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The prediction of toughness and strength in high integrity forgings

H. Pous-Romero[1], J. Talamantes-Silva[2], S. S. Al-Bermani[2], H. K. D. H. Bhadeshia[1] and B. P. Wynne[3]

[1]University of Cambridge, UK
[2]Sheffield Forgemasters RD26 Ltd, UK
[3]University of Sheffield, UK

Abstract

High integrity, safety critical SA508 Gr.3 forgings have very demanding requirements for strength and toughness. However due to the large size of components, up to a metre in thickness, there is an uncertainty in achieving the required mechanical properties at the largest sections after the quality heat treatment. This location based dissimilarity in mechanical properties occurs because of variations in the effective heat treatment and cooling rates experienced. A method, based on neural networks, has been developed using highly controlled, industrially relevant data capable of estimating tensile strength and toughness. Validation of the method in both independent data and through thickness measurements reveals considerable closure between experiments and predictions.

1. INTRODUCTION

High integrity, safety critical forgings have very demanding requirements for strength, toughness and resistance to extreme environmental conditions such as irradiation embrittlement over the intended service life. As a consequence, there are only a few steels that have sufficient accumulated experience for use in the construction of nuclear pressure vessels, partly because the qualification of such materials requires an enormous amount of time-consuming work. In this context low-alloy steels, such as the SA508 type alloy variants, have been the key materials for the manufacture of large, safety critical forgings over the last 40 years. This is because of the material's good balance between strength, toughness and cost.

The components made using SA508 Gr. 3 material, such as shells, heads and tubesheets can be very large. These high integrity parts are manufactured from ingots weighing up to 650 tonnes, where the wall thickness may vary between 150 and 900 mm. At the largest sections, the key challenge is achieving the required mechanical properties through thickness after the quality heat treatment. This location based dissimilarity in mechanical properties occurs by the variation of effective heat treatment and cooling rates.

Components are water quenched after the austenitising process during the final quality heat treatment. In spite of the water quench, the large size of the components means that the cooling rate following austenitisation will vary significantly as a function of depth, relative to the surface. A location-dependent microstructure may appear and, consequently, through-thickness variations of mechanical properties. Cooling rates of ≈ 0.3 °C s^{-1} are common at the 1/4 thickness position, and 0.2 °C s^{-1} has been measured at the mid-wall of a 340 mm thick forging component during the water quenching process [1, 2].

Figure 1 presents the measured cooling curve of a 320 mm thick SA508 Gr. 3 component during water quenching, where a rate of 0.2 °C s^{-1} is recorded at the mid-wall of the component.

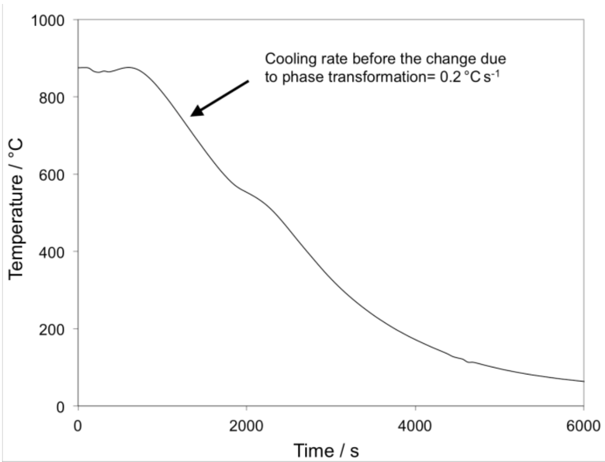

Figure 1. Measured cooling curve using thermocouples attached to the midwall position of a 320mm thick SA508 Gr. 3 component. Data courtesy of Rolls-Royce Plc.

It is therefore, of great interest to the industry to find a reliable method to accurately estimate the mechanical properties of large vessels as a function of depth from the surface and the thermal processing parameters.

Advanced numerical techniques can be used as a predictive tool to address these challenges. This work presents a methodology that combines industrially relevant experimental data and neural networks (NN), an approach by which a quantitative prediction can be made in situations where the complexity of the problem makes a physically rigorous treatment difficult. This has allowed the determination of the relationship among key processing parameters: austenite grain size, cooling rate and tempering parameter (TP) [3-5]. A method has been developed with high confidence for predicting through thickness tensile strength and toughness.

