Stretch-flangeability of strong multiphase steels

S. Chatterjee and H. K. D. H. Bhadeshia*

Stretch-flangeability measures the ability of a material to form into a complex shape. The parameter is often related to simple properties derived from tensile tests. An attempt is made here to discover the best way to exploit tensile test data to indicate flangeabilty. It is found that the ultimate tensile strength of steel is the single most important criterion that correlates with stretch-flangeability.

Introduction

Several methods have been designed to characterise formability, one of which is the hole expansion test which is of relevance in the manufacture of steel automobile components.[1–3] A hole is first made in the steel blank. It is then allowed to expand under a punch until cracks appear on the surface. The ratio of the increase in diameter to the initial diameter is called 'the hole expansion ratio'. The higher the ratio, the better is the stretch-flangeability.

There are examples of strong steels tested for stretch-flangeability.[2–7] Each of these materials possesses a similar ferrite rich microstructure with a dispersion of a hard phase which could be martensite or bainite or both; retained austenite may also be present. The ideal way of relating microstructure to properties such as the hole expansion ratio would be to create a finite element model for the component which is to be formed, containing as inputs the complete constitutive equations for each phase, the scale, distribution and failure criterion for each phase and a way of creating composite effects in such a model. This scenario is frequently impractical in steel development programmes, where parameters derived from tensile tests are suggested to correlate with the hole expansion ratio.

A recent although common example is the correlation of formability with the ultimate tensile strength (UTS) and ductility.[8] The argument for doing this is that the product is a measure of the energy absorbed by the steel during uniform plastic deformation. However, the UTS itself contains information about the onset of plastic instability, so it is not obvious that information is not double counted. The purpose of this work was to examine in detail how the tensile test should correlate against the hole expansion ratio.

Method

A good method for recognising patterns in complex data is the neural network in a Bayesian framework. The method has been extensively documented[9–12] and applied in materials science.[13–23] For this reason, only specific points of relevance are introduced here and details are available in a recent thesis.[24]

The network is a non-linear regression method which, because of its flexibility, is able to capture enormous complexity in the data, while at the same time, avoiding overfitting. There are a number of interesting outputs other than the coefficients which help recognise the significance of each input. First, there is the *noise* in the output, associated with the fact the input set is unlikely to be comprehensive, i.e. a different result is obtained from identical experiments. Secondly, there is the *uncertainty of modelling* because many mathematical functions may be able to adequately indicate known data, which behave differently when extrapolated. A knowledge of this uncertainty helps make the method less dangerous in extrapolation. Finally, there is the *significance* of each input in explaining variation in the output, akin to a partial correlation coefficient in multiple linear regression. The significance is dimensionless because the variables are all normalised between ± 0.5 for the purposes of creating the neural network model, e.g. equation (2), Ref. 14.

Data

The data presented in Table 1 were compiled from published literature.[1,2,4,25,26] They originate from steels with microstructures which are mixtures of ferrite, martensite, or ferrite and bainite, with or without retained austenite. The data were used to create models for predicting the hole expansion ratio λ against various combinations of the tensile properties, namely, yield strength (YS), UTS, uniform elongation (UEL), total elongation (TEL), yield ratio (YR) and the strength–elongation product (UTS–UEL and UTS–TEL).

Results and discussion

The first model included YS, UTS, UEL, YR and UTS–UEL as the inputs with the hole expansion ratio λ as the output. Figure 1a shows how well the model compares with the experimental data. There are a number of

Department of Materials Science and Metallurgy, University of Cambridge, Pembroke Street, Cambridge CB2 3QZ, UK

