Gaussian Process for FEM reduction applied to Fatigue life estimation of non linear model

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Introduction

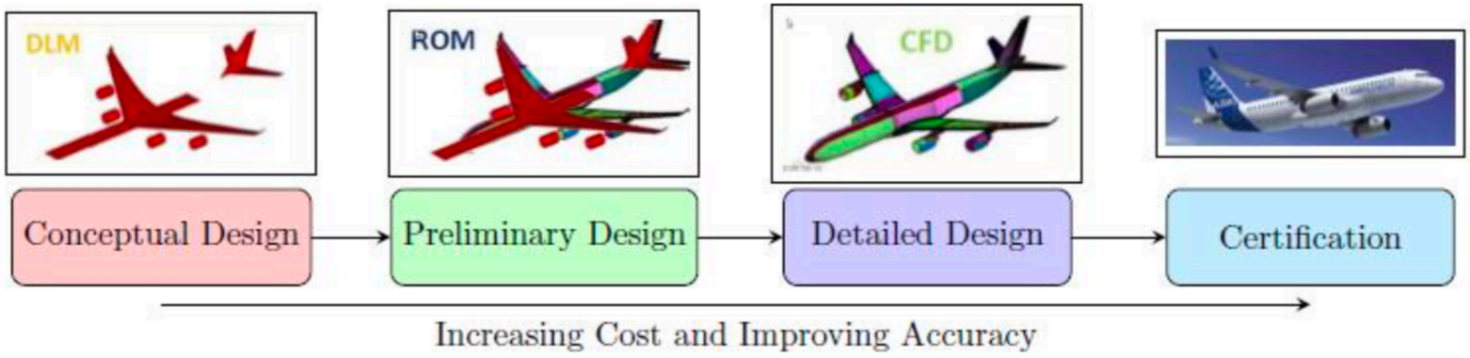


Figure 1. Aircraft Design

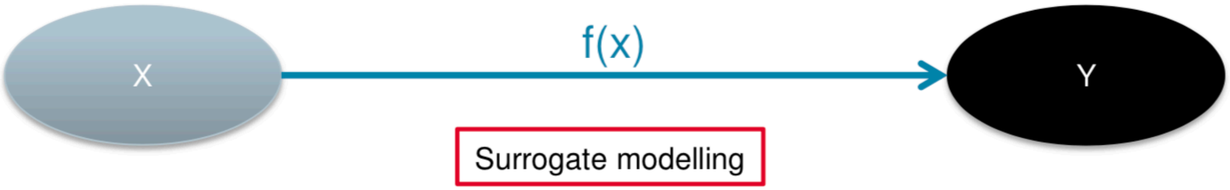


Figure 2. Surrogate Model

A quicker, cheaper representation

My Subject

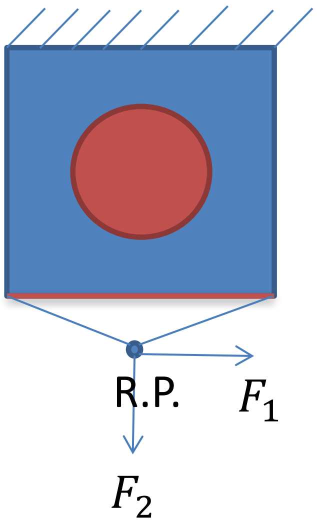


Figure 1. Component of Pylon

$$\begin{bmatrix} x & F_x \\ y & F_y \end{bmatrix} \longrightarrow \sigma$$

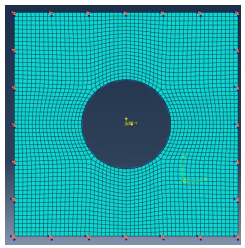
Figure 2. Simulation Process

- The Life cycle of this component can be reduced to a linear combination of loads F_1, F_2.
- model is non linear due to contact with the red pin in the middle of the structure.
- For this reason to analyze the life cycle one analysis for each load combination should be executed
- Since the FEA can be very expensive and the number of load combination can be of 5000 different load this approach can be prohibitive

My Subject

Input

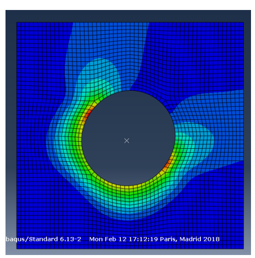
$$\begin{bmatrix} x & F_x \\ y & F_y \end{bmatrix}$$



ABAQUES

Response

σ



1. Building

$$\begin{bmatrix} x & F_x' \\ y & F_y' \end{bmatrix}$$

2. Prediction

Surrogate Model

2. Prediction

σ'

Related research

Engineering Design via Surrogate Modelling: A Practical Guide

A I. J. Forrester et. al.

