Application of Artificial Intelligence in Predicting Weld Properties of Nuclear Installations

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Abstract: Predicting weld properties such as Ferrite, Austenite and Martensite content in stainless steel welds is desirable in order to estimate the welded properties for safety of nuclear installations like (reactor vessels and piping system). Several methods have been used over the last years to estimate the Ferrite content as a function of the alloy composition. A new technique is developed which uses a neural network analysis to determine different phases of steel properties. The Artificial Neural Network (ANN) was trained on the same data set that was used to generate the Schaeffler constitution diagram. The accuracy of the neural network prediction is compared to that for the Schaeffler diagram. The results show that the neural network model was more accurate than that measured by Schaeffler diagram.

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Introduction

Improvement in the area of radiological safety engineering is connected inseparably with employment and development of mathematical modeling, numerical methods, computational intelligence methods, and artificial intelligence. Computer modeling and simulation make improvement of engineering materials properties possible, as well as prediction of their properties, even when the nuclear installations are welded and radiation may occur, with the major reduction of expenditures and time necessary for their analysis and application. Modeling becomes, therefore, the essential tool in materials science and in radiological engineering.

The artificial neural networks are worldwide tools for a numerical modeling capable of mapping of complex functions. The adaptation of neural networks to fulfilling a definite assignment does not require the determination of an algorithm or recording it in the form of a computer program. This process replaces learning using a series of typical stimulations and corresponding to them desirable reactions. The basic feature of neural networks is their capability to a generalization of knowledge for the new data not presented in the learning process. This fact allows applying them whenever there are problems with data processing and analysis, their classification, prediction or control. For several years, neural networks are more and more often used in the material engineering. This growing popularity of neural networks results from the possibilities of creating relations between the examined quantities without any knowledge concerning a physical pattern of described phenomena [1-4].

In the field of radiological safety, material properties used in the physical barriers or shielding against radiation is of interest. The nuclear reactor primary coolant circuit boundary is manufactured from carbon steel with many weldments in the piping system. The study of the weldments properties and their characteristics is very important relevant to shielding properties and hence to radiological safety. The possibilities of applying artificial neural networks for predicting stainless steel weld properties of nuclear installations such as (Austenite, Martensite), as most of the previous studies focused on the prediction of the Ferrite number and to judge their perspective use in this field, have been investigated.

Artificial Neural Networks

Neural networks use the distributed parallel processing of information during the execution of calculations, which means that information recording, processing and transferring are carried out by means of the whole neural network, and then by means of particular memory places. Learning is a basic and essential feature of neural networks. Knowledge is recorded especially through the strength of linkages between particular neurons. Linkages between neurons leading to a "correct answer" are strengthened and linkages leading to a "wrong answer" are weakened by means of the repeated exposure of examples describing the problem area. These examples create a so-called training set.

Neural networks are suitable for approximating complex mutual relations among different sensor-based data, especially among non-structured data, with a high grade of non-linearity, and with inaccurate and incomplete data.

Neural networks are able to realize and

appropriately express the general properties of data and the relations among them and on the contrary to suppress relationships which occur sporadically or are not sufficiently reliable and strong. Their usage enables the retrieval of relationships among the parameters of the process which can not use common methods to trace the reason of their mutual interactions, large number and dynamics.

A disadvantage of neural network application is the danger of network overtraining when a neural network fixates exceedingly on training data and it loses the capability of generalization and further there is an uncertainty if it is possible to achieve the required results because it is not possible to estimate beforehand the size of an error which is strongly dependent on network parameters and on training data. It is necessary to verify experimentally the usability of neural networks in any field and to try to retrieve optimal parameters by way of experiment, experience and suspicion to achieve the best possible results.

