Progress in Aerospace Sciences 119 (2020) 100649

Contents lists available at ScienceDirect

Progress in Aerospace Sciences

journal homepage: http://www.elsevier.com/locate/paerosci

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

T. Lefebvre [a,*,1], N. Bartoli [a,1], S. Dubreuil [a,1], M. Panzeri [b,2], R. Lombardi [b,2], P. Della Vecchia [c,3], L. Stingo [c,4], F. Nicolosi [c,5], A. De Marco [c,3], P.D. Ciampa [d,6], K. Anisimov [e,7], A. Savelyev [e,7], A. Mirzoyan [f,8], A. Isyanov [f,9]

[a] ONERA/DTIS, Université de Toulouse, Toulouse, France
[b] NOESIS Solutions N.V, Gaston Geenslaan 11, B4, 3001, Leuven, Belgium
[c] University of Naples "Federico II", Via Claudio 21, 80125, Napoli, Italy
[d] DLR, Air Transportation Systems Institute, Hamburg, Germany
[e] TsAGI, Zhukovsky, Moscow Region, 140180, Russia
[f] CIAM, 2, Aviamotornaya Str., Moscow, 111116, Russia

ARTICLE INFO

Keywords:
MDO
Optimization
Aircraft design
Mono and multi-objective optimization
Robust design

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 costs and time to market, leading to cheaper and greener aircraft. The paper introduces the AGILE project structure and describes the achievements of the 1st year that led to a reference distributed MDO system. A focus is then made on different novel optimization techniques studied during the 2nd 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.

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 teams

* Corresponding author.
E-mail address: thierry.lefebvre@onera.fr (T. Lefebvre).
[1] Research Engineer, Information Processing and Systems Department.
[2] Research Engineer, Research and Innovation.
[3] Assistant Professor, Department of Industrial Engineering (DII).
[4] Ph.D Student, Department of Industrial Engineering (DII).
[5] Professor, Department of Industrial Engineering (DII).
[6] Research associate & Team lead Multidisciplinary Design and Optimization group.
[7] Researcher, Propulsion Systems Aerodynamics Department.
[8] Propulsion and A/C Matching Department.
[9] Head of Propulsion and A/C Matching Department.

https://doi.org/10.1016/j.paerosci.2020.100649
Received 23 May 2020; Accepted 13 June 2020
Available online 11 September 2020
0376-0421/© 2020 Elsevier Ltd. All rights reserved.

Nomenclature

ADOE	Adaptive Design of Experiments
AGILE	Aircraft 3rd 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 Navier–Stokes
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

of experts. To keep up 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 modeling, 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 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 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 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 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 knowledge" 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 and 80% of the project time is spend in this phase [4].

Since 2015 the EU funded Horizon 2020 AGILE project [5] is developing the next generation of aircraft Multidisciplinary Design and Optimization environment that focuses on reducing the set up time for

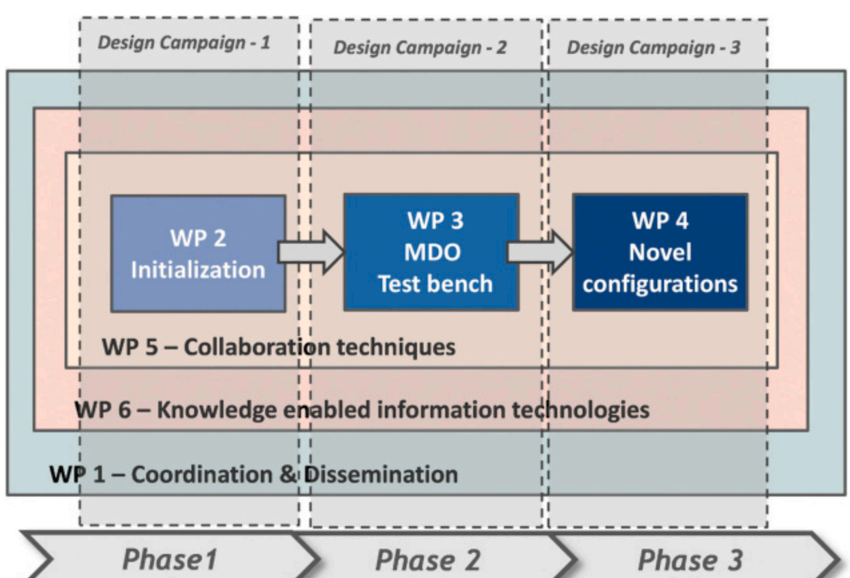


Fig. 1. AGILE project structure.

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 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 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 3rd 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 "1st generation", a monolithic environment still being used today (e.g. for dedicated high-fidelity applications), to the 3rd 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 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, 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 1st 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- and post-processing, visualization and the enhancement of the existing framework. 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 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 3rd MDO 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 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) provided by the aircraft manufacturer partner (Bombardier), an Overall Aircraft 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.

Table 1
Top level aircraft requirements.

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

Fig. 2 shows a representation of the DC-1 distributed OAD process.

The Figure indicates the domains of the specialists' competences that have been integrated 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 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[10] model corresponding to the AGILE aircraft product model. They 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:

$$\begin{cases} \text{min} & \text{Direct Operating Cost}: \ \text{DOC} \\ \text{w. r. t.} & \text{7 wing shape variables} \\ \text{s. t.} & 2.2 - \text{CLmax} < 0. \end{cases} \tag{1}$$

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 modeling. This use case and the results are presented in Refs. [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 Ref. [13] and illustrated in Fig. 4.
4. A multi-scale application is described in Ref. [14] aiming at investigating the improvement of involving an aircraft component

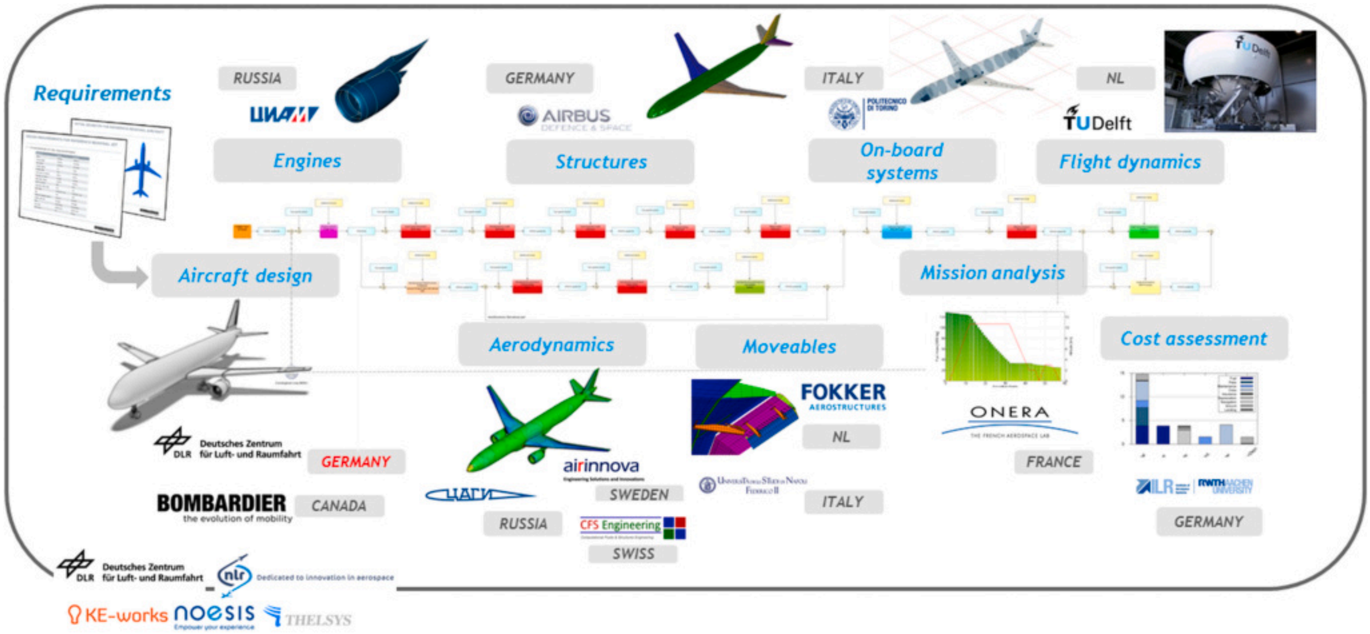


Fig. 2. AGILE Collaborative design process: individual competences are distributed multi-site, and hosted at the different partners' networks.

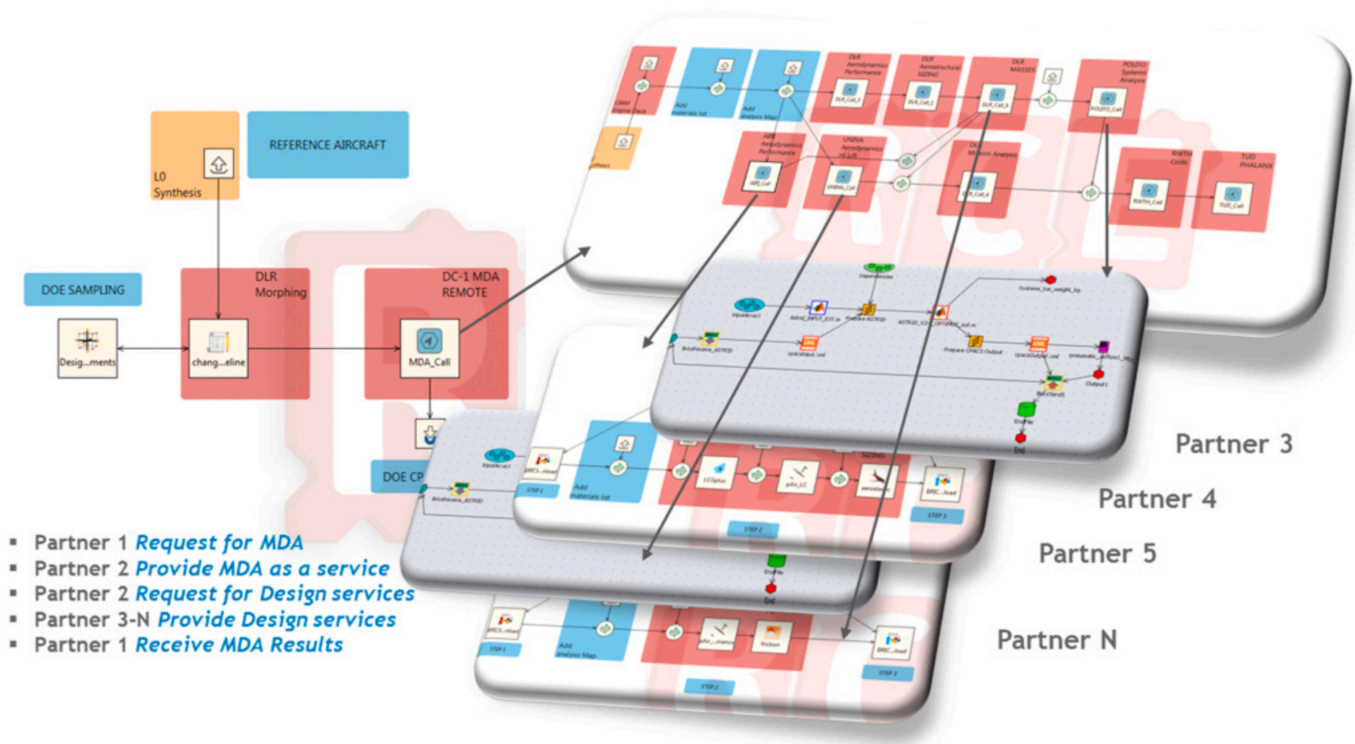


Fig. 3. AGILE DC-1 workflow. Partner 1 deploys a Design Of Experiment requesting as remote service the cross-organizational MDA workflow, deployed at Partner 2. The MDA is composed by disciplinary competences provided as remote services to Partner 2 by Partners 4 to N.

