41

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Elastic-plastic characterisation of aluminium bearing alloys

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Abstract. A method is proposed to determine the elasto-plastic properties of a thin aluminium alloy lining of a bearing system from micro-indentation tests. This indentation process was modelled using an axi-symmetric FE model which was validated against experimental force-indentation curves from materials with known elasto-plastic properties. A fuller database of force-indentation curves has been generated by running the FE model with a range of elasto-plastic properties. This larger database has been used in adaptive numerical modelling to derive a generic model for the indent size as a function of load, elastic limit, yield strength and strain hardening coefficient and exponent in aluminium alloys. The adaptive numerical model was subsequently used to interpolate between the time-intensive FE results. Based on iterations of the most appropriate adaptive model, the elastic limit, yield strength and strain hardening exponent of a bearing alloy have been determined from the experimental micro hardness force-indentation depth curves for the same material.

Introduction

Elastic-plastic properties of thin layers are hard to assess experimentally. These properties may be required to investigate the development of local stresses/strains within such layers. In bearing linings a complex rolling and heat treatment procedure is used to produce the final bearing and the properties of the lining are no longer the same as the original alloy billet and may vary spatially. Micro-hardness indent size variation with load may give some insight into the elastic-plastic properties of such thin layers. The aim of this paper is to establish a method to obtain elastic-plastic material properties from micro-hardness tests.

There has been a long history of experimental and analytical studies on the relation between indentation data of various kinds and elasto-plastic parameters. Tabor's [1] work with spherical indenters was among the most prominent early contributions. More recently, the emphasis of such investigations has shifted to the systematic use of the finite element method (FEM) [2,3]. It seems however that no previous attempt has been made to combine FEM data with adaptive numerical modelling (ANM) techniques which offer the advantage of obtaining optimum correlations with considerably reduced computing effort.

Methodology

The Vickers micro-hardness testing technique uses a square-based diamond pyramid as an indenter. In this paper the actual parameters measured during tests are the diagonal size of the indentation and the applied load so that the force-indentation relations can be plotted. Initially, micro-hardness tests and subsequent FE modelling were carried out on aluminium alloys with known elasto-plastic properties. The true stress-logarithmic strain curves of the analysed materials are shown in Fig. 1. The alloys considered were: AS1241, an Al-Sn-Si bearing lining alloy in a condition similar to that used in the finished bearing, B1Q2 and B1Q3, two differing extrusion batches of a 2014A Al alloy, and RTWQ and VQ1B, two differing extrusion batches of a 6082 Al alloy.

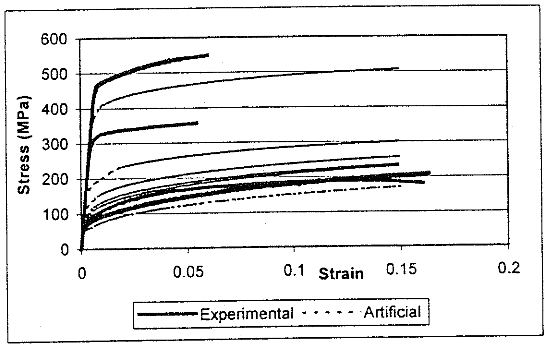

Fig. 1 True stress-logarithmic strain curves for experimental results and artificial curves used for FE

FE model

The FE model was generated using the general-purpose finite element package ANSYS [4]. Initially, a 3D Vickers model was developed to simulate the indentation process. The geometry of the process is symmetric with respect to four vertical planes. Applying these symmetry conditions in the modelling, only one-eighth of the specimen and indenter need be modelled. An axi-symmetric model was also developed to be compared with the 3D model. In this model the indenter was represented by a cone instead of the real square-based diamond pyramid. To achieve the same indentation effect, the corner angle is calculated based on the assumption that the cross-sections should be the same when the cone and the square-based pyramid indenter produce the same indentation depth. The bulk of the specimen was modelled using a 4-node solid axi-symmetric element. The results from the 3D model and the axi-symmetric model for an Al alloy with known elasto-plastic properties are given in Figure 2, which indicates that both these models produce results comparable to the experimental results. Considering the obvious advantage of the axi-symmetric model regarding computational time, the simpler model has been used in subsequent analyses.

