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Value-driven Model-Based Optimization coupling Design-Manufacturing-Supply Chain in the Early Stages of Aircraft Development: Strategy and Preliminary Results

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A value-driven model-based approach concurrently coupling design, manufacturing and supply chain in the early development stage of aircraft design has been developed within the European project AGILE4.0. The benefits of using this methodology have been highlighted by the aeronautical application case focused on the design, manufacturing and supply chain of an horizontal tail plane. Finding a Pareto-front simultaneously optimizing the design, manufacturing and supply chain domains is the next challenge to face. The research activity proposed in this paper represents the first step of this ambitious goal. The objective is to identify the optimization strategy to use for the global optimization campaign by exploring, first, simple and representative Multidisciplinary Design and Optimization (MDO) problems related to the supply chain domain. In the first MDO problem, a 4-objective optimization is executed and then the optimized attributes are aggregated in a single measure named *value*. In the second MDO problem instead, attributes are first aggregated in a value and then a bi-objective value-cost optimization is executed. Thus, two optimization strategies are investigated, but both lead to the value-cost Pareto-front investigation. The application case addressed in this research activity provides interesting insights for the value-driven

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optimization strategy to use for future-complex optimization problems involving design, manufacturing and supply chain domains.

Nomenclature

CPACS	=	Common Parametric Aircraft Configuration Schema
HTP	=	Horizontal Tail Plane
MBSE	=	Model Based Systems Engineering
MDO	=	Multidisciplinary Design Analysis Optimization
MfG	=	Manufacturing
OAD	=	Overall Aircraft Design
OEM	=	Original Equipment Manufacturers
SC	=	Supply Chain
TLAR	=	Top Level Aircraft Requirements
XDSM	=	eXtended Design Structure Matrix

I. Introduction

The top-level aircraft requirements (TLARs) historically lead the early phase of aircraft design with the objective to search for aircraft configurations with optimized performance. In the last decade, however, the European Commission introduced the Flightpath 2050, defining new challenges for the design of future innovative, sustainable and circular aircraft configurations. The objective of the sustainable and circular aviation is to reduce the environmental impact in terms of fuel consumption, waste and emissions associated with all the aeronautical system activities and operations. Hence, the necessity to extend the branches of the aeronautical research to the entire aircraft life-cycle, from the design to the production, to the waste disposal after the end of the system activity. The challenge is to account for these new requirements in the early design phase to take strategic decisions that would optimize the entire aircraft life-cycle.

In this frame, the European funded H2020 project AGILE 4.0 [1], follow-up of the AGILE project [2], led by DLR, aims to create a digital development of the systems throughout the entire life-cycle by leveraging Multidisciplinary Design Optimization (MDO) methods and Model Based Systems Engineering (MBSE) technologies [3]. Within this project, a value-driven model-based approach concurrently coupling design, manufacturing and supply chain in the early stage of aircraft development has been already developed [4]. This three-dimensional approach, applied to an aeronautical system component, highlights the advantages of including manufacturing and supply chain decisions in the early design stage. Furthermore, the value model theory, adopted as key enabler of the concurrent coupling of multi-domains, allows to quantify and simplify the multi-attribute decision making process [5]. Thus, a value-cost solution tradespace is generated by the value-driven three-dimensional approach.

The new challenge is to address an optimization design campaign aiming at finding the global optimum simultaneously accounting for design, manufacturing and supply chain variables. In this context, the research activity presented in this paper aims at identifying the best optimization strategy, in terms of computational time and cost, to use for this optimization campaign by addressing simplified, but representative, MDO problems. Hence, two optimization strategies are investigated focusing on the supply chain domain. Based on the same design variables, both MDO problems lead to the value-cost Pareto-front. However, the way through which the value is estimated differentiate the optimization strategies. In fact, the value aggregates multiple criteria, also called attributes, in a single measure. In one MDO study, attributes are first optimized and then aggregated in a value for the value-cost Pareto-front investigation. In the other case, attributes are first aggregated in a value and then a bi-objective optimization is executed to achieve the value-cost Pareto-front. Both optimization strategies are applied to a specific horizontal tail plane configuration. Preliminary results provide interesting insights on the computational advantages in using one or another approach.

Nevertheless, before introducing the MDO problems, the MBSE technologies adopted for system architecting modelling are introduced. In fact, the system architecting is identified as the link between the upstream MBSE modelling activities (e.g. modeling of system requirements) and the downstream MDO formulation and execution activities. Thus, having a complete overview of the architectures that can be generated by varying the design, manufacturing and supply chain decisions support the comprehension of the MDO problems that can be addressed.

An overview of the complex architectures that can be generated and optimized in the MDO system is provided in Section II. Instead, details of the value-driven MDO problem formulation in Section III. In the same section, the methods and tools used to implement the MDO process are addressed as well. Afterwards, Section IV describes the preliminary results obtained from the application of the optimization strategies to a specific horizontal tail plane configuration. Conclusions and possible future developments are finally provided in Section V.

II. MBSE Framework supporting the concurrent coupling of supply chain, manufacturing and aircraft design: focus on the system architecting

The MBSE framework developed within the European project AGILE 4.0 and showed in Figure 1 supports the development of complex aeronautical systems, from the modelling of stakeholders, needs and requirements to the MDO exploration, by generating multiple system architectures. In this context, the MBSE framework is adopted to support the modelling of the horizontal tail plan, manufacturing and supply chain systems. Details on how to leverage the MBSE framework for the modelling of stakeholders, needs and requirements with respect to these three systems have been already provided in [6]. Here after, instead, the focus is on the system architecting modelling. It aims to generate multiple configuration of systems characterized, for instance, by different components, materials or enterprises. The scope is to provide the reader the full comprehension of the architectures that can be generated by using the concurrent three-dimensional approach and that might be later optimized in the MDO system [7]. In fact, the system architecting modelling represents the link between the upstream system engineering modelling and the downstream MDO activities.

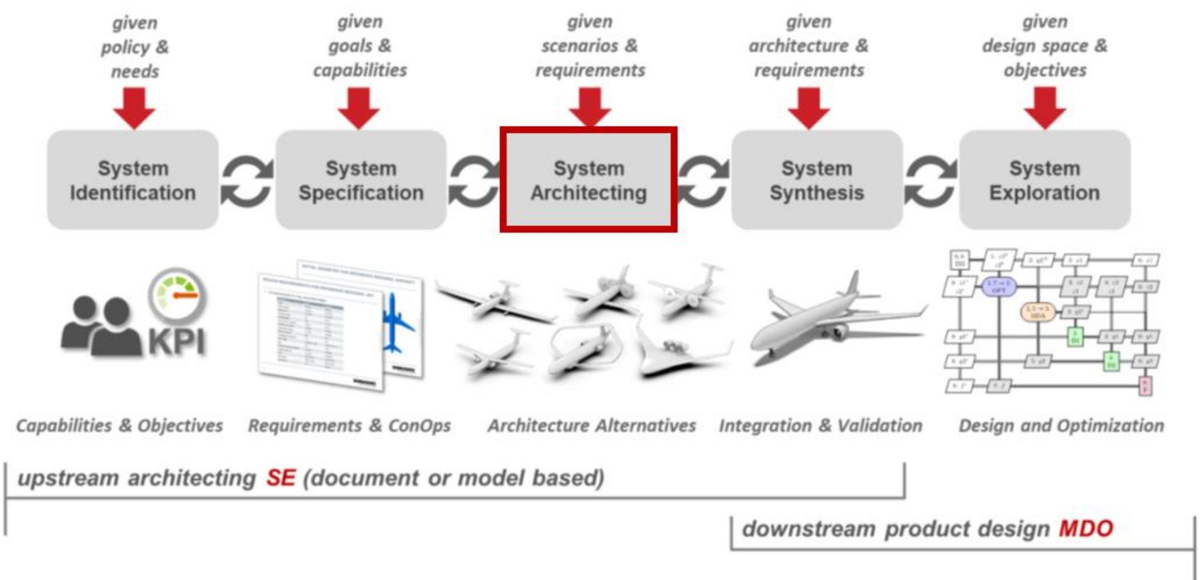


Figure 1 – Model-based System Engineering (MBSE) Framework supporting the development of complex aeronautical systems (adapted from [3]).

