Scatter in High Strength Steel Weld properties due to Interpass Temperature

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Abstract

High strength steel manual metal arc (MMA) welds containing low levels of carbon and significant additions of Mn, Ni, Cr and Si, have been reported to exhibit large variations in yield strength. Microscopy upon a typical weld of this class indicated a fine upper bainitic microstructure with no visible carbon precipitation. Charpy impact data revealed high levels of toughness with a gentle transition between brittle and ductile fracture regimes. Dilatometry showed that a typical MMA cooling curve would intersect the CCT curve in a critical regime close to the limit of hardenability. Neural network analysis revealed that the yield stress of a multirun joint is strongly dependent upon the interpass temperature for this alloy, a parameter that may affect the weld cooling rate. The ultimate tensile strength was predicted to be affected to a much lesser extent. Tensile test data from welds fabricated at interpass temperatures of 50 °C, 110 °C and 250 °C agreed well with the predictions. Charpy impact tests did not indicate a dependence of the toughness upon the interpass temperature.

Introduction

The extreme conditions that can be found in the offshore, mining and marine industries require steel welding alloys with exemplary mechanical properties. The rather rigid thermal history of the welding process itself places a severe limitation upon the control that can be exacted over the microstructure and this causes the maximum yield strength of steel welds to be below 900 MPa. The microstructures of such welds are based upon martensite or mixtures of martensite and bainitic/acicular ferrite. These microstructures are achieved with alloying additions such as Mn and Ni and C levels are kept low to improve toughness. It has been found that the mechanical properties of high strength welds are variable even though the chemical composition of the deposit does not change (Oldland, 1989). In particular, the yield strength does not seem reproducible to ±150 MPa whereas the ultimate tensile strength does not vary as much. The purpose of this work was to investigate the possible causes of these variations.

Experimental Details

Weld specifications

A number of welds were produced for analysis all having the nominal composition detailed in Table 1.

All experimental welds (multirun MMA) were fabricated to ISO 2560 using 20 mm plates, a 30 run sequence (3 beads per layer), and a backing plate. This configuration causes little dilution of the weld metal allowing accurate isolation and measurement of weld metal properties. Welding of the specimens was performed at 24 V, 180 A and a heat input of 1 kJ mm^{-1}. Prior to tensile testing the welds were degassed at 250 °C for 16 hours.

Weld	C	Mn	Si	Cr	Ni	Cu	Fe
H1	0.05	2.0	0.3	0.4	3.0	0.0	bal

Table 1: Concentration (in weight%) of the major alloying elements in the experimental weld.

Specimens for microscopy

Specimens for light microscopy were produced by hot mounting of the weld material in bakelite. Following grinding and polishing down to a 1 μm diamond grit finish, the samples were etched with 2% Nital.

Transmission electron microscopy samples were made from cylindrical rods of diameter 3 mm machined from sections of weld metal. Approximately 100 μm thick transverse slices were taken from these rods using a SiC disc saw. A further manual grinding stage was required to reduce the thickness of the slices to 60 μm foils. Final preparation was performed using a twin jet electropolisher at ambient temperature and a potential of 50 V. The electropolishing solution comprised 5% Perchloric Acid, 10% Glycerol and 85% Ethanol (Brammar, 1965). Imaging was performed in a Philips 400ST transmission electron microscope operating at 120 kV.

Dilatometry

A *Thermecmastor Z* thermomechanical simulator was used to study the phase transformations occurring within H1 as a function of applied cooling rates in order to produce an experimentally measured CCT curve. The transformations were monitored using laser dilatometry. Specimens for use in the simulator were machined into cylinders of length 12 mm and diameter 8 mm. A 5 mm diameter hole was drilled along the central length of the specimens, the reduction in material volume producing more accurate data.

Heating of the specimens was effected via an induction coil, cooling being similarly controlled using a combination of induction coil heating and jets of helium quenching gas. Computer control allows accurate thermal programs to be applied to the material within a sealed chamber. Temperature data from a Pt–Rh thermocouple were logged along with dilatation data throughout the experiments. Tests were performed in a low pressure helium atmosphere as required by the nature of the cooling process. This atmosphere protected the specimens from decarburisation during the heat treatments. In the production of a continuous cooling transformation (CCT) curve, the specimens were austenitised at 1200 °C for 10 minutes in order to reduce the effect of the austenite microstructure before each specific cooling cycle was applied. A range pf cooling rates were applied, from 100 °C s^{-1} to 0.05 °C s^{-1}.

