UNCERTAINTY PROPAGATION IN VALUE-DRIVEN DECISION-MAKING FOR THE AIRCRAFT, MANUFACTURING AND SUPPLY CHAIN DESIGN

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Abstract

Making decisions on future aircraft design configurations exploring all the possible solutions of the design space is essential to drastically reduce the overall cost. Usually, value-model theories are used to support the multi-criteria decision-making process. In this paper, the value model theory is leveraged for the identification of the best solution based on multiple criteria related to the design of the aircraft, its manufacturing and supply chain. In addition, uncertainty propagation analyses are performed for the identification of the robust and flexible solutions, thus the solutions minimizing the value oscillations and being optimal independently from the analyzed scenario. An aeronautical application case demonstrates how this approach increases the decision-makers ‘awareness when performing trade-off studies related to uncertain scenarios and/or expectations. It shows, for instance, how the best solution, in terms of value and cost, for a decision-maker in a specific scenario can drastically change its value under different conditions, being not robust.

Keywords: uncertainty propagation, value-driven decision-making, manufacturing, aircraft design, supply chain

1. Introduction

In the last decade, the European Commission introduced the Flightpath 2050 [1], the EU Aviation Sector’s vision for the future of aviation, placing new challenges for the design of innovative and sustainable aircraft configurations with the objective to reduce the environmental impact in terms of consumption, waste and emissions associated with all aeronautical activities and operations. Hence, the necessity to extend the branches of the aeronautical research to the entire aircraft life-cycle, from the design to production, to the disposal after the end of the system operative life. In this context, the DLR Institute of System Architecture in Aeronautics aims at developing methods, processes and tools supporting the design of aeronautical systems, while considering different life-cycle stages [2]. The challenge is to enable the *concurrent* design of the system of interest (i.e. the aircraft) and the enabling systems, defined as systems supporting the system of interest in one or more life-cycle stages [3]. Traditionally, in fact, the design of enabling systems is addressed once the aircraft design is completed [4]. Among others, enabling systems are the supply chain and manufacturing systems. The supply chain system is meant as combination of enterprises involved in the production of the aircraft; the manufacturing system as combination of machines needed to manufacture the aircraft. Indeed, the design of the enabling systems starts when the design of aircraft is already defined. For instance, the enterprises needed to produce the aircraft are chosen when the aircraft configuration is already fixed in terms of components, materials and processes. The main problem of this *sequential* approach is that issues in production which requires changes in the design cause drastically increase of cost [5]. Instead, the analysis of production aspects during the design of the aircraft might help experts foreseen the reduction of the overall cost and an increase of supply chain´s gains and product competitiveness [6] [3]. In this context, a methodology for the concurrent design of aircraft, manufacturing and supply chain has been already developed by DLR [7]. This methodology leads to a value-driven tradespace in which each solution provides information on the aircraft and production performance and thus on the fuel consumption mass, production time, quality, risk and cost. These parameters, identified as the most important for taking decisions, are aggregated in a *value* by leveraging the Multi Attributes Utility (MAU) Theory [8], as shown in Figure 1 by the gray, blue and green boxes.

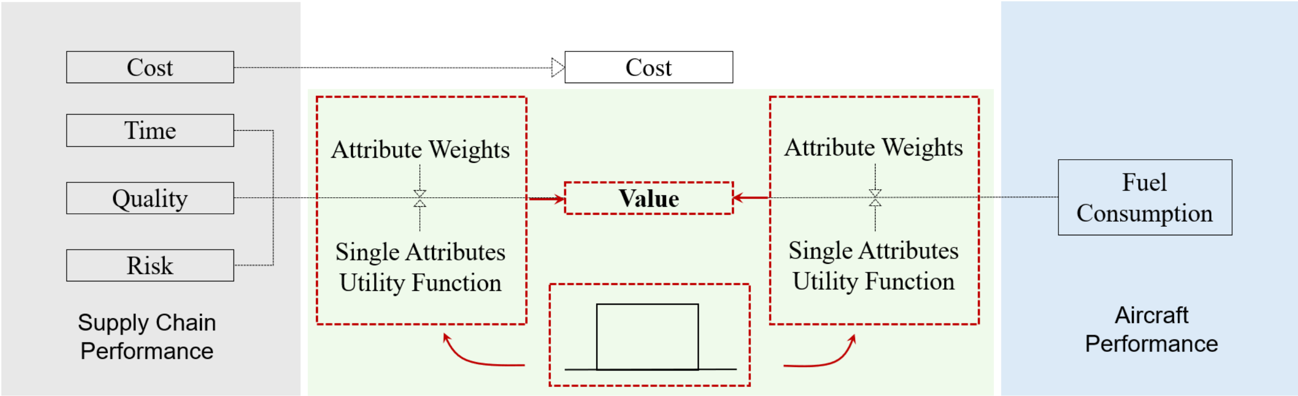


Figure 1 –Attributes Weights and Utility Functions Uniform Distribution for Value Uncertainty Propagation (red boxes): Value as Aggregation of Supply Chain and Aircraft Performance

The MAU theory therefore enables the exploration of a tradespace addressing the concurrent aircraft design, manufacturing and supply chain. Other value model theories are available in literature, having each one a unique interpretation, quantification and representation of the term *value*. Among others, there are the Net Present Value (NPV), Surplus Value (SV) and Cost–Benefit Analysis (CBA) [9] [10] [11]. However, the MAU has been selected in this work since it well suits the aim to increase the decision-makers' awareness during trade-off studies involving multiple criteria. The MAU theory, in fact, leverages the concept of single attribute utility (SAU) functions and attributes weights to aggregate these criteria a single dimensionless *value* and generate a ranked ordering of design alternatives in which the best solution can be easily identified as the one with the highest value [12]. In details, the weights represent the relative importance of these attributes. Instead, the utility functions represent the way decision-makers would take decisions. The best solution is therefore a solution well matching decision-makers' expectations with respect to all the aggregated criteria. Therefore, looking at Figure 1, the best solution is the alternative well matching decision-makers 'expectations in terms of time, quality, risk and fuel consumption. How to assess and quantify decision-makers 'expectations through single attribute utility functions and weights while considering production and design performance is already well explained in [13] [14]. Here, reader can also find more information about the possible trade-off studies that can be performed.

