6th International Conference on Creep, Fatigue and Creep-Fatigue Interaction (CF-6)
Mamallapuram, India, January 22-25, 2012

ANALYSIS OF DAMAGE IN HIGH STRENGTH STEELS

Arpan Das[*a], S. Sivaprasad[a], S. K. Das[b], M. Tarafder[c] and S. Tarafder[a]

[a]Fatigue & Fracture Group, [b]Structural Characterisation Group

(*Council of Scientific & Industrial Research*), Jamshedpur 831 007, India

e-mail: dasarpan1@yahoo.co.in

Abstract

In continuum damage mechanics (CDM) approach, *damage accumulation* takes place through void nucleation, growth and coalescence. It is controlled by the chemistry of the material, initial inclusions or second phase particles' fractions with their size/shape distribution, stress triaxility, strain, stress, strain rate, strain path, grain size, initial crystallographic microtexture and temperature of deformation. In this study, a model has been developed to calculate the complex relationship between the extents of damage accumulations (i.e. void area fraction) with its influencing parameters in a variety of high strength low alloy steels under tension. The model has been applied to confirm that the predictions are reasonable in the context of metallurgical principles.

Key words: void volume fraction, high strength low alloy steels, Bayesian neural network, ductile fracture micromechanisms, damage accumulations.

1.0 Introduction

Ductile fracture progresses through three stages namely void nucleation, void growth and coalescence under the influence of favourable plastic strain and hydrostatic stress, which is well established [1]. Considerable analytical and experimental research work on the nucleation, growth and coalescence of voids has been performed. The preferred sites for void nucleation are inclusions, second phase particles, or fine oxide particles.

There are extensive amount of theoretical, experimental and modelling work on the topic, ductile fracture micro-mechanisms by several pioneer researchers; some are required to mention in this context. Rice and Tracy [2] had shown that void growth increases exponentially with the hydrostatic stress. McClintock [3] investigated that fracture by coalescence of voids would be promoted by a high level of stress triaxility. Gurson [1] developed a constitutive model where a yield occurs for porous ductile material. Tvergaard [4] used constitutive model for describing ductile failure and void growth is the Gurson-Tvergaard model. Garrison and Moody [5] explained that low strength material exhibit very low tensile ductility if the volume fraction of a void nucleating second phase is sufficiently high.

There are many studies monitoring the accumulation of voids during the tensile deformation (i.e. just after UTS) of published data which are, in principle, effected by both the applied stress and the resulting plastic strain. It is not clear in these circumstances whether the damage accumulation is stress induced or whether the generation of defects during deformation helps nucleate void described as strain induce damage accumulation. Damage accumulation inside any material depends upon the chemistry of the material, initial inclusions or second phase particles' fractions and distribution, stress triaxility, strain, stress, strain rate, strain path, grain size, initial crystallographic microtexture and temperature of deformation. Hence the problem of damage accumulation clearly involves many variables and complex.

The objective of this study is to investigate the parameters which control the deformation and fracture and their isolated influence. A Bayesian neural network model has been developed to correlate the extent of damage accumulation with its influencing parameters for high strength low alloy steels under tensile deformation.

2.0 Method

As it is well established that neural network is a simple regression analysis in which a flexible non-linear function is fitted with the experimentally measured data, the detail of which have been reviewed extensively [6]. MacKay [7 – 10] has already explained the theory of Bayesian Neural Network and its application in his pioneer studies.

This Bayesian framework for neural networks has two advantages [7 – 10]. First, the significance of the input variables is quantified automatically. Consequently, the model perceived significance of each input variables can be compared against established metallurgical theory. Second, the network's predictions are accompanied by error bars which depend on the specific position in input space. This quantifies the model's certainty about its predictions. A potential difficulty with the use of regression analysis is the possibility of the over fitting. To avoid this, the experimental data can be divided into two sets, a training data set and a testing data set.

The Bayesian neural network model is produced using only the training data. Later the testing data are used to check that the model behaves itself when presented with previously unseen data. The training process involves a search for the optimum non-linear relationship between the inputs and the output data and is computer intensive. Once the network is trained, estimation of the outputs for any given set of inputs is fast.

3.0 Parameters

Extensive literature study has been carried out to understand the ductile fracture micro-mechanisms and their interpretations while explaining the mechanical behaviour of high strength low alloy steels under various operating conditions. Damage accumulation inside a material under tensile deformation strongly depends upon chemistry of the material, stress, strain, initial inclusion volume fraction, its size, shape, distribution, temperature of deformation, strain rate, stress triaxility, grain size and initial crystallographic microtexture of the material. Two kinds of steels are chosen for this analysis (i.e. HSLA 100 and HY 100 steels). Huge amount of research work about these steels is available elsewhere [11 – 17].

