Disclaimer

This project is funded by the European Union under the Horizon Europe Programme.

EASA
European Union Aviation Safety Agency

MODEL-SI
MODELING AND SIMULATION

MODEL-SI (Digital Transformation - Case Studies for Aviation Safety Standards - Modeling and Simulation)

Final dissemination event

12 November 2024

Your safety is our mission.

An Agency of the European Union

Introduction

Welcome to this webinar!

This webinar is the final dissemination event of this research project

Funded by
European Un

This project has received funding from the European Union’s Horizon Europe Research and Innovation Programme

European Commission

The EC delegated the contractual and technical management of this research action to EASA

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EASA contracted ZHAW for the implementation of the research action following a public tender procedure

EASA-managed projects are addressing research needs of aviation authorities and are an important pillar of the EASA R&I portfolio

Research & Innovation in EASA

Main objectives:

- Strengthen EASA's capacities as aviation authority and regulator
- Implement EASA Research Agenda and related strategic EPAS actions
- Contribute to EASA's competency management and knowledge development

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RES.CA.1

- Environment
- Rotorcraft safety
- Risk of drone impacts
- Safe air operations
- Cabin air quality

RES-CA.2

- Lessons-learnt from recent accidents/incidents
- Safety standards for new disruptive technologies
- Runway safety
- **Digital transformation of aviation**
- Aviation health safety standards
- Impact of security measures on safety

RES-CA.3

- Simulator vs. actual flying
- Big data and data science
- AW standards for new aircraft structure designs
- Cybersecurity Threat
- New health safety measures in aircraft
- Colour vision requirements for pilots and ATCOs
- Non-CO2 impact assessments

Agenda for today

14:00 - 14:10	Welcome by EASA
14:10 – 15:40	Introduction (EASA)
	Lecture 1
	Methodology and results
	Summary of Workshops 1 and 2
	Break
	Lecture 2
	Lessons learned and role played by AI/ML,
	Break
15:40 – 16:00	Q & A

Note: *this webinar will be recorded and made available at the EASA website after the event.*

Interaction

- Your questions are welcome

- During the presentation, please introduce them in Slido Q&A (not in the Webex chat)

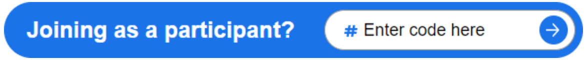
- The last 20 minutes will be dedicated to discussion. Please raise your hand to take the floor, or use Slido Q&A

Slido information

How to answer the questions?

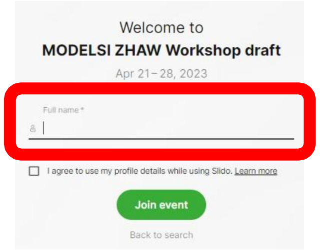
Scan QR code

go on slido.com



enter **#modelsi**

Enter you **real name** or **nickname**



MODEL-SI - FINAL DISSEMINATION EVENT

DIGITAL TRANSFORMATION – CASE STUDIES FOR AVIATION SAFETY STANDARDS

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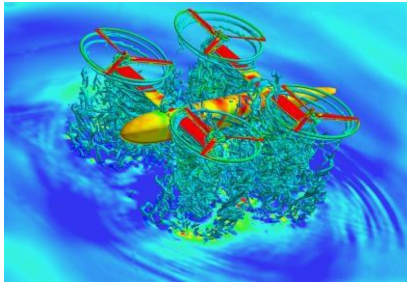
European Union Aviation Safety Agency

Zürcher Hochschule für Angewandte Wissenschaften
zh aw School of Engineering
ZAV Zentrum für Aviatik

Objective

- To develop models, using AI techniques with:
  - Complex aerodynamics
  - Flexible structure
  - Control system with a feedback loop



- To run simulations of:
  - Flight dynamics
  - Aeroelastic behaviour
  - Loads and strength

Documents prepared

Publicly available in the next weeks on the MODEL-SI project website:

- Review of existing literature and identification of digital solutions
- Report on the main investigations performed
- Report on the stakeholder workshops
- Regulation guidance with AI
- Case study presentation materials
- Case study training material

→ EASA is interested in feedback from the workshop participants

Observed potential + and challenges -

+

- → Complex phenomena can be captured (rotor wake interaction, aeroelasticity) effectively via data fusion
- → Faster computation (short simulation time)
- → Benefit of modular approach and multi-fidelity :
  - Accuracy
  - Computation time and cost reduced
- → ML can significantly improve the system's ability to address realistic scenarios and failure cases
- → Flight test data & correlation

-

- → Learning assurance may be complex
- → Training of ML models may be expensive
- → Uncertainty Quantification may be demanding and require experience
- → Experience may also be necessary to generate data and guarantee quality
- → Explainability difficult with black box
- → Reliability needs to improve to implement in certification
- → Difficult to investigate and catch errors
  - → Mitigation: multiple methods

Learning assurance

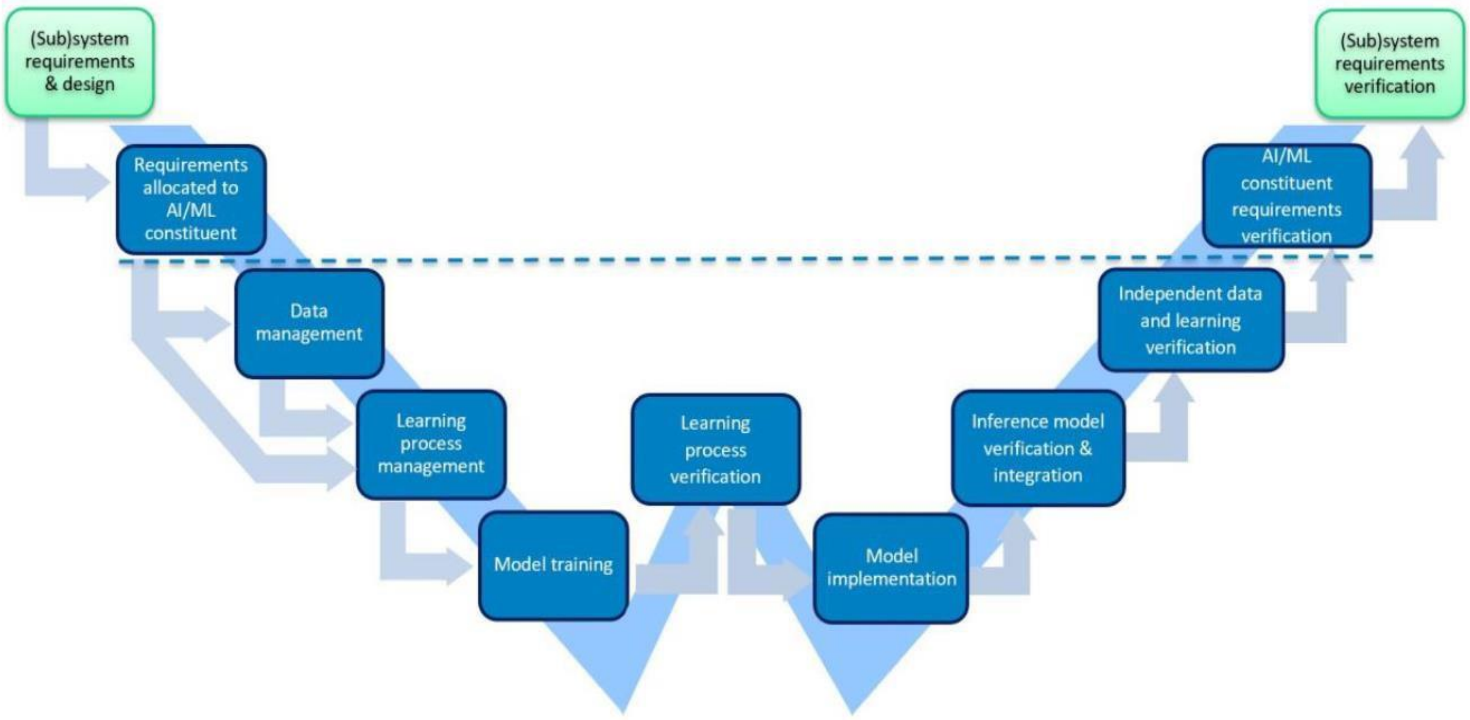


Figure 11 — Learning assurance W-shaped process

Learning process management

Objective LM-02: The applicant should capture the requirements pertaining to the learning management and training processes, including but not limited to:

— model family and model selection;

— learning algorithm(s) selection;

— cost/loss function selection describing the link to the performance metrics;

— model bias and variance metrics and acceptable levels;

— model robustness and stability metrics and acceptable levels;

— training environment (hardware and software) identification;

— model parameters initialisation strategy;

— hyper-parameters and parameters identification and setting;

— expected performance with training, validation and test data sets.

Explainability

Development & Post-operation	Operation
▪ Develop system trustworthiness ▪ Establish causal relationships between the input and the output of the model ▪ Catch the boundaries of the model and help in its fixing ▪ Highlight undesirable bias (data sets and model bias) ▪ Allow the relevant receivers to identify errors in the model ▪ Support continuous analysis of the AI-based system behaviour ▪ **Support the safety investigation of accidents and incidents where an AI-based system was involved**	▪ Contribute to building trust for the end user ▪ Contribute to predicting AI behaviour ▪ Contribute to understanding actions/decisions

Table 1 — Needs for AI explainability

Methodology

Methodology

Definition of model architecture

Low fidelity modelling, model set-up, data generation

High- and Mid-fidelity modelling, model set-up

High- and Mid-fidelity modellingdata generation

Multi-fidelity modelling, NN architecture, training

Uncertainty Quantification

Digital Twin

Flight Testing, validation

Methodology

→ Model Architecture

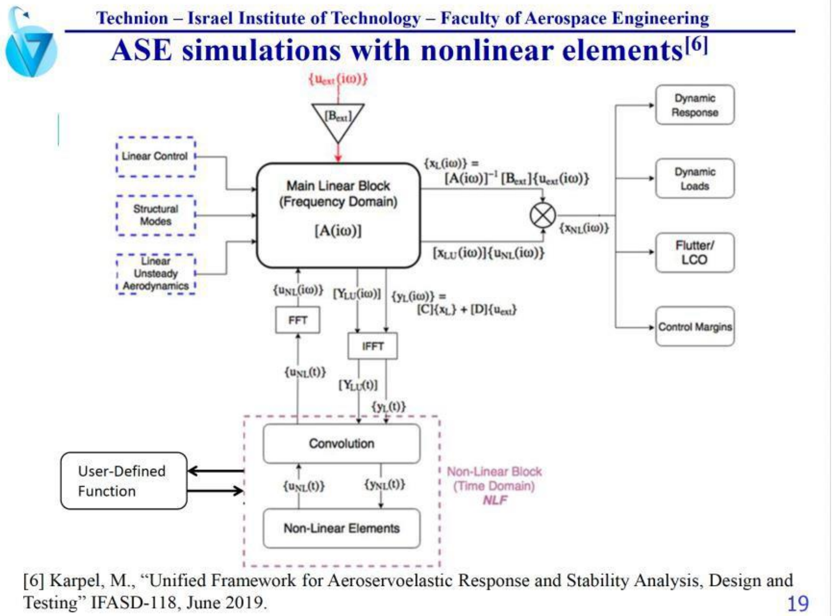
→ Multi-Fidelity Modelling

→ Uncertainty Quantification

→ Role played by AI/ML

Model Architecture

→ One notable example is the “increased order model” proposed by Prof. Karpel in the 1990-2000, also for certification purposes



Model Architecture

→ Conventional **Flight Mechanics** simulation software,

→ Conventional **aeroelastic** solver (dynamic response in time / frequency, linear stability assessment),

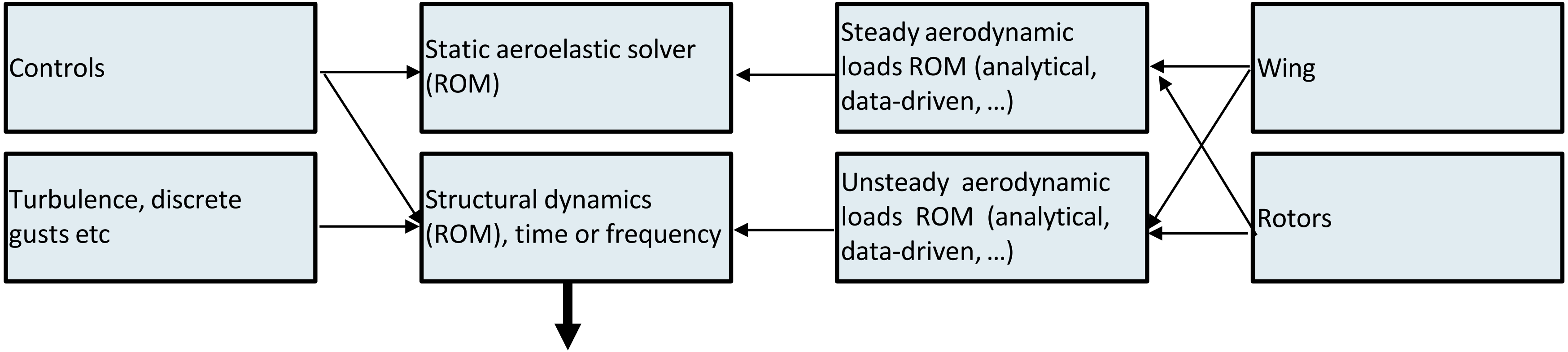
→ AI/ML-based **multi-fidelity surrogate modelling**, providing accurate aerodynamic forces to the other modules,

→ AI/ML is exploited also to provide a measure of the **uncertainty** associated with the data (in accordance with EASA AI concept paper),

→ Comparison with Prof Karpel approach: **nonlinear** time domain modules are (partially) replaced by **ML** modules.

→ Relevance of **legacy software**!

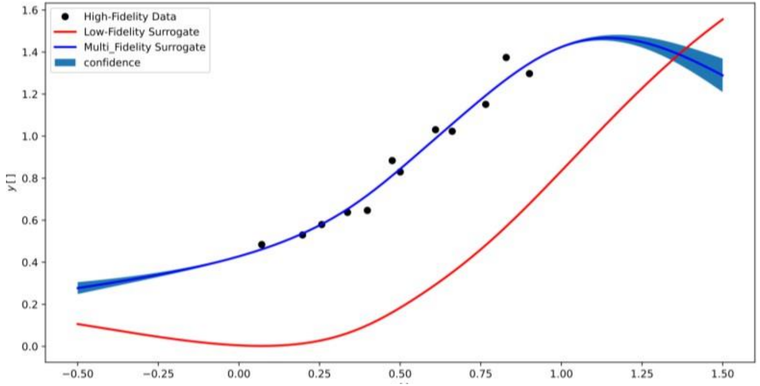
Model Architecture

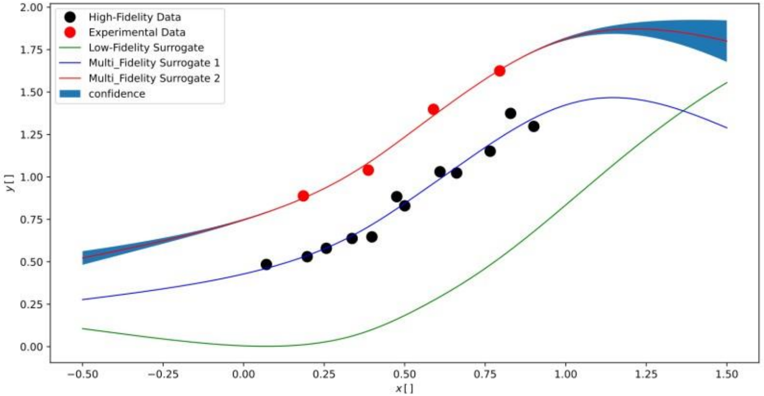


Linear stability analysis, gust response (time, frequency)

Multi-Fidelity Modelling

- Conventional approach for **physically complex** problems,
- It relies on lower fidelity models, which run **quickly**, and higher-fidelity models, which are more expensive and more **reliable**,
- Idea: the lower fidelity model can be exploited to "**interpolate**" between high-fidelity data points.





