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D-1.1 REVIEW OF EXISTING LITERATURE AND IDENTIFICATION OF DIGITAL SOLUTIONS

MODEL-SI

Digital Transformation – Case Studies for Aviation Safety Standards – Modelling and Simulation

An Agency of the European Union

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SUMMARY

This report is a deliverable document labelled D-1.1 about the “Literature and digital solutions review” of the research project number EASA.2022.C25 named MODEL-SI (Digital Transformation - Case Studies for Aviation Safety Standards - Modelling and Simulation).

We present the result of a literature survey carried in the first months of 2023 and concerning modelling and simulation of eVTOL aircraft. We divided the findings into different categories including modelling methodologies, the use of simulation for certification, the multi-fidelity approach to modelling. The fast increasing pace of publications in these areas is evident. The interest of the research and industrial community is so strong that as this report is submitted, a large number of newer papers are being presented at the AIAA AVIATION conference and published on scientific journals.

CONTENTS

ABBREVIATIONS

ACRONYM	DESCRIPTION
AI	Artificial Intelligence
ANN	Artificial Neural Networks
BEM	Blade Element Momentum
CAS	Control Augmentation System
CFD	Computational Fluid Dynamics
DES	Detached Eddy Simulation
DMD	Dynamic Mode Decomposition
DT	Digital Twin
EASA	European Union Aviation Safety Agency
eVTOL	electrical Vertical Takeoff and Landing
FCS	Flight Control System
FEM	Finite Element Method
GP	Gaussian process
ISS	International Space Station
LES	Large Eddy Simulation
MBC	Multi-Blade-Coordinates
ML	Machine Learning
NN	Neural Network
NS	Navier-Stokes
PID	Proportional-Derivative-Integral
POD	Proper Orthogonal Decomposition
QRM	Quarterly Report Meetings
RANS	Reynolds-averaged Navier–Stokes
ROM	Reduced Order Model
SA	Spalart-Allmaras
SAS	Stability Augmentation System
SMT	Surrogate Model Toolbox
SST	Shear Stress Transport
SVM	Support Vector Machine
VLM	Vortex Lattice Method
VPM	Vortex Particle Method

1. Literature survey

1.1 Background

Even though simulations have been exploited for the prediction of aircraft loads and performance for over half a century, methodologies and approaches represent still an active field of research. Broadly speaking, simulations are classified based on their ”closeness” - or fidelity - to reality. Higher fidelity approaches typically rely on Computational Fluid Dynamics (CFD) and Finite Element Method (FEM). Moreover, we tend to add the indication ”physics-based” to models which are developed from first principles.

Numerical simulations are a pre-requisite for Digital Twins; the term Digital Twin (DT) is increasingly popular to indicate a mathematical model with which the entire life of a product (aircraft) can be simulated with deviations expected not to affect flight safety and the behaviour of the aircraft significantly. Remarkably, DT can be exploited for design and certification, further cutting the costs associated with flight testing. This opportunity is more interesting for innovative configurations such as those associated with the so-called eVTOL aircraft, which are characterized by a substantial complexity of the aerodynamics and dynamic response of the structure and systems.

At the present time, the computational power and software programmes available at virtually all aircraft manufacturers allow high-fidelity analysis of complete aircraft configurations. However, the sheer quantity of test cases Digital Twins must run, make the high-fidelity approach alone impractical.

Historically, the industry has relied on lower-fidelity physics-based simulations for design and certification, with systematic use of CFD to assess steady-state aerodynamic loads, which is only sporadically used in unsteady analysis or aerodynamics-structure coupled analysis. Whereas these models are very reliable for known configurations, they may be unsuitable for innovative ones.

Multi-fidelity approaches are arguably the most promising option to exploit high-fidelity methodologies and data. These approaches may be exploited to punctually correct, or tune, low-fidelity models based on higher-fidelity analysis or experiments. The approach is well known, it has been systematically exploited ever since simulation was born. However, multi-fidelity approaches stand to benefit largely from newly available algorithms, mostly classified as Machine Learning (ML). To be fair, some of these algorithms are not new but only “re-packaged” in highly efficient form in software packages like TensorFlow or pytorch.

In practice, data-driven surrogate models can be efficiently derived from high-fidelity simulations and experiments (flight testing or wind tunnel measurements) and combined with the conventional lower-fidelity models, yielding higher accuracy at a negligible cost increase. The cost of training (building the surrogate model), how- ever, is substantial.

