# Multi-Fidelity Aerodynamic Data Set Generation for Early Aircraft Design Phases


**Mario Stradtner**
DLR – German Aerospace Center
Institute of Aerodynamics and Flow Technology
Lilienthalplatz 7, 38108 Braunschweig
GERMANY

Mario.Stradtner@dlr.de

**Carsten M. Liersch**
DLR – German Aerospace Center
Institute of Aerodynamics and Flow Technology
Lilienthalplatz 7, 38108 Braunschweig
GERMANY

Carsten.Liersch@dlr.de

**Patrick Löchert**
DLR – German Aerospace Center
Institute of Aerodynamics and Flow Technology
Lilienthalplatz 7, 38108 Braunschweig
GERMANY

Patrick.Loechert@dlr.de



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## *ABSTRACT*

*A widespread industrial adoption of Computational Fluid Dynamics in early design phases would significantly increase the modelling fidelity compared to classical conceptual design tools. However, relatively high computational cost to obtain comprehensive data sets and a significant manual effort needed for the creation of suitable geometries for meshing at early design stages are limiting factors today. In this light, this paper presents a multi-fidelity workflow for aerodynamic data set generation which addresses the two aforementioned bottlenecks. First, the automated generation of geometries coupled with meshing capabilities. Second, the capability to efficiently generate high-fidelity-based aerodynamic data sets. All tools of the workflow use a common parametric data exchange format for the integration into a conceptual design framework and share the same master geometry which is derived to create a tool specific geometrical representation. Computational Fluid Dynamics tools of varying fidelity provide the input for the framework for multi-fidelity surrogate modelling to efficiently enable comprehensive aerodynamic data set generation. Throughout the paper a generic triple-delta combat aircraft is considered as use case.*


## 1.0 INTRODUCTION

Throughout all phases of aircraft design, a reliable assessment of performance and flight characteristics of a new platform or concept based on comprehensive, highly accurate aerodynamic data is required. Advancements within the field of Computational Fluid Dynamics (CFD) together with shorter turnaround times due to the increased availability of high-performance computing (HPC) resources have enabled the application of high-fidelity CFD solvers during preliminary and conceptual design phases of an aircraft [1][2]. A higher flexibility due to an early detection of design deficiencies becomes possible. This might prevent or reduce the need of retroactive design modifications which typically involve significantly higher cost [3]. A future growth in computing resources and progression of HPC technologies such as revolutionary hardware technologies and implementation of CFD algorithms for extreme parallelism will most likely further accelerate this trend towards an extensive usage of these numerical simulation tools [4]. However, an evolving design demand for an evolving aerodynamic data set is raising the question of efficiency and possible limitations, e.g. cost, for a widespread industrial adoption of CFD during conceptual and preliminary design.

One of the key aspects of this adoption is a comprehensive parametric modelling including automation from the first representation of the geometry up to the aerodynamic model evaluation with regard to high throughput requirements for aerodynamic data set generation [4] and for CFD-based geometry optimization [5]. This modelling includes Computer Aided Design (CAD), CFD meshing and CFD code evaluation as well as surrogate modelling. In [6] an automated process was developed to combine CAD geometry modelling in CATIA [7] and CFD meshing using CENTAUR [8] which was used for a surrogate-based optimisation [9].

Even for each intermediate design the aerodynamic data set itself is evolving when applying various numerical methods hierarchically or in combination. For example, a combat aircraft has a great variation in its flight regimes where it often operates at high angles of attack and deals with flows being dominated by leading edge vortices which burst. Under such flow conditions, the use of highly accurate CFD solvers is inevitable. Nevertheless, for cruise and loiter flight phases the use of simple and fast aerodynamic simulation tools is sufficient for conceptual design studies to address some of the mission requirements [10][11]. Where the trends of simple simulation tools are not valid, simulation tools of increasing fidelity should be applied to increase the insight into these more challenging characteristics. As a consequence, the broad spectrum of numerical and empirical tools from lower to higher representation fidelity will play an important role throughout early design phases also in the future. Combining such different data sources with varying accuracies and uncertainties depending on the flight condition of interest is a challenging aspect which needs to be considered when developing reliable and efficient numerical process chains.

Statistical models, such as surrogate models, are able to provide predictions of aerodynamic quantities for any number of flow conditions at minimal cost compared to high-fidelity CFD while only requiring a finite number of expensive high-fidelity model evaluations to fit a parametric approximation model [12]. The linkage of data obtained from different sources can be implemented by means of multi-fidelity surrogate models [13][14] or by combining multiple sources into stochastic data sets [15]. In general, such models are able to provide good prediction capabilities and in consequence a comparable accuracy to high-fidelity CFD can be achieved. Moreover, the application of adaptive sampling techniques enables an efficient exploration and exploitation of the design space while still accounting for automation and high throughput requirements. Additionally, uncertainty could be propagated through the multi-fidelity surrogate models. Feldstein et al. [16] used a fidelity-weighted multi-fidelity approach which takes the quality of Gaussian Process approximation and designer’s confidence into account to additionally propagate uncertainties to overall system level. Other approaches on multi-fidelity modelling under uncertainty also rely on Gaussian Processes and either add noise to the high-fidelity CFD simulations through an eigenspace perturbation methodology [17] or to use the standard deviation of convergence histories in CFD [18].

This paper presents a workflow for multi-fidelity aerodynamic data set generation which is applied during the early aircraft design phase of a generic combat aircraft. Special emphasis is placed on the automation aspect of coupling geometry and mesh, multi-fidelity surrogate models as well as aerodynamic data set generation. This multi-fidelity framework shows the potential of reducing timescales and cost when incorporating high-fidelity CFD into the early design cycle of an aircraft. This further increases the flexibility within the design process itself. The paper is organized as follows. First, the methodology is described by means of the steps and tools within the workflow. Second, a generic triple-delta wing configuration called the DLR-Future Fighter

Demonstrator (DLR-FFD), is introduced and two scenarios for aerodynamic data set generation are presented. The work is concluded by a summary and an outlook.

## 2.0 METHODOLOGY

A multi-fidelity surrogate modelling approach for an unmanned combat aerial vehicle is already presented in [13]. This modelling approach is now being integrated into DLR's conceptual aircraft design system [19][20][21]. It is a flexible toolset being developed at DLR since 2005, connecting analysis tools from various disciplines and the corresponding experts at the different DLR sites in Germany. Here, the central integration framework is DLR's in-house software Remote Component Environment (RCE) [22]. Data exchange between the tools of different disciplines is based on a data exchange file format called Common Parametric Aircraft Configuration Schema (CPACS) [23] which is developed for the DLR aircraft design system. Both are available to the public under open source licences [24][25].

