MODEL-SI
MODELING AND SIMULATION

zhaw School of Engineering
ZAV Centre for Aviation

Horizon Europe Project

MODEL-SI Workshop #2

July 10th 2024, Cologne (DE) , Winterthur (CH)

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Workshop 2

- The objective of the MODEL-SI project is to assess the value of a **Digital Twin** in the certification of eVTOL (and similar) vehicles and to do so in light of the availability of AI/ML methods/algorithms,
- We held our first workshop on April 23, where we discussed our plans and showcased some initial results from rotor modeling and data fusion (multi-fidelity surrogate modeling),
- As the project approaches completion, most of our **models** have been developed, and we have obtained **flight testing data** from a well-established company specializing in unmanned aerial vehicles,
- In this second workshop, we aim to document the **progress** we have made and evaluate our ideas, plans, and models, particularly in light of the **EASA AI/ML concept paper**,
- We have prepared two slide decks: one detailing the process/methodology and the other presenting the results we have achieved so far.

Table of contents

A. Simulation software architecture

Modular simulation software architecture

- A Digital Twin is about **Reduced Order Modelling**,
- A **Modular** approach is probably the standard solution for software suites designed to provide simulations for certification,
- Modules concern different disciplines (flight mechanics, aeroelasticity, etc), treated with different levels of abstraction and / or fidelity, connected in a way to obtain a meaningful workflow,
- AI/ML allows an easier integration and a quantification of the uncertainties. Note the it is used here for simple **regression** problems, (**Model Order Reduction).**

One notable example is the "increased order model" proposed by Prof. Karpel in the 1990-2000, also for certification purposes (Airbus),

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Technion – Israel Institute of Technology – Faculty of Aerospace Engineering

Increased-Order Modeling for Dynamic Response and Stability of Aero-Servo-Elastic Systems

Moti Karpel

Technion – Israel Institute of Technology

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Presented at the International Forum on Aeroelasticity and Structural Dynamics, June 14, 2022

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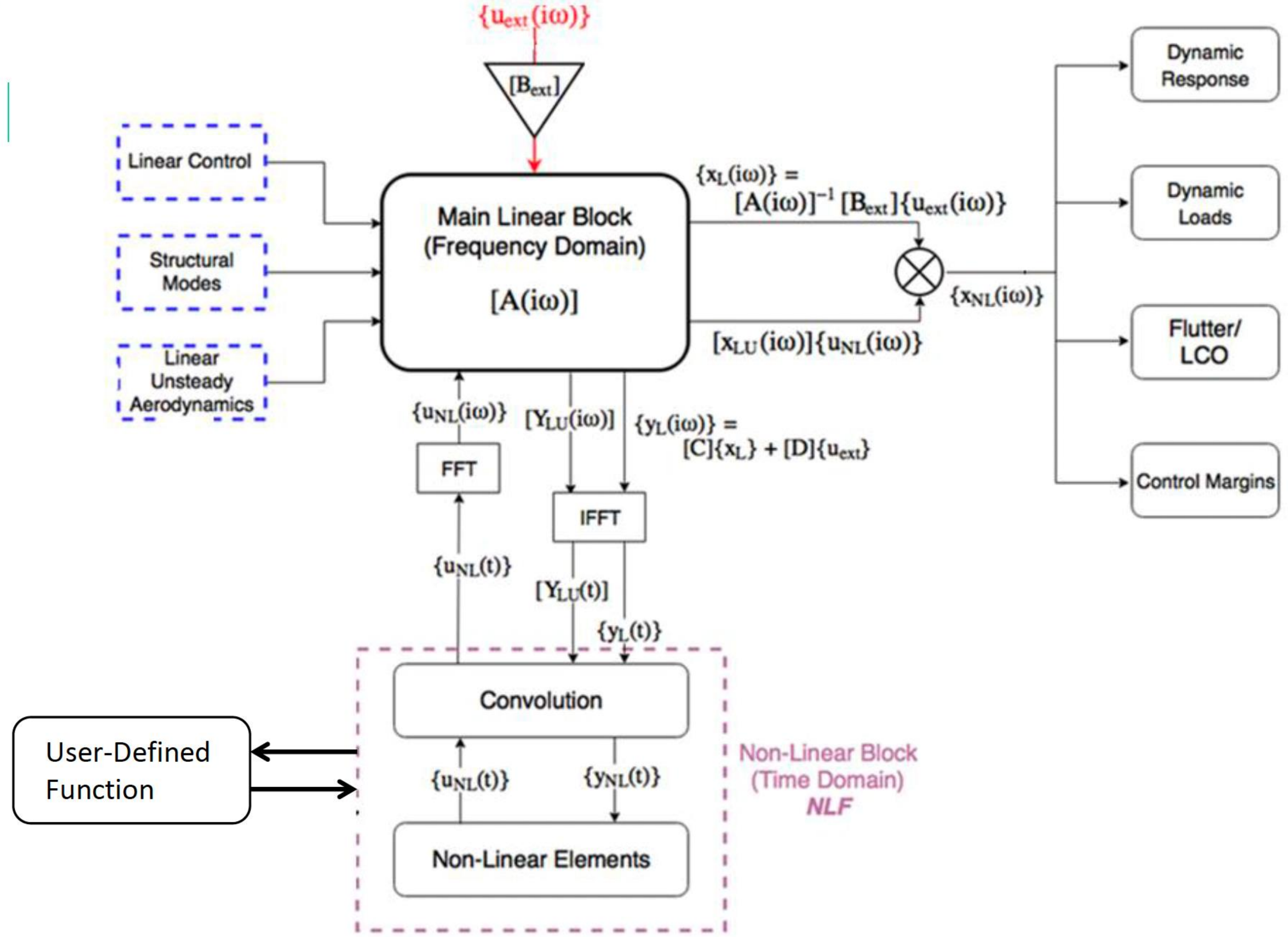
Technion – Israel Institute of Technology – Faculty of Aerospace Engineering

ASE simulations with nonlinear elements[6]



[6] Karpel, M., "Unified Framework for Aeroservoelastic Response and Stability Analysis, Design and Testing" IFASD-118, June 2019.

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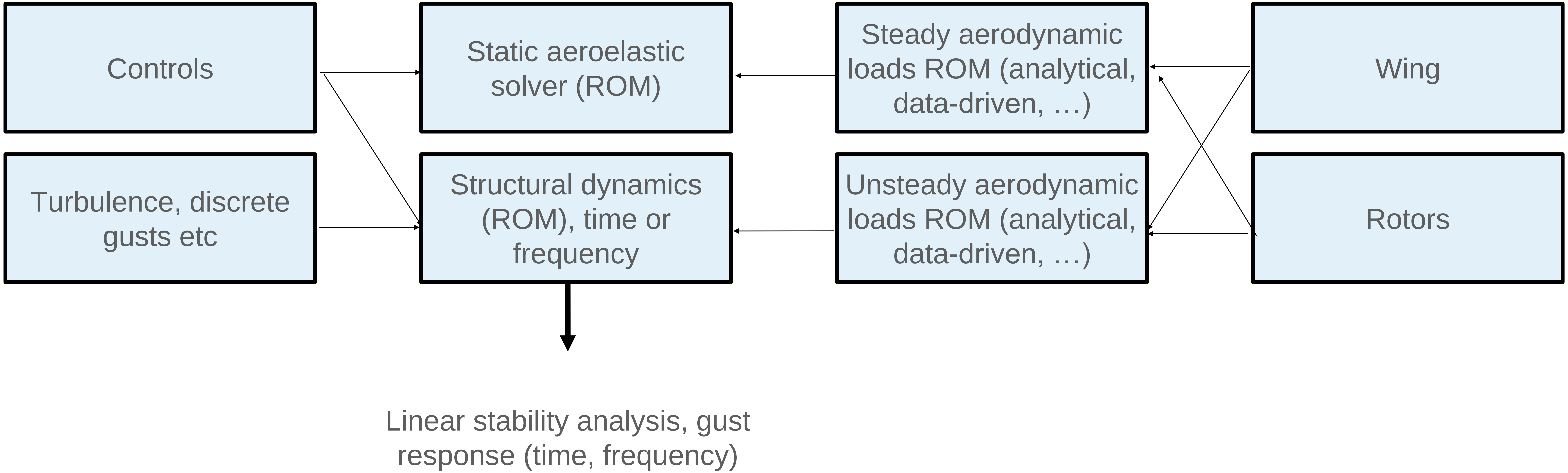
In the case of our model

- 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),

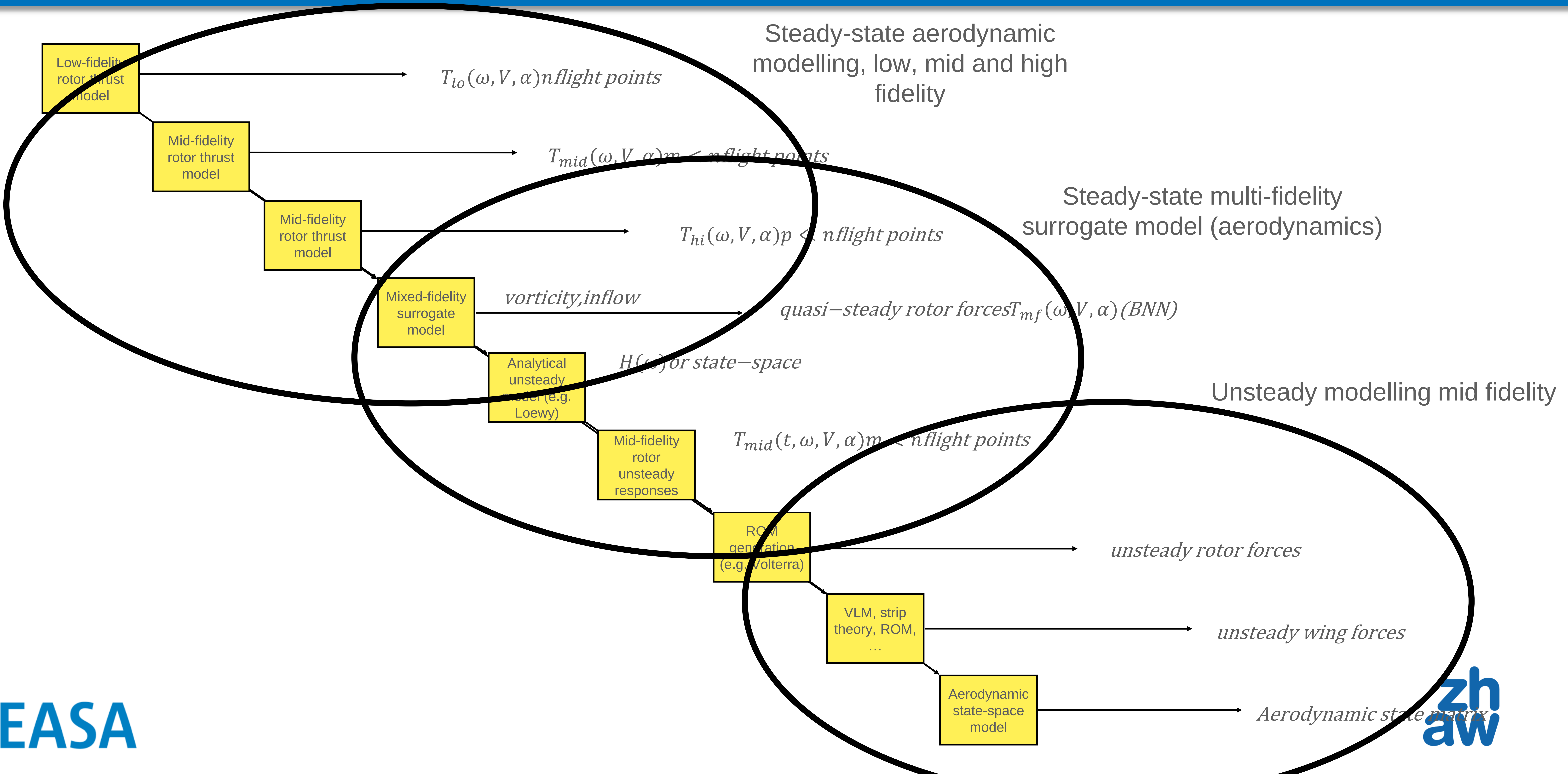
Relevance of Legacy Modelling / Simulation Software

- A modular flight mechanics / aeroelastic solver can be built out of **legacy** software, surrogate multi-fidelity models can be integrated into these legacy solvers,
- A necessary condition to benefit from AI/ML is that the **competences** in all phases / modules are available, AI/ML does not make the process easier but more effective,

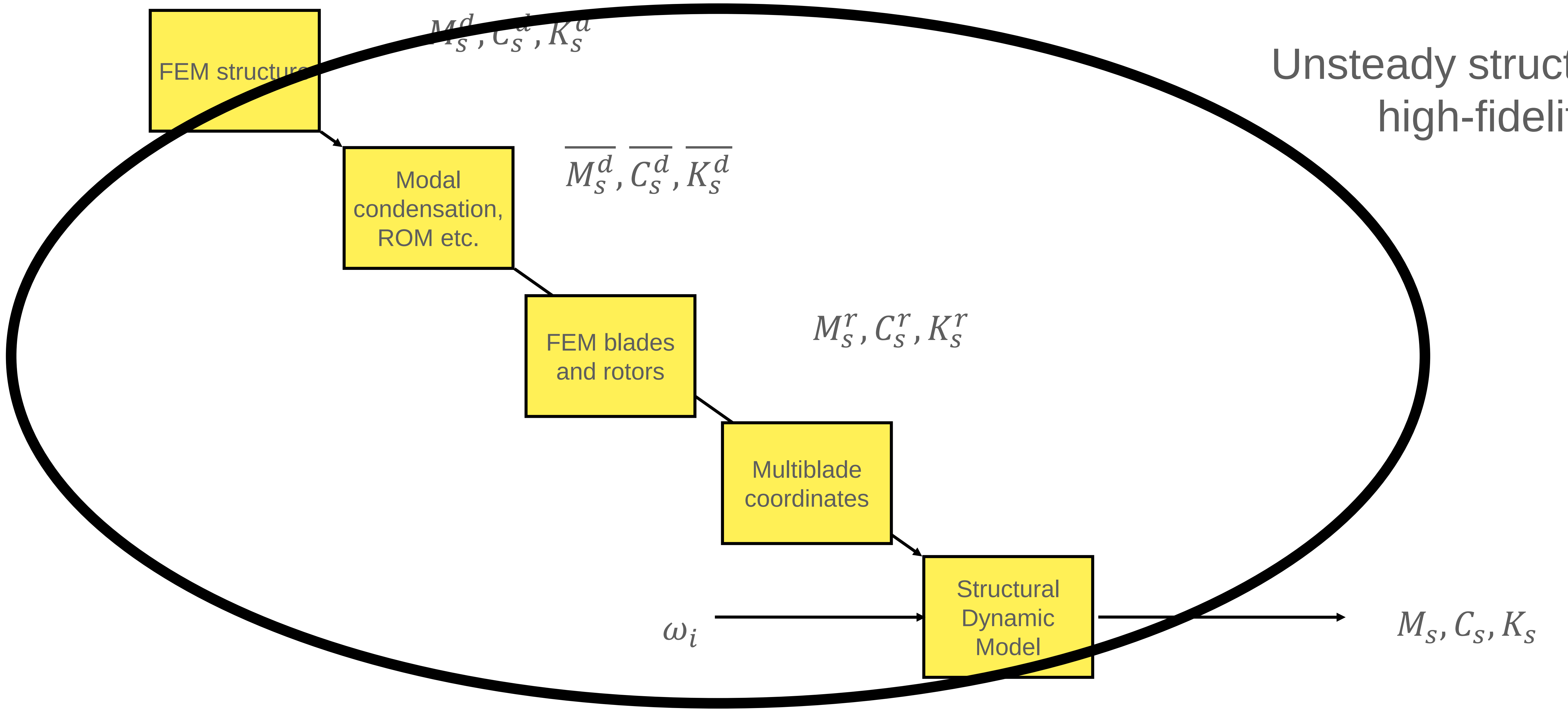
Similar SW architecture used in the past also for certification / qualification purposes



