Uncertainty quantification and robust design optimization applied to aircraft propulsion systems

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ABSTRACT

The standard way of formulating optimization problems applied to aircraft design is based on the assumption that the underlying system is deterministic, i.e., that the knowledge associated with the design variables and with the system dynamic is not characterized by uncertainty. However, in real conditions randomness impacts the formulation of the design process in multiple ways and the system outputs (i.e., the key performance indicators and the design constraints) are also affected by uncertainty. A system designed under deterministic assumptions may therefore have an unreliable behavior due to the fluctuations associated with the input random variables. This problem can be tackled by adopting a probabilistic approach and re-formulating the design optimization problem with an additional set of constraints associated with the robustness / reliability of the target system. This work addresses the problem of optimizing the geometry of a turbofan engine nacelle subject on reliability constraints. An advanced, machine-learning based framework is adopted in order to (a) investigate the system behavior through an adaptive design of experiments technique and (b) build accurate surrogate models of the system dynamics. These surrogate models are then employed to run a set of probabilistic studies at an affordable computational cost. The results of these investigations include (a) an extensive suite of analyses aimed at characterizing the uncertainty associated with the output quantities of interest; (b) a robust optimization of the engine nacelle geometry and (c) an assessment of the reliability of the optimized design. The improved performance and reliability of the design, together with the limited number of overall system evaluations required to run the analyses, demonstrate the effectiveness and the engineering applicability of the proposed approach.

KEYWORDS: Uncertainty Quantification, Computation Fluid Dynamics, Robust Design Optimization, Reliability Assessment, Propulsion System

NOMENCLATURE

Latin
ADOE - Adaptive Design of Experiments
CFD - Computational Fluid Dynamics
DOE - Design of Experiments
FOSM - First Order Second Moment
FORM - First Order Reliability Method
the engine axis
IGES - Initial Graphics Exchange Specification
LES - Large Eddy Simulation
MC - Monte Carlo
MPP - Most Probable Point
MUSCL - Monotonic Upwind Scheme for Conservation Laws
RANS - Reynolds-averaged Navier-Stokes
SORM - Second Order Reliability Method
TVD - Total variation diminishing
N_{MC} - Monte Carlo population size
pdf - Probability density function
p_f - Probability of failure
H - Altitude
M - Mach number
T_0 - Total temperature
p_0 - Total pressure
$p_{0,en}$ - Average total pressure at the engine intake
d_{th} - Inlet throat diameter
d_0 - Diameter of the inlet leading edge
K - Thickness coefficient of the inlet lip
R_{CURV} - Leading edge curvature radius
P - Engine thrust
P_{id} - Ideal engine thrust
P_{eff} - Effective engine thrust
dP_{eff} - Effective thrust loss
F_X - Projection of the external drag force on
Greek
σ - Standard deviation
β - Reliability index
δ - Total pressure loss ratio
ν - Total pressure recovery ratio
Subscripts
CR - Cruise
TO - Take off
∞ - Ambient flow

1 INTRODUCTION

In a typical design process developed under a deterministic paradigm, all input parameters are considered to be known without uncertainty. In this context, all manufacturing processes are assumed to produce identical structures that will operate at the same environmental conditions. This is typically not true because the presence of non-predictable effects associated, for example, with imperfections occurring in the manufacturing process or with the non-exact definition of the target operating conditions, have a considerable impact on the reliability of the system in terms of structural instabilities.
The aim of this study is to optimize the geometry of a turbofan engine nacelle by adopting a probabilistic approach, according to which the input system parameters are considered as random quantities and therefore also all the output quantities are associated with probability density functions. This approach allows re-formulating the optimization problem by introducing a new set of robustness / reliability constraints that are directly associated with the probability of failure or with the robustness of the target system instead of being inferred from implicit knowledge or experience.
The advantages of adopting this approach are multi-fold: it enables the possibility to assess the reliability of the target system in terms of quantities defined in a rigorous probabilistic context instead of handling subjective, experience-based and heuristic values; as a consequence, the approach can yield an optimized system that is sufficiently reliable but is typically associated with increased performances.
Uncertainty quantification techniques are well-known to be computationally demanding because an accurate characterization of the uncertainty associated with the output quantities of interest requires a large number of system evaluations. In this study, these burdens are circumvented by adopting an approach based on surrogate models, according to which a machine learning-based, adaptive Design of Experiments technique is used to build a dataset of system results together with the corresponding surrogate models. The latter are then employed to run the system evaluations associated with the uncertainty analyses and the reliability optimization.
This study is developed within the context of the European AGILE project [1]. AGILE targets a significant reduction (i.e., 40%) of the time required to implement and solve realistic multidisciplinary design optimization studies. The key enablers are provided by (a) a suite of advanced optimization techniques and strategies; (b) a framework that supports the collaboration aspects between the involved partners and (c) a knowledge-based information technology [2-5]. In the context of AGILE, a key target of the current work consists on assessing the effectiveness and the suitability of the uncertainty analyses techniques on conventional multi-disciplinary design problems. These

methodologies will then be applied to novel aircraft configurations during the upcoming phases of the project.
The remainder of this manuscript is organized as follows. Section 2 provides the theoretical framework and the methodologies adopted to optimize the geometry of a turbofan engine nacelle under reliability constraints. These techniques have been applied to the test case described in Section 3, while Sections 4 and 5 present the results and main conclusions, respectively.

