MODEL-SI
MODELING AND SIMULATION

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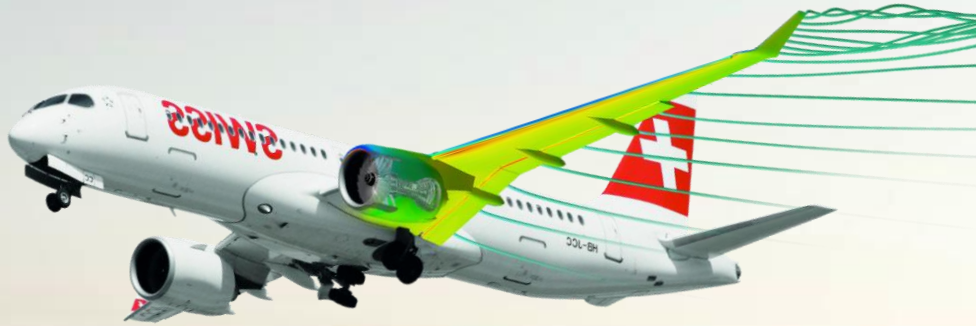
EASA MODEL-SI Project
D-3.2.3 – Regulation Guidance with AI



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June 2024, Winterthur

Regulation Guidance with AI: Overview problem

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Problem area

Can we use an aircraft Digital Twin (DT) to reduce the workload and computational costs to certify an eVTOL by maintaining or improving the safety standards? How can we trust an AI prediction?

Possible solution

A deep dive into current regulations is crucial to understand how AI can be safely integrated into certification processes. Standards from other industries or even the creation of new ones are required for the responsible use of a DT. A gap analysis would be performed to understand were actions are needed.

Regulation Guidance with AI: Analysis overview

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Documentation reviewed

- EU AI Act [1]
- ISO Guidelines for AI: e.g.
  - ISO/IEC JTC 1/SC 42 [2]: focuses on standardizing AI practices across different industries, on data quality, robustness, and transparency
  - ISO/IEC 24029 [3]: guidelines for evaluating the model robustness
- EASA AI Roadmap, EASA Concept Paper on ML Applications [4]
- NASA's "Certification by Analysis" [5]
- EU-Funded Project "Rotorcraft Certification by Simulation" [6]

High-level Gaps identified

- MOCs designed for deterministic system ➔ physics-based principles
- AI systems are non-deterministic ➔ driven by data, it depends on which datasets the model is trained
- Current MOCs lack provisions for such assessments, indicating a need for expanded protocols that address the unique challenges of AI systems

[1] European Union. EU AI Act: first regulation on artificial intelligence. Brussels, 2023.
[2] ISO/IEC JTC 1/SC 42 Artificial intelligence - Standardization in the area of Artificial Intelligence, 2017.
[3] ISO/IEC TR 24029 Artificial Intelligence - Assessment of the robustness of neural networks, 2024.
[4] Guillaume Soudain, Francois Triboulet, and Alain Leroy. EASA Concept Paper: Guidance for level 1 and 2 machine learning applications (Issue 02), 2024.
[5] Timothy Mauery et al. A guide for aircraft certification by analysis. Technical report, 2021.
[6] Linghai Lu et al. Preliminary guidelines for a requirements-based approach to certification by simulation for rotorcraft. 2022.

Regulation Guidance with AI

Certification activities: Which kind of actions should be performed to ensure the trustworthiness of our Digital Twin?