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].

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

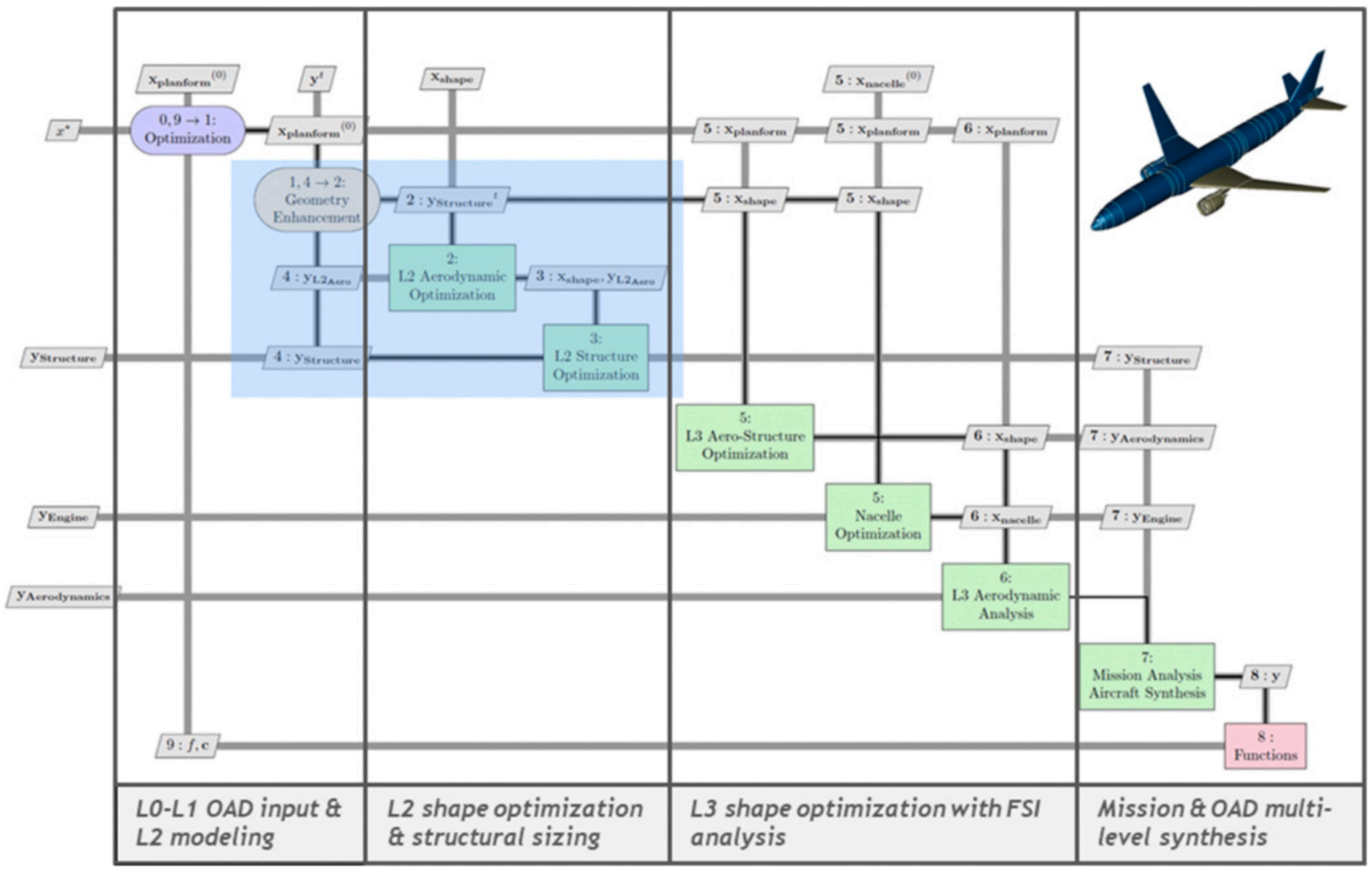


Fig. 4. DC-2 - Multi-level optimization formulation.

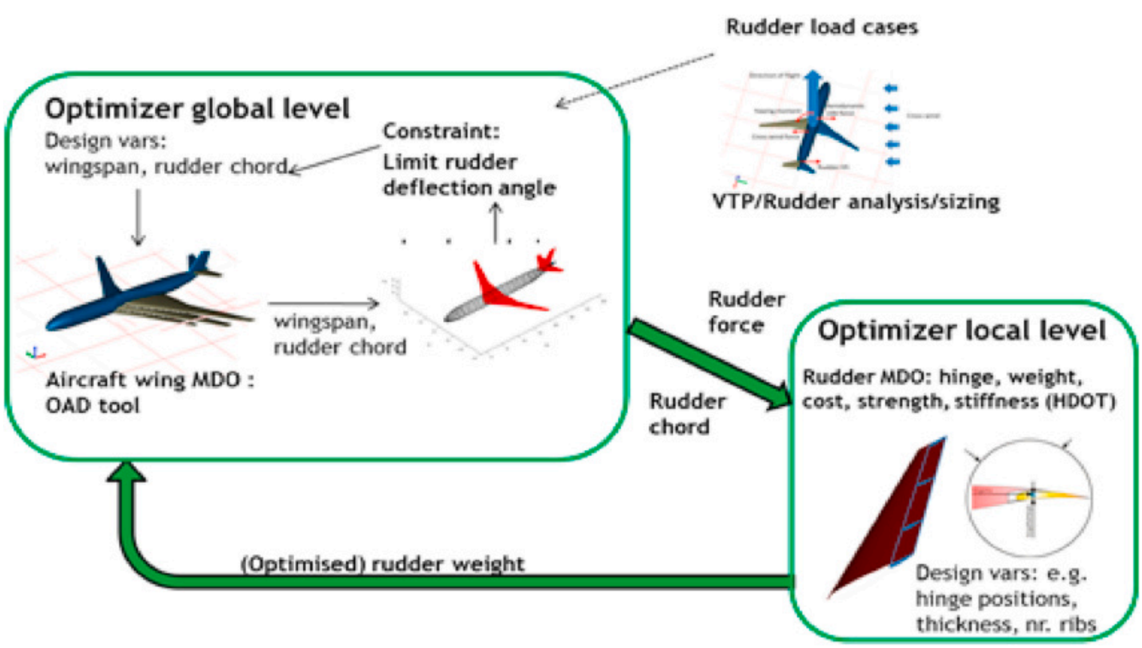


Fig. 5. DC-2 - Rudder optimization.

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 [18–20] 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 [20,21].

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 SEGO-MOE [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 Refs. [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 Ref. [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 Ref. [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 Ref. [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 SEGO-MOE algorithm has been validated on different aerodynamic use cases [7,31,41].

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 Ref. [43] and can also be built up using surrogate models [44–46].

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 objective functions [47]. A detailed description of NGA optimization used in the AGILE project is given in Ref. [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 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 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 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 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 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:

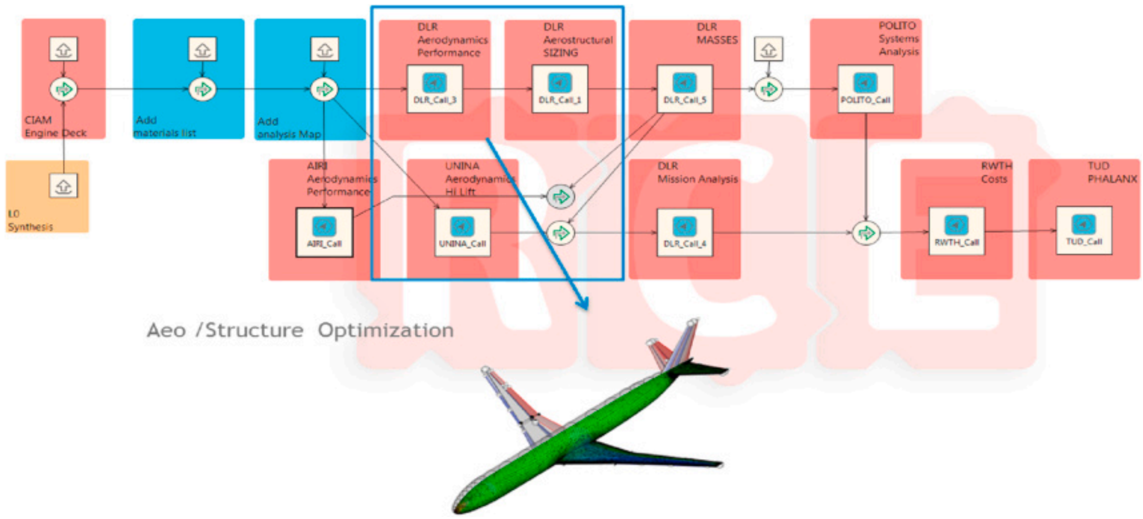


Fig. 6. Wing design test case.