2 THEORETICAL FRAMEWORK AND METHODOLOGIES

This section provides an overview of the techniques employed to run the uncertainty quantification analyses and of the numerical simulation tools used to model the behavior of the target propulsion system.

2.1 Uncertainty Quantification framework

A probabilistic approach is adopted to formalize the randomness associated with the input design variables and to characterize the uncertainty associated with the system outputs. Among the available numerical techniques, the current work considers the MC and the FOSM methods.
The Monte Carlo method requires generating a number of random samples distributed according to the pdfs of the input design variables. For each of these samples, a system evaluation is performed in order to obtain a collection of results that are used to approximate the target pdf of the outputs of interest.
The First Order Second Moment method approximates the system dynamics with a first-order Taylor expansion evaluated at the mean value of the input variables. The estimated variance, $\hat{\sigma}^2_{y_i}$, associated with a target system output, y_i, is then evaluated as

$$\hat{\sigma}^2_{y_i} = \sum_{j=1}^{N_x} \left(\frac{\partial y_i}{\partial x_j}\right)^2 \sigma^2_{x_j} \tag{1}$$

where N_x is the number of random design inputs while the terms $\left(\frac{\partial y_i}{\partial x_j}\right)$ and $\sigma^2_{x_j}$, $j = 1, \ldots, N_x$, are the coefficients of the Taylor expansion and the variance with respect to the design inputs x_j, respectively.
The main advantage of MC is to provide 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 indicator like the quantile values or the probability of failure. All these quantities can be directly inferred from the collection of system evaluations 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 (e.g., the sample mean and variance converge to their true values proportionally to $1/\sqrt{N_{MC}}$). Moreover, it suffers from the curse of dimensionality when the system behavior is strongly affected by the mutual interactions between the input variables.
The numerical evaluation of the derivatives defined in Eq. 1 typically requires a limited number of system evaluations (i.e., equal to N_x if they are computed through a forward finite-difference scheme) and this renders the FOSM approach more affordable from the computational point of view. Nevertheless, FOSM does not directly allow estimating the values of quantiles or probabilities of failure and the latter can only be assessed by introducing assumptions on the functional form of the corresponding pdf. Being FOSM a method based on a linear approximation of the system dynamics, it is not reliable when the dependence between inputs and outputs 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 constraints. The robustness of the system is assessed by analyzing the value of the standard deviation associated with output quantities of interest. In terms of reliability, the First Order Reliability Method and the Second Order Reliability Method will be considered in this study. The goal of FORM and FOSM consists on estimating a reliability index that can be used to assess how far the optimal design is from the boundary of the feasible region. The reliability index, β, associated with a given value of the design variable is calculated by identifying the closest point on the boundary of the feasible region, named Most Probable Point, through a gradient-based optimization algorithm. The

value of β is then set equal to the distance between the design point of interest and the MPP. This distance is computed in a standardized space where all random variables are mutually uncorrelated and characterized by values of the mean and of the standard deviation equal to 0 and 1, respectively. A first-order (FORM) or second-order (SORM) approximation of the feasible region boundary centered at the MPP is then computed in order to estimate the probability of failure, p_f, of the design under study.

2.2 Adaptive Design of Experiments and surrogate modelling framework

The ability to run accurate uncertainty analyses on the target design system is often limited by the large number of entailed system evaluations. These computational burdens can be alleviated by adopting an approach based on surrogate models.

Surrogate models are analytical functions built on the basis of the results obtained through a design of experiments and using regression (e.g., least squares) or interpolation (e.g., Kriging or Radial Basis Function) algorithms. By definition, they can provide only approximated outputs, the quality of which largely depends on: (a) the DOE plan (e.g., factorial, Latin Hypercube, etc.); (b) the number of experiments computed during the DOE and (c) the type of algorithm used to interpolate / fit the data produced by the DOE. The major difficulties in this context consist on the identification of (a) the most appropriate DOE plan and (b) the best algorithm for building the surrogate model once the results of the DOE have become available.

These aspects are addressed by adopting a machine-learning Adaptive DOE approach. The ADOE is an iterative DOE technique in which the data produced during previous iterations are analyzed to distribute the design points of the next iteration in areas of the parameters space considered of interest. A key aspect of the ADOE is the capability to automatically identify the best type of surrogate model on the basis of the available set of results. The reader is referred to [6] for more details on the machine-learning algorithms embedded in the ADOE methodology and on the relevant analytical and industrial benchmark studies.

