Creating a Difference

DETERMINATION OF COMPOSITE MATERIAL FINITE WIDTH CORRECTION FACTORS USING MACHINE LEARNING STRATEGIES

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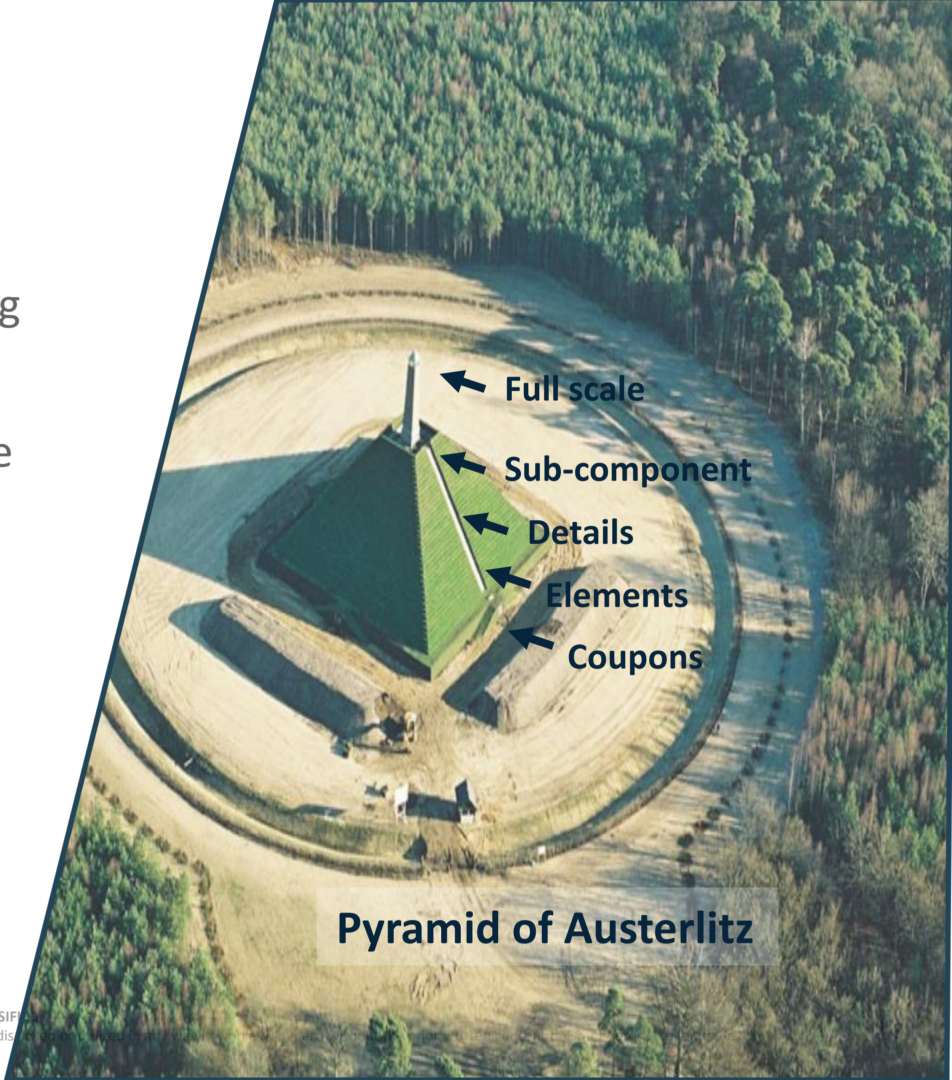
Outline

- Background
- Objective
- Case Study
- Machine Learning
- Methodology
- Finite Width Correction Factors
- Credibility and Acceptance of Results
- Summary and Conclusions

