Welding Procedures and Type IV Phenomena

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Abstract

In this work, we attempt a quantitative estimation of the type IV rupture stress for welds in ferritic power plant steels containing 9–12 wt. % chromium, using a neural network in a Bayesian framework. This article describes the methodology that was used in creating and evaluating the neural network model. The sensitivity of the rupture stress to the test conditions, the composition of the steel and the heat treatment schedule, as perceived by the model, appears to be consistent with engineering experience and known metallurgical effects. It has also been possible, for the first time, to infer the dependence of the stress on welding parameters. The rupture stress increases with the preheat and interpass temperature, whereas the heat input has a relatively insignificant effect. It is proposed that type IV effects can be ameliorated by welding with the highest preheat temperature that is consistent with the transformation characteristics of the steel and the practical aspects of welding.

Keywords: creep, ferritic steels, neural networks, Bayesian framework, type IV, welding parameters

Introduction

Type IV cracking is a feature of welded joints in creep-resistant steels. It is associated with an enhanced rate of creep void formation in the fine grained and intercritically annealed heat-affected zones of the weld, leading to premature failure when compared with creep tests on the unwelded steel.

Type IV cracking is particularly prominent in the stronger 9-12 wt. % chromium steels. Since the problem arises from the heterogeneous microstructure of the weld heat-affected zone, it can be eliminated by a reaustenitisation and tempering heat treatment. Unfortunately, this rarely is a practical option. Instead, components have to be designed allowing for a reduction in the creep strength (or equivalent reduction in creep life) due to type IV cracking.

There are many reported data on the creep rupture stress associated with type IV cracking, as a function of the steel composition, welding parameters and heat treatments. However, the interpretation of this phenomenon has essentially been based on the microstructures within the heat-affected zone and much of the work has been qualitative.

Neural networks can provide a means of developing quantitative models of physical phenomena when experimental data are available but a physical model, based on an understanding of the underlying mechanisms, is not. A neural network is a flexible non-linear function which is able to represent complex, multivariate phenomena. Neural networks are created through a training process in which a network uses a database to “learn” a mathematical relationship between designated inputs (or operating conditions) and the output (or behaviour) of the system being studied. Once created, a neural network can be used to predict how a system might behave under conditions that have not been tested by experiment. It can also reveal the degree to which the output of a system is correlated with each of the input conditions. Neural networks are particularly powerful when implemented within a Bayesian framework because they give an indication both of the noise in the output, and a modelling uncertainty. The latter is invaluable in identifying domains where data are sparse or where data are completely lacking. Furthermore, a careful use of the modelling uncertainty greatly reduces the dangers of extrapolating a non-linear function.

In this work we apply neural networks in a Bayesian framework to type IV cracking data. This builds on recent work in which we proposed that a strength offset could be applied to account for the reduction in the creep strength of 9-12 wt. % chromium steels due to welding and the associated type IV phenomenon.[1] In that work the magnitude of the offset was obtained by comparing the rupture stress of cross-weld creep specimens that had failed in the type IV region with the rupture stress that would be expected for the parent plate material without a weld present. The rupture stresses for the plate material were calculated as a function of chemical composition and heat treatment using an established neural network model.[2] Here we attempt to model the type IV failure stress directly, particularly as a function of welding parameters, and to identify the physical basis by which these parameters might influence failure.

The Database

A neural network analysis can be as ambitious as is necessary, with no particular limit on the number of variables. However, because published work frequently does not state all the variables that control type IV failure, an overambitious collection of variables can limit the data that can be used in the analysis.

A pragmatic list of variabes which allowed us to compile 53 sets of data on cross-weld tests associated with type IV failures is given in Table 1. Among these data, 50 sets are due to earlier sudies on type IV failure.[3-8] A further 3 sets have been obtained from an experimental programme that has been undertaken by the authors. These experiments are still underway and details will be reported at a later date. It is sufficient to state that the 3 data sets correspond to cross-weld creep specimens that were extracted from welded joints made in a P91 pipe section. The normalising, tempering and post-weld heat treatment parameters, together with the preheat temperature, were the same for all three experiments, while the weld heat input and the joint preparation angle were varied.