Multi-Fidelity Modelling – levels of fidelity

→ **Low-fidelity**, physics-based model,

→ **Mid-fidelity**, physics-based model, vorticity-based CFD solvers,

→ **High-fidelity**, physics-based model, CFD,

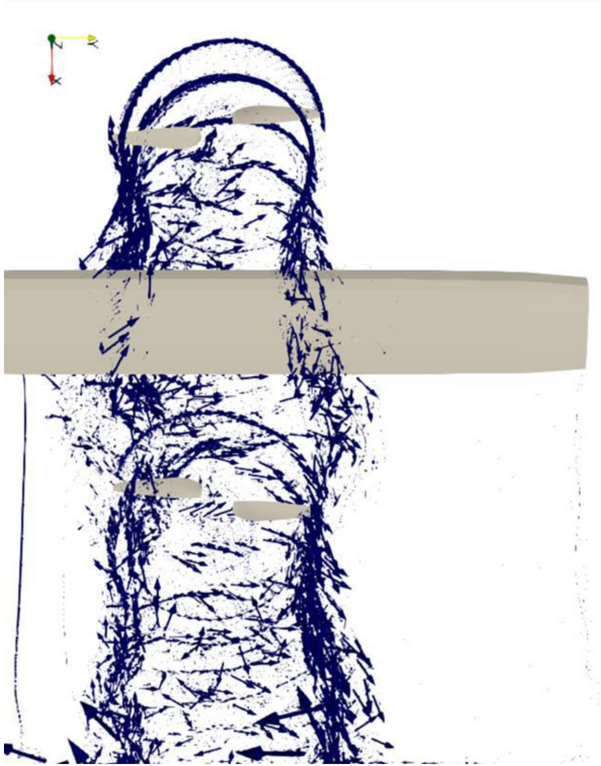
→ **Experiment**, flight-test data.

Multi-Fidelity Modelling – low-fidelity

- Low-order models for wing and rotor aerodynamics,
- Also, structural dynamics may benefit from an approach (for example) such as Ritz-Rayleigh. In our case a beam-element FEM (“stick model”) turned out to be a good choice,
- We also reminded that industrial codes such as CAMRAD or most of the solvers in the ZONA software suite are low-order,

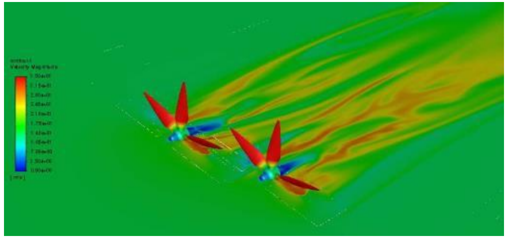
Multi-Fidelity Modelling – mid-fidelity

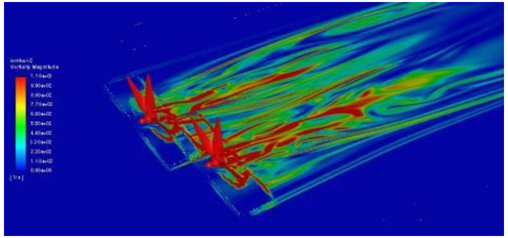
- Mid-fidelity was not planned at the beginning of the project,
- People refer to it to indicate mathematical models where aerodynamic surfaces are modelled following simplified aerodynamic approaches (lifting line, VLM, panels) but the wake is simulated with a Lagrangian approach (with *n* moving vortex particles),
- DUST (Polimi) (https://public.gitlab.polimi.it/DAER/dust) and FlowUnsteady (BYU) (https://github.com/byuflowlab/FLOWUnsteady) are two examples and are both open source,
- eVTOL developers are very familiar with this approach and apparently rely on it for design.



Multi-Fidelity Modelling – high-fidelity

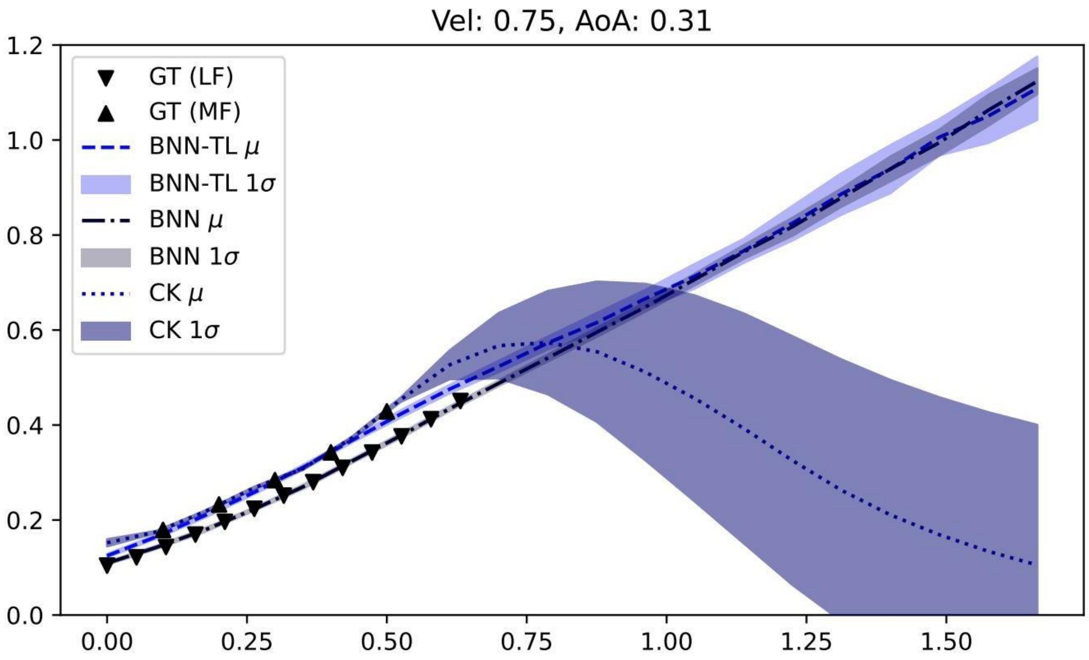
- High-fidelity modelling was expected to be the “**reference**” solution at the beginning of the project,
- We set on the **actuator disk** approach using the RANS physics: both choices turned out to be insufficient to capture rotor flow and wakes, mostly because the actuator disk approximation is only acceptable when the inflow angle is close to 90 degrees - which is not always the case here,
- It can be argued that **RANS** is acceptable but also that **DDES** (or other approaches of comparable physical consistency) would provide substantially better results,
- In conclusion, we did work on high-fidelity simulations, with rotating rotors, with some success; however, these simulations turned out to be **so expensive** that in a 20-months research project we could not exploit them to build a high-fidelity database,
- High-fidelity can be of help, however, with the modelling of the drone / aircraft in **airplane mode** and with the modelling of the isolated rotors,
- A special thanks to Wouter Remmerie of **Airshaper** to show us a valuable approach to CFD, which could provide an additional level of fidelity.





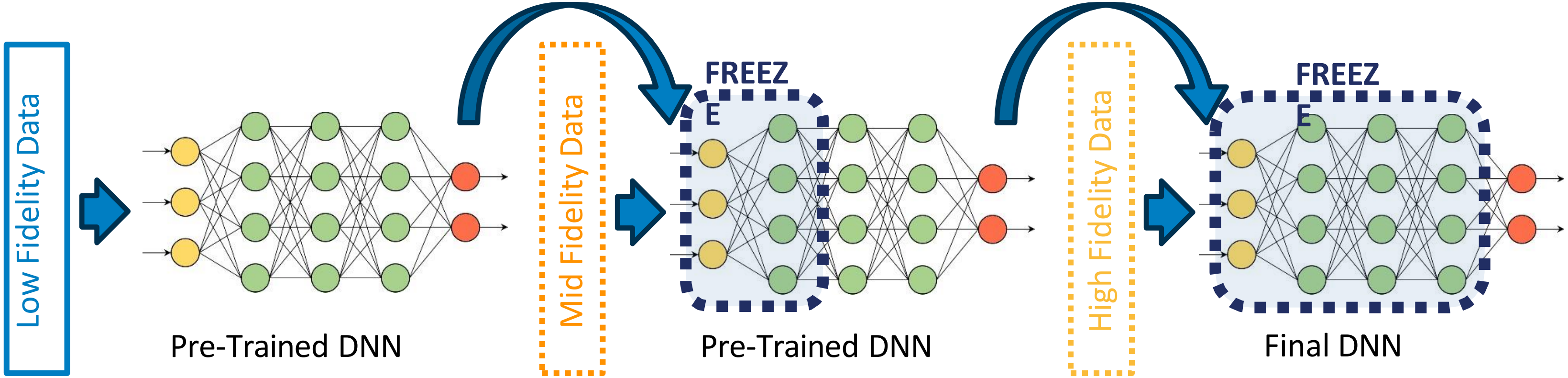
Multi-Fidelity Modelling – techniques

- Gaussian process (Co-Kriging),
- NN (Transfer Learning),
- Bayesian NN (Transfer Learning), https://arxiv.org/abs/2407.05684



Multi-Fidelity Modelling – Transfer Learning

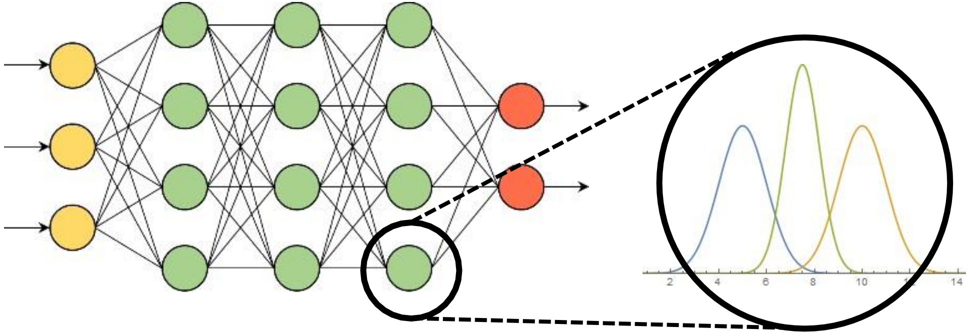
We created an optimized **Dense Neural Network** that uses **Transfer Learning (TL)** for Data Fusion.



We get improved accuracy for output predictions with feasible training time and real-time predictions. No uncertainty quantification available.

Multi-Fidelity Modelling – Transfer Learning

We decided to fuse the **Bayesian Neural Network (BNN)** approach **with TL** to get both Data Fusion and uncertainty quantification.



BNN generates a **nondeterministic model**. Using Monte Carlo sampling, it's possible to calculate the mean and the standard deviation of the model's predictions (uncertainty).

Multi-Fidelity Modelling – Transfer Learning

The biggest challenge was the building process of a complete **PyTorch library** that correctly uses Bayesian Layers for Transfer Learning. Ultimately, all network hyperparameters, including the number of frozen layers, were selected through **Bayesian Hyperparameter Optimization**.

We created an open-source PyTorch BNN-TL library, adhering to modular and object-oriented programming principles.

After trying various methods, we calculated the model's error and uncertainty using two custom percentage functions.

Multi-Fidelity Modelling – Transfer Learning

Model	Training Time	Prediction Time	Average Perc. Error	Average Perc. Confidence	N. Params
BNN LF	~41 min	~0.025 sec	4.88%	94.2%	174932
BNN MF	~35 min	~0.020 sec	10.8%	92.1%	19092
DF: BNN TL	~55 min	~0.025 sec	**3.06%**	97.3%	174932
DF: CoKriging	~4 min	~0.005 sec	3.9%	88.2%	-

Benchmarks on NVIDIA Quadro P2000 GPU – Timing is referred to the execution of one dataset fold – Results are calculated with k=5 folds

Final model hyperparameters:

- **Input dimension**: 8
- **Number of layers**: 5
- **Units per layer**: 224, 144, 160, 112, 96
- **Optimization Function**: LeakyReLU
- **Prior Standard Deviation**: 0.0351
- **Prior Mu**: 0
- **Output dimension**: 10
- **Learning rate**: 0.0016
- **Learing rate during TL**: 0.0081
- **N. parameters**: 174932

Uncertainty Quantification

- Typically, when calculating the estimated probability of a given hazard, applicable guidance, such as AMC 25.1309, requires that this **uncertainty** should be accounted for in a way that does not compromise safety. The need for such a conservative approach to deal with uncertainty is **unchanged with AI/ML applications,**
- Furthermore, AI/ML applications may be able to **estimate uncertainties** associated with their outputs. These estimations may then feed monitoring functions which in turn contribute to the safety case or provide valuable data for the continuous safety assessment (see Section C.2.2.4),
- To support anticipated MOC-SA-01-4 and MOC-SA-01-5, the following taxonomy for uncertainty based on Der Kiureghian and Ditlevsen (Ditlevsen, 2009) is considered in this concept paper:
  - **Epistemic** uncertainty refers to the deficiencies due to lack of knowledge or information. In the context of ML, epistemic uncertainty corresponds to the situation where the model **has not been exposed to data adequately covering the whole ODD or where the ODD definition needs to be refined or completed,**
  - **Aleatory** uncertainty refers to the intrinsic randomness in the data. This can derive from data collection errors, sensor noise, or noisy labels. In this case, the model **has learnt based on data suffering from such uncertainties.**

Uncertainty Quantification

- → *Anticipated MOC-SA-01-4: Identification and classification of uncertainties*
  - → **Sources of uncertainties** affecting the AI/ML constituent should be listed. Each should be classified to determine whether it is an aleatory or an epistemic source of uncertainties.
- → *Anticipated MOC-SA-01-5: Assessment and mitigation of uncertainties*
  - → **Aleatory uncertainties should be minimised** to the practical extent. Effects of aleatory uncertainties should be assessed at system level. In particular, when a quantitative assessment is required, the aleatory uncertainties should be accounted for in a way that does not compromise safety
  - → **Epistemic uncertainty** is addressed through the learning assurance objectives.

Uncertainty Quantification

- ***Aleatory uncertainties should be minimised*** *to the practical extent. Effects of aleatory uncertainties should be assessed at system level. In particular, when a quantitative assessment is required, the aleatory uncertainties should be accounted for in a way that does not compromise safety.*
  - This means making sure the data used for modelling is as good as it gets; this requirement does not affect AI/ML any differently than conventional approaches.
- **Epistemic uncertainty** is addressed through the learning assurance objectives.
  - This means making sure that we have sufficient data and we are using the it effectively - this requirement is specific to the learning process in AI/ML approaches.

Uncertainty Quantification

- Multi-fidelity modelling: GP and BNN provide an indication of the uncertainty (Stdev), acquired by the model based on the effectiveness of the training process,
- The latter can be affected by **epistemic** uncertainty (e.g. inadequacy of the model architecture, inadequate data quantity or distribution, inaccurate simulation environments, etc) and by **aleatory** uncertainty (e.g. inaccurate flight data, inaccurate modelling, etc),
- To address **epistemic** uncertainties: (1) NN optimisation (suitable packages available), (2) refinement of data sampling, (3) data augmentation, (4) use multiple solvers and/or multiple modelling strategies,
- To address **aleatory** uncertainties (part of learning assurance): this has to do with all the data used in our simulations (at all fidelity levels) and is dependent upon the use of good engineering practices.

Uncertainty Quantification

- Among best engineering practices, we might quantify the effect of uncertainties by propagating them; Monte Carlo is an intuitive approach which may be computationally expensive,
- Polynomial Chaos Theory is another popular approach which normally reduces the computational costs of the assessment, especially with complex processes,
- In practice, we should make assumptions about uncertainties as "input" (which quantities are subject to uncertainties?, how can these be characterised?) and use the mathematical models to calculate the quantities of interest (internal loads, stress, flutter speed, etc) *n* times, based on the assumed distribution of the uncertain quantities or random variables; via MC or PCT the distribution of the quantities of interest are recovered.

Role played by AI/ML

Level 1 AI : assistance to human

- Level 1A: Human augmentation
- Level 1B: Human cognitive assistance in decision and action selection

Level 2 AI : human-AI teaming

- Level 2A: Human and AI-based system cooperation
- Level 2B: Human and AI-based system collaboration

Level 3 AI : advanced automation

- Level 3A: The AI-based system makes decisions and performs actions, safeguarded by the human.
- Level 3B: The AI-based system makes non-supervised decisions and performs non-supervised actions.

