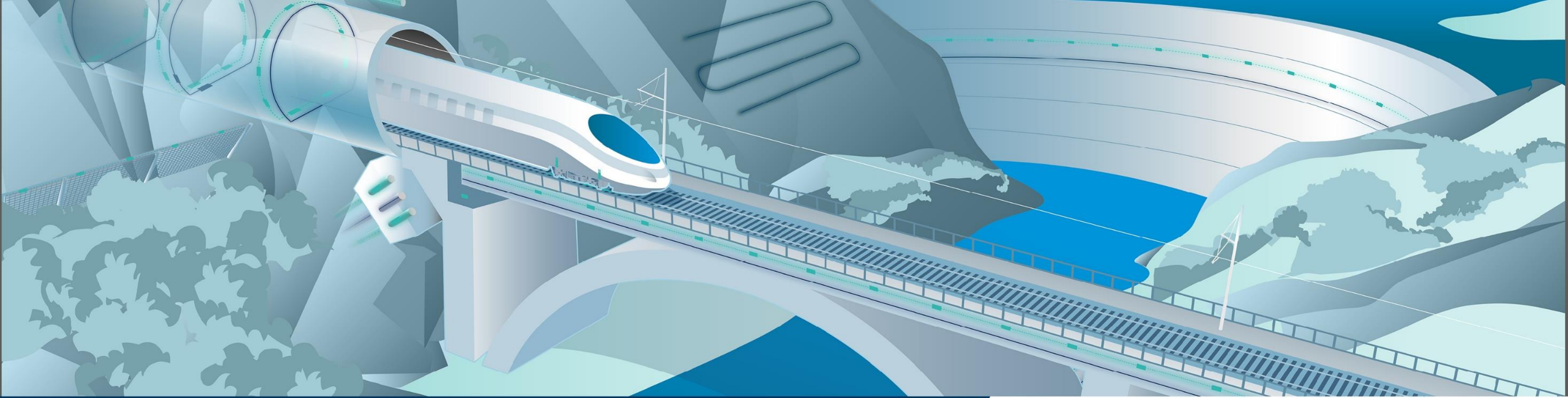

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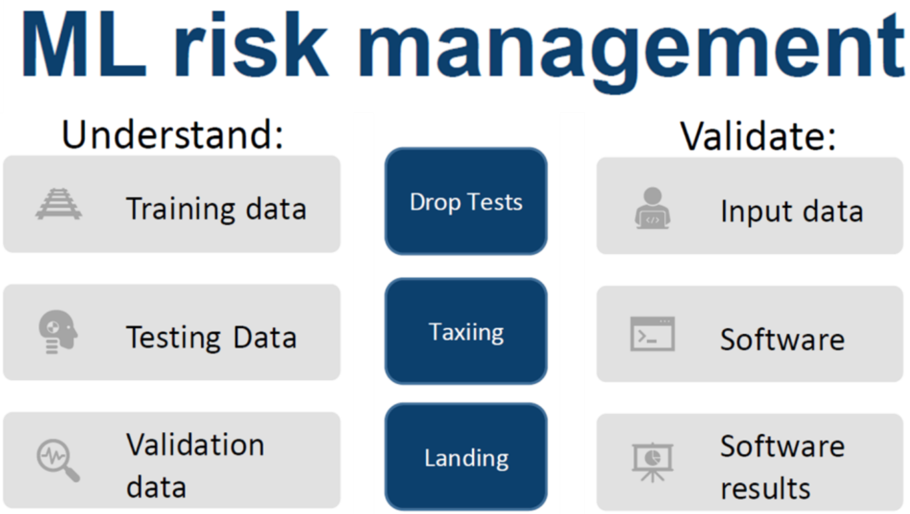

Uncertainties and Risk Management for Certification of Machine Learning for Landing Gear Remaining Useful Life

Presented by Haroun El Mir,
Transport Systems, Cranfield University

Uncertainties and Risk Management for Certification of Machine Learning for Landing Gear Remaining Useful Life

