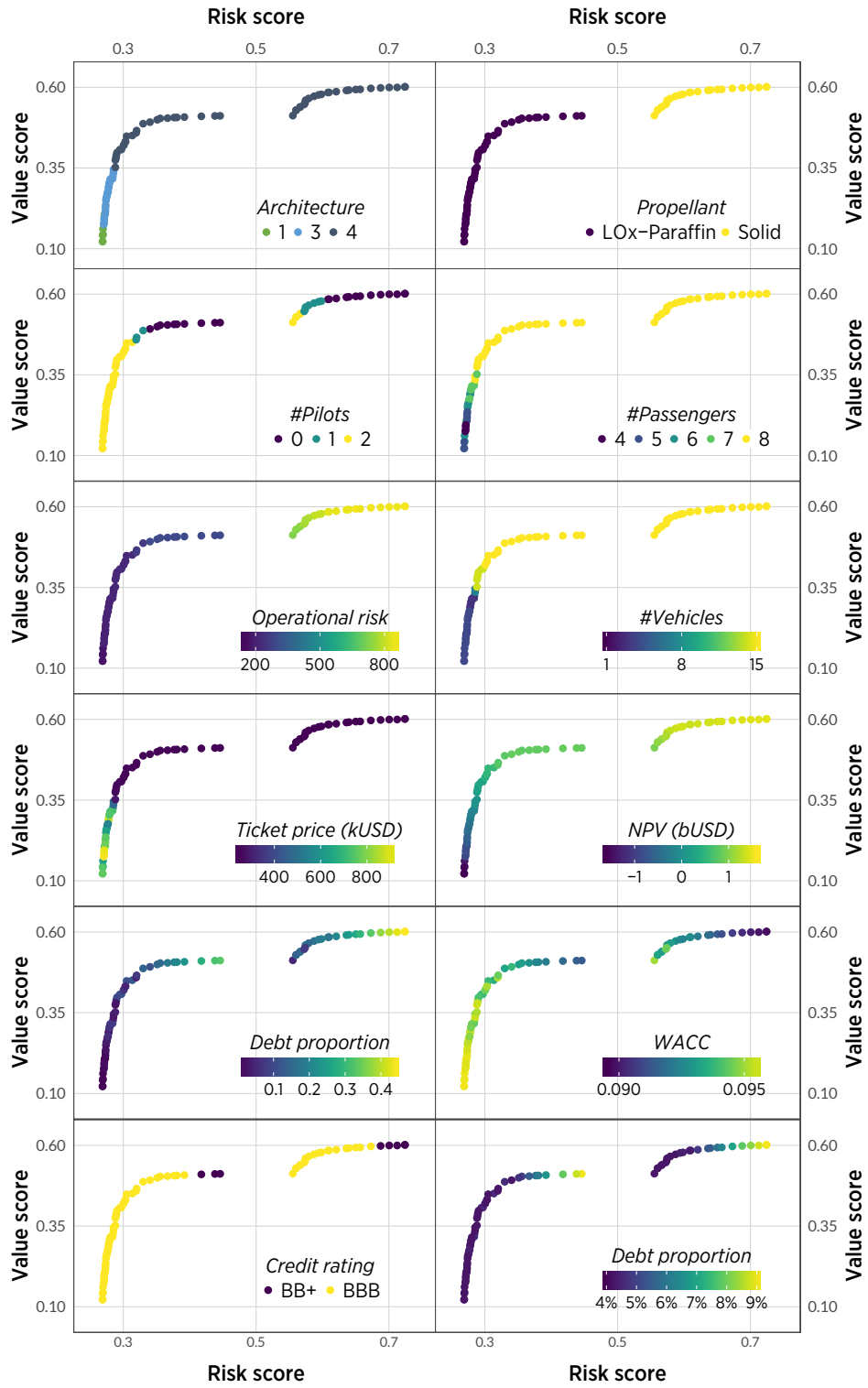
Figure 6.8: Dominant vehicle configurations

occurs because of the propellant type, as explained next. As a result, architecture 4 brings optimal solutions for both reasonably safe concepts with good value, and the most profitable, yet riskier vehicle programs. Overall, architecture 4 seems to dominate others in terms of profitability. It can finally be noticed that programs built around Architecture 2 are not in the final set of concepts. This seems to indicate that architecture 2 underperforms other architectures in terms of safety and profitability.

- **Propellant type:** Two types of propellant dominate: solid propellants, which are cheaper but significantly riskier, and a hybrid LOx/Paraffin, which maintains good profitability and is much safer. While the gap in operational risk level and risk score is substantial, the one in value is somehow smaller. As a consequence, hybrid engines appear to be a more robust solution and a better choice for safety-conscious decision makers. None of the concepts powered by liquid rocket engines are in the final set of concepts.

- **Number of pilots:** Changes in the number of pilots create small subclusters: adding pilots makes the flight slightly safer but increases the operating costs. In the two large clusters, significant increases in value happen before reducing the number of pilots becomes necessary. However, to get a program with the highest value score, the vehicle must include no pilot.

- **Number of passengers.** As this problem is profit-oriented, most of the Pareto frontier is made of vehicles carrying eight passengers, which can help satisfy larger amounts of demand. It is interesting to note, however, that programs with less value score (hence not as profitable) tend to include fewer passengers. This can be explained by the fact that these programs involve costlier vehicles, which therefore necessitate higher ticket prices to maintain their margins. As a consequence, demand is then lower, as is the need for capacity.

- **Ticket price and number of vehicles:** As concepts become more profitable (due to lower development and operating costs), companies can afford reducing prices to attract more customers, and increase overall revenue. Reversely, more expensive projects need a higher ticket price to ensure profitability. To satisfy the high demand, low ticket price programs use up to 15 vehicles, while those with high ticket prices only use between 4 and 5. Hence, a strong coupling is observed between the optimal number of vehicles and the optimal ticket price.

- **NPV:** Due to the problem formulation, the NPV is tightly correlated with the value score and increases almost linearly with it. Not all programs on the Pareto frontier are profitable enough to pass the hurdle rate granting positive NPV, although all are making net profits overall.

- **Financial metrics:** As projects become more profitable, the amount of debt for the company to carry to maximize the NPV increases. This is due to the implementation of the cost of debt model. Indeed, as a program becomes more profitable, the company makes larger profits, which results in higher interest coverage ratio, and therefore lower cost of debt. In other words, creditors are more willing to lend money to a company with a profitable project. However, due to the presence of the financial risk as a risk objective, the resulting debt proportion is actually much lower. However, this amount increases in the higher value score portions of the two Pareto frontier clusters, at the expense of a higher risk because of the higher chances of defaulting. As shown in chapter 4, debt proportion is correlated with credit rating and WACC. As the debt proportion increases, the credit rating degrades, but the WACC improves because solutions get closer to optimal leverage.

Once the Pareto frontier is generated, decision makers can downselect solutions using TOPSIS techniques. Figure 6.9 details the selected programs depending on the importance given to safety and profitability. This analysis shows, again, the domination of architecture

275

4, with other architectures being selected only when value score preference is below 10%. Similarly, solid propellant engines are selected when value score preference is over 75%. With an equal preference for value score and limitation of risk score, the optimal concept is an architecture 3 vehicle with eight passengers, 15 vehicles built in total, one pilot, hybrid propellant engine, a debt proportion close to 15% and a BBB credit rating. In the next subsection, this particular concept is further analyzed.

It is also interesting to see on Figure 6.9 that there are major changes due to variations in preference (as indicated by the red dashed lines). At 3%, 9%, and 75% preference for value, there are changes in architecture and propellant type: the highest-level design variables. These shifts in design also result in shifts in non-design variables. For example, at 9% preference, the preferred architecture changes from number 3 to number 4, while the number of vehicles used rises from 3 to 14, the number of passengers increases to 8 from 7, and the average ticket price drops from around $750,000 to $250,000. Additionally, the NPV changes from negative to positive. The design shift at 75% preference is significant as well. The propellant type changes from hybrid (LOx-Paraffin) to solid, which leads to a surge in profitability and risk. This increase in risk is mitigated by the addition of a pilot, while the higher profitability significantly decreases the probability of defaulting. Overall, it can be seen in Figure 6.9 that the design decisions are tightly correlated with the non-design ones, as changes in one type of variable significantly affect the other ones.
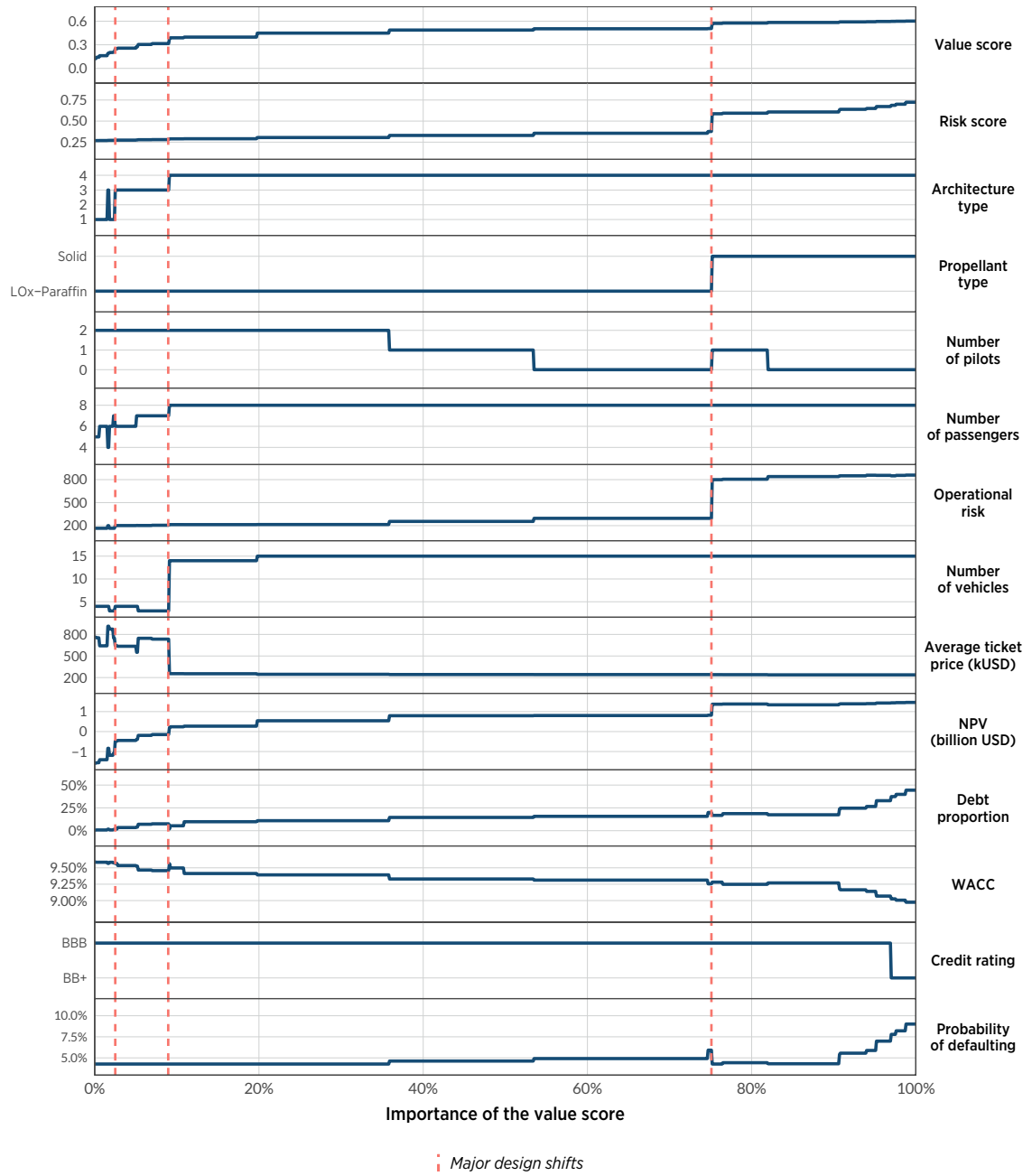
Figure 6.9: Detailed description of selected configurations as a function of the importance of value score
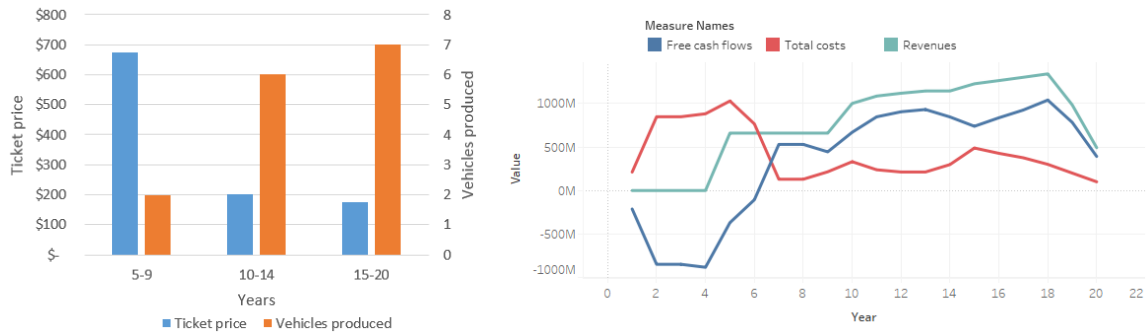
(a) Number of vehicles produced and ticket price by period

(b) Revenues, costs, and cash flows during the program life-cycle

Figure 6.10: Operational and financial forecast

6.3.3 Individual solution analysis

The concept selected in the previous subsection is now analyzed in more details. First, Figure 6.10a provided the optimal number of vehicles produced and ticket price for the selected alternative, during the three life-cycle periods. It is interesting to observe that at first, demand is not sufficient to make affordable travel profitable for the company, resulting in only 2 vehicles produced and operated during the first years, with a ticket price nearing $675,000. However, as demand grows, the most profitable way of operating changes and ticket prices are reduced. More vehicles are then produced to accommodate the attracted demand. Figure 6.10b shows revenues, costs, and cash flows during the life-cycle of the program. Initially, money is invested into development, and no revenue is made as no vehicle is produced yet. Operations start at year 5, with 2 spaceplanes. More vehicles are then produced in the following years to take advantage of the growing demand. Costs increase as well, as a consequence of the increased size of operations. However, due to economies of scales, cost per vehicle decreases, which ensures the profitability of operations.

278
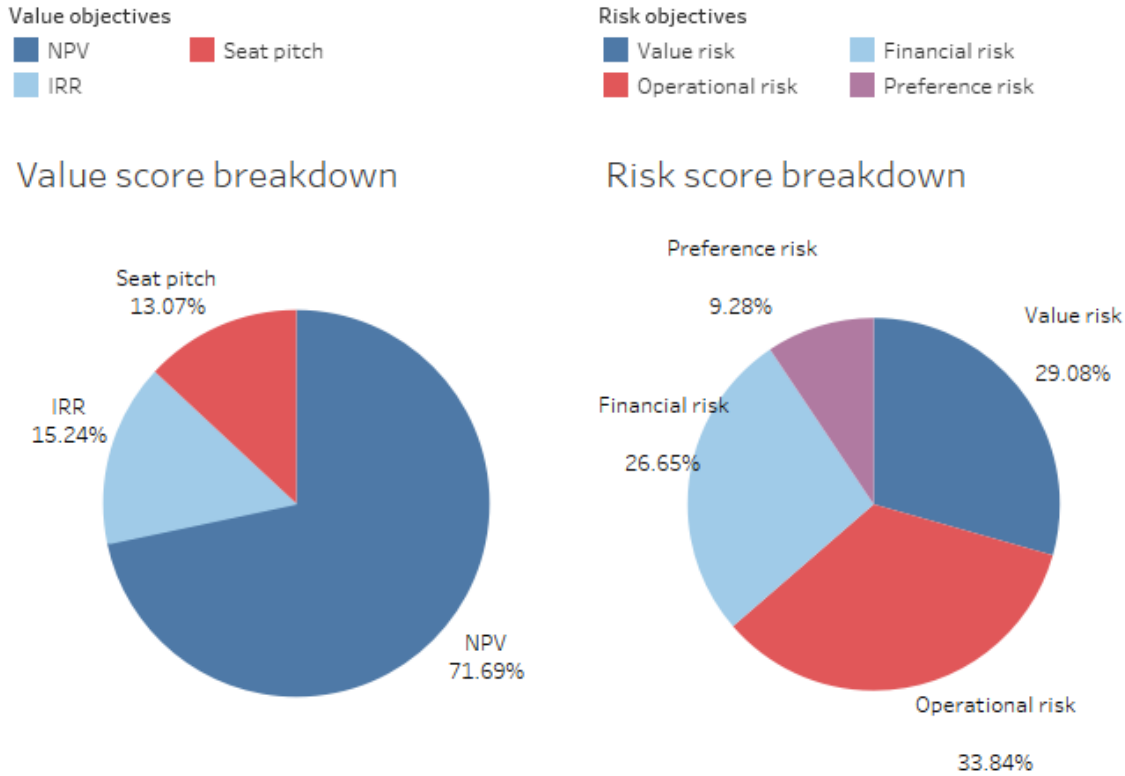
Figure 6.11: Value and risk scores breakdown

Additionally, value and risk scores can be broken down to determine what influenced those metrics. The percentage of influence of each of these measures is strongly correlated with the weightings they are given in the decision criteria selection step. Figure 6.11 shows the result of the breakdown analysis for the selected alternative. As expected, most of the value is gained by the NPV and IRR, with the contribution of the volume per passenger being small but still at 13%. More interestingly, the risk score breakdown helps better understand this individual. Indeed, operational risk is significant, not only because of the large weight it got assigned but also because architecture 4 is somehow riskier than the three others. Yet, the use of hybrid engine propulsion allows maintaining the operational risk to a reasonable amount. Financial risk, on the other hand, is relatively high for the weight it was given. This is due to the significant probability of defaulting of the selected program (4.62%; up 8% from the minimum of 4.27%). Indeed, to reduce its WACC and

therefore increase its NPV, more debt was issued by the company (14.5%). The is beneficial for profitability, but larger amounts of debt increase the chances of defaulting.

Table 6.2: Risk and value objectives for the considered scenario

Value objective	Weight	Risk objective	Weight
Net Present Value	10%	Value risk	50%
Internal Rate of Return	5%	Operational risk	30%
Volume per passenger	70%	Financial risk	5%
Sales count	15%	Preference risk	20%

6.3.4 Scenario solution comparison

The proposed method can also be applied to compare the outcome of two different scenarios, using a TOPSIS analysis and comparing the characteristics of the selected alternatives. In order to illustrate this function, another scenario is implemented. This scenario is more customer-oriented, with high weight on the volume per passenger (70%) in order to favor better customer experience, a significant emphasis on safety (30% weight on operational risk), and the addition of the sales count as one of the constituents of value, in order to try to make the service available to a larger number of customers. Reversely, the profitability weights have been greatly reduced (10% for the NPV, 5% for the IRR) although they are still considered. Weight on financial risk has also been reduced, but this objective remains present, as a way to ensure that even if a program does not result in a sufficient rate of return, it should still provide a net profit on the total life cycle. The objective is to minimize the risk score while maximizing the value score. Table 6.2 summarizes the selection of risk and value scores and weightings.