Aerodynamics

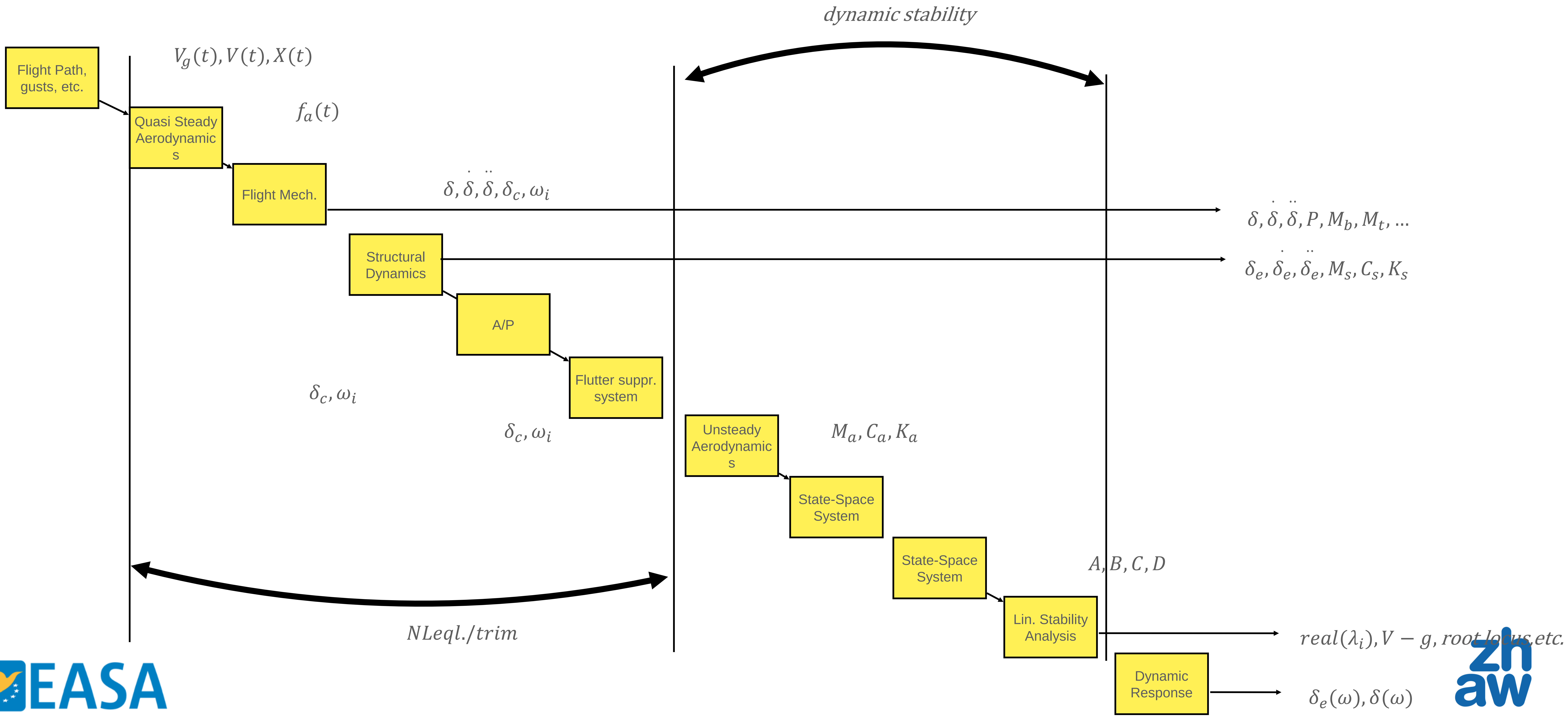


Structural Dynamics

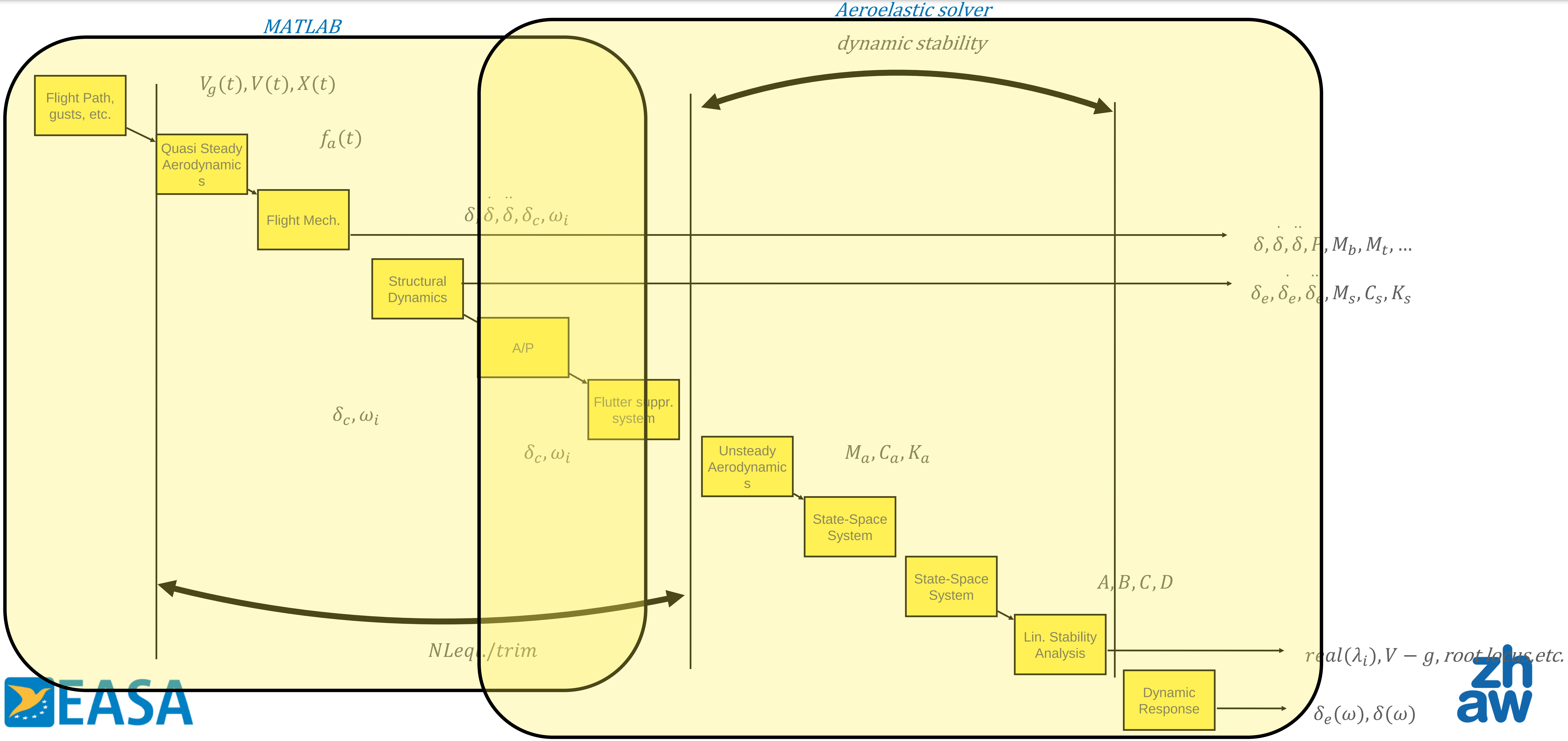


Unsteady structural dynamics, high-fidelity + ROM

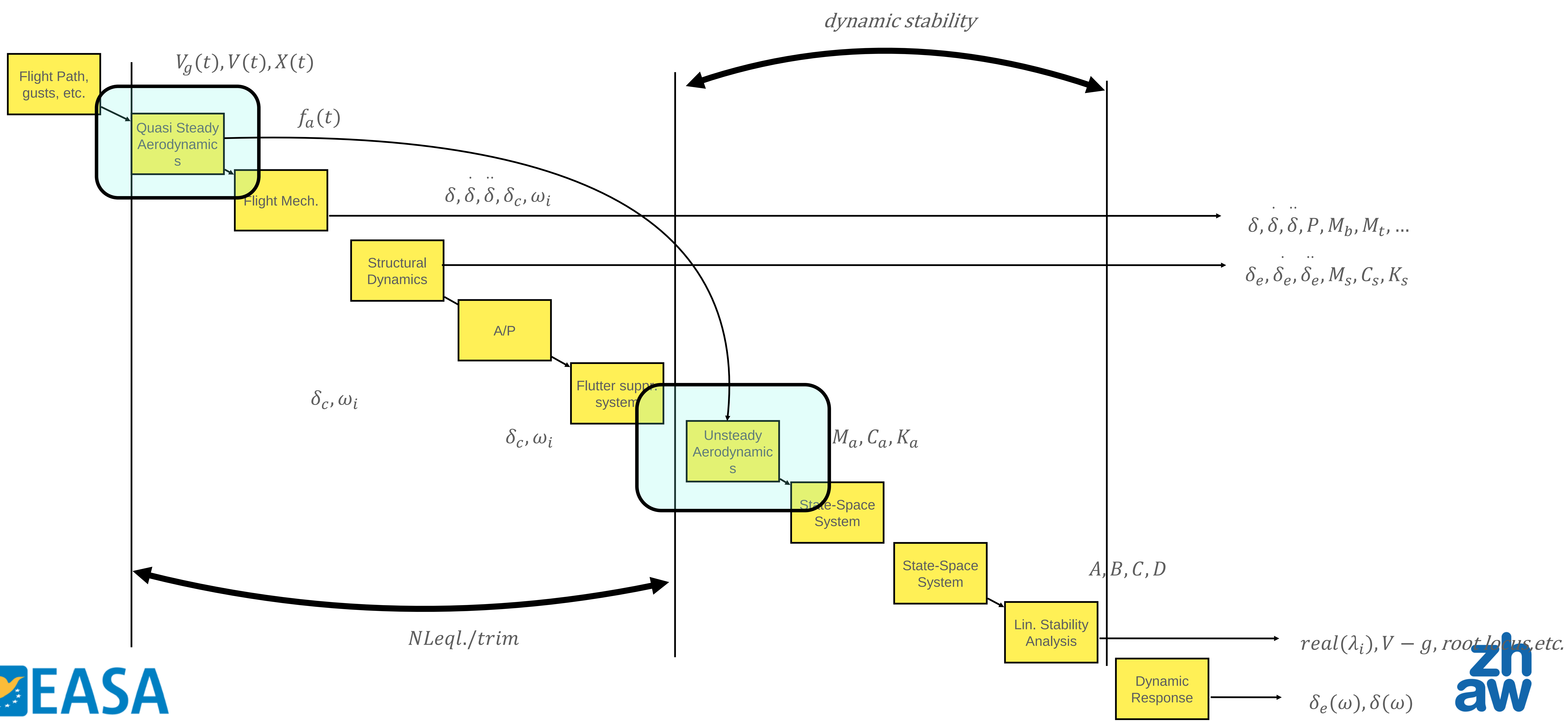
Modelling Strategy



Modelling Strategy



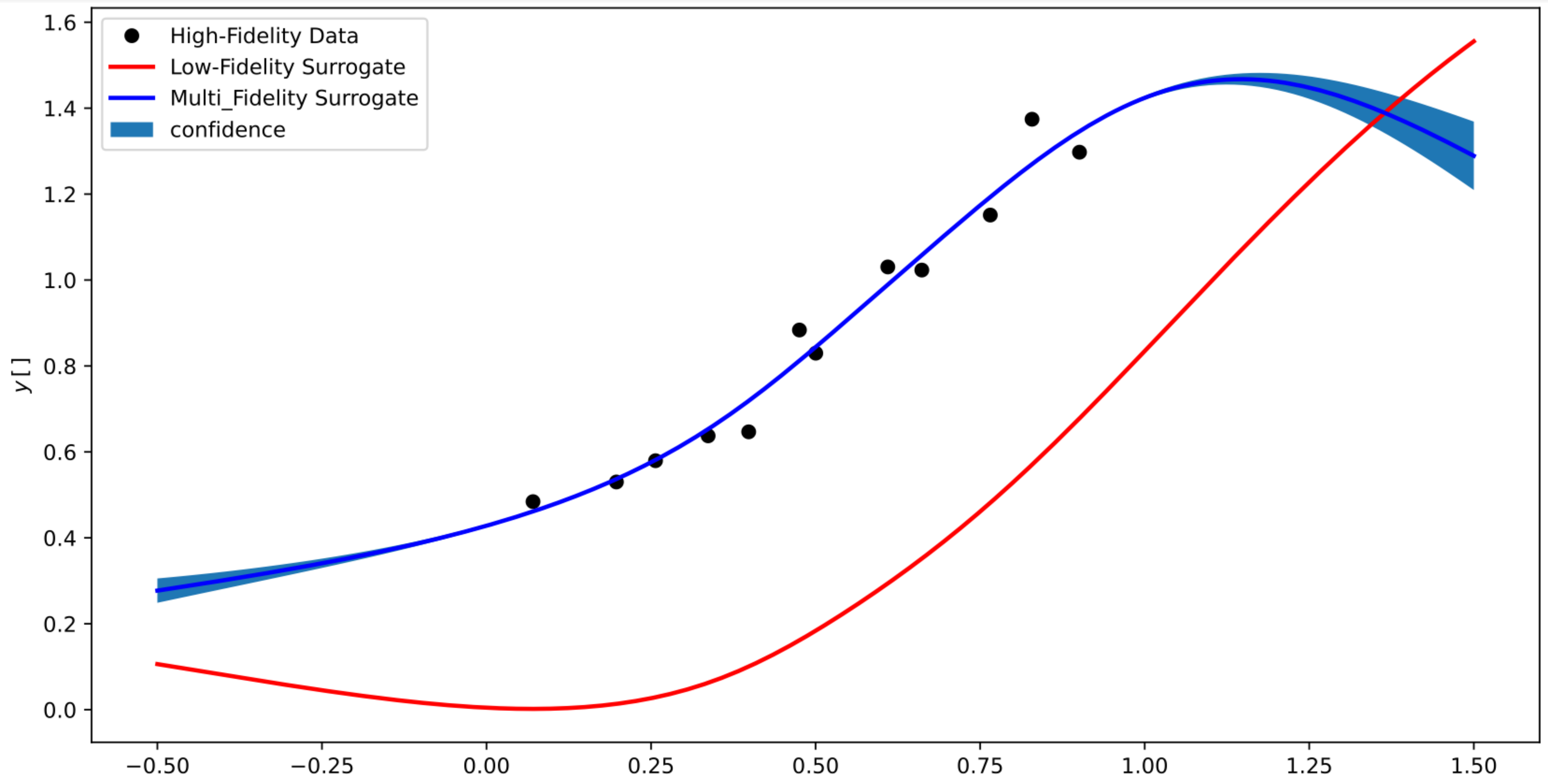
Modelling Strategy: AI/ML contribution

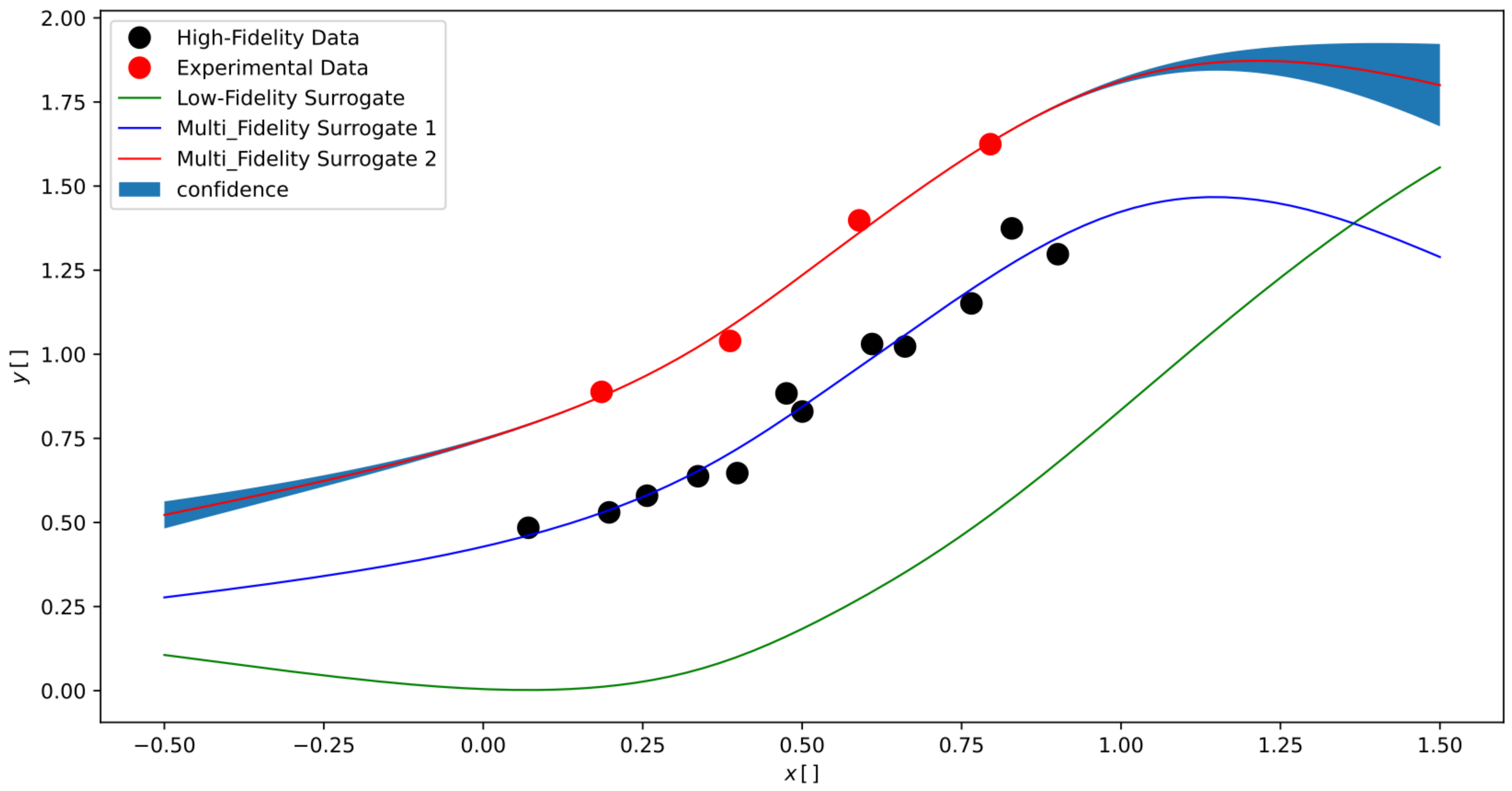


B. Multi-fidelity modelling

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,





Level 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,

Low-fidelity Modelling

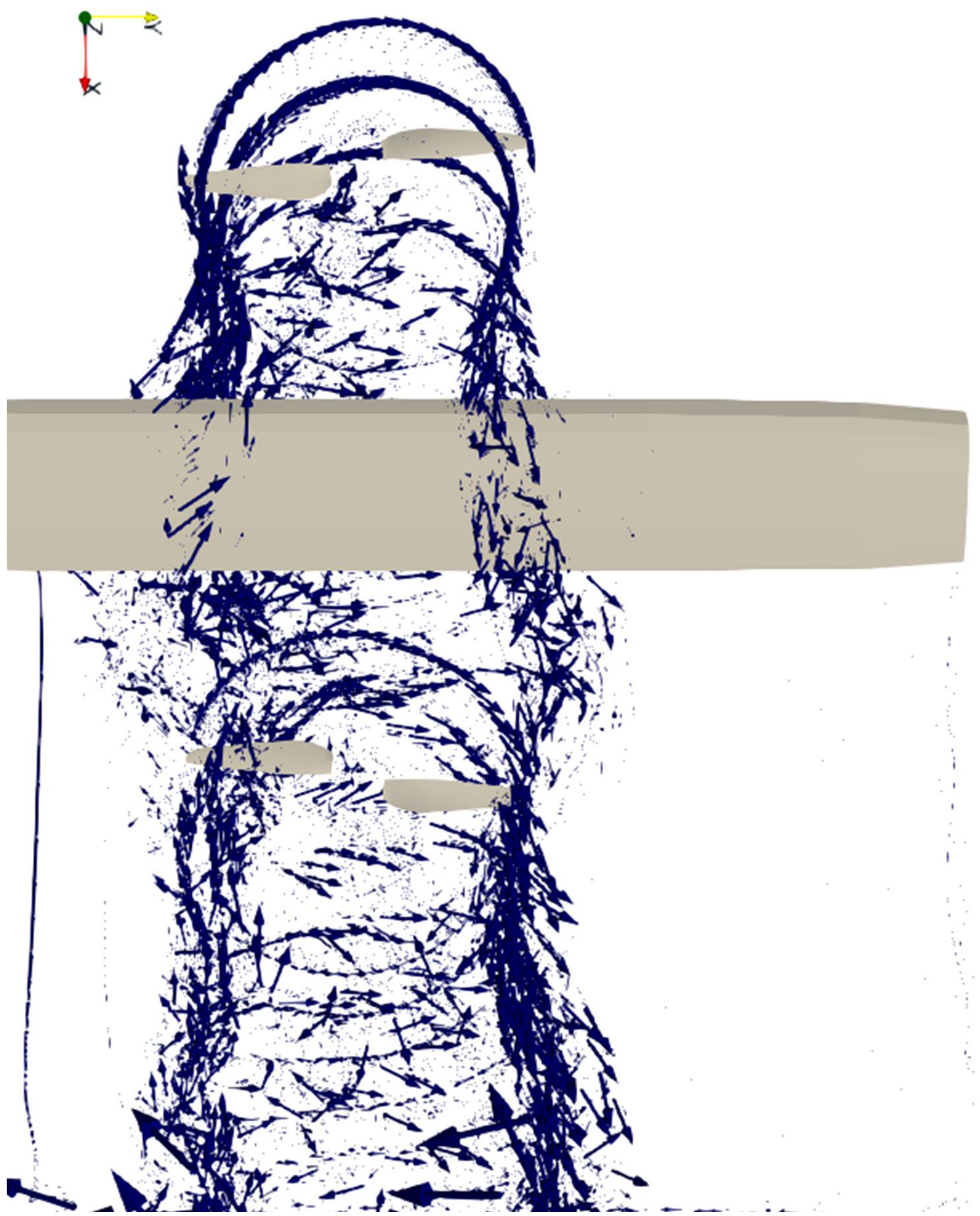
- This has been covered in Workshop 1 extensively,
- We used low-order models for wing and rotor aerodynamics,
- Also, structural dynamics may benefit from an approach (for example) such as Ritz-Rayleigh. In our case a beam-element FEM (“stick model”) turned out to be a good choice,
- We also reminded that industrial codes such as CAMRAD or most of the solvers in the ZONA software suite are low-order,