The MODEL-SI case study is carried out by enhancing an initial physics-based mathematical model, exploiting data from high-fidelity numerical simulations, computational fluid dynamics (CFD), and structural dynamics, as well as from flight testing. The “enhancement” concerns both accuracy and scope and is carried out via conventional and ML techniques, each exploited at its best. The final DT is expected to be a hybrid surrogate model-based DT, in which the necessary accuracy is provided by the initial physics-based model (partial differential equations) coupled to several surrogate models.

The expected result is a living DT able to reliably explore the entire flight envelope as well as the design space by accounting for changes in mass, centre of gravity, and configuration. The DT as such is expected to not only support certification but also continued airworthiness and follow the drone through its operative life. The availability of data from diverse sources is expected to provide sufficient information to also take uncertainties (environment, manufacturing tolerances, operative parameters…) into account and provide a “robust” modelling environment.

A low-fidelity model is meant to have a short execution time and usually low accuracy when compared to the ground truth. However, some codes, such as CAMRAD, run within reasonable computational times (in the order of seconds) and provide a good level of accuracy at the expense of a lack of flexibility and limited scope, as they also exploit empirical corrections and simpler mathematics.

On the other hand, high-fidelity models refer to those that have an execution time of several hours per test case and configuration.

1.2 Study objective and methodology

The goal of the literature review is to understand which are the most promising trends among the digital solution that can help to decrease the computational costs, time, and workload effort in the whole aircraft development, i.e. from initial design to certification.

The SciTech conference 2023, held in National Harbor from 23 to 27 January 2023, was the starting point and in particular the sessions devoted to multi-fidelity and surrogate modelling as well as the many talks involving electrical Vertical Takeoff and Landing (eVTOL) aircrafts. Subsequently, the most relevant references cited by the SciTech papers, were added. To complete the review, additional references were added independently.

1.3 Findings

1.3.1 White Papers

Initially, the AIAA white papers [1, 2] are cited as a prominent example of guideline documents. The paper [1] proposes DT definition and values by exploring its importance in the aerospace industry. It emphasizes the potential of digital twins to enhance engineering processes, improve system performance, and increase reliability. The paper's authors come from a wide range that includes the major part of the aerospace industry, i.e. from academia, industry, and government.

The paper has four major goals:

- DT shared definitions within the aerospace industry
- DT real-world applications to demonstrate its potential
- DT perspective, e.g. advantages and drawbacks, from the aerospace industry and US Department of Defense points of view
- outlook to improve and extend the DT use benefits

The most important definition is about the DT itself. It is described as:

A set of virtual information constructs that mimic the structure, context and behaviour of an individual/unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its life cycle and informs decisions that realize value.

The definition expresses perfectly what is our understanding of a DT applied to our case study.

On the other hand, the work of Pinon et al. [2] discusses the application of digital twin technology by introducing reference models and providing a conceptual framework for their development and utilization. It discusses various realizations of DT in different industries, highlighting their potential applications and benefits. In particular, they reviewed an interesting case of a Cygnus Orbital Ferry Vehicle of Northrop Grumman Corporation. It is a spacecraft cargo carrier for the International Space Station (ISS). The DT aims to simulate the spacecraft performance during several application stages, such as safe rendezvous, descent, and re-entry. Here the DT is built to estimate the propellant usage of the service module. The DT is continuously updated and gives real-time indications of propellant left and about Guidance Navigation and Control. For example, in this case, the service module stays in orbit more than planned. Surrogate models of spacecrafts are particularly interesting because of the small number of experimental data. In this field, the maximization of the ground truth data is even more important.

Another interesting DT is about the certification testing of Boeing commercial aircraft seat systems. The goal is to reduce the number of physical and simulation tests. In both cases, the effort required is significant and the DT shows a potential reduction in certification tests of 50% - 70%.

1.3.2 Low-fidelity modelling of eVTOL

A number of papers focused on low-fidelity modelling techniques were selected [3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]. They exploit a different number of techniques to model the eVTOL aerodynamics, rotors, structure and FCS. Table 1.1 classifies the papers for modelling areas and summarizes the reviewed numerical methods.