The optimization process is run for each architecture, and the results are provided in Figure 6.12, which also indicates which architecture each solution belongs to. Four clusters of points are present, and architecture 2 is absent again. Architecture 4 is, again, the most
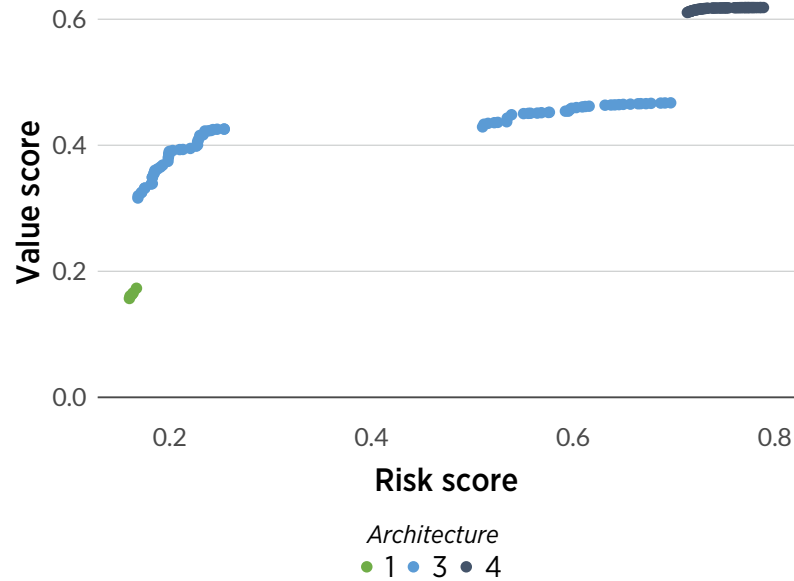
Figure 6.12: Pareto frontier of the second scenario

valuable but riskiest alternative. With these solutions outputted, the TOPSIS selection is performed for each level of risk aversion. The characteristics of these selected points can then be compared to those of the previously studied scenario, as shown in Figure 6.13. It is important to note that if the risk and value scores are shown, they are not present for comparison of the two scenarios as they are not representing the same objectives. Instead, they are shown to see the evolution of the risk and value score selected to understand at which point a decision maker can accept higher risk exposure. Several aspects of this new scenario can be observed. First, when risk aversion is high, and therefore preference for value is low, the profitable alternatives are selected, which results in solutions close to those of the previous scenario. However, when preference for value exceeds 62%, the approach changes, and an alternative gets selected with negative NPV but an 8-meter cabin space providing around 12 cubic meters for each of the two passengers. This concept is somehow risky due to significant operational risk, mostly. Indeed, only architecture 4 with solid propellant engines manages to provide such space while keeping net profits. However, these options are not the safest. Due to a more exclusive service, the ticket price nears $1.2

million. Hence, major shifts in design and business configurations can be observed. At the configuration shift at 62% preference, the architecture, propellant, number of passengers, cabin space, number of vehicles, ticket price, debt proportion, and multiple risks change very significantly and indicate a completely different business model. This shows the tight relation between business and design.
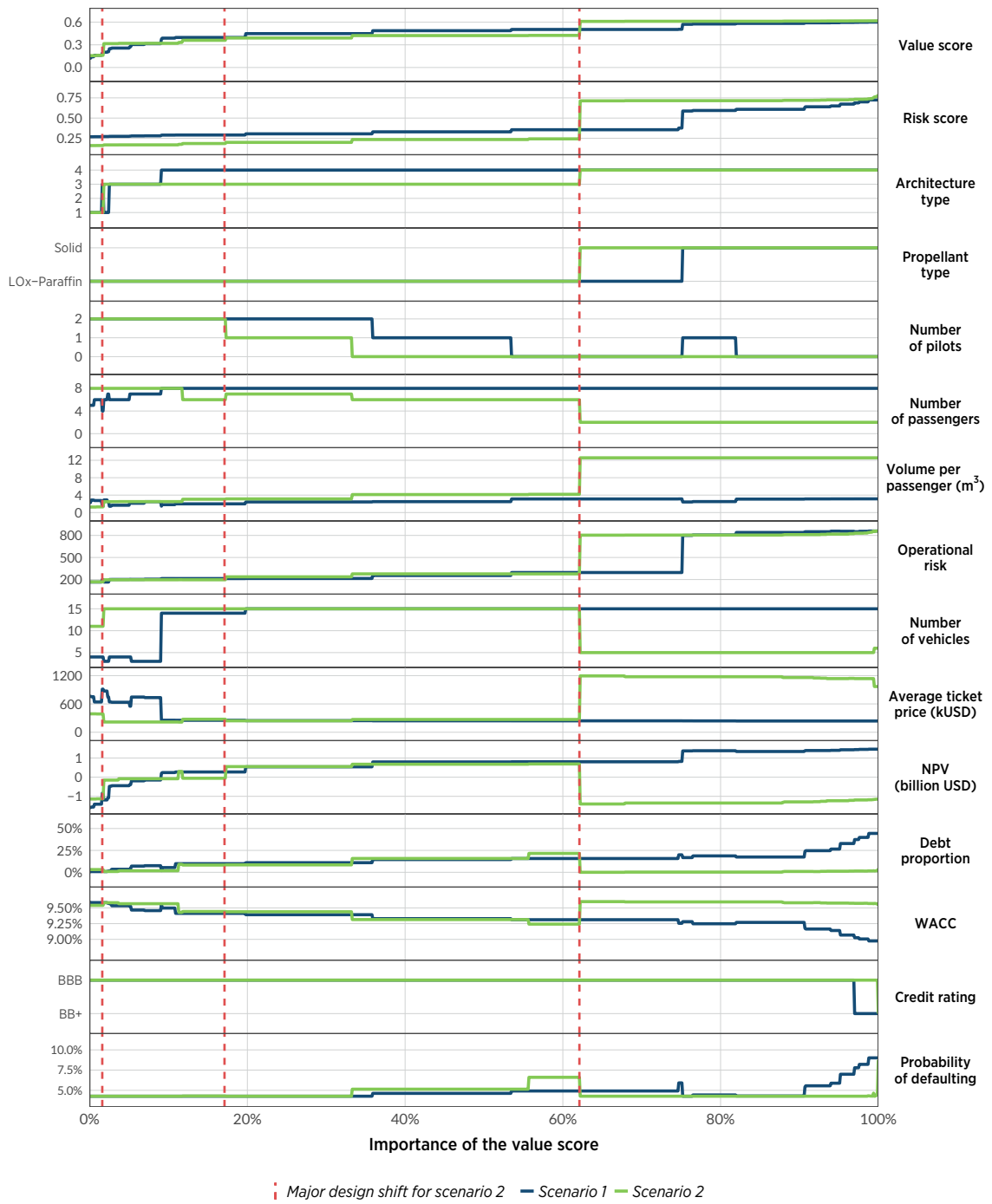
Figure 6.13: Comparison of selected solutions for the two scenarios

6.4 Chapter summary and comparison with common methods

In chapter 2, research question 2 brought the problematic of how to facilitate enterprise-level decision making – hence is a multi-objective and multi-risk environment. While traditional robust design methods are usually meant for the optimization of a single objective with only one measure of uncertainty, they fall short when the environment, as with enterprise-level approaches, becomes multi-objective and multi-risk. Additionally, the use of standard deviation as a measure of risk is ill-suited, as standard deviation is a symmetric and therefore neutral metric. As no approach seemed to be completely satisfactory, the literature was surveyed, and hypothesis 2 was formulated, by taking inspiration from financial methods: *if uncertain strategic objectives are combined into risk and value scores using a stochastic Multi-Attribute Utility functions, if an uncertainty propagation method is adopted that time-efficiently estimates downside deviation, and if an integrated trade-off environment facilitating programs ranking and visualization is used, then strategic leaders can easily make sound risk/value trade-offs in an uncertain multi-objective enterprise-level environment in conceptual design.* The studies and observations carried out in this chapter verify hypothesis 2, as explained in this section.

In this chapter, various aspects of hypothesis 2 were tested. First, it was shown that standard deviation cannot be used as a proxy for downside deviation. Indeed, doing so is equivalent to assuming the output distribution is normally distributed, or at least has constant skewness and kurtosis, as any variations in these two statistical moments would not be accounted for. Yet, downside deviation depends heavily on these two metrics, and therefore it is recommended to use this variable directly, as large estimation errors could be committed otherwise. Additionally, the benefits of using aggregated risk and value scores were listed. These benefits are both qualitative and quantitative. From a qualitative point of view, the use of only two objectives enables easy visualization of the solutions in the response, as it is only two-dimensional. Only one easy trade-off has to be made: risk

against value. It is also possible to use various straightforward visualization techniques, such as coloring in order to analyze the solution Pareto frontiers, and identify clusters and main patterns that show how input and output variables are connected to the trade-off between risk and value. From a quantitative standpoint, using only two objectives reduces dimensionality and as a consequence improves convergence. The creation of a Pareto frontier with more dimensions makes convergence much harder as the population gets spread out and scarce in the many dimensions. It was proven with an easy example that with 15 times more function calls, the non-aggregated approach still underperforms the aggregated one in the two-dimensional responses space. Finally, the capabilities of the overall methods were shown, for the identification, ranking, and analysis of optimal alternatives. A full-scale optimization process was implemented and performed, and the results were analyzed as an illustration.

Table 6.3: Comparison of proposed method with main design under uncertainty techniques

	Robust Design	RD Pareto frontiers	RBDO	Proposed method
Multiple risk and value objectives	◖		◖	●
Downside of uncertainty as risk objective			◖	●
Enables risk/value trade-offs		●		●
Facilitates risk/value trade-offs		◖		●

Table 6.3 summarizes these results, and it appears clear that the proposed method provides the best solution for facilitating risk/value trade-offs in an enterprise-level multi-objective multi-risk environment. Current approaches lack solutions when multiple objectives are uncertain and multiple. Traditional robust design usually considers a single objective, that it aggregates with its standard deviation, which therefore does not allow risk/value trade-offs. Robust design Pareto frontiers use the objective function and its standard deviation as two separate objectives, but this method is meant for a single objective

function and becomes too inconvenient when more objectives are considered, as the Pareto frontier gets scattered. RBDO, finally, mostly uses the quantiles of the output distribution as a constraint, rather than a potential objective, limiting the possibilities of trade-offs. Reversely, the proposed method outperforms these approaches in the context of research question 2, by providing the following features:

- **Ability to handle problems with multiple uncertain objectives and multiple types of risk.** Unlike previously described techniques, the proposed method can handle multiple types of risk, and multiple uncertain objectives, by using value and risk scores. Despite the partial aggregation, decision makers remain able to make meaningful trade-offs, and to observe the dependence of inputs and outputs of the system to the preference between risk and uncertainty, which checks verification criteria 2.3 and 2.5 (*decision makers can choose among multiple optima*; *the optimization process can handle more than one risk and one value objectives*).

- **Simplified and quick enterprise-level decision-making enabled.** The presence of risk and value scores make decision-making simpler, and faster. Indeed, this approach reduces dimensionality, which permits to represent the solutions in a two-dimensional response space, hence making it much simpler to visualize. Additionally, a trade-off environment can further leverage the bidimensionality of the Pareto frontier, by using color mappings that ultimately enable the identification of dominant configurations as well as subgroups of solutions, therefore helping understand better the characteristics of the best alternatives and the dependence of the responses to the inputs. Individual analysis of elements of the solution set is also possible. Overall, using this method, a decision-maker has access to numerous analysis capabilities, some of which answer some of the key questions related to the research objective of this thesis. What are the main value and risk drivers? What are the company-level and vehicle-level variables that result in an optimal solution? What is the effect of risk aversion on the optimal program plan? Are there any dominant con-

figurations? These questions can be answered using the proposed method. Hence, by construction, verification criterion 2.2 is checked (*multiple program and vehicle analyses or visualizations are integrated*). The presence of the trade-off environment also enables to check verification criterion 2.1 (*selecting a program with more than 3 objectives takes less than 15 minutes using the decision support tool*), as decision-making is very straightforward after collecting the results of the optimization, and as no other data processing must be performed.

- **Downside deviation instead of standard deviation.** As previously mentioned, standard deviation is not a very well suited measure for risk. Indeed, a decision-maker might be unsatisfied if performance is lower than expectations, rather than if it exceeds predictions. As such, downside deviation is a better decision criterion. It keeps some of the characteristics of standard deviation while measuring the risk of a detrimental event, rather than a neutral one. Using downside deviation rather than standard deviation is important, as downside deviation greatly varies when the third and fourth statistical moments of the distribution change. Hence, standard deviation cannot be used as a proxy for downside deviation. By construction, verification criterion 2.4 is checked (*downside uncertainty is taken into account in the decision-making process*).

These observations demonstrate that the proposed method is a compelling way to facilitate company-level risk/value trade-offs, in the presence of multiple objectives and types of risk. As all verification criteria are checked, hypothesis 2 is deemed verified as an answer to research question 2.

CHAPTER 7

INTEGRATED ENTERPRISE-LEVEL APPROACH

The previous chapter dealt with the facilitation of risk/value trade-offs at the enterprise-level, using MAU functions to aggregate objectives into a value and risk scores, by using a trade-off environment, and by using downside deviation instead of standard deviation as a better measure of value risk. It also showed the qualitative advantages of using an enterprise-level approach as it enables a broader analysis that helps identify, rank and analyze optimal concepts and their respective optimal enterprise-level variables. While it was therefore shown that the enterprise-level approach brought qualitative benefits, there can also be some quantitative ones. As such, this chapter tries to answer research question 1, which asks: *does the adoption of an enterprise-level optimization approach during conceptual design help executives capture more value from aerospace programs and lead to significantly different decision-making?* After reviewing the literature, and taking inspiration from supply chain optimization, hypothesis 1 was formulated: *if a holistic business-driven framework is developed that integrates enterprise-level disciplines and their inputs in conceptual design and if enterprise-level strategic objectives are implemented and targeted then more value from aerospace programs can be captured and significantly different decisions are made.* In this chapter, various experiments are carried out to accept or invalidate hypothesis 1. To do so, next sections are articulated around the two main benefits of adopting an enterprise-level approach: capturing interdependencies between disciplines by using an integrated optimization, as shown in section 7.1, and using multiple enterprise-level objectives, as presented in section 7.2. Section 7.3, finally, concludes this chapter by summarizing the benefits of the enterprise-level optimization from a quantitative point of view, and verifies hypothesis 1.

7.1 Exploiting interdependencies between enterprise-level disciplines

The objective of this section is to assess the impact on the optimal design and its performance of adding business-related variables and disciplines and integrating them in a holistic environment. To do so, a simple scenario is established, where quantities are deterministic, demand is constant, and the objective is to maximize the profits, measured by the NPV, and to minimize the operational risk.
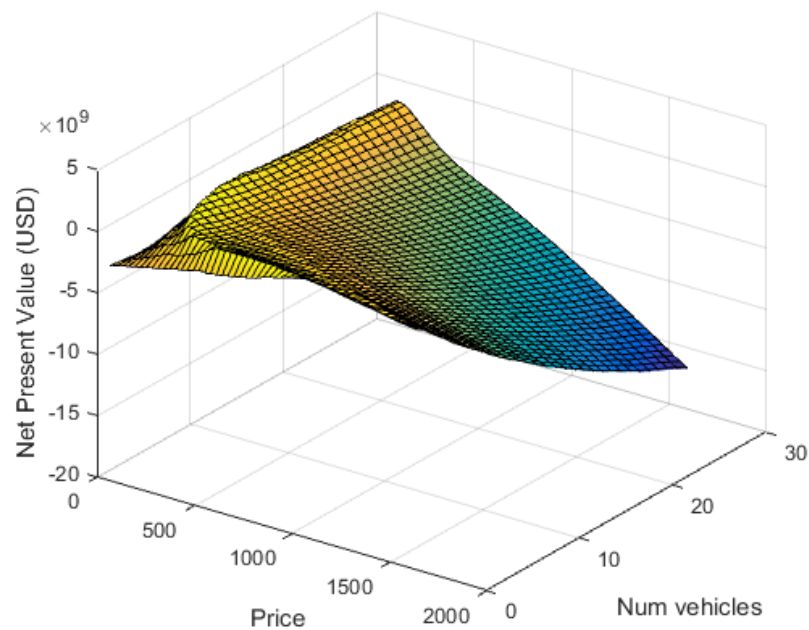
Figure 7.1: Impact of ticket price and number of vehicles built on the program NPV

An illustration of the presence of interdependencies between disciplines is given in Figure 7.1. Figure 7.1 shows the program NPV for a selected design as a function of the ticket price and the number of vehicles produced. The relation between these two variables is relatively straightforward, as the ticket price impacts demand, and the number of vehicles produced should be suited to the annual demand. This simple example shows the strong interdependence between some disciplines, and, therefore, the importance of accounting for it. While this only constitutes a single example, there can be additional and less intu-

itive ones, which motivates the assessment of the impact of such interdependencies on the optimal values of objectives, when they are accounted for and when they are not.

(a) Sequential optimization   (b) Integrated optimization
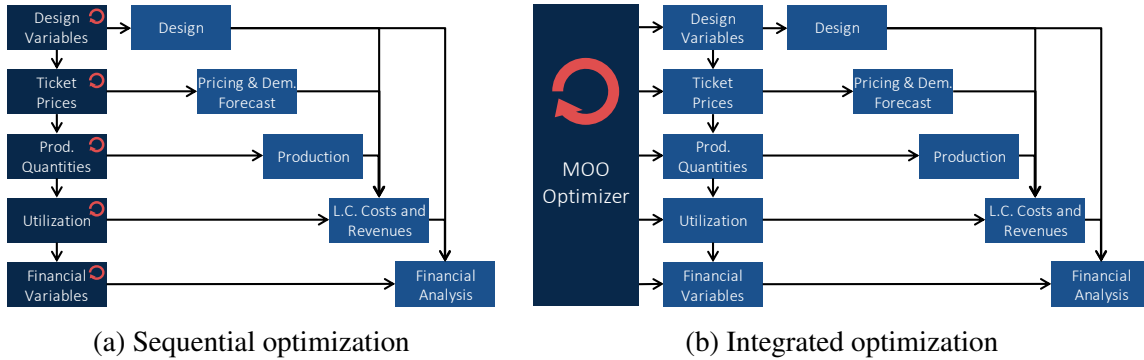
Figure 7.2: Integrated and sequential optimization study cases

To assess the potential of exploiting these interdependencies, three multi-objective optimizations are carried out. It enables the comparison of the performance of the different methods.

- **Design only.** This case only includes the optimization of the suborbital vehicle design and uses life-cycle costs and safety as objectives. This is an example of a design-for-costs approach.

- **Sequential optimization and business variables.** This case builds on the design-only case's results. Starting from a Pareto frontier on life-cycle costs and safety, the business disciplines are then sequentially optimized, with the objective to maximize the NPV (as safety is not affected by the following steps), as shown in Figure 7.2a. As such, the vehicle is first optimized, then the price of the tickets, followed by the number of planes produced, then their utilization, and the financial variables are finally optimized. If the design-for-costs approach is used, a sequential optimization process is most likely used at the enterprise level, as other disciplines have to be optimized at some point during the program.

- **Integrated optimization and business variables.** In this case, design and business frameworks are jointly considered in the optimization process. This is represented in Figure 7.2b and it represents a fully enterprise-level thinking of optimization, as proposed in this research.

