EUROCAE SAE INTERNATIONAL

AAAI CONFERENCE KEYNOTE

EUROCAE WG114 – SAE G34: a joint standardization initiative to support Artificial Intelligence revolution in aeronautics



Speakers:

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Agenda

- 1. General presentation of EUROCAE WG114 SAE G34
- 2. Certification Challenges of Machine Learning
- 3. System considerations
- 4. Machine Learning Development Lifecycle (MLDL)
- 5. Conclusion



General presentation of EUROCAE WG114 – SAE G34



Objective & Scope of EUROCAE WG-114

- ☐ Creation: June 2019 (KOM end of August 2019)
- □ Objective: establish common standards, guidance material and any related documents required to support the development and the certification/approval of aeronautical safety-related products based on Al-technology
- ☐ Scope:
 - ❖ Airborne: Aircrafts and UAS
 - Ground: UTM, ATM and Air Traffic Solution



A joint group with SAE G-34 (AI in Aviation)

500+ engineers

Researchers and Al scientists from across the globe, with representation from regulators and authorities (FAA. EASA, TCCA, ANAC, EDA, NASA, DOD, EUROCONTROL), major airframers, UAS/UAM/eVTOL manufacturers, engine manufacturers, component manufacturers. technology providers, and other stakeholders, including operators and airlines

Special thanks to all contributors

G-34/WG-114 focuses on implementation and certification related to Al technologies for the safer operation of aerospace systems and aerospace vehicles.

- G-34/WG-114 (comprised of 500+ members) promotes and standardizes Artificial Intelligence in the entire aviation ecosystem (both Airborne and Ground) addressing both manned and UAS.
- G-34/WG-114's Global contributors: Boeing, Airbus, ATR, Embraer, Textron, Gulfstream, Dassault, Mitsubishi, Lockheed, Northrop Grumman, GA-ASI, HondaJet, Daher, IAI, ICAO, FAA, EASA, TCCA, ANAC, DGAC, CAA UK, CAA NZ, JCAB, ENAC, FOCA, DOD, EDA. Lilium, Aerion Supersonic, Amazon, DXC, SAP, IBM, Joby, EUROCONTROL, NASA, EDA, Honeywell, Collins, Thales, GE, P&W. RR. Safran, Raytheon, BAE, Elbit, L3Harris, Iridium, Japan Manned Space Systems, FedEx, UPS, AF-KLM, Nodein, Lufthansa, Audi, Toyota, IATA, Leonardo, Leidos, NVIDIA, Intel, Saab, Volocopter, ANSPs, Skyguide, Searidge, Woodward, Vertical Aerospace, Diehl, ADB Safegate, AVSI, ANSYS, BNAE, Copenhagen Airports, D-Risg, Daedalean Al, KIAST, Infosys, Afuzion, Patmos Engineering, QinetiQ, RelmaTech, Rockdale Systems, DLR, drR2, Federated Safety, MathWorks, SRI, Oak Ridge National Lab, etc.

Works In Progress and deliverables:

SAE INTERNATIONAL

AS6983 Process Standard for Development and Certification/Approval of Aeronautical Safety-Related Products Implementing AI

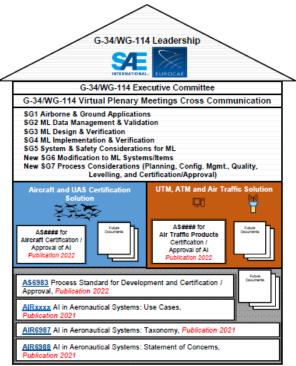
AIR6987 Artificial Intelligence in Aeronautical Systems: Taxonomy

AIR6988 Artificial Intelligence in Aeronautical Systems: Statement of Concerns

AIRxxxx Artificial Intelligence in Aeronautical Systems: Use Cases Considerations

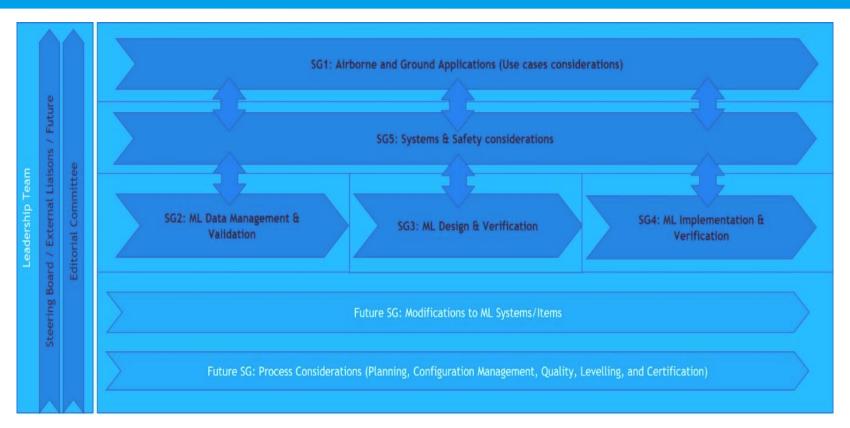
For more information and/or membership registration, contact: jordanna.bucciere@sae.org and/or anna.guegan@eurocae.net. EUROCAE

