Data-driven crack assessment

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Micro Abstract

Different methods of selection and feature creation are considered in order to discuss the chances and limits of a data driven assessment of cracks. We apply different methods of data mining to find correlations which yield an unconventional approach for the prediction of critical crack states and material failure. The results of different explorative multivariate analyses will be compared and discussed in the context of applicability in engineering science.

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Introduction

The existing approaches of the assessment of engineering system - introduced and enhanced in the last century - are mainly based on the consideration of physical relationships and the striving towards a full understanding of the driving mechanisms of material and structural behavior. However, the complex interplay between materials and structures in many applications or production processes is still an object of research and is not fully understood and computable yet. This yields the necessity of an incorporation of high safety parameters and in some fields an application of quite conservative assessment procedures. At the same time, the ongoing digitalization of the construction and production processes in all fields of engineering provides an increasing amount of available data, which yields, e.g. exact geometries of particular specimen, material usage, and information about process chains. The advancing progress in sensor technology enables the incorporation of sensors in almost all types of systems and materials, thus the collection of precise system data in real-time is a manageable task today. However, there exist only a few approaches to incorporate knowledge gained from collected process data into the component assessment process up to now. Related to the field of inverse engineering, data driven approaches can be found e.g. in [1–4].

In this contribution, we mimic an experimental setup of a simplified bending specimen controlled by surface sensor data. We apply different methods of data mining to find correlations which yield a data-driven approach for the prediction of critical crack states and material failure. The results of different explorative multivariate analyses are computed and discussed in the context of the applicability in engineering science. A focus is put on the feature creation and selection in order to yield a systematic approach of data driven crack assessment.

1 Engineering system and feature creation

A three-point bending specimen, see Fig. 1, with a notch and a predefined crack in the symmetry plane is modeled using FEM. A plane strain state is assumed and an adaptive mesh around the crack tip is applied. It is assumed that geometry and material parameters are subjected to a mean variation in real systems. Therefore, we consider variations to some of the system parameters: The geometry is varied by the notch angle ($\alpha \in [15^\circ; 105^\circ]$) and an initial crack length ($l \in [0; 0.2 \text{mm}]$). The elasto-plastic material behavior of the specimen is defined by the Young's modulus E=210GPa (±10%), Poisson's ratio $\nu = 0.3$, and a prescribed isotropic plastic yield function with the yield stress $\sigma_y = 460 \text{MPa} (\pm 10\%)$. Simplified, here just the normal and



Figure 1. Three point bending specimen.

the shear failure stresses are varied, given by $\sigma_f = 550$ MPa and $\tau_f = 0.75 \cdot \sigma_f$ with a standard deviation of $s_{\sigma_f} = 0.1 \cdot \sigma_f$.

A stress based failure criterion for the interface elements along the symmetry axis is defined by

$$f = \sqrt{\left(\frac{\sigma_n}{\sigma_f}\right)^2 + \left(\frac{\tau_n}{\tau_f}\right)^2} \ge f_{crit} \tag{1}$$

The failure criterion is assumed to characterize the state of the crack during the loading and will determine further crack opening if the corresponding nodal value overcomes the critical value $f_{crit} = 0.9$.

A number of 65k simulations has been processed applying an external loading by an increasing boundary displacement in the symmetry axis on the opposite side of the notch. The results of the displacements, the stresses, the maximum stress value and its position in each load step are measured along the cracked surface and saved in a data set. Then, a systematic feature creation has been applied to the data in order to identify characteristic values in the curve progression of the relations of all known input parameters related with computed output data, e.g. slope change, max, min, mean values, area under the curves. So, a number of 25 features has been identified, as exemplarily shown in Fig. 2.



Figure 2. Two examples for the selection of features.

2 Data analytics

A mapping of the failure criterion based on simulation data describes a n-dimensional space. The dimensionality is reduced by the restriction to a set of chosen, predefined input and surface output data. However, the functional $F \in f(\text{known parameter, output data})$ correlated with an applied loading is unknown and not easy to derive by classical engineering methods. Therefore, the statistical learning techniques of multiple regression, decision trees, and boosted trees are



Figure 3. Examples for derived features F_i .

used to evaluate a data-driven engineering approach. It is considered to be important that the techniques are applied in a manner, that the procedures yield a clear demonstration of physical correlations and avoid the creation of a 'black box' method.

First, a selection of data including geometry, material, and loading information, considered simulation output data, and prediction variable is preprocessed for all 65k simulations. On these data, we identify characteristics by subset feature selection filters and apply statistical classification in order to distinguish between specimen with stable and critical crack states. Based on the identified features - a selection is shown in Fig. 3 - a simple tree-based decision method is trained for the prediction of the failure criterion, see Fig.4, which shows good results. However, the loss of accuracy is significant, if the considered training data are reduced to an



Figure 4. Three point bending specimen.

early stage of specimen loading. This can be enhanced by the application of the boosted tree method, which couples sequentially grown trees by updating the current residuals. The method is compared with an approach of multiple regression, which couples the identified features F_i in a prediction function for the failure criterion f.

$$f = \sum_{i=1}^{n=25} \alpha_i F_i + C \tag{2}$$

3 Results

The prediction of the failure criterion as indicator for the critical crack state is based on a multiple regression considering features of correlated in- and output variables. We distinguish between a prediction of the actual failure criterion, yielding an assessment of the present crack state based on surface data, and a prediction of the failure criterion in a later load step, see Fig. 5.



Figure 5. Prediction of failure criterion in actual load step (left). Prediction of failure criterion for 'future' load step (right).

The results show, that an evaluation of the failure criterion based on surface data is possible. The prediction of the further development of the stress state in the crack tip region loses accuracy with increasing prediction intervals. However, the results suggest that the procedure is applicable at least as an indicator for the remaining life time of the specimen.

Conclusions

A study of crack assessment by the systematic evaluation of surface data of a bending specimen showed the applicability of data-driven techniques to predict materials failure and critical states of a specimen. The reasonable creation of features in the context of data mining is found to be most important to yield a reliable procedure of component assessment.

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References

- A. Agrawal, P. Deshpande, A. Cecen, G. Basavarsu, A. Choudhary, and S. Kalidindi. Integrating Materials and Manufacturing Innovation, Vol. 3(1):p. 468–493, 2014.
- [2] A. Chakraborty and P. Eisenlohr. European Journal of Mechanics-A/Solids, 2017.
- [3] N. Huber and C. Tsakmakis. Journal of the Mechanics and Physics of Solids, 47(7):1569–1588, 1999.
- [4] Y. Wen, C. Cai, X. Liu, J. Pei, X. Zhu, and T. Xiao. Corrosion Science, 51(2):349-355, 2009.