These three multi-objective optimizations are performed and result in Pareto frontiers as shown in Figure 7.3. This experiment fulfills the previously established objective of capturing more value by exploiting discipline interdependencies. Indeed, the design-only case is, as expected, the least profitable one. By adding business-disciplines and variables, a significant increase in NPV is observed.
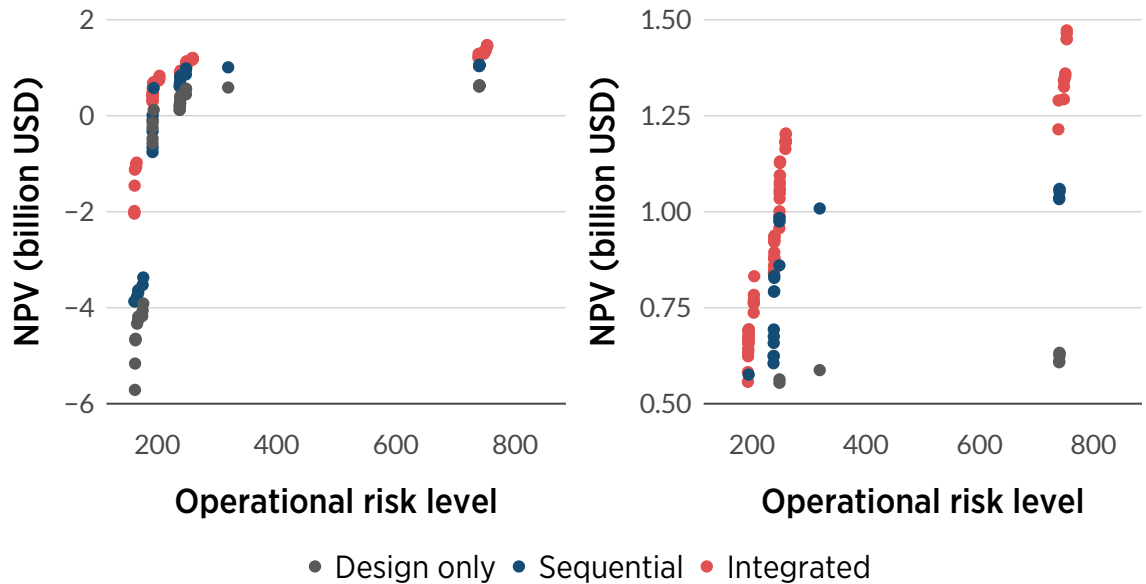
Figure 7.3: Optimum programs from different optimization approaches (full and zoomed views)

The improvement due to the use of integrated optimization instead of sequential optimization is harder to observe, because of the multiple discrete components of operational risk. This results in fairly vertical Pareto frontiers, which can eventually partially overlap. To facilitate visualization and evaluation of alternatives of interest, the Pareto frontier is filtered. Indeed, the decision-making process ultimately involves the use of TOPSIS to select the final concept. Therefore, only those that could be selected by this technique are

meaningful here. Hence, the selection includes all points that would be TOPSIS-selected for at least one possible preference between NPV and safety. Using this method, only the most profitable solutions of each of the vertical segments of the Pareto frontiers are kept, while the ones resulting in lesser profitability without observable gains in safety are rejected, facilitating visualization. Figure 7.4 shows the set of TOPSIS optima, and it becomes much more clear that integrated optimization achieves much greater profitability than sequential optimization.
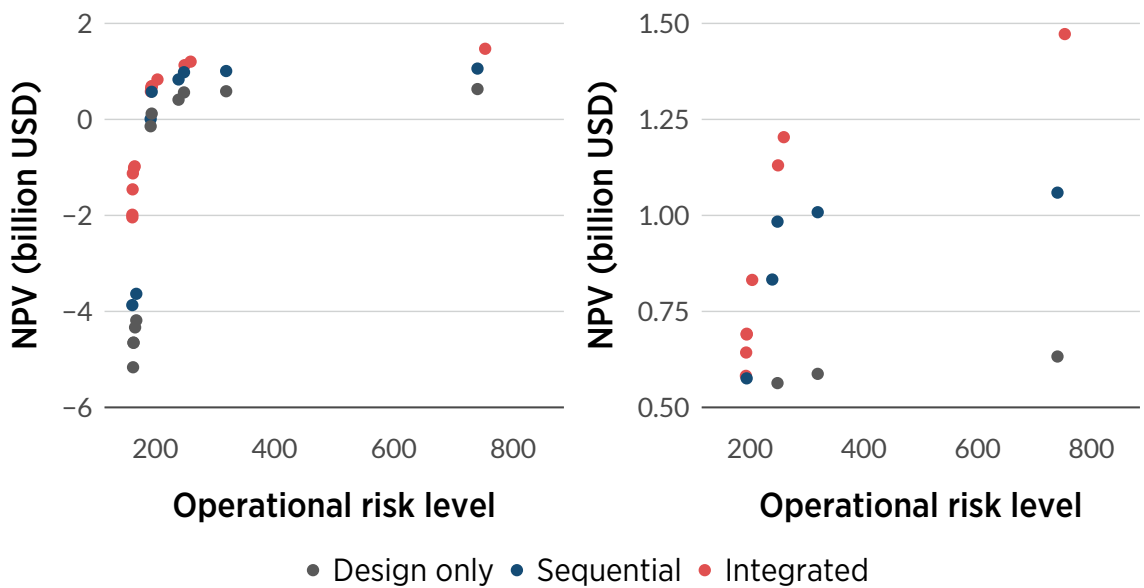
Figure 7.4: Set of TOPSIS-selected points (full and zoomed views)

Finally, the characteristics of selected programs are compared for different weightings between NPV and safety, as shown in Figure 7.5. It can be observed that selected programs significantly differ between sequential and integrated optimization. Overall, the sequential optimization results in much lower ticket prices, suggests to operate more vehicles, but not as frequently, and considers different numbers of passengers. Hence, as also observed in chapter 6, there is a strong interdependence between the optimal design variables and the business variables. The two different approaches result in very different decisions, with the selection of different business models and different designs. Therefore, using an integrated optimization significantly affects decision-making. By exploiting the interdependencies
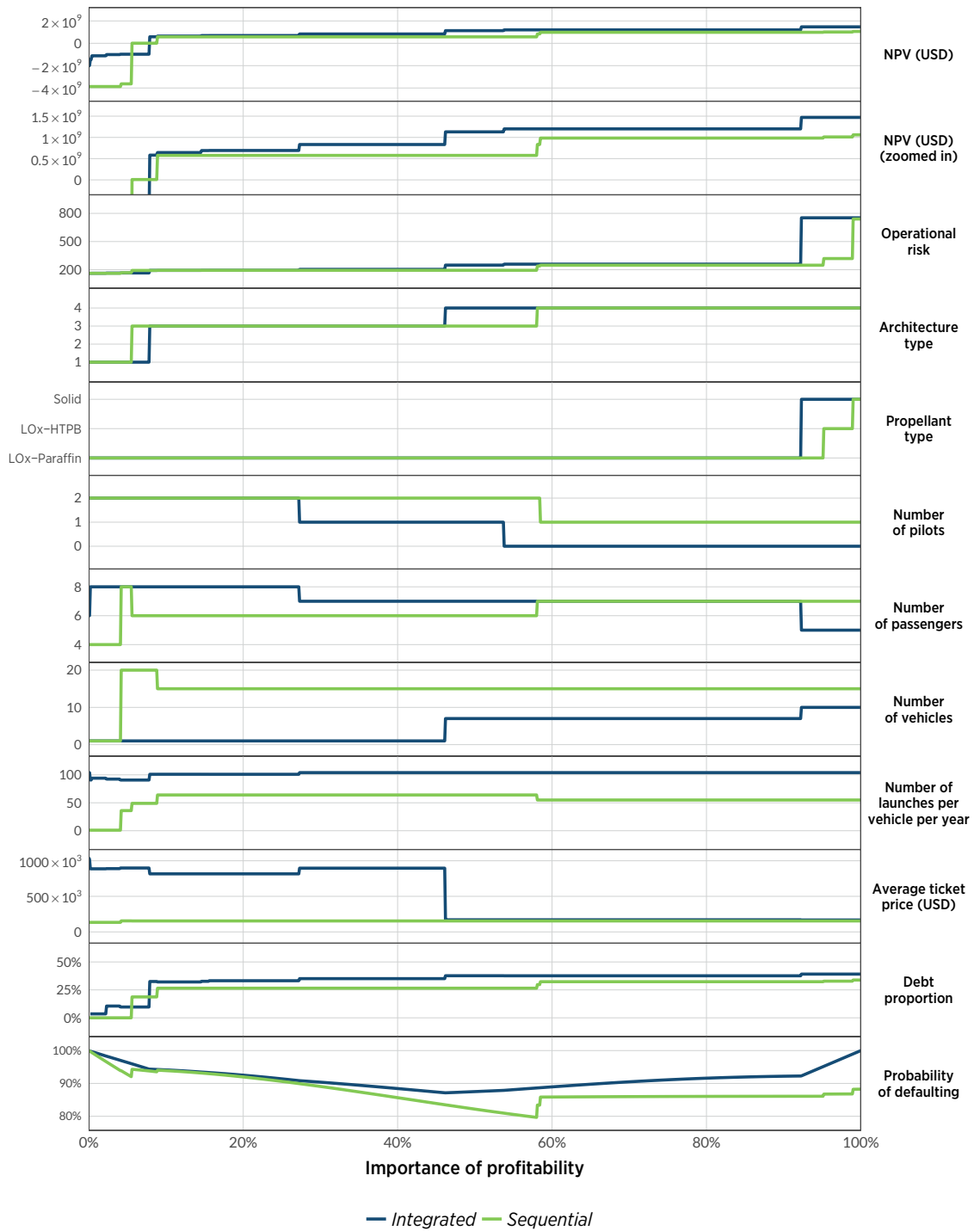
Figure 7.5: Characteristics comparison between sequential optimization and integrated optimization TOPSIS-selected points

between the various considered aspects of the program, the enterprise-level optimization provides more optimal solutions. In this example, the average TOPSIS score (with integrated optimization as a reference) obtained by the selected concept for each set of preference weightings is computed. The use of additional business disciplines and variables, while still using a sequential optimization, results in a 9.7% TOPSIS score improvement compared to the design-only approach. The integrated optimization approach results in a 4.4% improvement in average TOPSIS score compared to the sequential optimization case.

7.2 Importance of including several enterprise-level objectives

In this study, the advantages of including some additional strategic objectives rather than picking the major constituent of value and the major constituent of risk as objectives. To demonstrate the potential loss in value that would be incurred, a scenario with a strong emphasis on profitability and flight safety (a simplified version of the first scenario of chapter 6) is studied. Table 7.1 summarizes the weightings given to the considered objectives. This scenario is compared to one where only NPV and safety are considered.

Table 7.1: Risk and value objectives for the considered scenario

Value objective	Weight	Risk objective	Weight
Net Present Value	50%	Value risk	40%
Internal Rate of Return	30%	Operational risk	40%
Seat pitch	20%	Financial risk	20%
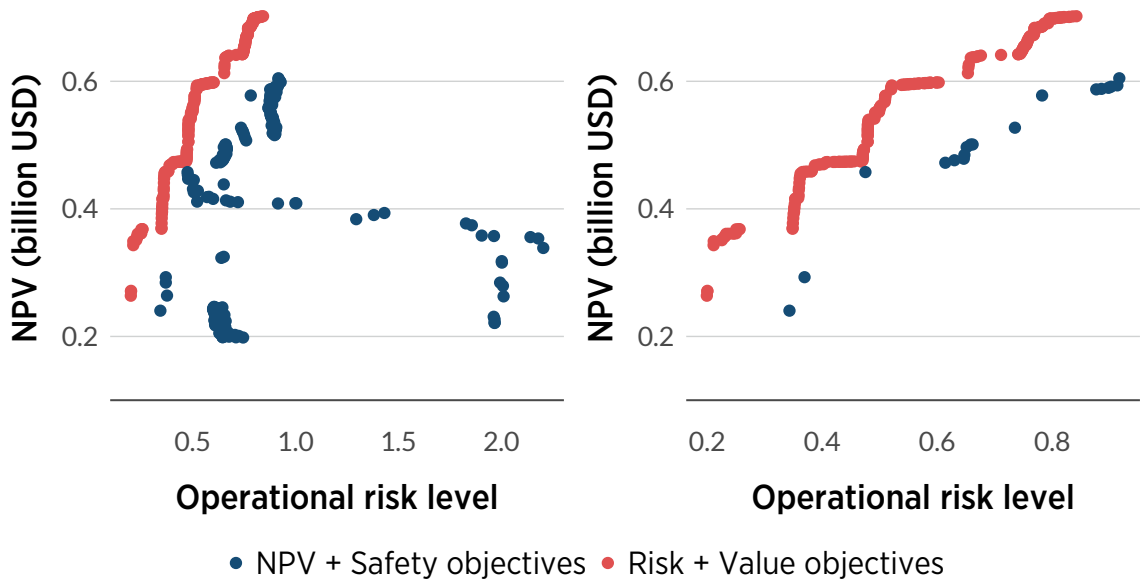
Figure 7.6: Comparison of optima from Risk/Value optimization against NPV/safety optimization, before and after Pareto-filtering

While emphasis has been put on profitability and safety for both scenarios, the results obtained from the risk/value optimization differ significantly from the NPV/safety optimization. These two scenarios were studied, and compared on a risk/value standpoint. Figure 7.6 and 7.7 show the comparison of the resulting optima. While it could be easy to think that using NPV and safety as the sole objectives would be a good proxy for an optimal vehicle when profitability and safety are the main drivers, the NPV/safety is not optimal anymore when converted to the risk and value scores response domain. The inclusion of additional objectives enabled to get much more value from the program. Indeed, some other minor objectives were enhanced as well, resulting in a superior product. Overall, the risk/value approach tends to be much more risk averse, due to the inclusion of an additional financial risk metric. This results in a much lower leverage than the NPV/safety optimization, but also lower chances of financial distress, for a minor reduction in NPV. Fewer vehicles are also produced. Besides, as volume per passenger was one of the other objectives, it results in a much roomier yet profitable space plane. Hence, both operational and design variables differ depending on the approach. Indeed, the selected architecture, propellant,
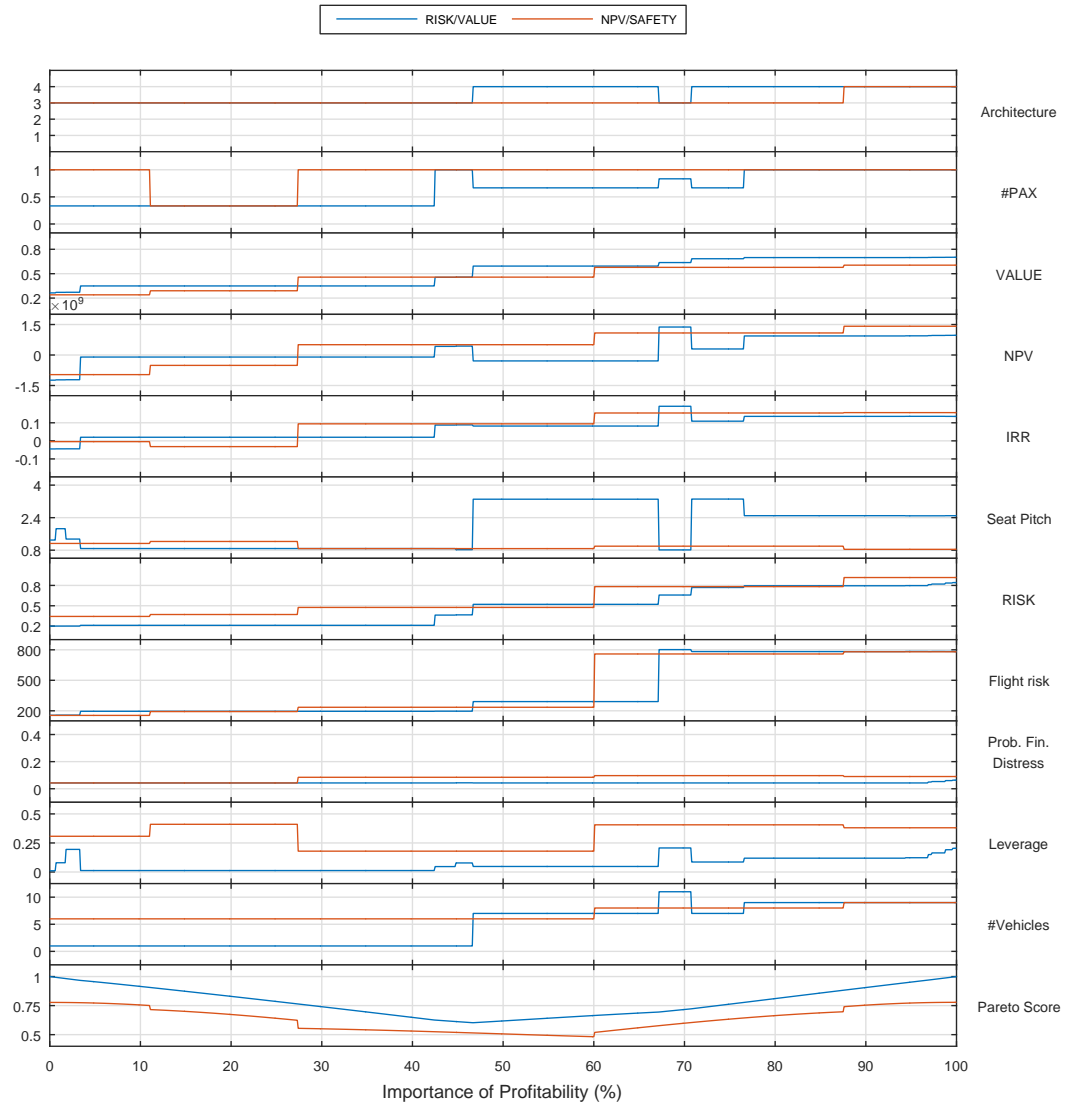
Figure 7.7: Comparison of points selected by TOPSIS from risk/value and NPV/safety optimizations

number of pilots, and number of passengers are different between the solutions of the two considered approaches. This shows strong interdependencies between business disciplines and design, and it is important to adopt a holistic enterprise-level early in the design process. Later changes to high-level design parameters would result in substantial additional expenses for the program, and compromise its profitability. Overall, the risk/value approach results in a 25% higher TOPSIS score, on average on the range of risk/value preferences.

7.3 Chapter conclusion and comparison with other methods

In chapter 2, research question 1 posed the question of whether an enterprise-level approach could help capture more value for the program. Current methodologies, as they remain very design-centric, cannot exploit the strong interdependencies that exist between business disciplines. VDD adds a profit-oriented evaluation step, but it does not have inputs to be optimized and remains therefore passive. Overall, most approaches do not involve enterprise-level disciplines, and only design is optimized. This leads to a de-facto sequential optimization process, where each division of the company sequentially optimize the decision variables they have control on, without accounting for other disciplines, and potentially being exposed to agency costs if their objectives differ from the company-level ones. As no approach seemed to significantly differ from a design-centric process, a new approach had to be followed. Taking inspiration from supply chain optimization, hypothesis 1 was formulated: *if a holistic business-driven framework is developed that integrates enterprise-level disciplines and their inputs in conceptual design and if enterprise-level strategic objectives are implemented and targeted then more value from aerospace programs can be captured, and significantly different decisions are made.* The studies and observations carried out in this chapter verify hypothesis 1, as explained in this section.

In this chapter, various aspects of hypothesis 1 were tested. First, it was shown that the use of integrated optimization led to superior results compared to sequential optimization. It was also shown that the presence of additional company-level disciplines and their

inputs helps increase the value of optimal solutions. Finally, the use of multiple strategic objectives can help find higher value compromise solutions.