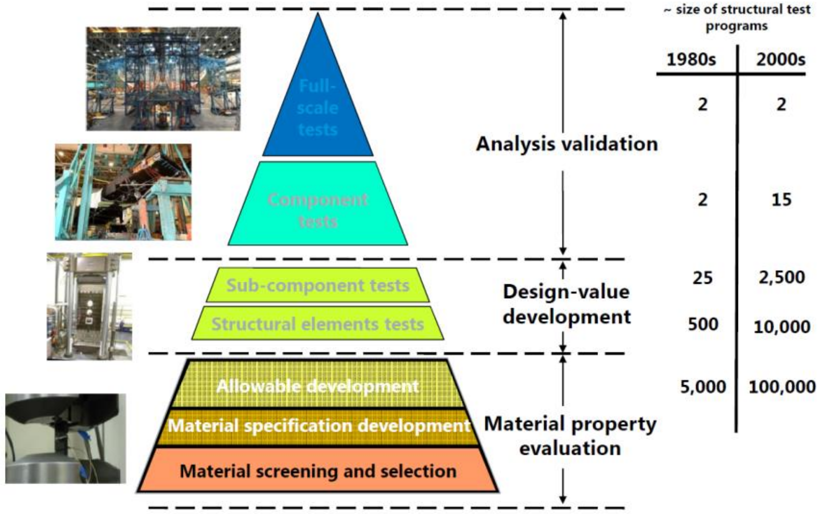
Background

- Structural components made of composite materials are substantiated using the building block approach (“test pyramid”)
- Simple and generic coupons are tested at the basis of the pyramid to obtain allowables to be used for strength substantiation



Background

- The structural testing required to established relevant strength allowbles is ***costly*** and ***time consuming***, especially for composite materials
- It is not uncommon that certain strength allowables are determined after the design kick-off. This raises a ***risk of costly redesigns*** later in the program and even ***retrofits at production aircraft***



Taken from: S. Eric Cregger, Composite Durability Workshop, 2013

Objective

- The objective of this study is ***to propose a data-driven methodology for determination of strength allowables for composite materials***

Goals

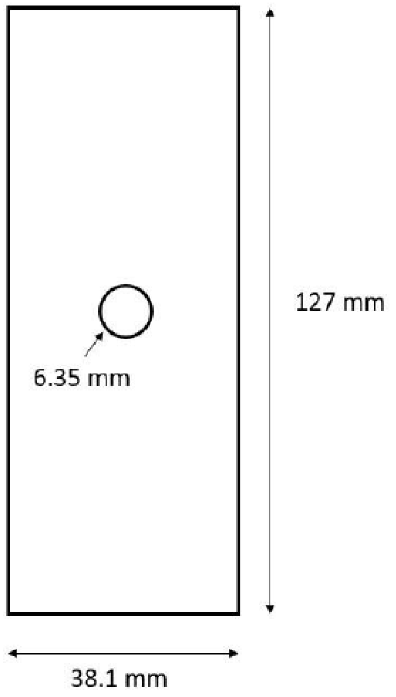
- Reduce testing effort
- Cost saving
- Shorter entry to market
- Minimize risk for redesigns

Case Study

- Open Hole Compression (OHC) specimen is used for this study
  - Similar approach can be used for other use cases
- OHC specimens are widely used to obtain damage tolerance compression strength allowables
- Easy to manufacture, minimize undesired scatter with suitable ASTM standard (ASTM D6484)

Case Study

- Test Specimen maintains aspect ratio of W/D = 6.0
- For design cases with W/D < 6.0, a finite width correction factor is applied to the strength allowables
  - Similar to classic Peterson's SCF in metallic structure
- The correction factor depends upon the composite ***layup*** and the ***W/D*** ratio
  - Typically 5 different features that describe the problem: layers at 0^o, $\pm45^o$, 90^o, W/D and correction factor
- ***Machine learning algorithms*** are suitable to efficiently address ***multi-dimensional problems***



