Overview Of MDO Enhancement In The AGILE Project: A Clustered And Surrogate-Based MDA Use Case

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ABSTRACT

This paper presents innovative methodological investigations performed as research activities in the field of MDO for conceptual aircraft design in the ongoing EU-funded research project AGILE. The next generation of aircraft Multidisciplinary Design and Optimization processes is developed in AGILE, which targets significant reductions in aircraft development costs and time to market, leading to cheaper and greener aircraft solutions. The paper introduces the AGILE project structure and recalls the achievements of the 1st year (Design Campaign 1 or DC-1) leading to a reference distributed MDO system. Design Campaign 2 (DC-2) is briefly described, investigating the ease of the optimization of complex workflows, characterized by a high degree of discipline interdependencies, high number of design variables in the context of multilevel processes and multipartner collaborative engineering projects. The paper focuses on an innovative approach where a complex aircraft design workflow has been simplified and implemented by using surrogate models for clusters of disciplines to reduce the computational time. The paper will detail the different steps of the retained approach to set up and operate this test case, involving a team of surrogate specialists, and taking advantage of the AGILE distributed MDO framework.

KEYWORDS: AGILE, MDO, surrogate models, optimization, collaborative framework, knowledge framework

NOMENCLATURE

AGILE	H2020 EU Project: Aircraft 3rd Generation MDO for Innovative Collaboration of Heterogeneous Teams of Experts
CMDOWS	Common MDO Workflow Schema
CPACS	Common Parametric Aircraft Configuration Schema
DACE	Design and Analysis of Computer Experiments
DC	Design Campaign
DOE	Design Of Experiments
DP	Design Process
FPG	Fundamental Problem Graph
IT	Information Technology
KADMOS	Knowledge- and graph-based Agile Design for Multidisciplinary Optimization System
LHS	Latin Hypercube Sampling
MDA	Multi-Disciplinary Analysis
MDAO	Multidisciplinary Design Analysis and Optimization
MDO	Multidisciplinary Design Optimization
MDPG	MDAO Data and Process Graph
MOE	Mixture Of Experts
MTOM	Maximum Take-Off Mass
OAD	Overall Aircraft Design
OBS	On Board Systems
OEM	Operating Empty Mass
PIDO	Process Integration and Design Optimization
POD	Proper Orthogonal Decomposition
RCE	Remote Component Environment
RCG	Repository Connectivity Graph
RSM	Response Surface Method
SEGOMOE	Super Efficient Global Optimization based on Mixture Of Experts
SM	Surrogate Model
VISTOMS	VISualization TOol for MDO Systems
XDSM	eXtended Design Structure Matrix

1. INTRODUCTION

Over the past century, the aircraft design and development process has evolved from pioneering - one or few people building a simple and small aircraft in a shed - into a highly complex but well-established engineering process. Today, aircraft are highly advanced technological and competitive products that are developed by multidisciplinary expert teams. To keep up with the growing demand for more complex and innovative products in shorter time and in higher volumes, the industry digitizes rapidly. The highly advanced aircraft industry increasingly applies innovative design approaches based on digital modelling, simulation and optimization technology to take design decisions as early as possible and hence develop state-of-the-art aircraft more timely and cost efficiently. Still, with the large computational power that is available nowadays, there remains the challenge to master the complexity of the multidisciplinary design workflow and all corresponding variables. High-dimensional data sets resulting from various design competences need to be handled in an efficient way.
In the last three decades, there has been a growing interest in improving the efficiency of vehicle design processes through the use of multidisciplinary design optimization (MDO) numerical tools and techniques.

Nevertheless, the exploitation of the full MDO potentials for the development of a complete aircraft is still an open challenge mainly due to the technical and management issues encountered during the set up and the operations of such a complex architecture. Even though many of the MDO algorithms have been applied into industrial applications, the necessity of novel methodology to encapsulate knowledge and skills has been identified [1,2] in order to be able to manage the increasing design complexities. In that aim, since 2015, EU funded Horizon2020 AGILE project is developing the next generation of aircraft Multidisciplinary Design and Optimization processes, focusing on the reduction of the aircraft development time at the early stages of the design process in the context of multi-level and multi-partner collaborative engineering projects. This paper presents an innovative approach investigated in the context of the project aiming at simplifying a complex workflow through the combination of clusters of design competences and the extensive use of surrogate models (SM).
The paper is organized as follows. Section 2 provides an overview of the EU H2020 AGILE project structure and the main achievements of Design Campaign (DC) 1 an 2 are exposed. Section 3 details the different scenarios to build associated multidisciplinary process based on surrogate models in order to compare several MDO strategies. In addition, improvements brought by AGILE framework, both by knowledge based technologies and IT solutions, to support the surrogate models scenarios are also presented. Section 4 describes the overall process to be apply to DC-1 MDA in order to obtain an equivalent workflow only involving surrogate models of the associated design competences. Section 5 presents the results obtained at the main steps of the process with a focus on the building of the surrogate models. Section 6 summarizes the work performed and identifies the future steps.

2. AGILE PROJECT OVERVIEW

AGILE [3] (Aircraft 3rd Generation MDO for Innovative Collaboration of Heterogeneous Teams of Experts) is an EU funded project under the research schema Horizon 2020 and coordinated by the German Aerospace Center (DLR). AGILE is developing the next generation of aircraft Multidisciplinary Design and Optimization processes, which target significant reductions in aircraft development costs and time to market, leading to cheaper and greener aircraft solutions [4]. The developed AGILE Paradigm [5] will enable the 3rd generation of multidisciplinary design and optimization through efficient collaboration among international multi-site aircraft design teams. The AGILE project is structured into three sequential phases, targeting design campaigns with increasing levels of complexity, addressing different aircraft configurations and dedicated MDO techniques. The overall structure is shown in Fig. 1. In the 1st phase (Initialization), a reference aircraft

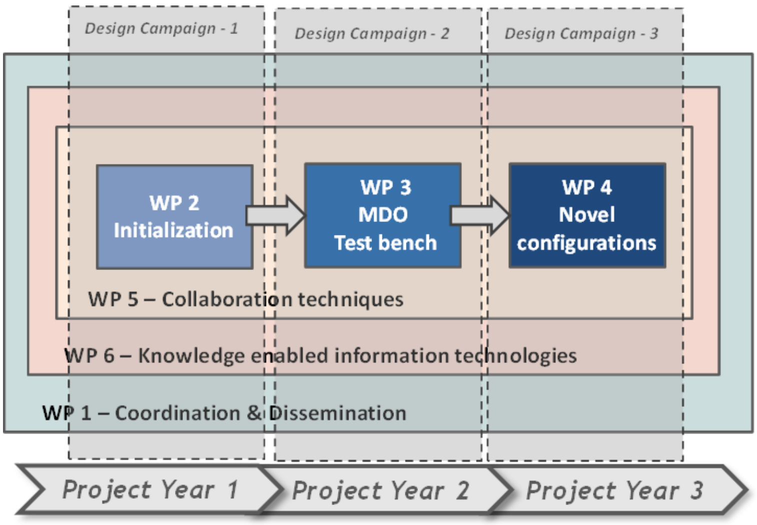


Figure 1. AGILE project structure

configuration is optimized using state-of-the-art techniques. The reference MDO problem is then used to investigate and benchmark novel optimization techniques individually and later in smart combinations (MDO test bench). Finally, the most successful MDO strategies are applied to significantly different aircraft configurations (Novel Configurations). The three sequential work packages are embedded within two enabling layers. The 1st enabling layer (Collaboration techniques) targets the development of the technologies enabling distributed collaboration, comprising the process of collaboration between involved specialists, collaborative pre- and post-processing, visualization and the enhancement of existing framework. The second enabling layer (Knowledge enabled technologies) develops the information technologies, which support the management and the formalization of knowledge within an MDO process. The parallel activities are clustered in three phases (or periods), Design Campaigns (DC), each one lasting one year. Each of the sequential design campaigns focus on the solution of the use cases, which are setup to develop specific collaborative and knowledge based technologies. Design Campaigns, address an increasing complexity from use case perspective (progressing from conventional aircraft to novel configurations), and from MDO environment perspective (from the state-of-the-art MDO system to the 3rd generation system).

2.1. Design campaign 1

The DC-1 is the first use case in the project that has been formulated and collaboratively solved by the AGILE team. This case consists of the design and optimization task for a large regional jet, with Entry Into Service 2020. Starting from the specification of the Top Level Aircraft Requirements provided by the aircraft manufacturer partner (Bombardier), an Overall Aircraft Design (OAD) task targeting conceptual and preliminary development stages was implemented in DC-1. Fig. 2 shows a representation of the DC-1 distributed OAD process. The figure indicates the domains of the specialists' competences which have been integrated into

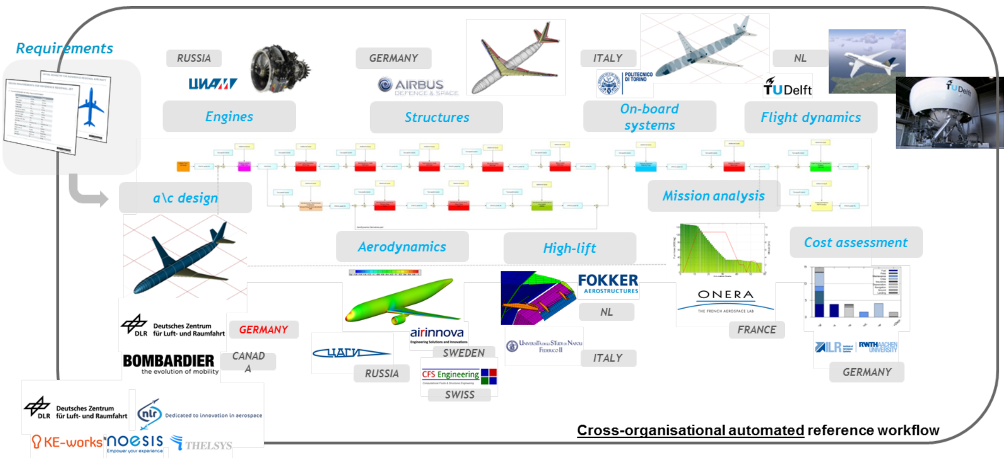


Figure 2. AGILE Collaborative design process: individual competences are distributed multi-site, and hosted at the different partners' networks

the process, the location where such simulation competences are hosted, and the specific partners providing such a competence within their IT networks. The corresponding deployed collaborative MDO workflow is represented in Fig. 3. A design exploration method is "calling" the OAD process (here labelled as MDA) as