1. Gap analysis: What is missing in the current regulations on this Digital Twin usecase?

Bridging the gap with:

- **Digital Twin "Process Requirements"**: show the construction details of your Digital Twin solution
- **Digital Twin "Tests List"**: perform a series of tests to assess the Digital Twin behaviour

Gap analysis on data-driven Flight Simulation Model

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Digital Twin "Process Requirements"

- Definition of the minimum requirements needed to describe the ML implementation into a Flight Simulation Model (FSM)
- Serve as reference documentation for understanding the model design, development process, and operational characteristics/performance
- Divided in:
  - AI trustworthiness analysis
  - **AI Assurance**
  - AI Risk Analysis

Digital Twin "Tests List"

- Definition of a comprehensive list of tests that the FSM needs to undergo
- These tests will rigorously evaluate its functionality, performance, and robustness across its intended operational domain

Digital Twin “Process Requirements”

The compliance guidance is based on the EASA AI Concept Paper [4]. Here, the most important points are extracted and divided into:

1. AI trustworthiness analysis
2. AI assurance
3. AI risk analysis

[4] Guillaume Soudain, Francois Triboulet, and Alain Leroy. EASA Concept Paper: Guidance for level 1 and 2 machine learning applications (Issue 02), 2024.

DT “Process Requirements”: AI trustworthiness analysis

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1. AI trustworthiness analysis

1.1 **End-user identification**: identification of end-users that are intended to interact with the AI system

1.2 **End-user task**: For each end-user, identify which high-level task(s) are intended to be performed

1.3 **AI system identification**: determine and define the AI-based system while considering the domain-specific definitions of “system”.

1.4 **Operational Design Domain (ODD):** define of application domain and clearly its ODD, including environmental conditions, operational scenarios, and system limitations.

1.5 **Concept of Operations**: define and document the ConOps with a focus on the operational design domain.

1.6 **Functional analysis**: Define the system purpose with their high- and sub-level function and how to validate them.

1.7 **AI classification**: based on the levels (1A, 1B, 2A, 2B, 3A, 3B) AI typology and definitions, with adequate justifications.

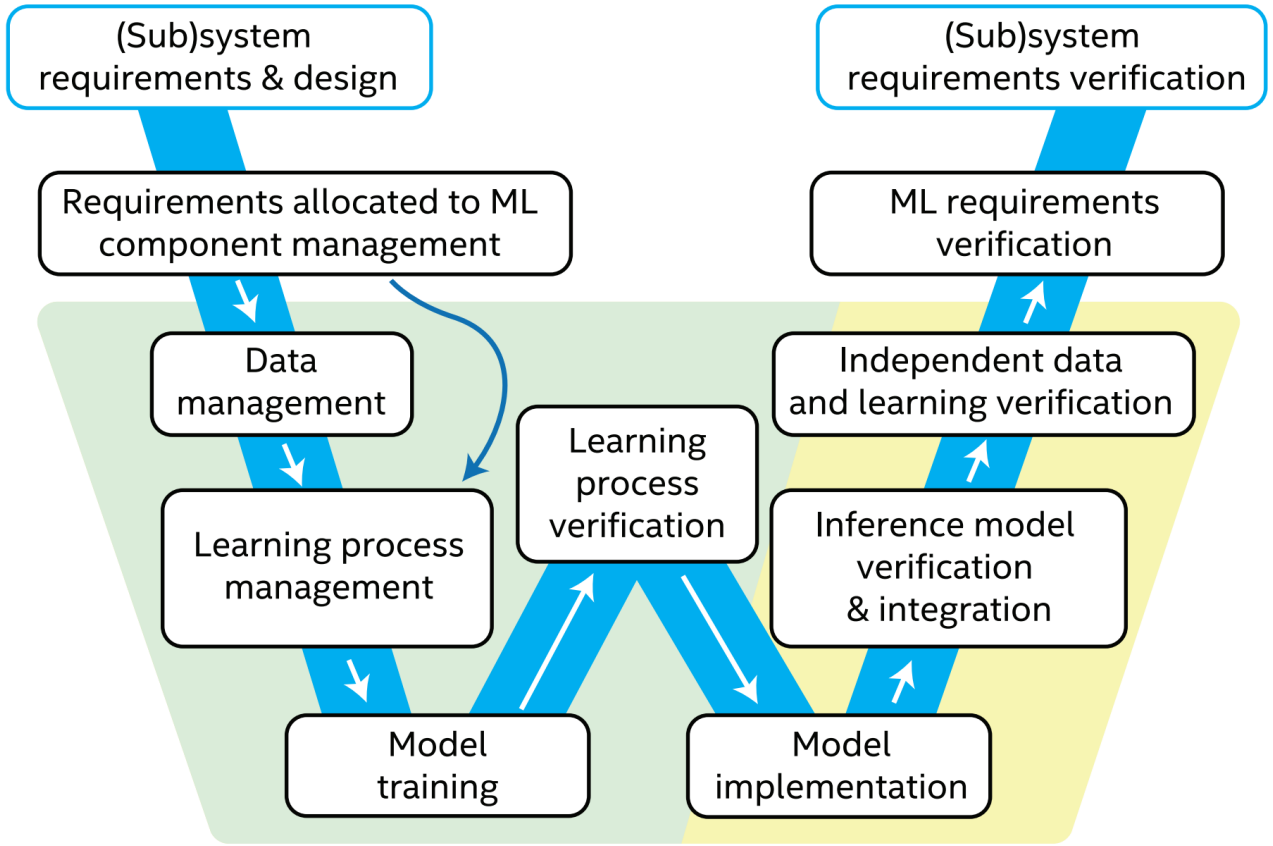
1.8 **Compliance with national regulations**

