Synopsis of the thesis

Modelling Tools for Efficient Design of Mechanical Properties of Ferritic Steel Welds

Submitted for the award of the degree

Of

DOCTOR OF PHILOSOPHY

In

(Metallurgical and Materials Engineering)

by

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2017

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Synopsis

Modelling Tools for Efficient Design of Mechanical Properties of Ferritic Steel Welds

Introduction:

Steels are used in the construction and fabrication of engineering structures, with service temperatures ranging from subzero to about 600°C over long periods of time. The vast majority of iron alloys are ferritic because they are cheap and it is easy to modify their microstructures to obtain an impressive range of desirable properties.

The fabrication of steels unavoidably involves welding, a complex process incorporating numerous metallurgical phenomena. It is not surprising therefore, that the final microstructure both inside the weld metal and in all adjacent regions affected by welding heat, is remarkably varied. Many of the important features of weld microstructure can now be calculated using a combination of thermodynamics and kinetic theory [1]. Such calculations are now being performed routinely in industry during the course of alloy design or when investigating customer quaries.

Naturally, it is the mechanical properties of the weld which enter the final design procedures. There has been some progress in estimating the yield strength from the microstructure using combinations of solution strengthening, grain size effects, precipitation hardening and dislocation strengthening [1]. The ultimate tensile strength can in a limited number of cases be calculated empirically from the yield strength [2]. However, there has been no progress at all in creating models for vital properties such as ductility, toughness, creep and fatigue strength [3].

Ferritic Steels

Heat Resistant Steels

Steels are used widely in the construction of power plant. They have to resist creep deformation, oxidation and corrosion. The superheater pipes carrying steam from boilers to high pressure(HP) turbines typically experience steam at 565°C under 15.8 MPa pressure and are made of low-alloy steels. In HP turbines the rotor is fabricated as a single forging of 1Cr-MoV steel. Tempering at 700℃ leads to the formation of stable carbides which are distributed uniformly in the ferrite matrix. These carbides improve the creep resistance at the service temperature [4]. Turbine blades experience both erosion and high tensile forces. High strength and corrosion resistant 12CrMoV steel is used in fabrication of turbine blades [5]. The 3½Ni-Cr-Mo-V alloy has good hardenability combined with high strength of about 1100 MPa and good toughness. These steels are air cooled from 870°C and tempered at 650°C. Due to their strength and toughness these materials are used to fabricate the low pressure turbine rotor, which is nearer to the generator. Thegenerator rotor is also fabricated with this material [6].

Table 1.Chemical composition of some steels have been used Power Plant [7], all units are in wt%.

Steel	C	Si	Mn	Mo	Cr	V
2¼Cr-1Mo	0.15	0.50	0.45	1.0	2.25	---
12Cr-1Mo	0.15	0.40	0.6	1.0	12	---
3½Ni-Cr-Mo-V	0.15	0.30	0.70	0.10	1.5	0.11

Cr-Mo Steels

These materials are resistant to corrosion by sulphur products and hence were used first in the petroleum industry. Once their oxidation resistance and high temperature strength were appreciated, they began to be applied in the steam power generating industry. More recently, these steels have been used in fabricating thick pressure vessels. The oxidation resistance and high temperature strength depends on the amount of chromium and molybdenum present in that alloy. Excellent high-temperature (565°C) strength is obtained in 2¼Cr-1Mo steels (Table.1), which are generally used in the bainitic condition. A tempering heat-treatment gives the required alloy carbides; the most important are M_2C, M_7C_3 and $M_{23}C_6$, where M represents a metallic element, where M represents a metallic element.

Structural steels

Steels for structural applications are used at ambient temperatures and the main property requirements are strength, ductility and toughness. The vast majority of these steels have a yield strength in the range 300-550 MPa with a mixed microstructure of ferrite and pearlite. These are used in critical applications, such as bridges, buildings or ship construction and may undergo sophisticated themomechanical processing to refine the microstructure and greatly improve the toughness. Such alloys may contain quantities of fine bainite or even martensite when the overall concentration is small.

