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# Enhancing optimization capabilities using the AGILE collaborative MDO framework with application to wing and nacelle design

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## Abstract

This paper presents methodological investigations performed in research activities in the field of Multi-disciplinary Design and Optimization (MDO) for overall aircraft design in the EU funded research project AGILE (2015-2018). In the AGILE project a team of 19 industrial, research and academic partners from Europe, Canada and Russia are working together to develop the next generation of MDO environment that targets significant reductions in aircraft development

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costs and time to market, leading to cheaper and greener aircraft. The paper introduces the AGILE project structure and describes the achievements of the 1<sup>st</sup> year that led to a reference distributed MDO system. A focus is then made on different novel optimization techniques studied during the 2<sup>nd</sup> year, all aiming at easing the optimization of complex workflows that are characterized by a high number of discipline interdependencies and a large number of design variables in the context of multi-level processes and multi-partner collaborative engineering projects. Three optimization strategies are introduced and validated for a conventional aircraft. First, a multi-objective technique based on Nash Games and Genetic Algorithm is used on a wing design problem. Then a zoom is made on the nacelle design where a surrogate-based optimizer is used to solve a mono-objective problem. Finally a robust approach is adopted to study the effects of uncertainty in parameters on the nacelle design process. These new capabilities have been integrated in the AGILE collaborative framework that in the future will be used to study and optimize novel unconventional aircraft configurations.

*Keywords:* MDO, Optimization, Aircraft design, mono and multi-objective optimization, robust design

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## Nomenclature

ADOE	=	Adaptive Design of Experiments
AGILE	=	Aircraft 3 <sup>rd</sup> Generation MDO for Innovative Collaboration of Heterogeneous Teams of Experts
BPR	=	Bypass Ratio
CFD	=	Computational Fluid Dynamics
CPACS	=	Common Parametric Aircraft Configuration Schema
DC	=	Design Campaign
DOE	=	Design Of Experiments
ED	=	Engine Deck
EGO	=	Efficient Global Optimization
FORM	=	First Order Reliability Method
FOSM	=	First Order Second Moment
GA	=	Genetic Algorithm
IT	=	Information Technology
MDA	=	Multi-Disciplinary Analysis
MDO	=	Multidisciplinary Design Optimization
MUSCL	=	Monotonic Upwind Scheme for Conservation Laws
MTOM	=	Maximum Take-Off Mass
NGA	=	Nash Genetic Algorithm
OBS	=	On-Board-Systems
pdf	=	probability density function
PIDO	=	Process Integration and Design Optimization
RANS	=	Reynolds-Averaged NavierStokes
RCE	=	Remote Component Environment
RSM	=	Response Surface Model
SEGOMOE	=	Super Efficient Global Optimization based on Mixture Of Experts
SM	=	Surrogate Model
SORM	=	Second Order Reliability Method
SOTA	=	State Of The Art
TLAR	=	Top Level Aircraft Requirements
TVD	=	Total Variation Diminishing
UQ	=	Uncertainty Quantification
SORM	=	Second Order Reliability Method
SOTA	=	State Of The Art
TLAR	=	Top Level Aircraft Requirements
TVD	=	Total Variation Diminishing
UQ	=	Uncertainty Quantification

## 1. Introduction

5 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 teams of experts. To keep up  
10 with the growing demand for more complex and innovative products in shorter time and in higher volumes, the aircraft industry digitizes rapidly. Innovative design approaches based on digital modelling, simulation and optimization technologies are more and more used to take major design decisions as early as possible in order to develop state-of-the-art aircraft quicker and more cost  
15 efficient. In addition, the exploration of unconventional aircraft configurations that might include disruptive technologies is a major challenge, and will not be achieved without the integration on system-level of physics-based simulation and optimization using the appropriate level of fidelity. With the large amount of computational power that is available today, there remains the challenge to  
20 master the complexity of the multidisciplinary design workflow and all its corresponding variables. High-dimensional data sets resulting from various design competences need to be handled in an efficient way.

Over the last three decades, there has been a growing interest in improving the efficiency of the aircraft design process through the use of multidisciplinary  
25 design and optimization (MDO) numerical tools and techniques. In the early 2000's very successful MDO applications were made for a subset of disciplines, but it was at that time already acknowledged that the ultimate value of MDO would be in its ability to optimize the aircraft as a system [1]. Today the exploitation of the full potential of MDO for the design and optimization of  
30 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 optimization work flow. More recently a novel methodology that encapsulates both knowledge and skills was identified [2] to be able to manage the increasing design complexities. The normalization towards modeling knowl-  
35 edge was mentioned [3] as the next required step for the evolution of complex aeronautical systems. One of the major obstacles in the current generation of MDO systems is the effort needed to set up complex collaborative frameworks, and between 60 to 80 % of the project time is spend in this phase [4].

Since 2015 the EU funded Horizon2020 AGILE project [5] is developing the  
40 next generation of aircraft Multidisciplinary Design and Optimization environment that focuses on reducing the set up time for multi-level and multi-partner collaborative workflows, with the aim to reduce the aircraft development time and costs.

The paper is organized as follows. Section 2 provides an overview of the  
45 EU H2020 AGILE project and presents the state-of-the-art distributed MDO system that has been formulated in the first year of the project as well as the main investigations that were performed in the second year. Section 3 discusses improvements made to different optimization strategies aiming at handling the increased complexity of workflows characterized by a large number of design  
50 variables and a high degree of multidisciplinary dependency. Section 4 describes the scenarios on which three optimization techniques are applied focusing on wing design and nacelle design activities and a detailed analysis of the results

obtained for both problems is presented.

## 2. AGILE Overview

AGILE [5] (Aircraft 3<sup>rd</sup> Generation MDO for Innovative Collaboration of Heterogeneous Teams of Experts) is an EU funded H2020 project coordinated by the German Aerospace Center (DLR). The AGILE project is developing the next generation of aircraft Multidisciplinary Design and Optimization environment, which targets significant reductions in aircraft development costs and time to market, leading to cheaper and greener aircraft solutions [4]. The evolution of MDO environments can be classified in three generations, evolving from the 1<sup>st</sup> generation, a monolithic environment still being used today (e.g. for dedicated high-fidelity applications), to the 3<sup>rd</sup> generation, consisting of a system of distributed competences across different organizations that might be located in different countries. The developed AGILE Paradigm [6] will enable the 3<sup>rd</sup> 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, carrying out 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

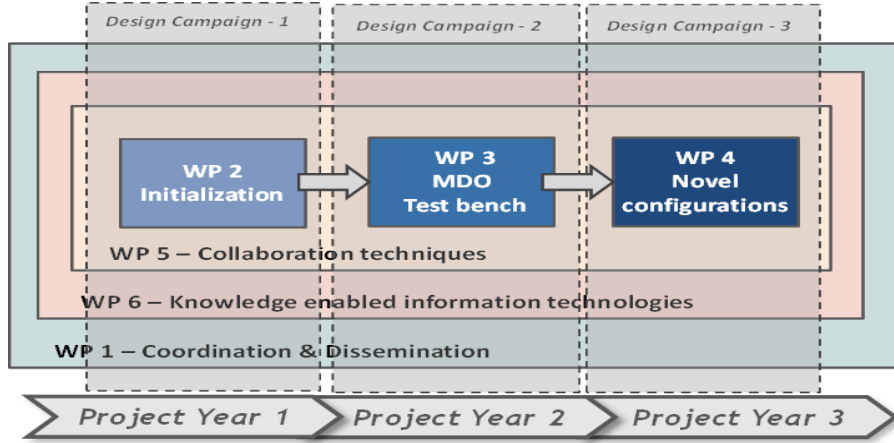


Figure 1: AGILE project structure.

1<sup>st</sup> phase (Initialization), a reference aircraft configuration is optimized using state-of-the-art techniques. The reference MDO problem is then used to investigate and benchmark novel optimization techniques, first 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 first enabling layer (Collaboration techniques) targets the development of the technologies enabling distributed collaboration, comprising

the processes of collaboration between the specialists involved, collaborative pre-  
 80 and post-processing, visualization and the enhancement of the existing frame-  
 work. The second enabling layer (Knowledge enabled technologies) provides the  
 information technologies that support the management and the formalization of  
 knowledge within an MDO process. The parallel activities are clustered in three  
 phases (or periods) called Design Campaign (DC), each lasting one year. Each  
 85 of the sequential design campaigns focuses on the solution of the use cases that  
 are setup to develop specific collaborative and knowledge based technologies.  
 These use cases progress from a conventional regional aircraft optimized using  
 the state-of-the-art MDO to several novel configurations investigated with the  
 3<sup>rd</sup> MDO generation system.

### 90 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 consisted in the design  
 and optimization of a large regional jet, with Entry Into Service (EIS) in 2020.  
 Starting from the specification of the Top Level Aircraft Requirements (TLAR)  
 95 provided by the aircraft manufacturer partner (Bombardier), an Overall Air-  
 craft Design (OAD) task targeting conceptual and preliminary development  
 design stages was implemented in DC-1. The initial TLAR, as well as the main  
 architectural choices are summarized in Table 1.

Description	Value
Range	3600 km
Cruise Mach number	0.78
Initial Climb altitude	11 000 m
Number of passengers	90 pax
Take-off field length	1500 m
Approach speed	130 kts
A/C configuration	Low-wing, wing-mounted engines

Table 1: Top level aircraft requirements.

Figure 2 shows a representation of the DC-1 distributed OAD process. The  
 100 Figure indicates the domains of the specialists' competences that have been in-  
 tegrated into the process, the location where such simulation competences are  
 hosted, and the specific partners providing such a competence within their IT  
 networks. The corresponding collaborative MDO workflow is shown in Fig. 3.  
 A design exploration method was "calling" the OAD process (here labelled as  
 105 MDA) as a remote service, which integrated all the distributed disciplinary  
 competences that in turn are called as remote services (deployed as disciplinary  
 workflows) within the MDA process. All competences communicated via a  
 CPACS<sup>10</sup> model corresponding to the AGILE aircraft product model. They

<sup>10</sup><http://www.cpacs.de> – A Common Language for Aircraft Design, accessed: August 28th  
 2017

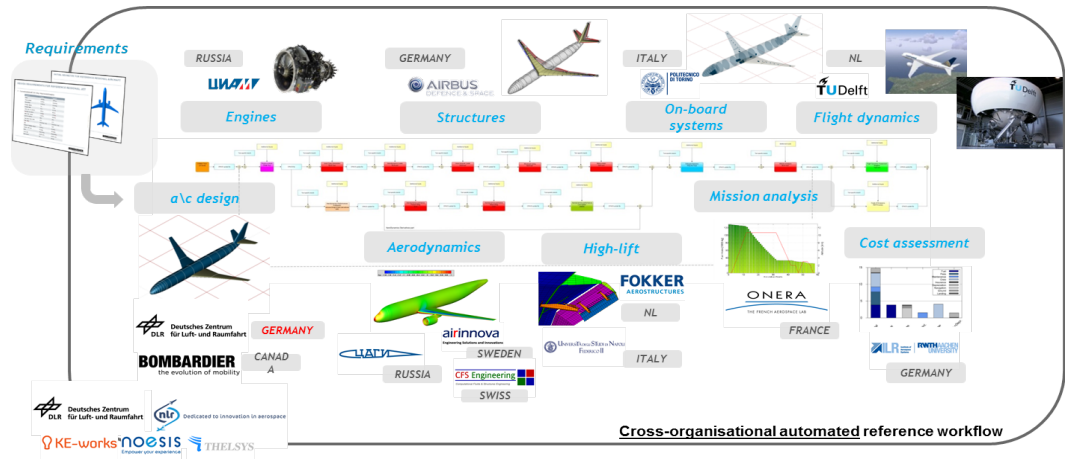


Figure 2: AGILE Collaborative design process: individual competences are distributed multi-site, and hosted at the different partners' networks.