In this work, the ADOE is employed to efficiently explore the design space and to build accurate surrogate models of the system under study. These surrogate models are then used to run the system evaluations entailed by the uncertainty analyses and by the robust optimization applied to the design of the engine nacelle.

2.3 Engine analyses

The engine analyses are performed using the commercial software GasTurb v12 [7-8] Level 1. The Level 1 engine simulation tool entails a set of 0-level simulations of engine components (compressors, turbines, combustor, etc.) that are considered as black-box systems and are characterized by a low detailed modelling capability.

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 on: engine installation losses, engine flight envelope, 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, automatic handling of air bleed.

In this work, 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.

2.4 Propulsion aerodynamic analyses

The propulsion aerodynamics analysis tool is based on the method of nacelle aerodynamic design and optimization described in [9]. It is a fully automated tool chain consisting of four blocks: geometry constructor, grid generator, CFD solver and post-processor (see Fig. 1). The result of the geometry constructor block run is an IGES file containing the geometrical model with specified values of input parameters. The generated file is used to build the computational grid. CFD calculations are then carried out using the TsAGI in-house code Electronic Wind Tunnel (EWT-TsAGI) [10]. The EWT-TsAGI software package realizes the concept of "Electronic Wind Tunnel" and has the capabilities to simulate a wide range of stationary or non-stationary gas flows with complex geometry on the basis of Euler, Navier-Stokes, LES or RANS equations. The CFD solver of EWT-TsAGI is based on the finite-volume numerical method that has the second-order approximation in all variables and includes the Godunovtype TVD scheme for approximation of convective fluxes (MUSCL). The stationary solution is obtained using a linearized implicit scheme which has the first approximation order in time. In the current work, it is used a stationary solver for RANS equation system closed by Spalart-Allmaras turbulence model [11]. For modeling the engine, special boundary conditions are used. The nozzle boundary condition is represented by the total pressure and total temperature values corresponding to the engine operating mode. The engine intake boundary condition is set by constraining the air mass flow rate through the nozzle with the intake mass flow rate.

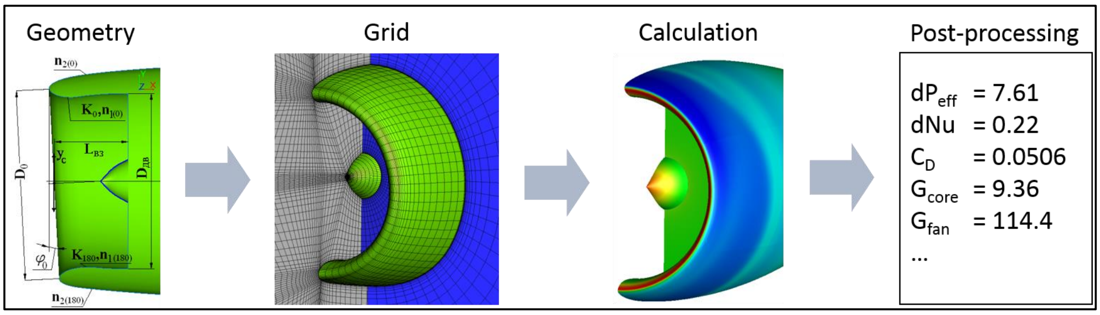

Figure 1: CFD analysis tool chain

3 TEST CASE AND SENSITIVITY ANALYSES

The objective of the test case is to apply uncertainty analyses and robust optimization techniques to the design of the nacelle of a turbofan engine. The design process has been set up by considering the technical requirements of a regional aircraft model conceived in the context of the AGILE project [1].
A key aspect concerning the engine simulations consists on the correct adjustment of the engine automatic control system. These adaptations have a direct influence on the engine output parameters computed on the basis of the random fluctuations affecting the input variables and are applied in order to match the same level of engine installed thrust as in the reference (deterministic) conditions. The assumption is realistic because the engine parameters associated with the engine automatic control system are typically tuned to match the thrust level required in the considered flight condition (such as takeoff or cruise).
Several sensitivity analyses were performed in order to identify (a) the most influencing geometrical parameters, (b) the input variables affected by uncertainty; (c) the key performance indicators and (d) the reliability constraints associated with the design of the target system. These aspects were analyzed by considering two different flight regimes: cruise ($M = 0.78$, $H = 11000$ m) and takeoff ($M = 0$, $H = 0$ m). The associated CFD analyses were performed on an axisymmetric structured grid composed by 57600 hexahedral cells (see Fig. 2). One CFD calculation took about 6 minutes using 50 cores of a supercomputer.