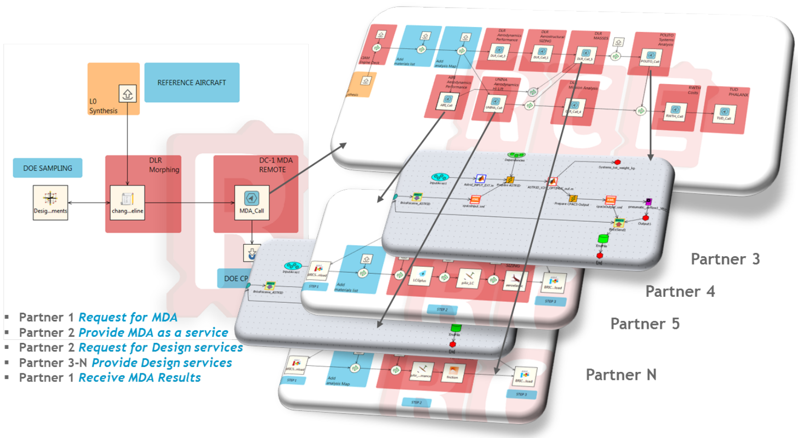


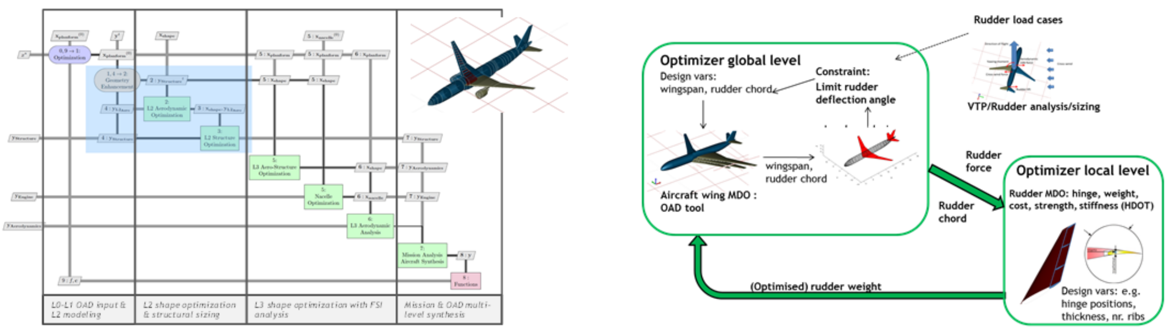
Figure 3. AGILE DC-1 workflow. Partner 1 deploys a Design Of Experiment requesting as remote service the cross-organizational MDA workflow, deployed at Partner 2. The MDA is composed by disciplinary competences provided as remote services to Partner 2 by Partners 4 to N

a remote service, which integrates all the distributed disciplinary competences, which are in turn called as remote services (deployed as disciplinary workflows) within the MDA process. All competences communicate via a CPACS model [6] corresponding to the AGILE aircraft product model. They are deployed as disciplinary workflows and provided as remote services. Furthermore, the deployed "workflow of workflows" has been provided as "service of services" and coupled to an optimization strategy, named SEGOMOE, developed by ONERA [7]. An MDO problem was therefore formulated for the optimization of the reference aircraft using a MDF formulation resulting in an improved design.

2.2. Design campaign 2

The DC-2 activities are based on the DC-1 work, and were implemented during the second year of the project. In addition, the number of use cases is expanded to five parallel ones. For each use case, a novel MDO strategy (addressing a specific collaborative scenario) was investigated and assessed for the resolution of the design of the reference aircraft. Depending on the test cases, classical MDO formulations (such as MDF, IDF [8] or Analytical Target Cascading [9]) or more adapted ones have been proposed.

- First use case focused on the improvement of MDO strategies with the development and integration of new design competences in terms of optimization algorithms and surrogates modelling. These investigations are presented in [10, 11].
- The implementation of Uncertainty Quantification (UQ) methods and robust based design optimization in complex, variable fidelity optimization was the objective of second use case [10].
- The development of mixed-fidelity MDO strategy was tackled with the integration of high-fidelity design competences and its combination with Overall Aircraft Design (OAD) level. The process is presented in [12] and illustrated on Fig. 4-a.
- A multi-scale application is described in [13] aiming at investigating the improvement of involving an aircraft component supplier (aircraft rudder) in the overall aircraft optimization process while keeping its specific framework. The coupled optimization problem is illustrated on Fig. 4-b.
- A large-scale system-of-systems application was also studied, coupling Aircraft - Engine - On-Board-Systems (OBS) - Emissions in a distributed framework approach with the involvement of disciplinary services from the other partners [14].



(a) Hi-Fi multi-level optimization formulation (b) Rudder optimization

Figure 4. DC-2 investigation examples

Furthermore, based on the best practice developed during the DC-1, during the DC-2 the overall AGILE framework was enhanced by knowledge based technologies [15] and IT solutions [16], which contribute to accelerate the deployment of the complex MDO processes addressed by the DC-2 use cases.
This paper will present DC-2 investigations performed on first use case and focusing on enhanced MDO strategies which took advantage of surrogate models aiming at converging the process more rapidly to the best solutions.

3. MDO THROUGH SURROGATES

All the methods developed during DC-2 have the common goal of enhancing the optimization of complex workflows, which are characterized by a high degree of discipline interdependencies, high number of design variables in the context of multilevel and multi-partner collaborative engineering projects. One of the most straightforward solutions is the use of surrogate models. A surrogate model (SM) is an analytical formula that replaces a complex model, or even a design analysis workflow, by means of data fitting. Consequently a surrogate model requires only little computation time, which is particularly useful for capturing complex analysis methods and applying them multiple times as part of a global optimization. In collaborative design studies during the early aircraft design phases, surrogate models are valuable to support the collaborative analysis of as many design alternatives as possible in a short time and at low cost, preferably with as much knowledge of the systems under consideration as possible.

3.1. Objectives

In the context of DC-2, two main scenarios were considered for the use of surrogate models to enhance MDO strategies:

- The 1st scenario (see Fig. 5) is related to the investigations of MDO formulations on complex workflows. The objective is to benchmark various MDO formulations such as MultiDisciplinary Feasible (MDF), Individual Discipline Feasible (IDF), Collaborative Optimization (CO). All of these different formulations are described in [8]. In order to compare these formulations in terms of number of function evaluations and/or accuracy of the optimal solution, the idea is to take advantage of surrogate models to reduce the computational costs. The key point here is to use surrogate models, instead of real tools while keeping the disciplinary results accurate. The accuracy of the surrogate models (computed for instance with the Root Mean Square Error criterion on a validation set of points) can be reduced with the use of a large database or with an iterative process to enrich the database as described in [17].

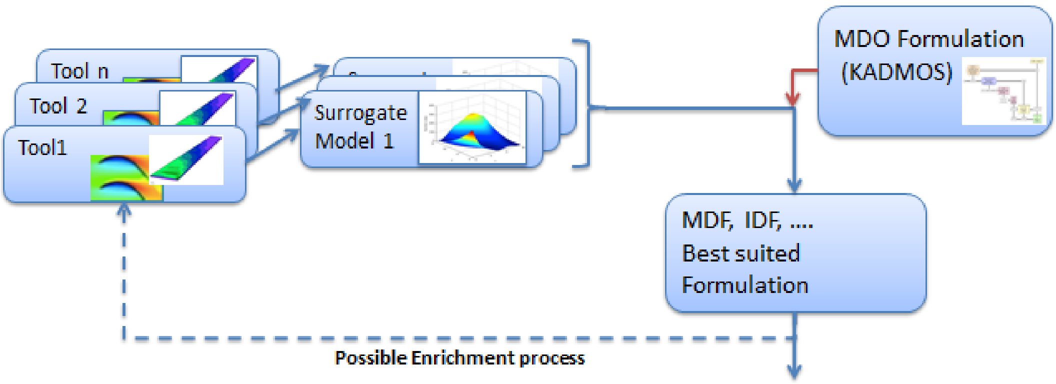


Figure 5. Scenario for automatic MDO process

- The 2nd scenario (see Fig. 6) concerns the optimization process using surrogate models and the propagation of uncertainty associated to each surrogate. By using surrogate models in an MDO instead of the real tools, some approximation errors are done and they are propagated within the process. The first objective is to quantify these uncertainties in the MDA in order to have the probability distribution of the objective function (dispersion of the objective function due to the use of surrogates) [18]. The second objective concerns the enrichment process to choose the next promising point and improve the surrogate models. This step is under investigation and implies some theoretical aspects linked to the probability distribution of the objective function and its discretization to determine its extreme values.

3.2. Enhanced framework

During DC-2 activities, the overall AGILE framework was enhanced both by knowledge based technologies and IT solutions enabling a quicker and more efficient understanding and deployment of the complex MDO processes. Next paragraphs will provide a brief description of two improvements brought by those enabling layers to support the surrogate models scenarios.

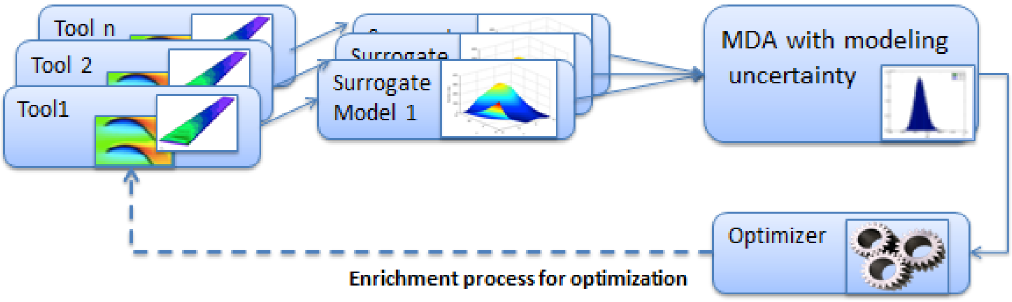


Figure 6. Scenario relative to propagation of the modeling uncertainty in the process

3.2.1. Collaborative architecture

In AGILE, the MDA/MDO workflows are configured, deployed and executed by making use of PIDO (Process Integration and Design Optimization) environments available at the different process integration sites. Multiple PIDO environments are available in AGILE. One integration environment used in AGILE is the “Remote Component Environment” (RCE) [19], developed by DLR. NOESIS provides an alternative/complementary collaborative framework by means of Optimus [20]. Both are deployed in AGILE to compose the main processes, as well as disciplinary sub-processes. The cross-organizational mechanism available in AGILE is Brics [21], developed by NLR. Brics provides technology for interconnecting PIDO environments. It comprises a protocol and supporting middleware for creating cross-organisation workflows as federations of native and legacy local workflows, tools and scripts, complying with the prevailing security constraints. Therefore, nested complex collaborative MDO workflows, connecting multiple organizations, can be deployed. Thanks to the standardized interface by means of CPACS [6], processes implemented using different PIDO platforms can be integrated in the same MDO. A schematic of workflows in different administrative domains is illustrated in Fig. 7. More information on all the developments of collaborative architecture is available in [15] and [22].