Figure 5 — Classification of AI applications

Role played by AI/ML

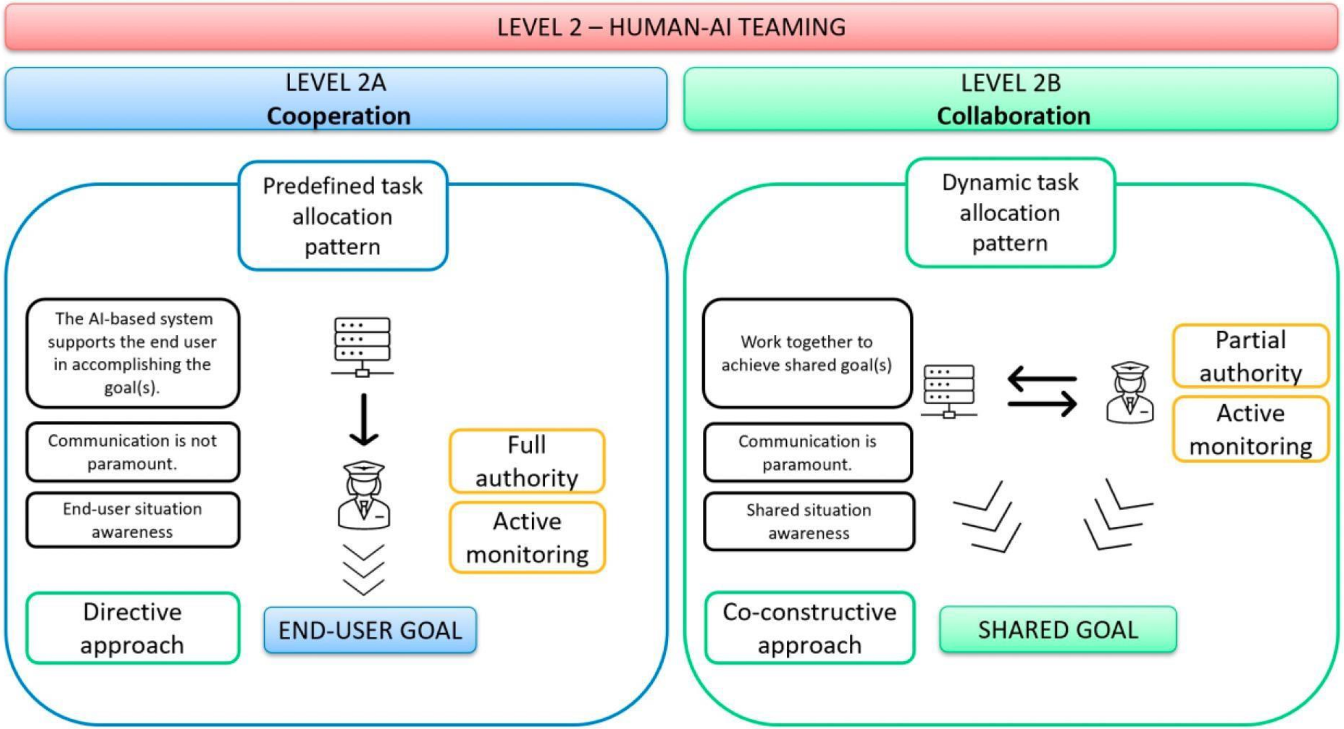


Figure 6 — HAT concept overview

Role played by AI/ML

- From the AIAA position paper (2020):
  - *A Digital Twin is a virtual representation of a connected physical asset and encompasses its entire product lifecycle. Its value stems from the ability to shift work from a physical environment into a* ***virtual or digital environment*** *and from the capability to predict asset conditions in the future, or when physically not desirable, by leveraging the digital model. This in turns leads to significant decreases in the resources needed to design, produce, and keep aerospace assets operational.*
  - *By moving much of the analysis to a virtual medium, the number of costly physical tests and iterative re-design cycle loops can be reduced, thus resulting in a reduced time and cost for the certification process. Data from physical tests (e.g. coupon tests, wind tunnel tests, ground tests, flight tests, operational tests, etc.) are also used to update assumptions made to construct virtual tests. The Digital Twin does not eliminate the need for physical measurements and testing, but only reduces the number and dependency on this form of information. The physical and virtual information can be fused to provide* ***a more robust and broader dataset****, which further enables the use of machine learning and data science approaches for decision making.*

Role played by AI/ML

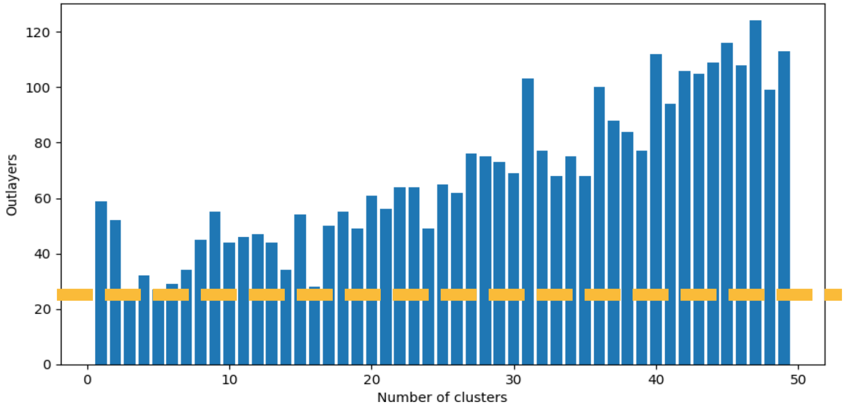
- **More** data can be generated / is available thanks to the DT,
- Ideally, the data is **higher quality** due to both higher accuracy and/or propagation of uncertainties,
- This implies not only an easier analysis (e.g. for certification) by humans but also an **AI/ML supported** analysis and decision,
- Explanation: AI/ML may analyse DT data, identify critical areas and **drive the DT** to generate additional data and so on,
- Decision making (by humans!) would be **supported** by making more and more in-depth assessment of the data; example: the interaction between RPM and structural dynamics may become "relevant" in particular combinations of the flight parameters,
- AI/ML could help finding them.

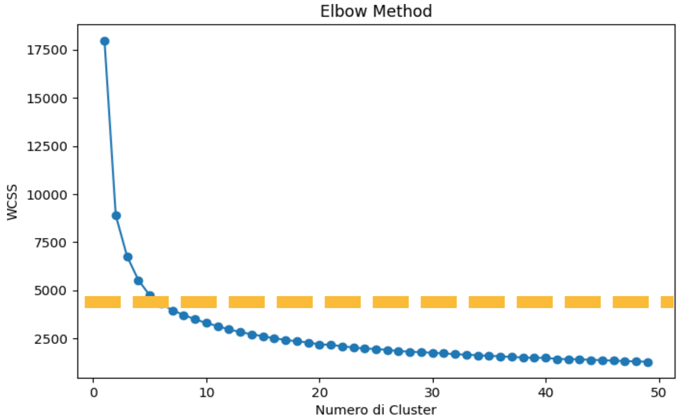
Role played by AI/ML

- **AI/ML** algorithms / methods could be various,
- We made some attempts with Clustering and found it useful to identify combination of parameters which cause given "danger indicators" to pass given thresholds or to rise above all other flight conditions,
- Using parameters to describe discrete gusts, the analysis (unsurprisingly) identified intensity and length as critical combinations (ok, humans can do this too),
- Adding drone mass as a parameter, clustering finds that a particular mass value may make structural loads rise (probably a resonance),
- Comment: big pharmaceutical companies are hiring AI companies (Open AI, Anthropics etc) to streamline /optimize clinical trials, i.e. a risky and expensive assessment/ validation process involving humans - there might be some analogy with certification and flight testing.

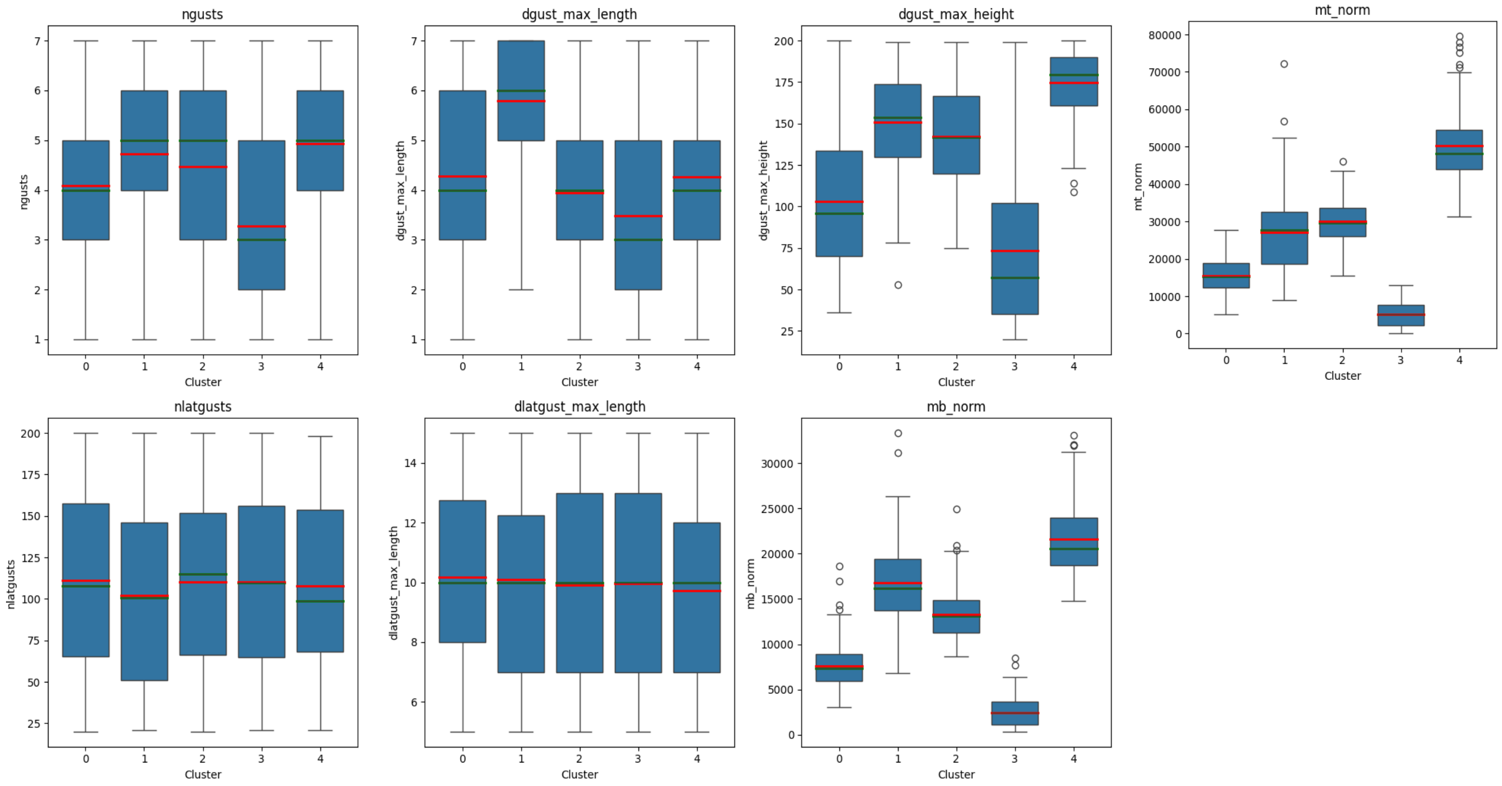
Role played by AI/ML

To get a good number of clusters with K-Means, it's important to minimize the number of outliers in the data. Then, use the elbow method by calculating the inertia for a range of k, and identify the point where the reduction in inertia starts to slow down significantly. This point represents the optimal number of clusters.





Role played by AI/ML



Role played by AI/ML

We studied the developing process of a GPT model to assist certification process for drones and eVTOL vehicles. The model is designed to streamline complex regulatory guidance and support stakeholders in meeting certification requirements.

Goals:

- The model provides correct information on certification requirements, processes, and guidelines, focusing on EASA standards
- Enables quick access to detailed regulatory insights in real time
- Assists operators, manufacturers, and regulators with certification needs, reducing time and resource investments

Role played by AI/ML

EASA Compliance: The model must be designed to strictly follow EASA guidelines, without making independent judgments on airworthiness. While it aids in certification guidance, it's not a replacement for professional regulatory or legal advice and only operates within EASA's framework.

Data Collection: Collection of key regulatory documents, such as CS-UAS, CS-23, CS-27, and VTOL guidelines, to get the model's foundational dataset.

Create a GPT: a GPT is a GPT-4o model based that can access a datasets to get additional context to augment the user's query via Semantic Search or Document Review.

Expert Feedback: Continuous feedback from domain experts further refines accuracy and enhances response accuracy.

Role played by AI/ML

Challenges that still need to be taken into account:

- **Overconfidence:** Set application-specific accuracy tolerances to limit consequences of model hallucinations.
- **Consistency:** Manage variability in responses to similar questions due to data biases.
- **Security:** Defining strict rules to control responses usage.
- **User adoption:** Building user trust and encouraging active engagement with the model.
- **Regulatory adaptation:** Adapting to AI regulations and risk-based classifications.
- **Methodology choice:** Finding the best reliable, scalable, effective and resource efficient models (GPT, LLaMA, BERT, etc...) and training techniques (GPTs, RAD, Finetuning, LoRA) to get a stable model that can adapt to evolving EASA regulation changes.
- **Metrics:** Chose a reliable metric to consistently evaluate model response quality.