Joint International Committee on Artificial Intelligence in Aviation Ecosystem





WG-114/G-34 setup to write the standard

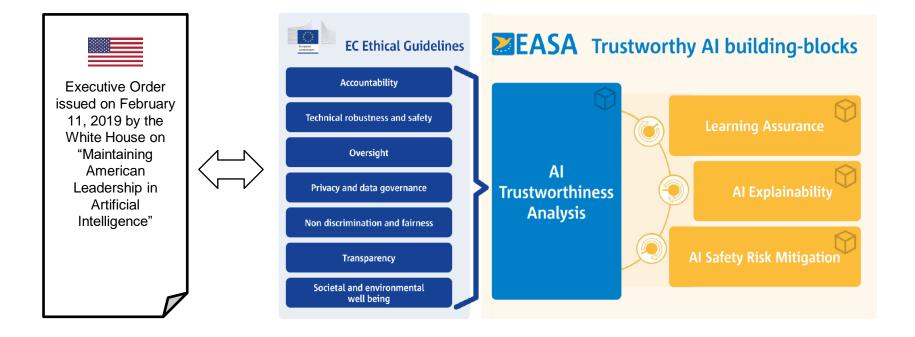




Certification Challenges of Machine Learning



EC / EASA Challenges for AI Trustworthiness

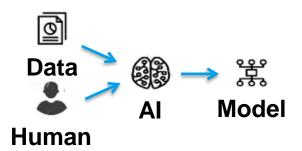




1. Specification (and validation) Challenge

ML applied very often to complex problems, difficult to specify (e.g. pedestrian detection)





Data-driven algorithms, implicit model

« Black box »:

- Difficult to relate SW code to requirements
- How to specify/verify data requirements?
- Quantifying model uncertainties

Trusting an ML model involves « opening the box » to a degree commensurate with its intended use



2. Data Challenge: Representativeness





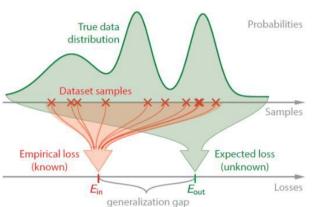
Main Data challenges:

- Detection and mitigation of bias and variance
- Dataset quality and completeness
- Change of paradigm: how datasets may contribute to the specification?



3. Robustness and Verification Challenges





- > Evaluate robustness of an algorithm to changes in the training set
- Detect unintended and unexpected behavior of NN
- Detect abnormal or adversarial inputs to the NN
- Asses intrinsic robustness of trained ML models through formal or empirical methods
- Assess training methodologies that can enhance or guarantee robustness
- Manage performance / robustness tradeoff
- Define safety process analysis and relevant architectural mitigations (bounding, voting, diversity, etc)

Source: EASA CodaNN IPC report



4. Explainability Challenges

Specific challenges:

- "Black-box" model
- **Correlation does not imply** causation:
 - ML models rely on correlation
 - Explanations need causality
- Prove the explanation is reliable and correct
- **Meaningful explanation for:**
 - Data scientist, SW dev
 - End user (ATCO, pilot, maintenance operator)
 - Regulation authority
 - Accident investigator





(a) Husky classified as wolf

Link with **Learning Assurance**: high level and low level features

Link with operational monitoring: OOD, performance

Link with **Human Factors** considerations

Link with data recording and traceability (inputs, internal states, outputs, derived features)



Explanation Accuracy: The explanation correctly reflects the system's process for generating the output

Knowledge Limits: The system only operates under conditions for which it was designed or when the system reaches a sufficient confidence in its output