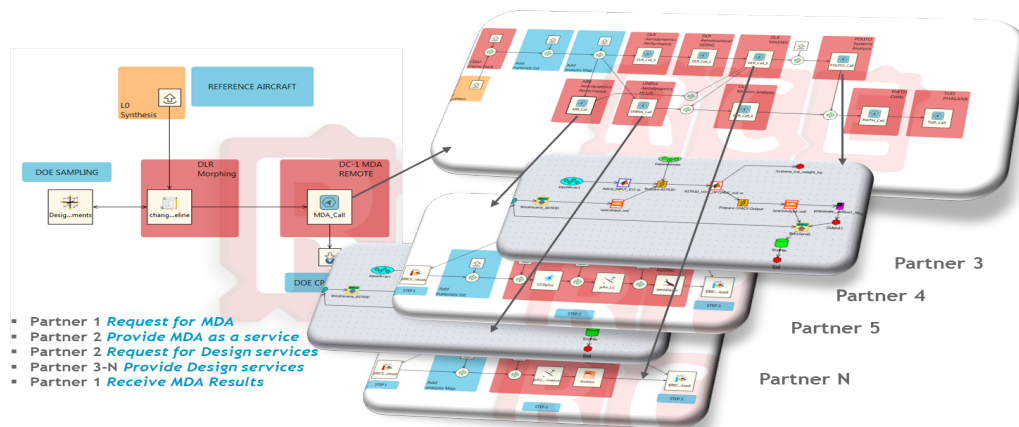


Figure 3: AGILE DC-1 workflow. Partner 1 deploys a Design Of Experiment requesting as remote service the cross-organizational MDA workflow, deployed at Partner 2. The MDA is composed by disciplinary competences provided as remote services to Partner 2 by Partners 4 to N.

were 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 a surrogate based optimization strategy, named SEGOMOE, developed by ONERA and ISAE-SUPAERO [7]. This approach was retained for the State-of-the-Art (SOTA) distributed MDO system as it combines the advantage of a MultiDisciplinary Feasible formulation (no modification of the MDA process, consistency of the design at each iteration of the optimization [8]) and of the use of surrogate models that permits to reduce the number of calls to the MDA. The optimization problem can be defined as follows:

$$\begin{cases} \min & \text{Direct Operating Cost: DOC} \\ \text{w. r. t.} & 7 \text{ wing shape variables} \\ \text{s. t.} & 2.2 - \text{CL}_{\max} < 0. \end{cases} \quad (1)$$

Only a few iterations were made during DC-1, resulting in an improved configuration that was selected as the DC-2 reference aircraft [9].

## 2.2. Design Campaign 2

The DC-2 activities were based on the outcome of the DC-1 work, and were implemented during the second year of the project. The number of use cases was 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 use case, classical MDO formulations (such as MDF, IDF [8] or Analytical Target Cascading [10]) or more adapted ones were used. The five use cases were:

1. 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. This use case and the results are presented in [11, 12].
2. The implementation of Uncertainty Quantification (UQ) methods and robust based design optimization in complex, variable fidelity optimization was the objective of the second use case [11].
3. The development of a 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 [13] and illustrated in Fig. 4.
4. A multi-scale application is described in [14] 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 shown in Fig. 5.
5. A large-scale system-of-systems application was studied, coupling Aircraft - Engine - On-board systems (OBS) - Emissions in a distributed framework approach with the involvement of disciplinary services from different partners [15].

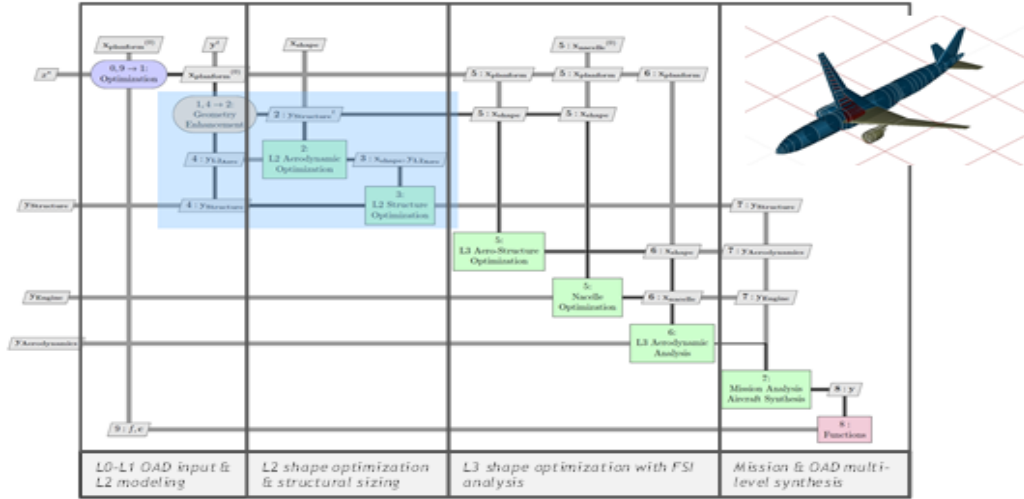


Figure 4: DC-2 - Multi-level optimization formulation.

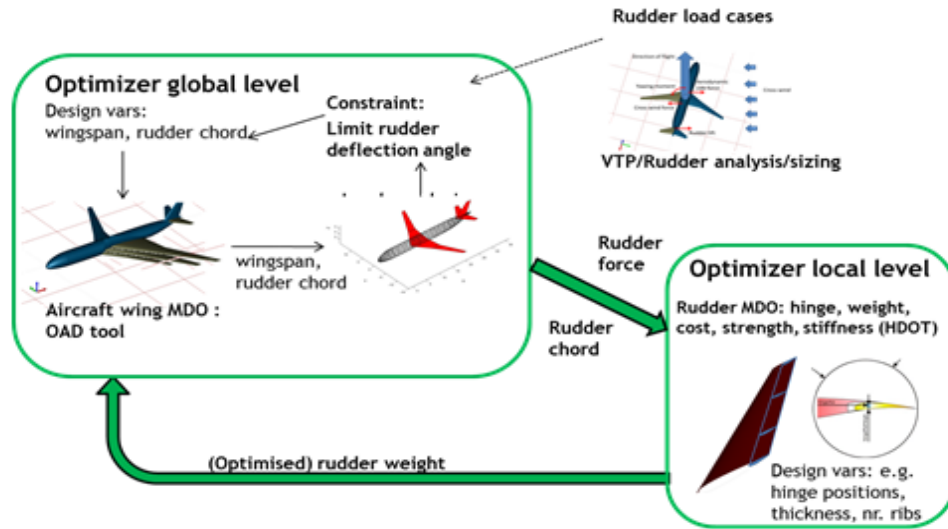


Figure 5: DC-2 - Rudder optimization.

Based on best practices developed in DC-1, the overall AGILE framework

was during DC-2 enhanced by knowledge-based technologies [16] and IT solutions [17], which contributed to an acceleration of the deployment of the complex MDO processes addressed by the DC-2 use cases.

Among the methodological improvements, most investigations were focused on the capabilities and differences among all the optimization approaches considered, all aiming at converging the process more rapidly to the best solutions. The following section will discuss the results of the research of three partners carried out during DC-2 in order to enhance the MDO capabilities of the AGILE process.

### 3. Optimization Methods

#### 3.1. Deterministic Optimization algorithms

In the field of aircraft design, optimization problems to be solved might be challenging as they can combine a multi-modality, high-dimensional design space with conflicting constraints. In addition, in particular for multidisciplinary studies, gradient information of the disciplines is not always available to ease the optimization process. Therefore efficient gradient-based algorithms [18, 19, 20] cannot be selected because finite-differences or complex step methods require a too large number of evaluations to approximate the gradient for use in an optimization process. On the other hand, industrial-standard black-box optimizers as the global Genetic Algorithms (GAs) and Covariance Matrix Adaptation (CMA) require a large numbers of function evaluations and might become unusable for high-dimensional design spaces [21, 20].

An alternative consists of using an Surrogate-Based Optimization (SBO) approach in which some inexpensive approximations of the objective and the constraints are build [22, 23] and a good balance between global and local search is performed [24, 25]. Such algorithm is considered here to perform a mono-objective constrained optimization.

Extensions of SBO to multiple objectives are still under investigation in order to get an infill sampling criterion easy to evaluate [22, 26, 27]. One could generate Pareto-Fronts that involve the solution of the optimization problem multiple times to assess a weighted sum of the individual objectives. However, this method like the Normal-Boundary Intersection [28] or the multi-Objective Particle Swarm Optimization (mPSO) [29] would lead to an impractical number of analyses to be performed. Here we consider an alternative that consists of coupling the Nash game theory (N) to a typical genetic evolutionary algorithm (GA), that starting from specific design variables permits to reduce the number of analysis [30].