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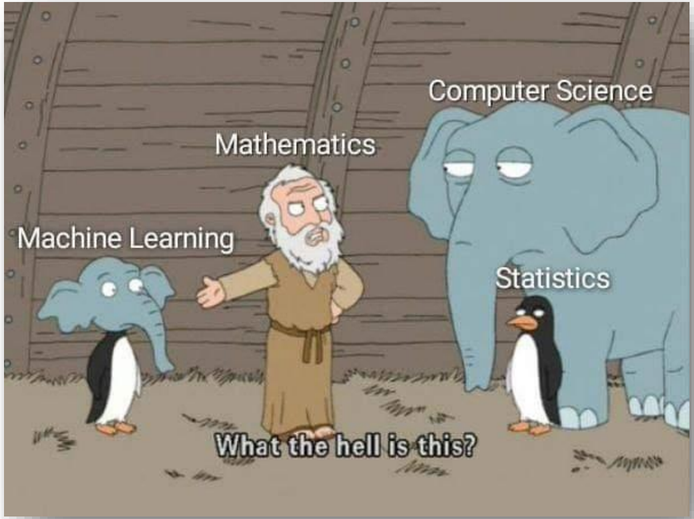
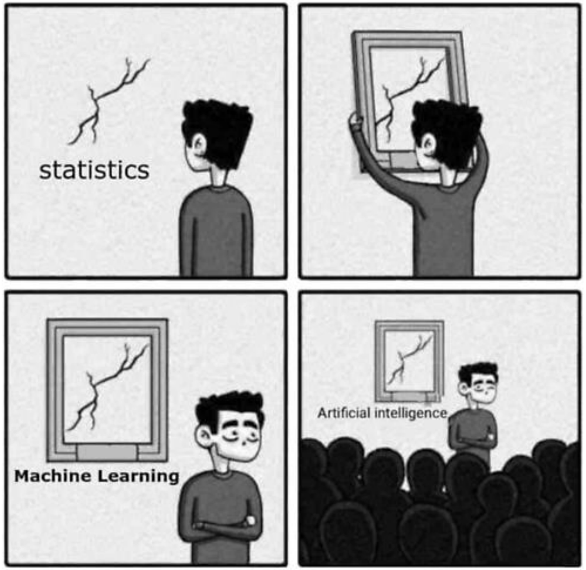
Machine Learning

- Disclaimer:
  - □ This presentation provides a very very very top-level description of machine learning algorithms
    - No mathematical background provided, only one equation ☺
  - □ What is really important to understand from the following slides is:
    - Why should we use machine learning here?
    - What are the advantages of the GPR approach?
    - Why is it so useful to engineering applications as we are dealing with?



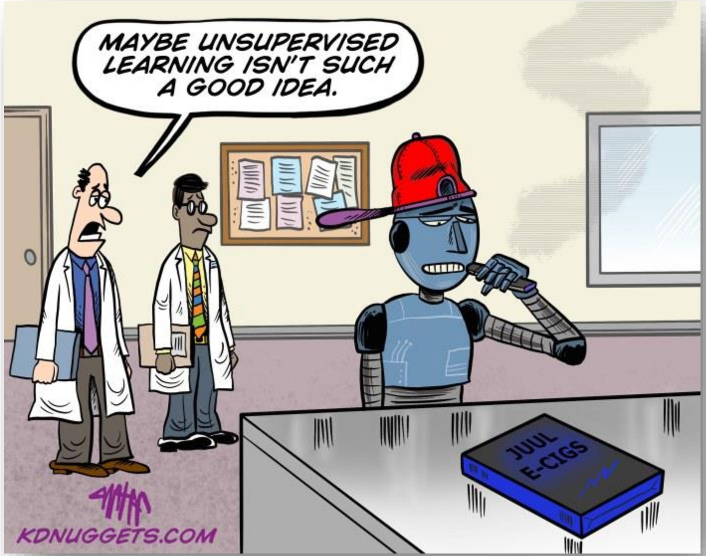
Machine Learning

- An algorithmic approach to:
  - Analyze large amount of data
  - Find patterns in the data
  - Allow prediction capability for new data



Machine Learning

- Machine learning algorithms are generally divided into several groups:
  - □ **Unsupervised methods** – the data is unlabeled
    - For example: trends in Twitter
    - Clustering techniques are employed, find patterns in the data
  - □ **Supervised methods** – data is labeled
    - For example, digits recognition
    - Classification and Regression techniques are employed
- In this study, we employ ***supervised machine learning algorithms***