In this research activity, instead, the ambition is to introduce uncertainty in the weights and single attribute utility functions to give decision-makers insights on the behavior of the alternatives populating the value-driven tradespace (red boxes in Figure 1). To reach this objective, first a so-called value-driven Reference Pareto-front is generated by assuming same weights and linear utility functions for all the attributes. Then, as shown in Figure 1, a uniform distribution is used to propagate uncertainty on the value through the weights and utility functions. It means that hundreds of weights combinations and utility functions trends are analyzed to understand how the value of the solutions on the Reference Pareto-front change. Particularly, three case studies are addressed in this paper of increasing complexity:

- Case Study I: a uniform distribution is used to propagate uncertainty on the value through the weights
- Case Study II: a uniform distribution is used to propagate uncertainty on the value through utility functions
- Case Study III: a uniform distribution is used to propagate uncertainty on the value through the weights and utility functions

The objective is to identify the ***robust*** and ***flexible*** solutions. The robust solution is the alternative minimizing the value oscillation in each of the case study. In situations in which decision-makers are not sure about possible future scenarios (e.g. which criteria to prioritize), the robust solution might

represent a good candidate to be considered with respect to the best solution (solution with highest value for specific weight combination). The flexible solution, instead, is here proposed as the alternative having the highest probability to be on the Pareto-front while considering each case study. The Pareto-front, per definition, is the set of all the optimal solutions. The solutions on the Pareto-front, thus the optimal solutions on the value-driven tradespace, might change when changing the weights and utility functions. In this study, the probability of the solutions identified on the Reference Pareto-front to be optimal, thus to be on the Pareto-front while changing weights and utility functions, is estimated. Summarizing, the flexible solution is the alternative on the Reference Pareto-front which has the highest probability to be optimal in all the analyzed case studies. These new information allows decision-makers to perform new trade-off studies among the best, robust and flexible solutions especially if these solutions are different. Decision-makers might decide to have a solution which is optimal in all the case studies (flexible solution) even do it has not the highest value in a specific scenarios of interest (e.g. for a specific weight combination prioritizing some criteria). As consequence, some designs and supply chains might be selected instead of others.
In this paper, more details on the approach proposed to perform uncertainty propagation analyses and on the meaning of adding uncertainty in the three case studies are provided in Section 2. Instead, in Section 3, the technologies used to automatize the analyses are presented. The results related to the aeronautical application case are presented and discussed in Section 4. Finally, conclusions are reported in Section 5.

2. Uncertainty Propagation Formulation: Best, Robust and Flexible Solutions

The MAU theory has been selected as value model theory since it well suits the aim to increase the decision-makers' awareness during trade-off studies involving multiple criteria. The formula to estimate the value is the following one [15]:

$$\text{value} = \sum_{i=1}^{N} \lambda_i \, U(X_i) \tag{1}$$

In which:

- N is the number of criteria;
- λ_i is the weight associate to the criteria X_i and the following condition must be respected: $0 < \lambda_i < 1$: $\sum_{i=1}^{N} \lambda_i = 1$;
- $U(X_i)$ is the utility function associate to the criteria X_i.

Therefore, once assigned the weights and utility functions per each attribute, the value model theory allows to aggregate multiple criteria in a single dimensionless one, called *value*. A ranked ordering of design alternatives is so generated and the best solution can be easily identified as the one with the highest *value*. In this study, a value-driven Reference Pareto-front is generated by assigning the same weight (0.25) and linear utility functions to the attributes. As shown in Figure 1, the attributes are the production risk, time, quality and fuel consumption. Instead cost is used as other independent variable for the value vs. cost trade-off studies. The linear utility functions used to generate the value-driven Reference Pareto-front are shown in Figure 2. These functions have a decreasing trend for risk, time and fuel consumption since the utility of the alternatives increases when these parameters are low. Opposite trend is for quality.
The value-driven Reference Pareto-front, generated by leveraging these functions and same weights, shows the optimal analytical solutions meaning the optimal alternatives not affected by the decision-makers' expectations. In fact, same weights imply same importance of attributes. Instead, linear utility functions simply translate criteria with different unit of measures (e.g. production risk and fuel consumption mass) in the single dimensionless one (utility). The best solution is anyway proposed as the alternative with the highest value on the Reference Pareto-front.
The challenge is to investigate the behavior of the alternatives populating the Reference Pareto-front when decision-makers' expectations are considered and particularly when decision-makers is not

completely sure on which weight combinations and utility functions analyze.

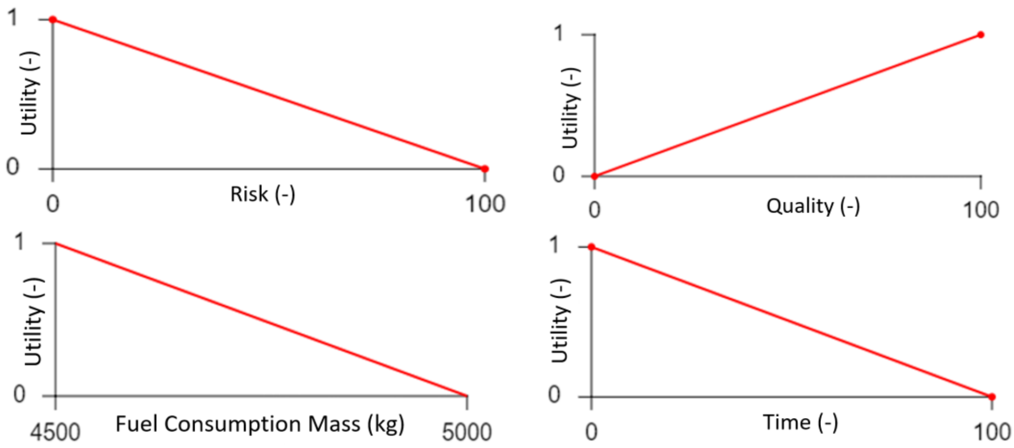
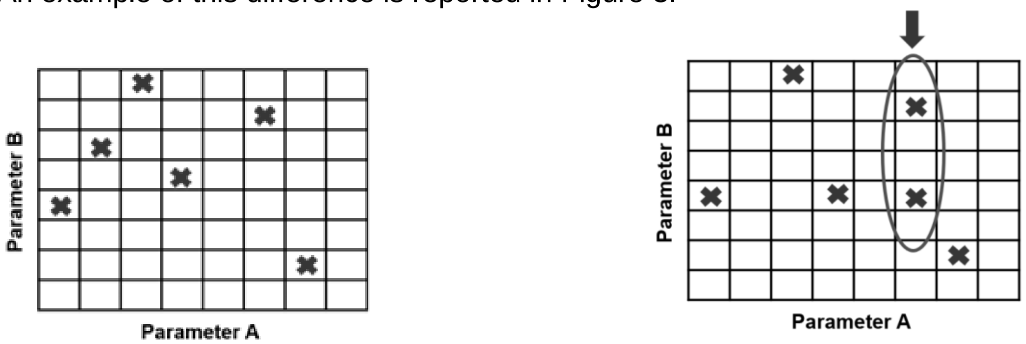


Figure 2 – Single Attributes Utility Functions for Time, Quality, Risk and Fuel Consumption