1.9 **Transparency analysis**: define what outputs need explanations, how those should be designed, when the AI system should provide them, and how well they meet criteria for clarity, relevance, consistency, and completeness.

DT “Process Requirements”: AI Assurance

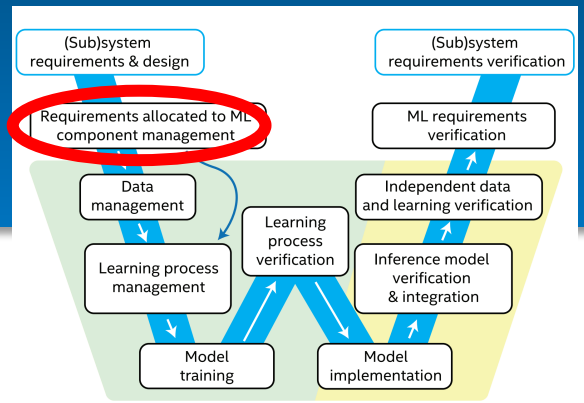
Simplified “Learning Assurance” process based on the W-shaped process of EASA and Daedalean [7]:

1. System requirements (AI/ML constituent requirements)
2. AI/ML constituents and model architecture
3. Performance Metrics
4. Learning process management and model training
5. Learning Process Verification
6. Model implementation
7. Evaluation of the performance of the inference model
8. ML Requirements Verification



[7] EASA and Daedalean. *Concepts of Design Assurance for Neural Networks*. Tech. rep. 2020. URL

DT “Process Requirements”: AI Assurance



2.1 System requirements (AI/ML constituent requirements)

Documents should be prepared to encompass the capture of the following minimum requirements:

a. Safety Requirements Allocated to the AI/ML Constituent.

b. Information Security Requirements Allocated to the AI/ML Constituent: These would detail how the system should protect data privacy and integrity.

c. Functional Requirements Allocated to the AI/ML Constituent: These would outline the functions the AI system needs to perform.

d. Operational Requirements Allocated to the AI/ML Constituent: These would state the conditions under which the system should operate (ODD) and how its performance should be monitored and recorded.

e. Non-Functional Requirements Allocated to the AI/ML Constituent: These would detail characteristics such as performance, scalability, reliability, and resilience.

f. Interface Requirements: These would describe how the AI system should interact with other systems and users.

DT “Process Requirements”: AI Assurance

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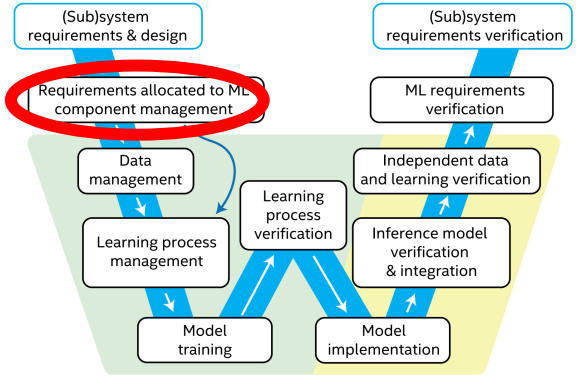
2.2 AI/ML constituents and model architecture

Documentation should describe the main AI/ML constituents that make up the system, including any classifiers, regressors, etc. along with their purpose. The interactions between the constituents should be explained. The model architecture should be described including model type and structure.