Aerodynamics

The most popular method used to model aerodynamics is the Vortex Lattice Method (VLM), but many different has been developed. A valuable and detailed summary can be found in [20]. Drela provides a comprehensive introduction to the fundamental principles, theories, and models that recap the basis of aerodynamics. It covers a wide range of low-fidelity methods, including the VLM, panel methods, and various analytical models.

The VLM can easily and quickly calculate the aerodynamic forces on any wing or tail. It originates from the lifting line theory, which is a potential flow method and therefore it does not consider viscous or dissipation effects. The lifting surfaces are discretized in thin panels or sheets and a corresponding horseshoe vortex. The determination of the forces is done by solving the circulation around each panel in a system of equations.

Another advantage is the relatively easy calculation of stability and control derivatives. They can be useful for several applications, such as a simple aerodynamic database for the development of a dynamic flight simulator.

Another convenient and rapid method takes advantage of the so-called strip theory. It originates from the Blade Element Momentum (BEM) theory, usually employed in rotor modelling, but it can be also applied to lifting surfaces. The wing is discretized into spanwise parallel strips each treated as 2D airfoil independently. The strips can rely on predefined look-up tables and they can be corrected for 3D effects caused by local relative speed variation. The 2D look-up tables can even derive from high-fidelity data such as CFD or wind tunnel testing.

Among our low-fidelity paper selection, the works of [5, 9, 10, 11] rely on the VLM approach. Clarke et al. [11] compared three different three passengers electric aircraft: a general aviation, a distributed propeller, and an eVTOL. They also coupled VLM with a BEM model for the propeller successfully. The papers exploiting strip theory are [3, 21, 17]. Even in this case, the approach was coupled with a rotor model of a tilt-wing eVTOL.

The comprehensive code SUAVE [22] is widely exploited. It is a cutting-edge platform for conceptual aircraft design that can assess and enhance both traditional and innovative designs. It differs from other software tools that rely on predetermined empirical relationships and handbook approximations for aircraft conceptualization. On the other hand, it offers a versatile framework with many physics-based methodologies that varies from aerodynamics, structures and noise. For mission performance optimization, it takes advantage of a force balance-based mission solver which can simulate predefined flight points on the mission path calculated from the other modules (such as aerodynamics, propulsion, weight and balance).

Rotors

The main critical issues of rotor modelling can be traced back to the following three aspects, mutually affecting one another:

- blade aerodynamics is different and more complex compared to a fixed wing, due to phenomena of reverse flow, dynamic stall, compressibility and radial flow;
- blade dynamics includes flapping (out-of-plane deflection), lead-lag (in-plane deflection) and feathering (torsion) motions;
- the complex vortex wake generated by the rotor interacts heavily with the blades as well as with the other airframe components and with the ground.

Each of these aspects can be modelled with varying levels of fidelity; a review of the available techniques can be found for instance in [23].

The simplest approach, the so-called actuator disk model, comes directly from the momentum theory [24]. The rotor is modelled as a continuous circular disk with an infinite number of blades, which induces an acceleration in the axial flow direction by generating a pressure difference across the rotor plane. A simplified, 2D airfoil aerodynamic model is typically used, in which the lift force is a linear function of the blade angle of attack and the drag force is a quadratic function of lift. The rotor-induced downwash is assumed to be uniform and calculated as a function of thrust using a simple formula derived from the momentum theory. The rotor equations of motion are expressed in Multi-Blade-Coordinates (MBC), i.e. considering the degrees of freedom of the rotor disc as a whole rather than the singe blades, and solved analytically [25, 26].

A more accurate approach to rotor modelling is the blade-element theory, which is based on the simple idea of splitting the rotor blade along its span into multiple thin sections [27, 28, 26]. The airfoil aerodynamic coefficients are usually stored in look-up tables as nonlinear functions of angle of attack and Mach number, with the data originating from wind tunnel tests, numerical or theoretical predictions; the forces and moments are calculated separately for each section and integrated over the entire blade span. Theoretical or empirical corrections can be used to account for dynamic stall effects [29, 30], tip losses [26], and other three dimensional effects [27, 31].

In most blade-element models, the equations of motion are solved independently for each blade using numerical methods. A classic approach consists in assuming rigid blades and concentrating the degrees of freedom in an equivalent hinge with spring constraint [32, 33]; more refined techniques including elastic blades also exist, based for instance on modal representation [34, 35, 36].