##### 3.1.1. Mono objective optimization through the use of metamodels

In order to handle constrained optimization problems with a large number of design variables, a surrogate based optimizer called SEGOMOE [31] for Super Efficient Global Optimization coupled with Mixture Of Experts has been developed by ONERA and ISAE-SUPAERO. This approach focuses on sequential

enrichment using adaptive surrogate models and is based on four main pillars. The first one concerns the Efficient Global Optimization (EGO) approach [24]. In this approach the objective function is replaced by a Gaussian process (GP) (also known as Kriging [32, 33]) defined initially from an initial design of experiments (DOE) of a few points. The EGO algorithm [24] iteratively adds points to the DOE to increase the accuracy of the GP in areas where the minimum is likely to be. The position of the added points is obtained by maximizing the expected improvement (EI) criterion using two key information outputs from GP: the mean and the variance of the objective function, providing a trade-off between exploration and exploitation. The second pillar concerns the evolution of EGO to handle mixed constraints (equality and inequality) using the SuperEGO algorithm [25]. The third pillar concerns the large number of design variables with the introduction of KPLS and KPLS+K surrogate models [34, 35], combinations between the Partial Least Squares (PLS) method and the Kriging model in order to reduce the number of kriging hyper-parameters that are costly to determine. The coupling between SuperEGO and KPLS models has been discussed in [36] leading to the SEGOKPLS algorithm. The last pillar concerns the introduction of Mixture of Experts surrogate models within SEGOKPLS. To better approximate a strongly non linear and/or discontinuous function (objective function or constraint), mixture of experts (MOE) models have been proposed in [37, 38]. The idea is to build local approximations (experts) in subsets of the design space and to recombine them in a global surrogate model. Here the local experts are kriging based models (including KPLS and KPLS+K models) for the objective function and the key contribution is the adaptation of the EI criterion to these local experts. For the constraints approximation, no restriction is made for the approximation and all of the available surrogates (polynomial regression models, Radial Basis Function, Kriging, KPLS, KPLS+K...) can be used as local experts. In addition, different criteria are used for selecting infill sample points like the Watson and Barnes criterion (WB2, see [39]) to give slightly more merit to local search. Finally, the search of the optimum is carried out using different optimizers capable of considering non linear constraints based either on a derivative free optimizer (such as COBYLA -Constrained Optimization BY Linear Approximation- see [40]) or based on gradient method as SLSQP (for Sequential Least Squares Programming [18]) using the Jacobian calculation of the mixture of experts (for the objective and the constraints functions). The resulting SEGOMOE algorithm has been validated on different aerodynamic use cases [41, 7, 31].

This algorithm was provided for the AGILE DC-1 (see Section 2) and was also used for DC-2.

### 3.1.2. Multi objective optimization through the use of Game Theory

One drawback of the approach presented in the preceding paragraph is that it can only be applied for single objective function (even though the extension of the EGO algorithm to multiple design objectives has been studied [22]).

As the aircraft design optimization field can involve multiple and often conflicting objectives, a multi-objective optimization approach [42] that permits to



consider many different parameters that could be a constraint or an objective function for a specific investigation. The design methodologies that allow to perform optimization studies during the aircraft preliminary design phase are already implemented in a software package, as shown in [43] and can also be  
240 built up using surrogate models [44, 45, 46].

The approach developed by the UniNa research group couples the Nash game theory (N) to a typical genetic evolutionary algorithm GA, reducing computational time and allowing a more realistic association among variables and  
245 objective functions [47]. A detailed description of NGA optimization used in the AGILE project is given in [12].

In the game theory approach, a multi-objective problem is considered as a game with  $n$  players, each one characterized by a pay-off. Each player wants to maximize his profit and will try to find an optimal game strategy. If each player has  
250 selected a strategy and no player can benefit from changing strategies while the other players keep theirs unchanged, then the current set of strategy choices and the corresponding payoffs constitute a Nash equilibrium; other feasible possibilities are either to merge the advantages of Nash game and Genetic Algorithms (Nash-GAs) strategy [30] or to use evolutionary optimization algorithms. In  
255 frame of AGILE DC-2, this multi-objective approach has been applied to the common test case (described in Section 4.1) in order to benchmark it against the mono-objective approach relying on a composite objective function.

### 3.2. Robust optimization approach

Standard optimization approaches rely on the implicit assumption that the  
260 underlying system is deterministic, i.e., that the knowledge associated with the design variables and with the system dynamics is not characterized by uncertainty. However, in real conditions randomness impacts the formulation of the design process in multiple ways. Typical examples of such random factors include (a) environmental and operative conditions that cannot be quantified *a*  
265 *priori* with a sufficient level of accuracy, (b) intrinsic fluctuations impacting the outcome of the manufacturing processes, (c) economical and financial trends.

An effective way to model these uncertainties consists in adopting a probabilistic approach, according to which probability distributions are used to model the random nature of the stochastic variables involved in the design process. In  
270 the following, the input random variables are concatenated into the random vector  $X$ . Moreover it is assumed that this random vector is absolutely continuous and can thus be characterized by its probability density function (pdf),  $f_X$ . Several approaches [48] can be adopted to address the following aspects of an uncertainty quantification (UQ) study:

- 275 • Characterization of the uncertainty associated with the system outputs (e.g., uncertainty propagation, variance estimation);
- Sensitivity analysis and quantification of the contributions of the input variables' variance on the outputs variance;

- Robustness and reliability design optimization, where objectives and constraints can be posed in terms of output variances and probabilities of failure rather than deterministic equality or inequality constraints.

Among the available numerical techniques, the current work considers the Monte Carlo (MC) and the First Order Second Moment (FOSM) methods [48]. The MC method requires generating a number of random samples distributed according to the pdf  $f_X$  of the random vector  $X$  used to model the input design variables. For each of these samples, a system evaluation is performed to obtain a collection of results that are used to approximate the target pdf of the outputs of interest. The FOSM method approximates the system dynamics with a first-order Taylor expansion evaluated at the mean value of the input variables. The main advantage of MC is that it provides an estimation of the entire pdf associated with the system outputs, enabling the possibility to infer the shape of the pdf and a set of key indicators like the quantile values or the probability of failure. All these quantities can be directly inferred from the collection of system evaluation results. On the other hand, MC typically requires a large number of system evaluations to obtain an accurate estimation of the quantities of interest, and the rate of convergence with respect to the size of the population,  $N_{MC}$ , is typically low (the variance of the MC estimator is proportional to  $1/\sqrt{N_{MC}}$ ). The main advantage of FOSM resides in its computational efficiency, i.e., only a limited number of system evaluations is required to compute the variance of the target outputs. On the other hand, the accuracy of FOSM strongly deteriorates when the system dynamics is highly non-linear. The use of a probabilistic approach opens the road to the possibility of defining the design optimization problem not only in terms of deterministic quantities but also by considering robustness and/or reliability constraints. The robustness of the system is in this study assessed by analyzing the value of the standard deviation associated with the output quantities of interest. In terms of reliability, both the First Order Reliability Method (FORM) and the Second Order Reliability Method (SORM) [48] are considered. A reliability problem is defined by the presence of one or more design constraints that can be expressed as  $g(X) \leq 0$  identifying a failure region  $\Omega_f$  in the design space. The probability of failure,  $p_f$ , describing the probability for a design to fall within the failure region is defined as:

$$p_f = P[g(X) \leq 0] = \int_{\Omega_f} f_X(x) dX . \quad (2)$$

Equation (2) is in general estimated numerically. Monte Carlo simulation is generally not affordable for the estimation of  $p_f$  as this one is usually small (less than  $10^{-3}$ ). To access this problem Hasofer and Lind [49] introduced the reliability index,  $\beta$ , which is the smallest distance in the standard normal space, between the mean values of the random variables and the limit state function (LSF) (i.e  $g(X) = 0$  in the standard normal space). Numerically,  $\beta$  is computed by identifying the closest point on the LSF, named Most Probable Point (MPP), through a gradient-based optimization algorithm. Once the MPP and  $\beta$  have been identified,  $p_f$  can be estimated by computing a first-order

(FORM) approximation of the limit state surface centered at the MPP. It can be shown that the FORM approximation of  $p_f$  reads,

$$p_f \approx p_f^{FORM} = \Phi(-\beta)$$

where  $\Phi$  is the cumulative distribution function of the standard normal probability distribution. The numerical cost of the FORM approximation is then only linked to the numerical resolution of the determination of  $\beta$  (gradient based optimization problem). The SORM approach consists in improving the FORM estimation of  $p_f$  using a second order approximation of the LSF at the MPP. However this improvement involves higher computational costs.

To deal with the complex, large scale and distributed design problems faced in the context of the AGILE project, a three-step approach is employed. First, a smart and efficient Adaptive Design of Experiments (ADOE) technique [50] is applied to the remote analyses tools in order to explore the design space under study. The results obtained during these DOE campaigns are then employed to build Response Surface Models (RSM) that accurately mimic the dynamics of the considered systems. Finally, different aspects related to uncertainty quantification are addressed by taking advantage of the use of these RSMs.

#### 4. Application to conventional aircraft

One of the objectives of DC-2 was to investigate the capabilities of partner's optimization approaches to converge more rapidly and more efficiently the complex workflows considered in the AGILE project, characterized by a high degree of discipline interdependencies and a large number of design variables.

A typical application of these investigations is the MDA workflow defined and implemented during DC-1 activities, but taking into account extensions towards multi-level and/or multi-component approaches.

##### 4.1. DC-1 derived scenario

During DC-2 the objective is to apply these novel optimization techniques on the reference MDO problem that is based on the MDA of DC-1 and, assess their impact on the overall MDO problem. Among the different use cases considered in DC-2 two different improvements of the MDA are discussed here:

- When considering the wing structural sizing competence, the DC-1 design process was performed through a specific approach aiming at optimizing the internal structure of the wing under loads constraints, thus decoupled from the aerodynamic optimization. The introduction of a multi-objective optimization competence was investigated to improve the capabilities of the AGILE system. The use of the NGA optimization process was applied to the wing design and permitted to consider both aerodynamic (including low-speed performance) and structural objectives in a single step (see Fig. 6).

- During DC-1, the engine and nacelle competences were only considered as input parameters for the overall aircraft design process. This consisted in using a pre-calculated engine performance map as well as using pre-computed engine and nacelle drag and weights. During DC-2, both engine and nacelle design competences were introduced to improve the capabilities of the AGILE framework. TsAGI provided the knowledge and competence to study the Nacelle impact using CFD, see Fig. 7. This permitted a stronger coupling between nacelle sizing and aircraft sizing taking into account the pylon design and the wing/pylon/nacelle interaction. Drawbacks of the implementation are that the nacelle shape optimization process might take as long as a week, and that the uncertainty of the operational conditions might degrade the performance of the optimized design around nominal cruise conditions. The use of ONERA and Noesis Solutions optimization competences were investigated to solve these issues.