Case Study Results

Mid-Fidelity simulations

Mid-Fidelity Simulations: DUST

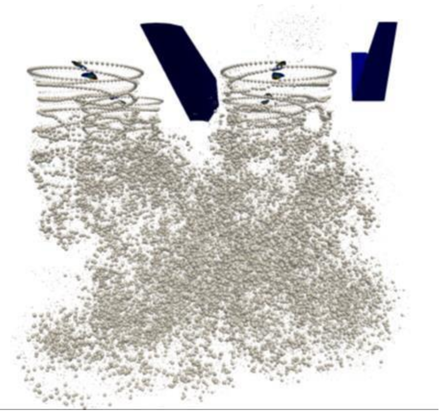
Hovering

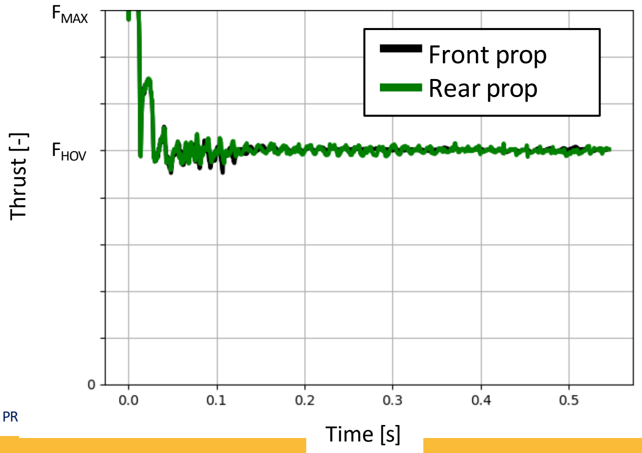
$AOA = AOS = 0°$

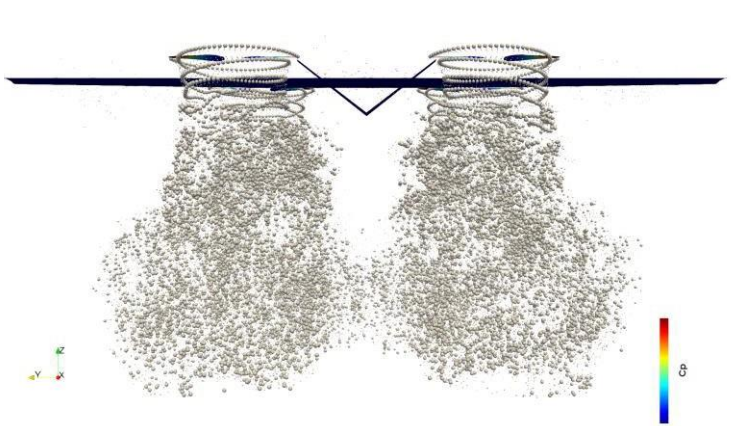
$U_\infty = 0\ m/s$

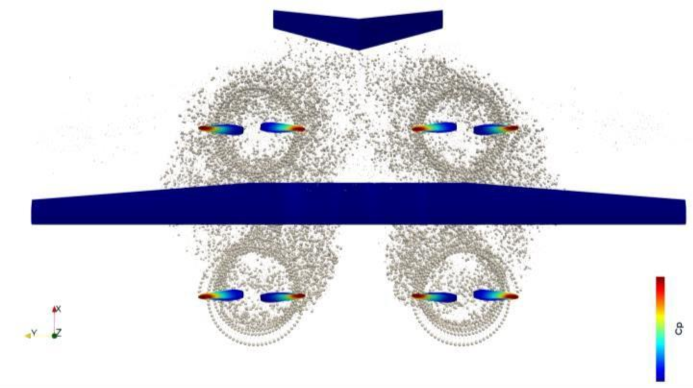
$N_{LP} = const.$

$N_{PP} = 0\ rpm$









Mid-Fidelity Simulations: DUST

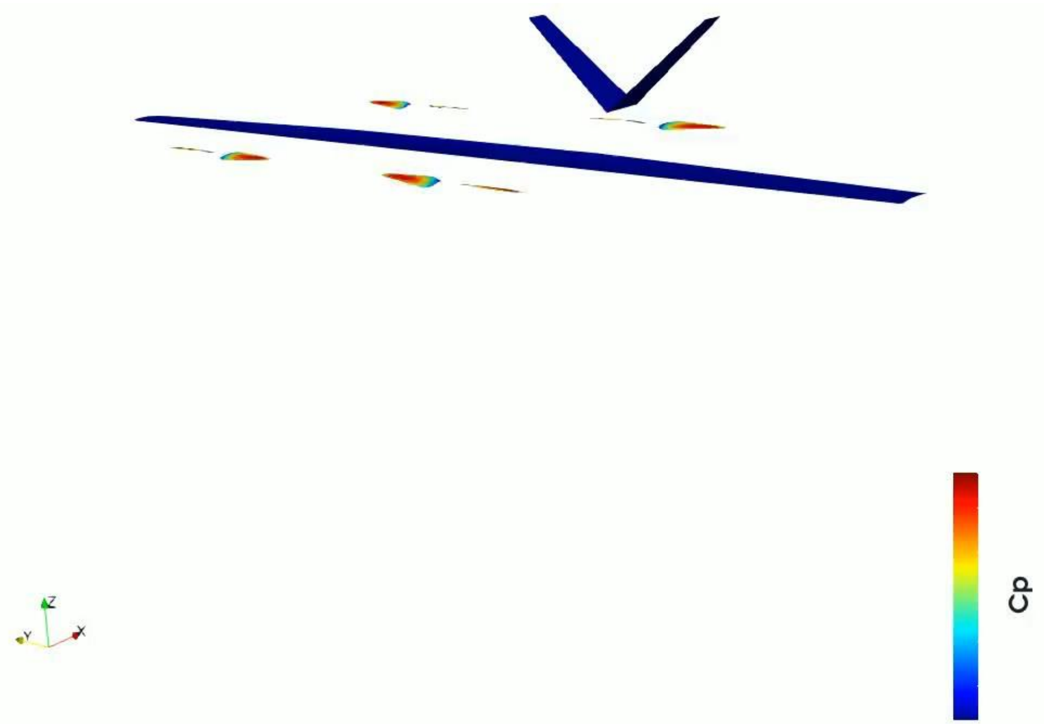
Hovering

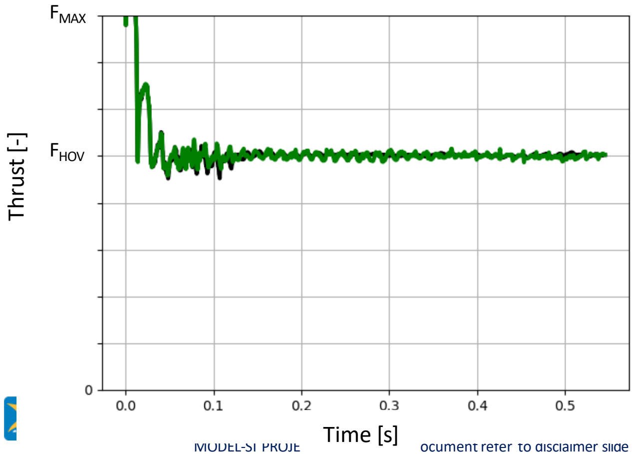
$AOA = AOS = 0°$

$U_\infty = 0\ m/s$

$N_{LP} = const.$

$N_{PP} = 0\ rpm$





Mid-Fidelity Simulations: DUST

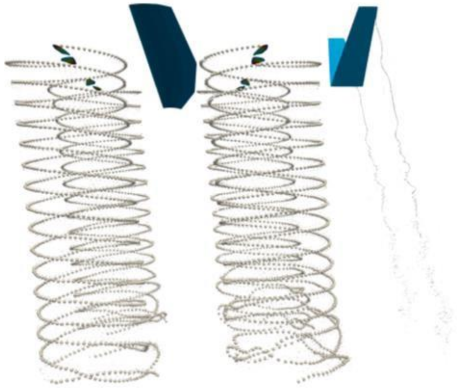
Hovering ascent

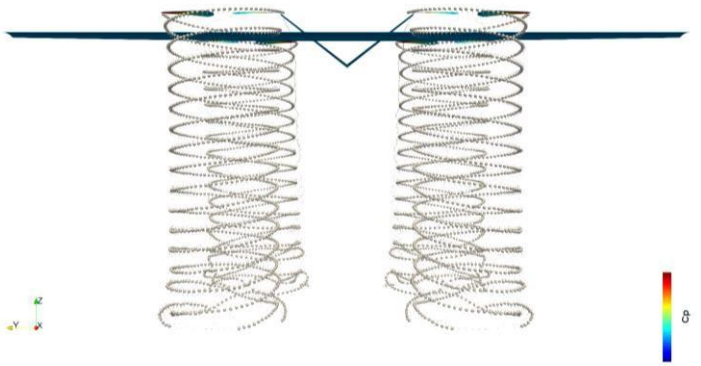
$AOA = -80° \; AOS = 0°$

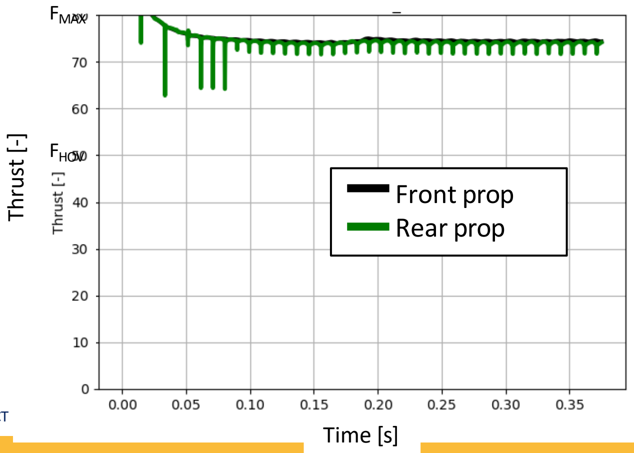
$U_{\infty} = 10 \; m/s$

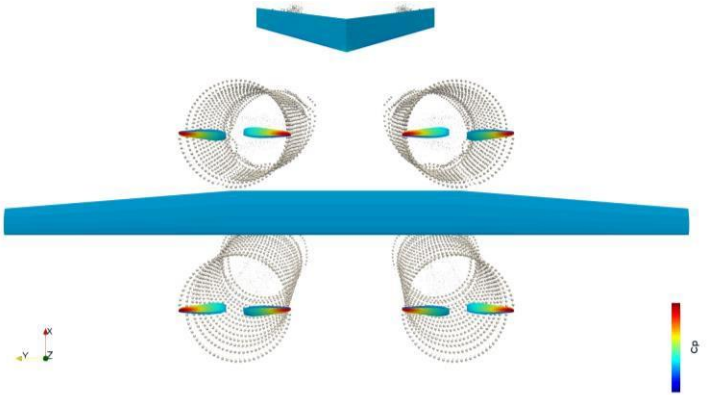
$N_{LP} = const.$

$N_{PP} = 0 \; rpm$









Mid-Fidelity Simulations: DUST

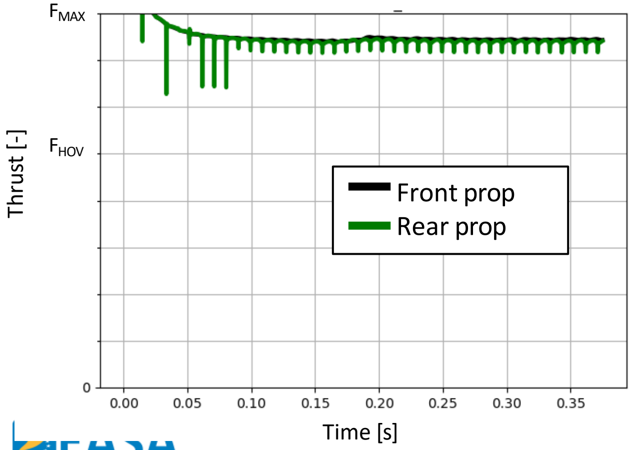
Hovering ascent

$AOA = -80° \; AOS = 0°$

$U_\infty = 10\, m/s$

$N_{LP} = const.$

$N_{PP} = 0\, rpm$



Mid-Fidelity Simulations: DUST

Transition

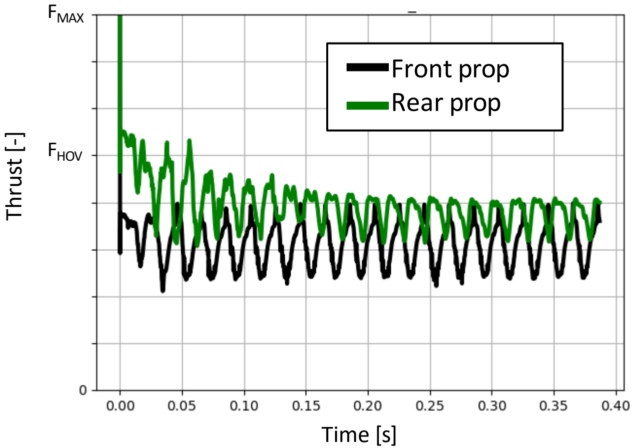
$AOA = -2°$

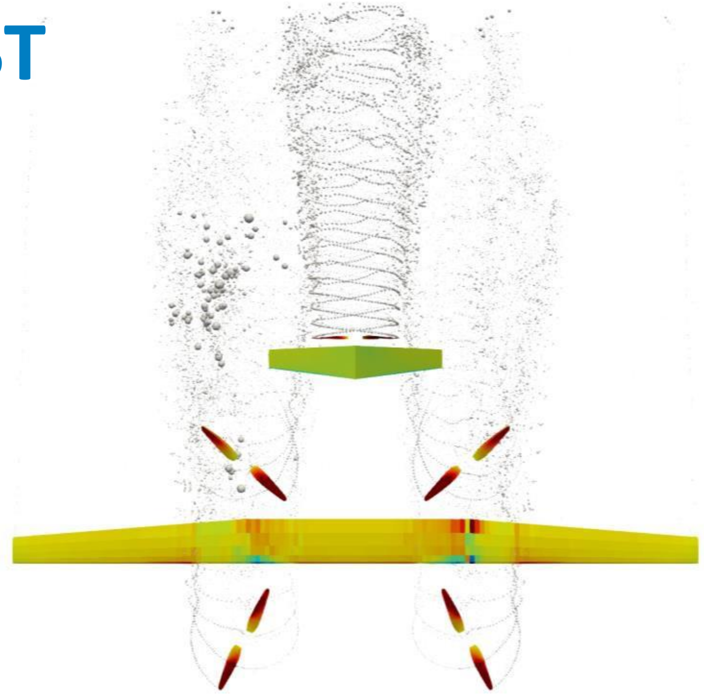
$AOS = 0°$

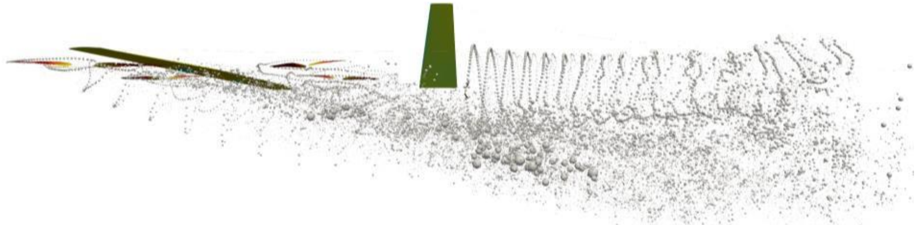
$U_\infty = 10\, m/s$

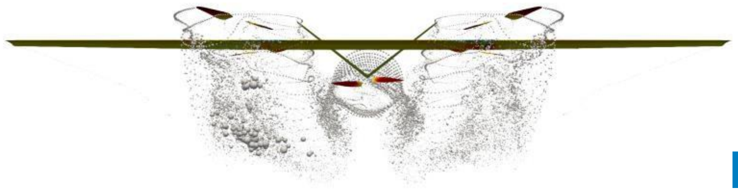
$N_{LP} = active$

$N_{PP} = active$









Mid-Fidelity Simulations: DUST

Transition

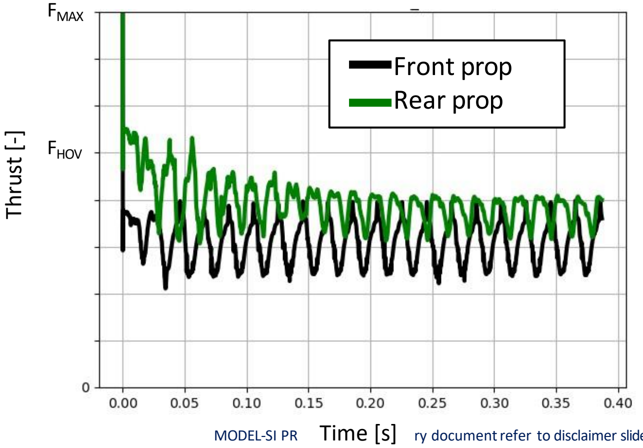
$AOA = -2°$

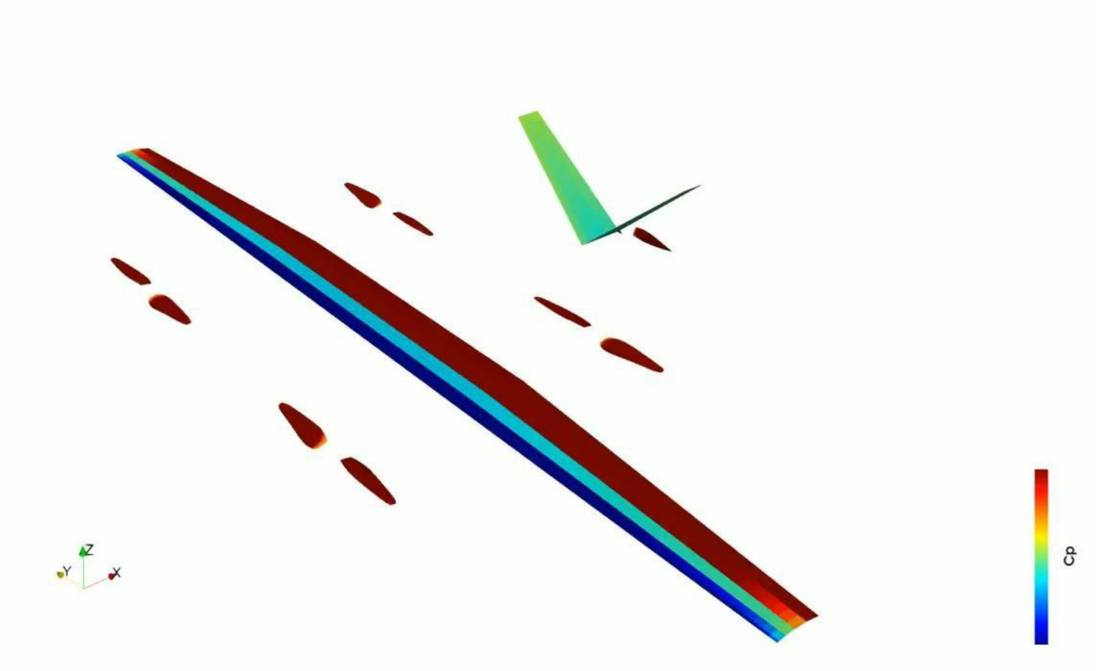
$AOS = 0°$

$U_\infty = 10\ m/s$

$N_{LP} = active$

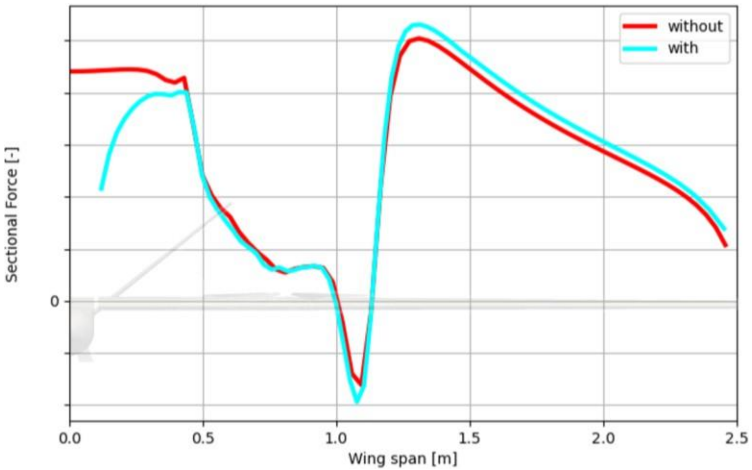
$N_{PP} = active$





Mid-Fidelity Simulations: DUST Load distribution

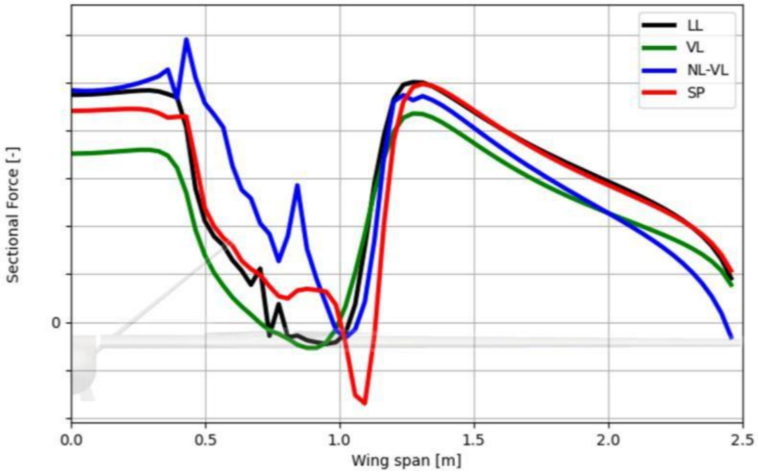
Fuselage comparison (with and without)