- 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 Ω_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:

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

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, β, 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, β 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 β 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 Φ 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 β (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

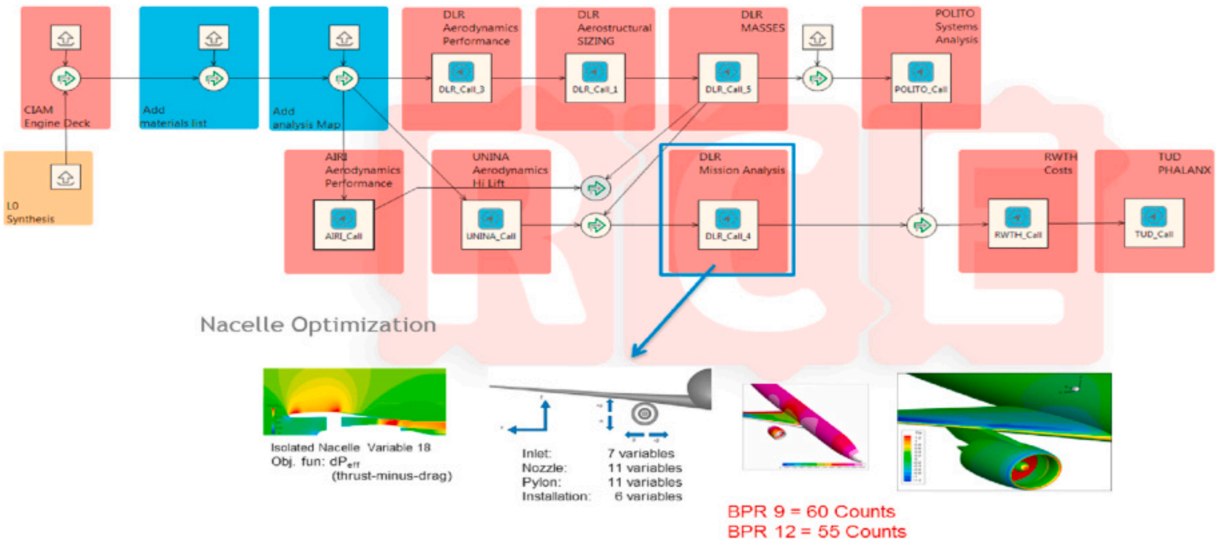


Fig. 7. Nacelle design test case.

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.

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 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 Ref. [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.

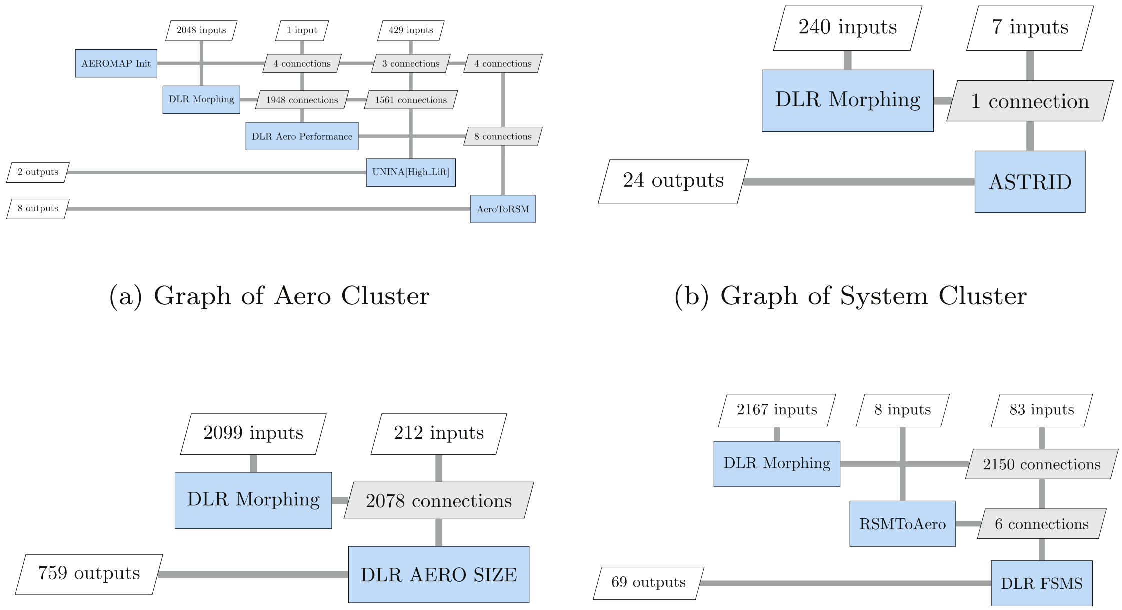
On-board systems Cluster This cluster aims at providing the On Board systems performance in terms of weights and power, using the wing design parameters and other inputs such as the Fuel Weight and operational weights such as MTOM (Maximum Take-Off Mass).

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.

Fig. 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.

The design competence clusters were then implemented as



(a) Graph of Aero Cluster (b) Graph of System Cluster

(c) Graph of Weight Cluster (d) Graph of Mission Cluster

Fig. 8. Graphs of the 4 retained clusters.

Table 2
Reference wing characteristics.

	b(m)	C_{root}(m)	Λ_{LE}(deg)	Taper Ratio	t/c	S_w(m^2)
Reference Wing	28.01	6.39	30	0.164	0.13	82.7
C_{Dw} - Wing Weight @ $C_L = 0.49$	0.0254–4887 kg					

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°.

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 [12,47]. 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 (λ), the maximum mean thickness percentage (t/c), the aspect ratio (AR), the leading edge sweep angle (Λ_{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, $S_w(m^2)$, $\Lambda_{LE}(deg)$, λ 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.

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

The design variables are assigned among the players in all possible

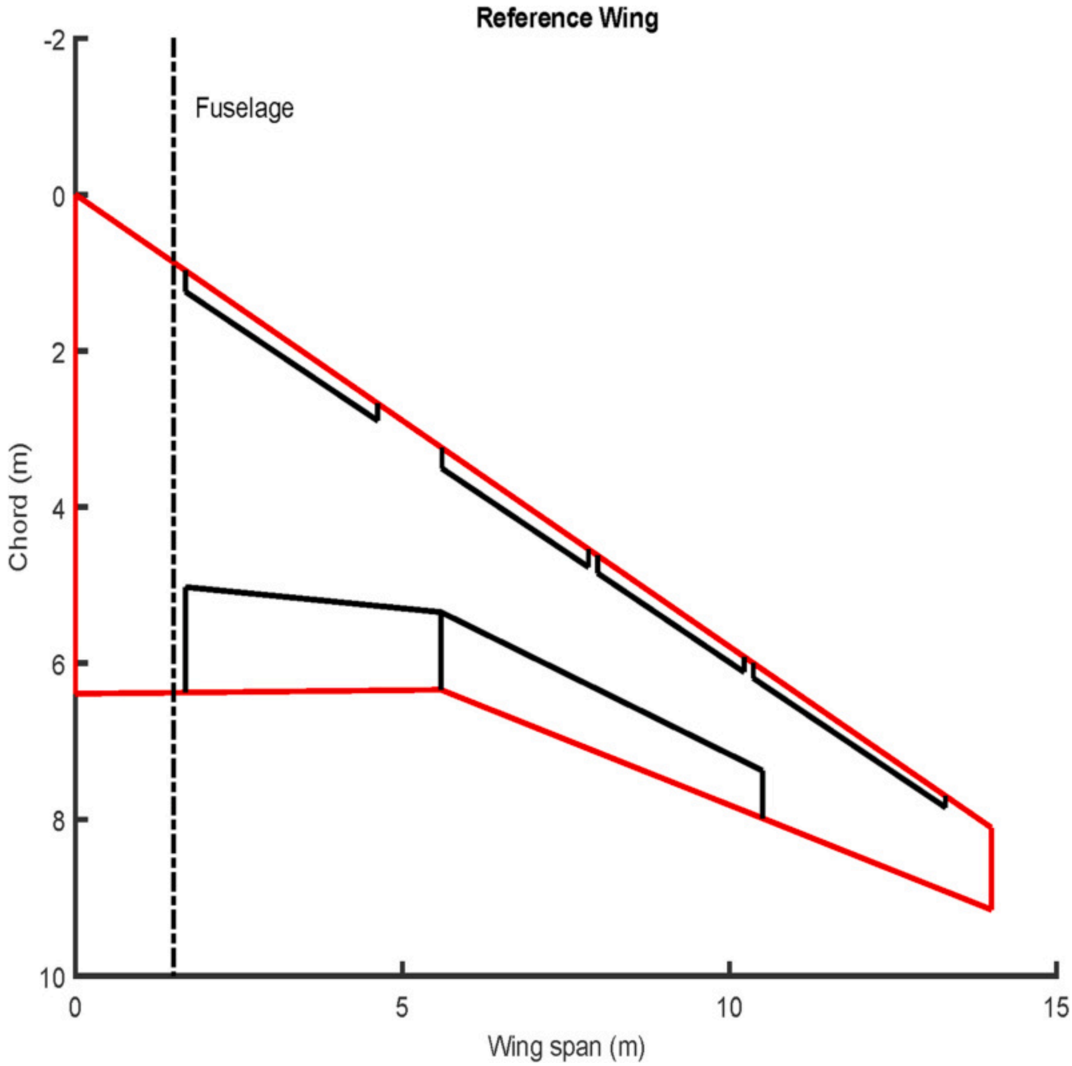


Fig. 9. Reference wing planform.

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
- $[1, 2, 2]$, 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.

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).

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

where:

$$F_{obj\_1} = C_{Dw} \tag{5}$$

$$F_{obj\_2} = \frac{W_{wing}}{W_{wing\_initial}} \tag{6}$$

$$F_{obj\_3} = C_{L_{max_w}} \tag{7}$$

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.