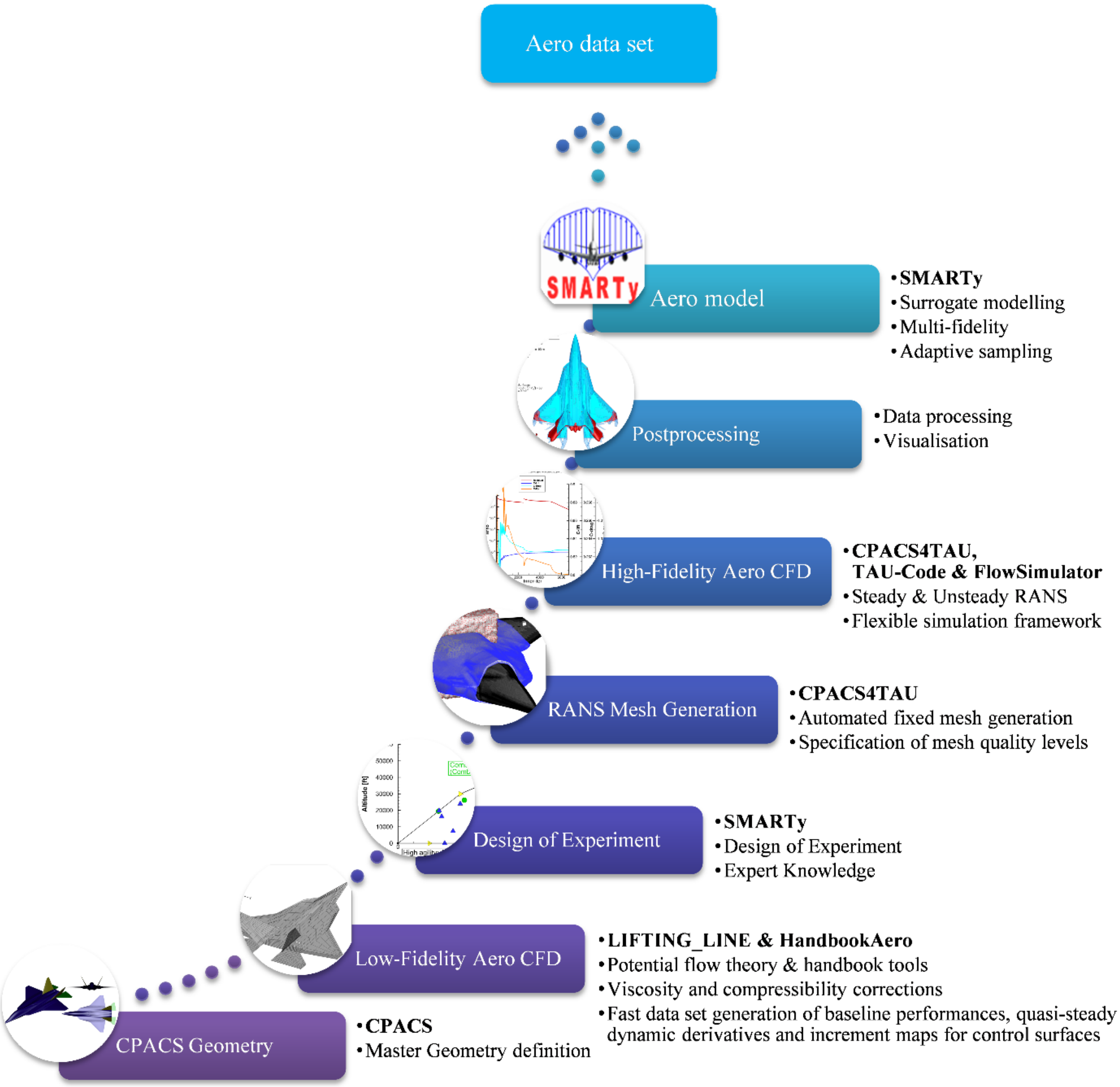



**Figure 2-1: Building blocks and features of the multi-fidelity aerodynamic data set generation workflow.**

A new workflow on multi-fidelity aerodynamic data set generation, to be integrated into DLR's conceptual aircraft design system, is shown in Figure 2-1. It starts with the parametric and hierarchical definition of the aircraft based on the CPACS data exchange format as input and provides an updated CPACS file containing a new aerodynamic data set as output. It consists of tools and tool wrappers to generate CFD meshes, to conduct CFD simulations of varying fidelity and uses DLR's Surrogate Modeling for AeRo data Toolbox Python package (SMARTy) [26][27] to generate aerodynamic data sets. All intermediate steps such as geometry preparation, automatic fixed mesh generation, design of experiment, low- and high-fidelity CFD and postprocessing are depicted in the workflow and rely on the same geometry definition. Details about each of the building blocks of the workflow are described subsequently. Most of these individual steps are fully automated processes on their own and partly already linked either via RCE or Python and Bash scripting. An overall workflow relying fully on RCE is envisaged in the near future.

## 2.1 Geometry Definition

The data exchange file format CPACS is an Extensible Markup Language (XML) based data format which is designed to store aircraft related data, such as requirements, geometrical properties, or analysis results in a hierarchical and parametric way. It was introduced mainly to serve as a common language between different disciplines' analysis tools. Two software libraries [28] called TiXI XML Interface (TiXI) and TiGL Geometry Library (TiGL) are being developed to ease the use of CPACS. While TiXI provides a simple interface to create, read, modify, and write XML datasets such as CPACS, TiGL generates a 3D CAD model of the aircraft from the parametric data and offers methods to query geometrical data from this model. In addition, TiGL provides functions to store the generated geometry using standard CAD exchange file formats. The TiGL Viewer application can be used to visualize the underlying CAD model. Figure 2-2 shows three different views of the TiGL CAD model generated from a CPACS geometry definition for a triple-delta wing configuration. The complete package of CPACS and libraries is available under open source licenses.