The system architecture is the combination of the allocation of system functions (e.g. *to provide lift*) to system components (e.g. *wing*) and the relationships among components [8]. The system architecture modelling starts with the collection of boundary functions, derived from functional requirements, for each system. In the problem under analysis, one boundary function has been identified for each system. Thus, the horizontal tail plan system has to *handle the longitudinal flight*, the manufacturing system has to *manufacture the horizontal tail plane*, while the supply chain system has to *perform manufacturing processes*. These boundaries functions already highlight the relationship between systems. The horizontal tail plane system requires the manufacturing system for its design. Instead, the manufacturing system needs the supply chain system for its execution. This allocation of functions and systems, schematically represented in Figure 2, defines the multi-systems architecture coupling the horizontal tail plane, manufacturing and supply chain systems.

The key aspect of this architecture modelling is the translation of an induced function of a system in the boundary function of the other one. For example, the horizontal tail plane (HTP) system has to handle the longitudinal flight (boundary function of HTP system), but it needs to be manufactured (induced function of HTP system, boundary function of manufacturing system). Same applies for manufacturing and supply chain systems.

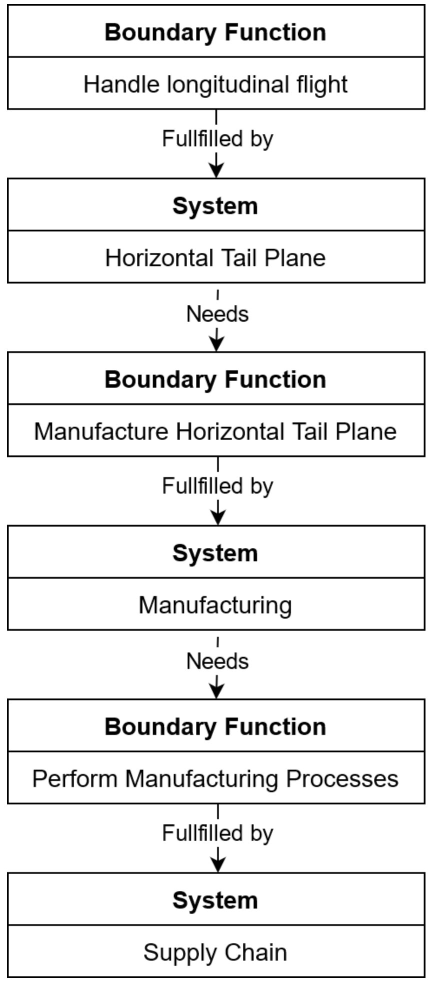


Figure 2 – Multi-systems architecture coupling horizontal tail plane, manufacturing and supply chain.

The mappings *functions – systems* applied at the systems level are also valid at the system components level. Thus, the HTP components, i.e. spars, stringers, ribs and skins perform other functions to assure that the HTP fulfills its boundary function. For instance, the skins maintain the aerodynamic shape to produce the lift needed to handle the longitudinal flight. For the manufacturing system, the manufacturing and assembly processes is defined as main components. Thus, the machining, the hand-lay-up, the riveting can be used to manufacture and assembly the HTP components. These manufacturing processes are then performed by the enterprises (OEM and suppliers) characterizing the supply chain to guarantee the production of the HTP. The main features of the system architecting are summarized in Table 1.

Table 1 – System Architecting: definition of boundary functions, systems and their respectively components.

Boundary Function	**System**	**Components**
Handle longitudinal flight	Horizontal Tail Plane	Spars, Stringers, Ribs, Skins
Manufacture the Horizontal Tail Plane	Manufacturing	Manufacturing and Assembly Processes
Produce the Horizontal Tail Plane	Supply Chain	OEM and Suppliers

The modelling of the architecture instead has been realized by using ADORE, the DLR tool supporting the MBSE framework for the system architecting [9]. A simplified but representative system architecting modelling coupling the three systems of HTP, manufacturing and supply chain is shown in Figure 3. In this figure, it is possible to recognize the boundary functions, the systems and components previously described.