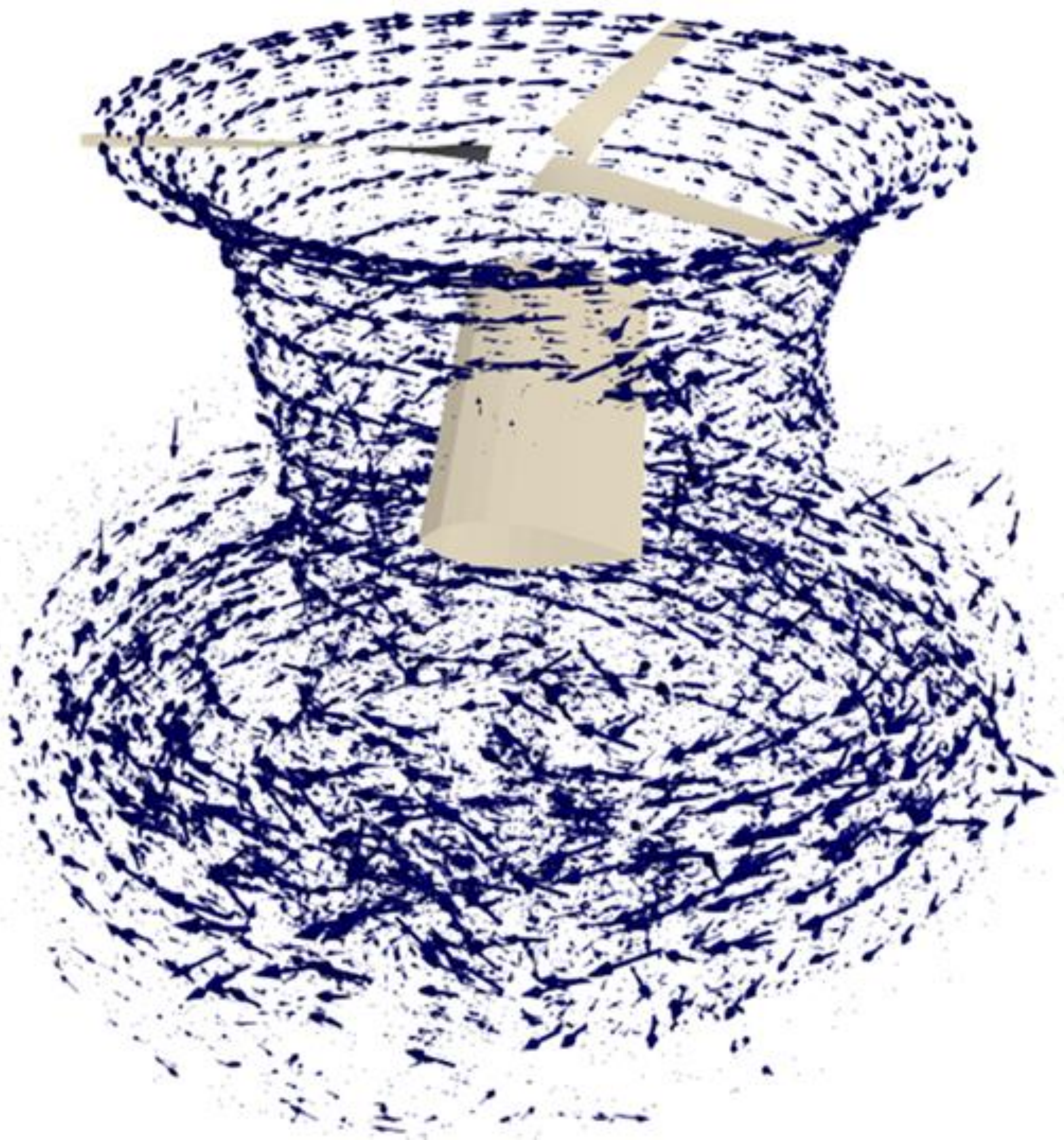
Mid-fidelity Modelling

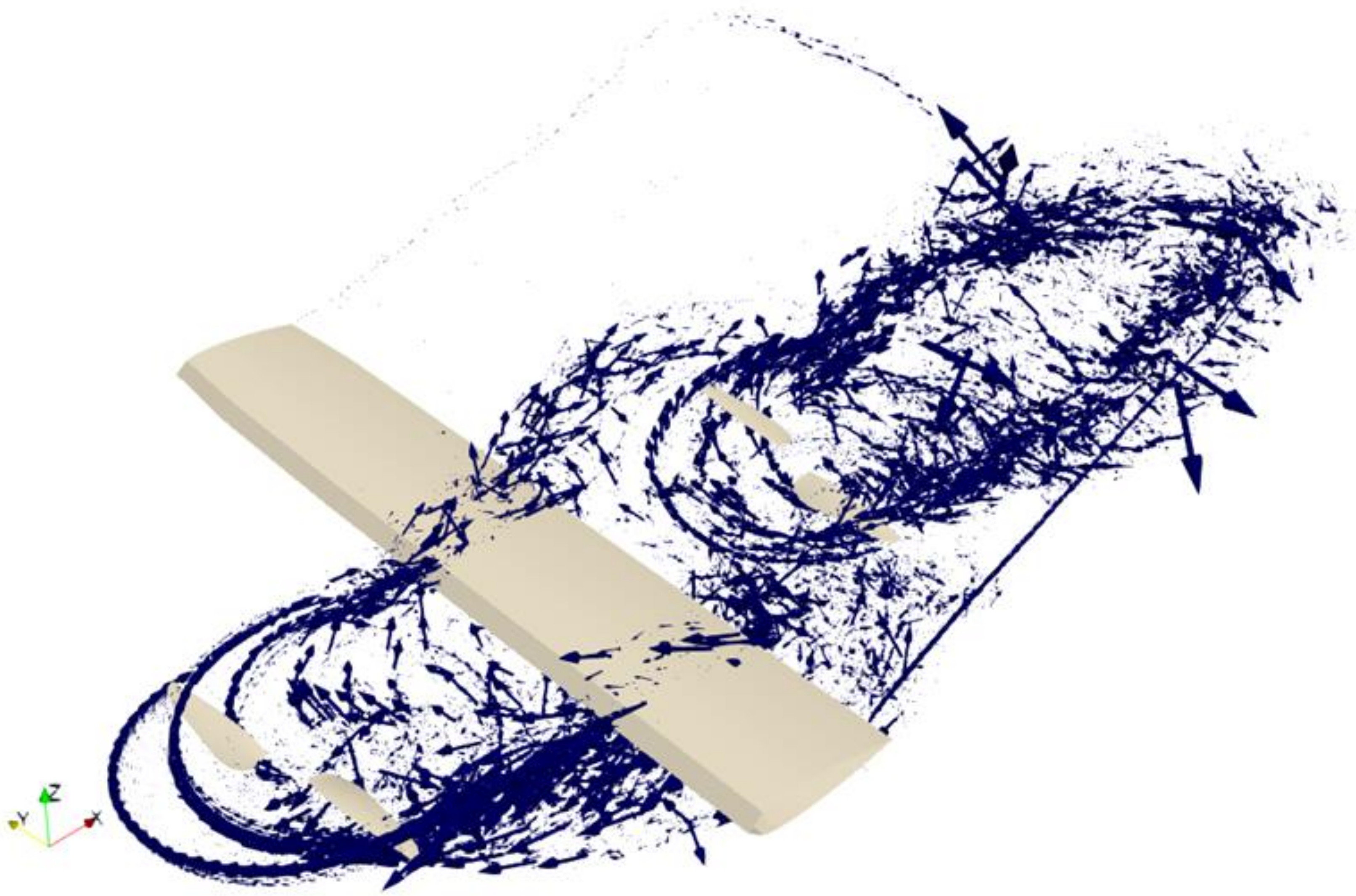
- Mid-fidelity was not planned at the beginning of the project,
- People refer to it to indicate mathematical models where aerodynamic surfaces are modelled following simplified aerodynamic approaches (lifting line, VLM, panels) but the wake is simulated with a Lagrangian approach (with *n* moving vortex particles),
- DUST (Polimi) [1] and FlowUnsteady (BYU) [2] are two examples and are both open source,
- eVTOL developers are very familiar with this approach and apparently rely on it for design,

[1] https://public.gitlab.polimi.it/DAER/dust
[2] https://github.com/byuflowlab/FLOWUnsteady

Physically consistent wake modelling







High-fidelity Modelling

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- 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,

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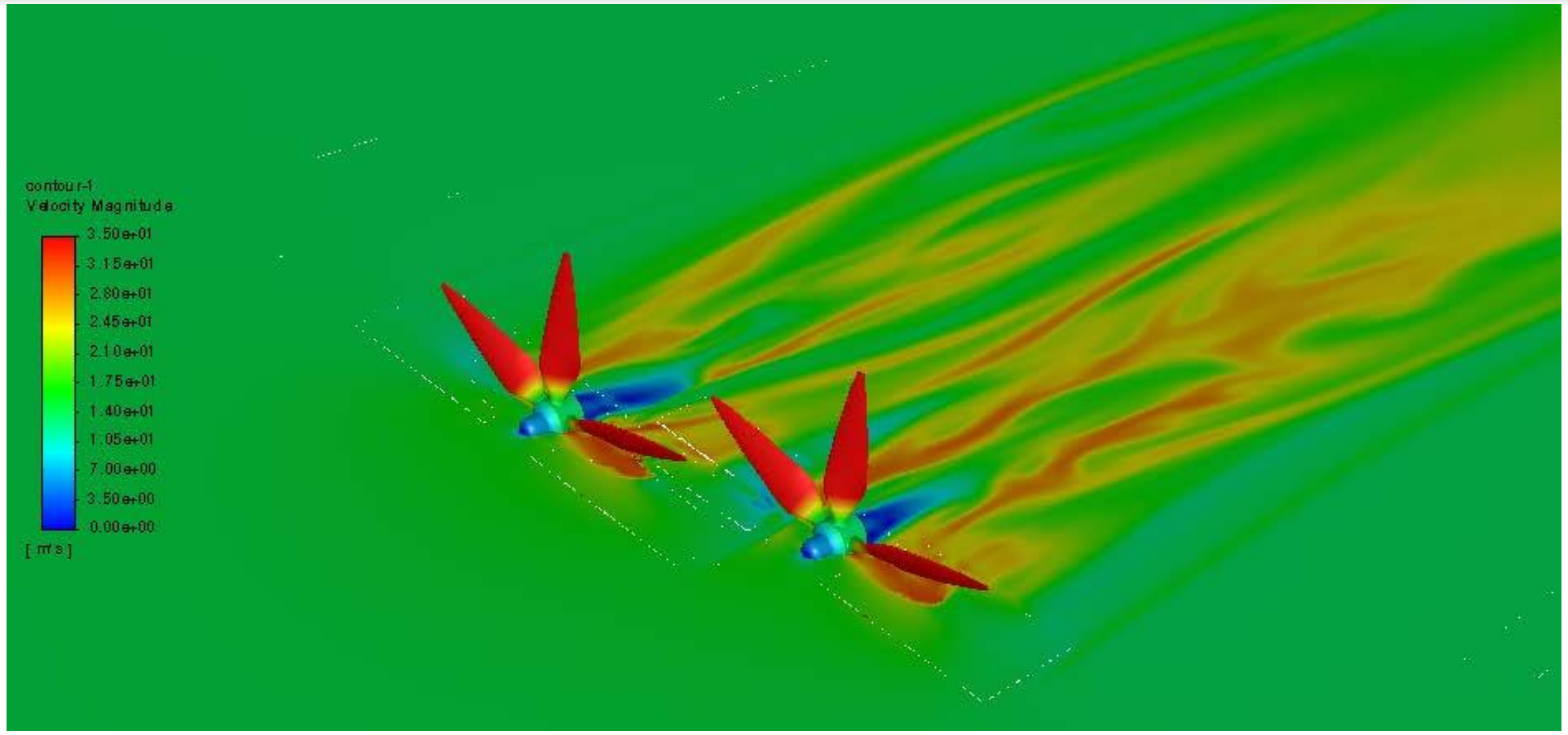
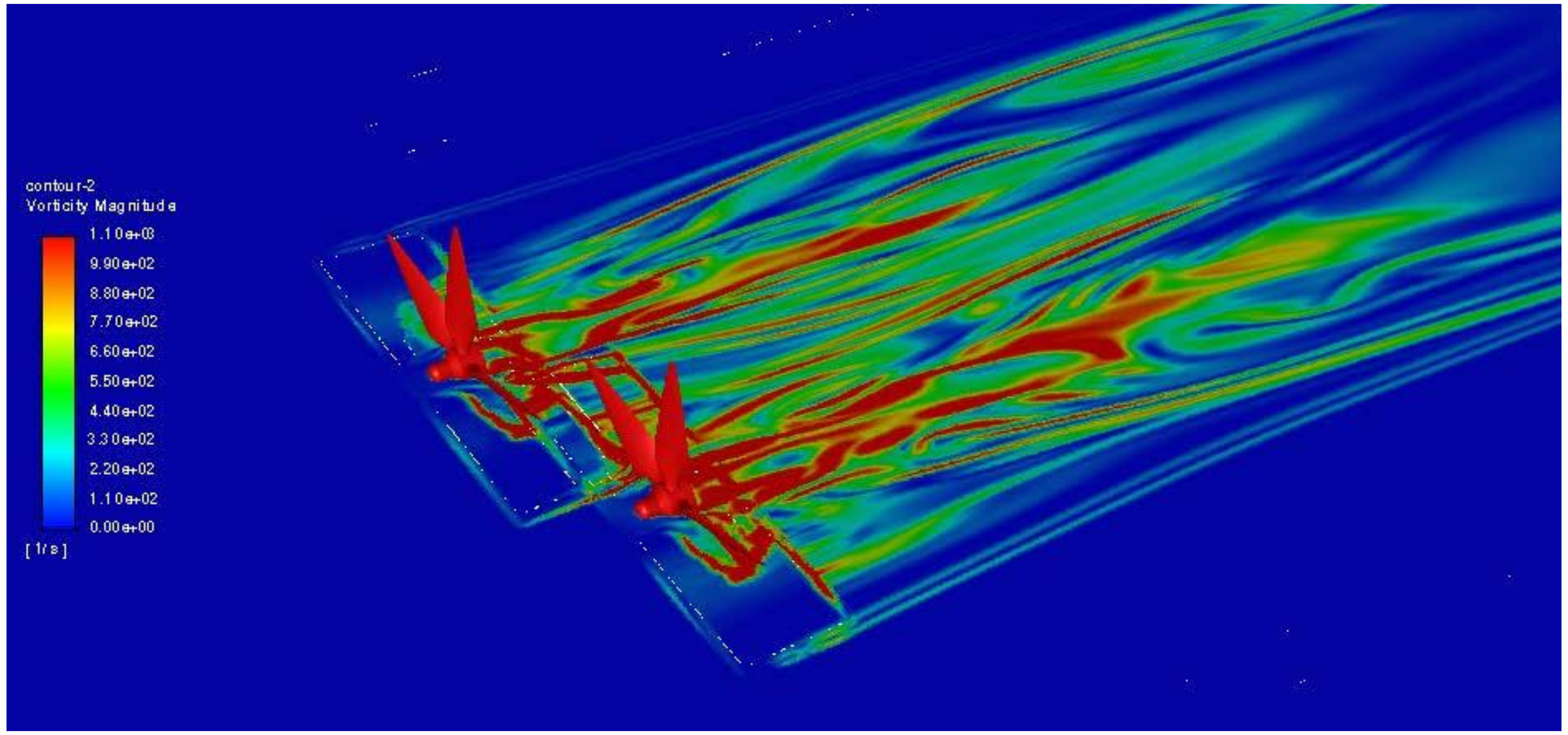
High-fidelity