All structural steels have to be welded. For this reason and to minimize the cost, the total alloy concentration is generally less than 5wt%. The weld metals used for joining structural steels also range in yield strength between 350 and 550 MPa, but can be much stronger (900MPa) for special steels used in the construction of submarines. The preferred weld microstructures contain large quantities of acicular ferrite which, because of its scale and chaotic arrangement, gives good toughness. However, quantities of allotriomorphic ferrite, Widmanstetten ferrite, martensite and retained austenite may also be present.

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

Scope of the work

Previous Weld Mechanical Property Models:

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

1. Regression Models
   There have been numerous attempts to model weld metal mechanical properties by using linear regression analysis.

Table.2: Yield and Ultimate tensile strength (MPa) regression models of weld metals [2]. The alloying element concentrations are expressed in wt%.

Carbon-Manganese	YS = 335 + 439C + 60Mn +361 (C.Mn) UTS = 379 + 754C + 63Mn +337 (C.Mn)
Silicon-Manganese	YS = 293 + 91Mn +228Si – 122Si^2 UTS = 365 + 89Mn + 169Si – 44Si^2
Chromium-Manganese	YS = 320 + 113Mn + 64Cr + 42 (Mn.Cr) UTS = 395 + 107Mn + 63Cr +36 (Mn.Cr)
Nickel-Manganese	YS = 332 + 99Mn + 9Ni +21 (Mn.Ni) UTS = 401 + 102Mn + 16Cr 15 (Mn.Ni)

The strength of 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 firm of the relationships used may not necessarily be justified in detail.

2. 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]. The model is based on the assumption that the strength can be factorised into components; strength of pure iron, solid solution strengthening and strength due to microstructure, equation 1. The chosen microstructural constituents are allotriomorphic ferrite (α), Widmanstatten ferrite (α_w), and acicular ferrite (α_a) with the following assumptions:

2.1 The total strength (σ_y) of as-welded deposit is assumed to be a linear combination of individual components:

$$\sigma_y = \sigma_{Fe} + \sum \sigma_{SS_i} + \sigma_{Micro} \quad \text{.......(1)}$$

where σ_{Fe} is the strength of fully annealed pure iron as a function of temperature and strain rate, σ_{ss1i} is the solid solution strengthening due to alloying element i and σ_{Micr} is strengthening due to weld microstructure.

The weld microstructure consists of allotriomorphic Ferrite (α), Wimanstetten ferrite (α_w) and acciular ferrite (α_a). The variation in grain sizes of α, $\alpha_{w,}$ and α_a are not taken in to account:

$$\sigma_{Micro} = \sigma_\alpha V_\alpha + \sigma_a V_a + \sigma_w V_w \quad ...(2)$$

where σ_α, σ_a and σ_w denote the contributions from 100% allotriomorphic ferrite, Widmanstetten ferrite an accicular ferrite respectively, and Vα, Va and Vw are their corresponding volume fraction.

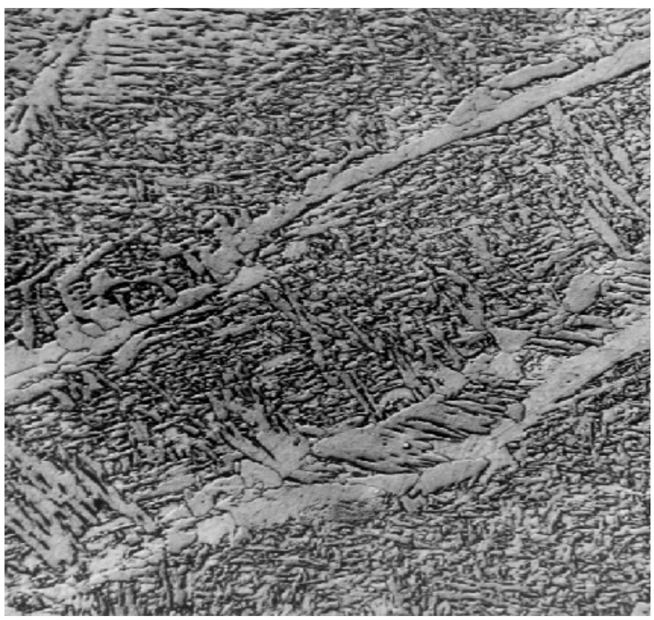


Figure.1 The weld microstructure consists of allotriomorphic ferrite (α),Wimanstetten ferrite (α_w) and acciular ferrite (α_a).

