The value of materials databases increased with machine learning

Introduction

In today's highly competitive global market, the pace of innovation is constantly accelerating. At the same time, budgets are limited and development cycles are shortening. At the core of efficient reliable simulations and optimised product designs, materials data are gaining more value to cope with these expectations. In this framework, Artificial Intelligence (AI) and Machine Learning (ML) (ML) accelerates data generation and enriches material databases in an intelligent, reliable and fast way at an unbeatable cost. Physical and virtual material data needs to be managed in order to ensure traceability and accessibility.

The qualification and certification processes for composites, especially in aerospace and defense, requires a myriad of coupon tests to be performed for characterising composite allowables. Allowables quantify the strength of a composite material system in each structural context. They are statistically derived values from various coupon tests considered to study the material and process variabilities. Hence, these experimental tests are very expensive and time consuming to produce, and their number rapidly increases with the different combinations of material systems, layups, test types and environmental conditions.

This article will discuss how the power of AI/ML technologies can be leveraged, together with structured data management for full pedigree and traceability of data, to assist engineers to access allowables data faster and cheaper. Indeed, by detecting correlations in a given database of experimental material data, AI/ML can be used to virtually generate material data for coupon configurations and load cases that weren't experimentally tested, enriching significantly the material database. These can then be compiled to compute allowables, enabling engineers to start designing parts much quicker. Hexagon worked with the major Aerospace Tier1 supplier Leonardo to demonstrate the power of such an approach. Allowables computed out of Leonardo's material database enriched by AI/ML are compared against those computed based on experimental data only, confirming the accuracy of the approach. Furthermore, it is discussed how Digimat-VA can be as well leveraged to generate virtual allowables (VA) to complement the experimental test data and build more effective AI/ML models for the prediction of new composite performances. Overall, AI/ML techniques can be used in different ways to minimise the experimental cost and maximise the value of materials data.

AI/ML methodology

For any endeavour in this field, the journey starts with data, referencing and structuring these in a way that empowers AI/ML engines to analyse connections between the material data and characteristics. In that regard, the MaterialCentre data lifecycle management system is key to manage test data, processing data and material cards with full traceability on their origin. In addition to the commercial databanks it integrates, the system allows automated import of raw test data for building your own company private database. Among others, it is possible to search and compare across databases, perform physical test data entry and reduction, model multi-scale materials, generate CAE cards etc. This led Leonardo to implement the storage of their experimental test data into MaterialCentre.

Based on Leonardo's raw test data, data reduction processes are performed to compute the corresponding allowable curves. As illustrated in Figure 1, users can at any time link the computed allowable curve with the corresponding experimental test data with full traceability.

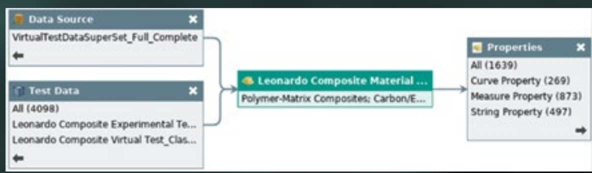

Figure 1: MaterialCentre traceability throughout the materials lifecycle

The next step is to select test data stored in MaterialCentre to create the input package of data for the AI/ML process. Generally engineers have access to material systems that are being only partially characterised, with some systems better characterised than others. As this point it is useful to analyse what data are and aren't available. Figure 2 illustrates an option for displaying this, where the rows correspond to material systems (e.g. different composite layups here) and the columns correspond to various material properties and coupon behaviours (different test types and test conditions: e.g. open hole tension, filled hole tension… room/dry, hot/wet…). This particular database matrix view, with the blue cells corresponding to available input test data and the white cells corresponding to unavailable material properties, helps visualise and assess what can be considered to train an AI/ML engine and where AI/ML can come into play to complement experimental data with virtual testing. In the particular case of Leonardo, it is observed that the greatest part of the test data matrix is empty and the question is, what and how can an AI/ML process fill some of that up.