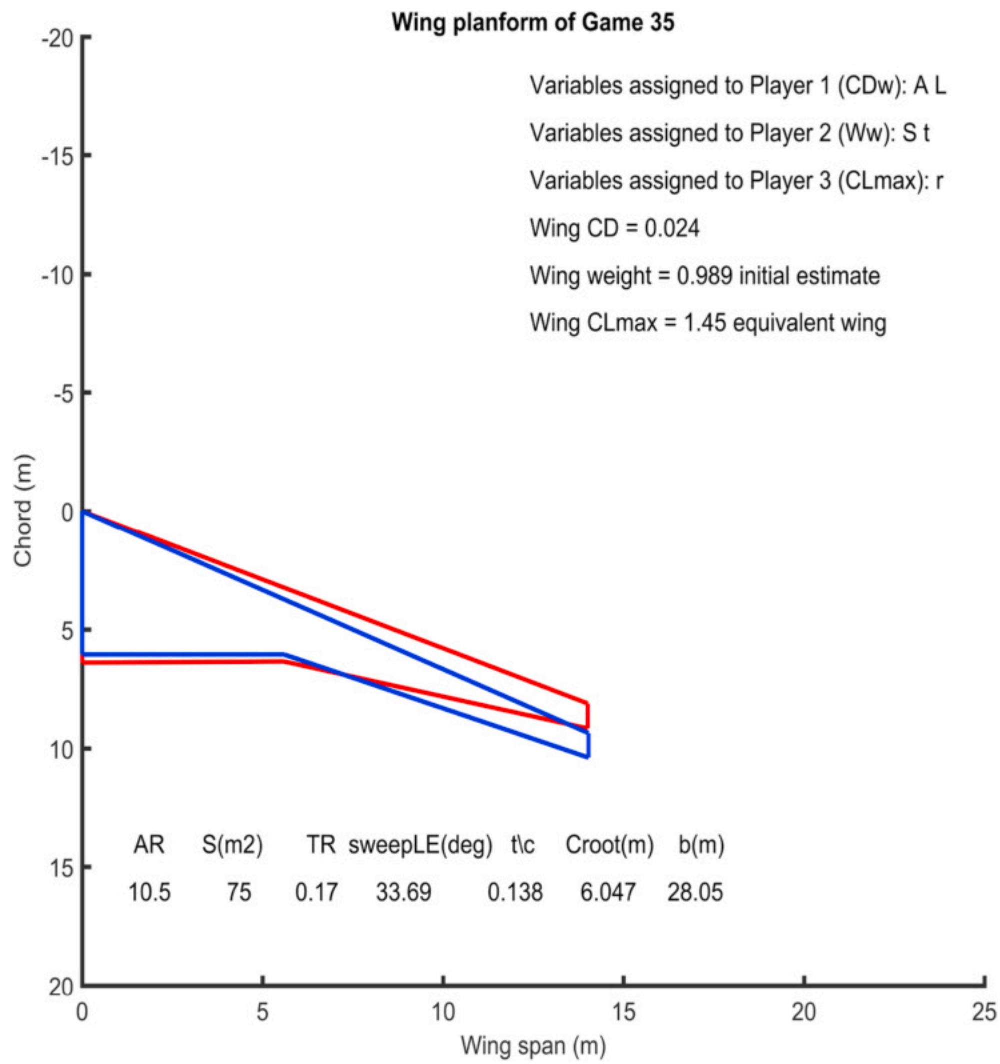


Fig. 10. Wing planform (Game 35) three players' optimization for reference wing (blue) and optimized wing (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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

	AR	Λ_{LE}(deg)	b(m)	λ	t/c	S_w(m^2)
Reference Wing	9.43	30	28.01	0.164	0.13	82.7
C_{Dw} - Wing Weight - $C_{L_{max_w}}$	0.0254–4887 (kg) - 1.39					
Game 35 (NGA)	10.5	33.69	28.05	0.17	0.138	75
C_{Dw} - Wing Weight - $C_{L_{max_w}}$	0.0240–4837 (kg) - 1.53					
GA best solution	10.5	33.69	28.05	0.17	0.138	75
C_{Dw} - Wing Weight - $C_{L_{max_w}}$	0.0240–4837 (kg) - 1.53					

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 reference's 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.

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

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 Λ_{LE} to F_{obj_1}, S_w and (t/c) to F_{obj_2}, λ 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* weigths and does not take into account the association among variables and objective functions.

Fig. 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.

This application showed that the Nash game theory coupled with a typical genetic evolutionary algorithm (NGA) is a viable approach to use in the optimization field since firstly it permits a more realistic association among variables and objective functions and secondly it reduces the computational time. Moreover, the reduced distance between NGA solution points and the Pareto front demonstrates the reasonableness and the feasibility of the results obtained. Finally, a verification of the computational time between the Pareto front, a single game of the NGA, and the GA scalarization approach has been performed on a laptop

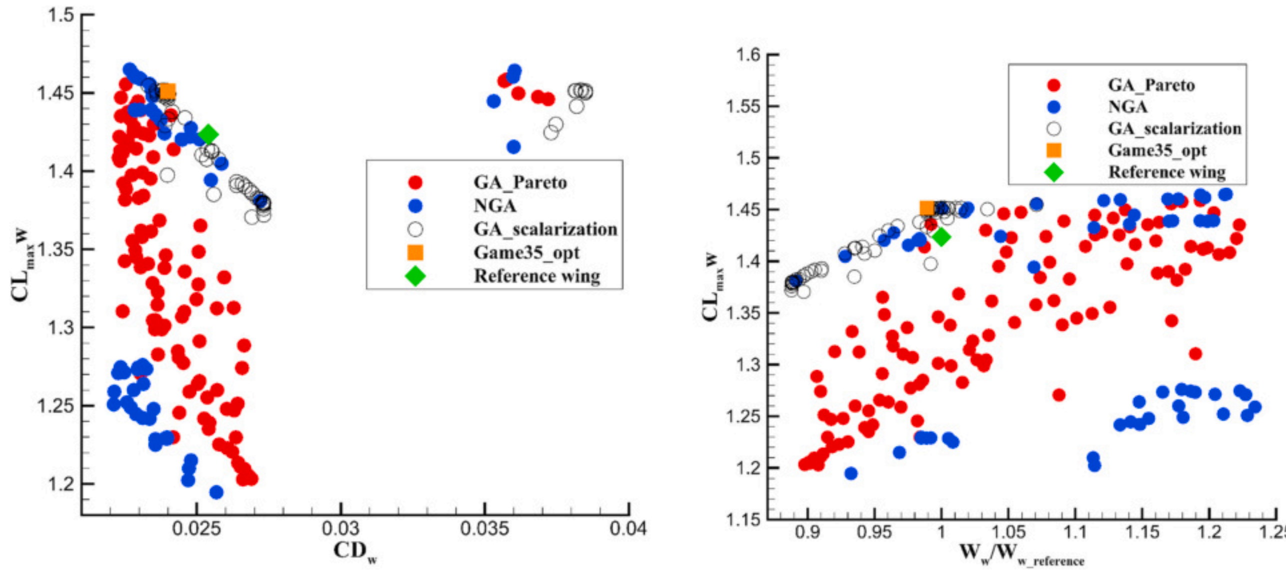


Fig. 11. Results comparison among the three optimization approaches (data referred to the equivalent wing); on the left ($C_{L\max_w}$ - C_{Dw}), on the right ($C_{L\max_w}$ - W_w/W_{w_ref}).

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 s, for a single scalarization GA solution point it equals 59 s, and for the Pareto front it is 76 s. The larger the number of variables or objective functions, 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 enhanced 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.

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 overall optimization time and the robustness of the optimal design around nominal cruise conditions. The nacelle shape optimization process focuses on the following 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 practice 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 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 ensure acceptable behavior (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, 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-

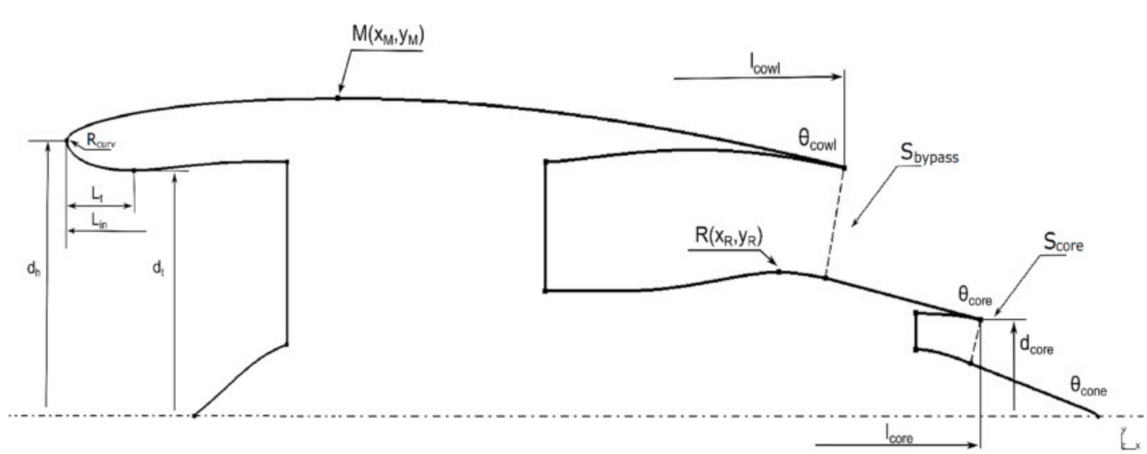


Fig. 12. Nacelle geometrical description.

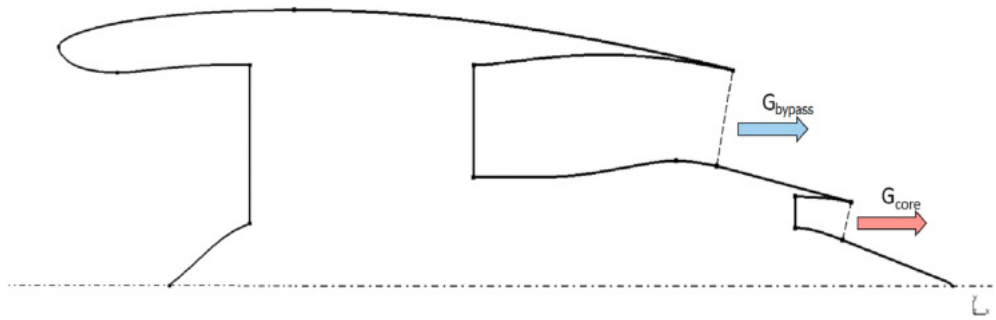


Fig. 13. Core and bypass mass flow rates of the engine.

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 Ref. [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.

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:

$$dP_{\mathrm{eff}} = 1 - \frac{P_{\mathrm{eff}}}{P_{\mathrm{id}}} \tag{8}$$

with.

- P_{id} the ideal engine trust,
- $P_{\mathrm{eff}} = P - F_X$ 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:

$$\mathrm{G}_{\mathrm{core}} - \mathrm{G}_{\mathrm{core}}^{\mathrm{target}} = 0 \tag{9}$$

$$\mathrm{G}_{\mathrm{bypass}} - \mathrm{G}_{\mathrm{bypass}}^{\mathrm{target}} = 0 \tag{10}$$

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

$$\left|1 - \frac{\mathrm{G}_{\mathrm{core}}}{\mathrm{G}_{\mathrm{core}}^{\mathrm{target}}}\right| < \varepsilon_{core} \tag{11}$$

$$\left|1 - \frac{\mathrm{G}_{\mathrm{bypass}}}{\mathrm{G}_{\mathrm{bypass}}^{\mathrm{target}}}\right| < \varepsilon_{bypass} \tag{12}$$

where the two thresholds ε_{core} and ε_{bypass} are set equal to 10^{-2} and $2.5\ 10^{-3}$ respectively based on the required accuracy. These constraints ensure that, within the required accuracy, the equality of core and bypass mass flow rates ($\mathrm{G}_{\mathrm{core}}$ and $\mathrm{G}_{\mathrm{bypass}}$) 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 $2.5\ 10^{-3}$ approximately correspond to the physical air flow of 100 g for the hot nozzle and 300 g 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.