For all types of predictions, neural networks are suitable to be used for their learning Backpropagation algorithms. This algorithm is convenient for multilayer feedforward network learning which is created minimally by three layers of neurons: input, output and at least one hidden layer (Figure 1). Between the two adjoining layers there is always a so-called total connection of neurons, thus each neuron of the lower layer is connected to all neurons of the higher layer. Learning in the neural network is realized by setting the values of synaptic weights *wij* between neurons, biases or inclines of activation functions of neurons. The adaptation at Backpropagation types of networks is also called "supervised learning", when the neural network learns by comparing the actual and the required output and by setting the values of the synaptic weights so that the difference between the actual and the required output decreases [5-8].

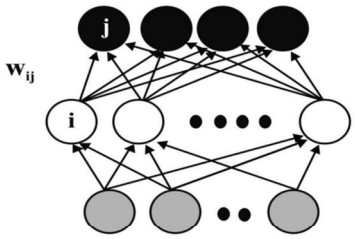


Figure 1. Topology of a multilayer feedforward neural network

Prediction of Stainless Steel Different Phases

Neural networks are modeled after learning process in the human brain. A network structure consists of interconnected layers of nodes; the nodes include input and output nodes as well as internal hidden nodes. These nodes are connected to each other so that the value of one node will affect the value of another.

In this study the Schaeffler diagram shown in Figure 2 is representing two input variables [9]; Nickel equivalent and Chromium equivalent. The output layer contains one or two or three nodes, corresponding to one output variable such as Ferrite number, two nodes corresponding to two variables such as Martensite and Ferrite and three nodes corresponding to three output variables such as Austenite, Martensite and Ferrite.

The neural network is trained by introducing a training data set for input and corresponding outputs from the Schaeffler diagram. A training routine is then carried out in which outputs are predicted and these are compared with the actual output. A feed forward network with a back propagation learning scheme was utilized. The analysis scheme to develop the final neural network for weld properties prediction was summariezed in Figure 3, [10].

An attempt was made for quantifying the predictability of the final network that was developed. This was done by removing at random five or ten point from the entire data set of points and training a network with the same optimum architecture. The resultant network was tested on the removed data. This was repeated for different phases of Schaffler diagram. The error in predicting each phase is a reasonable estimate of error that can be expected when the network is applied to new data set.

