Analysis of toughness of welding alloys for high strength low alloy shipbuilding steels

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In previous work by the present authors a model was developed for the estimation of the tensile properties (strength and ductility) of ferrous alloys intended for the welding of high strength low alloy steels used in the construction of ships. The method used to model the properties as a function of a large number of variables was based on a neural network within a Bayesian framework. This method is particularly useful when attempting to understand complex non-linear phenomena where the distribution of data within the input space is not obvious. In the present work, a similar approach is used to model the toughness (characterised by Charpy and dynamic tear tests) of the same alloys. The level of noise in the experimental data is perceived to be high, but it has nevertheless been possible to recognise reasonable trends and uncertainties when making predictions. For example, the toughness shows a non-linear deterioration as the oxygen concentration is increased; this behaviour is expected but can now be expressed quantitatively. STWJ/248

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INTRODUCTION

The toughness of weld metals remains a property that is especially difficult to understand and more so to model. This is because the ability of a metal to absorb energy during failure depends on a very large number of variables; furthermore, the tests that are frequently used to characterise this property are empirical (although reliable indicators of quality). In a previous study,[1] the tensile properties of a particular class of experimental welding alloys were modelled using a neural network method[2–5] within a Bayesian framework. However, neither strength nor ductility alone is a sufficient indicator of weld performance. The toughness must also meet design specifications. The purpose of the present work, therefore, was to develop similar models for the toughness of the weld metals, as characterised by Charpy and dynamic tear tests.

Both the prior study[1] and the present work utilise a data set that originated in research that had the intention of developing welding consumables for joining high strength low alloy steels for ship construction.[6]

Ferritic steels have a ductile to brittle transition that is a function of composition and temperature. The Charpy V notch test is a quality control test used to select steels that are resistant to brittle fracture. Knowledge of the Charpy energy at only one temperature is not sufficient to indicate the transition curve. The Charpy energy is therefore measured at two different temperatures (−18 and −51°C); for steels of the 600 MPa class it is necessary to achieve values of 81 J at −18°C and 47 J at −51°C. The dynamic tear test is also a measure of resistance to brittle fracture and it too is measured at two temperatures (−1 and −29°C); the minimum requirements in this instance are 610 J at −1°C and 407 J at −29°C. Satisfying the specifications at both temperatures is an important quality control requirement based on experience.

The correlation between the chemical composition of the steel and its toughness is inexact, although for steels and weld metals various indicators abound. Increasing the strength usually decreases the fracture toughness if the microstructure remains the same. Carbon can drastically change the transition curve in steel, as can manganese.[7] Nickel is sometimes known to promote low temperature resistance to brittle fracture. Notch toughness is particularly influenced by oxygen. In wrought steels, this is evidenced by the lower transition temperatures in steels that are fully killed by the addition of silicon and aluminium, as compared with semikilled or rimmed steels.

DATABASE

The set of experimental data is identical to that used in the previous study;[1] most of the experimental details have been described there. The Charpy samples were of standard size and geometry, i.e. 10 mm square sectioned specimens with 2 mm depth notches of radius 0·25 mm and an included angle of 45°. The rectangular dynamic tear test samples were 181 mm in length, 38 mm in width, and 15·8 mm in thickness, with a machined 9·5 mm depth parallel sided notch of root radius 0·13 mm. The tip root radius after pressing becomes 0·025 mm.

The input variables are the chemical compositions of the as deposited weld beads, either the measured Charpy values at −18 or −51°C or the dynamic tear test values at −1 or −29°C, and the cooling rate at 538°C. It should be noted that some of the temperatures stated in the present paper appear unusual because they are conversions from Fahrenheit to Celsius (e.g. 538°C is 1000°F). The cooling rate was determined from the welding parameters (voltage, current, welding speed), preheat, and thickness of the plate.[8,9] Table 1 gives the minimum, maximum, mean, and standard deviations of each of the variables.

Figure 1*a* and *b* illustrate the range of the experimental data; the scatter evident on the graphs shows that the behaviour expected at the two different test temperatures may often be different. A further point to note is that many of the data fail the Charpy and tear test requirements outlined above; it is important in creating models to include the results of both successful and unsuccessful experiments.

Aside from the temperature effects, both Charpy and dynamic tear tests are subject to considerable scatter, particularly in the region of the transition temperature.