Impact Tests

Standard 10 mm × 10 mm Charpy V-notch specimens were prepared for impact testing. The specimens were cut from transverse sections on the weld material and were tested over a range of temperatures from -100 °Cto 20 °C. Multiple tests were performed at each temperature.

Neural Network Modelling

Regression analysis is commonly used where data are best-fitted to a specified relationship which is often linear. An equation is produced in which each of the inputs x_j is multiplied by a weight w_j the sum of all such products and a constant C then gives an estimate of the output

$$y = w_1 x_1 + w_2 x_2 + \ldots + C$$

A more general computational method of regression is neural network analysis. As before, the input data x_j are multiplied by weights, but the sum of all these products forms the argument of a hyperbolic tangent. The output y is therefore a non-linear function of x_j, the function usually chosen being the hyperbolic tangent because of its flexibility. The method is able to capture almost arbitrarily non-linear relationships A potential concern with the neural network technique is the possibility of overfitting the data. Scatter in measured data can cause the neural network to fit a more complicated function to the data than can be justified, i.e. both the scatter and errors within the data are modelled in addition to the physical trends. To avoid this difficulty, the experimental data can be randomly 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 behaves itself when presented with previously unseen data.

Whilst there are many varities of neural network, the type used in this work can be expressed diagramatically as below. Here, the network comprises three 'layers'. The first layer contains the model's input data provided by the user such as compositional details (simply entered as normalised values), the second 'hidden' layer is an internal stage within the computer software and describes the degree of complexity of the substructure of the network. The third 'output' layer contains the predicted value of the parameter in question on running a calculation. Fig. 1 shows a simplified network with five example input parameters.

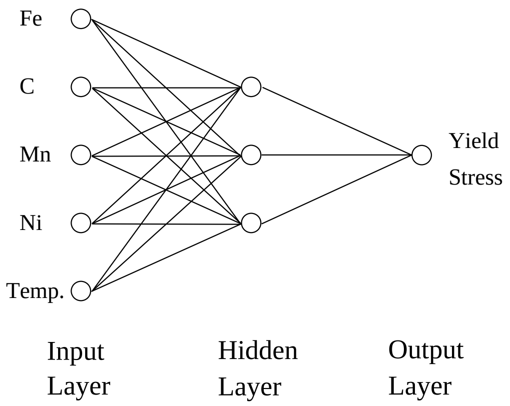

Fig. 1 : Graphical representation of a neural network. Some example of input node parameters are also presented.

The circles within the diagram are called nodes or units, hence here there are five 'input nodes', each of which describes one parameter of the system being modelled, e.g. carbon concentration. The hidden layer comprises three hidden nodes and the output layer is simply a single output node, for example, the yield strength. The number of nodes in the hidden layer limits the complexity of the possible relationships between the input and output nodes. The lines connecting the nodes represent mathematical functions performed on the values as they pass from the input to the output layer. In this network hyperbolic tangent functions are utilised, as they are always single valued, exhibit both near-linear and non-linear regions and are relatively easy to manipulate. On performing a 'prediction' using a neural network, data are operated upon by a hyperbolic tangent function as they are passed between the input and hidden layers. This function is of the form:-

$$h_i = \tanh(\sum_j w_{ij}^{(1)} x_j + \theta_i^{(1)}) \quad (1)$$

where x_j are the normalised values of the input variables, $w_{ij}^{(1)}$ are a set of 'weights' associated with each input and hidden unit and $\theta_i^{(1)}$ are bias values analogous to constants found in linear regression.

The values h_i are transferred from the hidden layer to the output layer via a second function of the form:-

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

where, y is the value of the output node (e.g. yield strength), $w_i^{(2)}$ are a second set of weights and $\theta^{(2)}$ is a further constant known as a 'bias'.

The numerous weighting coefficients and constants ($w_{ij}^{(1)}, \theta_i^{(1)}, w_i^{(2)} h_i$ and $\theta^{(2)}$) are required in order to provide the flexibility to calculate accurate output values from input data. At the heart of the neural network technique are algorithms designed to evaluate these coefficients and constants in order to produce satisfactory results.

Training the network

Training involves repeatedly exposing the training algorithms to data for the network inputs (e.g. compositions) and crucially, the output (e.g. yield stress). The quality of the database at least in part determines the final accuracy of the network predictions. The required size of the database may vary depending on the complexity of the problem being modelled. In general the larger the number of accurate data, the better the resultant network's predictions. The training algorithms refine the coefficients and variables in the above equations by comparing predicted and actual output values of the output node. Through a complicated back propagation process the computer program attempts to reduce the differences between predicted and actual values until they reach acceptably low levels. The problem of 'overtraining' (modelling errors and scatter within the data) is reduced by using a number of different hidden nodes and training on a randomly chosen half of the available data. The best network can be picked which strikes a balance between modelling real trends and overtraining on noise in the data. The second half of the dataset is used for comparing the predictions of this trained network. Ideally plots of predicted versus measured values for both the training and testing halves of the dataset should contain equal degrees of scatter.

