Improved Ferrite Number Prediction that Accounts for Cooling Rate Effects

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INTRODUCTION

Stainless steel welds characteristically consist of a two-phase austenite plus ferrite microstructure. Ferrite levels may vary from a few percent in austenitic stainless steel welds to more than 50% in duplex stainless steel welds. The ability to predict the ferrite content in these welds is essential for many reasons. To a large extent, the final ferrite content determines a weldment's properties such as strength, toughness, corrosion resistance, and long-term phase stability. In addition, ferrite content is a useful indicator of the mode of solidification, which strongly influences the hot-cracking propensity during welding. Over the years, various models have evolved to try to accurately predict the ferrite content in stainless steel welds. Constitution diagrams, in which the overall alloy composition is converted into two factors, a chromium equivalent (Cr_{eq}) and a nickel equivalent (Ni_{eq}), have been developed to predict FN in welds. Many diagrams have been proposed since the original diagram of Schaeffler[1-7], with the WRC-1992 diagram[7] being the most recent and most accurate. The various versions of constitution diagrams differ primarily in the coefficients that are used to convert the alloy composition into the Cr_{eq} and Ni_{eq}; an extensive review is given in reference 5.

In most commonly used constitution diagrams, the weighted coefficients are constant, and this means that a given alloy addition's influence is the same regardless of that element's concentration or the concentration of any other alloying additions. In those cases where non-constant coefficients were proposed, the applicability of the diagram is limited to a restricted composition range. Clearly, constant coefficients cannot represent real behavior very well. For example, the effect of carbon should be very different depending on whether carbide forming elements are present or not. This limitation has been removed with the development of predictive models based on an artificial neural network analysis[8-11]. Artificial neural networks are ideally suited for predicting ferrite content because they offer improved flexibility, robustness, and accuracy as a consequence of their use of non-linear regression methods. Two recently developed neural network models predict FN as a function of the concentration of 13 elements[8-10]. These models have been shown to be more accurate than the WRC-1992 constitution diagram. Furthermore, they account for interactions among alloying elements so that the predicted impact of a given alloying addition depends on the actual alloy composition.

In addition to the effect of alloy composition, it has been well documented that cooling rate can have a significant impact on the final ferrite content[12-19]. Cooling rate can influence the ferrite level in two ways: (a) it can change the mode of solidification from primary ferrite formation at low cooling rates to primary austenite formation at high cooling rates, and (b) it can suppress the solid-state transformation of ferrite to austenite after solidification, with the extent of suppression increasing with increasing cooling rate. The effect of cooling rate was considered qualitatively by David et al[14] but a more quantitative tool for predicting FN as a function of weld conditions is needed. This paper describes such a model (ORFN©), based on a neural network analysis. A complete

description of the model can be found in reference 11.

COOLING-RATE-INCLUSIVE MODEL DEVELOPMENT

Neural networks are trained with a training dataset that includes both the input parameters and the outputs. In the present case, the input parameters included 13 elemental concentrations and an additional input relating to the cooling rate. An optimum network architecture, consisting of 14 input nodes, 6 hidden nodes, and 1 output node was identified. The model was trained using the back-propagation method. Further details are provided elsewhere[11].

The training dataset was comprised of data from three sources. First, the extensive dataset that was used to develop the WRC-1992 constitution diagram[7] as well as the two composition-only neural network models[8-10] was used. Unfortunately, there was no information in this dataset regarding the welding conditions used to generate the data and therefore a quantitative evaluation of a cooling rate associated with each data point was not possible. This problem was resolved by assigning a nominal cooling rate of 10 °C/s to all of the data in this set. Although somewhat arbitrary, this solution was unavoidable. As noted below, the errors associated with this assigned value are not considered to be excessive. A second dataset was generated from the work of David et al[14]. These data consisted of a series of pulsed laser welds made at different power levels and weld speeds on several stainless steel alloys. Cooling rates were calculated using the method described below. Finally, a third dataset was generated by making GTA and pulsed laser welds on several stainless steel alloys, including many duplex stainless steel compositions. Calculated cooling rates were used in this dataset as well. The total training dataset contained nearly 1200 data points.