Abstract

Landing Gear Systems on Aircraft undergo a multitude of forces during their life cycle, leading to the eventual replacement of this system based on a ‘safe life’ approach that at certain circumstances underestimates the component’s remaining useful life. The efficacy of fatigue life approximation methodologies is studied and compared to the ongoing Structural Health Monitoring techniques being researched, which will forecast failures based on the system’s specific life and withstanding abilities, ranging from creating a digital twin to applying neural network technologies, in order to simulate and approximate locations and levels of failure along the structure. Explainable Artificial Intelligence allows for the ease-of-integration of Deep Neural Network data into Predictive Maintenance, which is a procedure focused on the health of a system and its efficient upkeep via the use of sensor-based data. Test data from a flight includes a multitude of conditions and varying parameters such as the surface of the landing strip as well as the aircraft itself, requiring the use of Deep Neural Network models for damage assessment and failure anticipation, where compliance to standards is a major question raised, as the EASA AI roadmap is followed, as well as the ICAO and FAA. This presentation additionally discusses the challenges faced with respect to standardizing the Explainable AI methodologies and their parameters specifically for the case of Landing Gear.

About the presenter, Haroun El Mir, Transport Systems, Cranfield University

Haroun completed his BSc in Mechanical Engineering at the American University of Sharjah, with a focus on Aircraft Stability & Propulsion. He worked right after as a research assistant in Composite Materials with a Publication on "Improving the buckling strength of honeycomb cores". Moving thereon to Cranfield University for an MSc in Aerospace Vehicle Design with a concentration in Avionics Systems Design, he focused on Landing Gear fatigue prediction using modelling and FE software, later pursuing a PhD in Transport Systems, seeking the continuation of his MSc Thesis and integrating it with a neural network approach & application in SHM.

Uncertainties and risk management for the certification of ML & LG RUL assessment

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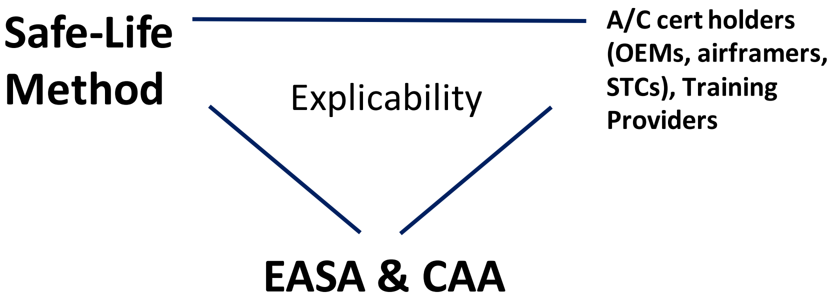
The why, when, and how

- MRO needs to accommodate for an increased no. of aircraft
- SHM, damage monitoring, OLM
- Incorporate uncertainties affecting the ML Model as well as external environmental uncertainties affecting the Landing Gear.
- Explicability:



A certification methodology for a new approach to fatigue-monitoring in landing gear components.

Replacement of a portion of sensors used as part of the SHM approach, requiring less maintenance & cost.

The development of an explainable landing gear focused system which makes use of ML as part of its process.

