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Improved Ferrite Number Prediction that Accounts for Cooling Rate Effects

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Introduction

Constitution diagrams are routinely used for predicting ferrite number in stainless steel welds. The most recent diagram is the WRC-1992 diagram[1]. Recently, a neural network model has been proposed as a more accurate means for predicting ferrite content[2,3]. In all of these predictive models, cooling rate is not taken into account even though there is extensive evidence that cooling rate can strongly affect the ferrite content in stainless steel welds[4,5]. At the 82nd AWS Convention, preliminary results from a neural network model that included cooling rate effects was presented[6]. The model development work has been completed and this paper will demonstrate the cooling rate effects that are predicted by the model.

Significance

For the first time, a quantitative model for ferrite number prediction in stainless steel welds that includes cooling rate and alloy composition has been developed.

Procedure

An extensive data set for stainless steel welds was developed that included cooling rate information as well as composition and ferrite content data. A simple analytical expression for cooling rate as a function of weld conditions was employed. The data set was a compilation of the data used to generate the WRC-1992 constitution diagram as well as additional experimental data for several austenitic and duplex stainless steels welded under a range of arc-welding and laser-welding conditions. The neural network was trained with a standard back-propagation learning procedure. Several network architectures were tested and a single hidden layer with six hidden nodes was used in the final model.

The final model was trained on the entire data set of 1196 data points.

Results, Discussion

The model predictions for ferrite content as a function of cooling rate are in agreement with general experimental trends and with expectations based on transformation behavior in stainless steel welds. Examples of the variation in ferrite content as a function of calculated cooling rate for a typical austenitic stainless steel weld and a duplex stainless steel weld are shown in Fig. 1. For the austenitic stainless steel weld, ferrite content initially increases with cooling rate, as the transformation of as-solidified ferrite to austenite during cooling is increasingly suppressed. At the highest cooling rates, the ferrite content

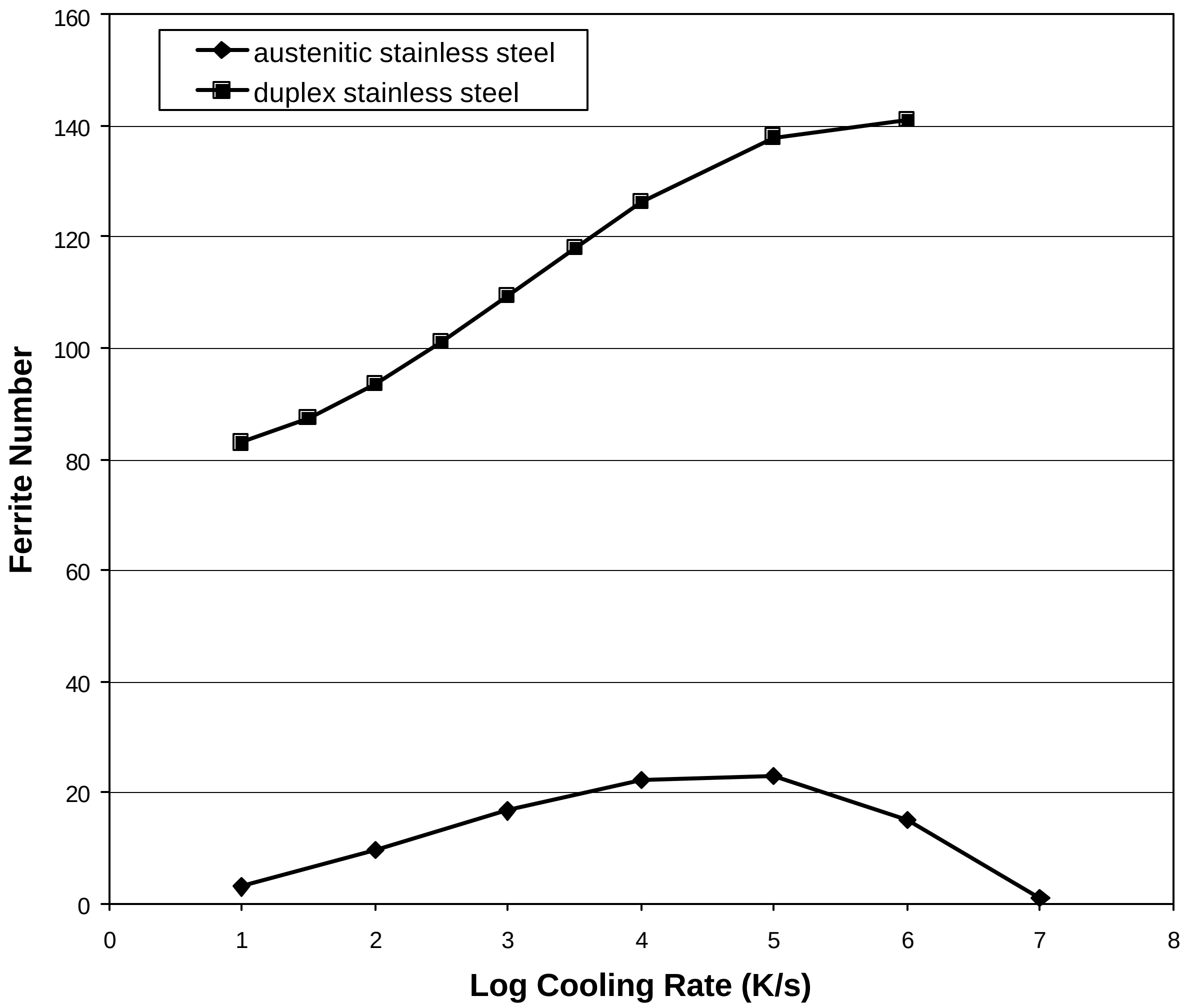

Fig. 1: Ferrite number versus log (cooling rate) for a typical austenitic and duplex stainless steel calculated with the present model.

decreases with cooling rate, corresponding to the change in solidification mode at high cooling rates from primary ferrite formation to primary austenite formation. For the duplex stainless steel weld, the model predicts the ferrite content increases with increasing cooling rate until the weld is 100% ferritic (FN . 140). This increase in ferrite content corresponds to the suppression of the ferrite-to-austenite solid state transformation during cooling, which results in higher residual ferrite levels at room temperature. The predicted variations in ferrite content with cooling rate have been found experimentally[5]. Thus, the new model predicts a cooling rate dependency of ferrite content that is well-known and has been documented extensively by experiment but has, heretofore, been absent in any predictive model.

Much like the earliest constitution diagram models, there is much room for improvement in the current model. The determination of cooling rate as a function of welding conditions can be improved. In fact, for much of the data, welding conditions were not known and estimated cooling rates were used. A more extensive data set, generated by a consortium of groups, would be extremely valuable. Nonetheless, this model is a significant improvement over presently available methods for predicting ferrite content since, for the first time, the influence of cooling rate is taken into account. Furthermore, the variation in ferrite content with cooling rate is in agreement with theoretical expectations and experimental observations.

Conclusion

The potential for quantitatively predicting ferrite number as a function of cooling rate and alloy composition was demonstrated. Although problems in generating a database for training the neural network exist, the present model predicts trends that agree with experiment and theory and have been, up to now, totally ignored in ferrite prediction models. Further work is recommended to test the predictive accuracy of the neural network model and to establish a broader database for developing a more accurate model.

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