Nitrogen is assumed to be in solid solution and any Strain ageing effects in the as-welded microstructure are assumed to be negligible.The solid solution strengthening (σss) is expressed as the sum of the contributions from each solute:

$$\sigma_{SS} = a \text{ Mn wt\%} + b \text{ Si wt\%} + \ldots \quad ..(3)$$

where the coefficients a, b, .. are functions of temperature, defining the role of the respective alloying elements. The values for these coefficients are taken from the published experimental data which are based on studies in which solid solution strengthening is studied in isolation.

An alloying element naturally influences more than just solid solution effect. However, the other consequences are included in the analysis via incorporation of microstructure. The authors were able to estimate the strength of individual microstructures ($\sigma\alpha$, σa and σw) by studying three welds which are made with identical welding conditions [8]. The chemical compositions were adjusted to give different fractions of microstructure in order to deduce the strengthening due to each microstructure (α, α_a and α_w). The final form of developed equation is:

$$\sigma_y = \sigma_{Fe} + \sigma_{ss} + 27V_\alpha + 402V_a + 480V_w \text{ (MPa)} \quad ...(4)$$

where σ_{Fe} and σ_{SS} can be obtained from referred published literature [8].

Although the Sugden-Bhadeshia model has more physical meaning when compared with the empirical equation presented in Table.1.,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. Young and Bhadeshia have developed the work for microstructures which are mixtures of bainite and martensite but this model has yet to be applied to weld metal microsructures. The model is nevertheless discussed below because it is interesting.

3. The Young-Bhadeshia Model

   The Young-Bhadeshia strength model for high-strength steels [4] considered microstructures which are mixtures of martensite and bainite;

$$\sigma = \sigma_{Fe} + \sum \sigma_{ss1i} + \sigma_c + K_L (L)^{-1} + K_D\rho_D^{0.5} + K_p\Delta^{-1} \quad ....(5)$$

where K_L, K_D and K_p are constants, σ_c is the solid solution strengthening due to carbon, L is a measure of the ferrite plate width, ρ_D is the dislocation density and Δ is the distance between any carbide particles. The other terms have their usual meanings.

The Young and Bhadeshia model can be applied to estimate the strength of bainite and martensite welds by using rule of mixtures. 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 [2,9,10] 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.

Modelling Work and Results:

Database for Modelling:

All of the data collected are from weld deposits in which the joint is designed to minimize dilution from the base metal, to enable specifically the measurement of all`weld metal properties. Furthermore, they all represent electric arc welds made using one of the following processes: manual metal arc (MMAW), submerged arc welding (SAW) and tungsten inert gas (TIG). The welding process itself was represented only by the level of heat input. This is because a large number of published papers did not specify welding parameters in sufficient detail to enable the creation of a dataset without missing values. Missing values cannot be tolerated in the method used here. If the effect of a welding process is not properly represented by the heat input and chemical composition, then neglect of any important parameters will make the predictions more ‘noisy'. As discussed below, the noise in the output was found to be acceptable; a greater uncertainty arises from the lack of a uniform coverage of the input space. The data were collected from a large number of sources.

The aim of the neural network analysis was to predict the Mechanical Properties as a function of a large number of variables, including the chemical composition, the welding heat input and any heat treatment.

. As a consequence, the yield strength database consists of **2121** separate experiments with **17** input variables, %elongation database consists of **1827** experimentwith **18** input variables,charpy toughness database consists of **3449** experiments with **20** input variables whereas the UTS database is slightly smaller at **2091** experiments with **18** input variables. Neural network method used in this work cannot cope with missing values of any of the variables. In some cases the sulphur and phosphorus concentrations were not available. Since these impurities might be important, it would not be satisfactory to set them to zero. Missing values of sulphur and phosphorus were therefore set at the average of the database. See Scatter data plots of Charpy Toughness.(Page.No.7a,7b,7c)

Neural network Methods:

In present work neural network methods are used like Generalised Regression work, Bayesian feed forword neural network, Multilayer perceptron, Radial basis function [11]