The status of AI certification in aviation

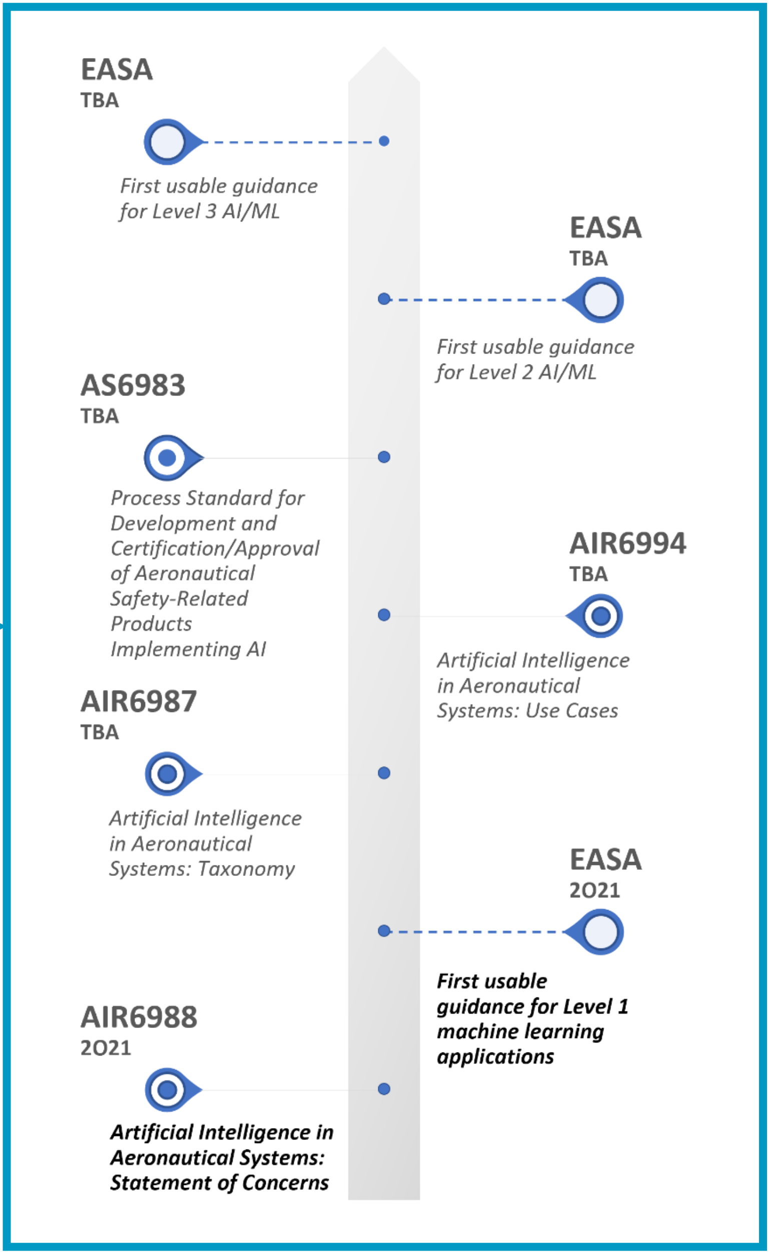
Avionics airworthiness requirements

- ARP4754A
- ARP4761
- DO-178C
- DO-254

AI in aviation certification advisories

- AIR6988
- EASA L1
- AMLAS

SAG G-34/EUROCAE WG-114 & EASA MILESTONE ROADMAP Phase I: exploration and first guidance development 2019-2024