Table 7.2: Comparison of proposed method with main design techniques

	Design for performance	VDD	Proposed method
Additional company-level disciplines		◗	●
Company-level decision variables			●
Broad range of company-level objectives		◖	●
Exploits discipline interdependencies			●
Exploits value potential	◣	◗	●

Table 7.2 summarizes these results and outlines that the proposed method provides the best solution for providing higher value compromise solutions. By limiting themselves to design, or a simple valuation of a design, other approaches do not give decision makers the levers to exploit all the potential value of a program. Reversely, this method provides several key features that help capture more value:

- **Additional business disciplines and their inputs.** To depart from a design-centric process, the proposed method implements several key elements of the company's value chain as additional business disciplines. While approaches such as VDD use an additional valuation step to emphasize the economic aspects of the design vehicle, it remains limited to a vehicle-level approach. Reversely, the proposed method extends the design space to the company level and new disciplines, creating more opportunities for increasing the program's value. It was shown in this chapter that the addition of such disciplines and inputs significantly increased the optimality of solutions, hence checking verification criterion 1.2 (*the approach with additional business disciplines Pareto-dominates the one without them*).

- **Use of a broad range of strategic objectives.** To provide decision makers with greater flexibility, and because multiple objectives can be concurrently followed, a broad range of objectives are considered, rather than a single performance metric, or the sole use of the NPV as in VDD. Including some secondary objectives can help getting significant improvements on these minor targets with a limited expense on the main objectives. As a consequence, value can be further increased. As such, verification criterion 1.1 is checked (*the approach with multiple strategic objectives Pareto-dominates the one with only two objectives*).

- **Holistic company model enabling integrated optimization.** The proposed methodology includes the creation of a holistic environment, which allows for integrated optimization. The use of integrated optimization allows the exploitation of the interdependencies that exist between the different disciplines that are involved in the lifecycle of the program. If left separate, disciplines will end up following a sequential optimization process, which is suboptimal and can create principal-agent problems. Additionally, the interdependencies between business disciplines and design require a holistic approach, as sequential optimization results in significant differences in design and business decisions. Hence, it is crucial to adopt an enterprise-level approach early in the design process, in order to find the true optima, as modifications in design later in the process can result in substantial costs that can compromise the profitability of the project. The use of integrated optimization leads to more optimal solutions with significantly different designs, and therefore verification criteria 1.3 and 1.4 are checked (*integrated optimization Pareto-dominates sequential optimization*; *optima from the enterprise-level approach significantly differs from the baseline case*).

These observations demonstrate that the proposed method is a compelling way to increase solutions' value by providing a holistic enterprise-level framework that integrates multiple company-level disciplines, inputs, and objectives. As all verification criteria are checked, hypothesis 1 is deemed verified as an answer to research question 1.

CHAPTER 8

CONCLUSION

In this final chapter, the research presented in this dissertation is summarized. The overall proposed method is outlined, and the main steps are enumerated and briefly described. Key contributions in the main study areas are then listed. Finally, some future research outlooks are provided.

8.1 Research summary

Aerospace, despite its long-lasting existence, remains a non-commoditized field. Only a few countries and companies can achieve significance presence in this market. Most often, projects are characterized by a large monetary commitment and a late payback period. Often, great engineering products fail from the financial side. The presence of multiple sources of uncertainty makes these programs particularly risky. However, this high exposure to risk has been rewarded by consequent financial returns. As such, Chapter 1 establishes a motivation for this research by emphasizing the need for capturing as much value as possible from such programs while reducing risk, in particular by having a well-designed financial planning. Additionally, the importance of strategy in a company, combined with the presence of multiple strategic alternatives, makes this context particularly multi-objective. Additionally, the involvement of several divisions in the life-cycle of a program makes it necessary to adopt an enterprise-level approach. Indeed, finance, sales, and production are other critical disciplines that have decision power and influence on the outcome of the program. They also are tightly coupled, and the interdependencies existing between these disciplines should be exploited to unlock as much value potential as possible for the overall program. Finally, while these motivations apply to aerospace programs in general, the case of suborbital vehicle programs is particularly well suited for this re-

search, as the relatively small size of the participating companies make it both necessary and more easily feasible to implement an enterprise-level approach. The aforementioned motivations led to the formulation of this dissertation's research objective: *to establish a methodology that enables informed enterprise-level decision-making under uncertainty and provides higher-value compromise solutions.*

Chapter 2 follows by identifying the gaps in the current literature that must be bridged to fulfill the research objective. The research objective can be decomposed into two main directions of study. First, one can wonder whether the adoption of an enterprise-level approach can help capture more value for the overall program. Current approaches are usually limited to the design aspect of the program, and although they sometimes use profit-driven objectives, they do not provide the optimization of other disciplines. This ultimately results in a de-facto sequential optimization, where principal-agent problems arise. It is instead proposed to use a holistic implementation, which will enable an integrated enterprise-level optimization and significantly different decision-making. The second part of this problem deals with decision-making with multiple objectives and multiple risks. Current methods of design under uncertainty usually involve one objective and its variance as targets (or the quantiles of an output as a constraint). These techniques are insufficient for this problem for several reasons. First, they are unlikely to provide compelling results when several metrics are targeted. Additionally, variance does not properly fit the definition of risk. Indeed, risk carries a detrimental aspect, which variance or standard deviation, which are neutral quantities, do not. Taking inspiration from financial methods, the deviation of the Conditional Value at Risk (called here downside deviation) is used as a measure of value risk. Furthermore, objectives are categorized as risk and value and aggregated into risk and value scores to facilitate convergence, visualization, and decision-making. As suborbital vehicles are complex non-linear systems, with many infeasible concepts and computationally expensive M&S environments, a time-efficient way to estimate the downside deviation needs to be used. As such, a new uncertainty propagation structure is used that involves

regression and classification neural networks, as well as a Second-Order Third-Moment (SOTM) technique to compute statistical moments.

In chapter 3, the proposed process elements are combined, and integrated to a method following a modified Integrated Product and Process Development (IPPD) approach, using five main steps: establishing value, generating alternatives, surrogate modeling, evaluating alternatives, and making decisions. A new M&S environment is implemented and involves a design framework to which several business disciplines are added. The analysis of typical financial valuation methods used in aerospace shows their limitation: all of them rely on a very arbitrary discount rate despite its critical impact on the final value of the NPV. A new and more objective financial framework is implemented based on corporate finance theory. It also adds capabilities to the model for the evaluation of financial risk, and to be able to find optimal financial trade-offs.

A bottom-up approach is used to study the four research questions of this dissertation. Indeed, research question 3 deals with financial implementation is at the lowest level. Once solved, research question 2.1, which is related to uncertainty propagation, can be studied. The research then goes to the level of research question 2, which regards design and decision making with multiple objectives and multiple risks. Finally, the issue of whether an enterprise-level approach can help capture more value (research question 1) can be addressed. Table 8.1 summarizes the four research questions formulated in this dissertation, the gaps in the current literature, and the solution proposed.

The aforementioned bottom-up processed is followed in the remaining chapters. As such, chapter 4 raises the question of the objectivity and usefulness of a more in-depth financial analysis is asked. By studying a particular example, it is possible to observe the benefits of the proposed methods from a qualitative and a quantitative point of view. First, the proposed implementation enables the evaluation of multiple financial metrics of the company (WACC, NPV, credit rating, interests paid, etc.). It also permits a complete analysis of the impact of leverage on these factors. Additionally, it enables the computation

Table 8.1: Research questions summary

Area	Gap	Proposed solution
RQ 1 (section 2.1)		
Enterprise-level approach to capture more value	Current approaches limited to vehicle design	Holistic environment and integrated optimization (chapter 7)
RQ 2 (section 2.2)		
Multi-objective multi-risk decision-making	Usually one risk: variance	Risk and value scores and downside deviation (chapter 6)
RQ 2.1 (section 2.2)		
Efficiently estimate downside deviation	Quick evaluation missing	Regression and classification NNs and SOTM (chapter 5)
RQ 3 (section 3.4)		
More objective financial analysis	Arbitrary discount rates	In-depth modeling of costs of debt and equity (chapter 4)

of a financial risk, based on the chance of the company to incur financial distress and defaulting. Finally, it can find the optimal company structure, which helps increase the overall program value and avoid destroying some by carrying excessive debt.

Chapter 5 details the second step in the study and implementation, which is to time-efficiently evaluate the downside deviation. As such, regression and classification neural networks are implemented to estimate the base costs of the vehicle and speed up the vehicle sizing process. Business analyses can be vectorized and are therefore maintained. These neural networks ultimately show good validation set prediction RMSE, which confirms their accuracy. The SOTM method is also checked and shows a downside deviation prediction accuracy equivalent to a 750-point Monte Carlo method. Finally, methods are compared from a computation time standpoint, and it is showed that the use of neural networks is required for a reasonable convergence time and that SOTM used jointly with

neural networks results in an optimization time below 1 hour, hence being a reasonably time-efficient way to estimate downside deviation.

In chapter 6, the proposed approach for making risk/value trade-offs in the presence of multiple risks and objectives is then tested. First, the importance of using downside deviation is demonstrated by showing the risk estimation error made when using the standard deviation rather than the actual downside deviation. As this error can be significant, it is necessary to directly use the downside deviation. Additionally, the use of risk and value scores also helps decision making from a qualitative and quantitative point of view. Indeed, it facilitates visualization by making it easier to visualize the Pareto frontier in only two dimensions, while still being able to color it to observe some program features and some cluster patterns. It also helps select better programs, because it reduces the dimensionality of the multi-objective optimization process. It is found with a 7-dimensional example that considering a high number of risk and objectives tends to scatter the population used by the algorithm, resulting in a scarce Pareto frontier constituted of non-converged and suboptimal concepts. On the other hand, the problem with risk and value scores provides superior performance unless very large errors in weightings are committed. Finally, the proposed method provides good capabilities to identify, rank, and select optimal concepts and programs.

Finally, in chapter 7, the last research question presents the following interrogation: does an enterprise-level approach help improve the optimality of the overall program, and does it significantly affect decision-making? Two elements of the enterprise-level approach are tested: the integrated optimization, and the use of additional enterprise-level objectives. In both cases, the resulting Pareto frontiers are significantly dominating their counterparts, demonstrating the usefulness of the enterprise-level approach from a quantitative point of view. Additionally, it shows that the enterprise-level approach results in significantly different business and design decisions by exploiting the interdependencies existing between the

company-level disciplines. Hence, this demonstrates the importance of using this approach early in the program life cycle.

8.2 Proposed methodology summary

In this dissertation, the proposed method and implementation have been thoroughly described in chapter 3 and applied in chapter 6. This method consists of the four steps of the IPPD: establish value, generate alternatives, evaluate alternatives, and make decisions.

8.2.1 Step 1: Selection of the decision criteria

To start with, decision makers need to define what they are trying to achieve. They need to identify a set of objectives and a set of constraints that apply to their problem. Objectives should be thought of from an enterprise-level point of view. Objectives can reflect all relevant strategies: performance objectives, financial objectives, risks, etc. Risks evaluation metrics should be defined following whether the observed risk is due to a distribution or a more punctual event, and whether it reflects known or not well-known distributions. Objectives should then be categorized either as value objectives or risk objectives. Weights have to be associated with each objective to formulate a risk score and a value score, which constitute the two targets of the problem.

8.2.2 Step 2: Design and uncertain spaces definition

Design and uncertain spaces must be defined, as these constitute inputs to the evaluation process. The design space is fairly irregular, as it represents vehicle architectures with different characteristic variables, and its two levels must be modeled: the enterprise level and the vehicle level. As such, a morphological matrix tree structure is used, which has the capability of fulfilling these requirements. As for uncertain variables, these can either be simple probability distributions or can be time-dependent. Is this case, it is suggested to represent the variables using one or two non-time-dependent random variables (such as

initial demand and growth) in a time-dependent equation, that would somehow match the Brownian motion distributions.

8.2.3 Step 3: Modeling, simulation, and evaluation of alternatives

To evaluate alternatives, a modeling and simulation environment must be developed. A new M&S process is created, based on Frank et al.'s design and sizing framework to which are added several enterprise-level disciplines. These disciplines should model the important parts of the value chain which are involved in the calculation of the identified objectives. As suborbital vehicles are complex systems, they may (as it is the case for the considered design framework) require significant computational time to be sized. They are also very non-linear, and result in some infeasible alternatives. As such, to speed up the evaluation process while maintaining the capability to estimate feasibility, regression and classification neural networks are trained. The regression networks predict the base costs and the operational risk of the vehicle, while the classification neural networks estimate feasibility. To ensure goodness of fit, validation and test sets are added to the training set. The validation set is used to determine the optimal neural network structure. As the training algorithm ignores the validation and test sets, these sets are used to ensure the predictive performance of the neural networks in unexplored areas of the data set. Once trained, a structure composed of the classification and regression neural networks is used to replace the design disciplines, while the enterprise-level ones remain unchanged.

8.2.4 Step 4: Make decisions

To make decisions, a multi-optimization process is first run. This process results in a Pareto frontier with two dimensions: the value score and the risk score. Once obtained, further selection can be done. First, the Pareto frontier can be studied in its whole using coloring, to indicate the value of various key factors characterizing each of its points (e.g. number of vehicles produced, architecture type, propellant, etc.). Additionally, individual solutions can

be analyzed, by visualizing the breakdown of risk and value, as well as the time distribution of cumulative cash flows, for example. Finally, a point can be selected using TOPSIS, based on a risk-aversion preference. This technique can also be used for all set of preferences, in order to isolate the solutions that would be picked by TOPSIS and analyze their attributes.

By using these four steps, a decision maker can easily identify, rank, and select alternatives at an enterprise level.

8.3 Main contributions

This research focused on establishing a methodology that enables informed enterprise-level decision-making under uncertainty and provides higher-value compromise solutions. To fulfill this objective, contributions have been made in several distinct areas.

8.3.1 Financial analysis in aerospace applications

As part of this research, a contribution has been made to financial analysis implementation in aerospace applications. Indeed, current approaches rely on a very arbitrary discount rate. This is problematic because the discount rate has a very significant impact on the value of the NPV. By poorly evaluating the NPV, profitable opportunities can be missed and unprofitable ones pursued. By proposing a more in-depth financial analysis based on the simulated free cash flows of the company, this proposed method provides the following features and contributions:

- **More objective measure of the NPV for aerospace programs.** By modeling crucial elements in the calculation of the costs of debt and equity (ultimately the calculation of the NPV), this method enables a more objective estimation of the NPV. Indeed, the sensitivity of the NPV to the additional terms is at least 20% of that of the discount rate, which is very impactful. By adding and modeling variables that have a large impact on the NPV, it is possible to better capture its variations with the value of leverage (or other company inputs).

- **More information on financial metrics.** By modeling additional financial terms, it is possible to evaluate them. This gives more information about the financial aspects of the program, which can then provide interesting insights when performing decision-making. For example, the proposed method can estimate the risk of defaulting for the company.

- **Provide optimal financial trade-offs.** Due to the dynamics of the proposed method, and unlike current approaches, the optimal capital structure of the company can be found. This enables to easily capture additional value for the company, while also avoiding making poor financial decisions that could potentially destroy financial value.

8.3.2   Uncertainty propagation

Current methods of uncertainty propagation in aerospace are usually more focused on the mean and variance of the output distribution or its quantiles in RBDO. The value of the downside deviation is not estimated. The full distribution can be obtained using Monte Carlo methods, but the required number of sample points makes it complicated to be used in the context of multi-objective optimization. Surrogate modeling can improve computation time, although it remains hard to use Monte Carlo methods. Moreover, direct use of regression models loses the capability of estimating the feasibility of a concept. The proposed method involves:

- **Improved surrogate modeling.** By creating a structure based on classification and regression neural networks, the design part of the M&S environment can be replaced by the surrogate model without loss of functionality, as the feasibility of concepts can still be estimated. This reduces the potential risk of errors for decision makers who could select a concept and later realize that it is not a converging configuration, resulting in potential time loss, cost overruns, and safety issues.

308

- **Improved accuracy compared to usual methods of moments.** Typical method-of-moments approaches (FOSM and SOSM) are limited to the estimation of the first two statistical moments. The output distribution is estimated to be a normal distribution. However, with uncertain inputs which are typically bounded, and a very non-linear M&S environment, outputs might not be normally distributed and instead be skewed. The proposed method also includes the skewness in order to approximate the output to a Pearson distribution. The additional degrees of freedom of this distribution permit a closer fit, ultimately resulting in better estimations of the downside deviation.

- **Quickly estimate downside deviation.** The proposed method quickly estimates the three first statistical moments using an SOTM method of moments. This type of approach only requires the estimation of the Jacobian and Hessian of the output distribution as a function of the uncertain inputs. It then uses an interpolating model that gives the value of the downside deviation as a function of the standard deviation, skewness, and kurtosis of the output distribution. With four uncertain inputs, this method only requires 15 sample points and is equivalent in accuracy to a 750-point Monte Carlo method. The process is further sped up with the necessary use of neural networks.

8.3.3 Design under uncertainty

Main approaches to design under uncertainty are robust design, robust design Pareto frontiers, and RBDO. RBDO sees uncertainty as a quantity that should be constrained. For robust design, usually, one objective is considered, along with its standard deviation. Regular robust design uses an aggregate function resulting in single-objective optimization, while robust design Pareto frontiers keep the objective and its standard deviation as two separate objectives and construct a Pareto frontier. These approaches are limited when multiple objectives and multiple risks are present, as it is the case at the enterprise level. To bridge this gap, the proposed method provides the following contributions:

- **Simpler and better trade-offs in multi-objective multi-risk environments.** The proposed method relies on the use of value and risk scores, which enable to aggregate the data into two objectives only. There are two advantages to this dimensionality reduction. First, from a qualitative point of view, it is simpler for decision makers to visualize data on a two-dimensional Pareto frontier. Only two targets have to be traded. Other visualization assistance can also help viewing the underlying attributes of points of the Pareto frontier to help make decisions. The user can drill down, and analyze each concept individually, as components of value and risk are preserved. While dimensionality reduction seems to limit decision-making freedom, it actually enables to consider multiple objectives and multiple sources of risk. From a quantitative point of view, the use of only two objectives greatly facilitates the convergence of the multi-objective optimization, which in return results in more optimal solutions compared to a high dimensionality case. Additionally, the separation between risk and value is preserved, which allows decision makers to trade one for the other, which would be impossible for a fully aggregated objective. As such, the method with risk and value scores enables to combine the advantages of the two traditional approaches, while eliminating some of its disadvantages.

- **Better definition of risk due to uncertainty.** Currently, uncertainty is only characterized by its standard deviation when used as an objective. However, standard deviation does not fit very well the definition of risk, as it is neutral rather than detrimental. Instead, this research makes the use of the downside deviation of the value score, as inspired by financial methods. The standard deviation cannot be used as a proxy for downside deviation, as its value significantly differs for non-normal distributions.

8.3.4 Design optimization

Typical approaches to design in aerospace are usually design-centric. Most decision variables are related to design. VDD adds a profit-oriented evaluation step, but it does not have inputs to be optimized and remains therefore passive. Overall, most approaches do not involve enterprise-level disciplines, and only design is optimized. This results in a de-facto sequential optimization and therefore the presence of principal-agent problems. Reversely, the proposed approach brings the following features and contributions:

- **Enterprise-level disciplines and integrated optimization.** The proposed approach incorporates the main disciplines of the value chain in a holistic environment. As a consequence, integrated optimization becomes feasible, and is implemented in this research. The benefits to this method are two-fold. First, the inclusion of additional business disciplines along with their inputs enable the capture of more value from the program by providing more degrees of freedom for improvement. Additionally, the use of integrated optimization permits to take advantage of the interdependencies existing between disciplines, and to exploit them, further resulting in value gains.