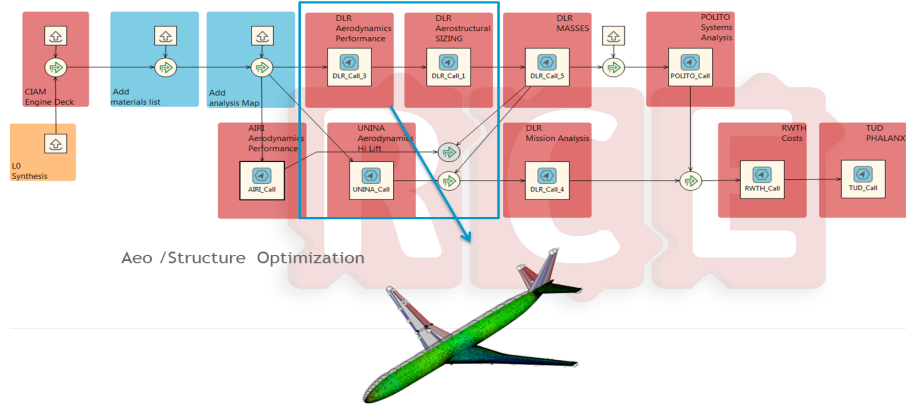


Figure 6: Wing design test case.

These two uses cases, built on the DC1 workflow, ensure that a common part is shared between the partners investigating the enhancements of the AGILE framework. In addition, these use cases are in line with the other use cases of DC-2, all increasing its complexity with extension to multi-fidelity, multi-level and multi-component considerations.

#### 4.2. Wing Optimization

This use case focuses on the optimization of the wing shape both from the structural and aerodynamic point of view. The improvement brought by the use of UniNa NGA optimizer will be evaluated in this section to assess the impact of a multi-objective optimization approach. As the target workflow is characterized by both a high degree of discipline interdependency and a large

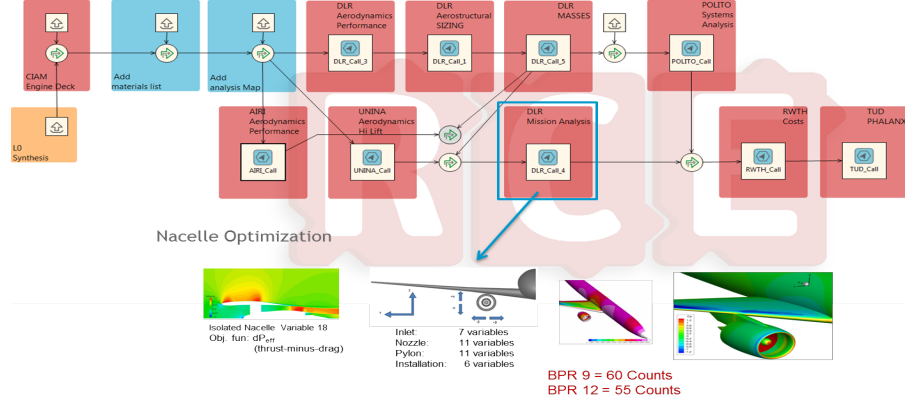


Figure 7: Nacelle design test case.

number of design variables, one of the most straightforward solutions is the use of surrogate models. A surrogate model (SM) is an analytical formulation that replaces a complex model, or even a design analysis workflow, by means of data fitting. As a results a surrogate model requires only little computation time, which is in particular useful for capturing complex analysis methods and applying them multiple times as part of a global optimization process.

In the MDA workflow of DC-1, more than 2000 connections were identified between design competences; to reduce the complexity of the problem while keeping as much as possible its similarity with respect to the aircraft design process, several modifications were made and four clusters were built using a selection of design competences (see [51] for a complete description):

**Aerodynamic Cluster** This cluster gathers a morphing tool (that enables the modification of the full wing geometry from a set of design parameters) and aerodynamic performance computations including low-speed configurations. It takes as input the wing design parameters and provides 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 operational weights such as MTOM (Maximum Take-Off Mass).

**Structural sizing and Weight Cluster** This cluster provides the weight breakdown of the entire 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.

Figure 8 provides the enriched graph [17, 52] of the four clusters. One can observe that each cluster contains design competences of different partners that will be called using the AGILE framework.

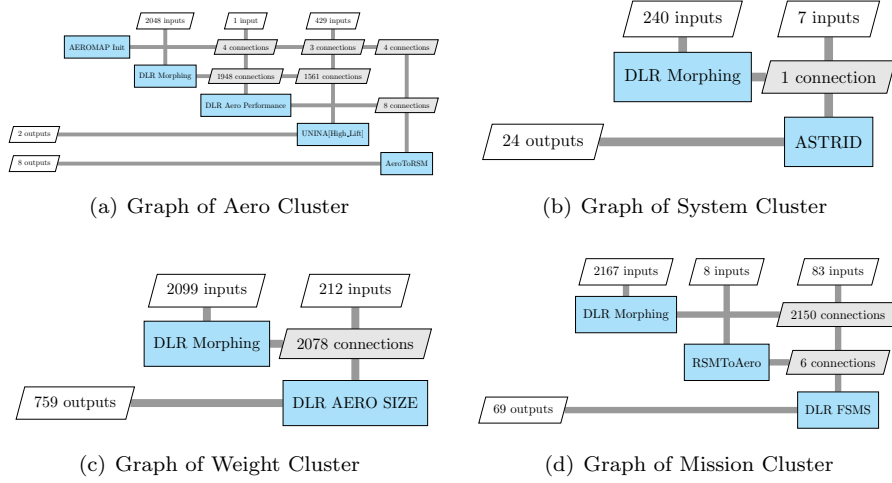


Figure 8: Graphs of the 4 retained clusters.

The design competence clusters were then implemented as collaborative service oriented workflows, and executed within Design of Experiments (DOE) studies in order to generate the databases for the clusters' surrogate models.

The multi-objective optimization approach used at UniNa is based on the NGA optimizer and was used for the abovementioned clusters' surrogate models. They were translated in executable blocks that could be easily queried, as examples the executable version of the Aerodynamic Cluster was used to evaluate the zero-lift drag coefficient and the maximum achievable lift coefficient, and the Structural sizing and Weight Cluster was employed to calculate the wing weight.

#### 4.2.1. Wing optimization problem

The main objective of this use case is the wing optimization in terms of weight, zero-lift drag coefficient and maximum achievable lift coefficient using the NGA algorithm and then comparing the results obtained to a classical Pareto front and single objective scalarization (GA). The TLAR of the aircraft are given in Table 1, and the resulting wing design from DC-1 is characterized by a reference area equal to 82.7 square meters and a sweep angle at the quarter of the chord equal to 30 degrees.

The idea to apply NGA equilibrium solutions to the aircraft design and optimization leads to the chance to avoid a more arbitrary and less physically based variables association among the different objective functions, using, instead, a more engineering reliable variables assignment based on well-known parameter association [47, 12]. In the NGA optimization approach, variables cards can be assigned to players (objective functions) in a unique case, assigning in a static manner these variables, or in multiples combinations, choosing cases to be optimized (until to the maximum number of possible combinations).

The DC-1 main wing parameters are summarized in Table 2 and the wing is shown in Fig. 9. A multi-objective optimization was performed involving five design variables: the taper ratio ( $\lambda$ ), the maximum mean thickness percentage ( $t/c$ ), the aspect ratio (AR), the leading edge sweep angle ( $\Lambda_{LE}$ ) and the wing area ( $S_w$ ). The three objective functions (players) are the wing drag coefficient (computed according the Aerodynamic Cluster), the wing weight (computer according to the Structural sizing and Weight Cluster) and the wing maximum lift coefficient in clean configuration (computed again according the Aerodynamic Cluster), as shown in Fig. 8. During each loop the five design variables and the resulting objective functions change.

Formally, the game can be written as shown in Eq. (3) where the first number represents the number of players involved, inside the curly brackets the upper and lower values of the five cards of the game (AR,  $t/c$ ,  $S_w(m^2)$ ,  $\Lambda_{LE}(deg)$ ,  $\lambda$  respectively) and finally the specific players (objectives). The 3 players could play with these 5 cards, with player 1 optimizing the wing drag coefficient, player 2 optimizing the wing weight and player 3 optimizing the maximum lift coefficient in clean configuration.

$$\Gamma = \langle 3; \{9 - 10.5\}, \{0.125 - 0.138\}, \{75 - 95\}, \{30 - 34\}, \{0.12 - 0.17\}; C_{Dw}, W_w, C_{Lmax_w} \rangle \quad (3)$$

	<b>b(m)</b>	<b>C<sub>root</sub>(m)</b>	<b><math>\Lambda_{LE}(deg)</math></b>	<b>Taper Ratio</b>	<b>t/c</b>	<b><math>S_w(m^2)</math></b>
<b>Reference Wing</b>	28.01	6.39	30	0.164	0.13	82.7
<b>C<sub>Dw</sub> - Wing Weight @ <math>C_L = 0.49</math></b>	0.0254 - 4887kg					

Table 2: Reference wing characteristics.

The design variables are assigned among the players in all possible combinations, leading to  $n$  games among players. In this specific case, considering 5 design variables and 3 players, there are six way of assigning these variables:

- [3, 1, 1], that means 3 parameters to Player 1, 1 to Player 2, 1 to Player 3
- [1, 1, 3], that means 1 parameters to Player 1, 1 to Player 2, 3 to Player 3
- [1, 3, 1], that means 1 parameters to Player 1, 3 to Player 2, 1 to Player 3
- [2, 2, 1], that means 2 parameters to Player 1, 2 to Player 2, 1 to Player 3

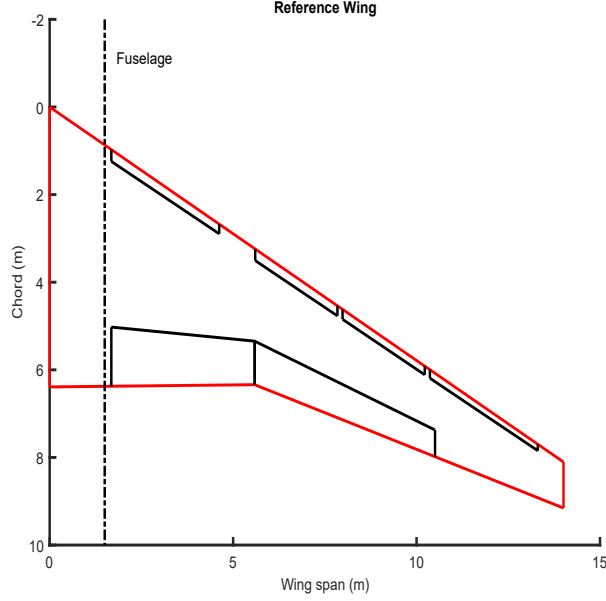


Figure 9: Reference wing planform.

