Technische Hochschule Ulm

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Calibration of a material model for high-purity (OFHC) copper using classic and modern methods

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Agenda

- Motivation
- Environment
- Important basics
- Global response fit
  - Root Mean Square Error (RMSE) approach
  - Dynamic Time Warping (DTW)
  - Statistics on Structures (SoS)
  - Comparison
- Summary

Motivation

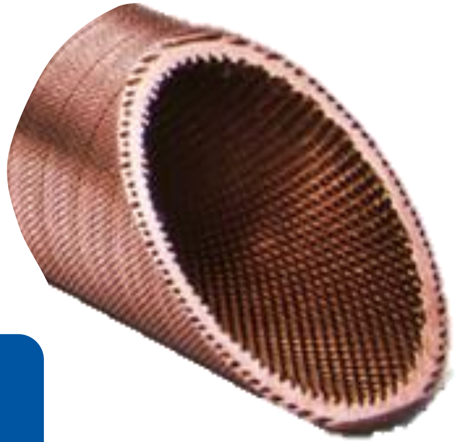
FEM

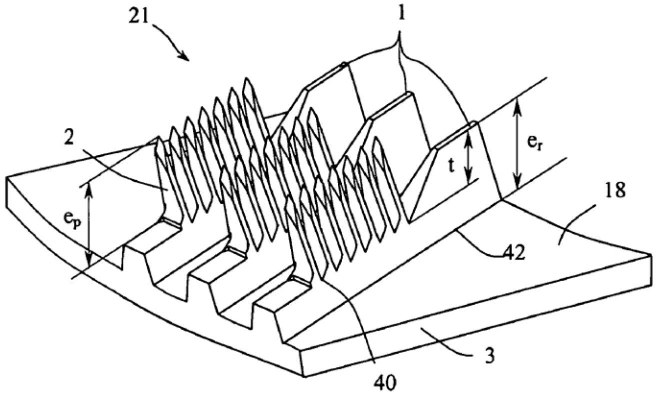
Cost estimation

Structure prediction

CFD

16 mm

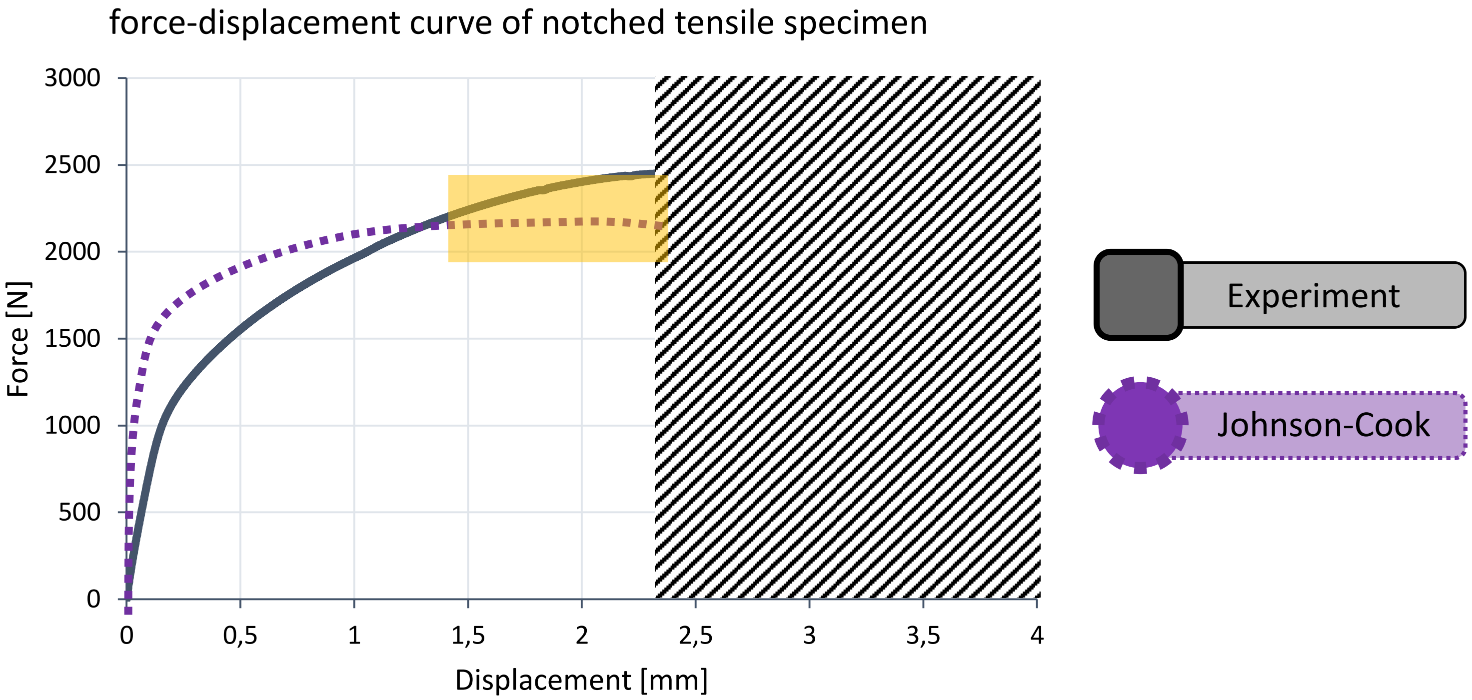




United States Patent No. 7,509,828 B2

https://www.wieland-thermalsolutions.com/de/rippenrohre/hochleistungsrohre

Motivation



Simulations based on material models from literature do not fit the experiments.
A manufacturer-specific flow curve needs to be created to make predictions with FEM.