High-fidelity

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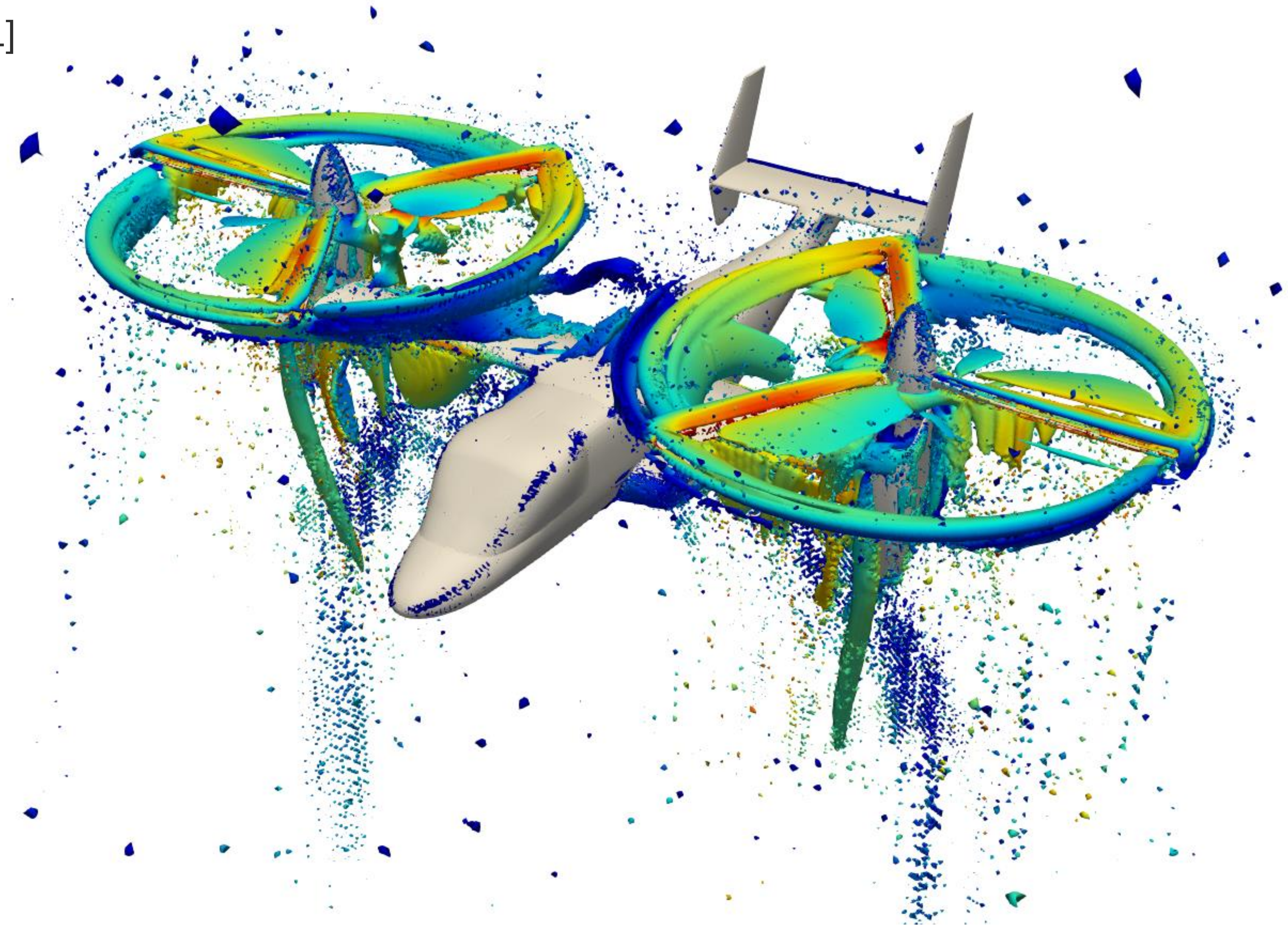
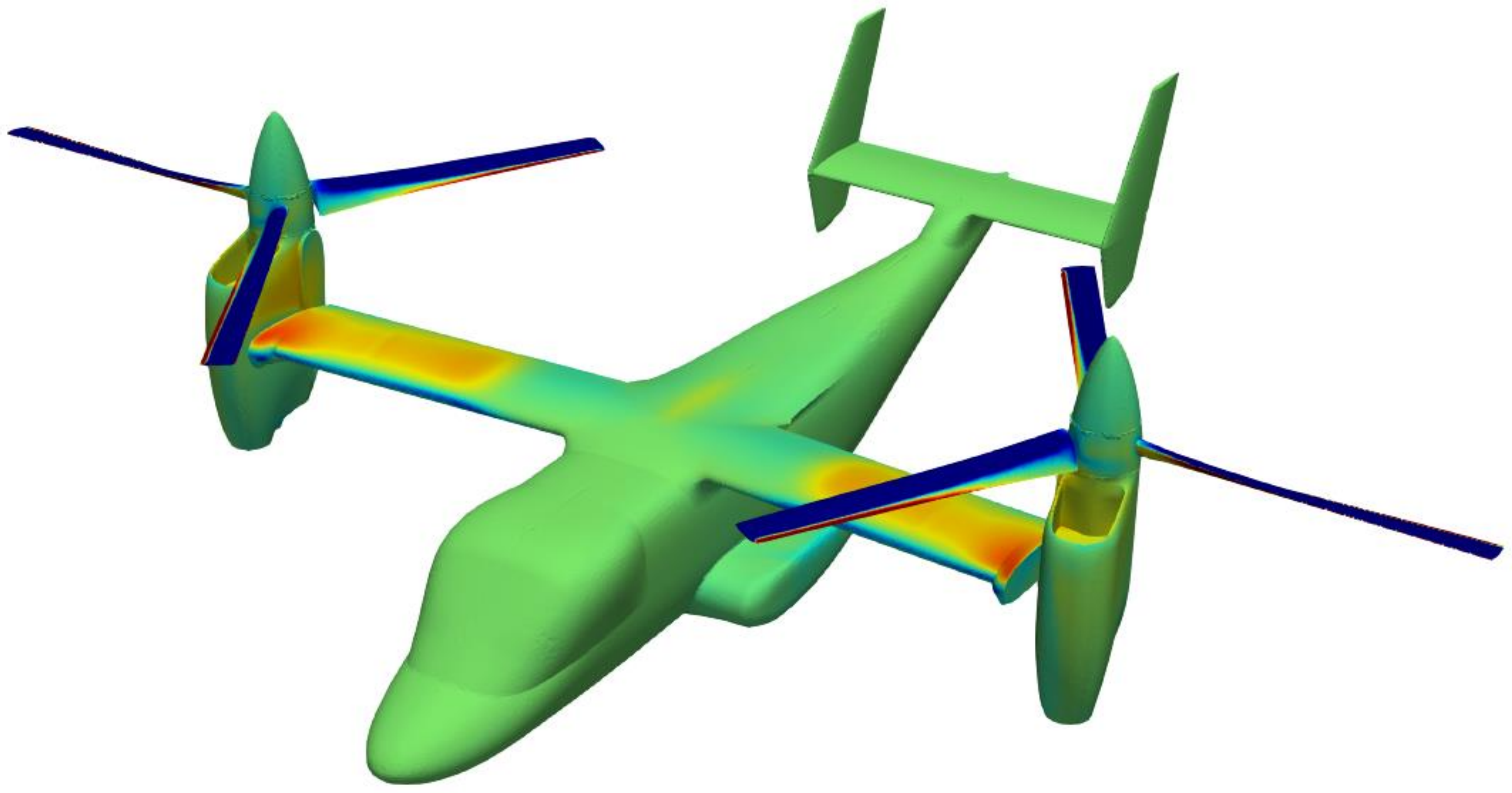
[1]



Q-criterion colored by speed



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[1] Calculation provided by AirShaper https://airshaper.com/

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Multi-fidelity Modelling (in some detail)

- Gaussian Process (Co-Kriging),
- NN (Transfer Learning),
- BNN (Transfer Learning),

Data generation

Input: Flow Conditions → Simulation: Digital Model → Output: Physical Response

Sim. Flow Condition: Input

Input data label	Data Type	Description
aoa	Float32	Angle Of Attack
aos	Float32	Angle Of Sideslip
u_inf	Float32	Freestream Velocity
PP	Int32	Pusher Propeller RPM value
FR	Int32	Front Right Propeller RPM value
FL	Int32	Front Left Propeller RPM value
RR	Int32	Rear Right Propeller RPM value
RL	Int32	Rear Left Propeller RPM value

Sim. Physical Response: Output

Output data label	Data Type	Description
T_PP	Float32	Thrust value of Pusher Propeller
Q_PP	Float32	Torque value of Pusher Propeller
T_FR	Float32	Thrust value of Front Right Propeller
Q_FR	Float32	Torque value of Front Right Propeller
T_FL	Float32	Thrust value of Front Left Propeller
Q_FL	Float32	Torque value of Front Left Propeller
T_RR	Float32	Thrust value of Rear Right Propeller
Q_RR	Float32	Torque value of Rear Right Propeller
T_RL	Float32	Thrust value of Rear Left Propeller
Q_RL	Float32	Torque value of Rear Left Propeller

Levels of fidelity

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High Fidelity CFD

One week per sample
High accuracy

Medium Fidelity Simulations

A few hour per sample
Good accuracy in certain flow conditions

Low Fidelity Methods

A few seconds per sample
Low accuracy

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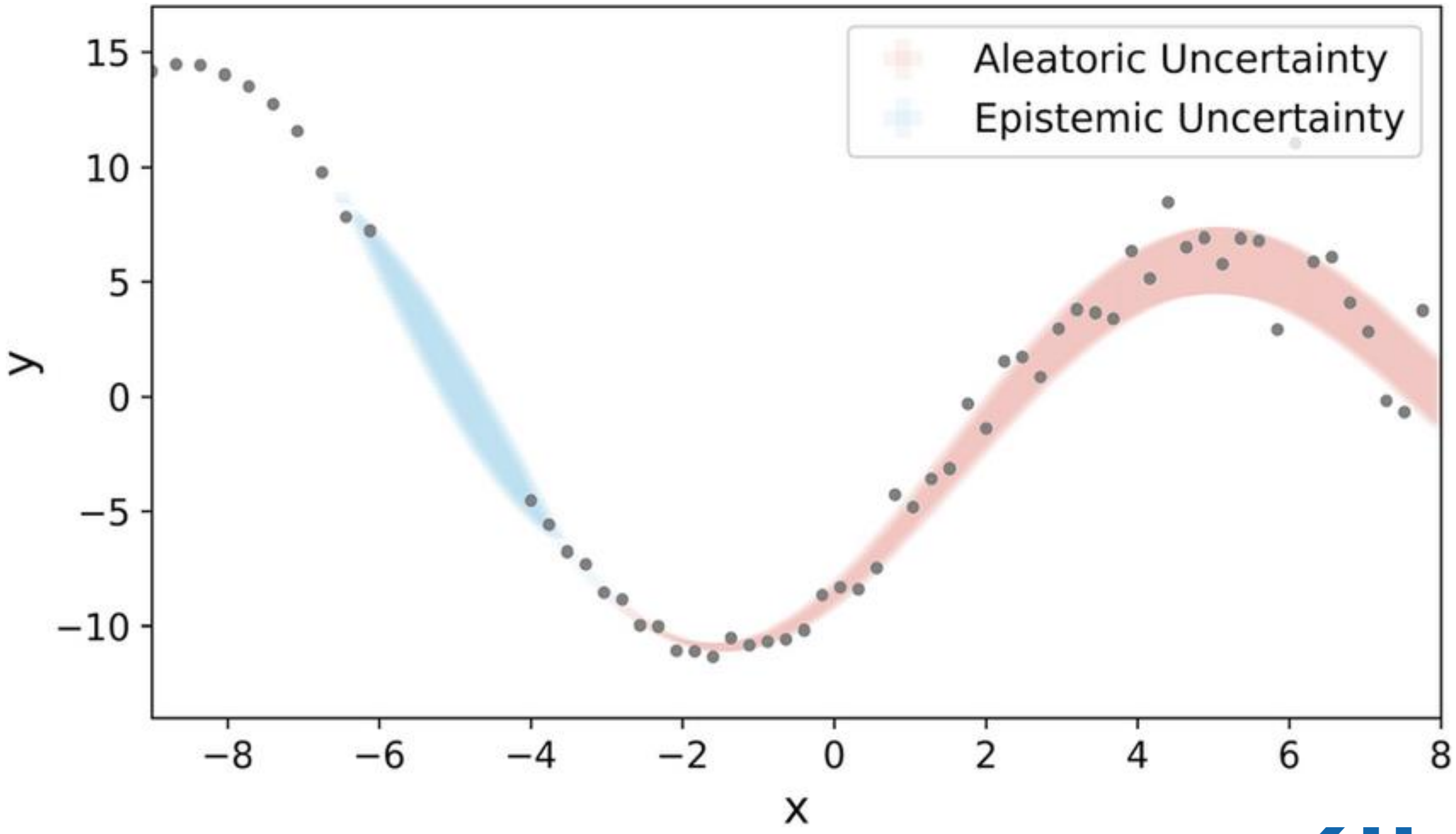
Uncertainty quantification is crucial for understanding the reliability of the model’s predictions.

Aleatoric uncertainty is referred to uncertainty of the data

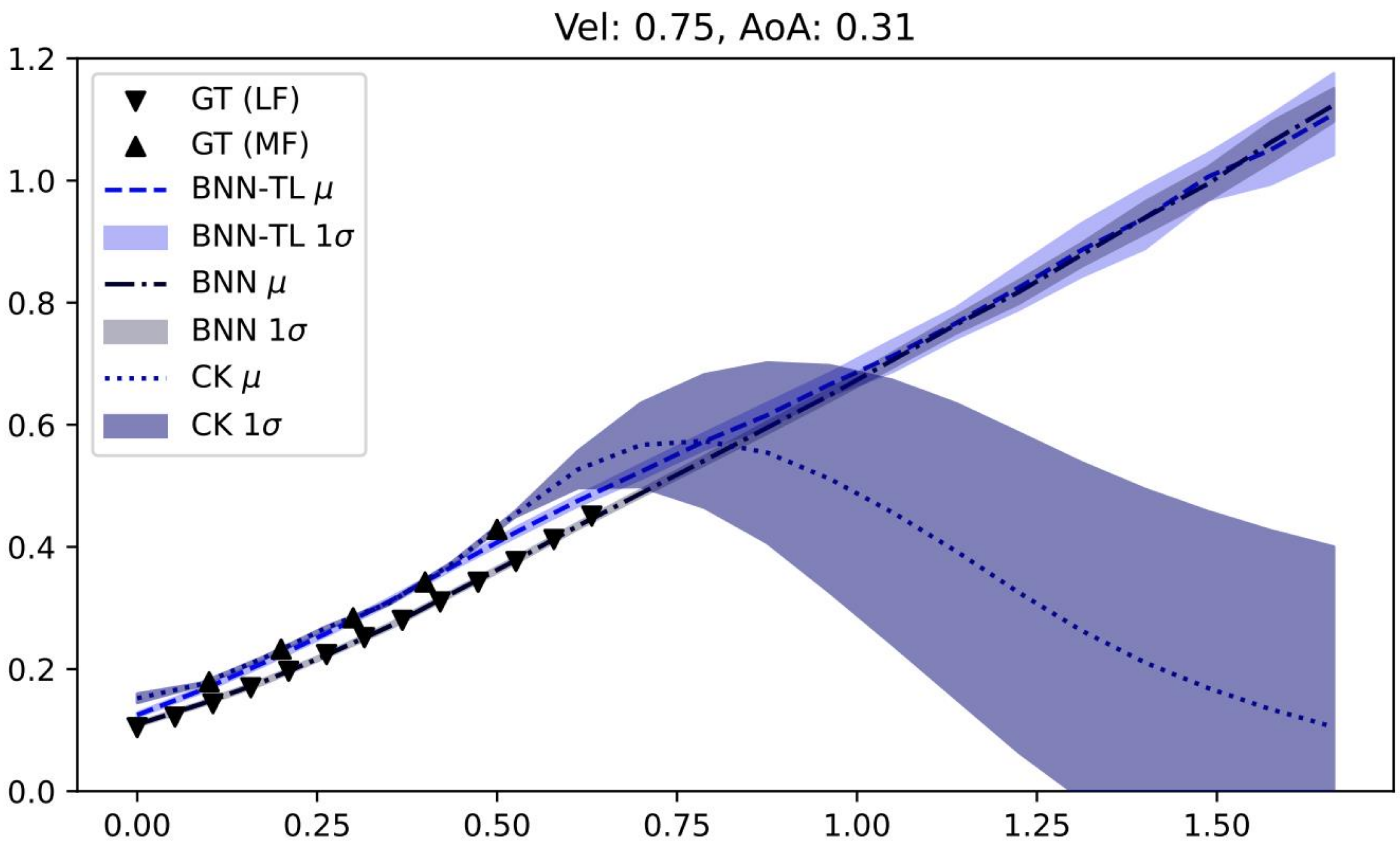
Epistemic uncertainty is referred to uncertainty of the model



A physical simulation model should also provide information about uncertainty of the generated data

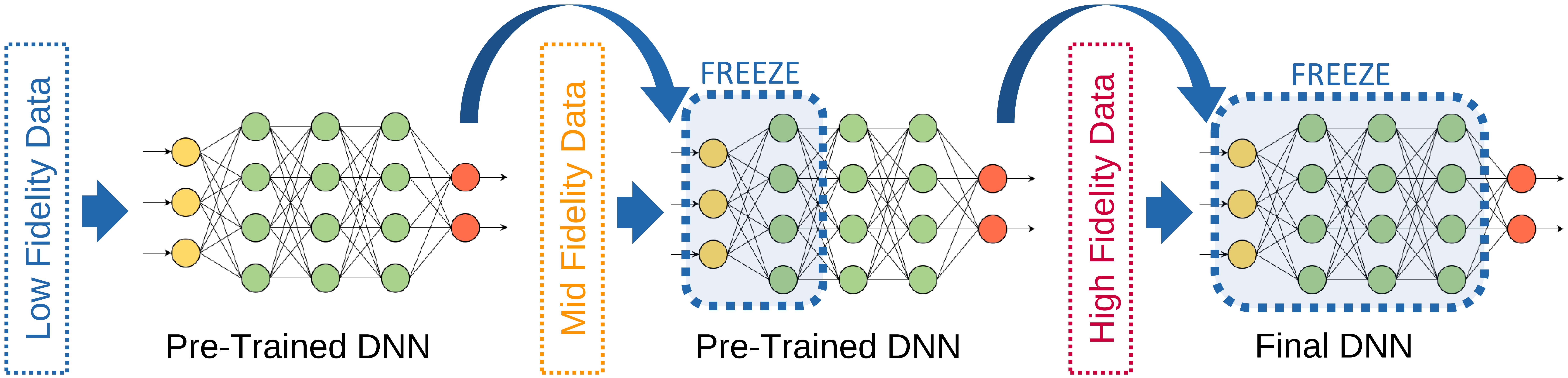
First Approach: Co-Kriging

Compared to more complex machine learning methods based on neural networks, Co-Kriging has shown **poor generalization capabilities** outside the training input space and in highly nonlinear regions of the input.



