ENABLING THE JOURNEY TOWARDS CONDITION BASED MAINTENANCE FOR AIRFRAME

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Abstract: Airlines are constantly looking for solutions both to reduce their operational costs and increase aircraft availability. Currently, maintenance programs are based on conservative aircraft usage assumptions, which aim to cover a high variety of usage in the fleet and ensure safety.

As every aircraft is operated differently and each flight performed is unique (due to changing weather conditions, payload, routes etc.), there is a high potential benefit in moving away from a "one size fits all" approach to more efficient and optimised structural maintenance requirements tailored to individual aircraft.

Several initiatives have been undertaken to incrementally optimise maintenance programs with the ultimate objective to offer full Condition Based Maintenance and enable operators to:

- Reduce direct maintenance costs by adjusting maintenance requirements based on 'actual' aircraft usage;
- Reduce the unknowns and conservatism inherent in design assumptions;
- Ensure that safety of aircraft operations is maintained at the highest level;
- Increase the residual value of aircraft or aircraft parts.

The rapid development of Digital Twins and the growing performance of Artificial Intelligence could be key enablers for such optimisation.

A huge volume of in-service 'big data' obtained from flight-by-flight recordings and aircraft sensors has to be processed, leading to new challenges in the capability to exploit all of the available information. With a large number of flights being operated every day, classical approaches (e.g. finite element analysis etc.) has reached their limits to process such volumes of data. Therefore, alternatives to the existing models used for certification have to be exploited, such as for instance (but not limited to):

- Improvements of existing methodologies;
- Support from Artificial Intelligence;
- Enhanced computational capabilities;
- …

Nonetheless, any solutions implemented must always guarantee the highest level of safety.

Keywords: Maintenance, Optimisation, Safety, Artificial Intelligence

INTRODUCTION

Currently, structural maintenance programs are based on conservative design assumptions, which aim to cover a high variety of usage in the fleet. However, in the increasingly competitive marketplace of commercial aircraft, there is a constant push for optimisation and cost-saving at all levels - the product is not only the aircraft itself but also encompasses the wider support system that goes with it. A manufacturer who can offer a more balanced and complete package will undoubtedly pose a more attractive prospect for the operator. Since a significant part of operating cost is devoted to maintenance (both unscheduled and scheduled), airlines are constantly looking for solutions both to reduce their operational costs and increase aircraft availability.

The structural maintenance program for fatigue is based on a set of general usage assumptions and must be adhered to by all operators, regardless of how they operate their aircraft. This approach leads to stringent requirements for operators flying their aircraft under less severe conditions than those considered for maintenance tasks definition. Since it is now becoming easier to closely monitor fatigue-impacting factors for individual aircraft, the "one-size-fits-all" approach for maintenance can be challenged to move towards a "fit-for-purpose" approach.

Several initiatives (e.g. ref.[2]) have been undertaken to incrementally optimise maintenance programs with the ultimate objective to offer full Condition Based Maintenance and enable operators to increase the availability of aircraft during operations as well as their residual value. It shall be noted that these initiatives are not solely aimed at reducing the maintenance costs (e.g. by adjusting maintenance requirements based on 'actual' aircraft usage), or at relaxing the assumptions and conservatism inherent in design assumptions, but especially in ensuring that safety of aircraft operations is maintained at the highest level (e.g. thanks to operational monitoring).

Monitoring the aircraft implies that a huge volume of in-service 'big data' obtained from flight-by-flight recordings and aircraft sensors has to be processed, leading to new challenges in order to exploit all of the available information. With a large number of flights being performed every day, it is unlikely to be practical to process such volumes of data with classical approaches (e.g. evaluating structural stresses using finite element analysis, etc.) or analyses infrastructures or architectures. Therefore, alternatives to the existing models used for certification might have to be exploited, such as for instance (but not limited to): improvements or simplifications of existing methodologies; support from Artificial Intelligence; enhanced brute force computational capabilities (e.g. higher computing resources); etc.

Arguably, if such a transition (i.e. from a "classical" approach to a "state-of-the-art" approach) is to be sustainable, it would require a global transformation of the current system. This article provides an overview of the key motivations to improve maintenance requirements, examples of the associated challenges, a proposal for a roadmap and an introduction of airworthiness requirements to be considered in the implementation of Condition Based Maintenance. This transformation is not only focussed on "digitalizing" the current system but also on taking the opportunity to rethink (and improve) the current way of working while guaranteeing the highest level of safety.