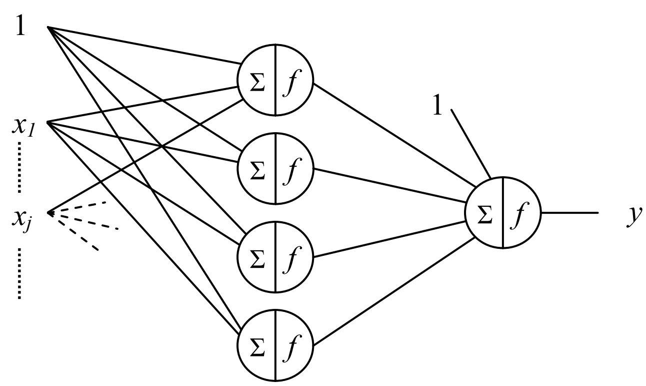
Table 1: The range in concentration, heat treatment, welding parameters and test conditions covered by the database on type IV failures. The shaded rows indicate input variables that were not included in the final analysis.

Variable	***Minimum***	***Maximum***
C wt. %	0.09	0.13
N	0.041	0.078
B	0	0.003
Cr	8.45	12.0
Mo	0.34	0.96
V	0.19	0.22
Nb	0.05	0.13
W	0	2.21
Mn	0.40	0.81
Si	0.02	0.35
Cu	0	3
Ni	0.06	0.35
Al	0.008	0.019
Normalising Temperature (^{o}C)	1050	1080
Normalising Time (h)	0.5	2
Tempering Temperature (^{o}C)	760	820
Tempering Time (h)	1	6
Heat Input (kJ/mm)	0.8	3.8
Preheat Temperature (^{o}C)	100	250
Preparation Angle (degrees)	0	45
PWHT Temperature (^{o}C)	740	760
PWHT Time (h)	0.25	8
Internal Pressure Test? (0/1)	0	1
Test Temperature (^{o}C)	600	700
Test Duration (h)	113	11220
Rupture Stress (MPa)	40	150

Among the 53 data sets, it was not always possible to access the nickel, aluminium, phosphorus and sulphur concentrations. A preliminary analysis indicated that over the range of concentrations available in the literature, these elements did not have a significant effect on the failure stress; they were therefore eliminated from the analysis. The concentration of vanadium in the whole database only varied from 0.19 to 0.22 wt. %, which is probably within the limits of experimental error. Vanadium was also therefore eliminated from the analysis. This procedure does not imply that Ni, Al, P, S and V may not be important in other circumstances; simply that the data available are incomplete or over such a narrow range as to make it impossible to percieve a significant effect on the failure stress.

Creation of the Model

The neural network methdology has been described elsewhere.[9-11] Suffice it to say that three-layer feedforward networks are used here, similar to the network represented schematically in Figure 1. The activation function for the neurons in the second layer is a hyperbolic tangent (equation (1)), while a linear activation function was used in the third layer (equation (2)). The specification of the transfer function together with the weight distributions completely defines the model, which is a fully transparent mathematical function. It is noted that committees of models are used here, as described elsewhere.[11]



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

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

Figure 1: A schematic representation of the three-layer feedforward neural networks used in the current work. The first layer contains the inputs, x_j, which are multiplied by weights, $w_{ij}^{(1)}$, and summed with the biases $\theta_i^{(1)}$ to obtain the arguments for the transfer functions in the second (hidden) layer of nodes. The outputs from the hidden layer, h_i, become the inputs for the third (output) layer. The network output is y.

In this article we focus on the 'tricks' that were used to produce a robust model that is not overfitted to the data; which respects the level of noise in type IV experiments; and which gives physically meaningful relationships between the input and output variables.

The Overfitting Problem

The process of training a neural network involves fitting a flexible non-linear function to a training database. There is, therefore, a possibility of fitting the training data too closely, so that experimental noise is incorporated in to the model. Networks that have been overfitted to the training data generally will not make accurate predictions for input conditions that differ from those used in the training process.