Second Approach: Neural Network with TL

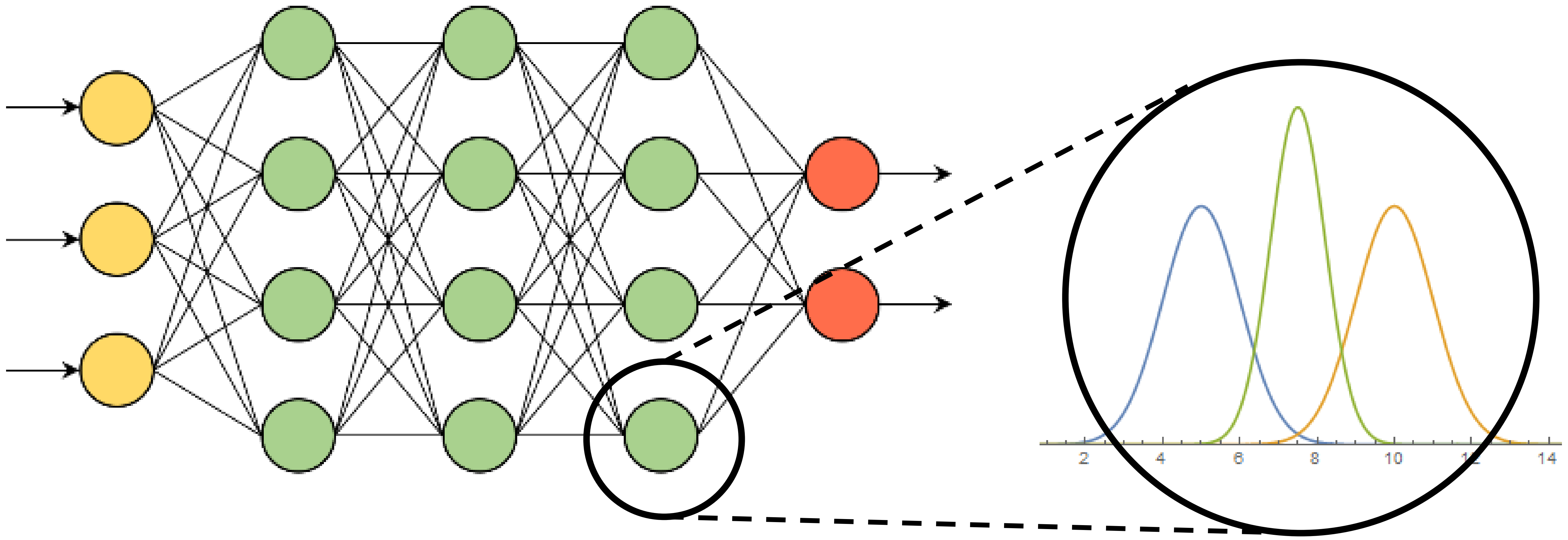
We created an optimized **Dense Neural Network** that uses **Transfer Learning (TL)** for Data Fusion.



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

Third Approach: BNN with TL

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.

Third Approach: BNN with TL

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- 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.

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Results

Model	Training Time	Prediction Time	Average Perc. Error	Average Perc. Confidence	N. Params
BNN LF	~41 min	~0.02 sec	8.5%	94.2%	174932
BNN MF	~35 min	~0.02 sec	6.4%	92.1%	19092
DF: BNN TL	~55 min	~0.02 sec	1.8%	97.3%	174932
DF: CoKriging	~4 min	~0.005 sec	5.9%	88.2%	-

Benchmarks on NVIDIA Quadro P2000 GPU

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

C. Uncertainty quantification

Relevance of 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**.

Relevance of 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.

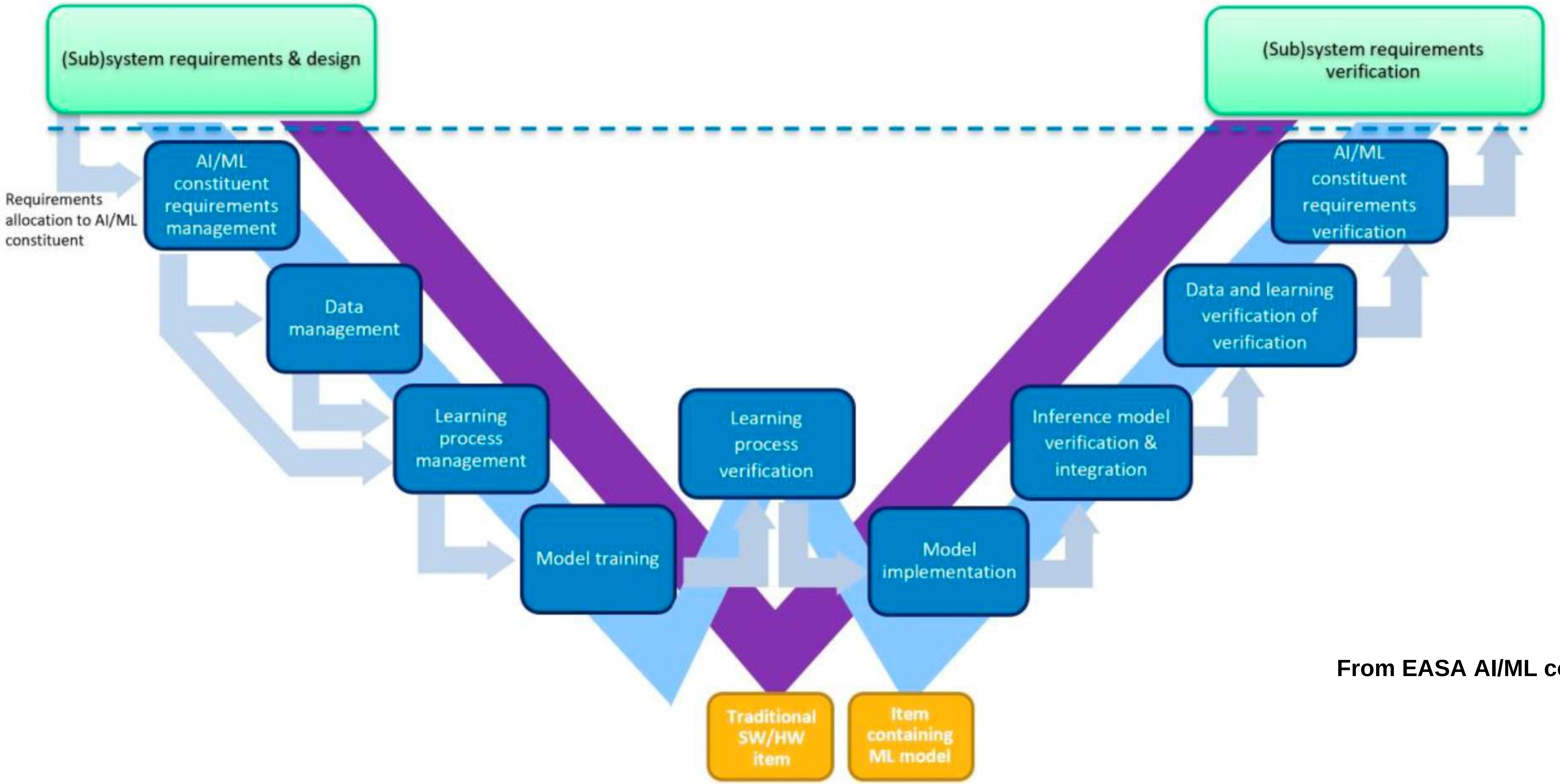
Relevance of Uncertainty Quantification

- ***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,

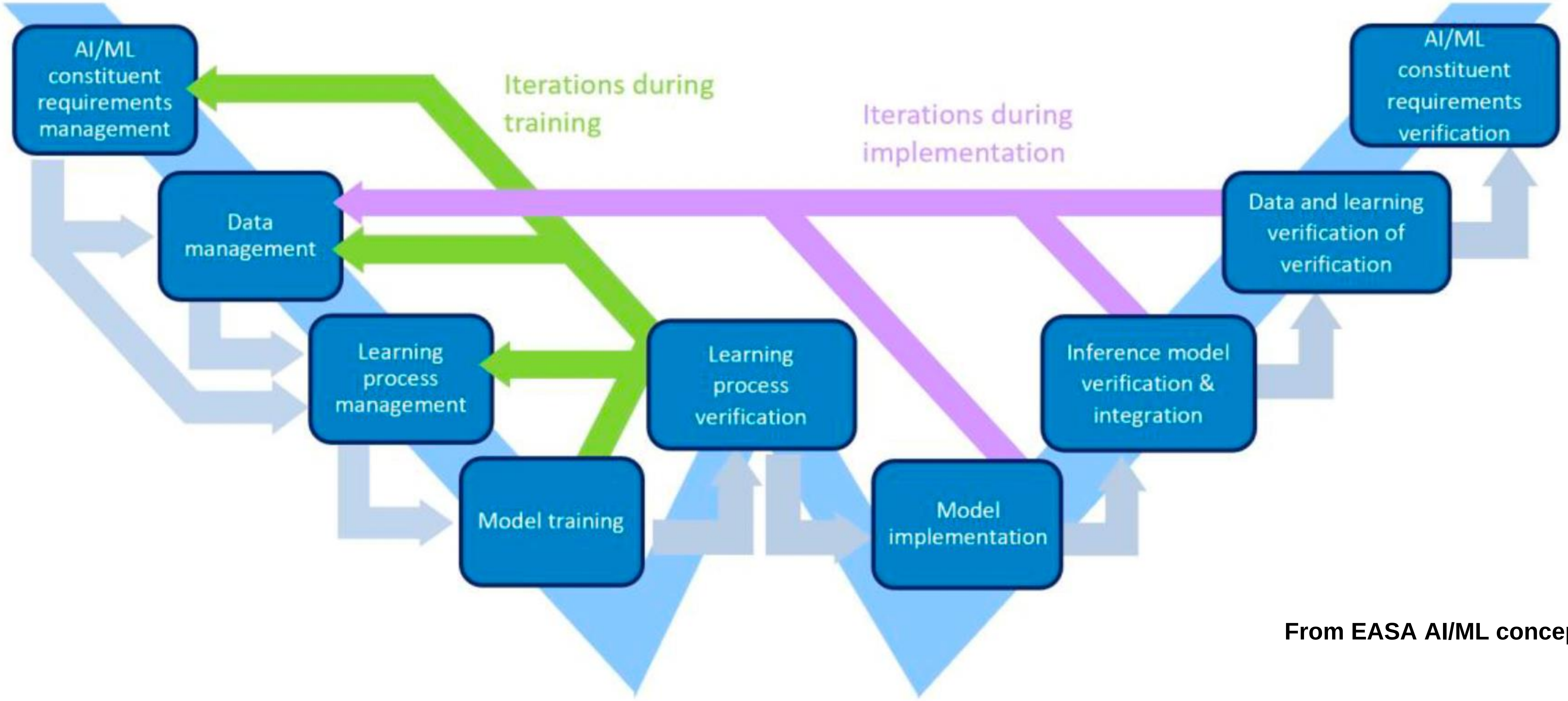
- ***Epistemic uncertainty** is addressed through the learning assurance objectives.*

- 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.



From EASA AI/ML concept paper

Figure 12 — Global view of learning assurance W-shaped process, non-AI/ML constituent V-cycle process



From EASA AI/ML concept paper

Figure 13 — Iterative nature of the learning assurance process

The same concept independently from EASA concept paper: uncertainty as by product of GP and BNN

- 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.

Comment: aleatory uncertainties quantification via PCT / MC

- 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.

D. Modelling details

How different is our intended approach from a conventional one

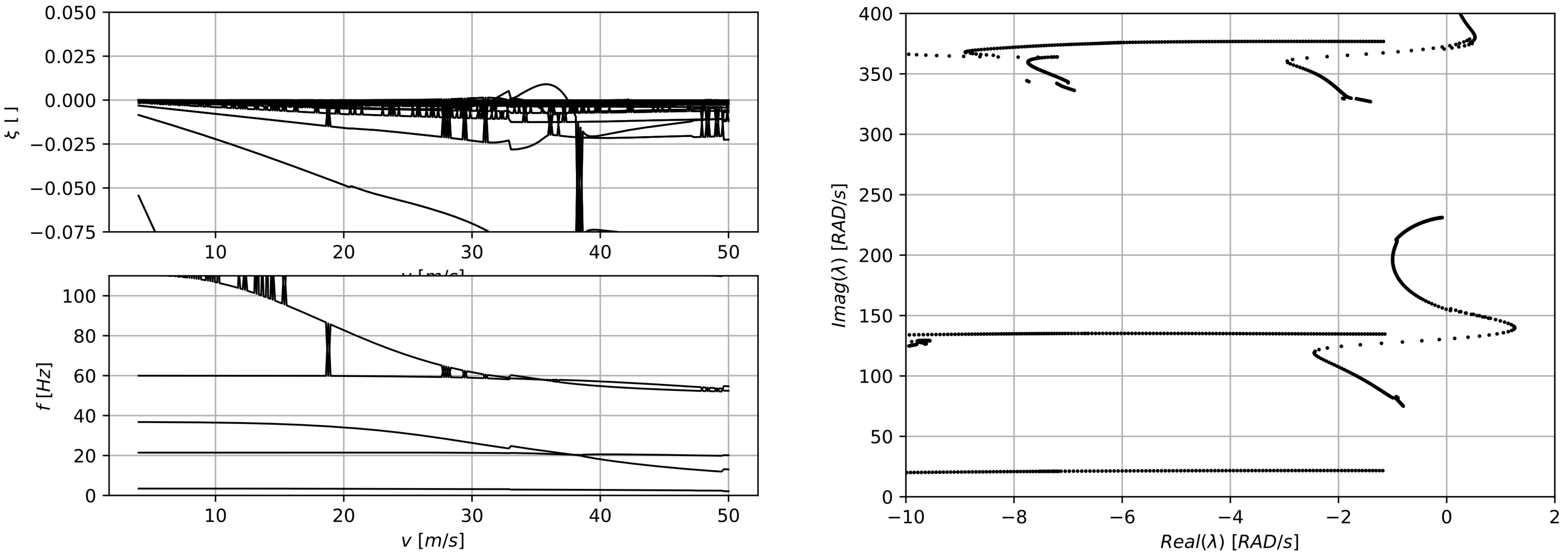
Modelling details, results etc

1. What does our model calculates?
2. Unsteady responses (wing, rotors etc)
3. Control system (aeroservoelasticity)
4. Blades / rotor elasticity

1. What the model shall provide

- **Linear stability assessment**, in the whole flight envelope, incl. failure conditions, (this implies: for all relevant flight points, equilibrium, linearisation, eigenvalues analysis in time domain and methods like p-k in frequency),
- Response to all relevant **wind gusts**, in the whole flight envelope, incl. failure conditions, (this implies: response in time or frequency, nonlinear in the first case),
- In some cases, the Authorities may request the analysis of **LCOs**, (this implies: nonlinear response in time),

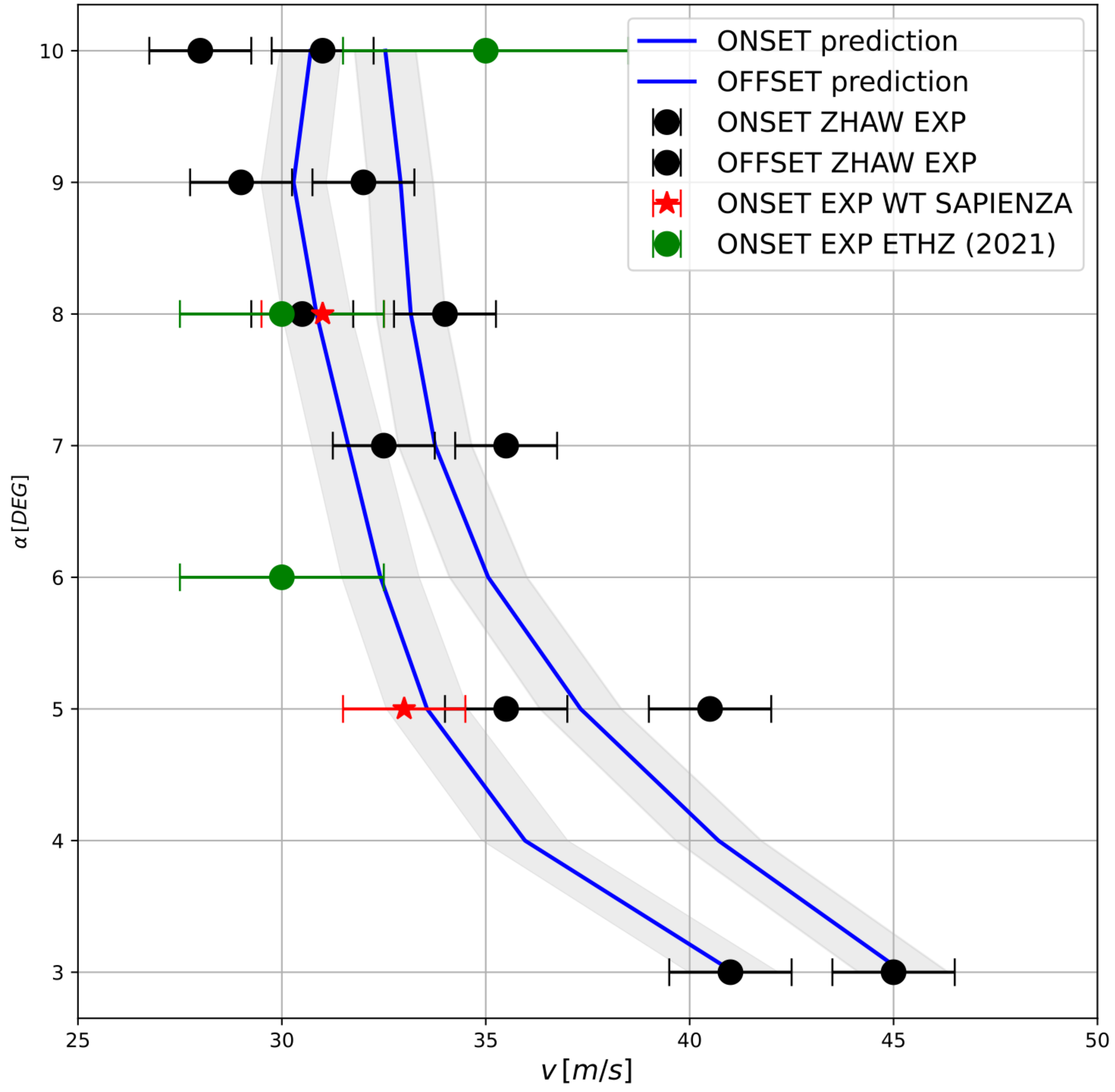
Linear stability analysis



Conventional V-g plot and root locus, in this case, flutter mechanisms are detected.