2. EXPERIMENTAL

The chemical composition of the SA508 Gr.3 steel used in this work is given in Table 1. Specimens from the as-received condition were quality heat treated at a total of 18 conditions, varying austenitisation temperature, cooling media (cooling rates monitored by thermocouples) and tempering time. The different conditions were assessed by means of tensile strength and Charpy impact energy in order to understand the effects of the previously identified key processing parameters. Testing was carried out at Sheffield Forgemasters International Ltd.

Table 1. Chemical composition of as-received SA508 Gr. 3 steel (wt%).

C	Mn	Ni	Mo	Cr	Si	Al	N
0.17	1.32	0.76	0.51	0.2	0.23	0.019	0.010

Tensile testing was performed following the ASTM-370 standard [6]. Parameters recorded during testing include yield strength (by using the offset method at 0.2% strain), the ultimate tensile strength (UTS), the elongation, the reduction of area and the Young's modulus. Tensile tests were carried out at room temperature and at 350ºC at a controlled strain rate of 0.012 min^{-1} until the yield strength and then at 0.25 min^{-1} through to break. Charpy V-notch impact testing was performed complying with the ASTM E23 standard [7]. Impact tests were performed over the temperature range -196 to 250 ºC. A total of 36 tensile and 360 Charpy samples were tested.

3. NEURAL NETWORK MODELLING

To investigate the influence of the processing parameters on yield strength, ultimate tensile strength and impact energy at different temperatures testing results were collected as databases and three neural networks produced in the Bayesian framework following MacKay [8–10]. The database for the impact energy contained 360 values representing 78 different conditions in terms of austenite grain size, cooling rate and TP at various temperatures.

Databases for the yield strength and ultimate tensile strength incorporated 36 values representing 18 different conditions, for each case. Details of composition of the steel have been omitted from the models so as to make it more generally applicable to SA508 Gr. 3 steels where there is relatively small compositional range. Differences due to microstructure can be regarded as being incorporated into the uncertainty that accompanies the predicted values. Table 2 summarises the range in the input data used to create the models.

Table 2. Summary of the databases input data for neural network modelling.

	Impact energy	Yield strength	Ultimate tensile strength
Austenite grain size / µm	14 & 68	14 & 68	14 & 68
Cooling rate / ºC s^{-1}	0.17 to 9.96	0.17 to 10.45	0.17 to 10.45
Tempering parameter / K h	18.5 to 19.5	18.5 to 19.5	18.5 to 19.5
Test temperature / ºC	-196 to 250	21 & 350	21 & 350

The data were randomly divided in two groups, a training set and a testing set. In the training stage of the network, different sub-models were trained allowing a maximum of 25 hidden units. Nine different random seeds were used to control the initial weights of each input parameter, so as to ensure convergence from different positions in weight space. This meant a total of 225 initial conditions in each case, resulting in 224, 222 and 221 sub-models being successfully trained for the impact energy, yield strength and ultimate tensile strength models respectively.

To test for over fitting, each of the sub-models was tested to predict the unseen testing set, allowing a ranking by the log predictive error. A committee of the best models as ranked by log-predictive-error was selected to minimise the combined test error, with two sub-models for the impact energy model and one sub-model for the yield and ultimate strength models as best solutions. The significances of the input parameters for each model are shown in Figure 2.

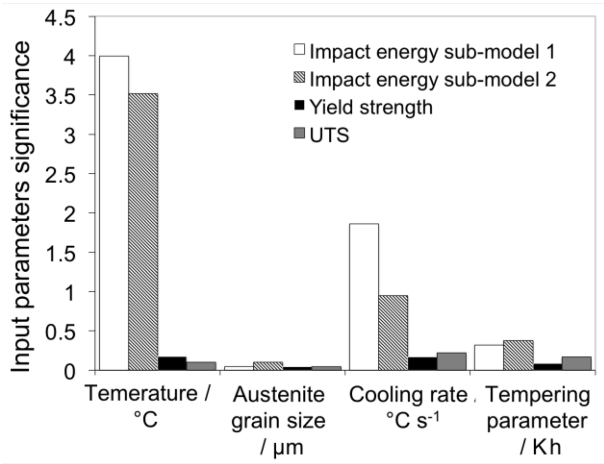

Figure 2. Significance for the input parameters.