A detailed review of wake modelling methods for flight dynamics applications can be found in [37]. Among the lower-fidelity techniques, a widely used approach is the so-called finite-state wake model: here, the inflow at the rotor is modelled as a series of harmonic and radial modal functions, each satisfying the rotor boundary conditions as well as the continuity and momentum equations, through the relationship with the blade lift distribution; this results in a series of first-order ordinary differential equations for the coupled inflow/lift, which can be added to the rotor dynamic model without excessively increasing the computational load. The original dynamic inflow model was introduced by Pitt and Peters [38, 39], and subsequently generalized by Peters and He [40, 41] to accommodate an arbitrary number of modal functions; in addition, enhancements to both models have been introduced to account for wake distortions during manoeuvring flight [42, 43, 44, 45, 46, 47, 48, 49, 50].

Another technique for wake modelling is based on ”prescribed” wakes, where wake geometry parameters are prescribed in space based on experimental studies, and the wake vorticity is transported downstream by sheets or filaments; the strength of the vorticity is a function of the lift when the vorticity was shed from the rotor, and the induced velocity at any point in the wake can be calculated using the Biot-Savart law [27, 28, 51]. Prescribed wake methods were frequently used in the past to model rotor wake-induced velocities on other helicopter components such as the tail empennages and tail rotor [33, 52, 53]; other available approaches range from extensions of the finite-state dynamic wake model [54, 55, 56], to simple empirical corrections derived from flight test data [57, 58].

Among our papers selection on eVTOL modelling, the most used method is the Blade Element Momentum (BEM), which combines the momentum theory and the blade-element theory [4, 8, 9, 10, 11]. In the BEM approach, the blade forces and moments are evaluated separately for each blade section and integrated along the span; the induced velocity at each section is instead calculated using the momentum theory. Apart from some hover empirical correction, the papers do not model the motors further. The inflow is considered steady and there is no wake interaction.

Structures

The most well-known methods to model aircraft structure are Finite Element Method (FEM) [59] and Rayleigh–Ritz method [60]. The former is based on the system breakdown in finite elements, such as beams and nodes. Each element has its properties, such as stiffness and inertia, and it is interconnected with each other. Then based on the structural problem complexity, a set of partial differential equations is needed. In the low-fidelity case, we are talking about linear equilibrium equations solvable analytically with the help of linear algebra.

On the other hand, the Rayleigh–Ritz method can be applied to simpler problems with accurate results. It is based on the variational formulation of the boundary value problem. For example, the well-known code CAM-RAD [61] is using this method for the rotor structure modelling. However, thanks to its implementation simplicity, FEM models were widely used for eVTOL structural simulation [4, 8, 18, 19, 10]. Relevant for low-fidelity implementation is the implementation of the tool OpenAeroStruct. The toolbox is described in the work of Jasa et al. [19], where they coupled a VLM with a six-degree of freedom FEM for multi-disciplinary design and optimization purposes. Hendricks et al. use it as well to represent the wing of the tilt-wing vehicle concept of NASA.

Flight Control System

A simple way to model the flight dynamics behaviour is through linear control techniques. Detailed information can be found on [62, 63], which are often used as a reference during Flight Control System (FCS) lectures. The first step would be to model the system dynamics using a set of differential questions. The classical equations of motion best describe aircraft dynamics.

The states of the system represent the motion variables in translation and rotation. Input and outputs are defined depending on the eVTOL type and needs. The next step would be to trim the aircraft at a given condition and linearize it around that point. The small perturbation method is a valuable approach. By doing so, the resulting linearized model captures the system local behaviour near the operating point. We can express the system in a classical state-space form and design a suitable controller.

Various control design approaches are known, such as Proportional-Derivative-Integral (PID) cascaded controllers. It involves selecting appropriate control gains or designing feedback control laws to achieve desired stability, performance, and robustness. Finally, we can analyse the stability and performance of the designed controller using tools such as eigenvalue analysis, or simply by simulation.

Several papers do not develop an aircraft controller although they optimize the eVTOL geometry over a specific mission profile. In general, the aircraft is trimmed under the required conditions of the flight mission, such as in [3, 5, 9, 8, 4].

A trim routine is the baseline for an effective eVTOL design. For example, we can start defining the conversion corridor and therefore better understand the aircraft behaviour. The analysis of the transition between helicopter/airplane is one of the most challenging design tasks. In fact, the eVTOL needs to be dimensioned considering the conversion corridor required size as well.

