

How Artificial Intelligence Supports Airbus Helicopters to Develop, Qualify and Certify Faster

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Abstract: Nowadays, artificial intelligence is increasingly used to develop and support progress in many fields and industries, such as finance, medical, transportation..., especially for complex problem resolution. The paper presents how Airbus Helicopters introduces artificial intelligence in material & process activities, aiming, amongst other things, to reduce the time to market and optimize qualification then certification costs/risks. The paper integrates the results of a proof of concept, achieved on flame resistance behavior of composite materials, related to interior compartment/cargo self-extinguishing requirements (EASA regulation for Rotorcraft CS27/29 §853 and 855) and demonstrates how artificial intelligence supports engineering activities. The significant novelty introduced in this work is the use of advanced data-analysis software to support engineers and experts throughout development and qualification steps. Within this study, various artificial intelligence (AI) models have been trained using available experimental datasets from Airbus Helicopters and suppliers as described in Fig. 1. Following that, the trained AI model has permitted to identify the most influencing parameters and allowed to focus interest on both critical and optimal setups to help materials experts to reach targets in terms of material performance. In addition, AI model also allows predicting the fire behavior of the material, for resin/fiber reinforcement/fire agent combinations that have not been tested experimentally. This point could be particularly useful for material development purpose. This work demonstrates that, thanks to artificial intelligence support, Airbus Helicopters has improved its understanding of complex phenomenolike flame resistance behavior. Main influencing parameters have been identified for the different tests configurations. And for each parameter, strong/weak ranges have been established. Doing tests in such critical conditions during materials screening phase should help to avoid failing tests in representative helicopter configurations and permit to speed up helicopter development and certification. The presented study also paves the way for material and processes optimizations for helicopter designs.

Key words: Artificial intelligence, machine learning, composite, fire, self-extinguishing.

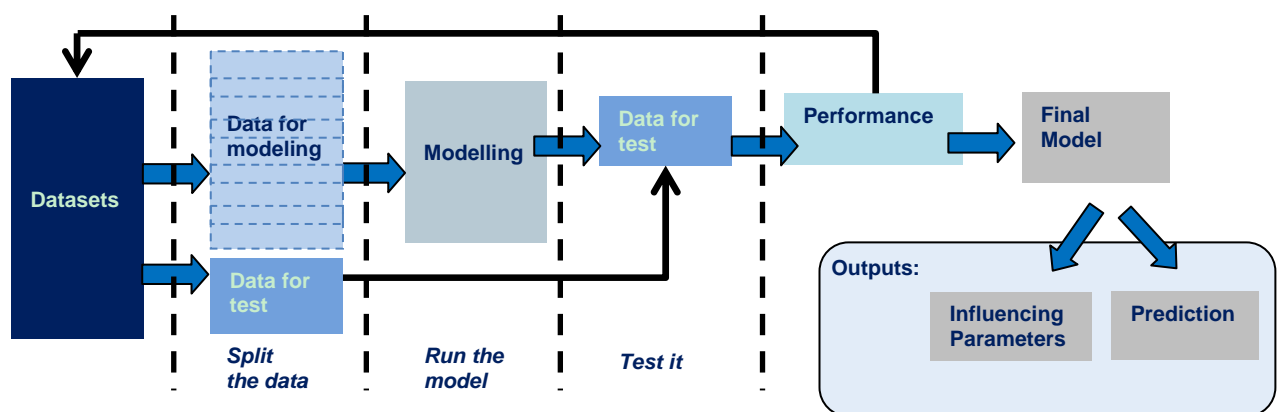


Fig. 1 Train and test machine learning algorithm principle.

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1. List of Acronyms & Definition

AI: Artificial Intelligence;

CS25-27-29: EASA Certification Specification for Large Aeroplanes (CS25), Small Rotorcraft (CS27), Large Rotorcraft (CS29);

EASA: European Aviation Safety Agency;

FAA: Federal Aviation Administration;

PoC: Proof of Concept;

M&P: Materials and Processes.