Therefore, the idea is to propagate the uncertainty to the value through the weights, utility functions or both of them. Two different techniques can be used to propagate uncertainty in the value model theory: the Monte Carlo and the Latin Hypercube Sampling (LHS) [16]. The main difference among them is related to the correlation between the inputs and outputs. In fact, differently from the Latin Hypercube sampling method, in the Monte Carlo method for the same input two different outputs can be found. An example of this difference is reported in Figure 3.



a) Latin Hypercube Sampling Method

b) Monte Carlo Method

Figure 3 – Latin Hypercube Sampling (LHS) and Monte Carlo Methods Comparison [16]: a) LHS b) Monte Carlo

In this case study, however, the Latin Hypercube sampling method is chosen because a single correlation between inputs (weights, functions or both) and outputs (*value*) is required. As starting point, the LHS method needs the definition of number of samplings (N). The number of samplings is used for the generation of the matrix shown in Figure 3. An exact formula to calculate N does not exist in literature, although, an inequality that must be satisfied ($N > 4/3\ K$ with K number of parameters) has been empirically established. The range of each parameter is then divided into N not-overlapping equiprobable intervals and each interval is sequentially assigned to a sampling index from 1 to N. To propagate uncertainty in the weights (Case Study I), in the utility functions (Case Study II) and in both weights and utility functions (Case Studies), 250 samplings are generated by leveraging uniform distributions. More details on the case studies are provided in the next sections 2.2.1, 2.2.2 and 2.2.3. However, once estimated the value of the solutions in each case study, the robust and flexible solutions are identified respectively as the alternative minimizing the value oscillation and the alternative having the higher probability to be optimal. In particular, to identify the robust solution, the maximum and minimum value of each solution of the Reference Pareto-front is estimated considering all the combinations of each case study. The value oscillation of each solution is then proposed as the difference between these boundaries. The alternative with the lowest difference between the highest and lowest value is then recognized as the robust solution. Instead, to identify the flexible solution, the Pareto-front is estimated for each combination of the case study and a check is made to verify if the alternatives populating the Reference Pareto-front are on the new estimated Pareto-front. The number of positive cases (solution is on the Pareto-front) with respect to the total cases provides the probability that this is solution is optimal. The flexible solution is then the alternative having the highest probability to stay on the Pareto-front.

2.2.1 Case Study I: Weights Uncertainty Propagation

In the value model theory weights are used to prioritize attributes. Each weight combination therefore corresponds to a specific strategic scenario that a decision-maker can investigate by prioritizing the attributes of interest. For instance, decision-makers might decide to prioritize time with respect to risk with the objective to identify the best solution in a scenario in which production rate increases and time gets the priority. The best solution in this scenario might be different from another one, for instance form the reference case in which same weights is assigned to all the attributes. Adding uncertainty in the weights is extremely useful to analyze the behavior of the solutions in many scenarios and identify the one minimizing the value oscillations (that is the robust solution). This solution can be an alternative which has not the highest value. However, its value surely does not change drastically in all the other scenarios. Having this information allows decision-makers to perform trade-off studies between the best solution (highest *value*) and the robust solution (minimum value oscillation).

To propagate uncertainty through the weights, a uniform distribution is used as input for the Latin Hypercube sampling method. The choice of such distribution for the samplings allows decision-makers to analyze all the possible combinations that can be generated. Each weight changes from 0 to 1, but a constraint is set to assure that their sum is 1.

2.2.2 Case Study II: Utility functions Uncertainty Propagation

Utility functions are used in the value model to quantify the qualitative decision-makers ‘expectations with respect to each attribute. Therefore, they quantify the way decision-makers would take decisions with respect to each attribute. The Reference Pareto-front is built considering linear utility functions. However, changing these functions, the value of the alternative populating the Reference Pareto-front might change. Usually the utility functions are drawn by decision-makers and several techniques are available in literature. However, decision-makers might be not sure about the slope of the functions to use and thus about the way they would model their expectations. Adding uncertainty in the utility functions gives decision-makers the possibility to analyze many function slopes and identify the robust solution, that is the alternative minimizing the *value* oscillations. As in the previous case, this solution might not be the one with the highest *value* for a given function trend. However, the value of this solution surely does not change drastically if the function change, thus if decision-makers decide to modify the way they would take decisions.

Introducing uncertainty in the utility functions is more challenging than the previous case study. In fact, the trend of each function (increasing/decreasing) must be preserved while changing the slope of the function. To assure this condition, boundaries have to be set and a control point defined. To add uncertainty in the functions, a uniform distribution can be defined for the samplings of the control point. An example of uncertainty propagation in the utility functions is reported in Figure 4. For simplicity, in this study, uncertainty is propagated through a utility function of one attribute assumed to have a decreasing trend (for instance time).

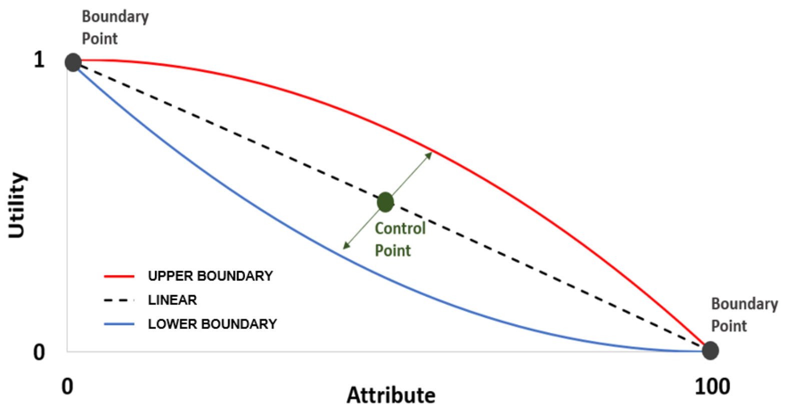


Figure 4 – Utility Functions Uncertainty Propagation: Control Point (green) and Boundary Points (gray) as way to propagate Uncertainty

Two boundary Points (gray points) are defined to assure the constraints on the utility (y axis ranging from 0 to 1) and the trend of the functions (decreasing). Instead, a control point (green point) is used to add uncertainty in the function, meaning to change the slope of the function between the lower boundary (blue curve) and the upper boundary (red curve). These boundary functions are defined by the utility or trend function constraints. For instance, functions out of the upper function boundary might provide points with utility higher than 1 (not feasible according to utility definition).
The equations of the boundary functions (lower and upper) and the coordinates of the control points on these functions are reported in Table 1.

Function	Equation	Control Point Coordinates	
		X	Y
Lower Boundary (LB)	$(1.01 \cdot 10^{-4})\,x^2 - (2 \cdot 10^{-2})x + 1$	25	0.56
Upper Boundary (UB)	$(-1 \cdot 10^{-4})\,x^2 + (4.17 \cdot 10^{-4})x + 1$	40	0.85

Table 1 – Boundaries Functions and Control Points Coordinates

To generate all the functions between the upper boundary (red curve) and low boundary (blue curve) functions, a uniform distribution is defined for the samplings of each coordinate of the control point.