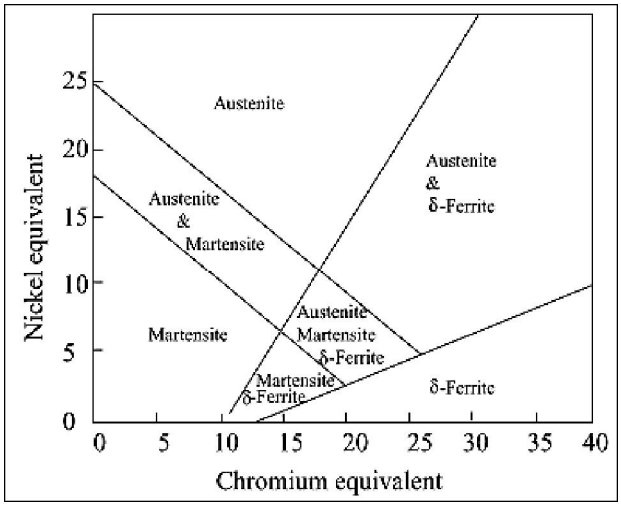


Figure 2. Schaeffler Diagram

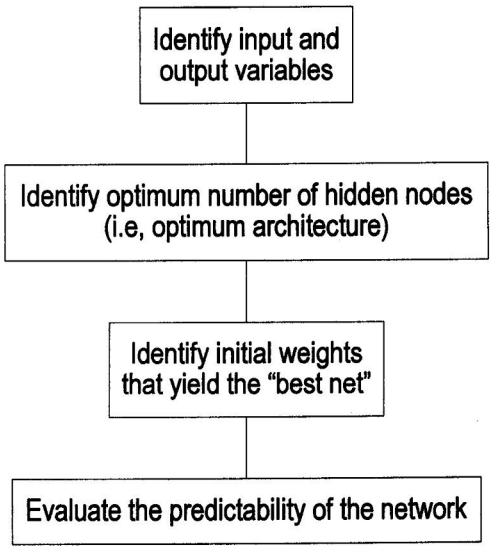


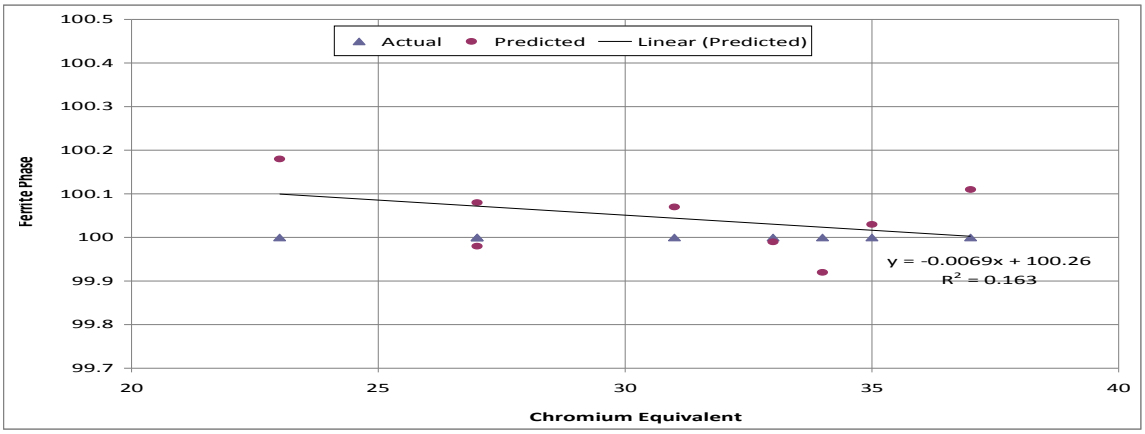
Figure 3. Flow chart showing the four basic steps to identify the optimum neural network architecture and the best neural network

Ferrite Phase Zone

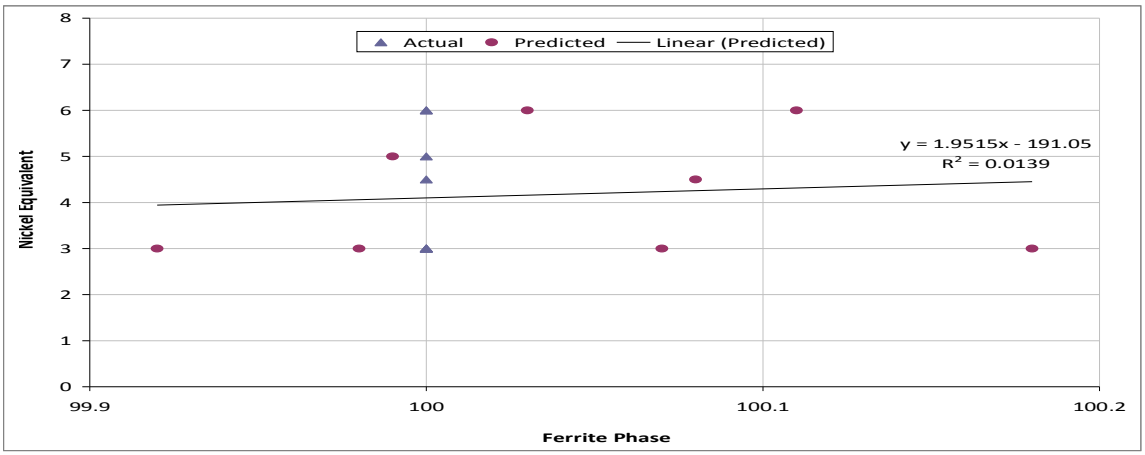
In Ferrite phase zone, the input layer has two nodes, chromium and nickel , the output layer has one node representing ferrite number. The ANN is trained by actual data for inputs and corresponding outputs from Schaffler diagram. A training routine is then carried out in which output are predicted and compared with the true output as shown in Table 1 and Figure 4. The results illustrated in Table 1 indicates that ANN gives accurate result. The straight line in Figure 4(a) and (b) represent the linear least square fit line between the predicted and actual ferrite number values, its equation and the coefficient of determination (R^2) values were shown in Figure 4 (a) and (b). As seen in this figure good results were obtained from multilayer feed-forward.