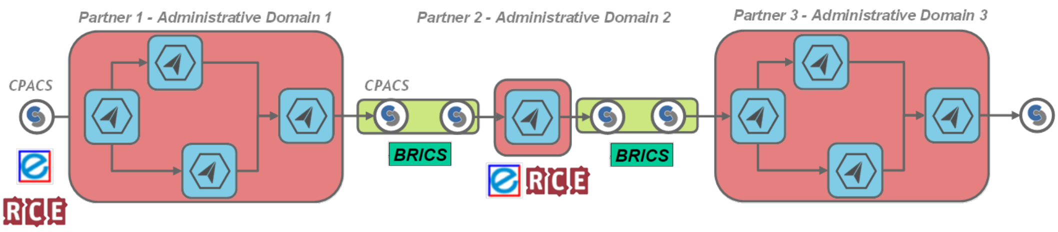


Figure 7. Connection of PIDO workflows hosted at multiple administrative domains

3.2.2. Knowledge architecture

The knowledge architecture under development in AGILE integrates different applications to enhance the MDO development process. The full AGILE knowledge architecture is discussed in [16]. Here, two elements of the architecture have been used to support the creation of the different surrogate models: the graph-based MDO formulation system KADMOS (Knowledge- and graph-based Agile Design for Multidisciplinary Optimization System) [23] and the visualization tool for MDO systems VISTOMS (VISualization TOol for MDO Systems) [24].
The five main stages of the AGILE development framework are shown in Fig. 8. KADMOS and VISTOMS support the development process in the first three steps of the framework and enable the design team to formulate MDO systems of any size and complexity. This support is provided by KADMOS using a graph-theoretic approach for the set-up and manipulation of multidisciplinary systems. In this approach, different graphs are created to represent the three different formulation stages shown in Fig. 8.

Repository Connectivity Graph (RCG): The RCG is a graph that represents the repository of (CPACS-compatible) tools that are available to the design team. CPACS-compatible tools all operate on a CPACS input file and create a CPACS output file. KADMOS interprets these different files and establishes the interdisciplinary dependencies (couplings), system inputs and system outputs.

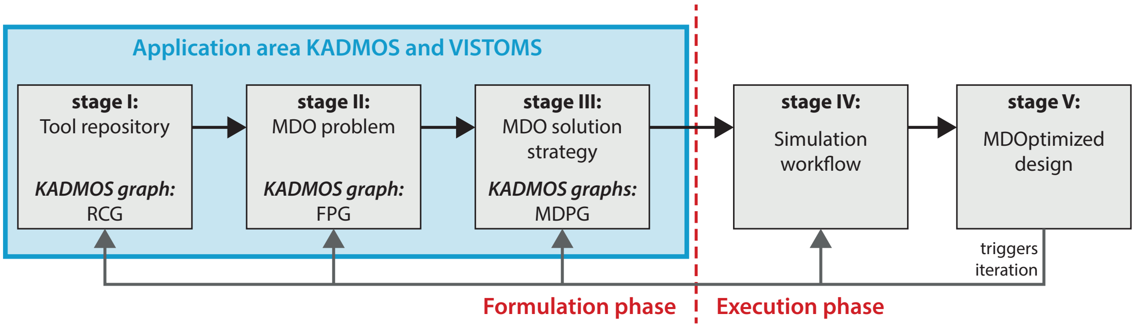


Figure 8. The five stages of a multidisciplinary system in the AGILE development framework

Fundamental Problem Graph (FPG): Based on the RCG an FPG can be created by the design team. This FPG is an enriched subgraph of the RCG, hence only a selection of the RCG tools which are necessary to solve a certain problem are still in the graph. Furthermore, key variables are indicated in the FPG, such as design variables and quantities of interest, which are necessary to define a Multidisciplinary Design Analysis and Optimization (MDAO) strategy. In this paper, the FPG is used to define different clusters for which Designs of Experiments (DOE) are executed to be able to create the surrogate models of a subset of disciplinary tools.

MDAO Data and Process Graph (MDPG): The MDPGs are automatically created by KADMOS based on the FPG. If the FPG contains a definition of a DOE strategy for a cluster of tools, then the MDPG will contain the description of the data and process flow required to execute this DOE. The MDPG itself is still just a combination of two graphs in KADMOS and cannot be executed.

Note that the link to the execution of the solution strategy is also enabled by KADMOS through the CMDOWS (Common MDO Workflow Schema) format [25], however, this development is not discussed in this paper and all workflows have been built manually based on the formulation provided by the KADMOS graphs.
As the graphs grow in size very quickly, their visualization becomes a challenge, while at the same time this would help the design team to inspect and debug the multidisciplinary system in each stage of the process. In AGILE, VISTOMS has been developed for this purpose and it is used in this paper to visualize the different KADMOS graphs. Throughout this paper the dynamic eXtended Design Structure Matrix (XDSM) [26] view from VISTOMS is used to represent the different KADMOS graphs.

4. APPLICATION TO DC-1 MDA

The scenarios described in Section 3.1 should demonstrate the improvements brought by the use of surrogate models on the optimization of complex workflows in the context of multilevel and multi-partner collaborative projects. A typical application of these investigations is the former MDA workflow defined and implemented during DC-1 activities with a realistic complexity of the problem w.r.t. industrial aircraft design (in terms of number of design competences, amount of coupling ...). Fig. 9 provides an overview of DC-1 MDA in XDSM format [26].
The objective was therefore the preparation of the workflows for the envisaged scenarios, using the DC-1 MDA as use case. Fig. 10 describes the different steps required to build the "MDA through surrogates" process:

- Identify the disciplinary tools and their associated domain of variation for each of the inputs.
- Create the associated DOEs and build the associated surrogate models.
- Build the associated workflow within any PIDO framework.
- Run the scenarios.

Next paragraphs will expose the pre-processing modifications applied to DC-1 MDA taking advantage of KADMOS and VISTOMS capabilities.

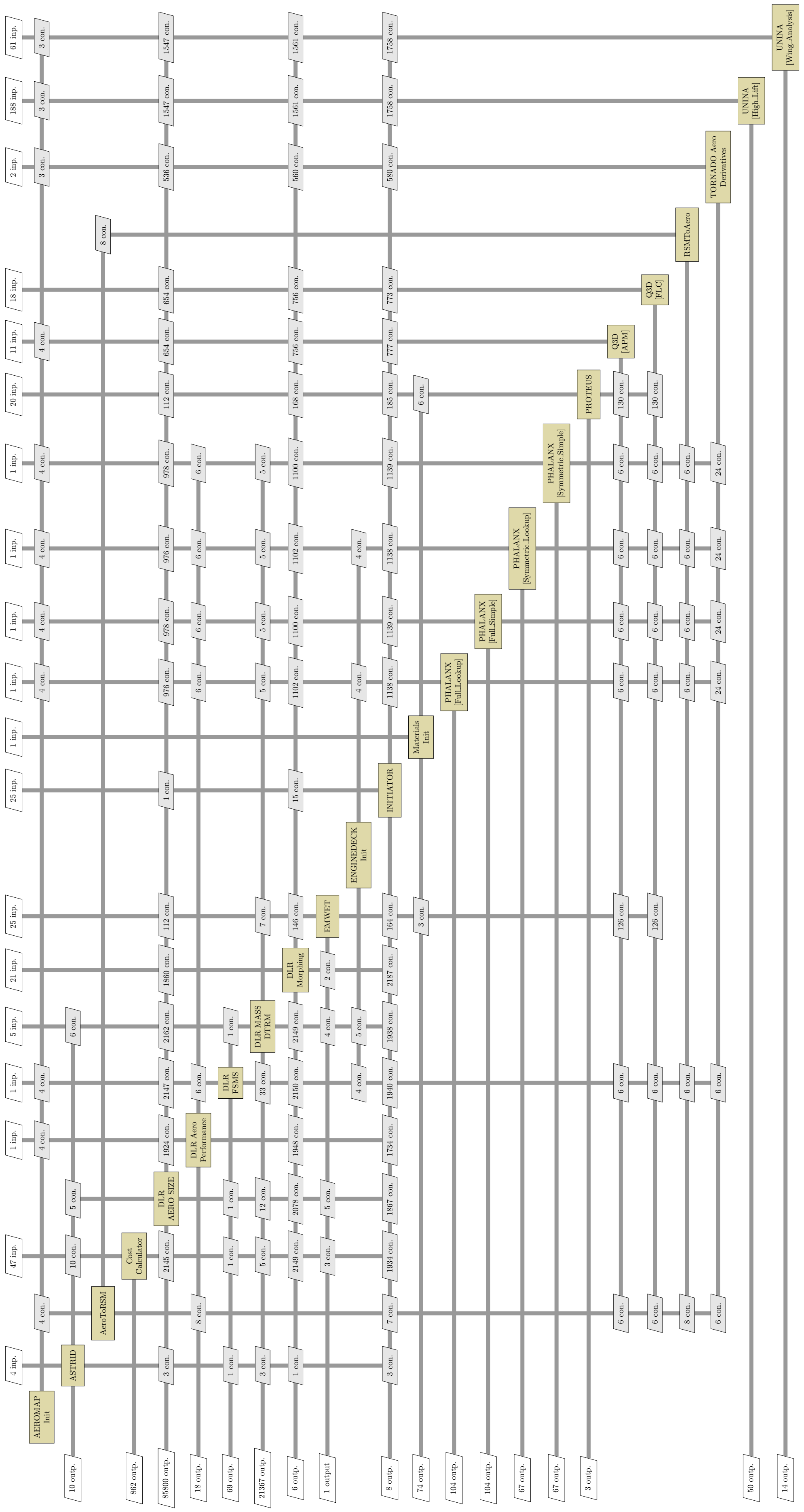


Figure 9. Overview of the DC-1 disciplinary tool repository (RCG visualized with XDSM data flow view)