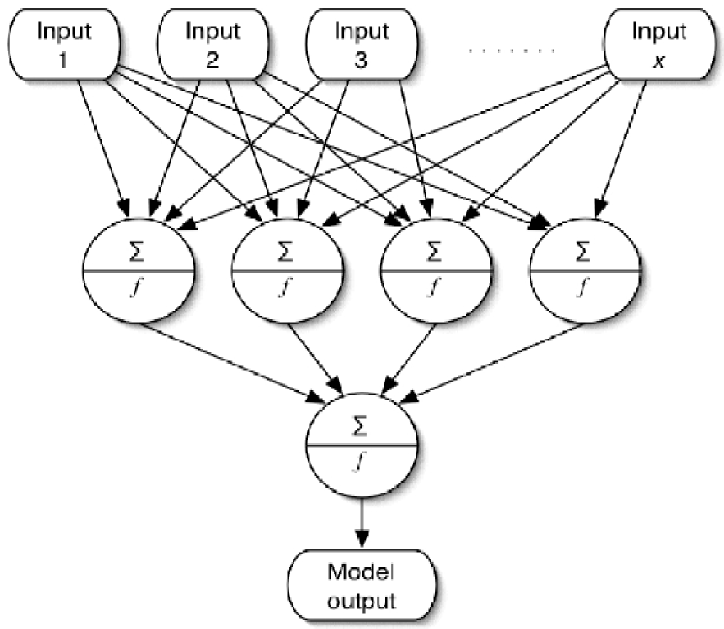


Fig.2 **Three layers neural network**

This figure above is a schematic representative of a simple three layers neural network. The raw data that are contained in the x input or independent variables need to be transformed to a range of values that can be used in the neural network. In neural networks, separate conversion or pre-processing layer that is a part of the network architecture performs the transformation. In case of continuous input variables employed in this example network, the raw values simply need to be rescaled. The transformed values are fed to the input layer of neurons (also referred to as nodes or units). The input layer contains one unit for each of the input variables. Each unit in the input layer is connected to each unit in the hidden layer. The hidden layer is the layer that controls the amount of complexity that can be represented in the relationship between input and output variables. The larger number of units in the hidden layer, the more complex/nonlinear is the relationship that can be represented. If no hidden layer were present, then the neural network would describe a linear relationship between the input and output variables. Some network types used to model extremely complex relationship may contain two hidden layers. In turn, each unit the hidden layer is connected to each unit in the output layer. The output layer in this instance contains one unit for dependent variable.

Gereralized Regression networks have exactly four layers input, a layer of radial centers, a layer of regression units, and output. Bayesian feed forword neural networks have three layers input, a layer of hidden units, and output. Multilayer perceptron neural networks have three layers input, , a layer of hidden units, and output. Radial basis function neural networks have an input layer, a hidden layer of radial units and output of linear units.[11]

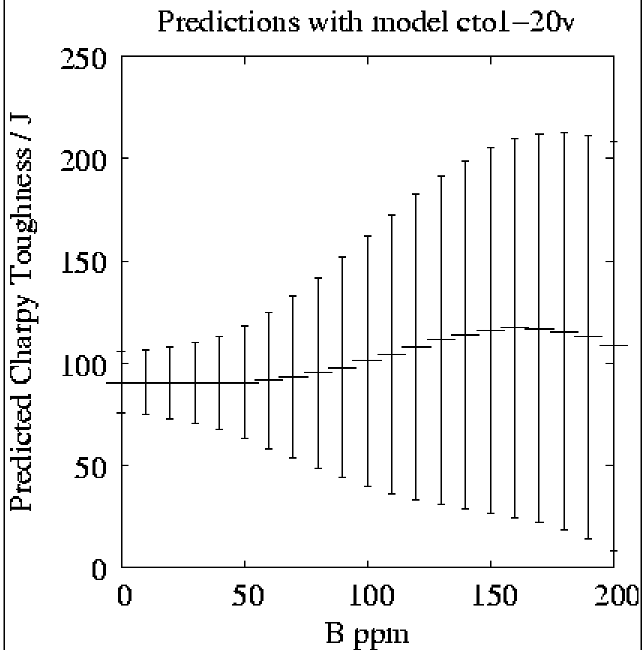
The hundred and thousand of models were trained with various neural network methods. The training errors and testing errors of training data set and testing data set of all properties were compared. The lowest errors models were selected because they are best for practical applications. Table. 1 shows the comparison of neural network methods. GRNN is the best method as a single model. BNN is used in present work as a committee model (more than one models present in a committee).

