Chapter 5

Conclusions

The Neural Network and Genetic algorithms Methods have been used for efficient design of the Mechanical Properties of Ferritic Steel Welds. From the Modeling works and Results and Discussion, some useful conclusions can be drawn:

The distribution of the Data of the Mechanical Properties of Ferritic Steel Welds is uniform for some Input variables and non-uniform for some Input variables. The distribution is clearly observed in Scatter plots.

In this case, of Bayesian Neural Network method, all the response graphs show error bars when the concentration of Nickel and Chromium is respectively below 8 and 6 wt%, the prediction can be reliable. But above those limits (7 wt% for Ni and 6 wt% for Cr), the model can no more be trusted and this is inferred by the large error bars. Similarly, it is applicable to other graphs where larger error bars are present. More experiments with concentrations in this range of values need to be carried out to improve the model. Uncertainty because of a lack of data is one of the limitations of a neural network. The error bars and output variable (Mechanical Properties of Ferritic Steel Welds) sometimes showing unphysical (negative) values, this is because of the empirical equation in Neural Network modelling. This error bars feature of Bayesian Neural Network is an excellent guideline for research and Development.

In the case of General Regression Neural Network method, there are no problems of noisy data. It can handle noise in the Inputs. The Response graphs of the GRNN show more define about the non linearity or complexity between the Input variables and the Mechanical Properties of Ferritic Steel Welds. The Response graphs of the GRNN mention Input variables and Output variables (Mechanical Properties of Ferritic Steel Welds) accurately by quantity. The efficient design of Mechanical properties of Ferritic Steel Welds becomes very easy by the Response graphs of GRNN.

The Response Graphs show about the individual relationship between the input variables and Output variables (Mechanical Properties). The 3D contour plots show the relationship between the two Input variables with Output variables (Mechanical Properties).

The individual effect of any Input variable is traditional or general on Mechanical Properties of Ferritic Steel Welds.

The cumulative effect of Input variables in the group has a complex pattern on the Mechanical properties of Ferritic Steel Welds.

These trends are confirmed in the present analysis as illustrated in both the types of the Graphs. They are impossible to reproduce in practice. They give a clear understanding of the relationship between the Input variables and the Mechanical properties of Ferritic Steel Welds. These pieces of information are very valuable for design, as well as understanding the existing theory and also guiding about new research and new finding for the Ferritic steel Welds.

3D contour Plot gives the relations between the **three input variables** and **one output variable.** The relations between **Nickel, Manganese** and **Testing Temperature for Charpy toughness > 213K (-60C) and Charpy Toughness** by **GRNN.** Graph gives the information about how these three **Nickel, Manganese** and **Testing Temperature for Charpy toughness > 213K** control the **Charpy Toughness** from **10J to 80J.** Traditionally in alloy design it is known that ***increase in*** the **Nickel** ***increases*** the **Toughness but it is not true.** It is very critical to maintain the **toughness** with **Nickel, Manganese** and **Testing Temperature for Charpy toughness > 213K**. To achieve a **80J and more,** the compositions of **Nickel** ***must be maintained*** in **range** of **3.5 to 5.8** wt% and **Manganese** ***must be maintained*** **maximum 0.9 wt%(GRNN).** In ***literature,*** to these values are **6 to 10.8 wt% Nickel** and **0.6 wt% Manganese**.(BNN)

The relations between **Nickel, Manganese** and **Testing Temperature for Charpy toughness > 233K (-40C) and Charpy Toughness** by GRNN. It is very critical to maintain the **toughness** with **Nickel, Manganese** and **Testing Temperature for Charpy toughness > 233K.** To achieve a **75J and more,** the compositions of **Nickel** must be maintained **less than 5.8 wt%** and **Manganese** must be maintained in range of **0.7 to 2.1 wt% (GRNN).** In ***literature,*** to these values are 6 **to 8 wt% Nickel** and **0.8 wt% Manganese.(BNN**)

For more accurate design of Mechanical Properties Ferritic Steel Welds, use more modeling methods to understand the complexity of the variables interactions.

The 3D contour plots show the relationship between the two Input variables with Charpy Toughness. There is a total combination of hundred and more 3D contour plots formed by 20 Input variables with the Charpy Toughness of Ferritic Steel Welds. The Ternary Categorized plots show the relationship between the four Input variables with Charpy Toughness. There is a total combination of (three input variables) 1140 Ternary plots formed by 20 Input variables with the Charpy Toughness. In the present work, 18 3D contour plots and 4 Ternary Categorized plots are given with their important relationship with the Charpy Toughness. These 3D contour plots show some hidden complex behavior of the input variables with the Charpy Toughness which is also not available or understood. Some innovative theoretical relations can be established by the proper interpretation of these 3D contour plots which become the new knowledge base for the future work on Ferritic Steel Welds. The Input variables show complex trends because during welding, there are formations of various types of the microstructures in Ferritic Steel Welds, qualitatively and quantitatively.

The Ternary Categorized plots show the relations between Chromium, Manganese, Nickel, Heat Input and Charpy Toughness by GRNN model. Graphs give the information about how these four Chromium, Manganese, Nickel, and Heat Input control the Charpy Toughness from 25J to 300J. At High Heat Input > 5.1 kJ mm-1 can give wide range of Toughness, 25J to 300J. The alloying elements require for higher toughness more than 275J, Manganese less than 0.14 wt%, Chromium 9.0 to 11.78 wt% and Nickel less than 1.35 wt%. This finding is totally new that with increase in the Chromium content and decreasing both Manganese and Nickel, increases the Charpy Toughness at higher input value greater than 5.1 kJ mm-1 (i.e. Chromium has a significant role in increase the Charpy Toughness of Ferritic Steel Welds). This is a new finding for the Ferritic Steel Welds. These types of more new findings can be established by the Ternary Categorized plots and 3D contour plots which are not discovered. Figure.6.8.4 indicates more convenience for alloy design or weld deposit design because very small region available for input variable selection. This region also mentions that control of three alloying elements must be done very precisely for the desired Charpy Toughness.

Each contour line of mechanical property in 3D contour plots and Ternary Categorized plots gives a large number of combinations of Input variables for that fix quantity of Mechanical property which make the design of the Ferritic Steel Welds more flexible.

The trained BNN and GRNN models give the accurate predictions of unseen data which is useful in designing the Ferritic Steel Welds for the welding electrodes industries. With simply change the quantity of Input variables in model and run it, the predicted Mechanical Property is obtained in the seconds.

The Genetic Algorithms method gives the prediction of the Input Variables for the Targeted Mechanical Property value. It also predicted Input variables for the Targeted Mechanical Property value which is beyond the range of data. The results are excellent. The calculation of Genetic Algorithms takes more times, in hours and this method must be run every time with a new targeted value of Mechanical Property.

Neural network models are extremely useful in Modeling of Ferritic Steel Welds accurately, not only in the study of mechanical properties, but wherever the complexity of the problem is overwhelming from a fundamental perspective and where simplification is unacceptable.

The model formulated has been applied towards the understanding of Ferritic Steels Alloys used in welding for various equipment constructions in industries (eg. Power plants, Submarines, Heat resistant applications, Creep resistance applications, Structural applications..etc.). It has been used successfully on unseen data on Ferritic Steels Welds for various applications.

The design of the ferritic weld alloys become easier, accurate, economical and time-saving with the help of the Neural Networks and Genetic Algorithms modeling Tools. The control of the effective input variables gives the desired Mechanical Properties of weld alloys for real applications in industries.