- **Enterprise-level objectives.** Due to its design, the proposed approach enables targeting enterprise-level objectives rather than discipline-level ones, which results in the identification of more optimal solutions.

- **Enterprise-level decision-making and planning.** By using a holistic M&S environment, this approach provides an overall overview of the most important enterprise-level metrics. It creates a complete planning for the program and company, by including vehicle-related variables, but also key planning variables such as the number of vehicles built, when to build them, how often to operate them, the ticket price, and the capital structure of the company. Hence, the enterprise-level optimization approach helps make decisions in all most important steps of the value chain, and to centralize decision-making at the highest level, rather than at the discipline level. The

enterprise-level optimization results in significantly different decisions compared to discipline-level optimization and sequential approaches, as it exploits the interdependencies between disciplines to supply more optimal solutions. Hence, it is important to apply this methodology early in the design process, as later changes in design would entail substantial costs that could compromise the profitability and viability of the program. Additionally, the trade-off environment facilitates decision-making even more by providing various visual analyses and gathering all these analyses to a single place, which enables a broad and company-level overview of the potential program plans. Overall, using this method, a decision maker has access to numerous analysis capabilities, some of which answering some of the key questions related to the research objective of this thesis. What are the main value and risk drivers? What are the company-level and vehicle-level variables that result in an optimal solution? What is the effect of risk aversion on the optimal program plan? Are there any dominant configurations? What is the value creation of using an integrated enterprise-level approach? As such, all required elements are placed into the hands of decision-makers in order to make the most informed decision.

8.4   Future research prospects

During this dissertation, multiple techniques were developed to develop an enterprise-level approach that would help achieve higher value solutions. This method involved the modeling of several major enterprise-level disciplines such as pricing, production, and finance. As the objective of this research was to provide a proof of concept for enterprise-level approaches, these disciplines (design and finance excepted) were using simple models. Due to its modular structure, the proposed method is well suited for incorporating more complex representations of company-level disciplines, with potentially more inputs to be optimally set. This would allow for even more value creation, would provide more accurate estimates, and ultimately lead to a complete business plan for the company.

Additionally, the method described in this document has mostly been applied to suborbital vehicles. However, the motivations for such approach remain valid for other aerospace applications. As such, this approach could easily be extended to aircraft design. For example, Burgaud et al. [303] study the impact of adopting such an enterprise-level approach for a company that develops, manufactures, and sells commercial planes.

Finally, this method can also extend to most engineering programs which involve significant and multiple sources of risk, are business-driven and would benefit from a company-wide insight over their considered concepts. Hence, industries such as automotive or naval, for example, would be suitable and interesting applications of this work.

Appendices

APPENDIX A

ALTERNATIVE GENERATION

In this chapter, the main alternative generation methods are presented. As such, the 6-3-5 method, design catalogs, chi-matrix, TRIZ, decision trees, A-design, morphological matrices, IRMA, and M-IRMA are described in the following sections.

A.1   6-3-5 method

The 6-3-5 method is an approach of alternative generation through brainstorming, first introduced by Rohrbach in 1969 [237]. Its name comes from the structure of the method: 6 designers have to write down and propose three ideas each in 5 minutes. After 5 minutes, each participant gives his or her ideas to the next one. The new iteration enables to sketch three new ideas, inspired from those given by other participants. This process is repeated a few times to generate a sufficient number of ideas. Variations of the 6-3-5 method can be found in the literature. For example, Wodehouse and Ion [304] augment the 6-3-5 method with design information, which increases the quality of outputted ideas. Another evolution of the 6-3-5 method is the C-Sketching method [305, 306], which provides a slightly different structure of the approach (5-1-4), and emphasizes graphical representations of solutions. Overall, while the 6-3-5 method can provide quality ideas for problem-solving, it only generates a few ideas, and, therefore, does not allow for a very exhaustive generation of concepts. Moreover, it is highly dependent on the participants' expertise, which results in variability in the quality of the outcome.

A.2 Design catalog

Design catalogs are introduced by Roth [238, 239], and include various possible options for subcomponents of a system. They are mostly based on historical data and store extensive information about each option to help designers make sound decisions, and utilize previously acquired knowledge. While such catalogs enable to generate alternatives, they usually include only a subset of all possibilities and do not allow for more creative combinations.

A.3 Chi-matrix

The chi-matrix is an extension of design catalogs. It uses a design catalog containing the list of components and their respective functions [240, 241]. Additionally, however, it also contains a filtering function, which enables to downselect only the components performing the functions required by the decision maker. Based on design catalogs, the Chi-matrix suffers identical issues, as it mostly relies on historical data, and therefore remains limited. However, the filtering module enables to increase the relevance and quality of the suggested alternatives.

A.4 TRIZ

The Theory of Inventive Problem Solving, or TRIZ, from the Russian-based acronym, was developed by the Soviet inventor Genrich Altshuller [242, 243]. It is a problem-solving methodology based on logic and analysis of previous problems, rather than intuition. TRIZ is based on several key principles:

1. The same problems get repeated across industries, leading to the same trade-offs, compromises, and dilemma.

2. Technological innovation consistently follows a certain pattern.
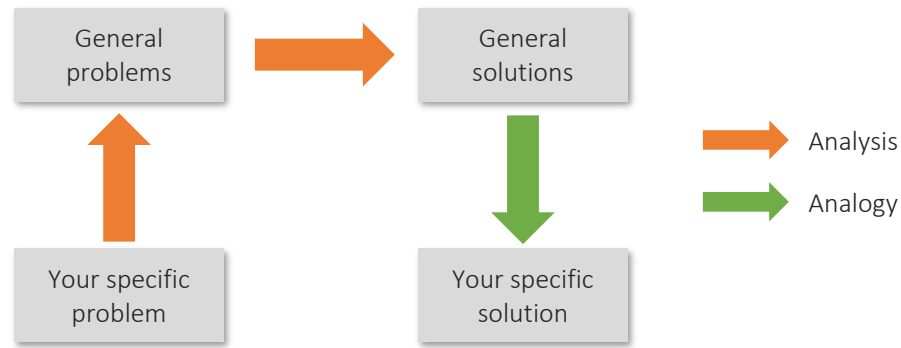
Figure A.1: Simplified TRIZ process [243]

3. Innovation is often inspired by knowledge that is out of its own field.

The main process followed by the TRIZ method is the Algorithm to Solve an Inventive Problem (or ARIZ in its Russian acronym). It follows a 9-step process [243], which is represented in Figure A.1. A summary of the algorithm is the following: 1) problem analysis: precisely identify the problem statement; 2) problem's model analysis: identify gaps and challenges in solving the problem; 3) use outside information on well-solved problems; 4) think by analogy to adapt the solution to outside problems to your own. While this technique can be a powerful tool to solve intricate problems, it mostly provides a set of alternatives based on historical solutions, although taken from outside of the industry of interest, and therefore is not exhaustive. As this method is not very easily made automated, this solution will not be able to provide enough alternatives for conceptual design.

A.5 Decision tree

Decision trees create a hierarchical structure that sequentially establishes the attributes to possible solutions to a problem [245]. On a design's point-of-view, it would define the possible combinations of components. Because of the way they are defined, decision trees automatically enforce the compatibility of selected options, as the available options at a certain step depend on the path previously taken in the tree. It makes it also a fairly suitable approach for multi-level design spaces. The advantage reveals itself as a double-edged

sword: as a counterpart, designers need to define each branch of the tree, which greatly limits the potential exhaustiveness of the process.

A.6 A-design

The A-design method is not an alternative generation technique per se, but rather a dynamic design methodology. It is an iterative process that sequentially evolves its population of designs, evaluates them, and evolves its population of agents (those selecting the designs) based on the performance of the designs they selected [244]. Because of its evolutionary aspect, this method is very dynamic and selects high-quality alternatives. The main weakness of this method is that it is part of a larger process, and cannot generate alternatives on its own. It is closer to an optimization algorithm.

A.7 Morphological matrix

The concept of morphological analysis is first introduced by the astrophysicist Fritz Zwicky [246, 247]. The morphological analysis enables to identify and examine all potential solutions to multidimensional, non-quantifiable, complex problems [307]. It involves decomposing the problem or system into subcomponents, brainstorming the potential options for each component, create a morphological matrix, and finally, systematically generate alternatives from this matrix. The use of morphological analysis and matrices is widespread for the conceptual design of mechanical and aerospace systems [308–311]. Its popularity stems from its intuitiveness, ease of use, and ability to generate a lot of alternatives, including more creative, unconventional combinations of options. Recent work also aims at automating the whole process, to make it even more efficient [241, 312, 313]. While morphological matrices are simple and reliable, their structure is not well adapted to multi-level design spaces, which makes it hard to use for complex aerospace vehicle programs.

A.8   IRMA

The IRMA, or Interactive Reconfigurable Matrix of Alternatives, is a tool first developed by Soban and Upton [248], and later used in various applications [314–317]. This environment is an evolution of the more common Morphological Matrix of Alternatives and adds several interesting features. First, a compatibility matrix is integrated and permits the rejection of infeasible combinations of alternatives. Second, it also allows for filtering some of the alternatives, to bring their number down, and further increase the quality of remaining alternatives. For example, one could only desire alternatives with a high Technology Readiness Level (TRL). Computational time is also evaluated to better control the size of the design space. While the IRMA's compatibility checks and filtering enhance the morphological matrix's capabilities, it still does not allow for multi-level systems' alternative generation.

A.9   M-IRMA

The M-IRMA is an evolution of the regular IRMA, to fulfill the needs of MAST (Micro Autonomous Systems and Technologies) applications. It is developed in 2013 by Mian et al. [249, 250] and incorporates additional small tree structures to enable multi-level mapping of subcomponents. Indeed, each component alternative has specific sub-alternatives to determine its attributes. The characteristics of the decision trees that M-IRMA adds help define more dynamic design spaces. The filtering process is also improved using a scoring and ranking process, leaving in only the best alternatives. However, this technique was mostly developed with the application to MAST in mind, rather than aerospace programs, and therefore is not generic enough. Moreover, each feature only branches to one sub-feature, which is not sufficient. Finally, the implementation of such process is too complex, and it is sometimes complicated to rate component alternatives before going through the evaluation process.

APPENDIX B

MODELING UNCERTAINTY FOR TIME-DEPENDENT VARIABLES

This chapter aims at reviewing various techniques used for simulating and forecasting diverse macroeconomic parameters of interest, useful in the evaluation of the operational and financial performance of a program or vehicle. Such parameters include oil prices, interest rates, and market demand. First, a general review of forecasting and simulation techniques is carried out, followed by a review of these techniques for these specific applications.

B.1 General forecasting techniques

Several techniques are commonly used to simulate the time variations of uncertain variables. These methods include time series, binomial lattice models, Brownian motion, and scenario-based models. A more detailed description of each approach is presented next.

B.1.1 Time series (Autoregressive Moving Average (ARMA), Vector Autoregression (VAR))

ARMA is a time-series method providing a way to model and simulate stationary stochastic processes in terms of the previously realized values of the variable of interest. An $ARMA(p, q)$ model follows Equation B.1, where X_t is the value of the series at time t, c, ϕ_i and θ_i are constants to be determined, and ϵ_i is a white noise process [251].

$$X_t = c + \epsilon_t + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{B.1}$$

Vector autoregression is a model from the fields of econometrics that is used to account for the linear dependencies between several time series. It is a multivariate version of time series. However, time series are more suited for short-term forecasting and simulation.
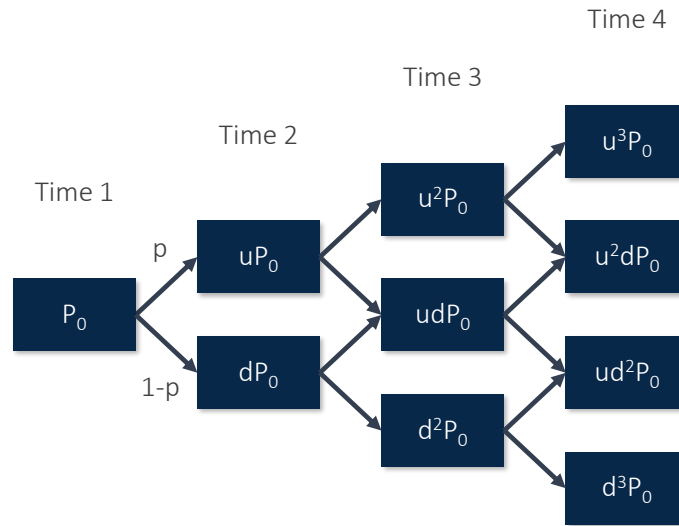
Figure B.1: Binomial lattice

B.1.2 Binomial lattice model

The binomial lattice model is a simple model that enables easy time simulation of uncertain variables. It consists in an evolution following a probabilistic binomial tree. In other terms, at each period, the variable has a certain probability p to change to an upper value, and a probability $(1-p)$ to change to a lower value. Time is discretized in a finite number of periods, and the binomial draw is repeated at each period. This process is illustrated by Figure B.1. Because of the limited number of time periods, the binomial lattice is not as continuous as the Brownian motion (described next), but also has a much lower dimensionality, which helps reduce the number of cases necessary to describe the probability distribution.
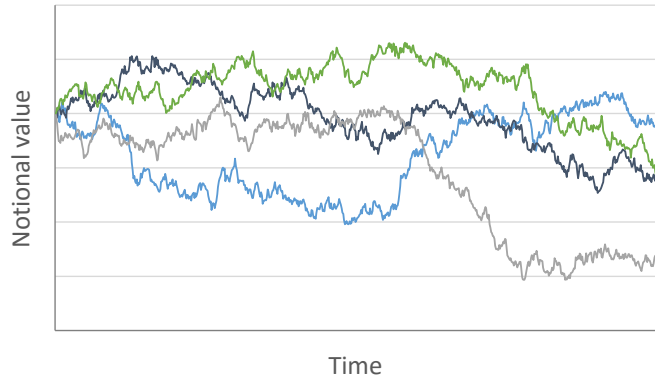
Figure B.2: Several Brownian motion simulations

B.1.3 Random walk (Brownian motion)

Brownian motion is the continuous version of the binomial lattice. Although it is not possible to simulate purely continuous evolution, the short time step considered enables to converge to the desired asymptotic behavior. Each step in a Brownian motion has a normally distributed magnitude [318]. This also results in a normally distributed future value of a variable. A few Brownian motion simulations are shown in Figure B.2. Brownian motions are particularly used for financial markets, and therefore could present some interest in the context of this research. While Brownian motions are more continuous than binomial lattices, their higher dimensionality make them unfit for this problem.

B.1.4 Scenario-based model

Scenario-based models explore the range of future outcomes one can forecast for the uncertain environment. One can assess the robustness of a design or program by evaluating their performance against all scenarios. Schoemaker [252, 253] provides a detailed overview of the method and implementation advice. Easy to use and intuitive, scenario-based models have been extensively used and are popular in the literature [254–258, 319, 320].

B.1.5 Crude oil price

Oil price forecasting is a popular topic in the literature, due to the importance of this commodity, and many different methods were proposed. A first way to provide forecasts consists in using the time-series properties of the historical crude oil prices, using VAR. Morana et al. [259], for example, use the GARCH properties of oil price changes to forecast crude oil prices one month in the future. Ye et al. [262] also take the oil inventories and production into consideration to achieve greater accuracy of their short-term estimates. Baumeister and Kilian [260] prove that the VAR forecasts are more accurate than futures prices forecasts, no-change forecasts, or simpler time-series forecasts (AR, ARMA). Another method to forecast the price of crude oil is to directly use the price of futures contracts. According to the European Central Bank (ECB), the futures prices are used as a baseline forecast by many international policy institutions. Many authors, however, suggest that futures have poor forecasting efficiency, because of their variability. Moreover, their price also includes a risk premium component. To compensate for these aspects, Pagano and Pisani [261] introduced a risk adjusted futures price. Based on these observations, the literature seems to favor oil price simulation using simple random walks, for long term predictions.

B.2 Interest Rates

A few different ways to simulate interest rates are treated in the literature. The simple Gaussian process approach is called the Ho-Lee model. A more popular approach is the Vasicek model [263], that enables the interest rates to drift towards a more long-term interest rate target. Both the Ho-Lee and Vasicek model are available in a binomial tree or continuous version. More complicated models exist but are meant to provide capabilities out of the scope of this methodology.

APPENDIX C

NEURAL NETWORK PREDICTION ACCURACY

In this chapter, the predictive accuracy of the classification and regression neural networks used for this research is provided.

Table C.1: Predictive accuracy of architecture 1 regression neural networks

Response	NN structure	R^2	$RMSE_{train}$	$RMSE_{val}$	$RMSE_{test}$
Development costs	60 nodes	0.986	0.0095	0.0148	0.0136
Manufacturing costs	16+8 nodes	0.993	0.0086	0.0105	0.0102
Operating costs	30+15 nodes	0.983	0.0141	0.0206	0.0209
Carrier aircraft costs	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Operational risk	16+8 nodes	1.000	0.0000	0.0000	0.0000

Table C.2: Predictive accuracy of architecture 2 regression neural networks

Response	NN structure	R^2	$RMSE_{train}$	$RMSE_{val}$	$RMSE_{test}$
Development costs	100 nodes	0.987	0.0091	0.0205	0.0221
Manufacturing costs	20+10 nodes	0.992	0.0096	0.0115	0.0112
Operating costs	30+15 nodes	0.983	0.0122	0.0132	0.0163
Carrier aircraft costs	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Operational risk	16+8 nodes	1.000	0.0002	0.0004	0.0004

Table C.3: Predictive accuracy of architecture 3 regression neural networks

Response	NN structure	R^2	$RMSE_{train}$	$RMSE_{val}$	$RMSE_{test}$
Development costs	100 nodes	0.982	0.0140	0.0175	0.0182
Manufacturing costs	30+15 nodes	0.976	0.0202	0.0250	0.0234
Operating costs	40+20 nodes	0.983	0.0111	0.190	0.0188
Carrier aircraft costs	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Operational risk	16+8 nodes	1.000	0.0003	0.0004	0.0004

Table C.4: Predictive accuracy of architecture 4 regression neural networks

Response	NN structure	R^2	$RMSE_{train}$	$RMSE_{val}$	$RMSE_{test}$
Development costs	100 nodes	0.983	0.0121	0.0205	0.0221
Manufacturing costs	30+15 nodes	0.978	0.0232	0.0242	0.0243
Operating costs	40+20 nodes	0.981	0.0152	0.0191	0.0181
Carrier aircraft costs	20+10 nodes	0.990	0.0097	0.0125	0.0133
Operational risk	15 nodes	1.000	0.0003	0.0003	0.0003

Table C.5: Predictive accuracy of classification neural networks

Response	Architecture 1	Architecture 2	Architecture 3	Architecture 4
NN structure	48+24 nodes	11+5 nodes	32+16 nodes	40+20 nodes
Cross-entropy	0.0504	0.0729	0.0533	0.0736

REFERENCES

[1]   Alexander Simoes. *Planes, helicopters, and/or spacecraft trade - 2014*. The Observatory of Economic Complexity, Massachusetts Institute of Technology. (Visited on 05/17/2016). Available at: http://atlas.media.mit.edu/2omx00.

[2]   John Newhouse. "A sporty game I - Betting the company". In: *The New Yorker* (1982), p. 48.

[3]   William Spitz et al. *Development cycle time simulation for civil aircraft*. Tech. rep. NASA Langley Research Center, 2001.