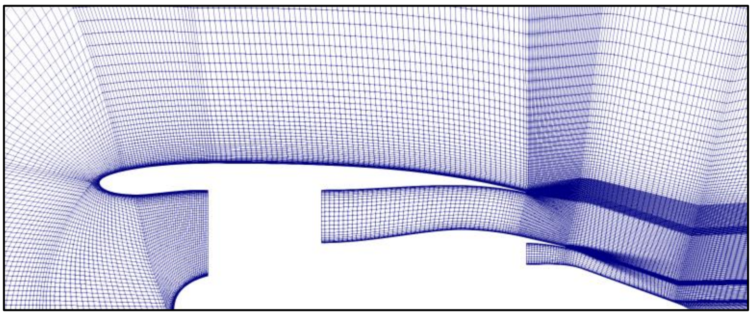

Figure 2: General overview of the computational grid used to run CFD calculations

Experimental and numerical studies have shown that the aerodynamic performance of the nacelle of a turbofan engine with separate jets depends on approximately twenty parameters defining the geometry of the nozzle, the inlet and the outer cowl. The most critical step is to design the geometry of the air intake by taking into account two competing behaviours: it should ensure a flow without separation in the inlet duct and minimize the aerodynamic drag. The greatest interest in the inlet design process is the cruise and takeoff regimes. Fig. 3 displays the typical flow patterns observed at the inlet region and shows that the streamlines evaluated at takeoff regime are characterized by a pronounced curvature. The flow turns around the lip of the inlet and, if the inlet is too sharp, flow separation may occur.

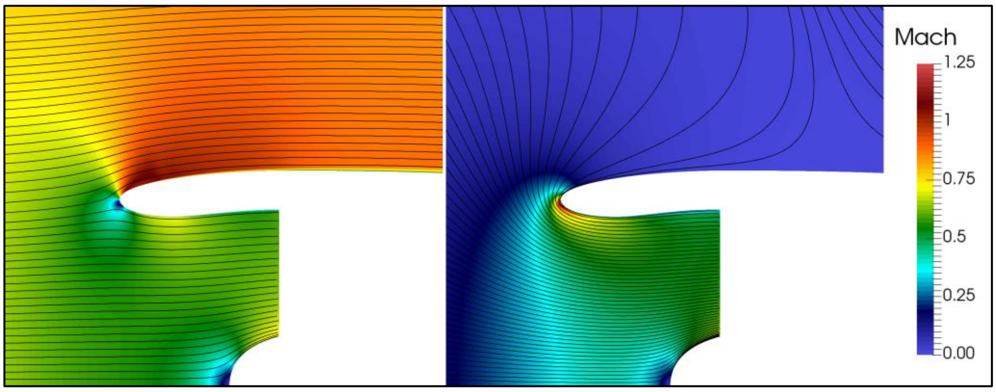

Figure 3: Flow patterns at cruise (left) and takeoff (right) regimes

Previous studies (for example [12]) showed that the key geometrical parameters affecting the characteristics of the inlet flow are (a) the leading edge curvature radius, R_{CURV}, and (b) the thickness coefficient of the inlet lip, K, determined as (see Fig. 4)

$$K = \frac{d_0}{d_{th}} - 1 \quad (2)$$

The dimensionless lower and upper boundaries for R_{CURV} and K were defined as [0, 1].

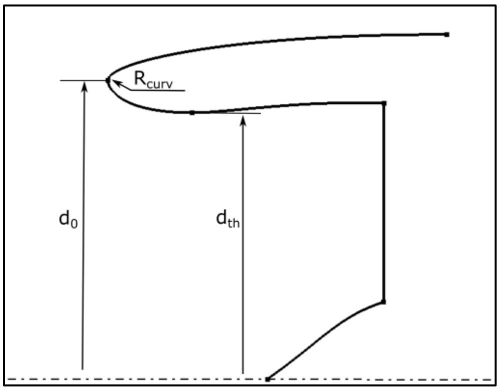

Figure 4: Inlet geometrical parameters

An example of how the lip thickness coefficient and the leading edge curvature radius can impact the flow field at the engine intake is provided by Fig. 5, showing that the appearance of flow separation in the inlet duct is typically associated with small values of K and small values of R_{CURV}.

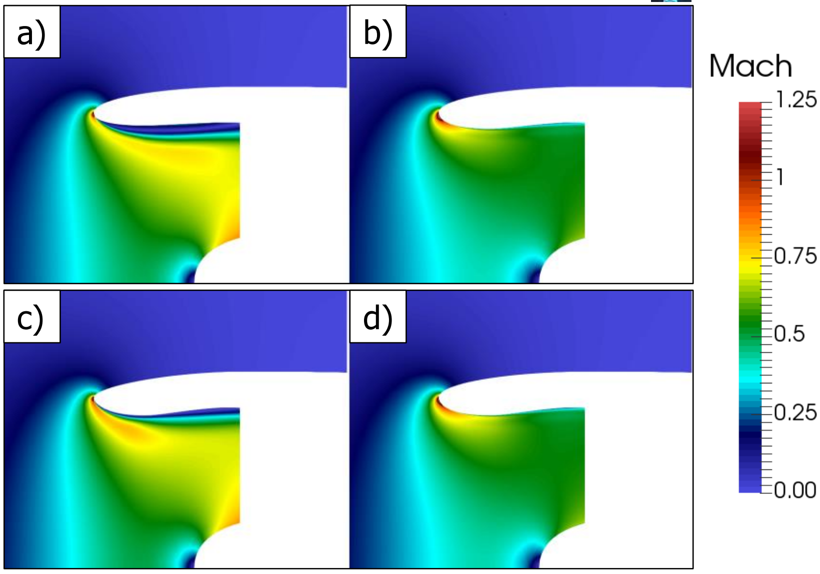

Figure 5: Flow field computed at takeoff regime by adopting small (a) or standard (b) values of K and small (c) or standard (d) values of R_{CURV}