Self-extinguishing or flame resistant [1]: means not susceptible to combustion to the point of propagating a flame, beyond safe limits, after the ignition source is removed. Test to demonstrate self-extinguishing properties is defined in Appendix F of CS-25 with a vertical test (vertical flame applied under vertical panel) (Fig. 2). Three (3) criteria are required to pass tests: the burn length, the flame time after removal of the flame source and the drippings from the test specimen.

Burn length: length of the specimen burned during exposition to the flame (Fig. 2).

Afterflame time: duration after removal of the

flame where specimen continue to burn (Fig. 2).

Dripping: duration after removal of the flame where specimens continue to drop (for the purpose of this article, dripping is not considered as materials studied were always compliant regarding dripping).

2. Introduction

In digital era, aeronautic industry transforms the whole product chain to be faster, stronger and safer. In order to evaluate how new digital tools like artificial intelligence should support engineering activities, a first Proof of Concept (PoC) has been initiated by Airbus Helicopters on flame resistance behavior of composite materials [2]. This characteristic is related to helicopter interior compartment and cargo area with self-extinguishing requirements according to rotorcraft regulation (CS27/29 §853 and §855 for EASA certification).

This PoC case was selected for its reasonable scope (in terms of available data and potential parameters) as well as the high interest to better understand the phenomena, which have sometimes induced delays due to qualification tests failure.

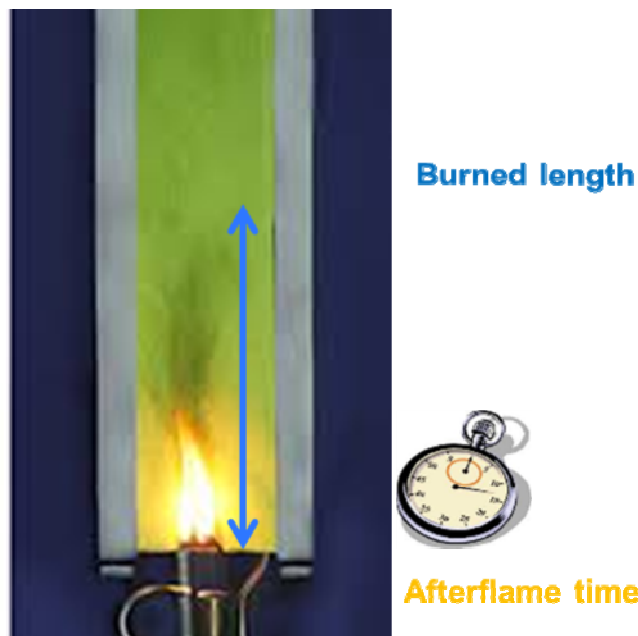


Fig. 2 Flame resistant test (vertical benzene burner, vertical coupons).

But Materials and Processes (M&P) engineering for aeronautics has most of the time the specificity to have low quantity of available data ($\approx 10^2$ examples) compared to big data (up to $\approx 10^8$ examples). Referring to the PoC, for fire resistance test, a unique set of coupons is tested per material configuration, as proposed by FAA in the *Flammability Testing of Interior Materials Policy Statement* [3]. So one of our first interrogation regarding AI tool was: do we have enough data to get an acceptable accuracy?

3. 1st Stage: Identification of the Need

The first step to be considered before starting that kind of study is the need. What would you like to see? In this case, different needs came up:

- identification of the main influencing parameters regarding the results;
- for these main parameters, the way they influence (e.g. is carbon fiber better or worse than glass fiber?);
- the identification of the quantity of tests needed to get a good overview of the material behaviour;
- the configurations to be avoided for aircraft/helicopter design.

4. 2nd Stage: Data Collection

4.1 Table Width

Before starting to collect data and prepare the data mining, the parameters to be included had to be identified. Those should include several kinds of parameters, the ones related to the fingerprint of the material (resin name, fibre name, manufacturing batch number, ...), the ones to build some families and make some merging (type of fiber (e.g. glass or carbon; epoxy or phenolic, ...)); the potential other parameters (specimen parameters like thickness, process/facility used to manufacture it, and tests parameters like test laboratory, gas used for the tests, ...) and the tests results with also a family classification (digital value translated in Pass by far, Pass but close to the limit, Fail). For the PoC case, 36

parameters have been identified by materials and tests experts.