- $[1, 2, 2]$ , that means 1 parameters to Player 1, 2 to Player 2, 2 to Player 3
- $[2, 1, 2]$ , that means 2 parameters to Player 1, 1 to Player 2, 2 to Player 3

Each of these assignments leads to 10 possible combinations, and so 60 games in total.

460 The NGA optimization has been compared with a GA scalarization and a multi-objective GA (Pareto front). In the scalarization optimization the GA algorithm was used and the objective function was simply defined as an average weighted function as shown in Eq. (4).

$$F_{obj} = F_{obj\_1} \cdot k_{CDw} \cdot s_{CDw} + F_{obj\_2} \cdot k_w - F_{obj\_3} \cdot k_{CL} \quad (4)$$

where:

$$F_{obj\_1} = C_{Dw} \quad (5)$$

$$F_{obj\_2} = \frac{W_{wing}}{W_{wing\_initial}} \quad (6)$$

$$F_{obj\_3} = C_{L_{maxw}} \quad (7)$$

465 and

- $k_w$  is the weight which represents the importance of the wing weight in the optimization process.



- $k_{CD}$  is the weight which represents the importance of the wing drag coefficient in the optimization process.
  - $s_{CDw}$  is the scale factor useful to keep the same order of magnitude between the objective functions. It was set equal to 10 to work with objective functions characterized by the same order of magnitude.
  - $k_{CL}$  is the weight which represents the importance of the wing maximum lift coefficient in the optimization process.
- The  $k$  weights take values within the range  $[0, 1]$  so that the sum of them is equal to 1.

#### 4.2.2. Results for multi objective optimization

The NGA algorithm scans 60 possible solutions, selecting only those for which the values of the objective functions are simultaneously better than the references wing weight and drag coefficient and greater than maximum lift coefficient. Between them the algorithm will select the wing characterized by the maximum lift coefficient.

Figure 10 shows the best solution in terms of wing planform compared with the reference wing planform (red line).

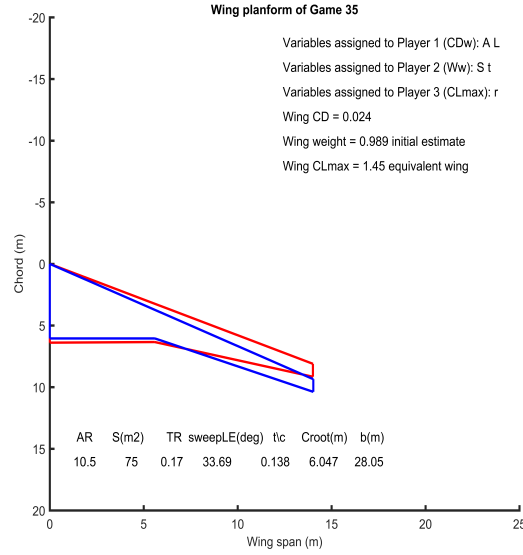


Figure 10: Wing planform (Game 35) three players' optimization for reference wing (blue) and optimized wing (red).

Table 3 provides the comparison between the reference wing planform, the best solution chosen at the end of the NGA optimization and the best solution

obtained through GA scalarization. The latter solution was obtained by associating AR and  $\Lambda_{LE}$  to  $F_{obj\_1}$ ,  $S_w$  and (t/c) to  $F_{obj\_2}$ ,  $\lambda$  to  $F_{obj\_3}$ . As can be seen, the optimum solution simultaneously improves the drag coefficient (reduction of about 14 drag counts), the wing weight (reduction of about 40 kg) and increases the maximum achievable lift coefficient (increase with 0.12). Although the best solution obtained using the GA scalarization approach is similar to the one obtained using NGA, the solution obtained using the scalarization approach is largely dependent on the values of the  $k$  weights and does not take into account the association among variables and objective functions.

	AR	$\Lambda_{LE}(\text{deg})$	b(m)	$\lambda$	t/c	$S_w(\text{m}^2)$
<b>Reference Wing</b>	9.43	30	28.01	0.164	0.13	82.7
<b><math>C_{Dw}</math> - Wing Weight - <math>C_{Lmax_w}</math></b>	0.0254 - 4887 (kg) - 1.39					
<b>Game 35 (NGA)</b>	10.5	33.69	28.05	0.17	0.138	75
<b><math>C_{Dw}</math> - Wing Weight - <math>C_{Lmax_w}</math></b>	0.0240 - 4837 (kg) - 1.53					
<b>GA best solution</b>	10.5	33.69	28.05	0.17	0.138	75
<b><math>C_{Dw}</math> - Wing Weight - <math>C_{Lmax_w}</math></b>	0.0240 - 4837 (kg) - 1.53					

Table 3: Comparison between AGILE DC-1 wing and the best solution of NGA and GA applications with 3 players.

Figure 11 shows a comparison of all the NGA points (60 games) with a typical Pareto frontier and scalarization optimization approach. One can see that the NGA points are characterized by a better spread compared to the GA scalarization points which are only located in a specific portion of the feasible area bounded by the Pareto front. It is useful to underline that Fig. 11 shows only a cutting plane of the multi-objective optimization among the three players/variables involved.

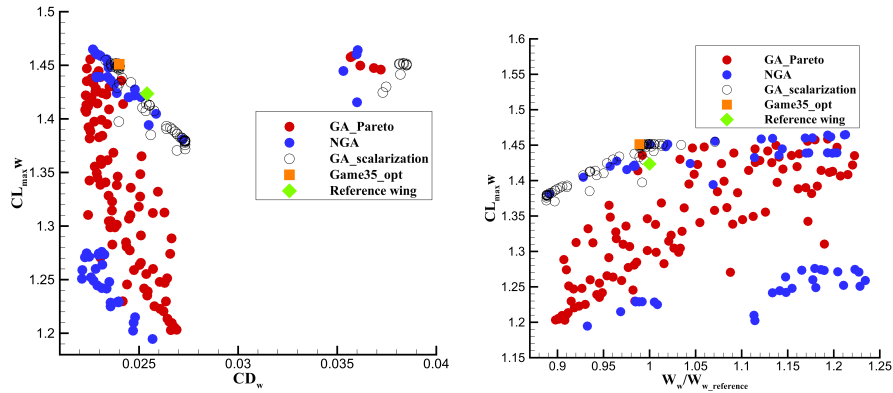


Figure 11: Results comparison among the three optimization approaches (data referred to the equivalent wing); on the left ( $C_{Lmax_w}$  -  $C_{Dw}$ ), on the right ( $C_{Lmax_w}$  -  $W_w/W_{w\_ref}$ ).

505 This application showed that the Nash game theory coupled with a typical  
genetic evolutionary algorithm (NGA) is a viable approach to use in the opti-  
mization field since firstly it permits a more realistic association among variables  
and objective functions and secondly it reduces the computational time. More-  
over, the reduced distance between NGA solution points and the Pareto front  
demonstrates the reasonableness and the feasibility of the results obtained. Fi-  
nally, a verification of the computational time between the Pareto front, a single  
510 game of the NGA, and the GA scalarization approach has been performed on  
a laptop equipped with a single CPU (2.0 GHz). The elapsed time for a single  
NGA solution point for the 3 players application is equal to 50 seconds, for a  
single scalarization GA solution point it equals 59 seconds, and for the Pareto  
front it is 76 seconds. The larger the number of variables or objective functions,  
515 the larger the computational time that can be saved using the NGA approach.

These results show the benefits of introducing this new feature in the en-  
hanced AGILE framework in order to apply it to multidisciplinary wing design  
optimization. This new capability will be used during Design Campaign 3 where  
the AGILE environment will be applied to different novel aircraft configurations.

### 520 4.3. Nacelle Optimization

#### 4.3.1. Nacelle optimization problem

This use case focuses on improvements of the nacelle shape optimization  
process that were investigated during DC-2 in order to reduce both the over-  
all optimization time and the robustness of the optimal design around nominal  
525 cruise conditions. The nacelle shape optimization process focuses on the follow-  
ing two issues:

- One of the objectives in optimizing the geometry of a turbofan nozzle is  
to reproduce the mass flow rate through the core (hot) and bypass (cold)  
nozzles specified in the engine technical specification. The standard prac-  
530 tice when designing the nozzle is to fix the value of the cross-sectional area  
of the nozzle exit during optimization. The disadvantage of this approach  
is that the nozzle mass flow rate depends on the entire geometry of the  
nacelle that is changing during the optimization, even for a fixed value of  
the exit section area. As a result the optimal shape of the nacelle does not  
535 necessarily fulfill the requirement in terms of operating conditions. For  
this reason one should add to the optimization process the constraint that  
the required mass flow rate is satisfied.
- Although the aforementioned approach improves the nacelle design, only  
cruise conditions are considered whereas the nacelle design should also  
540 ensure acceptable behaviour (in terms of engine intake flow conditions)  
in take-off configuration. This constraint can be taken into account by  
limiting the range of variation of the inlet geometrical parameters within  
known bounds — mainly by expert judgment — to ensure that they are in  
the region that satisfies the take-off configuration performance. However,  
545 improvements can be expected by considering both the cruise and take-off

configurations in the same optimization problem. The second problem therefore considers the robust optimization of the inlet geometry shape taking into account the impact of four random input variables: ambient temperature and ambient pressure both evaluated at cruise and take-off conditions. As a consequence, both engine and nacelle modules have to be considered in this approach.

The deterministic optimization problem deals with the entire nacelle geometry. Following the parametric model described in [53] the input parameters of the problem are 17 geometrical parameters as illustrated in Fig. 12:

- 7 variables concern the inlet geometry
- 10 variables are concerned with the nozzle.

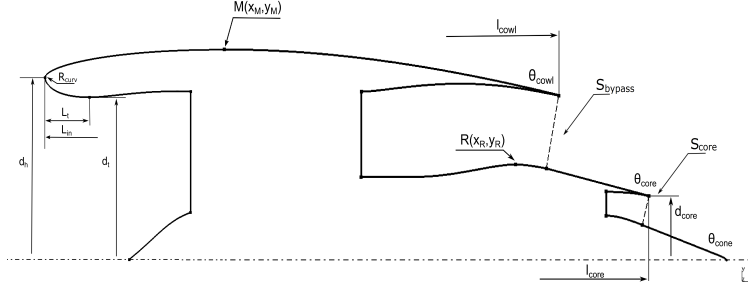


Figure 12: Nacelle geometrical description.

The value of the effective thrust in cruise regime has been used as the objective function for the nacelle optimization. This value depends on the difference between the ideal and the real engine thrust obtained during the calculation:

$$dP_{\text{eff}} = 1 - \frac{P_{\text{eff}}}{P_{\text{id}}} \quad (8)$$

with

- $P_{\text{id}}$  the ideal engine thrust,
- $P_{\text{eff}} = P - F_X$  the effective engine thrust (thrust-minus-drag),
- $P$  the engine thrust determined with the use of the internal parameters,
- $F_X$  the projection of the external drag force on the engine axis.

