

Non-Axisymmetric Aero-Engine Nacelle Design by Surrogate-Based Methods

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Abstract

For many aerodynamic design tasks, a key challenge is the balance between the non-linearity of the transonic flow, the inherent 3D nature of the geometry and flow field, the computational cost and the level of accuracy. Within an optimisation process this is further compounded by the high degrees of freedom to define the geometry and the requirement for 3D computations at both design and off-design conditions. An example of this is the design of compact nacelles for future civil aero-engines which will have larger bypass ratios than current in-service architectures. This paper presents an approach for the design and optimisation of 3D drooped and scarfed non-axisymmetric nacelles. To reduce the computational expense, a range of surrogate-based adapted methods are investigated. Relative to the conventional approach of full numerical simulations in the optimisation loop, the adapted method identifies an acceptable design space with a 65% reduction in the total computational cost. Overall, this demonstrates a useful approach for reducing the time and cost of high-dimensional, aerodynamic design problems.

Keywords: nacelle; multi-objective optimisation; non-axisymmetric; CFD; surrogate model.

Nomenclature

Roman Symbols

A	Matrix of coefficients for the iCST formulation
B	Matrix of constants for the iCST formulation
X	Matrix of Bernstein polynomial coefficients
<i>A</i>	Area
<i>C</i>	Class function
<i>c</i>	chord length
$C_{D-cruise}$	Nacelle drag evaluated at cruise point
C_{D-Mach}	Nacelle drag evaluated between increased cruise Mach number and mid-cruise
$C_{D-spill}$	Nacelle drag evaluated between end of cruise and mid-cruise
C_D	Nacelle drag
<i>D</i>	Drag
<i>f</i>	Non-dimensional factor
<i>h</i>	Altitude
<i>k</i>	Degree of Bernstein polynomial
<i>L</i>	Length

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M Mach Number

$N_{Pearson}$ Pearson's product moment of correlation

r Radius

S Shape function

x Abscissa

z Offset

bp Bernstein polynomial weighting coefficient

Greek Symbols

β Boat-tail angle

ψ Non-dimensional abscissa

ρ Density

σ root mean square error

θ_{droop} Droop angle

θ_{scarf} Scarf angle

ξ Non-dimensional ordinate

Superscripts and Subscripts

∞ Freestream

$fore$ Nacelle forebody

hi Highlight

if Initial Forebody

<i>int</i>	Intake
<i>is</i>	Isentropic
<i>max</i>	Maximum radius
<i>nac</i>	Nacelle
<i>spin</i>	Spinner
<i>te</i>	Trailing Edge
<i>th</i>	Throat

Acronyms

AM	Adapted Method
CFD	Computational Fluid Dynamics
CM	Conventional Method
CST	Class Shape Transformation
DoF	Degree of Freedom
GA	Genetic Algorithm
GPR	Gaussian Process Regression
iCST	intuitive Class Shape Transformation
LHS	Latin Hypercube Sampling
MFCR	Mass Flow Capture Ratio
MOO	Multi-objective optimisation
RSM	Response Surface Model
SST	Shear Stress Transport

1. Introduction

During an aerodynamic design process there is always a trade-off between the fidelity of the computational model, the degrees of freedom (DoFs) to describe the geometry, the associated computational cost and the overall design time. The number of input variables and the associated computational overhead to evaluate the performance metrics with high-fidelity CFD are closely linked. This cost increases exponentially with the DoFs and the curse of dimensionality could lead to an unfeasible design method. In this respect, design strategies are being developed to overcome the challenges of high-dimensional spaces. They include the use of different CFD fidelities [1], the combination of low order models and CFD data [2] or the deployment of dimensionality reduction techniques [3]. Likeng *et al.* [4] carried the multi-fidelity aerodynamic optimisation of the F6 wing-body configuration at a flight Mach number (M_∞) of 0.785. Overall, 36 design variables were used to define the wing shape. Due to the large computational cost associated to the RANS CFD evaluations, a multi-fidelity approach based on a co-Kriging interpolation method was used. The low order evaluations were based on a potential method and the higher-fidelity on RANS CFD simulations. The approach yielded to a new configuration with a 14% reduction on airframe drag with respect to the baseline geometry. Han *et al.* [5] developed a weighted gradient-enhanced Kriging (WGEK) for high-dimensional surrogate modeling. The method builds a series of submodels with the appropriate weightings to form a global model that covers the full design space. To prove the capabilities of the WGEK approach the inverse design of the ONERA M6 transonic wing ($M_\infty = 0.84$) with 108 design variables was considered. It was demonstrated that the wing shape derived from WGEK matched better the target pressure distribution than the one obtained from a model built with the ordinary interpolation Kriging. Grey and Constantine [6] carried out the

aerodynamic optimisation of an airfoil shape at $M_\infty = 0.8$ with the active subspace dimensionality reduction technique [7]. The airfoil was defined with 10 variables and the Class-Shape Transformation (CST) parametrisation [8]. The analysis revealed the possibility to project in one- and two-dimensional active subspaces the lift and drag, respectively. Then, a multi-objective optimisation was successfully carried out in the reduced dimensions to identify a set of Pareto optimal solutions.

Civil aero-engine nacelles are a clear example of complex aerodynamic shapes. They are non-axisymmetric configurations controlled with a relatively large number of DoFs and different operating conditions must be considered during the design process to ensure aerodynamic robustness. This includes transonic and subsonic operating conditions such as mid-cruise conditions [9], sensitivity to flight Mach number, end-of-cruise conditions, take-off at high angles of attack [10] or engine-out windmilling scenarios [11]. Nacelles are typically defined by the highlight radius (r_{hi}), the normalised length (L_{nac}/r_{hi}) and the normalised trailing edge radius (r_{te}/r_{hi}) (Figure 1), which all can vary azimuthally. Besides, each controlled aero-line is described by at least 4 extra input variables and typically 5 aero-lines are used to define the 3D configuration [12]. The combination of these nacelle variables and the required inclusion of droop ($\theta_{droop} = \tan^{-1}(\Delta z_{int}/l_{int})$) and scarf angles (θ_{scarf}) [13] (Figure 1) can result on a design problem of approximately 40 degrees of freedom. As such, there is a clear need to develop a robust design method to reduce the computational cost, while maintaining the DoFs and fidelity of the final results.

Within the context of future civil aero-engines, it is expected that they will operate at higher bypass-ratios (BPR) than current designs [14] to reduce the specific thrust, and to improve the overall propulsive efficiency and the engine specific fuel consumption (SFC) [15, 16]. However, these new architectures are

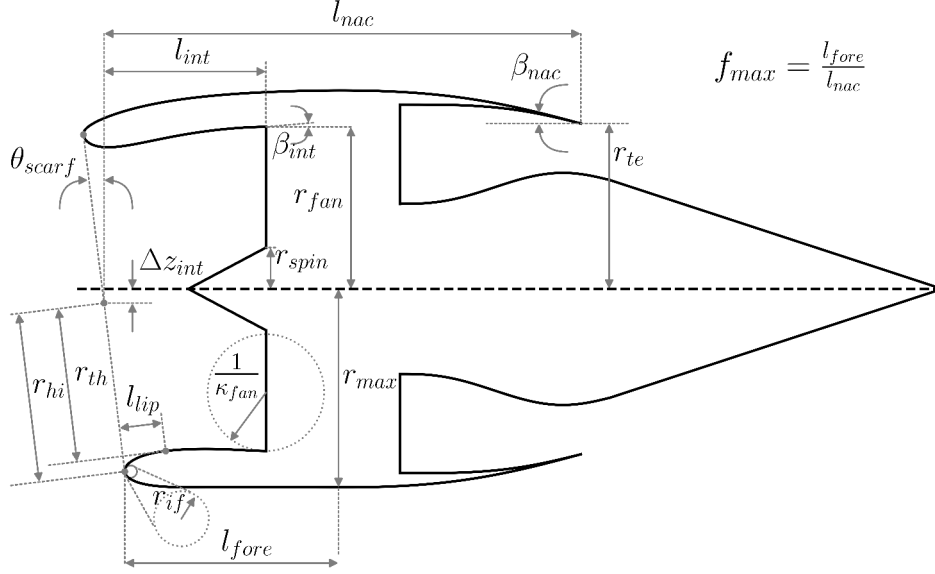


Figure 1: Fan cowl and intake geometric parameters for a drooped and scarfed nacelle

likely to have larger fan diameters which increases the overall engine weight, nacelle size and might present larger adverse impact on the installation effects [17, 9]. Thus, it is envisaged that nacelle performance will have a notable impact in the success of the next generation of civil aero-engines [18]. Therefore it is necessary to design compact nacelles which will not counteract the benefits obtained from the new engine cycles [19]. The effects of aircraft integration on aero-engine nacelles were investigated by Tejero *et al.* [9]. Two different nacelle architectures with $L_{nac}/r_{hi} = 3.8$ and 3.1 were considered and was demonstrated that the compact ($L_{nac}/r_{hi}=3.1$) is more sensitive to close-couple installation positions than the conventional configuration.

Previous investigations have carried out the multi-objective optimisation (MOO) of compact single aero-lines in which the degrees of freedom were relatively low. Robinson *et al.* [20] performed the MOO for a conventional engine

nacelle with $L_{nac}/r_{hi} = 4.3$ and for 2 compact engines with $L_{nac}/r_{hi} = 3.8$ and 3.1 with a CFD in-the-loop approach, in which 5 DoF were used during the optimisation process. Relative to the conventional design, it was demonstrated that the minimum achievable drag at cruise conditions can be reduced by 6.5% and 16.1% for the configurations with $L_{nac}/r_{hi} = 3.8$ and 3.1, respectively. Nevertheless, both compact designs presented larger sensitivities to the changes in flight Mach number and massflow capture ratio. Tejero *et al.* [21] investigated the feasible design space within the cruise segment for axisymmetric compact configurations. The design sensitivities to the pertinent geometric parameters of normalised nacelle length (L_{nac}/r_{hi}) and trailing edge radius (r_{te}/r_{hi}), as well as to operating conditions, were quantified and basic design guidelines were derived. The optimisation and design method was based on a CFD in-the-loop approach in which all nacelle design were evaluated with RANS simulations. In this previous study, the nacelle geometry was defined with 5 DoF. The tool was extended to accommodate the capability of MOO with surrogate models [22] in which a new adapted approach was developed. The method starts with numerical simulations to guide a genetic algorithm through subsequent generations and combines the CFD results with evolving surrogate models to determine a set of Pareto optimal nacelles. Relative to a pure CFD in-the-loop optimisation approach, the proposed method showed a 25% reduction in the computational cost. Schreiner *et al.* [11] used the same nacelle design framework to quantify the trade-off between compact and conventional axisymmetric aero-engine nacelles. A series of MOOs for different L_{nac}/r_{hi} and r_{te}/r_{hi} were conducted and it was demonstrated that compact architectures are more sensitive to windmilling off-design conditions. Albert *et al.* [23] carried out a combined intake/nacelle MOO to minimize the peak Mach number at cruise ($M_\infty = 0.73$) and static conditions ($M_\infty = 0.05$). Different parametrisations were considered and the

Class-Shape Transformation (CST) model, with 4 DoF to describe the nacelle, was proven to identify the most optimal configurations.