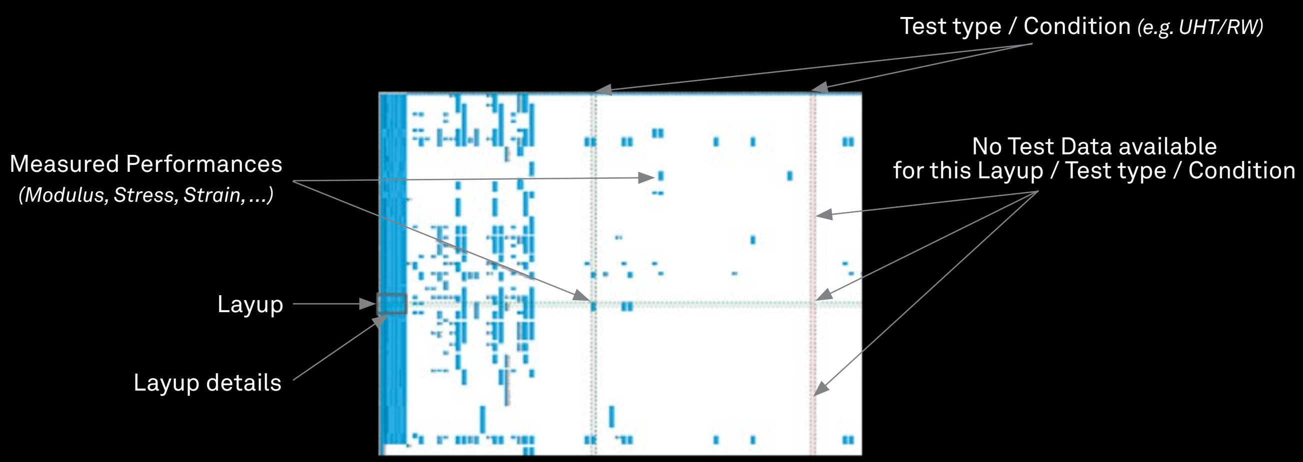

Figure 2: Matrix display of the test data, depicting in blue the available input data/properties and the empty cells referencing the missing ones

The AI/ML process consists of three steps. To start with, the raw database is read and correlations are detected to define an optimised input for the AI/ML model. Next, the test data are trained in order to build the AI/ML model. The process includes iterations where the quality of the AI/ML model is measured according to different criteria and completes when a certain accuracy target is reached. Finally, the empty cells of the database are filled with the predicted layup performances of non-tested test types and environmental conditions.

The last step is to import the virtually generated test data back into MaterialCentre. For Leonardo, the enriched database extracted from the AI/ML process constituted 70 % of the database.

AI/ML to enrich material databases

Based on the described AI/ML methodology, the enriched database results are discussed and validated across three different examples. In Figure 3, the unnotched tensile strain is plotted against the percent of 0° plies for experimental data and AI/ML enriched data. It is observed that there is no deviation between the allowable curves derived from the experimental and from the AI/ML enriched data, the results perfectly overlay. Another example is shown in Figure 4 for an open hole compression at 22 % of plies at +-45°, here again the allowable curves fully overlap. The last example displayed in Figure 5 shows the open hole compression at 30 % of plies at +-45°. In this case, a very slight deviation of less than 1 % is observed between experimental and AI/ML enriched data.

Overall, an excellent agreement between AI/ML enriched and experimental data is achieved. The allowables derived from AI/ML enriched data are validated and the consistency of the materials database is confirmed.

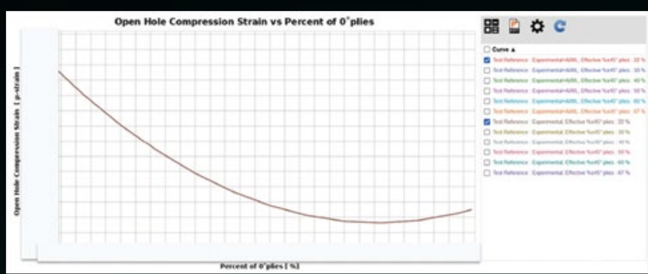

Figure 4: AI/ML enriched and experimental open hole compression at 22 % of plies at +-45°

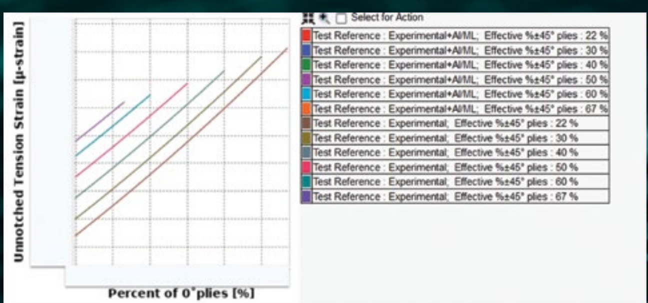

Figure 3: AI/ML enriched and experimental unnotched tension

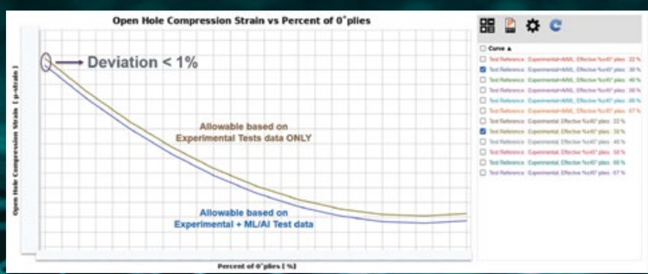

Figure 5: AI/ML enriched and experimental open hole compression at 30 % of plies at +-45°

AI/ML to leverage virtual testing

AI/ML techniques provide a fantastic opportunity to minimise the size and cost of experimental test campaigns by detecting and smartly determining the tests that must be experimentally performed as opposed to those that can be virtually computed. In that framework, it is also possible to complement the experimental tests with virtual material testing using numerical modelling tools and workflows. Digimat-VA can for instance be considered to virtually generate composite data and allowables faster and cheaper, and this can be leveraged in combination with AI/ML to further increase the accuracy and efficiency of the virtual data generation workflows.

