Estimation of mechanical properties of ferritic steel welds

Part 1: Yield and tensile strength

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The yield strength and ultimate tensile strength of ferritic steel weld metal have been expressed as functions of chemical composition, the heat input during welding, and the heat treatment given after welding is completed. The method involved a neural network analysis of a vast and fairly general database assembled from publications on weld metal properties. The outputs of the model have been assessed in a variety of ways, including specific studies of model predictions for the so called C–Mn and 2·25Cr–1Mo systems. Where possible, comparisons have also been made with corresponding methods which use simple physical metallurgical principles. The models created are believed to have been trained on the largest weld metal database to date, and are shown to capture vital metallurgical trends. The computer programs associated with the work have been made freely available on the World Wide Web.

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INTRODUCTION

It has been possible for some time to estimate the microstructure of ferritic steel weld metals from their chemical composition and welding parameters,[1] although the full effects of heat treatment have yet to be modelled. This has been useful in the development of alloys, given a broad understanding of what constitutes a good microstructure. The methodology cannot, however, be used directly in engineering design because that requires specific values of the mechanical properties.

The yield strength is one of the simpler mechanical properties and, to a small extent, it has been possible to apply physical metallurgy principles towards its estimation for weld metals.[1] The method begins with the assumption that the yield strength σ of steel microstructures can be factorised into a number of intrinsic components

$$\sigma = \sigma_{Fe} + \sum_i x_i \sigma_{SS_i} + x_C \sigma_C + K_L (\bar{L})^{-1} + K_D \rho_D^{0.5} \qquad (1)$$

where x_i is the concentration of a substitutional solute represented here by subscript i and x_C is the concentration of carbon. The other terms in equation (1) can be listed as

K_L = coefficent for strengthening due to 'grain' size, 115 MN m^{-1}

K_D = coefficient for strengthening due to dislocations, $7{\cdot}34 \times 10^{-6}$ MN m^{-1}

σ_{Fe} = strength of pure, annealed iron, 219 MN m^{-2} at 300 K

σ_{SS_i} = substitutional solute (i) strengthening

σ_C = solid solution strengthening due to carbon

ρ_D = dislocation density, typically 10^{16} m^{-2}

$\bar{L}$ = measure of ferrite plate size, typically 0·2 μm

The individual strengthening contributions are not described here; suffice it to say that is is possible to obtain reasonable estimates for all of the coefficients from data which are independent of welding. Equation (1) covers just one microstructure; similar equations are needed for each of the phases present. The contributions from each phase then have to be appropriately summed to obtain the overall strength.[1]

The application of such work is obviously limited, since it fails to address the complexity inherent in real welds; the number of variables influencing the strength is actually far greater than implied above. For example, many welds are heat treated after fabrication and there is no satisfactory theory available to deal with this. Many other complexities exist, as described below in the present paper.

Linear regression analysis is frequently used to overcome these difficulties.[2] In the present work, a much more general form of regression, i.e. neural network analysis, is applied to enable the estimation of the yield and tensile strengths of ferritic weld metals. These represent by far the largest group of welding materials. The present work builds on an earlier study[3] which was more limited in scope. Part 2 of this paper will attempt to deal with the elongation and Charpy impact properties of ferritic steel welds.

METHOD

A neural network is a general method of regression analysis in which a very flexible non-linear function is fitted to experimental data, the details of which have been extensively reviewed.[4] It is nevertheless useful to present some salient features, to place the technique in context.

The flexibility of the non-linear function scales with the number of hidden nodes i. Thus, the dependent variable y is given in the present work by

$$y = \sum_i w_i^{(2)} h_i + \theta^{(2)} \qquad (2)$$

where

$$h_i = \tanh\left(\sum_j w_{ij}^{(1)} x_j + \theta_i^{(1)} \right) \qquad (3)$$

where x_j are the j variables on which the output y depends, w_i are the weights (coefficients), and θ_i are the biases (equivalent to the constants in linear regression analysis). The combination of equation (3) with a set of weights, biases, a value of i, and the minimum and maximum values of the input variables defines the network completely. The

availability of a sufficiently complex and flexible function means that the analysis is not as restricted as in linear regression where the form of the equation has to be specified before the analysis.

The neural network can capture interactions between the inputs because the hidden units are non-linear. The nature of these interactions is implicit in the values of the weights, but the weights may not always be easy to interpret. For example, there may exist more than just pairwise interactions, in which case the problem becomes difficult to visualise from an examination of the weights. A better method is actually to use the network to make predictions, and to see how these depend on various combinations of input.

Error estimates

The input parameters are generally assumed in the analysis to be precise, and it is normal to calculate an overall error E_D by comparing the predicted values y_j of the output with those measured t_j, for example

$$E_D \propto \sum_j (t_j - y_j)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

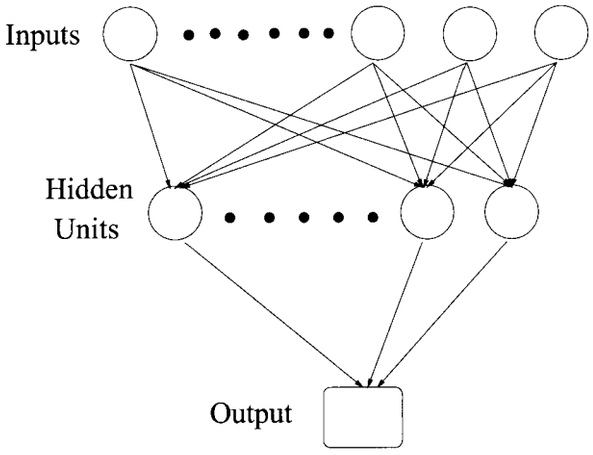
The value of E_D is expected to increase if important input variables have been excluded from the analysis. While E_D gives an overall perceived level of noise in the output parameter, it is, on its own, an unsatisfying description of the uncertainties of prediction.

MacKay has developed a particularly useful treatment of neural networks in a Bayesian framework,[5] which allows the calculation of error bars representing the uncertainty in the fitting parameters. The method recognises that there are many functions which can be fitted or extrapolated into uncertain regions of the input space, without unduly compromising the fit in adjacent regions which are rich in accurate data. Instead of calculating a unique set of weights, a probability distribution of sets of weights is used to define the fitting uncertainty. The error bars therefore become large when data are sparse or locally noisy.

In this context, a very useful measure is the log predictive error (LPE), because the penalty for making a wild prediction is reduced if that wild prediction is accompanied by appropriately large error bars[6]

$$\mathrm{LPE} = \sum_n [\tfrac{1}{2}(t^{(n)} - y^{(n)})^2/\sigma_y^{(n)^2} + \log(2\pi\sigma_y^{(n)})^{1/2}]$$

Note that a larger value of the log predictive error implies a better model.