Although the MOO investigations have been recently extended to 3D drooped and scarfed nacelle designs [24, 25, 26], it is still required to reduce the overall computing cost. The open literature on the optimisation of 3D nacelles is very limited. The studies are mainly based on low order methods that drive the Genetic Algorithm (GA) to a set of optimum designs [24, 25]. The optimisation approach uses meta-models to identify Pareto front solutions which are consequently computed with higher fidelity RANS CFD. The low order model is updated with the new computed designs and used recurrently in a closed loop. As such, this method relies on the proper identification of the optimal design space with the low order model and the subsequent updates are used to improve its prediction capabilities. Nevertheless, the main disadvantage of this algorithm for complex non-linear problems is the inherent difficulties to ensure the convergence on the optimal design space with the meta-model [22]. Fang *et al.* [24] reported the multi-objective optimisation of a non-axisymmetric nacelle with $L_{nac}/r_{hi} = 3.5$. The aero-engine was parametrised using Class Shape Transformation (CST) curves and 20 design variables. An optimisation strategy that included a design of experiments (DOE) capability, Kriging interpolation for the surrogate modelling and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) genetic algorithm [27] was applied to optimise the nacelle cruise drag ($C_{D-cruise}$) at transonic conditions ($M_\infty = 0.80$) for AoA = 0° and 4° . Geometric and aerodynamic constraints were applied to guarantee adequate nacelle designs. Due to the large computing cost to solve the 3D Reynolds-Averaged Navier-Stokes (RANS) equations, the DOE and subsequent generations were only formed by 32 configurations. Following this process, an optimum aero-engine was achieved with similar nacelle drag at AoA = 0° and

a reduction of 4% at $\text{AoA} = 4^\circ$ relative to a baseline configuration. Zhong *et al.* [25] developed a framework for laminar flow nacelle design. The numerical approach encompassed RANS sTimations with the transition SST $\gamma - Re_\theta$ model [28], response surface modeling by a Kriging method and an adaptive simulated annealing (ASA) algorithm [29] to maximize the delay of boundary layer transition at transonic conditions ($M_\infty = 0.78$). The full 3D geometry was defined with four aero-lines and each one parametrised with the PARSEC method developed originally by Sobieczky [30]. Overall, 18 design variables were used to generate the 3D nacelle shape. A design space exploration was carried out and a structured RSM was built with 41 data samples. With the combined process, an optimum design with 7% larger laminar area with respect to a baseline configuration was found. On the other hand, Toubin *et al.* [26] performed a multipoint shape optimisation of a benign aero-engine of $L_{nac}/r_{hi} = 6.49$ with only higher fidelity numerical simulations. The nacelle cruise drag at $M_\infty = 0.80$ and the intake circumferential distortion index (CDI) at cross-wind conditions were used as objective functions. The nacelle shape was parametrised with B-splines at four azimuthal sections with 5 control points per section. As such, the nacelle shape is defined with 20 input variables. The evolutionary algorithm MOEA/D [31] was selected to carry out the bi-objective optimisation during five generations. It resulted in an optimum geometry with a similar $C_{D-cruise}$ and a reduction on CDI of 3.62% relative to a baseline design. The impact of the droop and scarf angles on the nacelle drag characteristics of a compact configuration ($L_{nac}/r_{hi} = 3.1$) was quantified by Tejero *et al.* [12]. It was demonstrated that across a range of 5 degrees, the nacelle mid-cruise could vary by 3.5%.

A thorough investigation into the multi-objective optimisation of 3D drooped and scarfed non-axisymmetric nacelles is not available in the open literature due

to the associated large computational cost. In this respect, methods to reduce the overall CFD overhead are required. An existing framework for the MOO of aero-engine nacelles is further developed and the overall computational overhead of a CFD in-the-loop approach and adapted surrogate-based methods are quantified. These strategies have been successfully deployed in the past for 2D nacelle work where the geometric degrees of freedom were relatively low [22]. The novelty of this work is in the development of a new parametric representation of non-axisymmetric nacelles using intuitive Class Shapes Transformation and in the demonstration and testing of the adapted design optimisation strategy for 3D nacelle configurations for a problem with a substantially larger number of DoF.

The tool presents a significant development in the design of compact nacelles for the next generation of engine architectures. The framework is initially used with a higher fidelity method of CFD RANS simulations to identify a set of Pareto optimal solutions. These results are employed as a baseline to quantify the reduction in the overall computing overhead cost when the optimisation routine is driven by meta-models. Within this study two strategies are considered to structure the surrogate models: (a) based on a design space exploration and (b) adapted method. The findings are used to derive guidelines for the multi-objective optimisation of 3D drooped and scarfed non-axisymmetric nacelles.

2. Methodology

This work extends the computational framework previously developed by Tejero *et al.* [21, 22] for the aerodynamic design of civil aero-engine nacelles. The tool has been expanded to accomodate a multi-objective optimisation capability by surrogate models with an adapted method approach.

2.1. Nacelle Optimisation Framework

The framework incorporates a parametric nacelle geometry definition based on the Class-Shape Transformation (CST) method [8]. It was originally developed by Kulfan and has been extended to use intuitive design variables as described by Christie *et al.* [32]. This formulation enables the 3D parametric representation of the nacelle which is controlled with different aero-lines and azimuthal variations as a function of intuitive parameters (Section 2.2). The tool uses an automated mesh generation method to create the multi-block, structured grid [33] in which the viscous and compressible steady Favre-averaged Navier-Stokes equations are resolved [34]. The CFD simulations use a double-precision compressible, implicit, density-based solver [34]. A second-order accurate upwind spatial discretization with the Green-Gauss node based scheme was set for the computation of the flow-field gradients. The thermal conductivity was computed according to kinetic theory and the Sutherland’s law was used for the calculation of the dynamic viscosity. The CFD simulations were carried out with the $k-\omega$ Shear-Stress Transport (SST) turbulence model [35] (Section 2.3). The turbulence model uses a compressibility correction that is applied in the term of the dissipation of ω due to turbulence [34]. The solver does not account for dilatation terms such as pressure-dilatation [36]. These terms are important for high-speed flow at hypersonic regimes with $M > 5.0$ [37]. For civil aero-engine nacelles these flow regimes are not encountered, and as such, the dilatation terms were neglected. The pertinent nacelle performance metrics are automatically post-processed within the framework. The nacelle drag is extracted from a modified near-field method [38] using an industry standard thrust-drag accounting approach [39]. The tool includes a multi-objective optimiser based on the NSGA-II due to its global convergence characteristics [27]. The selection of multi-objective optimisation with genetic algorithm (GA) within this frame-

work is based on the demonstrated capabilities for aerodynamic shape design [40, 41]. For this study, the GA is driven by evaluating the nacelle designs with RANS CFD simulations as a higher fidelity method and with meta-models as a lower fidelity approach.

The tool has the capability for surrogate modelling methods. It uses the nacelle drag data generated with CFD and builds response surface models, in which the inputs are the intuitive nacelle design variables used in the current parametrisation and the outputs are the drag values at the various operating conditions. As such, an analytical model is built to predict the aerodynamic response of the nonlinear system. For this study, the surrogate models are structured with a Gaussian Process Regression (GPR) based on the Kriging interpolation method [42]. A range of regression functions (constant, linear and quadratic), correlations (absolute exponential, squared exponential and cubic) and nugget values (1e-7, 1e-6, 1e-5) were considered to build the RSMs. A full factorial for the different combinations was carried out to identify the hyperparameters that minimised the drag prediction error based on the Leave-One-Out cross-validation method [43]. The final RSM models were built with a quadratic regression function, squared exponential correlation and a nugget value of 1e-6. A thorough description of the underlying theory to build a Kriging model was reported by Giangaspero *et al.* [44]. The Kriging interpolation method has been proven for aircraft optimisation applications [45] and, as such, is employed in this investigation.

2.2. Parametric geometry definition of 3D nacelles

The proposed intuitive iCST parametrisation has been developed [46, 47, 48] to enable the optimisation of non-axisymmetric compact nacelle aero-engines. A detailed description of the parametrisation is provided below.

2.2.1. *iCST curves*

A CST curve is constructed from a Class Function ($C(\psi)$) and a Shape Function ($S(\psi)$) in conjunction with a parameter ($\Delta\xi_{te}$) which sets the y offset between the curve endpoints as follows,

$$\xi(\psi) = S(\psi)C(\psi) + \psi\Delta\xi_{te} ; \quad \xi = \frac{y}{c} , \quad \psi = \frac{x}{c} \quad (1)$$

where c is the curve length in the x-direction [49, 50].

The round-nosed, sharp trailing-edge airfoil class function which has been used to describe aero-engine fan cowls and intakes [21, 32] is given by:

$$C_{1,0}^{0.5}(\psi) = \psi^{0.5}[1 - \psi]^{1.0} \text{ for } 0 \leq \psi \leq 1 \quad (2)$$

Bernstein polynomials (BP) (Eq. 4) are commonly employed as the shape function

$$BP(\psi) = \sum_{i=0}^n \binom{n}{i} \psi^i (1 - \psi)^{n-1} \quad (3)$$

The shape function can then be manipulated by the variation of Bernstein polynomial coefficients(bp) which are usually employed as a weighting shape function [32] (Eq. 4). The shape function, which is formed by $n+1$ Bernstein polynomials, is equal to one for unweighted Bernstein coefficients ($b_{ci}=1$) and can be adjusted to any value when the coefficients are changing.

$$S(\psi) = \sum_{i=0}^n bp_i \binom{n}{i} \psi^i (1 - \psi)^{n-1} \quad (4)$$

For this Class function the 0^{th} and n^{th} Bernstein polynomial coefficients can

be analytically calculated with

$$bp_0 = \sqrt{\frac{2R_{le}}{c}} ; bp_n = \tan(\beta) + \frac{\delta z_{te}}{c} \quad (5)$$

where R_{le} is the radius of curvature at $\psi = 0$ and $\tan \beta$ is the gradient at $\psi = 1$ [49]. CST curves are manipulated by modifying the Bernstein polynomial coefficients. However, this approach is non-intuitive to the aerodynamic designer where there is no obvious correlation between the Bernstein polynomial coefficients and the resultant curve or aerodynamic performance. This shortcoming in the CST parameterisation approach has been addressed by the intuitive Class Shape Transformation (iCST) approach [32], wherein the Bernstein polynomial coefficients are analytically expressed in terms of designer imposed constraints. These constraints can be hard-points through which the curve must pass or an imposed n^{th} degree derivative at a specified ordinate. Each imposed constraint corresponds to a linear equation which relates that constraint to a Bernstein polynomial coefficient through Equation 6 [32].

$$\xi^{(k)}(\psi) = S(\psi)C(\psi) + \psi\Delta\xi_{te} = \left[\sum_{i=0}^N \left[bp_i \binom{n}{i} \left(\psi^i (1-\psi)^{n-1} \right) \right] C(\psi) + \psi\Delta\xi_{te} \right]^{(k)} \quad (6)$$

A linear set of equations can be constructed in matrix form[51],

$$\mathbf{A} \cdot \mathbf{X} = \mathbf{B} \quad (7)$$

where $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{X}$ are the coefficient matrix, the column vector of inhomogeneous terms and the vector of Bernstein polynomial coefficients, respectively [51].