4.2 Table Length

After the 36 columns identification, table had to be filled with the different tests sets found in company and partners databases. This task sometime requests kinds of “archaeological” investigations in order to find the parameters used three to five decades ago. But it is an important pre-requisite to get the expected feedback from the tool.

4.3 Cleaning

The last step before using the data is fundamental regarding the quality and accuracy of the outcome. In detail, data have to be checked several times to be sure that no mistake was integrated. During the PoC exercise, we have seen that only 6 wrong cells could generate a significantly different conclusion. This is clearly the drawback of small data analysis; the very low amount of data does not permit to consider mistaken data as only “noise” in the outcome.

5. 3rd Stage: Tools & Models

During the PoC, several tools and associated models were evaluated regarding model accuracy, user-friendly interface and output capability. Various algorithms have been tested to select the one leading to the best predictions. Rapid miner® platform was used at the beginning initially for its ability to try several algorithms:

- Naive Bayes, generalized linear model;
- decision trees;
- random forest;
- logistic regression;
- deep learning;
- neural networks;
- gradient boosting trees, etc.

This platform has then been replaced by a partnership with AXIODIS (a French company

focused on data science) in order to dig in data mining with domain experts.

Axiadis used R programming to develop mathematic models (Machine Learning Algorithm) and use Data Science Approach. For the PoC, due to the shape and size of the datasets, classification tree or random forest has proven to be the most accurate ones regarding the targeted parameters.

Dataset has been gradually increased during the study, which has as well permitted to evaluate the minimum amount of tests to get reasonable prediction accuracy (Fig. 3). Two hundred (200) sets of data enable to reach an accuracy higher than 80% and an associated kappa (gap regarding prediction and reality based on raw data from the 100 loops) around 60%, which was considered as a reasonable first approach to focus on the selected influencing parameters.

6. 4th Stage: Results Analysis and Utilization

Once the level of confidence was assessed, we could go and start to dig on outcomes.

Instead of just providing an exhaustive list of results, the following examples will illustrate possibilities behind data mining on this PoC.

6.1 Influencing Parameters Results

If we focus on the epoxy resin family (Fig. 4), the model highlights the resin (its formulation) as the most influencing parameter. But other parameters seem to have a significant influence: thickness, resin density, prepreg resin rate but also type of tests done: vertical 60 seconds (according to CS29 §853 a)1)) or vertical 12 seconds (according to CS29 §853 a)2))

So a first utilization of the results could be linked to the type of test (because some parts require 12 seconds compliance and others 60 seconds).

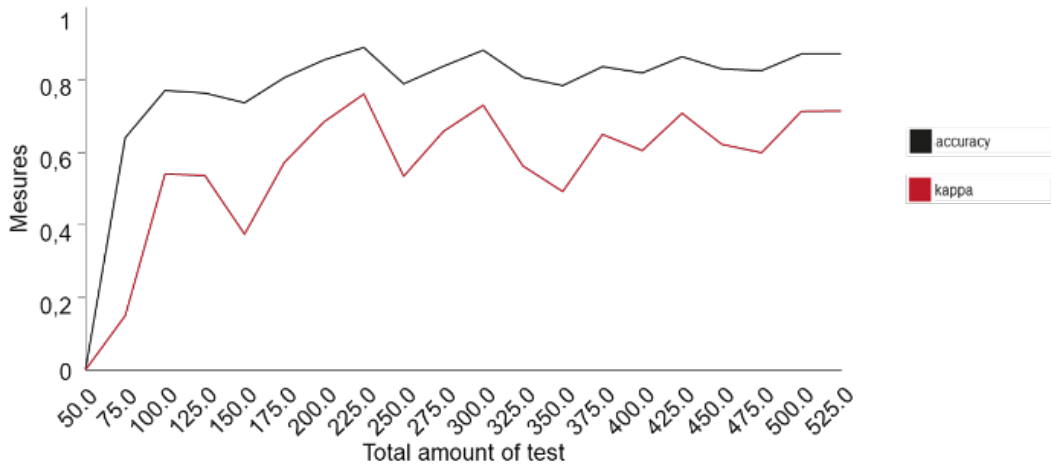


Fig. 3 Learning curve.