Environment

LS-DYNA R11, GISSMO specimen geometry

Optislang,
Statistics on Structures

GOM Correlate
Professional

Important Basics

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Engineering Curve

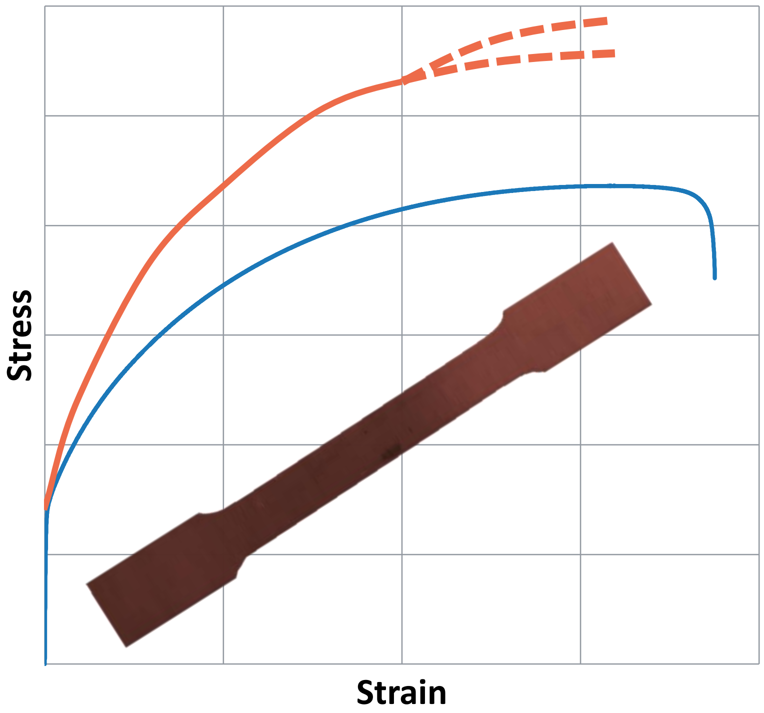
$$\sigma_{Eng} = \frac{\text{force}}{\text{area}_0}$$

$$\varepsilon_{Eng} = \frac{\text{disp.}}{\text{length}_0}$$

+ Easy

- Global

Difference between engineering and „true“ plastic curve



True plastic Curve

$$\sigma_{True} = \sigma_{Eng} \cdot (1 + \varepsilon_{Eng})$$

$$\varepsilon_{True} = \ln(1 + \varepsilon_{Eng})$$

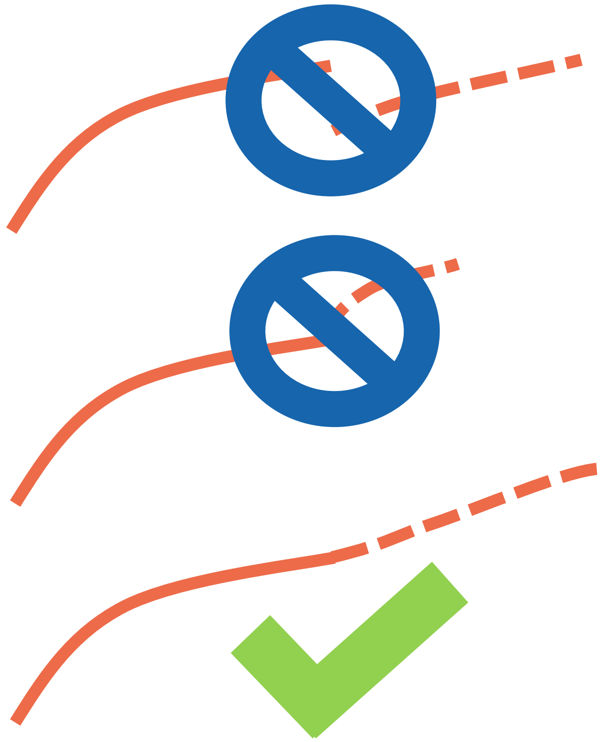
$$\varepsilon_{True,pl} = \varepsilon_{True} - \frac{\sigma_{Eng}}{E}$$

+ Universal

- Extension necessary

Important Basics

- Swift $\sigma_{True} = \cancel{K}(\varepsilon_0 + \varepsilon_{pl})^{\cancel{n}}$
- Voce $\sigma_{True} = \cancel{A} - \cancel{B} \cdot e^{-C \cdot \varepsilon_{pl}}$
- Hockett-Sherby $\sigma_{True} = \cancel{A} - \cancel{B} \cdot e^{-C \cdot \varepsilon_{pl}^{n}}$
- Johnson-Cook $\sigma_{True} = \cancel{A} + \cancel{B} \cdot \varepsilon_{pl}^{n}$
- And many more!



We eliminate two variables so c1 continuity is preserved.
I prefer Hockett-Sherby because the two remaining variables offer great flexibility.

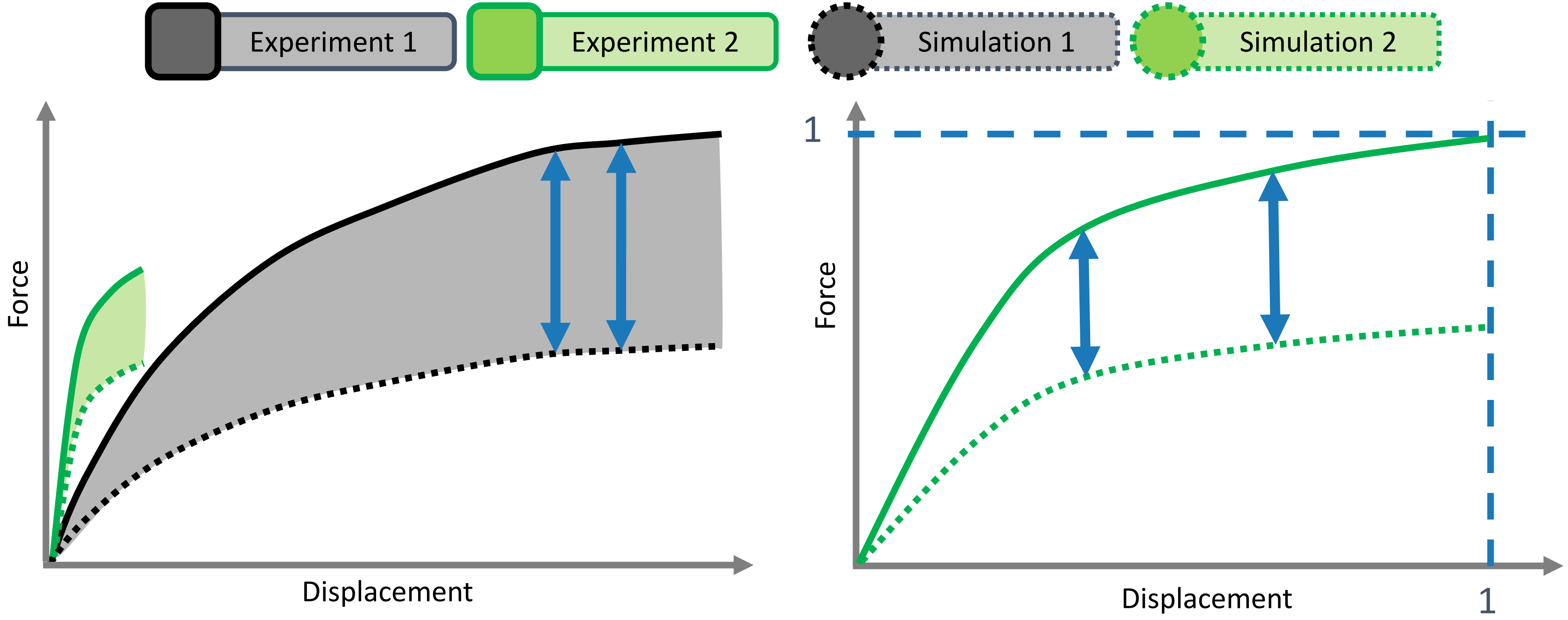
Important Basics

$$\text{Total Error} = \text{Error1} + \text{Error2} + \text{Error3} + \text{Error4}$$

Let us just define the total error as the sum of errors for each individual specimen.