The derivatives of the k^{th} degree Bernstein Polynomials are polynomials of degree $k-1$ and can be written as a linear combination of Bernstein Polynomials

(Eq. 8) [32]. Once $\mathbf{A}$ and $\mathbf{B}$ are constructed from the constraints the vector of Bernstein polynomial coefficients, $\mathbf{X}$, is solved for by a rearrangement of Eq. 7 which results in Eq. 9. A worked example of this process is given in Section 2.2.2.

$$\frac{d}{d\psi}BP_{i,n}(\psi) = n[BP_{k-1,n-1}(\psi) - BP_{k,n-1}(\psi)] \quad (8)$$

$$\mathbf{X} = \mathbf{A}^{-1} \cdot \mathbf{B} \quad (9)$$

2.2.2. Fan cowl parameterisation

The fan cowl is constructed from 2-D aerolines with non-axisymmetry controlled by azimuthal variation of the constraints imposed on the 2-D aerolines. This azimuthal variation is described in Section 2.2.3. The 2-D aero-line geometry is controlled by 7 parameters ($P.x_{fc}$ in Table 1), where r_{hi} , r_{te} and r_{max} are the highlight, trailing edge and maximum radii, respectively. The fan cowl length is set by L_{nac} which is defined as the fan cowl length as measured at the nacelle sideline (Figure 1). The axial location of the point of maximum radius is controlled with f_{max} . Finally β_{nac} and r_{if} are the fan cowl boat-tail angle and initial forebody radius of curvature respectively (Figure 1). These parameters (Table 1) can be transformed into iCST curve constraints ($C.x$ in Table 2) by non-dimensionalising by the aero-line length .

#	Parameter
P.1 _{fc}	r_{hi}
P.2 _{fc}	r_{te}
P.3 _{fc}	l_{nac}
P.4 _{fc}	r_{if}
P.5 _{fc}	r_{max}
P.6 _{fc}	f_{max}
P.7 _{fc}	β_{nac}

Table 1: Fan cowl parameters (Figure 1).

This parameterisation uses the round nosed, sharp trailing edge airfoil Class Function ($C_{0.5}^{1.0}$). The radius of curvature (R) is specified at the leading edge,

#	Type	ψ	$\xi^{(k)}(\psi)$
C.1	Position	0.0	$\xi _{\psi=0.0}$
C.2	Position	1.0	$\xi _{\psi=1.0}$
C.3	R	0.0	$R _{\psi=0.0}$
C.4	Position	ψ_{int}	$\xi _{\psi_{int}}$
C.5	Gradient	ψ_{int}	0.0
C.6	2nd derivative	1.0	$\xi^{(2)} _{\psi=1.0}$
C.7	Gradient	1.0	$\xi^{(1)} _{\psi=1.0}$

Table 2: iCST curve constraints for the fan cowl in non-dimensional $\psi - \xi$ space

a local maximum is imposed and a gradient and 2nd derivative is specified at the trailing edge. Outlined here is the methodology to calculate the 5 Bernstein Polynomial coefficients for the iCST aero-line. For this Class Function ($C_{1.0}^{0.5}$) the first and fourth Bernstein Polynomial coefficients for the iCST aero-line can be calculated with Equation 5. As constraints $C.3$ and $C.7$ (Table 2) are expressed in non-dimensional $\psi - \xi$ space and $c = 1$, the y offset term can be expressed as Equation 10 which together with Equation 5 result in Equation 11.

$$\Delta\xi_{te} = \xi|_{\psi=1} - \xi|_{\psi=0} \quad (10)$$

$$bp_0 = \sqrt{2R|_{\psi=0.0}} ; bp_4 = \xi^{(1)}|_{\psi=1.0} + \xi|_{\psi=1.0} - \xi|_{\psi=0.0} \quad (11)$$

The remaining three Bernstein Polynomial coefficients depend on constraints $C.4$, $C.5$ and $C.6$ and can be calculated with Equation 9. $\mathbf{A}$ is the matrix of coefficients and is given by:

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{bmatrix} \quad (12)$$

$\mathbf{B}$ is the column vector of inhomogeneous terms which is defined as:

$$\mathbf{B} = \begin{bmatrix} b_{1,0} & b_{2,0} & b_{3,0} \end{bmatrix}^T \quad (13)$$

Finally $\mathbf{X}$ is the vector of Bernstein Polynomial coefficients:

$$\mathbf{X} = \begin{bmatrix} bp_1 & bp_2 & bp_3 \end{bmatrix}^T \quad (14)$$

Constraint C.4 (Table 2) is a positional constraint, therefore $k = 0$ and Eq. 6 can be rearranged to isolate the function coefficients and constant terms as given by Eq. 15 and Eq. 16 respectively.

$$a_{1,n} = [BP_{1,n} + BP_{2,n} \dots + BP_{n-1,n}]C(\psi) \quad (15)$$

$$b_{1,0} = \xi - A_0BP_{0,n}C(\psi) - A_nBP_{n,n}C(\psi) - \psi\Delta\xi_{te} \quad (16)$$

$k = 1$ for constraint C.5 (Table 2) as it is a first derivative constraint. The coefficients and constant terms in Eq. 6 are given by Eq. 17 and Eq. 18.

$$a_{2,n} = [BP_{1,n} + BP_{2,n} \dots + BP_{n-1,n}]'C(\psi) + [BP_{1,n} + BP_{2,n} \dots + BP_{n-1,n}]C'(\psi) \quad (17)$$

$$b_{2,0} = \xi'(\psi) - \Delta\xi_{te} - A_0BP_{0,n}C'(\psi) - A_nBP_{n,n}C'\psi - A_0BP_{0,n}'C_\psi - A_nBP_{n,n}'C_\psi \quad (18)$$

The third and final constraint for the iCST aero-line, C.6, is a second derivative constraint. The function coefficients and constant terms from Eq. 6 can therefore

be written as:

$$\begin{aligned}
a_{3,n} = & [BP_{1,n} + BP_{2,n}\dots + BP_{n-1,n}]''C(\psi) \\
& + 2([BP_{1,n} + BP_{2,n}\dots + BP_{n-1,n}]'C(\psi)') \\
& + [BP_{1,n} + BP_{2,n}\dots + BP_{n-1,n}]C''(\psi) \quad (19)
\end{aligned}$$

$$\begin{aligned}
b_{3,0} = & \xi''(\psi) - A_0BP_{0,n}C''(\psi) - A_nBP_{n,n}C''\psi \\
& - 2[A_0BP'_{0,n}C'(\psi) + A_nBP'_{n,n}C'\psi] - A_0BP''_{0,n}C_\psi - A_nBP''_{n,n}C_\psi \quad (20)
\end{aligned}$$

2.2.3. Azimuthal variation

Non-axisymmetric aero-engine nacelles are achieved with an azimuthal variation of the constraints applied to the 2-D aero-lines (e.g. Table 2). If these constraints are set at azimuthal control points, for example at azimuthal angles equal to 0° , 45° , 90° , 135° and 180° (Figure 2a), the azimuthal variation of these constraints can be described by an iCST curve in a cylindrical coordinate system with a linear class shape function fit through the azimuthal control points. As such, a new set of equations can be defined with the same form of Eq. 9 and the Bernstein polynomial coefficients can be calculated to analytically represent the azimuthal variation of each design variable. Therefore, the fan cowl surface as a whole is also analytically defined. For example, the azimuthal variation of radii is illustrated in Figure 2b. The general form of this construction can accommodate fully asymmetric configurations. However, in the present work left-right symmetry of the configuration is assumed and 5 control aero-lines are employed to define the full 3D configuration (Figure 2a).

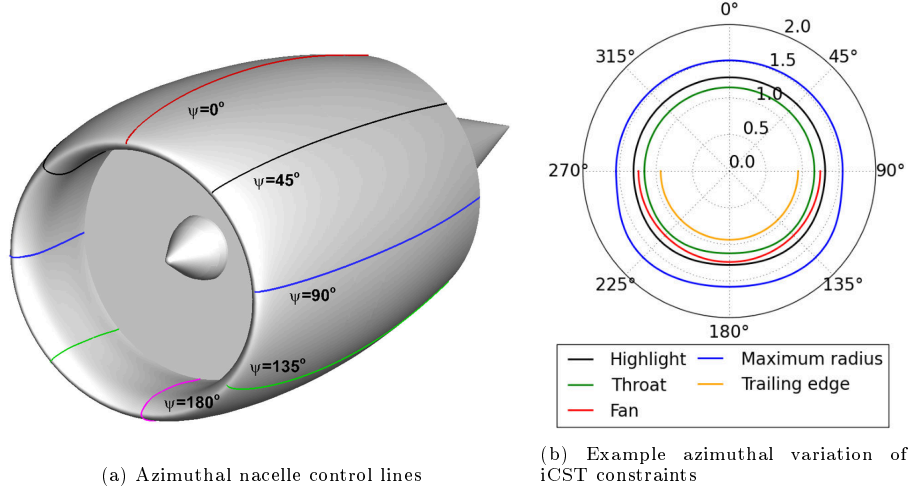


Figure 2: Non-axisymmetric nacelle geometric control

2.3. Computational domain and CFD validation

An automated structured grid generation process was implemented in the framework and domain and grid independence studies were carried out. Four different domain sizes ($60r_{max}$, $80r_{max}$, $100r_{max}$ and $120r_{max}$) were considered and across this range the cruise nacelle drag increased monotonically with a 0.05% reduction between the $100r_{max}$ and $120r_{max}$ configurations. Finally, the $100r_{max}$ domain size was employed throughout this study. The grid convergence was calculated for four different mesh sizes (200k, 400k, 800k and 1,600k), with boundary layer blocks discretized to satisfy a y^+ of approximately 50 so that the boundary layers were modelled by the wall function model implemented in the $k - \omega$ SST turbulence closure. A key aspect within an optimisation framework based on a GA with CFD in-the-loop is to enable a tractable investigation with sufficient populations in each generation as well as convergence across the required number of generations. The solutions using the 800k mesh demonstrated a grid convergence index [52] of 2.5% on C_D at cruise conditions ($M_\infty = 0.85$ and $MFCR = 0.70$) and, considering the GA requirements, was adopted within

this study. During the optimisation studies, the block topology, cell sizing and local refinements are kept constant. It is important to note that the mesh independence study was carried out for a compact nacelle configuration with a flow field topology with a single shockwave. Although it is expected to encounter different flow features during an optimisation process of a compact aero-engine, for example single or double shock structures, the refinement and cell sizing in the different regions on the nacelle are similar. As such, the employed mesh is expected to be sufficient.

The boundary conditions are imposed to fulfil the user prescribed flight conditions of Mach number, MFCR, altitude and incidence angle. A no-slip, adiabatic wall condition is used for the spinner, intake and fan cowl. The inlet fan face uses a pressure-outlet boundary condition with a target massflow to achieve the prescribed MFCR. As the present investigation is focused on nacelle drag characteristics, a simplified nozzle with a conical shape is used to produce a representative post-exit streamtube for the nacelle drag extraction. As such, no core nozzle is used. At the inlet of the conical nozzle the total temperature and total pressures are specified and match the freestream values. This is used to minimize the influence of the exhaust flow on the nacelle drag.

The numerical approach was tested to determine the accuracy of the computational model on a 3D drooped and scarfed non-axisymmetric configuration [53]. A range of freestream Mach numbers from 0.80 to 0.88, MFCR from 0.55 to 0.85 and incidence angles from 4.0° to 6.0° were simulated and compared with the available experimental data. The computed normalised cruise nacelle drag was within 0.5% of the measurements and the drag rise Mach number within 0.007 [53].