Gaussian Process Regression

- The GPR is a nonparametric Bayesian regression approach
- This algorithm provides predictions of the **mean** and **standard deviation** value of each point in the domain studied, assuming a Gaussian distribution
  - Very important feature!
- The ML algorithm is trained with respect to the existing data points. In other words, the model establishes relations between datapoints in the entire domain investigated

Gaussian Process Regression

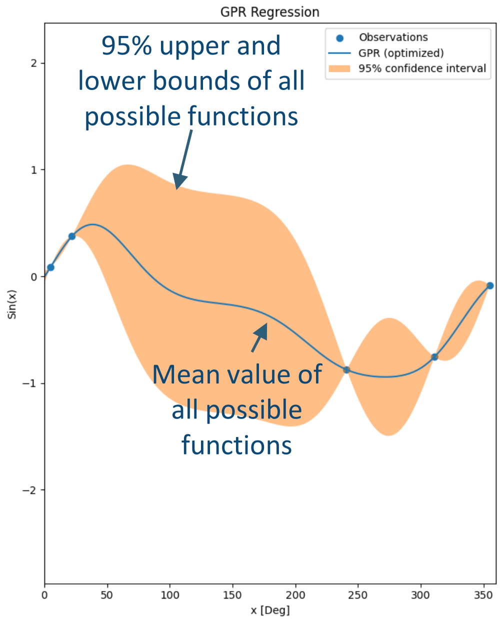
- Kernels are used to define the relations between datapoints in the domain investigated
- For example, the Radial Basis Function (RBF) enforces strong correlations between adjacent points

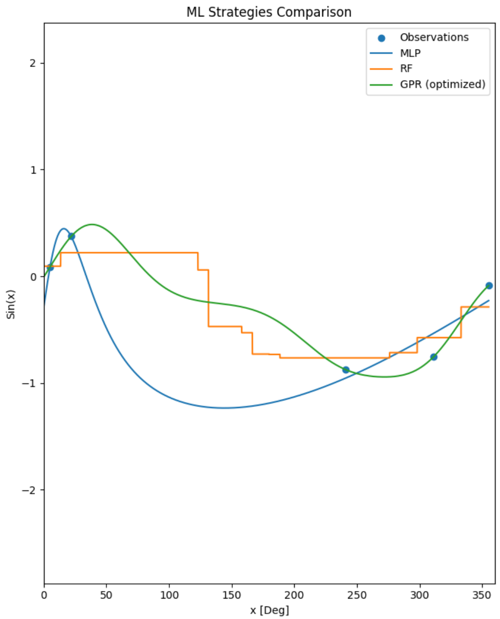
$$k_{RBF}(x_i, x_j) = \sigma^2 exp\left[-\frac{(x_i - x_j)^2}{2l^2}\right]$$

- In case of large scatter of the test data, the **WhiteKernel** algorithm can also be employed

Gaussian Process Regression

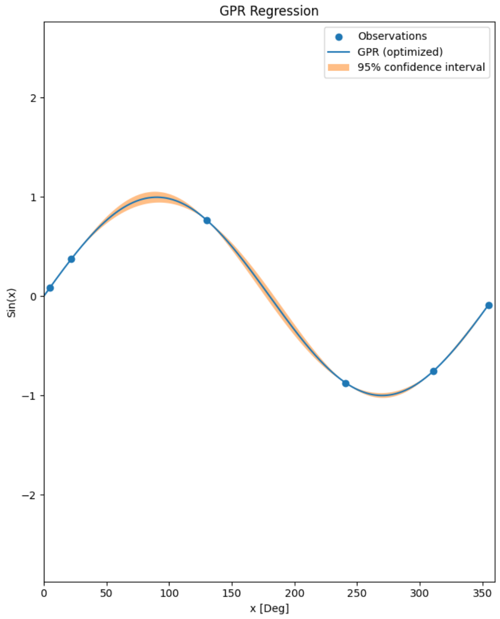
- Example – prediction of sin(x) based on training data
- 5 training points
- Regression is poor
- However, knowledge of the accuracy (via standard deviation) provides an important insight on which additional point will improve the regression significantly