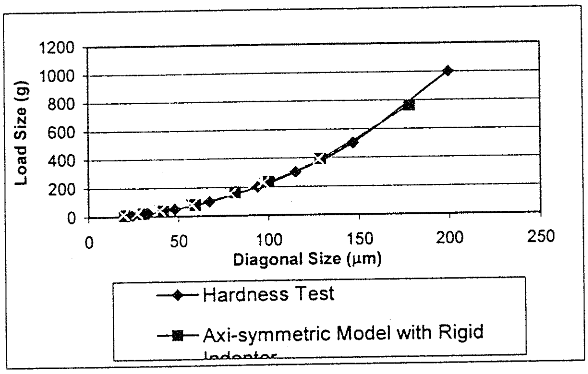

Fig. 2 FE results validation

A larger database of load indentation curves was then generated by running the FE model for a wider range of elasto-plastic properties, as shown in Figure 1, where the "artificial" stress-strain ($\sigma-\varepsilon$) curves can be compared with the experimental curves. In the case of each $\sigma-\varepsilon$ curve, 4 descriptors of the curve were identified: the elastic limit, σ_{el}, the 0.2% proof stress, $\sigma_{0.2}$, and the two stain-hardening parameters A and n, assuming that the plastic behaviour beyond $\sigma_{0.2}$ is described by:

$$\sigma = A\varepsilon^n \quad (1)$$

The Young's modulus, E, was taken to be 70 GPa in all cases. Independently varying all these input variables is not appropriate as they are correlated (particularly yield stress and A and n) so self-consistent sets of inputs that describe a curve had to be generated in all cases. In terms of an adaptive numerical modelling dataset, the indent size could then be taken to vary as a function of these 4 parameters and the applied load, P.

Adaptive numerical modelling

A dataset consisting of inputs, $x_1, x_2 \ldots x_n$ which are believed to contribute to an output (property) y can be assessed by many possible regression approaches. Purely adaptive numeric modelling (ANM) methods will search for non-linear relationships for the mapping between $x_1, x_2 \ldots x_n \Rightarrow y$ without needing any specification of the form of the relationship. These methods (e.g. neural networks) may be considered as statistical, or machine learning, techniques, and are many and varied and new ones are developed continuously. They can be of considerable help in the analysis of complex problems, where a detailed understanding has not yet been reached, by supplying specific (though often highly complex) mathematical equations linking the inputs to the properties and allowing predictions. Other examples of ANM methods applied to Al alloy property modelling have been reported elsewhere.[5,6,7] A necessity with ANM techniques is well-distributed and plentiful data – allowing the "best fit" to the data to be obtained unambiguously. Unfortunately, with experimental work, obtaining sufficient well-distributed data may be a lengthy and expensive process, and this was the case for the current work. Consequently, the use of FE to supply us with additional data not only greatly enlarged our data set but since we could specify/design some of the properties of the simulated materials, we were able to fill gaps in the input data space, not covered by the experimental data; thus increasing the applicability of the ensuing models.

The method used in this work, SUPANOVA [8], is based on support vector machines and supplies sparse models of specified complexity (based on an ANOVA [9] decomposition); for this study we chose models containing additive uni-, bi-, and trivariate terms (depending on one, two and three inputs, respectively). This kept the resultant models relatively simple, hence ensuring transparency (i.e. an understanding of how the inputs affect the output property prediction) whilst still allowing considerable flexibility (i.e. good predictive fit).