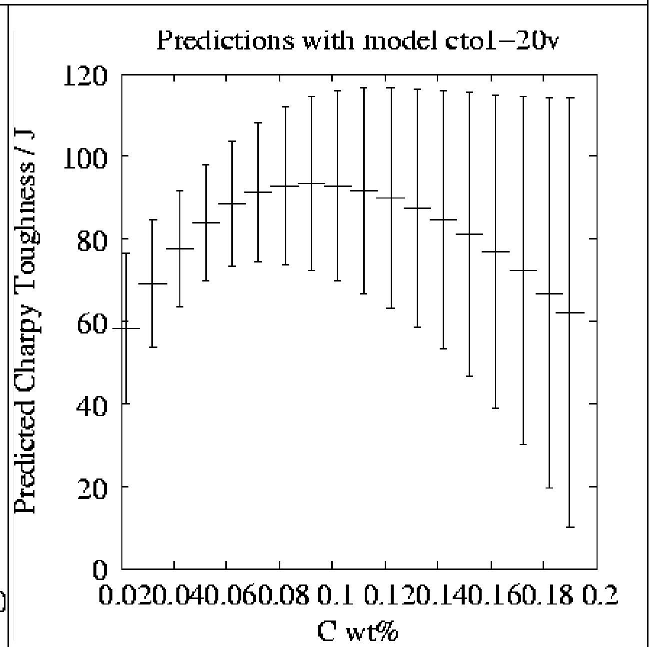
Table.1 : Models Selected for final Results on the basis of their lowest errors					
Elongation		T:\PhD-SNN-ModellingWork-14082014\Elongation\MLP\mlp-m13-140814-3layers-tr-0.056			
SR No.	MLP	Train Error	Test Error	Training/Members	Remarks
1	MLP 18:18-15-10-5-1:1 (Model:No.11)	0.056027	0.071757	BP100,CG462b	3 H layers
		T:\PhD-SNN-Modelling Work-1-15092013\M Elongation-Models\MLP-EL-Models\MLP-160913-EL-15m32H			
1	MLP 18:18-29-1:1 (Model:No.11)	0.05845	0.076457	BP100,CG498b	1 H layer
		T:\PhD-SNN-Modelling Work-1-15092013\M Elongation-Models\MLP-EL-Models\MLP-240913-EL-46m-6T-Algo			
1	MLP 18:18-8-1:1 (Model:No.43)	0.056123	0.191787	DD100,LM187b	1 H layer
		T:\PhD-SNN-ModellingWork-14082014\Elongation\MLP\mlp-m18-2Lsum-260814			
1	MLP 18:18-11-7-1:1 (Model:No.15)	0.061902	0.077359	BP100,CG475b	2 H layer
Elongation		T:\PhD-SNN-Modelling Work-1-15092013\M Elongation-Models\RBF-EL-Models\RBF-180913-EL-51m			
SR No.	RBF	Train Error	Test Error	Training/Members	Remarks
1	RBF 18:18-193-1:1 (Model:No.46)	0.0787	0.1125	SS,EX,PI	1 H layer
Elongation		T:\PhD-SNN-Modelling Work-1-15092013\M Elongation-Models\GRNN-EL-Models\GRNN-290913-EL-21m			
SR No.	GRNN	Train Error	Test Error	Training/Members	Remarks
1	GRNN 18:18-915-2-1:1 (Model:No.02)	0.027363	0.128123	SS	2 H layer
Yield Strength		T:\PhD-SNN-Modelling Work-1-15092013\M YS –Models\MLP-021013-YS-10m			
SR No.	MLP	Train Error	Test Error	Training/Members	Remarks
1	MLP 17:17-10-1:1 (Model:No.05)	0.062442	0.078690	BP100,CG20,CG18b	1 H layer
		T:\PhD-SNN-Modelling Work-1-15092013\M YS -Models\MLP-YS-Models\MLP-021013-YS-25m			
2	MLP 17:17-13-6-1:1 (Model:No.25)	0.058963	0.067180	BP100,CG20,CG59b	2 H layers
		T:\PhD-SNN-ModellingWork-14082014\Yield Strength\MLP\ mlp-3L4L-ys-18m-250814			
3	MLP 17:17-6-8-13-1:1	0.058458	0.065638	BP100,CG396b	3 H layers