*Corresponding author, email hkdb@cam.ac.uk
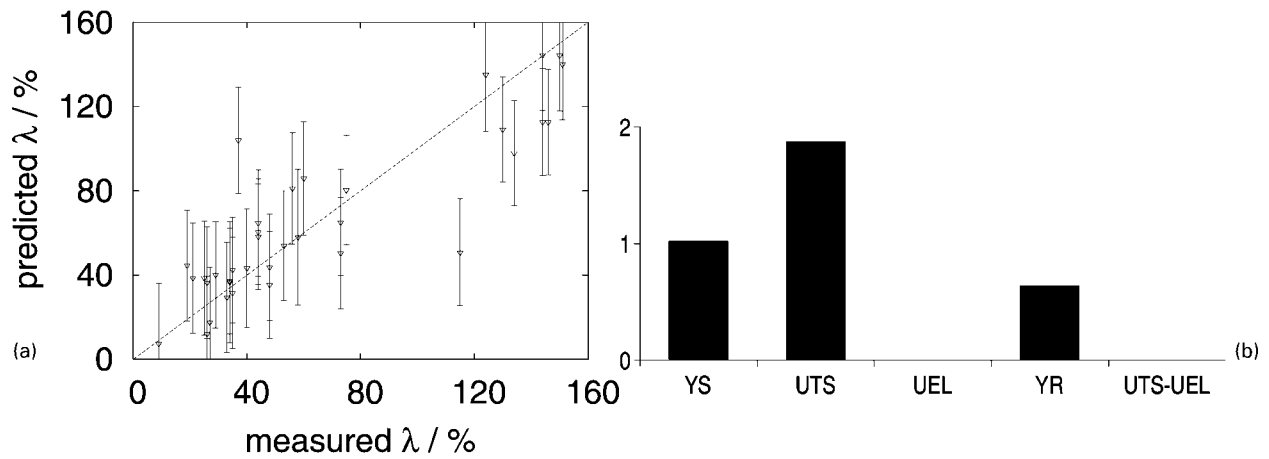
1 *a* predicted hole expansion ratios compared with measured values using model with YS, UTS, UEL, YR and UTS–UEL as input parameters, and *b* significance of each input
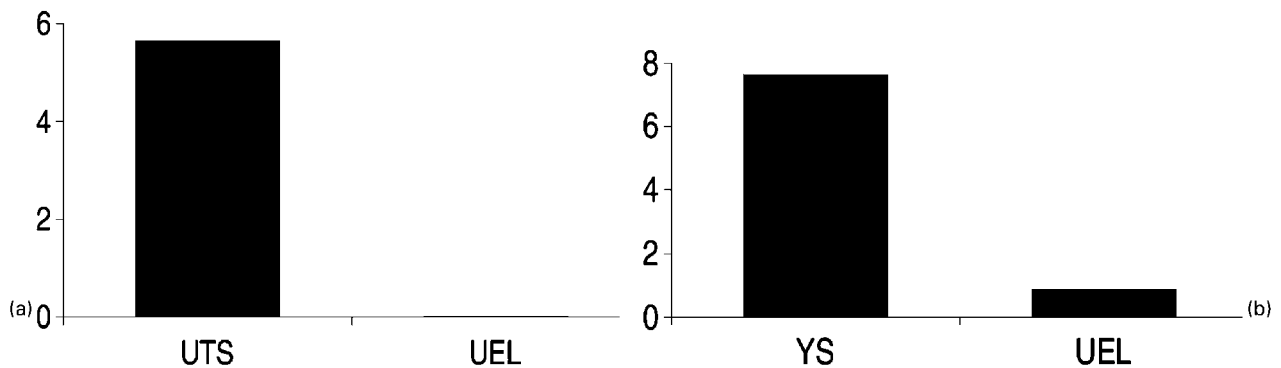
2 Significances of *a* UTS and UEL and *b* YS and UEL as input variables

outliers and the modelling uncertainty is large. However, the interesting outcome seen in Fig. 1*b* is that neither the UEL nor the product of the UTS with it (UTS–UEL) is perceived to be significant when compared with strength. The apparent lack of relevance of the UEL was further tested, first using only the UTS with the UEL as the inputs and second with only YS and UEL as inputs. Figure 2 shows that in the first case, the UTS has an overwhelming contribution with the UEL having a negligible influence on λ. When the YS is substituted for the UTS, the significance of the UEL increases only slightly.

Repeating this exercise using UTS, TEL and UTS–TEL led to the most interesting results and the least noise in the predictions. In Fig. 3*a* and *b*, the significances of both UTS–TEL and TEL can be seen to be appreciable, although quantitatively these are less than that of the UTS. Figure 3*c* and *d* shows that the predictions made over the entire dataset compare well with the corresponding measured values. The role of the

TEL appears to be physically reasonable, given that the hole must be allowed to expand until cracks appear on the surface and UEL in contrast does not designate failure.