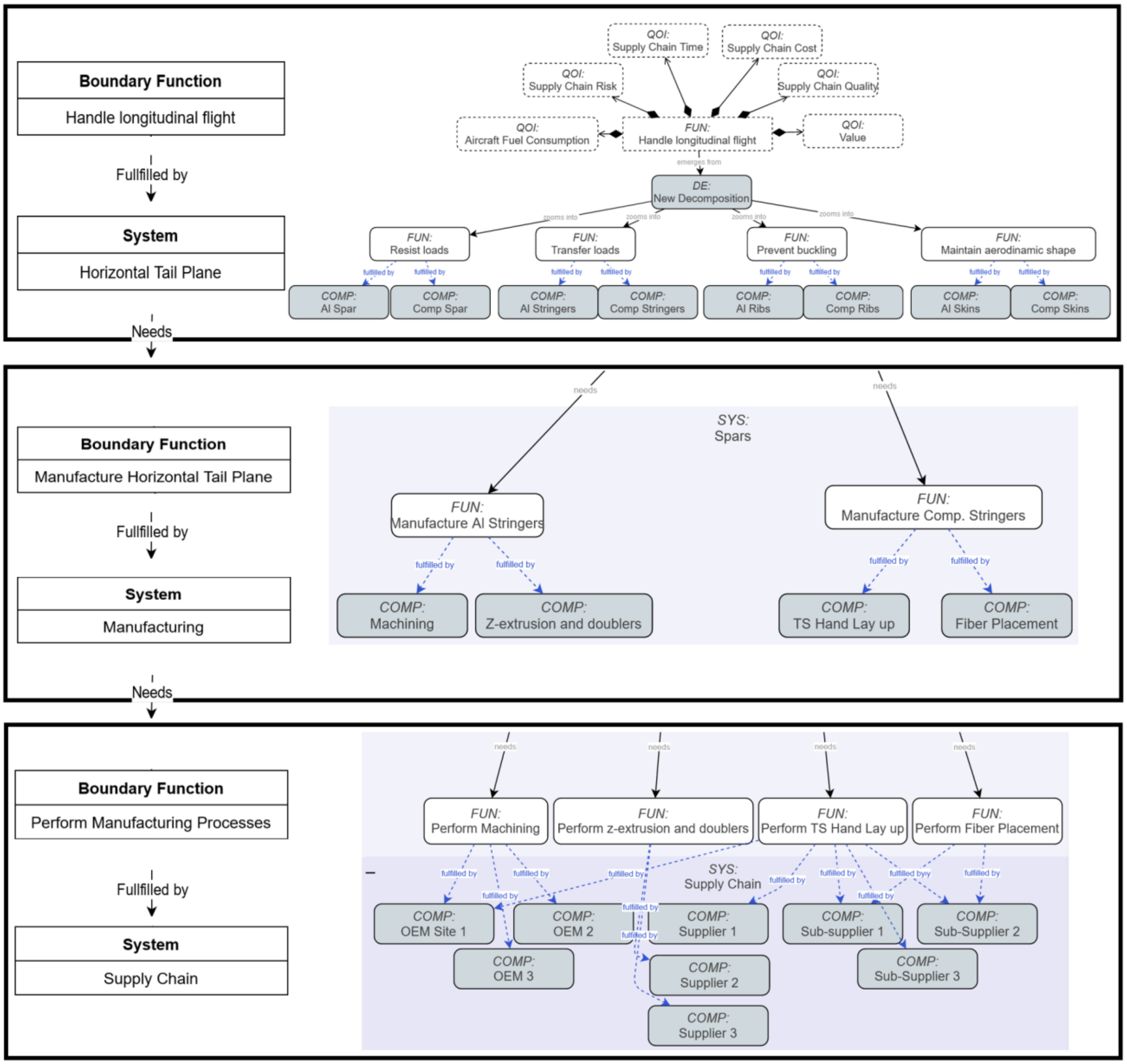


Figure 3 – Multi-systems architecture modelling in ADORE coupling the horizontal tail plane, manufacturing and supply chain systems.

From the systems architecting modelling, multiple architectures can be generated based on decisions related to the choice of:

- materials for each HTP component
- manufacturing and assembly processes for each material (and so for each HTP component)
- production quantity performed by each OEM and supplier site
- OEM and supplier site performing assembly processes

Thus, many architectures can be generated given the large number of variables and decisions that can be taken. Each of these architectures can be optimized once the optimization parameters are defined. This can be done in

ADORE, by assigning the quantities of interest that can be used in the MDO problems as design variables, constraints or objectives. In Figure 3, multiple quantities of interest are shown as example. In the next section, some of these quantities of interest are used as objectives of the MDO problems. However, simplified MDO studies are investigated since the main objective of this research activity is to identify the best optimization strategy to be used later for even more complex architecture optimization activities. Therefore, in the next section are analyzed architectures that differ each other only for the production quantity performed by each OEM and supplier site as well as for the choice of OEM and supplier site performing assembly processes. All the other decisions (materials, manufacturing and assembly processes) are assumed as frozen.

III. Value-driven optimization strategies definition and MDO process implementation

The system architecting bridges the upstream MBSE modelling and the downstream MDO activities. It is a powerful mean that simplifies the set-up of the MDO process providing directly the architecture models to analyze in the MDO system. As described in the previous section, complex architectures can be investigated if considering all the variables related to the HTP, manufacturing and supply chain systems. However, only simplified architectures are optimized in the following MDO problems. In fact, the main objective of this research activity is to find the best optimization strategy to use later for more complex MDO problems. Analyzing simplified architectures allows to perform multiple analyses quickly and efficiently. Particularly, the simplification assumes frozen the choices related to the design and manufacturing of the HTP, thus the materials, manufacturing and assembly processes that can be selected. The optimization is therefore related only to the supply chain system. Details on the definition of the optimization strategies and on the MDO process implementation are provided here-after.

A. MDO Value-driven problems definition

Two MDO problems, schematically represented in Figure 4 and Figure 5, are addressed in this research activity. They represent two different optimization strategies. Both lead to the value-cost Pareto-front, but they differ on how the value, aggregating multiple attributes in one measure, is estimated. The definition of the MDO value-driven problems relays on the identification of the main parameters characterizing an optimization problem. Therefore, the design variables, the objectives functions, the constraints and the algorithms of these MDO studies are described in details.

In both MDO problems, as also shown in Figure 4 and Figure 5, the optimization is focused on the supply chain domain. In this domain, the supply chain cost, time, quality and risk are estimated based on the individual characteristics of each OEM and supplier. Particularly, the supply chain performance parameters depend on the manufacturing and transportation contributions. The first one is mainly related to the production quantity performed by each company, the second one to the distance between the production and assembly sites. The production quantity performed by each OEM and supplier is the first design variable of the investigated MDO problems. Defined as a categorical variable, it indicates the number of components produced by each OEM and supplier site. The production quantity is assigned for each component of the HTP. Therefore, there is a production quantity for skin, stringers, spars and ribs. The second design variable is instead the location of the assembly site responsible for the assembly of some components of the HTP. It is defined as a flag. When it is equal to 1, it means that the selected OEM or supplier is an assembly site. The properties of the design variables characterizing these MDO problems are summarized in Table 2.

Table 2 – Design variables characterizing the value-driven MDO problems.

Design Variables	Type	Content	Meaning
Production Quantity	Categorical Variable	0.5	Half of total components
		1	Total components
Assembly Site	Categorical Variable	0	No assembly site
		1	Assembly site

Changing the production quantity allocated to each company of a supply chain automatically impacts the supply chain cost, risk, quality and time. In fact, a given company might have higher production cost than another, for instance. Consequently, the production of the same number of components lead to a different supply chain cost depending on the selected company. At the same way, the choice of the assembly site impacts the supply chain performance, particularly the transportation cost, time and risk. In fact, the HTP components are moved from the production sites, in which the manufacturing processes are performed, to the assembly sites, in which the assembly processes are executed among multiple components. The supply chain parameters vary depending on the distances between assembly sites and productions sites. Due to this dependency, the supply chain cost, time, risk and quality are chosen as objective functions of the first MDO problem, see Figure 4. This figure highlights the design variables of this optimization problem, thus the production quantity and the assembly site, as well as the 4-objective functions, i.e. the supply chain cost, time, quality and risk. However, instead of a four-objective Pareto-front, it ends with the value-cost Pareto-front investigation. The value therefore aggregates, in this case, the optimized attributes. Thus, first the optimization is executed, then the attributes are aggregated in the value. As results, the optimized value-cost solution tradespace is achieved. This is the first optimization strategy investigated in this research activity.

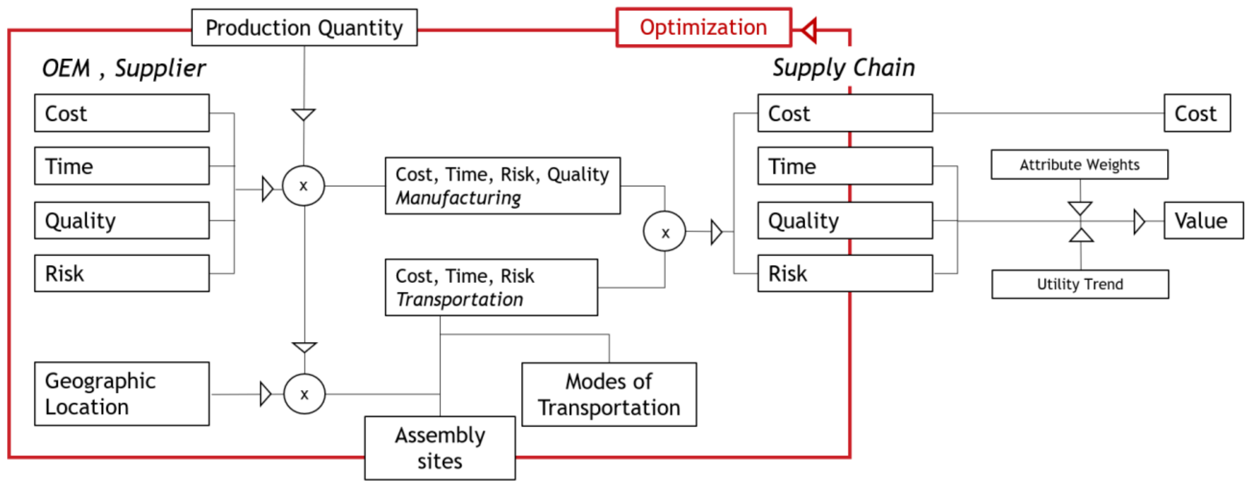


Figure 4 – First optimization strategy addressing a MDO problem having the production quantity and assembly site as design variables, the supply chain cost, time, quality and risk as objective functions. First the optimization is executed, then the optimized attributes are aggregated in a value to investigate the cost-value Pareto-front.