IMPROVED STRUCTURAL MAINTENANCE THROUGH AIRCRAFT MONITORING

In comparison to traditional approaches, what is new is that aircraft usage can now be actively monitored. Having detailed information about how each aircraft is operated brings several benefits:

- Improved knowledge of in-service fleet operations e.g. to provide performance feedback for improving fuel efficiency, to decrease maintenance costs, to shorten grounding times, to increase aircraft availability, etc;
- Improved design assumptions for future aircraft developments: e.g. by better anticipating variety of usage, weather conditions and airports runways;
- Improved overall safety of aircraft products e.g. by ensuring operations are aligned with certification assumptions, overload monitoring, etc;
- Optimization of scheduled maintenance of metallic & hybrid structures.

Implemented strategically, this will without doubt add a new dimension of safety to the current robust airworthiness approach. The questions however are, what could be the enablers, and how could such benefits be sustainably harvested?

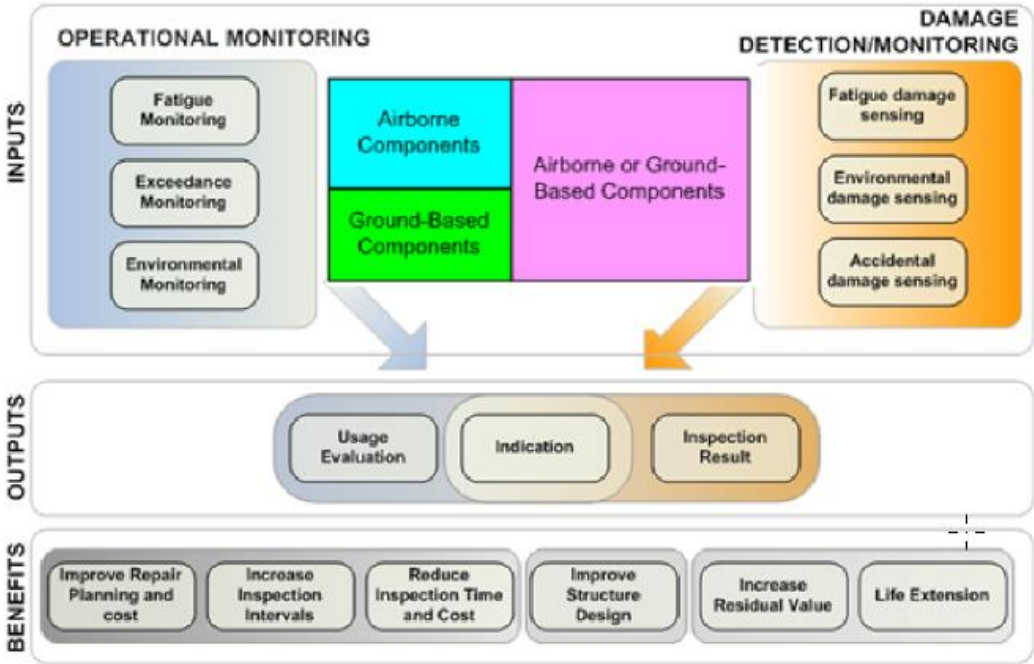


Figure 1*: Structural Health Monitoring overview (ref.[1] ARP 6461)*

Since the aircraft is monitored, the underlying idea is that maintenance could be simply optimised by adapting to individual utilisation i.e. going from “typical loading spectra” to “in-service loading spectra”. As it will be required to remain comparable to the certification standard, the main enablers have to include similarly validated engineering models. Due to the large volume of data involved, additional enablers must include some form of high-performance computing capabilities, including but not limited to digital twin approaches, integration of artificial intelligence, processes automation, etc. In addition, the selected implementation of the overall monitoring system will significantly impact the requirements to be met: whether analyses are performed on-board or off-board, what level of human interaction is considered, which fall-back solutions are needed in case of missing data, etc.