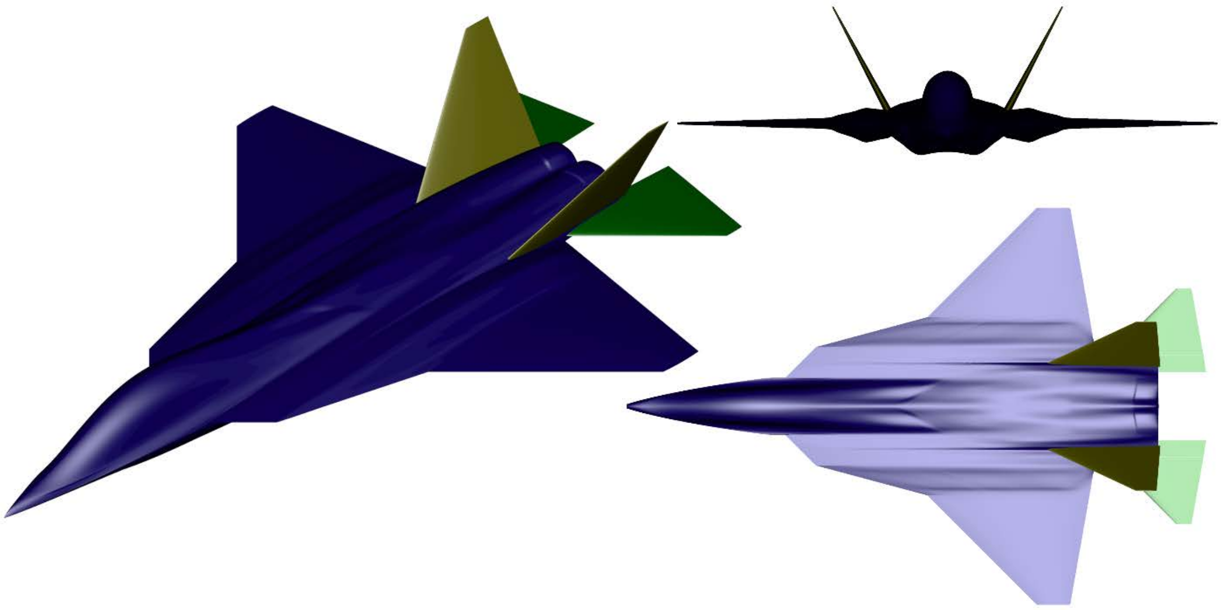


**Figure 2-2: TiGL Viewer visualisation of the DLR-FFD described in the CPACS data format.**

For connecting different disciplinary analysis tools with CPACS, typically so-called tool wrappers are used. A tool wrapper is a small program that reads a CPACS file, writes an input file for the tool, runs the tool, reads the output file of the tool and finally writes the results as a CPACS file. This enables, by using TiXI and TiGL, the capability to derive specific geometry representations for each disciplinary tool from the initial CPACS geometry definition. This initial CPACS geometry definition is called the master geometry. Each derived geometric representation is appropriate for the needed level of fidelity of the CFD tools used is this workflow. This reflects future needs and current progress in the field of geometry modelling as stated for the CFD Vision 2030 [4].

## 2.2 Low-Fidelity Aero CFD

As a good compromise between computing speed and accuracy, the DLR open source tool LIFTING_LINE [29][30][31] has proven its value in generating aerodynamic data sets for conceptual aircraft design for decades. Based on the linearized potential flow equations for thin aerofoils, LIFTING_LINE can simulate steady and quasi-steady flow fields around nearly arbitrary systems of three-dimensional wings, including the deflection of control surfaces. The wings are modelled as structured grids of flat plate panels in spanwise and chordwise direction. Along the quarter-chord line of each of these panels, a bound vortex line with a second order polynomial describing the local circulation is applied. Thus, the spanwise changes in circulation are transported downstream by a free, linearly changing vortex sheet. Together with the CPACS4LILI tool wrapper as CPACS interface, LIFTING_LINE can be used to calculate huge performance maps containing aerodynamic coefficients for a variety of altitudes, Mach numbers, angles of sideslip and angles of attack in a quite short time. Furthermore, corresponding damping derivatives, as well as increment maps for specified control device deflections can be computed. However, based on its underlying theory, LIFTING_LINE can only compute inviscid, incompressible flow conditions, extended by the application of a compressibility correction according to Goethert. The missing effects of viscosity, thickness, and possibly transonic effects can either be considered by using higher fidelity aerofoil data within a 2.5D approach (see [31]), or by applying the DLR HandbookAero tool upon the LIFTING_LINE performance maps. HandbookAero accounts for viscous drag effects by using a flat plate analogy in conjunction with an empirical thickness correction according to Raymer [32]. An automatic estimation of wave drag effects is not yet included in HandbookAero, but planned for the future.

The generation of aerodynamic datasets using LIFTING_LINE and HandbookAero can be performed fast and very robust within automatized workflows inside the RCE framework. However, transonic and supersonic flow conditions cannot be predicted at all, just as highly vortex-dominated flows with vortex breakdown and flow separation effects. Thus, in contrast to the design of subsonic transport aircraft, the design of highly agile supersonic fighter aircraft can only be satisfied partially with aerodynamic datasets coming from these tools.

## 2.3 High-Fidelity Aero CFD

As described in the previous section low-fidelity methods, such as potential flow codes, are not able to predict the complex aerodynamics of low-aspect ratio delta wing combat aircrafts. As those aircrafts often operate at high incidences featuring near- and post-stall conditions while exploiting nonlinear lift characteristics—which is present already at low and moderate angles of attack—high-fidelity CFD solvers become inevitable to be used. Nevertheless, attention needs to be paid on efficiency when using high-fidelity CFD in early design phases, as typically a large amount of high-fidelity CFD solutions would be needed to build aerodynamic data sets. Automatic and robust CFD solvers as well as processes becomes necessary. In particular, the aspect to automate the whole process to obtain a flow solution via high-fidelity CFD solvers starting from the master geometry is considered next. An efficient usage of high-fidelity CFD is realized by combining CFD with surrogate modelling (see Sec. 2.4). This allows to generalize information learned from CFD solutions obtained at only a few flight points within the flight envelope. A good placement of samples, which is discussed next, is of great importance for surrogate models.

### 2.3.1 Design of Experiment

For computationally expensive simulations often only a limited number of simulations is affordable and therefore, a careful selection of parameter combinations describing flight conditions within a flight envelope is needed for a design cycle. A good exploration of the complete design space is crucial in terms of surrogate modelling to prevent extrapolation. Several modern design of experiment methods such as Full Factorial grids, Halton or Sobol's sequence and Latin hypercube samplings are available via SMARTy. These algorithms provide space-filling sampling designs which can be further restricted or mapped onto non-rectangular bounded regions such as flight envelopes. Within some regions of a flight envelope the aerodynamics change nonlinearly or, at worst, abruptly where it might be expedient to exploit the design space more. For these scenarios the sampling design could be supplemented by expert-knowledge and adaptive sampling strategies to place special emphasis on these specific flight regimes. All features are integrated into the workflow by means of Python scripts based on SMARTy and can easily customized for individual needs.