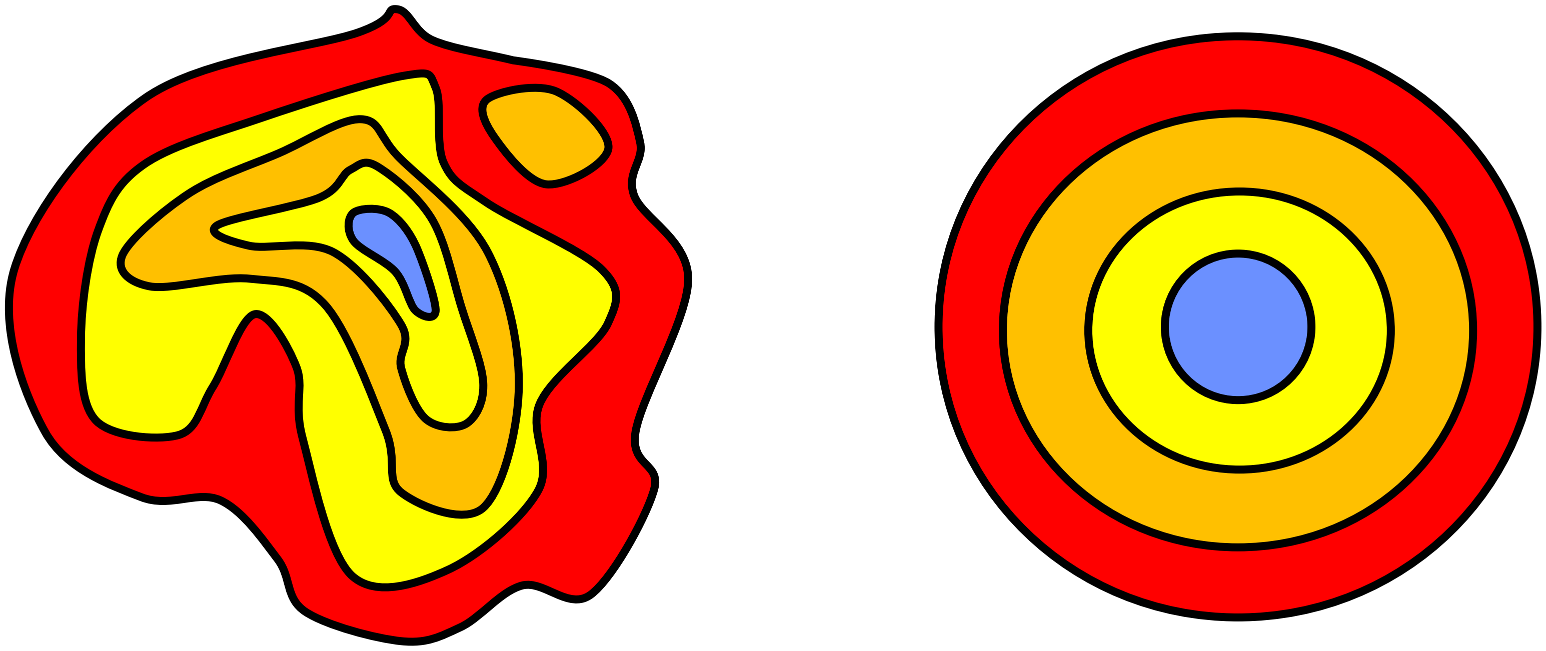
This is a simple approach but is a good description if no biasing occurs.

Important Basics



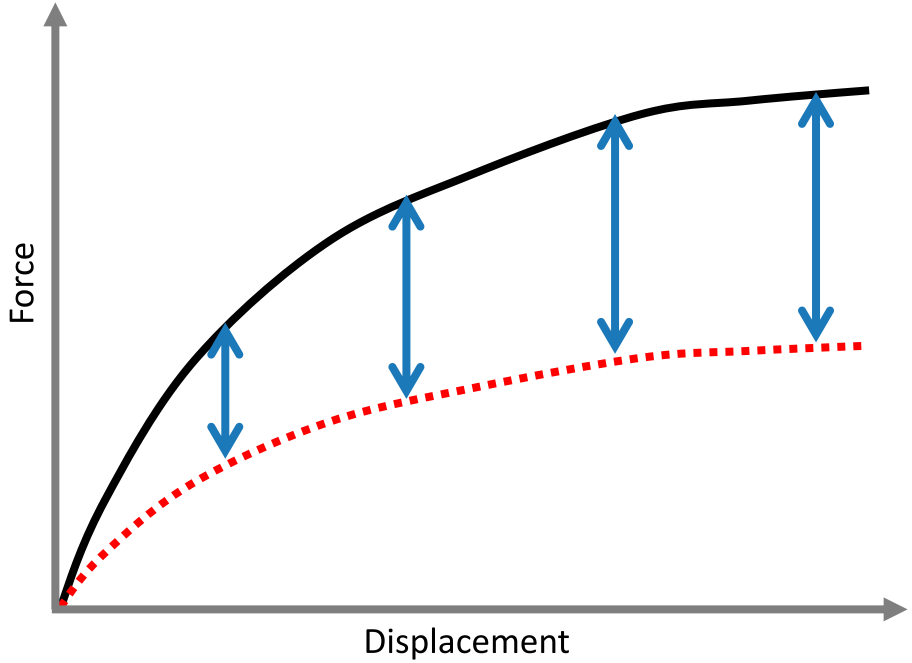
When undertaking a multi-objective optimization the data needs to be adjusted.
We eliminate inherent data bias by scaling and resampling.

Important Basics



All of this data processing serves to make our cost-function well-behaved.
Our way of measuring error should be robust so our MOP is accurate with few designs.