To solve the problem of optimal nacelle design with the constraints of providing the required mass flow rates, it is necessary to change the formulation of the initial optimization problem [54]: the areas of the exit sections are no longer

fixed, but varied among the 17 geometrical parameters mentioned above. There are two equality type constraints in the optimization problem:

$$G_{\text{core}} - G_{\text{core}}^{\text{target}} = 0 \quad (9)$$

$$G_{\text{bypass}} - G_{\text{bypass}}^{\text{target}} = 0 \quad (10)$$

570 These two equality constraints are transformed into two inequality constraints as follows:

$$\left| 1 - \frac{G_{\text{core}}}{G_{\text{core}}^{\text{target}}} \right| < \epsilon_{\text{core}} \quad (11)$$

$$\left| 1 - \frac{G_{\text{bypass}}}{G_{\text{bypass}}^{\text{target}}} \right| < \epsilon_{\text{bypass}} \quad (12)$$

where the two thresholds  $\epsilon_{\text{core}}$  and  $\epsilon_{\text{bypass}}$  are set equal to  $10^{-2}$  and  $2.5 \cdot 10^{-3}$  respectively based on the required accuracy. These constraints ensure that, within the required accuracy, the equality of core and bypass mass flow rates ( $G_{\text{core}}$  and  $G_{\text{bypass}}$ ) to the target values (see Fig. 13). The values of the thresholds are based on the requirements of aircraft engine manufacturers for the accuracy of determining the air flow for the nozzle design phase. For example, for the engines under consideration, the values  $10^{-2}$  and  $2.5 \cdot 10^{-3}$  approximately correspond to the physical air flow of 100 grams for the hot nozzle and 300 grams for the cold one. The target values are determined by the engine regime parameters and are specified in the engine deck definition. After optimization, the nacelle geometry suitable for installation on the aircraft is obtained. All the necessary airflows values are computed by the nacelle design tool code developed by TsAGI described in Section 4.3.2.

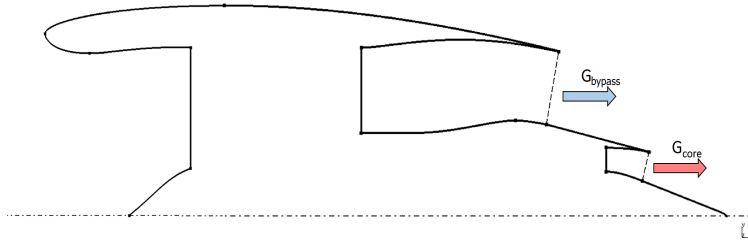


Figure 13: Core and bypass mass flow rates of the engine.

585 The nacelle shape optimization case presents two aspects that have been improved through the application of novel techniques that were made available by the AGILE partners:

- a reduction of the number of function evaluations for the shape optimization process, compared to the original optimizer (EGO by DAKOTA [55]).



*Engine tool.* The engine simulation provides the engine parameters and engine performance map for different engine design cycle parameters and size. A steady state engine performance is represented by an engine deck (ED). The ED provides the engine performance for the engine operating envelope. The ED can be presented in table format or as a computer program providing a limited number of required engine parameters. An Extended Engine Deck (EED) has been made to provide the engine parameters and performance maps of the different engines required by the AGILE partners. The technical specifications of the EED were agreed by the AGILE partners to fix adoptions and constraints for the engine simulations. To generate the EED, commercial software tools level 1 (L1) for engine modeling were used. A L1 entire engine simulation tool corresponds to an engine simulation using 0-level simulation of engine components (compressors, turbines, combustor, etc.), i.e. black boxes without detailed (1D-3D) modeling. The commercial software GasTurb v12 [59, 60] L1 was employed to evaluate the on-design and off-design engine parameters and to generate the performance map. The program scope has different degrees of simulation detail. The engine component maps can be presented in the engine tools in different ways from generalizations up to approximations of rig test data. Engine model technology constraints and design rules are used in engine cycle design, off-design simulation, engine overall geometry and mass assessments. Technology constraints and design rules were applied to generate an EED consistent with the specified engine technology level. The engine analysis module evaluation is based on the following inputs: operational assumptions, Entry into Service time, engine configuration, power offtake/overboard bleed. The set of output variables delivered by the tool consists of: engine installation losses, engine flight envelope (see for example Fig. 15), intake pressure recovery description, thrust specifications and engine sizing, thrust reverser ability, engine technical deliveries, engine performance for different operating conditions, engine dimensions description, engine sizing rules and automatic handling of air bleed. In this study the engine performance characteristics for the target operating envelope are calculated according to a steady state engine performance simulation for an unmixed Geared Turbo Fan with high By-Pass Ratio.

#### 4.3.3. Results for Deterministic Optimization

Two test problems are considered: nacelle design optimization of engines with  $BPR = 9$  and  $BPR = 12$ . Both problems are solved in the same setting by two optimizers — EGO-DAKOTA (Sandia National Laboratories) [55] and SEGOMOE [31] described in Section 3.1.1.

As for the wing design test case all processes are integrated into one analysis workflow with the help of the RCE framework (see Fig. 16). The aerodynamic analysis block includes geometry construction, meshing, CFD calculation and post-processing.

*Results for the  $BPR=9$  nacelle optimization.* The convergence curves for the nacelle optimization of the engine with  $BPR = 9$  are shown in Fig. 17. The

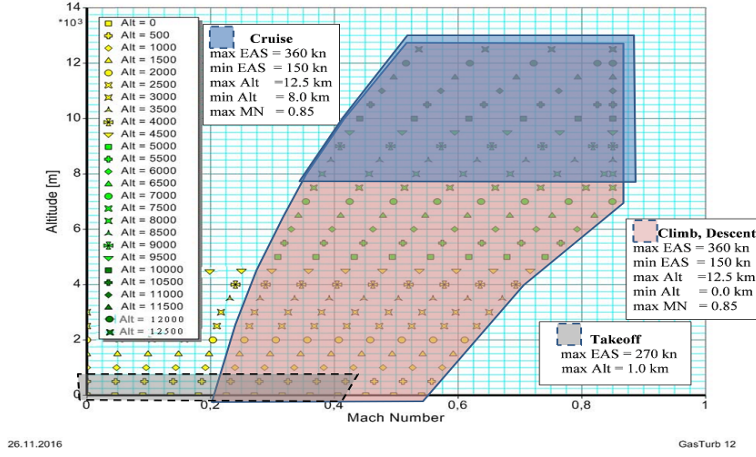


Figure 15: Engine operating envelope spot points agreed for aircraft mission calculation.

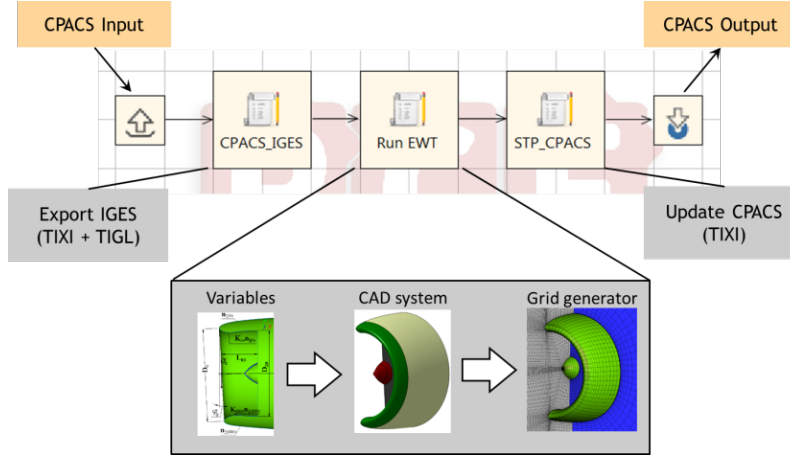


Figure 16: Nacelle design analysis workflow.

two optimal solutions of EGO-DAKOTA and SEGOMOE are compared in Table 4. The number of function evaluations to reach the optimal value of the objective function is the most common criterion to compare two optimization algorithms. Here we compare also the error with to respect the two inequality constraints (Eq. (11) and Eq. (12)) according to the two thresholds  $\epsilon_{core}$  and  $\epsilon_{bypass}$  fixed at 1% and 0.25% respectively. Compared to DAKOTA, SEGOMOE converges to an optimal design not only with a lower objective value for which the two constraints are respected, but also involving a smaller number of function evaluations.



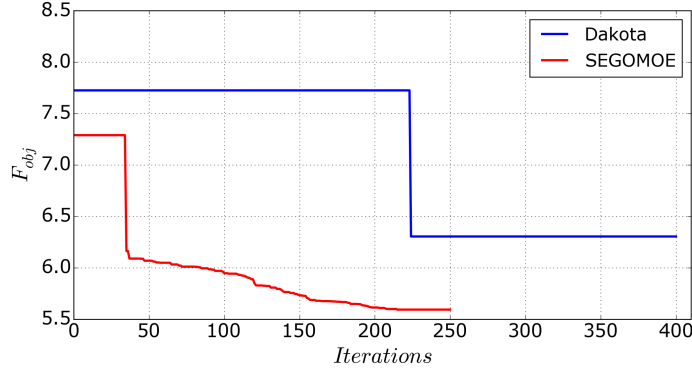


Figure 17: Convergence History of EGO-DAKOTA and SEGOMOE, case BPR=9. The red line is associated to the best found point with SEGOMOE, the blue line refers to the solution of EGO-DAKOTA.

	Size of the initial DOE	Number of function evaluations	Core mass flow error, %	Bypass mass flow error, %	Objective value
EGO-DAKOTA	171	224	-0.21	-0.24	6.30
SEGOMOE	30	215	+0.64	+0.15	5.59

Table 4: Comparisons between EGO-DAKOTA and SEGOMOE in terms of function evaluations and objective value case; case BPR=9.

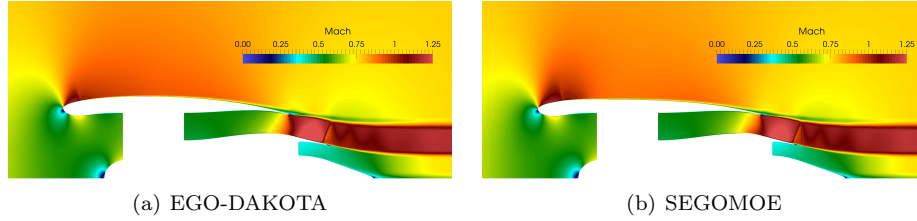


Figure 18: Mach number distribution at the optimal design with EGO-DAKOTA (a), or SEGOMOE (b); case BPR=9.