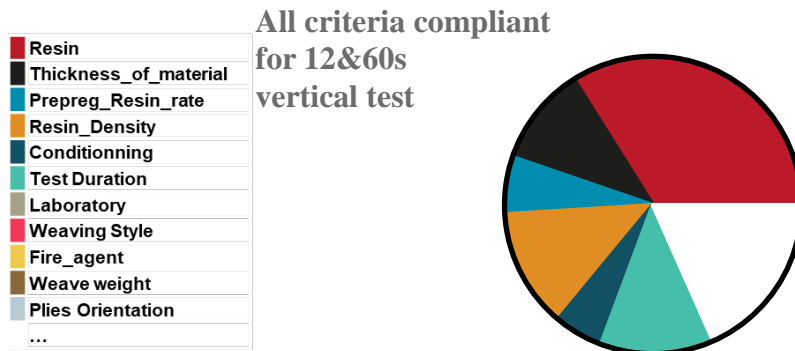


Fig. 4 Influencing parameters for self-extinguishing tests on reinforced epoxy laminates (all criteria, all vertical tests).

After selecting separately the 12 seconds and 60 seconds sets of data and running again the model, the detailed outcomes were different, for the 12 seconds test is mainly influenced by the resin formula (including the choice of the fire agent), whereas the 60 seconds test is mainly driven by the panel thickness.

So here, data mining starts to challenge the know-how of the expert and gives him grist to the mill.

For example (Fig. 5), we can see that thickness of laminates is not that important for the 12 s test success but is quite decisive for the 60 s test. Resin density is an important factor for the 60 s test, this must probably be linked to the reticulation density and/or quantity of toughener agent used.

Digging further wondering what are the influencers of the separated criteria (burn length and after flame time) (Fig. 6), it becomes clear that thickness is the main influencing parameter for the afterflame time of the 60 s tests and that resin pedigree mainly governs burn length results.

Another lesson learned in this exercise is the influence of the fire agent additive, sometimes present

in epoxy prepreg. Data mining investigations have identified that the currently used agent does not influence the 60 s tests results but is significant for 12 s success (Fig. 7).

6.2 Influencing Parameters Use

Based on these results, one can easily imagine the following stages, and the possibility to identify quickly the key parameters to be tested in order to solve some material development, qualification or certification issues (laminate nature or thickness in our example).

6.3 Predictions Results

If we focus on the thickness of epoxy laminates, we started using the model for prediction analysis. Based on the developed model, the tool was used to try to predict for each thickness what would be the results for all possible combinations of parameters, generating a large number of predictions. As an example, for thickness, based on 540 sets of tests, the tool should provide up to 35,000 results per thickness.