Figure 3 shows reasonable agreement between the experimental data and the calculation using NN for the case of the data used to generate the databases. However, to assess the ability of the models unseen data needs to be tested.

3.1 Testing against unseen data

As shown in Figure 4, the neural network predictions compare favourably with independent data obtained from the literature even outside the range seen in the database. This proves that the identified processing parameters, austenite grain size, cooling rate and tempering parameter are in fact controlling the material behaviour in terms of strength and toughness, as independent data from different compositions of SA508 Gr. 3 steels can be predicted.

The methodology presented here appears to compare well for tensile strength and toughness from unseen data. Therefore, these models have the potential to be used with the aid of thermal processing data from finite element software to map the distribution of strength and toughness in large components.

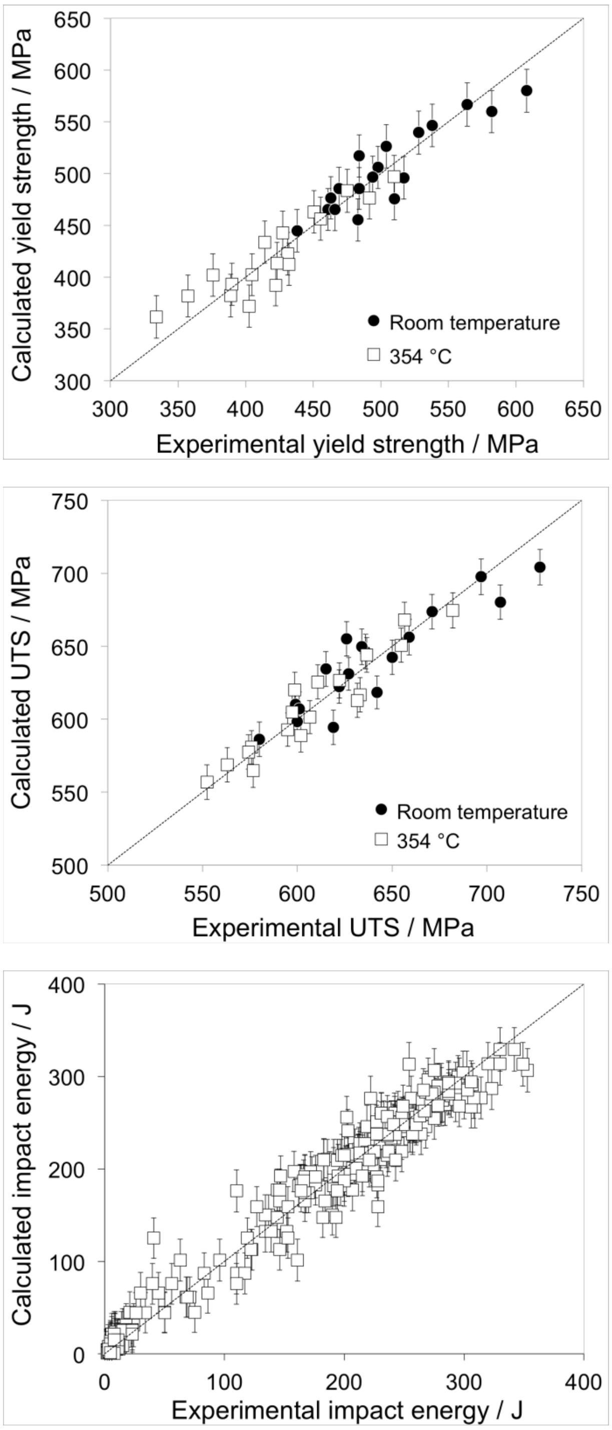

Figure 3. Neural network prediction of the data used to generate the databases.