[4]   Spike Aerospace. *Concorde*. 2013. (Visited on 11/18/2015). Available at: http://www.spikeaerospace.com/wp-content/uploads/2013/03/concorde4.jpg.

[5]   Airbus Group. *Airbus A340*. Nov. 17, 2015. (Visited on 12/08/2015). Available at: http://www.airbus.com/fileadmin/_processed_/csm_A340-300_CFM_AIRBUS_V10_300dpi_7c4a4da33f.jpg.

[6]   NASA. *NASA's Space Shuttle*. (Visited on 11/10/2015). Available at: http://www.nasa.gov/centers/marshall/images/content/454952main_2010-3416.jpg.

[7]   Airbus Group. *Airbus A380*. (Visited on 11/18/2015). Available at: http://www.airbus.com/fileadmin/media_gallery/aircraft_pages_photo_galleries/a380-gallery/A380_On_Ground.jpg.

[8]   Nadia Drake. "Last week, I went to space". In: *National Geographic* (Feb. 4, 2016).

[9]   "48 years ago in AW&ST". In: *Aviation Week & Space Technology* (May 25, 2015), p. 14.

[10] "Concorde crash kills 113". In: *BBC News* (July 25, 2000).

[11] Daniel Michaels. "Concorde can't speed away from airlines' profit woes". In: *The Wall Street Journal* (Apr. 11, 2003).

[12] Mark Lardas. *Space Shuttle launch system 1972-2004*. Osprey Publishing, 2004.

[13] NASA's Kennedy Space Center. *Space Shuttle and International Space Station*. (Visited on 07/12/2016). Available at: http://www.nasa.gov/centers/kennedy/about/information/shuttle_faq.html.

[14]   Carol Pinchefsky. "5 horrifying facts you didn't know about the Space Shuttle". In: *Forbes* (Apr. 18, 2012).

[15]   Carl Bialik. "As Shuttle sails through space, costs are tough to pin down". In: *The Wall Street Journal* (July 9, 2011).

[16]   Roger A. Pielke Jr. "The rise and fall of the Space Shuttle. Book review - Final countdown: NASA and the end of the Space Shuttle program by Pat Duggins". In: *American Scientist* 96 (2008), pp. 432–433.

[17]   Andrea Rothman. "Airbus's longest plane proves short-lived as A340 orders dry up". In: *Bloomberg Business* (2011).

[18]   European Space Research and Technology Centre. *Skylon assessment report*. Tech. rep. Issue 1 Revision 2. European Space Agency, 2011.

[19]   Andrea Rothman and Steve Rothwell. "Airbus A380 fleet needs full inspection of wings amid cracks". In: *Bloomberg Technology* (2012).

[20]   Robert Wall. "Ten years of the Airbus A380, but demand remains soft". In: *The Wall Street Journal* (Apr. 26, 2015).

[21]   Alan Tovey. "Is Airbus's A380 a 'superjumbo' with a future or an aerospace white elephant?" In: *The Telegraph* (Jan. 18, 2015).

[22]   Jeff Foust. "XCOR Aerospace co-founders leave the company". In: *SpaceNews* (Nov. 23, 2015).

[23]   Jeff Foust. "XCOR lays off employees to focus on engine development". In: *SpaceNews* (May 31, 2016).

[24]   Joe Pappalardo. "The XCOR Lynx spaceplane might be down for the count". In: *Popular Mechanics* (May 31, 2016).

[25]   U.S. Energy Information Administration. *Weekly cushing, OK WTI spot price FOB*. (Visited on 05/10/2016). Available at: `http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RWTC&f=W`.

[26]   U.S. Energy Information Administration. *Weekly U.S. Gulf Coast kerosene-type jet fuel spot price FOB*. (Visited on 05/15/2016). Available at: `http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPJK_PF4_RGC_DPG&f=W`.

[27]   USForex. *Historical exchange rates*. (Visited on 05/10/2016). Available at: `https://www.ofx.com/en-us/forex-news/historical-exchange-rates/`.

[28] Federal Reserve Bank of St. Louis. *Economic research - FRED economic data - 30-year treasury constant maturity rate*. (Visited on 05/10/2016). Available at: https://fred.stlouisfed.org/series/DGS30.

[29] Nicole Friedman. "Oil hits new lows, Brent crude nears $50". In: *The Wall Street Journal* (Jan. 6, 2015).

[30] Carl Burleson. *Civil supersonic airplane noise type certification standards and operating rules*. Tech. rep. Federal Aviation Administration, 2008. Available at: https://www.faa.gov/about/office_org/headquarters_offices/apl/noise_emissions/supersonic_aircraft_noise/media/noise_policy_on_supersonics.pdf.

[31] Christopher P. Frank, Olivia J. Pinon-Fischer, and Dimitri N. Mavris. "A design space exploration methodology to support decisions under evolving requirements' uncertainty and its application to suborbital vehicles". In: *53rd AIAA Aerospace Sciences Meeting, Kissimmee, FL*. 2015.

[32] "Airbus A380 'may face new delays'". In: *BBC News* (Sept. 14, 2006).

[33] Peter Sanders, Daniel Michaels, and August Cole. "Boeing delays new jet again". In: *The Wall Street Journal* (June 24, 2009).

[34] Daniel Michaels. "Airbus expects military albatross to finally take wing". In: *The Wall Street Journal* (Dec. 18, 2012).

[35] Jeff Foust. "Virgin Galactic delays first commercial flights to 2015". In: *SpaceNews* (Sept. 11, 2014).

[36] Kari Lundgren and Cory Johnson. "Branson sees year delay to Virgin Galactic spaceship after crash". In: *Bloomberg* (Apr. 9, 2015).

[37] Rob Coppinger. *Whatever happened to Blue Origin?* Seradata. 2008. (Visited on 06/01/2016). Available at: http://seradata.com/SSI/2008/12/whatever_happened_to_blue_orig/.

[38] Jon Fingas. *John Carmack says Armadillo Aerospace is in 'hibernation' following setbacks*. Engadget. 2013. (Visited on 05/09/2016). Available at: https://www.engadget.com/2013/08/03/john-carmack-says-armadillo-aerospace-is-in-hibernation/.

[39] Andy Pasztor and Jon Ostrower. "Virgin Galactic spacecraft crashes, killing one". In: *Wall Street Journal* (Oct. 31, 2014).

[40] Jeff Cole. "Boeing agrees to acquire archrival McDonnell Douglas". In: *The Wall Street Journal* (Dec. 16, 1996).

[41] Safran Group. *Safran - Strong revenue growth in third quarter 2015*. 2015. (Visited on 07/11/2016). Available at: http://www.safran-group.com/media/20151022_safran-strong-revenue-growth-third-quarter-2015.

[42] Tom Enders and Harald Wilhelm. *H1 results 2015*. Airbus Group. 2015. (Visited on 07/20/2016).

[43] Jon Ostrower. "Boeing shares fall sharply following weak 2016 forecast". In: *The Wall Street Journal* (Jan. 27, 2016).

[44] Susan Carey. "American Airlines reports record profit". In: *The Wall Street Journal* (Oct. 23, 2015).

[45] Bureau of Transportation Statistics. *Airline fuel cost and consumption (U.S. carriers - scheduled)*. (Visited on 07/21/2016). Available at: http://www.transtats.bts.gov/fuel.asp.

[46] Bureau of Transportation Statistics. *Schedule P-1.2*. 2016. Available at: http://www.transtats.bts.gov/Fields.asp?Table_ID=295.

[47] Boeing Commercial Airplanes. *Current market outlook 2015 - 2034*. 2015. Available at: http://www.boeing.com/resources/boeingdotcom/commercial/about-our-market/assets/downloads/Boeing_Current_Market_Outlook_2015.pdf.

[48] Alwyn Scott, Tim Hepher, and Richard Chang. "Boeing sees $5.2 trln jet market, win vs Airbus on twin-aisles". In: *Reuters* (July 10, 2014).

[49] Yahoo! Finance. *AIR.PA historical prices*. (Visited on 04/12/2016). Available at: http://finance.yahoo.com/q/hp?s=AIR.PA.

[50] Yahoo! Finance. *BA historical prices*. (Visited on 04/12/2016). Available at: http://finance.yahoo.com/q/hp?s=BA.

[51] Yahoo! Finance. *LUV historical prices*. (Visited on 06/12/2016). Available at: http://finance.yahoo.com/q/hp?s=LUV.

[52] Yahoo! Finance. *^GSPC historical prices — S&P 500 stock*. (Visited on 06/12/2016). Available at: https://finance.yahoo.com/q/hp?s=%5EGSPC+Historical+Prices.

[53] Airbus Group. *Global market forecast 2015-2034 - Flying by numbers*. 2015. (Visited on 07/12/2016). Available at: http://www.airbus.com/company/market/forecast / ?eID = maglisting_push & tx_maglisting_pi1 % 5BdocID % 5D = 89373.

[54] Airbus Group. *Global market forecast 2015-2034*. 2015. (Visited on 07/12/2016). Available at: http://www.airbus.com/company/market/forecast/?eID= maglisting_push&tx_maglisting_pi1%5BdocID%5D=86756.

[55] Futron Corporation. *Space tourism market study. Orbital space travel and destinations, with suborbital space travel*. Tech. rep. 2002.

[56] Futron Corporation. *Suborbital space tourism demand revisited*. Tech. rep. 2006.

[57] Thierry Le Goff and Antoine Moreau. "Astrium suborbital spaceplane project: demand analysis of suborbital space tourism". In: *Acta Astronautica* 92.2 (2013), pp. 144–149.

[58] The Tauri Group. *Suborbital reusable vehicles: a 10-year forecast of market demand*. Tech. rep. 2012.

[59] Frederic Burgaud, Christopher P. Frank, and Dimitri N. Mavris. "A business-driven optimization methodology applied to suborbital vehicle programs". In: *AIAA SPACE 2016, Long Beach, CA*. 2016.

[60] Michael E. Porter. "What is strategy?" In: *Harvard Business Review* (2000).

[61] Michael E. Porter. *Competitive strategy: Techniques for analyzing industries and competitors*. Simon and Schuster, 2008.

[62] Gary S. Hansen and Birger Wernerfelt. "Determinants of firm performance: The relative importance of economic and organizational factors". In: *Strategic Management Journal* 10.5 (1989), pp. 399–411.

[63] Anita M. McGahan and Michael E. Porter. "How much does industry matter, really?" In: *Strategic Management Journal* 18 (1997), pp. 15–30.

[64] Gabriel Hawawini, Venkat Subramanian, and Paul Verdin. "Is performance driven by industry- or firm-specific factors? A new look at the evidence". In: *Strategic Management Journal* 24.1 (2003), pp. 1–16.

[65] Frank Rothaermel. *Strategic Management*. McGraw-Hill, 2012.

[66] Neil Dickson. *Local air quality and ICAO engine emissions standards*. Tech. rep. ICAO Air Transport Bureau, 2014.

[67] Michael E. Porter. "How competitive forces shape strategy". In: *Harvard Business Review* (1979).

[68] Michael E. Porter. "The five competitive forces that shape strategy". In: *Harvard Business Review* (2008).

[69] Robert Wall and Jon Ostrower. "Bombardier faces off with Airbus, Boeing". In: *The Wall Street Journal* (May 1, 2016).

[70] Chun Han Wong. "China rolls out first large passenger jet". In: *The Wall Street Journal* (Nov. 2, 2015).

[71] "Beijing-Shanghai bullet train targets flyers sick of delays". In: *Bloomberg News* (2011).

[72] Moshe Givoni. "Aircraft and high speed train substitution: the case for airline and railway integration". PhD thesis. University of London, 2005.

[73] Jeff Plungis. "Megabus, BoltBus overcome U.S. stigma with cheap travel". In: *Bloomberg* (Jan. 7, 2013).

[74] Michael E. Porter. "The value chain and competitive advantage". In: *Understanding Business: Processes* (2001), pp. 50–66.

[75] Michael E. Porter and Victor E. Millar. *How information gives you competitive advantage*. 1985.

[76] Henry Mintzberg. "The strategy concept I: five Ps for strategy". In: *California Management Review* 30.1 (1987), pp. 11–24.

[77] Nirmalya Kumar. *Marketing as strategy*. 1st edition. Harvard Business School Press, Boston, 2004, pp. 7–9.

[78] Mark McNeilly. "Gathering information for strategic decisions, routinely". In: *Strategy & Leadership* 30.5 (2002), pp. 29 –34.

[79] Eugene Calvasina et al. "Information requirements for strategic decision making in the production environment". In: *Proceedings of the 36th Annual Conference of the Southwest Region Decision Sciences Institute*. 2006, pp. 574 –579.

[80] Johan Frishammar. "Information use in strategic decision making". In: *Management Decision* 41.4 (2003), pp. 318–326.

[81]   Daniel P. Schrage. "Technology for rotorcraft affordability through Integrated Product/Process Development (IPPD)". In: *Proceedings of the 55th National Forum of the American Helicopter Society, Montreal, Canada*. 1999.

[82]   Peter F. Drucker. "The information executives truly need". In: *Harvard Business Review* 73.1 (1995), pp. 54–62.

[83]   *AMZN company financials*. NASDAQ. 2016. Available at: `http://www.nasdaq.com/symbol/amzn/financials?query=income-statement`.

[84]   David B. Yoffie. "Collision course in commercial aircraft: Boeing-Airbus-McDonnell Douglas–1991 (A)". In: *HBS Case Collection* (1991).

[85]   W. Chan Kim and Renée Mauborgne. "Blue ocean strategy". In: *Harvard Business Review* (2004), pp. 71–79.

[86]   W. Chan Kim and Renée Mauborgne. "Value innovation: a leap into the blue ocean". In: *Journal of Business Strategy* 26.4 (2005), pp. 22–28.

[87]   John Elkington. *Cannibals with forks: the triple bottom line of 21st century business*. Capstone Publishing Ltd, 1999.

[88]   Airbus Group. *Orders and Deliveries*. (Visited on 07/06/2016). Available at: `http://www.aircraft.airbus.com/market/orders-deliveries/`.

[89]   Boeing Commercial Airplanes. *Orders and Deliveries*. (Visited on 07/20/2016). Available at: `http://www.boeing.com/commercial/#/orders-deliveries`.

[90]   James K. D. Morrison. "Game theory analysis of aircraft manufacturer innovation strategies in the face of increasing airline fuel costs". MA thesis. Massachusetts Institute of Technology, 2011.

[91]   Michael C. Jensen and William H. Meckling. "Theory of the firm: Managerial behavior, agency costs and ownership structure". In: *Journal of Financial Economics* 3.4 (1976), pp. 305–360.

[92]   Kathleen M. Eisenhardt. "Agency theory: an assessment and review". In: *Academy of Management Review* 14.1 (1989), pp. 57–74.

[93]   Thomas G Cummings. *Handbook of organization development*. Sage, 2008.

[94]   J. B. Vos et al. "Navier–Stokes solvers in European aircraft design". In: *Progress in Aerospace Sciences* 38.8 (2002), pp. 601–697.

[95]   Ernst H. Hirschel and Claus Weiland. "Multidisciplinary design aspects". In: *Selected Aerothermodynamic Design Problems of Hypersonic Flight Vehicles*. Springer, 2009, pp. 371–412.

[96]   Dimitri N. Mavris et al. "A stochastic approach to multi-disciplinary aircraft analysis and design". In: *36th Aerospace Sciences Meeting & Exhibit, Reno, NV*. 1998.

[97]   Dimitri N. Mavris, Oliver Bandte, and Daniel A. DeLaurentis. "Robust design simulation: a probabilistic approach to multidisciplinary design". In: *Journal of Aircraft* 36.1 (1999), pp. 298–307.

[98]   National Transportation Safety Board Office of Public Affairs. *Lack of consideration for human factors led to in-flight breakup of SpaceShipTwo*. 2015. (Visited on 04/11/2016). Available at: `https://www.ntsb.gov/news/press-releases/Pages/PR20150728.aspx`.

[99]   Jack D. Mattingly, William H. Heiser, and David T. Pratt. *Aircraft engine design*. 2nd edition. 2002.

[100]   Joaquim R. R. A. Martins, Juan J. Alonso, and James J. Reuther. "High-fidelity aerostructural design optimization of a supersonic business jet". In: *Journal of Aircraft* 41.3 (2004), pp. 523–530.

[101]   Juan J. Alonso, Patrick LeGresley, and V. Pereyra. "Aircraft design optimization". In: *Mathematics and Computers in Simulation* 79.6 (2009), pp. 1948–1958.

[102]   Vivek Mukhopadhyay et al. "Analysis, design, and optimization of noncylindrical fuselage for blended-wing-body vehicle". In: *Journal of Aircraft* 41.4 (2004), pp. 925–930.

[103]   Lars U. Hansen and Peter Horst. "Multilevel optimization in aircraft structural design evaluation". In: *Computers & Structures* 86.1 (2008), pp. 104–118.

[104]   Gregory Wrenn and Augustine Dovi. "Multilevel/multidisciplinary optimization scheme for sizing a transport aircraft wing". In: *28th Structures, Structural Dynamics and Materials Conference, Monterey, CA*. 1987.

[105]   Marti Sarigul-Klijn and Nesrin Sarigul-Klijn. "Flight mechanics of manned suborbital reusable launch vehicles with recommendations for launch and recovery". In: *41st Aerospace Sciences Meeting and Exhibit, Reno, NV*. 2003.

[106]   Xiao Huang and Bernd Chudoba. "A trajectory synthesis simulation program for the conceptual design of a suborbital tourism vehicle". In: *AIAA Modeling and Simulation Technologies Conference and Exhibit, San Francisco, CA*. 2005.

[107]   Chun-Lin Gong, Liang-Xian Gu, and Hua Su. "Multidisciplinary design optimization method for suborbital reusable launch vehicle". In: *Journal of Solid Rocket Technology (JSRT)* 35.1 (2012), pp. 5–10.

[108]   Guobiao Cai et al. "Optimal design of hybrid rocket motor powered vehicle for suborbital flight". In: *Aerospace Science and Technology* 25.1 (2013), pp. 114–124.

[109]   Hao Zhu et al. "Uncertainty analysis and design optimization of hybrid rocket motor powered vehicle for suborbital flight". In: *Chinese Journal of Aeronautics* 28.3 (2015), pp. 676–686.

[110]   Dimitri N. Mavris and Daniel A. DeLaurentis. "A stochastic design approach for aircraft affordability". In: *Proceedings of the 21st Congress of the International Council on the Aeronautical Sciences (ICAS), Melbourne, Australia*. 1998.

[111]   Paul D. Collopy and Peter M. Hollingsworth. "Value-Driven Design". In: *Journal of Aircraft* 48.3 (2011), pp. 749–759.

[112]   M. Gregory O'Neill et al. "Comparing and optimizing the DARPA system F6 program value-centric design methodologies". In: *AIAA SPACE 2010 Conference & Exposition, Anaheim, CA*. 2010.

[113]   Joseph H. Saleh, Nicole C. Jordan, and Dava J. Newman. "Shifting the emphasis: from cost models to satellite utility or revenue models". In: *Acta Astronautica* 61.10 (2007), pp. 889–900.

[114]   Joy Brathwaite and Joseph H. Saleh. "Value-centric framework and pareto optimality for design and acquisition of communication satellites". In: *International Journal of Satellite Communications and Networking* 27.6 (2009), pp. 330–348.

[115]   Gregory Richardson, Jay Penn, and Paul D. Collopy. "Value-centric analysis and value-centric design". In: *AIAA SPACE 2010 Conference & Exposition, Anaheim, CA*. 2010.