The inputs parameters for the model are: stress, strain, stress triaxility, strain rate and temperature and the output is the extent of void area fraction. The other influencing parameters for damage accumulations are initial microtexture and grain size, which were not, included as input parameters because there is lack of published data available. A total 536 experimental data were collected from published sources [11 - 17] and tabulated in a spreadsheet. The statistics of the whole database are given in Table 1. It is noted from Table 1 that the output has been converted to *LN (1/VAF)* to get rid of complexity in calculations. This has been done because the extent of void area fraction is very small. Yescas et *al.* [18] has demonstrated the similar kind of neural network analysis in their pioneer study for the calculation of retained austenite in austempered ductile irons.

Table 1: Statistics of the database used for neural network analysis. SD: standard deviation, VAF: void area fraction.

Inputs	**Unit**	**Maximum**	**Minimum**	**Mean**	**SD**	**Example**
Stress	MPa	1365.7	763.4	1128.4	126.6	959.4
Triaxility (σ_m/σ_{eq})	-	1.4	0.8	1.14	0.22	0.8
Strain rate	s^{-1}	1.0	0.0001	0.60	0.49	0.001
Temperature	^0C	298	188	233.2	42.7	298
Strain	-	0.51	0.01	0.14	0.10	0.179
Output	**Unit**	**Maximum**	**Minimum**	**Mean**	**SD**	-
LN (1/VAF)	-	9.16	3.63	6.33	1.06	

4.0 Bayesian neural network

All the experimental data digitized have been tabulated in a single spreadsheet and randomised and partitioned equally into test and training sets. The later was used to create a large variety of neural networks models whereas the test data was used to see how the trained models generalised on unseen data.

The training involves a minimisation of the regularised sum of squared errors. The term, σ_v used below is the framework estimate of the noise level of the data, which has been discussed elsewhere [11 - 17]. The complexity of the model is controlled by the number of hidden units (Figure 2 (a)). Figure 2 (a) shows that the inferred noise level decreases as the number of hidden unit increases. The number of hidden units is set by examining the performance of the

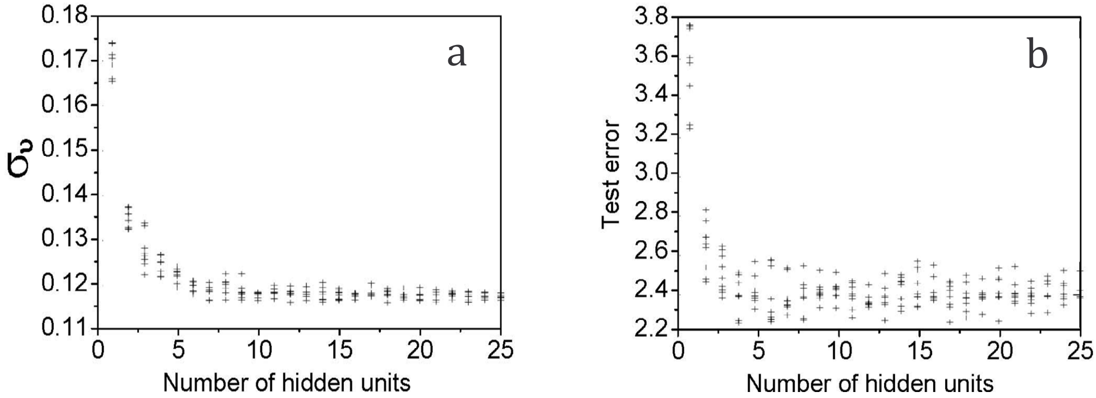

Figure 2: (a) Variation in σ_ν as a function of the number of hidden units. Several values are presented for each set of hidden units because the training for each network was started with a variety of random seeds, (b) the test error as a function of the number of hidden units.

model on unseen data. The test set error tends to go through a minimum at an optimum complexity (Figure 2 (b)). It is possible that a committee of models can make a reliable and reasonable estimate than an individual model [7 - 10]. The best models are ranked using the values of the test errors. Committees are then formed by combining the predictions of the best models. MacKay [7 – 10] has shown when making predictions with error bars, the best model should be decided according to a quantity the *log predicted error*. However, the committee with three models was found to have an optimum membership with the smallest test error. Once the optimum committee is chosen, it is retrained on the entire dataset without changing the complexity of each model, with the exception of the inevitable and relatively small adjustments to the weights. Figure 3 (a) and 3 (b) shows the normalised predicted values versus experimental values for the best model in the training and test datasets.