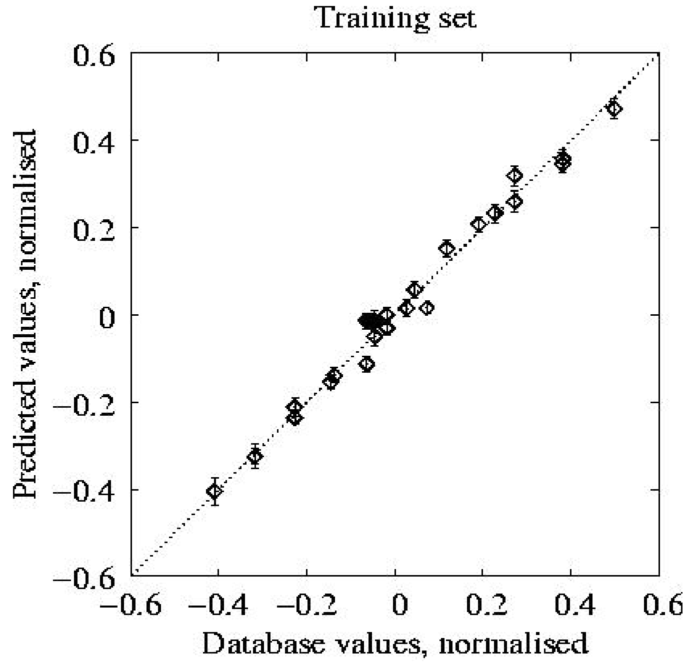
The method used here has procedures for avoiding overfitting. The first such procedure involves the use of only half of the experimental data to train the network. The remainder of the data (not used in creating the model) are then used to test how the model generalises. A good model should show a similar level of prediction error for both the training and test data.

Overfitting is also avoided by the Bayesian framework in which both simplicity and accuracy are rewarded. Conversely, models with greater complexity are assumed to be less probable and are penalised accordingly. However, as will become clear later, both of these methods turned out to be insufficient to avoid overfitting, given a noisy and limited database.

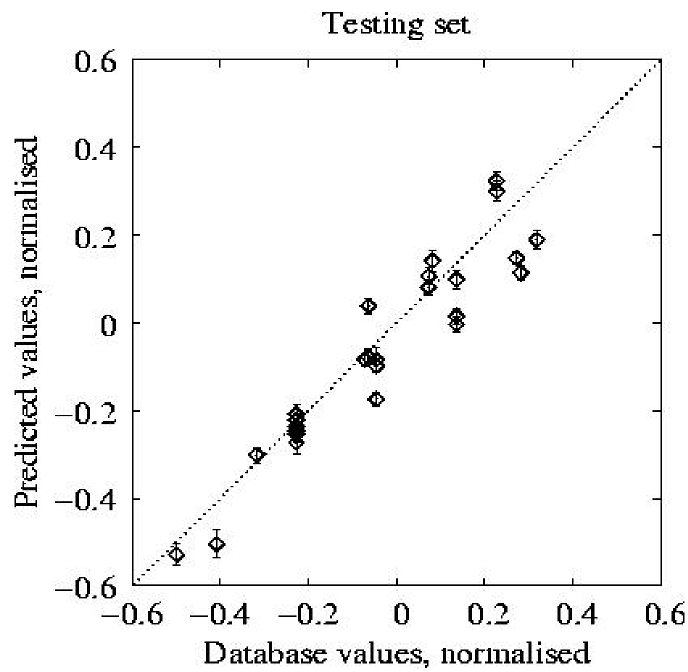
The problem is illustrated in Figure 2; throughout this paper, the error bars plotted represent modelling uncertainty (+/- 1 σ) rather than the level of model-perceived noise, σ_v, in the output. In spite of the two procedures for avoiding overfitting, the training data show a smaller scatter than the unseen test data. With our best efforts, it was not possible to obtain equal levels of scatter in the test and training data. In this case, the model-perceived noise level in the output was only 5%.

Recognising that the actual level of noise in type IV experiments is likely to be higher, a procedure was adopted to force the model to stop training once a selected level of noise in the output is reached. What then determines this 'selected level' of noise, σ_v, in the failure stress?

To find the answer, models were created by setting the minimum permissible value of σ_v that can be achieved to a variety of values (the network-perceived value, 10% and 15%). There were two criteria to judge the quality of the resulting models: (1) that the test and training data should show similar levels of noise when compared with predictions; (2) that the model-perceived 'significance' of each input variable in explaining variations in the output does not depend on the random numbers used to initiate the training.