Table 1. Schaeffler Diagram input data for training ANN and actual input data for prediction using ANN

Input data for training using ANN		Input data for prediction using ANN		ANN output values for comparison	
Chromium Equivalent	Nickel Equivalent	Chromium Equivalent	Nickel Equivalent	Fn actual values (%)	Fn prediction values (%)
16	1	23	3	100	100.18
22	3	27	3	100	99.98
28	5	27	4.5	100	100.08
32	6	31	3	100	100.07
34	7	33	5	100	99.99
25	3	34	3	100	99.92
32	3	35	6	100	100.03
34	6	37	6	100	100.11



(a)



(b)

Figure 4. Comparison between Sachaeffler diagram ferrite phase actual values and ferrite phase predicted values using ANN w.r.to (a) Chromium Equivalent. (b) Nickel Equivalent.

Ferrite and Austenite phases zone

In Ferrite and Austenite phases zone, the input layer has two nodes, Chromium and Nickel , the output layer has two nodes corresponding to Ferrite number and Austenite. A plot for actual data used for training the neural network is shown in Figure 5**.** A comparison between actual and predicted Ferrite number with respect to (w.r.to) Chromium equivalent is shown in Figure 6 and for austenite w.r.to Nickel equivalent is shown in Figure 7. The results show that the actual data in most of the selected points are approximately the same as the predicting values by the feed forward neural network.