In general, the selected studies goal was mainly focused to explore the interactions, and characteristics of eVTOLs during different flight regimes, such as cruise and landing for multidisciplinary design improvements, sensitivity analysis and design control strategies.

Modelling area	Numerical Methods	References
Aerodynamics	VLM, strip theory, empirical models	[20, 5, 9, 10, 11, 3, 21, 17, 22]
Structures	FEM, Rayleigh–Ritz method	[59, 60, 61, 4, 8, 18, 19, 10, 19]
Rotors	BEM, Actuator disk	[23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 4, 8, 9, 10, 11]
FCS	Transfer functions, State-space models	[62, 63, 3, 5, 9, 8, 4]

Table 1.1: Summary of low-fidelity methods.

1.3.3 High-fidelity modelling of eVTOL

High-fidelity methods are more accurate but more computationally expensive than low-fidelity methods, firstly by the aerodynamics simulation of external forces. Usually, when one grasps high-fidelity methods, it focuses on a few aircraft components and physical phenomena, for example on the interaction of rotor-wing which, depending on the geometry arrangement, can influence each other.

Aerodynamics

Nowadays, CFD is ubiquitous, the level of complexity to carry out a simulation is always decreasing in the so-called democratization of simulations. Even the number of numerical methods is large and the choice of the correct approach depends heavily on which physical phenomenon you want to capture and what are your computational resources. High-fidelity models require heavy computational grids, i.e. millions of cells to solve the flow correctly. The vast majority of the methods tried to solve the Navier-Stokes (NS) equations, but unfortunately, the computing time to solve them directly in a full aircraft configuration is in the scale of decades. Therefore, modelling of NS equations is required and many different methods have been developed.

Among them, the most used ones are the Reynolds-averaged Navier–Stokes (RANS) equations. They are based on the averaged NS equations in time and coupled with a turbulence model. Many different approaches are available and successfully used by the aerospace industry, among them the Spalart-Allmaras (SA) and k-omega Shear Stress Transport (SST) models. They use a one and two-equations turbulence model, respectively. If RANS equations are not sufficient to capture the flow physics, more computationally expensive approaches are Large Eddy Simulation (LES) and Detached Eddy Simulation (DES). The former solves large-scale turbulent flows, e.g. large eddies, and it filters out sub-grid scale ones. Depending on the case, they could significantly improve the simulation results, especially when flow separation occurs. However, the computational costs can be even one order of magnitude higher than that. While the latter is a hybrid method that takes advantage of RANS and LES. Usually, you solve the boundary layer near the walls with RANS turbulence modelling, while the rest of the domain with LES.

A large number of papers that exploits high-fidelity methods in the framework of urban mobility were published in the lasts years [64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 74]. In order to keep the problem simpler, some works [70, 72, 73, 76] model only the rotor-wing interaction. The wing surface area is discretized and simulated with a state-of-the-art CFD RANS model, whereas the rotor contribution is considered by means of CFD-embedded BEM or actuator disk models. The analyses aim to optimize the wing and/or rotor shape under a certain type of constraint.
On the other hand, other works are centred on the analysis of an entire aircraft, in particular the NASA urban air mobility concept vehicles [77], where the studies goal are related to multi-disciplinary analysis and optimization. Those concept vehicles were introduced as reference aircrafts in different eVTOL categories.
They address the simultaneous optimization of various design aspects, including aerodynamics, structures, actuator parameters, and propulsion configurations, to achieve enhanced performance and safer trajectories.

Rotors
A well-known class of mid-fidelity rotor analysis tools is represented by the so-called comprehensive analyses, typically combining finite-element, multi-body models of the blades structural dynamics with lifting-line aero-dynamics models and free-wake models of the rotor vortex wake [78, 37, 23]. Today, these features are also offered by well-known commercial codes such as CAMRAD [61, 79] and FLIGHTLAB [80].

A modern, mid-fidelity and promising approach is the so-called Vortex Particle Method (VPM) [81]. It is based on a free-mesh Lagrangian approach that solves the Navier-Stokes equation in its vorticity form. Compared to conventional CFD, it can be one to four orders of magnitude faster with similar results [82]. However, the available codes still have some limitations, in particular, they are limited to low angle of attack simulations. Two of the most promising of these types of research codes are DUST [83] and FLOWUnsteady [84]. They are both based on VPM but the implementations are slightly different. The image below portrays the flow field of a two-blade propeller simulated with a VPM code. This could be a reasonable approach instead of using brute force and grasping CFD by discretizing the real rotor blades.