The second optimization strategy, related to the other MDO problem here analyzed, is instead schematically represented in Figure 5. As in the previous MDO problem, the production quantity and the assembly site are used as design variables. However, the objective functions are different. In this case, the attributes (i.e. the supply chain quality, risk and time) aggregated in the value are not individually optimized anymore. Instead, the value, which aggregates all the attributes, is optimized. Thus, a bi-objective optimization problem is executed and the value-cost Pareto front is obtained and investigated. So, with respect to the previous MDO problem, in this case, the attributes are first aggregated in a value and then the optimization is executed. This is the second optimization strategy adopted to achieve the optimized value-cost solution tradespace.

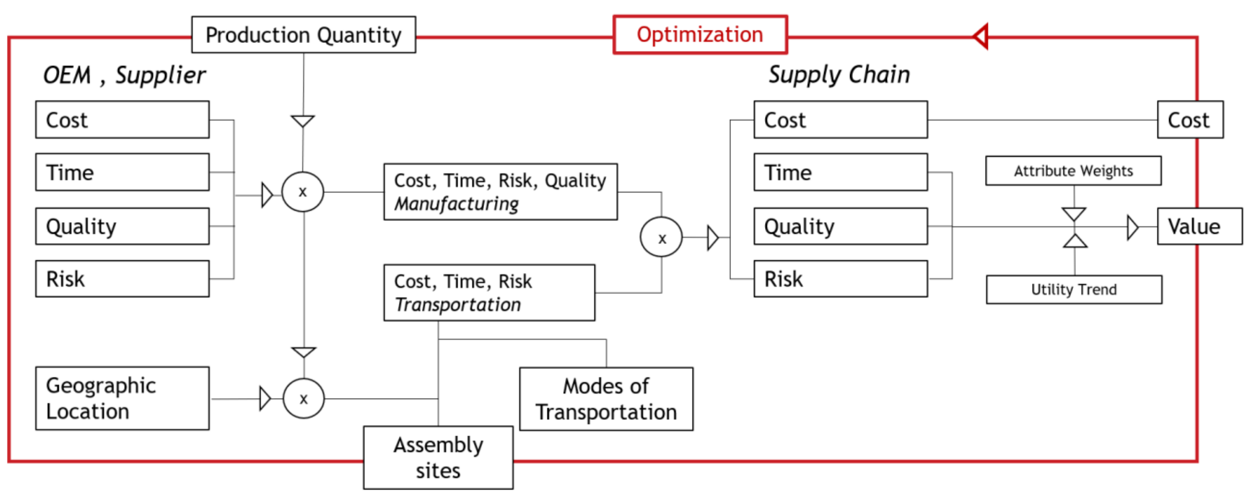


Figure 5 – Second optimization strategy addressing a MDO problem having the production quantity and assembly site as design variables, the supply chain cost and value as objective functions. First the attributes are aggregated in a value, then the optimization is executed to investigate the cost-value Pareto-front.

The main optimization characteristics of the already introduced value-driven MDO problems are summarized in Table 3. In both cases, the supply chain domain is optimized, constraints have not been applied and the value-cost Pareto-front is investigated. The main difference relays in the objective functions and thus in the way that the value is estimated, before or after the optimization execution. However, it is worth to underline, that the weights and utility functions needed to estimate the value are assumed to be equal in both MDO problems.

Table 3 – Value-driven MDO problems formulation focused on the supply chain (SC) domain: definition of design variables, constraints, objective functions and Pareto-front

Case Study	Domain	Design Variable	Constraints	Objective Functions	Pareto-front
1	SC	Production Quantity, Assembly Site	-	Minimize cost, time, risk Maximize quality	Value-Cost
2	SC	Production Quantity, Assembly Site	-	Minimize cost Maximize value	Value-Cost

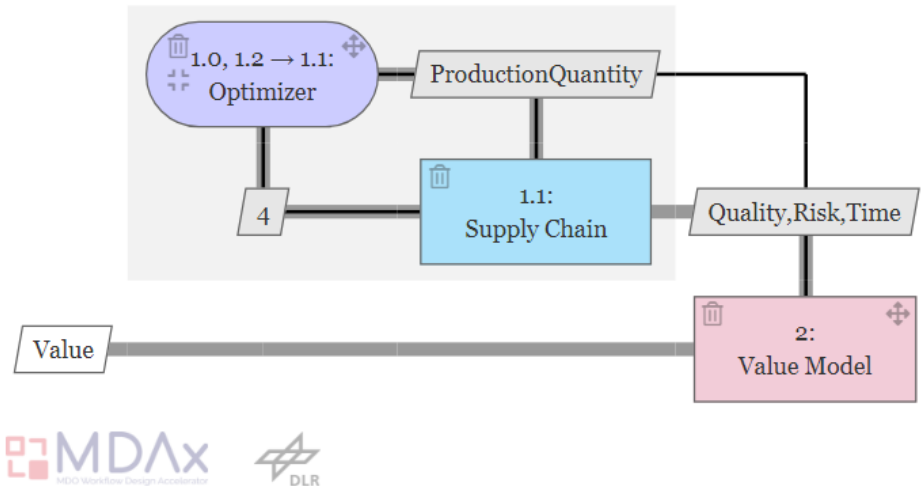
Regarding the optimization algorithm, both 4 objective and 2 objective case studies are solved using surrogate based optimizer. The proposed optimization algorithm is a constrained Bayesian optimizer where the expensive black boxes (objectives and constraints functions) are approximated by some surrogate models in order to reduce CPU time. The main idea of SEGOMOE (Super-Efficient Global Optimization using Mixture Of Experts), developed by ONERA, is to use some adaptive mixture of kriging based models to tackle high dimension problems. The initial version of SEGOMOE aimed at solving mono-objective problems involving an intermediate number of design variables (up to 100) and potentially constrained by both inequality and equality nonlinear constraints. Its competitiveness relies essentially on the use of a sequential enrichment strategy, performed on adaptive surrogate models. SEGOMOE fully described in [8] has been successful applied for different applications: aerodynamic shape optimization [10], nacelle optimization [9], overall aircraft configurations [11], as some industrial test case in collaboration with Bombardier [10].

Some recent developments have been made to consider highly non-linear constraints [11] or mixed integer variables [12]. The newest capability concerns multi-objective described in [12]From few initial points, an adaptive process is used to add some Pareto-optimal points chosen from an acquisition function that assigns a maximum value to the points having a high probability of improving our knowledge of the objectives and respecting the constraints in the probably optimal areas. Then, after some iterations, final surrogate models are trained on the enriched database and an evolutionary algorithm such as NSGA-II [13] is applied to obtain the Pareto front. Since only surrogate models are used, this usually expensive step is performed here at no additional cost. The challenge in the current case studies is the use of categorical variables in a multi-objective context.