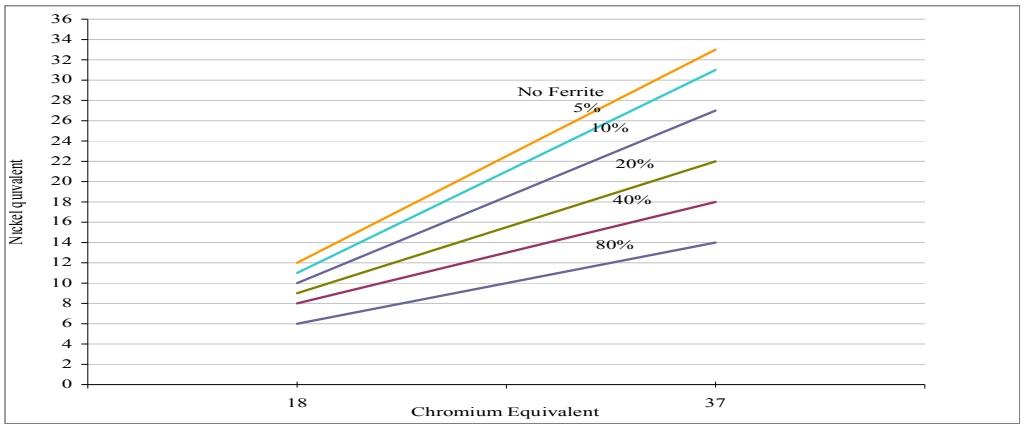


Figure 5. Schaeffler Diagram input data for training ANN

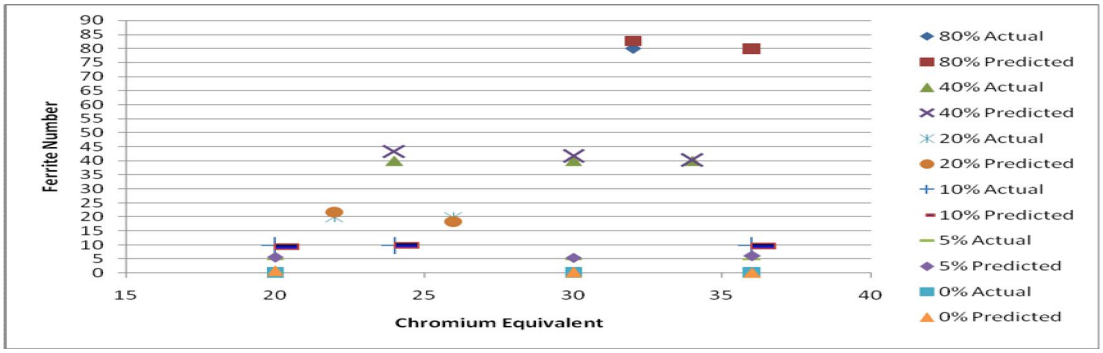


Figure 6. Comparison between Sachaeffler diagram ferrite phase actual values and ferrite phase predicted values using ANN w.r.to Chromium Equivalent.

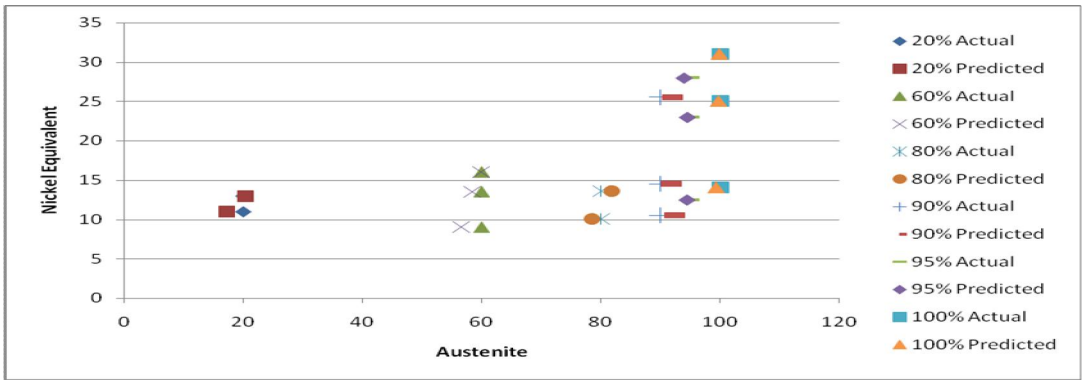


Figure 7. Comparison between Sachaeffler diagram Austenite phase actual values and Austenite phase predicted values using ANN w.r.to Nickel Equivalent.

Ferrite, Martensite & Austenite phases

In Ferrite, Martensite and Austenite phases, neural networks with classical three layer structure have been used for prediction. Training data were given as Chromium and Nickel equivalent for inputs and Ferrite, Martensite and Austenite for output as shown in Figure 8. The results illustrated in Figure 9 and 10 show that the actual data in all of the selected points are approximately the same as the predicting values.