ML model's position within the LG testing environment

Controlled Tests

- Drop Tests
- Taxiing
- Landing

Sensors

- Shock absorber
- Steering system
- Wheels and braking system

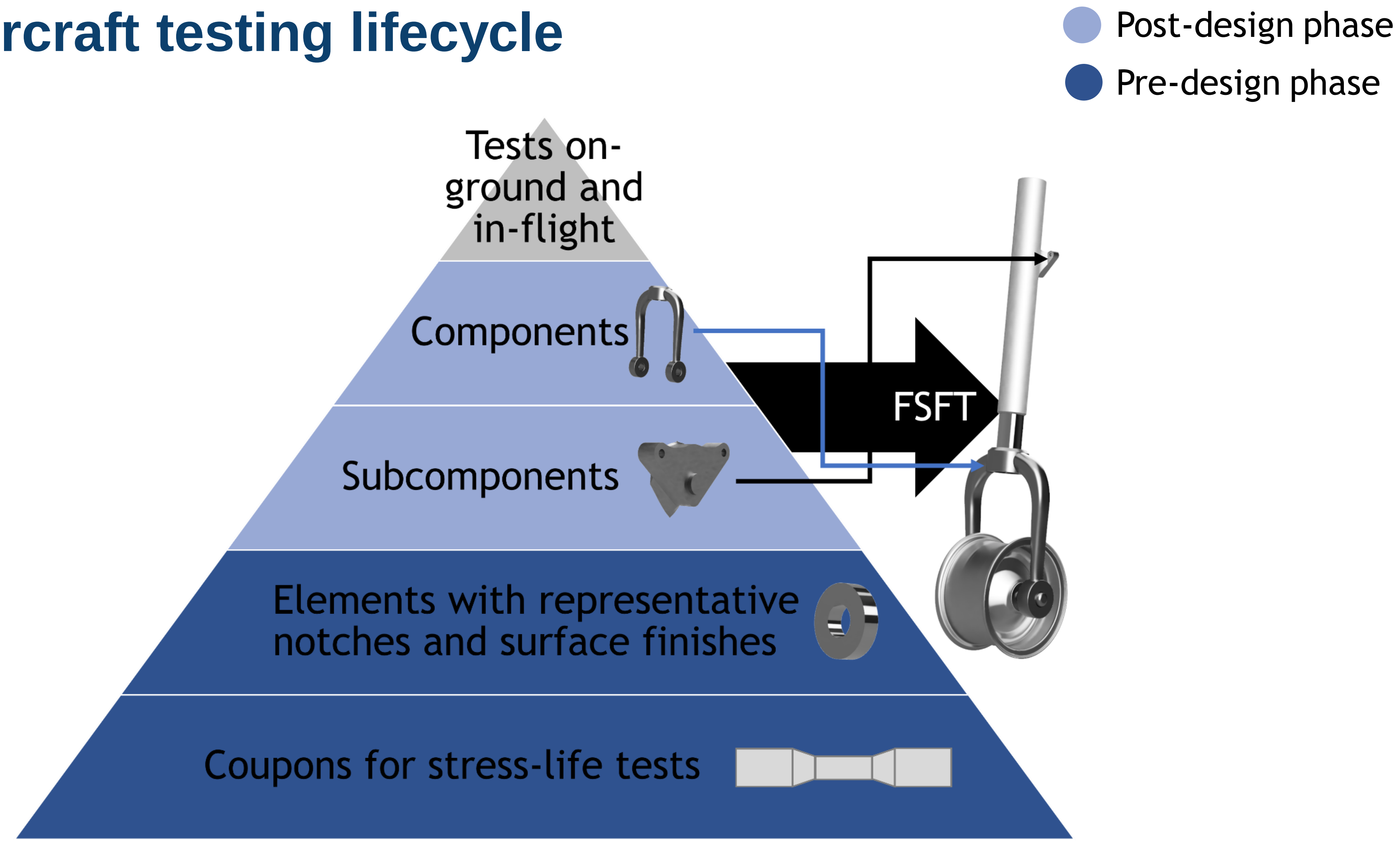
Data Collected

- Shock-absorber travel
- Tyre closure
- Shock-absorber pressure
- Wheel speed
- Drop carriage accelerations
- Landing gear accelerations

Learning and Prediction

ML Black Box → Safe-life prediction

Fatigue: Aircraft testing lifecycle



Current fatigue assessment approaches used by OEMs, MROs, airframers

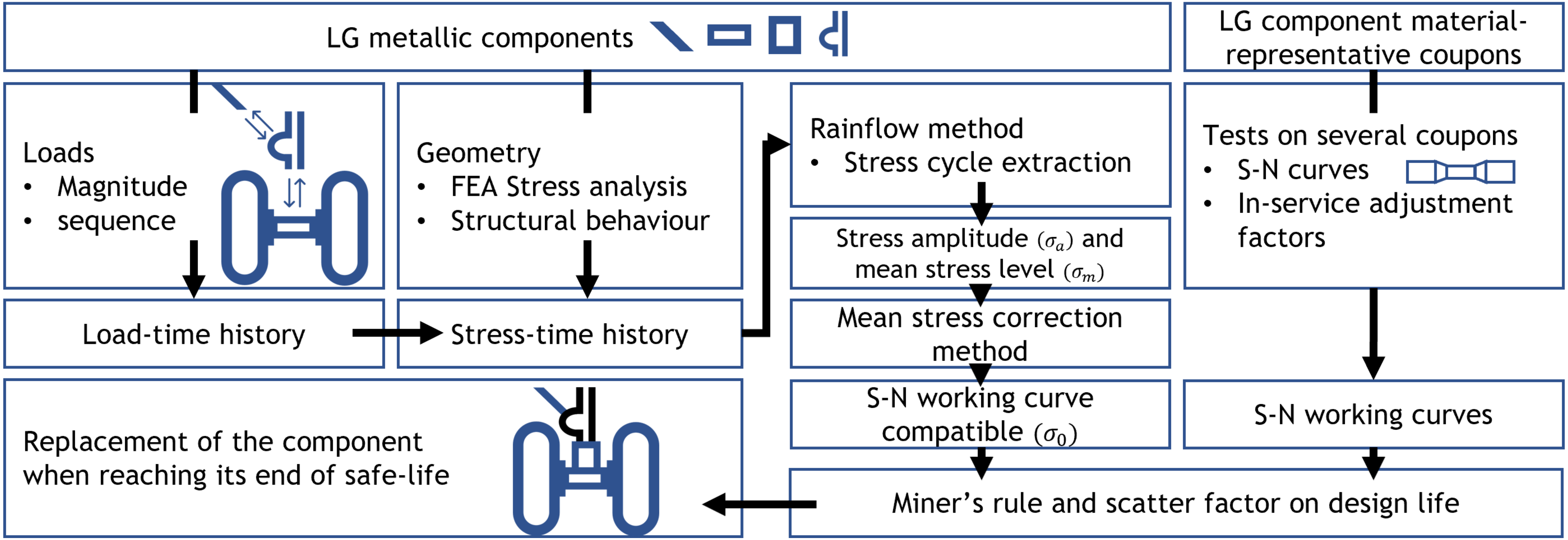
- ML models are currently being used to predict loads on LG systems in place of the safe-life approach traditionally used.