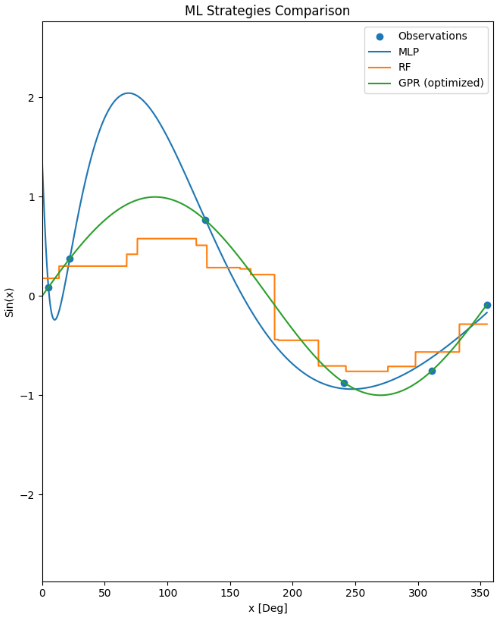




Gaussian Process Regression

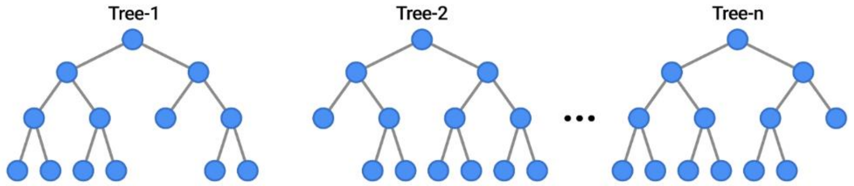
- Example – prediction of sin(x) based on training data
- Additional training point was added at ~130º
- The regression is improved significantly
- Relatively small number of training points (with respect to other ML algorithms)





Neural Networks and Random Forest

- Two other machine learning algorithms are employed in this study
  - Multilayer Perceptron (MLP, Neural Network)
  - Random Forest (RF)
- Both methods are used for data regressions
- The mathematics behind these methods is beyond the scope of this presentation

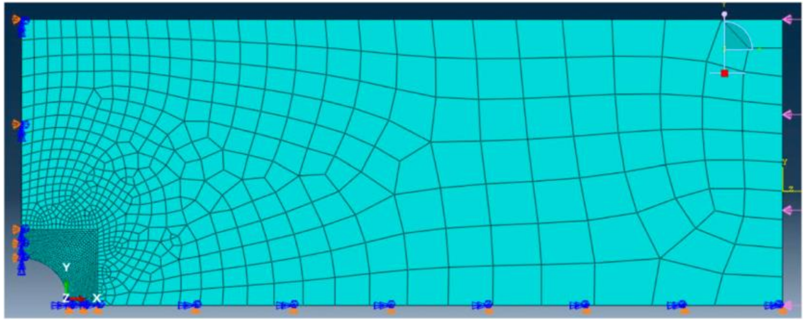


Methodology

1. Collect data from test specimens
2. Construct finite element models that span the expected ranges of finite width parameters and layups
3. Train machine learning algorithm based on data points (test + FEM)
4. Produce regression surfaces spanning the entire domain of layups and W/D
5. Validate the proposed regression surface with respect to benchmark problems
6. Produce carpet plots to be used for design of composite structures

Training Data

- Test data combined with FEM predictions were used to train the ML algorithms
- The GPR algorithm was employed to asses if additional training points are required to properly span the entire domain of layups and W/D ratios