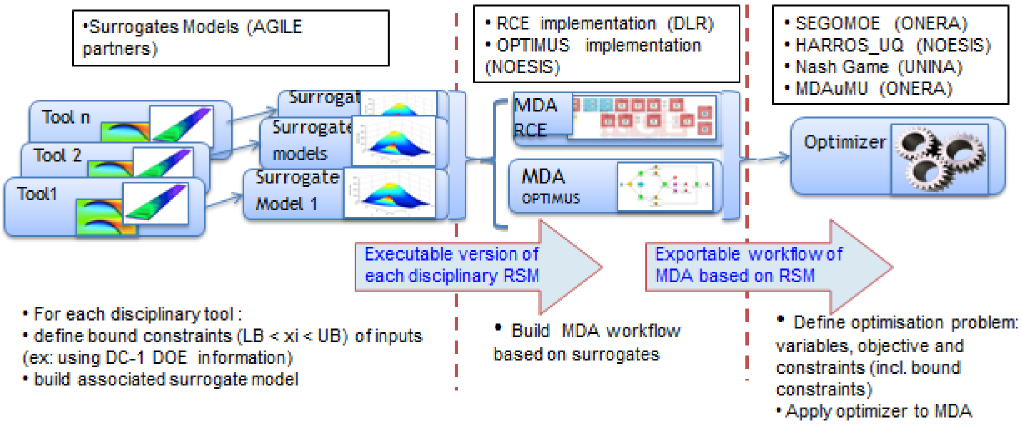


Figure 10. Description of the approach to optimize the MDA using surrogate models

4.1. DC-1 simplification

Fig. 9 presents the RCG of the full DC-1 MDA process. A first analysis indicated that more than 2000 connections can exist between design competences and that some design competences have more than one hundred inputs and outputs. In order to reduce the complexity of the problem while keeping as much as possible its similarity w.r.t aircraft design process, several adaptations were performed:

- Reduction of the number of design competences to be considered, mainly removing the Flight Dynamics assessment part and the Cost assessment part, both used as post processing tools in the DC-1 workflow. In addition, the engine characteristics are fixed. The retained design competences from DC-1 MDA, mainly made of low to medium fidelity tools, are the following:
  - Aerodynamics performance provided by DLR (German Aerospace Center)
  - High Lift Performance provided by UNINA (University of Naples "Federico II")
  - Propulsion system performance provided by CIAM (Central Institute of Aviation Motors)
  - Loads and structural sizing provided by DLR
  - On-board systems design provided by POLITO (Politecnico di Torino)
  - Mission performance provided by DLR
- Slight reduction of the complexity of the optimization problem to be considered compared to DC-1. Here, only seven inputs, linked to the wing design are selected as global variables (wing area, wing sweep, aspect ratio, thickness at tip and at kink, twist at tip and at kink) and outputs will be linked to the aircraft performances, such as weights (fuel weight, MTOM (Maximum Take-Off Mass), OEM (Operating Empty Mass) ...) or low speed characteristics (CLmax).

All these modifications were not sufficient to reduce the dimensions of the coupling variables (ie connections between the design competences) that would prevent the use of surrogates' capabilities. Indeed the main difficulty to build a SM is driven by the input characteristics: their number and their location. Two main sources of high number of coupling variables can be identified as follows:

1. The coupling between the Geometry and most of the other design competences, such as Aerodynamic performance one, need as inputs, the whole geometry of the aircraft, stored in multiple CPACS branches.
2. The coupling between the Aerodynamic performances and the Mission performance as the Mission performance tools need, as inputs, the whole aerodynamic performance map, stored in a CPACS branch. This lookup table of aerodynamic coefficients is given as function of the mission dependent parameters Mach, Reynolds Number (Re), Angle of Yaw (AoY) and Angle of Attack (AoA).

In order to reduce drastically the 1st source of coupling, a design competence was introduced in the workflow: the Aircraft Morphing design competence (provided by DLR) that enables the modification of wing geometry from a set of design parameters which are not explicitly defined/directly accessible in CPACS. Therefore the

full wing geometry, representing hundreds of variables can be controlled by less than a dozen parameters. This design competence was already used for the MDO application of DC-1 as a pre-processing tool and is now introduced inside the workflow.
For the 2nd source of coupling, another approach was retained through the use of a specific surrogate model that should embed the Aerodynamic look up table and that is described more in detail in the next paragraph.

4.2. Clustering of design competences

Adding new tools, such as Aircraft Morphing Tool in the workflow, will only lead to reduce the coupling if it is clustered with the other design competences. For instance, making a cluster of the Morphing tool and a Structural sizing tool will expose a limited set of inputs, here the wing design parameters, of the cluster and a limited set of outputs, here the wing weight, as outputs, while keeping the full geometry description as an internal coupling variables between the clustered tools. As an extension of this approach, it was decided to make clusters of design competences of the MDA exposing the following characteristics:

- These clusters should exhibit low dimensions of inputs (less than 20) in order to be accurately represented by a surrogate model.
- These clusters should not have internal feedback coupling between design competences (to prevent the use of convergence process inside the cluster).
- These clusters should be representative of an aircraft design process.

In order to fulfill those requirements, four clusters were built using the retained design competences.

Aerodynamic Cluster This cluster gathers Morphing tool and aerodynamic performance computations including the low- speed configurations. It takes as input the wing design parameters and provides the lookup tables for aerodynamic coefficients, related to the specified wing design.

On-board systems Cluster This cluster aims at providing the On Board systems performance, in terms of weights and power, using the wing design parameters and other inputs such as the Fuel Weight and other operational weights such as MTOM (Maximum Take-Off Mass).

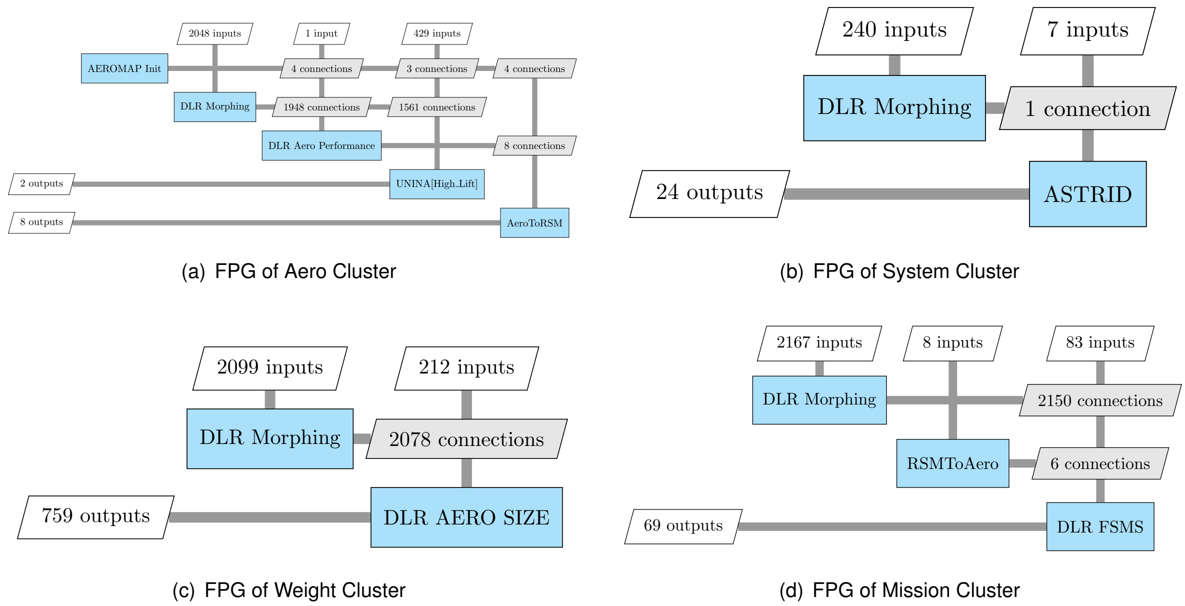
Structural sizing and Weight Cluster This cluster provides the weight breakdown of the whole aircraft, using as inputs the wing design parameters, the fuel weight and the systems weight. It also contains the Load and structural sizing competence that sizes the wing structure and computes its weight.

Mission performance Cluster This cluster contains the Mission performance tool and uses as inputs, the wing design parameters, the operational weights and the Aerodynamic look up tables to run the full mission and provides the fuel weight.

Fig. 11 provides the FPG of the four clusters. One can notice that, each cluster can contain design competences of various partners that will be called through AGILE framework.
At this step, two approaches have been identified in order to derive a surrogate model of the Aero Cluster and link it to the Mission Cluster.

- A two-step approach: In this case the AeroClusterSM predicts - as a function of wing design parameters - a representation of the aero lookup tables, e.g. by predicting polynomial coefficients that will be transferred to the MissionClusterSM.
- An "all-in-one" approach: In this case the AeroCluster SM directly predicts the aerodynamic coefficients as a function of wing design parameters and mission parameters (Mach, Re, AoY and AoA). As such the AeroClusterSM becomes an integrated part of the MissionCluster (and therefore also of the MissionCluster SM which is to be derived).

Eventually, Fig. 12 summarizes the MDA workflows obtained with the clusters defined above for the two possible approaches. In agreement with the clusters' requirements, both MDA are representative of an aircraft design problem with different disciplines (Aerodynamic, Structure, Performance) coupled together. A surrogate model of each cluster now needs to be created in order to build the MDA workflow.



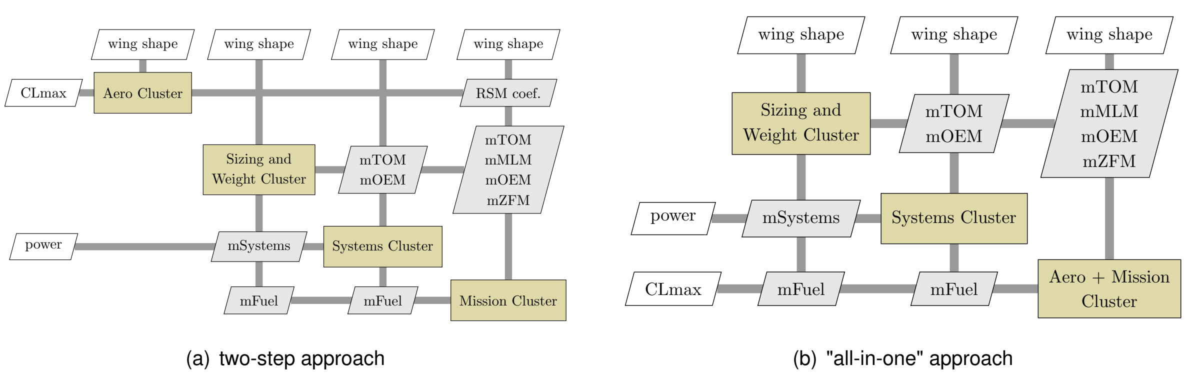
(a) FPG of Aero Cluster

(b) FPG of System Cluster

(c) FPG of Weight Cluster

(d) FPG of Mission Cluster

Figure 11. FPG of the 4 retained clusters (2-steps approach)