A more complex and computationally expensive approach is to model completely the rotor blade thanks to multi-domain CFD. The works of [75, 85, 86, 87] pursue this path successfully for various aerospace applications.

The method used is very similar and it discretized and resolve completely the blade rotation. Apart from the large grid size, the domain needs to be divided into a fixed, which contains the farfield domain and fixed aircraft parts such as fuselage and wings, and a moving reference frame for the rotors. For example, Lewis et al. [75] studied the rotor performance related to the hybrid VTOL SureFly S250. It is a single seater aircraft with four pair of counter-rotating propellers. By means of CFD, they analysed and compared the rotors efficiency in normal and critical conditions, such as integrated loads and vortex ring state.

Structures
From a structural point of view, FEM is always used, but with higher model complexity. For example, instead of modelling the wing only as a spatial beam elements, one could model the entire aircraft with wing lay-ups and internal spars. This approach results as well in better prediction of the aircraft weight and its distribution. In the frame of the development of new aircrafts design, Hansen et al. [88] performed a multidisciplinary optimization of a blended wing body. Their process included a parametric creation of the aircraft primary structure to be then modelled and simulated by a classical FEM solver.

The structures were coupled with an aerodynamic panel method to assess the loads and aircraft performance to better size the new configuration. Another interesting work that models an entire aircraft was done by Hermanutz et al. [89]. They optimized a UAV demonstrator under flutter-related constraints.

Here the main aircraft parts were considered: rigid fuselage, rigid empennage and wings. The last part was modelled in detail including a composite sandwich shell with corresponding spars. On the other hand, the works of [90, 76] modelled only the aircraft wing with FEM. Both these researches concern the structural optimization of a high-aspect-ratio wing and analyse their flutter behaviour.

Flight Control System

An improvement of the FCS could be related to the flight dynamic model and the flight controllers. The book of Stevens [63] covers several classical techniques, such as stability augmentation systems (SAS) or control augmentation systems (CAS) to improve the aircraft flight behaviour. The SAS is usually designed to help the pilot to maintain the aircraft under control, e.g. the attitude, introducing automated control inputs to prevent not desired movements or oscillations. On the other hand, a CAS is designed to facilitate the pilots work enabling him to operate the aircraft easily.

In addition, it covers modern approaches, such as linear-quadratic regulator optimal control and robust control. The former method is used in the works of Wang et al. [91, 74]. They designed an optimal control for various flight phases, such as cruise, descent, and landing under operational constraints. The aircraft modelled was a single seater eVTOL and the goal was to implement an optimal controller with real-time trajectory optimization.

Finally, the works of [92, 93] exploited another modern control technique, the nonlinear dynamic inversion. As the name suggests, this method involves the inversion of the system dynamics to achieve desired control objectives. This process results in having an equivalent linear system and therefore we could apply linear control techniques, like PID controllers. The research focused on hover and landing controllers, respectively.

Table 1.2 classifies the papers for modelling areas and summarizes the reviewed numerical methods.

Modelling area	Numerical Methods	References
Aerodynamics	CFD, RANS, DES, LES	[64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75]
Structures	VPM, multi-domain CFD	[78, 37, 23, 61, 79, 80, 81, 82, 83, 84, 75, 85, 86, 87]
Rotors	FEM	[76, 90, 89, 88]
FCS	SAS, CAS, optimal control, nonlinear dynamic inversion	[63, 91, 74, 92, 93]

Table 1.2: Summary of high-fidelity methods.

1.3.4 Certification

This section is devoted to the use of analysis for certification purposes. Ref. [94] stands out for relevance and publication date. This work is focused on the concept of ”Certification by Analysis” of airplane and engine certification. The proposed approach provides several advantages such as targeted testing programs at reduced costs while maintaining safety levels.

The development of advanced numerical flight models, including high fidelity methods such as CFD, is crucial for the effectiveness of this approach. The document emphasizes the need for improved analysis capabilities, validation against full-scale aircraft data, and the quantification of modelling uncertainties. It proposes a technology roadmap by identifying technical challenges and provides recommendations to overcome the current challenges and to successfully pursue the Certification by Analysis.