Ultimately, reaching the goal of Condition Based Maintenance will require significant transformation of the maintenance environment, with validation and implementation of monitoring systems. Therefore, a step-by-step approach should be followed in order to avoid having to solve all the complex challenges involved at once. The objective is to incrementally mature the new solutions developed and deploy them in-service, enabling to reach more quickly a high level of confidence and explore multiple technological solutions (ref.[4]):

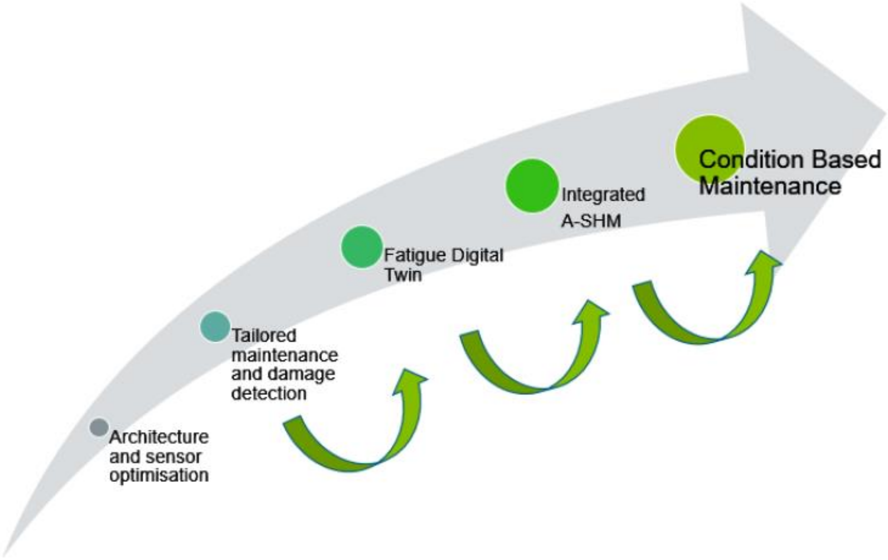


***Figure 2**: Incremental Development of Maintenance Optimisation and Pilot Projects for Airframe Structural Health Monitoring (A-SHM) introduction*

All these developments shall be undertaken jointly together with aircraft operators and airworthiness authorities, in order to robustly evaluate the benefits and impacts on the overall system, and take into consideration the new constraints it could introduce. Several pilot projects are proposed to explore all these aspects:

- Start with single task solutions to more integrated concepts;
- Tailored Maintenance: initiate simple usage monitoring based on a few selected aircraft parameters;
- Predictive Maintenance: dedicated fatigue analysis for each aircraft with a Fatigue Digital Twin;
- Damage Monitoring: integration of sensors for automatic damage diagnostics;
- Integrated Structural Health Monitoring (SHM) to Condition Based Maintenance (CBM): fatigue, conditional events, high load events, damages and growth predictions, environmental degradation.

ENGINEERING DATA AND AIRCRAFT OPERATIONS AT THE SERVICE OF STRUCTURAL MAINTENANCE

The main prerequisites to introduce structural maintenance based on the actual aircraft utilisation are, as a first step, anticipated to include the availability of:

- Relevant engineering data;
- In-service aircraft data;
- Validated models and methodologies to exploit the above data; based on experience, structural tests, engineering judgement, etc.;
- Process automation and sufficient computational capabilities to exploit the high volume of data involved.

<u>Availability of the engineering data</u>

The engineering data is probably the most important enabler and preferably encompasses a study of all major parameters affecting the fatigue performance of the airframe structure. Such parameters can already be deduced from a parametric study, and can include for passenger aircraft as an example:

- Range effects i.e., the variation of fatigue life due to longer or shorter mission durations compared to a baseline mission;
- Effects of payload and payload distribution, etc.;
- Effects from quantity of fuel on-boarded;
- etc.

Note that some tailoring of the maintenance is already feasible if the above engineering data is available. For example, if the exact range missions flown, the payload, etc. were recorded (or are deductible) for any specific aircraft, its maintenance requirements could be revised based on these parameters.

<u>Large computational capabilities and automation</u>

Where large amounts of data need to be interrogated, it is obvious that this will require robust and sustainable processing, with some significant level of automation (especially when large scale application is required). It is important to note that executing such processing of data on-ground (i.e., downloading the data from the aircraft) is a prerequisite since on-board data processing might require an update of the aircraft system design. On-ground processing also allows for engineering or human intervention for results interpretation before usage, and makes it easier for interfacing with large computation capabilities and solutions.