[116]   Adam M. Ross. "Multi-attribute tradespace exploration with concurrent design as a value-centric framework for space system architecture and design". MA thesis. Massachusetts Institute of Technology, 2003.

[117]   Owen Brown and Paul Eremenko. "The value proposition for fractionated space architectures". In: *Space 2006, San Jose, CA*. 2006.

[118]   Owen Brown and Paul Eremenko. "Application of value-centric design to space architectures: the case of fractionated spacecraft". In: *AIAA SPACE 2008 Conference & Exposition, San Diego, CA*. 2008.

[119] Owen Brown, Paul Eremenko, and Paul D. Collopy. "Value-centric design methodologies for fractionated spacecraft: progress summary from Phase I of the DARPA system F6 program". In: *AIAA SPACE 2009 Conference & Exposition, Pasadena, CA*. 2009.

[120] David McCormick, Brent Barrett, and Mitchell Burnside-Clapp. "Analyzing fractionated satellite architectures using RAFTIMATE - a Boeing tool for value-centric design". In: *AIAA SPACE 2009 Conference & Exposition, Pasadena, CA*. Vol. 6767. 2009, p. 2009.

[121] Robert Thompson, Michael Violet, and Olivier de Weck. "A value-centric approach for quantitative risk management". In: *AIAA SPACE 2011 Conference & Exposition, Reston, VA*. 2011.

[122] Paul D. Collopy. "Surplus value in propulsion system design optimization". In: *33rd Joint Propulsion Conference & Exhibit, Seattle, WA*. 1997.

[123] Paul D. Collopy. "Economic-based distributed optimal design". In: *AIAA SPACE 2010 Conference & Exposition, Albuquerque, NM*. 2001.

[124] Paul D. Collopy and Randy Horton. "Value modeling for technology evaluation". In: *38th AIAA/ASME/SAE/ASEE Joint Propulsion Conference & Exhibit, Indianapolis, IN*. 2002.

[125] Julie Cheung et al. "Application of value-driven design to commercial aeroengine systems". In: *Journal of Aircraft* 49.3 (2012), pp. 688–702.

[126] Richard Curran et al. "Value operations methodology for value driven design: medium range passenger airliner validation". In: *48th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition, Orlando, FL*. 2010.

[127] Adam M. Ross et al. "Aligning perspectives and methods for value-driven design". In: *AIAA SPACE 2010 Conference & Exposition, Anaheim, CA*. 2010.

[128] Karen E. Willcox and Sean Wakayama. "Simultaneous optimization of a multiple-aircraft family". In: *43rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, Denver, CO*. 2002.

[129] Karen E. Willcox and Sean Wakayama. "Simultaneous optimization of a multiple-aircraft family". In: *Journal of Aircraft* 40.4 (2003), pp. 616–622.

[130] Ryan E. Peoples and Karen E. Willcox. "Value-based multidisciplinary optimization for commercial aircraft design". In: *45th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics & Materials Conference, Palm Springs, CA*. 2004.

[131]   Ryan E. Peoples and Karen E. Willcox. "Value-based multidisciplinary optimization for commercial aircraft design and business risk assessment". In: *Journal of Aircraft* 43.4 (2006), pp. 913–921.

[132]   Jacob Markish and Karen E. Willcox. "Value-based multidisciplinary techniques for commercial aircraft system design". In: *AIAA Journal* 41.10 (2003), pp. 2004–2012.

[133]   Sylvie Castagne, Richard Curran, and Paul D. Collopy. "Implementation of value-driven optimisation for the design of aircraft fuselage panels". In: *International Journal of Production Economics* 117.2 (2009), pp. 381–388.

[134]   Johanna Ceisel et al. "A non-weight based, Manufacturing Influenced Design (MInD) methodology for preliminary design". In: *28th International Congress of the Aeronautical Sciences (ICAS)*. 2012.

[135]   Chandrashekar Sundaresan et al. "A methodology for parametric production planning in preliminary aircraft design". In: *28th International Congress of the Aeronautical Sciences (ICAS), Brisbane, Australia*. 2012.

[136]   Apinut Sirirojvisuth. "Development of hybrid lifecycle cost estimating tool (hlcet) for manufacturing influenced design tradeoff". PhD thesis. Georgia Institute of Technology, 2012.

[137]   Dennis J. L. Siedlak et al. "A methodology for the parametric exploration of the impact of production planning on the early stages of design". In: *ASME 2014 International Manufacturing Science and Engineering Conference collocated with the JSME 2014 International Conference on Materials and Processing and the 42nd North American Manufacturing Research Conference*. Vol. 1. 2014.

[138]   Dennis J. L. Siedlak et al. "Supporting affordability-based design decisions in the presence of demand variability". In: *ASME 2015 International Manufacturing Science and Engineering Conference, Charlotte, NC*. Vol. 2. 2015.

[139]   Simon I. Briceno and Dimitri N. Mavris. "Strategic decision-making: applications of game theory in a systems approach to commercial engine selection". In: *AIAA 5th Aviation, Technology, Integration, and Operations Conference (ATIO), Arlington, VA*. 2005.

[140]   Simon I. Briceno and Dimitri N. Mavris. "Applications of game theory in a systems design approach to strategic engine selection". In: *25th International Congress of the Aeronautical Sciences, Hamburg, Germany*. 2006.

[141]   Simon I. Briceno. "A game-based decision support methodology for competitive systems design". PhD thesis. Georgia Institute of Technology, 2008.

[142]   James K. D. Morrison, R. John Hansman, and Sgouris Sgouridis. "Game theory analysis of the impact of single-aisle aircraft competition on emissions". In: *Journal of Aircraft* 49.2 (2012), pp. 483–494.

[143]   Cedric Justin, Simon I. Briceno, and Dimitri N. Mavris. "Strategic analysis of competitive markets: a case study for the narrowbody market". In: *11th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference, Virginia Beach, VA*. 2011.

[144]   Geoffrey Bower and Ilan Kroo. "Multi-objective aircraft optimization for minimum cost and emissions over specific route networks". In: *26th International Congress of the Aeronautical Sciences ICAS, Anchorage, AK*. 2008.

[145]   Jacob Markish and Karen E. Willcox. "A value-based approach for commercial aircraft conceptual design". In: *Proceedings of the ICAS2002 Congress, Toronto*. 2002.

[146]   David Simchi-Levi. *Managing uncertainty in the supply chain*. University Lecture. 2003.

[147]   Jay W. Forrester. *Industrial dynamics*. 1st Edition. MIT Press, 1961.

[148]   Hosung Lee and John R. Olds. "Integration of cost modeling and business simulation into conceptual launch vehicle design". In: *AIAA Defense and Space Programs Conference and Exhibit, Huntsville, AL*. 1997.

[149]   Fangruo Chen. "Echelon reorder points, installation reorder points, and the value of centralized demand information". In: *Management Science* 44.12-part-2 (1998), S221–S234.

[150]   Joseph J. Spengler. "Vertical integration and antitrust policy". In: *The Journal of Political Economy* (1950), pp. 347–352.

[151]   Gérard P. Cachon and Paul H. Zipkin. "Competitive and cooperative inventory policies in a two-stage supply chain". In: *Management Science* 45.7 (1999), pp. 936–953.

[152]   Jing Chen, Hui Zhang, and Ying Sun. "Implementing coordination contracts in a manufacturer Stackelberg dual-channel supply chain". In: *Omega* 40.5 (2012), pp. 571–583.

[153]   Natalia M. Alexandrov and M. Yousuff Hussaini. *Multidisciplinary design optimization: state of the art*. Vol. 80. SIAM, 1997.

[154] Ludwig Prandtl. "Uber tragflugel des kleinsten induzierten widerstandes". In: *Zeitshrift fur Flugtechnik und Motorluftschiffahrt* 24 (1933).

[155] Jean-Guillaume Durand et al. "A design optimization technique for multi-robot systems". In: *55th AIAA Aerospace Sciences Meeting*. Grapeving, TX, 2017.

[156] Garret N. Vanderplaats. *Numerical optimization rechniques for engineering design*. 4th edition. Vanderplaats Research & Development, 2005.

[157] Dimitri N. Mavris and Daniel A. DeLaurentis. "An integrated approach to military aircraft selection and concept evaluation". In: *1st AIAA Aircraft Engineering, Technology, and Operations Congress, Anaheim, CA*. 1995.

[158] "Risk (n.)" In: *Oxford English Dictionary Online*. Ed. by Oxford University Press. Available at: `http://www.oed.com/`.

[159] "Risk (n.) risk (n.)" In: *American Heritage Dictionary*. Available at: `https://ahdictionary.com/`.

[160] "Risk (n.) risk (n.)" In: *Merriam-Webster Collegiate Dictionary*. Available at: `https://www.merriam-webster.com/`.

[161] Michael Stamatelatos et al. *Probabilistic risk assessment procedures guide for NASA managers and practitioners*. Tech. rep. NASA, 2011.

[162] David G. Robinson. *A survey of probabilistic methods used in reliability, risk and uncertainty analysis: analytical techniques I*. Tech. rep. SAND98. Sandia National Lab, 1998.

[163] John L. Vian and John R. Moore. "Trajectory optimization with risk minimization for military aircraft". In: *Journal of Guidance, Control, and Dynamics* 12.3 (1989), pp. 311–317.

[164] Christopher P. Frank et al. "A conceptual design framework for performance, life-cycle cost, and safety evaluation of suborbital vehicles". In: *54th AIAA Aerospace Sciences Meeting, San Diego, CA*. 2016.

[165] Philip Young. "FRISK-Formal risk assessment of system cost estimates". In: *Aerospace Design Conference*. American lnstitute of Aeronautics and Astronautics (AIAA). Irvine, CA, 1992.

[166] Brian German. *Multi-objective optimization: principles and algorithms*. University lecture. Aerospace Systems Design Laboratory, Georgia Institude of Technology, 2013.

[167]   Kalyanmoy Deb and Himanshu Gupta. "Introducing robustness in multi-objective optimization". In: *Evolutionary Computation* 14.4 (2006), pp. 463–494.

[168]   Yaochu Jin and Bernhard Sendhoff. "Trade-off between performance and robustness: an evolutionary multiobjective approach". In: *Evolutionary Multi-Criterion Optimization*. Vol. 2632. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2003, pp. 237–251.

[169]   A. Parkinson, C. Sorensen, and N. Pourhassan. "A general approach for robust optimal design". In: *Journal of Mechanical Design* 115 (1993), pp. 74–80.

[170]   Sivakumar Sundaresan, Kosuke Ishii, and Donald R. Houser. "A robust optimization procedure with variations on design variables and constraints". In: *Engineering Optimization* 24 (2 1995), pp. 101–117.

[171]   Wei Chen and Xiaoping Du. "Toward a better understanding of modeling feasibility robustness in engineering design". In: *Journal of Mechanical Design* 122.4 (2000), pp. 385–394.

[172]   Dimitri N. Mavris, George Mantis, and Michelle R. Kirby. "Demonstration of a probabilistic technique for the determination of aircraft economic viability". In: *2nd World Aviation Congress and Exposition, Anaheim, CA*. 1997.

[173]   Dimitri N. Mavris and Oliver Bandte. "A probabilistic approach to multivariate constrained robust design simulation". In: *SAE Technical Paper* 975508 (1997).

[174]   Dimitri N. Mavris, Oliver Bandte, and Daniel A. DeLaurentis. "Determination of system feasibility and viability employing a joint probabilistic formulation". In: *37th Aerospace Sciences Meeting and Exhibit*. 1997.

[175]   Oliver Bandte, Dimitri N. Mavris, and Daniel A. DeLaurentis. *Viable designs through a joint probabilistic estimation technique*. Tech. rep. SAE International, 1999.

[176]   Frederic Burgaud, Jean-Guillaume Durand, and Dimitri N. Mavris. "A risk-aversion-based project valuation method to determine optimal technology infusion in aircraft design". In: *17th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Washington, DC*. 2016.

[177]   William F. Sharpe. "Capital asset price: a theory of market equilibrium under conditions of risk". In: *The Journal of Finance* 19.3 (1964), pp. 425–442.

[178]   John Lintner. "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets". In: *The Review of Economics and Statistics* 47.1 (1965), pp. 13–37.

[179]   John J. Clark, Thomas J. Hindelang, and Robert E. Pritchard. *Capital budgeting - Planning and control of capital expenditure*. Prentice-Hall, Inc., 1979.

[180]   Harry Markowitz. "Portfolio selection". In: *The Journal of Finance* 7.1 (1952), pp. 77–91.

[181]   Frank A. Sortino and Robert Van Der Meer. "Downside risk". In: *The Journal of Portfolio Management* 17.4 (1991), pp. 27–31.

[182]   Frank A Sortino and Lee N Price. "Performance Measurement in a Downside Risk Framework". In: *The Journal of Investing* 3.3 (1994), pp. 59–64.

[183]   Brian M. Rom and Kathleen W. Ferguson. "Post-modern portfolio theory comes of age". In: *The Journal of Investing* 3.3 (1994), pp. 11–17.

[184]   Brian M. Rom and Kathleen W. Ferguson. "Using post-modern portfolio theory to improve investment performance measurement". In: *Journal of Performance Measurement* 2.2 (1997), pp. 5–13.

[185]   Pete Swisher and Gregory W. Kasten. "Post-modern portfolio theory". In: *Journal of Financial Planning* 18.9 (2005).

[186]   Iyiola Omisore, Munirat Yusuf, and Nwufo Christopher. "The modern portfolio theory as an investment decision tool". In: *Journal of Accounting and Taxation* 4.2 (2012), pp. 19–28.

[187]   Philippe Jorion. *Value at Risk: the new benchmark for controlling market risk*. 3rd. McGraw-Hill Education, 2006.

[188]   Darrell Duffie and Jun Pan. "An overview of Value at Risk". In: *The Journal of Derivatives* 4.3 (1997), pp. 7–49.

[189]   R. Tyrrell Rockafellar and Stanislav Uryasev. "Optimization of conditional Value-at-Risk". In: *Journal of Risk* 2 (2000), pp. 21–42.

[190]   R. Tyrrell Rockafellar and Stanislav Uryasev. "Conditional Value-at-Risk for general loss distributions". In: *Journal of Banking & Finance* 26.7 (2002), pp. 1443–1471.

[191]   Pavlo Krokhmal, Jonas Palmquist, and Stanislav Uryasev. "Portfolio optimization with conditional value-at-risk objective and constraints". In: *Journal of Risk* 4 (2002), pp. 43–68.

[192]   Stan Uryasev et al. "VaR vs CVaR in risk management and optimization". In: *CARISMA Conference*. 2010.

[193] Deborah Kidd. "Value at risk and conditional value at risk: a comparison". In: *Investment Risk and Performance Feature Articles* 2012.1 (2012).

[194] Wen Yao et al. "Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles". In: *Progress in Aerospace Sciences* 47.6 (2011), pp. 450–479.

[195] Daniel A. DeLaurentis and Dimitri N. Mavris. "Uncertainty modeling and management in multidisciplinary analysis and synthesis". In: *38th Aerospace Sciences Meeting and Exhibit, Reno, NV*. (Jan. 10, 2000). Reno, NV, 2000.

[196] Michael S. Eldred and John Burkardt. "Comparison of non-intrusive polynomial chaos and stochastic collocation methods for uncertainty quantification". In: *47th AIAA Aerospace Sciences Meeting including The New Horizons Forum and Aerospace Exposition, Orlando, FL*. 2009.

[197] Rüdiger Rackwitz and Bernd Fiessler. "Structural reliability under combined random load sequences". In: *Computers & Structures* 9.5 (1978), pp. 489–494.

[198] X. Chen and N. C. Lind. "Fast probability integration by three-parameter normal tail approximation". In: *Structural Safety* 1.4 (1983), pp. 269–276.

[199] Lawrence L. Green, Hong-Zong Lin, and Mohammad R. Khalessi. "Probabilistic methods for uncertainty propagation applied to aircraft design". In: *20th AIAA Applied Aerodynamics Conference, Saint Louis, MO*. 2002.

[200] M.-H. Herman Shen. "Reliability assessment of high cycle fatigue design of gas turbine blades using the probabilistic Goodman Diagram". In: *International Journal of Fatigue* 21.7 (1999), pp. 699–708.

[201] Michelle R. Kirby. "A methodology for technology identification, evaluation, and selection in conceptual and preliminary aircraft design". PhD thesis. Georgia Institute of Technology, 2001.

[202] Lotfi A. Zadeh. "Fuzzy sets". In: *Information and Control* 8.3 (1965), pp. 338–353.

[203] Joseph A. Goguen. "The logic of inexact concepts". In: *Synthese* 19.3-4 (1969), pp. 325–373.

[204] Hans-Jürgen Zimmermann. *Fuzzy set theory – And its applications*. 4th edition. Springer Science+Business Media, 2011.

[205] Singiresu S. Rao and Li Chen. "Numerical solution of fuzzy linear equations in engineering analysis". In: *International Journal for Numerical Methods in Engineering* 43.3 (1998), pp. 391–408.

[206]   Tien-Chin Wang and Tsung-Han Chang. "Application of TOPSIS in evaluating initial training aircraft under a fuzzy environment". In: *Expert Systems with Applications* 33.4 (2007), pp. 870–880.

[207]   Tuğba Efendigil, Semih Önüt, and Elif Kongar. "A holistic approach for selecting a third-party reverse logistics provider in the presence of vagueness". In: *Computers & Industrial Engineering* 54.2 (2008), pp. 269–287.

[208]   Dušan Teodorović, Milica Kalić, and Goran Pavković. "The potential for using fuzzy set theory in airline network design". In: *Transportation Research Part B: Methodological* 28.2 (1994), pp. 103–121.

[209]   Tohid Erfani and Sergei V. Utyuzhnikov. "Handling uncertainty and finding robust pareto frontier in multiobjective optimization using fuzzy set theory". In: *51st AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, Orlando, FL.* 2010.

[210]   Christopher P. Frank. "A design space exploration methodology to support decisions under evolving uncertainty in requirements and its application to advanced vehicles". PhD thesis. Georgia Institute of Technology, 2016.

[211]   Govindan Kannan, Shaligram Pokharel, and P. Sasi Kumar. "A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider". In: *Resources, Conservation and Recycling* 54.1 (2009), pp. 28–36.

[212]   Ramon E. Moore and C. T. Yang. *Interval analysis I*. Tech. rep. Lockheed Aircraft Corporation, 1959.

[213]   Ramon E. Moore, R. Baker Kearfott, and Michael J. Cloud. *Introduction to interval analysis*. Society for Industrial and Applied Mathematics, 2009.

[214]   Götz Alefeld and Günter Mayer. "Interval analysis: theory and applications". In: *Journal of Computational and Applied Mathematics* 121.1 (2000), pp. 421–464.

[215]   Singiresu S. Rao and L. Berke. "Analysis of uncertain structural systems using interval analysis". In: *AIAA Journal* 35.4 (1997), pp. 727–735.

[216]   Singiresu S. Rao and Luna Majumder. "Optimization of aircraft wings for gust loads: interval analysis-based approach". In: *AIAA Journal* 46.3 (2008), pp. 723–732.

[217]   F. Tonon, A. Bernardini, and I. Elishakoff. "Concept of random sets as applied to the design of structures and analysis of expert opinions for aircraft crash". In: *Chaos, Solitons & Fractals* 10.11 (1999), pp. 1855–1868.

[218]   Ravi C. Penmetsa and Ramana V. Grandhi. "Efficient estimation of structural reliability for problems with uncertain intervals". In: *Computers & Structures* 80.12 (2002), pp. 1103–1112.