(a) two-step approach

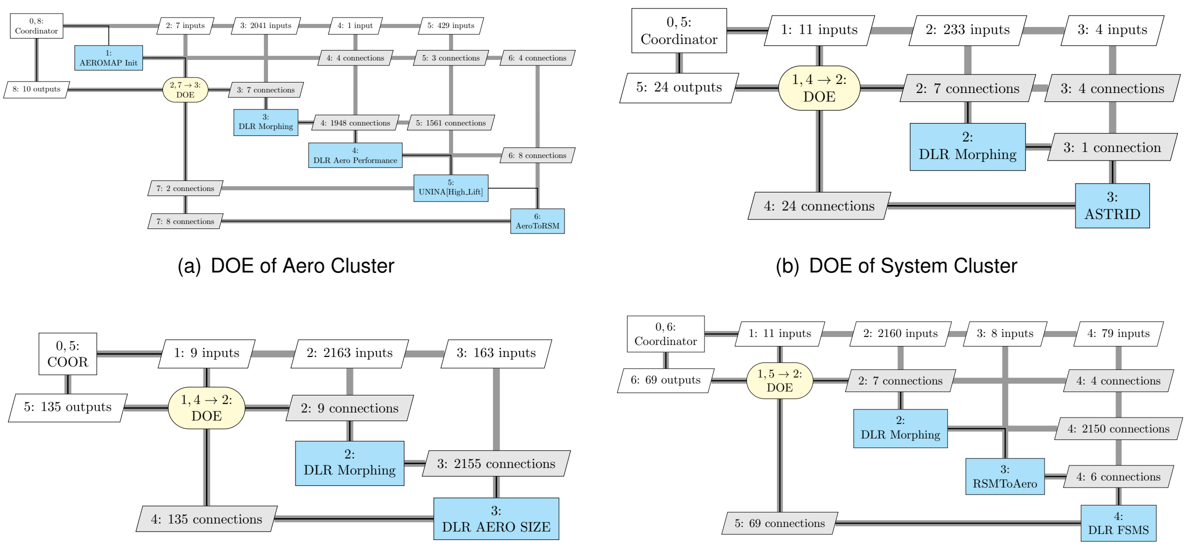
(b) "all-in-one" approach

Figure 12. Workflow(s) of MDA through surrogates with the two different approaches

5. RESULTS

5.1. DOE

After the formulation of design competence clusters, these have been implemented as collaborative service oriented workflows, and executed within DOE studies in order to generate the databases for the clusters' surrogate models. An XDSM view of the clusters DOEs, automatically created by KADMOS (i.e. MDPG), for the two-step approach are provided in Fig. 13. Each DOE study only exposes from 7 to 11 independent variables, including wing design parameters (7) and aircraft masses (e.g. Operating Empty Mass (OEM)) as coupling variables (0 to 4) that will be provided by the other clusters. In order to generate the individual clusters database, the first challenge is the selection of the range of variation of the coupling variables. The adopted approach was to make use of the results from DOEs performed during the DC-1 optimization activity Since in the clusters DOEs, the range of variation for the wing shape parameters has been kept similar to the DOEs performed during the DC-1, the 15 configurations in the DC-1 database have been used to estimate the range of variation of the coupling variables between the clusters (i.e. inputs of DOE of the clusters).



(a) DOE of Aero Cluster

(b) DOE of System Cluster

(c) DOE of Weight Cluster

(d) DOE of Mission Cluster

Figure 13. XDSM view of the DOE architectures for 4 competence clusters (two-step approach). The XDSMs are a visualization by VISTOMS package of the MDPG created by KADMOS.

Once the range of each design variable has been determined, the DOE sampling plans have been generated for each cluster, by using a LHS (Latin Hypercube Sampling) sampling method. The number of DOE samples was selected to minimize the numbers of calls to the cluster while providing a sufficient accuracy. Thereafter, the 4 clusters have been integrated and executed as collaborative workflows. The characteristics of the DOE sampling plan are given in Table 1.

	Initial DOE samples	Number of design variables
Aero Cluster	40	7
System Cluster	60	10
Weight Cluster	60	10
Mission Cluster	70	11

Table 1. Characteristics of cluster DOE studies database

A collaborative DOE study service approach, has been developed within the DC-2 by DLR with the objective to facilitate the execution of collaborative DOE studies, whose different steps are performed at different organization. The nested steps are illustrated in Fig. 14 and briefly addressed in the following.

- Step 1: A DOE sampling plan is generated by a specialized Partner, stored in a dedicated CPACS study branch, and provided to the Partner which is responsible for the integration and the execution of the DOE samples via the so-called DOE Study service.

- Step 2: The Partner responsible for the DOE Study service receives the complete sampling plan, and the contained input and output quantities are mapped to the parameters which need to be varied within the specific clusters' workflows. For the described DOE clusters, the sampling plan quantities have been mapped to the DLR aircraft geometry morphing tool, which provides the input (a CPACS aircraft) to the specific cluster's workflow to be executed for each DOE point. Note that such a cluster workflow is also hosted at a different Partner, which is responsible for the specific cluster's workflow integration, and offered as a remote service to the Partner initializing the DOE sampling plan in the previous step.

- Step 3: The specific cluster's workflow receives the DOE sample point as input, it is executed as a remote service requested in step 2. The specific cluster's workflow is also composed by multiple competences, which are CPACS compatible and hosted at different Partners' sites and provided as remote services. The list of the design competences used in the 4 clusters is provided in Section 4.1.

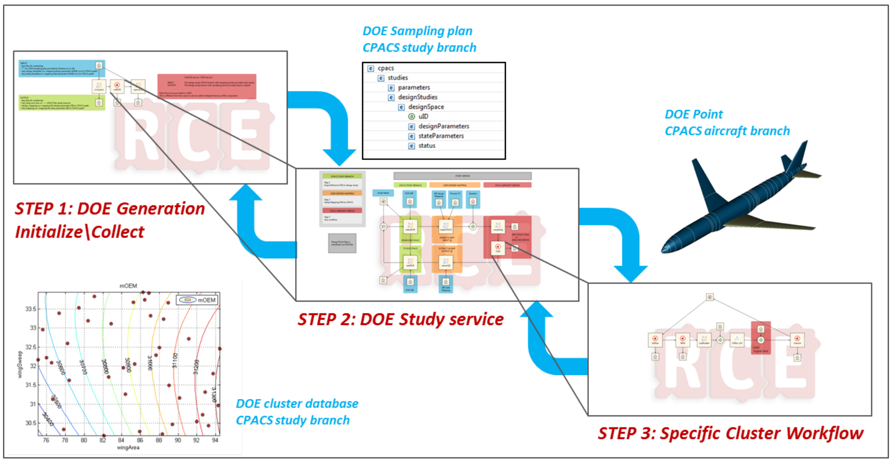


Figure 14. Collaborative DOE study: nested steps approach

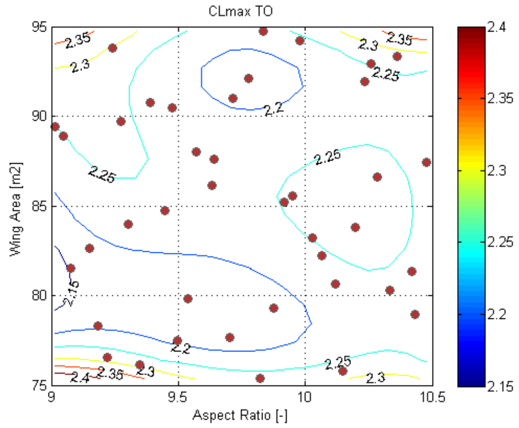
The results obtained within the cluster's workflows (in step 3) are collected by the DOE Study service workflow (in step 2) and mapped back as DOE output for each sampling point, and the complete DOE database is provided back to the Partner initializing the DOE (in step 1). Afterwards, the DOE database stored as CPACS study branch is forwarded to the Partners responsible for the generation of the cluster surrogate models, or for the further enhancement of the DOE sampling plan. For all the 4 DOE clusters shown in Fig. 13, the described three steps have been implemented as individual RCE workflows hosted at different Partners' sites. The deployed approach makes use of the AGILE Collaborative Architecture's elements for requesting and providing the remote services. The complete process for the DOE sampling generation-execution-enhancement is fully automated. As described in Section 4.2 each of the DOE has a specific set of input parameters, and output parameters provided by the distributed design competences which are selected for the cluster. Therefore, for each of the DOE 4 clusters illustrated by the XDSM in Fig. 13, a selection of output parameters is shown in Fig. 15, and briefly summarized in the following.

- Aero Cluster: wing planform parameters (aspect ratio and wing area displayed) are provided as DOE input to the cluster's workflow composed by the aerodynamics analysis modules provided by DLR and UNINA (maximum lift coefficient at take-off displayed).

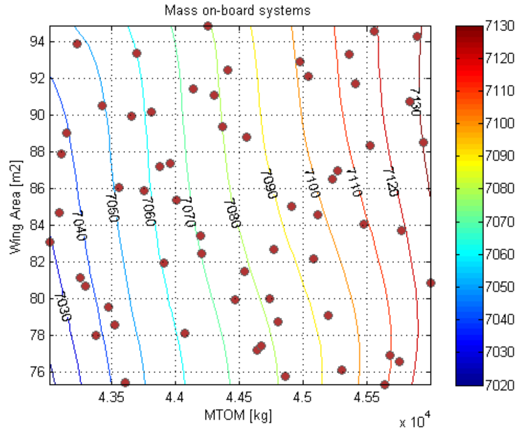
- System Cluster: wing planform (wing area displayed) and design masses (Maximum Take-Off Mass displayed) are provided as DOE input to the cluster's workflow composed by the on-board systems design competence provided by POLITO (mass of the sized on-board systems displayed).

- Weight Cluster: wing planform parameters (wing sweep angle and wing area displayed) are provided as DOE input to the cluster's workflow composed by the loads analysis and structural sizing design competence provided by DLR (operating Empty Mass displayed).

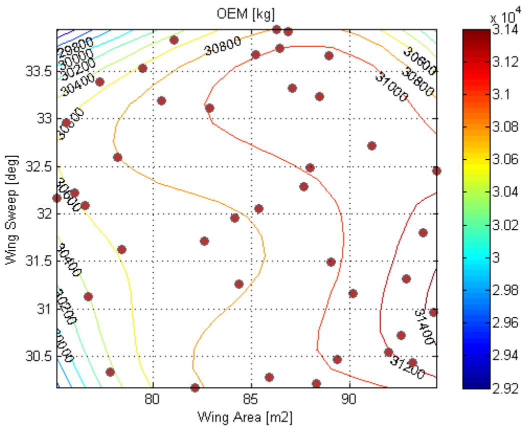
- Mission Cluster: wing planform (wing area displayed) and design masses (Operating Empty Mass displayed) are provided as DOE input to the cluster's workflow composed by the mission performance analysis module provided by DLR (mass of the mission fuel displayed).