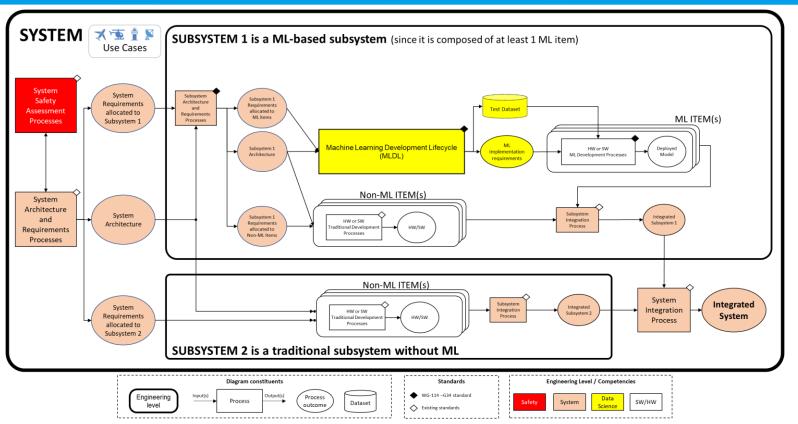


System considerations

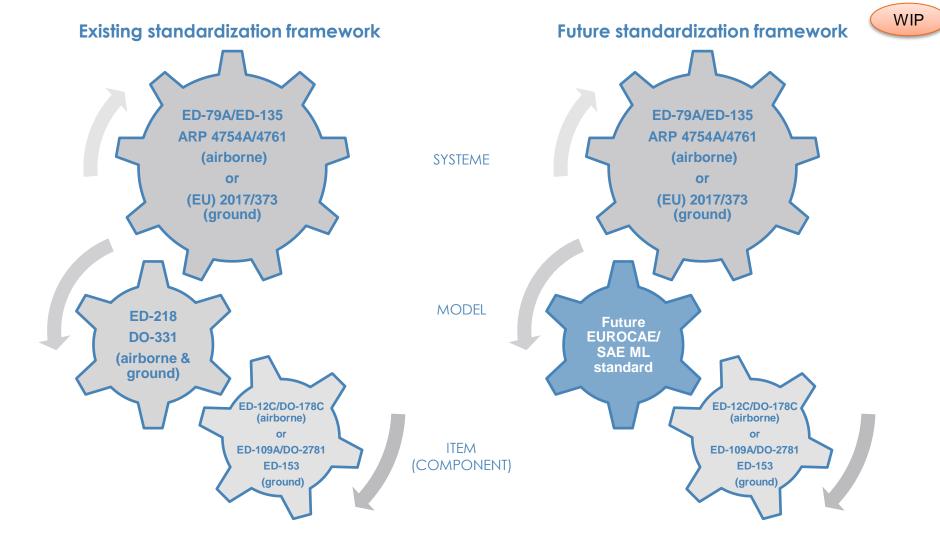


End-to-End System Lifecycle with Machine Learning









Machine Learning Development Lifecycle (MLDL)



Scope and desired attributes of the MLDL

The MLDL should be:

Generic

- The MLDL is applicable to offline ML technologies considered in G34-WG114 scope
- Any technology-specific MLDL phase should be addressed as a second step (further updates of the MLDL)

Process/Environment Agnostic

- The MLDL does not impose a specific development process
- The MLDL does not impose a specific learning environment

Support certification/approval

- ML assurance objectives should be well organized consistently with MLDL
- ML assurance objectives should be simple and clear

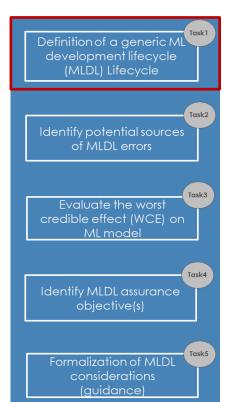
Counter-examples

e.g. The MLDL is only applicable to supervised learning using Artificial Neural Network

- •e.g. The MLDL is only applicable for V or W development process
- •e.g. The MLDL is only applicable to ML models built using tensorflow framework
- e.g. ML assurance objectives are organized using phases and steps that are not consistent with the MLDL definition



Methodology to build Machine Learning Assurance Objectives



Task 1 Objective:

Define a generic ML development lifecycle (MLDL) to support:

- · the analysis of fault injection all along the ML developement lifecycle
- · the identification of ML development assurance objectives (MLDAO) to avoid fault injection or detect resulting errors
- the evaluation of proposed MLDAO with appropriate use cases.

This MLDL should be approved by the full SG3 group

Task 2 Objective:

Identify the possible source of errors called either ML development fault injection cases or ML development failure modes. They are described with at least the following attributes: Name, Rationale (if not obvious)

The completness of the failure modes should be assessed using appropriate method(s).

The list of MLDL failure modes can be classified per MLDL phase and should be approved by the full SG3 group

Task 3 Objective:

Study the worst credible effect (WCE) on the ML model of all ML development failure modes. The adverserial effects that are considered to establish WCEs come from SG5 safety objectives (e.g. impact on ML model integrity, performance, explainability, etc.). When not obvious, a rationale should be provided to explain WCEs. When there is no adverserial effect on safety, the WCE should be « No identified effect ».

Task 4 Objective:

Identify MLDL assurance objective(s) to mitigate any adverserial WCE on SG5 safety objectives allocated to the ML model (e.g. adverserial impact on ML model integrity, performance, explainability, etc.). MLDL assurance objectives should be classified by DAL/AL/SWAL levels. A gradation of these assurance objectives is expected according to the DAL/AL/SWAL levels. Airborne and Ground specificities should be taken into account. A rationale should be provided to explain each MLDL assurance objective. When there is no adverserial effect on safety (i.e., WCE = No identified effect »), no assurance objective is needed.