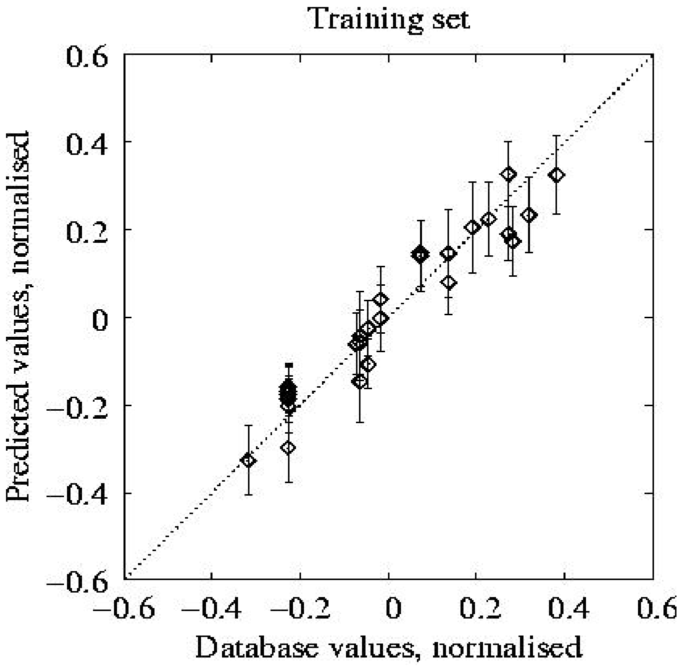


(a)

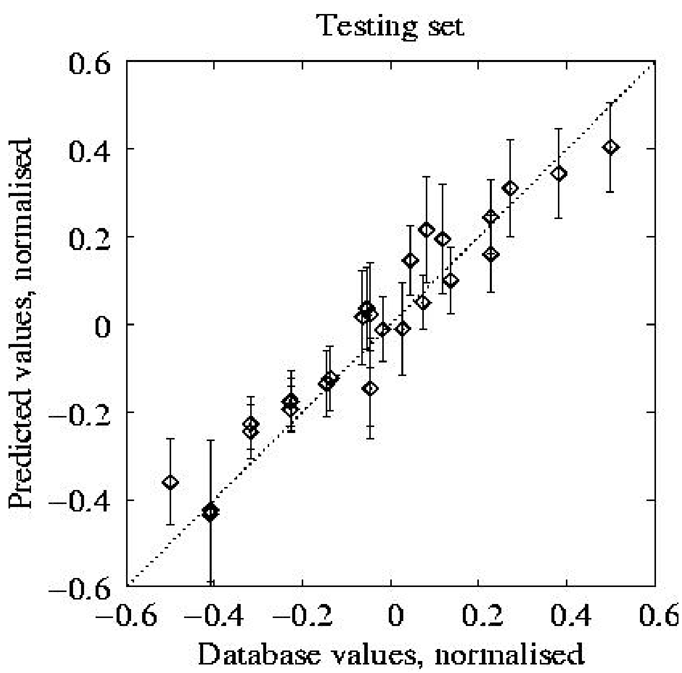


(b)

Figure 2: A comparison of the predictions made by a neural network with the database values for input conditions corresponding to (a) the training data set and (b) the test data set. In this case the network was allowed to minimise the level of perceived noise in the output. This network is over trained.



(a)



(b)

Figure 3: A comparison of the predictions made by the selected model with the database values for input conditions corresponding to (a) *the training data set and* (b) *the test data set. In this case the level of perceived noise was pre-set to 15%.*

These difficulties arise because of the nature of the database, i.e. a realtively large number of input variables and comparatively few data. These features make for an objective function with several local minima, thus making the analysis sensitive to the way in which training is initiated.

As stated earlier, Figure 2 shows a case where the minimum permissible σ_v value is too low, resulting in the overfitting of the training data. By contrast, Figure 3 shows a case where the minimum permissible σ_v value has been set to 15%, resulting in a similar level of scatter in the training and test datasets. Furthermore, the significances obtained for each variable then did not depend on the initiation of the training process. For this reason, the minimum permissible σ_v value of 15% is used for all subsequent analysis.