2.2.3 Case Study III: Weights and Utility functions Uncertainty Propagation

In the value model theory, weights are used to prioritize attributes while utility functions to quantify the qualitative decision-makers' expectations with respect to each attribute. In this case study, uncertainty is introduced both in weights and utility functions. This allows decision-makers to identify the alternative minimizing the value oscillations, i.e. the robust solution, when they are not sure about the scenarios to analysed (weights) and way they would take decisions (utility functions).
This case study is a combination of the previous two. Therefore, for the weights a uniform distribution between 0 and 1 is defined while for functions a uniform distribution for the samplings of the control point are used to assure the consistency of the trend functions.

3. Implementation

The approach introduced in the previous section is executed by leveraging some tools developed at DLR. In particular, to estimate the *value* of the alternatives populating the value-driven Reference Pareto-front, the workflow shown in Figure 5 is run within the Remote Component Environment (RCE) [17]. This workflow includes tools needed for the estimation of the fuel consumption, production cost, risk, time and quality. More information is provided here [18]. All the tools are able to automatically exchange information through CPACS, the Common Parametric Aircraft Configuration Schema (CPACS) [19].

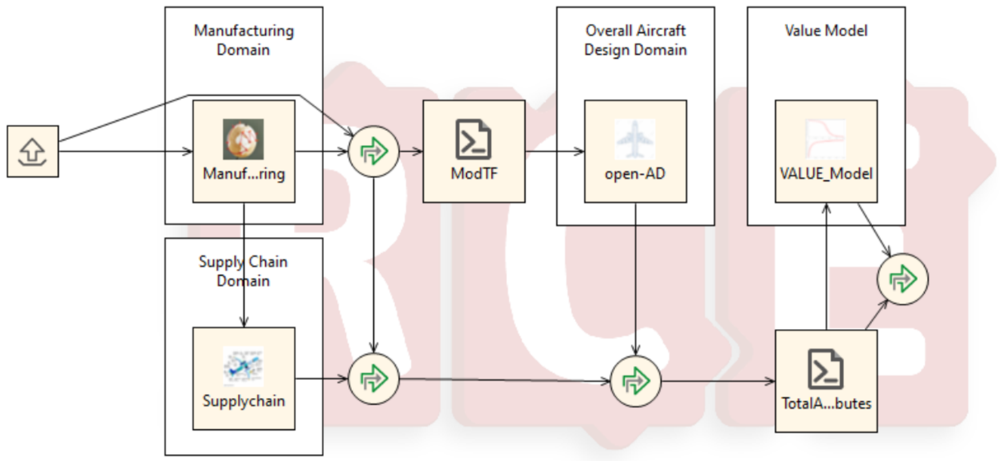


Figure 5 – Workflow to estimate the Reference value-driven Pareto-front

To run the uncertainty analysis, instead, a tool called UPinSMA is implemented. This tool has been also “CPACSized” to allow the automatically exchange of information with the other tools, in particular with the value model tool for the value estimation. The CPACS structure used to execute the uncertainty analyses is shown in Figure 6. The address <toolspecific> allows users to add new specifications about the aircraft and create new custom ones. In this case, new branches are added to include the uncertainty results in the CPACS.

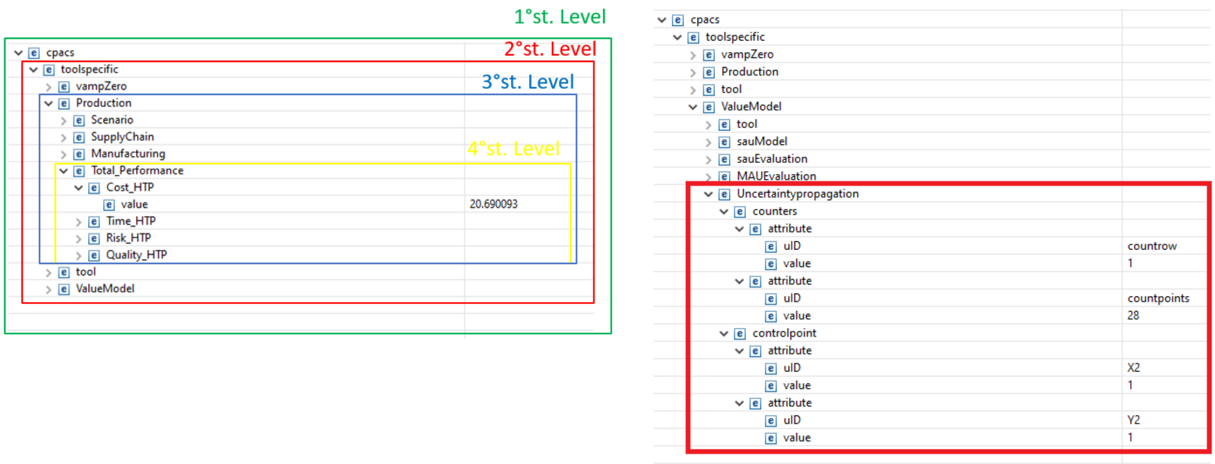


Figure 6 – CPACS having Information about Uncertainty Propagation Analyses

The workflow used to run the three uncertainty case studies is instead reported in Figure 7. A Design of Experiment (DOE) is set up to analyze all the combinations in terms of weights and/or functions depending on the case study executed. The value model tool is used to estimate the *value* for each combination while UPinSMA is used to perform the uncertainty propagation analysis and store the information needed to identify the robust and flexible solutions.

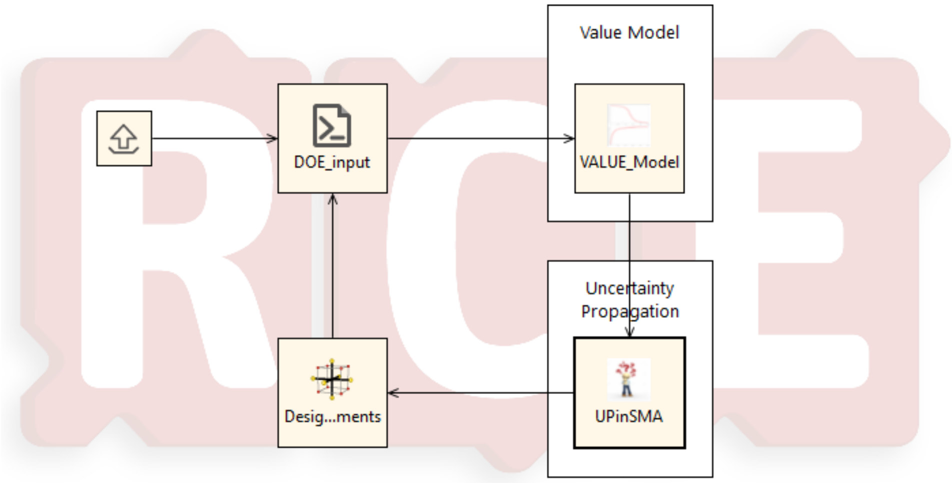


Figure 7 – Workflow to execute Uncertainty Propagation Analyses

In particular, the inputs needed by the UPinSMA are the number of samples (points) to consider for the uncertainty analysis and the number of different combinations. The evaluation of the value per each point and combination, that is the output of the UPinSMA tool, is allocated in the Value Table as shown in Figure 8.

