Prediction of Ferrite Number in Stainless Steel Welds

**EXECUTIVE SUMMARY**

The ability to predict the delta-ferrite content expressed in terms of Ferrite Number (FN) accurately has proven very useful in assessing the performance and predicting various properties of austenitic stainless steel welds. The generalized Bayesian Neural Network model for predicting Ferrite Number in stainless steel welds has been developed using the database used for generating the WRC-1992 diagram and our laboratory data. The accuracy of the model is superior to the other existing Ferrite Number prediction methods. The optimized neural network model reveals the influence of compositional variations on ferrite content and examines the significance of individual elements on ferrite content in stainless steel welds.

**OUTLINE**

Constitution diagrams are routinely used for predicting ferrite number in stainless steel welds. The latest one is the WRC – 1992 diagram. Recently, a back propagation neural network model has been proposed as a more accurate means of predicting ferrite content. The prediction and measurement of ferrite content in stainless steel welds is of scientific and technological interest due to limitations in all the well-known methods, including some of the newer methods. In the present work, Bayesian neural network analysis has been used to develop an accurate model for predicting the ferrite content in stainless steel welds. This neural network model for ferrite prediction in stainless steel welds has been developed using database of 1020 datasets, collated from literature and our laboratory, comprising chemical composition and ferrite number for shielded metal arc (SMA) welds, representing the common 300-series austenitic stainless steel weld compositions (viz., 308, 308L, 309, 309L, 316, 316L, etc.) and the duplex stainless steel welds. Of the 1020 datasets, 948 data are those that had been used to generate WRC-1992 diagram, and the remainder datasets are from our laboratory experiments. The network employed consists of 13 input nodes \( x \) representing the 13 composition variables, a number of hidden nodes \( h \), and one output node \( y \) representing the FN value. As many as 80 different neural network models were created using the datasets, with the number of hidden units varying from 1 to 16 in which, 5 different sets of random number seeds were used to initiate each network, for a given number of hidden units. All these models were trained on the same training dataset that consisted of a random selection of one-half, i.e. 510, of the total 1020 datasets, while the remaining half were used as the test dataset to examine how the model generalises with unseen data.

Excellent agreement over the entire database is obtained between the predicted and measured FN values for the committee of models (Fig. 1), with a correlation coefficient of 0.98. Fig. 2 indicates the perceived significance \( \sigma \) of each of the input variables by all the nine neural network models in the committee. The \( \sigma \) value represents the extent to which a particular input explains the variation in the output, as for a partial correlation coefficient in linear regression analysis. It is observed from Fig. 2 that the elements Mn and Nb are not significant in influencing the FN. The optimised committee model predicts the FN in stainless steel welds with better accuracy than the constitution diagrams and other FN prediction methods (Table 1). Excellent agreement between the predicted and measured FN has also been observed for test dataset [Fig.3]. Using this generalised Bayesian Neural Network (BNN) model, the influence of variations of the individual elements on the FN in austenitic and duplex stainless steel welds has been determined. It is found that the change in FN is a non-linear function of the variation in the concentration of the elements. Elements such as chromium, nickel, nitrogen, molybdenum, silicon, titanium and vanadium are found to influence the FN more significantly than the rest of the elements in stainless steel welds. Manganese is found to have less influence on the FN. While titanium influences the FN more significantly than niobium, the WRC-1992 diagram considers only niobium for calculating the chromium equivalent. The role of silicon and titanium in influencing the FN in stainless steel welds has been brought out clearly, while these elements are not given due considerations in the WRC-1992 diagram.

![Fig. 1: Comparison of predicted ferrite number using optimum committee of models and measured ferrite number for entire dataset (1020 datasets)](image1)

![Fig. 2: Perceived significance \( \sigma \) values of all first nine ferrite number models in the committee for each input](image2)
## SIGNIFICANCE OF FERRITE CONTENT

A minimum ferrite content is necessary to avoid hot cracking in stainless steel welds. The amount of ferrite in the weld metal also controls the micro structural evolution during high temperature service. Moreover the amount of ferrite controls the corrosion and stress corrosion resistance. The low temperature toughness of the weld metal is also related to the weld metal ferrite content. Research is focused on quantifying the effect of various alloying elements on the ferrite content so that it is possible to control the amount of ferrite by modifying the weld metal composition. To achieve this objective, accurate predictive tool for the estimation of ferrite content as a function of weld metal composition is necessary.

<table>
<thead>
<tr>
<th>FN Prediction method</th>
<th>RMS error for complete training database</th>
<th>RMS error for independent dataset not used in training</th>
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</thead>
<tbody>
<tr>
<td>Bayesian Neural Network (BNN) model</td>
<td>2.1</td>
<td>2.03</td>
</tr>
<tr>
<td>FNN-1999 (Back Propagation Neural Network) model</td>
<td>3.5</td>
<td>2.3</td>
</tr>
<tr>
<td>WRC-1992 Diagram</td>
<td>5.8</td>
<td>2.6</td>
</tr>
<tr>
<td>Function Fit model</td>
<td>5.6</td>
<td>5.1</td>
</tr>
</tbody>
</table>

Fig. 3: Comparison between predicted and measured FN for an independent dataset not used in the training (265 datasets)

## BRIEF DESCRIPTION OF THEORETICAL BACKGROUND

The neural network is a simple combination of transfer functions and weights. The influence of the inputs on the output variable is together with the transfer functions implicit in the values of the weights. Neural network in a Bayesian framework allows the calculation of error bars representing the uncertainty in the fitting parameters. The method recognises that there are many functions that can be fitted into uncertain regions of the input space, without unduly compromising the fit in adjacent regions, which are rich in accurate data. Instead of calculating a unique set of weights, a probability distribution of a set of weights is used to define the fitting uncertainty. The error bars, therefore, become large when data are sparse or locally noisy.

## ACHIEVEMENT

The model is the most accurate composition only dependent FN prediction method currently reported in literature. The RMS error for the predicted Ferrite Number using this model is less than 2. This model is 65% more accurate than the WRC – 1992 diagram and 40% more accurate than the other neural network model reported in the literature. The model published as a manuscript has been approved and published as a document by International Institute of Welding.

## PUBLICATIONS ARISING OUT OF THIS STUDY AND RELATED WORK


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