This large level of noise indicates that there may be (unknown) variables unaccounted for, i.e., not present in the database, which contribute to variations in the rupture stress. In addition, it is possible that there are inputs in Table 1 which themselves are noisy. For example, it may be impractical to exercise tight control on the actual preheat and interpass temperature.

Significance of Input Variables

In Figure 4, the magnitude of the bar indicates the extent to which a particular parameter explains the variation in the rupture stress (the output). A small magnitude implies an unimportant input within the context of the present analysis, or alternatively, its influence is lost in the 15% noise imposed on the output. In spite of this, it is evident that the major effects perceived to be important have been recognised by the model. These include the obvious effects of the test duration and temperature, the normalising[12] and tempering heat treatments, and the well-known effect of tungsten.[13]

Bearing in mind that our major aim was to discover the effects of the welding parameters, it is fascinating that the preheat temperature has been recognised to be significant and at the same time the heat input has been perceived to be insignificant. This is illustrated in Figure 4.

Trends

The predicted type IV rupture stresses for welds in a P91 steel are plotted as a function of preheat temperature in Figure 5. It can be seen that an increase in the preheat temperature is expected to translate to a corresponding increase in the rupture stress. It is also evident that as temperatures progressively larger than 250°C (the highest preheat temperature in the database) are considered, there is an increasing level of uncertainty in the predictions. Nevertheless, the effect of increasing the preheat temperature is unambiguous.

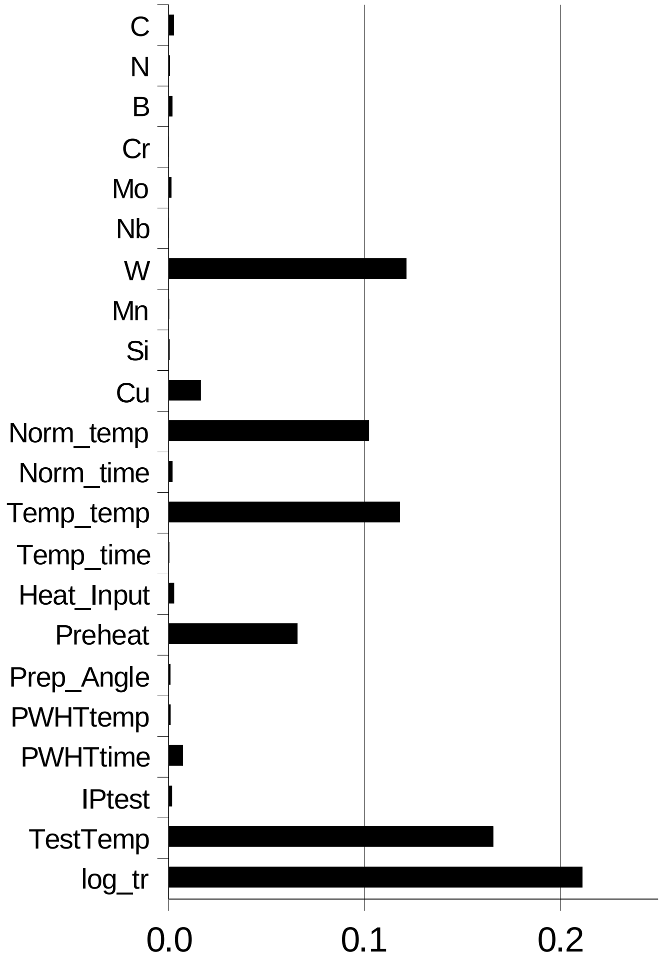


Figure 4: A graphical representation of the degree to which the rupture stress correlates with each input variable, as perceived by the selected model.

The predicted type IV rupture stresses for welds in a P91 steel are plotted as a function of heat input in Figure 6. The predictions assume a preheat temperature of 250°C in all cases, and all other conditions are identical to those used in the generation of Figure 5. It can be seen that the neural network model does not perceive any significant effect of weld heat input in determining the type IV rupture stress.