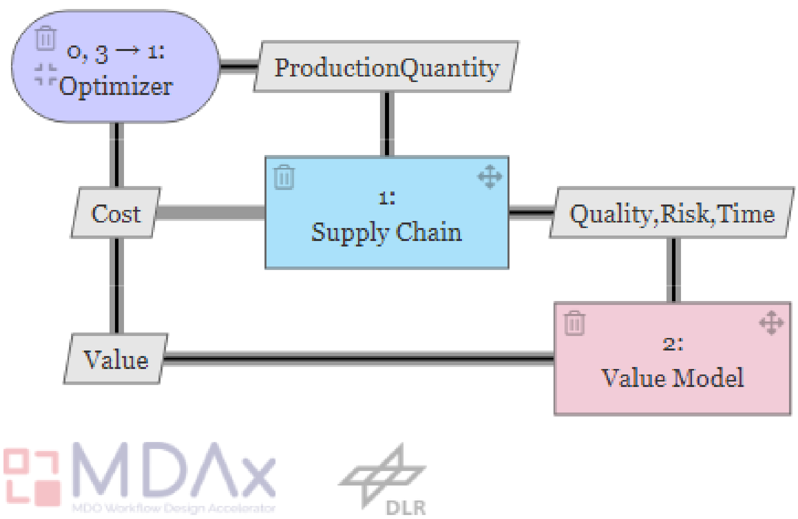
B. MDO Process implementation

The two optimization strategies previously described have been applied to a selected HTP configuration, as explained in the next section. However, to achieve some preliminary results, the value-driven MDO problems have been set-up and executed by using some tools and technologies, as described here-after.

The supply chain domain and the value model theory were already implemented in disciplinary codes able to automatically exchange information through CPACS [4]. The MDO process coupling the disciplinary codes in a single workflow has been automatically generated by the MDAO Workflow Design Accelerator, short MDAx [14]. It provides an intuitive workflow modelling environment using an expansion of the XDSM format [15]. The XDSM of both MDO problems are reported in Figure 6. The optimizer and the disciplinary codes are placed on the main diagonal, the inputs of each tool are represented vertically, the outputs horizontally.



a) First optimization strategy - XDSM 4-objective MDO workflow.



b) Second optimization strategy - XDSM 2-objective MDO workflow.

Figure 6 – XDSM MDO workflows obtained by using MDAx: a) XDSM 4-objective MDO workflow - the value is estimated and then the optimization is executed for the value-cost Pareto-front investigation; b) XDSM 2-objective MDO workflow - the optimization is executed and then the optimized attributes are aggregated in a value for the value-cost Pareto-front investigation.

Once set-up the MDO workflow, MDAx also provides the possibility to export the workflow configurations to be executed within the Remote Component Environment (RCE). In this platform, workflows made by tools belonging to different partners can be automatically executed through BRICS, provided by NLR partners [16]. However, before proceeding in this direction, it has been decided to execute the workflow step-by-step to test the optimizer, the disciplinary tools and to align the exchange of information among them. The execution flow, used to obtain preliminary results for both MDO problems, is illustrated in Figure 7.

Thus, a Design of Experiments (DOE), corresponding to the full enumeration of solutions, is created and executed for a total of 3136 points. In a second step, the database created is used as a black- box in order to apply the optimization algorithms. The approach enabled to both obtain the true Pareto front of the problem and to assess the capability of the optimizer to find it in a minimal amount of iterations. Preliminary results are reported in the next sections.

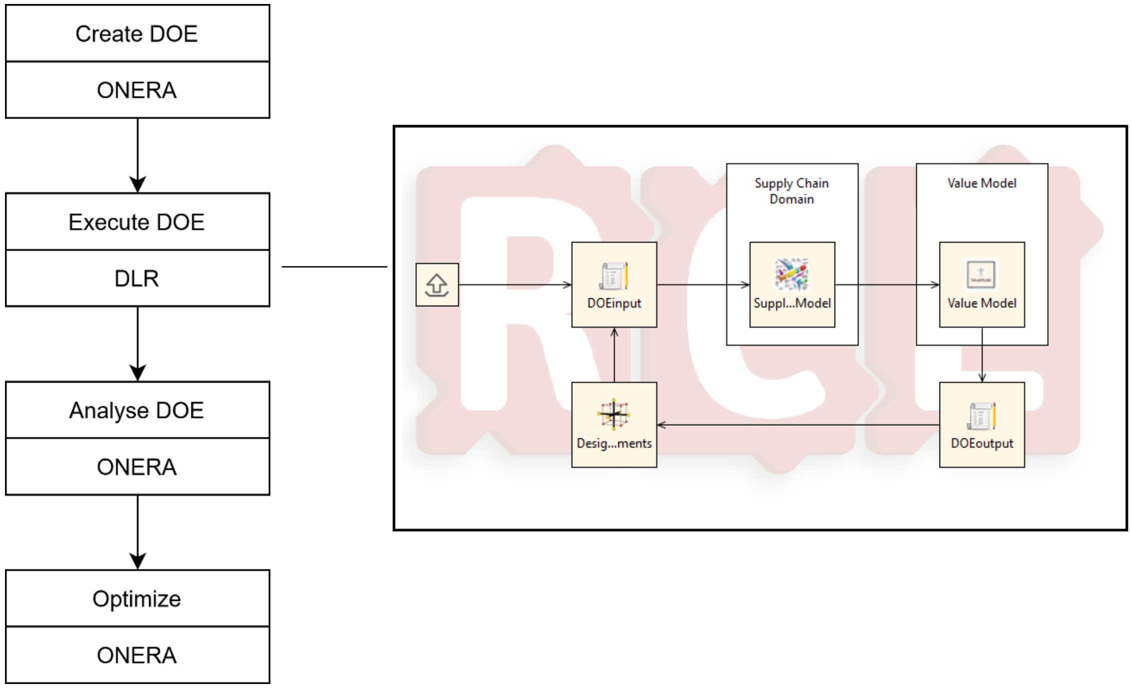


Figure 7 – Execution flow used to test the optimizer, the disciplinary tools and to align the exchange of information among them.

IV. Value-driven model-based MDAO problems application and preliminary results

The value-driven MDO problems described in the previous sections lead to two optimization strategies. In the first case, a four-objective optimization study is executed and then the optimized attributes are aggregated in a value, as shown in Figure 4. In the second case study instead, attributes are first aggregated in a value and then a bi-objective optimization study is performed, as illustrated in Figure 5. In both cases, the value-cost Pareto-front is investigated. Identify the advantages and differences between these two optimization strategies is important to define a guideline for the future complex optimization campaign aiming at searching for the global optimum accounting for design, manufacturing and supply chain variables. In this section, the preliminary results of the value-driven MDO problems are addressed for a specific HTP configuration, whose main characteristics in terms of materials and manufacturing processes, are reported in Table 4. In the same table, it is also specified the number of components characterizing the HTP.

Table 4 – Components and manufacturing properties of the HTP configuration analyzed in the value-driven MDO problems.