### 2.3.2 Geometry and CFD Mesh Coupling

A tighter coupling between the master geometry and suitable, automatically generated CFD meshes for high-fidelity data generation is realized with DLR's recently developed tool wrapper CPACS4TAU. It enables an automated process by connecting all relevant stages and tools required to achieve a flow solution given a flight condition and the master geometry. Hereby, the master geometry is given in the CPACS data exchange format which is converted into a geometry representation in Initial Graphics Exchange Specification (IGES) format suitable for CAD software tools. For building and exporting the geometry files the TiXI and TiGL libraries are used. Further, these libraries also allow to automatically retrieve all necessary geometrical information for grid generation. With this information the grid generation is prepared for the unstructured grid generator CENTAUR using best practices.

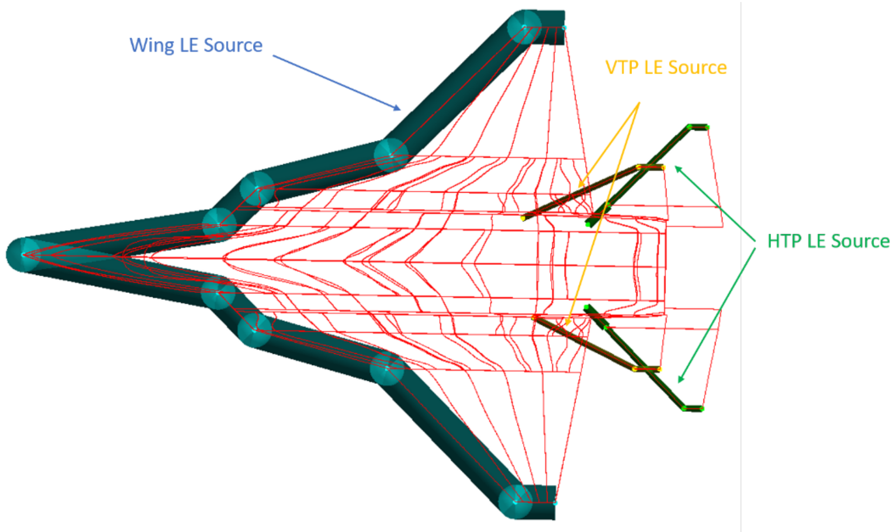



**Figure 2-3: Local control of mesh resolution in CENTAUR automatically set by CPACS4TAU.**

Due to the possibility to create mesh families of varying resolution CPACS4TAU is well-suited for multi-fidelity modelling. As CPACS4TAU additionally comprises the DLR TAU-Code [33] as flow solver, a direct and automated workflow-driven computation becomes feasible. A so-called grid quality factor is implemented to adapt the mesh resolution in different steps from very coarse to very fine. To assure accuracy and avoid numerical effects, like mesh induced separation due to a too coarse grid, several requirements to the grid are established.

These encompass an additional grid refinement along the wing's leading and side edges by placing an angled tube as shown in Figure 2-3. Exactly the same treatment is applied for horizontal and vertical tail planes. The boundary layer is resolved with prismatic layers and the dimensionless wall distance $y^+$of the first layer satisfies values of $y^+ \leq 1$. A stretching factor of the accumulated prism layers is currently chosen in accordance to best-practices for using the Spalart-Allmaras turbulence model [34] to ensure the first three layers to lie below a dimensionless wall distance of $y^+ \leq 5$. The total number of prism layers is determined by the thickness of the boundary layer, which is approximated by the theory of the flat plate. Here, a relaxation factor is used to add additional layers in terms of resolving the boundary layer properly also for more complex geometries. Finally, tetrahedral cells are used outside of the shear layer. An example of a mesh that is generated in accordance with these requirements is shown in Figure 2-4. Here, the refinement of the surface grid at the leading edge due to the angled tube sources as well as the hybrid mesh structure with prismatic layers in the boundary layer region and tetrahedra cells away from the wall becomes apparent.

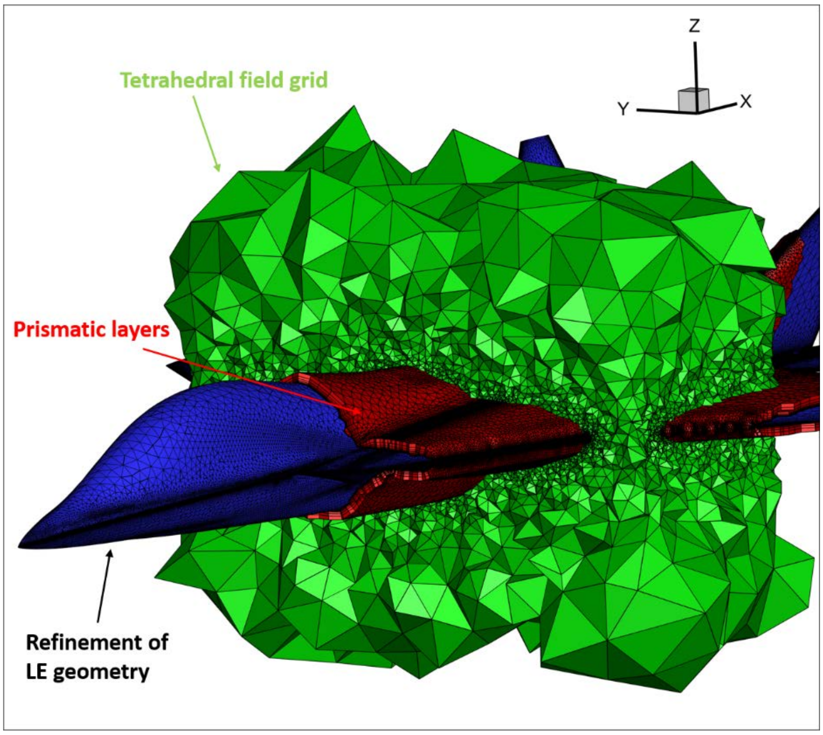



**Figure 2-4: Hybrid mesh with leading edge refinement and prismatic layers in the boundary layer.**

### 2.3.3 CFD Simulation

Besides geometry and mesh linkage, CPACS4TAU offers the possibility to automatically obtain high-fidelity CFD solutions with the flow solver DLR TAU-Code. The DLR TAU-Code is an unstructured hybrid flow solver appropriate for viscous and inviscid complex flow simulations ranging from the subsonic to the hypersonic flow regime. For viscous simulations CPACS4TAU currently uses the one equation Spalart-Allmaras turbulence model in its negative form [35]. In case of multiple requested CFD simulations, CPACS4TAU checks automatically if previously generated meshes could be re-used for the new operating condition.

