

International Committee on Aeronautical Fatigue and Structural Integrity

Digital Trends in Aeronautical Fatigue & Structural Integrity

Min Liao, Thierry Ansart, Carlos Chaves, Marcel Bos | June 30th, 2021



Digital technology and engineering are increasingly used for aeronautical fatigue and structural integrity assessment in the past decade. The trend is also seen from the number of publications in the previous ICAF Conference and Symposium.



ICAF Publications on Virtual Testing, Digital Twin, and Machine Learning (since 2011)



- To provide a brief, collective overview on Digital Trends in aeronautical fatigue and structural integrity, including,
 - some examples and discussions on key technologies, impacts, and challenges
- To provide a list of relevant references from the ICAF proceedings and National Reviews since 2011

<u>Note:</u> due to the time limit and keywords used, this overview might still miss some ICAF papers/examples; our observations might not be entirely the same as the original papers.



Digital Trends in Aeronautic Fatigue and Structural Integrity

- Major Digital Trends
 - Virtual Testing: a simulation of a physical test to support smart /smarter testing
 - Aircraft Digital Twin: a virtual representation of a connected physical asset
 - Machine Learning: a method of data analysis that automates analytical model building/ human learning

A Definition

<u>Virtual Testing</u> is the simulation of a physical test, using *finite element analysis tools, multi-body dynamic analysis tools* and Remote Parameter Control iteration techniques (*fatigue analysis*) to derive accurate loads, motion and damage information of a vehicle system very early in the development process (Source: MTS, <u>https://corp.mts.com/en/forceandmotion/groundvehicletesting/</u><u>MTS_4036300?article=1</u>).

Digital twin is an integrated *multi-physics, multi-scale, probabilistic simulation* of an as-built system, enabled by Digital Thread that uses the best *available models, sensor information, and input data* to *mirror and predict* activities/performance over the life of its corresponding physical twin (Source: DAU Glossary of Defense Acquisition Acronyms and Terms. https://www.dau.edu/glossary/Pages/Glossary.aspx#!both|D|27349)

<u>Machine learning</u> is a branch of *artificial intelligence (AI)* and computer science which focuses on the use of data and algorithms to imitate the way that *humans learn*, gradually improving its accuracy (Source: IBM, <u>https://www.ibm.com/cloud/</u><u>learn/machine-learning</u>)

Note: in this review, we include papers using Neural Network/Artificial Neural Network, Deep Learning, Machine Leaning, and AI in this category.



Virtual Testing – Predictive Virtual Testing (PVT) (ICAF2017)

AIRBUS PVT*– "...the capability to predict the actual behaviour of Aircraft Structure under applied loads up to failure for the purpose of replacing or reducing structure tests"

- Vision to replace full scale static and fatigue test
- Mind-set change from Test pyramid to test ladder
- Challenges/factors related to fatigue and damage tolerance, and uncertainty process
- Currently not able to replace full-scale fatigue testing by PVT



Test Pyramid to Test Ladder

Virtual Testing -- Smarter Testing Thru Simulation (ICAF2019)

Boeing "Smarter" Testing * – "Use of advanced analysis techniques using fundamental (coupon-derived) inputs can lead to reduced quantities of program-led mid-level structural tests, reducing airplane development costs and risks",

- Key ideas:
 - Virtual testing prior to physical testing
 - · Analysis-enhanced test point allocation
 - DOE to reduce testing matrix
 - Replace sub-component tests by element/coupon
- Examples:
 - Composite damage tolerance (3 examples)
 - Airframe crashworthiness and seat certification by dynamic simulations



Ex. Good blind prediction on the residual strength of notched composite panels using the Cohesive Zone Modeling (CZM) technique

^{*} Chisholm SA, Castro JF, Chapman BD, Karayev KZ, Gunther AJ, Kabir MH. Smarter Testing Through Simulation for Efficient Design and Attainment of Regulatory Compliance. In International Committee on Aeronautical Fatigue 2019 Jun 2 (pp. 292-307). Springer, Cham

F Virtual Testing – TITANS / ASSIST (ICAF2017, 2019)

TITANS* - a consortium comprising of an international network... to progressively closing the gaps between testing and modeling results on structural fatigue problems on airframe level