	DOE_run1	DOE_run2	DOE_runN
Point_1	..	..	..
Point_2	..	..	..
Point_N	..	..	..
	REFRENCE PARETO FRONT	PARETO FRONT DOE RUN 2	PARETO FRONT DOE RUN N

Figure 8 – Value Table storing the value per each sample point (Point) and combination (DOE_run)

Once created the Value Table, each obtained Pareto-front is compared with the Reference Pareto-front and a specific binary matrix is created. The binary matrix contains binary digits 0 and 1 that respectively indicate if the point is or not on the Pareto-front. When the binary matrix is completed, then probability that the point is on the Pareto-front is estimated considering how many 1 are on each row of the binary matrix. This allows to easily identify the flexible solution being this solution the alternative with the highest probably to stay on the Pareto-front. Instead, to estimate the robust solution, the difference between the maximum and minimum value is estimated per each combination per each solution.

4. Application case

The approach and technologies introduced in the previous section are applied to an aeronautical case study aiming at identifying the robust and flexible solutions while considering the design and production of a specific aircraft component that is the horizontal tail plane (HTP). In the following sections, first the assumptions generating the alternatives populating the value-driven Reference Pareto-front are introduced. Then, the main results of the three case studies related to the uncertainty propagation are reported.

4.1 Value-driven Reference Pareto-front

The *value* of the solutions populating the Reference Pareto-front depends on the aggregated attributes and thus on the production risk, cost, quality, time and fuel consumption. These attributes, in turn, depend on other choices. In particular, the production cost, time, quality and risk vary based on the enterprises selected to produce the HTP. In fact, the different skills and geographic locations of enterprises as well as the quantity that enterprises have to produce lead to different fixed, transportation and manufacturing performance of the supply chain. On the other side, the different choice of materials and processes characterizing the main HTP components influence the HTP performance (like mass and drag) and consequently the aircraft fuel mass consumption. To generate the alternatives of the value-driven Reference Pareto-front, three materials, processes and enterprises can be selected for each of the main HTP components, as reported in Figure 9. Combining all the choices, 6765 alternatives can be generated. However, only 1891 are feasible solutions because of some manufacturing and production constraints.

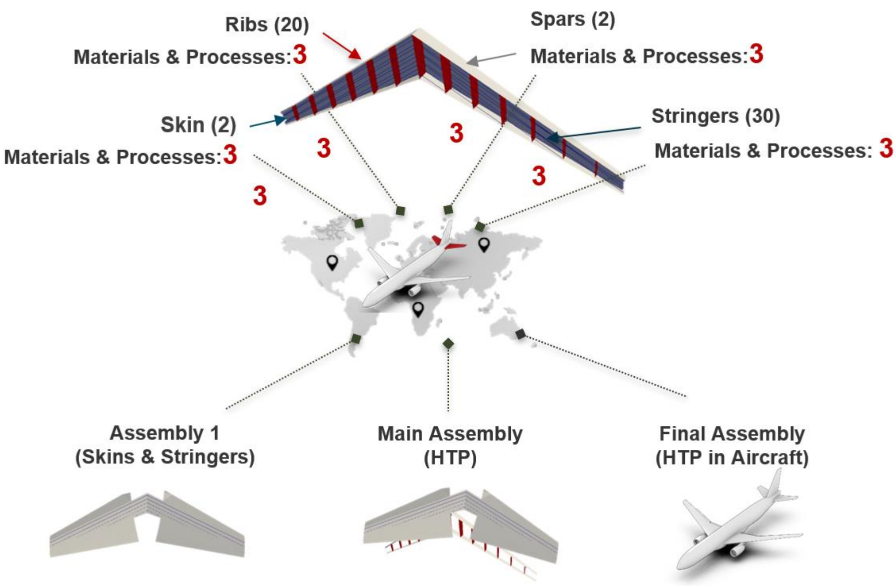


Figure 9 – Aeronautical Application Case Assumptions

Once assigned the same weights and the linear utility functions shown in Figure 4, the value-driven Reference Pareto-front of Figure 10 is obtained. It includes the optimal analytical solutions. Among the six alternatives populating the value-driven Reference Pareto-front, the best solution that is the solution with highest value, is solution 23. These solutions refer simultaneously to the supply chain and aircraft performance being these parameters aggregated in the value. Details in terms of supply chain and HTP configurations characterizing the solutions of the Reference Pareto-front are shown in Figure 11 and quickly discussed here-after. The same colors of icons mean that solutions share the same information in terms of materials and/or processes and/or supply chains.