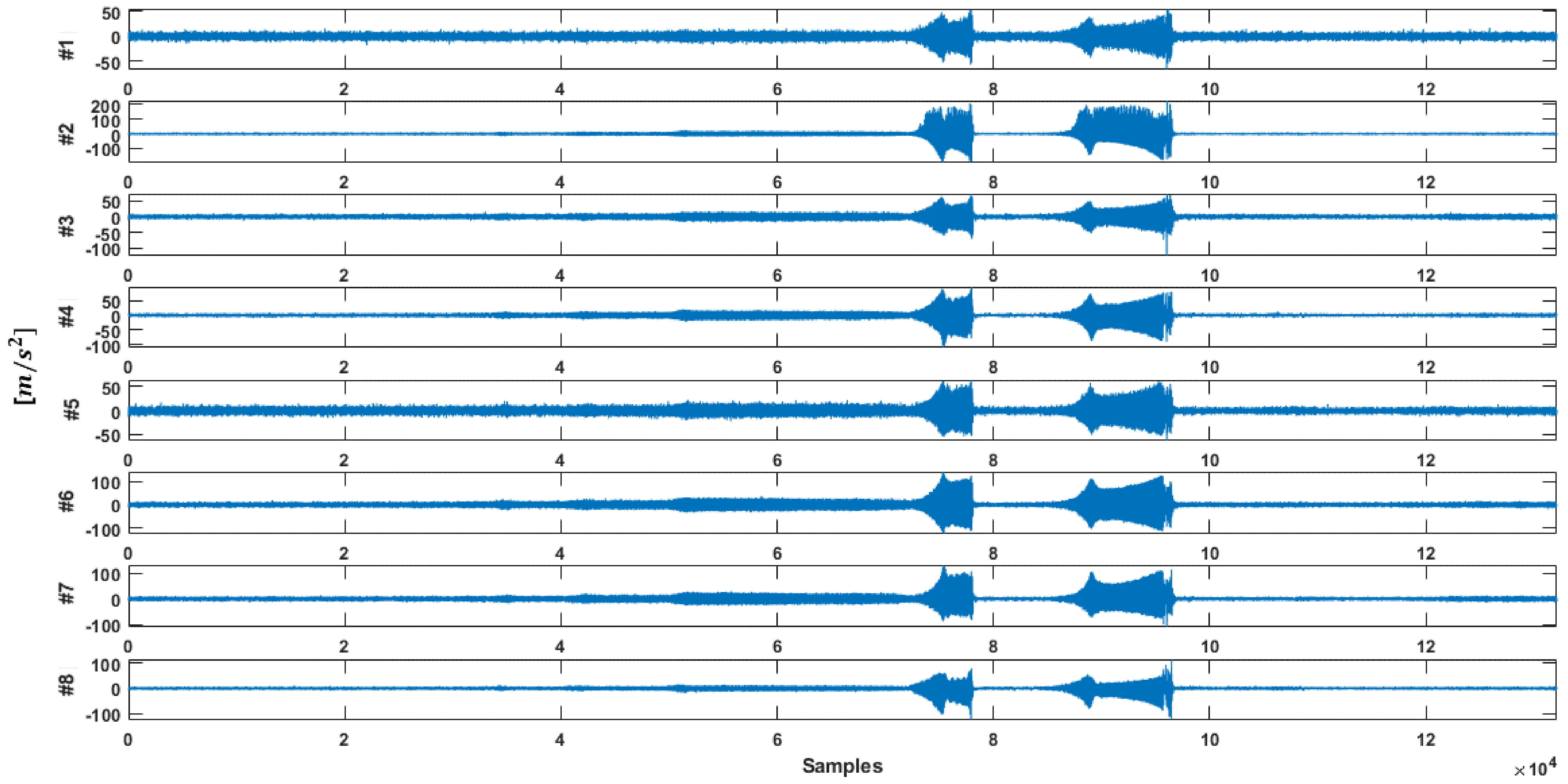
Linear stability analysis

- Stability boundaries in flight envelope (wind tunnel model),
- Uncertainties / confidence,
- Comparison with experimental data,
- Stability boundary is specific of one configuration.



Limit Cycle Oscillations

- Instabilities detected by (linear) flutter analysis may be dominated by (aerodynamic and/or structural) nonlinearities,
- Oscillations have finite amplitude and in some cases may be "tolerated".



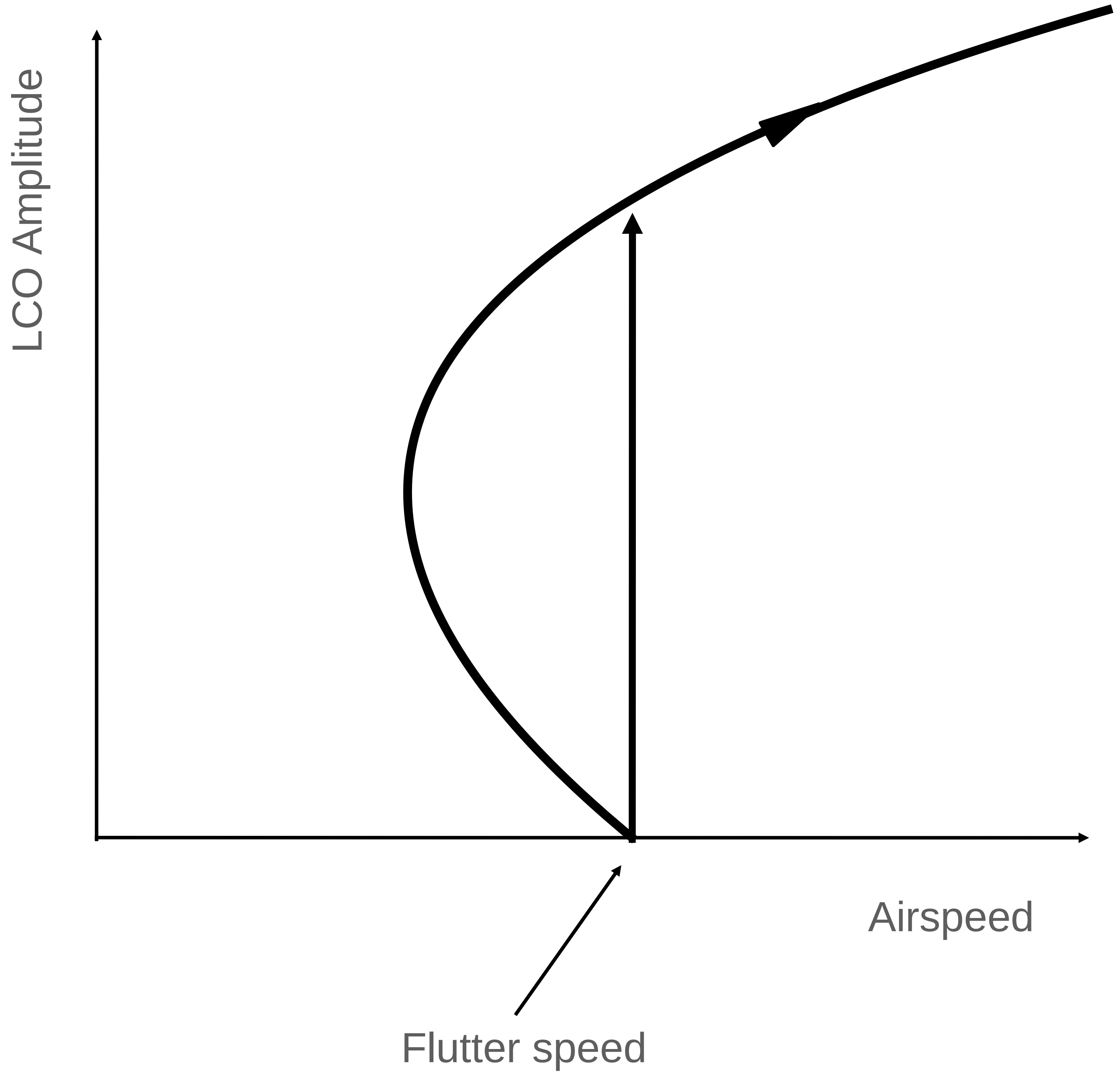
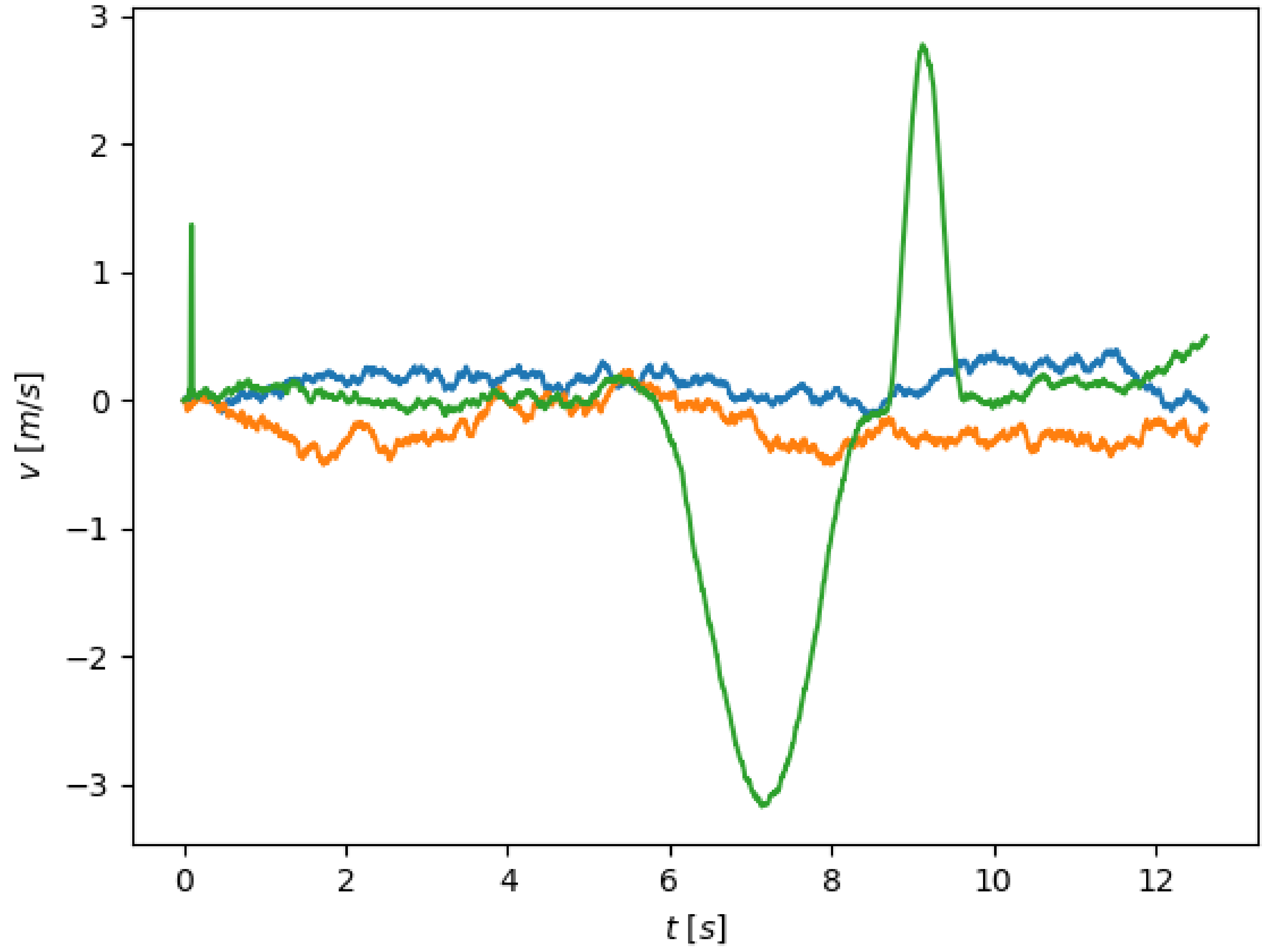
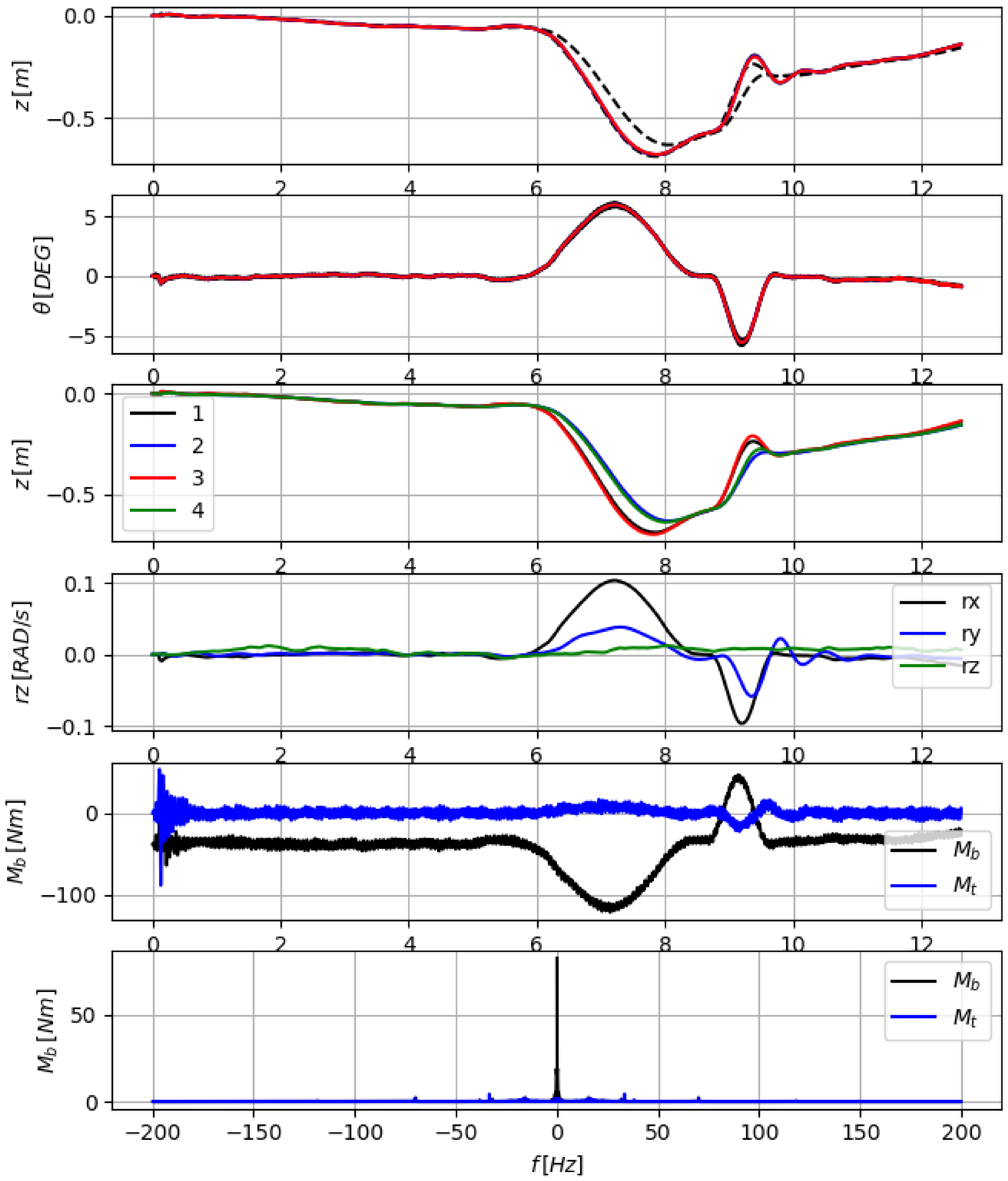


Image inspired by E. Dowell, A Modern Course in Aeroelasticity, Springer, 6th edition, 2022

