Summary

1.1 Summary of PhD Work:

The development of new welding alloys for Ferritic Steel Welds has in the past been achieved by trial and experience. The purpose of this work was to enable a significant proportion of the development procedure to be done by computation. A variety of methods have been used towards this end, ranging from Neural Network methods to Genetic Algorithm methods which rely heavily on patterns in experimental data.

The review of literature indicates that Weld metal models can in general be categorized into two classes, those which are empirical and others founded on physical metallurgy. The latter is more meaningful, but as will be seen later, they are generally over-simplified and deal only with simple properties other than the range of properties important in engineering design.

Regression Models: There have been numerous attempts to model weld metal mechanical properties by using linear regression analysis. Table 2.2 Yield and Ultimate tensile strength (MPa) regression models of weld metals [1]. The strength of the weld metal is frequently modeled as a function of chemical composition of weld metal, for cases where all the remaining variables associated with welding approximately constant. Equations like these are useful within the context of the experiments they represent. Naturally, the strongness of the relationships used may not necessarily be justified in detail. Physical Metallurgy based Models: (1) The Sugden-Bhadeshia Model: Sugden and Bhadeshia tried to predict the strength of the as-deposited weld as a function of the chemical composition and microstructure [8]. (2) The Young-Bhadeshia Model

The Young-Bhadeshia strength model for high-strength steels [4] considered microstructures which are mixtures of martensite and bainite. Although the Sugden-Bhadeshia model has more physical meaning when compared with the empirical equation presented in Table.2.2., the model still has linear approximations which are not justified in detail. It is resticted to structural steel welds which have simple, untempered microstructures bainite and martensite are excluded from the analysis,as is precipitation hardening. The Young and Bhadeshia model can be applied to estimate the strength of bainite and martensite welds. Even though the model had considered the microstructural influence the model still built on the some of the assumptions made in Sugden and Bhadeshia model like linear summation effect of solid solution strengthening.

It appears from the literature reviewed that the failure of the previous work [1,2,3,4,8] to create models with wide applicability comes largely from constraints due to the linear or pseudo-linear regression methods used, with poor error assessments and most importantly from very limited variables and data considered in the analysis.

In this work an attempt has been made for ferritic steel welds typically might contain more than fifteen important solute additions. Its properties also depend on the welding conditions and post weld heat treatment. It is a formidable task, therefore, to attempt to predict the yield and ultimate tensile strengths, elongation and Charpy toughness, all of which are elementary design parameters. A massive dataset was compiled using detailed data from the published literature and industries, and subjected to various neural network analysis like BNN, MLP, RBF, GRNN as well as Genetic Algorithms with BNN models. The Neural Networks are a highly flexible and powerful empirical method, but it is demonstrated that with care the network can be trained to recognize metallurgically sound relationships. The resulting **best models of GRNN and BNN** have been validated in a variety of ways with an emphasis on data previously unseen by the models. Having done this, the models have been used to successfully design a new welding alloy. The Input Variables can be changed or fixed in models to design or to predict mechanical properties of Ferritic Steel Welds accurately in seconds. The Genetic Algorithms method has been tested for the prediction of the Input Variables for the Targeted Mechanical Property value within the data and beyond the data successfully.

The trends are confirmed in the present analysis as illustrated in all the types of the Graphs as results. 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. The design of the ferritic weld alloys becomes 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 give the desired Mechanical Properties of weld alloys for real applications in industries.

The experimental validation of all predictions and trends are not possible because it required technological and economic support from welding industries related to the ferritic steel welds.

These best neural network models can predict accurately as given in neural network modelling literature. The trends are observed in the various graphs open new horizons of research and understanding of the ferritic steel welds.

1.2 Important Research findings

The **General Regression Neural Network method** is used **first time for the Ferritic Steel Welds.** The results of this research work have shown that the **General Regression Neural Network is the best modelling method** compare to other like MLP, RBF and BNN for the Ferritic Steel Welds.

The Response graphs of the **GRNN show more accuracy about the non linearity or complexity** between the Input variables and the Mechanical Properties of Ferritic Steel Welds **compare to the BNN.** 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.

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.

The Ternary Categorized plots presented in this work, to plot the output of Neural Network models **are not given in literature**. This is **first time** presented in this research work.

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 heat 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.4.13.4) 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 Genetic Algorithms method gives the prediction of the Input Variables for the Targeted Mechanical Property value of ferritic steel weld. It also predicted Input variables for the Targeted Mechanical Property value of ferritic steel weld which is beyond the range of data. The **Genetic Algorithms method with BNN model** used for the ferritic steel welds **first time** in present work. The results are excellent.

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 any data on Ferritic Steels Welds for various applications.

1.3 Research work layout

This thesis contains six chapters, as given below:

Chapter one explains about the Introduction of Ferritic Steel Welds, Modellling work, Scope of Work, Important Research Findings

Chapter two describes the Physical metallurgy of Ferritic Steels, Mechanical Properties of Welds, Welding processes, Weld Microstructures, Strengthening Mechanisms, Previous Weld Mechanical Property Models, Regression Models, Neural Network Overview, Neural Network Methods, and Genetic Algorithms.

Chapter three includes details about the Modelling Work of the Yield Strength, Ultimate Tensile Strength, Elongation and Charpy Toughness of Ferritic Steel Welds containing the Data preparation, Neural Network Modeling, Genetic Algorithms Modeling.

Chapter four describes details about the Results and Discussion of Modelling Work in form of various types of Graphs and Predictions qualitatively and quantitatively

Chapter five has the conclusions of the work

Chapter six has suggestions for futher scope of Work.

In the present work, various neural network methods and genetic algorithms have been applied to large data of input variables (weld compositions, Welding process variables) and output variables (Mechanical properties of welds) of ferritic steel welds to understand the complex relations between them. The relations are presented in various graphs show the new trends between the variables.