1.Preparing the Data and
Choosing a Modelling Approach

2: Parameter Estimation and Training

3. Model Testing

- Polynomial Model
- Radial Basis Function Model
- Kriging Model
- Support vector Regression

Figure 1. Process of building a surrogate model

$$\operatorname{cor}[Y(\mathbf{x}^{(i)}), Y(\mathbf{x}^{(l)})] = \exp\left(-\sum_{j=1}^{k} \theta_j \mid x_j^{(i)} - x_j^{(l)} \mid^{p_j}\right).$$

Formula 1. Correlated outputs

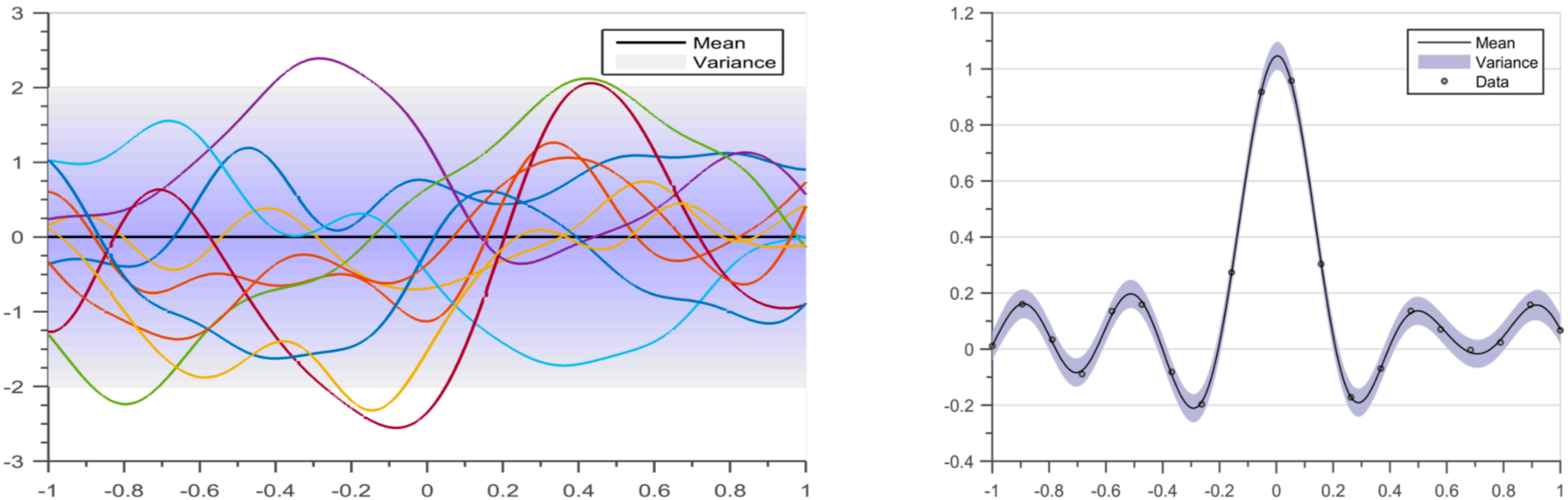
$$\hat{y}(\boldsymbol{x}) = \sum_{i=1}^{n} w^{(i)} y^{(i)}$$

Formula 2. Kriging prediction

Related research

Gaussian Processes for Machine Learning

C. E. Rasmussen & C. K. I. Williams



Prior

$$p(f|M) = GP(0, K(\theta))$$

$$k(x, x', \theta) = \theta_1{}^2 \exp\left(-\frac{(x-x')^2}{2\theta_2{}^2}\right)$$

Posterior

$$m(x_*) = K_*[K + \sigma_n{}^2 I]^{-1} y$$

$$var(x_*, x'_*) = K_{**} + \sigma_n^2 I - K_*^T [K + \sigma_n{}^2 I]^{-1} K_*$$

Figure 1. Gaussian process regression from Function-space View

Related research

Towards Optimization of Multi-Material Structure Metamodeling of Mixed-Variable Problems

Hongyi XU et. al.