*Results for the BPR=12 nacelle optimization.* The convergence curves for the nacelle optimization of the engine with BPR = 12 are given in Fig. 19.

The two optimal solutions of EGO-DAKOTA and SEGOMOE are compared in Table 5 in terms of number of function evaluations and in Fig. 20 in terms of Mach number distribution. The good performance of SEGOMOE is also demonstrated for this test case in terms of objective value, constraints respected and the number of function evaluations.

The EGO-DAKOTA algorithm imposes an initial DOE of size equal to  $(d+1)(d+2)/2$ , with  $d$  the dimension of the design variables. So in this case ( $d = 17$ ) a minimum of 171 points is required. A sequential enrichment process such as SEGOMOE would be preferred over an approach with a minimum number of

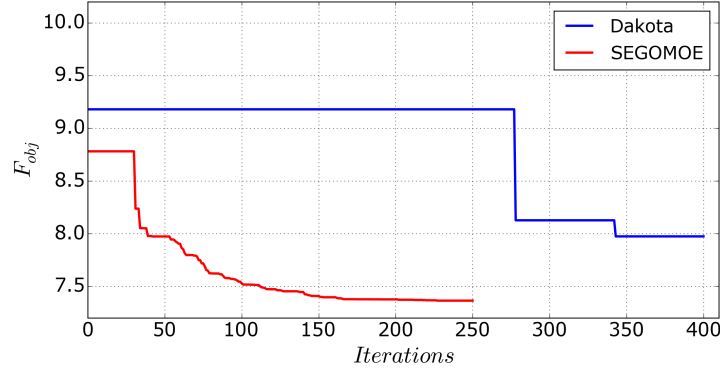


Figure 19: Convergence History of EGO-DAKOTA and SEGOMOE, case BPR=12. The red line is associated to the best found point with SEGOMOE, the blue line refers to the solution of EGO-DAKOTA.

	Size of the initial DOE	Number of function evaluations	Core mass , % flow error, %	Bypass mass flow error, %	Objective value
EGO-DAKOTA	171	343	+0.04	-0.17	7.97
SEGOMOE	30	227	+0.68	+0.04	7.36

Table 5: Comparisons between EGO-DAKOTA and SEGOMOE in terms of function evaluations and objective value; case BPR=12.

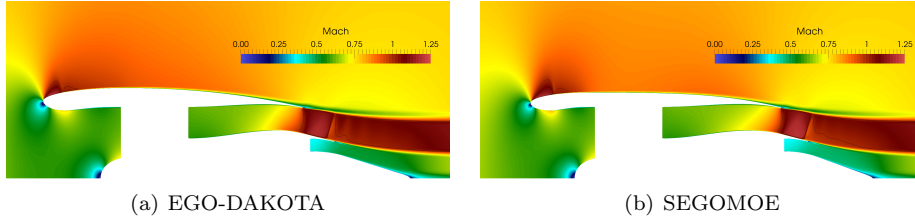


Figure 20: Mach number distribution at the optimal design with EGO-DAKOTA (a), or SEGOMOE (b); case BPR=12.

points required (such as EGO-DAKOTA) if the objective is to minimize the number of function evaluations.

Another aspect concerns the constraint handling for EGO-DAKOTA; Figs. 17 and 19 show that the best objective value when using EGO-DAKOTA (blue curve) is quite constant for both the test cases because the successive enrichment points proposed at each iteration do not respect the two constraints, and the best value is not updated. For instance, for the test case BPR=12 over the 400 iterations (see Fig. 21), only ten points were in the feasible domain. These investigations demonstrate the interest of the optimization method provided by ONERA that has been implemented as a new capability in the enhanced AGILE framework.

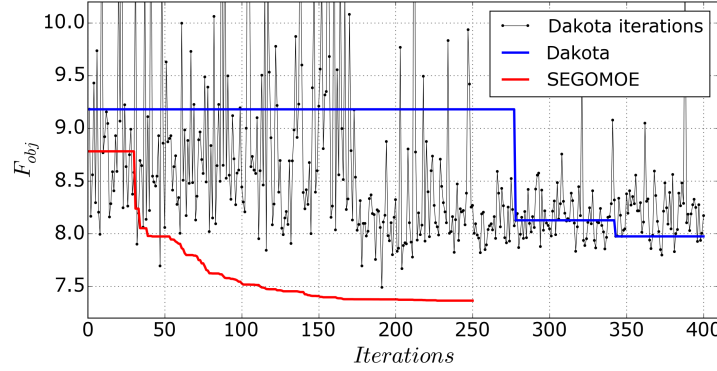


Figure 21: Convergence History and Iterative Process of EGO-DAKOTA and SEGOMOE, case BPR=12. The red line is associated to the best found point with SEGOMOE, the blue line refers to the solution of EGO-DAKOTA and the black curve represents all the evaluations done during the EGO-DAKOTA optimization process.

In conclusion the preliminary optimal design of the engine nacelle has been solved, the mass flow rate requirements are met with the required accuracy, and the outcome is an optimized inlet and nozzle geometry. Further improvements in the intake geometry can be carried out only when constraints on the level of flow distortion at the fan face are taken into account. This requires that it is necessary to consider at least a take-off condition characterized by the maximum air flow rate through the intake. Moreover, considering the possible uncertainties regarding operational conditions is of major interest.

#### 4.3.4. Results for robust design optimization

The use case adopted to perform the robust optimization of the engine nacelle is built starting from the results discussed in the previous section for the engine with  $BPR = 12$ . To cope with the complexity arising when uncertainty is considered, only 2 design variables are taken into account out of the 17 handled before. The remaining 15 variables are considered as static parameters and set to their optimal values found before. In this study, randomness will be associated with a set of ambient parameters (i.e., temperatures and pressures) characterizing the operational conditions of the engine. Two disciplinary modules (i.e., the engine module provided by CIAM and the nacelle aerodynamic module provided by TsAGI, both described in Section 4.3.2) will be taken into account to better characterize the statistical dependence of the engine parameters and improve the technical soundness of the overall approach.

*Problem definition.* A sketch representing the dependencies between the disciplines and the variables involved is shown in Fig. 22.

The workflow described in Fig. 22 has been implemented in the process integration and design optimization platform Noesis Optimus [61, 62]. The built-in capabilities of Optimus are also used to (a) run the machine-learning based

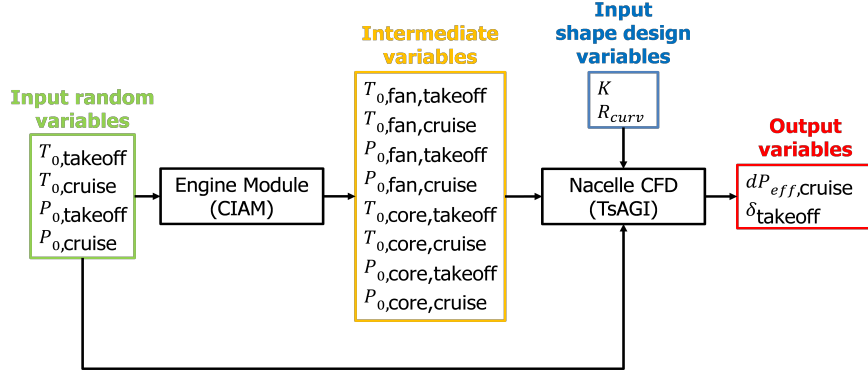


Figure 22: Graphical depiction of the use case workflow and of the dependencies between the involved variables.

ADOE [50] plan with the automatic submission of the CFD simulations to a supercomputer hosted at the TsAGI facilities, (b) build the required surrogate models and (c) run all the required uncertainty quantification analyses and reliability / robust optimization algorithms. The corresponding simulation workflow is displayed in Fig. 23.

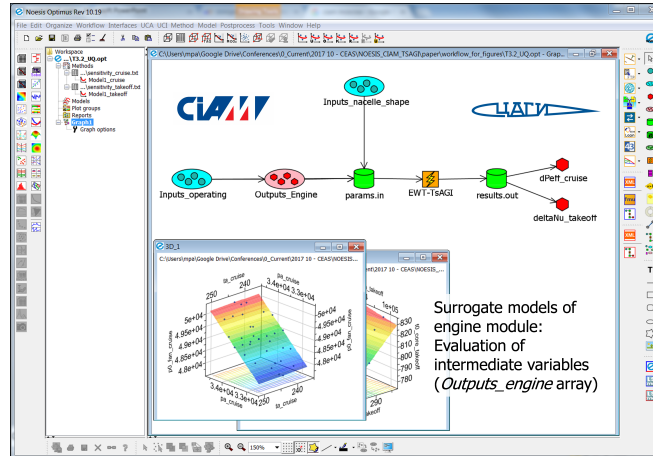


Figure 23: Optumus workflow used to integrate the two analysis tools and to automate the CFD analyses.

Table 6 lists the four random input variables considered in this use case, consisting off ambient temperature and ambient pressure evaluated at cruise and take-off conditions.

The input variables listed in Table 6 are associated with low and high boundaries defined as their reference values  $\pm 3\%$  respectively. Their probability density functions are of Gaussian type and are defined in such a way that the values

	Variable name	Description	Reference value
1	$T_{0,\text{takeoff}}$	Ambient temperature at takeoff condition	288.15 K
2	$P_{0,\text{takeoff}}$	Ambient pressure at takeoff condition	98960 Pa
3	$T_{0,\text{cruise}}$	Ambient temperature at cruise condition	243.07 K
4	$P_{0,\text{cruise}}$	Ambient pressure at cruise condition	33685 Pa

Table 6: Input variables considered in the use case and corresponding reference values.

730 corresponding to the mean  $\pm 3$  standard deviations are equal to the higher /  
lower bounds. A set of variables are calculated from the engine discipline and  
are used as inputs by the nacelle aerodynamic discipline. These variables are  
considered as "intermediate variables" and consist of engine core and bypass  
temperature and pressure evaluated at takeoff and cruise regimes, for a total of  
735 8 variables. As mentioned above, the number of variable geometrical parameters  
has been reduced to a minimum. The two parameters that the most influence  
the shape of the inlet duct (and thus the inlet flow distortion) are varied: (a) the  
leading edge curvature radius,  $R_{\text{curv}}$ , and (b) the ratio of highlight diameter to  
throat diameter,  $K = d_h/d_t$  (see Fig. 24). The dimensionless lower and upper  
740 boundaries for  $R_{\text{curv}}$  and  $K$  were defined as  $[0, 1]$ .