Also important in such a setup will be a robust platform which allows downloading, storing and processing all the aircraft data (e.g. Airbus Skywise see ref.[9]).

ARTIFICIAL INTELLIGENCE AT THE SERVICE OF OPERATIONAL MONITORING

With the implementation of operational monitoring, the main concept is to continuously collect more data and parameters recorded for each individual aircraft, in order to obtain detailed knowledge regarding its operation that will enable:

- Provision of customised services to improve operations: reduction of maintenance efforts when possible, operations optimisation, etc;
- Anticipation of potential in-service issues: apply maintenance actions in due time to avoid unscheduled events (e.g. assessing the probability to find cracks or corrosion according to specific A/C usage);
- Improvement of investigation of in-service findings: better knowledge of the aircraft life and specific operations.

The overall approach consists of a few key steps:

1. **Aircraft data collection and validation**
   Various parameters shall be registered through each flight performed (e.g. accelerations, altitude, environmental conditions, …) and gathered in large data-lakes for storage and further exploitation. This part of the process is key, as the availability and quality of the data is the main driver for the benefits evaluated later.
2. **In-Service data processing**
   All of the gathered data is processed through validated and approved engineering models. The main objective of this step is to exploit the available data in order to produce the in-service loading spectrum for each individual aircraft, and evaluate its severity from a fatigue damage perspective compared to the typical loading spectrum.
3. **Feedback to Operations**
   Based on the obtained in-service loading spectrum and corresponding severity, the potential reduction in maintenance efforts, improvement on operations or particular actions to be put in place are evaluated. The outcomes may then be provided back to the operators in an automatic and systematic manner.

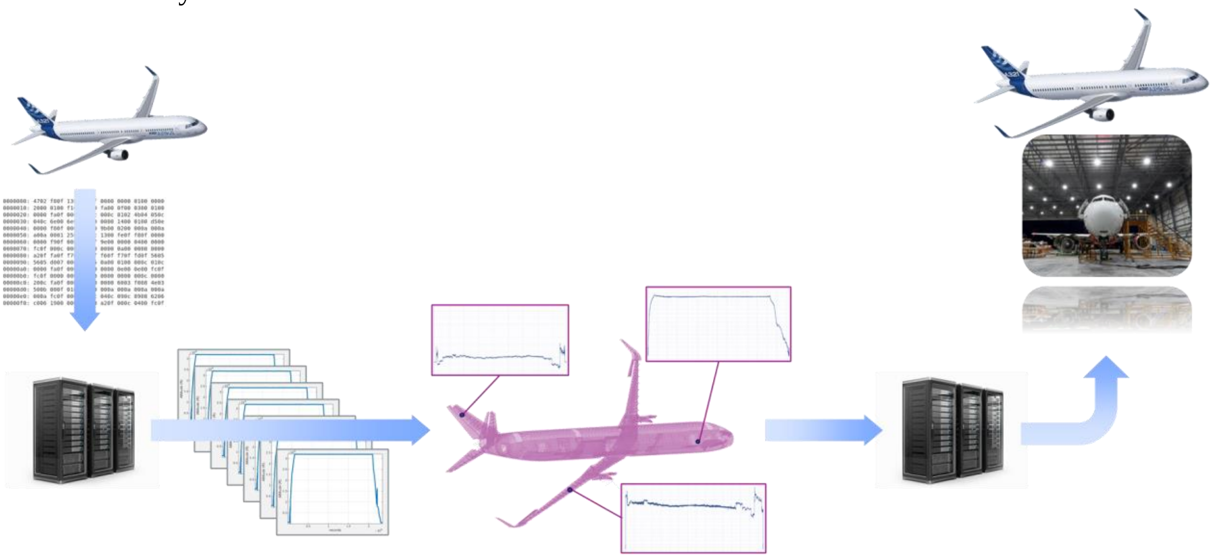


***Figure 3**: Overview of Operation Monitoring Process*

<u>In-Service data processing</u>

When processing in-service data, a key aspect to be considered is the usage of certified engineering models to ensure the validity of the final results obtained.