Given that both of the models shown in Fig. 3 include significant variables and that the accuracies of the predictions are comparable, it would be better to select the model in which the inputs are independent, i.e. the UTS and TEL model. Figure 4 shows that the UTS has a more powerful effect on the hole expansion ratio than the TEL.

That the UTS has such a large effect on λ should not be surprising in hindsight. First, the UTS is measured at the point where plastic instability sets in, and hence already contains information about UEL. Second, it is generally true in the type of steels considered here that a higher UTS leads to a lower UEL. Finally, it is worth noting that the correlation of the hole expansion ratio versus the popular product UTS $\times$ TEL is not impressive. Figure 5 shows the performance of a neural network

Table 1 Data used in analysis

Inputs	Minimum	Maximum	Average	Standard deviation
YS, MPa	335	783	444	92
UTS, MPa	484	1028	675	155
UEL, %	8	39	18	7
TEL, %	10	43	27	8
YR	0·49	0·82	0·67	0·09
UTS–UEL, MPa %	6992	29 715	12 192	6113
UTS–TEL, MPa %	9016	32 379	18 069	6894
λ, %	9	151	65	45
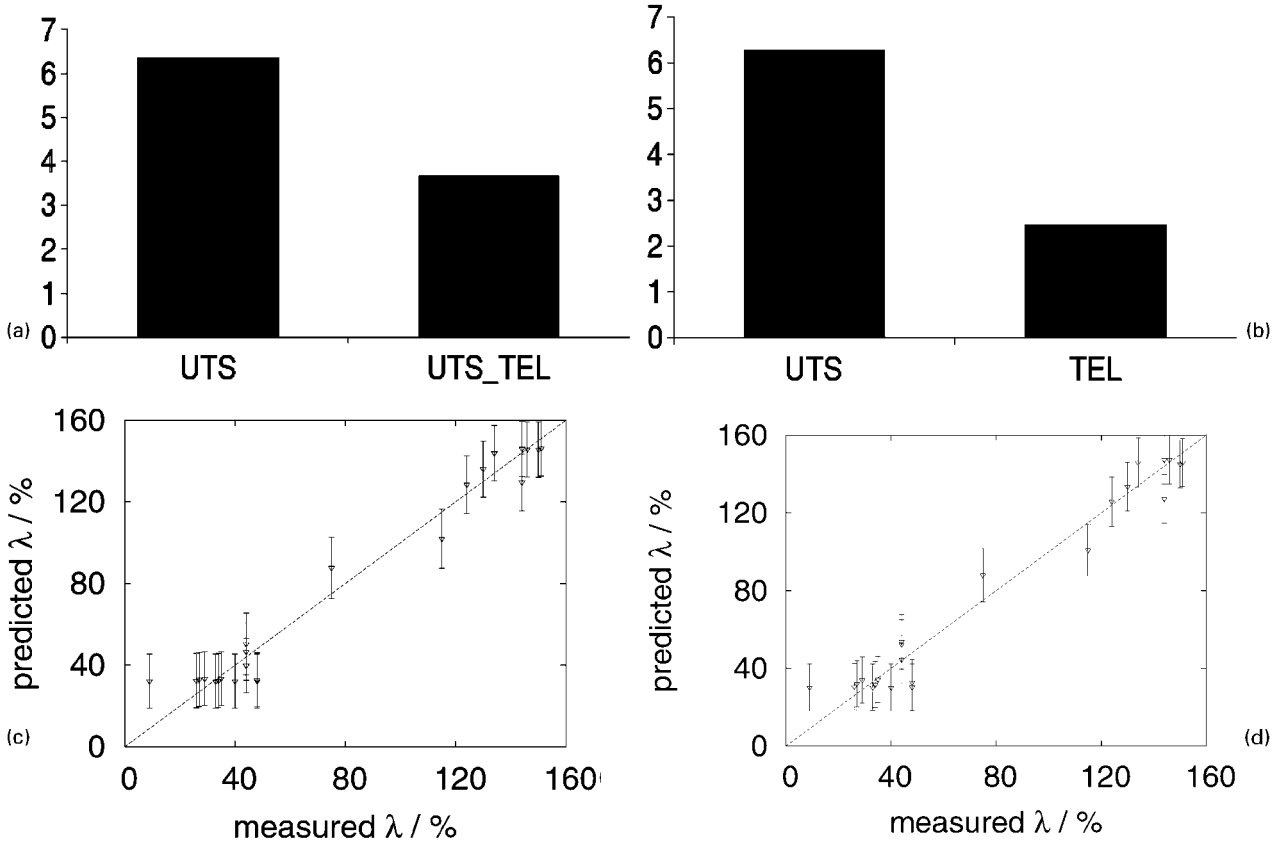
3 Significances of *a* UTS and UTS–TEL and *b* UTS and TEL as input variables, and *c* and *d* predicted hole expansion ratios compared with measured values using models with *a* UTS and UTS–TEL and *b* UTS and TEL as input parameters
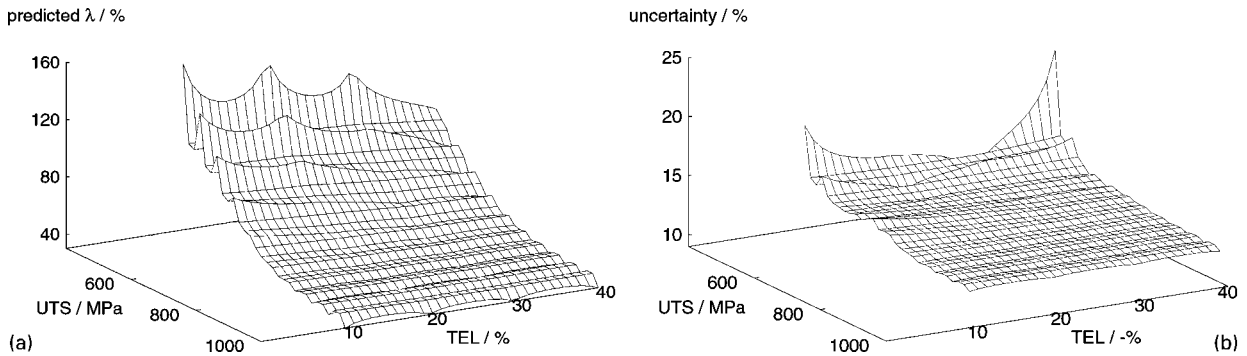
4 Predicted variation in *a* hole expansion ratio with UTS and TEL and *b* corresponding uncertainties
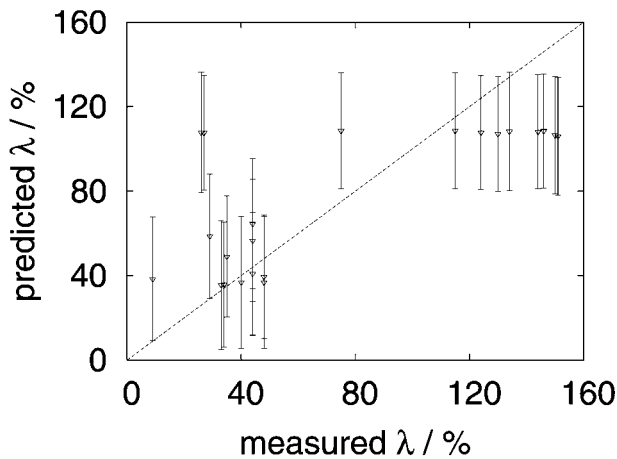
5 Performance of neural network containing just product UTS × TEL as input

model for λ as the output with only the product as the input.

Conclusions

It is found that the UTS is of overwhelming importance in determining the hole expansion ratio, and hence the stretch-flangeability. In contrast, the UEL should not be used in analysing the ratio. The TEL is a significant parameter but the ratio λ is less sensitive to this than the UTS. It does not appear justified to expect a correlation between the hole expansion ratio and the product of strength and TEL.

Acknowledgements

provision of laboratory facilities at the University of Cambridge.