Nonlinear unsteady response

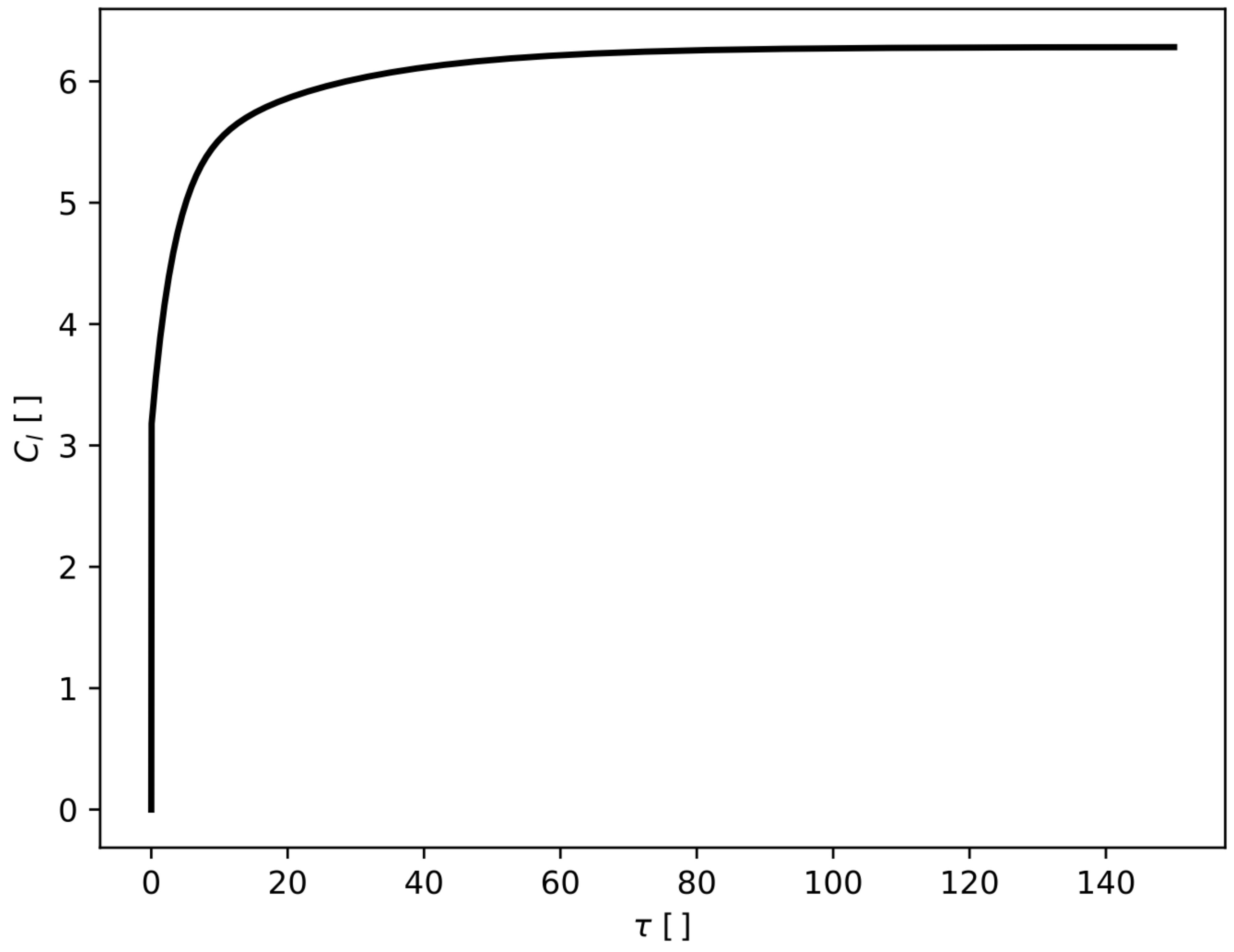


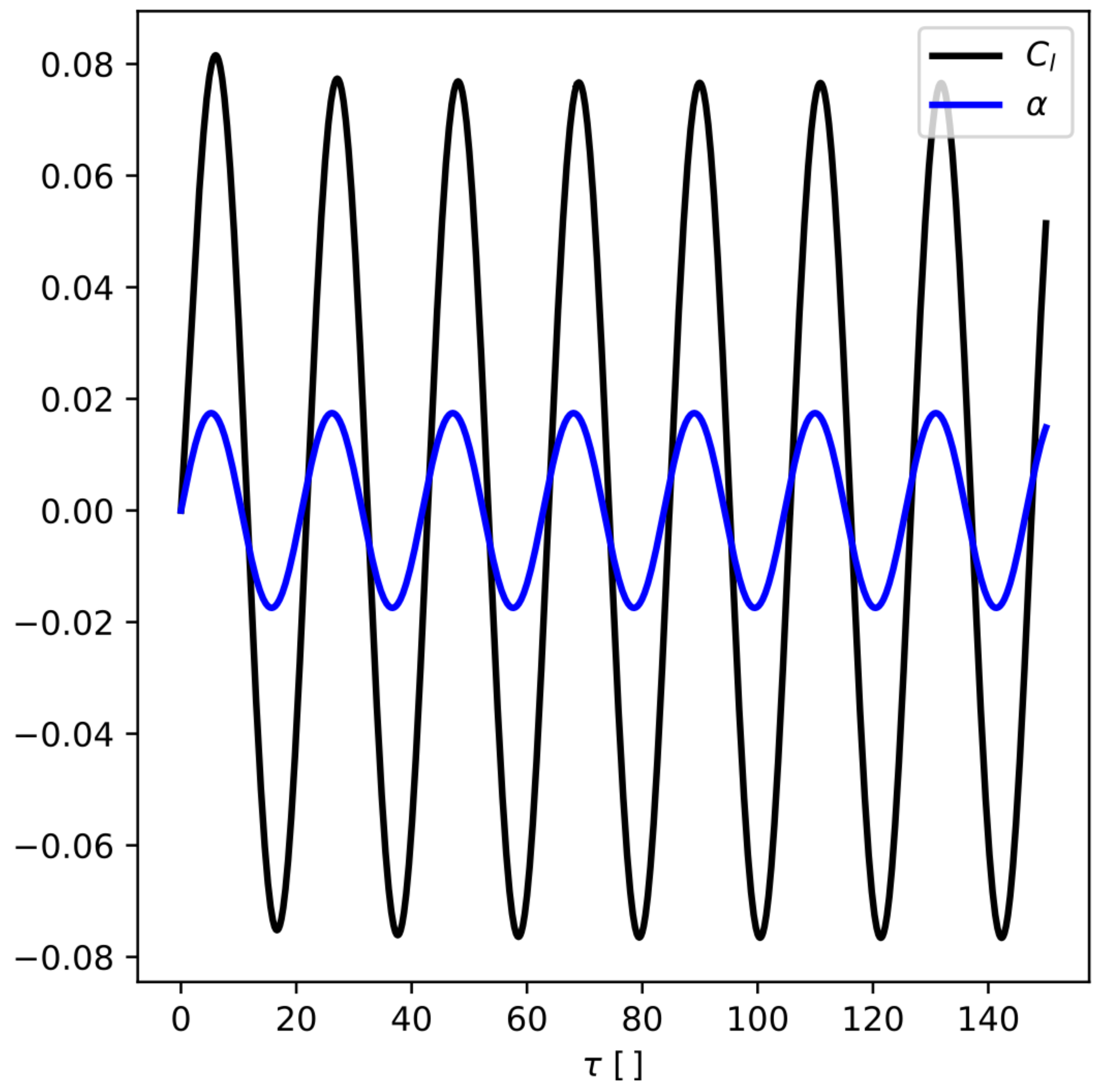


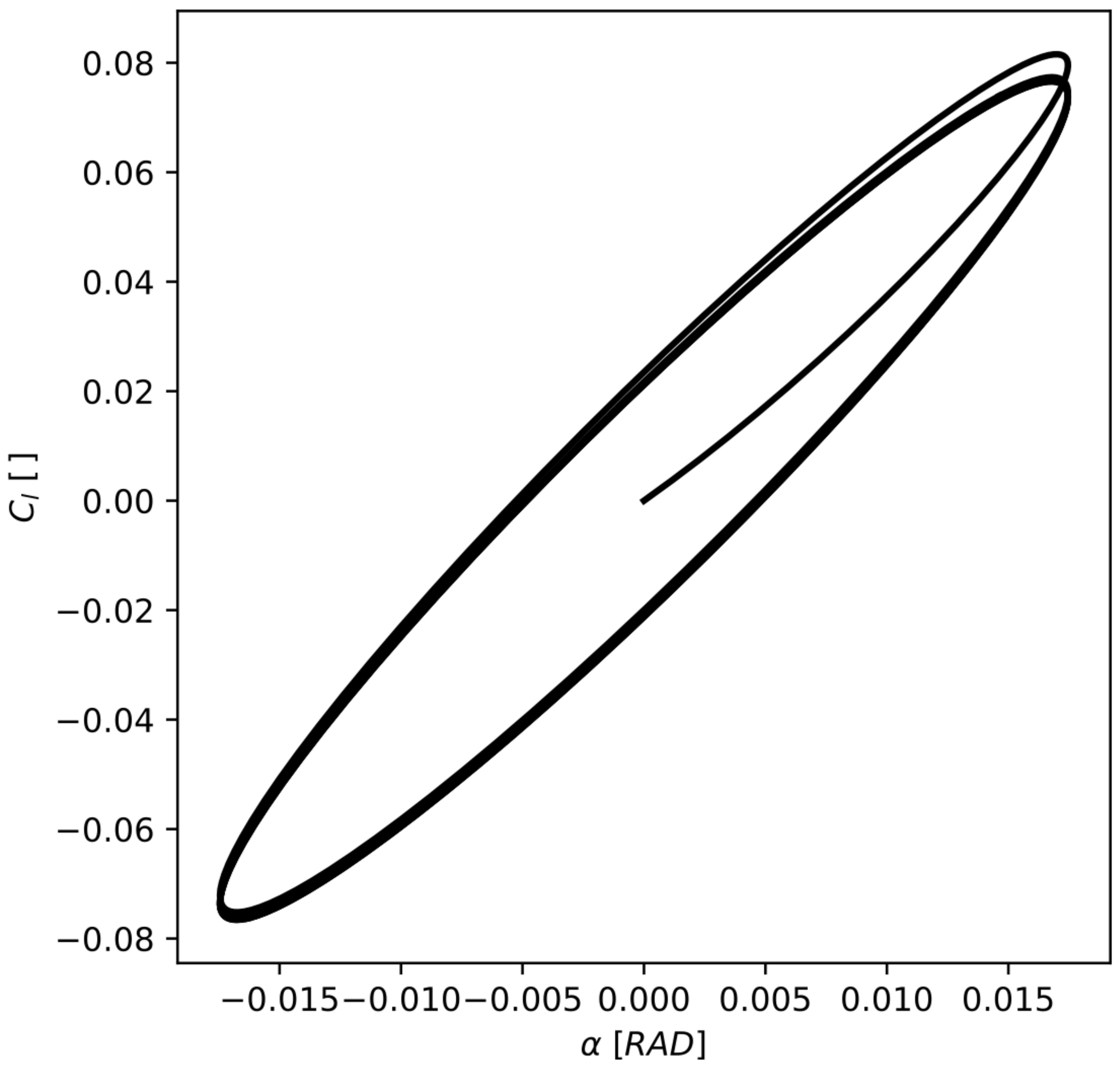
2. Unsteady modelling

- Whereas the unsteady response of wings can be modelled analytically or numerically following well known approaches (e.g. Theodorsen), for the response of rotors to the variation of its attitude the methodologies are far less validated (e.g. Loewy, dynamic inflow),
- Moreover, the response to variations of RPM are completely disregarded by the literature as helicopters rotors RPM tend to be constant and variations of wind turbines ROM are very slow,
- Mid-fidelity simulations show that the transient following a variation of RPM (either an indicial step change or a harmonic function) is far from negligible and must therefore be taken into account,
- This type of unsteady behaviour can be modelled via ROM, AI/ML can also here be exploited.

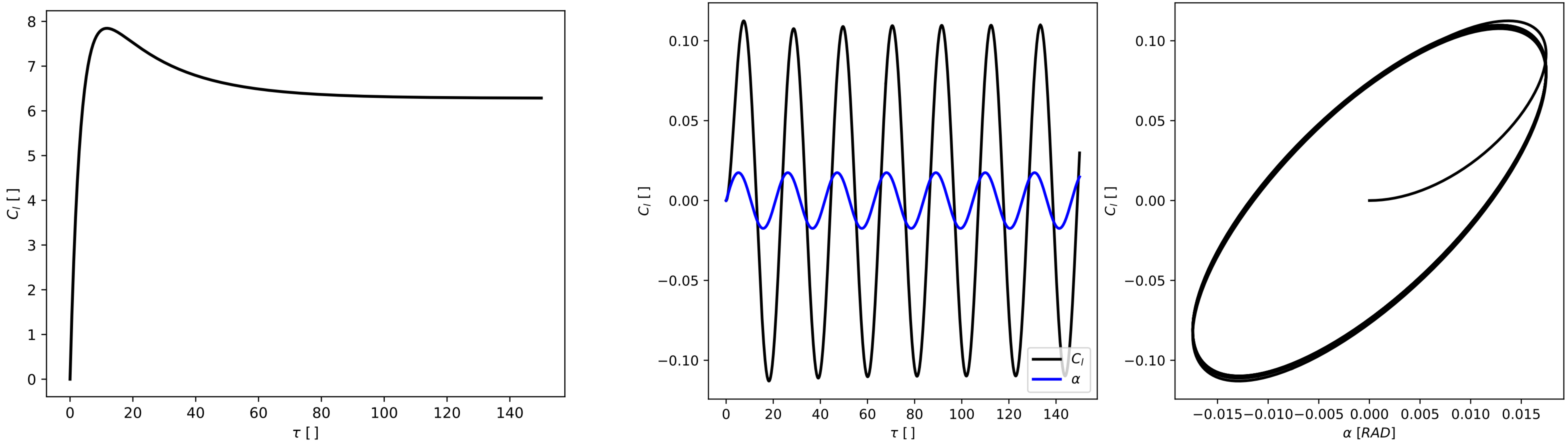
Airfoil, unsteady response: Wagner function



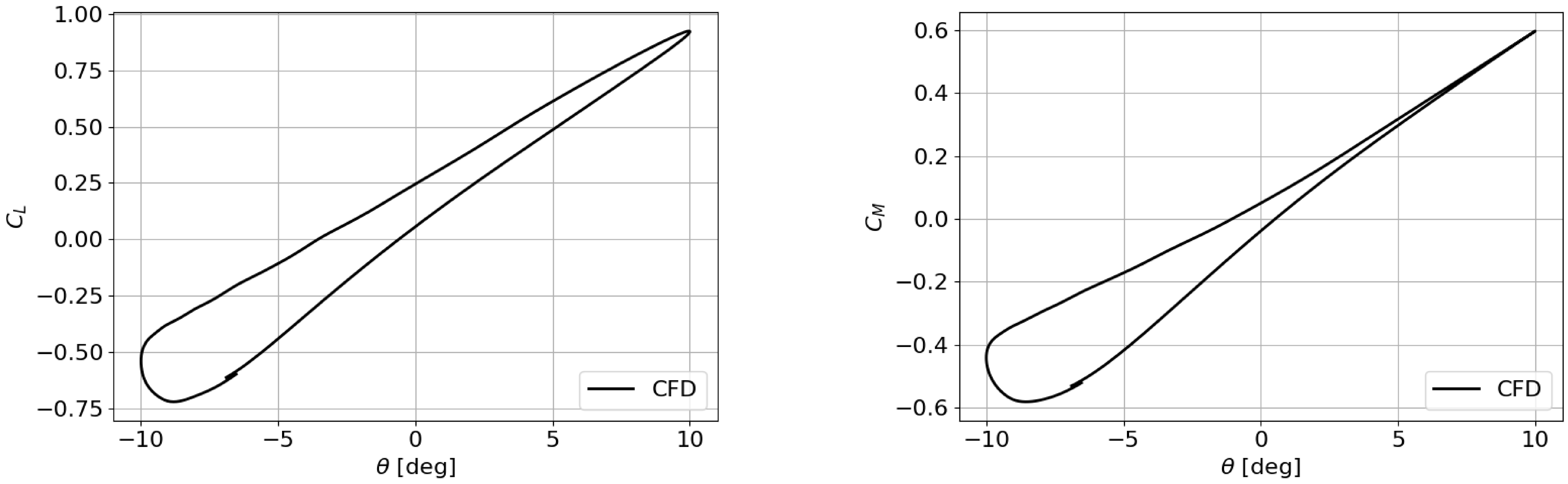




Unsteady response of a rotor: ???



Wing, dynamic stall



3. Comment: coupling controls - structural dynamics

- Control systems normally operate at low frequencies, suitable for instance to correct flight mechanics modes,
- The relevant frequencies for structure and rotors are often higher, this also concerns the RPM,
- It is reasonable to assume that no strong feedback loop is expected to occur between flight control systems and the structural modes,
- Conversely, interactions between the rotational speed of the rotors and structural dynamics are always possible,

4. Comment: multiblade coordinates

MODEL-SI
MODELING AND SIMULATION

- **Multiblade** coordinates are non-rotating coordinates which allow modelling the blade elastic displacement (in a single structural model),
- Yet the resulting system of equations may retain a dependence on the azimuth angle,
- Introduced to capture **whirl flutter** in helicopters and airplanes (propeller), they are now widely used in the modelling of wind turbines,
- eVTOL may suffer from the same weakness; moreover, we might have to consider interactions between rotational speed and structural dynamics.

EASA

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Impact on loads / safety

- eVTOL blades tend to be short and **stiff**, with no mechanical hinges,
- However, it is reasonable to assume a dominating **first flapping mode**, with natural frequency slightly above the rotational speed,
- By neglecting blade elasticity, one would neglect the dynamic loading of the structure (including the periodic aerodynamic loading of the wing) and of the blades,
- Multiblade coordinates allow a relatively easy inclusion of the blades elastic degrees of freedom; the equations of motion may become periodic, i.e. dependent on the angle of rotation of the rotors (which brings along the Floquet method for the assessment of the dynamic stability).