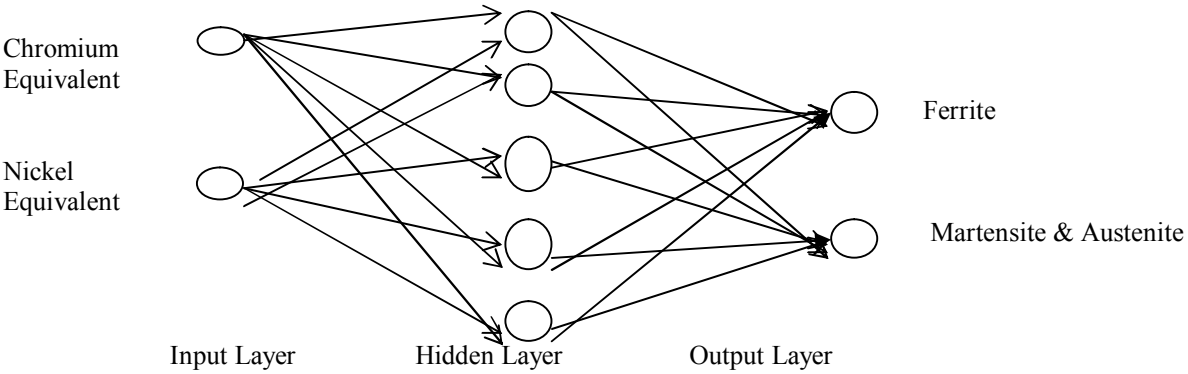


Figure 8. Schematic diagram showing the multiple layer structure of a neural network used inpredicting Ferrite , Martensite & Austenite phases.

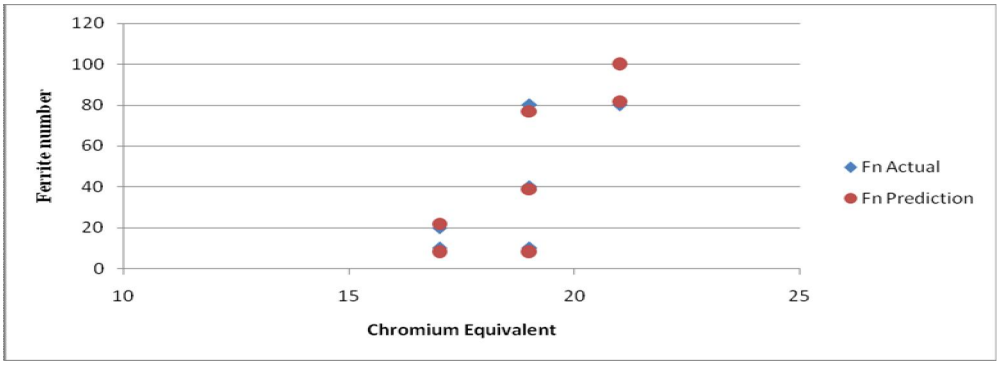


Figure 9. Comparison between Sachaeffler diagram Ferrite phase actual values and Ferrite phasepredicted values using ANN w.r.to Chromium Equivalent

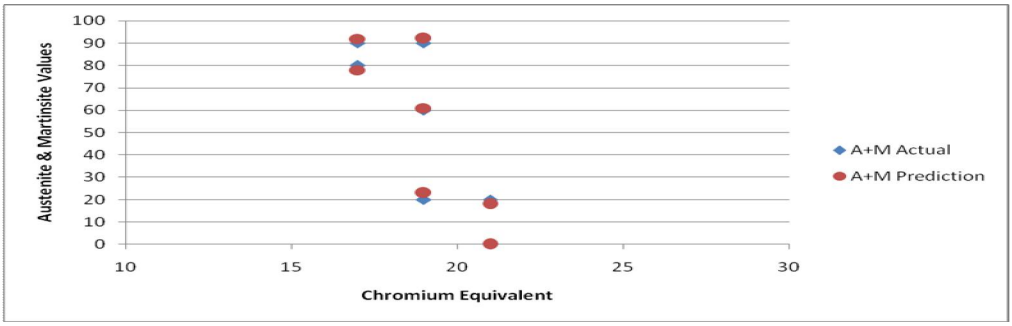
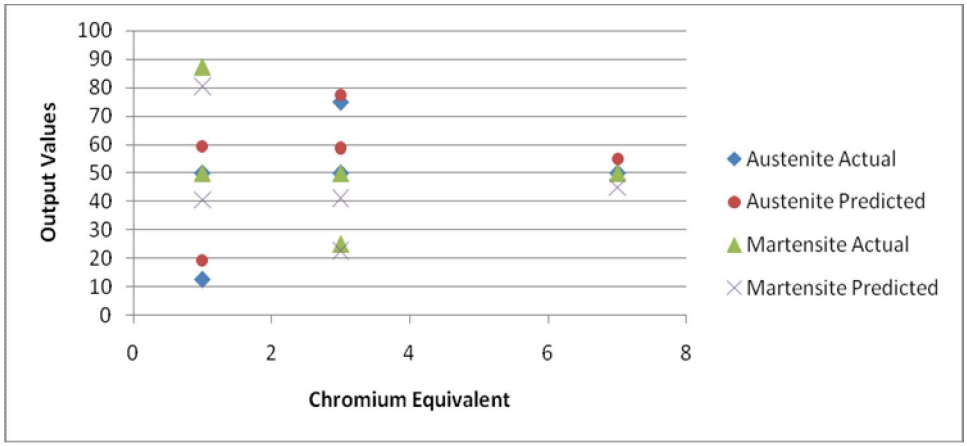