3. Results and analysis

A comprehensive numerical investigation was carried out to evaluate three different multi-objective optimisation methods for the design of compact non-axisymmetric nacelles. Initially, the framework has been deployed with a higher fidelity approach based on RANS CFD in-the-loop to identify a set of optimal Pareto front solutions for non-axisymmetric configurations. These results are used as a baseline converged optimisation solution for comparison purposes with other lower cost optimisation algorithms. Two methods based on surrogate modelling have been considered in this study. Firstly, a meta-model built from the standard Latin hypercube sample design space exploration [54, 55] was employed to drive the genetic algorithm to a set of optimum nacelle designs. The influence of the design of experiments (DOE) sampling size on the predictive accuracy of the Pareto front has been evaluated. Secondly, an adapted meta-modelling approach that uses higher fidelity results along with surrogate models has been investigated.

Within the context of this work a civil aero-engine nacelle with $L_{nac}/r_{hi} = 3.1$, $r_{te}/r_{hi} = 0.91$, $\theta_{scarf} = 2.5^\circ$ and $\Delta z_{int}/r_{hi} = 0.03$ is used. This is a compact configuration compared with conventional in-service nacelle architectures [21, 11]. As such, it represents a challenging nacelle design to evaluate the different multi-objective optimisation methods. Three objective functions within the cruise segment are considered: (a) mid-cruise nacelle drag ($C_{D-cruise}$) (Eq. 21), (b) the sensitivity to flight Mach number (ΔC_{D-Mach}) (Eq. 22) and (c) the sensitivity to the change in MFCR between end-of-cruise and mid-cruise conditions ($C_{D-spill}$) (Eq. 23). During the optimisation process the three objectives functions are minimised. The mid-cruise conditions were selected to reflect the flight conditions of future civil aero-engines with $M_\infty = 0.85$, $MFCR = 0.70$, $h = 10668\text{m}$ and $\text{AoA} = 3.0^\circ$. To account for the change of mass flow capture

ratio during the aircraft cruise mission, the end-of-cruise was set to $M_\infty = 0.85$, $MFCR = 0.65$, $h = 10668\text{m}$ and $\text{AoA} = 3.0^\circ$.

$$C_{D-cruise} = \frac{D_{nac}}{\frac{1}{2}\rho_\infty V_{ref}^2 A_{hi}} \quad (21)$$

$$\Delta C_{D-Mach} = \frac{D_{nac, M=M_{ref}+0.02} - D_{nac, M=M_{ref}}}{\frac{1}{2}\rho_\infty V_{ref}^2 A_{hi}} \quad (22)$$

$$C_{D-spill} = \frac{D_{nac, MFCR_{cruise}} - D_{nac, MFCR_{EOC}}}{\frac{1}{2}\rho_\infty V_{ref}^2 A_{hi}} \quad (23)$$

During the nacelle design process, the design variables of L_{nac}/r_{hi} , r_{te}/r_{hi} , θ_{scarf} and $\Delta z/r_{hi}$ are fixed while the 4 variables (f_{max} , r_{max} , r_{if} , β_{nac}) that describe each of the 5 controlled aero-lines float during the optimisation routine. Therefore, the proposed parametrisation uses a total number of 20 intuitive design variables, which highlights the relatively large high-dimensional aerodynamic design space explored with the framework. The upper and lower bound of the design variables was the same for the different azimuthal aero-lines and selected to avoid non-monotonic curvature distributions. Throughout this study, a generic intake and exhaust system were used to provide representative flow-fields as the main focus is on the nacelle design [21].

3.1. Nacelle Multi-Objective Optimisation based on the full CFD in-the-loop method

The multi-objective optimisation was started with a Latin Hypercube Sampling (LHS) to efficiently cover the twenty-dimensional design space. To reduce the computational overhead cost the nacelle geometries that were not fully convex, which are expected to present unacceptable drag characteristics [56], were removed from the optimisation process. This geometrical filtering aims to

concentrate the CFD effort in the regions of the design space where optimum configurations are likely to be located. The initial DOE consisted of 2000 designs which is a densely populated design space with a sample size to variable number ratio equal to 100. After filtering, a total of 400 nacelle configurations were evaluated with CFD. A convergence criteria based on a reduction of the hypervolume lower than 1% in the last 3 generations was used to ensure a fully converged solution of the Pareto front.

The inherent non-linearity of transonic flow aerodynamics associated with compact aero-engines is highlighted in Figure 3, where the optimisation process results in a three-dimensional Pareto surface. The optimal set of designs is presented with a projection into the $C_{D-cruise}$ - ΔC_{D-Mach} space and coloured by $C_{D-spill}$. This representation demonstrates the sensitivity of this part of the design space to the different operating conditions that are met throughout the cruise segment. For example, while nacelle designs with $\Delta C_{D-Mach} \approx 0$ have a large concomitant $C_{D-spill}$ and $C_{D-cruise}$, the optimal designs for $C_{D-spill}$ present a large sensitivity to flight Mach number (ΔC_{D-Mach}) and large penalty in terms of nacelle cruise drag ($C_{D-cruise}$).

From the MOO the nacelle configurations with minimum $C_{D-cruise}$ (sample A1), ΔC_{D-Mach} (sample A2) and $C_{D-spill}$ (sample A3) have been identified (Figure 3). It clearly highlights the typical trade-offs between the aerodynamic performance and key operating points for future civil aero-engine nacelles. Relative to the Sample A1, which was the lowest cruise drag, the nacelle A2 has a 8.5% increment in $C_{D-cruise}$ and a larger sensitivity to the change of mass flow capture ratio, as a result of presenting negligible changes on ΔC_{D-Mach} . On the other hand the configuration A3, with $C_{D-spill} \approx 0$, presents an increment of 14.8% in $C_{D-cruise}$ with respect to A1 and a large penalty in terms of ΔC_{D-Mach} .

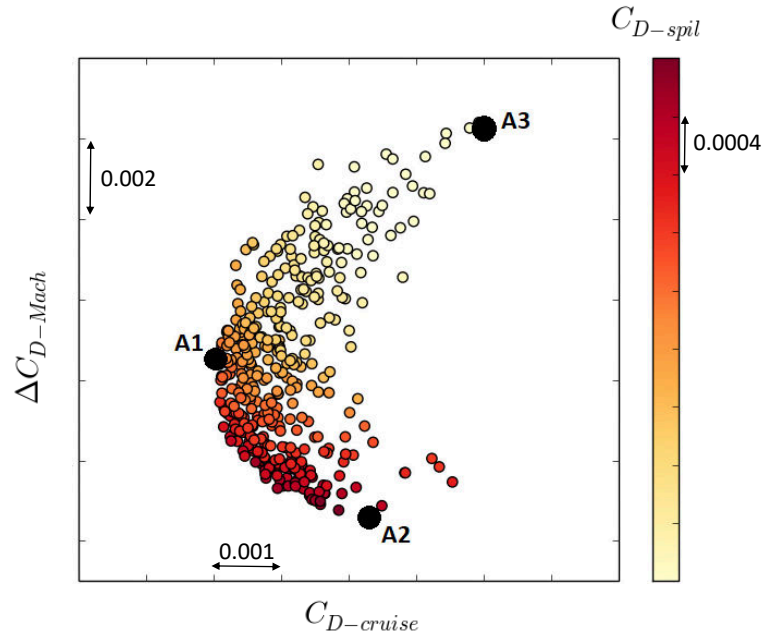


Figure 3: Pareto front obtained with the MOO CFD in-the-loop approach for the compact nacelle with $L_{nac}/r_{hi} = 3.1$, $r_{te}/r_{hi} = 0.91$, $\theta_{scarf} = 2.5^\circ$ and $\Delta z_{int}/r_{hi} = 0.03$

There are significant changes on the transonic flow features that manifest in the three different downselected configurations A1, A2 and A3 (Figure 4). The sample A1, which is the lowest $C_{D-cruise}$ found throughout the MOO, has a relatively low peak and pre-shock M_{is} with comparison to the other selected designs (Figure 4a). As the mid-cruise nacelle drag increases within the individuals identified in the Pareto front (Figure 3), there is a larger acceleration around the nacelle lip and a stronger shock wave (Figures 4b and 4c). The nacelles A2 and A3 have significant differences on their flow characteristics which are favorable for the off-designs conditions (ΔC_{D-Mach} and $C_{D-spill}$) at which they are optimal. For mid-cruise conditions, the design A2 presents a double shock structure with shock locations at $X/L_{nac} = 0.12$ and $X/L_{nac} = 0.62$. For this geometry, at the increased of flight Mach number condition ($M_\infty = 0.87$) both shock-waves combine into a single stronger one which results in a low sensitivity to changes on flight Mach number (ΔC_{D-Mach}). The configuration A3 has the shock location downstream of the nacelle crest which results in a large $C_{D-cruise}$ but a low sensitivity to changes on MFCR ($C_{D-spill}$). For all three designs the acceleration over the nacelle lip is larger for the control lines $\psi = 0^\circ$ and 45° than for the other nacelle lines ($\psi = 90^\circ$, 135° and 180°). It highlights the significant impact that the top half of the nacelle might have on the aerodynamic performance.

The developed design framework has been successfully used for 3D non-axisymmetric nacelle design and to identify the transonic flow characteristics of future civil aero-engine nacelles. The proposed method can be employed within the new design space for future civil aero-engine configurations. Nevertheless, it has been found that the method has a relatively large computational cost to fully converge to a set of Pareto optimal solutions (Figure 3). To put this in context, for a 3D nacelle optimisation process using 16 compute nodes of

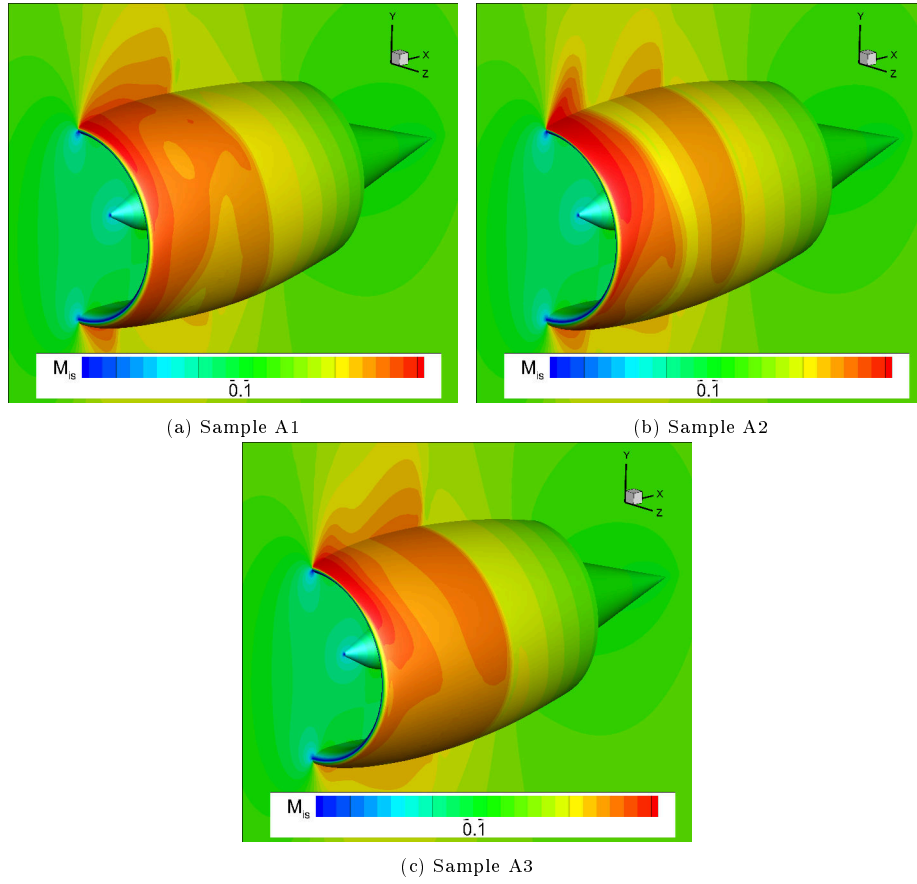


Figure 4: Mach contour map for selected designs obtained during the multi-objective optimisation with the CFD in-the-loop approach

an Intel Xeon Processor 2x E5-2643v4 (6-core) the overall CFD in-the-loop optimisation process required about 36,000 core hours, which highlights the large computational cost of this approach. Therefore, there is a clear desire to reduce the cost associated but still maintain the required accuracy for the nacelle design.