1 Schematic illustration of input, hidden, and output layers of neural network model used in present work

Overfitting

A potential difficulty with the use of powerful non-linear regression methods is the possibility of overfitting data. To avoid this, the experimental data can be divided into two sets, a training dataset and a test dataset. The model is produced using only the training data. The test data are then used to check that the model functions when presented with previously unseen data. The training error tends to decrease continuously as the model complexity increases. It is the minimum in the test error that enables the model which generalises best on unseen data to be chosen.[6] There are other important features in the control of complexity which are discussed elsewhere.[6]

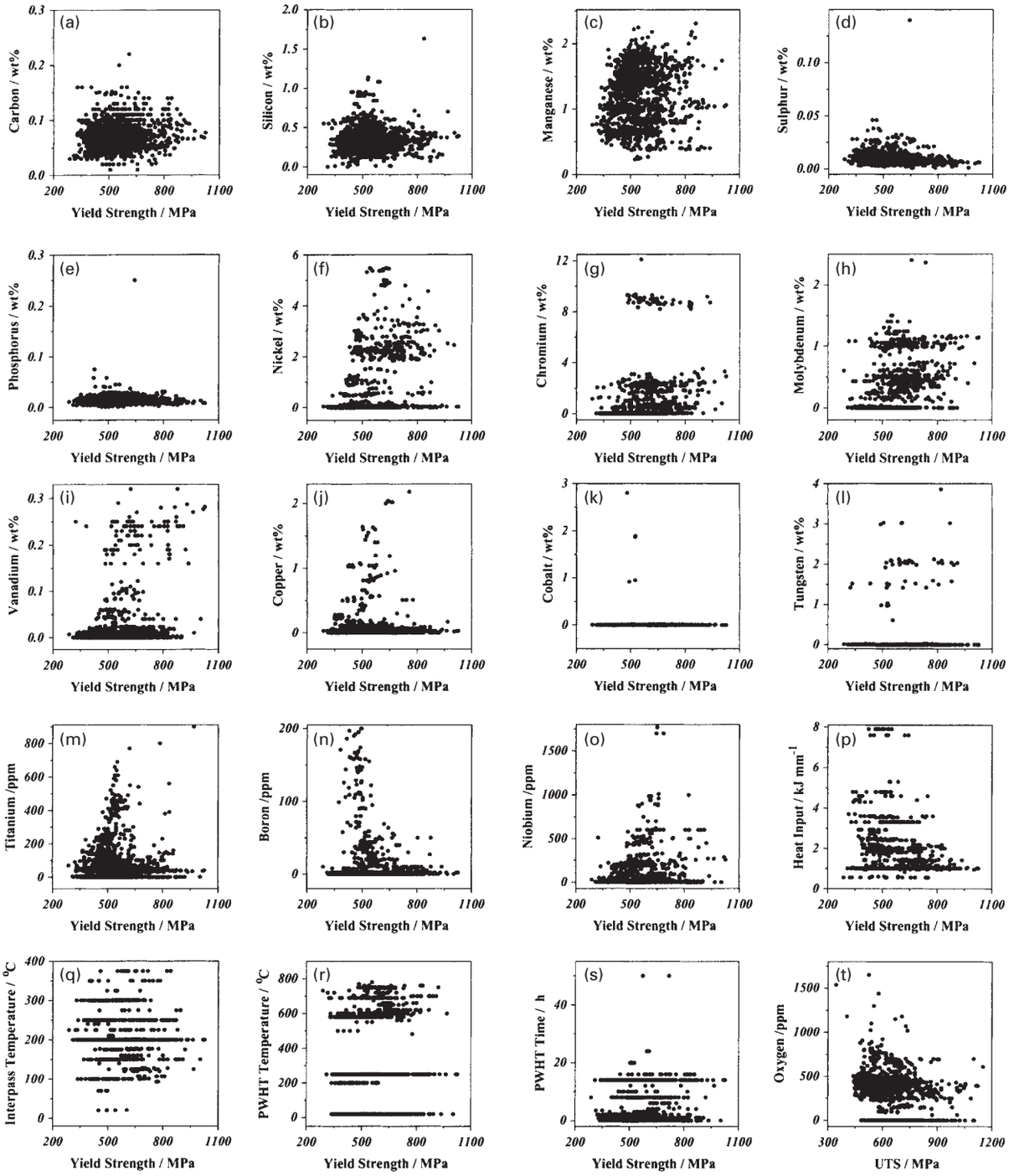
Finally, it should be noted that the analysis uses normalised values of the variables in the range $\pm 0{\cdot}5$ according to

$$x_N = \frac{x - x_{min}}{x_{max} - x_{min}} - 0{\cdot}5$$

where x is the original value from the database, x_{max} and x_{min} are the respective maximum and minimum of each variable in the original data, and x_N is the normalised value. This step is not essential to the running of the neural network, but is a convenient way of comparing the effect of different variables on the output. Figure 1 shows the general structure of the simple three layer neural network.

Table 1 Inputs for yield strength model

Input element	Minimum	Maximum	Mean	Standard deviation
C, wt-%	0·01	0·22	0·072	0·025
Si, wt-%	0·01	1·63	0·344	0·138
Mn, wt-%	0·27	2·31	1·192	0·41
P, wt-%	0·001	0·25	0·012	0·009
S, wt-%	0·001	0·14	0·009	0·006
Cr, wt-%	0·0	12·1	0·808	1·952
Mo, wt-%	0·0	2·4	0·221	0·368
Ni, wt-%	0·0	4·79	0·43	0·888
Co, wt-%	0·0	2·8	0·007	0·115
Cu, wt-%	0·0	2·18	0·063	0·185
V, wt-%	0·0	0·32	0·026	0·06
W, wt-%	0·0	3·86	0·091	0·427
B, ppm wt	0·0	195	5·8	19·08
Nb, ppm wt	0·0	1770	69·6	168·13
Ti, ppm wt	0·0	900	64·9	112·14
Heat input, kJ mm^{-1}	0·55	7·9	1·6	1·234
Interpass temperature, °C	20	375	207·8	52·67
Tempering temperature, °C	20	780	358·3	249·29
Tempering time, h	0·0	50	6·5	6·45
Yield strength, MPa	288	1003	533·9	113·64



a C; *b* Si; *c* Mn; *d* S; *e* P; *f* Ni; *g* Cr; *h* Mo; *i* V; *j* Cu; *k* Co; *l* W; *m* Ti; *n* B; *o* Nb; *p* heat input; *q* interpass temperature; *r* PWHT temperature; *s* PWHT time; *t* O *v.* UTS

2 Database values of each variable versus yield strength

DATABASE

All of the data collected are from multirun weld deposits designed for low dilution, to enable specifically the measurement of all weld metal properties. Furthermore, they all represent electric arc welds made using one of the following processes: manual metal arc (MMA), submerged arc welding (SAW), and tungsten inert gas (TIG). The welding process itself was represented only by the level of heat input. This is because a large number of published papers did not specify welding parameters in sufficient detail to enable the creation of a dataset without missing values. Missing values cannot be tolerated in the method used here. If the effect of a welding process is not properly represented by the heat input and chemical composition, then neglect of any other parameters will make the predictions more 'noisy'. As discussed below, the noise in the output was found to be acceptable; a greater uncertainty arises from the lack of a uniform coverage of the input space. The sources of all data are provided.[2,7–28,30–73]

The aim of the neural network analysis was to predict the yield and tensile strengths as functions of a large number of

variables, including the chemical composition, the welding heat input, and any heat treatment. The databases for the yield strength (YS) and the ultimate tensile strength (UTS) are different because the UTS database also included the oxygen concentration, since tensile failure should depend on inclusions which nucleate voids. As a consequence, the yield strength database consists of 2002 separate experiments whereas the UTS database is slightly smaller at 1972 experiments, as the oxygen concentration was not always reported. (This compares with previous work based on 770 yield strength and 520 UTS experiments.[3]) The present method cannot cope with missing values of any of the variables. In 14 cases the sulphur and phosphorus concentrations were not available. Since these impurities might be important, it would not be satisfactory to set the values to zero. Missing concentrations of sulphur and phosphorus were therefore set at the average of the database.