DT “Process Requirements”: AI Assurance

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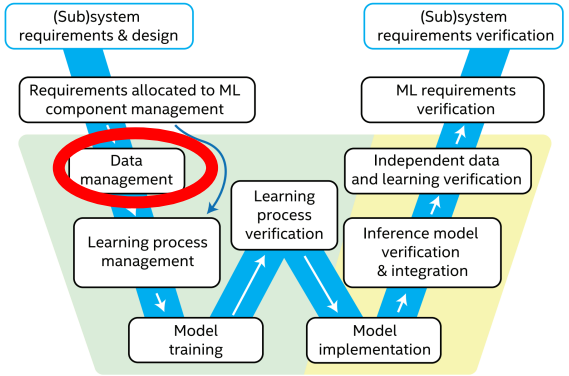
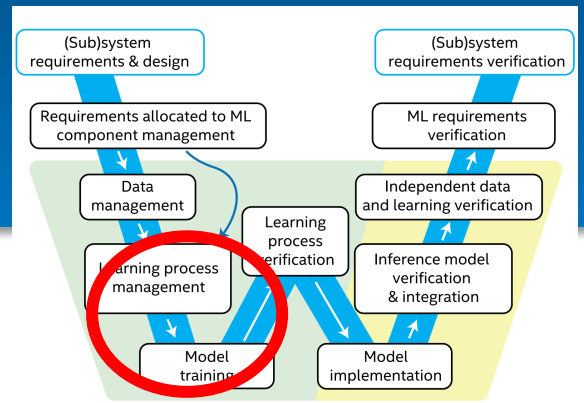
2.3 Performance Metrics

- Documentation should provide rationales for metrics selection and their target intervals or values.



DT “Process Requirements”: AI Assurance



2.4 Learning management and training process

a. Documentation should include data requirements, training process, training infrastructure, and model selection and evaluation process.

b. Documentation should include the rationale for loss function selection, techniques/algorithms used for optimization, and their target intervals or values.

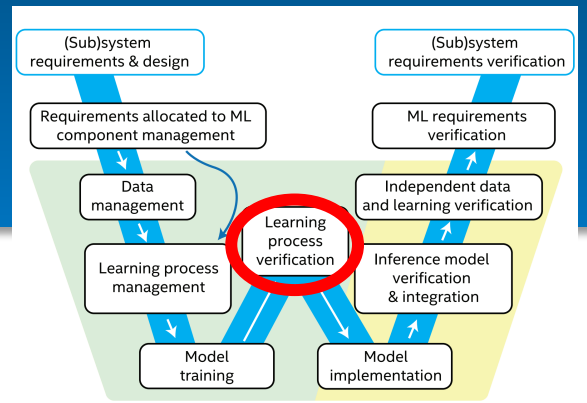
c. Documentation includes training loss and accuracy, validation loss and accuracy, and learning curves.

d. Documentation should include a list of optimizations performed, and their rationales.

e. Documentation should model complexity, model selection strategy to provide such a tradeoff, and description of any techniques used (e.g., regularization).

f. Documentation should outline measures taken to ensure reproducibility including data handling, training configuration, hardware and software used, and model versioning.

DT “Process Requirements”: AI Assurance



2.5 Learning Process Verification

a. Performance evaluation on test data: Documentation should describe the test dataset, evaluation metrics, evaluation methodology (e.g., Cross-Validation), and the results.

b. Requirements-based verification of the trained model behavior: Documentation should include the verification methods, and a coverage assessment evaluating the extent to which these methods provide sufficient coverage of the requirements. Any limitations and assumptions made should be stated.

c. Robustness optimization during training and developing: Documentation should describe how development and training increase the robustness of the AI component.

d. Stability analysis: Documentation should provide a stability analysis of the algorithms and the trained model including sensitivity and robustness analysis along with the results.