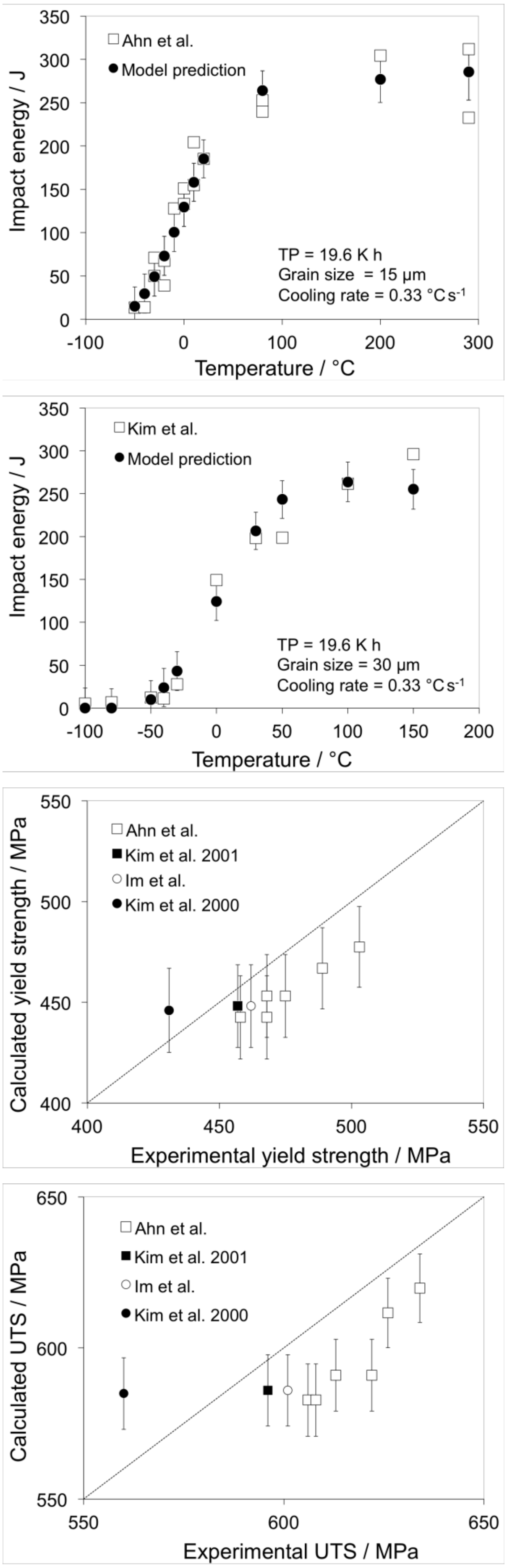

Figure 4. Predictions for unseen data from various authors [11-15]

4. PREDICTING TOUGHNESS AND STRENGTH IN LARGE FORGINGS

As previously discussed, thermal processing parameters vary as a function of depth relative to the surface during the quality heat treatment of large components. In particular, the cooling rate from austenitisation temperatures is of crucial importance to determine the ratio between diffusive and displacive transformation products [5], which will control material properties.

An accurate determination of the location dependent cooling rate from a known geometry can be obtained with the aid of finite element (FE) software. In the present work, FE simulations were carried out to the determine the cooling rates at different locations: ½ thickness, ¼ thickness and 50 mm from the quenched surface in a SA508 Gr. 3 experimental forging, approximately one metre thick. Mechanical property data from the experimental forging was collated and compared with results from the NN calculations. Figure 5 presents the reproduced cooling rates for the mentioned locations.

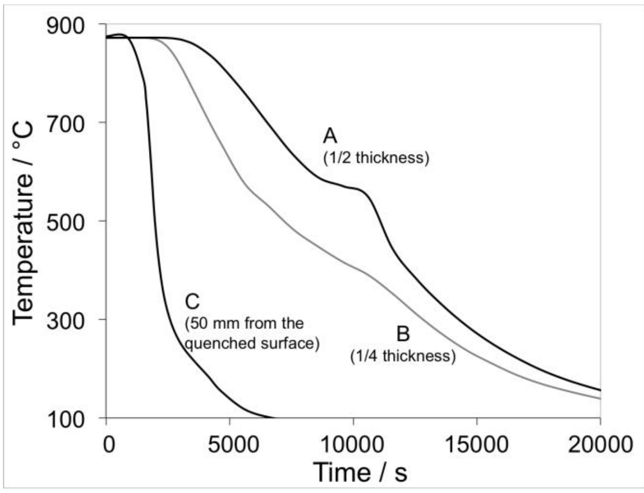

Figure 5. Cooling rates at different locations through thickness.

Figure 6 compares the calculated and the experimental data as a function of cooling rate. Neural network predictions are able to reproduce impact energy values for the tested cooling rates. These results prove that the model developed here is able to predict, with reasonable accuracy, toughness through thickness in large components.