More complex simulation processes can be achieved when additionally using the FlowSimulator framework [36]. This gives even more flexibility when either simply running customized CFD process chains or in terms of enabling multi-disciplinary simulations. The FlowSimulator is a mainstay of DLR’s CFD-based multi-disciplinary analysis and optimization capabilities. Due to the Python control layer of the FlowSimulator as the main user access layer, user-defined process chains and scenarios could be easily implemented. Several plug-ins for different tasks such as CFD simulations, mesh deformation, fluid-structure coupling, trimming or surrogate modelling are integrated into the FlowSimulator framework. All plug-ins share a common data manager allowing efficient in-memory exchange of data. By extending CPACS4TAU with a FlowSimulator interface, such types of mono- and multi-disciplinary CFD-based simulations will become available in CPACS4TAU as well. So far, grids generated with CPACS4TAU are either used internally by CPACS4TAU or within FlowSimulator based process chains as it has been implemented in this work.

Each high-fidelity CFD result is either automatically postprocessed by CPACS4TAU which stores the resulting forces and moments directly in the CPACS aerodynamic performance map or by user-defined Python and Bash scripts to enable additionally requested analysis or visualisation of the results.

## 2.4 Multi-Fidelity Aerodynamic Model

The aerodynamic model which now generalizes the information of only a few high-fidelity CFD solutions and allows to predict a comprehensive aerodynamic data set is a multi-fidelity surrogate model based on SMARTy. A multi-fidelity surrogate model combines data of varying fidelity, such as integral aerodynamic force and moment coefficients obtained by low- and high-fidelity CFD tools, into a fast-to-evaluate aerodynamic model. A detailed description of the multi-fidelity surrogate modelling process is given in [13]. After the aerodynamic surrogate model is built using the low- and high-fidelity CFD data, the model assessment and its evaluation takes place. The generalization performance is either assessed on a given test set or by means of cross-validation techniques. Subsequently, if the quality of the aerodynamic surrogate model is considered to be sufficiently good, the model is evaluated to predict a aerodynamic data set. An iterative adaptive sampling refinement could be used to draw additional high-fidelity samples to improve the prediction capabilities of the aerodynamic surrogate model.

In general, surrogate models are used to approximate a computationally expensive simulation. Suppose the original function is modelled through a linear regression model $f(x)$ which differs from the response values $y$ by additive noise ε

$$y(x) = f(x) + \varepsilon, \qquad f(x) = x^{\top}\beta. \tag{1}$$

Let the $\boldsymbol{F}$ denote the design matrix, then the unknown weight coefficients $\beta$ are obtained by the generalized least squares estimate [37]

$$\hat{\beta} = (\boldsymbol{F}^{\top}\boldsymbol{F})^{-1}\boldsymbol{F}^{\top}\boldsymbol{y}. \tag{2}$$

Thus, the surrogate model $\hat{y}$ to approximate the full order model for a set of input variables $\boldsymbol{x}$ is given by

$$\hat{y}(x) = x^{\top}\hat{\beta} + \varepsilon, \qquad E(\varepsilon) = 0, \qquad V(\varepsilon) = \sigma^2 I. \tag{3}$$

In this work multi-fidelity models are used which have been introduced in [38] by means of a hierarchical kriging surrogate model. This model, on the one hand incorporates a low-fidelity surrogate model as a global trend function $\hat{y}(\boldsymbol{x_{lf}})$, and on the other hand it interpolates the high-fidelity CFD data. Hence, the linear regression model $f(x)$ in Eq. (1) takes the form of an approximated low-fidelity function $\hat{y}(\boldsymbol{x_{lf}})$ (e.g. a Radial Basis Function (RBF) or a kriging surrogate model) which is scaled by an unknown weighting factor $\beta$

$$f(x) = \hat{y}_{lf}(x)\beta. \tag{4}$$

With this assumption, the construction of a hierarchical kriging surrogate model follows the same methodology as to construct a conventional kriging surrogate model [38][39] and results in the best linear unbiased estimate of the hierarchical model

$$\hat{y}(x) = \hat{y}_{lf}(x)\hat{\beta} + r^{\top}(x)R^{-1}\left(y - F\hat{\beta}\right). \tag{5}$$

The design matrix $\boldsymbol{F}$ is now given by a column vector of the low-fidelity surrogate model evaluations at the $n$ sample locations of the high-fidelity data.

$$F = \left[\hat{y}_{lf}(x_1), \ldots, \hat{y}_{lf}(x_n)\right]^{\top}. \tag{6}$$

Similar to as in [13], such hierarchical multi-fidelity surrogate models are also built in this work.

## 3.0 RESULTS

The multi-fidelity aerodynamic data set generation workflow is demonstrated on the DLR-FFD. Here, aerodynamic data sets are generated by applying the numerical simulation techniques of varying fidelity and multi-fidelity surrogate models at different design stages.

### 3.1 DLR-Future Fighter Demonstrator

The DLR-FFD is a generic fighter aircraft configuration, which is designed for research purposes. It is a double-seated, twin-engine aircraft concept with a big internal weapon bay, driven by ambitious and contradicting requirements for agility and range. Furthermore, it is intended to be capable to fly speeds up to Mach 2 with reheat and Mach 1.4 without (supercruise). In order to design and assess such a concept, it is not possible to rely purely on classical handbook methods for aircraft design, as such methods cannot sufficiently cover the geometric aspects which are driving the design. Instead, it is essential to verify the assumed relations between geometry (especially planform) and aerodynamics by providing sufficiently accurate aerodynamic data for the critical flight regimes in a fast and automated way. This aerodynamic data can then be used to verify design decisions by calibrating handbook methods in the conceptual design phase and by providing comprehensive aerodynamic performance maps for the more detailed investigations in the subsequent preliminary design phase. In Figure 3-1 a visualisation of the DLR-FFD is exemplary shown as a time-averaged Unsteady Reynolds-averaged Navier-Stokes (URANS) solution obtained by the DLR TAU-Code using the workflow described above.