CASE	FRONT PROPELLER THRUST	REAR PROPELLER THRUST	WING LIFT FORCE
% DIFF WITH/WO FUSELAGE	+0.1	-0.2	-7.03

Wing aerodynamic comparison:

- Lifting Line (LL)
- Vortex Lattice Method (VL)
- Non-Linear Vortex Lattice Method (NL-VL)
- Surface Panels (SP)



% DIFF BETWEEN METHODS	FRONT PROPELLER THRUST	REAR PROPELLER THRUST	WING LIFT FORCE
SP	-	-	-
NL-VL	+2.1	+0.3	+6.1
VL	-0.4	+3.0	-19.2
LL	+1.2	+7.0	+3.8

Mid-Fidelity Simulations: DUST

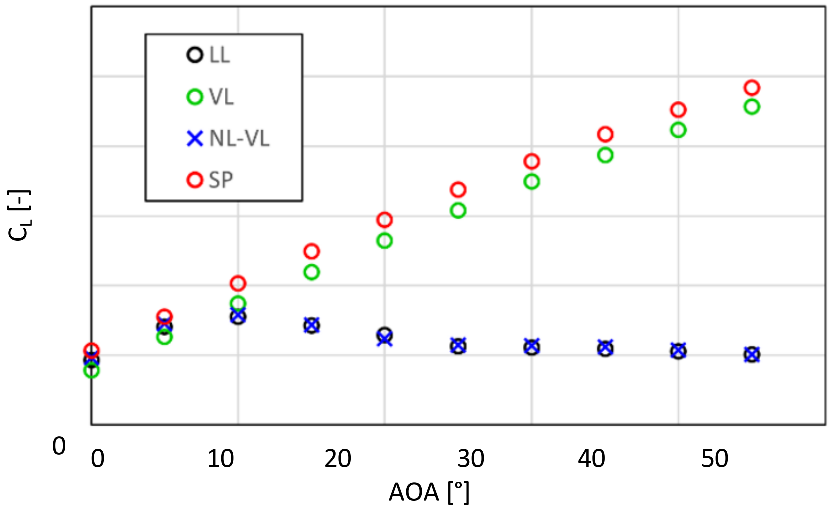
Comparison of the wing aerodynamic modeling:

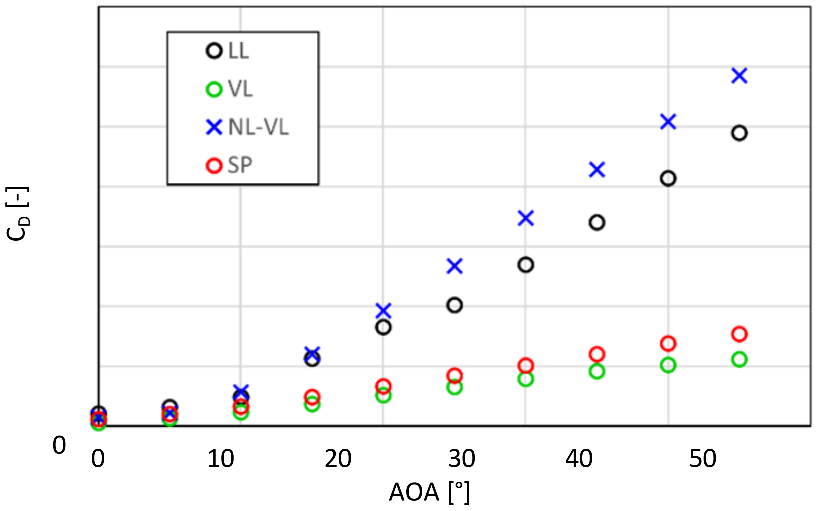
→ Lifting Line (LL)

→ Vortex Lattice Method (VL)

→ Non-Linear Vortex Lattice Method (NL-VL)

→ Surface Panels (SP)





High-Fidelity simulations

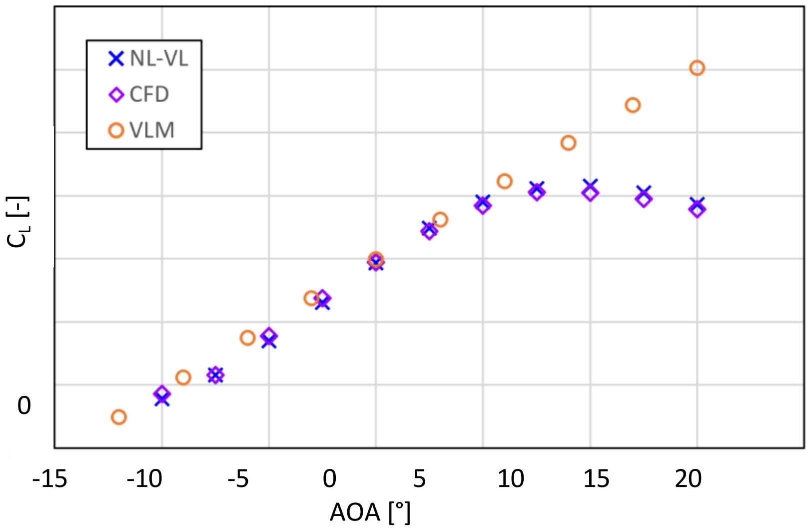
High-fidelity sims: Wing aerodynamics wo props

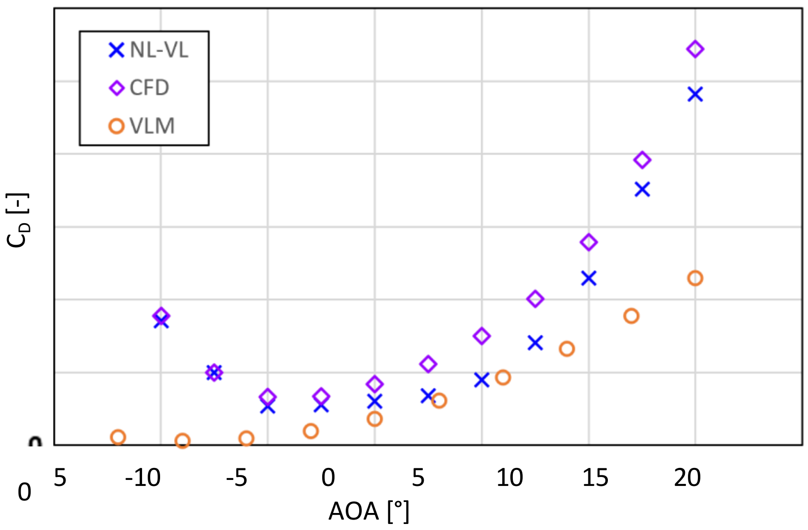
Comparison of the aircraft WITHOUT props between different models fidelity:

→ Low-fidelity: Vortex Lattice Method (Tornado)

→ Mid-fidelity: Vortex Particle Method (DUST)

→ High-fidelity: CFD steady RANS





High-fidelity sim: complete eVTOL with props

Three different HF CFD simulaitons of the eVTOL WITH props

- Steady-state coarse grid CFD RANS (Airshaper automatic cloud-based solver)
- Steady-state fine grid CFD RANS (Airshaper automatic cloud-based solver)
- Transient fine grid CFD RANS (Ansys Fluent)

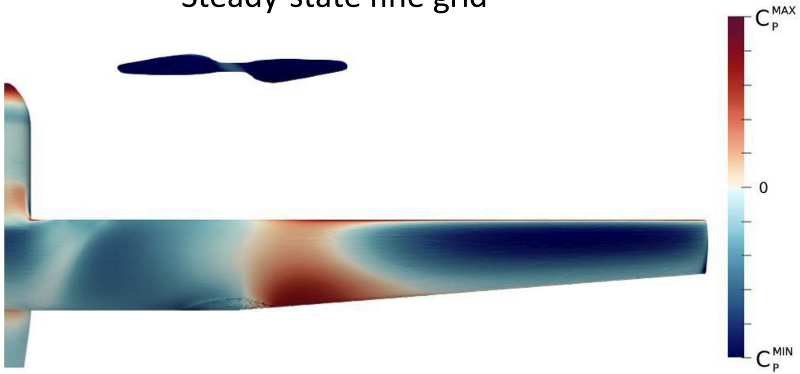
METHOD	# OF ELEMENTS	FRONT PROPELLER THRUST [N]	REAR PROPELLER THRUST [N]	C_Z^{WING}
DUST	~1 M particles	22.72	19.5	0.373
STEADY CFD COARSE	~24 M cells	26.81	21.02	0.263
STEADY CFD FINE	~115 M cells	27.63	22.13	0.267
TRANS CFD FINE	~180 M cells	24.9	17.8	0.282

High-fidelity sim: complete eVTOL with props

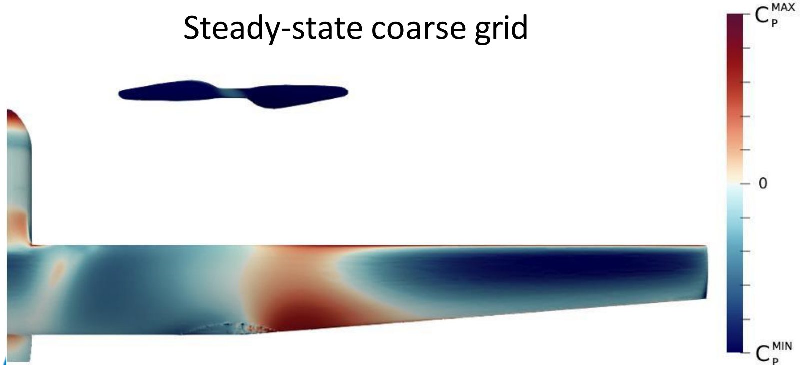
Pressure distribution comparison:

- Front and back rotor interaction over the wing present in all sims
- Wing-fuselage interaction is very similar

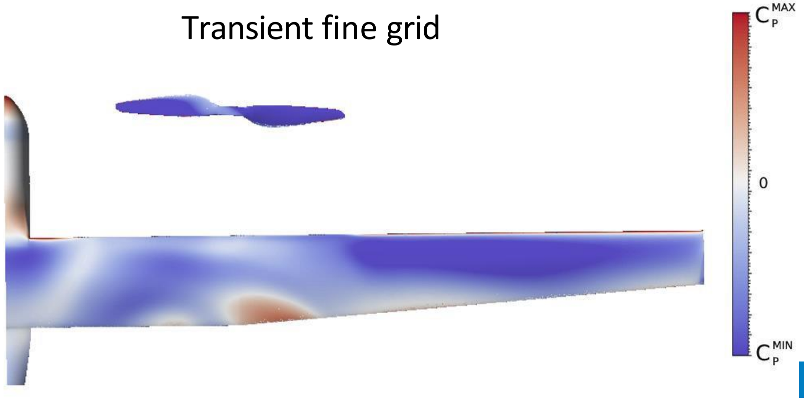
Steady-state fine grid



Steady-state coarse grid

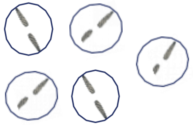


Transient fine grid



Multi-fidelity modeling - results

Multi-fidelity results: ML-based rotors model



LF simulations

Rotors:

- Blade Element Momentum (BEM) model corrected with an inflow model

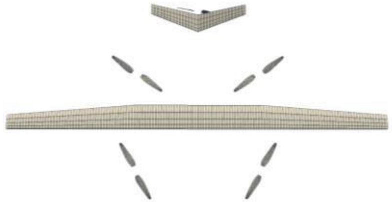
~2000 data points

MF simulations

Wing/Tail/Rotors:

- Vortex Particle Method (DUST)

~60 data points



Multi-fidelity dataset

LF DATASET + MF DATASET

Training

DATA-DRIVEN MODEL

Data fusion:

- Gaussian Process: Co-Kriging
- DNN: Bayesian Neural Network with Transfer Learning

Inputs

- AOA
- AOS
- U_∞
- Rotors rotational speeds

$[N_{FR}\ N_{FL}\ N_{BR}\ N_{BL}\ N_{PP}]$

Outputs

- Rotors Thrust T and Torque Q

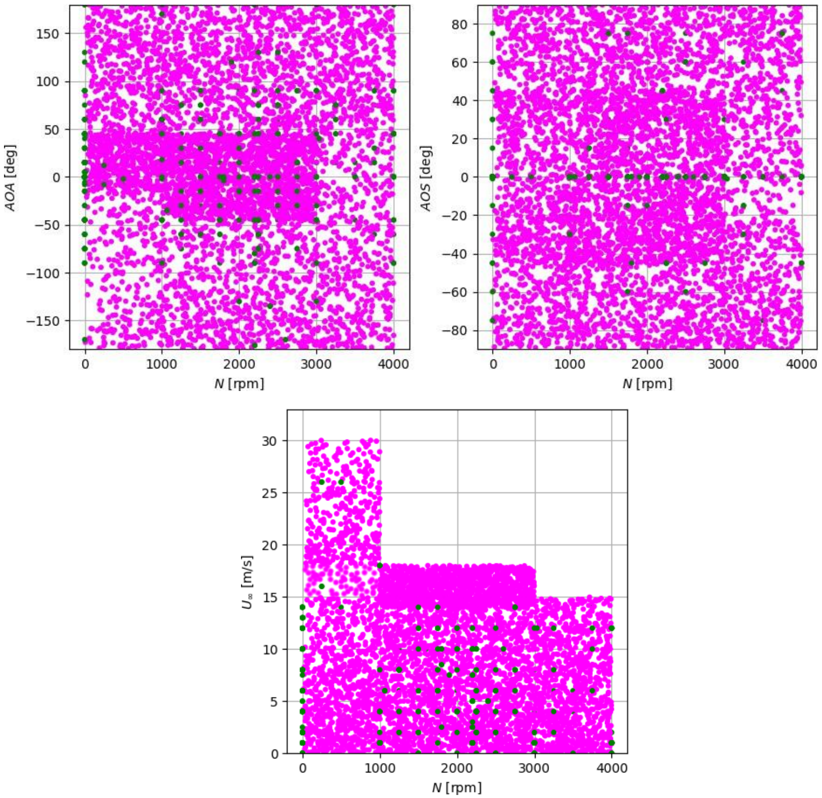
$[T_{FR}\ T_{FL}\ T_{BR}\ T_{BL}\ T_{PP}$
$Q_{FR}\ Q_{FL}\ Q_{BR}\ Q_{BL}\ Q_{PP}]$

- Uncertainties for each quantity

$[\sigma_{T_{FR}} \sigma_{T_{FL}}\ \sigma_{T_{BR}}\ \sigma_{T_{BL}}\ \sigma_{T_{PP}}$
$\sigma_{Q_{FR}}\ \sigma_{Q_{FL}}\ \sigma_{Q_{BR}}\ \sigma_{Q_{BL}}\ \sigma_{Q_{PP}}]$

Multi-fidelity results: ML-based rotors model

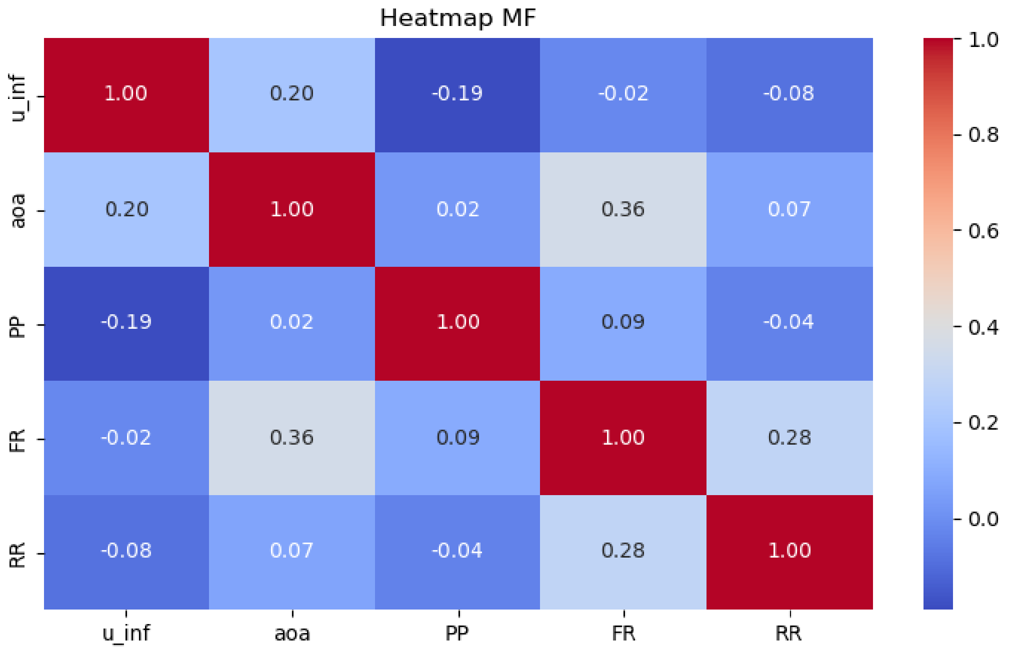
- LF dataset
  - Generated using a simple BEM model with inflow
  - Latin Hypercube Sampling (LHS) was used to ensure an efficient and comprehensive spread across propeller operating conditions
- MF dataset
  - Generated using DUST
  - Most of the point are generated with LHS, narrowed to the most representative points (e.g. hover, ascen)from high-cost (HC),/descent, transition, and cruise)
  - Covering about 10% of the total dataset