Yield strength database

Table 1 gives the range, mean, and standard deviation of each variable, including the output (yield strength). The purpose here is simply to list the variables and provide an idea of the range covered. However, it is emphasised that, unlike in linear regression analysis, the information in Table 1 cannot be used to define the range of applicability of the neural network model. This is because the inputs are in general expected to interact. It is the Bayesian framework of the present neural network analysis that allows the calculation of error bars which define the range of useful applicability of the trained network, as discussed below. A visual impression of the spread of data is shown in Fig. 2. It can be concluded from Fig. 2 that the effects on yield strength of carbon, manganese, silicon, nickel, molybdenum, and heat input have been systematically studied. Hence, future experiments could focus on examining the effect of chromium in the range 3–8 wt-%, vanadium at 0·1–0·2 wt-%, cobalt at all concentrations but in a greater variety of alloy systems, tungsten at low and high concentrations, and titanium and boron in high strength welds. The effect of tempering temperature in the range 250–500°C also needs to be studied.

UTS database

Table 2 gives the range, mean, and standard deviation of each variable, including the output (ultimate tensile strength). The corresponding visual impression of the UTS database is similar to that of the yield strength, although the UTS database contains the extra input variable oxygen (Fig. 2*t*), the effect of which at higher concentrations (above 900 ppm by weight) needs to be studied.

YIELD STRENGTH MODEL

Some 80 yield strength neural network models were trained on a training dataset which consisted of a random selection of half the data (1001) from the yield strength dataset. The remaining 1001 data formed the test dataset, which was used to see how the model generalises on unseen data. Each model contained the 19 inputs listed in Table 1 but with different numbers of hidden units or the random seeds used to initiate the values of the weights. Figure 3 shows the results. As expected, the perceived level of noise σ_v in the normalised yield strength decreases as the model becomes more complex, i.e. the number of hidden units increases (Fig. 3*a*). This is not the case for the test error, which goes through a minimum at three hidden units (Fig. 3*b*), or for the log predictive error, which reaches a maximum at six hidden units (Fig. 3*c*).

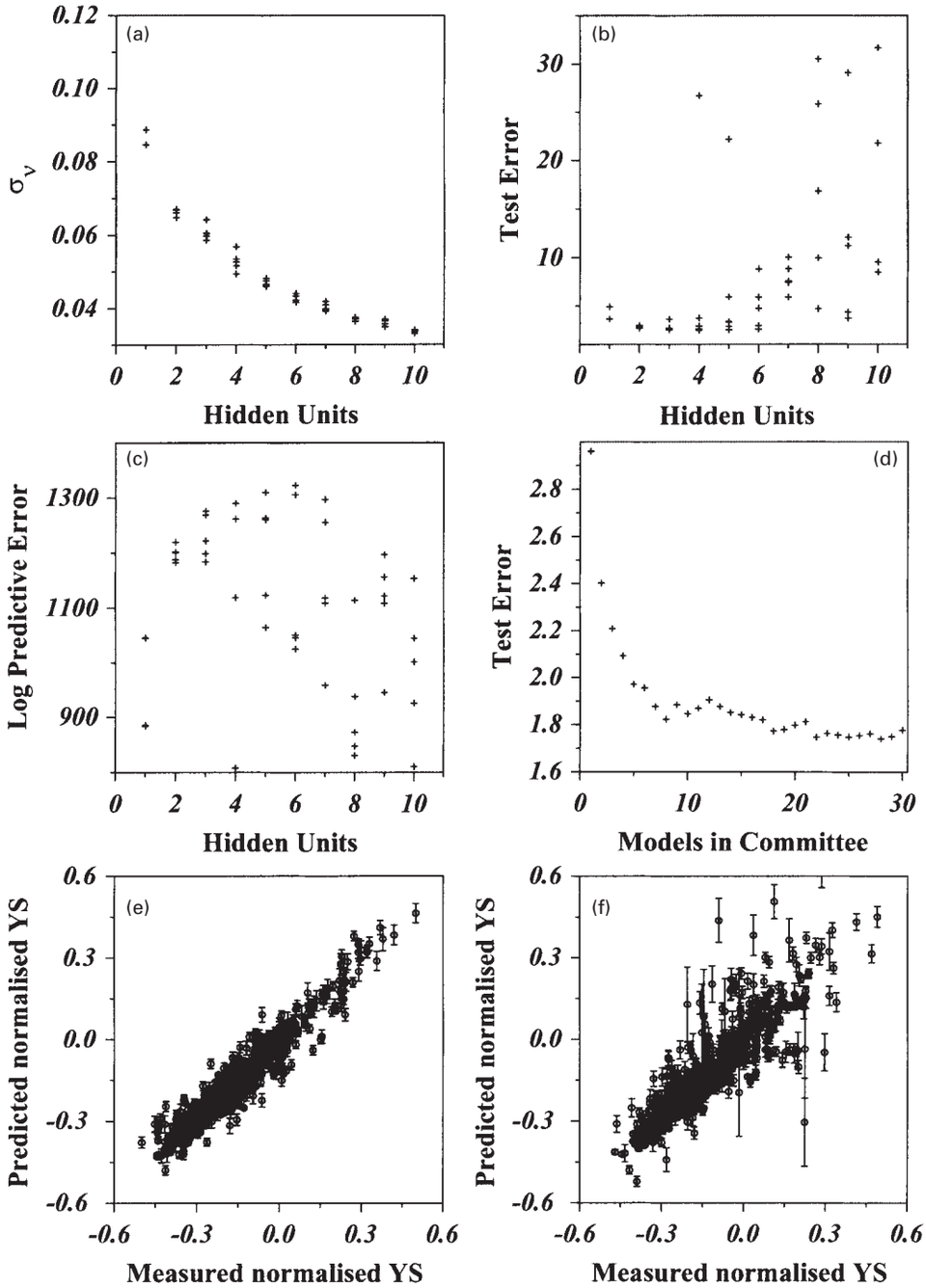
The error bars throughout the present work represent a combination of the perceived level of noise σ_v in the output and the fitting uncertainty estimated from the Bayesian framework. It is evident that there are a few outliers in the plot of the predicted versus measured yield strength for the test dataset (Fig. 3*f*). Each of these outliers has been investigated and found to represent unique data not represented in the training dataset. For example, there is a weld with a sulphur concentration of 0·15 wt-% and another with a phosphorus concentration of 0·25 wt-%, both extremely high and unusual levels of impurities in weld metals.

It is possible that a committee of models can make a more reliable prediction than an individual model.[74] The best models are ranked using the values of the log predictive errors (Fig. 3*c*). Committees are then formed by combining the predictions of the best L models, where $L=1, 2, \ldots$; the size of the committee is therefore given by the value of L. A plot of the test error of the committee versus its size gives a minimum which defines the optimum size of the committee, as shown in Fig. 3*d*.