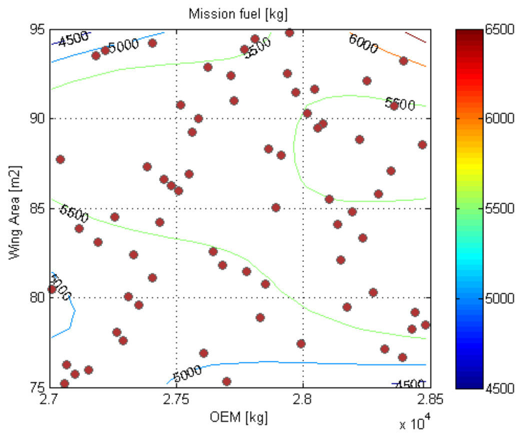
(a) DOE output of Aero Cluster: CLmax at take-off



(b) DOE output of System Cluster: Mass on-board systems



(c) DOE output of Weight Cluster: Operating Empty Mass (OEM)



(d) DOE output of Mission Cluster: Mass mission fuel

Figure 15. DOE clusters sample points results

5.2. Surrogate models

5.2.1. Available methods

Thanks to AGILE consortium, multiple methods are available regarding surrogate models (SM) competence. During DC-2, one of the objective was to make these methods accessible to the partners through their integration as remote services in one of the PIDO framework, like any other design competence. Multiple SM competences were investigated in the frame of this use case.

- NLR's toolbox, called MultiFit [27] which provides a MATLAB based integration of multiple data fitting methods (e.g. polynomial, kriging, spline, neural network). The toolbox guides the user through the steps of deriving and delivering an optimal surrogate model. This includes data analysis and selection, fit method assessment, and deployment of the surrogate model. MultiFit has been used in AGILE to derive surrogate models of wing MDA, loads analysis, engine behaviour and rudder design. Developed surrogate models are made available to partners through the Surrogate Model Repository (SMR), which has also been developed in AGILE [22].

- ONERA's tool, MOE, a Mixture of Experts technique which combines local surrogate models [28]. Mixture of Experts method [29, 30] for surrogate modeling provided uses a clustering of the training basis into regions where the function to be approximated is expected to be continuous or at least more simple. It strongly relies on the Expectation-Maximization (EM) algorithm for Gaussian mixture models (GMM). With an aim of regression, the inputs are clustered together with their output values by means of parameter estimation of the joint distribution. A local expert is then built (linear, quadratic, cubic, radial basis functions, or different forms of kriging) on each cluster and all the local experts are finally combined using the Gaussian mixture model parameters found by the EM algorithm to get a global model. MOE has been made available to AGILE partners for different applications [17].

- NOESIS Optimus kernel which provides a set of surrogate models and accuracy evaluation tools. Three main classes of surrogate models are available:

  - Least squares fit for Taylor polynomial (linear, quadratic, cubic order) or user defined model. The definition of the model terms can be changed by the user or performed automatically to identify an optimal set of terms.
  - Interpolating, either Kriging or radial basis function (linear, thin-plate, quadratic, cubic).
  - User: Optimus offers the possibility to calculate a User-defined RSM. This type of models uses shared libraries and is configured in XML-files.

  Generated models can be evaluated from Optimus or exported and integrated in other application as executable or Functional Mockup Units.

- Surrogate model built by AIRINNOVA is Kriging & co-Kriging [31] based on Matlab DACE toolbox [32]. This process is built initially to provide a "data fusion" technique in AGILE, where a great quantity of low-fidelity data is coupled with a small amount of high-fidelity data to enhance the accuracy of a surrogate model. Using DACE toolbox the surrogate model can be built by choosing the proper regression model (polynomials of order N = 0 (constant), 1(linear) or 2 (quadratic)) and correlation function.

  AIRINNOVA provides an alternative (Matlab-license independent) to DACE co-Kriging, Python's built-in persistence *model* (*scikit-learn*), containing the co-Kriging model parameters corresponding to the co-Kriging surrogate trained with incoming training data. The co-Kriging (Kriging) predictor is inherently strongly coupled with its Hessian computation, which will be examined and the suggested new training data can be provided according to maximum Hessian [17].

5.2.2. Modeling of the Aero Cluster

This subsection analyses multiple methods for creating a surrogate model (SM) of the Aerodynamic analysis cluster (AeroCluster) and describes the results obtained with the MultiFit toolbox. The AeroCluster takes as input the wing design parameters. As a result of the performed analysis the AeroCluster provides lookup tables for aerodynamic coefficients, related to the specified wing design. The lookup tables are given as function of the mission dependent parameters Mach, Reynolds Number (Re), Angle of Yaw (AoY) and Angle of Attack (AoA). The lookup tables will be used later on in the Mission performance Cluster, in order to calculate the actual values of the aerodynamic coefficients and from there contribute to the overall design objectives, e.g. fuel mass.

As already mentionned in Section 4.2, two approaches have been identified in order to derive a surrogate model of the AeroCluster (AeroClusterSM) and relate it to the MissionCluster:

- A two-step approach. In this case the AeroClusterSM predicts - as a function of wing design parameters - a (representation of) the aero lookup tables, e.g. by predicting polynomial coefficients. This approach is illustrated in Fig. 16.
- A "all-in-one" (AI1) approach. In this case the AeroClusterSM directly predicts the aerodynamic coefficients as a function of wing design parameters and mission parameters. As such the AeroClusterSM becomes an integrated part of the MissionClusterSM. This approach is depicted in Fig. 17.

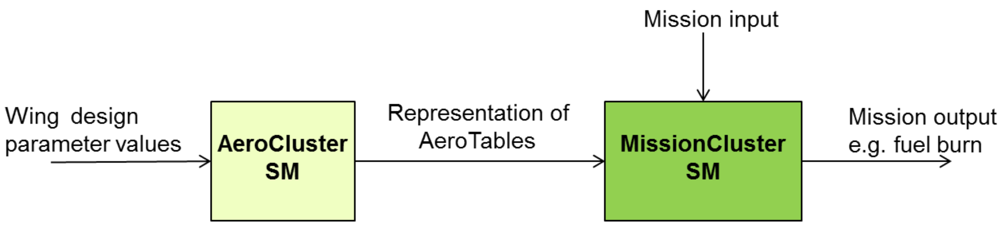


Figure 16. Depiction of the "two-step" approach. For simplicity the other clusters have been left out here.

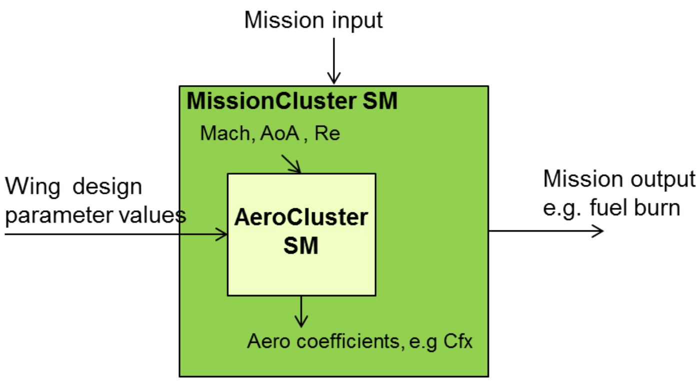


Figure 17. Depiction of the "all-in-one" (AI1) approach. For simplicity the other clusters have been left out here.

As indicated in Section 5.1, a database of 40 aircraft configurations (with varying wing design parameter values) have been processed by the AeroCluster. The aero table parameter AoY was not varied and is therefore ignored. Below surrogate model derivations are described both for the two-step and the AI1 approach. In each case the surrogate model is created using a training set based on the first 39 configurations. The 40^{th} configuration is used for validation of the surrogate models. Only the first aerodynamic output Cfx is considered here, for simplification. The other aerodynamic coefficients (e.g. Cfy, Cfz) could be predicted in a similar fashion.

Two-step approach With this approach two methods for creating the AeroClusterSM have been applied.

- Method1: Approximation of the aero lookup tables using polynomials and prediction of these polynomial coefficients (as function of wing design) again using polynomials.
- Method2: Prediction of the aero lookup tables using Proper Orthogonal Decomposition (POD) [33] and polynomial prediction of the POD coefficients (as function of wing design).

1. Method1: For all configurations the stepwise fit resulted in a 2^{nd} order polynomial (as a function of Mach, Re and AoA) with 7 coefficients: using the constant term, three linear terms, the cross term $\mathrm{Mach} \times \mathrm{AoA}$ and the quadratic terms Mach^2 and AoA^2. Fig. 18 shows that all 40 sets of polynomial coefficients have a piecewise similar order of magnitude. Therefore they could be fitted as well as function of the design configuration. The sets of polynomial coefficients have again been stepwise fitted by a 2nd order polynomial, leaving the 40^{th} polynomial out for validation. This last stepwise fit represents the AeroClusterSM. The 40^{th} polynomial (consisting of 7 coefficients) has been predicted with the AeroClusterSM and has been applied in order to predict the aero lookup

table values of the 40^{th} configuration. The results are depicted in Fig. 19. A maximum absolute Cfx prediction error of less than 0.02 has been achieved. Fig. 19 shows that this corresponds to a relative error of about 10 percent. Other methods (e.g. kriging) for fitting the set of polynomial coefficients have been tried as well, but they gave worse prediction results on the 40^{th} configuration than the stepwise fit AeroClusterSM. Concluding, the AeroClusterSM derived with this method predicts 7 polynomial coefficients that can be passed on to the mission cluster for prediction of the aerodynamic coefficients later on.