3.2. Nacelle Multi-Objective Optimisation by surrogate modelling

Once the framework has been established and proven to identify a set of optimal 3D nacelle configurations, the tool has been adapted to accommodate a more computationally efficient strategy based on surrogate modelling. This investigation develops an evolving meta-modelling approach for the multi-objective optimisation of non-axisymmetric compact aero-engine nacelles. The surrogate model is built with the combination of numerical simulations carried out during the design space exploration and a fixed number of subsequent generations. It guides the genetic algorithm to the regions of the design space where optimum designs are likely to be located because the GA is directed with CFD simulations. This adapted method, referred in the text as AM, improves the metamodel prediction capabilities in the optimal regions of the design space. The computational effort and the nacelle designs derived with the proposed method are compared with the benchmark CFD in-the-loop optimisation method (Section 3.1) as well as with a conventional surrogate optimisation routine. The conventional surrogate optimisation method collects higher-fidelity CFD samples from a design space exploration (DSE) based on an isotropic latin hypercube sampling (LHS) and structures the RSM. Then the optimisation routine is driven by the interrogation to the low order model. To compare both surrogate-based optimisation methods, different RSM were generated with a total computational cost that varied from 10% to 50% with respect to the full CFD in-the-loop approach (Table 3).

Table 3: Summary of the cases considered for the nacelle aero-line multi-objective optimisation

Method for MOO	CFD in LHS $N_{seed-CFD}$	CFD gen. N_{gen}	CFD des./gen. N_s	RSM gen. $N_{gen-RSM}$	RSM des./gen. N_{s-RSM}	Total CFD cost
CFD	400	18	200	-	-	12000
CM1	400	-	-	30	200	1200
CM2	1000	-	-	30	200	3000
CM3	1600	-	-	30	200	4800
CM4	2000	-	-	30	200	6000
AM2	400	3	200	30	200	3000
AM3	400	6	200	30	200	4800
AM4	400	8	200	30	200	6000

3.2.1. Surrogate Model from a Latin Hypercube Sampling

For the four independent meta-models based on a LHS the three investigated performance metrics, i.e. $C_{D-cruise}$, ΔC_{D-Mach} and $C_{D-spill}$, were calculated by CFD simulations. The computational results were used to build structured RSMs with a Gaussian Process Regression (Kriging interpolation method [42]) with a quadratic regression function and an squared exponential auto-correlation. The predictive accuracy of each model was statistically assessed with the Leave-One-Out (LOO) cross-validation [43], in which the Pearson coefficient ($N_{Pearson}$) and the root mean square error (σ_{CM}) were evaluated. Whilst CM1 has $N_{Pearson} \approx 0.90$ and $\sigma_{CM} \approx 8\%$ for the three performance metrics of interest, the more refined surrogate models of CM2, CM3 and CM4 present a Pearson coefficient of ≈ 0.95 and a root mean square error of $\sigma_{CM} \approx 6\%$.

All the CM models have a prediction uncertainty below 10% which is a typical target for nacelle design by meta-models [56]. Nevertheless, a fundamental aspect for surrogate models that are employed within an optimisation framework is the precision on the regions of the design space where optimal configurations are located. In this respect, each CM model was employed to drive

the NSGA-II genetic algorithm to identify 4 independent sets of Pareto optimal designs. This allowed a direct comparison with the baseline Pareto front derived from the computationally expensive CFD in-the-loop method (Figure 3). The comparison of the Pareto fronts from the surrogate CM models and the CFD in-the-loop approach is based on the $C_{D-cruise} - \Delta C_{D-Mach}$ space (Figure 5) to facilitate the identification of the projected optimal front. It clearly highlights the limitations of this optimisation strategy based on reduced-order models from a DOE LHS to identify the same Pareto front shape. The Pareto front identified with CM1 surrogate model, which was generated with the least amount of data (Table 3), is notably different than the ones from CM2-CM4. While the CM2-CM4 RSMs had a similar root mean square error of 6%, the CM1 model had $\sigma_{CM} \approx 8\%$. This is caused by the larger prediction uncertainty of this low order model and the reduced capabilities of the genetic algorithm to reliably identify, and quantify, those regions of the design space. This is primarily due to the number and distribution of the fewer samples used in CM1.

Subsequently, each optimal nacelle design found with the surrogate models was evaluated by means of numerical simulations to statistically quantify the meta-model accuracy on the Pareto design space ($\sigma_{CM,PF}$) (Figure 6). Each sub-figure shows the lines of 5% and 10% prediction error based on the mid-cruise nacelle drag of the low order model with respect to the CFD result, where + refers to a drag overprediction of the low order model relative to the CFD evaluation. For example, the CM1 model drove the GA to a set of optimal nacelle configurations, with an standard error in cruise drag ($C_{D-cruise}$) of $\sigma_{CM,PF} = 17.7\%$ (Figure 6a). The majority of the configurations do not fulfill the targeted uncertainty below 10% considered for preliminary nacelle design [56]. As such, although the RSM model was *a priori* acceptable for nacelle design on the overall design space, the application within an optimisation framework highlights

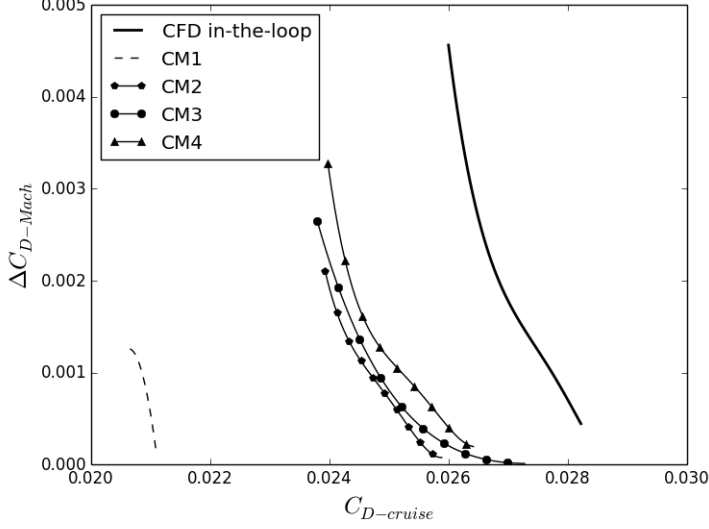


Figure 5: Pareto front comparison in the $C_{D-cruise}$ - ΔC_{D-Mach} space for the CM models and the baseline from the CFD in-the-loop method

its limitations (Figure 6a). When the meta-model CM2 which has an overhead computational cost of 25% with respect to the CFD in-the-loop is employed to drive the evolutionary algorithm, a set of optimal compact designs is identified with a mean prediction error of 14.3% (Figure 6b). As the surrogate model is built with more nacelle samples on CM3 and CM4, the predictive uncertainty of the Pareto optimal set reduces to $\sigma_{CM,PF} = 11.8\%$ and 9.8% , respectively (Figures 6c and 6d). This demonstrates the difficulties to build surrogate models to predict the inherent non-linearity of transonic flow aerodynamics associated with compact non-axisymmetric aero-engine nacelles.

Within the context of an optimisation routine with RSMs, it is important to ensure an acceptable predictive accuracy of the Pareto optimal solutions, as well as that the identified aero-engine nacelles have similar aerodynamics as the designs from a computationally expensive CFD in-the-loop approach. It has been demonstrated that within the Pareto front of the CFD in-the-loop method

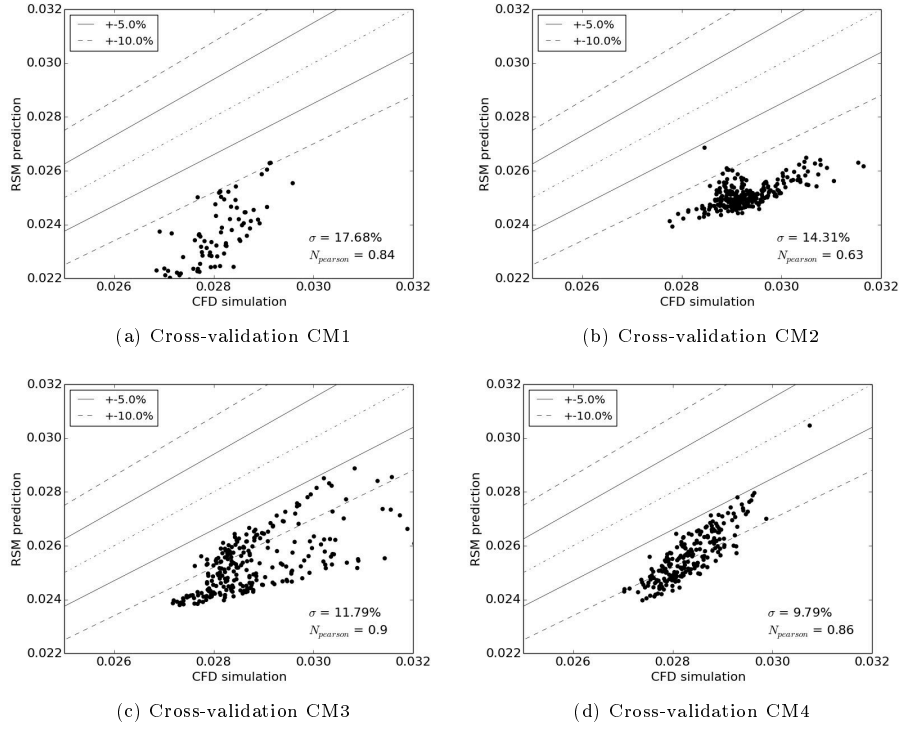


Figure 6: Cross-validation for $C_{D-cruise}$ of the Pareto front prediction obtained with the different CM models

Table 4: $C_{D-cruise}$ comparison between RSM and CFD for the Pareto fronts identified with the CM models (B1-B4 designs)

Model	Cost relative to CFD in-the-loop	Design	RSM prediction	CFD result	Difference [%]
CM1	10%	B1	0.0204	0.0279	-26.9
CM2	25%	B2	0.0239	0.0278	-14.0
CM3	40%	B3	0.0239	0.0273	-12.5
CM4	50%	B4	0.0240	0.0274	-12.4

there are significant changes on the flow topology due to the transonic non-linear flow of the investigated compact aero-engine nacelle configuration (Figure 4). Although the three flight conditions considered ($C_{D-cruise}$, ΔC_{D-Mach} and $C_{D-spill}$) are crucial during the nacelle design process, for long-range applications a key aerodynamic point is the mid-cruise condition ($C_{D-cruise}$). For this reason, the nacelle architectures with minimum $C_{D-cruise}$ found with the CM1, CM2, CM3 and CM4 models, referred in the text as B1, B2, B3 and B4 respectively, have been further investigated and compared with the A1 (minimum $C_{D-cruise}$ identified with the CFD in-the-loop approach). The predictive error in terms of $C_{D-cruise}$ with respect to numerical simulations for all four designs is summarized in Table 4, which shows the prediction uncertainty of all surrogate models. The transonic flow aerodynamics on the A1 nacelle and the B1-B4 designs are fundamentally different (Figure 7). While A1 presents a well defined shock-wave on the nacelle top-line ($\psi = 0^\circ$) at $X/L_{nac} = 0.40$, all the B designs have a double shock topology. It highlights the inability of the standard method to identify the same nacelle aerodynamics as the higher-fidelity RANS CFD in-the-loop approach.