The test error associated with the best single model is clearly greater than that of any of the committees (Fig. 3*d*). The committee with 28 models was found to have an

Table 2 Inputs for ultimate tensile strength (UTS) model

Input element	Minimum	Maximum	Mean	Standard deviation
C, wt-%	0·01	0·22	0·072	0·024
Si, wt-%	0·01	1·63	0·345	0·142
Mn, wt-%	0·27	2·31	1·191	0·410
P, wt-%	0·001	0·25	0·012	0·009
S, wt-%	0·001	0·14	0·009	0·006
Cr, wt-%	0·0	12·1	0·748	1·810
Mo, wt-%	0·0	2·4	0·219	0·370
Ni, wt-%	0·0	4·79	0·426	0·900
Co, wt-%	0·0	2·8	0·008	0·110
Cu, wt-%	0·0	2·18	0·053	0·160
V, wt-%	0·0	0·32	0·0252	0·060
W, wt-%	0·0	3·86	0·093	0·500
B, ppm wt	0·0	195	6	19·3
Nb, ppm wt	0·0	1770	66	163·6
Ti, ppm wt	0·0	900	67	116·5
O, ppm wt	0·0	1650	362	200·8
Heat input, kJ mm^{-1}	0·55	7·9	1·56	1·17
Interpass temperature, °C	20	375	209	51·8
Tempering temperature, °C	20	770	368	241·8
Tempering time, h	0·0	50	6·9	6·5
UTS, MPa	440	1151	624	117·5



a σ_v *v.* hidden units; *b* test error *v.* hidden units; *c* log predictive error *v.* hidden units; *d* test error *v.* models in committee; *e* predicted *v.* measured yield strength (training); *f* predicted *v.* measured yield strength (test)

3 Characteristics of yield strength model

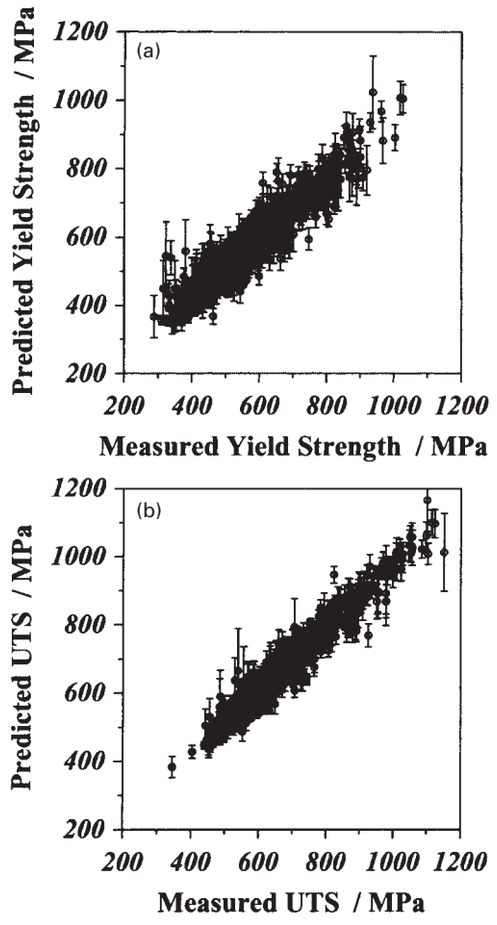
optimum membership with the smallest test error. The committee was therefore retrained on the entire dataset without changing the complexity of any of its member models. The final comparison between the predicted and measured values of the yield strength for the committee of 28 is shown in Fig. 4*a*. Details of the 28 members of the optimum committee are given in Table 3.

Figure 5*a* indicates the significance σ_w of each of the input variables, as perceived by the first five neural network models in the committee. The σ_w value represents the extent to which a particular input explains the variation in the output, rather like a partial correlation coefficient in linear regression analysis.

The post-weld heat treatment (PWHT) temperature on the whole explains a large proportion of the variation in the yield strength (Fig. 5*a*). All of the variables considered were found to have a significant effect on the output, indicating a good choice of inputs.

ULTIMATE TENSILE STRENGTH MODEL

The models were trained on 1972 individual experimental measurements, of which a random half of the data formed the training dataset and the other half the test dataset. The procedures are otherwise identical to those described for the yield strength model, resulting in the characteristics



a yield strength; *b* UTS

4 Comparison of predicted and measured values of yield strength and ultimate tensile strength (UTS) for optimum committee models

illustrated in Fig. 6. The performance of the optimum committee of best models is illustrated in Fig. 4*b*. Details of the 24 members of the optimum committee are given in Table 4.The perceived significance of the first five models is shown in Fig. 5*b*. In this case the additional input variable oxygen has a significant effect, along with PWHT variables.

APPLICATION TO C–Mn WELDS

Carbon–manganese weld metals refer to a popular class of ferritic steels in which the substitutional solutes other than silicon and manganese are generally kept to low concentration levels. They are interesting because there is a great deal already known about them, making it easy to interpret the physical significance of the neural network model. Furthermore, there exists an alternative semiempirical model for the estimation of the yield and tensile strengths of such multirun welds,[75] enabling a further comparison. The semiempirical model is henceforth referred to as the 'physical model' or PM. The basic values of the variables used in applying the model to C–Mn welds are listed in Table 5. The specified low temperature heat treatment is simply a standard hydrogen removal treatment (250°C for 14 h) applied to most welds before mechanical testing.