At first, “classical” models and approaches as used for type certification (physical modelling, finite elements, …) are exploited, in order to support the incremental development and initial deployment of maintenance optimisation solutions. However, in doing so, the intrinsic limitations of these models are included in the process, and as the volume of in-service data is continuously growing (through increasing fleet and daily flights performed), the so-called classical approach quickly becomes impractical due to the amount of resources and computing time required.

In order to overcome these restrictions, new technologies have to be introduced. Automation enables data to be processed for each of the flights gathered through all of the required steps in an orchestrated manner. It is also a robust solution to perform systematic checks at any stage, and to reduce the need for manual data manipulation, minimising as much as possible the potential source of errors. Implementation of automation is a must for the development of a complex and reproducible process such as operational monitoring - but automation alone is not sufficient to solve all of the challenges inherent to classical approaches.

One of the next solutions to consider is the introduction of Artificial Intelligence, in particular in areas where computing time and / or resources are identified as the main constraints. Artificial Intelligence techniques (such as Machine Learning, Deep Neural Networks, etc) can offer robust alternatives to using physical models when operated in a well understood and controlled environment, and where responsiveness and efficiency are key. Nonetheless, its implementation comes at a price: depending on the type of algorithms used and the nature of the overall system it is integrated in, particular care must be taken and additional requirements may need to be demonstrated.

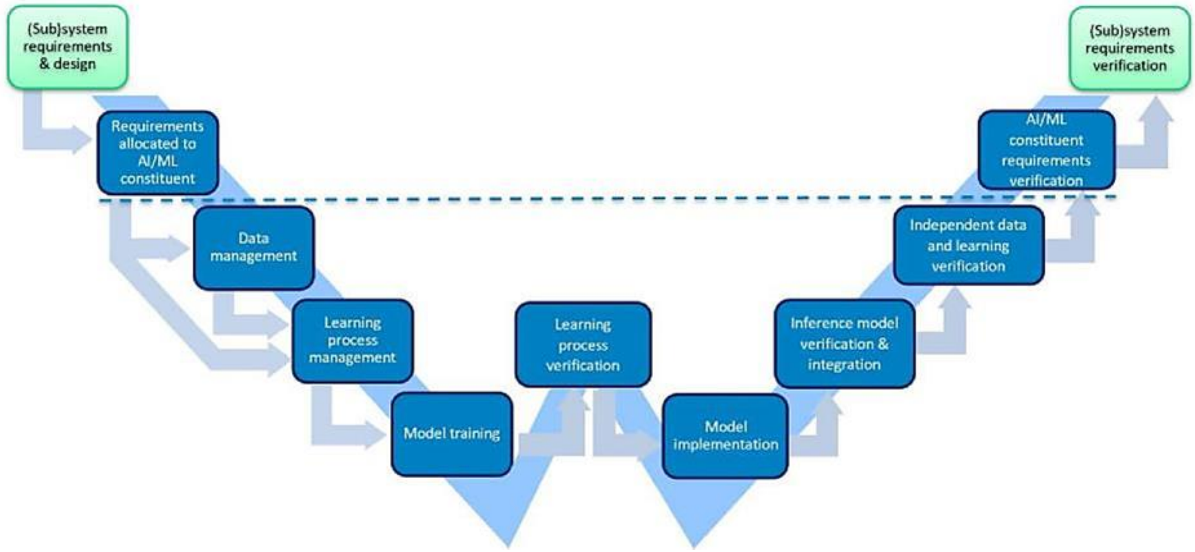


Figure 4*: Machine Learning: Learning assurance W-shaped process (from ref.[5])*

As a consequence, implementation of Machine Learning requires development of new solutions to support the overall verification and validation process, and to support specific means of compliance typically not required with more classical models and approaches.