Cooling rate was calculated, where possible, using the Rosenthal equations for 2D and 3D cooling conditions. The calculated cooling rates may not be accurate in an absolute sense, but absolute accuracy is not necessary. The key to the neural network analysis is that the calculated cooling rates place the data in the proper order, that is to say, for two different welding conditions, the calculations need to properly identify which condition corresponds to a higher cooling rate, and the absolute values of the cooling rates are not critical. This is true because the neural network is trained using these calculated cooling rates and as long as the same cooling rate analysis is used when implementing the model, the neural network will properly predict the FN. It was necessary to define the appropriate conditions for using either the 2D or 3D cooling rate formulations, and an appropriate procedure was established. Additional details can be found in reference 11.

The original data contained a mixture of FN measurements and ferrite volume fraction measurements. In order to implement the model, one measure of ferrite content was required inthe training dataset. Therefore, FN was used as the single measure of ferrite content. This required the conversion of ferrite volume fraction data to FN. This was accomplished by using a linear conversion of volume fraction to FN and implementing the concept of a normalized FN, scaled according to the Fe content in the alloy. Once again, further details may be found in reference 11.

MODEL RESULTS

The neural network model that evolves from the training process produces a series of weighting factors that are used to relate the inputs to the outputs, via a hidden layer. The model can be easily implemented in the form of a spreadsheet, and the calculation of the predicted FN is a simple process that can be carried out on any modern computer instantaneously. A comparison of the

predicted versus measured FN for the entire dataset is shown in Figure 1 using three different models: WRC-1992, FNN-1999 (composition-only neural network model[8-9]), and ORFN© (cooling rate inclusive model[11]). It is readily apparent that the ORFN© model shows considerably better agreement with the experimental data than either of the other two models. Quantitatively, the root mean square errors for the models are: 9.9 (WRC-1992), 11.0 (FNN-1999), and 4.7 (ORFN©). As an example of the improved predictability of the new ORFN© model, a series of data points are encircled in Figures 1a and 1b. These represent one of several cases where the same alloy was welded under different conditions, resulting in different cooling rates and different values of FN. For the WRC-1992 and FNN-1999 models, the predicted FN values are constant since these models do not account for welding conditions. However, the experimental data points clearly show that the FN values vary, and this variation is totally missed in these two models. In contrast, the ORFN© model predicts different FN values for the same alloy, depending upon the weld conditions, and thus the ORFN©-predicted values are in much better agreement with the experimental measurements.

One more example is shown in Figure 2, where the FN is plotted against the calculated cooling rate for a 316 austenitic stainless steel alloy. Experimental data are shown as individual data points. At moderate cooling rates, the experimental data show a slight increase in FN with increasing cooling rate. However, beyond a calculated cooling rate of ~$3x10^5$ °C/s, the measured FN drops precipitously to 0. This is an indication that the solidification mode has changed from primary ferrite formation to primary austenite formation. The model predictions are also shown in Figure 2. The predicted FN for both the WRC-1992 and FNN-1999 models are constant since they do not account for any cooling rate effects. In contrast, the predicted FN using the ORFN© model shows an increase in FN followed by a drop to 0 as the cooling rate increases, and the predictions are in good agreement with the experimental data. It is also noteworthy that the ORFN© model predicts the same FN as the other two models at low cooling rates. In fact, it was found that the new ORFN© model does not sacrifice accuracy at low cooling rates compared to the other two models[11]. Additional information on the ORFN© model, and further examples of predictions can be found elsewhere[11,20].

SUMMARY and CONCLUSIONS

A new model (ORFN©) that takes welding conditions into account when predicting FN of stainless steel welds has been developed. Several simplifications and assumptions were required during the development of the model. However, the new ORFN© model represents the first prediction model that quantitatively accounts for the effect of weld conditions on FN. It has been shown that the ORFN© model correctly predicts the variation in FN due to solidification mode changes and suppression of the solid-state ferrite to austenite transformation at high cooling rates. The ORFN© model is particularly useful for high-speed welds, duplex stainless steel welds, and high-power density process welds.