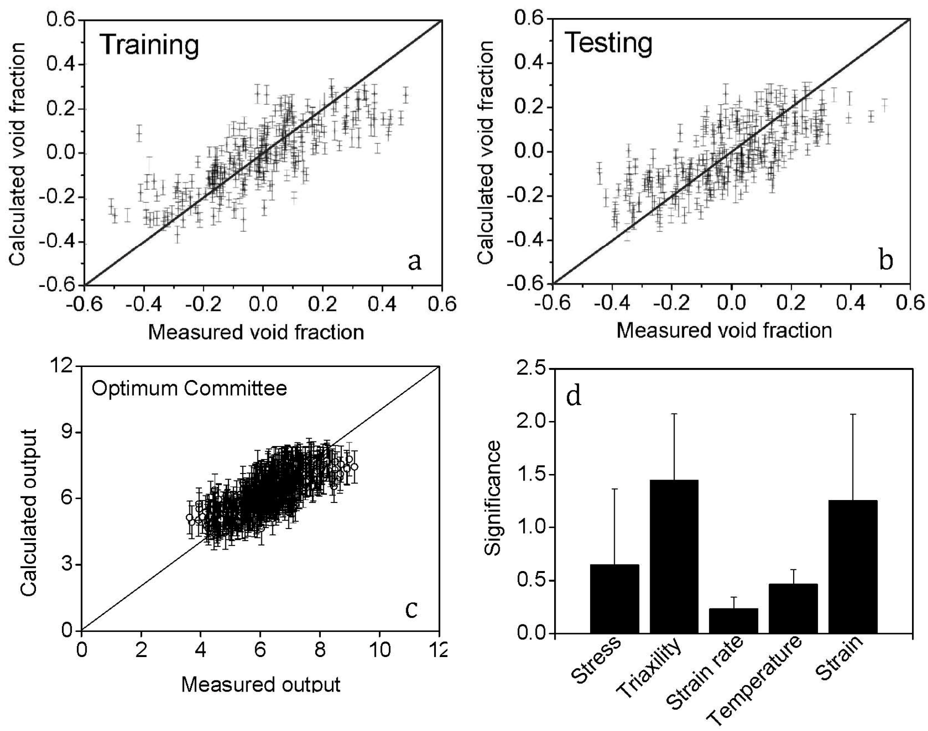

Figure 3: (a) Plot of the estimated versus measured void area fraction - training dataset, (b) testing dataset, (c) committee model (best model) and (d) model perceived significance. It is noted that output = LN (1/VAF).

5.0 Prediction

The predictions made using the optimum committee of models are illustrated in Figure 3 (c). Figure 3 (d) illustrates the significance of each of the input variables, as perceived by the analysis. From this analysis, it is investigated that the stress triaxility is having tremendous influence in damage accumulation. After that strain comes. Figure 4 (a) shows that with the increase in stress, damage accumulation increases drastically and beyond a certain stress value (i.e. 1000 MPa), it decreases drastically. Figure 4 (b) shows that with the increase in strain, void fraction increases drastically towards higher strain. At strains very near to fracture, but at void volume fraction levels of 0.01, these results show void growth accelerates rather abruptly into a second, very rapid growth stage and imminent material failure, consistent with the deformation localization process associated the void sheet coalescence [11 - 17]. Figure 4 (c) demonstrate that with the increase in strain rate damage accumulation suppresses drastically. Increasing strain rate promotes void sheet mode of coalescence abruptly. This is in agreement with the published theory [11 – 17]. A well known characteristic of void growth is its strong sensitivity to the stress triaxiality which is investigated in Figure 4 (d). Figure 4 (e) explains that with the increase in testing temperature void area fraction increases drastically. This is in agreement with the published theory.