It is worth considering how these interesting trends might arise. We know that type IV cracking occurs in a creep-softened region which is sandwiched between regions that are harder in creep. This will lead to a mismatch in creep strain across the heat-affected zone during a cross-weld test. Previous studies have shown that the effect of this mismatch is to create triaxiality of stresses in the type IV region,[14, 15] which would be expected to encourage the growth of voids, and hence lead to localised failure.

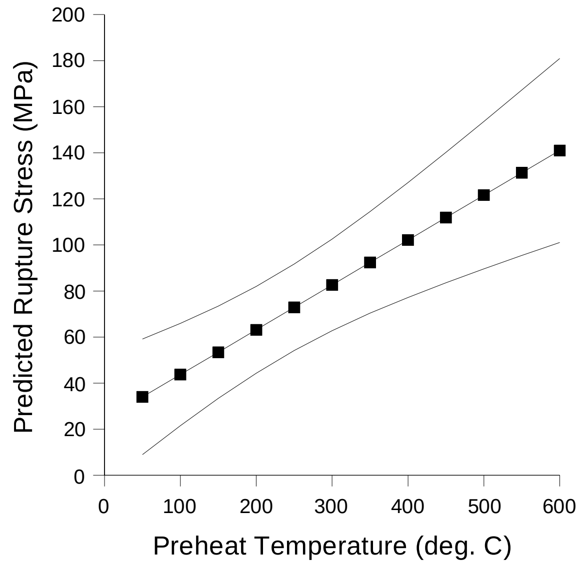


Figure 5: The predicted rupture stress as a function of preheat temperature at 600°C for a P91 steel and a creep life of 10,000 hours. The normalising temperature was assumed to be 1060°C, the tempering temperature 770°C, and the post-weld heat treatment 760°C for 2 hours. The confidence limits correspond to +/- one standard deviation in rupture stress.

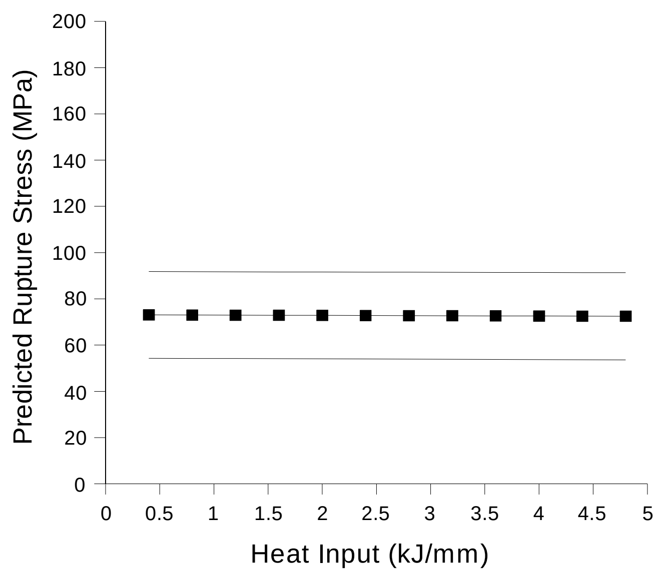


Figure 6: The predicted rupture stress as a function of heat input at 600°C for a P91 steel and a creep life of 10,000 hours. The normalising temperature was assumed to be 1060°C, the tempering temperature 770°C, the preheat temperature 250°C, and the post-weld heat treatment 760°C for 2 hours. The confidence limits correspond to +/- one standard deviation in rupture stress.

It is possible that the triaxiality diminishes as the type IV region becomes wider, and in addition, the creep strain in this region becomes distributed over a greater volume of material. Wider type IV zones are of course associated with wider heat-affected zones. An increase in preheat temperature achieves exactly this. However, in this context, an increase in heat input would also achieve a wider HAZ. It appears, therefore, that further work is required to reveal why the heat input does not affect the rupture stress in the same way that the preheat temperature does.

Nevertheless, the remarkable result is that it would be better to control the preheat and interpass temperature to the maximum consistent with the welding circumstances in order to ameliorate type IV effects. On the other hand, other welding parameters can be chosen on the basis of welding productivity since the type IV rupture stress was not perceived to be sensitive to heat input.