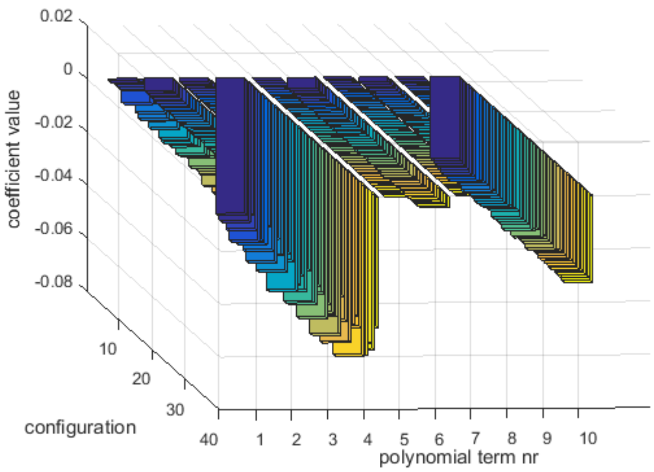


Figure 18. Coefficient values of a 2nd degree polynomial (derived with stepwise fit of the aero lookup tables), for all 40 aircraft configurations

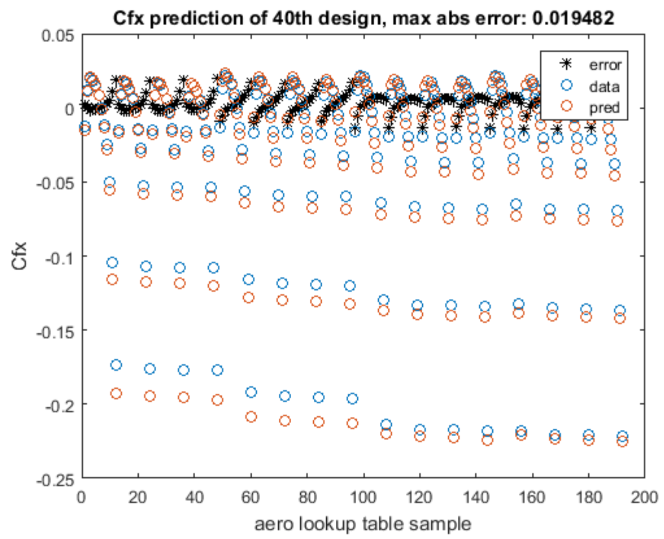


Figure 19. Prediction of the Cfx aero table values on the 40^{th} configuration : Method1 with Nested stepwise polynomial fits

2. Method2: Alternatively, when the lookup table values of Cfx are ordered into one long row (of 192 samples) they can be considered as a "snapshot" of the i^{th} aircraft configuration. This results in a "snapshot-matrix" A of 40 x 192. A can be reduced using POD. A singular value decomposition

$$A = U \times S \times V^T$$

is derived. From S the dominant singular values are selected, in this case the first three. The matrix $U \times S$ contains the POD vectors (row-wise). The first three columns of this matrix are to be fitted, as a function of aircraft configuration. The 40^{th} row of $U \times S$ is left out and the remaining 39 rows are fitted, again using stepwise fit of a 2nd order polynomial. The 40^{th} POD vector is

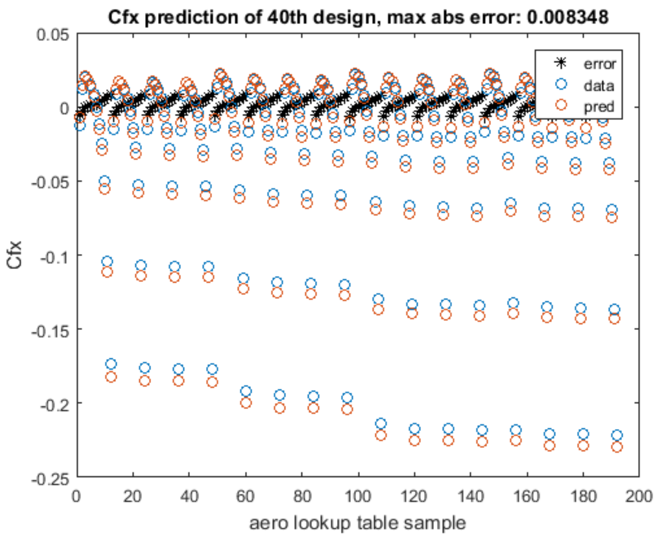


Figure 20. Prediction of the Cfx aero table values on the 40^{th} configuration: Method2 with Stepwise polynomial fit of POD vectors.

predicted using this polynomial and back transformed to a prediction of the 40^{th} row of A (40^{th} aero table "snapshot"). The results are depicted in Fig. 20. This result is a maximum prediction error of less than 0.01, which is better than the validation result with Method1.

Concluding, the AeroClusterSM derived with this method is composed by a stepwise polynomial fit and POD transformation functions. The AeroClusterSM predicts the full aero lookup table (as function of wing design parameters) which can be passed on to the mission cluster for prediction of the aerodynamic coefficients later on.

All-in-one approach With the AI1 approach the 7 wing design parameters and the 3 mission parameters have been combined, resulting in a dataset of 40 x 192 = 7680 points, with 10 inputs and 1 output (Cfx). An Artificial Neural Network (ANN) has been fitted on to the first 7488 points, which correspond with the 39 configurations. One hidden layer with 10 neurons has been used. The aero lookup table values of the 40^{th} configuration are predicted as validation of the method. The results are depicted in Fig. 21. This result is a maximum prediction error of less than 0.01, which is comparable to the validation result with Method2 of the previous approach.

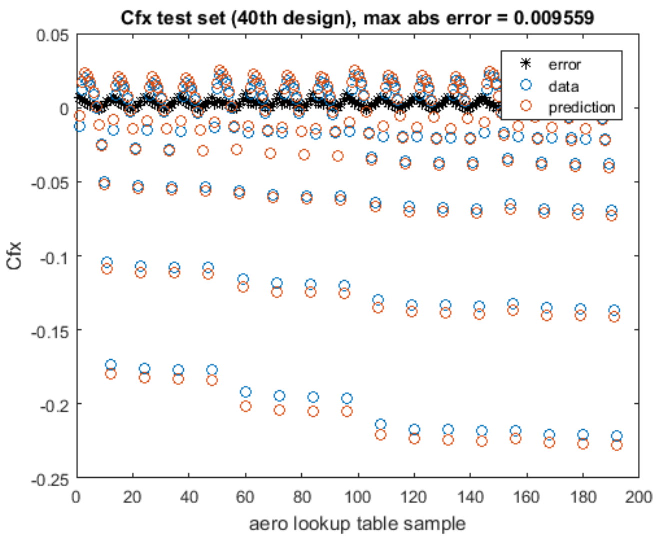


Figure 21. ANN Prediction of the Cfx aero table values on the 40^{th} configuration based on the AI1 approach

Concluding, the AeroClusterSM derived with this approach consists of an ANN that must be integrated with the MissionClusterSM, as illustrated Fig. 17.

Similar investigations were performed by other partners on the AeroCluster and similar approach was also applied to the other clusters once the database was made available. One should note that the objective, here, was not to benchmark the various SMs of the partners but to make accessible multiple surrogate Design Competences through the AGILE framework to build the surrogate-based MDA workflow.

5.3. MDA clusters workflow

This paragraph presents the next step of the approach: the building of the MDA workflow of surrogate models in a PIDO framework. The results shown here were obtained using the Optimus framework and the surrogate models were provided by NOESIS but, thanks to AGILE framework, this workflow could also be established using the RCE PIDO framework and surrogate models provided by other partners could be applied (as a remote competence or as an executable version).
To illustrate the approach, the four clusters have been embedded in a single Optimus MDA workflow depicted on Fig. 22 that reproduces the simplified connection schema depicted in the XDSM (see Fig. 9). As the SMs were already available on the same platform, a non-collaborative implementation of the MDA has been preferred. The MDA does not exploit neither the potentiality offered by Brics to connect remote tools nor the unified file CPACS to enrich the information space. It has been implemented using a single PIDO platform and the surrogate models have been deployed on the same workstation used for the simulations. This direct implementation has been made possible by the clusters created using the knowledge-based part of the AGILE framework, that minimized the number of variables and connections from the complexity represented in Fig. 9 to something manageable by hand. The information exchange between the cluster has been managed using the Optimus native variables. The SMs, exported as binary models, have been prepared for execution via an external evaluator (thus their analysis is triggered from within the workflow, but run independently). The highlighted blocks in the Fig. 22 are:

Yellow color: Aero Cluster	Green color: Structural sizing and Weight Cluster
Red color: On-board systems Cluster	Azure color: Mission Cluster

The structure of the workflow can be adapted with minimal efforts to match the collaborative framework methodology; each colored block can be replaced with a 3-components assembly that performs the CPACS mapping, Brics task creation and extraction of the output values from the enriched CPACS. The operations with the surrogate models operated as remote discipline have been successfully tested using the Multi-task feature of Brics.
There are 2 nested convergence loops (represented by the circular icons on Fig. 22). They are required as the connections among the tools, which have been severed for the DOEs, have to be re-established to ensure the MDA functionality; in some cases this implies that a cluster may receive the input before the corresponding output has been generated by another cluster. To this end, a nominal initialization value, subsequently refined in the following iterations, has been used. Each loop has been addressed using a fixed point iteration until the assigned tolerance is reached (difference between 2 successive iterations lesser than 0.1%). The inner loop connects weight and system clusters and is required to ensure the consistency of the systems weight value (mSystem coupling variable). The outer also includes the Mission cluster and is mandatory to achieve convergence on the fuel weight (mFuel coupling variable) information. On average to achieve convergence on both loops, 45 evaluations have to be performed (9 runs of the outer loop, each requiring 5 runs of the inner). Input values have been gathered on the top of the workflow; the two main array are InputWingGeometry (top left, which include all the AeroCluster inputs) and the InputMission (top right). The design variables for Structural sizing and Weight and On-board systems Clusters are either inherited or generated as output. System and fuel mass are not to be considered independent design variables.
A single run of the non-collaborative MDA takes about 10 seconds; 4 iterations of the internal loop and 5 of the outer one are required to achieve the convergence requirements. The total number of calls to the SM evaluator is 46 (Aero 1, Weight 20, Systems 20, Mission 5). The equivalent collaborative workflow requires around 300 seconds, due to the overhead introduced by data upload and download on the sharedpoint server. The overhead is particularly relevant using SM because of the significantly reduced execution time of the modeled discipline, from seconds/minutes to less than a second. The non-collaborative version of the MDA has been used for the following analysis.
Thanks to the reduced execution time it has been possible to perform a DOE to explore the design space and investigate the impact of the design variables. A 100 experiments Latin Hypercube Sampling has been used. The analysis of the Pearson (measure of the linear correlation) coefficients has been reported in Fig. 23. Values can vary between $+1$ (total positive linear correlation) and -1 (total negative linear correlation). Colors are proportional to the absolute value of the coefficient and emphasize outputs that are significantly affected