Datset analysis: understanding the data

Correlation matrix:

- → effectively spot patterns, trends
- → eelationships within the data ➔ if a value is close to 1.0 means that we often have the same or close value (see ehere FR and RR)
- → quickly identify areas of interest or potential anomalies/bias
- → Help to select which input is useful and which could be redundant

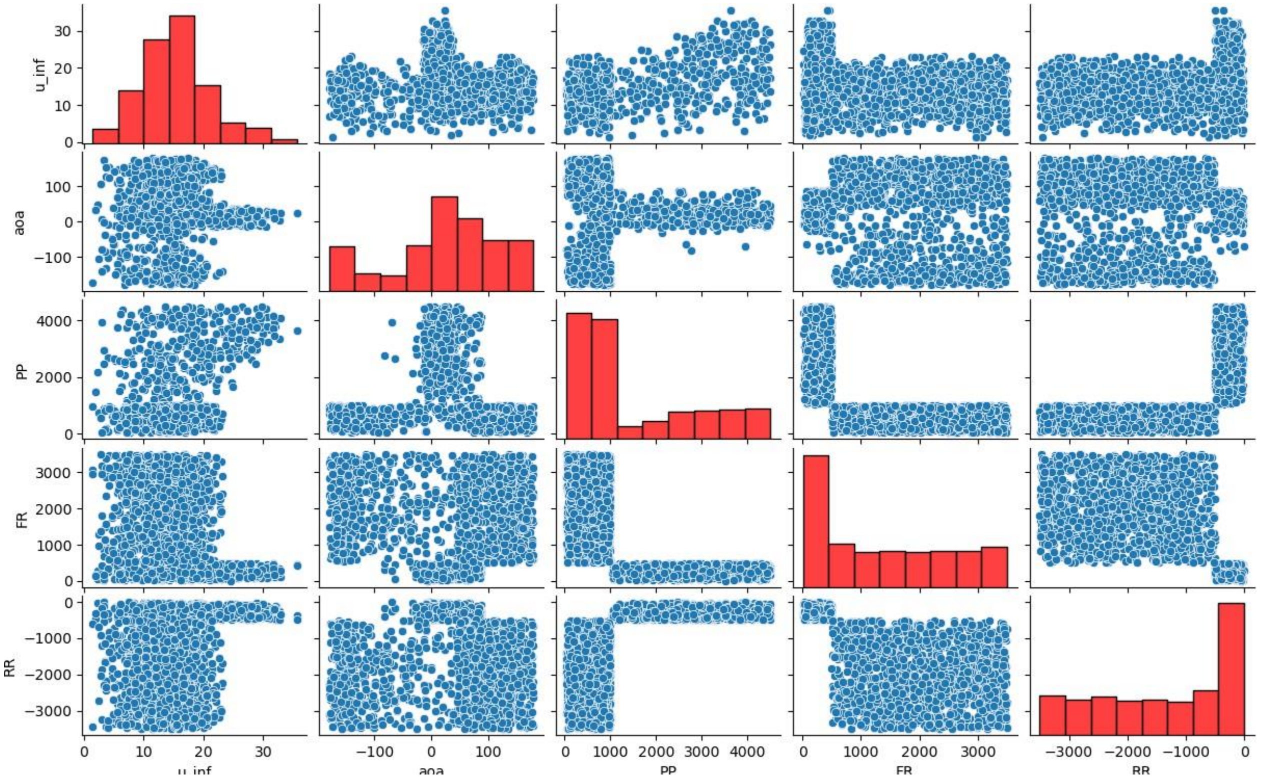


65

Datset analysis: understanding the data

Relationship between inputs:

- → How is the data distributed?
- → Check if in some areas (or envelope) some data is missing or if you have too much data



Multi-Fidelity Modelling – Transfer Learning

Model	Training Time	Prediction Time	Average Perc. Error	Average Perc. Confidence	N. Params
BNN LF	~41 min	~0.025 sec	4.88%	94.2%	174932
BNN MF	~35 min	~0.020 sec	10.8%	92.1%	19092
DF: BNN TL	~55 min	~0.025 sec	**3.06%**	97.3%	174932
DF: CoKriging	~4 min	~0.005 sec	3.9%	88.2%	-

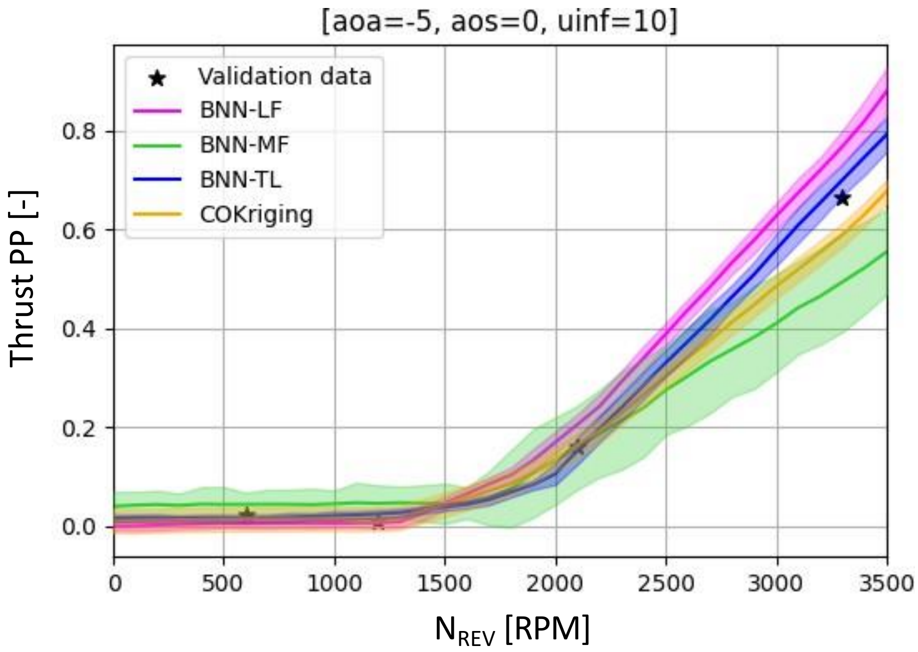
Benchmarks on NVIDIA Quadro P2000 GPU – Timing is referred to the execution of one dataset fold – Results are calculated with k=5 folds

Final model hyperparameters:

- **Input dimension**: 8
- **Number of layers**: 5
- **Units per layer**: 224, 144, 160, 112, 96
- **Optimization Function**: LeakyReLU
- **Prior Standard Deviation**: 0.0351
- **Prior Mu**: 0
- **Output dimension**: 10
- **Learning rate**: 0.0016
- **Learing rate during TL**: 0.0081
- **N. parameters**: 174932

Multi-fidelity results: ML-based rotors model

- BNN-TL achieves good accuracy and consistently
- BNN-TL better than GP Co-Kriging and single BNN models
- Uncertainty Quantification provided valuable insights into the model's convergence capability (epistemic) and data coherence (aleatoric)
- ML-based model was ultimately integrated into the system.



Flight Mechanics Module - results

Flight Tests

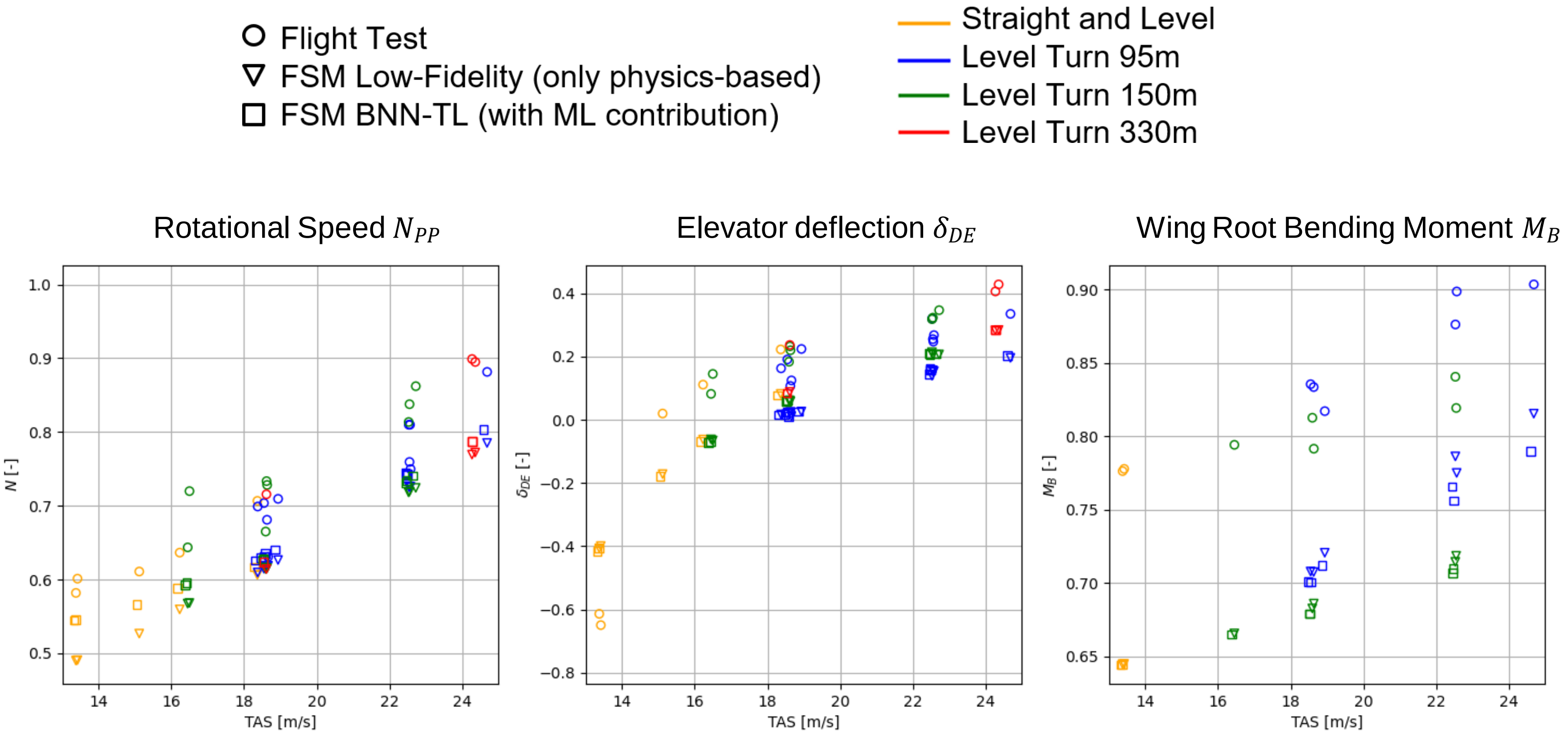
The eVTOL is equipped with standard sensors and additionally:

- accelerometrs
- strain gauges

Key notes:

- Several flights were accomplished in the entire flight envelope in both Helicopter and Airplane mode
- Structural modes were identified
- Flight test data is compared with simulation data

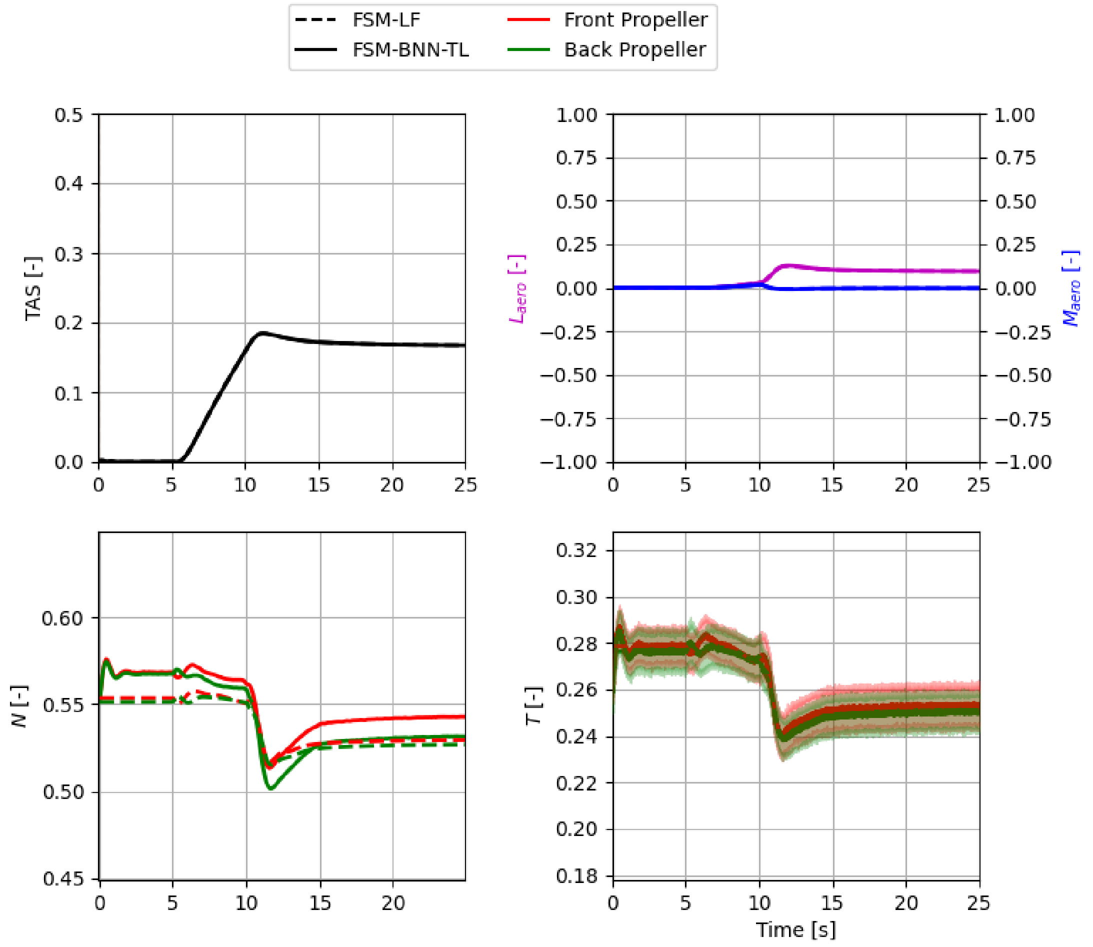
Flight Mechanics comparison



Hover Forward

Forward flight in HC mode:

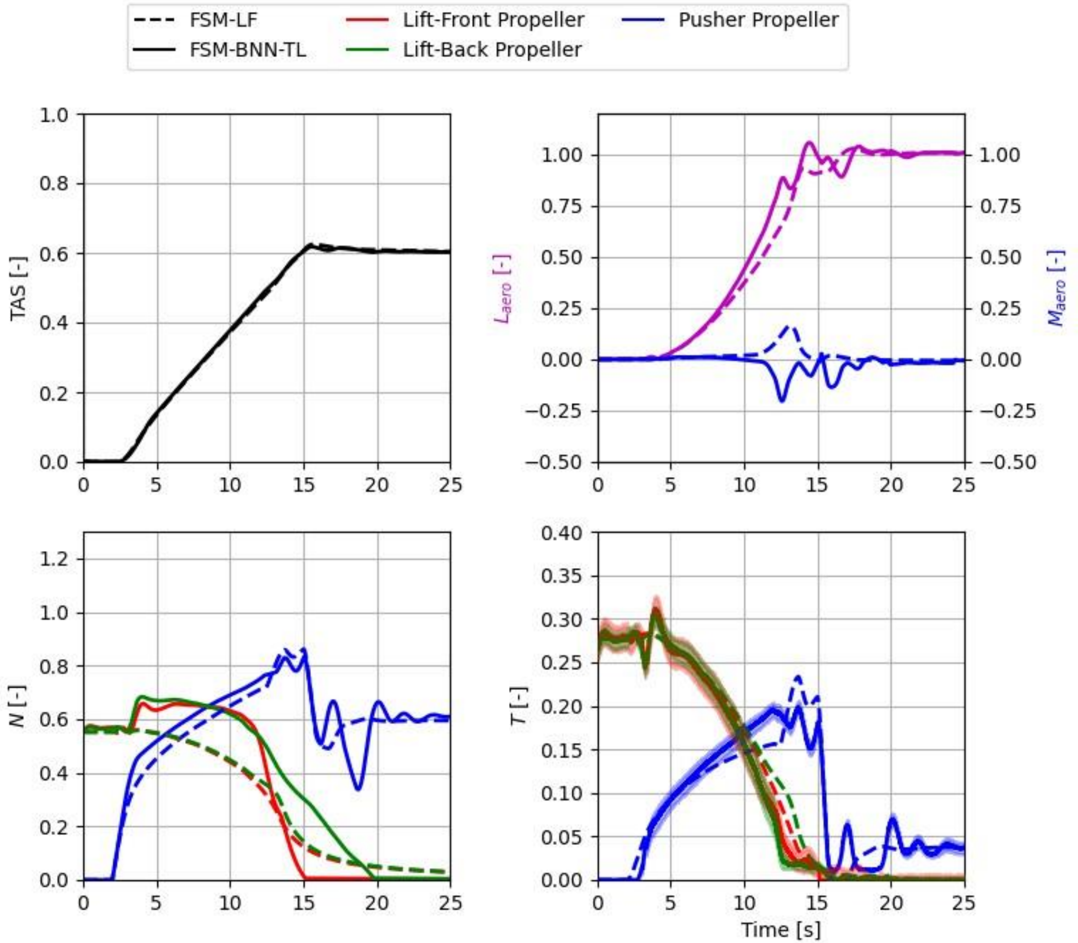
- → Some Lift is generated but not enough to sustain the eVTOL
- → Thrust T curves align closely
- → Rotational speed N shows differences: the ML-based model (FSM-BNN-TL) requires higher RPM for equivalent thrust, could be due to rotor-wing-rotor interactions (not captured in the LF model)