Figure 10. Comparison between Sachaeffler diagram Austenite , Martensite phase actual values and predicted values using ANN w.r.to Chromium Equivalent.

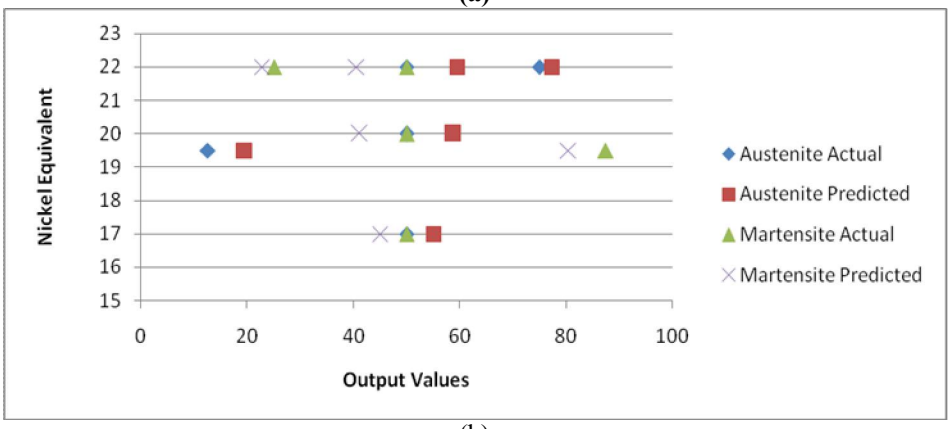
Austenite and Martensite phase

In austenite and Martensite phase zone, the input layer corresponding to Chromium and Nickel equivalents and the output layer represent the predicting values for Autensite and Martensite.

Figures 11, a and b show a comparison between actual values for Austenite, Martensite and neural network predicted values. It can be seen that for most of the point the actual values are similar to the predicted values for either austenite or Martensite.



(a)

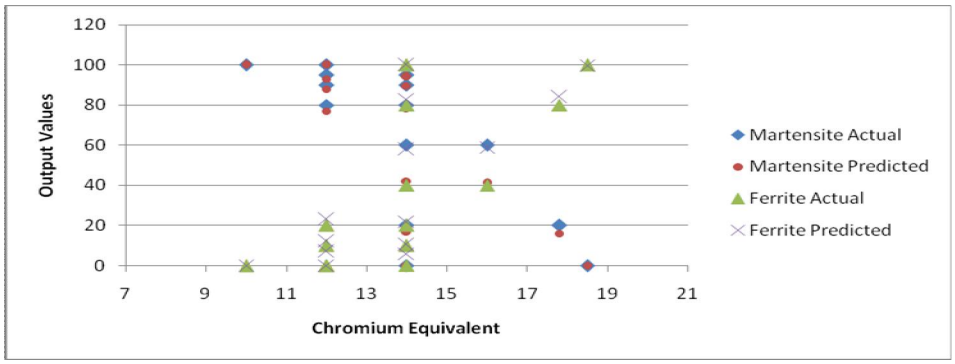


(b)