In terms of the dataset produced here, 40 datalines were available for the purely experimental dataset, where micro-hardness indentation size variation as a function of applied load and varying elastic-plastic properties was known (5 inputs giving one output). For the extended dataset (experimental and FE) the number of datalines was extended to 93, enabling a more robust SUPANOVA model to be generated. In both cases, 90% of the data was used as training data to define the model and 10% of data was reserved as "unseen" or test data to assess the performance of the model. The training and testing data were randomly selected 10 times to assess the effect of data sampling on the models produced. Predictions presented here are therefore averages of the 10 models produced by the 10 data sampling runs. Consistency of input selection by the sparse ANOVA representation of SUPANOVA was also assessed as it revealed the stability of the modelling process.

SUPANOVA model results

Table 1 SUPANOVA model stability and prediction accuracy

Input		Dataset: Experimental	Dataset: Experimental and FE
P	Univariate terms	100%	100%
n	Univariate terms	50%	80%
A	Univariate terms	-	10%
σ_{el}	Univariate terms	-	20%
P & n	Bivariate terms	100%	100%
P & A	Bivariate terms	-	10%
P & σ_{el}	Bivariate terms	-	10%
P & $\sigma_{0.2}$	Bivariate terms	-	10%
P & $\sigma_{0.2}$ & A	Trivariate terms	90%	30%
P & σ_{el} & A	Trivariate terms	10%	10%
RMSE on indent size prediction		3.686μm	3.756 μm
Experimental: Indent size $=f(P)+f(P\&n)+sometimes\ f(n)+sometimes\ f(P\&\ \sigma_{0.2}\&A)+sometimes\ f(P\&\sigma_{el}\&A)$			
Experimental and FE: Indent size $=f(P)+f(P\&n)+sometimes\ f(n)+sometimes\ f(A)+sometimes\ f(\sigma_{el})+sometimes\ f(P\&A)+sometimes\ f(P\&\sigma_{el})+sometimes\ f(P\&\sigma_{0.2})+sometimes\ f(P\&\sigma_{0.2}\&A)+sometimes\ f(P\&\sigma_{el}\&A)$			

The predictions from the SUPANOVA model for the experimental dataset reveal that a univariate load term and a bivariate term of $P\&n$ always contribute to the output, and sometimes the function picks up the trivariate terms $P\&\sigma_y\&A$ and $P\&\sigma_e\&A$. Whereas for the more data-rich experimental and FE combined dataset we see a more complex input selection. The predictive performance is summarised in terms of the root mean squared error (RMSE) on the indent size prediction which is similar for both datasets (accuracies to within approximately 4 μm were achieved). Due to the better dataset distribution for the combined experimental and FE dataset, the results from SUPANOVA models based on this dataset were used for the next step of the modelling process.

Using the SUPANOVA model

Comparisons of force-indentation relationships with known $\sigma-\varepsilon$ experimental curves and the particular force-indentation relationship for an AS16 bearing lining (an Al-Sn alloy) with unknown properties enabled identification of the likely range of input values. A further series of $\sigma-\varepsilon$ curves were generated using the SUPANOVA model around the likely input values of interest, with systematic variations in elastic limit, yield point and strain hardening exponent. The MSE in the force-indentation curves produced by the SUPANOVA model and the force-indentation curve of interest was then assessed. This identified 3 possible $\sigma-\varepsilon$ curves that all gave similar low MSE (~50 μm^2) in the SUPANOVA predictions of their force-indentation curves c.f. the AS16 force-indentation curve. Figure 3 shows the 3 different $\sigma-\varepsilon$ curves identified as giving the closest fit to the force-indentation curve of interest. These curves have fairly significant differences in yield stress and n.