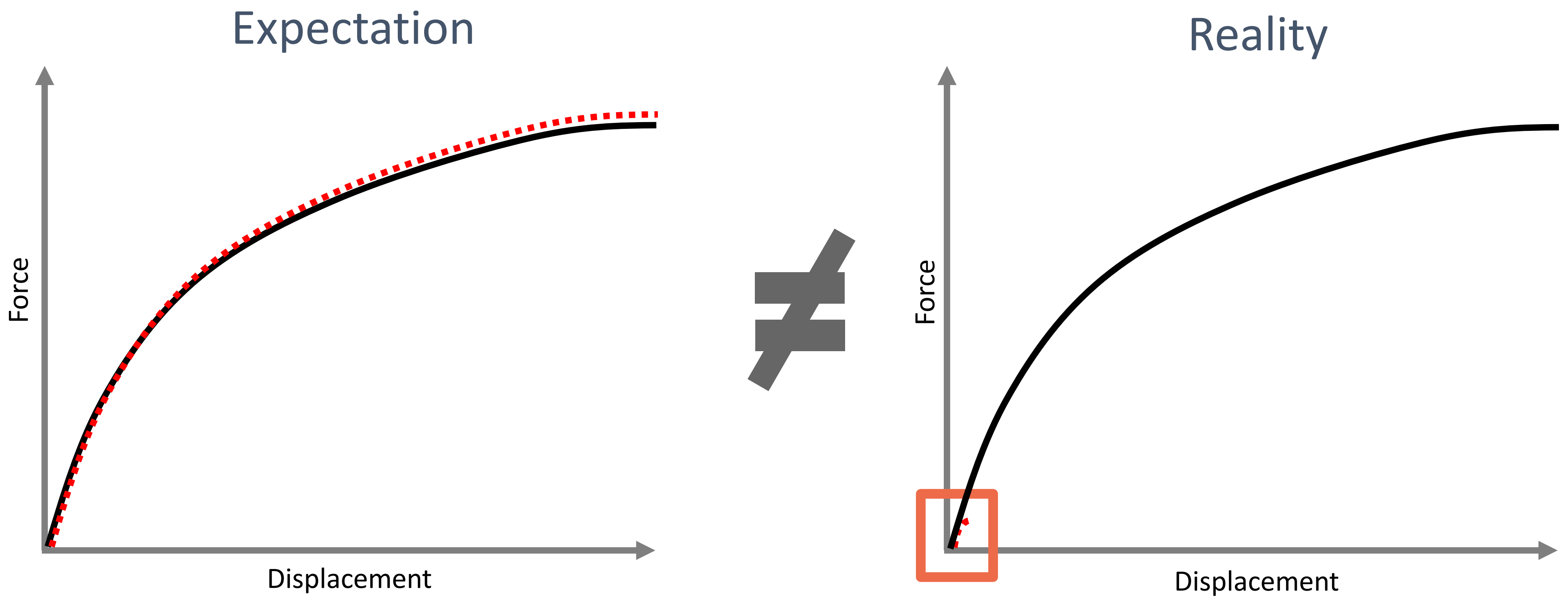
Global Response fit – RMSE



$$Error_{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \Delta y^2}$$

The easiest way to determine the difference between simulation and experiment is the root mean square error approach. Interpolation is required for this approach to work.

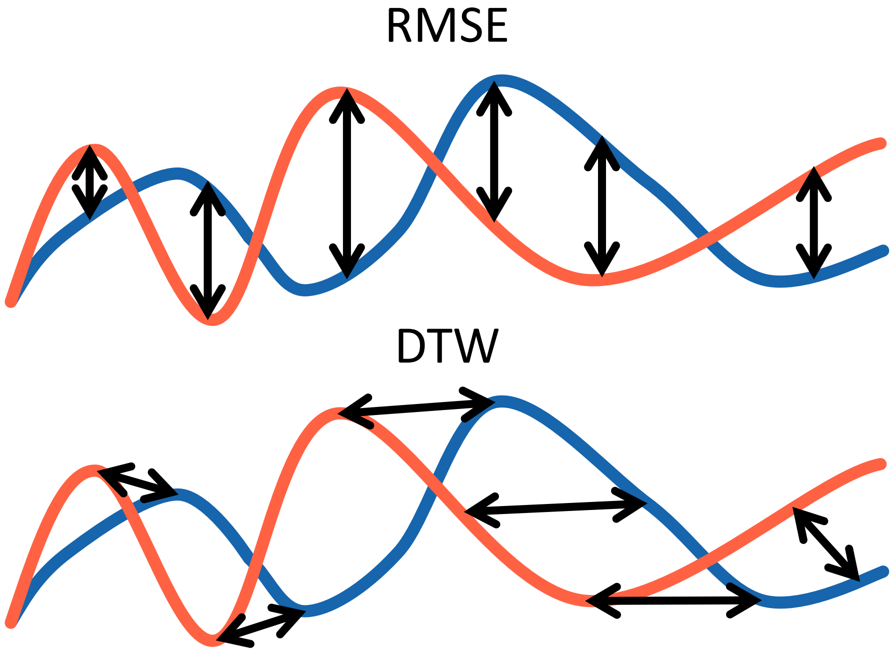
Global Response fit – RMSE



My error measure describes the optimum perfectly, however the behaviour is not robust and leads to many local minima which lead to a less than satisfactory optimization result.

Global Response fit – Dynamic Time Warping

https://www.cio.com/article/3239924/cios-listen-up-voice-recognition-meets-the-printer.html

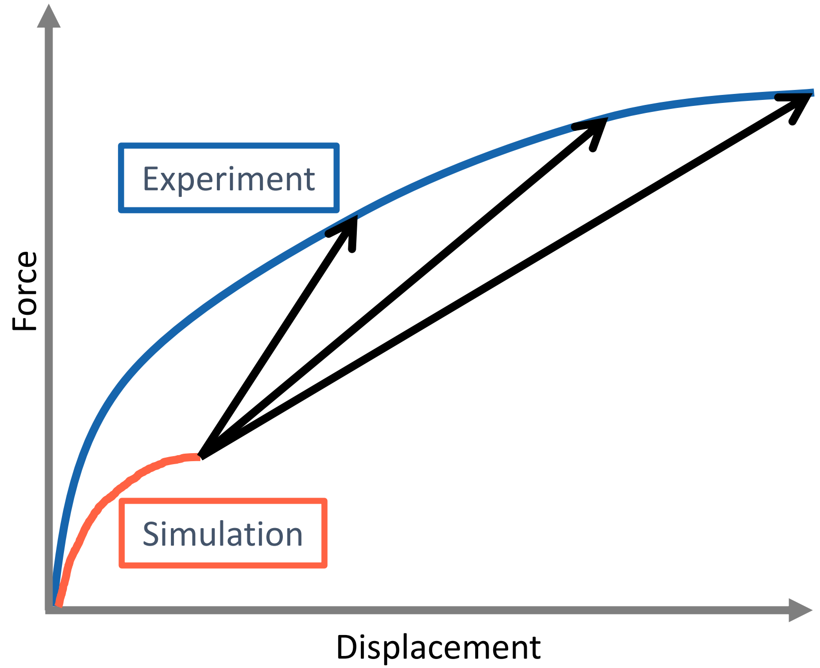


A great way of measuring the similarity between curves is dynamic time warping. Originally used in voice recognition it‘s applicable to material science as well.