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]). For this the SEGOMOE approach [31] provided by ONERA and described in Section 3.1.1 was used and results obtained are presented in Section 4.3.3,
- assessment of the performance of the optimal nacelle shape around nominal aerodynamic conditions. The uncertainty analyses approach available in the Optimus framework (see Section 3.2) was evaluated and the results are discussed in Section 4.3.4.

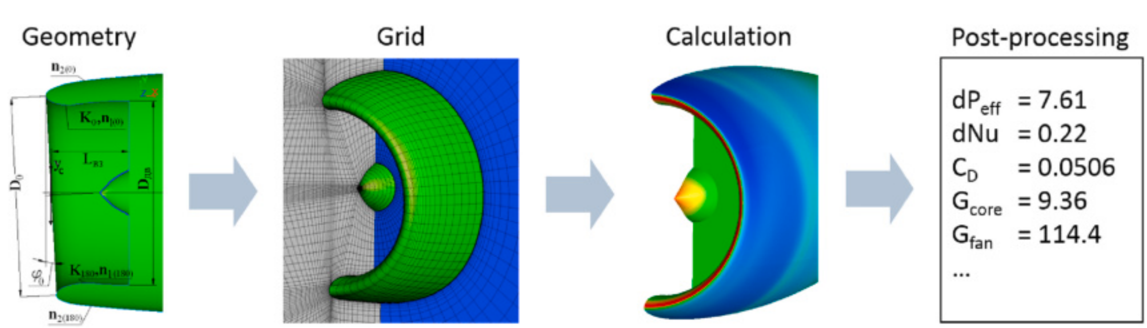


Fig. 14. Nacelle CFD analysis tool chain.

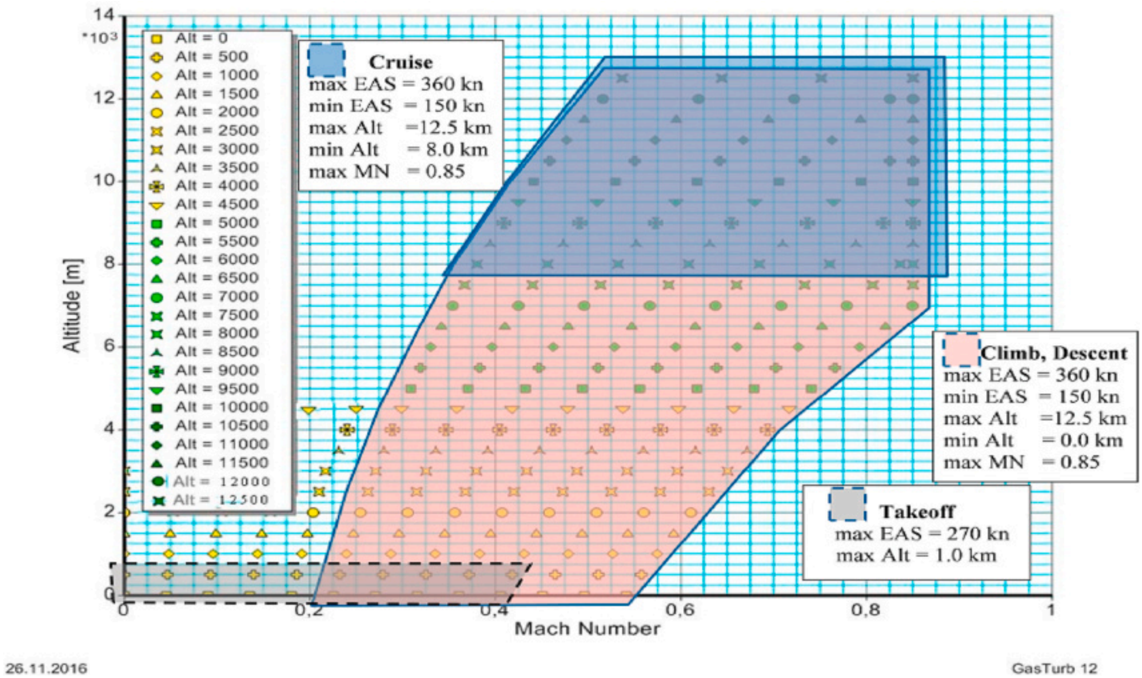


Fig. 15. Engine operating envelope spot points agreed for aircraft mission calculation.

4.3.2. Description of the design tools

4.3.2.1. Nacelle hi-fi tool. The introduction of this design competence is based on the method of nacelle aerodynamic design and optimization described in Ref. [56,57]. It is a fully automated tool chain composed of four blocks: geometry builder, grid generator, CFD solver and post-processor (see Fig. 14). The output of the geometry builder block is an IGES file containing the geometrical model with specified values of input parameters (i.e. nacelle geometry variables). This file is then used to build the computational grid. CFD calculations are then carried out using the TsAGI in-house code Electronic Wind Tunnel (EWT-TsAGI [58]). The steady RANS equations are solved using a finite-volume numerical solver that employs a second-order approximation in space for all variables and is based on the Godunov-type TVD scheme for the approximation of the convective fluxes (MUSCL). For the results presented here the Spalart-Allmaras turbulence model has been used. The calculations are performed on a multiblock structured grid with hexahedral cells. The axisymmetric grid used for this study has approximately 60 000 cells. The CFD calculations were made for cruise ($M = 0.78$, $H = 11\ km$) and take-off ($M = 0$, $H = 0\ km$) conditions. In the post-processing block the following parameters are extracted from the computed solution:

- the effective thrust losses at cruise as a measure of aerodynamic efficiency;
- the total pressure losses at the fan face at take-off as a measure of flow distortion.

4.3.2.2. Engine tool. The engine simulation provides the engine parameters and engine performance map for different engine design cycle

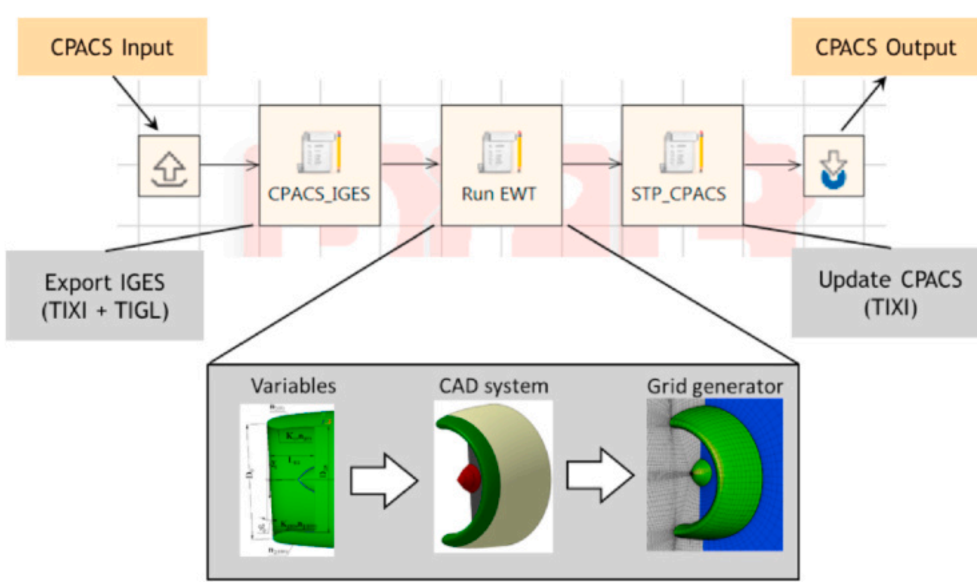


Fig. 16. Nacelle design analysis workflow.

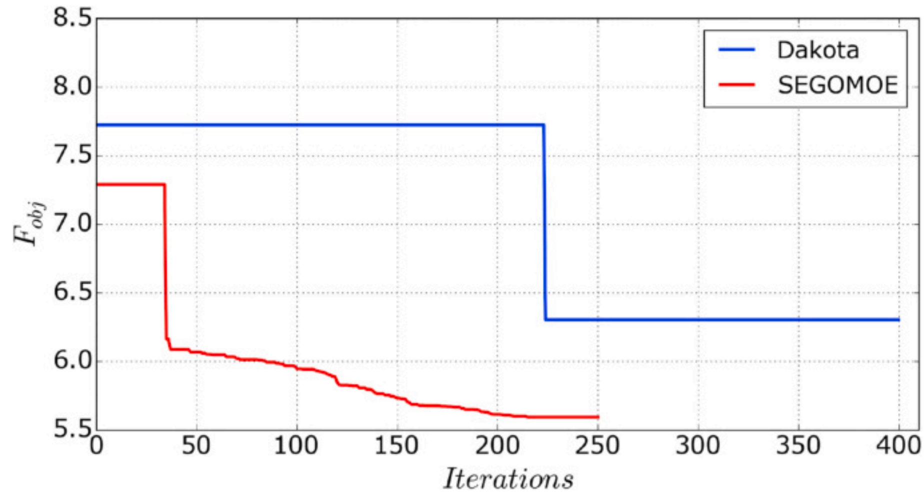


Fig. 17. Convergence History of EGO-DAKOTA and SEGOMOE, case BPR = 9. The red line is associated to the best found point with SEGOMOE, the blue line refers to the solution of EGO-DAKOTA.

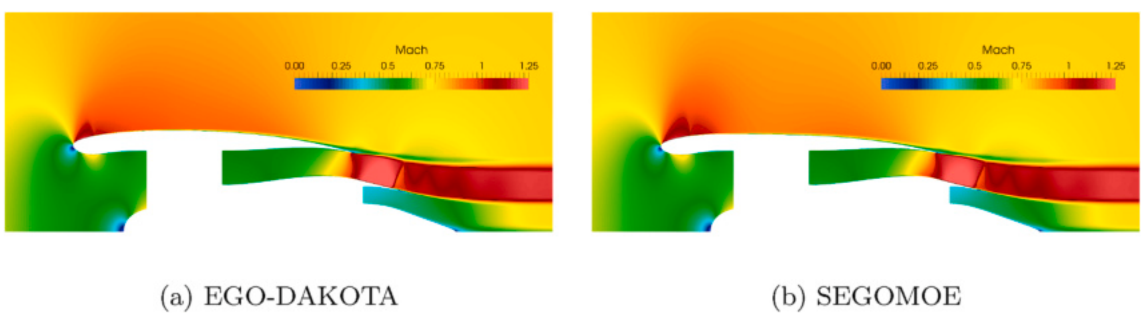


Fig. 18. Mach number distribution at the optimal design with EGO-DAKOTA (a), or SEGOMOE (b); case BPR = 9.