DT “Process Requirements”: AI Assurance

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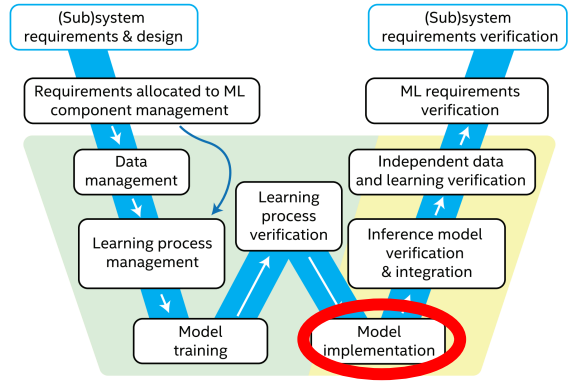
2.6 Model implementation

Identify and validate all model transformations, including conversion and optimization steps, ensuring that each change maintains model behavior and performance when deployed in the software environment.



DT “Process Requirements”: AI Assurance

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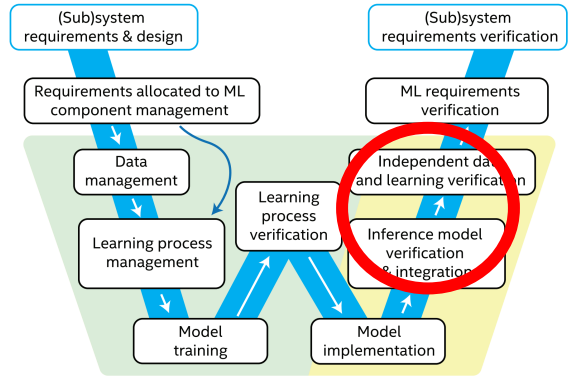
2.7 Evaluation of the performance of the inference model

Documentation should include a description of the test environment (setup, conditions, etc.), test methodology (cases, metrics, execution procedure), and test results (real environment testing) compared to the trained model.



DT “Process Requirements”: AI Assurance

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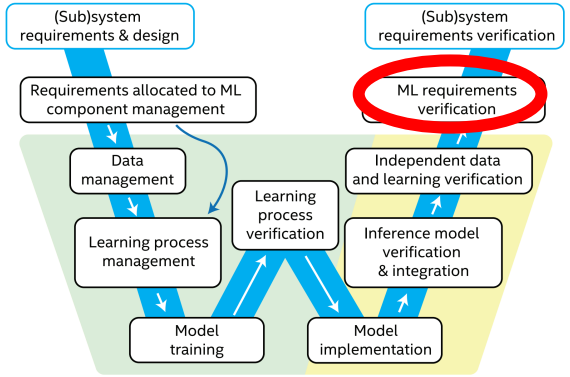
2.8 ML Requirements Verification

The requirements verification addresses the verification of the AI/ML component fully integrated in the overall system.



2.9 Vulnerability assessment

Documentation should describe the methodology and the result of the assessment.

DT “Process Requirements”: AI Risk Analysis

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3. AI risk analysis

3.1 Documentation should include objective, methodology (e.g., FMEA, FTA), assumption, risk identification, risk assessment, risk mitigation, residual risk assessment, and monitoring and review.

3.2 Documentation should include stakeholder identification, transparency challenges associated with each stakeholder, risk assessment, and mitigation strategies.

3.3 Documentation should include system decomposition, dataset identification, and risk analysis associated with the robustness of each component.