ASSIST** (Advancing Structural Simulation to Drive Innovation Sustainment Technologies) a collaborative online space, uploaded with a series of **Airframe challenges**

- blind predict the problems based on real structures/loads
- intent to improve fatigue life prediction technologies - a pathway to virtual testing



Airframe Challenge 1: Fighter Wing Root Shear-Tie Post Various blind predictions vs. test results

^{*} Wong AK. Blueprint TITANS: a roadmap towards the virtual fatigue test through a collaborative international effort. In 29th Symposium International Conference on Aeronautical Fatigue, Japan, June 2017 ** Dixon B, Burchill M, Main B, Stehlin T, Rigoli R. Progress on the Pathway to a Virtual Fatigue Test. In International Committee on Aeronautical Fatigue 2019 Jun 2 (pp. 816-830). Springer, Cham



A virtual testing system* -- for static strength of large aircraft uses virtual simulation technology to quickly and accurately simulate the loading status of structure and predict the dangerous parts and failure modes of the aircraft in advance.

- Virtual assembly and interference inspection technology
- Analysis technology of *post-buckling* bearing of stiffened wall structure
- Virtual monitoring and real-time warning technology





Virtual Assembly Model: Initial vs. Final

Digital Twin -- Aircraft Digital Twin (ADT) (ICAF2013)

Airframe Digital Twin (ADT)* -- "a concept for enabling the Condition-Based Maintenance Plus Structural Integrity (CBM+SI)"... represents the integration of data and models/analysis tools of an individual aircraft, from as-built to through service lifecycle.

Key Technologies of ADT Spiral 1 Program** : Probabilistic and Prognostic IAT (P²IAT), dynamic Bayesian network; High-fidelity model; Stick-to-stress model; Probabilistic load forecasting; NDI/sensor data fusion; Probabilistic risk analysis.





* Rudd J. "Airframe Digital Twin,". In The 27th Symposium of the International Committee on Aeronautical Fatigue 2013 (http://icaf-dev/ajax/showPDF.php?filename=2013_-_Rudd_-_Airframe_Digital_Twin.pdf&pad=docs/Plantema_lectures/)



Digital Twin - Aircraft Digital Twin (ADT) Technology Development and Demonstration (ICAF2019)

Objectives*: to assess the Digital Twin concept and adaptability for the RCAF, develop and demonstrate the technology for aircraft structural life-cycle management.

Technologies: Hi-fidelity structural modeling; Probabilistic IAT load/usage forecasting; Bayesian updating with NDI; Experimental mechanics (DIC, XRD residual stress); Risk-based life prediction.

Outcomes: Feasibility study of ADT for RCAF fleets; NRC in-house ADT algorithms; ADT tech-demo on CF188 test



NRC ADT tech-demo on a full-scale CF188 certification test shows potential benefits on life extension, compared to existing lifing method

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Aircraft Digital Twin and ASIP (Aircraft Structural Integrity Process)

- Desired outputs on Digital Twin for Aircraft Structures (Chuck Babish, AFLCMC/USAF, 8 Apr 2021)
 - Authoritative source of the as-built, as-operated, and as-maintained configuration of each aircraft.
 - Current health (fatigue, corrosion, etc.) assessment that is more accurate and efficient than current ASIP force management execution methods.
 - Future health forecast that is more accurate and efficient than current ASIP force management execution methods. This includes determining future MX inspection requirements, repair needs, structural (failure) risk, remaining useful life, MX cost, aircraft availability impacts, etc.







Machine Learning – Neural Network Based Fatigue Life Monitoring (ICAF2015)

- A neural network (NN)* based fatigue life monitoring system developed and applied for Finnish F-18 fleet since 2007, by using flight parameter data to model strain history.
- NN modelling error is below 20% in fatigue life expenditure (FLE), comparing to strain gauge based FLE
 - Reasonable accuracy for *V-tail and Fuselage longeron* areas (buffeting, dynamic loading)
 - Incapable for *H-tail* areas due to insufficient data

The NN based analysis brings, at low cost, valuable data to location specific fatigue life tracking, and to enable adjusting inspections/repairs individually

The Neural Network Based Fatigue Life Analysis



* Jarkko Tikka, Tuomo Salonen, Practical Experience of Neural Network Based Fatigue Life Monitoring. InProc 28th ICAF Symposium–Helsinki, 3–5 June 2015.