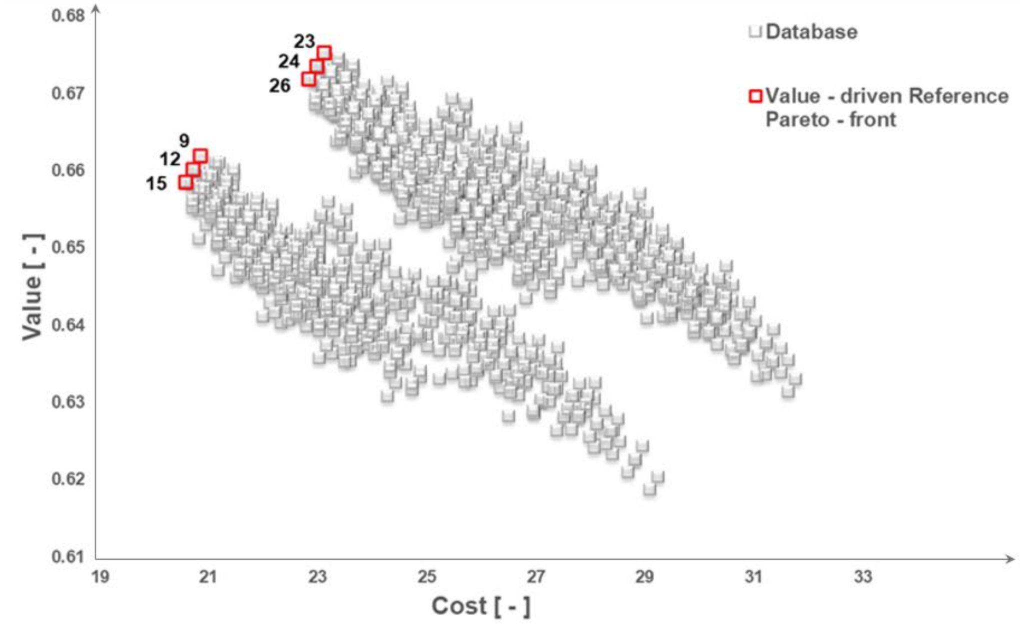


Figure 10 – Value-driven Reference Pareto-front

The alternatives 9,12 and 15 are characterized by the same HTP configuration. For this reason, these solutions have the same fuel mass. However, the value associated to them is different because of the supply chain performance. In particular, solutions 9 and 12 have a lower *value* since some of the HTP components are outsourced to suppliers and not produced in house. This leads to higher risk and lower quality with a consequent decrease of *value*. The alternative 23, 24 and 26 instead are characterized by the same HTP configuration which differ from the one related to the other three solutions for the materials and processes used for the ribs. This HTP is made only by composite. This difference implies a lower fuel mass and therefore a higher *value*. In addition, the competences of the enterprises involved in the manufacturing of these HTP configurations are high. As consequence, the *value* of these solutions is higher than the *value* of others. Finally, among them, solution 23 has the highest *value* since mostly produced in house.

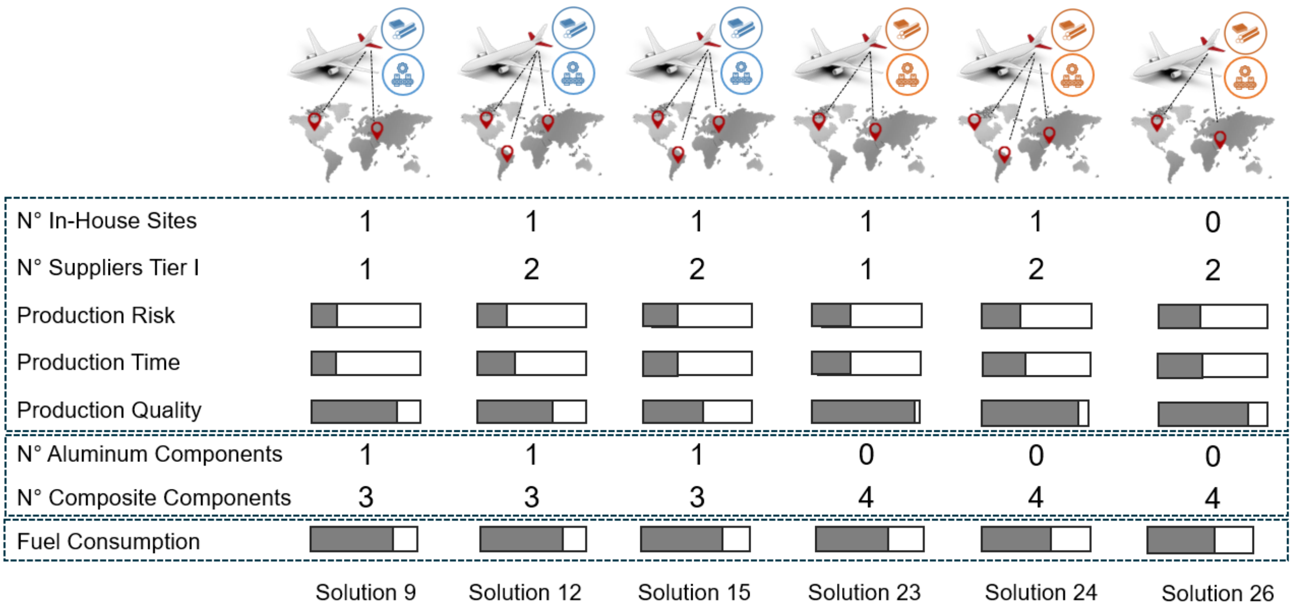
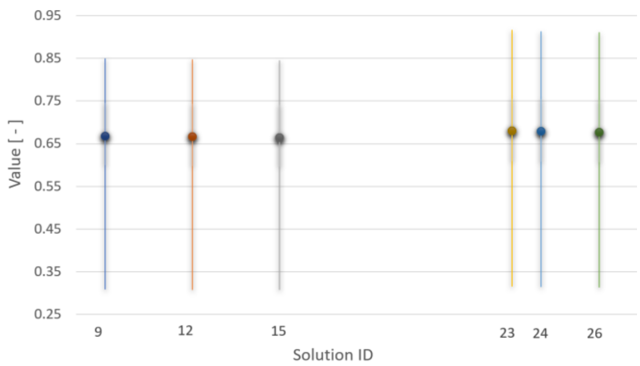


Figure 11 – Details of the Alternatives populating the Value-driven Reference Pareto-front

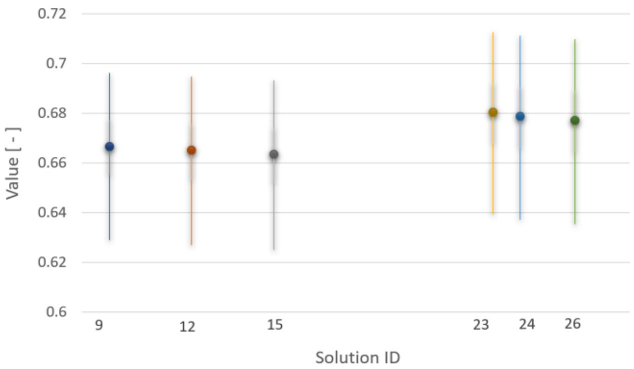
In the next section, uncertainty is introduced in the value model theory to analyze the behavior of these solutions in terms of value when changing the weights, utility functions or both.

4.2 Uncertainty Propagation Case Studies: Robust and Flexible Solutions Identification

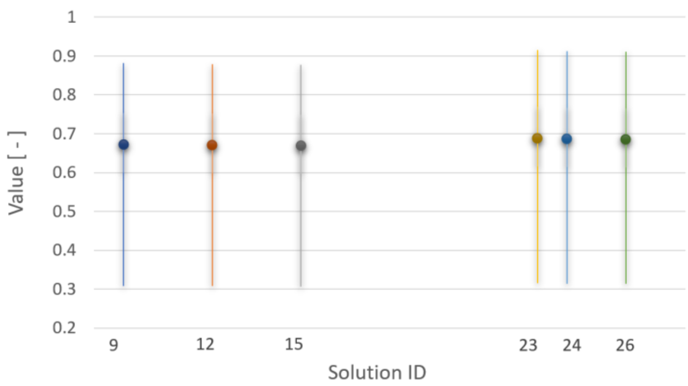
Uncertainty is propagated to the *value* through the weights, utility functions or both by leveraging the LHS method, as explained in Section 2. The results of the three case studies are reported in Figure 12. In particular, in this Figure, the *value* oscillation of the solutions populating the Reference Pareto-front is shown. The *value* oscillation represents the range in which the *value* of the specific solution can vary. Lower is the oscillation, better is the solution for decision-makers since its variability with the scenario is low.