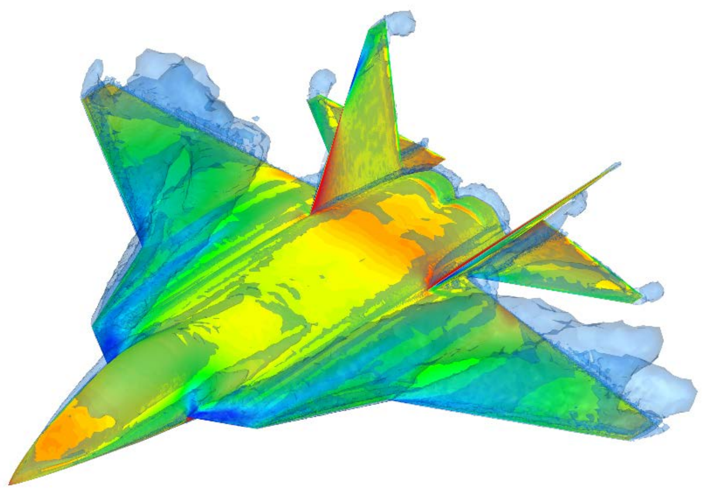


**Figure 3-1: CFD solution of the DLR-Future Fighter Demonstrator.**

### 3.2 Aerodynamic Data Set Modelling

After a conceptual layout of the DLR-FFD based on previous studies was fixed, multiple aerodynamic data sets are generated. These data sets showcase an evolving data set on the one hand and a design on the other. The first scenario represents evolving data from low- to high-fidelity by means of a multi-fidelity surrogate model for the initial design while the second represents a further development of the geometric. Up to now three data sets are generated: The first two data sets represent the initial design. While the first is directly obtained by solely evaluating low-fidelity methods, the second one includes additional data of higher fidelity which is combined with the low-fidelity data by means of a multi-fidelity surrogate model. At this first step of evolving the data set the main focus lies on an assessment of flight performances in terms of the level-flight operating envelope and mission requirements such as range or endurance. Thus, high-fidelity data which belongs to this assessment is built primarily focussing on symmetric flight conditions at varying Mach number, altitude and angle of attack. After adapting design modifications, which resulted from this assessment, the third aerodynamic data set is predicted via multi-fidelity surrogate modelling and represents the aerodynamic characteristics after a first design iteration as illustrated in Figure 3-2. This final data set uses high-fidelity data obtained for symmetric and non-symmetric flight conditions to enable an assessment of handling qualities and level turning flight performance.

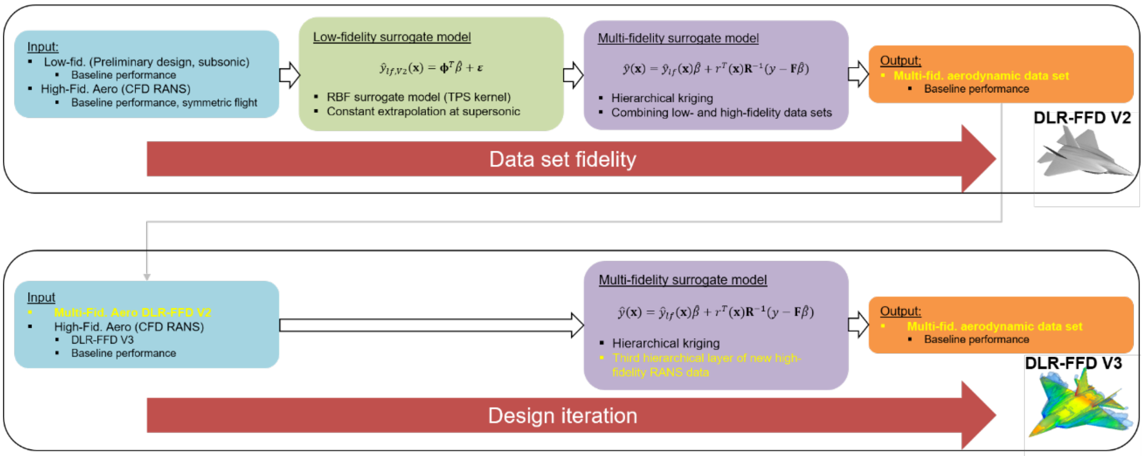



**Figure 3-2: Multi-fidelity modelling approach of the DLR-FFD use case.**

All three aerodynamic data sets of the DLR-FFD encompass the complete flight envelope with only one exception, the low-fidelity data set is restricted to subsonic flight speeds. The flight envelope covers a Mach number range from 0 to 2.0, altitudes between 0 and 50’000 feet as shown in Figure 3-3. The angle of attack range considered in high-fidelity simulations goes up well-beyond cruise conditions—at subsonic speed up to 50 degrees.

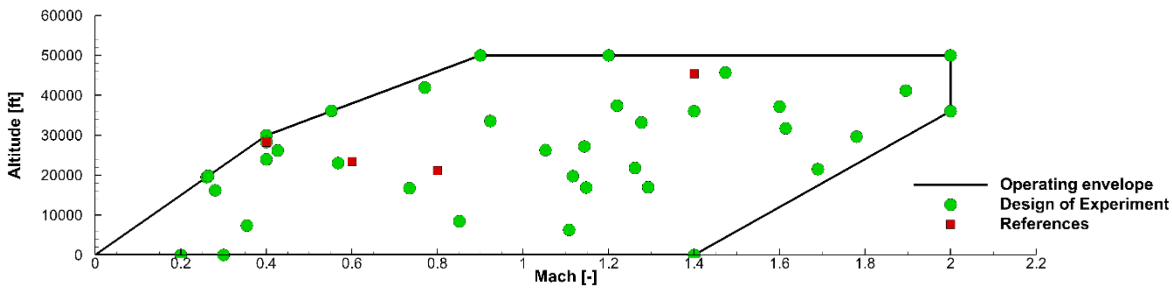
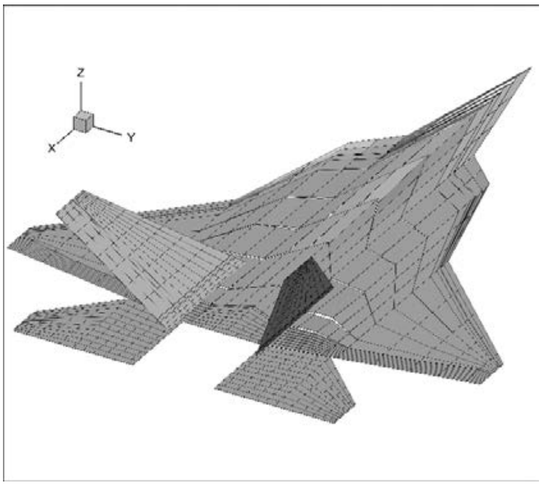