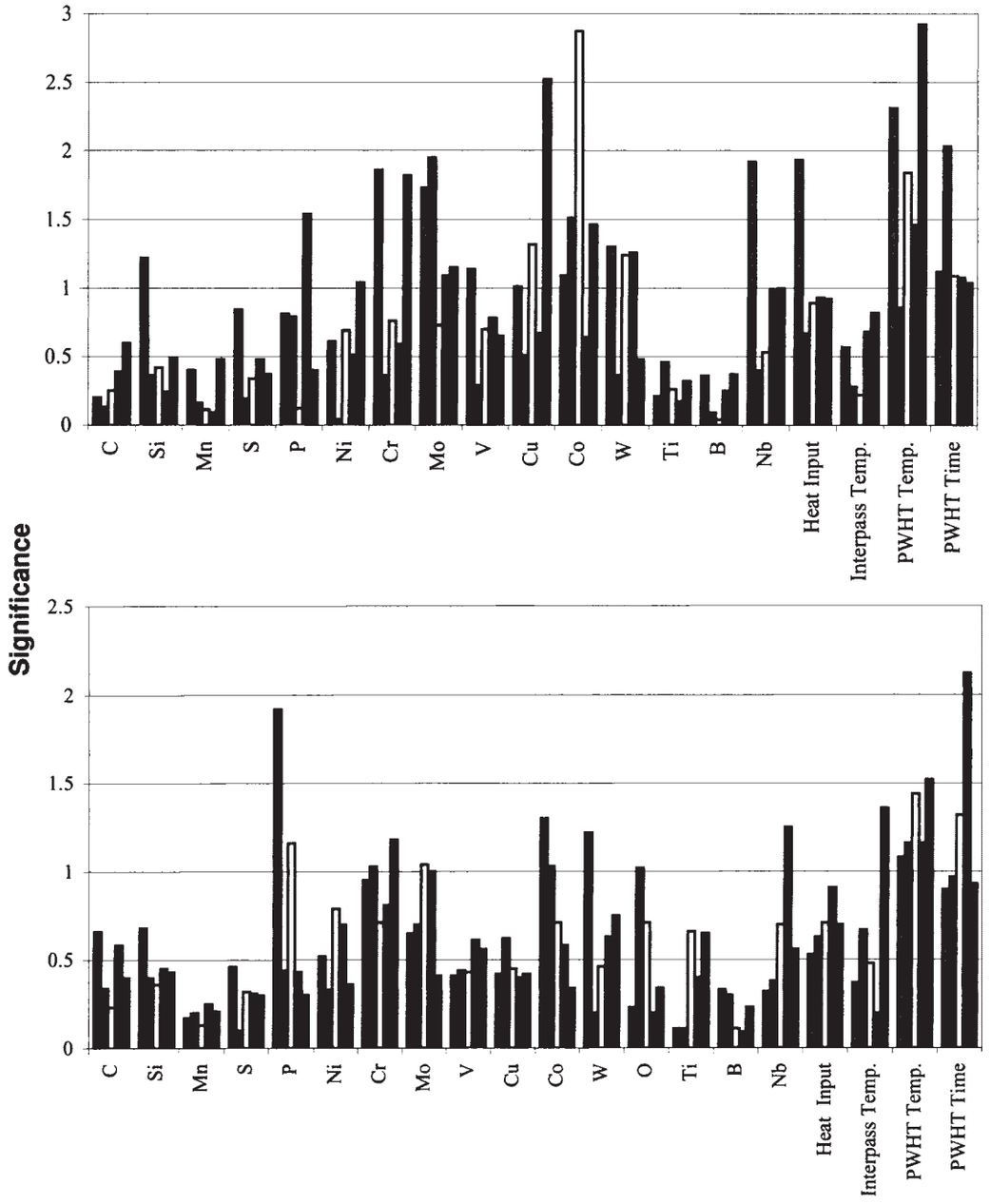
The results as a function of the carbon and manganese concentrations are illustrated in Fig. 7 for a variety of interesting cases. The calculated yield strength can be seen to be consistent with that expected from the physical model, although there are systematic differences at high yield strength values for all cases other than at the highest manganese concentration. However, the deviations are all within the error bounds of the neural network (NN) model for yield strength. The major discrepancies arise with the UTS, especially at high UTS values. It is believed that the physical model is poorly constructed since the UTS is essentially taken arbitrarily to be linearly related to a single variable, the yield strength. Figure 8 shows a comparison between the measured strength and that estimated by the

Table 3 Twenty-eight members of optimum committee for yield strength model: σ_v is perceived level of noise in yield strength and complexity of model increases with number of hidden units

Model	Hidden units	σ_v
1	6	0·044062
2	5	0·048167
3	6	0·043382
4	7	0·040949
5	4	0·053474
6	4	0·052702
7	3	0·058641
8	3	0·060561
9	5	0·047489
10	4	0·047489
11	5	0·046503
12	7	0·039873
13	3	0·064206
14	2	0·067036
15	5	0·066848
16	2	0·064810
17	3	0·059811
18	9	0·036538
19	2	0·066146
20	3	0·060487
21	2	0·066151
22	9	0·035645
23	10	0·033591
24	5	0·045975
25	9	0·034897
26	4	0·051630
27	7	0·039677
28	8	0·036436

Table 4 Hidden units and σ_v in optimum ultimate tensile strength (UTS) committee model

Model	Hidden units	σ_v
1	8	0·029323
2	9	0·026503
3	6	0·027177
4	10	0·025500
5	9	0·031034
6	6	0·026604
7	4	0·027218
8	10	0·026010
9	6	0·025530
10	5	0·031240
11	8	0·026471
12	9	0·026485
13	7	0·027016
14	8	0·060074
15	3	0·028483
16	3	0·039529
17	2	0·065098
18	2	0·052619
19	2	0·029716
20	2	0·045941
21	4	0·053212
22	9	0·053929
23	4	0·033334
24	3	0·034551



a yield strength; *b* UTS

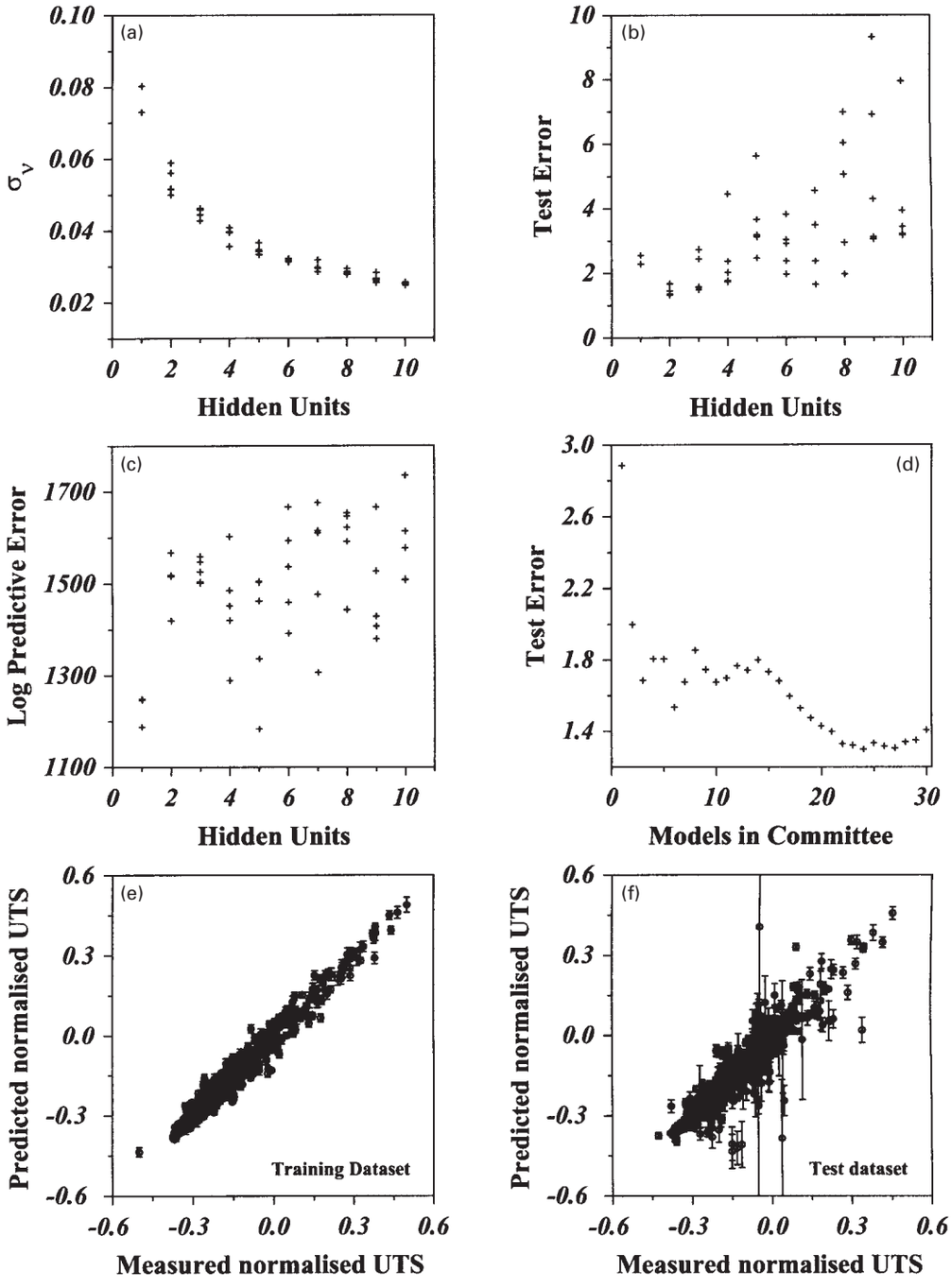
5 Perceived significance σ_w values of first five yield strength and UTS models for each input

physical model. Physical models at higher strength values have functioned very poorly, estimating the strength to be higher than that measured.