a) Alternative 12 as Robust Solution



b) Alternative 9 as Robust Solution



c) Alternative 15 as Robust Solution

Figure 12 – Value Oscillations: Robust Solutions Identification: a) Case Study I, b) Case Study II, c) Case Study III

In the Case Study I, in which a uniform distribution is used to propagate uncertainty on the value through the weights, the alternative minimizing the value oscillation is solution 12. Instead, in the Case Study II, in which a uniform distribution is used to propagate uncertainty on the *value* through utility functions, the alternative 9 is the robust solution. Finally, in the Case Study III, in which a uniform distribution is used to propagate uncertainty on the *value* through the weights and utility functions, the alternative 15 is identified as robust solution. In addition, the gray boxes in Figure 12 highlights the 0.25 and 0.75 percentiles for each alternative. They show where most of solutions are located in terms of *value* when considering all the combinations per each case study. Indeed, the variation in *value* for the alternatives 12, 9 and 15 are the smallest in each case study. The same results, more in details, are reported in Table 2. Indeed, the minimum variation in terms of *value* is provided by the solutions 12, 9 and 15 respectively in the Case Study I, II and III.

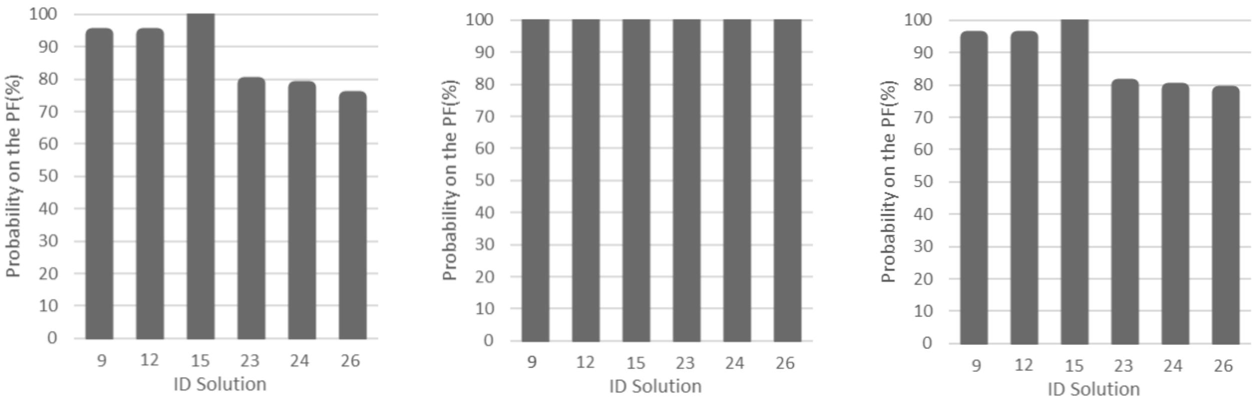
	Case Study	Solution ID					
		9	12	15	23	24	26
ΔValue	I	0.563	**0.562**	0.567	0.630	0.628	0.626
	II	**0.067**	0.068	0.068	0.073	0.074	0.074
	III	0.570	0.569	**0.568**	0.598	0.596	0.594

Table 2 – Numerical Value Oscillation of the Refence Pareto-front solutions for the three Cases Studies

The Table also highlights how the solutions with highest *value* in the Reference Pareto-front, thus the alternatives 23, 24 and 26 have the highest *value* oscillation in the case studies. As previously explained, these solutions refer to HTP configuration mainly made by composite. Then, depending on the solution, this HTP is more or less produced in house or outsourced to suppliers. Instead, the solutions 9,12,15 also have some components in aluminum and again, depending on the specific solution, this HTP is mainly made in house or outsourced. In any case, considering these two groups of solutions (9,12,15 and 23,24,25), one of the trade-off study that decision-makers can perform is for example the following one:

- Invest for a quite expensive HTP configuration, produced in house or outsourced, that provides the highest value in a specific scenario (the reference case – no prioritization of attributes) but whose value change a lot depending on the scenario analyzed (solutions 23,24,26).
- Invest for a less expensive HTP configuration, produced in house or outsourced, that provides not the highest value in a specific scenario (the reference case – no prioritization of attributes) but whose value does not change a lot in relation with the analyzed scenario (solutions 9,12,15)

In addition, as explained in Section 2, the probably of the Reference Pareto-front solutions to stay on the Pareto-front is also estimated for each case study to identify the flexible solution. The results of this investigations are reported in Figure 13. In the Case Study I, Solution 15 is always on the Pareto-front. In the Case Study II, all the alternatives are flexible solutions. In the Case Study III, solution 15 is again the flexible solution.



a) Alternative 15 as Flexible Solution

b) All Alternatives as Flexible Solutions

c) Alternative 15 as Flexible Solution

Figure 13 – Probability of Solutions to be on the Pareto-front: Flexible Solutions Identification: a) Case Study I, b) Case Study II, c) Case Study III

The alternative 15 is therefore an optimal solution in all the case studies analyzed. This solution has the lowest *value* in the value-driven Reference Pareto-front (Figure 10). However, as previously discussed, it is robust when changing both the utility functions and weights (Figure 12). It means that this solution doesn´t change drastically the *value* when changing the scenario of interest (weight) for decision-makers, neither their expectations (utility function). In addition, this alternative is always on the Pareto-front in all the case studies analyzed, meaning that this solution is always among the solutions optimizing the fuel consumption, production risk, time and quality. From the decision-makers perspective, new trade-off studies can be performed to increase the awareness in taking decisions. For instance, they might invest in a solution which has the highest *value* in a specific scenario (solution 23 in the Reference Pareto-front) but whose probability to remain optimal strongly depends on the analyzed case. On the other side, instead, they might invest in a solution which has a lower value but also cost and remains on the Pareto-front in any scenario.

Concluding, the three case studies of this aeronautical application case highlights the importance of including uncertainty in the value-driven decision-making. It increases the decision-makers ‘awareness when performing trade-off studies related to uncertain scenarios and/or expectations showing, for instance, that the best solution in a specific scenario might not be the robust solution.