Safe-life → Fail-safe → Damage Tolerance → Structural Health Monitoring

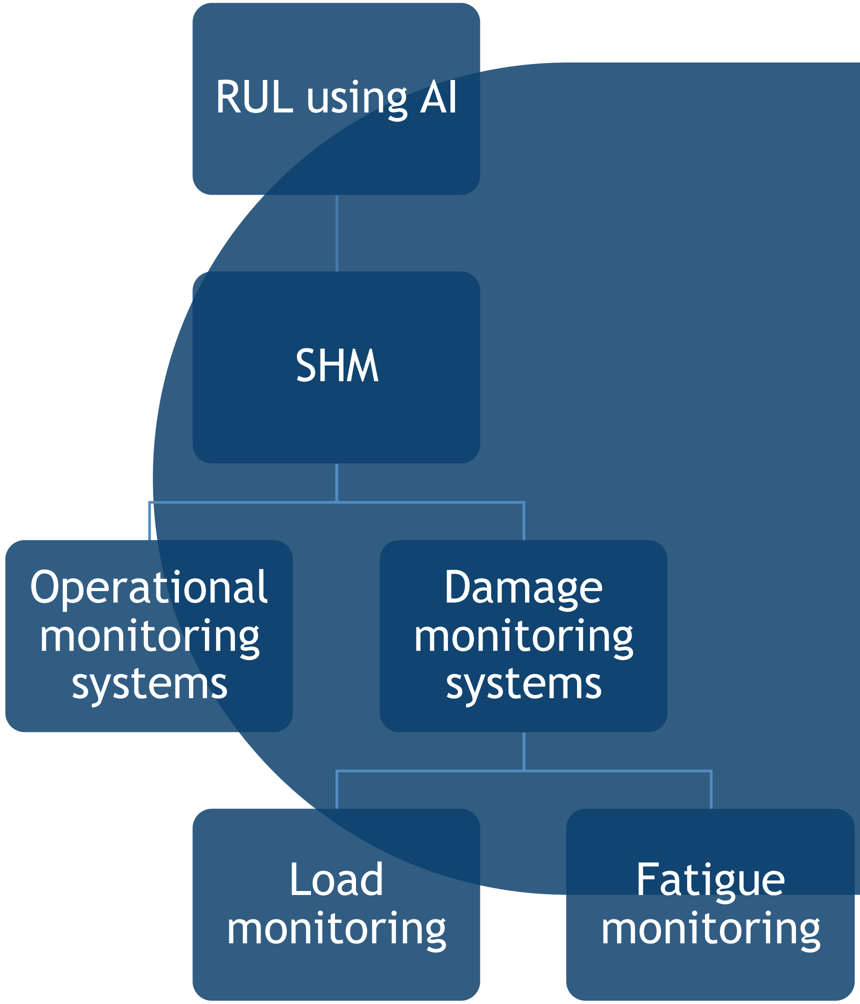
- Landing Gear structures are still based on the safe-life fatigue failure approach due to their components being formed of high-strength steels and the relative difficulty of planned crack inspections.

The safe-life approach to fatigue is the benchmark to be used to validate the ML model.

Safe-life of landing gear



Fundamental principles of SHM and the relative role of ML



- Sensors cannot measure damage.
- Without intelligent feature extraction, measurement sensitivity to damage and conditions=positive correlation
- The length and time-scales associated with damage initiation and evolution dictate the required properties of the SHM sensing system.
- Unsupervised for damage location, supervised for damage specifics[1].