Global Response fit – Dynamic Time Warping

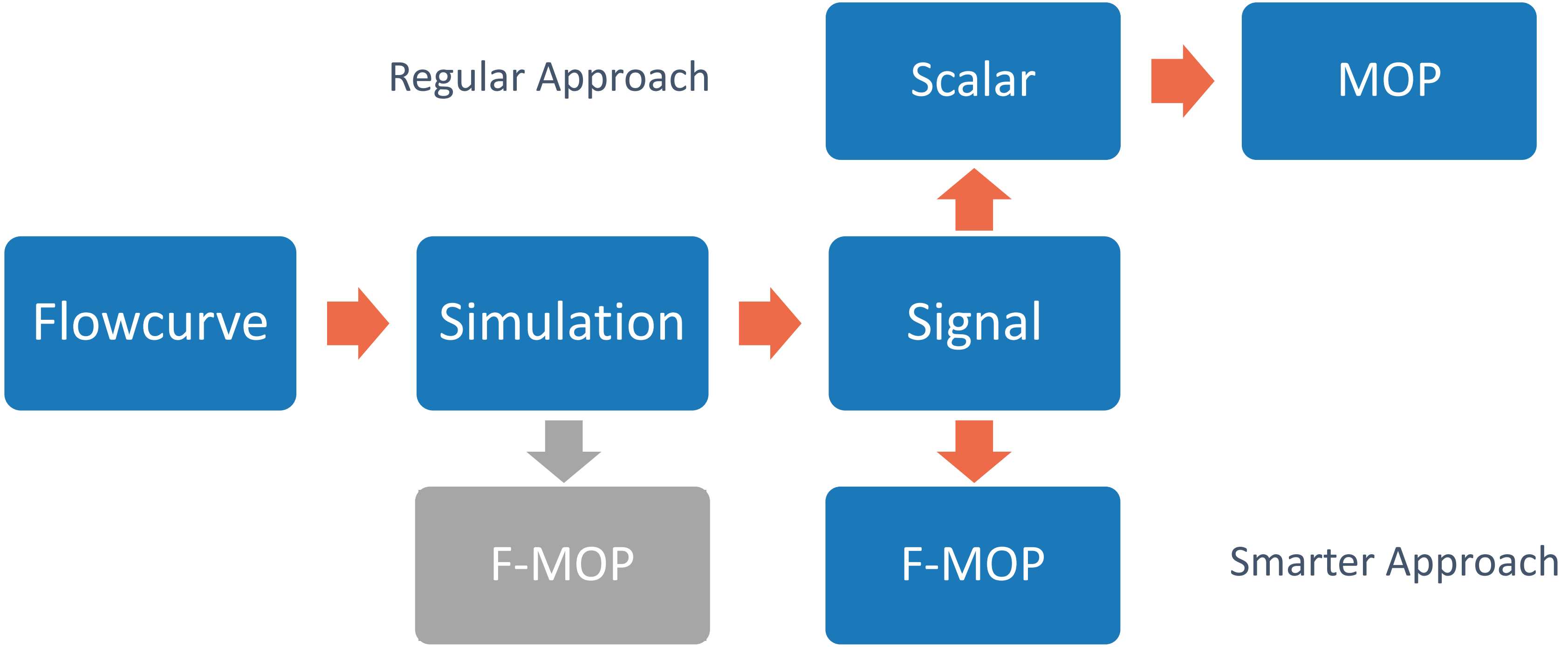
$$\begin{bmatrix} a_{00} & a_{01} & a_{02} & a_{03} & a_{04} & a_{05} & a_{06} & a_{07} \\ a_{10} & a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{20} & a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{30} & a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{40} & a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & a_{47} \\ a_{50} & a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & a_{57} \\ a_{60} & a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & a_{67} \\ a_{70} & a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \\ a_{80} & a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & a_{86} & a_{87} \\ a_{90} & a_{91} & a_{92} & a_{93} & a_{94} & \cancel{a_{95}} & \cancel{a_{96}} & \cancel{a_{97}} \end{bmatrix}$$

https://www.quora.com/How-do-I-create-a-rm-LaTeX-macro-that-generates-an-m-times-n-matrix



A matrix is produced by the DTW algorithm which pairs individual points of the signals. The distance (error) is easily quantified and agrees with my qualitative estimations.

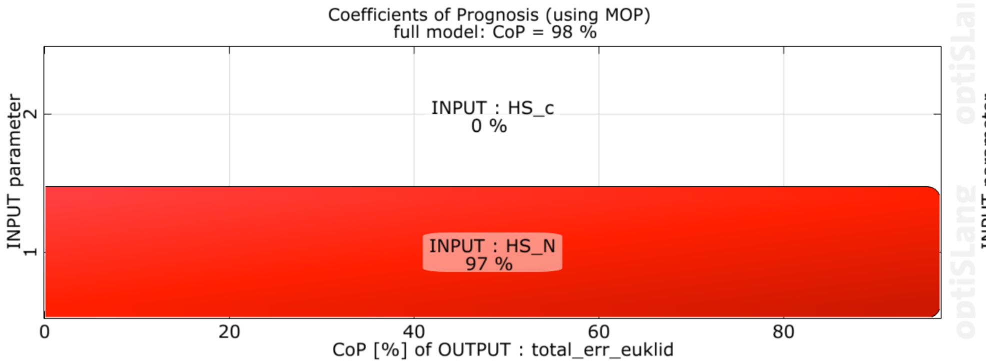
Global Response fit - SoS



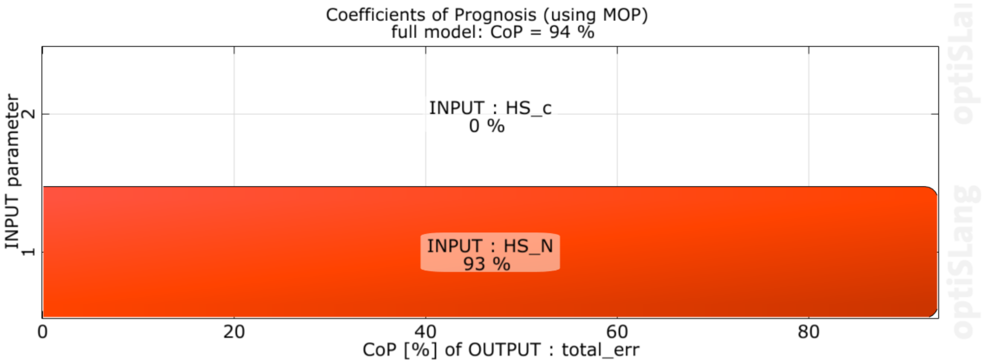
While the other approaches certainly work, using SoS is far more elegant and all the information we obtain in our signal can be used to gauge the sensitivity with a F-MOP.