For the case of tensile properties, predictions present an offset between the data and the prediction of about 60 MPa for the faster cooling rates (positions A and B). This may indicate that more tensile data is needed in order to create a more robust model. However, the predictions are not giving unreasonable values.

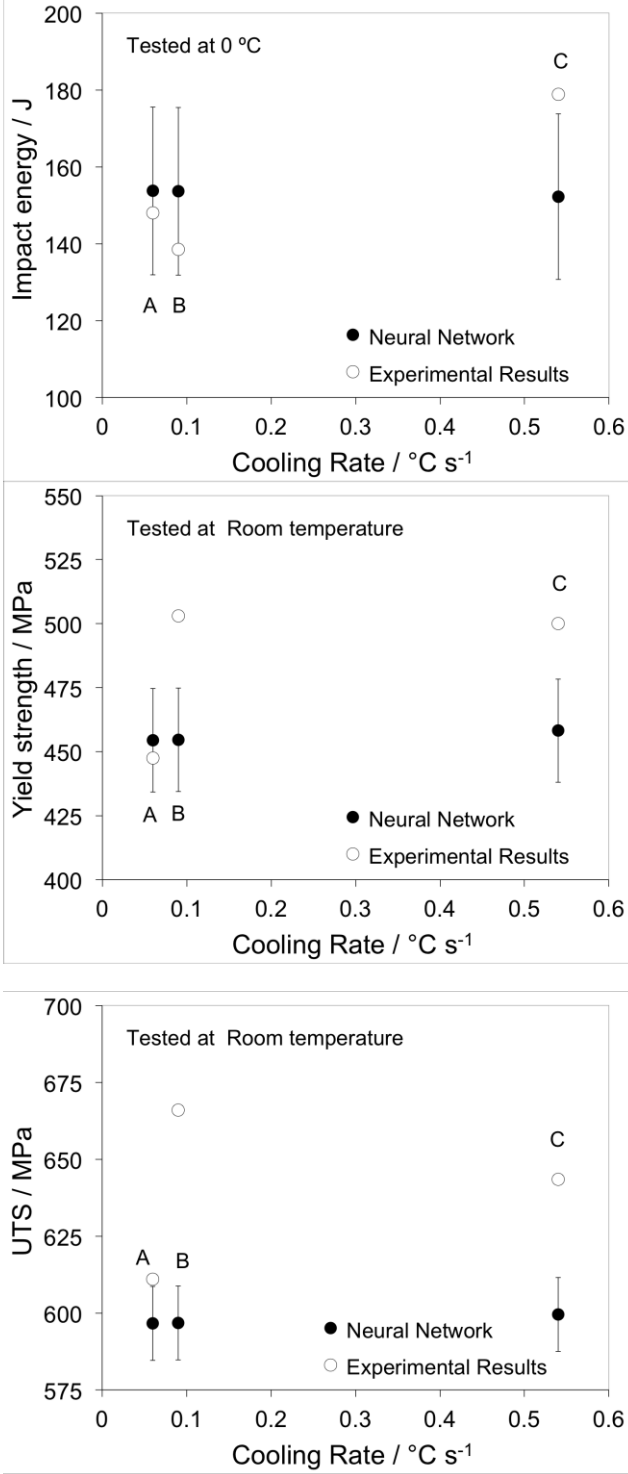

Figure 6. Comparison between experimental and calculated data of properties through the thickness. Austenite grain size of 20 µm and a temper parameter of 19.3 Kh were used for the calculations. A, B and C refer to locations as previously indicated in Figure 5.

5. CONCLUSIONS

A reliable method based on neural networks has been developed to predict strength and toughness in a nuclear pressure vessel steel (SA508 Gr.3). The essential conclusions of the can be summarised as follows:

1- Highly controlled, industry relevant experimental data have been used as input for the neural networks modelling.

2- Processing parameters, austenite grain size, cooling rate and tempering parameter, have been identified as key variables that control material performance.
3- Reasonable agreement between independent data and predictions has been found. It is established that the models developed here are not composition dependent and can be applied widely to SA508 Gr. 3 steels.
4- Models have the potential to be used with the aid of thermal processing data from finite element software to map the distribution of strength and toughness in large components.
5- It may be necessary to collect and include more tensile data as database for the neural network to have a model capable of predicting more conditions.

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