Here in Fig. 8, model confirms FAA guidance that a

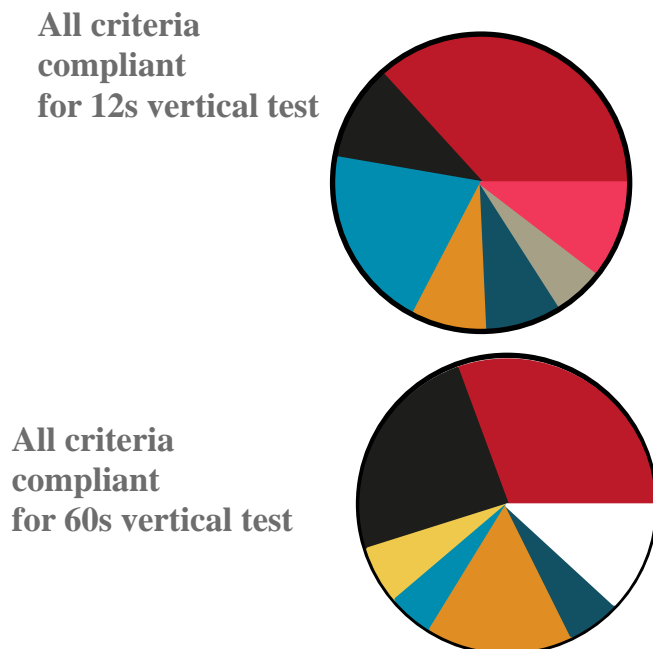


Fig. 5 Influencing parameters for self-extinguishing tests on reinforced epoxy laminates (all criteria, 12 or 60 s vertical tests).

Burn Length compliant for 60s vertical test



Afterflame Time compliant for 60s vertical test

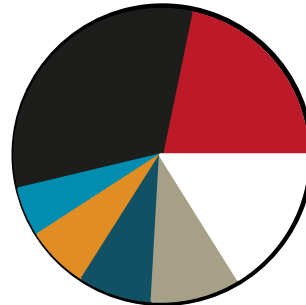


Fig. 6 Influencing parameters for self-extinguishing tests on reinforced epoxy laminates (burn length or afterflame time for 60 s vertical tests).

Afterflame Time compliant for 12s vertical test

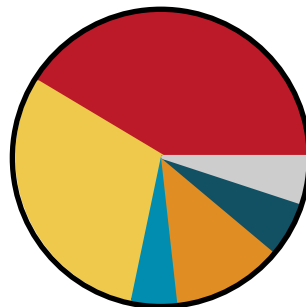


Fig. 7 Influencing parameters for self-extinguishing tests on reinforced epoxy laminates (afterflame time for 12 s vertical tests).

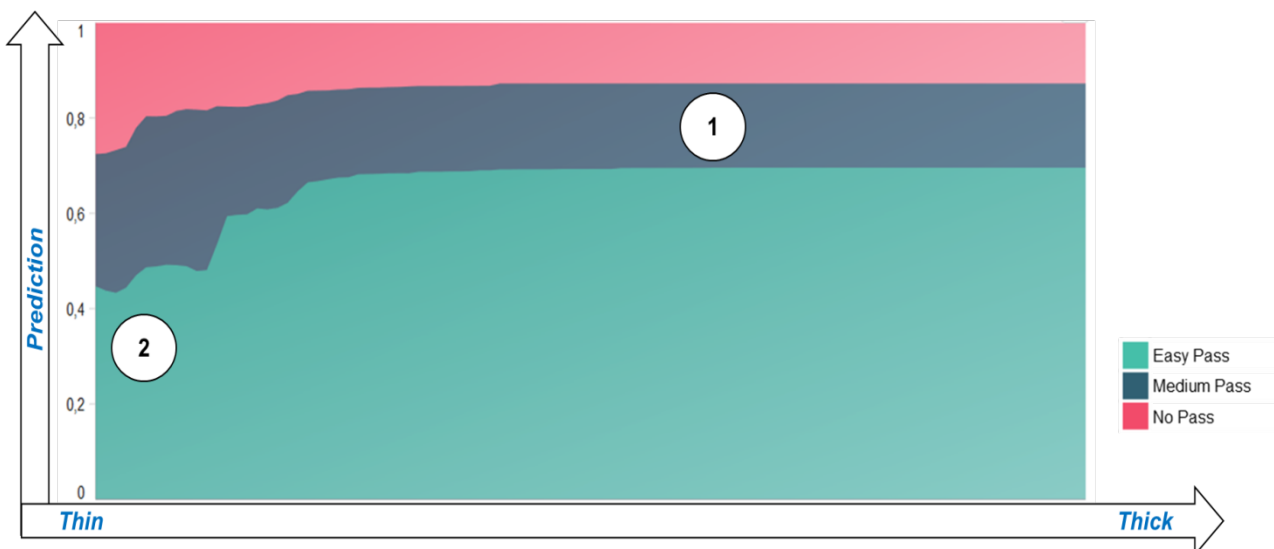


Fig. 8 Prediction of fail (red), medium pass (grey) and pass by far (green) depending on the thickness of reinforced epoxy laminates for 60 s vertical tests, burn length criteria.