Conclusions

The most important and novel outcome, from both a technological and scientific viewpoint, is that it shoud be possible to ameliorate the type IV phenomenon by welding using as high a preheat temperature as is consistent with the transformation characteristics of the steel and with the practical aspects of welding.

On the other hand, the type IV rupture stress was not perceived to be sensitive to heat input. This conclusion is significant since it reveals that other welding parameters can be selected with a view to optimising the productivity of welding operations.

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References

1. J.A. Francis, W. Mazur and H.K.D.H. Bhadeshia, *Estimation of Type IV Cracking Tendency in Power Plant Steels*, *ISIJ Int.,* **44**, 1966-1968 (2004)
2. M. Murugananth and H.K.D.H. Bhadeshia, *Components of the Creep Strength of Welds*, in *Mathematical Modelling of Weld Phenomena 6*, eds. H. Cerjak and H.K.D.H. Bhadeshia, *Institute of Materials*, London, 243-260 (2002)
3. S.K. Albert, M. Matsui, T. Watanabe, H. Hongo, K. Kubo and M. Tabuchi*, Microstructural Investigations on Type IV Cracking in a High Chromium Steel, ISIJ Int.,* **42**, 1497-1504 (2002)
4. T. Kojima, K. Hayashi and Y. Kajita, *HAZ Softening and Creep Rupture Strength of High Cr Ferritic Steel Weldments*, *ISIJ Int.*, **35**, 1284-1290 (1995)
5. M. Matsui, M. Tabuchi, T. Watanabe, K. Kubo, J. Kinugawa and F. Abe, *Degradation of Creep Strength in Welded Joint of 9%Cr Steel*, *ISIJ Int.*, **41**, S126-S130 (2001)
6. F. Abe and M. Tabuchi, *Microstructure and Creep Strength of Welds in Advanced Ferritic Power Plant Steels*, *Sci. Technol. Weld. Join.*, **9**, 22-30 (2004)
7. K. Shinozaki, D. Li, H. Kuroki, H. Harada, K. Ohishi and T. Sato, *Observation of Type IV Cracking in Welded Joints of High Chromium Ferritic Heat Resistant Steels*, *Sci. Technol. Weld. Join.*, **8**, 289-295 (2003)
8. R. Wu, R. Sandstrom and F. Seitisleam, *Influence of Extra Coarse Grains on the Creep Properties of 9 Percent CrMoV (P91) Steel Weldment*, *J. Eng. Mater. Technol.*, **126**, 87-94 (2004)
9. D.J.C. MacKay, *A Practical Bayesian Framework for Back Propagation Networks*, *Neural Comput.*, **4**, 448-472 (1992)
10. H.K.D.H. Bhadeshia, *Neural Networks in Materials Science*, *ISIJ Int.*, **39**, 966-979 (1999)
11. T. Sourmail, H.K.D.H. Bhadeshia and D.J.C. MacKay, *Neural Network Model of Creep Strength of Austenitic Stainless Steels*, *Mat. Sci. Technol.*, **18**, 655-663 (2002)
12. F. Brun, T. Yoshida, J.D. Robson, V. Narayan, H.K.D.H. Bhadeshia and D.J.C. MacKay, *Theoretical Design of Ferritic Creep Resistant Steels Using Neural Network, Kinetic, and Thermodynamic Models*, *Mat. Sci. Technol.*, **15**, 547-554 (1999)
13. C.D. Lundin, P. Liu and Y. Cui, *A Literature Review on Characteristics of High Temperature Ferritic Cr-Mo Steels and Weldments*, WRC Bulletin 454 – August 2000, *Welding Research Council, Inc.*, New York.
14. S.K. Albert, M. Matsui, H. Hongo, T. Watanabe, K. Kubo and M. Tabuchi, *Creep Rupture Properties of HAZs of a High Cr Ferritic Steel Simulated by a Weld Simulator, Int. J. Pressure Vessels Piping*, **81**, 221-234 (2004)
15. D. Li, K. Shinozaki and H. Kuroki, *Stress-strain Analysis of Creep Deterioration in Heat Affected Weld Zone in High Cr Ferritic Heat Resistant Steel*, *Mat. Sci. Technol.*, **19**, 1253-1260 (2003)