E. Digital Twin relevance

From EASA AI/ML concept paper

Level 1 AI : assistance to human	Level 2 AI : human-AI teaming	Level 3 AI : advanced automation
• Level 1A: Human augmentation • Level 1B: Human cognitive assistance in decision and action selection	• Level 2A: Human and AI-based system cooperation • Level 2B: Human and AI-based system collaboration	• 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

From EASA AI/ML concept paper

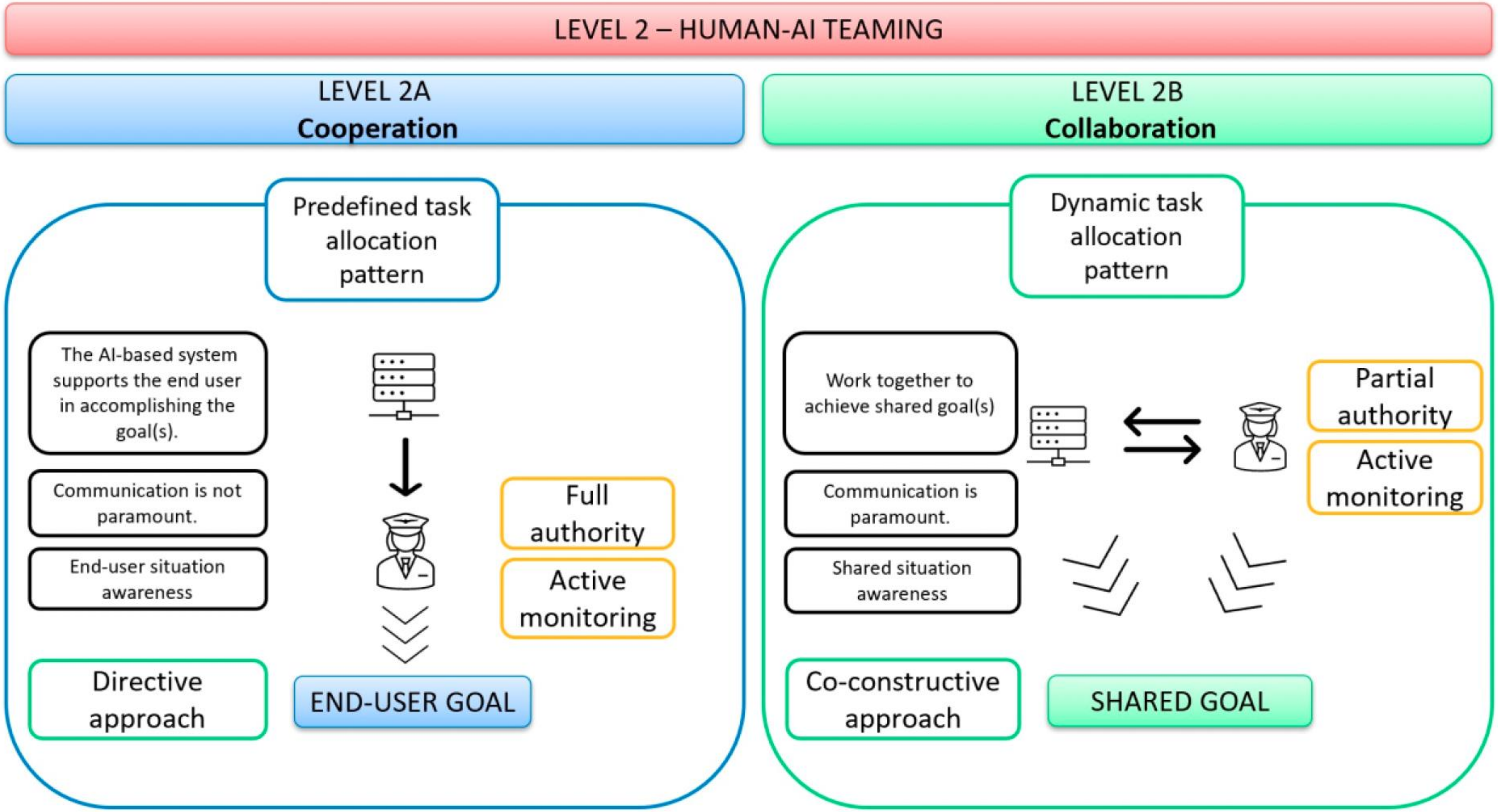


Figure 6 — HAT concept overview

Digital Twin, definition(s)

MODEL-SI MODELING AND SIMULATION

- 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.*

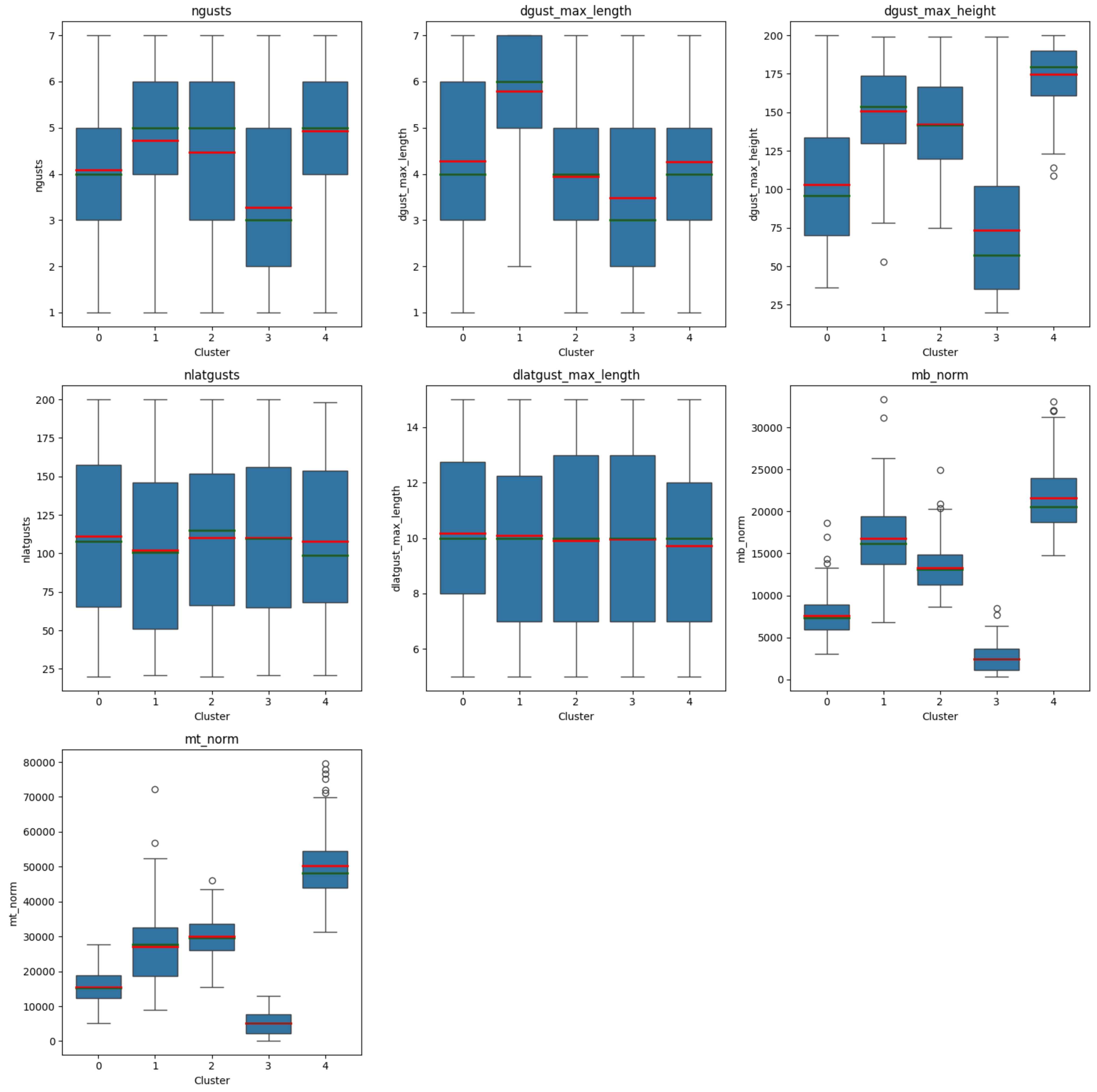
Data-driven analysis of flight envelope

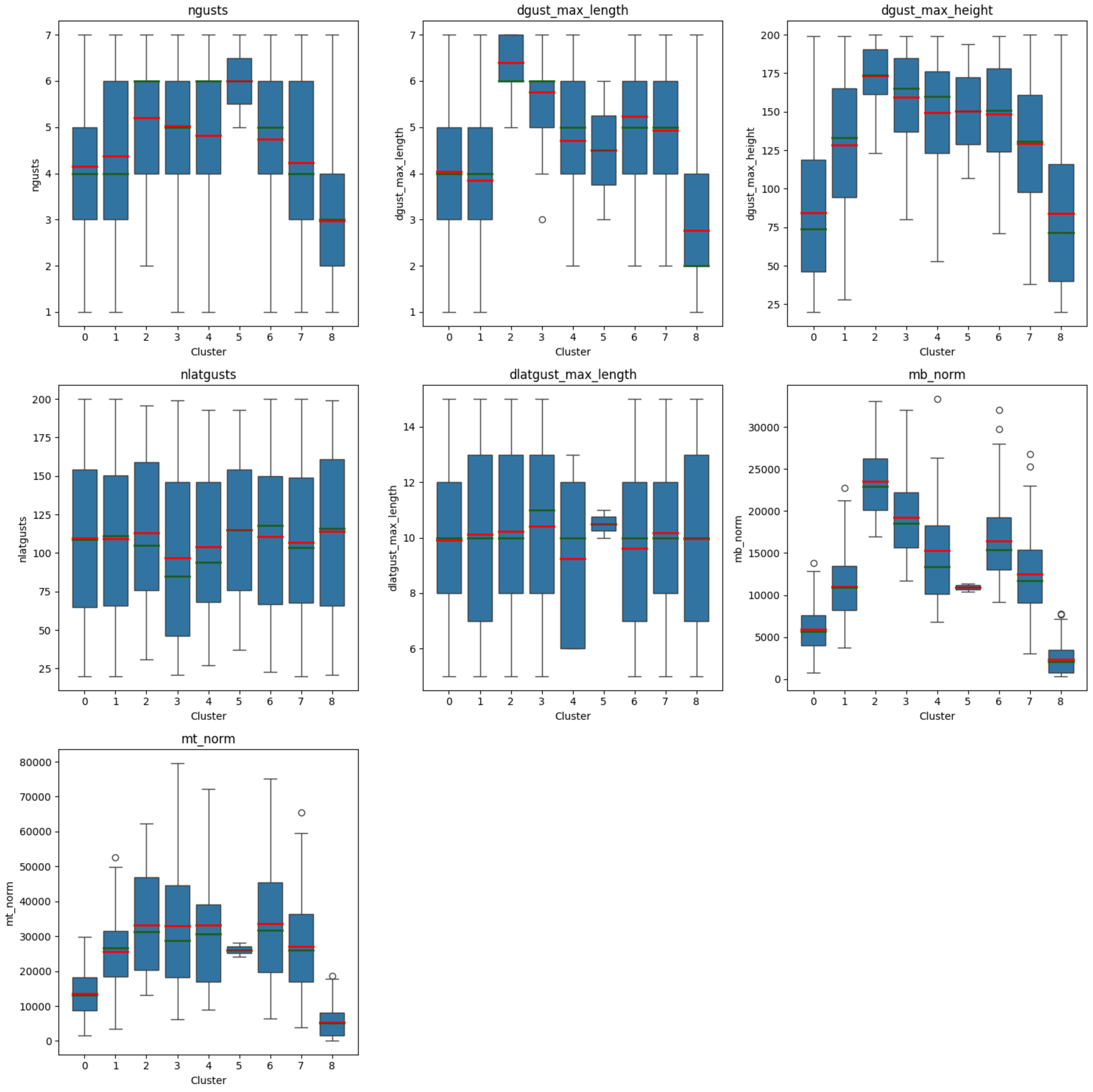
- **More** data can be generated / is available thanks to the DT,
- Ideally, the data is **higher quality** due to both higher accuracy and/or an propagation of uncertainties,
- This implies not only an easier analysis (e.g. for certification) by humans but also an **AI/ML supported** analysis and decision,
- 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,

Data-driven analysis of flight envelope

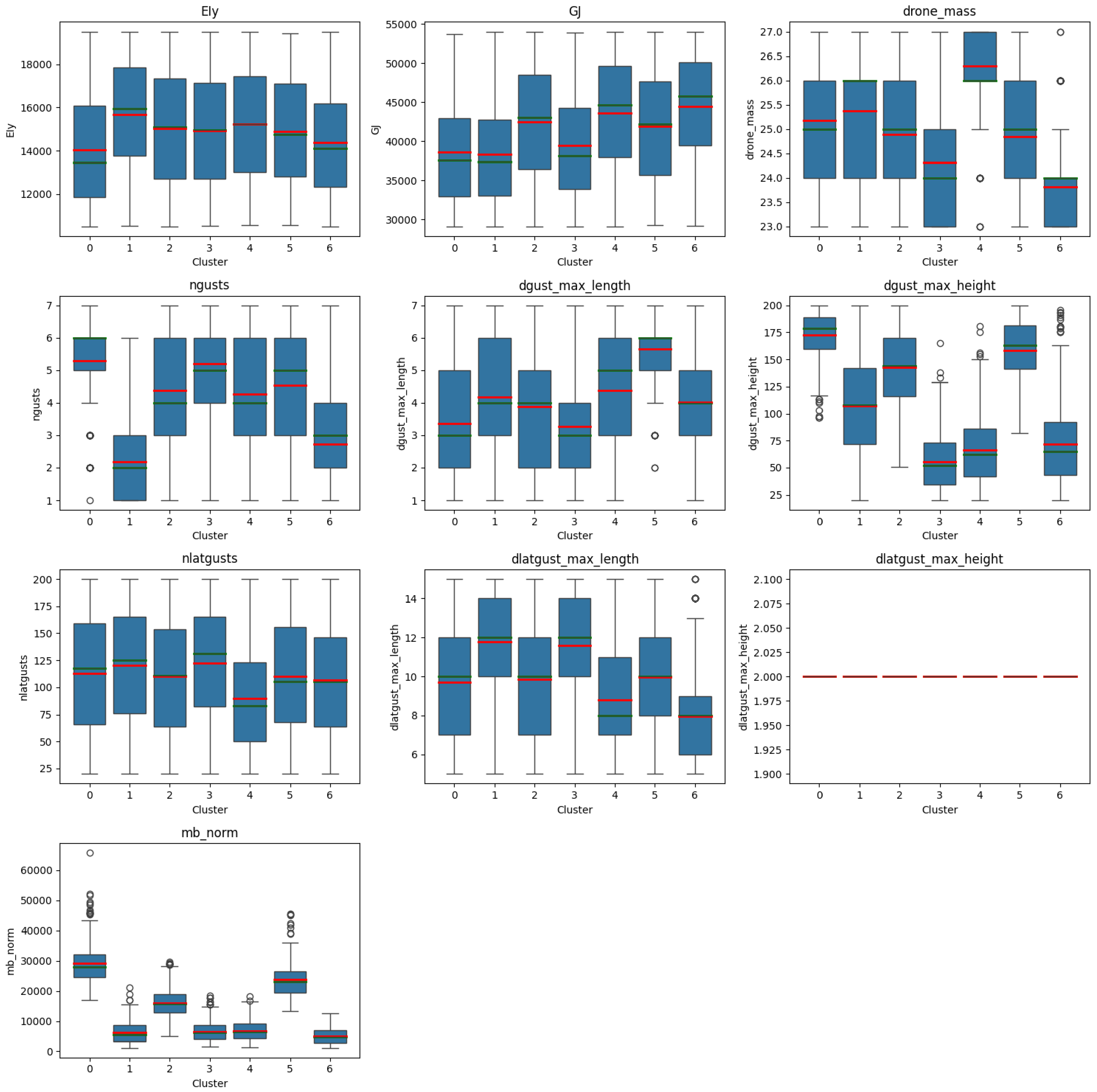
- **AI/ML** algorithms / methods could be various,
- We made some attempts with Clustering and found it useful to identify combination of parameters which cause given “danger indicators” to pass given thresholds or to rise above all other flight conditions,
- Using parameters to describe discrete gusts, 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.

Example of data clustering, with discrete gust parametrization





Same clustering approach with more parameters (including configuration and failure conditions)



Relevance of more complex AI/ML approaches

- Large pharmaceutical companies are hiring AI companies (Open AI, Anthropics etc) - this is public domain - 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.
- By analogy, AI/ML may be able to identify innovative approaches, more thorough analysis of the flight envelope of regular and failure conditions (extremely relevant for eVTOL), with the aim of minimising flight testing efforts and increase safety of both flight testing and operations,
- With reference to EASA AI concept paper, this implies moving up the level scale and allow AI/ML to cooperate with humans in taking decisions,

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 to **eVTOL**, dynamic / aeroelastic modelling is demanding with a number of specific aspects, e.g. unsteady rotor response to changes in RPM,
- AI/ML may also contribute to the certification process at a **higher level**.

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Thank you!
Questions?

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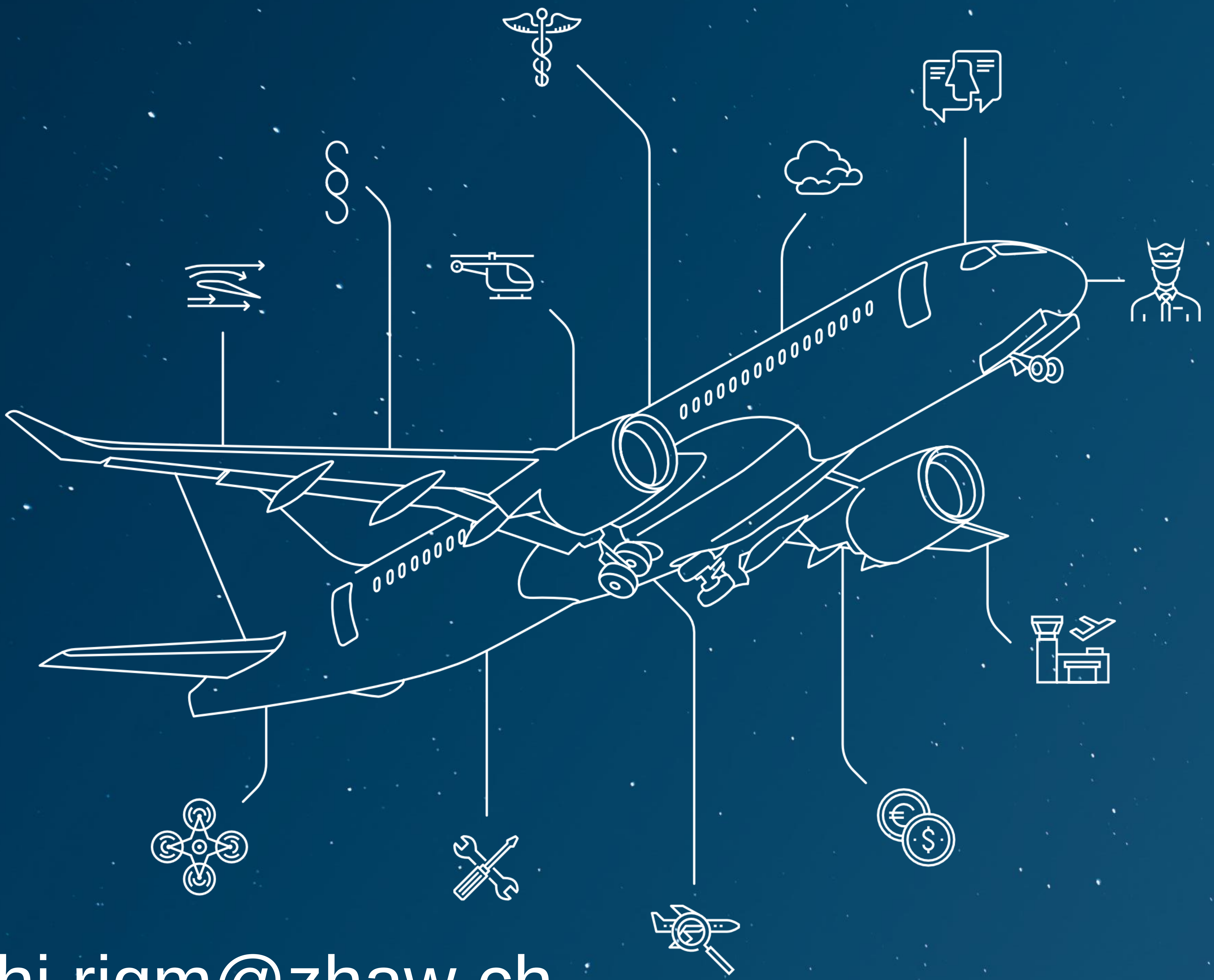

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