An interesting feature of strengthening due to substitutional solutes is the synergistic effect with carbon. Figure 9*a* and *b* shows that the dependence of the strengthening effect of molybdenum on the carbon concentration is particularly large, the effect of molybdenum in strengthening the weld being greater than that of chromium or manganese. This is consistent with the published literature.[75] Elements such as molybdenum and vanadium are associated with strong secondary hardening effects, which frequently trigger a reduction in toughness. In ordinary C–Mn multirun welds, the secondary microstructure, i.e. regions of weld metal tempered by subsequent weld runs, loses most of its microstructural strength. This is not necessarily the case in weld metal containing strong carbide formers. For example, it is well established that the yield strength calculated using equation (1) is always underestimated with molybdenum containing welds, the degree of underestimation increasing with the molybdenum concentration.[1] The behaviour observed in Fig. 9*a* is therefore not surprising.

The sensitivity to carbon concentration, and the net magnitude of the strengthening effect, decreases for the ultimate tensile strength (Fig. 9*b*). This is expected since the UTS is measured at large plastic strains whereas the yield strength is more sensitive to the initial microstructure.

The predicted dependence of the strengthening effect of niobium on the carbon concentration is shown in Fig. 9*d*. The strength increment plotted on the vertical axis is based on the average effect of niobium in the concentration range



a σ_v *v.* hidden units; *b* test error *v.* hidden units; *c* log predictive error *v.* hidden units; *d* test error *v.* models in committee; *e* predicted *v.* measured UTS (training); *f* predicted *v.* measured UTS (test)

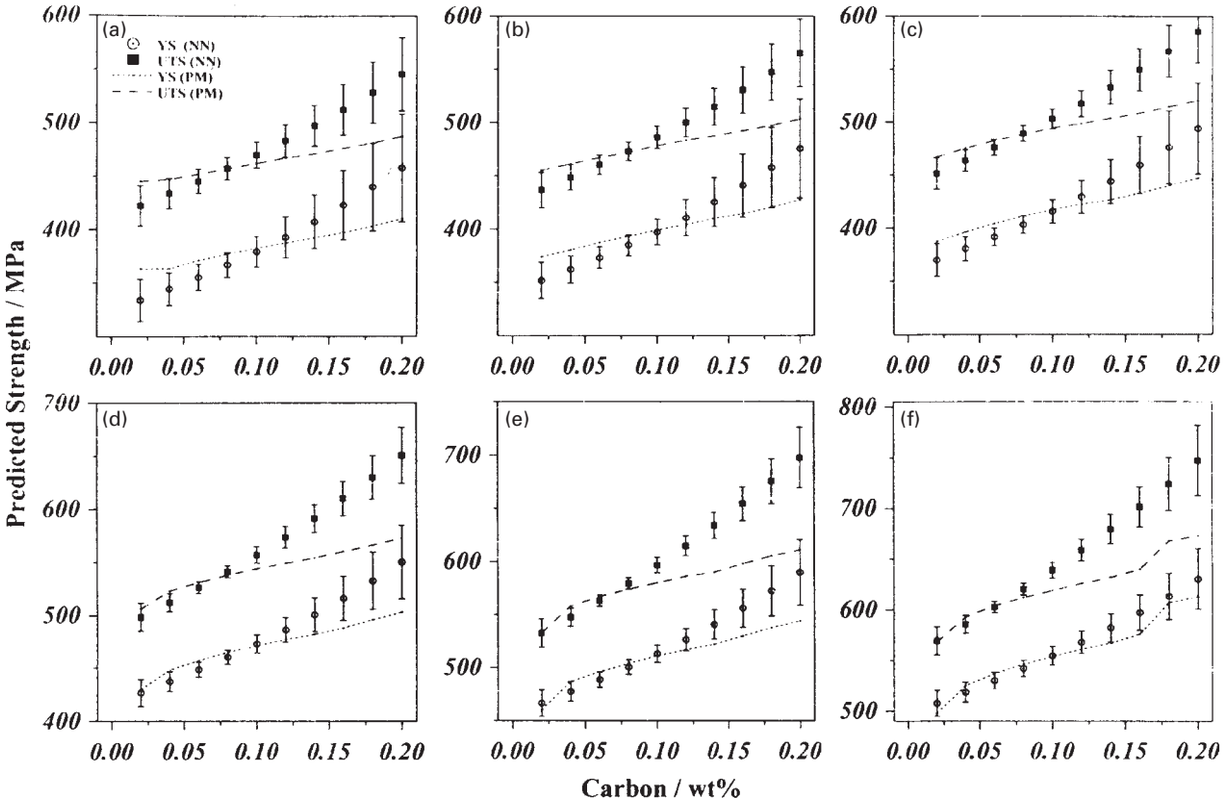
6 Characteristics of ultimate tensile strength (UTS) model

0–1500 ppm by weight, for any given carbon concentration. The increment per weight per cent of niobium is obviously very large, and this may be the reason why niobium is generally found to be detrimental to toughness.[29]

Figure 10 shows other predictions; although there are no surprises, it is worth noting the error bars. These error bars can be used to identify regions of the input space where further experiments would be useful. For example, the prediction uncertainties associated with niobium, or with high heat inputs, are much larger than say with changes in the manganese concentration. Future experiments could be focused on these variables.

APPLICATION TO 2·25Cr–1Mo WELDS

The 2·25Cr–1Mo weld metal system is designed primarily for applications where the components will serve at elevated temperatures (450–565°C) for long periods of time (~30 years). This in contrast to C–Mn weld metals which are used in structural applications such as buildings and bridges essentially at ambient temperature. Consequently, the PWHT is of vital importance to 2·25Cr–1Mo weld metals, not only to relieve residual stresses but also to generate a stable microstructure in which the carbides hinder creep deformation. The basic values of the variables



a 0·10Mn; *b* 0·30Mn; *c* 0·50Mn; *d* 1·10Mn; *e* 1·50Mn; *f* 1·90Mn

7 Series of calculations for C–Mn welds, using both neural network (NN) committee models and alternative published model (PM)[75]

used in applying the models to 2·25Cr–1Mo welds are listed in Table 5. The specified high temperature heat treatment is a typical PWHT.

It is notable from the predictions illustrated in Fig. 11 that there are greater uncertainties (larger error bars) associated with the estimation of mechanical properties for the 2·25Cr–1Mo system when compared with the C–Mn welds. This is largely because there are fewer data available for 2·25Cr–1Mo welds.