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Table 1 Input and output variables (concentrations are in wt-% except where shown)

Variable	Minimum	Maximum	Mean	Standard deviation
C	0·001	0·06	0·0307	0·0098
Mn	1·05	3·44	1·4361	0·1915
Si	0·05	0·4	0·2618	0·0555
Cr	0	0·21	0·0664	0·0530
Ni	1·66	5·63	3·1324	0·7800
Mo	0	1·23	0·5048	0·1452
Cu	0	0·48	0·1018	0·0766
S	0·001	0·012	0·0034	0·0019
P	0·001	0·015	0·0041	0·0026
Al	0·001	0·082	0·0066	0·0060
Ti	0·0008	0·3	0·0089	0·0181
Nb	0	0·069	0·0016	0·0041
V	0	0·031	0·0032	0·0042
B	0	0·01	0·0011	0·0021
O, wt-ppm	109	627	216·7565	58·6969
N, wt-ppm	6	135	29·8164	25·2642
Cooling rate, K s^{-1}	1·32	76·17	27·1079	23·0104
CVN (−18°C), J	8	358	181·9955	57·0641
CVN (−51°C), J	3·8	242	143·6876	64·3903
DT (−1°C), J	128	2606	1322·4916	538·1394
DT (−29°C), J	80	2380	950·2694	583·3663

CVN Charpy V notch; DT dynamic tear. Dynamic tear test data are generated on welds that did not contain titanium. A more detailed description of both the data set and the neural network employed can be found elsewhere.[1]

Table 2 Number of models in committee and largest value of additional error σ_v associated with any member of committee

Data set	Models in committee	σ_v
CVN (−18°C)	1	0·055
CVN (−51°C)	6	0·081
DT (−1°C)	6	0·091
DT (−29°C)	77	0·222

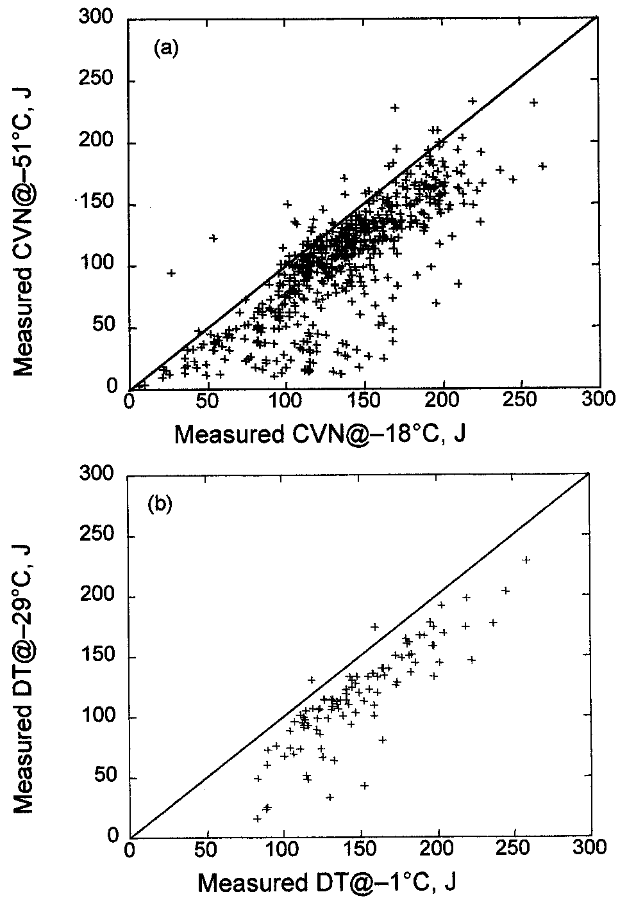
Most of the scatter is due to local variations in the properties of the steel plate or weld, whereas some is due to difficulties in preparing perfectly reproducible notches. The inhomogeneity of a weld is considerably greater than that of plate steel and the corresponding scatter in experimental values is expected to be greater.

RESULTS AND DISCUSSION

To avoid overfitting during the training process, the data were divided into parts for training and testing.[2–6] The model is at first produced using only the training data and then tested for its ability to generalise on unseen data against the remaining (test) data. The performance of the best models in predicting the training and test data is shown in Fig. 2 for the Charpy tests and Fig. 3 for the dynamic tear tests.

A committee of models can make more reliable predictions.[5] To create an appropriate committee, the best models are ranked using the values of the test errors. Committees are then formed by combining the predictions of the best L models, where $L=1, 2,\ldots$ and the size of the committee is given by the value L. A plot of the test error of the committee versus its size L gives a minimum that defines the optimum size of the committee. Using this procedure, the optimum size of the committee for the four experimental data sets is given in Table 2.

Once the optimum committee is selected, it is retrained on the entire data set without changing the complexity of each model, with the exception of the inevitable, although relatively small, adjustments to the weights.