Transition

Transition from HC to AP mode:

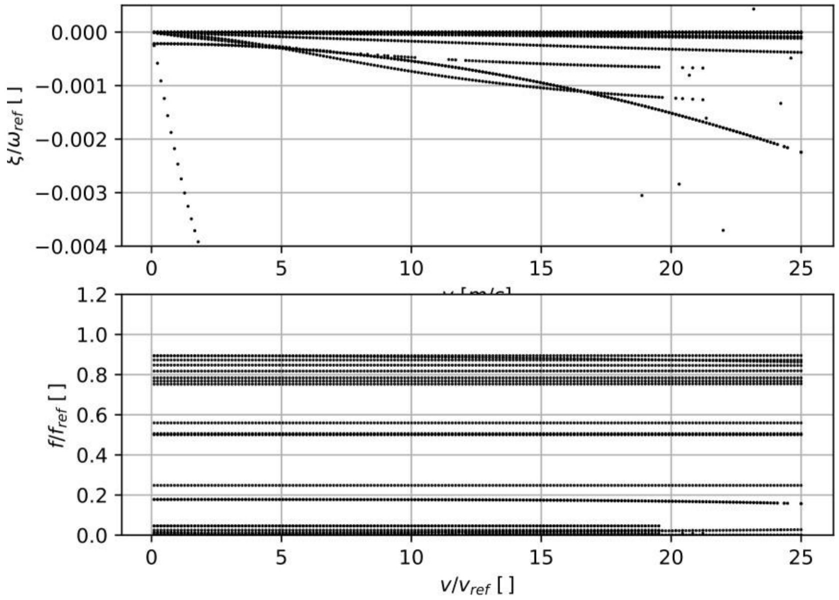
- → Aero forces and moments are generated ➔ after $t > 17\,s$ enough to switch off lift props
- → Thrust T curves align closely
- → As before ➔ Rotational speed N differences: FSM-BNN-TL higher RPM for equivalent thrust is required due to rotor-wing-rotor interactions (not captured in the LF model)

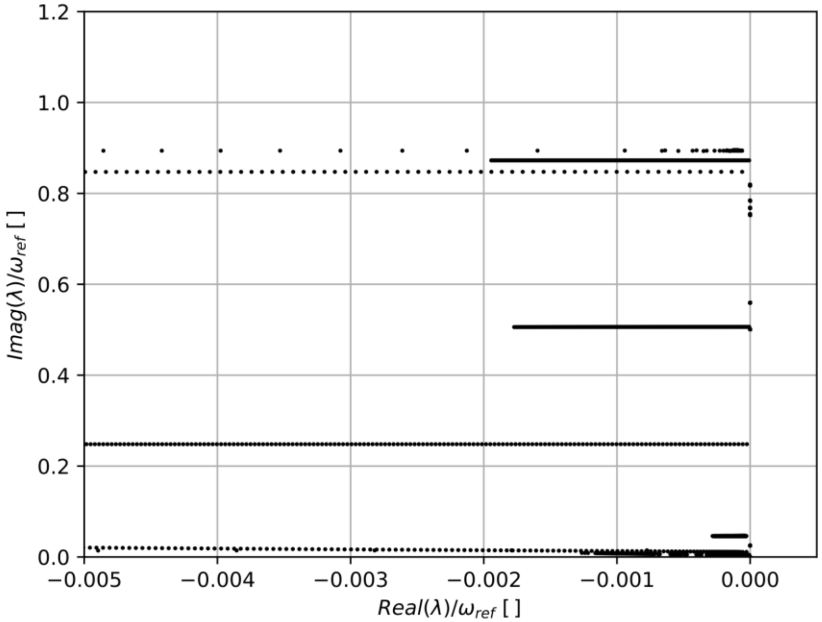


Aeroelastic Module - results

Aeroelastic results: Linear stability analysis

→ Airplane mode

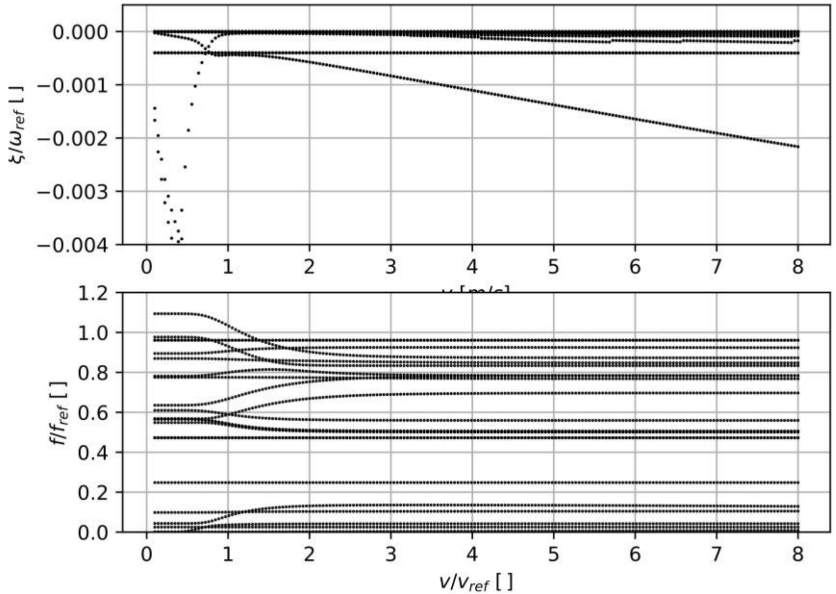


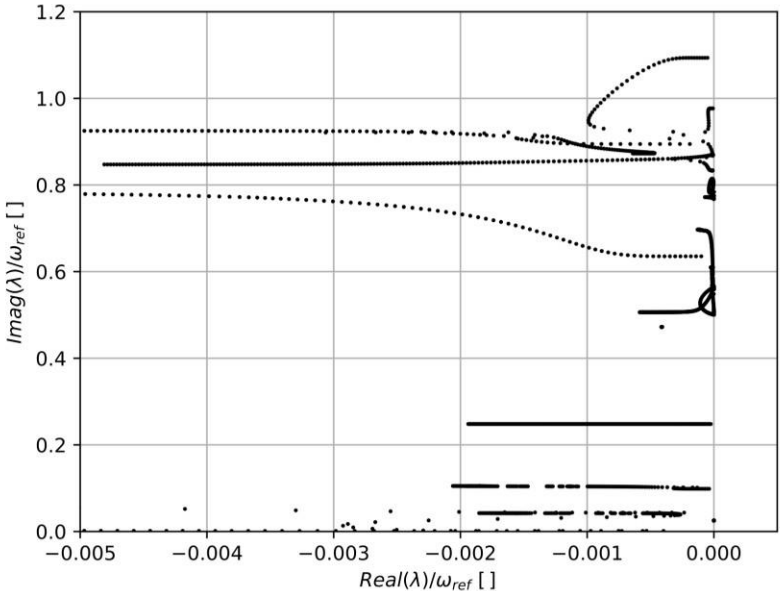


Conventional V-g plot and root locus, in this case, no unstable mode is detected.

Aeroelastic results: Linear stability analysis

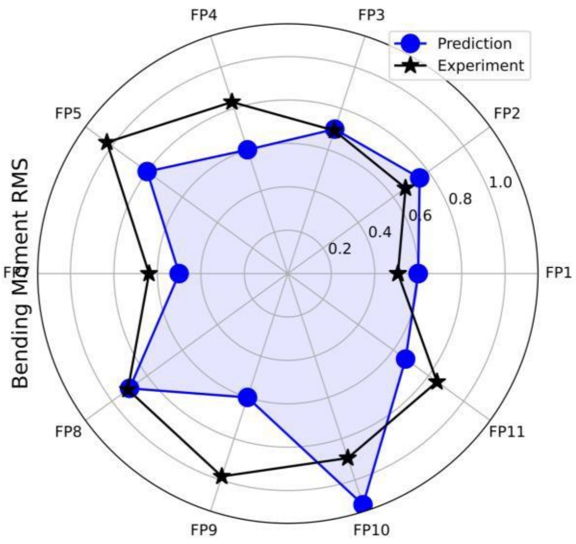
→ helicopter mode





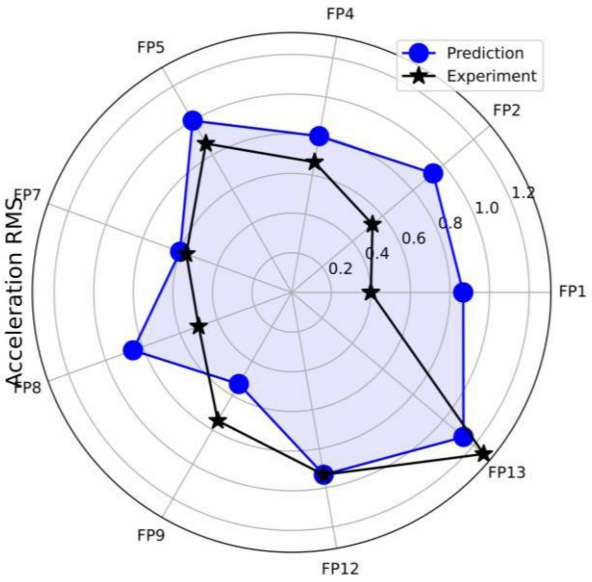
Conventional V-g plot and root locus, in this case, no unstable mode is detected. Note that in helicopter mode, the eigenvalues analysis is only possible if multi blade transformation provides a time constant system of equations. Conversely, an approach like Floquet is necessary.

Aeroelastic results: Bending moment RMS



- FP1, FP2, Level Turn 150 m
- FP3, FP4, FP5, Level Turn 95 m
- FP6, Hover,
- FP7, FP8, Level Turn 95 m
- FP9, Level Turn 185 m
- FP10, Level Turn 160 m
- FP11, Level Turn 95 m
- FP12, FP13, FP14, Hover

Aeroelastic results: Acceleration CoG RMS



- FP1, FP2, Level Turn 150 m
- FP3, FP4, FP5, Level Turn 95 m
- FP6, Hover,
- FP7, FP8, Level Turn 95 m
- FP9, Level Turn 185 m
- FP10, Level Turn 160 m
- FP11, Level Turn 95 m
- FP12, FP13, FP14, Hover

Workshops Summary

Workshops #1 Summary

Topics

- Scope of the project
- Case study plan:
    - Quantities of interest definition
    - Low-fidelity and high-fidelity model
    - Flight test
    - Multi-fidelity Surrogate Model
    - Surrogate Model uncertainty quantification
- Literature review: the digital twin state-of-the-art
- Stakeholder discussion
- Conclusions

Feedback

- Motivation for AI
- Execution time of AI
- Validation with simpler aircraft than eVTOL?
- Non-deterministic nature of AI
- Verification and Validation of AI
- Acceptance for Certification purposes

Workshops #2 Summary

Topics

- Introduction: Digital Twin data and decision making
- Flight simulation model modules: Flight mechanics and Aeroelasticity
- Multi-fidelity surrogate model through transfer learning
    - Fidelity levels
    - Multi-fidelity realization
    - Steady and unsteady physics
- Uncertainties quantification: Bayesian Neural Networks (BNN)
    - Aleatoric uncertainties
    - Epistemic uncertainties
- Modeling details and relevance to Special Condition VTOL:
    - Rotor thrust unsteadiness
    - Role played by control systems
    - Blades elasticity
- Role played by Artificial Intelligence

Workshops #2 Summary

Feedback

- Project Motivation: EASA final goal is to eventually implement certification requirements for AI-based models?
- Model Fidelity and Impact: The influence of including wing and tail models on the hover case was explored, along with the impact of structural flexibility on flight mechanics.
- Training Material and Knowledge Transfer: The potential for creating training materials and sharing knowledge
  - ➔ github page of **ML-based model** MF-BayNet
  - ➔ github page of a rigid-body **flight dynamics model** of a generic lift+cruise eVTOL is going to be released in the next months
- Flight Resonance and Model Development: The importance of modelling flight resonance and the interaction between propellers with different RPMs was highlighted.
- AI and Future Outlook: The potential impact of AI on simulation and the overall project were explored.

Lessons Learned

LL1: High-fidelity approach

- CFD as high-fidelity approach turned out to be more challenging than expected:
  - Actuator disc not usable if freestream velocity not perpedicular to rotor plane,
  - Simulations with rotating rotors are of course computationally expensive …
  - … and even more so, for fully unsteady simulations.

LL2: Mid-fidelity approach

- → Simulations with mid-fidelity („vorticity based“ solvers) turned out to be much easier / accurate than expected and are the de facto standard for eVTOL.
- → Conservation of vorticity guarantees a suitable resolution of the rotor wake in both time and space.
- → However, this approach is not free from errors either:
  - → Aerodynamic loading on blades and wing surface is approximated (panels, vortex lattice, lifting line, etc),
  - → the error may become particularly large in case of non detected separations of the boundary layer from wing / blades surface.

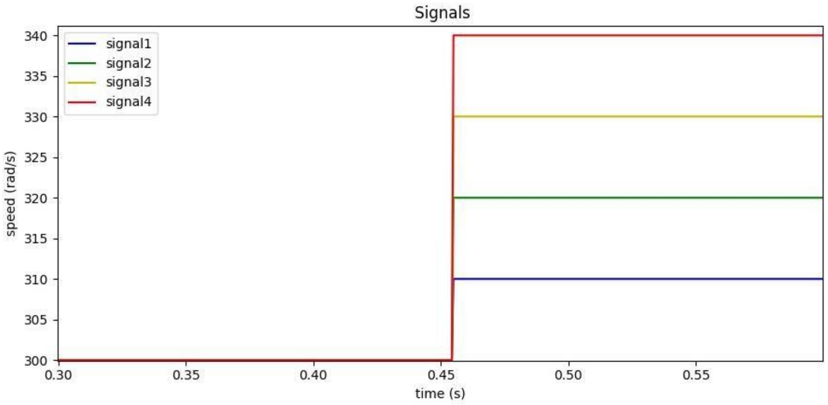
LL3: CFD – vorticity-based solvers

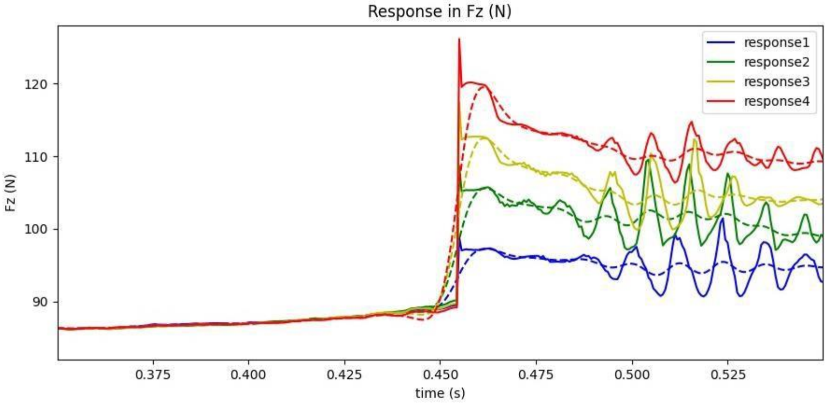
- → Error sources from both approaches are different.
  - → They could complete each other if „fused“ with techniques similar to waht we have been using in this project.
- → A safer approach to the Digital Twin development could have exploited CFD and vorticity-based solvers in order to detect each other‘s errors.
- → Transient responses (vorticity-based) may also be added.

LL4: Rotors unsteady response

Relevance of unsteady analysis,
Unsteady simulations show that the wake build-up requires some time – this delay is not negligible.