Machine Learning – Helicopter Loads Estimation (ICAF2019)

Machine Learning techniques* have been developed at NRC to estimate helicopter component (main rotor) loads and tracking usage, based on existing aircraft sensor data and flight data from an Australian Black Hawk (S-70-A-9) helicopter and CH-146 (Bell 412) Griffon helicopter.

Recent results:

- Validated methodology on larger data sets of CH146 Griffon and S-70A-9 Black Hawk
- Revamped computational framework for more efficient data processing: from several minutes to hours of flight data



NRC load estimation approach using ML techniques

^{*} Cheung C, Sehgal S, Valdés JJ. A machine learning approach to load tracking and usage monitoring for legacy fleets. In International Committee on Aeronautical Fatigue 2019 Jun 2 (pp. 922-937). Springer, Cham.



Machine Learning – Fatigue Stress Predictions (ICAF2019)

Machine Learning*: an engineering application that is based on either probabilistic, ensemble or neural networks that allows for engineering predictions based on validated structured data.

- "Supervised" and "Unsupervised" ML capabilities for *Stress Sizing and Design*, *Predictive Aircraft Maintenance*
- Controlling Possible Uncertainties in ML Predictions, "fencing" techniques by applying
 - multiple prediction methods and a check for unusual deviations;
 - enforced exploitation of an arsenal of inbuilt validation methods
 - deterministic methods on selected cases based on engineering judgement and experience



From external loads to individual aircraft stress with a real loading sequence

Discussions – Challenges and Enabling Technologies

Challenges (related to Fatigue&Damage Tolerance)

- Loads/usage uncertainty (fleet vs. individual)
- Scatter in fatigue, nonlinear stochastic process
- Scale effects from coupon to full-scale, BCs
- 3D effects with triaxiality, small crack, nucleation
- Other degradation mechanisms

. . . .

- Environmental age degradation, corrosion
- Multi-physics modeling (ex. CFD-FEA/CSD)
 - Modeling confidence/credibility assurance
- Computational efficiency (multi-variables)
 - Extreme small failure risk, distribution tail
- Sensor/NDI reliability, uncertainty, human factors
- Data quality/integrity, lifecycle (design to sustainment) data/configuration management



- Probabilistic IAT, OLM
- Neural network/Artificial neural network
- Probabilistic, statistical, and reliability modeling
- Uncertainty quantification (UQ), parametric sensitivity study
- High-fidelity M&S (microstructure to structure)
- Modeling and testing V&V, closed-loop feedback
- Sensor/NDI reliability analysis, model-assisted probability of detection (MAPOD)
- Data fusion/Bayesian updating
- Big data (vehicle level) management/analysis, IoT



Digital vs. Reality -- the Gaps, the Unknowns

As far as the laws of mathematics refer to reality, they are <u>not certain</u>; and as far as they are <u>certain</u>, they do not refer to reality

Albert Einstein





- Virtual Testing: has shown some success to simulate *quasi-static, impact or crash testing*, so is able to reduce some tests for product development and sustainment.
 - Major challenges: highly non-linear behaviors (including material and geometry) simulation, and cyclic fatigue loading cases.
- Aircraft Digital Twin: has shown promising results to include multi-physics, multiscale models, using probabilistic methods and in-service feedback/information to close the gap between the twin and individual aircraft location/component; it can enable individual aircraft condition-based maintenance (CBM).
 - Major challenges: complexity of multi-physics, multi-scale, high-fidelity models; computing techniques and power for implementing complex models and systems with acceptable accuracy and efficiency; enabling/managing with a digital thread framework through the whole lifecycle.



- Machine Learning (NN/ANN): has shown some success on flight load/usage estimation with multiple flight parameters including dynamic loaded cases, and internal load distributions; It is also increasingly used for NDI analysis.
 - Major challenges: input data quality/integrity; predictability/validation/credibility (of "black-box"); highly nonlinear cases; multi-layered neural network (deep learning).
- These emerging digital technologies have potential to optimize the traditional building-block pyramid approach in aircraft development, and realize individual aircraft condition-based management.
 - Major benefits/impacts shown for both aircraft design/development and sustainment in terms of increased efficiency, reducing lead time/cost/risk, maintaining/improving safety, and maximizing availability
- A list of References from ICAF Proceedings and National Reviews is provided in the following slides.