1 Plots of *a* measured Charpy V notch energy at −51°C as function of that measured at −18°C, and *b* dynamic tear energy measured at −29°C as function of that measured at −1°C

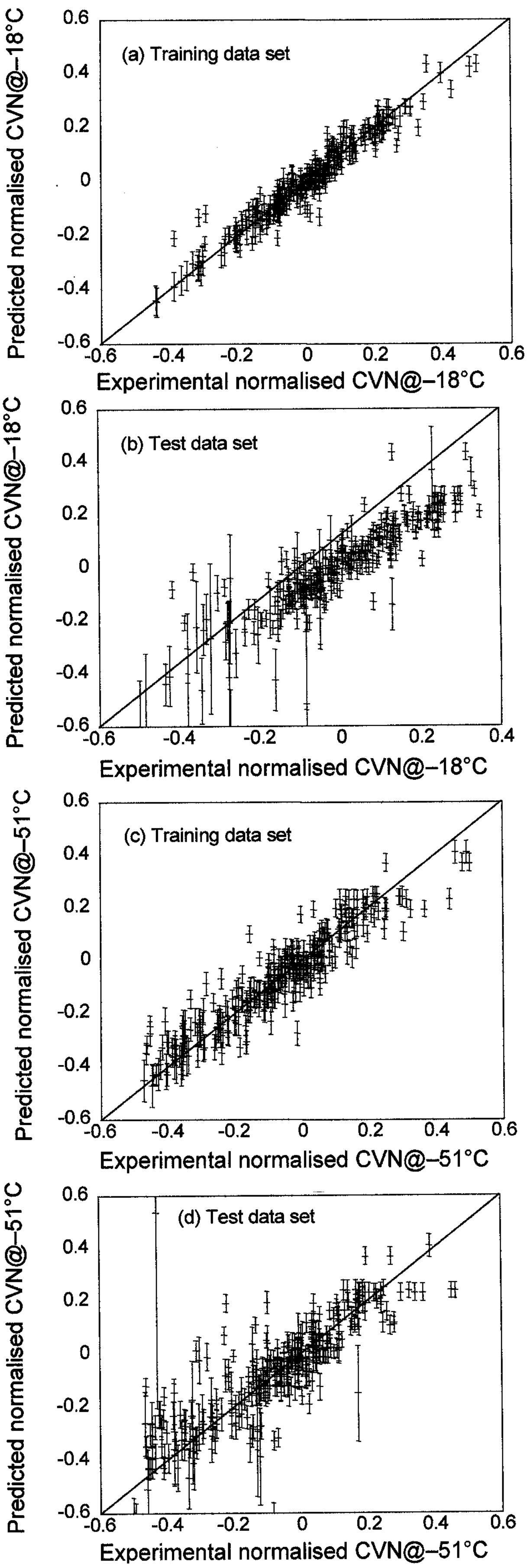
Charpy V notch tests

Results

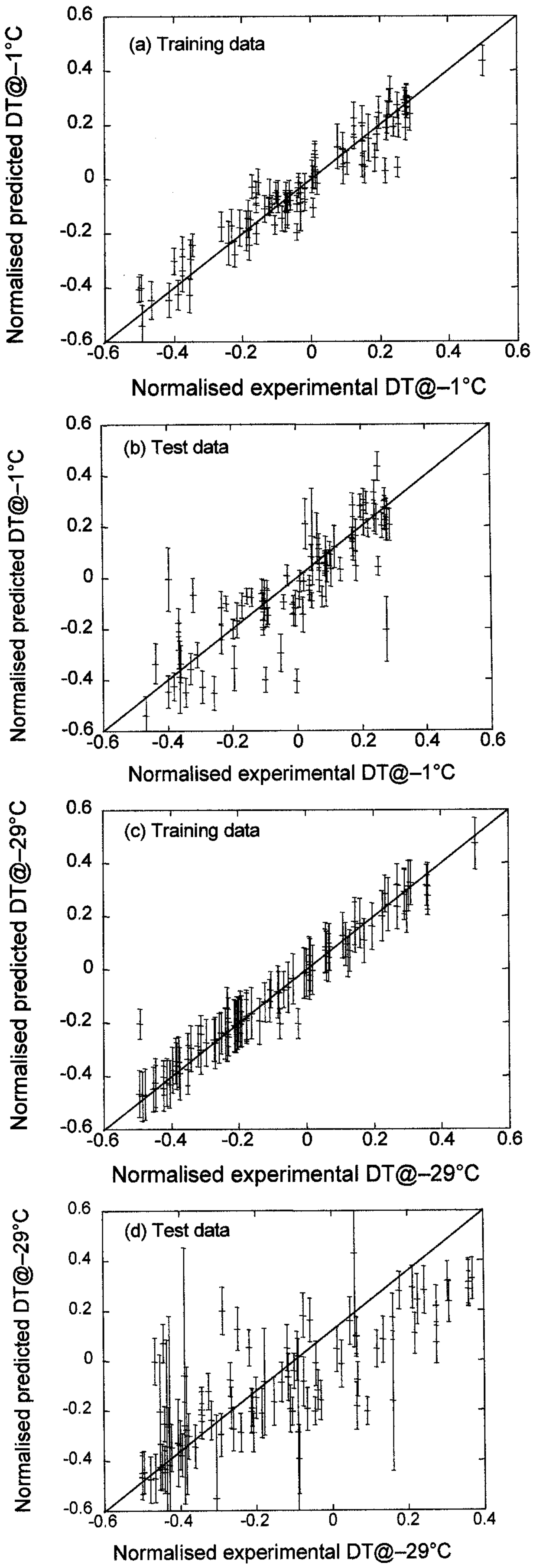
The correlation between the experimental Charpy tests at −18 and −51°C and the values predicted using the committee models is shown in Fig. 4. The committees evidently perform rather well. It is emphasised that the error bars plotted in Fig. 4 and all subsequent graphs represent the fitting error, the magnitude of which depends on the position in the input space. The additional error σ_v is taken as the largest value of σ_v for any member in the committee of models. These σ_v values are given in Table 2. The rather large perceived noise in the Charpy values at −51°C is not surprising given the scatter in the data at the lower test temperature. Only the fitting error, which is a function of position in the input space, is plotted on all the diagrams included in the present paper.