[1] Nick, W., Shelton, J., Asamene, K. and Esterline, A.C., 2015. A Study of Supervised Machine Learning Techniques for Structural Health Monitoring. *MAICS*, *1353*, p.36.

ML risk management

Important questions for the setting of requirements in the ML uncertainties capture

- ‘Is it using recognized libraries?’; code pre-written for repeated usage.
- ‘What was the quality process used in creating that software?’ A framework by Murphy, Kaiser and Arias proposes a ranking for supervised ML algorithms [2].
- ‘What is the validation process of the model itself (the data-driven part of the training)?’

Understand:

- Training data
- Testing Data
- Validation data

Drop Tests

Taxiing

Landing

Validate:

- Input data
- Software
- Software results

[2] Murphy, C., Kaiser, G., and Arias, M. (2006). A Framework for Quality Assurance of Machine Learning Applications. CUCS-034-06. doi: https://doi.org/10.7916/D8MP5B4B.

ML risk management

Imbalanced data and inadequate taxonomy

- Specific deep learning architectures and their categorisations into the most suitable pertaining applications have not been yet solidified.
- Comparison of the architectures has not been standardised, whether it be in terms of time consumption, resource management, computational requirements, or data loss.
- Deep learning applications will have to recognise the failures or faults according to their corresponding environments and be able to diagnose issues, such as no fault found [3].
- Imbalanced data due to classification and clustering issues, overcome by:
  - Pre-processing.
  - Cost-sensitive learning.
  - Algorithm-centred methods.
  - Hybrid methods.

[3] Khan, S., Phillips, P., Hockley, C., and Jennions, I. (2014). No Fault Found events in maintenance engineering Part 2: Root causes, technical developments and future research. *Reliab. Eng. Syst. Saf.* 123, 196–208. doi: https://doi.org/10.1016/j.ress.2013.10.013.

ML risk management

More standardisation issues

- Bias and variance are key issues in ML applications. They are to be addressed, according to EASA and Daedalean AG based on the following two methodologies[4]:
- 1. Datasets with bias and variance need to be distinguished from opposing datasets and effort shall be put into reducing such bias and variance within the data itself.
- 2. The bias and variance need to be evaluated based on the level of risk they impose upon the ML model.
- ML Workspace: According to SAE AIR6988, the workspace should be covered with a certain level of protection to prevent “data poisoning or tampering [5].

[4]EASA and Daedalean AG (2020). Concepts of Design Assurance for Neural Networks (CoDANN) Public Extract. Available at: https://www.easa.europa.eu/en/document-library/general-publications/concepts-design-assurance-neural-networks-codann [Accessed May 13, 2021].
[5] SAE International (2021a). AIR6988: Artificial Intelligence in Aeronautical Systems: Statement of Concerns. Available at: https://saemobilus.sae.org/content/AIR6988 [Accessed May 13, 2021].

Use cases-high level (taken from SAE AIR6988)

Example	ID	Goal	Inputs	Outputs
Off-Board Predictive Maintenance	UC-SC322	Predict with high-specificity and high-accuracy an on-board failure with enough lead time to plan an optimized reaction	Low-level time-series sensor data collected and sent through a digital acquisition unit or data gateway.	Failure message (can be EICAS/ECAMS message) + anticipated failure time + confidence of failure prediction
	Details		**Integration**	
	Combination of existing data cleansing/ETL + ML and other statistical methods to do big-data predictive maintenance		Aircraft owner, maintenance operation	
			Safety Concerns	
			Minimal, assuming existing procedures + instructions for parts handling are followed, and that scheduled maintenance is performed, as required.	
Example	**ID**	**Goal**	**Inputs**	**Outputs**
On-Board Predictive Maintenance	UC-SC23	Predict with high-specificity and high-accuracy an on-board failure without having to send data to an off-board data center for analysis.	Low-level time-series sensor data managed through high-bandwidth digital acquisition unit	EICAS/ECAMS message with predictive notation + anticipated failure time + confidence of failure prediction
	Details		**Integration**	
	Embedded NNs + other existing statistical methods (embedded) + on-board hardware for complex analytical processing		Aircraft owner, maintenance operation	
			Safety Concerns	
			Minimal, assuming existing procedures + instructions for parts handling are followed, and that scheduled maintenance is performed, as required.	