Global Response fit – Comparison

RMSE

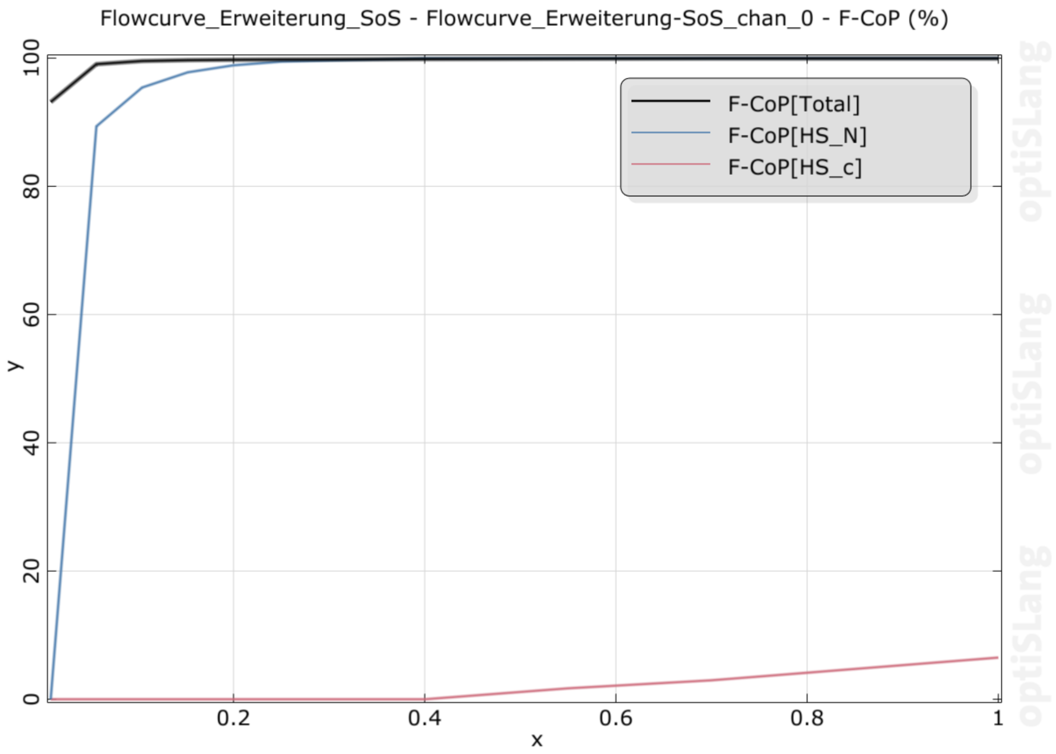


DTW



Judging from just the CoP you would think that RMSE is a better measure.
This is deceptive and not the case, otherwise I would not give this presentation!

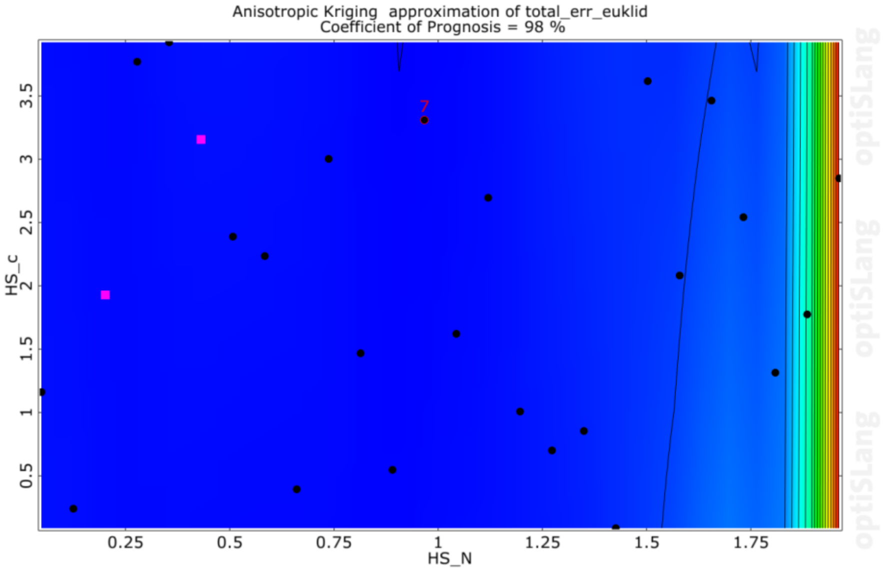
Global Response fit – Comparison



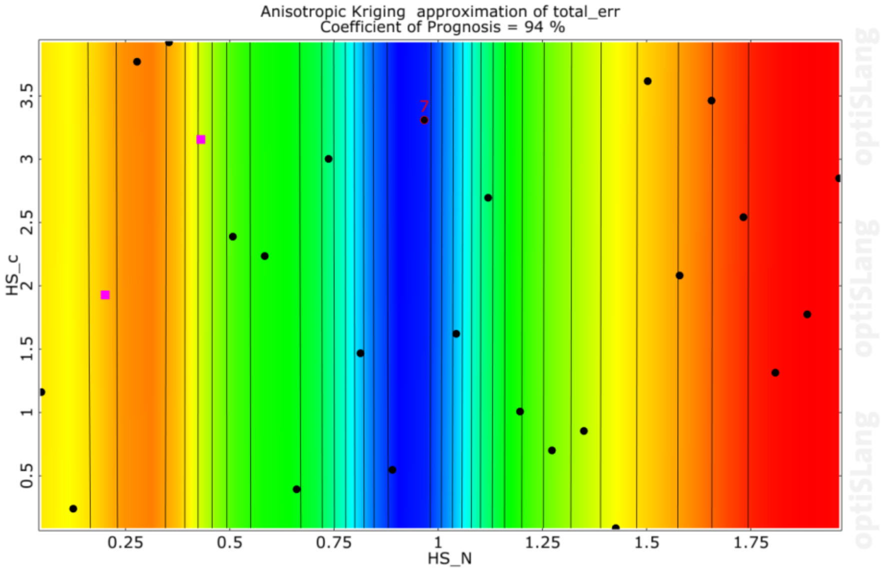
Of course, our variable C has a significant impact on the results but due to the large influence of N our MOP does not capture this. With SoS and its‘ F-MOP, the influence is easily shown.