References

1. M. Sudo, I. Tsukatani and Z. Shibata: in 'Metallurgy of continuous annealed sheet steel', (ed. B. L. Bramfitt and P. L. Mangonon, Jr), 310–319; 1982, Warrendale, PA, AIME.
2. K. I. Sugimoto, A. Nagasaka, M. Kobayashi and S. I. Hashimoto: *ISIJ Int.*, 1999, **39**, 56–63.
3. O. Matsumura, Y. Sakuma, Y. Ishi and J. Zhao: *ISIJ Int.*, 1992, **32**, 1110–1116.
4. K. Hasegawa, K. Kawamura, K. Urabe and Y. Hosoya: *ISIJ Int.*, 2004, **44**, 603–609.
5. K. I. Sugimoto, J. Sakaguchi, T. Iida and T. Kashima: *ISIJ Int.*, 2000, **40**, 920–926.
6. K. I. Sugimoto, A. Kanada, R. Kikuchi, S. I. Hashimoto, T. Kashima and S. Ikeda: *ISIJ Int.*, 2002, **42**, 910–915.
7. K. I. Sugimoto, K. Nakano, S. M. Song and T. Kashima: *ISIJ Int.*, 2002, **42**, 450–455.
8. K. Sugimoto, N. Usui, M. Kobayashi and S. Hashimoto: *ISIJ Int.*, 1992, **32**, 1311–1318.
9. D. J. C. MacKay: *Neural Comput.*, 1992, **4**, 448–472.
10. D. J. C. MacKay: *Neural Comput.*, 1992, **4**, 415–447.
11. H. K. D. H. Bhadeshia: *ISIJ Int.*, 1999, **39**, 966–979.
12. D. J. C. MacKay: 'Information theory, inference, and learning algorithms'; 2003, Cambridge, Cambridge University Press.
13. S. B. Singh, H. K. D. H. Bhadeshia, D. J. C. MacKay, H. Carey and I. Martin: *Ironmaking Steelmaking*, 1998, **25**, 355–365.
14. F. Brun, T. Yoshida, J. D. Robson, V. Narayan, H. K. D. H. Bhadeshia and D. J. C. MacKay: *Mater. Sci. Technol.*, 1999, **15**, 547–554.
15. S. Yoshitake, V. Narayan, H. Harada, H. K. D. H. Bhadeshia and D. J. C. MacKay: *ISIJ Int.*, 1998, **38**, 496–502.
16. S. H. Lalam, H. K. D. H. Bhadeshia and D. J. C. MacKay: *Sci. Technol. Weld. Join.*, 2000, **5**, 135–147.
17. S. H. Lalam, H. K. D. H. Bhadeshia and D. J. C. MacKay: *Sci. Technol. Weld. Join.*, 2000, **5**, 149–160.
18. E. A. Metzbower, J. J. DeLoach, S. H. Lalam and H. K. D. H. Bhadeshia: *Sci. Technol. Weld. Join.*, 2001, **6**, 116–121.
19. C. Capdevila, F. G. Caballero and C. Garcia de Andrés: *ISIJ Int.*, 2002, **42**, 894–902.
20. C. Capdevila, F. G. Caballero and C. Garcia de Andrés: *Mater. Sci. Technol.*, 2003, **19**, 581–586.
21. T. Sourmail and C. Garcia-Mateo: *Comput. Mater. Sci.*, 2005, **34**, 213–218.
22. C. Garcia-Mateo, T. Sourmail, F. G. Caballero and C. Garcia de Andrés: *Mater. Sci. Technol.*, 2005, **21**, 934–940.
23. C. Capdevila, C. Garcia-Mateo, F. G. Caballero and C. Garcia de Andrés: *Mater. Sci. Technol.*, 2006, **22**, 1163–1170.
24. S. Chatterjee: 'TRIP-assisted steels', PhD thesis, University of Cambridge, Cambridge, UK, 2006.
25. X. Fang, Z. Fan, B. Ralph, P. Evans and R. Underhill: *J. Mater. Process. Technol.*, 2003, **132**, 215–218.
26. X. Fang, Z. Fan, B. Ralph, P. Evans and R. Underhill: *J. Mater. Sci.*, 2003, **38**, 3877–3882.