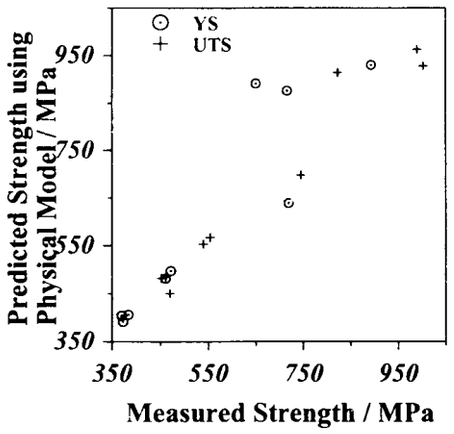
Another striking feature is that the sensitivity of the strength to alloying elements, in the PWHT condition, is far smaller than in the as welded condition. This is not surprising given the severe nature of the PWHT at 690°C for 8 h. It is emphasised that, although the yield and tensile strengths are not particularly sensitive to composition in the PWHT condition, this will not be the case for creep properties where the tempering heat treatment is essential for the generation of alloy carbides and to provide a microstructure that has long term stability.

Table 5 Inputs relevant for typical weld metals

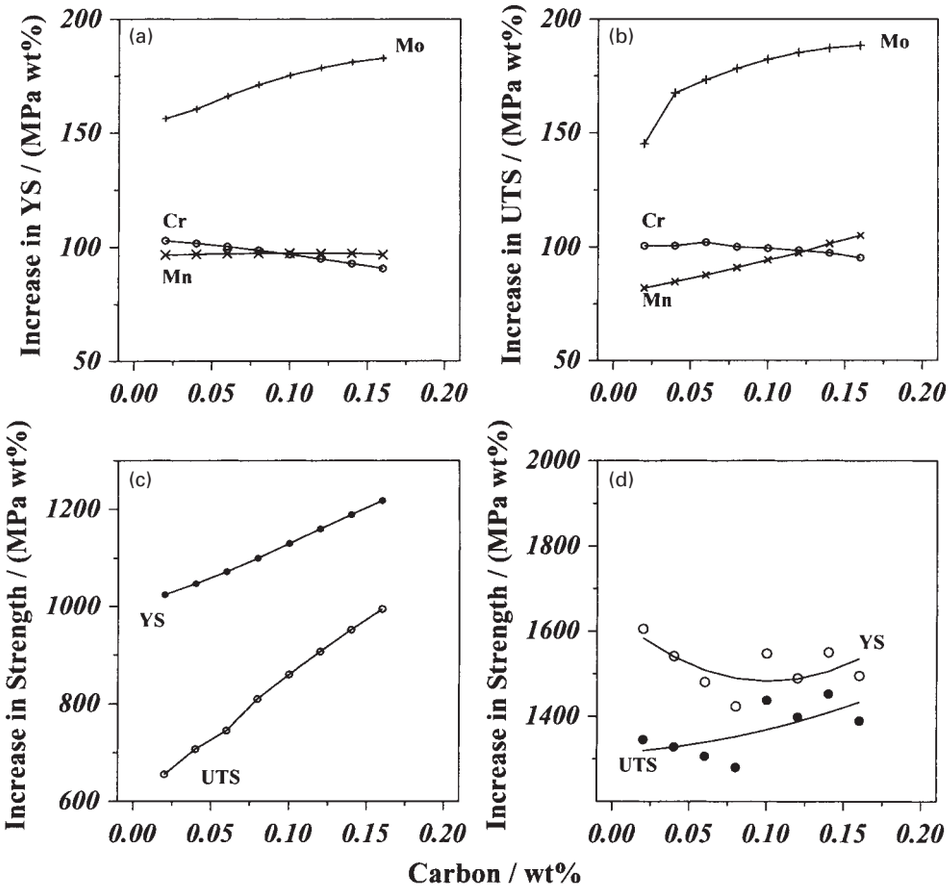
Input element	C–Mn	2·25Cr–1Mo
C, wt-%	0·06	0·11
Si, wt-%	0·50	0·20
Mn, wt-%	1·50	0·80
P, wt-%	0·008	0·005
S, wt-%	0·006	0·002
Cr, wt-%	0·0	2·25
Mo, wt-%	0·0	1·0
Ni, wt-%	0·0	0·20
Co, wt-%	0·0	0·0
Cu, wt-%	0·0	0·0
V, wt-%	0·0	0·0
W, wt-%	0·0	0·0
B, ppm wt	0·0	0·0
Nb, ppm wt	0·0	0·0
Ti, ppm wt	0·0	0·0
O, ppm wt	300	300
Heat input, kJ mm^{-1}	1·00	1·5
Interpass temperature, °C	175	200
Tempering temperature, °C	250	690
Tempering time, h	14·0	8·0

SOFTWARE

A vast number of other trends predicted by the models have been examined. It is not practical to report all the results in the present paper; suffice it to say that the trends have been found to be reasonable from a metallurgical point of view.



8 Comparison between measured and published physical model calculations



a increase in YS with Mo, Cr, Mn; *b* increase in UTS with Mo, Cr, Mn; *c* increase in YS and UTS with V; *d* increase in YS and UTS with Nb

9 Change in strength and YS/UTS ratio as function of wt-% of substitutional solute content in C–Mn steel welds: error bars are not included for clarity, but maximum values are 60 MPa wt-%

Models such as these cannot be fully studied because the number of possibilities is very large indeed. In addition, although those for C–Mn and 2·25Cr–1Mo have been described in the present paper, the work is much more widely applicable since the database from which the neural network models were created covers a vast range of alloys.

The software capable of doing these calculations can be obtained freely from http://www.msm.cam.ac.uk/map/map.html.

SUMMARY AND CONCLUSIONS

The yield strength and ultimate tensile strength of ferritic steel weld metal have been analysed using a neural network method within a Bayesian framework. The data used were mostly obtained from the published literature and represent a wide cross-section of alloy compositions and arc welding processes.

Trends predicted by the models appear to be consistent with those expected metallurgically, although it must be emphasised that only the simplest of trends have been examined since the number of variables involved is very large. The models can be applied widely because the calculation of error bars whose magnitude depends on the local position in the input space is an inherent feature of the neural network used. The error bar is not simply an estimate of the perceived level of noise in the output but also includes an uncertainty associated with fitting the function in the local region of input space. This means that the method is less dangerous in extrapolation or interpolation since it effectively warns when experimental data are lacking or are exceptionally noisy. The work has clearly identified regions of the input space where further experiments should be encouraged.