As a reminder, Digimat-VA is an integrative solution that allows easy and efficient prediction of virtual allowables. Its numerical guided workflow is structured around three steps: test matrix, simulation and allowables. The test matrix is defined with the number of materials, layups, tests and environmental conditions to be tested. Thereafter, the Digimat material model and the finite element model are required to run the corresponding simulations and finally, the resulting allowables are post-processed.

Overall, AI/ML can suggest the best mix of experimental and virtual tests to be used for maximising the accuracy of AI/ML models. Whether using experimental data, AI/ML enriched data or virtual data via numerical methods, MaterialCentre is able to manage the data tracking full pedigree and traceability of the data. Figure 6 shows MaterialCentre's capability to maintain the link with the test classification to clearly identify AI/ML, experimental or virtual data.

Conclusions

In today's industrial context, materials data are gaining a lot of value. Experimental tests campaigns are heavily expensive and time consuming, they often aren't an affordable solution that can be considered for characterising all composite material systems engineers do consider in their design and innovation work. Using AI/ML models trained on existing experimental tests, an AI/ML process has shown to be a valuable solution to predicting the performance of non-tested composite layups, under different loads and in different environmental conditions, with good accuracy. Hence, applying AI/ML on Leonardo's database of composite test data, the database has been heavily enriched thanks to AI/ML methods. For three different examples, the AI/ML predictions were in excellent agreement with the experimental data. Furthermore, the experimental and AI/ML enriched data can be complemented with numerical modelling solutions such as Digimat-VA to maximise the accuracy of the AI/ML model while minimising the number and cost of experimental tests. Along this line, this AI/ML process has paved the way for the prediction of new composite performances, with new layups, new materials systems and new environmental conditions. MaterialCentre has been used in this context to easily store and manage any material data, maintaining full pedigree and traceability on the experimental, AI/ML enriched and virtually generated data.

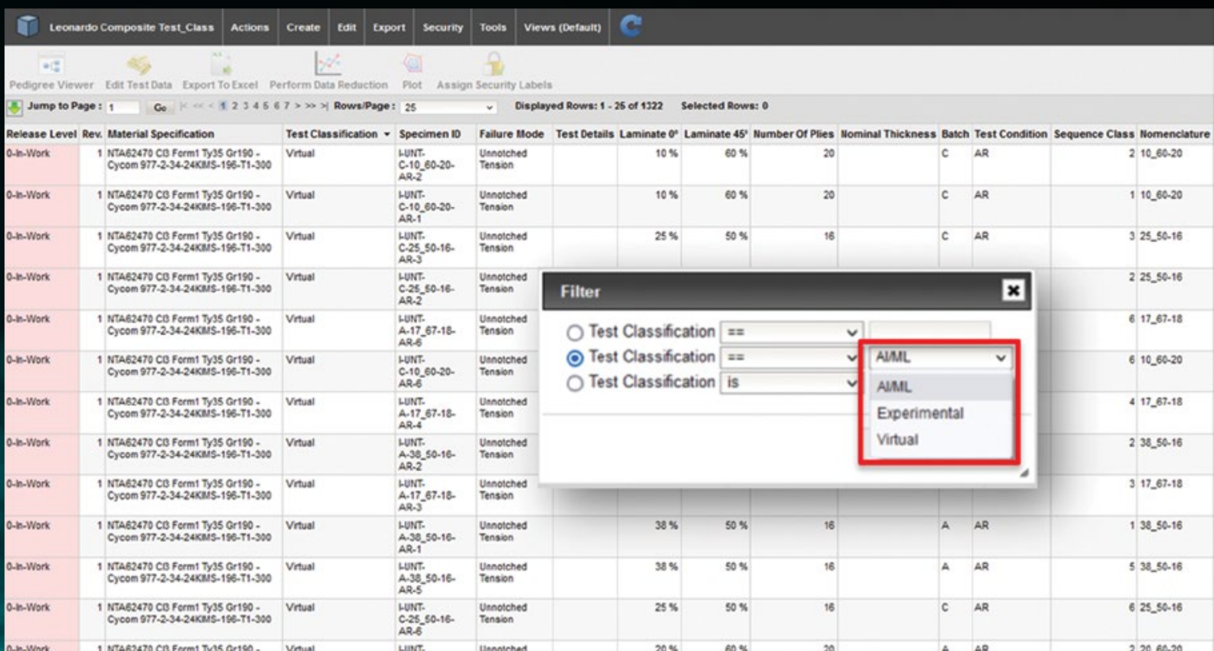

Figure 6: MaterialCentre traceability of AI/ML, experimental and virtual test classification