The effective thrust loss, dP_{eff}, evaluated at cruise regime is associated with the aerodynamic efficiency of the nacelle and is therefore adopted as the key performance indicator to be minimized during the optimization of the design. The value of dP_{eff} is computed as

$$dP_{eff} = \left(1 - \frac{P_{eff}}{P_{id}}\right) \cdot 100\% \quad (3)$$

where

$$P_{eff} = P - F_X \quad (4)$$

From a reliability point of view, the variable that quantitatively describes the presence of flow separation in the inlet duct is the total pressure loss ratio, δ, evaluated at takeoff regime. δ is defined as

$$\delta = (1 - \nu) \cdot 100\% = \frac{p_{0,\infty} - p_{0,en}}{p_{0,\infty}} \cdot 100\% \quad (5)$$

Values of $\delta > 1$ indicates the occurrence of flow separation and are therefore associated with unfeasible designs.

From a probabilistic point of view, the random input variables are those associated with the operating conditions of the target system. A set of probability density functions has been defined for the ambient total temperature and pressure values at cruise and takeoff regimes. As reported in Table 1, these pdfs are assumed to be normal and characterized by a mean and standard deviation equal to the reference value and to 1% of the reference value of the quantity of interest, respectively.

Table 1: Reference values and probability density functions associated with the input random variables

Name	Description	Statistical distribution	Reference and mean value	Standard deviation
$T_{0,\infty,TO}$	Ambient total temperature at takeoff	Gaussian	288.15 K	2.88 K
$p_{0,\infty,TO}$	Ambient total pressure at takeoff	Gaussian	98960 Pa	989.60 Pa
$T_{0,\infty,CR}$	Ambient total temperature at cruise	Gaussian	243.07 K	2.43 K
$p_{0,\infty,CR}$	Ambient total pressure at cruise	Gaussian	33685 Pa	336.85 Pa

A set of intermediate variables, namely temperatures and pressures evaluated at engine core and fan and at cruise and takeoff flight conditions (for a total of 8 variables) are also considered. The flow chart depicted in Fig. 6 describes the variables involved in the test case together with their inter-dependencies and the inputs / outputs of the involved analysis tools.

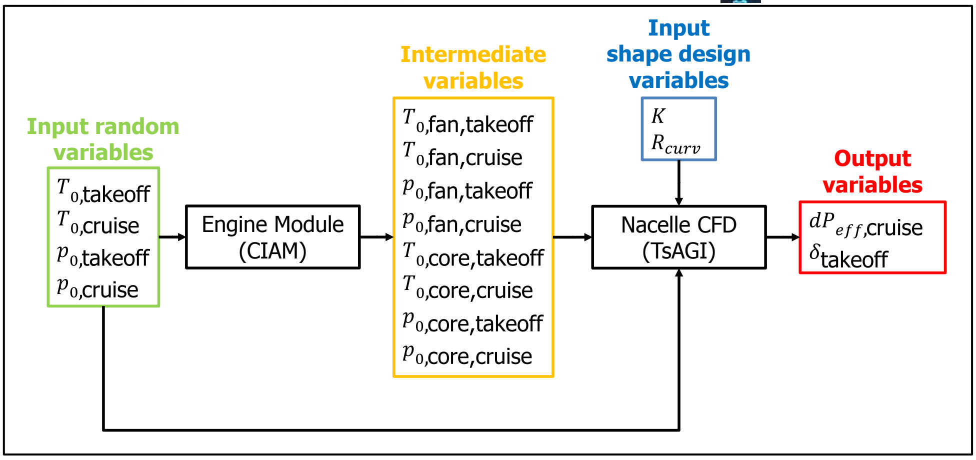

Figure 6: Flow chart describing tools and variables considered in the test case.

The workflow described in Fig. 6 has been implemented in the process integration and design optimization platform Noesis Optimus [13]. The built-in capabilities of Optimus are also used to (a) run the machine-learning based ADOE 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 the uncertainty quantification analyses described in Section 4. The corresponding simulation workflow is displayed in Fig. 7. In this workflow, the random input variables contained in the "Inputs_operating" array are used to compute the outputs of the engine analysis through a surrogate model. These outputs, together with the values of the nacelle geometry parameters, are mapped to the file "params.in" that is employed to run two CFD simulations at takeoff and cruise regimes, as described in Section 2.4. The output file produced by the calculation, "results.out", is then parsed in order to extract the values of δ and dP_{eff} at takeoff and cruise conditions, respectively.