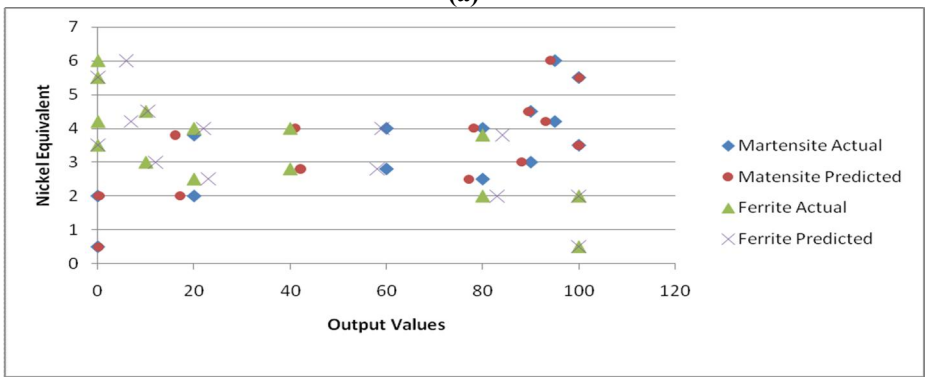
Figure 11. Comparison between Sachaeffler diagram Austenite, Martensite actual values and predicted values using ANN w.r.to, (a) Chromium (B) Nickel Equivalent.

Martensite and Ferrite phase

Figure 12, shows a comparison between Martensite and Ferrite actual and predicted values w.r.to (a) Chromium and (b) Nickel equivalent the result indicates that there is a small difference between the two values.



(a)



(b)

Figure 12. Comparison between Sachaeffler diagram Martensite, Ferrite actual values and predicted values using ANN w.r.to (a) Chromium, (b) Nickel Equivalent.

Austenite phase

In Austenite phase zone, the input data used for predicting Austenite are shown in Table2 (columns 1,2) and the output values for austenite predicted by ANN are illustrated in (column 3). The results indicate that the output values for Austenite are 100% which exactly equal the actual values from Schaeffler diagram.

Table 2. Schaeffler Diagram input data for prediction and Austenite predicted values using ANN

Input data for prediction using ANN		ANN output values (%)
Chromium Equivalent	Nickel Equivalent	
0	28	100
4	27	100
8	24	100
12	21	100
16	27	100
20	21	100
24	24	100
28	27	100

Martensite phase

In Martensite phase zone, the input layer has two nodes corresponding to nodes, Chromium and Nickel and the output layer nodes represent Martensite values as shown in Figure 13. The results indicates that artificial neural network gives no error as Martensite predicted values is 100% exactly as the actual values in Schaeffler diagram.

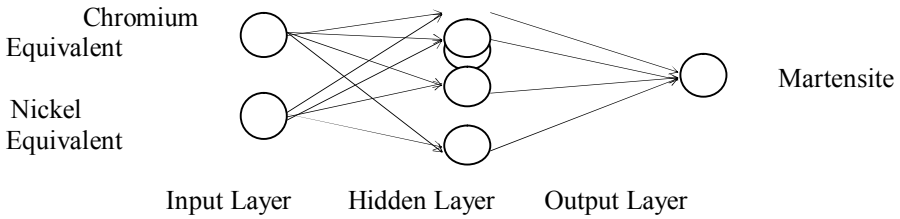


Figure 13. Schematic diagram showing the multiple layer structure of a neural network used in predicting Martensite phase

Conclusion

Neural network model for weld properties prediction in stainless steel have been developed using the database which was used for generating Schaeffler diagram. The best model was chosen based on minimum in the test error. The result indicates that new model can be used for predicting different phases of stainless steel weld properties with a better accuracy than the constitution diagram.

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