Two types of network were trained on data from 770 welds drawn from a variety of sources, the first giving yield stress as an output, the second, ultimate tensile strength (Cool, 1997). Nineteen input variables were provided for each of these welds, fifteen of which were due to alloying elements, the remaining four due to the heat input, interpass temperature and tempering time and temperature values if applicable.

A number of different networks were trained and tested. In the case of the yield stress models, the five best models were then combined into a 'committee'. A committee of networks is superior to a single one as collectively they should capture the trends in the data more effectively. Each network within the committee was retrained on the complete dataset to provide greater accuracy before committee predictions were made. Similarly a committee of four models was used in the predictions of ultimate tensile strength.

Results

Microscopy

Observations of H1 with an optical microscope showed apparently plate–like features but these were believed to represent clusters of plates which are much finer. The fine structure could not really be revealed and was not found to change much with position within the multirun weld (Fig. 2).

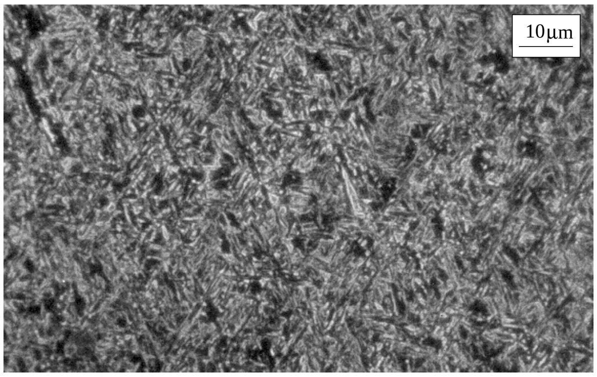

Fig. 2 : Dark field optical micrograph of H1 showing little resolvable detail.

Thin foil observations using transmission electron microscopy (TEM) revealed a fine microstructure comprising bainite plates with a width of the order 0.3 μm. Electron diffraction proved the presence of retained austenite films between the bainitic ferrite plates. The crystallographic orientation between the austenite and adjacent ferrite was found to be consistent with that expected from a rational Kurdjumov–Sachs relationship in which a pair of closely–packed planes of the austenite and ferrite are parallel as is a corresponding pair of close–packed directions within the planes (Fig. 3).

The observation of distinct regions of austenite in such a low–carbon alloy can be simply explained by the bainitic nature of the primary microstructure. Carbon is partitioned from the bainite after it stops growing and this stabilises the austenite which is enriched in carbon (Bhadeshia, 1992). The observation of thick austenite films in such a low–carbon alloy is direct evidence of a primarily bainitic rather than martensitic microstructure. No carbides were found within the TEM specimens in accordance with a low–carbon bainitic microstructure.

The microstructural studies did not reveal any obvious reason for the reported variations in yield strength. A typical TEM micrograph from H1 is shown in Fig. 4.

Fig. 4 : TEM micrograph of the bainitic microstructure of H1.

Impact tests

Toughness measurements were made on specimens of H1 over a temperature range of -100 °Cto 20 °C. The experimental data (Fig. 5) shows a limited degree of scatter and a slow transition from a brittle to a ductile fracture mechanism as a function of temperature (a feature of high strength welds of this type). Upper bainite shows a similar slow transition in toughness values as a function of temperature (Bhadeshia, 1992b).

Dilatometry for production of a CCT curve

Dilatometric measurements were performed upon H1 in order to provide further evidence concerning the nature of microstructure. Dilatometry was performed

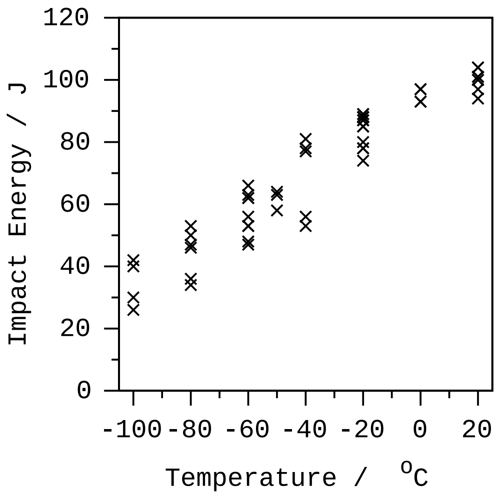

Fig. 5 : Charpy impact measurements for weld H1 as a function of temperature. All samples welded with an interpass temperature of 250 °C.