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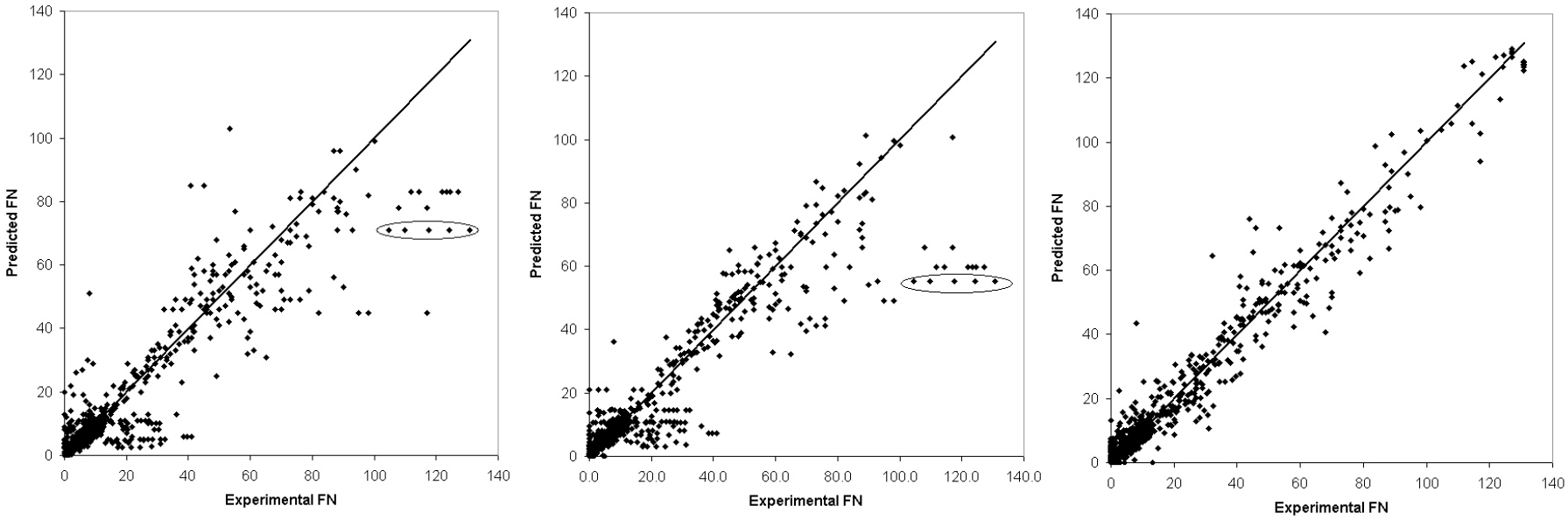

(a) (b) (c)

Figure 1: Plots of predicted FN versus measured FN for the expanded dataset that includes high-speed welds, laser welds, and additional duplex stainless steel welds. The predictions are made using the three different models: (a) WRC-1992, (b) FNN-1999, and (c) ORFN©.

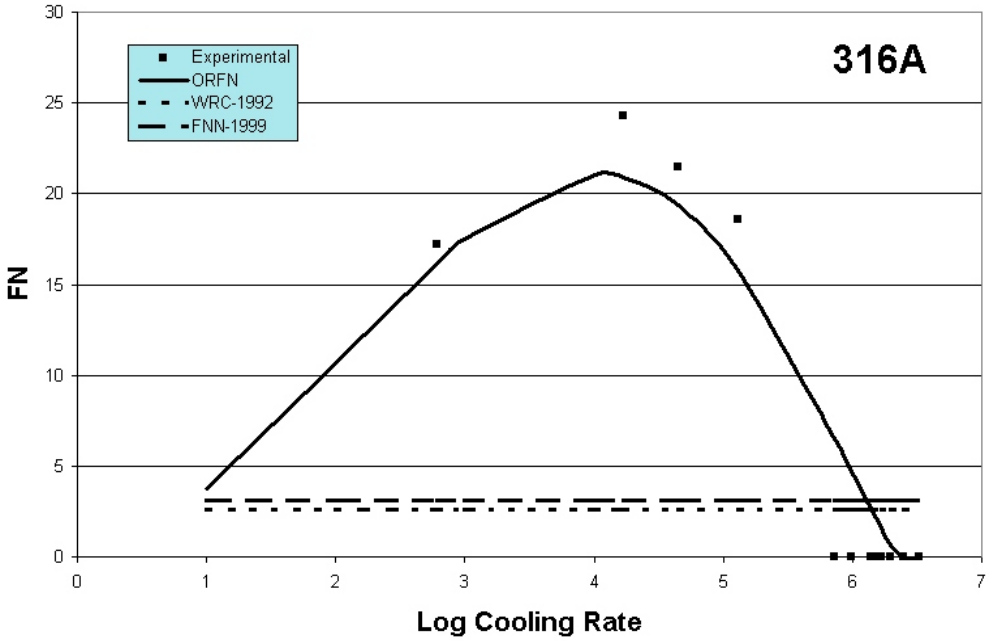

Figure 2: Plot of FN versus (log) cooling rate. Filled squares represent experimental data and lines represent predicted FN for three different models: WRC-1992 (short dashed line), FNN-1999 (long dashed line), and ORFN© (solid line).