Although it has been demonstrated that the meta-model accuracy on the drag prediction of compact non-axisymmetric nacelles improves with the CFD overhead cost, the standard method of surrogate modelling from a design space

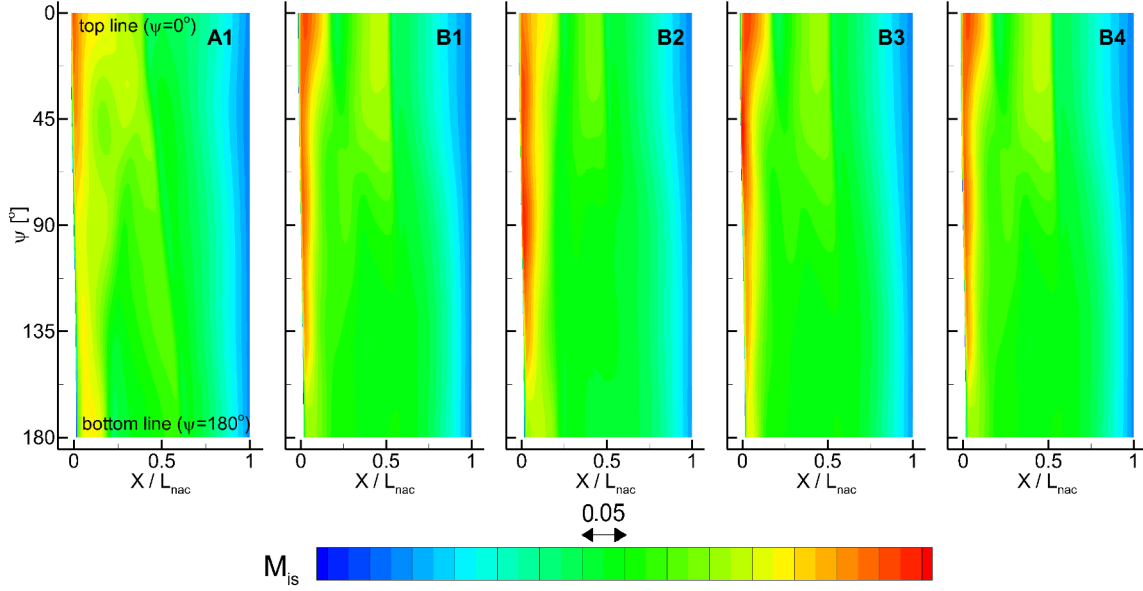


Figure 7: Isentropic Mach number distribution for the selected A1, B1, B2, B3 and B4 compact nacelle configurations

exploration was unable to identify the same flow aerodynamics as the CFD in-the-loop approach. Therefore, more advanced optimisation techniques are required to reduce the computational cost while also identifying the same optimal design space than the higher fidelity RANS CFD in-the-loop methods. In this respect, the proposed evolving approach to build meta-models is presented in Section 3.2.2 and its prediction capabilities are quantified.

3.2.2. Surrogate Model from the Adapted Method

This strategy starts as the CFD in-the-loop approach in which the design space exploration as well as subsequent generations are evaluated with higher fidelity RANS CFD simulations. The process is stopped before reaching convergence to the Pareto front and all the samples are used to generate a low order model. Then, the RSM is used to drive further the optimisation routine until convergence is achieved. For this study the process has been stopped at

three different generations (Table 3) to investigate the influence of the relative computational cost on the capabilities to identify the same Pareto front as the CFD in-the-loop approach. Overall, three different optimisations were carried out with the adapted method with an overall computational cost of 25%, 40% and 50% with respect to the full CFD in-the-loop process. A key aspect of this approach is to identify the number of generations required with CFD to build a surrogate model that meets the required RSM prediction uncertainty. In this respect, a statistical analysis of the impact of subsequent generations with higher fidelity CFD on the Pareto prediction accuracy has been carried out. The main principle of the proposed method is that as the genetic algorithm progresses through generations, the optimisation focuses in narrower parts of the design space where optimal designs are likely to be located. Therefore, if more higher fidelity samples are added on those regions, the overall RSM predictive accuracy on the optimal parts of the design space will increase.

For the proposed adapted strategy, three different meta-models were created with a total computational overhead cost of 25%, 40% and 50% with respect to the benchmark CFD in-the-loop approach and referred in the text as AM2, AM3 and AM4, respectively. For comparison purposes, the total CFD cost of the AM models is the same as the equivalent CM (Table 3). For each AM model the Leave-One-Out cross-validation was carried out to assess the predictive accuracy on the overall design space. The structured RSMs built with the AM models have a root mean square error lower than 10% and similar values as the equivalent CM models. The structured RSMs built with the AM method were used to drive the GA during the optimisation process. Three independent optimisation routines were carried out to generate three Pareto surface fronts. As previously, the comparison of each Pareto front with the computationally expensive CFD in-the-loop was done in the $C_{D-cruise} - \Delta C_{D-Mach}$ space (Fig-

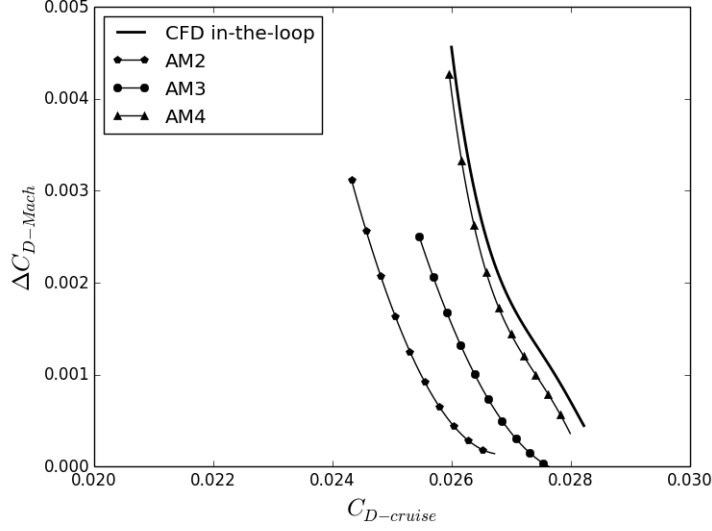


Figure 8: Pareto front comparison in the $C_{D-cruise}$ - ΔC_{D-Mach} space for the AM models and the baseline from the CFD in-the-loop method

ure 8). Compared to the set of Pareto optimal solutions obtained with the CM models (Figure 5), the AM approach improves the accuracy of the Pareto front identification at the same computational cost. This highlights the benefits of the proposed adapted method for optimisation purposes over the traditional approach based only on a design space exploration.

A statistical analysis of the predictive accuracy of each AM model on the Pareto optimal design space was carried out and the root mean square error on the drag prediction calculated ($\sigma_{AM,PF}$) (Figure 9). The structured RSM of the AM2 model identified a Pareto surface with an overall standard error in cruise drag ($C_{D-cruise}$) of $\sigma_{AM,PF} = 7.0\%$ (Figure 9a), in which the majority of the nacelle designs depict a prediction error below 10%. This is a significant improvement in comparison with the same computational cost of the CM2 model in which the predictive error was $\sigma_{CM,PF} = 14.3\%$ (Figure 6b). When the surrogate model is built with more data samples the standard deviation $\sigma_{AM,PF}$

on the $C_{D-cruise}$ prediction reduces. For example, the AM3 model, which has a total CFD computational cost of 40% relative to the CFD in-the-loop method, presents a predictive accuracy of the Pareto front of $\sigma_{AM,PF} = 1.64\%$ (Figure 9b). In addition, all the nacelle samples are within the 5% error band. The most refined surrogate model considered in this work AM4, which has a 50% cost relative to the CFD in-the-loop, has a standard deviation $\sigma_{AM,PF} = 0.94\%$ (Figure 9c). Both CM and AM methods have been previously employed for single nacelle aero-line design [22]. For example, for a surrogate-model with a 50% of the computational cost of the CFD in-the-loop approach, the CM method lead to a Pareto front with a prediction error on nacelle cruise drag of 5.2%. The proposed adapted method reduced the error to 1.2%, which it is a reduction on the prediction uncertainty by a factor of approximately 4. For 3D non-axisymmetric configurations with significantly more degrees of freedom, this reduction is larger. For the current CM4 meta-model, with a 50% computational cost of the CFD in-the-loop approach, the prediction uncertainty on the optimal designs is 9.8% (Figure 6d). This is reduced on the AM4 surrogate-model to 0.94% (Figure 9c) at the same computational cost, which is a reduction of a factor of 10. It highlights that as the degrees of freedom increase, the relative benefits of the proposed AM method improve. As such, the capabilities of the adapted method for complex and relatively high-dimensional aerodynamic shape design optimisation problems have been demonstrated.

Within the context of nacelle design for long-range applications, the mid-cruise drag is a key metric for the downselection of a nacelle configuration. In this respect, the designs with minimum $C_{D-cruise}$ found with AM2, AM3 and AM4 throughout the optimisation process, and referred in the text as C2, C3, and C4 respectively, have been further investigated. Each design was evaluated with higher fidelity CFD and the error on the nacelle cruise drag prediction for

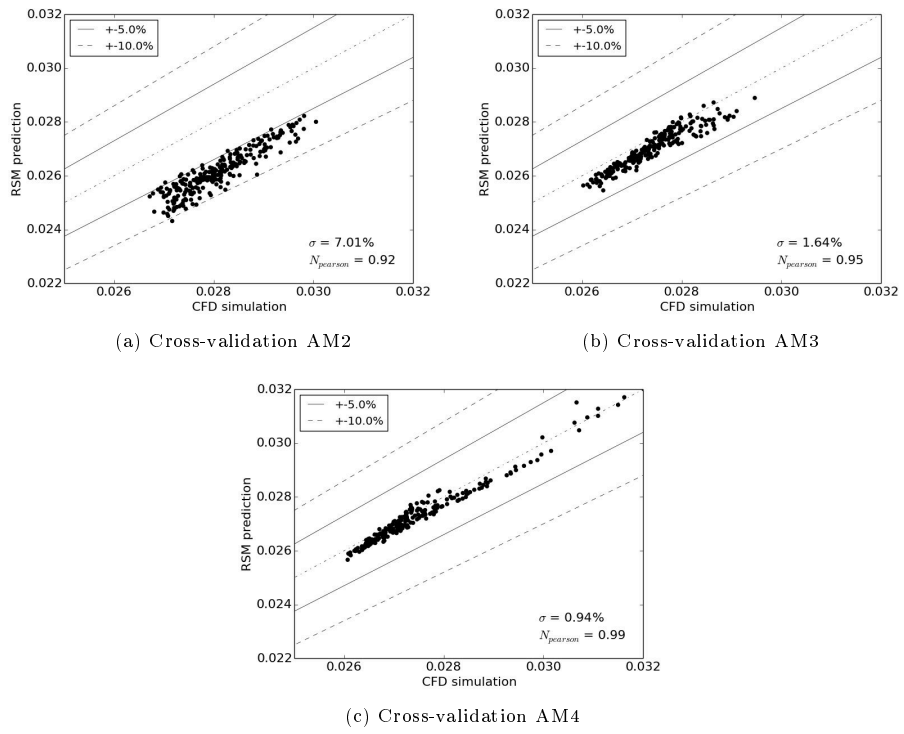


Figure 9: Cross-validation for $C_{D-cruise}$ of the Pareto front prediction obtained with the different AM models