Table 3 Standard set of inputs used to observe trends (wt-%, except where indicated)

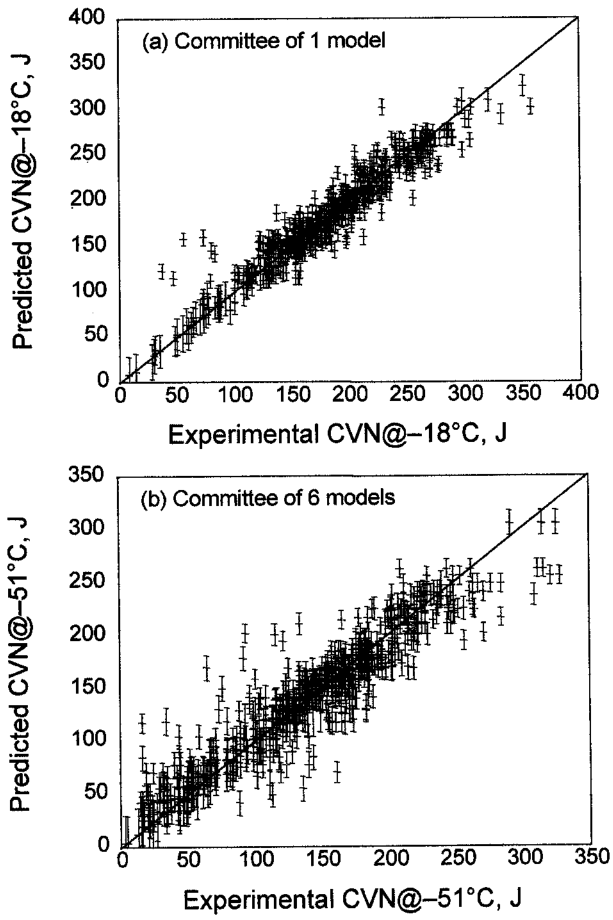
C	Si	Mn	P	S	Cr	Mo	Ni	Al	B	Cu	N, wt-ppm	Nb	Ti	V	O, wt-ppm
0·036	0·31	1·72	0·001	0·004	0·03	0·59	2·63	0·005	0	0·061	8	0	0·007	0·001	181