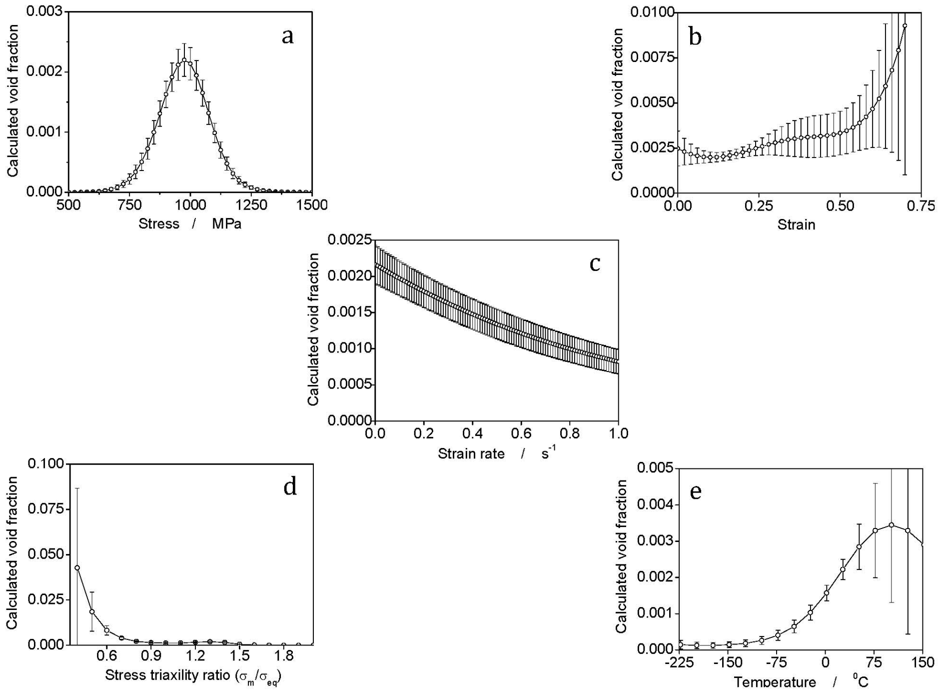

Figure 4: Predictions of damage accumulation in high strength low alloy steels as a function of: (a) stress, (b) strain, (c) strain rate, (d) stress triaxility and (e) temperature of deformation. It is noted from these figures that when we see the individual influence of variables on damage accumulation, other parameters are kept constant.

6.0 Conclusions

A Bayesian neural network model has been developed to estimate the fraction of void in high strength low alloy steels as a function of stress, strain, stress triaxility ratio, strain rate and temperature of deformation. In is concluded that the stress triaxility is having strong influence on damage accumulation rather strain and stress. Nevertheless, it would have been better model if we could have included initial inclusions fraction and its shape factor and distribution which also play a major role in damage accumulation.

7.0 Acknowledgement

Arpan Das is grateful to Professor H. K. D. H. Bhadeshia for the provision of Model Manager for Bayesian Neural Network analysis.

References

[1] A. L. Gurson, *ASME J. of Engg. Mat. & Tech. 99 (1977) 1.*

[2] J. R. Rice and D. M. Tracey, *J. of Mech. and Phy. of Sol. 17 (1969) 201.*

[3] F. A. McClintock, *J. of App. Mech. 35 (1968) 363.*

[4] V. Tvergaard and A. Needleman, *Acta Met. 32 (1984) 157.*

[5] W. M. Garrison Jr. and N. R. Moody, *J. of Phy. & Chem. of Sol. 48 11 (1987) 1035.*

[6] H. Fujii, D. J. C. Mackay and H. K. D. H. Bhadeshia, *ISIJ Int. 36 (11) (1996) 1373.*

[7] D. J. C. MacKay, *Neu. Comp. 4 (1992a) 415.*

[8] D. J. C. MacKay, *Neu. Comp. 4 (1992b) 448.*

[9] D. J. C. MacKay, *ASHRAE Trans. 100 (2) (1994) 1053.*

[10] D. J. C. MacKay, *Network: Comp. Neu. Sys. 6 (1995) 469.*

[11] D. Chae and D. A. Koss, *Mat. Sci. & Engg. A 366 (2004) 299.*

[12] V. Jablokov, D. M.Goto and D. A. Koss, *Met. & Mat. Trans. A 32A (2001) 2985.*

[13] V. Jablokov, D. M.Goto, D. A. Koss and J. B. McKirgan, *Mat. Sci. & Engg. A302 (2001) 197.*

[14] D. Chae, C. J. Young, D. M. Goto and D. A. Koss, *Met. & Mat. Trans. A 32 A (2001) 2229.*

[15] D. Chae, J. P. Bandstra and D. A. Koss, *Mat. Sci. & Engg. A285 (2000) 165.*

[16] J. P. Bandstra and D. A. Koss, *Acta Mat. 56 (2008) 4429.*

[17] D. M. Goto, J. F. Bingert, S. R. Chn, G. T. Gray III and R. K. Garrett Jr., *Met. & Mat. Trans. A 31A (2000) 1985.*

[18] M. A. Yescas, H. K. D. H. Bhadeshia and D. J. MacKay, *Mat. Sci. & Engg. A311 (2001) 162.*