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AN AUTOMATED PROCESS FOR SOLVING DUCTILE DAMAGE PARAMETER SELECTION USING MACHINE LEARNING AND FINITE ELEMENT ANALYSIS

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Abstract

In this work we show how a machine learning algorithm based on a Bayesian optimization framework can be used in conjunction with finite element analysis to autonomously select parameter values for a ductile damage model representative of experimental test data.

1. Introduction

Ductile damage is a common failure mechanism for engineering alloys, typically involving micro-void initiation, growth and coalesence[1]. Finite element analysis can successfully model ductile damage using analytical material models such as the Gurson-Tvergaard-Needleman (GTN) model[1] (The yield surface for the Gurson model is provided in Equation 1; additional equations define void initiation and final failure).

$$\Phi = \left(\frac{q}{\sigma_y}\right)^2 + 2q_1 f \cosh\left(-q_2 \frac{3p}{2\sigma_y}\right) - (1 - q_3 f^2) = 0 \qquad \textbf{Equation 1}$$

where q is equivalent (von Mises), p is hydrostatic stress, σ_y is yield stress, f is void volume fraction and q_1, q_2 and q_3 are material parameters. The GTN model requires parameter values, selected by the user (e.g. q_1, q_2 and q_3), to accurately predict the behaviour of experimental test data. However, selecting the appropriate parameter values is an iterative, time-consuming task subject to errors. Machine learning techniques offer solutions to solving such complex, multi-interaction engineering challenges. In this work Bayesian optimization, a machine learning algorithm that uses probabilistic methods, identifies parameter values likely to minimize the error between the experiment and simulated data based on a limited initial dataset. The algorithm iteratively selects new parameters and, using the commercial finite element code, Abaqus 2021[2] explicit solver, performs a new simulation. In this work we show the algorithm successfully applied to analysis of tensile test data for a martensitic steel (P91).

2. Results

Figure 1 shows results for P91 material tested at 20 °C. The error is measured in terms of mean absolute percentage error (MAPE), indicating the difference between the simulated Abaqus result and the experimental data over the range of the test data. Here we see that the Bayesian optimization algorithm successfully found GTN parameter permutations that are excellent approximations of the experimental data after 110 attempts (MAPE ≈ 2%).

3. Conclusions

- Bayesian optimization successfully selected parameters for the GTN model for three tensile test results. In most cases the optimized parameters provided an excellent fit when compared to experimental damage.

- The model has been successfully deployed to several experimental test results conducted at various test temperatures.

4. References

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Figures

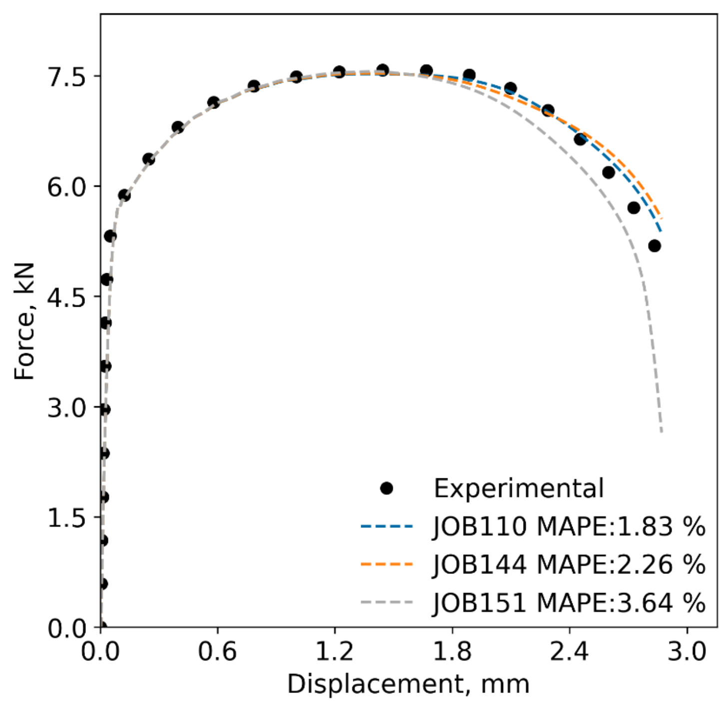

Figure 1 Comparison of experimental data with three Bayesian optimization results for P91 material at test temperature of 20 °C.