References from ICAF Proceedings and National Reviews

Since 2011, on Virtual Testing, Digital Twin, Machine Learning

ICAF2011

1) A. Oldersma and M.J. Bos, *Airframe loads & usage monitoring of the CH-46D "Chinook" helicopter of the Royal Netherlands Air Force*, In Proc 26th ICAF Symposium–Montreal, 2011 Jun.

ICAF2013

1) Rudd J. "*Airframe Digital Twin*,". In The 27th Symposium of the International Committee on Aeronautical Fatigue 2013 (<u>http://icaf-dev/ajax/showPDF.php?</u> <u>filename=2013_-_Rudd_-_Airframe_Digital_Twin.pdf&pad=docs/Plantema_lectures/</u>)

ICAF2015

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- Albert K. Wong, Phil Jackson, Towards the Virtual Fatigue Test: Hardware-in-the-Loop integrated Fatigue Test Simulation (HiLiFTS), In Proc 28th ICAF Symposium–Helsinki, 3–5 June 2015.
- 3) Wallbrink C, Opie M, Yu X. Fatigue analysis of a virtual airframe structure. In Proc 28th ICAF Symposium–Helsinki, 3–5 June 2015.
- 4) Jarkko Tikka, Tuomo Salonen, *Practical Experience of Neural Network Based Fatigue Life Monitoring.* In Proc 28th ICAF Symposium–Helsinki, 3–5 June 2015.
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- 6) Alexis Falga, Dr. Jean-Pascal Kleinermann, Dr. Alain Santgerma, *The A400M Usage Monitoring Function*, In Proc 28th ICAF Symposium–Helsinki, 3–5 June 2015.
- 7) Geoffrey Holmes, Valerijan Cokonaj, Paul Southern, Keith Worden, Elizabeth Cross, *Non-stationary models for predicting strain on aircraft landing gear from flight data measurements*, In Proc 28th ICAF Symposium–Helsinki, 3–5 June 2015.
- 8) Hazen Sedgwich, NDI and Maintenance Data Collection in a Digital Environment, USA 2015ICAF National Review.
- 9) Rob Plaskitt, Using Virtual Strain Gauges to Correlate with Bending and Torsion Measured on a Helicopter Tail Cone Using Strain Gauges, USA 2015ICAF National Review.



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Since 2011, on Virtual Testing, Digital Twin, Machine Learning

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- 2) Wong AK. *Blueprint TITANS: a roadmap towards the virtual fatigue test through a collaborative international effort*. In 29th Symposium International Conference on Aeronautical Fatigue, Japan, June 2017.
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- 5) Guillaume Renaud, Min Liao, Gang Li. Verification and Validation of Analytical Methods to Determine Life Improvement Factor Induced by Engineered Residual Stresses. In 29th Symposium International Conference on Aeronautical Fatigue, Japan, June 2017.
- 6) Yongjun Wang, Jiang Dong, Hongna Dui, Liu Xiaodong, *Aircraft structural load identification technology with high accuracy in SPHM system*. In 29th Symposium International Conference on Aeronautical Fatigue, Japan, June 2017.
- 7) Kyle Graham, M. Artim, D. Daverschot, *Aircraft Fatigue Analysis in the Digital Age*, In 29th Symposium International Conference on Aeronautical Fatigue, Japan, June 2017.
- 8) Joe Loughheed, Dale Ball, Kevin Welch, *Thread/Digital Twin Benefits Assessment*, USA 2017 ICAF National Review.