Another document relevant to this topic is the European Union Aviation Safety Agency (EASA) certification memorandum on CS-25 Structural Certification Specifications [95]. It focuses on some more high level aspects of the Certification by Analysis, such as the verification and validation of the model itself and its related errors/uncertainties. Another interesting work is the so-called ”Rotorcraft Certification by Simulation” [96].

It is related to the development of guidelines on the exploitation of rotorcraft flight models and simulators for certification purposes. The method should shorten the certification process, and reduce the costs and risks during the process of an innovative vehicle. Some ideas could be also used for the certification of eVTOL aircrafts.

Related to certification, the following papers address the propagation of uncertainties and the validation of computational modelling [97, 98, 99, 100, 101, 102, 103]. They include the assessment and quantification of uncertainties in computational models and validation methods used for certification. The understanding of these uncertainties allows aircraft developers for a more accurate and reliable prediction of their vehicles, ensuring their safety and regulatory compliance.

In addition, the EASA proposed several interesting papers about Artificial Intelligence (AI) and certification. The concept paper [104] is part of the EASA AI Roadmap, which should help developers that want to grasp AI technology for safety-related tasks.
The objective is to provide guidance to applicants on the integration of AI or ML technologies across all activities governed by the EASA Basic Regulation. It defines four ”AI trustworthiness building blocks”, which are trustworthiness analysis: AI assurance, AI human-factors and AI safety risk mitigation. These blocks are all linked together with seven ”gears”, where each gear corresponds to a specific topic, such as privacy and data governance. The paper tries as well to identify the impact of AI in all major domains of the EASA Basic Regulation. Finally, it provides some use cases as well. Among them, the visual landing guidance system developed by Daedalean is analysed. Their AI-based system should reduce the workload of the pilot during a landing. They also suggest how the user should interact and interface with the Daedalean landing system. Always in the EASA AI roadmap, these two documents should also be considered [105, 106].

The former goal is to assess if Formal Methods techniques can potentially be used in evaluating the reliability of ML applications, while the latter analyses novel concepts for assessing and certifying AI-based systems. Both aim to assist industry stakeholders in the development of AI applications.

1.3.5 Multi-fidelity modelling and data fusion

This section shows references to the actual building of the mathematical model and in particular, the techniques exploited to match data with different fidelity levels [107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 114, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143].

Gaussian Processes
Gaussian processes (GP) are stochastic models that describe a certain amount of data with functions. It is composed of a mean function and covariance function, also known as kernel function. The former represents the average behaviour of the data distribution, while the latter determines how the functions vary with each other across different data points. They are widely used in statistics for regression, interpolation and uncertainty

quantification. In fact, one of the advantages of GP is that it can predict the evolution of observed data alongside with its confidence. GP regression is the branch where the observed data is fitted using a function, often referred to Kriging.

In this method, it is assumed that the spatial relationship between data points, whether in terms of distance or direction, can be utilized to explain the changes or differences observed in the space being studied. In the framework of our research, GP regression can be applied to relieve the computational cost.

Rasmussen's book [117] contains an extensive overview of GP. It explains what kernel machines are and their basic principles. In the last few years, the ML community is also looking into GP to build data-driven models. It contains both theoretical and practical aspects of GP covering supervised learning for regression and classification and it provides detailed algorithms. For example, it describes the most used covariance functions along with their properties.

Reduced Order Models

Another popular technique used in the framework of multi-fidelity modelling is called reduced order models (ROM). This method reduces the complexity of a mathematical model by decreasing its degrees of freedom. The resulting ROM is an efficient but still accurate representation of a complex system. Various algorithms can be exploited, such as Proper Orthogonal Decomposition (POD) and Dynamic Mode Decomposition (DMD). The works of [76, 108, 109, 113] used ROM.

Neural Networks

On the other hand, other applications exist to make predictions based on prior data. Another popular area involves the employment of Artificial Neural Networks (ANN). They are a consolidated powerful data processing technique used as well in the aerospace sector. They consist of interconnected layers, each composed of neurons, where the input layer typically represents the original input variables, such as speed, density, and temperature. While the output layer, located at the end of the ANN, provides the desired output data, such as aerodynamic coefficients. The hidden layers are intermediate connections between the input and output layers. The neurons within a layer are the weighted sum of inputs from the preceding layer, then an activation function is applied to them and it is transmitted to the next layer. Being usually the activation function nonlinear, it allows the ANN to learn the trend between the input and output. The training task optimizes the values of the weights to achieve the best correlation with the train data set.