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 off-take/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.

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

	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

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.

4.3.3.1. 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. In Fig. 18 is presented the Mach distribution around the

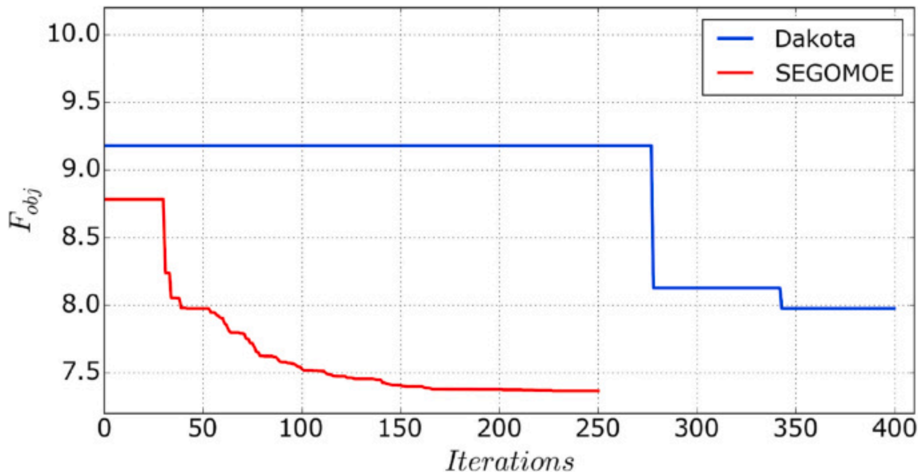


Fig. 19. Convergence History of EGO-DAKOTA and SEGOMOE, case BPR = 12. The red line is associated to the best found point with SEGOMOE, the blue line refers to the solution of EGO-DAKOTA. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

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

	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

optimal nacelles.

The 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 ε_{core} and ε_{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.

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

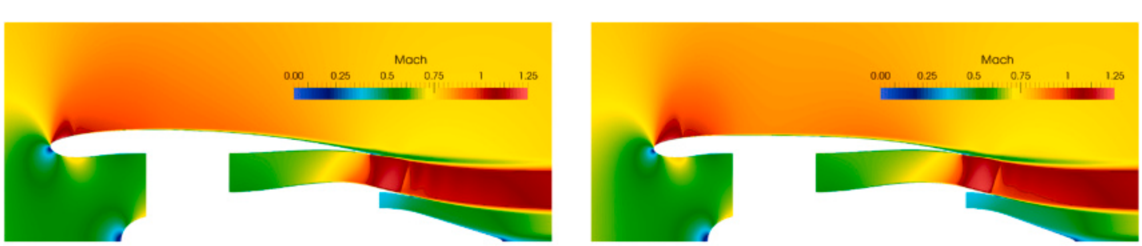
Another aspect concerns the constraint handling for EGO-DAKOTA; Figs. 17 and 19 show that the best objective value when using EGO-DAKOTA (blue curve) is quite constant for both the test cases because the successive enrichment points proposed at each iteration do not respect the two constraints, and the 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.

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



(a) EGO-DAKOTA (b) SEGOMOE

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

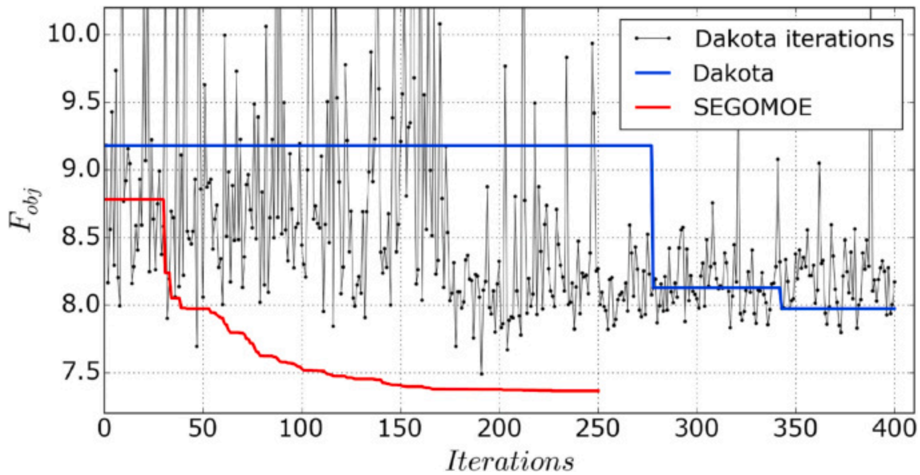


Fig. 21. Convergence History and Iterative Process of EGO-DAKOTA and SEGOMOE, case BPR = 12. The red line is associated to the best found point with SEGOMOE, the blue line refers to the solution of EGO-DAKOTA and the black curve represents all the evaluations done during the EGO-DAKOTA optimization process. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

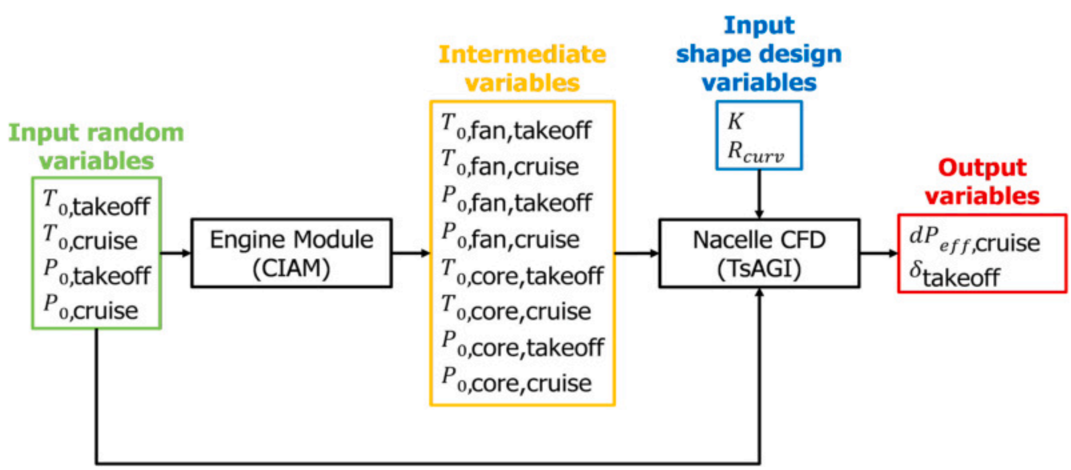


Fig. 22. Graphical depiction of the use case workflow and of the dependencies between the involved variables.

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.

4.3.4.1. 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 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.

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 ± 3% respectively. Their probability density functions are of Gaussian type and are defined in such a way that the values corresponding to the mean ± 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 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_{curv}, and (b) the ratio of highlight diameter to throat diameter, $K = d_h/d_t$ (see Fig. 24). The dimensionless lower and upper boundaries for R_{curv} and K were defined as $[0,\ 1]$.

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

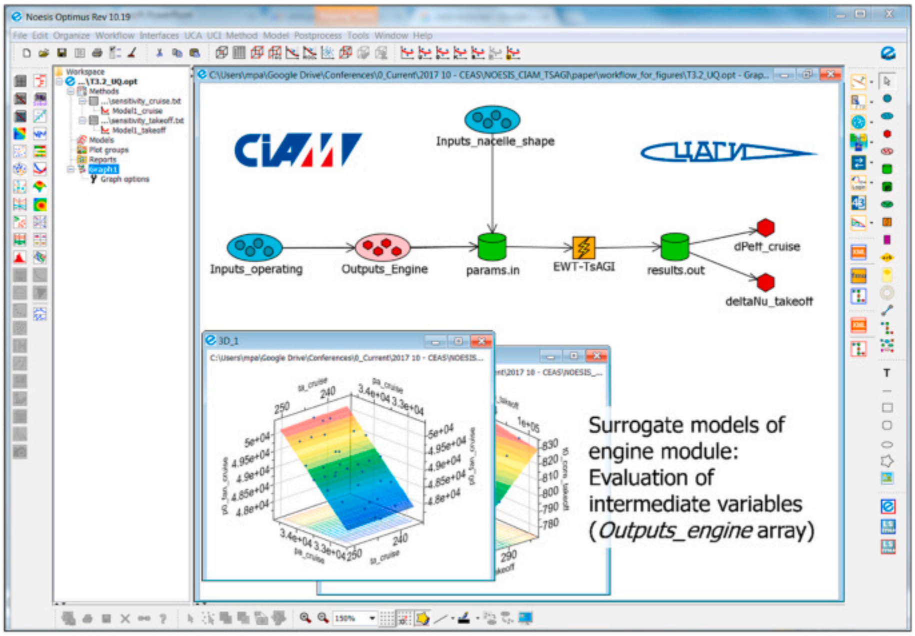


Fig. 23. Optimus workflow used to integrate the two analysis tools and to automate the CFD analyses.

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

	Variable name	Description	Reference value
1	$T_{0,takeoff}$	Ambient temperature at takeoff condition	288.15 K
2	$P_{0,takeoff}$	Ambient pressure at takeoff condition	98 960 Pa
3	$T_{0,cruise}$	Ambient temperature at cruise condition	243.07 K
4	$P_{0,ruise}$	Ambient pressure at cruise condition	33 685 Pa

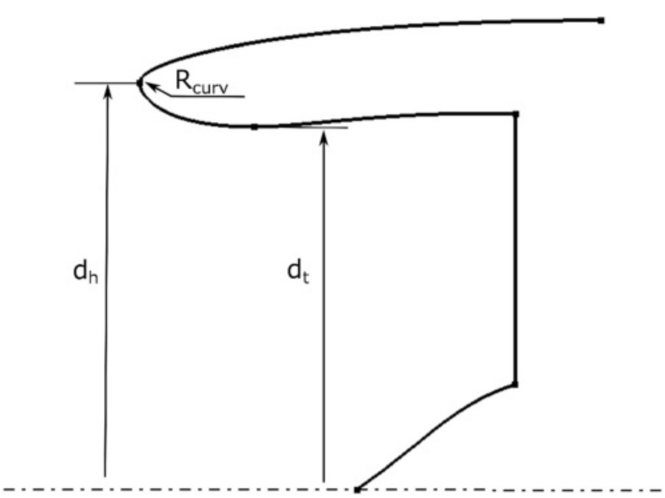


Fig. 24. Inlet geometrical parameters.

intake section during takeoff conditions.