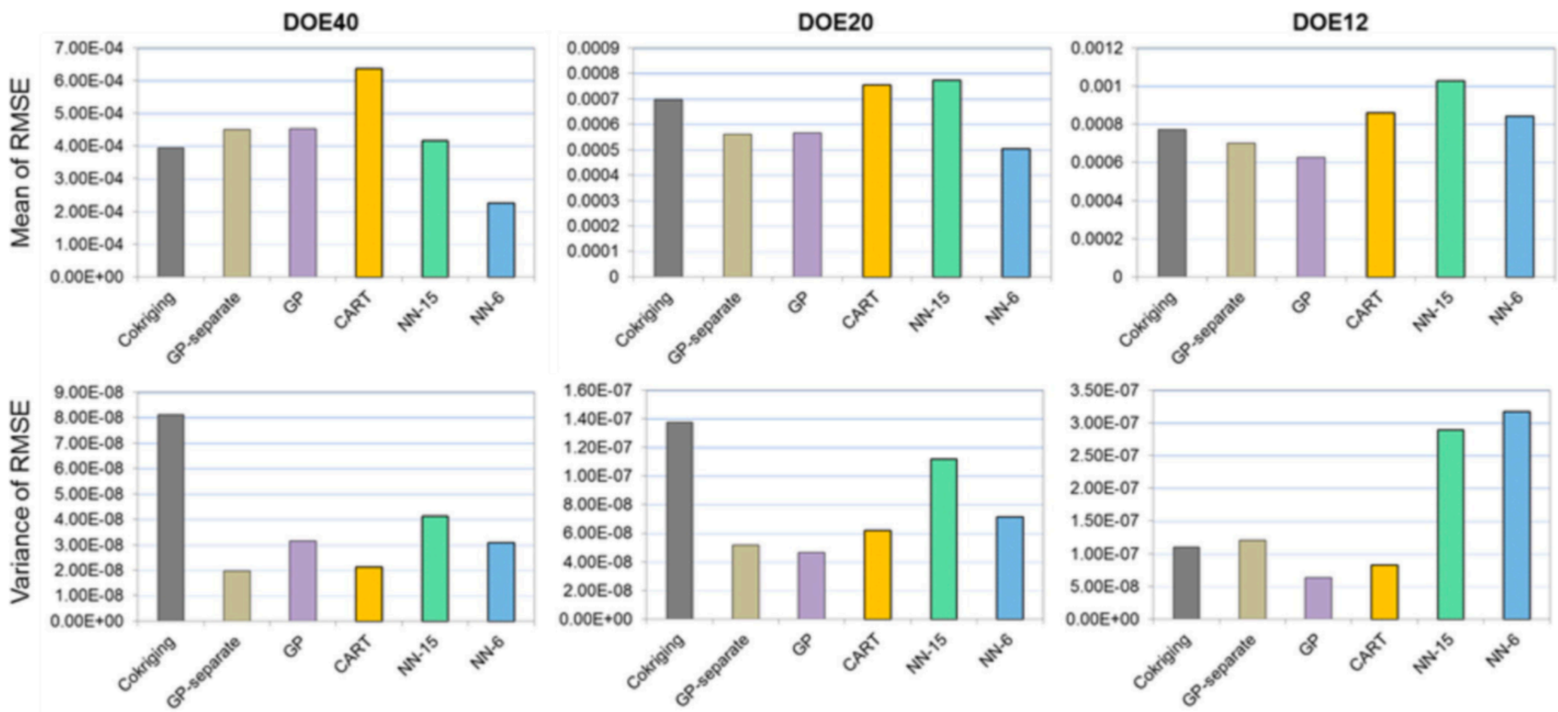


Figure 1. Comparison of RMSE (mean and variance) of six metamodels

Conclusion & Planning

Conclusion

1. Surrogate Model provides an approximate model while greatly reducing time and cost
2. Gaussian Process Regression is a very important machine learning approaches that can helps with the project
3. GPML can be applied to solve aeronautical engineering problems

Planning

1. Read the data from the ABAQUS
2. Construct a surrogate model to predict the max principle stress
3. Further predict the max principle stress and its location
4. Construct a surrogate model to predict the principle stress distribution
5. Compare the results with singular value decomposition (SVD) based learning algorithm and reduce a code with SVD

Thank you!