Digital Twin «Tests List»

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List of tests to be performed on the DT solution (i.e our Flight Simulation Model):

- Applications-specific tests: use-case specific tests tailored to the model's application (e.g., DT for eVTOL simulation)
- Generic test plan: general lifecycle stages (data, training, validation)
- Performance evaluation and reliability assessment: compare the DT results with HF data, test the DT stability and reliability
- Operational testing: test the DT under realistic comprehensive applications

Digital Twin «Tests List»: Applications-specific tests

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Use-case specific tests tailored to the model's application: these test are performed to address the following problems:

- **Periodic cross-validation tests**: DT predictions are compared against ground-truth data (e.g. experimental measurements) are imperative for model continuity and accuracy
- **Continuous learning**:
  - Implement a process to continuously ingest new data points throughout the eVTOL lifespan.
  - This ensures the model reflects real-world conditions and maintains certification standards
- **Key Performance indicators**:
  - Define Key Performance Indicators (KPIs) to quantitatively assess the DT accuracy against ground-truth data
- **Model Reliability and Validity**:
  - Integrate monitoring systems and feedback mechanisms.
  - This allows for early detection of accuracy deviations and prompts preemptive recalibration to maintain model reliability and validity for certification

Digital Twin «Tests List»: Applications-specific tests

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In our case, these tests could be performed:

- Model Validation Tests: e.g. Hovering Performance at Different Weights, Altitudes, and Temperatures, Performance Over Full Flight Condition
- Operational Envelope Tests: e.g. Maximum Safe Hovering
- Dynamic Stability Tests: e.g. Static Longitudinal Stability in Diverse Conditions
- Maneuverability and Control Tests: e.g. Transition and Maneuvering Capability
- Trim Capability Tests: e.g. Trim Control at Approved IFR Airspeeds and Configurations
- Turn and Slip Maneuver Tests: e.g. Turns and Slips under Different Operating Conditions

Digital Twin «Tests List»: Generic test plan

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Generic test plan for the ML model: general lifecycle stages (data, training, validation)

These tests are related to ML safety and reliability in general but adapted to the use case where possible. While they do not point to any specific clause in any direct certification documentation, they play a key role in establishing a trustworthy framework of ML development and deployment for such a critical use case. The following areas should be addressed:

- **Verification and Validation (V&V) strategies**: the goal is to ensure reliable outputs by confirming it performs as intended and behave correctly to unseen input data
- **Testing against low-fidelity and high-fidelity models**: needed for ensuring that the resulting FSM can stand up to rigorous assessment of its predictive capabilities and fidelity within the eVTOL flight envelope
- **Testing against operational data**: Operational data is essential for validating ML models, as it represents the real-world scenarios in which the eVTOL will operate
- **Sensitivity analysis and uncertainty quantification tests**: provide crucial insights into the robustness of a NN by revealing how variations within the input data impact the final outputs. This allows for a more comprehensive understanding of the NN predictions and potential vulnerabilities.

Digital Twin «Tests List»: Performance evaluation and reliability assessment

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Performance evaluation and reliability assessment: compare the DT results with HF data, test the DT stability and reliability. To achieve this comprehensive assessment, we will explore four key areas:

- **Statistical accuracy and reliability**: We will leverage established statistical measures to quantify the DT's accuracy and reliability in predicting relevant outcomes.
- **Predictive capability across flight conditions**: A rigorous evaluation will be conducted to assess the DT's ability to make accurate predictions under a diverse range of flight conditions. This ensures the model's generalizability and applicability in various operational scenarios.
- **Outlier detection and edge case handling**: We will examine the model's capability to identify and handle outliers within the data. Additionally, its performance in unconventional or extreme situations (edge cases) will be scrutinized.
- **Robustness under perturbations and variabilities**: The DT robustness will be assessed against potential model perturbations, such as slight changes in input parameters. This testing also encompasses operational variabilities that might occur during real-world use. Evaluating robustness ensures the model's stability and its ability to deliver reliable predictions even in the presence of uncertainties.