HTP components	N° Components	Materials & Processes
Skins	2	Sheet Metal Stretch Formed
Stringers	30	Metal by Z-Extrusion
Spars	2	Machined Aluminum
Ribs	20	Machined Aluminum, Sheet Metal Stretch Formed

Once frozen the HTP configuration, thus the design and manufacturing domains, the optimization is executed considering the design variables of production quantity and assembly site, as widely explained in the previous section. Particularly, the production quantity is here changing only for the skins and stringers. Hence, the production of spars and ribs is assumed fixed at specific OEM and supplier sites. As shown in Table 5, a different number of production sites has been selected for the production of skins and stringers. The motivation is linked to the competences characterizing each site. Only the OEM and supplier with the highest competences in performing the selected materials and manufacturing processes have been selected. Same applies for the choice of the assembly site. These details are summarized in Table 5. However, these assumptions have been necessary to limit the dimension of the MDO problems. In the future MDO activities even more production and assembly sites will be considered.

Table 5 – Value-driven MDO problems application case definition.

HTP Components	Production quantity	N° Components	N° Production sites	N° Assembly sites
Skins	0.5 - 1	0 – 1 – 2	4	4
Stringers	0.5 – 1	0 – 15 – 30	7	
Spars	Not included	Not included	Not included	Not included
Ribs	Not included	Not included	Not included	

Following the implementation process, described in the previous section, some preliminary results have been achieved for both optimization strategies. The same weights and the same linear function have been assigned to each attribute for the value estimation. As already specified, the value assumptions are the same for both MDO problems. However, in one case, optimized attributes are aggregated in the value; while in the other one, the value is itself an objective function and thus attributes are first aggregated in a value and then the value is optimized.
Before applying the optimization, approach presented in Section III, an analysis of the DOE results can be performed. As the DOE contains the full enumeration with a total of 3136 points, the true Pareto front can be extracted both for 4-objective or 2-objective problem.

First for the 4-objectives, the Pareto front can be highlighted and Figure 8 presents both the database and the Pareto front composed of 8 points. Each subfigure of Figure 8 illustrates a couple of two objectives chosen among the four. As the Quality has to be maximized, its opposite is minimized and represented in the figure.

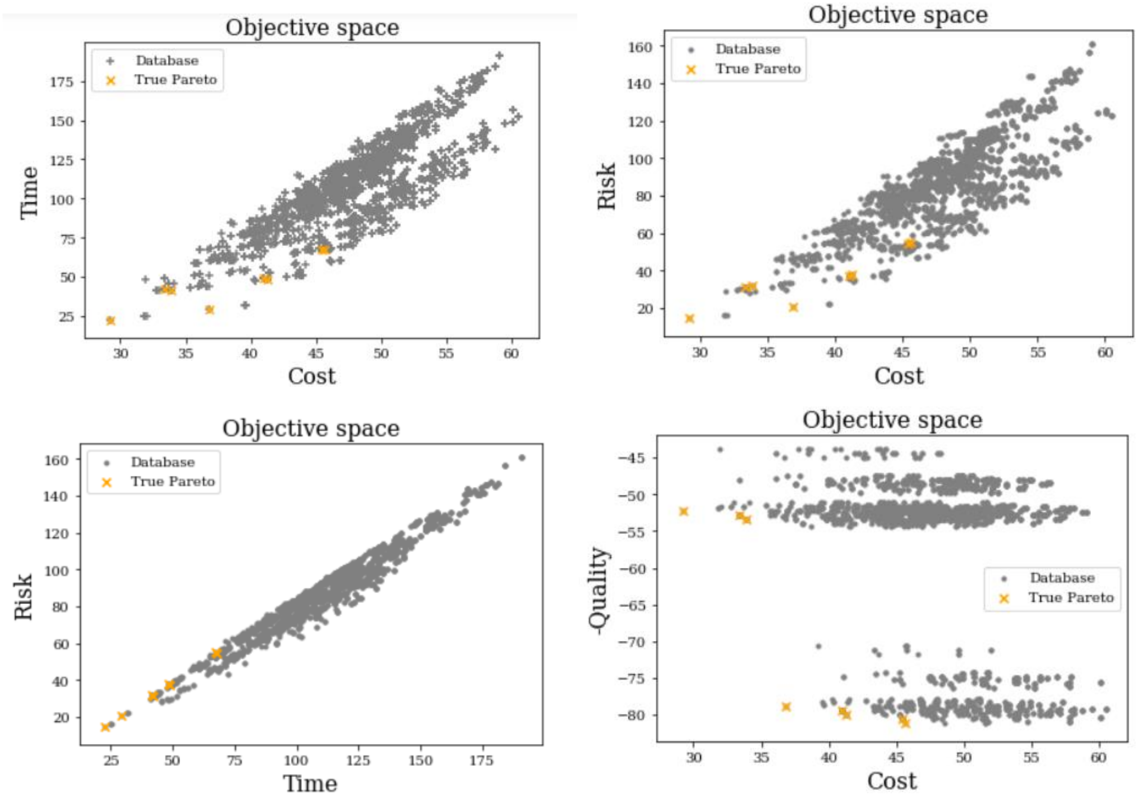


Figure 8: 4-objective Pareto front (8 points in orange) and complete database (3136 points in grey). Different objectives are represented: Time versus Cost, Risk versus Risk, Time versus Risk and Cost versus Quality

For the 2-objectives, the same process is applied and the Pareto front, of 2 points, can be extracted and is presented on Figure 9 (left). Then the optimized attributes of the 4-objective Pareto front are aggregated in a value and plotted on the same figure (Figure 9 (right)).

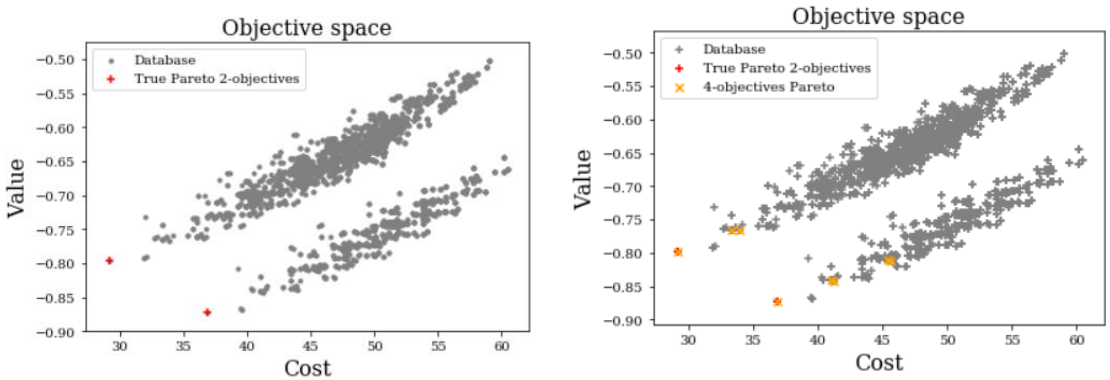


Figure 9: 2-objective Pareto front (2 points in red) (left) and 2-objective (2 points in red) and 4-objective Pareto front (8 points in orange) (right)

The 2-objective Pareto front therefore contained among the 4-objective Pareto front. This point observed numerically here could be demonstrated theoretically (see Appendix VII), as the 2-objective problem is deduced from linear transformation of the 4-objective problem.

Once assessed the true Pareto front, the optimization process can be performed. Details on both MDO problems are reported in Table 6 and Table 7. Particularly, in the tables, the quantity indicates the number of variables characterizing the problem. Each quantity is estimated considering the values that can assume the design variable (reported in Table 2) and the number of levels, which represents the number of production and assembly sites (see Table 5). Making an example for skins, the production quantity can be 0.5 or 1 (therefore 2 values for this design variable) and the skins can be produced at 4 different production sites (therefore 4 levels). For both MDO problems 26 design variables are defined. The main advantage of the approach is to remove all the constraints in terms of maximum production quantity (as always satisfied) but to increase the number of variables. Indeed, each categorical variable needs to be relaxed through one-hot encoding approach. It means that a new continuous variable is created for each level taken by the categorical variable. Therefore, for the current problem the real dimension of the optimization problem is increased from 6 variables up to 26, as each skin variable has 4 levels, each stringer has 7 levels and the assembly variable has 4 levels (2*4+2*7+1*4= 26).