in which samples of H1 were cooled at rates spanning the cooling conditions of a weld. If the observed transformation temperature remains constant than it can be concluded that the final microstructure must be martensitic since the martensite–start (M_s) temperature does not depend on the cooling rate for low–alloy steels (Kumar, 1967). On the other hand, the temperature at which a detectable fraction of bainite forms does depend on the cooling rate because the overall kinetics of the reaction can be described in terms of a C–curve on a continuous cooling transformation (CCT) diagram. Fig. 6 shows the experimental CCT curve, along with the calculated $\mathrm{M_s}$ temperature (Bhadeshia, 1981) and a calculated MMA weld bead cooling rate with an interpass temperature of 250 °C (Svensson, 1986) denoted '250 °C ITP'.

The calculated weld bead cooling rate clearly cuts the CCT curve beyond the limit of hardenability in a region which should produce a bainitic microstructure. TEM micrographs showed fine plates which confirm a displacive mechanism of transformation. The intersection of these two curves is at a position where the gradient of the CCT curve is very large. Consequently small variations in the cooling rate of the material could drastically alter the transformation temperature and therefore, the resultant mechanical properties. This hypothesis led to questions concerning the possible causes of such variations.

Neural Network predictions

A trained neural network is a valuable tool in an investigation such as this in that the effect can be predicted of individual parameters upon the mechanical properties without the requirement of costly experimentation.

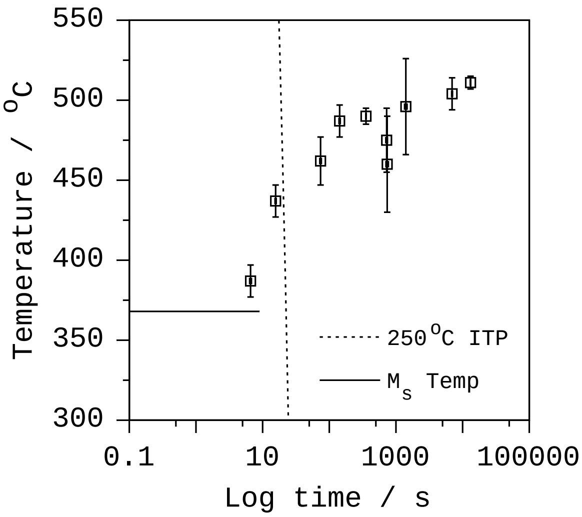

Fig. 6 : Experimental CCT curve for H1. A measured MMA cooling curve is superposed (250 °C interpass temperature).

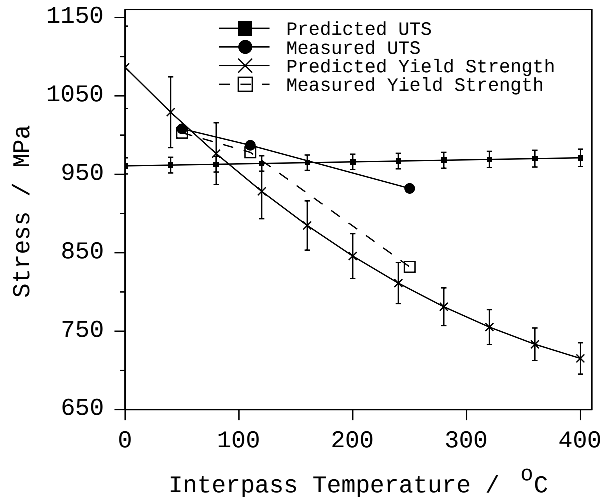

Fig. 6 : Predicted and measured values of yield stress and UTS for H1 as a function of interpass temperature.

The observed scatter in the yield strength of high strength welds was thought not to be due to compositional variations as chemical analysis of the alloys had revealed them to be very similar in composition. The neural networks' predictions supported this theory, revealing no drastic variation in properties as a function of composition. In the case of the interpass temperature, it was noticed that the networks predicted a divergence of the yield and ultimate tensile strength curves as a function of increasing interpass temperature. The predicted effect of increasing the interpass temperature is to slightly reduce the ultimate tensile strength but to reduce the yield strength by a more significant amount. In order to test the accuracy of these predictions specimens of H1 were welded at three different interpass temperatures of 50 °C, 110 °Cand 250 °C, the latter being the standard used commercially for this alloy. Tensile and Charpy impact measurements were made on these specimens. Fig. 7 compares the experimental results with the predictions of the neural network.