**Figure 3-3: Operating envelope of the DLR-FFD and the design of experiment for the high-fidelity CFD simulations of the initial design. Alpha curves at certain Mach-Altitude combinations are selected as reference simulations.**

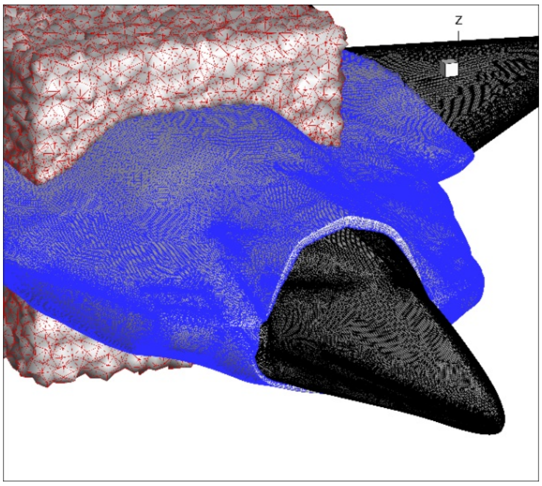
All data sets follow the superposition principle of the CPACS data format for aerodynamic analysis and are subdivided into three sections: First, a full-factorial baseline performance map, second, quasi-steady dynamic derivatives obtained at the flight points of the baseline map and, third, multiple increment maps of the aerodynamic coefficients due to control surface deflections. The baseline map is defined for parameter combinations of altitude, Mach, angle of sideslip and angle of attack. All coefficients related to control surface deflections are computed as increment values to the baseline map for multiple deflection angles. Under this assumption of superposition, it is possible to provide data sets which are built from different sources, e.g. increment maps with low-fidelity aerodynamics and a baseline performance map predicted by multi-fidelity surrogate models which are built by using both, low- and high-fidelity data sources. This approach enables the provision of comprehensive data sets covering the complete flight envelope at early design phases to subsequent disciplines such as flight mechanics or control system design without lacking important information only because the fact that not for all parts high-fidelity data is already available. As soon as high-fidelity data becomes available for another control surface for instance, this can be easily integrated into the existing data set. In the following only the baseline performance map is considered where aerodynamic data from different sources is available to build multi-fidelity surrogate models.

### 3.2.1 Initial Geometry

Low-fidelity CFD tools are evaluated for the initial design and the corresponding data set contains more than 300’000 entries for the full subsonic flight envelope from which 9’120 points belong to the baseline performance map. This is in a full factorial design order and subsequently used by the multi-fidelity surrogate model. As a first guess for high speed performances and control surface increments constant extrapolation from the highest Mach number available is applied to fill up the complete operating envelope. Regarding the high-fidelity CFD simulations, the design of experiment is shown in Figure 3-3 and consists of a Latin hypercube sampling design for the full operating envelope which is supplemented by two Halton sequences at sub- and supersonic conditions together with few manually selected samples which sums up to 44 samples in total. In addition, alpha sweeps at three different Mach numbers as test set for the multi-fidelity surrogate model (16 reference samples) are computed. Both computational grids used for low- and high-fidelity are shown in Figure 3-4. The master geometry is discretized into 1138 panels by LIFTING_LINE. All low-fidelity samples are computed within only a few hours on a common desktop computer. In contrast, the computation of high-fidelity solutions using RANS or time-averaged Unsteady RANS (URANS) varies between one hour and about a week for one flow solution on an HPC system using 640 processors for a computational grid with 26 million grid nodes.




**a) Low-fidelity LIFTING_LINE panel mesh.**




**b) High-fidelity RANS mesh.**

**Figure 3-4: Computational grids of the initial design for the DLR-FFD.**

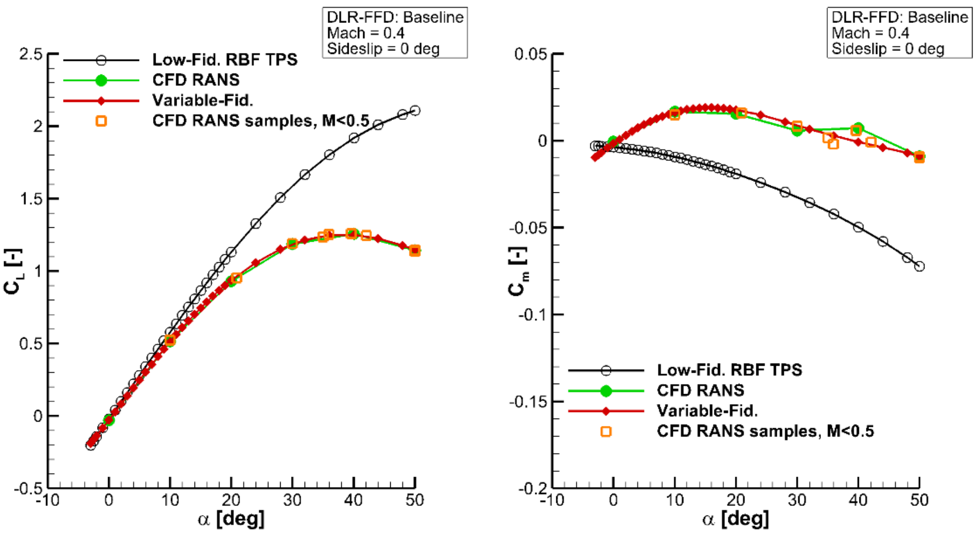



**Figure 3-5: Lift and pitching moment coefficients obtained by low- and high-fidelity CFD and combined by means of a multi-fidelity surrogate model at Mach 0.4. CFD RANS and time-averaged (U)RANS samples shown are distributed over a range from Mach 0.2 to 0.5.**

In Figure 3-5 the lift and pitching moment coefficients at Mach 0.4, an altitude of 28'250 ft and zero-sideslip for varying angles of attack are shown. RBF surrogate models are built for the complete set of low-fidelity data points using a Thin-Plate-Spline (TPS) kernel function, which interpolate the LIFTING_LINE results exactly. The multi-fidelity surrogate models combine the CFD (U)RANS samples with the RBF-TPS models as global trend models in a hierarchical manner. Additional CFD (U)RANS samples (depicted in green), which are unseen by the multi-fidelity surrogate models, represent reference solutions. During this first iteration a correction of the low-fidelity baseline based on only a few high-fidelity CFD (U)RANS evaluations (44 samples in total) is performed. In general, it can be stated that the multi-fidelity surrogate models are able to correct the global trend of the underlying low-fidelity solutions using high-fidelity information for both coefficients. In particular the lift slope and the maximum lift coefficient are in good agreement with the reference solutions. Regarding the pitching moment coefficient, the magnitude is well aligned with the reference solution, even though the multi-fidelity surrogate model was not able to detect local nonlinearities when the primary vortex system is broken down and massive flow separation occurs at high angles of attack.

