Prediction of Carbon Fibre Composite Failure using Machine Learning

Goal summary: This project aims to apply machine learning to a real engineering problem: predicting when carbon-fibre composite structures will fail. Students will use a synthetic dataset randomly generated to train models that approximate expensive finite-element calculations. The challenge is to predict the maximum failure index, a scalar indicator of material damage, directly from global stress-strain data, bypassing costly ply-level modelling.

Carbon fibre-reinforced plastics (CFRPs) combine high strength, stiffness, and low weight in a way that few materials can achieve. They are widely used across industries where weight reduction improves performance, such as aerospace, wind energy, racing, and sporting goods. To provide a concrete example, 53% of the structural weight of the most recent Airbus aircraft model, the A350 XWB, is composed of CFRPs.

CFRPs are laminated materials, meaning they are made of multiple thin layers, called plies, made of carbon fibre embedded in a polymer matrix, each oriented differently to achieve desired stiffness and strength. As manufacturing methods continue to evolve, thicker CFRP laminates are becoming more common. These thicker parts are more likely to experience complex loadings than traditional thinner ones, making their structural design more challenging. The failure behaviour of CFRPs is highly dependent on these loading modes and the interactions between layers/plies.

To design such parts, engineers rely on numerical simulations, typically using Finite Element Analysis (FEA). In these simulations, the stress-strain state of the part is used to evaluate failure criteria that return scalar failure indices (FIs) indicating how close the part is to damage. However, considering these criteria accurately requires modelling each constitutive ply, which is computationally expensive, challenging to implement, and does not scale easily.

To address this challenge, the proposed project explores the use of machine learning (ML) to reduce the complexity of composite failure analysis modelling. Synthetic data are generated numerically: random laminate-level stress-strain states are created, the corresponding ply-level responses are computed, and failure criteria are evaluated for each ply. The resulting dataset contains the laminate-level stress-strain inputs, the ply-level FIs for different failure modes, and the maximum FI across all plies, which represents the onset of damage for the entire part.

The resulting dataset contains:

- Input: laminate-level stress–strain state represented as a 6-dimensional vector of floating-point values (strain components).
- Outputs:
    - FIs for each ply and failure mode.
    - The maximum FI (maxFI) across all plies, which represents the onset of failure for the entire part (damage onset corresponds to FI = 1).
    - The identifier of the critical failure mode, i.e., the mode corresponding to the maximum FI.

The overall objective is to train ML models capable of predicting laminate-level failure behaviour directly from global stress–strain data, without performing explicit ply-level simulations.

Different ML formulations can be explored depending on how the problem is framed. Possible approaches include:

1. **Regression:** Predict maxFI as a scalar floating-point value.
2. **Classification / Clustering:** Identify the critical failure mode ID corresponding to the highest FI.
3. **Hybrid:** Combine both tasks: for instance, first classify the likely failure mode, then perform a targeted regression of its FI.

Each student group will focus on one of these approaches.