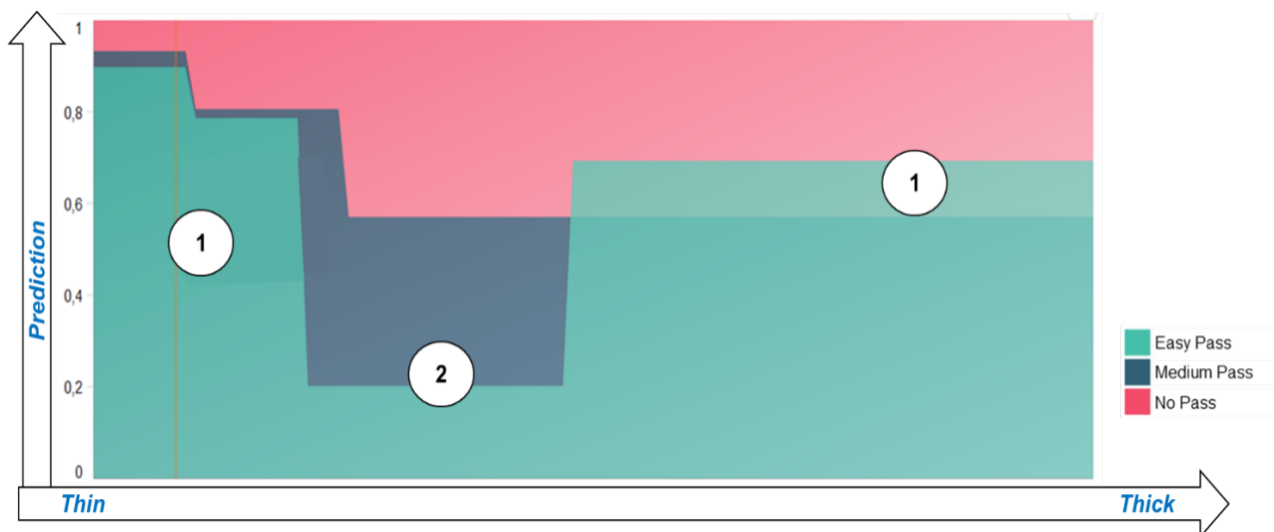


Fig. 9 Prediction of fail (red), easily pass (green) depending on the thickness of reinforced epoxy laminates for 60 s vertical tests, afterflame time criteria.

thin panel test (area 1), where results are closer to the criteria or may fail, permits to cover thicker configurations with regards to area 2 where only few configurations would fail.

However, if we focus on other criteria (afterflame time), Fig. 9 shows good fire behaviour for thin and thick specimen. But also an intermediate area (area 2) has very low chances of success. Physical comprehension of this phenomenon is still in progress but the difficulties to pass criteria have been confirmed by several additional real tests in this area.

6.4 Predictions Use

The use of prediction should have large potential. Few examples identified, in relation with our PoC, are:

- define the most appropriate screening tests to know material behaviour in the worst cases;
- define the most reliable leads to follow in order to solve issues (be thinner or thicker for example);
 - update material formulation to change behaviour;
 - select best behaviour materials;
 - etc.

7. Conclusion

Through this PoC, Airbus Helicopters has confirmed the possible application of data mining and

artificial intelligence to Material and Processes Engineering activities. It was also highlighted that a small amount of data available should not be a barrier and is sufficient to get results with an acceptable level of accuracy. Regarding the outcome, the analysis of the model predictions allowed to identify the most influencing parameters and to challenge the expert beliefs. It also permits to focus interest on both critical and optimal setups to help materials experts to reach expected targets in terms of material performance or production quality.

Within the study, Airbus Helicopters enters in a new era to use AI support in order to increase the robustness of products, in addition to speeding up helicopters qualification/certification campaigns. And as you could imagine, declinations of this PoC are already in the loop for other engineering activities in Airbus.

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