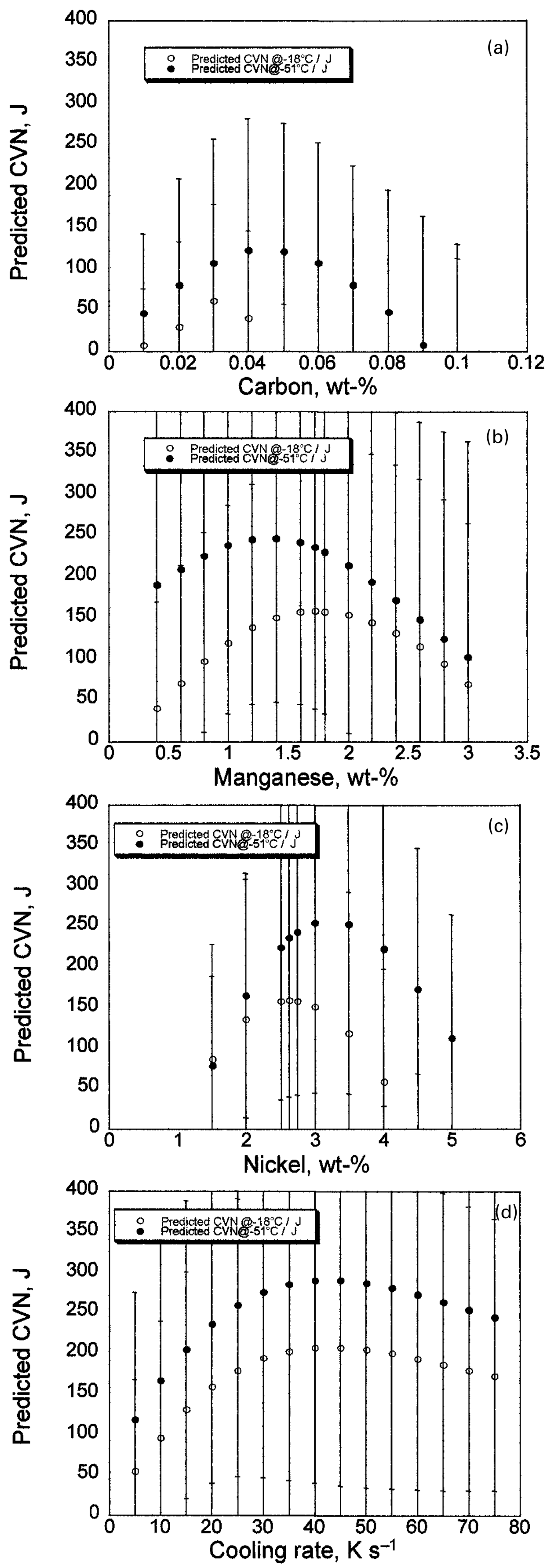
2 Predicted values using best models versus measured values for Charpy V notch tests at *a,b* −18 and *c,d* −51°C for training and test data: all data are normalised



3 Predicted values using best models versus measured values for dynamic tear tests at *a,b* −1 and *c,d* −29°C for training and test data: all data are normalised



4 Comparison of predicted and measured Charpy V notch values for as deposited weld metal tested at *a* −18 and *b* −51°C: calculations were carried out using committees of models (error bars represent $\pm 1\sigma$ values, where σ is standard deviation)



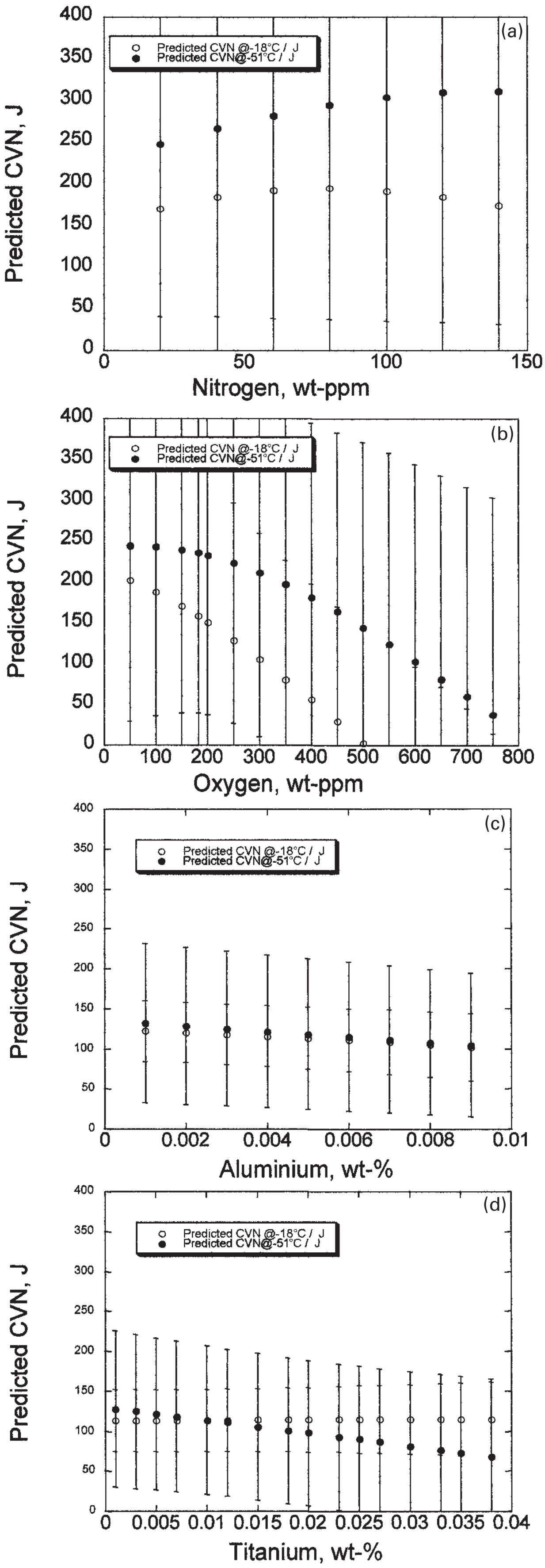
5 Variations of Charpy V notch values at −18 and −51°C, calculated using committee models, as functions of *a* carbon, *b* manganese, and *c* nickel concentrations and *d* cooling rate: error bars represent $\pm 1\sigma$ values