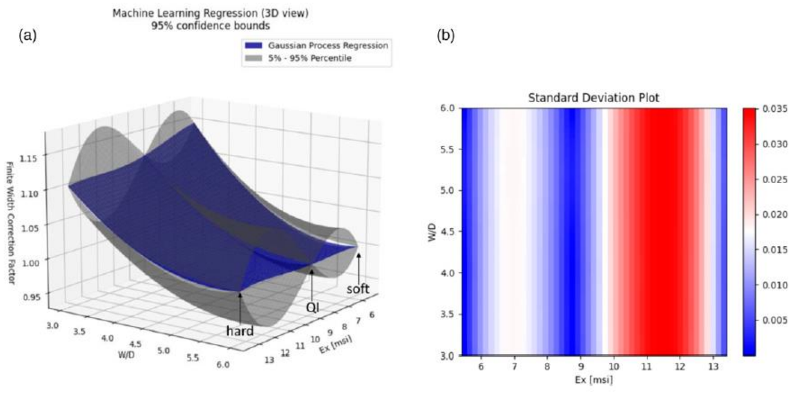


ID	% 0°	% ±45°	% 90°
1	10	80	10
2	15	70	15
3	25	50	25
4	35	50	15
5	45	30	25
6	50	40	10

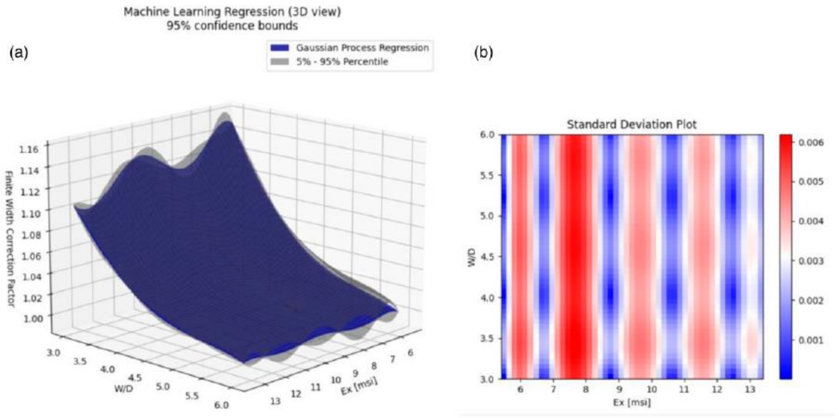
Initial test data

Training Data

- Standard deviation is significantly reduced with additional training points at W/D = 5.2