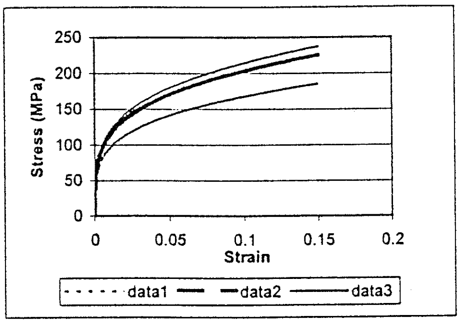

Fig. 3 σ–ε curves

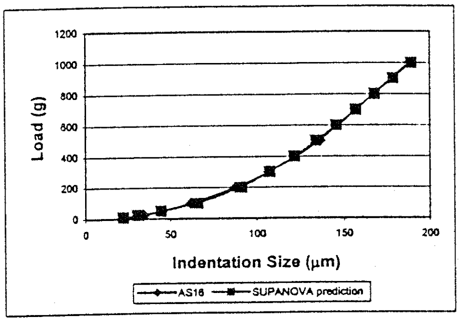

Fig. 4 The SUPANOVA prediction

For each of the 3 curves, a MATLAB program combined with the SUPANOVA model was then used to further minimize the MSE by varying the elastic limit, yield point and strain hardening exponent by very small increments systematically. The lowest MSE from all possible variations (e.g. increase yield point, leave other two constant, or all three parameters increase, etc.) was selected and the corresponding varying input was chosen as the new input curve. A final comparison between the three sets of data enabled the σ–ε curve of the unknown property AS16 alloy to be identified. Figure 4 shows the experimentally measured force-indentation curves of the bearing aluminium alloy layer and the SUPANOVA model prediction based on the optimum σ–ε curve. This newly-determined σ–ε curve has then been used to re-calculate the plastic strain amplitude experienced during fatigue testing of AS16 bearings. Figure 5 shows the fatigue lifetime of the AS16 bearing system as a function of calculated plastic strain amplitude, one calculation is based on the known σ–ε curve for a similar bearing (AS1241), while the other is based on σ–ε curve derived from the SUPANOVA model prediction. The difference in the two curves indicates the necessity of accurately accounting for the σ–ε relations of the aluminium alloy lining when investigating the fatigue behaviour of the bearing.

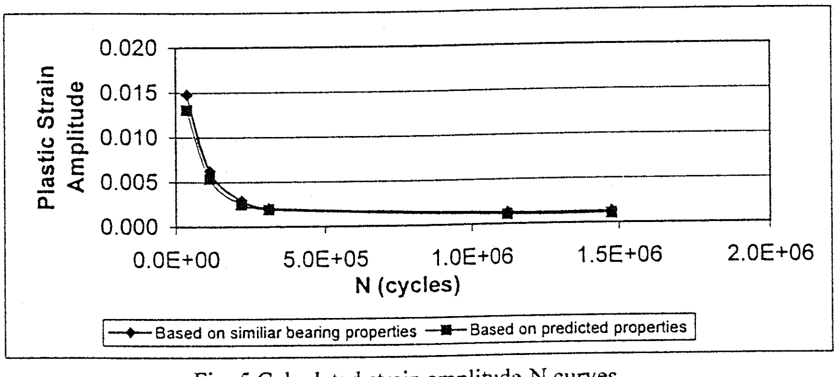

Fig. 5 Calculated strain amplitude-N curves

SUMMARY and conclusions

This paper has described a method to identify the elasto-plastic material properties of a thin layer of a bearing system from Vickers micro-hardness tests. An axi-symmetric FE model simulating the Vickers micro-hardness process was developed and validated. A fuller database of force-indentation curves was generated for a realistic range of all relevant material properties. Adaptive numerical modelling methods to enable prediction of the indent size as a function of load and all the key elasto-plastic properties considered. The adaptive numeric models were then used to generate large numbers of force-indentation curves with systematic variations in input values. Optimization work was then undertaken based on those datasets that gave the closest fit to experimental force-indentation curves of interest. Thus the $\sigma-\varepsilon$ curve of bearing lining alloys can be determined directly from the optimization curve, which has the best fit to the micro-hardness force-indentation depth curve determined in the thin lining.

Among all the variables, the yield stress and n appear to have greater influence on the predicted indentation (in addition to the expected effect of the applied load). The prediction accuracy can be improved in the future with more experimental load- indentation data and more consideration to the representation of key elasto-plastic parameters.

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