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- 5) Ocampo J, Millwater H, Crosby N, Gamble B, Hurst C, Reyer M, Mottaghi S, Nuss M. *An Ultrafast Crack Growth Lifing Model to Support Digital Twin, Virtual Testing, and Probabilistic Damage Tolerance Applications*. InInternational Committee on Aeronautical Fatigue 2019 Jun 2 (pp. 145-158). Springer, Cham.
- 6) Renaud G, Liao M, Bombardier Y. *Demonstration of an airframe digital twin framework using a CF-188 full-scale component test*. In International committee on aeronautical fatigue 2019 Jun 2 (pp. 176-186). Springer, Cham.
- 7) Joshua Hoole, Pia Sartor, Julian Booker, Jonathan Cooper, Xenofon V. Gogouvitis, Amine Ghouali, and R. Kyle Schmidt, A Framework to Implement Probabilistic Fatigue Design of Safe-Life Components, In International Committee on Aeronautical Fatigue 2019 Jun 2 (pp. 1031-1042). Springer, Cham.
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- 11) Marguerite Kassinger, Challenges and Success: The Road from Old Style Manufacturing to Digital, USA 2019 ICAF National Review.
- 12) Eric Lindgren, John Brausch, Charles Buynak, David Campbell, Ward Fong and Tommy Mullis, Michael Paulk, *Digital Nondestructive Evaluation/Inspection (NDE/I) Data Capture*, USA 2019 ICAF National Review.
- 13) Meng Min, Research on Virtual Load Calibration Test Technology, China 2019 ICAF National Review.
- 14) Airbus Operation, Large Scale Simulation and Test, France 2019 ICAF National Review.



Thank you, hope to see you at ICAF2023 (Xi'an, China)



including technical topics of,

- Digital Design and Digital Twin
- Structural Virtual Testing/Smart Testing



M&S must properly address:

- Scale effects and 3D effects (note 2 & 3)
- Scatter in fatigue \rightarrow development of Probabilistic Damage Tolerance analysis (note 6)
- Other degradation mechanisms than fatigue (ex. corrosion)

Accuracy and reliability

- Accurate material databases to be available (note 4)
- Predictive capability of models to be shown (note 7)
- Part of physical testing to be kept (note 8)

Completeness of data exchange and data flows between databases and models (note 12)

- Incorporation of SHM data and NDI data (note 10)
- Regular/frequent synchronisation (e.g. with maintenance data) (note 13)
- Efficiency of M&S techniques
 - Computational costs must remain reasonable (note 5)
- New breakdown in building block approach (substantiation pyramid) with VT (note 9)
- Configuration control
 - Models must remain representative of (changing) physical asset (note 14)

Notes for "Discussions: Challenges/Underpinning Technologies"

- 1. In the future, derivation of representative loads will rely on extensive in-service data. Using available flight parameters recordings combined with AI techniques (such as Artificial Neural Networks) will allow to derive more representative loads and always in line with real usage which is a significant advantage in case real usage is not in accordance with design assumptions.
- 2. ADT is based on high fidelity models at all scales (See J. RUDD slide). Having models able to transfer/cascade information (damage state, fatigue behaviour) in a consistent way from material scale to full scale structure is a key feature for success and efficiency of ADT.
- 3. 3D effects (triaxiality) is linked to scale effect as typically being encountered in large structure. Both fatigue initiation fatigue propagation (3D cracking) impacted.
- 4. Simulations require to be fed with material data. Need to define kind of data to be measured, expected accuracy, scatter information (in case of probabilistic approach)
- 5. Computational strategy vs efficiency and /or accuracy is a key feature for costs and lead time

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- 6. Objective quite clear but still a lot to do on methodology/approach. Scatter issue vs scale still needs to be further investigate. Refer to relevant papers
- 7. In particular for virtual testing : in most recent FSFT, damages/cracks appeared at unexpected areas and sometimes at quite early stage in fatigue life => confidence in virtual testing will rely to a large extent on the ability to predict such hotspots (known unknowns)
- 8. Specific to virtual testing : for sure part of physical testing will remain. What kind ? For which purpose ?
- 9. Specific to virtual testing : see Linden Harris presentation (test pyramid to test pagoda/ladder)
- 10. A lot of information to be introduced in ADT for describing current state of an individual A/C will require to process, analyse and transfer data from SHM to models. Data needed, classification, ... ?
- 11. ADT will clearly use various sources of data collected from different stakeholders. Processing/analysis of the data will require to use Big Data techniques. Refer to relevant papers.
- 12. Accurate ADT requires data exchange with many submodels and data bases. Identify complete and correct data flow is absolutely necessary Refer to relevant papers.
- 13. ADT is to be fed up with different sources of information (manufacturing, design, operators including maintenance). Data to implemented in the ADT as well as frequency for updating data will drive ADT representativeness.
- 14. How to control change configuration to the global ADT as being fed up by many other models and data bases ? How to quantify ADT global representativeness wrt submodels, data being implemented in it?