The optimization problem has been set up by considering the value of dP_{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_{curv} and K.

4.3.4.2. 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 σ_δ at a given point of the design space. The MC-based approach requires a number of evaluations equal to N_{MC}. The uncertainty associated with dP_{eff} was always very small in magnitude (not shown) and was therefore considered negligible. Fig. 25 displays the contour plots of σ_δ 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 largest discrepancies are observed for small values of K and values of R_{curv} close to 0 and 1, where the values of σ_δ 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

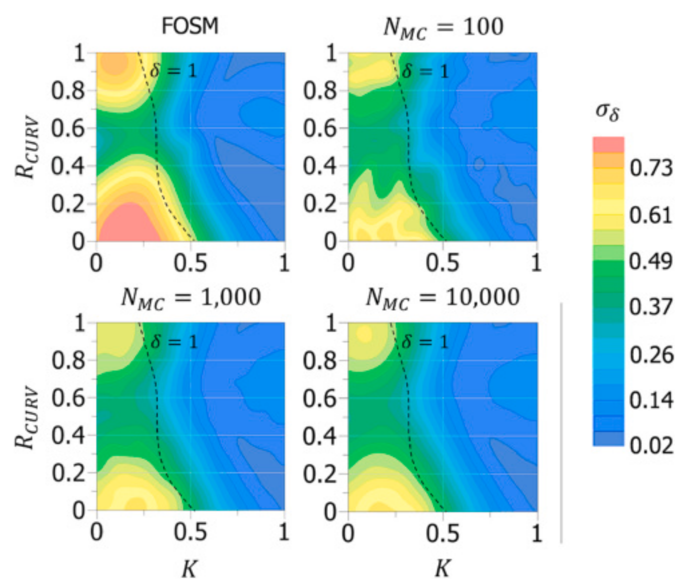


Fig. 25. Variation of σ_δ with K and R_{curv} evaluated with FOSM and MC for different values of N_{MC}. The dashed line identifies the boundary of the feasible region ($\delta = 1$).

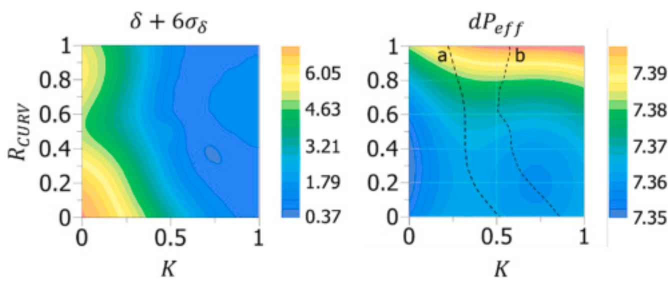


Fig. 26. Contour plots showing the dependency of $\sigma + 6\sigma_\delta$ (left) and dP_{eff} (right) on K and R_{curv}. The dashed lines on the right plot denote the boundary of the feasible region obtained by setting $\delta = 1$ (a) and $\sigma + 6\sigma_\delta = 1$ (b).

converge to a smooth solution as N_{MC} approaches the value of 10 000.

The contour plots presented in Fig. 25 show that the areas located near the boundary of the feasibility region (i.e., where δ is close to 1) are associated with relatively large values of σ_δ whose magnitude is close to the values of δ itself. For this reason, the design optimization problem cannot be defined adopting a traditional deterministic approach where (a) the operating conditions are set 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. Fig. 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. (13) on the position of the boundary of the feasible region. Clearly, the adoption of this constraint reduces the area of the feasibility region.

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 $R_{\mathrm{curv}} = 0.19$. The histograms representing the pdfs of the estimated geometrical parameters and a summary of their key statistical characteristics are shown in Fig. 27.

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 β, 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 $p_f = 3.8\ 10^{-5}$ while the estimates obtained through SORM are $\beta = 4.44$ and $p_f = 4.5 \cdot 10^{-6}$. Regarding β, the two results are in good agreement with each other. The discrepancies observed for the estimated probability of failures can be attributed to the different levels of the approximation of the limit state function adopted by the two approaches. Given the relatively small number of additional system evaluations used by SORM compared to FORM (for this test case) it can be concluded that the second-order 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 distributed MDO problem was selected and implemented, taking advantage of both 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 investigated for different MDO problems, all based on the evolution of the MDA of Design Campaign 1. These techniques were selected for their expected capabilities 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 were successful to handle the increasing complexity of the workflows.

For the wing optimization process the innovative multi-optimization approach 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 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 a better solution using less computational resources than a classical EGO approach. 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 outputs and successfully found an optimal design for the geometry of the engine 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 were already used in the System of System use case [15]. The smart combination of the MDO enhancements, knowledge based technologies [63,64] and IT solutions provide a powerful approach for handling the challenges of the reduction of the aircraft

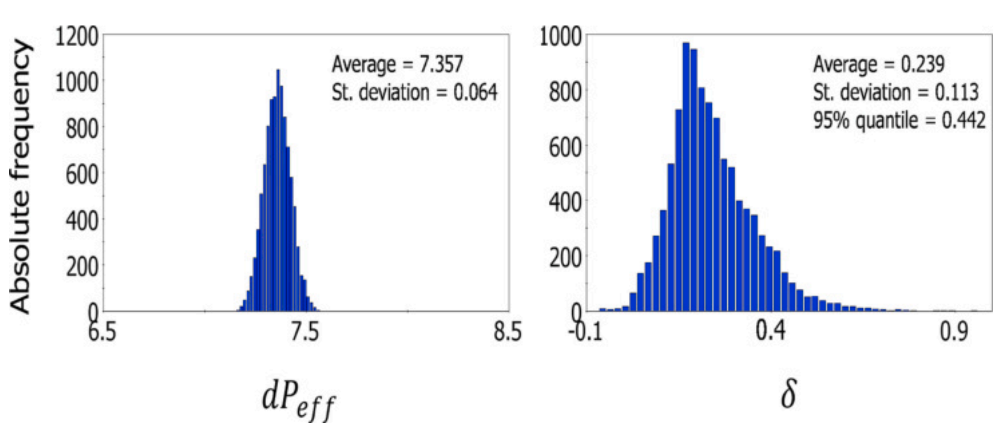


Fig. 27. Histograms of dP_{eff} (left) and δ (right) obtained on the basis of a MC analysis with $N_{MC} = 10{,}000$ and by setting K and R_{curv} to their optimal values.

development time at the early stages of the design process. 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].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The research presented in this paper has been performed in the framework of the AGILE project (Aircraft 3rd Generation MDO for Innovative Collaboration of Heterogeneous Teams of Experts) and has received funding from the European Union Horizon 2020 Programme (H2020-MG-2014-2015) under grant agreement n° 636202. The authors are grateful to the partners of the AGILE consortium for their contributions and feedback. The Ministry of Education and Science of the Russian Federation financially supports the TsAGI studies. All TsAGI studies mentioned in this article were carried out in the framework agreement n° 14.628.21.0004 (Project unique identifier RFMEFI62815X0004).