Predictions

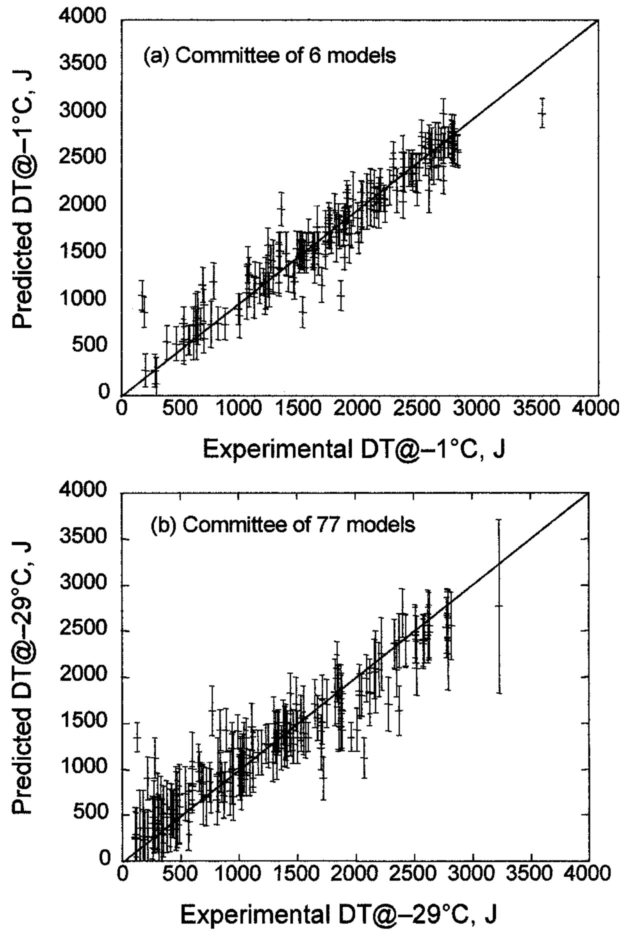
The most effective method of examining the performance of the models is to use them to make predictions regarding trends as a function of each of the inputs, for a reasonable selection of baseline inputs. The set of baseline inputs is given in Table 3. The cooling rate was set at 61·2 K s^{-1}. These inputs were selected to represent a weld metal of particular interest in the context of ship construction. As pointed out in Ref. 1, an alloy such as this should have a mixed microstructure of bainite and low carbon martensite, given the combination of high manganese and nickel concentrations and the presence of molybdenum.

Figure 5 shows example plots of the effects on the Charpy values of varying the carbon, manganese, and nickel concentrations and the cooling rate. All the plots have the same vertical scale. It is particularly interesting that all these factors cause a substantial increase in strength[1] but have a different effect on the Charpy values. Figure 5 shows that to achieve the combined strength and toughness in the weld, limits must be placed on the concentration of different elements; for example, contrary to the general assumption, the presence of nickel in the range 2–4 wt-% does not lead to an improvement in toughness in the present context. Varying the molybdenum concentration from 0 to 1 wt-% did not affect the Charpy toughness values significantly.

Figure 6 shows example plots of the effects of varying the concentrations of nitrogen, oxygen, aluminium, and titanium. Nitrogen is expected to increase the strength of the weld metal and thus decrease its toughness, so the reason for the initial increase is not understood. By contrast, those



6 Variations of Charpy V notch values at −18 and −51°C, predicted using committee models, as functions of *a* nitrogen, *b* oxygen, *c* aluminium, and *d* titanium concentrations: error bars represent ±1σ values



7 Comparison of predicted and measured dynamic tear values for as deposited weld metal tested at *a* −1 and *b* −29°C: calculations were carried out using committee models (error bars represent ±1σ values)

elements that form oxides or carbides show a significant deterioration in toughness and ductility as their concentrations are increased. It can be concluded that in the present class of welds, the main role of the inclusions is to nucleate voids or brittle fracture, rather than leading to improvements in microstructure via their ability to nucleate phase transformations.

It is noteworthy that in Fig. 6*c* and *d*, the effects of aluminium and titanium can be seen to be rather small, again consistent with the hypothesis that the inclusions are not a key feature of microstructural development.