Unsteady rotors’ response and interaction with structural dynamics,





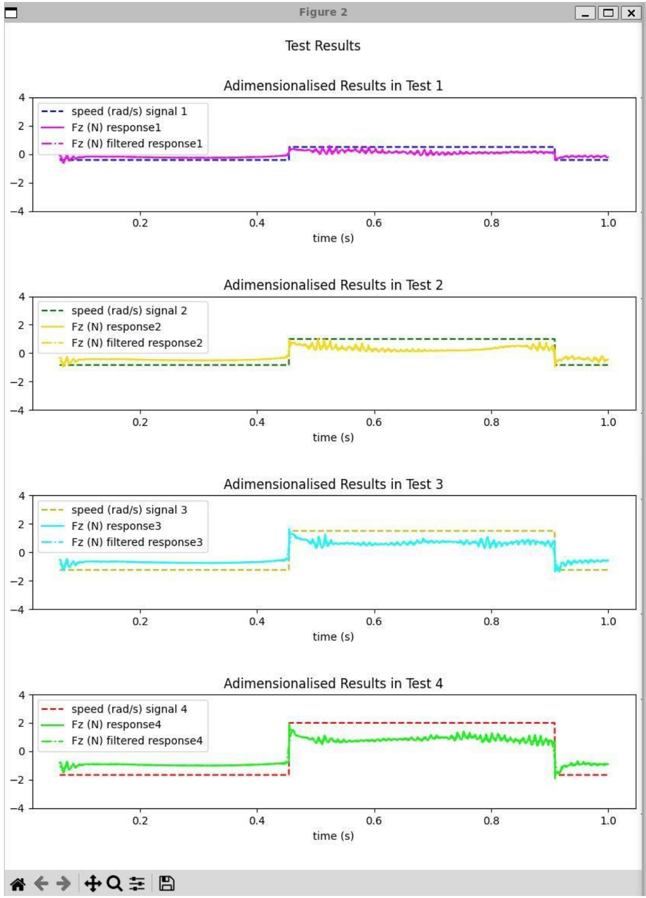


Figure 2
Test Results
Adimensionalised Results in Test 1
speed (rad/s) signal 1
Fz (N) response1
Fz (N) filtered response1
Adimensionalised Results in Test 2
speed (rad/s) signal 2
Fz (N) response2
Fz (N) filtered response2
Adimensionalised Results in Test 3
speed (rad/s) signal 3
Fz (N) response3
Fz (N) filtered response3
Adimensionalised Results in Test 4
speed (rad/s) signal 4
Fz (N) response4
Fz (N) filtered response4
time (s)

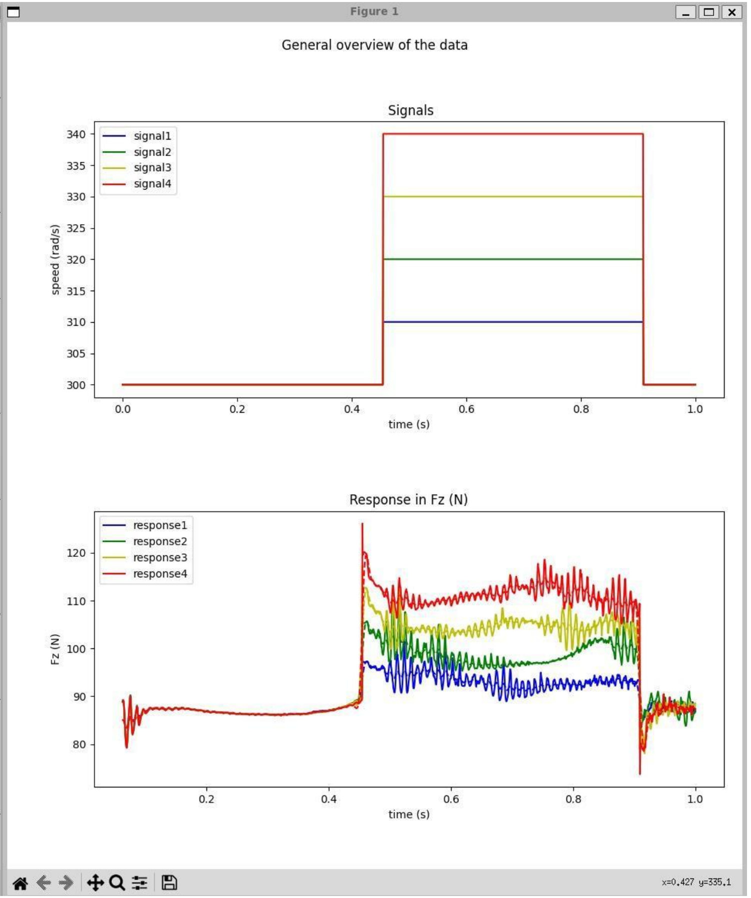
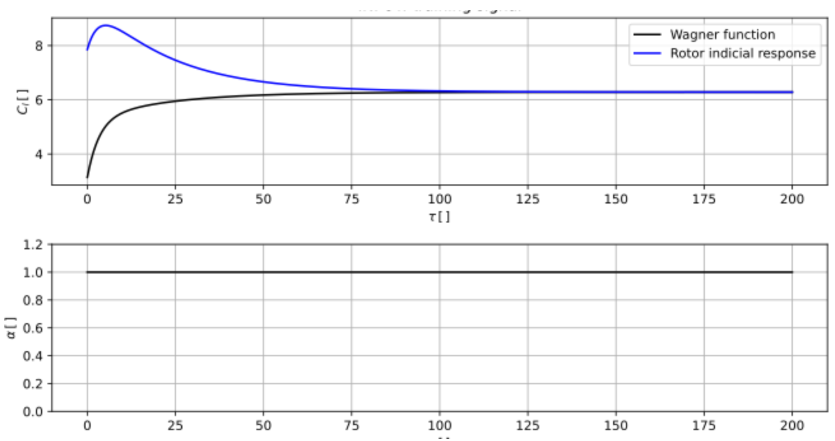
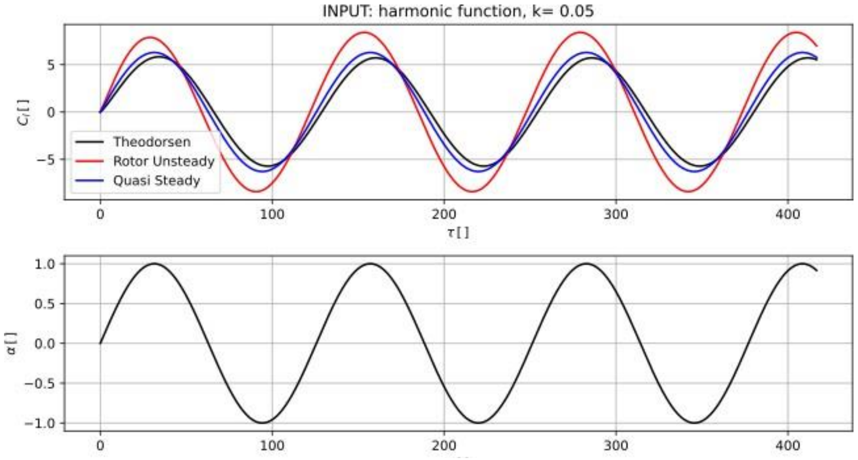
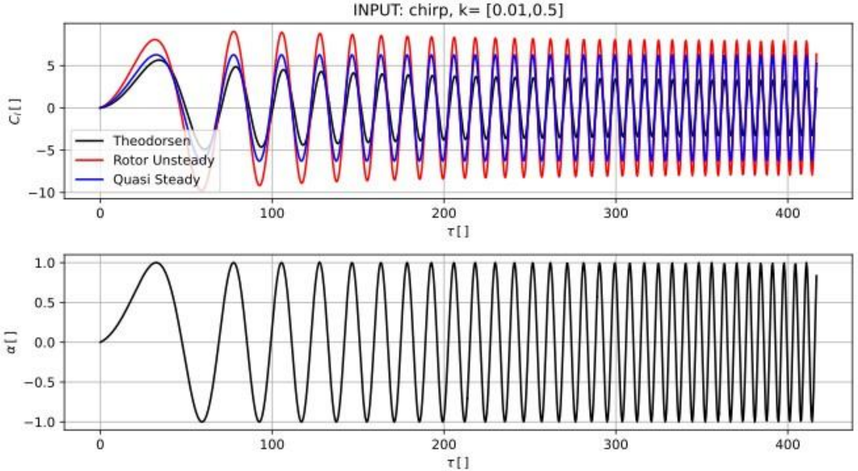
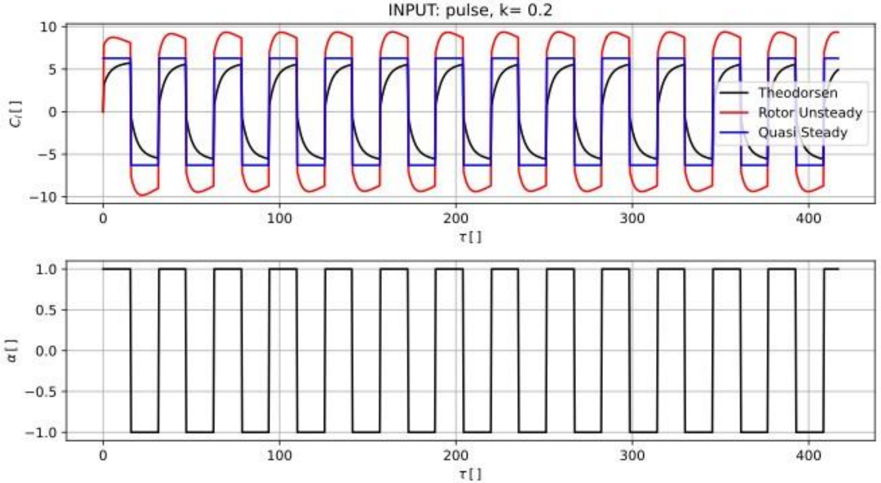


Figure 1
General overview of the data
Signals
signal1
signal2
signal3
signal4
speed (rad/s)
time (s)
Response in Fz (N)
response1
response2
response3
response4
Fz (N)
time (s)
x=0.427 y=335.1


Wagner function
Rotor indicial response
C_l [ ]
τ [ ]
α [ ]


INPUT: harmonic function, k= 0.05
Theodorsen
Rotor Unsteady
Quasi Steady
C_l [ ]
τ [ ]
α [ ]


INPUT: chirp, k= [0.01,0.5]
Theodorsen
Rotor Unsteady
Quasi Steady
C_l [ ]
τ [ ]
α [ ]
τ [ ]

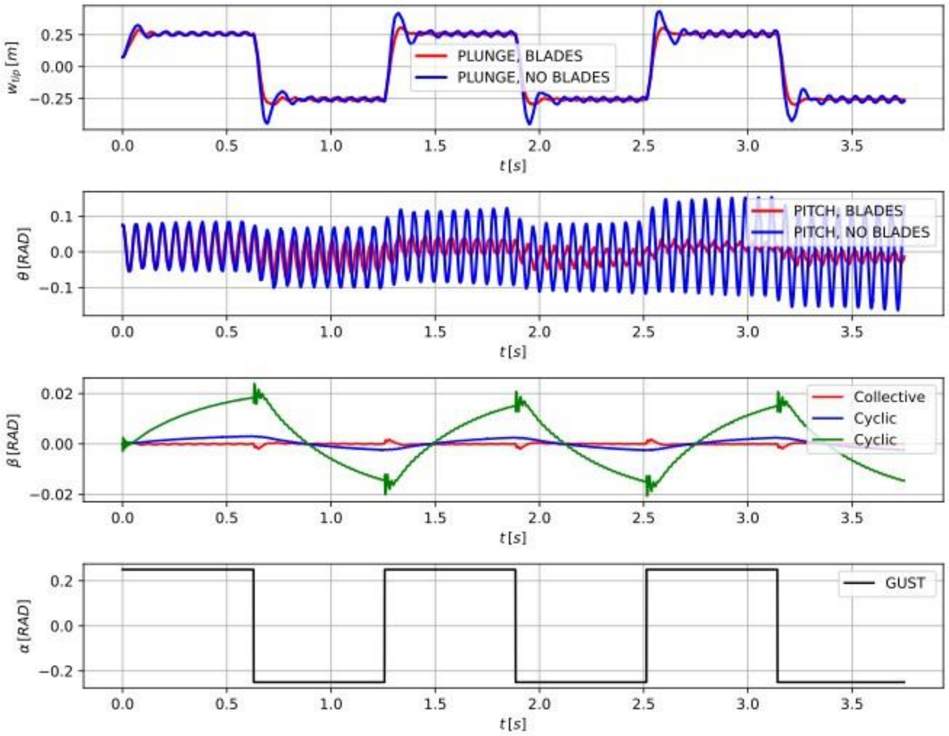

INPUT: pulse, k= 0.2
Theodorsen
Rotor Unsteady
Quasi Steady
C_l [ ]
τ [ ]
α [ ]
τ [ ]

LL5: Relevance of rotors blades flexibility

- → eVTOL blades may be stiff in bending and torsion, with no mechanical hinges,
- → It could be meaningful to assume a dominant first flapping mode, with a natural frequency slightly above the rotational frequency.
- → By neglecting blade elasticity, one would neglect dynamic loading of blades and wing – which could be conservative or not.
- → Multi-blade coordinates provide a framework to take blades DoFs into account.

LL5: Relevance of rotors blades flexibility

- Modelling blades‘ elastic response may improve accuracy:
  - Effect 1: on wing / aircraft dynamic response and stability,
  - Effect 2: blades / rotor vibrations.
- Some results from a „toy problem“



LL6: Role played by AI/ML

- We have been using AI/ML for regression only, relying on NN ability to capture nonlinearity and obtaining uncertainty as a by product (Bayesian NN).
- However, some AI/ML algorithms could by exploited to do more in the framework of the certification process:
  - Analysis of DT data (e.g. clustering) to identify areas (in parameters space) where safety margins are small or negative,
  - AI/ML to drive the DT in those areas,
  - AI/ML to plan the use of DT and recommend a flight testing planning as a function of the uncertainty of DT data,
  - AI/ML to drive the whole certification process!

LL6: Are these good ideas? Have AI/ML algortihms reached the sufficient level of maturity?

1. Analysis of DT data (e.g. clustering) to identify areas (in parameters space) where safety margins are small or negative,
2. AI/ML to drive the DT in those areas,
3. AI/ML to plan the use of DT and recommend a flight testing planning as a function of the uncertainty of DT data,
4. AI/ML to drive the whole certification process!

1. Yes, this could be a good idea and would save time to EASA and the applicants,
2. NN used for regression are mature, reliable and realtively easy to use. Difficult to say if we imply models such as LLMs.
3. Same as 2. Note that EASA requests careful validation of AI/ML methodologies.
4. Probably not or not yet.

LL7: Training

- Learning assurance must be demonstrated (ref. to EASA AI/ML concept paper) and this is neither easy nor cheap.
- Regardless, training is associated with high costs in resources and long duration in time. Data production must be carefully planned. Data quality must be monitored.
  - Data augmentation
  - Hyperparameters optimization

LL8: Training-specific

- → **Iterative model implementation**: set-up a number of tests to check the NN reliability. It could be needed to create additional data points or apply data augmentation techniques.
- → **Integration with physics-based model**: classical trim problems are solved with a method where the calculations need to be deterministic. Further adaptations of the strategy were needed.
- → **Simulation time**: compared to LF simulations, the introduction of the BNN increased the simulation time greatly. Despite better fidelity, real-time simulation could not possible anymore in some conditions.
- → **Model stability**: it's important to check that the datasets (train, validation, test) is representative. K-fold or stratified sampling is needed to assure model stability, as well as hyperparameter optimization.
- → **Reliable metrics:** in any case, the error metrics on test set could not be always reliable. Human manual check is needed to verify the robustness of the model's results.
- → **Data pre-processing**: Removing unconverged examples or outliers can be useful to get better results and avoid model misleading.
- → **Potential Limitation in Uncertainty Handling**: The stability of uncertainty in this models, despite higher error values, could point to a model limitation where it fails to express higher uncertainty when faced with more challenging data points.

Conclusions

- → **Digital Twin**: a collection of ROMs, where AI/ML is exploited as a robust and reliable “regression" method (“level 1”),
- → **Uncertainty** can (and must) be kept under control, AI/ML methods allow it,
- → **Multi-fidelity modelling** looks like a good idea; however, data generation, definition and optimisation of NN architecture, training effectiveness require specific competences and time,
- → Specifically, **eVTOL** dynamic / aeroelastic modelling is demanding; a number of specific aspects must be handled carefully, e.g. unsteady rotor response to changes in RPM.
- → AI/ML: despite some methodologies have reached maturity, exploiting them in certification may not be straight forward as EASA requires the evidence of **learning assurance**.

Thank you!

Questions?

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