The measurements indicate that the yield and ultimate tensile strengths of the weld do indeed diverge as a function of interpass temperature, the reduction in the yield strength being greater than the UTS. It should be noted that the neural network is not aware of the physical impossibility of the yield stress exceeding the UTS and this serves as a good example of the caution that is required when using this method.

Effect upon Charpy Impact results

The effect of the interpass temperature upon the toughness values was similarly investigated. Fig. 8 shows no discernable increase in toughness on increasing the interpass temperature. The scatter in the data covers any slight trends if they are present.

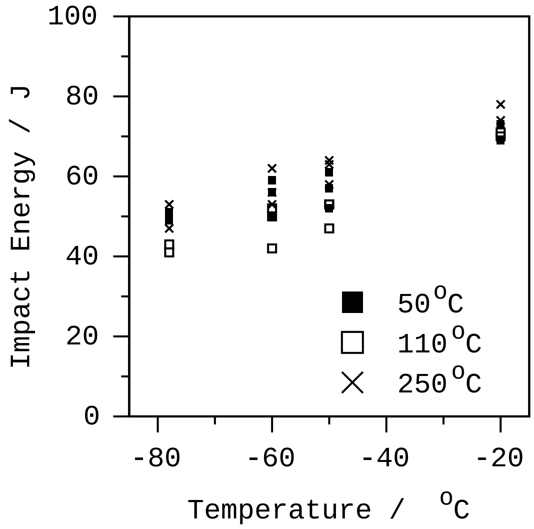

Fig. 8 : Measured values of toughness for specimens welded with an interpass temperature of 50 °C, 110 °C, 250 °C.

Discussion

Initial investigations with microscopy and impact testing revealed little of the possible causes of yield strength variations in H1. The microstructure was concluded to be primarily of upper bainitic ferrite which is in accordance with the weld cycle, the large austenitic regions, the lack of observed carbides and dilatometry data. The CCT curve produced from the dilatometer showed typical MMA measured cooling rates could fall within a critical region, close to the 'nose' of the CCT curve in a region of high gradient. Small variations in the weld cooling rate could considerably affect the transformation temperature for this alloy. It was thought likely that such a variation in the displacive transformation temperatures of the material would have a large enough effect to significantly alter mechanical properties. The majority of the transformation occuring at a higher temperatures for example would lead to a reduction in yield stress as the effects of diffusion on both carbon mobility and dislocations are temperature dependent. Compositional variations alone could not be held responsible for the large variations in yield strength reported for this material.

The neural network analysis of the problem pointed strongly to the interpass temperature as the only input parameter capable of having a large effect upon the yield strength and a lesser one upon the tensile strength. The measured values at three interpass temperatures seemed to support this prediction although the physical reasons for this effect cannot be gleaned from neural network analysis. If, as these results indicate, the interpass temperature is responsible for the measured strength variations then a question must be asked concerning how this may have come about. Traditionally the interpass temperature was not rigorously measured and controlled due to the physical difficulty in recording an accurate value. Indeed in other welds this parameter is not viewed as a critical one and its control is not made a priority. It would appear that such an assumption cannot be made in this case of this alloy in view of the dilatometry results. The most important result of the Charpy impact tests is that there is no discernable decrease in the toughness of the material if the interpass temperature is lowered in order to increase the yield stress. This fact may allow future use of alloys of this class at high strengths without a loss in toughness, although it should be recognised that the close approach of the yield and ultimate tensile strengths at low interpass temperatures may not be acceptable. It is clearly imperative with this weld composition that precautions are taken in controlling the interpass temperature.

CONCLUSIONS

A high strength steel weld alloy, known to show large variations in yield strength, has been investigated using both experimental and modelling techniques. Microscopy and impact testing revealed no obvious cause of the variations in yield strength measurements. Dilatometry data did indicate that the CCT curve for this composition would be cut in a critical region just beyond the limit of hardenability by a typical MMA cooling curve. It was surmised that small variations in the cooling rate may have a significant effect upon the transformation temperature. The mechanical properties would be affected as a result. Neural network analysis showed that the interpass temperature could be the cause of such temperature variations. The neural networks predicted a divergence of the yield and ultimate tensile strengths of the weld as a function of the interpass temperature. The yield strength was predicted to drop much more rapidly as the interpass temperature is increased. Experimental data supported the predictions of the neural networks, the measured values being close to those predicted for this alloy. Toughness tests did not show a discernable dependence of toughness upon the interpass temperature within the measured range. The conclusion of this investigation is that multirun welds fabricated from this alloy can exhibit high yield strengths whilst maintaining good toughness levels if the interpass temperature is carefully monitored and controlled.

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