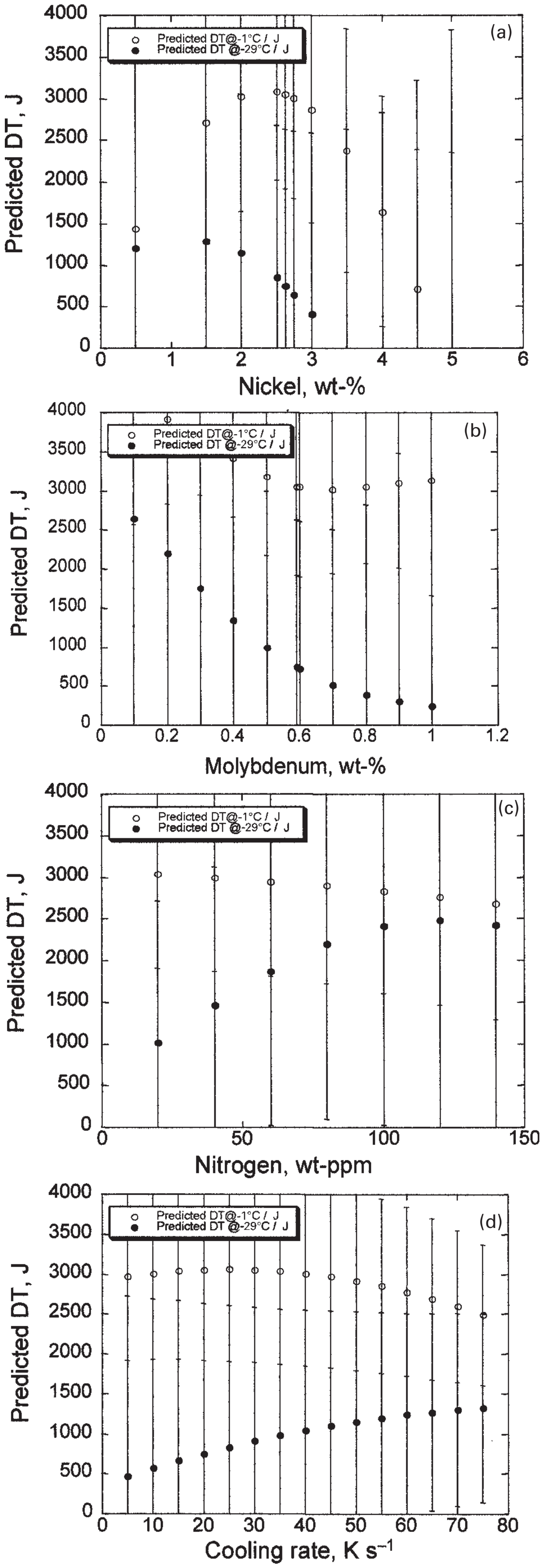
Dynamic tear tests

Results

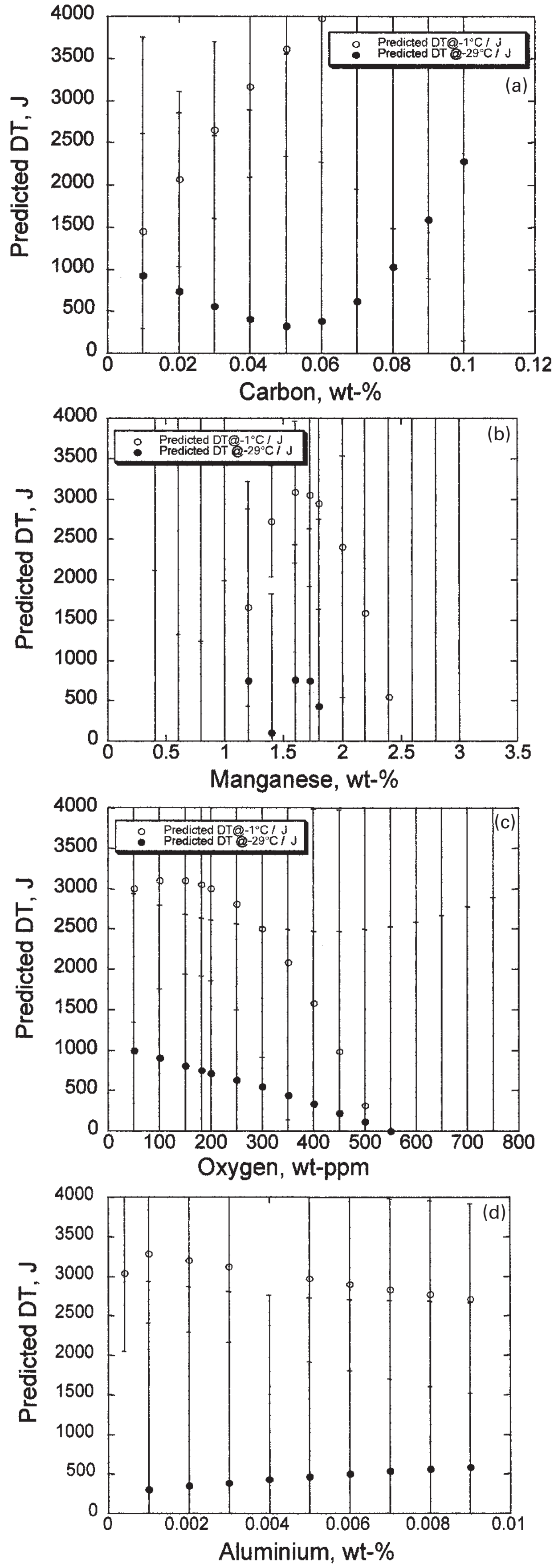
The correlation between the experimental measurements and data predicted using the committee of models is shown in Fig. 7. The committees evidently perform rather well. It is emphasised again that the error bars that are plotted here represent the fitting error, the magnitude of which depends on the position in the input space. The additional error σ_v is given in Table 2 and is taken as the largest value of σ_v for any member in the committee of models. The rather large perceived noise in the dynamic tear values is not surprising given the scatter in the data. Only the fitting error, which is a function of position in the input space, is plotted on all the diagrams included in the present paper.