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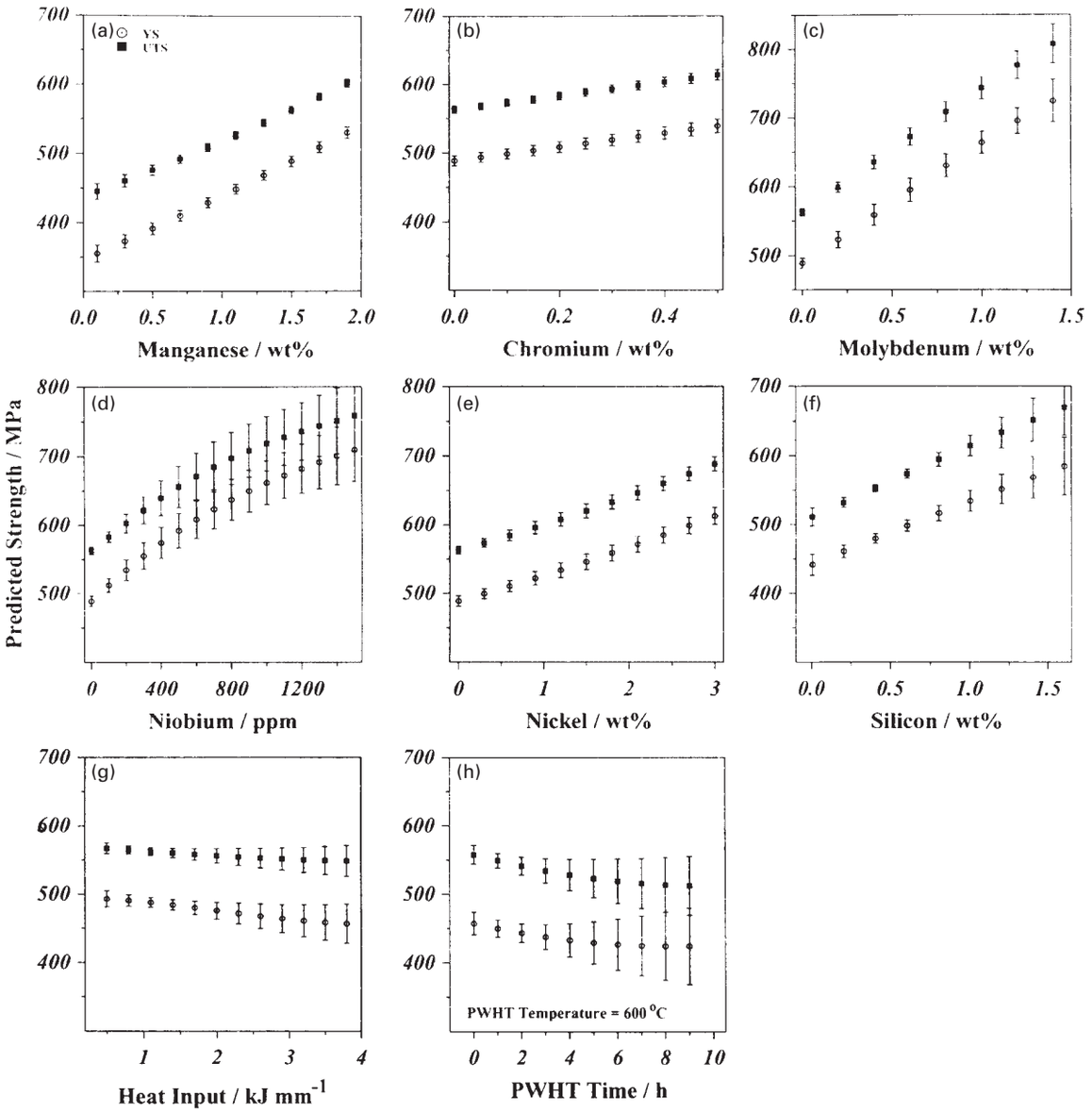

a Mn; *b* Cr; *c* Mo; *d* Nb; *e* Ni; *f* Si; *g* heat input; *h* PWHT time

10 Variations in yield and ultimate tensile strengths of C–Mn weld metal as function of given alloying elements and heat treatment

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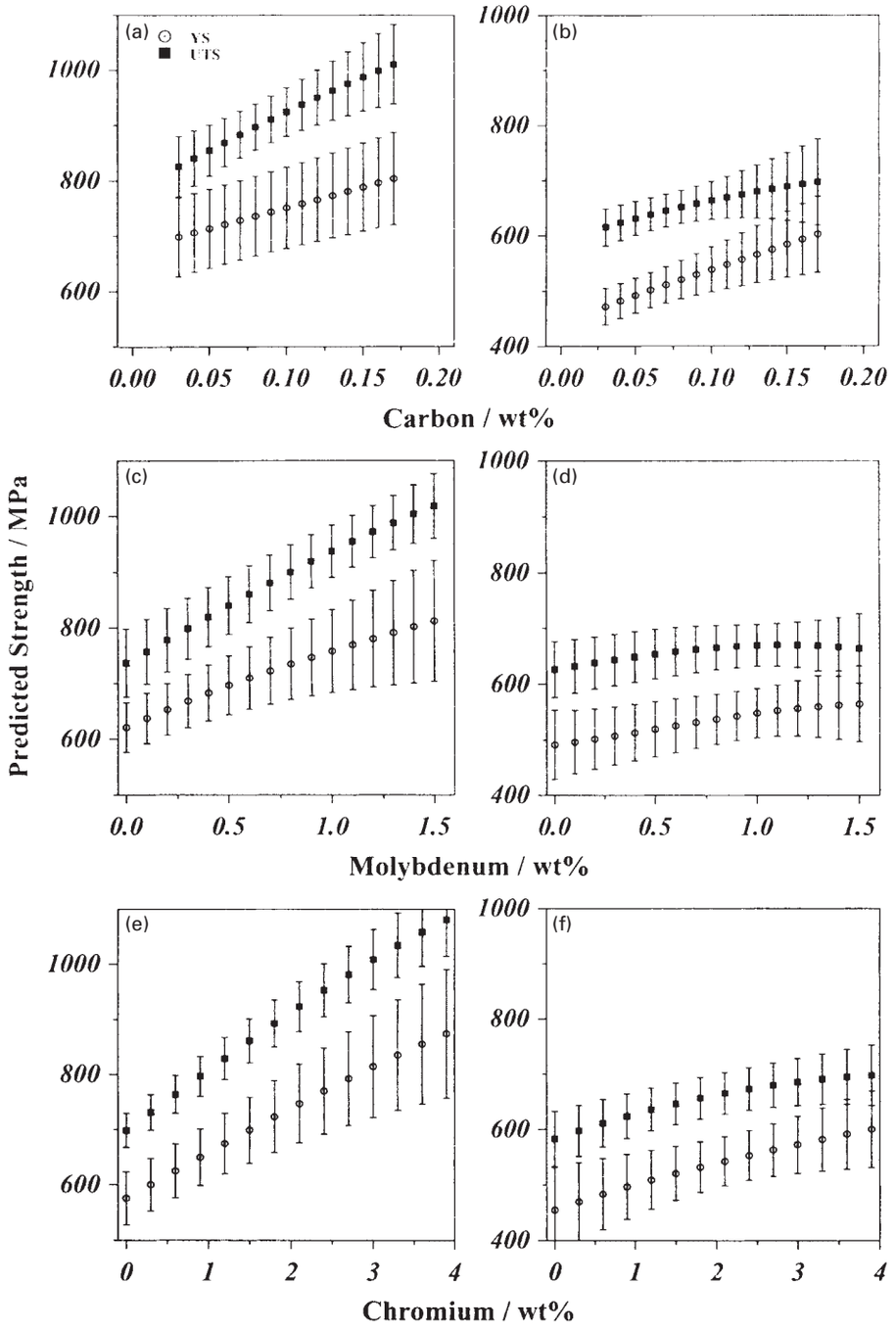

a C, as welded; *b* C, PWHT; *c* Mo, as welded; *d* Mo, PWHT; *e* Cr, as welded; *f* Cr, PWHT

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