Some particular properties inherent to the use of Machine Learning techniques should be verified and checked in order to support the AI Trustworthiness Analysis (see ref.[5], [6], and Figure 4) - such as (but not limited to):

- Stability: characterises a model where output result is not sensitive to small input perturbations - as an example, when dealing with measured in-service data, the stability of the results obtained in case of small input data variation in the range of measurement sensors’ accuracy;
- Generalisation: characterises a model which is consistently accurate across the complete Operational Design Domain - for example, if a model is able to predict strains with a certain

accuracy at high confidence level, it has a good generalisation capability if the same accuracy is observed in any region of the validated operational domain;

- Robustness: characterises a model demonstrating good Stability and Generalization capabilities and therefore also demonstrating good operational behaviour in the presence of normal inputs (valid results) and abnormal input (systematic answers and warnings / alerts to detect usage outside of defined scope);

Development for Stability demonstration

In order to evaluate the stability of a trained machine learning model, multiple approaches can be envisaged. As an example, a dedicated tool is being developed based on Formal Methods[1] (see ref.[7] and [8]). This method uses the knowledge of the neural network's parameters (architecture, weights and biases) to outer-approximate the neural network f by two functions $\underline{f}$ and $\underline{f}$ on a specific input domain X:

$$\forall \boldsymbol{x} \in \boldsymbol{X}:\ \underline{\boldsymbol{f}}(\boldsymbol{x}) \leq \boldsymbol{f}(\boldsymbol{x}) \leq \underline{\boldsymbol{f}}(\boldsymbol{x}) \tag{1}$$

The two functions $\underline{f}$ and $\underline{f}$ have the specificity to be easily optimised: it is trivial to deduce maximum or minimum values with those functions. Hence, upper bound value (a value that is strictly greater than any prediction of f on X) and lower bound value (a value that is strictly lower than any prediction of f on X) can be evaluated. With implementation of Formal Methods[1], a specific type of function is considered: linear relaxations. That means both functions $\underline{f}$ and $\underline{f}$ will be two linear functions.

In brief, providing:

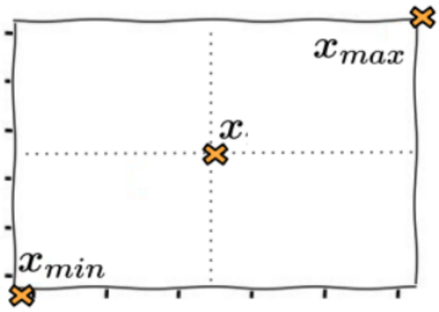
- A trained Neural Network ***f***;
- An input domain ***X***, ideally consistent with the targeted Operational Design Domain of the model.

The Formal Method implemented will compute:

- An upper bound value that is strictly greater than any prediction of ***f*** on ***X***;
- A lower bound value that is strictly lower than any prediction of ***f*** on ***X***.

To illustrate, below is an example for a typical Regression use-case:

1. Train Neural Network ***f*** to perform a Regression
2. Define input domain ***X***: for instance, defining a variation of 5% around a test sample x enables the definition of the input domain:



$$x_{max} = x - 0.05|x|$$
$$x_{min} = x + 0.05|x|$$

Figure 5*: Illustration of input domain defined*

3. Formal Method implemented to compute upper and lower bounds of the model response:

[1] *Formal methods encompass a set of methods based on logics, optimization in order to provide guaranteed correctness, reliability and robustness of computer software.*

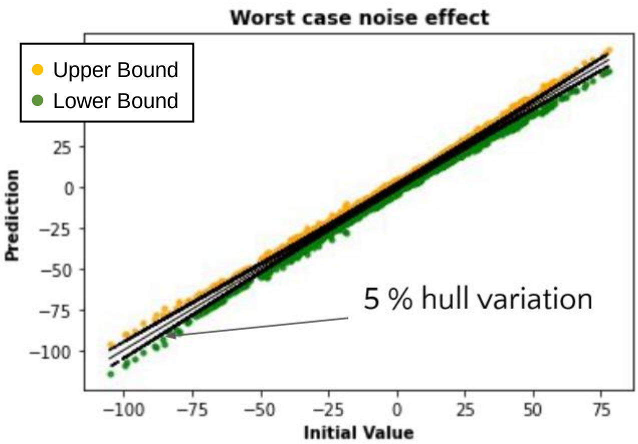


Figure 6*: Illustration of model response upper and lower bounds computed*

Such an approach can enable computation of strictly identified boundaries for the predictions of a model on a specified input domain; it gives formal deterministic bounds, which a sampling approach cannot provide.