[219]   Luna Majumder and Singiresu S. Rao. "Interval-based optimization of aircraft wings under landing loads". In: *Computers & Structures* 87.3 (2009), pp. 225–235.

[220]   Karl Pearson. "Contributions to the Mathematical Theory of Evolution". In: *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences* 185 (1894), pp. 71–110. eprint: http : // rsta . royalsocietypublishing.org/content/185/71.full.pdf.

[221]   I. Elishakoff, S. Van Manen, and J. Arbocz. "First-order second-moment analysis of the buckling of shells with random imperfections". In: *AIAA Journal* 25.8 (1987), pp. 1113–1117.

[222]   Xiaodong Luo and Ramana V. Grandhi. "Astros for reliability-based multidisciplinary structural analysis and optimization". In: *Computers & Structures* 62.4 (1997), pp. 737–745.

[223]   Chris L. Pettit and Ramana V. Grandhi. "Multidisciplinary optimization of aerospace structures with high reliability". In: *8th ASCE Specialty Conference on Probabilistic Mechanics and Structural Reliability, Notre Dame, IN*. 2000.

[224]   Luc Huyse and Dennis M. Bushnell. *Free-form airfoil shape optimization under uncertainty using maximum expected value and second-order second-moment strategies*. ICASE Report. NASA, 2001.

[225]   Marcin Kaminski. "Stochastic second-order perturbation approach to the stress-based finite element method". In: *International Journal of Solids and Structures* 38.21 (2001), pp. 3831–3852.

[226]   Harry H. Ku. "Notes on the use of propagation of error formulas". In: *Journal of Research of the National Bureau of Standards* 70.4 (1966), pp. 263–273.

[227]   Milík Tichỳ. "First-order third-moment reliability method". In: *Structural Safety* 16.3 (1994), pp. 189–200.

[228]   Y. J. Hong, J. Xing, and J. B. Wang. "A second-order third-moment method for calculating the reliability of fatigue". In: *International Journal of Pressure Vessels and Piping* 76.8 (1999), pp. 567–570.

[229]   Yan-Gang Zhao, Tetsuro Ono, and Masahiro Kato. "Second-order third-moment reliability method". In: *Journal of Structural Engineering* 128.8 (2002), pp. 1087–1090.

[230]   Benedikt Kriegesmann et al. "Probabilistic second-order third-moment approach for design of axially compressed composite shells". In: *51st AIAA/ASME/ASCE/ AHS/ASC Structures, Structural Dynamics, and Materials Conference, Orlando, FL*. 2010.

[231]   Tiantian Xie, Hao Yu, and Bogdan Wilamowski. "Comparison between traditional neural networks and radial basis function networks". In: *2011 IEEE International Symposium on Industrial Electronics (ISIE), Gdansk, Poland*. 2011, pp. 1194–1199.

[232]   Amy Gallo. "A refresher on Net Present Value". In: *Harvard Business Review* (2014).

[233]   Lawrence D. Schall, Gary L. Sundem, and William R. Geijsbeek. "Survey and analysis of capital budgeting methods". In: *The Journal of Finance* 33.1 (1978), pp. 281–287.

[234]   Lawrence J. Gitman and John R. Forrester Jr. "A survey of capital budgeting techniques used by major US firms". In: *Financial Management* 6.3 (1977), pp. 66–71.

[235]   Richard Pike. "A longitudinal survey on capital budgeting practices". In: *Journal of Business Finance & Accounting* 23.1 (1996), pp. 79–92.

[236]   William E. Gibson and Peter Morrell. "Airline finance and aircraft financial evaluation: evidence from the field". In: *9th Air Transport Research Society World Conference (ATRS), Rio de Janeiro, Brazil*. 2005.

[237]   Bernd Rohrbach. "Kreativ nach Regeln – Methode 635, eine neue Technik zum Lösen von Problemen". In: *Absatzwirtschaft* 12.19 (1969), pp. 73–75.

[238]   Karlheinz Roth. "Design models and design catalogs". In: *Proceedings of the International Conference on Engineering Design, ICED*. Vol. 87. 1987.

[239]   Karlheinz Roth. "Design catalogues and their usage". In: *Engineering Design Synthesis: Understanding, Approaches and Tools*. Ed. by Amaresh Chakrabarti. Springer London, 2002. Chap. 8, pp. 121–129.

[240]   Zeke Strawbridge, Daniel A. McAdams, and Robert B. Stone. "A computational approach to conceptual design". In: *ASME 2002 International Design Engineer-*

ing Technical Conferences and Computers and Information in Engineering Conference. 2002, pp. 15–25.

[241] Cari R. Bryant et al. "An interactive morphological matrix computational design tool: a hybrid of two methods". In: *Proceedings of the ASME 2007 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, Las Vegas, NV.* 2007, pp. 249–261.

[242] Genrikh Saulovich Altshuller. *Creativity as an exact science.* Gordon and Breach, 1984.

[243] Genrikh Saulovich Altshuller, Lev Shulyak, and Steven Rodman. *40 Principles: TRIZ keys to innovation.* Vol. 1. Technical Innovation Center, Inc., 1998.

[244] Matthew I. Campbell, Jonathan Cagan, and Kenneth Kotovsky. "A-design: an agent-based approach to conceptual design in a dynamic environment". In: *Research in Engineering Design* 11.3 (1999), pp. 172–192.

[245] L. Robin Keller and Joanna L. Ho. "Decision problem structuring: generating options". In: *IEEE Transactions on Systems, Man, and Cybernetics* 18.5 (1988), pp. 715–728.

[246] Fritz Zwicky. *The morphological method of analysis and construction.* California Institute of Technology, 1948.

[247] Fritz Zwicky. "The morphological approach to discovery, invention, research and construction". In: *New Methods of Thought and Procedure.* Springer Science+ Business Media, 1967, pp. 273–297.

[248] Dani Soban and Eric Upton. "Design of a UAV to optimize use of fuel cell propulsion technology". In: *Infotech@Aerospace, Arlington, VA.* 2005.

[249] Zohaib T. Mian et al. "Development and implementation of Micro Autonomous Systems and Technologies (MAST) Interactive Reconfigurable Matrix of Alternatives (M-IRMA) for concept selection". In: *Conference on Systems Engineering Research (CSER'13), Atlanta, GA.* 2013.

[250] Zohaib T. Mian and Dimitri N. Mavris. "Mission effectiveness quantification and assessment of Micro Autonomous Systems and Technologies". In: *Proceedings of the 2013 IEEE Systems and Information Engineering Design Symposium, Charlottesville, VA.* 2013.

[251] James Douglas Hamilton. *Time series analysis.* Princeton University Press, 1994.

[252] Paul J. H. Schoemaker. "When and how to use scenario planning: a heuristic approach with illustration". In: *Journal of Forecasting* 10.6 (1991), pp. 549–564.

[253] Paul J. H. Schoemaker. "Scenario planning: a tool for strategic thinking". In: *Sloan Management Review* 36.2 (1995), pp. 25–50.

[254] Jean-Charles Pomerol. "Scenario development and practical decision making under uncertainty". In: *Decision Support Systems* 31.2 (2001), pp. 197–204.

[255] Joseph F. Coates. "Scenario planning". In: *Technological Forecasting and Social Change* 65.1 (2000), pp. 115–123.

[256] Gilbert F. Ducos. "Two complementary cross-impact models: MIP 1 and MIP 2". In: *Futures* 12.5 (1980), pp. 405–419.

[257] Olaf Helmer. "Cross-impact gaming". In: *Futures* 4.2 (1972), pp. 149–167.

[258] J. C. Duperrin and Michel Godet. "SMIC 74 – a method for constructing and ranking scenarios". In: *Futures* 7.4 (1975), pp. 302–312.

[259] Claudio Morana. "A semiparametric approach to short-term oil price forecasting". In: *Energy Economics* 23.3 (2001), pp. 325–338.

[260] Christiane Baumeister and Lutz Kilian. "Real-time forecasts of the real price of oil". In: *Journal of Business & Economic Statistics* 30.2 (2012), pp. 326–336.

[261] Patrizio Pagano and Massimiliano Pisani. "Risk-adjusted forecasts of oil prices". In: *The B.E. Journal of Macroeconomics* 9.1 (2009).

[262] Michael Ye, John Zyren, and Joanne Shore. "Forecasting short-run crude oil price using high-and low-inventory variables". In: *Energy Policy* 34.17 (2006), pp. 2736–2743.

[263] Pietro Veronesi. *Fixed income securities: valuation, risk, and risk management.* Wiley and Sons, 2010.

[264] Astos Solutions. *ASTOS, aerospace trajectory analysis tool for launch, reentry and orbit vehicles.* Tech. rep. Astos Solutions GmbH, 2008.

[265] David J. Kinney et al. "Conceptual design of a 'SHARP'-CTV". In: *35th AIAA Thermophysics Conference, Anaheim, CA.* 2001.

[266] Douglas O. Stanley et al. "Conceptual design of a fully reusable manned launch system". In: *Journal of Spacecraft and Rockets* 29.4 (1992), pp. 529 –537.

[267] John R. Olds. "Multidisciplinary design techniques applied to conceptual aerospace vehicle design". PhD thesis. North Carolina State University, 1993.

[268] Frederic Villeneuve and Dimitri N. Mavris. "A new method of architecture selection for launch vehicles". In: *AIAA/CIRA 13th International Space Planes and Hypersonics Systems and Technologies Conference, Capua, Italy*. 2005.

[269] Taewoo Nam. *Introduction to FLOPS modeling*. University lecture. 2012.

[270] Robert D. Braun, Arlene A. Moore, and Ilan M. Kroo. "Collaborative approach to launch vehicle design". In: *Journal of Spacecraft and Rockets* 34.4 (1997), pp. 478–486.

[271] Jan Roskam. *Airplane design: preliminary calculation of aerodynamic, thrust and power characteristics.* Design, Analysis and Research Corporation, 1990.

[272] Dietrich E. Koelle. *Handbook of cost engineering and design of space transportation systems*. TransCostSystems, 2013.

[273] The United States Air Force. *Mil-S-38130. General requirements for safety engineering of systems and associated subsytems and equipment*. Tech. rep. 1963.

[274] Jean-Luc Boiffier. *Dynamique du vol de l'avion*. SupAéro - Département Aéronefs, 2001.

[275] I-Shih Chang. "Investigation of space launch vehicle catastrophic failures". In: *Journal of Spacecraft and Rockets* 33.2 (1996), pp. 198–205.

[276] Schonfeld & Associates, Inc. *SG&A expense as a percentage of sales by industry sector*. http://saibooks.com/index.php?option=com_content&view=article&id=64&Itemid=61. 2016.

[277] Shari Keller and Paul Collopy. "Value modeling for a space launch system". In: *Procedia Computer Science* 16 (2013), pp. 1152–1160.

[278] Bruno Miller and John-Paul Clarke. "Strategic guidance in the development of new aircraft programs: a practical real options approach". In: *IEEE Transactions on Engineering Management* 55.4 (2008), pp. 566–578.

[279] Peter Brooker. "Civil aircraft design priorities: air quality? climate change? noise?" In: *The Aeronautical Journal* 110.1110 (2006), pp. 517–532.

[280] William E. Gibson. "Airline fleet planning and aircraft investment valuation". In: *12th Air Transport Research Society (ATRS) World Conference, Berkeley, CA*. 2007.

[281] Aswath Damodaran. *Estimating beta*. University lecture. New York University Stern School of Business. 2012. (Visited on 07/19/2016). Available at: `http://people.stern.nyu.edu/adamodar/pdfiles/eqnotes/discrate2.pdf`.

[282] S&P Global Ratings. *S&P Global Ratings definitions*. 2016. (Visited on 07/19/2016). Available at: `https://www.standardandpoors.com/en_EU/delegate/getPDF?articleId=1663724&type=COMMENTS&subType=REGULATORY`.

[283] Moody's Investor Service. *Rating symbols and definitions*. 2016. (Visited on 07/26/2016). Available at: `https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_79004`.

[284] Fitch Ratings. *Definitions of ratings and other forms of opinion*. Fitch Ratings. 2014. (Visited on 07/07/2016). Available at: `https://www.fitchratings.com/web_content/ratings/fitch_ratings_definitions_and_scales.pdf`.

[285] Federal Reserve Bank of St. Louis. *Economic search - FRED economic data - BOAML yield spread*. Federal Reserve Bank of St. Louis. (Visited on 08/24/2016). Available at: `https://fred.stlouisfed.org`.

[286] Edwin J. Elton et al. "Explaining the rate spread on corporate bonds". In: *The Journal of Finance* 56.1 (2001), pp. 247–277.

[287] Aswath Damodaran. *Defining and estimating the cost of debt*. University lecture. New York University Stern School of Business. 2012. (Visited on 07/19/2016). Available at: `http://www.stern.nyu.edu/~adamodar/podcasts/BVR/BVR7ppt.ppt`.

[288] Aswath Damodaran. *Ratings, interest coverage ratios and default spread*. Online resources. New York University Stern School of Business. 2016. (Visited on 07/19/2016). Available at: `http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ratings.htm`.

[289] Aswath Damodaran. *The cost of distress: survival, truncation risk and valuation*. University paper, New York University Stern School of Business. 2006.

[290] Emanuele Borgonovo and L Peccati. "Sensitivity analysis in investment project evaluation". In: *International Journal of Production Economics* 90.1 (2004), pp. 17–25.

[291] Emanuele Borgonovo and George E. Apostolakis. "A new importance measure for risk-informed decision making". In: *Reliability Engineering & System Safety* 72.2 (2001), pp. 193–212.

[292]   Emanuele Borgonovo. "Importance relations and sensitivity analysis in decision theory". In: *Proceedings of the 10th International Conference on Foundations and Applications of Utility, Risk and Decision Theory, Torino*. 2001, pp. 20–23.

[293]   Michael C. Cheok, Gareth W. Parry, and Richard R. Sherry. "Use of importance measures in risk-informed regulatory applications". In: *Reliability Engineering & System Safety* 60.3 (1998), pp. 213–226.

[294]   Jon C. Helton. "Uncertainty and sensitivity analysis techniques for use in performance assessment for radioactive waste disposal". In: *Reliability Engineering & System Safety* 42.2-3 (1993), pp. 327–367.

[295]   Tamás Koltai and Tamás Terlaky. "The difference between the managerial and mathematical interpretation of sensitivity analysis results in linear programming". In: *International Journal of Production Economics* 65.3 (2000), pp. 257–274.

[296]   Sharyn OHalloran. *Model checking*. University lecture. Columbia University, 2016.

[297]   Irad Ben-Gal. *Outlier detection*. In: *Data Mining and Knowledge Discovery Handbook: A Complete Guide for Practitioners and Researchers*. 2005.

[298]   Michael A. Buonanno and Dimitri N. Mavris. "Aerospace vehicle concept selection using parallel, variable fidelity genetic algorithms". In: *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Albany, NY*. 2004.

[299]   Hyoung-Seog Chung, Seongim Choi, and Juan Alonso. "Supersonic business jet design using knowledge-based genetic algorithm with adaptive, unstructured grid methodology". In: *21st AIAA Applied Aerodynamics Conference, Orlando, FL*. 2003.

[300]   Hugh L. McManus, Daniel E. Hastings, and Joyce M. Warmkessel. "New methods for rapid architecture selection and conceptual design". In: *Journal of Spacecraft and Rockets* 41.1 (2004), pp. 10 –19.

[301]   Young-Jou Lai, Ting-Yun Liu, and Ching-Lai Hwang. "TOPSIS for MODM". In: *European Journal of Operational Research* 76.3 (1994), pp. 486 –500.

[302]   Dimitri N. Mavris. *Introduction to decision making and Multi-Attribute Decision Making (MADM)*. University lecture. Aerospace Systems Design Laboratory, Georgia Institude of Technology, 2012.

[303]   Frederic Burgaud, Manish Pokhrel, and Dimitri N Mavris. "A business-driven optimization methodology applied to commercial aviation programs". In: *55th AIAA Aerospace Sciences Meeting, Grapevine, TX*. 2017.

[304] Andrew Wodehouse and William Ion. "Augmenting the 6-3-5 method with design information". In: *Research in Engineering Design* 23.1 (2011), pp. 5–15.

[305] Jami J. Shah et al. "Collaborative Sketching (C-Sketch) - An Idea Generation Technique for Engineering Design". In: *The Journal of Creative Behavior* 35.3 (2001), pp. 168–198.

[306] Jami J. Shah. *Method 5-1-4 G-A variation on Method 635*. MAE 540 Class Notes. Arizona State University, Tempe, AZ. 1993.

[307] Tom Ritchey. "General morphological analysis". In: *16th EURO Conference on Operational Analysis*. 1998.

[308] Johan Ölvander, Björn Lundén, and Hampus Gavel. "A computerized optimization framework for the morphological matrix applied to aircraft conceptual design". In: *Computer-Aided Design* 41.3 (2009), pp. 187–196.

[309] Richard G. Weber and Sridhar S. Condoor. "Conceptual design using a synergistically compatible morphological matrix". In: *28th Annual Frontiers in Education Conference, 1998. FIE'98*. Institute of Electrical & Electronics Engineers (IEEE), 1998.

[310] Tolga Kurtoglu and Matthew I. Campbell. "Automated synthesis of electromechanical design configurations from empirical analysis of function to form mapping". In: *Journal of Engineering Design* 20.1 (2009), pp. 83–104.

[311] Dimitri N. Mavris and Michelle R. Kirby. "Technology identification, evaluation, and selection for commercial transport aircraft". In: *Proceedings of the 58th Annual Conference Of Society of Allied Weight Engineers, Inc., San Jose, CA*. 1999.

[312] Cari R. Bryant Arnold, Robert B. Stone, and Daniel A. McAdams. "MEMIC: an interactive morphological matrix tool for automated concept generation". In: *Proceedings of the 2008 Industrial Engineering Research Conference*. Institute of Industrial Engineers-Publisher. 2008, pp. 1196–1201.

[313] Yong Chen et al. "Automated conceptual design of mechanisms using improved morphological matrix". In: *Journal of Mechanical Design* 128.3 (2006), pp. 516–526.

[314] William Engler, Patrick Biltgen, and Dimitri N. Mavris. "Concept selection using an Interactive Reconfigurable Matrix of Alternatives (IRMA)". In: *45th AIAA Aerospace Sciences Meeting and Exhibit, Reno, NV*. 2007.

[315] Ryan Hughes et al. "Modeling of an Integrated Reconfigurable Intelligent System (IRIS) for ship design". In: *Proceedings of the 2006 ASNE Ship and Ship Systems Technology (S3T) Symposium*. 2006.

[316] Hernando Jimenez and Dimitri N. Mavris. "An evolution of morphological analysis applications in systems engineering". In: *48th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition, Orlando, FL*. 2010.

[317] Blaine Laughlin, Simon I. Briceno, and Dimitri N. Mavris. "A virtual experimentation platform enabling the design, testing, and verification of an unmanned aerial vehicle through cyber-physical, component-based design". In: *14th AIAA Aviation Technology, Integration, and Operations Conference, Atlanta, GA*. 2014.

[318] Peter Mörters and Yuval Peres. *Brownian motion*. Vol. 30. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press, 2010.

[319] Hugh Courtney, Jane Kirkland, and Patrick Viguerie. "Strategy under uncertainty". In: *Harvard Business Review* 75.6 (1997), pp. 67–79.

[320] Hugh Courtney. "Decision-driven scenarios for assessing four levels of uncertainty". In: *Strategy & Leadership* 31.1 (2003), pp. 14–22.