5. Conclusions and Future Developments

Value model theories are usually used to identify the best solution when multiple criteria have to be considered at the same time. In this paper, the MAU theory is applied for the identification of the robust and flexible solutions when considering the design, manufacturing and supply chain of a specific aircraft component that is the horizontal tail plane. To achieve this objective, first a value-driven Reference Pareto-front is generated while assuming the same weights and linear utility functions for all the attributes. Then, three case studies are analyzed in which a uniform distribution is used to propagate uncertainty on the value first through the weights, the utility functions and both of them. Therefore, hundreds of weight combinations and utility functions slopes are explored and the behavior of the solutions identified on the Reference Pareto-front investigated. The robust and flexible solutions are identified, respectively, as the solution minimizing the value oscillations and the solution having the high probability to be on Pareto-front, thus be optimal in all the evaluated combinations of each case study. The approach used to perform these investigations are explained in Section 2, instead the technologies used to run these analysis in Section 3. The aeronautical application case, presented in Section 4, highlights the importance of including decision-makers ‘expectations and uncertainty in it. The solution with the lowest value in the value-driven Reference Pareto-front, solution 15, has the lowest value oscillation when including uncertainty in the weights and functions. In addition, this solution is always on the Pareto-front in all the case studies analyzed. From decision-makers perspective, this results provides even more insights on the decisions to take. For instance, they might invest in a solution which has the highest value in a specific scenario (solution 23 in the Reference Pareto-front) whose value drastically change in others. On the other side, they might decide to invest in a solution which has the lowest value in a scenario, but remains robust and optimal in all the others. These two solutions correspond to two different HTP configuration and supply chains. Invest in solution 23 means to invest in a HTP configuration made in composite mostly produced in house. Instead, solution 15 is a HTP configuration mainly made by aluminum and outsourced to suppliers. In addition, the application case shows that the best solution in a specific scenario, i.e. the solution with highest value in the Reference Pareto-front (solution 23) might not be the robust and flexible solution. This information increases decision-makers ‘awareness when taking decisions.

Concluding, the methodology is useful to provide more insights and information to decision-makers before investing for a solution. The case study proposed here it´s however a simplification study and uncertainty has been added only on one single utility functions (time). Uncertainty might be added in more functions to investigate the behavior of solutions in other case studies. In addition, the reference Pareto-front has been obtained by considering same weights and linear utility functions for all the attributes. Therefore, the behavior of analytical optimal solutions has been investigated in the case studies. Further analysis will be done to investigate the differences between the Reference Pareto-front and the Pareto-front obtained by considering the utility functions provided by stakeholders for all the attributes [7]. In this paper, the choice of having the Pareto-front not influenced by decision-makers as reference has been done to simplify the validation of the results.

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7. Copyright Statement

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References

[1] ACARE, “Flightpath 2050. Europe’s Vision for Aviation; Maintaining Global Leadership and Serving Society’s Needs; Report of the High-Level Group on Aviation Research,” Publications Office of the European Union, Luxembourg; ISBN 978-92-79-19724-6., 2011.

[2] L. Boggero, J. Bussemaker, G. Donelli, F. Torrigiani and B. Nagel, “Processes, Methods and Tools supporting the development of aeronautical systems,” in *ICAS Conference*, Florence, 2024.

[3] D. D. Walden, G. J. Roedler and K. Forsberg, INCOSE system engineering handbook version 4, INCOSE International Symposium, 2015.

[4] N. M. Gokhan, K. L. Needy, B. A. Norman and B. Hunsaker, “Benefits of Incorporating Supply Chain Decisions into the Product Deisgn via Design for Supply Chain,” in *IIE Annual Conference Proceedings (p.390)*, Institute of Industrial and Systems Engineering (IISE), 2008.

[5] O. Labbi, L. Ouzizi and M. Douimi, “Simultaneous design of a product and its supply chain integrating reverse logistic operations: An optimization model.,” in *Xème Conférence Internationale: Conception et Production Intégrées*, 2015.

[6] T. Wu and P. O'Grad, “A concurrent engineering approach to design for assembly,” *Concurrent Engineering,* pp. 231-243, 1999.

[7] G. Donelli, P. D. Ciampa, J. M. Mello, F. I. Odaguil, A. P. Cuco and T. Van den Laan, “A Value-driven Concurrent Approach for Aircraft Design-Manufacturing-Supply Chain.,” *Production & Manufacturing Research,* vol. 11, no. 1, p. 2279709, 2023.

[8] P. D. Collopy and P. M. Hollingsworth, “Value-driven design.,” *Journal of aircraft,* vol. 48, no. 3, pp. 749-759, 2011.

[9] A. M. Ross, D. H. Rhodes and M. E. Fitzgerald, "Interactive value model trading for resilient systems decisions.," *Procedia Computer Science,* vol. 44, pp. 639-648., 2005.

[10] M. Bertoni, A. Bertoni and O. Isaksson, "Evoke: A value-driven concept selection method for early system design," *Journal of Systems Science and Systems Engineering,* pp. 46-77, 2018.

[11] M. Panarotto, O. Isaksson, I. Habbassi and N. Cornu, “Value-Based development connecting engineering and business: A case on electric space propulsion.,” *IEEE Transactions on engineering management.,* vol. 69, no. 4, pp. 1650-1663, 2020.

[12] A. M. Ross, D. E. Hastings, J. M. Warmkessel and N. P. Diller, "Multi-attribute tradespace exploration as front end for effective space system design," *Journal of Spacecraft and Rockets,* pp. 20-28, 2004.

[13] G. Donelli, J. M. Mello, F. I. Odaguil, T. Van der Laan, L. Boggero and B. Nagel, "Value-driven Tradespace Exploration for Aircraft Design, Manufacturing and Supply Chain," in *ICAS 2024*, Florence, 2024.

[14] G. Donelli, L. Boggero and B. Nagel, “Concurrent Value-Driven Decision-Making Process for the Aircraft, Supply Chain and Manufacturing Design,” *MDPI Systems,* vol. 11, no. 12, p. 578, 2023.

[15] A. Ross and D. Rhodes, “Value-Driven Tradespace Exploration ofr System Design, Lecture 5: Basics of Applied Utility Theory,” System Engineering Advancement Research Initiative (SEAri), MIT, 2010.

[16] M. D. McKay, W. J. Conover and R. J. Beckman, “A comparison of three methods for selecting values of inputs variables in the analysis of output from a computer code,” 1979.

[17] DLR, "Official RCE Website," German Aerospace Center, 20 07 2022. [Online]. Available: https://rcenvironment.de/. [Accessed 23 10 2020].

[18] G. Donelli, P. D. Ciampa, T. Lefebvre, N. Bartoli, J. G. Mello, F. I. Odaguil and T. van der Laan, “Value-driven Model-Based Optimization coupling Design-Manufacturing-Supply Chain in the Early Stages of Aircraft Development: Strategy and Preliminary Results,” in *ICAS Conference*, Chicago, 2022.

[19] DLR, "Official CPACS Webpage," 20 07 2022. [Online]. Available: http://cpacs.de. [Accessed 23 10 2020].

[20] G. Donelli, J. M. Mello, F. Odaguil, T. Lefebvre , N. Bartoli, T. van der Laan, L. Boggero and B. Nagel, "Value-driven Systems Engineering Approach addressing Manufacturing, Supply-chain and Aircraft Design in the Decision-Making Process," in *INCOSE*, Honolulu, 2023.