Task 5 Objective:

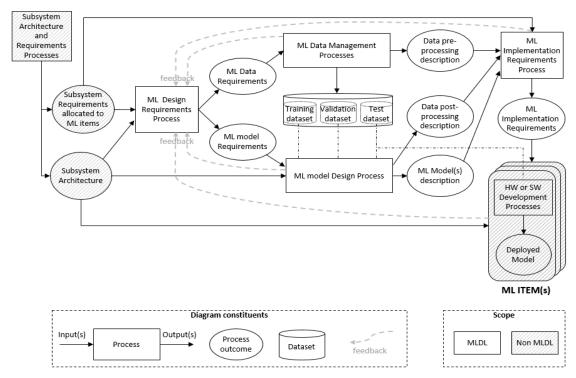
Formalize the outputs of all tasks into a guidance material that follows AS6983/ED-XXX Outline. This guidance is expected to be part of the final AS6983/ED-XXX standard. The need to issue a FAQ should be assessed by SG3 leaders.



Machine Learning Development Lifecycle (MLDL)



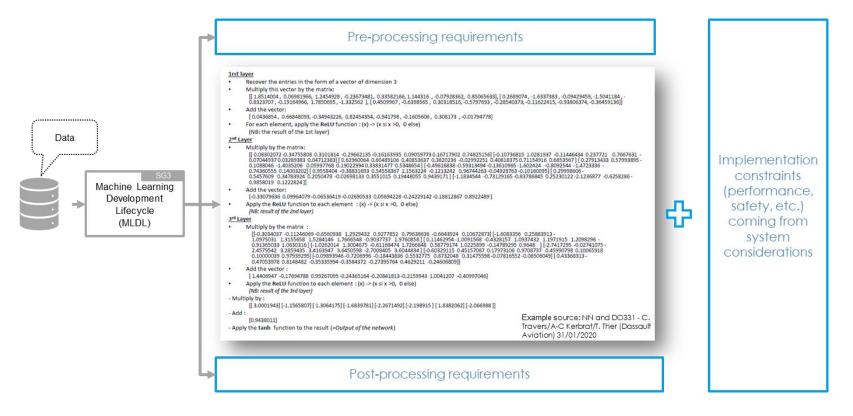
Subsystem





Outcome of the MLDL to implementation phase





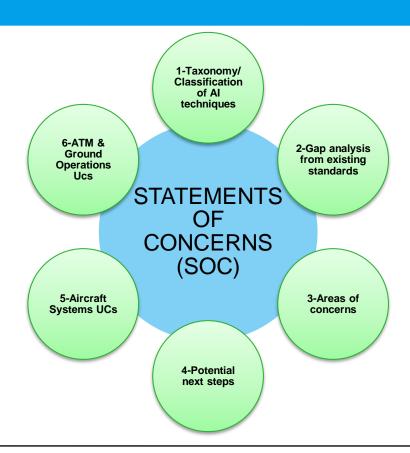


Conclusion



2021 Outcomes: Statement of Concerns







WG-114/G-34 Roadmap





Liaisons with other Groups

(*) active ones are bolded

EUROCAE

- WG-63 (Complex A/C systems)
- WG-72 (Aeronautical Systems Security)
- WG-105 (Unmanned A/C Systems UAS)
- WG-112 (Vertical Take-Off and Landing VTOL)
- WG-117 (Topics on SW advancement)

SAE

- S-18 (Complex A/C systems & UAS Autonomy)
- G-32 (Cyber Security)

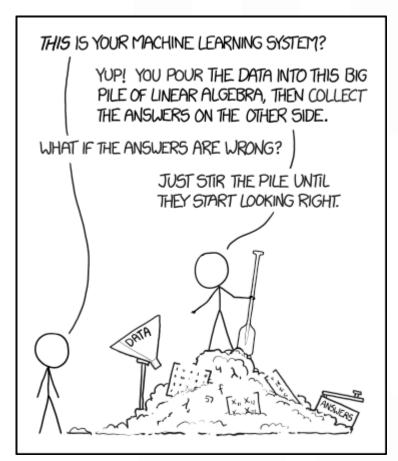
Others

- AVSI AFE87
- EUROCONTROL Al High Level Experts Group
- ISO/IEC JTC 1/SC 42
- French Grand Defi CONFIANCE.AI
- JARUS (Joint Authorities for Rulemaking on Unmanned Systems)
- ASTM



THANK YOU FOR YOUR ATTENTION!

Questions?



Source: https://xkcd.com/