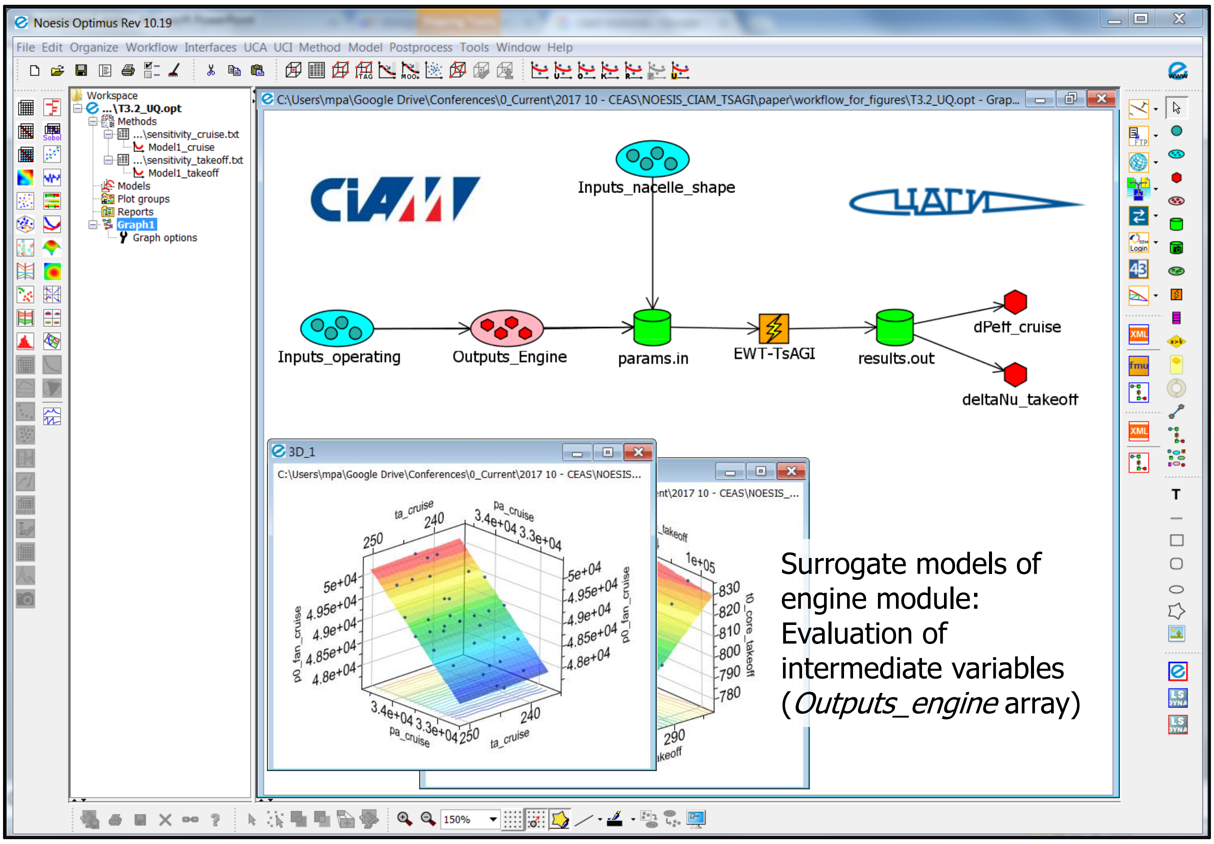

Figure 7: Optimus workflow used to integrate the two analysis tools and to automate the CFD analyses

4 RESULTS AND DISCUSSION

The robust optimization of the target design relies on the presence of an accurate surrogate model of the system under study. This surrogate model is evaluated as follows:

1. A DOE plan was executed for the engine analysis tool described in Section 2.3. Considering the relatively regular shape of the system response, this DOE analysis was performed by merging the results obtained from an orthogonal and a Latin Hypercube [14] sampling plans;
2. The results of these experiments were then imported in Optimus and employed to (a) build a first-order Least Squares model of the engine analysis tool and (b) embed this surrogate model in the Optimus workflow depicted in Fig. 7;
3. The ADOE strategy (see Section 2.2) was finally applied to execute a total number of 305 workflow runs and to automatically identify the best surrogate model that links the system inputs (i.e., random variables and geometrical parameters) to the output quantities of interest. All the uncertainty analyses described below have been performed by means of the surrogate models identified by the ADOE algorithm.

The first study aims at characterizing the behavior of dP_{eff} and δ within the design space. Fig. 8 shows that the most efficient designs (represented by lower values of dP_{eff}) are associated with small values of R_{CURV} and K. The impact of these geometrical parameters on the feasibility of the design is demonstrated by the fact that δ displays values greater than 1 (i.e., indicating the presence of flow separation) in areas of the domain associated with small values of K.