References

[1] G. Belie, Non-technical barriers to multidisciplinary optimization in the aerospace industry, in: 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, 2002, p. 5439.
[2] S.X. Ying, Report from ICAS workshop on complex systems integration in aeronautics, in: 30th ICAS Congress, Daejeon, Korea, 2016.
[3] X. Zhang, Co-evolution of aeronautical complex system & complex system engineering, in: ICAS Workshop - Complex Systems Integration in Aeronautics, Krakow, 2015.
[4] P.D. Ciampa, B. Nagel, Towards the 3rd generation MDO collaboration environment, in: 30th ICAS Congress, Daejeon, Korea, 2016.
[5] AGILE EU project portal. http://www.agile-project.eu.
[6] P.D. Ciampa, B. Nagel, The AGILE paradigm: the next generation of collaborative mdo, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[7] N. Bartoli, T. Lefebvre, S. Dubreuil, R. Olivanti, N. Bons, J.R.R.A. Martins, M.-A. Bouhlel, J. Morlier, An adaptive optimization strategy based on mixture of experts for wing aerodynamic design optimization, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[8] J.R.R.A. Martins, A.B. Lambe, Multidisciplinary design optimization: a survey of architectures, AIAA J. 59 (9) (2013) 2049–2075.
[9] T. Lefebvre, N. Bartoli, R. Lafage, P.D. Ciampa, AGILE DC-1 MDO process using an efficient global optimization approach, in: 6th EASN International Conference on Innovation in European Aeronautics Research, Porto, Portugal, 2016.
[10] L. Tosserams, S. Etman, P. Papalambors, J. Rooda, An augmented Lagrangian relaxation for analytical target cascading, Struct. Multidiscip. Optim. 31 (3) (2006) 113–122.
[11] T. Lefebvre, N. Bartoli, S. Dubreuil, M. Panzeri, R. Lombardi, P.D. Vecchia, F. Nicolosi, P.D. Ciampa, K. Anisimov, A. Savelyev, Methodological enhancements in MDO process investigated in the AGILE european project, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[12] P. Della Vecchia, L. Stingo, S. Corcione, D. Ciliberti, F. Nicolosi, A. De Marco, Game theory and evolutionary algorithms applied to MDO in the AGILE european project, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[13] F. Daoud, R. Maierl, P.D. Ciampa, X. Gu, Aeroelastic shape and sizing optimization of aircraft products supported by AGILE design paradigm, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[14] W. Lammen, B. de Wit, J. Vankan, H. Timmermans, T. van der Laan, P.D. Ciampa, Collaborative design of aircraft systems - multi-level optimization of an aircraft rudder, in: 6th CEAS Aerospace Europe Conference, 2017.
[15] P.S. Prakasha, A. Mirzoyana, P.D. Ciampa, Collaborative system of systems multidisciplinary design optimization for civil aircraft: AGILE EU project, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[16] P.D. Ciampa, E. Moerland, D. Seider, E. Baalbergen, R. Lombardi, R. D'Ippolito, A collaborative architecture supporting AGILE design of complex aeronautics products, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[17] I. van Gent, P.D. Ciampa, B. Aigner, J. Jepsen, G.L. Rocca, J. Schut, Knowledge architecture supporting collaborative MDO in the AGILE paradigm, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[18] D. Kraft, et al., A Software Package for Sequential Quadratic Programming, DFVLR Obersfaffeuhofen, Germany, 1988.
[19] P.E. Gill, W. Murray, M.A. Saunders, Snopt: an SQP algorithm for large-scale constrained optimization, SIAM Rev. 47 (1) (2005) 99–131.
[20] G.A. Jastrebski, D.V. Arnold, Improving evolution strategies through active covariance matrix adaptation, in: IEEE International Conference on Evolutionary Computation, IEEE, 2006, pp. 2814–2821, 2006.
[21] N. Hansen, S. Kern, Evaluating the CMA evolution strategy on multimodal test functions, in: International Conference on Parallel Problem Solving from Nature, Springer, 2004, pp. 282–291.
[22] A. Forrester, A. Sobester, A. Keane, Engineering Design via Surrogate Modelling: a Practical Guide, John Wiley & Sons, 2008.
[23] C. Audet, W. Hare, Derivative-free and Blackbox Optimization, Springer, 2017.
[24] D.R. Jones, M. Schonlau, W.J. Welch, Efficient global optimization of expensive black-box functions, J. Global Optim. 13 (4) (1998) 455–492.
[25] M. Sasena, Flexibility and Efficiency Enhancements for Constrained Global Design Optimization with Kriging Approximations, Ph.D. thesis, University of Michigan, 2002.
[26] N. Beume, B. Naujoks, M. Emmerich, Sms-Emoa, Multiobjective selection based on dominated hypervolume, Eur. J. Oper. Res. 181 (3) (2007) 1653–1669.
[27] A. Hebbal, L. Brevault, M. Balesdent, E.-G. Talbi, N. Melab, Multi-objective optimization using deep Gaussian processes: application to aerospace vehicle design, in: AIAA Scitech 2019 Forum, 2019, p. 1973.
[28] I. Das, J.E. Dennis, Normal-boundary intersection: a new method for generating the pareto surface in nonlinear multicriteria optimization problems, SIAM J. Optim. 8 (3) (1998) 631–657.
[29] C.C. Coello, M.S. Lechuga, Mopso: a proposal for multiple objective particle swarm optimization, in: Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600), vol. 2, IEEE, 2002, pp. 1051–1056.
[30] J. Périaux, H. Chen, B. Mantel, M. Sefrioui, H. Sui, Combining game theory and genetic algorithms with application to ddm-nozzle optimization problems, Finite Elem. Anal. Des. 37 (5) (2001) 417–429.
[31] N. Bartoli, T. Lefebvre, S. Dubreuil, R. Olivanti, R. Priem, N. Bons, J.R. Martins, J. Morlier, Adaptive modeling strategy for constrained global optimization with application to aerodynamic wing design, Aero. Sci. Technol. 90 (2019) 85–102, https://doi.org/10.1016/j.ast.2019.03.041.
[32] D.G. Krige, A Statistical Approach to Some Mine Evaluations and Allied Problems at the Witwatersrand, Master's Thesis, University of Witwatersrand, 1951.
[33] C.E. Rasmussen, C.K. Williams, Gaussian Processes for Machine Learning, vol. 1, MIT press Cambridge, 2006.
[34] M.A. Bouhlel, N. Bartoli, A. Otsmane, J. Morlier, Improving kriging surrogates of high-dimensional design models by partial least squares dimension reduction, Struct. Multidiscip. Optim. 53 (5) (2016) 935–952, https://doi.org/10.1007/s00158-015-1395-9.
[35] M.A. Bouhlel, N. Bartoli, A. Otsmane, J. Morlier, An improved approach for estimating the hyperparameters of the kriging model for high-dimensional problems through the partial least squares method, Math. Probl Eng. 2016 (2016), 6723410, https://doi.org/10.1155/2016/6723410.
[36] M.A. Bouhlel, N. Bartoli, R.G. Regis, A. Otsmane, J. Morlier, Efficient global optimization for high-dimensional constrained problems by using the kriging models combined with the partial least squares method, Eng. Optim. (2018) 1–16, https://doi.org/10.1080/0305215X.2017.1419344, 0 (0).
[37] D. Bettebghor, N. Bartoli, S. Grihon, J. Morlier, M. Samuelides, Surrogate modeling approximation using a mixture of experts based on em joint estimation, Struct. Multidiscip. Optim. 43 (2) (2011) 243–259, https://doi.org/10.1007/s00158-010-0554-2.
[38] R.P. Liem, C.A. Mader, J.R.R.A. Martins, Surrogate models and mixtures of experts in aerodynamic performance prediction for mission analysis, Aero. Sci. Technol. 43 (2015) 126–151, https://doi.org/10.1016/j.ast.2015.02.019.
[39] A.G. Watson, R.J. Barnes, Infill sampling criteria to locate extremes, Math. Geol. 27 (5) (1995) 589–608.
[40] M.J. Powell, A direct search optimization method that models the objective and constraint functions by linear interpolation, in: Advances in Optimization and Numerical Analysis, Springer, 1994, pp. 51–67.
[41] N. Bartoli, I. Kurek, R. Lafage, T. Lefebvre, R. Priem, M.-A. Bouhlel, J. Morlier, V. Stilz, R. Regis, Improvement of efficient global optimization with mixture of experts: methodology developments and preliminary results in aircraft wing design, in: 17th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Washington D.C., USA, 2016, https://doi.org/10.2514/6.2016-4001.
[42] K. Deb, Multi-objective Optimization Using Evolutionary Algorithms, Wiley, 2005.
[43] F. Nicolosi, A. De Marco, L. Attanasio, P. Della Vecchia, Development of a java-based framework for aircraft preliminary design and optimization, J. Aero. Inf. Syst. 13 (6) (2016) 234–242.
[44] F. Nicolosi, P. Della Vecchia, D. Ciliberti, An investigation on vertical tailplane contribution to aircraft sideforce, Aero. Sci. Technol. 28 (2013) 401–416.
[45] F. Nicolosi, P. Della Vecchia, D. Ciliberti, V. Cusati, Fuselage aerodynamic prediction methods, Aero. Sci. Technol. 55 (2016) 332–343.
[46] F. Nicolosi, P. Della Vecchia, Ciliberti, Aerodynamic interference issues in aircraft directional control, J. Aero. Eng. 28 (1) (2015) 401–416.
[47] P. Della Vecchia, E. Daniele, E. D'Amato, An airfoil shape optimization technique coupling parsec parameterization and evolutionary algorithm, Aero. Sci. Technol. 32 (1) (2014) 103–110.
[48] R.E. Melchers, Structural Reliability Analysis and Prediction, John Wiley, 1999.

[49] A.M. Hasofer, N.C. Lind, Exact and invariant second moment code format, Journal of Engineering Mechnanics 100 (1974) 111–121.
[50] A. Da Ronch, M. Panzeri, M. Abd Bari, R. d'Ippolito, M. Franciolini, Adaptive Design of Experiments for Efficient and Accurate Estimation of Aerodynamic Loads, Aircraft Engineering and Aerospace Technology (to be published).
[51] T. Lefebvre, N. Bartoli, S. Dubreuil, R. Lombardi, M. Panzeri, W. Lammen, M. Zhang, I. van Gent, P. Ciampa, Overview of MDO enhancement in the AGILE project: a clustered and surrogate-based MDA use case, in: 6th CEAS Aerospace Europe Conference, Paper no.956, Bucharest, Romania, 2017.
[52] B. Aigner, I. van Gent, G. La Rocca, E. Stumpf, L.L.M. Veldhuis, Graph-based algorithms and data-driven documents for formulation and visualization of large MDO systems, in: 6th CEAS Air and Space Conference, 2017.
[53] A. Savelyev, K. Anisimov, E. Kazhan, I. Kursakov, A. Lysenkov, Computational study of engine external aerodynamics as a part of multidisciplinary optimization procedure, AIP Conference Proceedings 1770 (2016), https://doi.org/10.1063/1.4963941.
[54] T. Lefebvre, N. Bartoli, S. Dubreuil, M. Panzeri, R. Lombardi, R. D'Ippolito, P. D. Vecchia, F. Nicolosi, P.D. Ciampa, K. Anisomov, A. Savelyev, Methodological enhancements in MDO process investigated in the AGILE european project, in: AVIATION/AIAA 2017, 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, United States, 2017, https://doi.org/10.2514/6.2017-4140.
[55] B.M. Adams, L.E. Bauman, W.J. Bohnhoff, K.R. Dalbey, J.P. Eddy, M.S. Ebeida, M. S. Eldred, P.D. Hough, K.T. Hu, J.D. Jakeman, L.P. Swiler, J.A. Stephens, D. M. Vigil, T.M. Wildey, Dakota, a Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 6.1 Users Manual, Tech. Rep. SAND2014-4633, Sandia National Laboratories, Albuquerque, NM, November 2014 available online from: http://dakota.sandia.gov/documentation.html.
[56] N.A. Zlenko, S.V. Mikhaylov, A.A. Savelyev, Aerodynamic inlet design for civil aircraft nacelle, in: 29th Congress of the International Council of the Aeronautical Sciences, ICAS 2014, St. Petersburg, Russia, 2014.
[57] N.A. Zlenko, S.V. Mikhaylov, A.A. Savelyev, A.V. Shenkin, Method of optimal aerodynamic design of the nacelle assembly for the main propulsion system with a high bypass ratio, TsAGI Sci. J. 46 (6) (2015) 533–558.
[58] S. Bosnyakov, I. Kursakov, A. Lysenkov, S. Mikhailov, V. Vlasenko, J. Quest, Computational tools for supporting the testing of civil aircraft configurations in wind tunnels, Prog. Aero. Sci. 44 (2) (2008) 67–120.
[59] Gasturb 12, in: Design and Off-Design Performance of Gas Turbines, GasTurb GmbH, 2015. Tech. rep.
[60] J. Kurzke, Performance modeling methodology: efficiency definitions for cooled single and multistage turbines, in: ASME Turbo Expo, Amsterdam, Netherlands, 2012.
[61] Noesis Solutions, Optimus Rev 10.19 - Users Manual, 2017.
[62] Noesis Solutions, Optimus - Theoretical Background, 2017.
[63] I. van Gent, G. La Rocca, L.L.M. Veldhuis, Composing MDAO symphonies: graph-based generation and manipulation of large multidisciplinary systems, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.
[64] I. van Gent, P.D. Ciampa, B. Aigner, J. Jepsen, G. La Rocca, E.J. Schut, Knowledge architecture supporting collaborative MDO in the AGILE paradigm, in: 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Denver, USA, 2017.