Table 6 – 4-objective optimization problem.

Objective	**Function/variable**	**Quantity**
minimize	Cost	
	Time	
	Risk	
maximize	Quality	
with respect to	Skins	2 * 4 levels
	Stringers	2 * 7 levels
	Assembly	1 * 4 levels
	Total design variables	26

Table 7 – 2-objective optimization problem

Objective	Function/variable	Quantity
minimize	Cost	
maximize	Value	
	Skins	2 * 4 levels
with respect to	Stringers	2 * 7 levels
	Assembly	1 * 4 levels
	Total design variables	26

Defined the MDO features, for each problem, an initial DOE of 40 points is created with a Latin Hypercube Sampling (LHS) approach and 160 iterations are run. Figure 10 presents the comparison between the predicted Pareto front computed by the optimization algorithm (20 points) and the true Pareto front from the database (8 points) as described above. As it is obtained through the predictions of the surrogate models, the points belonging to the predicted Pareto front are not exactly located on the True Pareto front.

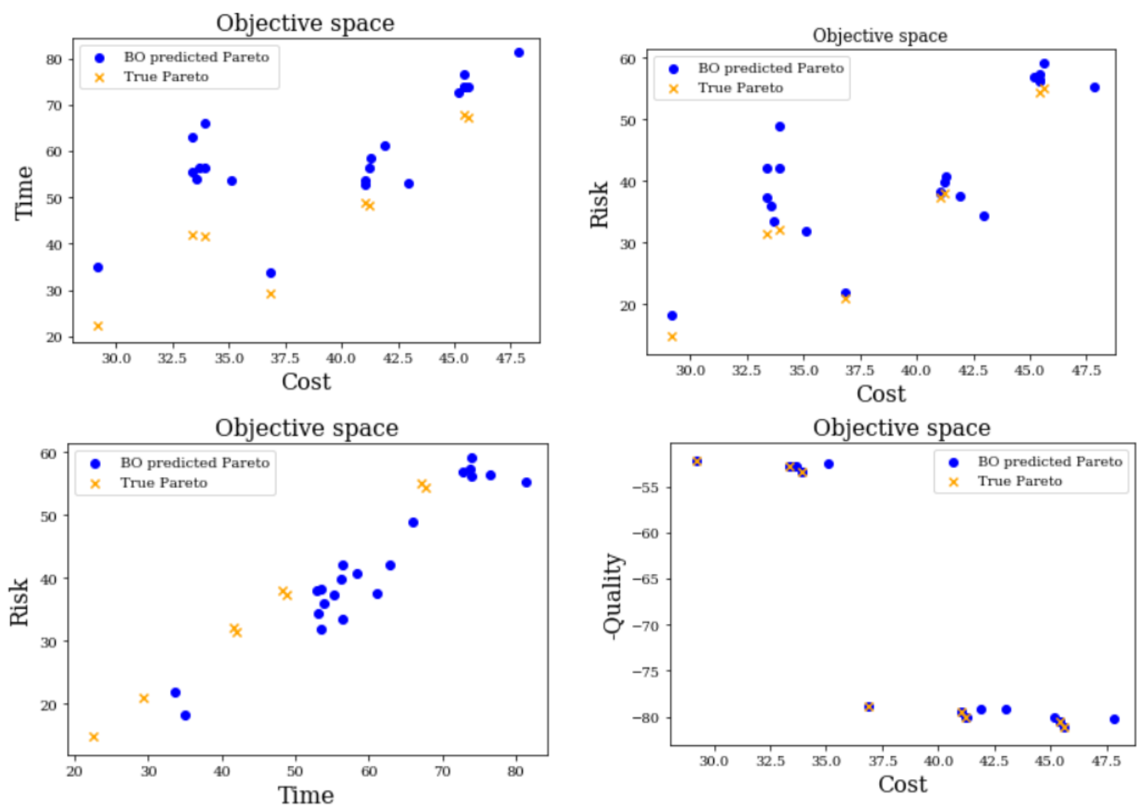


Figure 10 – 4-objective true Pareto front (8 points in orange) and predicted Pareto front proposed by the optimizer (20 points in blue).

Therefore, a last step to be performed should be to evaluate the true values of the predicted Pareto front and then to filter it by extracting the Pareto optimal points among this evaluated front. From an initial set of 20 points, only 8 points are kept after the filtering process.

Figure 11 depicts the new comparison between the filtered Pareto front coming from the optimization and the true Pareto front from the database. Now, both Pareto fronts are fully overlapping, thus proving the good performance of the algorithm.

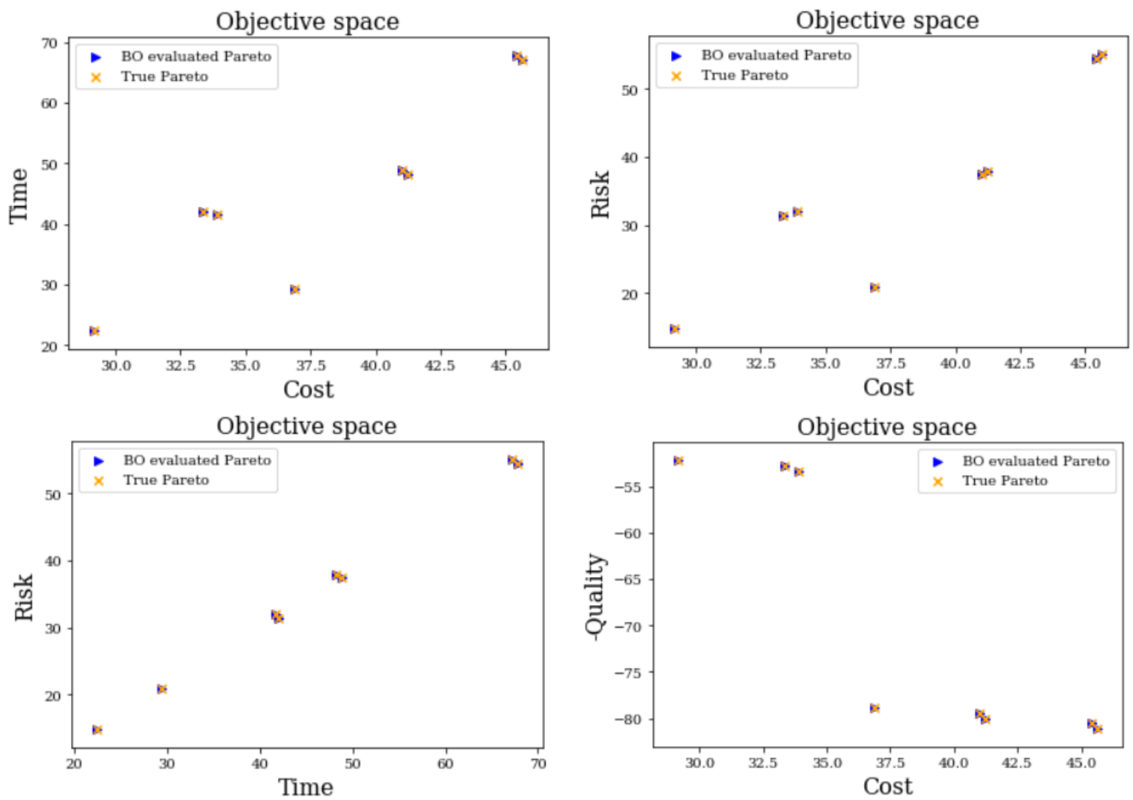


Figure 11 – 4-objective true Pareto front (8 points in orange) and evaluated Pareto front proposed by the optimizer (8 points in blue).