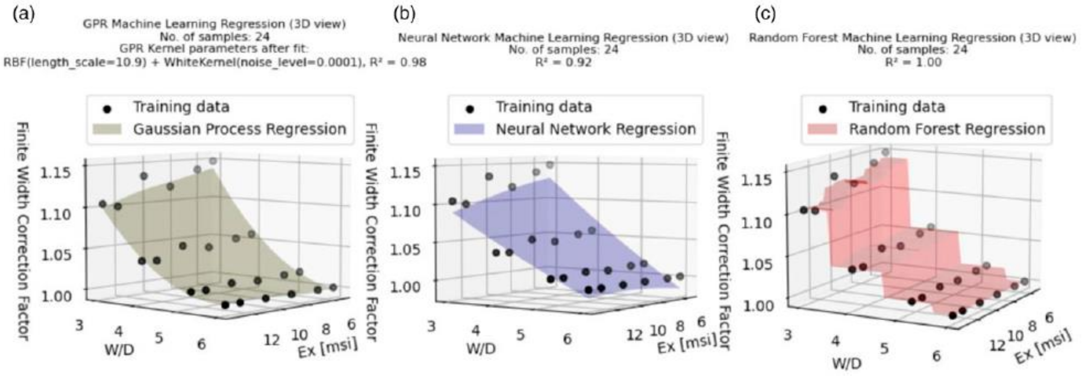
Training data at W/D = 3, 4 and 6

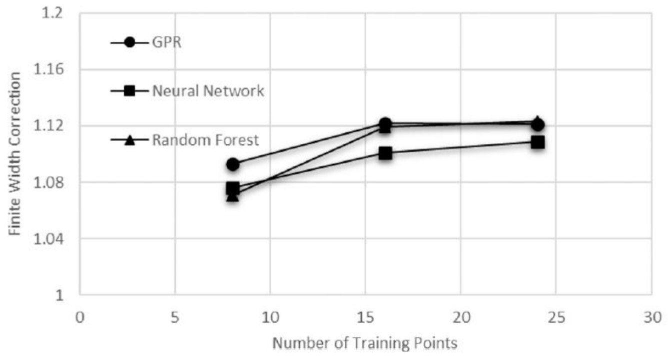


Training data at W/D = 3, 4, 5.2 and 6

Regression

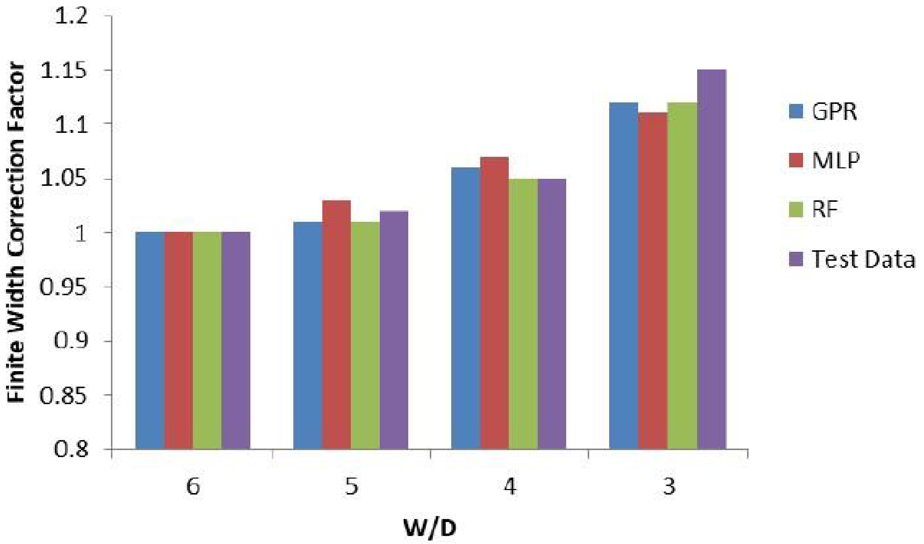
- Next, regression surfaces were obtained using the three algorithms
- Good agreement with training data was obtained (R^2 ~ 1.0) with no over-fitting
- Convergence of training data points was verified as well