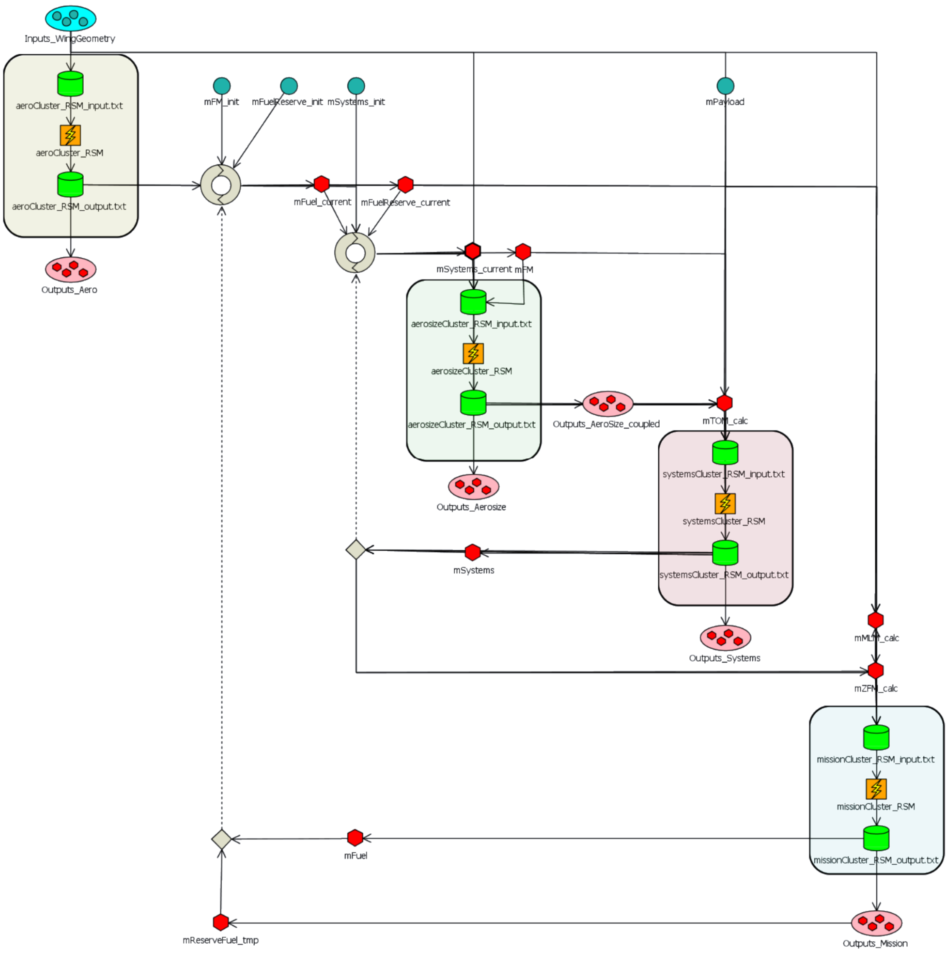


Figure 22. MDA through surrogates with 4 clusters

Pearson	aspectRatio	tcKink	tcTip	twistKink	twistTip	wingArea	wingSweep	CLmaxL	CLmaxTO	mFuel	mOEM	mSystems	mTOM	mWing
aspectRatio	1.000	-0.010	-0.018	-0.035	-0.007	-0.029	0.005	0.034	0.068	-0.564	0.450	-0.051	-0.474	0.457
tcKink	-0.010	1.000	-0.037	-0.018	0.001	0.022	-0.035	0.311	0.192	-0.190	-0.007	-0.324	-0.299	0.004
tcTip	-0.018	-0.037	1.000	0.012	-0.017	0.036	0.046	0.132	0.135	0.033	0.036	0.113	0.099	0.032
twistKink	-0.035	-0.018	0.012	1.000	0.018	0.021	0.016	0.145	0.201	-0.151	0.093	-0.159	-0.132	0.099
twistTip	-0.007	0.001	-0.017	0.018	1.000	-0.046	0.045	-0.860	-0.887	0.149	0.229	0.451	0.444	0.216
wingArea	-0.029	0.022	0.036	0.021	-0.046	1.000	-0.011	0.180	0.155	-0.665	0.832	0.257	-0.252	0.832
wingSweep	0.005	-0.035	0.046	0.016	0.045	-0.011	1.000	-0.290	-0.262	-0.150	0.033	-0.367	-0.225	0.046

Figure 23. MDA through surrogates, design variable influence on evaluated outputs - Pearson coefficient

by a specific design variable (i.e. wing mass and wing area). As an example in Fig. 23, are highlighted the (almost linear) influence that the wing area has on Wing Total Mass, Operative Empty Weight and Systems Weight and the negative effect on both the evaluated lift coefficients due to wing tip twist.
The MDA has been used to test an optimization aimed at minimize the maximum Take Off Mass with a constraint on the minimum range. A global search method, the Self Adaptive Evolution [20] has been selected as optimization algorithm. The method performs an expensive initial exploration of the entire design space but is robust against local minima. The evolution of design variables, outputs and objective has been reported in Fig. 24. The colors represent the iteration number; a convergence pattern is clearly visible. The final configuration has been reported in Table 2. The optimization algorithm selected a thinner, larger wing in order to minimize the drag and consequently fuel consumption; the range improvement has been accompanied by an estimated reduction of total fuel mass. This has a negative effect on the (unconstrained) lift coefficients.

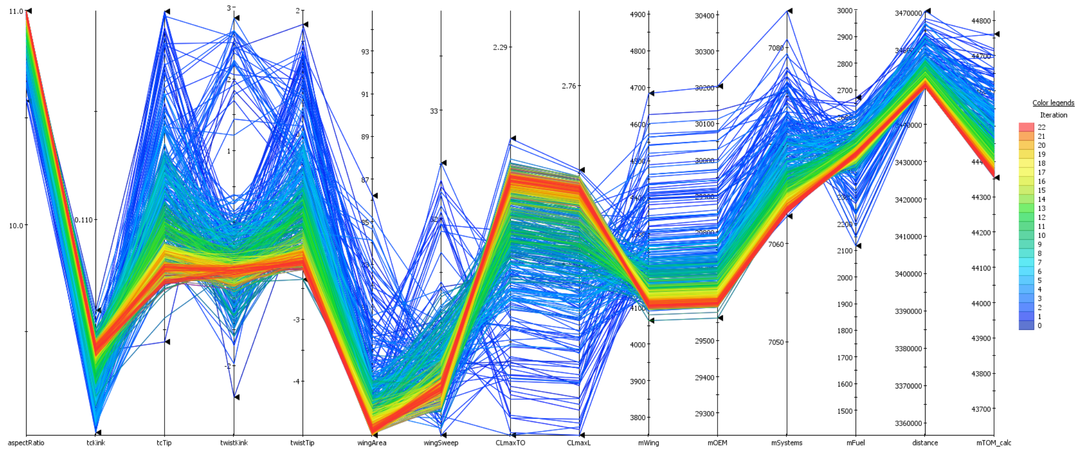


Figure 24. MDA through surrogates, parallel coordinates

	Start	End (983)	Low	High
Inputs				
aspectRatio	10	10.99915	9	11
tcKink	0.11	0.1042	0.1	0.12
tcTip	0.1	0.0971	0.09	0.11
twistKink	0	-0.6882	-3	3
twistTip	-1.5	-2.075	-5	2
wingArea $[m^2]$	85	75.2221	75	95
wingSweep	32	30.4007	30	34
Outputs				
CLmaxTO	2.2584	2.2234		
CLmaxL	2.7255	2.7021		
mWing $[kg]$	4330.23	4108.19		
mOEM $[kg]$	29824.72	29606.31		
mSystems $[kg]$	7059.62	7063.26		
mFuel $[kg]$	2956.61	2452.57		
distance $[m]$	3396172.04	3450220	3450000	
reserveFuelMass $[kg]$	754.65	796.75		
mTOM $[kg]$	44281	44355.64		

Table 2. Optimization, initial and final configurations

The optimization has been performed only to test the MDA through surrogates functionality and the achieved results are for demonstration purposes only. Next step will be to evaluate the optimal configuration with the real MDA in order to quantify the error induced by the simplified process. Nevertheless, the target workflow, representative of the DC-1 MDA through the use of surrogate models, was successfully implemented in a PIDO framework, enabling the explorations of new MDO strategies.

6. CONCLUSIONS AND FUTURE DEVELOPMENTS

This paper has presented an innovative approach where a complex workflow, representative of a conventional aircraft MDA, has been successfully simplified and implemented using surrogate models for clusters of disciplines to reduce the computational time. Taking advantage of the improvements brought by the knowledge based architecture, the set-up phase of the process was strongly eased and the clustering of design competences was investigated in a collaborative way involving all tools' specialists. A field of improvement concerns the clustering process which could be partially automated as it is currently an expert-based and manual process.

During the operational phase, the features implemented in the collaborative architectures, such as DOE service workflow, enabled a quick execution of all the DOEs for all the clusters, each one being a distributed workflow of partners' design competences. In addition, multiple methods regarding surrogate models (SM) competence were investigated and SM were made available to the partners in different formats, such as executable or remote access through a PIDO framework. Eventually, the target workflow, coupling the surrogate models of the clusters, was successfully implemented in Optimus and provided encouraging preliminary results, thus demonstrating the success of the proposed approach.

The next step will be to use the MDA workflow in the two identified scenarios to investigate classical and innovative MDO formulations, potentially with an increase of complexity (adding local variables in some clusters for instance). In addition, this use case will also be used as a mock-up for testing the automation of the execution phase of an MDO system, mainly the execution of the DOE strategy, enabled by KADMOS, through the CMDOWS (Common MDO Workflow Schema) [25] format. Last but not least, the use of surrogate models for clusters of design competences has proven to be a feasible and effective approach and will also be applied to novel configurations in the frame of Design Campaign 3 of AGILE.

Another main consideration concerns the propagation of modeling uncertainties induced by the errors associated to the use of surrogate models. Surrogate model must provide mean value of the output of the discipline as well as an uncertainty on this mean value. Solving the MDA only based on surrogate models implies that the quantity of interest is computed approximately (due to the uncertainty associated to each surrogate). Taking into account the uncertainty associated to each surrogate in the resolution of the MDA implies the resolution of a stochastic non linear system. In order to solve this system an approach based on semi-intrusive polynomial chaos expansion has been proposed in [18] and will be applied in this MDA workflow in order to enrich the surrogate models in area of interest for the objective function.

Significant reduction in aircraft development costs and time to market is essential to achieve cheaper and greener aircraft solutions. The AGILE project is developing the next generation of aircraft Multidisciplinary Design and Optimization processes, focusing on the reduction of the aircraft development time at the early stages of the design process. Many challenges have been identified to ease the optimization of complex workflows in the context of multi-level and multi-partner collaborative engineering projects that characterize aircraft design. However, it can be concluded that the technical solutions developed by AGILE, by smart combination of knowledge based technologies, IT solutions, and MDO strategies provide a fruitful approach for handling those challenges and therefore contribute to a shorter aircraft development time.

ACKNOWLEDGMENTS

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