Predictions

The set of baseline inputs for the predictions is given in Table 3. Setting the cooling rate at 61·2 K s^{-1} should lead



8 **Variations of dynamic tear values at −1 and −29°C predicted using committee models, as functions of *a* nickel, *b* molybdenum, and *c* nitrogen concentrations and *d* cooling rate: error bars represent ±1σ values**



9 **Variations of dynamic tear values at −1 and −29°C predicted using committee models, as functions of *a* carbon, *b* manganese, *c* oxygen, and *d* aluminium concentrations: error bars represent ±1σ values**

to a microstructure consisting of a mixture of bainite and low carbon martensite, given the combination of high manganese and nickel concentrations and the presence of molybdenum.[1]

Figure 8 shows plots of the effects on the dynamic tear values of varying the nickel, molybdenum, and nitrogen concentrations and the cooling rate. It is particularly interesting that all of these factors cause a substantial increase in strength[1] but have a different effect on the dynamic tear values. These plots show the contrary effects of strength[1] and toughness. All the plots have the same vertical scale.

In contrast, carbon and manganese, which both increase the strength,[1] show a different effect on the dynamic tear values (Fig. 9). At -1°C carbon increases the dynamic tear value, whereas at -29°C carbon shows the expected behaviour of decreasing the dynamic tear values as the carbon content is increased. Figure 9 indicates that manganese, a strengthening element, must be limited to a surprisingly small range of values for the weld to surpass the minimum levels required. This plot shows that to achieve a desirable combination of strength and toughness in the weld, limits must be placed on the concentration of different elements; these limits are ordinarily problematic to assess given the complex effects of the individual elements. However, models such as those presented here allow the exploration of the input space to determine the optimum combination of inputs.

Figure 9*c* and *d* show the effects of oxygen and aluminium on the dynamic tear values. As expected from the presence of oxide, increasing the oxygen content decreases the dynamic tear values. Conversely, aluminium can be either beneficial or harmful depending on the test temperature. Over the range of values calculated, the present requirements are satisfied for all aluminium contents.

The addition of chromium from zero to 0·3 wt-% reduces the dynamic tear values at both temperatures from approximately 1500 J to less than 1000 J. In Ref. 1, increasing the amount of chromium was found to have very little effect on the yield strength of the weld metal.

One important feature to be noted from all the data presented in Figs. 8 and 9 is that unlike the Charpy models, there are great uncertainties in extrapolating the ductile tear models. The error bars become very large, indicating that the models frequently lack the knowledge to make reliable predictions given the experimental data.

CONCLUSIONS

A neural network method within a Bayesian framework has been used to model experimental data for both the Charpy toughness values at -18 and -51°C and the dynamic tear test values at -1 and -29°C for ferritic steel weld metals appropriate for the welding of high strength low alloy steels. The inputs for the neural network were the concentrations of sixteen chemical elements and the weld cooling rate at 538°C.

The Charpy model behaves well and can often be used to make reliable predictions. By contrast, the dynamic tear data do not seem to be sufficiently comprehensive to give reliable extrapolation behaviour, the predictions being associated with large uncertainties. This information in itself is valuable and would not have been revealed without the Bayesian framework.

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