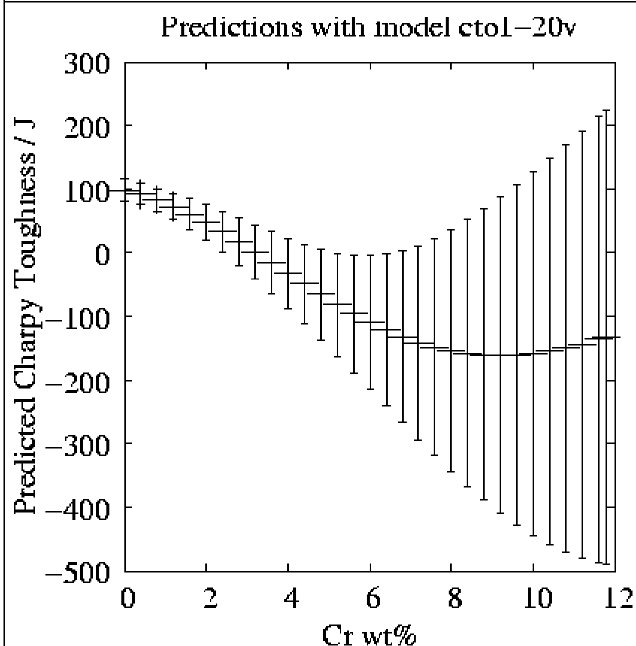
	(Model:No.14)				
4	MLP 17:17-14-9-1:1 (Model:No.07)	0.036248	0.063303	BP100,CG458b	2 H layers
5	MLP 17:17-9-14-1:1 (Model:No.10)	0.047847	0.058474	BP100,CG492b	2 H layers
6	MLP 17:17-6-7-1:1 (Model:No.18)	0.054954	0.065891	BP100,CG353b	2 H layers
Yield Strength		T:\PhD-SNN-Modelling Work-1-15092013\M YS -Models\RBF-YS-Models\RBF-021013-YS-50m			
SR No.	RBF	Train Error	Test Error	Training/Members	Remarks
1	RBF 17:17-530-1:1 (Model:No.10)	0.001791	0.002782	SS,KN,PI	1 H layer
Yield Strength		T:\PhD-SNN-Modelling Work-1-15092013\M YS -Models\GRNN-YS-Models\GRNN-290913-YS-30m			
SR No.	GRNN	Train Error	Test Error	Training/Members	Remarks
1	GRNN 17:17-1061-2-1:1 (Model:No.21)	0.000668	0.004186	SS	2 H layer
Ultimate Tensile Strength		T:\PhD-SNN-ModellingWork-14082014\Ultimate Tensile Strength\MLP\mlp-uts-9m-160814			
SR No.	MLP	Train Error	Test Error	Training/Members	Remarks
1	MLP 18:18-12-1:1 (Model:No.3)	0.035736	0.044758	BP100,CG481b	1 H layer
		T:\PhD-SNN-ModellingWork-14082014\Ultimate Tensile Strength\MLP\mlp-4L-uts-12m-180814			
2	MLP 18:18-13-7-1:1 (Model:No.8)	0.039741	0.060027	BP100,CG454b	2 H layer
		T:\PhD-SNN-ModellingWork-14082014\Ultimate Tensile Strength\MLP\mlp-2L3L-uts-7m-260814			
3	MLP 18:18-13-8-10-1:1 (Model:No.6)	0.039139	0.046157	BP100,CG478b	3 H layer
Ultimate Tensile Strength		T:\PhD-SNN-ModellingWork-14082014\Ultimate Tensile Strength\RBF\rbf-uts-22m-180814			
SR No.	RBF	Train Error	Test Error	Training/Members	Remarks
1	RBF 18:18-81-1:1 (Model:No.18)	0.002626	0.003150	SS,EX,PI	1 H layer
Ultimate Tensile Strength		T:\PhD-SNN-Modelling Work-1-15092013\M UTS-Models\GRNN-UTS-Models\GRNN-290913-UTS-30m			
SR No.	GRNN	Train Error	Test Error	Training/Members	Remarks
1	GRNN 18:18-1047-2-1:1 (Model:No.1)	0.000290	0.003402	SS	2 H layer