<u>Enhancing the model's Generalisation capability through Adversarial Training</u>

The main objective of adversarial training is to exploit adversarial examples during the machine learning model training phase, in order to improve its generalisation capability. Adversarial examples are inputs to a machine learning model which are specifically designed to make the model produce wrong outputs - it has gained notoriety particularly in the field of computer vision (e.g. by performing adversarial attacks to make a model predict the picture of a dog to be a cat, etc.).

This seeming weakness of machine learning algorithms can also be exploited in order to reinforce the training of models, and drastically reduce their sensitivity to adversarial attacks:

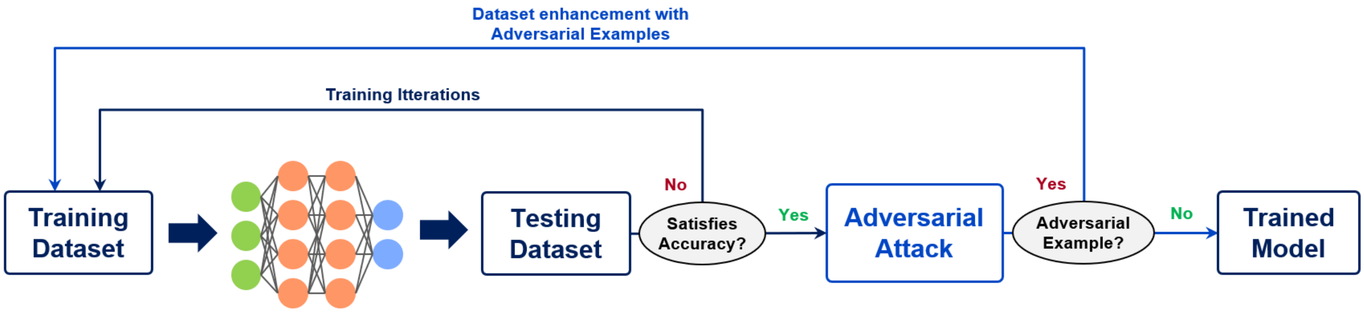


Figure 7*: Illustration of Adversarial Training concept*

The main idea is to introduce an additional step to typical training approaches, evaluating if adversarial examples can be identified (i.e. corresponding to potentially encountered sets of parameters within the Operational Design Domain of the model). If such examples are found, they are added to the training dataset in order to reinforce the training of the model in the region of the adversarial examples. This process is iteratively repeated until both the targeted accuracy and vulnerability to adversarial examples are achieved. Such an approach can be used as the enabler to increase the Generalisation capability of a machine learning model.

In the context of operational monitoring, these techniques can be of great value to improve the overall accuracy of the models exploited, and to support identifying the limitations of applicability of the system developed.

CONDITION BASED MAINTENANCE: A CHANGE OF PARADIGM

Ultimately, the objective is to move towards Condition Based Maintenance, where:

- Fixed maintenance tasks are reduced to the minimum required while keeping the safety standard;
- A Maintenance Planning Window needs to be introduced, which is a validated period of time to safely operate the aircraft before maintenance actions are required, up to an Operational Limit as illustrated in Figure 8.