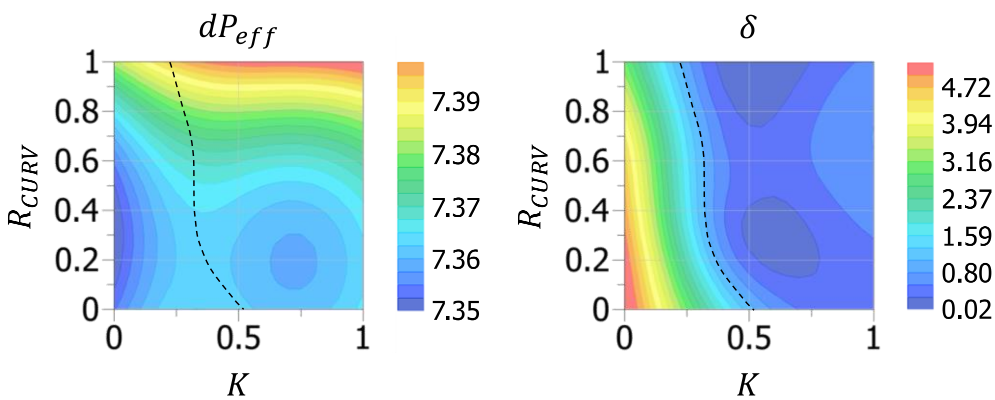

Figure 8: Contour plots describing the dependency of dP_{eff} and δ on K and R_{CURV} at reference ambient pressures and temperatures. The dashed line identifies the boundary of the feasible region ($\delta = 1$)

An uncertainty quantification study was performed to investigate the impact of the randomness associated with the ambient pressure and temperature values on the standard deviation of δ, σ_δ. A set of analyses was performed through FOSM and MC by evaluating σ_δ as a function of R_{CURV} and K at 400 points uniformly distributed within the design space. The impact of the Monte Carlo population size, N_{MC}, was also assessed by considering three different values of N_{MC} equal to 100, 1,000 and 10,000. In this study, FOSM was coupled with a forward finite difference scheme to compute the derivatives defined in Eq. 1 and therefore required only 5 system evaluations (i.e., one plus the number of random variables) in order 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. 9 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 of 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.

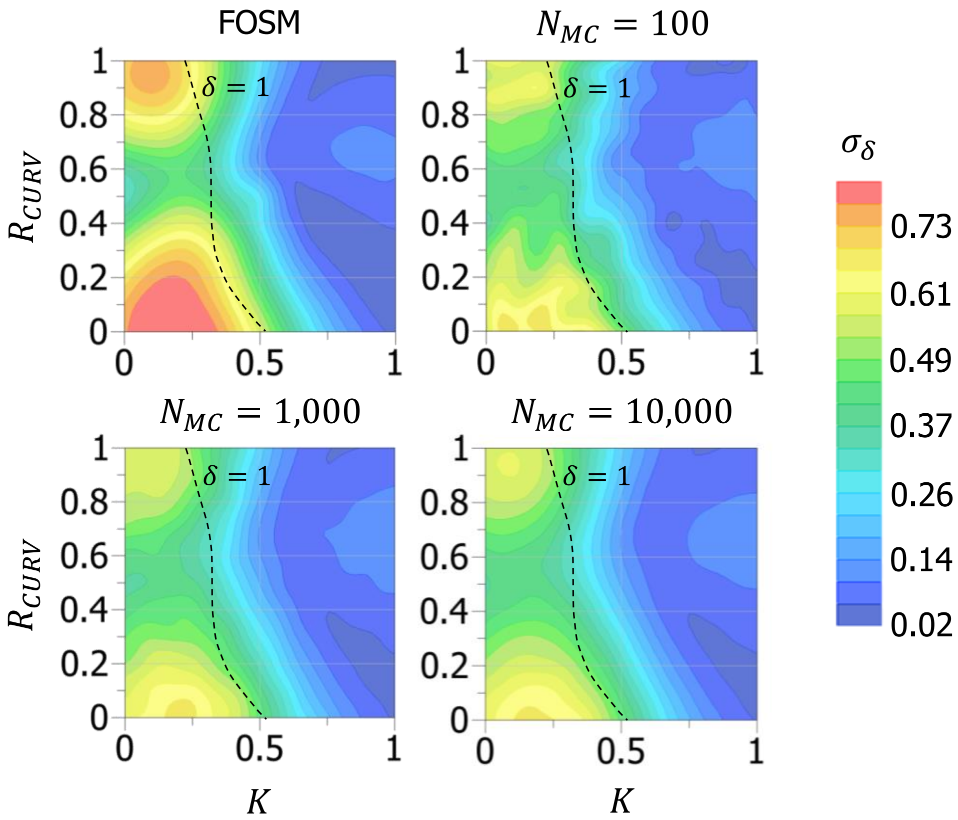

Figure 9: Variation of σ_δ with K and R_{CURV} evaluated with FOSM and with MC for different values of N_{MC}. The dashed line identifies the boundary of the feasible region ($\delta = 1$)

The contour plots depicted in Fig. 9 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. For this reason, the design optimization problem cannot be defined adopting a traditional deterministic approach where (a) the operating condition are set equal to their reference values and (b) the constraint is defined by imposing the inequality $\delta < 1$. In fact, this would most likely lead to an unreliable system, where flow separation phenomena will occur due to the random deviations affecting the real operating conditions.