As described above, even though only the accuracy of the baseline performance map is improved at this stage, the updated aerodynamic data set consists still of all damping derivatives and increment maps for all control surfaces that are obtained by low-fidelity methods. This allows to hand over a comprehensive data set by means of a CPACS file to subsequent disciplines without losing any other information.

### 3.2.2 First Design Iteration

The second scenario represents one design iteration which takes place after the assessment of the flight performances based on the multi-fidelity aerodynamic data set of the initial configuration. Instead of incorporating data from the low-fidelity CFD tools into the multi-fidelity surrogate modelling approach, the data set of the previous design iteration, the initial design, is used (see Figure 3-2). This means, the underlying trend models of the hierarchical kriging models include now high-fidelity data and, therefore, are able to provide more accurate information about the nonlinear aerodynamic effects. Even though, the geometry differs between the two design iterations, it is assumed that during such a design study, both configurations belong to the same family. With this assumption, the multi-fidelity aerodynamic data set of the initial configuration is corrected by now interpolating new high-fidelity data which is obtained for the updated design as shown in Figure 3-6 at an example of the lateral force and moment coefficients under sideslip conditions. The hierarchical definition of the models ensures a stronger weighting of the data of latest design iteration.

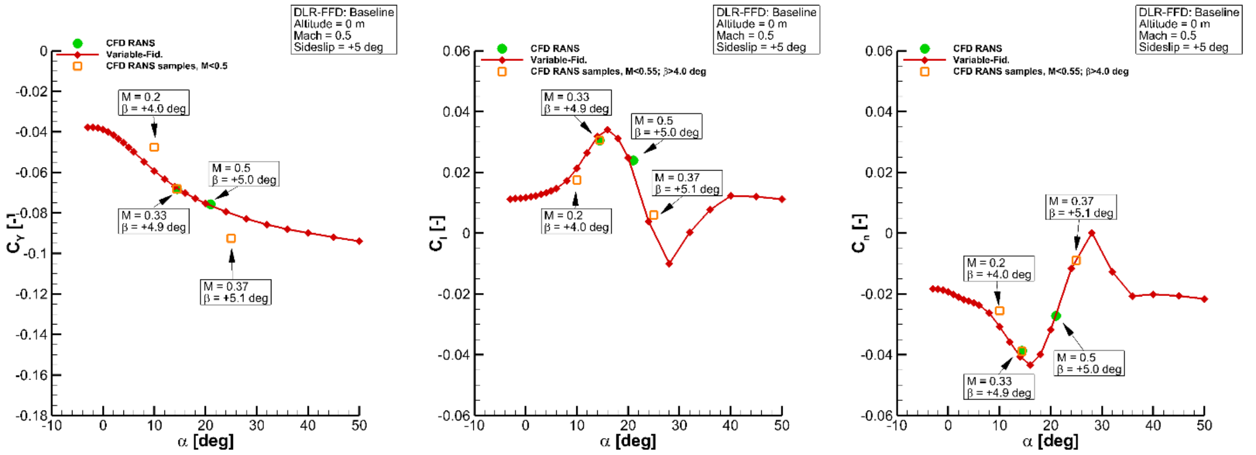



**Figure 3-6: Multi-fidelity surrogate model predictions of the side force, rolling moment and the yawing moment coefficients at Mach 0.5 and non-zero sideslip conditions. CFD RANS and time-averaged (U)RANS samples shown are distributed over a range from Mach 0.2 to 0.5 for varying angles of sideslip.**

Further, SMARTy allows to re-use the hierarchical models from the first iteration, which results in three or more hierarchical layers. Consequently, in this scenario the geometry only needs to be prepared for the high-fidelity mesh generation. The low-fidelity tool is omitted when executing the workflow.

## 4.0 CONCLUSION

A new multi-fidelity aerodynamic data set generation framework is presented to be integrated into conceptual aircraft design frameworks. One of the key aspects that enables an early use of high-fidelity CFD during aircraft design is a comprehensive automation and parametric modelling from the first representation of a geometry up to CFD solver evaluation and prediction of aerodynamic data sets. The workflow is based on a common data exchange file format, the CPACS format, and its benefits for usage during early design phases, in particular in terms of a master geometry definition and aerodynamic performance maps based on a superposition principle, are outlined. Tool specific geometrical representations can be derived from the master geometry providing the required representation fidelity for either classical aerodynamic conceptual design tools, such as potential flow codes, or highly accurate CFD solvers. The latter includes an automatic geometry and mesh coupling for automated, fixed mesh generation suitable for RANS flow solvers. Finally, surrogate models which efficiently combine low- and high-fidelity data sources and having rapid prediction capabilities to create aerodynamic data sets are described. Multi-fidelity surrogate models, such as hierarchical kriging, incorporate a low-fidelity model as a global trend model, while interpolating only few high-fidelity CFD samples. In addition to data set generation for a fixed geometry, the scenario for a design iteration is outlined, which follows the same multi-fidelity surrogate modelling approach but with the previous initial multi-fidelity surrogate model as global trend model instead of a low-fidelity surrogate model.

Results are presented for a generic triple-delta combat aircraft, the DLR-FFD. Aerodynamic force and moment coefficients are predicted in a scenario reflecting an evolving aerodynamic data set. The accuracy of the data set is improved as soon as higher fidelity data becomes available in a conceptual design process. Here, the baseline performance map is improved. Even though the design of experiment for the high-fidelity CFD simulations is done with regard to an assessment of flight performance for the level-flight operating envelope, handling qualities for instance can still be assessed based on low-fidelity results stored in the same data set.

Important future steps for preparing the workflow towards a widespread usage in industry are, with regard to the geometry and mesh coupling, to further increase robustness of the automated processes and to derive best-practices. Envisaged extensions for CPACS4TAU are to enable adaptive mesh refinement and to create an interface with the FlowSimulator for an increased flexibility of customized process chains and possible multi-disciplinary applications. Further, implementations for automatic computation of damping derivatives and an extension towards control surface deflections via mesh deformation are in progress. Future work on multi-fidelity surrogate models will focus on quantification and propagation of uncertainties. Moreover, the multi-fidelity surrogate models shall be used within six degrees of freedom manoeuvre simulations.

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