Regarding the 2-objective approaches, the same process was applied and here again, both optimization Pareto front and true Pareto front are overlapping.

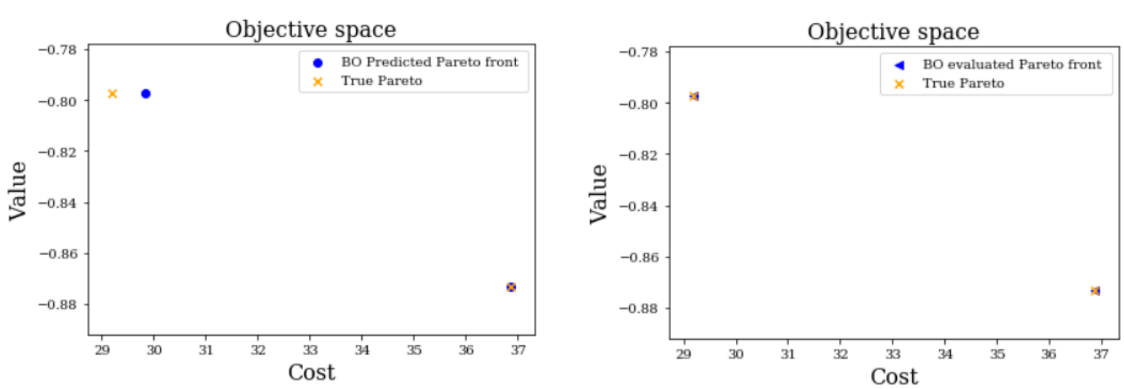


Figure 12 – 2-objective true Pareto front (2Points in orange) and predicted Pareto front (2points in blue) (left) and 2-objective true Pareto front & evaluated Pareto front (right)

These preliminary investigations have demonstrated the efficiency of the optimization approach to find the true Pareto front, both for 2-objectives and 4-objectives. Nevertheless, additional investigations need to be performed in order to identify the best combination of initial DOE size and number of iterations to perform.

V. Conclusions and Outlook

A value-driven model-based three-dimensional approach concurrent coupling manufacturing, design and supply chain in the early design phase has been already developed within the European project AGILE4.0 [4]. In the same research activity, also the MBSE technologies supporting the modelling of stakeholders, needs and requirements have been briefly addressed. The following MBSE step, that is the system architecting, is instead introduced in this paper. Defined as the link between the upstream MBSE modelling and the downstream MDO process, it simplifies the set-up of the MDO process by providing the models of the architectures to optimize in the MDO system. Thus, a description of the architecture modelling, addressed in Section II, provides the reader a clear comprehension of the optimization studies that can be performed by coupling manufacturing, design and supply chain domains. In fact, the new challenge is to address an optimization design campaign aiming at finding the global optimum simultaneously accounting for these domains. However, the complexity of this activity relays in the huge number of variables characterizing each domain. For this reason, this research activity aims at identifying the optimization strategy to use for the next optimization campaign by exploring, first, simple and representative MDO problems only related to the supply chain domain. Therefore, two value-driven MDO problems have been here addressed. In both MDO studies, the value-cost Pareto-front is investigated, considering the same design variables. The main difference between the two optimization strategies relays in the way through witch the value is estimated. In one MDO problem, a 4-objective optimization is first executed and then the optimized attributes are aggregated in a value. In the other MDO problem, the attributes are first aggregate in a value and then a bi-objective value-cost optimization is executed. More details related to MDO problems definition are provided in Section III. In the same section also details on the technologies and tools used to achieve some preliminary results are briefly described. For the execution of these first MDO problems, a sequential approach has been used to test the optimizer and the disciplinary codes involved in the MDO process. However, in the next optimization execution, an automatic process will be tested and utilized.

The preliminary results are scratched in Section IV. The optimization strategies have been applied to a specific HTP configuration, mainly made by aluminum. The results highlight that a 2-objective Pareto front is contained among the 8-objective Pareto front. Hence, both strategies lead to the same results. However, a 4-objectives MDO problem is more expensive, in terms of computation cost, with respect to the 2-objective MDO problem. But, the 4-objective strategy allows to execute the optimization process only once and then play around with the weights and utility functions needed to estimate the value [17], [18]. Instead, with the 2-objectives strategy the MDO process should be run anytime that the weights and utility functions change. Preliminary optimization investigations have instead demonstrated the efficiency of the optimization approach to find the true Pareto front, both for 2-objectives and 4-objectives. Nevertheless, additional investigations need to be performed in order to identify the best combination of initial DOE size and number of iterations.

The same MDO problems will be executed for another HTP configuration. However, it is already planned to add new design variables in the future optimization run. The production quantity related to the spars and ribs will be added as well as the assembly site responsible for the assembly of the entire HTP. Due to the increasing size of the problem and because of the promising results already obtained, this MDO problem will be automatically executed via BRICS in RCE.

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VII. Appendix

The objective is to prove that a point Pareto stationary for the 2 objectives is also Pareto-stationary for the 4 objectives.

The 4-objective Pareto front consists of Pareto-stationary points, called "weakly Pareto-optimal", i.e. points where a certain convex combination of the gradients is equal to 0. In the present application case with 4 objectives (f_1, f_2, f_3, f_4) we have:

$$\sum_{j=1}^{4} \alpha_j \nabla f_j(x) = 0 \qquad (1)$$

where the α_j coefficients define a convex combination:

$$0 \leq \alpha_j \quad \forall j \quad \sum_{j=1}^{4} \alpha_j = 1$$

Let us define two aggregate criteria:

$$\varphi_1(x) = \sum_{j=1}^{4} a_j f_j(x) \quad a_j \geq 0 \; \forall j \quad \sum_{j=1}^{4} a_j = 1 \qquad \text{and} \qquad \varphi_2(x) = \sum_{j=1}^{4} b_j f_j(x) \quad b_j \geq 0 \; \forall j \quad \sum_{j=1}^{4} b_j = 1$$

We now consider a point $\tilde{x}$ Pareto-stationary with respect to φ_1 and φ_2 satisfying:

$$(1-\beta)\nabla\varphi_1(\tilde{x}) + \beta\nabla\varphi_2(\tilde{x}) = 0 \quad \text{with} \quad 0 \leq \beta \leq 1$$

By using Eq. (1), we get $\alpha_j = (1-\beta)a_j + \beta b_j$ where the coefficients α_j are clearly positive. Moreover, we have:

$$\sum_{j=1}^{4} \alpha_j = (1-\beta)\sum_{j=1}^{4} a_j + \beta \sum_{j=1}^{4} b_j = (1-\beta) + \beta = 1$$

And we can conclude by using Eq. (1) that we have a convex combination and the point $\tilde{x}$ Pareto-stationary with respect to φ_1 and φ_2 is also Pareto-stationary with respect to 4 objectives (f_1, f_2, f_3, f_4).

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