Digital Twin «Tests List»: Operational testing

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Operational testing: test the DT under realistic comprehensive applications. The simulation of realistic mission profiles and operational scenarios is crucial for the development, validation, and certification of the DT for eVTOLs. This operational testing encompasses the following key aspects:

- Simulation of realistic mission profiles and operational scenarios
  - Flight Simulation Requirement Specification
  - Realistic Mission Profiles
  - Operational Scenario Testing
- Real-time monitoring and adaptive learning considerations
  - Context-Sensitive Mechanisms:
  - Timeliness of Explainability
  - Continual Learning and Model Evolution
  - Monitoring of Model Performance
  - Issue Detection and Resolution
  - Safety Margin Preservation
- Pilot-in-the-loop and human factors integration
  - Virtual Pilot Models and Abuse-Case Testing
  - Handling Qualities and Human-Factors Assessments
  - Realism in Pilot Interactions
  - Selection of Simulation Type Based on Requirements

Gap Analysis on SC-VTOL 2245 Aeroelasticity Usecase

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MOC VTOL.2245 Aeroelasticity

(a) General. The aeroelastic stability evaluations referred to in this MOC include flutter, divergence, control reversal and any undue loss of stability and control as a result of structural deformation. The aeroelastic evaluation should include whirl modes associated with any lift/thrust unit or other rotating device that contributes significant dynamic forces. Compliance with this paragraph should be shown by analyses, tests, or some combination thereof.

(b) Aeroelastic stability envelopes. The aircraft should be designed to be free from aeroelastic instability for all configurations and design conditions within the aeroelastic stability envelopes as follows:

(1) For normal conditions without failures, malfunctions, or adverse conditions, all combinations of altitudes and speeds encompassed by the V_D versus altitude envelope

[…]

[8] https://www.easa.europa.eu/sites/default/files/dfu/moc-2_sc-vtol_-_Issue_1_-_23-06-2021.pdf

Everything is gap!

The current MOC cannot ensure the safety and reliability of an ML model specialized in aeroelasticity modeling. **No requirements** are requested to give information on the use of an AI/ML application.

Analysis and Recommendations on MOC VTOL.2245

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- **Stability Analysis for AI/ML Models**
  - Unlike traditional evaluations, data-driven models need stability assessments that consider extreme scenarios, noise, and outliers.
  - Stability means that the model output remains consistent despite minor input changes, important for robust performance under all conditions.

- **Comprehensive Testing Requirements**
  - ML models must be tested across all failure modes, malfunctions, and adverse conditions required from the MOC. A certain amount of data representing these scenarios, often limited in typical datasets, is anyway required to avoid bias toward normal conditions.

- **Robustness**
  - A robustness assessment, including stability, sensitivity, relevance, and reachability, is essential for deploying data-driven models in safety-critical applications, using a mix of statistical, empirical, or formal analyses suited to the model and context.

- **Uncertainty Quantification**
  - ML model outputs should include quantified uncertainty or confidence levels, with documented methods and rationales, to assess their impact on system stability.

Analysis and Recommendations on MOC VTOL.2245

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- **Operational and Lifecycle Considerations**
  - Stability and robustness criteria should apply throughout the AI lifecycle, from design to deployment
  - Data-driven model outputs should be continuously monitored, with processes for timely human intervention or automatic fail-safes when inputs exceed predefined conditions.

- **Challenges in Representing Real-World Dynamics**
  - Gathering adequate data for complex maneuvers and structural deformation simulations is challenging: Both training and testing datasets should cover all relevant physical conditions, including high-stress conditions, to ensure data-driven models perform well across VTOL's unique operational conditions.