Global Response fit – Comparison

RMSE



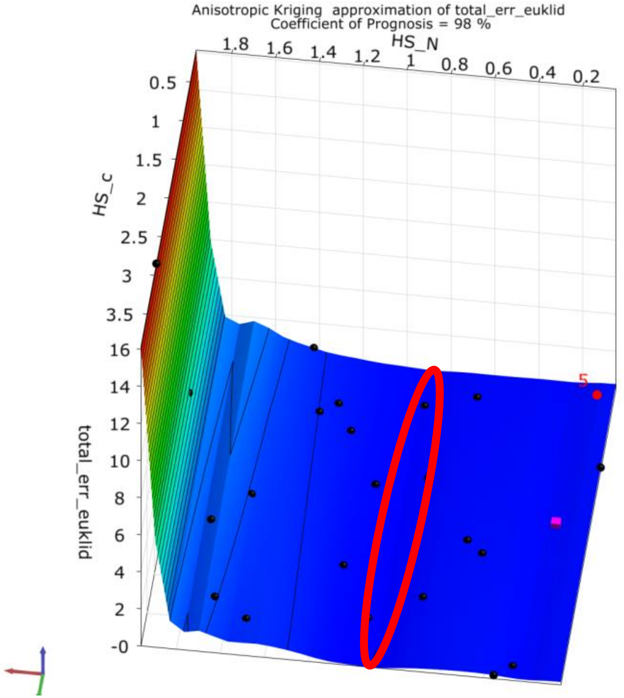
DTW



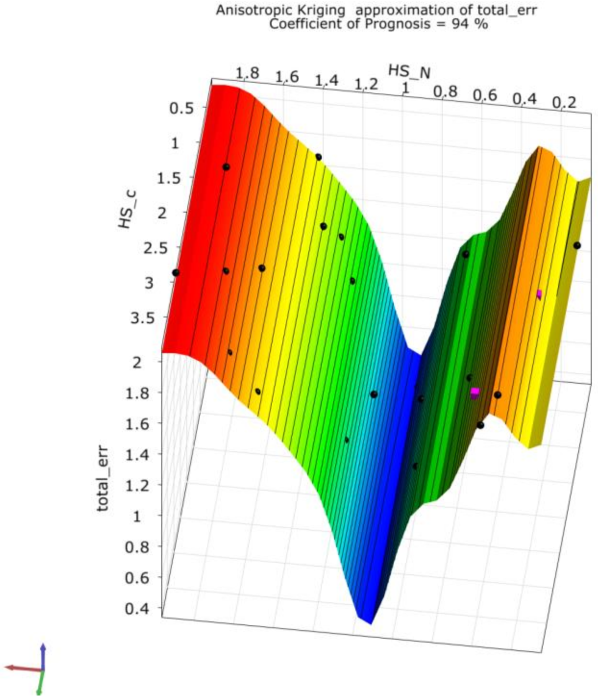
The response surface however, tells a very different story. While most of the area with RMSE is quite flat and kind of useless. With DTW every design provides information.

Global Response fit – Comparison

RMSE



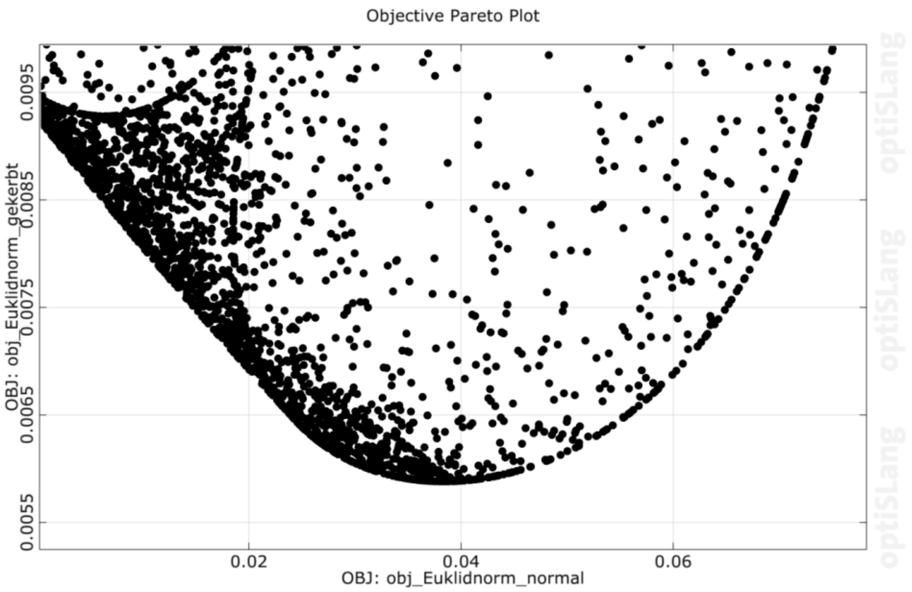
DTW



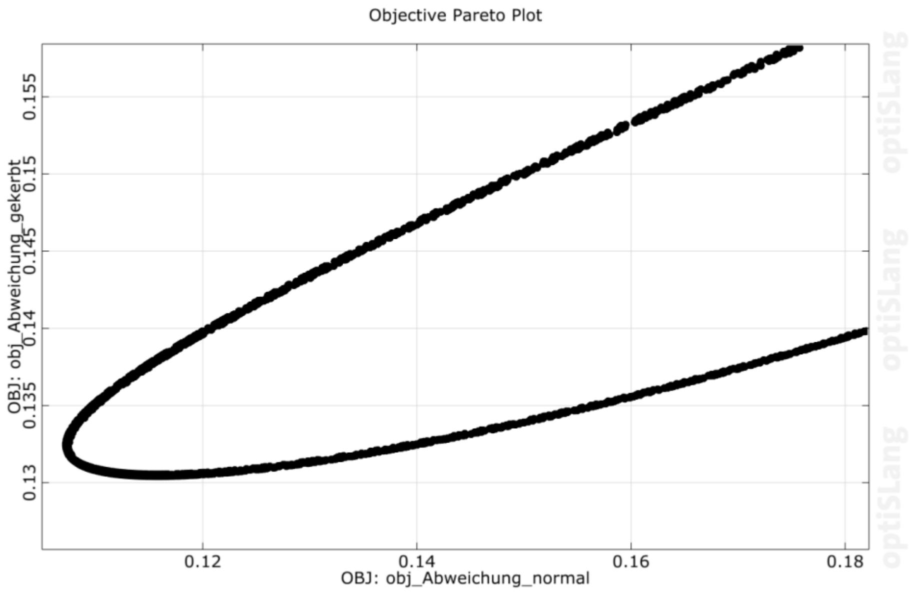
The response surface however, tells a very different story. While most of the area with RMSE is quite flat and kind of useless. With DTW every design provides information.