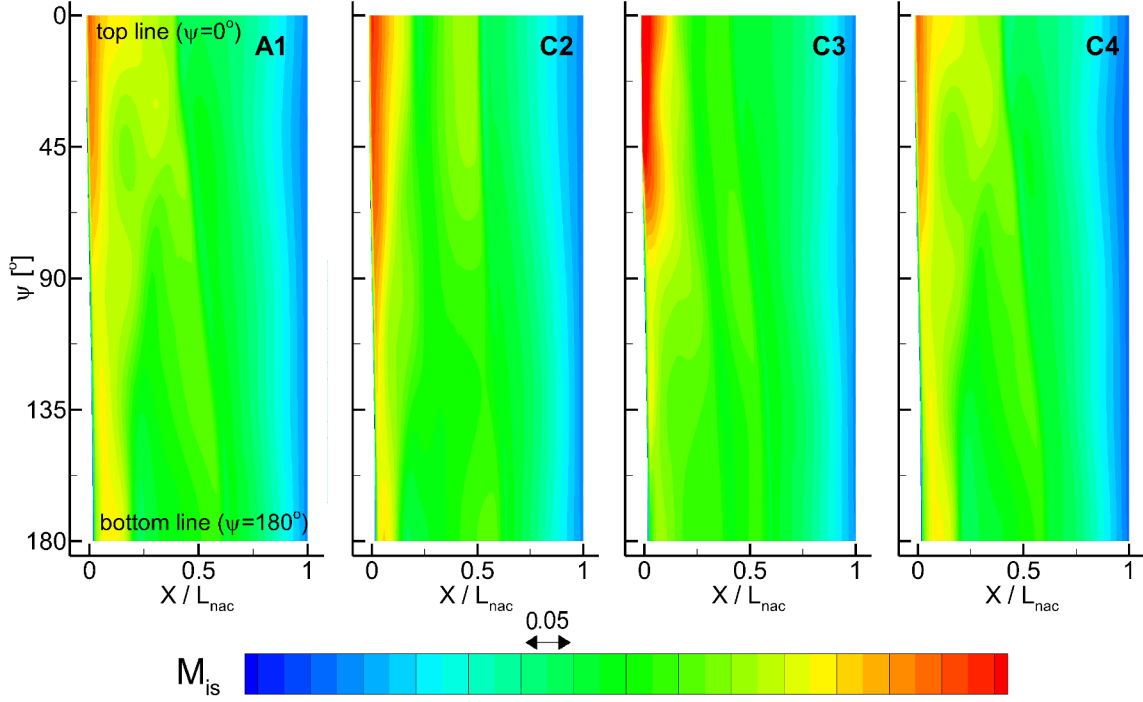


Figure 10: Isentropic Mach number distribution for the selected A1, C2, C3 and C4 compact nacelle configurations

the C2, C3 and C4 designs was 10.7%, 3.8% and 1.5%, respectively (Table 5). This is a notable improvement with the respect to the B2-B4 designs obtained with the traditional method, i.e. CM meta-models, in which the prediction error was 14.0%, 12.5% and 12.4%, respectively. Figure 10 presents the variation of isentropic Mach number over the nacelle for the A1 design (minimum $C_{D-cruise}$ identified with the CFD in-the-loop approach) and the C2-C4 designs. Although C2 and C3 presents differences with respect to A1, the C4 design has a similar nacelle loading as the reference A1 nacelle (Figure 10). It confirms the capabilities of the AM4 low order model to identify a similar transonic flow aerodynamics as the computationally expensive CFD in-the-loop method.

A direct comparison of the predictive accuracy, in terms of $C_{D-cruise}$, for the

Table 5: $C_{D-cruise}$ comparison between RSM and CFD for the Pareto fronts identified with the AM models (C2-C4 designs)

Model	Cost relative to CFD in-the-loop	Design	RSM prediction	CFD result	Difference [%]
AM2	25%	C2	0.0243	0.0272	-10.7
AM3	40%	C3	0.0254	0.0264	-3.8
AM4	50%	C4	0.0257	0.0260	-1.5

CM and AM models on the Pareto front surface highlights the benefits of the proposed evolving method (Figure 11). Within an early stage design context, it is required to define an acceptable trade-off between model uncertainty and design time. For example, an uncertainty level in the order of 5-10% is usually targeted in aircraft applications [56]. Within this investigation aiming at nacelle design optimisation, for a 95% confidence level with a 2σ of approximately 5%, the adapted method AM provides a substantial improvement caused by the accelerated convergence to the desirable parts of the design space. It reduces the computational cost by about 65% with respect to the CFD in-the-loop algorithm.

Whilst one important aspect within an optimisation framework with meta-models is the expected predictive accuracy of the nacelle aerodynamic performance, another key consideration is to adequately identify the parts of the design space for optimal candidate designs. In this respect, an optimisation routine driven by low order models should aim to convergence to the same regions as the computationally expensive CFD in-the-loop approach. In order to quantify the deviation in the geometry variables that define the nacelles within the Pareto front, the mean value of the nacelle design variables from the AM4 and CM4 RSMs have been compared to the baseline CFD in-the-loop method (Figure 12). It presents the percentage difference with respect to the target CFD in-the-loop approach. The comparison is presented for the azimuthal changes

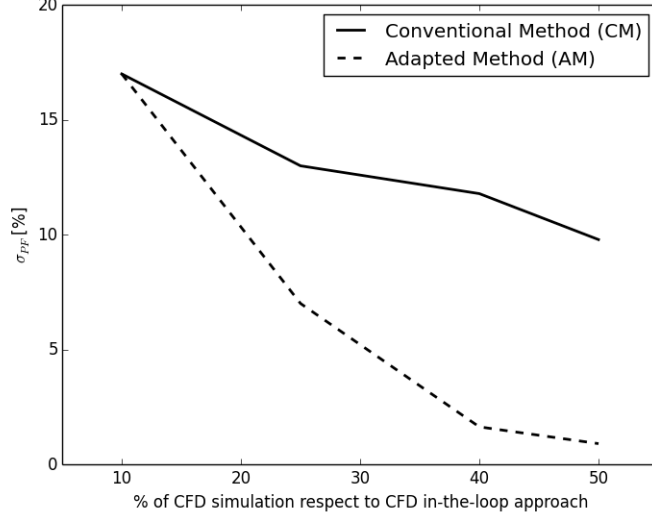


Figure 11: Prediction uncertainty of the surrogate models on the Pareto optimal set. Comparison of surrogate modelling by the traditional design space exploration (CM) and the proposed adapted method (AM)

of the nacelle design variables f_{max} and r_{max} , which have a significant impact on the nacelle drag characteristics of compact aero-engines [21]. The largest geometry deviation of the AM4 model is 3.6% which is considerably better than the 20.0% of the CM4 RSM strategy. As such, it confirms the capabilities of the proposed AM method to identify a similar Pareto optimal design space as the computationally expensive CFD in-the-loop method.

This research has demonstrated the complexity of MOOs for compact aero-engine nacelles due to the associated non-linearity of the problem. For this reason, a large computational cost was required to identify the set of Pareto optimal configurations. An adapted method that combines CFD and surrogate modelling was used to reduce the overall computational overhead of a CFD in-the-loop strategy. It was found that the AM4 model, which required fewer subsequent generations evaluated with CFD, was able to identify a similar Pareto front as the baseline CFD in-the-loop. This work clearly shows that

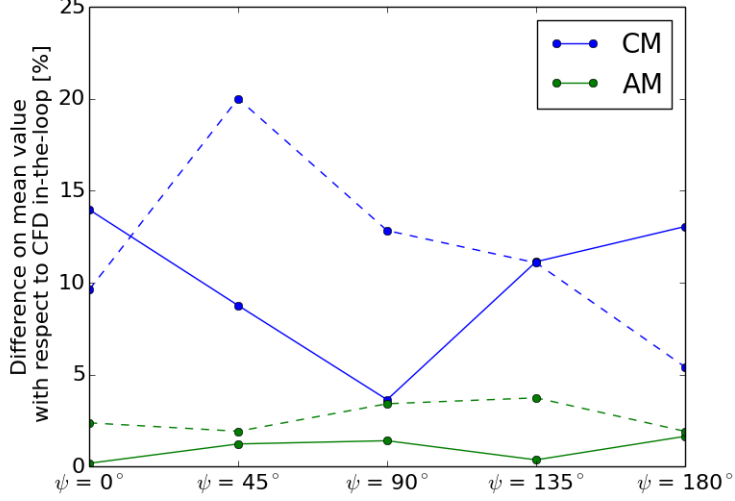


Figure 12: Difference on the mean value of f_{max} (solid) and r_{max} (dashed) for the Pareto front identified with the AM4 and CM4 models with respect to the CFD in-the-loop approach

computational cost can be reduced and lays the foundation and justification for the future development of an approach to include an automatic stopping criteria based on the convergence of the design solution.

4. Conclusions

A method for the multi-objective optimisation of drooped and scarfed non-axisymmetric nacelle aero-engines has been developed. The tool consists of a set of geometry definitions based on intuitive Class Shape Transformations, automatic mesh generation, CFD solution, extraction of the performance metrics, surrogate modelling capability and a genetic algorithm. A fully parametric representation of the 3D nacelle aero-engine based on intuitive design parameters has been implemented. The method enables the aerodynamic design of future civil aero-engines that aim at the reduction of specific fuel consumption.

The framework has successfully identified a set of Pareto optimal solutions

with the CFD in-the-loop optimisation method at the expense of large computational cost. The inherent non-linearity associated to transonic flow aerodynamics of nacelles have been presented. The prediction capabilities of surrogate models for nacelle aerodynamic design have been quantified. This research has highlighted the difficulties to build accurate low order models based on the standard Latin hypercube sampling design space exploration. As such, an adapted method has been proposed and the capabilities to identify optimal nacelle configuration assessed. The proposed method is capable of identifying a set of Pareto optimal solutions with a 65% reduction in the computational cost with respect to the CFD in-the-loop algorithm at the targeted prediction uncertainty of 5%.

5. Acknowledgments

The authors thank Rolls-Royce plc for supporting this research. Due to commercial confidentiality agreements the supporting data is not available.

References

- [1] A. Amrit, L. Leifsson, S. Koziel, Multi-Fidelity Aerodynamic Design Trade-Off Exploration using Point-by-Point Pareto Set Identification, *Aerospace Science and Technology* 79 (2018) 399–412.
- [2] M. van Rooij, N. Frink, B. Hiller, M. Ghoreyshi, M. Voskuijl, Generation of a Reduced-Order Model of an Unmanned Combat Air Vehicle using Indicial Response Functions, *Aerospace Science and Technology* 105510.
- [3] Y. Qiu, J. Bai, N. Liu, C. Wang, Global Aerodynamic Design Optimization Based on Data Dimensionality Reduction, *Chinese Journal of Aeronautics* 31 (4) (2018) 643–659.
- [4] H. Likeng, G. Zhenghong, Z. Dehu, Research on Multi-Fidelity Aerodynamic Optimization Methods, *Chinese Journal of Aeronautics* 26 (2) (2013) 279–286.
- [5] Z. Han, Y. Zhang, C. Song, K. Zhang, Weighted Gradient-Enhanced Kriging for High-Dimensional Surrogate Modeling and Design Optimization, *AIAA Journal* 55 (12) (2017) 4330–4346.
- [6] Z. Grey, P. Constantine, Active Subspaces of Airfoil Shape Parameterizations, *AIAA Journal* 56 (5) (2018) 2003–2017.
- [7] P. Constantine, Active Subspaces: Emerging Ideas for Dimension Reduction in Parameter Studies, *Society for Industrial and Applied Mathematics*, 2015.