An effective approach consists of introducing a constraint in order to enforce the system reliability within an appropriate confidence interval. Fig. 10 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 as $\delta + 6\sigma_\delta < 1$ on the position of the boundary of the feasible region. Clearly, the adoption of this constraint reduces the area of the feasibility region.

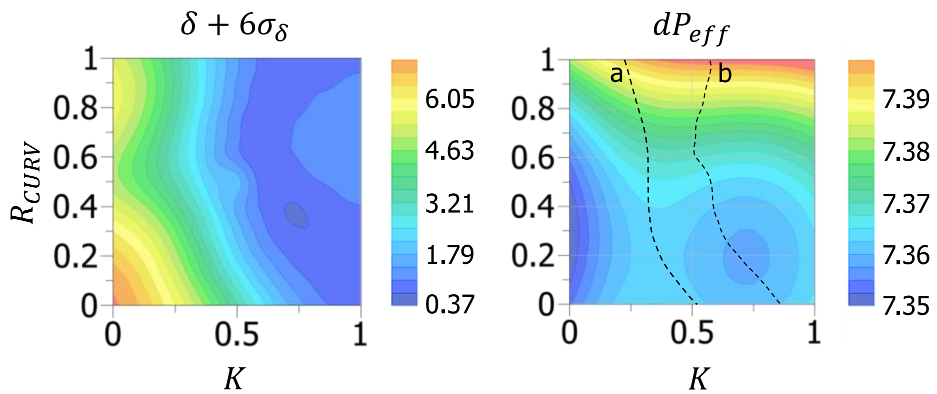

Figure 10: Contour plots showing the dependency of $\delta + 6\sigma_\delta$ (center) and dP_{eff} (right) on K and R_{CURV}. The dashed lines denote the boundary of the feasible region obtained by setting $\delta = 1$ (a) and $\delta + 6\sigma_\delta = 1$ (b)

A robust design optimization strategy has been defined in order to identify the most efficient design subject to the reliability constraint defined as $\delta + 6\sigma_\delta < 1$. The optimal values of the design variables are found on the basis of a gradient-based algorithm and corresponds 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 reported in Fig. 11.

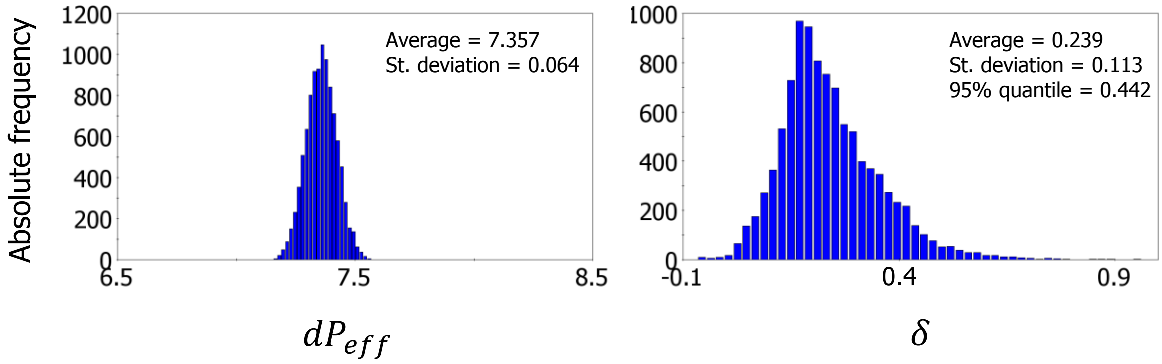

Figure 11: Histograms of dP_{eff} (left) and δ (right) obtained on the basis of a MC analysis with $N_{MC} = 10,000$ and by setting K and R_{CURV} to their optimal values

A conclusive analysis is performed through FORM and 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 $p_f = 3.8 \cdot 10^{-5}$ 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 ascribed 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 entailed by SORM with respect to FORM, for the test case under study 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 CONCLUSIONS

The aerodynamic efficiency and the reliability of a turbofan engine nacelle are strongly influenced by its target operating conditions. Considering that these conditions in reality are affected by random fluctuations, optimizing the nacelle geometry under deterministic assumptions is likely to produce an output design whose efficiency and reliability do not encompass the entire spectrum of operating conditions. This work adopts a probabilistic approach to formulate a design optimization problem subject to reliability constraints. A key aspect consists on the employment of a framework based on machine learning techniques in order to reduce the number of system evaluations required to perform the uncertainty analyses. The proposed methodology allowed characterizing the uncertainty of the system outputs and to find an optimal design for the geometry of the engine nacelle subject to the target reliability constraint. The results include an assessment of the reliability of the optimized design measured according to the reliability index, β, and the probability of failure.

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