Use cases-low level

As is the case with applications that would be deemed safety-critical, the following have requirements imposed upon them by learning assurance standards:

- Datasets that are important for the development of the system.
- The method and order in which this development takes place.
- The behaviour of the system while both the development and operational stages take place.

RUL ML black-box issue	Corresponding mitigation
ML models need to cater to the varying nature of fatigue life scatter in data points	capture fatigue life scatter data and be able to predict fatigue life probabilistically.
ML models learn correlations between data input and output via the means of data extraction	adapt to models trained with different datasets
Using a model trained on one data range may result inaccurately when implemented on a different framework	incorporate vital landing gear operational uncertainties, such as hard landings, as well as temperature and environmental variations.

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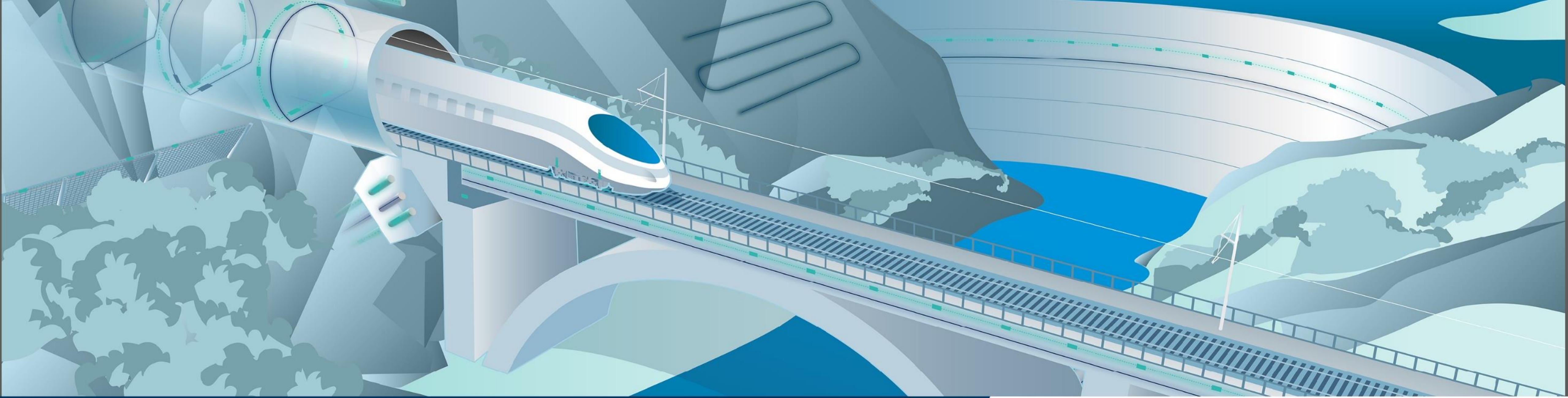

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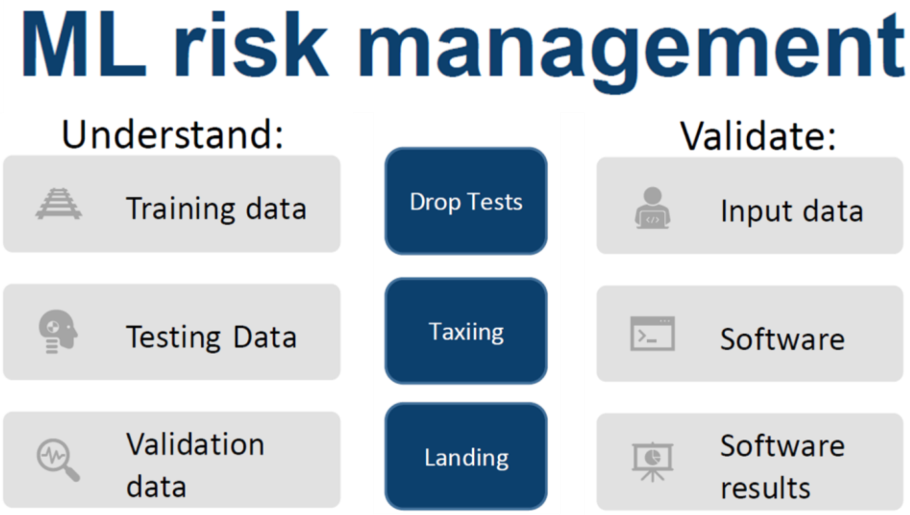

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