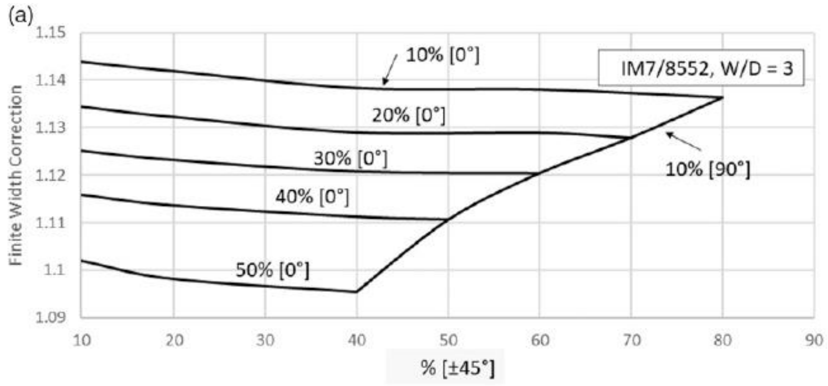
Validation

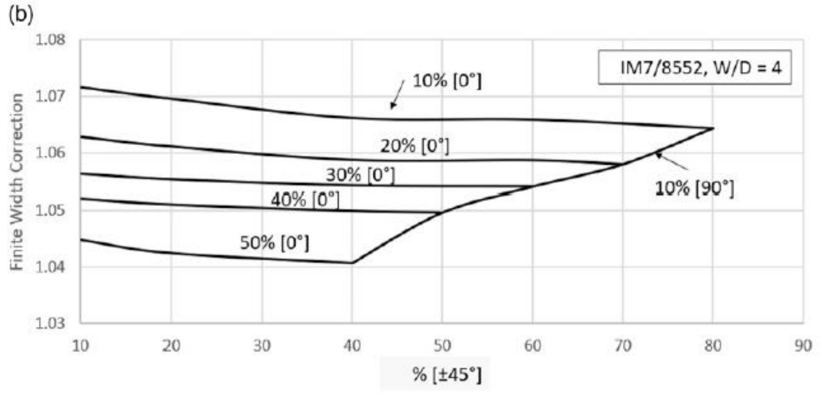
- The performance of the three algorithms was validated with respect to test data



Carpet Plots

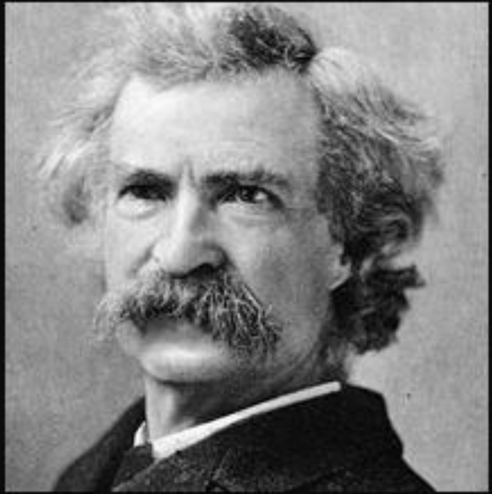
- Once the regression surfaces are validated, carpet plots can be produced and used as part of the design process of new composite aviation parts





Credibility and Acceptance

- Questions to be answered when using data-driven methods:
  - What sort of validation is sufficient (also refer to EASA Proposed CM-S-014)?
  - What sort of uncertainties are covered?
  - Can evidence be substituted by credibility?
  - Can new models be substantiated by existing models?
  - At which level we have a safety issue?

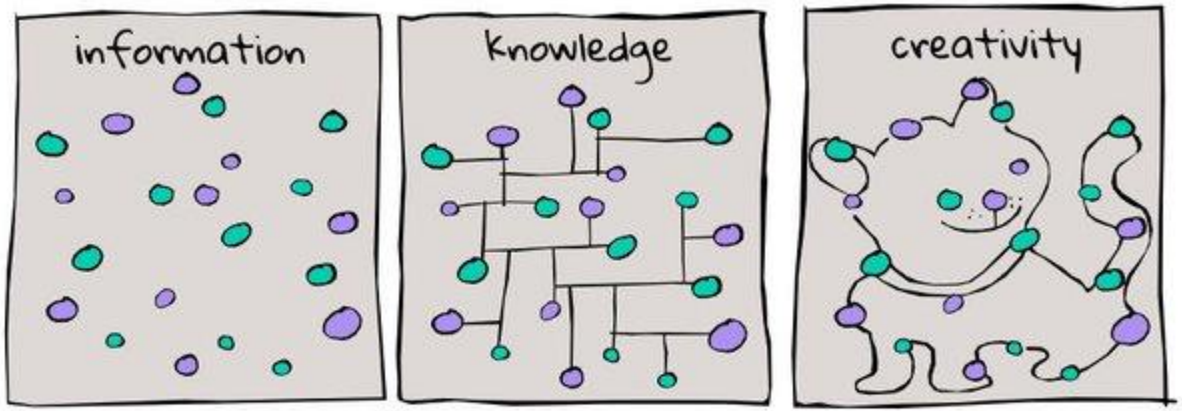


Good decisions come from experience. Experience comes from making bad decisions.

~ Mark Twain

Summary and Conclusions

- A new methodology for determination of strength allowables was studied
  - Finite width correction factors of composite material were taken as a case study
- Machine learning algorithms are employed to predict regression surfaces of multi-dimensional problems
- With only handful of test data, the predictions of finite width effect were found to be accurate
- Similar approach can be employed for determination of other design values, leading to reduced costs and development durations, and providing more reliable database to be used for design

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