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

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

Engineering Curve

\[ \sigma_{\text{Eng}} = \frac{\text{force}}{\text{area}_0} \]
\[ \varepsilon_{\text{Eng}} = \frac{\text{disp.}}{\text{length}_0} \]

Difference between engineering and „true“ plastic curve

True plastic Curve

\[ \sigma_{\text{True}} = \sigma_{\text{Eng}} \cdot (1 + \varepsilon_{\text{Eng}}) \]
\[ \varepsilon_{\text{True}} = \ln(1 + \varepsilon_{\text{Eng}}) \]
\[ \varepsilon_{\text{True,pl}} = \varepsilon_{\text{True}} - \frac{\sigma_{\text{Eng}}}{E} \]

Easy

Universal

Global

Extension necessary

23.06.2020
Important Basics

- Swift
  \[ \sigma_{True} = K (\varepsilon_0 + \varepsilon_{pl})^n \]

- Voce
  \[ \sigma_{True} = A - B \cdot e^{-C \cdot \varepsilon_{pl}} \]

- Hockett-Sherby
  \[ \sigma_{True} = A - B \cdot e^{-C \cdot \varepsilon_{pl}^n} \]

- Johnson-Cook
  \[ \sigma_{True} = A + B \cdot \varepsilon_{pl}^n \]

- 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

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.

Total Error = Error1 + Error2 + Error3 + Error4
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.

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Global Response fit – RMSE

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.

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

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.

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

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!
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.
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

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Global Response fit – Comparison

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 response 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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  Proceedings of the Seventh International Symposium on Ballistics, 1983

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