Lesson Learned

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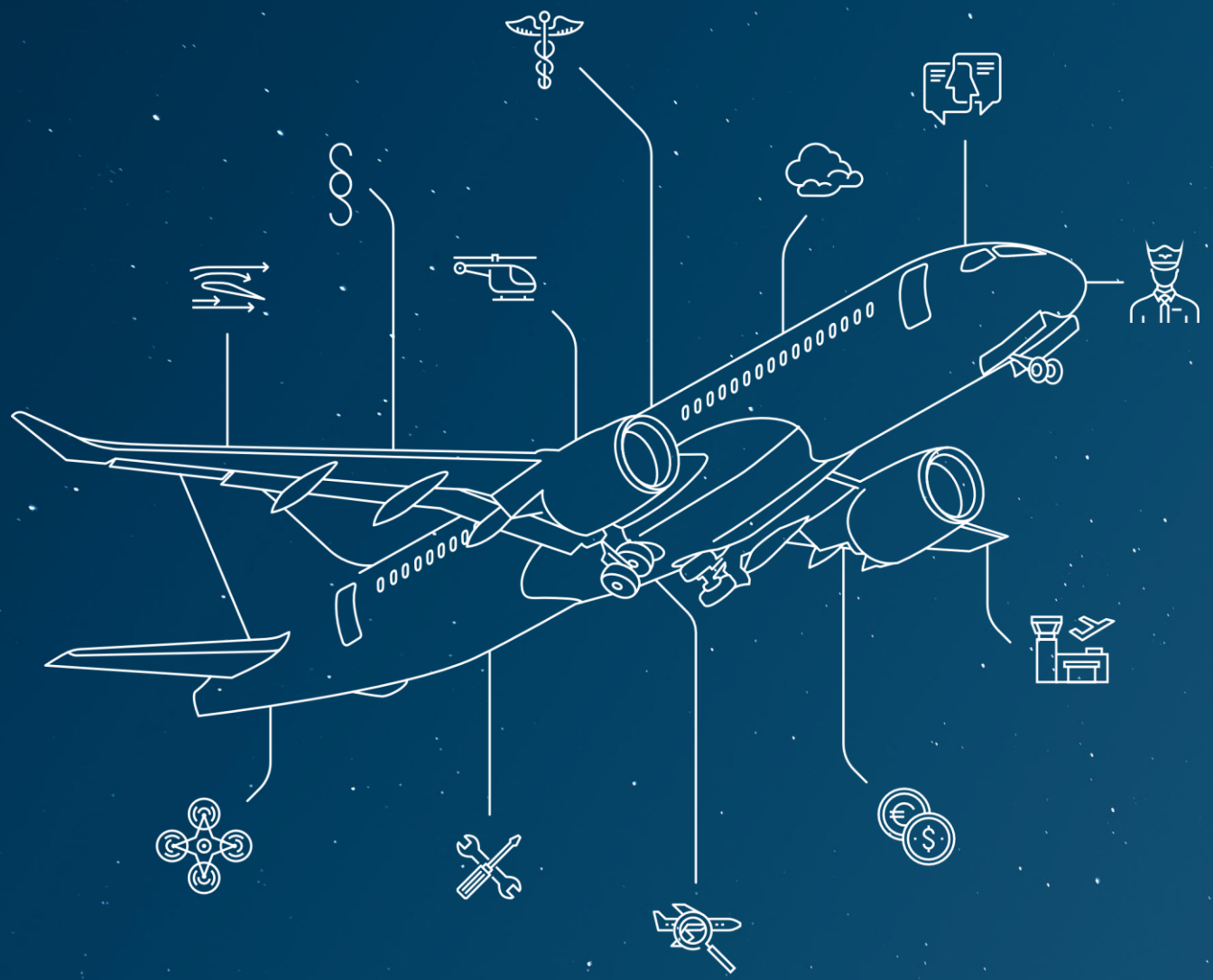
- In safety-critical domains, high-fidelity data points are crucial for training ML models
  - Collecting these data from controlled field tests may be challenging, especially for corner cases
- High-fidelity models still need to be used to generate such data for model training.
- When using a mix of both LF cheap data and HF expensive data, there's an optimal proportion, but the more HF data the more reliable the ML model
- Training and validation should encompass all possible scenarios and real-world conditions which is challenging
- Model validation must be done on the high-fidelity data points, unseen during model training
  - This implies more HF data is needed.
- Domain experts must be involved in the verification of generated data by the ML model.
- Current norms, regulations and standards for trustworthy AI are generic
  - more industry-specific standards are required to harmonize development and deployment of AI and ML in aerospace.
  - Following EASA concept paper and other AI ISO standards help with building trustworthy processes, but not the products

Thank you!
Questions?



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