Global Response fit – Comparison

RMSE



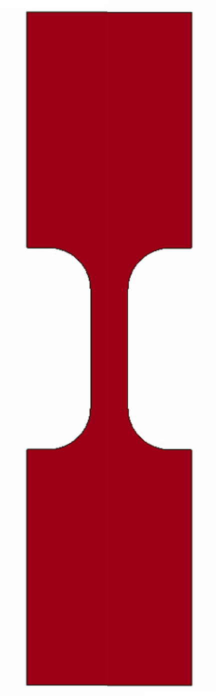
DTW

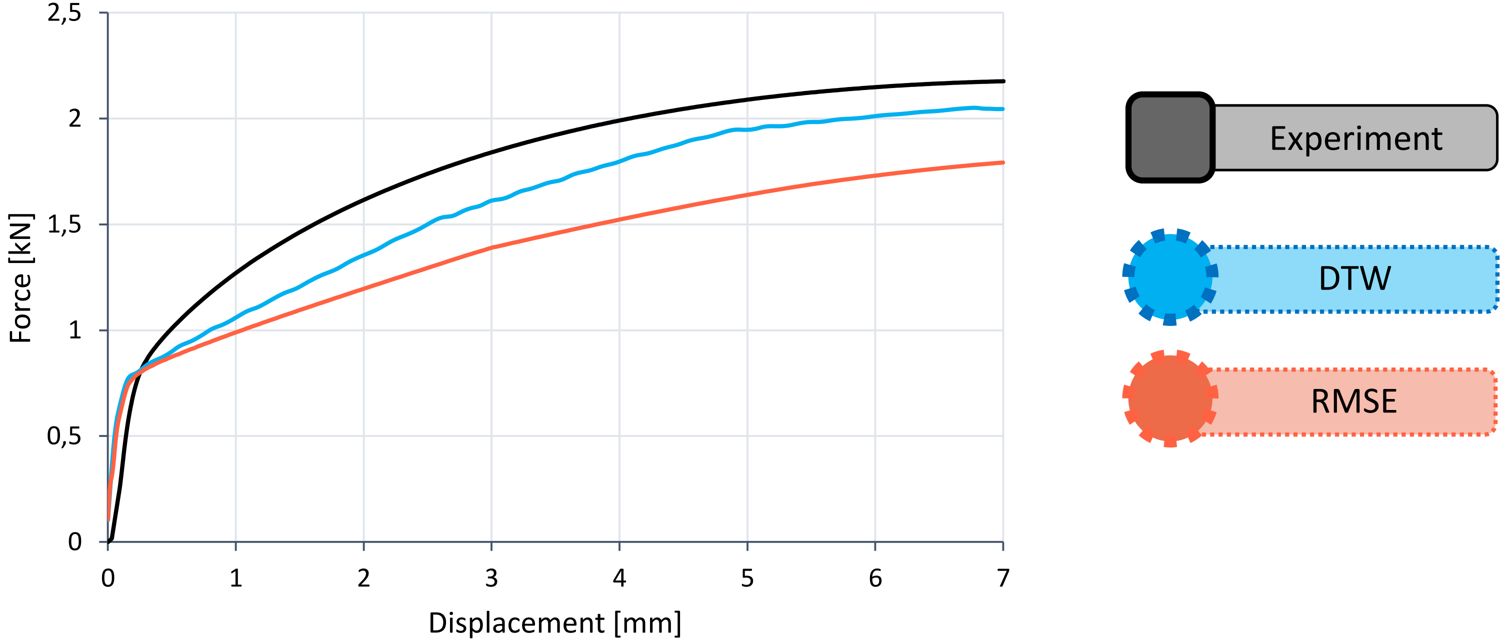


The results become even more apparent if you look at the pareto set.

With DTW we are able to detect our best design easily.

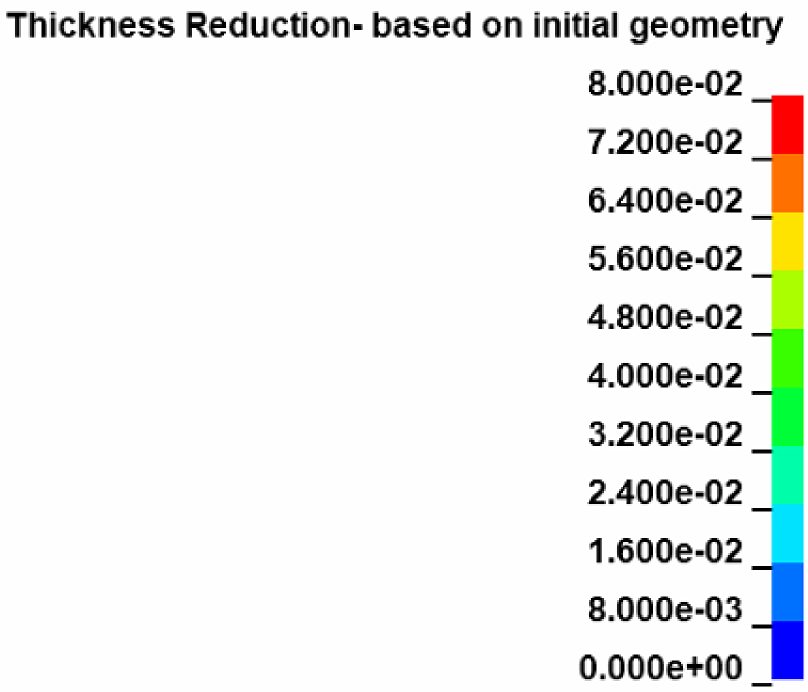
Global Response fit – Comparison





Both flowcurve parameters suggested by the MOPs do not fit the experiment exactly.
However, the suggestion based on the data from DTW is a lot closer.

Global Response fit - Outlook



Thanks to Digital Image Correlation (DIC) we can take a closer look at our „black box“ experiment.
In the future a fit based on the local reponse with SoS will reduce data loss.

Summary

Multiple adjustments to the data are necessary to remove bias:

- Normalize axes for all experiments and simulations
- Resample so every signal has the same amount of points

While a good CoP can be reached with these adjustments and RMSE, the MOP obtained is not suitable for an optimization.

Dynamic Time Warping is a better description of signal deviation and leads to a „well behaved“ MOP. The optimum in this MOP delivers acceptable results on another specimen.

Sources

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  IEEE Trans. Acoustic Speech and Signal Processing, V26, 1978

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