ANNs are discussed by Neal [123], where he discusses the use of ANN models with limited training data for classification and regression tasks. It describes theoretical investigations into the underlying priors of complex Bayesian models and provides practical implementation using Markov chain Monte Carlo methods.

Data fusion

In addition, and since we will have more than one fidelity level for each quantity of interest, such as a lift coefficient, we can exploit further GP methods to fuse the data together. The approach refers to co-Kringing and it belongs to the GP regression family. It leverages a densely sampled first data set, generated with low-fidelity methods, that is correlated with a second data set, generated with high-fidelity methods, to improve the function prediction. In order to be successful, the two data sets need to be somehow correlated, and the sampling density of the first data set should be higher than the second.

Data fusion can be performed as well from ML. Different techniques exist, and Mneg et al. [144] made an extensive survey about this topic by introducing some performance evaluation criteria. such as efficiency, stability, robustness, extensibility. They also divided the techniques based on data fusion type: signal, feature and decision levels. Among the ML methods analysed, support vector machine (SVM), ANN and backpropagation NN are distinguished for their efficiency and applicability.

Multi-fidelity modelling

The applications of principles described in the previous section can surely be applied to data-driven models with single fidelity. Often the raw data comes from only one source and therefore, researchers try to grasp them as effectively as possible.

On the other hand, it is possible to have different data sources that describe the same quantity of interest, for example, the wing displacement from both numerical and experimental tests. In this case, multi-fidelity methods can be exploited. The theory is very similar to the one used to build a surrogate model with single fidelity, but here data fusion techniques are applied. Two surveys on multi-fidelity methods stand out for relevance by comparing the methods from different points of view.

Peherstorfer et al. [135] analyses the combination of multi-fidelity models for outer-loop applications (e.g. optimization) and categorizes them into adaptation, filtering, and fusion methods. The latter one, nowadays seems to be the most used method in the aerospace sector. Among the different approaches in fusion, co-Kriging is also present.

Whereas, Fernandez et al. [136] divide multi-fidelity methods by their year of publication, area of study (e.g. fluid dynamics, solid mechanics), application field (e.g. optimization, uncertainty quantification), surrogate method (e.g. Kriging, basis regression function), and fidelity combination. They also explained that non-deterministic methods, such as co-Kringing, are preferred to the deterministic ones. Another interesting finding is about the choice of low and high-fidelity models in fluid dynamics: the lowest category is represented here by analytical, empirical and linear theories, whereas the highest one by RANS-based simulations.

Another work [137] stands out for relevance and year of publication. Brevault et al. gave an overview of only GP-based approaches to build a multi-fidelity model. They tested co-Kriging, Auto-Regressive (AR1), nonlinear Auto-Regressive and deep GP methods in several aerospace problems. The most interesting is an aerostructural multidisciplinary analysis problem of a flying wing. The best method was found to be a multi-fidelity deep GP followed closely by co-Kriging.

Recently, the same institute, published a paper about the Surrogate Model Toolbox (SMT) [145]. It is a collection of surrogate modelling methods, Kriging and co-Kriging included, sampling methods, along with benchmark problems. It aims to facilitate the development of new surrogate models by offering a python open-source platform with a comprehensive library of surrogate modelling methods.

Table 1.3 collect several works divided between number of fidelity and ML method, i.e. GP and NN:

Fidelity	GP	NN
Single-fidelity	[117, 118, 125]	[110, 111, 112, 116, 120, 121, 124]
Multi-fidelity	[114, 131, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 141, 142, 143]	[115, 122, 144, 146]

Table 1.3: ML methods division.

1.4 Conclusions

The interest in eVTOL is strong and rapidly increasing. This is more than evident from our findings. Researchers rely on low and higher fidelity approaches to analyse and optimize configurations, in order to maximize performance, operational effectiveness and minimize the environmental impact, including the acoustic footprint.

Researchers are also actively investigating numerical simulation approaches; on one hand, Digital Twins are systematically exploited to improve the design and certification process. On the other hand, newer algorithms are proposed in order to raise the accuracy and reliability of numerical simulations.

These two trends combine in the analysis of eVTOL aircraft, showing a rapidly evolving design environment.

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