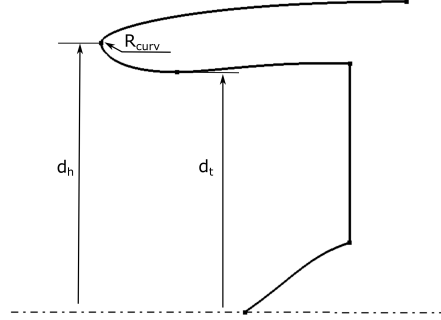


Figure 24: Inlet geometrical parameters.

The output variables are calculated by the nacelle aerodynamic discipline  
and consist of (a) the engine effective thrust loss evaluated at cruise regime,  
 $dP_{\text{eff}}$ , and (b) the total pressure recovery ratio at engine intake section,  $\delta$ . The  
latter is a feasibility variable evaluated at takeoff condition and associated with  
745 an upper constraint equal to 1. The variable  $\delta$  is used to indicate the appearance  
of flow separation at the engine intake section during takeoff conditions.

The optimization problem has been set up by considering the value of  $dP_{\text{eff}}$   
as the objective to be minimized subject to the reliability constraint

$$\delta + 6\sigma_\delta < 1. \quad (13)$$

The design variables are the geometrical parameters of the nacelle,  $R_{\text{curv}}$  and  $K$ .

750 *Results analysis.* First, an uncertainty quantification study was performed using the First Order Second Moment (FOSM) as well as the Monte Carlo (MC). The FOSM approach was coupled with a forward finite difference scheme to compute the required derivatives and therefore only 5 system evaluations (i.e., one plus the number of random variables) are needed to evaluate  $\sigma_\delta$  at a given point of the design space. The MC-based approach requires a number of evaluations  
755 equal to  $N_{MC}$ . The uncertainty associated with  $dP_{eff}$  was always very small in magnitude (not shown) and was therefore considered negligible. Figure 25 displays the contour plots of  $\sigma_\delta$  as a function of  $R_{curv}$  and  $K$  and shows that the FOSM- and MC-based results are in good agreement with each other. The  
760 largest discrepancies are observed for small values of  $K$  and values of  $R_{curv}$  close to 0 and 1, where the values of  $\sigma_\delta$  obtained by FOSM are overestimated by about 10% with respect to their MC counterparts. As expected, the MC-based results are affected by random noise and tend to converge to a smooth solution as  $N_{MC}$  approaches the value of 10,000.

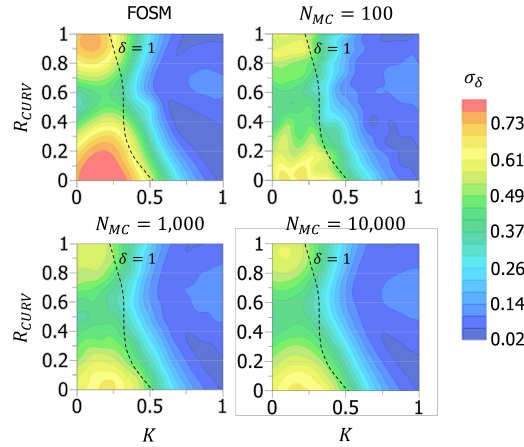


Figure 25: Variation of  $\sigma_\delta$  with  $K$  and  $R_{curv}$  evaluated with FOSM and MC for different values of  $N_{MC}$ . The dashed line identifies the boundary of the feasible region ( $\delta = 1$ ).

765 The contour plots presented in Fig. 25 show that the areas located near the boundary of the feasibility region (i.e., where  $\delta$  is close to 1) are associated with relatively large values of  $\sigma_\delta$  whose magnitude is close to the values of  $\delta$  itself. For this reason, the design optimization problem cannot be defined adopting a traditional deterministic approach where (a) the operating conditions are set  
770 equal to their reference values and (b) the constraint is defined by imposing the inequality  $\delta < 1$ . An effective approach consists in introducing a constraint in order to enforce the system reliability within an appropriate confidence interval. Figure 26 illustrates the behavior of the variable equal to  $\delta + 6\sigma_\delta$  within the design space and the effect of adopting the reliability constraint defined by Eq.  
775 (13) on the position of the boundary of the feasible region. Clearly, the adoption of this constraint reduces the area of the feasibility region

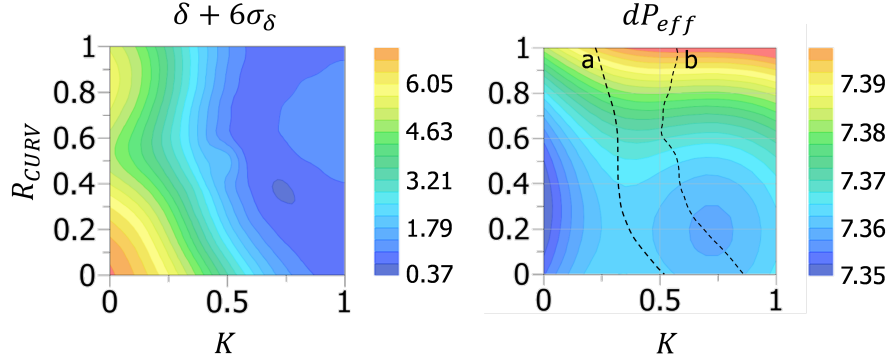


Figure 26: Contour plots showing the dependency of  $\sigma + 6\sigma_\delta$  (left) and  $dP_{eff}$  (right) on  $K$  and  $R_{curv}$ . The dashed lines on the right plot denote the boundary of the feasible region obtained by setting  $\delta = 1$  (a) and  $\sigma + 6\sigma_\delta = 1$  (b).

A robust design optimization strategy has been defined in order to identify the most efficient design subject to the reliability constraint defined by Eq. (13). The optimal values of the design variables are found on the basis of a gradient-based algorithm and correspond to  $K = 0.72$  and  $R_{curv} = 0.19$ . The histograms representing the pdfs of the estimated geometrical parameters and a summary of their key statistical characteristics are shown in Fig. 27.

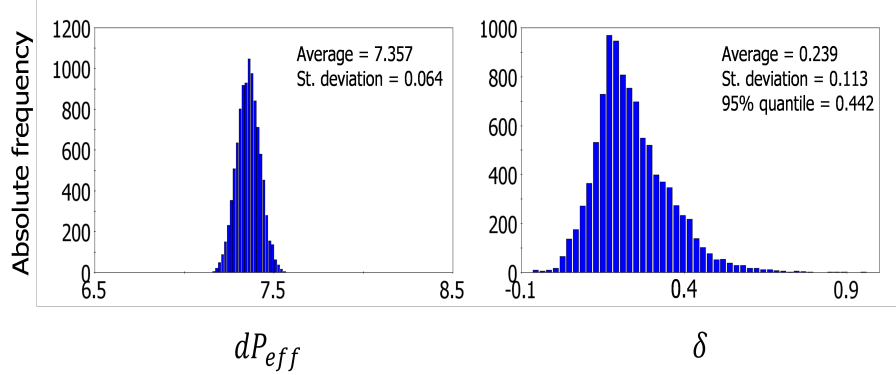


Figure 27: Histograms of  $dP_{eff}$  (left) and  $\delta$  (right) obtained on the basis of a MC analysis with  $N_{MC} = 10,000$  and by setting  $K$  and  $R_{curv}$  to their optimal values.

A conclusive analysis is performed through the First Order Reliability Method (FORM) and Second Order Reliability Method (SORM) in order to compute the reliability index  $\beta$ , and the probability of failure  $p_f$ , associated with the optimized design. The two approaches required an additional number of 146 and 156 system evaluations, respectively. The output values of the FORM analysis are given by  $\beta = 3.96$  and  $p_f = 3.8 \cdot 10^{-5}$  while the estimates obtained through SORM are  $\beta = 4.44$  and  $p_f = 4.5 \cdot 10^{-6}$ . Regarding  $\beta$ , the two results are in

790 good agreement with each other. The discrepancies observed for the estimated  
probability of failures can be attributed to the different levels of the approxi-  
mation of the limit state function adopted by the two approaches. Given the  
relatively small number of additional system evaluations used by SORM com-  
pared to FORM (for this test case) it can be concluded that the second-order  
795 based approach should be preferred over the first-order one for the assessment  
of the target system reliability.

## 5. Conclusion and Future work

During the first year of AGILE project (Design Campaign 1), a reference dis-  
tributed MDO problem was selected and implemented, taking advantage of both  
800 the design competences and methodologies available in the AGILE consortium.  
During DC-1 this MDO process was successfully applied to the optimization of  
a large regional jet aircraft. In the second year of the project (Design Campaign  
2), novel optimization techniques developed by the AGILE partners were inves-  
tigated for different MDO problems, all based on the evolution of the MDA of  
805 Design Campaign 1. These techniques were selected for their expected capabil-  
ities to converge more rapidly and more efficiently for the distributed complex  
workflows characterized by a high degree of discipline interdependencies and a  
high number of design variables that are considered in the AGILE project. The  
results presented in this paper confirm that the selected optimization techniques  
810 were successful to handle the increasing complexity of the workflows.

For the wing optimization process the innovative multi-optimization ap-  
proach combining Nash Games and Genetic Algorithm was investigated and  
demonstrated its capabilities to handle a three objectives problem aiming at  
increasing both the aerodynamic performance (at high speed and low-speed  
815 conditions) and structural objectives. For this case the optimal design using  
the assignment of the NGA variables to the players led to a reduction of more  
than 30% in terms of computational time compared to the Pareto front approach

The approaches selected for the nacelle design optimization problem were  
shown to be effective. The use of the SEGOMOE optimizer permitted to reach  
820 a better solution using less computational resources than a classical EGO ap-  
proach. Moreover, the optimum is reached using a budget reduced by a factor  
8. Considering the effect of random fluctuations around operating conditions,  
Optimus' UQ strategy allowed characterizing the uncertainty of the system out-  
puts and successfully found an optimal design for the geometry of the engine  
825 nacelle subject to the target reliability constraint. The multiple techniques that  
were selected during DC-2 (including the optimization methods presented in the  
paper) have been implemented as new competences in the AGILE framework  
and are accessible by other partners for collaborative use cases. Some of these  
features, such as the SEGOMOE and Noesis' robust optimization capabilities  
830 were already used in the System of System use case [15]. The smart combina-  
tion of the MDO enhancements, knowledge based technologies [63, 64] and IT  
solutions provide a powerful approach for handling the challenges of the reduc-  
tion of the aircraft development time at the early stages of the design process.



835 In the frame of Design campaign 3, these developments will be used to seven  
novel configurations of aircraft. The main results of the different test cases are  
available in a dissemination package on the AGILE web portal [5].

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