- [8] B. Kulfan, Recent Extensions and Applications of the 'CST' Universal Parametric Geometry Representation Method, *Aeronautical Journal* 114 (1153) (2010) 157–176.
- [9] F. Tejero, I. Goulos, D. MacManus, C. Sheaf, Effects of Aircraft Integration on Compact Nacelle Aerodynamics, in: *AIAA SciTech 2020 Forum and Exposition*, AIAA Paper 2020-2225, 2020.
- [10] A. Peters, Z. S. Spakovszky, W. Lord, B. Rose, Ultrashort Nacelles for Low Fan Pressure Ratio Propulsors, *Journal of Turbomachinery* 137 (2).
- [11] B. D. J. Schreiner, F. Tejero, D. MacManus, C. Sheaf, Robust aerodynamic design of nacelles for future civil aero-engines, in: *Proceedings of ASME Turbo Expo 2020: Turbomachinery Technical Conference and Exposition*, GT2020-14470, 2020.
- [12] F. Tejero, D. MacManus, C. Sheaf, Impact of Droop and Scarf on the Aerodynamic Performance of Compact Aero-Engine Nacelles, in: *AIAA SciTech 2020 Forum and Exposition*, AIAA Paper 2020-1522, 2020.
- [13] T. S. Crum, D. E. Yates, T. L. Andrew, N. O. Stockman, Low Speed Test Results of Subsonic, Turbofan Scarf Inlets, in: *AIAA/SAE/ASME/ASME 29th Joint Propulsion Conference and Exhibit*, AIAA 93-2301, 1993.
- [14] N. Birch, 2020 Vision: The Prospects for Large Civil Aircraft Propulsion, *The Aeronautical Journal* 104 (1038) (2000) 347–352.
- [15] A. Guha, Optimum Fan Pressure Ratio for Bypass Engines with Separate or Mixed Exhaust Streams, *Journal of Propulsion and Power* 17 (5) (2011) 1117–1122.
- [16] I. Goulos, J. Otter, F. Tejero, J. H. Rebassa, D. MacManus, C. Sheaf, Civil Turbofan Propulsion Aerodynamics: Thrust-Drag Accounting and

- Impact of Engine Installation Position, *Aerospace Science and Technology* 111 (2021) 106533.
- [17] M. Waters, E. Schairer, Analysis of Turbofan Propulsion System Weight and Dimensions, Tech. Rep. TM X-73, NASA (1977).
 - [18] D. Daggett, S. Brown, R. Kawat, Ultra-Efficient Engine Diameter Study, Tech. Rep. CR-2003-212309, NASA (2003).
 - [19] W. Burgsmuller, S. Thome, Close Coupling of Very High-Bypass Engines in Combination with Take-Off/Landing, *Notes on Numerical Fluid Mechanics* 60 (1997) 95–102.
 - [20] M. Robinson, D. MacManus, K. Richards, C. Sheaf, Short and Slim Nacelle Design for Ultra-High BPR Engines, in: 55th AIAA Aerospace Sciences Meeting, AIAA SciTech Forum, AIAA Paper Number 2017-0707, 2017.
 - [21] F. Tejero, M. Robinson, D. MacManus, C. Sheaf, Multi-Objective Optimization of Short Nacelles for High Bypass Ratio Engines, *Aerospace Science and Technology* 91 (2019) 410–421.
 - [22] F. Tejero, D. MacManus, C. Sheaf, Surrogate-Based Aerodynamic Optimisation of Compact Nacelle Aero-Engines, *Aerospace Science and Technology* 93 (2019) 105207.
 - [23] M. Albert, D. Bestle, Aerodynamic Design Optimization of Nacelle and Intake, in: Proceedings of ASME Turbo Expo 2013: Turbine Technical Conference and Exposition, no. GT2013-94857, American Society of Mechanical Engineers, 2013.
 - [24] X. Fang, Y. Zhang, S. Li, , H. Chen, Transonic Nacelle Aerodynamic Optimization Based on Hybrid Genetic Algorithm, in: 17th AIAA/ISSMO Mul-

tidisciplinary Analysis and Optimization Conference, AIAA AVIATION Forum, AIAA Paper Number 2016-3833, 2016.

- [25] Y. Zhong, S. Li, A 3D Shape Design and Optimization Method for Natural Laminar Flow Nacelle, in: Proceedings of ASME Turbo Expo 2017: Turbomachinery Technical Conference and Exposition, Paper Number GT2017-64379, Vol. 1, 2017, pp. 825–830.
- [26] H. Toubin, I. S. E. Dim, M. Meheut, Multipoint Aerodynamic High Fidelity Shape Optimization of an Isolated Engine Nacelle, in: AIAA SciTech Forum 52nd Aerospace Sciences Meeting, AIAA Paper Number 014-0903, Virginia Beach, VA, USA, 2014.
- [27] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation 6, (2) (2002) 182 – 197.
- [28] R. B. Langtry, F. R. Menter, Correlation-Based Transition Modeling for Unstructured Parallelized Computational Fluid Dynamics Codes, AIAA Journal 47 (12) (2009) 2894–2906.
- [29] S.Kirkpatrick, C. D. Gelatt, M. P.Vecchi, Optimization by Simulated Annealing, Science 220 (4598) (1983) 671–680.
- [30] H. Sobieczky, Parametric Airfoils and Wings, Notes on Numerical Fluid Mechanics, edited by K. Fujii and G.S. Dulikravich 68 (1998) 71–88.
- [31] Q. Zhang, H. Li, MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition, IEEE Transactions on Evolutionary Computation 11 (6) (2007) 712–731.
- [32] R. Christie, A. Heidebrecht, D. G. MacManus, An Automated Approach to Nacelle Parameterisation Using Intuitive Class Shape Transformation

- Curves, *Journal of Engineering for Gas Turbines and Power* 139 (6) (2017) 062601–1 – 062601–9.
- [33] Ansys Inc., 275 Technology Drive, Canonsburg, PA 15317, ANSYS ICEM CFD Tutorial Manual.
- [34] Ansys Inc., 275 Technology Drive, Canonsburg, PA 15317, ANSYS FLUENT User’s Guide.
- [35] F. R. Menter, Two-Equation Eddy-Viscosity Turbulence Models for Engineering Applications, *AIAA Journal* 32 (8) (1994) 1598–1605.
- [36] S. Sarkar, B. Lakshmanan, Application of a Reynolds Stress Turbulence Model to the Compressible Shear Layer, *AIAA Journal* 29 (5) (1991) 743–749.
- [37] A. Mittal, S. Girimaji, Nonlinear Evolution of Perturbations in High Mach Number Wall-Bounded Flow: Pressure-Dilatation Effects, *Physics of Fluids* 32 (2020) 036101.
- [38] T. Stankowski, D. G. MacManus, C. Sheaf, R. Christie, Aerodynamics of Aero-Engine Installation, *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering* 230 (14) (2016) 2673–2692.
- [39] AGARDograph AG-237, Guide to In-Flight Thrust Measurement of Turbojets and Fan Engines, Tech. rep., AGARD Report (1979).
- [40] I. C. Karpolis, K. Giannakoglou, A Multilevel Approach to Single- and Multiobjective Aerodynamic Optimization, *Computer Methods in Applied Mechanics and Engineering* 197 (33-40) (2008) 2963–2975.

- [41] K. Giannakoglou, D. Papadimitriou, I.C.Kampolis, Aerodynamic Shape Design using Evolutionary Algorithms and New Gradient-Assisted Meta-models, *Computer Methods in Applied Mechanics and Engineering* 195 (44-47) (2006) 6312–6329.
- [42] G. Venturelli, E. Benini, Kriging-assisted Design Optimization of S-Shape supersonic compressor cascades, *Aerospace Science and Technology* 58 (2016) 275–297.
- [43] R. Kohavi, A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection, in: *Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence*, Vol. 2, 1995, pp. 1137–1143.
- [44] G. Giangaspero, D. MacManus, I. Goulos, Surrogate Models for the Prediction of the Aerodynamic Performance of Exhaust Systems, *Aerospace Science and Technology* 92 (2019) 77–90.
- [45] A. I. J. Forrester, A. J. Keane, Recent Advances in Surrogate-Based Optimization, *Progress in Aerospace Sciences* 45 (2009) 50–79.
- [46] R. Christie, M. Robinson, F. Tejero, D. MacManus, The Use of Hybrid Intuitive Class Shape Transformation Curves in Aerodynamic Design, *Aerospace Science and Technology*, doi: 10.1016/j.ast.2019.105473 95 (2019) 105473.
- [47] J. Matesanz-Garcia, R. Christie, F. Tejero, D. MacManus, A. Heidebrecht, An Automated Approach for the Aerodynamic Design of Close-Coupled Propulsion/Airframe Configurations, in: *Aerospace Europe Conference 2020*, 2020.
- [48] J. H. Rebassa, F. Tejero, J. Otter, I. Goulos, D. MacManus, Multi-fidelity

Assessment of Exhaust Systems for Complete Engine-Airframe Integrations, in: Aerospace Europe Conference 2020, 2020.

- [49] B. M. Kulfan, J. E. Bussioletti, Fundamental parametric geometry representations for aircraft component shapes, in: 11th AIAA/ISSMO multidisciplinary analysis and optimization, AIAA-2006-6948, Renaissance Portsmouth, VA, 2006.
- [50] B. M. Kulfan, Universal parametric geometry representation method, *Journal of Aircraft* 45 (1) (2008) 142–158.
- [51] G. Strang, *Linear Algebra and its Applications*, Thomson, 2006.
- [52] P. Roache, A Method for Uniform Reporting of Grid Refinement Studies, *Journal of Fluids Engineering* 116 (3) (1994) 405–413.
- [53] M. Robinson, D. MacManus, C. Sheaf, Aspects of Aero-Engine Nacelle Drag, *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering* 233 (5) (2018) 1667–1682.
- [54] J. C. Helton, F. J. Davis, Latin Hypercube Sampling and the Propagation of Uncertainty in Analyses of Complex Systems, *Engineering and System Safety* 81 (2003) 23–69.
- [55] Y. He, J. Sun, P. song, X. Wang, A. S. Usmani, Preference-driven Kriging-based Multiobjective Optimization Method with a Novel Multipoint Infill Criterion and Application to Airfoil Shape Design, *Aerospace Science and Technology* 96 (2020) 105555.
- [56] A. Heidebrecht, D. MacManus, Surrogate Model of Complex Non-Linear Data for Preliminary Nacelle Design, *Aerospace Science and Technology* 84 (2019) 399–411.



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Tejero, Fernando; Christie, Robert; MacManus, David G.; Sheaf, Christopher T.

2021-06-15

Elsevier

<https://doi.org/10.1016/j.ast.2021.106890>

Tejero F, Christie R, MacManus D, Sheaf C. (2021) Non-axisymmetric aero-engine nacelle design by surrogate-based methods. Aerospace Science and Technology, Volume 117, October 2021, Article number 106890