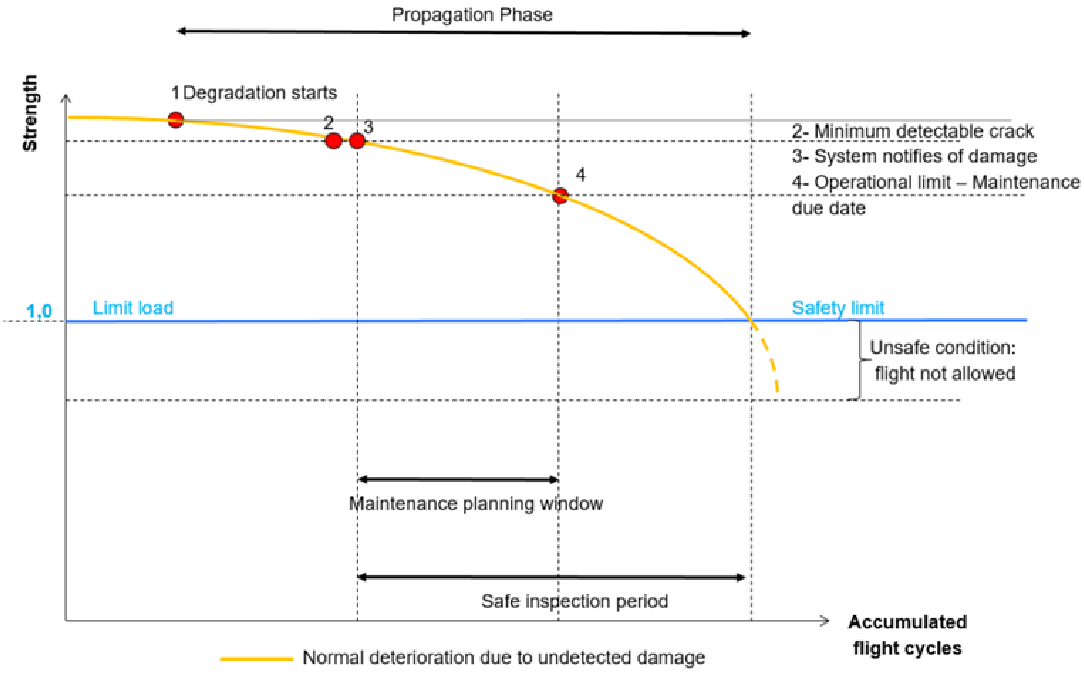


***Figure 8**: Condition Based Maintenance approach*

Such an approach requires the combination of all of the developments previously mentioned (see figure 2) in order to secure:

- Robust and detailed knowledge of the in-service fleet, to evaluate the operability severity of each individual aircraft and to support demonstration of a safe inspection period;
- Implementation of specific computational architectures, to enable automatic processing, storage and feedback;
- Integration of new sensors dedicated to damages and abnormal event detection.

Besides the development and implementation of all technological needs, moving towards condition based maintenance requires a transformation of the larger maintenance ecosystem. Although the regulatory framework exists for the implementation of Structural Health Monitoring, a change of policy is needed to enable continuation of operation for an aircraft with known cracks within certain limits still to be defined (e.g. Maintenance Planning window, Operational Limit, etc.).

In addition, the level of autonomy of such a system shall be carefully defined. A minimum degree of human supervision must be retained to validate decisions directly impacting the Continuous Airworthiness of the flying aircraft. Redundancy in the solutions implemented will be required when introducing new technologies, such as damage detection sensors (e.g. by using visual or non-destructive testing inspections) or artificial intelligence (e.g. ensuring classical approaches can be used as back-up). Guidance on the subject exists (see ref.[5] and [6]), but further developments are needed to incorporate the appropriate compromise on autonomy and yield benefits for both safety and operations optimisation. The defined step-by-step approach (see figure 2) is key regarding these aspects, as each of the solutions implemented can be used to support validation of new developments or as back-up.

SUMMARY AND OUTLOOK

Certainly, safety and airworthiness will benefit from active monitoring of the actual aircraft utilization. This is also because operational monitoring may not only include fatigue monitoring, but could also include both exceedance and environmental monitoring with all the obvious additional benefits (e.g. detection of overload events, detection of events not considered in design assumptions, or accelerate the understanding of root causes in case of an in-service finding, etc). Nonetheless, measures must be put in place to at least ensure no degradation of the integrity of the "as-is" process, and certainly to avoid over-optimistic conclusions - results will need to be actively controlled by the fatigue engineer.

It is important to add that the implementation of Condition Based Maintenance could be complex since it has many facets that will need to be tackled:

- It directly affects the maintenance processes;
- It incorporates the utilization of actual flight-by-flight aircraft data which must be tediously collected, managed and secured;
- It could require developing, installing and maintaining dedicated sensors for damage diagnostics, etc.;
- It has to embrace new digitalization capabilities (e.g. artificial intelligence, etc) to attain the required levels of efficiency and sustainability;
- It will need to adhere to existing and new regulations (e.g. ref.[5] and [6]), which are strict by design to ensure safety is not compromised.

Therefore, instead of an abrupt introduction, condition based maintenance is best implemented in a step-by-step approach into service and through pilot projects with airlines. Such a controlled introduction, by deploying incremental steps that gradually build on existing technological solutions, will allow de-risking of the implementation while gaining confidence and maturity.

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