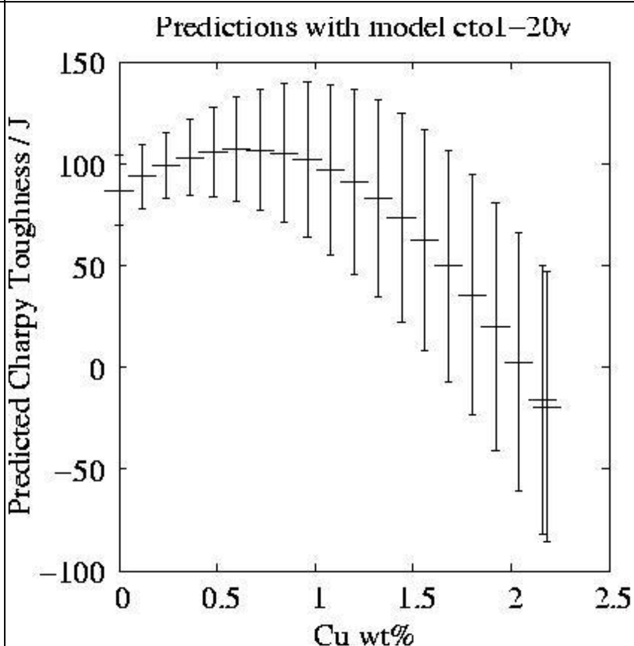
Charpy Toughness		T:\PhD-SNN-ModellingWork-14082014\CharpyToughness\MLP\ **mlp-3L-CT-9m-180814**			
SR No.	**MLP**	Train Error	Test Error	Training/Members	Remarks
1	**MLP 20:20-11-1:1 (Model:No.7)**	**0.090335**	**0.096968**	**BP100,CG289b**	**1 H layer**
		T:\PhD-SNN-ModellingWork-14082014\CharpyToughness\MLP\ **mlp-4L-CT-10m-180814**			
2	**MLP 20:20-14-8-1:1 (Model:No.8)**	**0.085442**	**0.093736**	**BP100,CG488b**	**2 H layer**
		T:\PhD-SNN-ModellingWork-14082014\CharpyToughness\MLP\ **mlp-2HL-CT-4m-270814**			
3	**MLP 20:20-14-8-10-1:1 (Model:No.3)**	**0.080723**	**0.091685**	**BP100,CG499b**	**3 H layer**
Charpy Toughness		T:\PhD-SNN-Modelling Work-1-**15092013**\M Charpy Toughness-Models\RBF-CT-Models\ **RBF-021013-CT-20m**			
SR No.	**RBF**	Train Error	Test Error	Training/Members	Remarks
1	**RBF 20:20-862-1:1 (Model:No.5)**	**0.07513**	**0.013794**	**SS,KN,PI**	**1 H layer**
Charpy Toughness		T:\PhD-SNN-Modelling Work-1-**15092013**\M Charpy Toughness-Models\GRNN-CT-Models\ **GRNN-290913-CT-20m**			
SR No.	**GRNN**	Train Error	Test Error	Training/Members	Remarks
1	**GRNN 20:20-1725-2-1:1 (Model:No.)**	**0.011310**	**0.017288**	**SS**	**2 H layer**
2	**GRNN 20:20-1725-2-1:1 (Model:No.16)**	**0.011953**	**0.018632**	**SS**	**2 H layer**
3	**GRNN 20:20-1725-2-1:1 (Model:No.7)**	**0.011404**	**0.018669**	**SS**	**2 H layer**

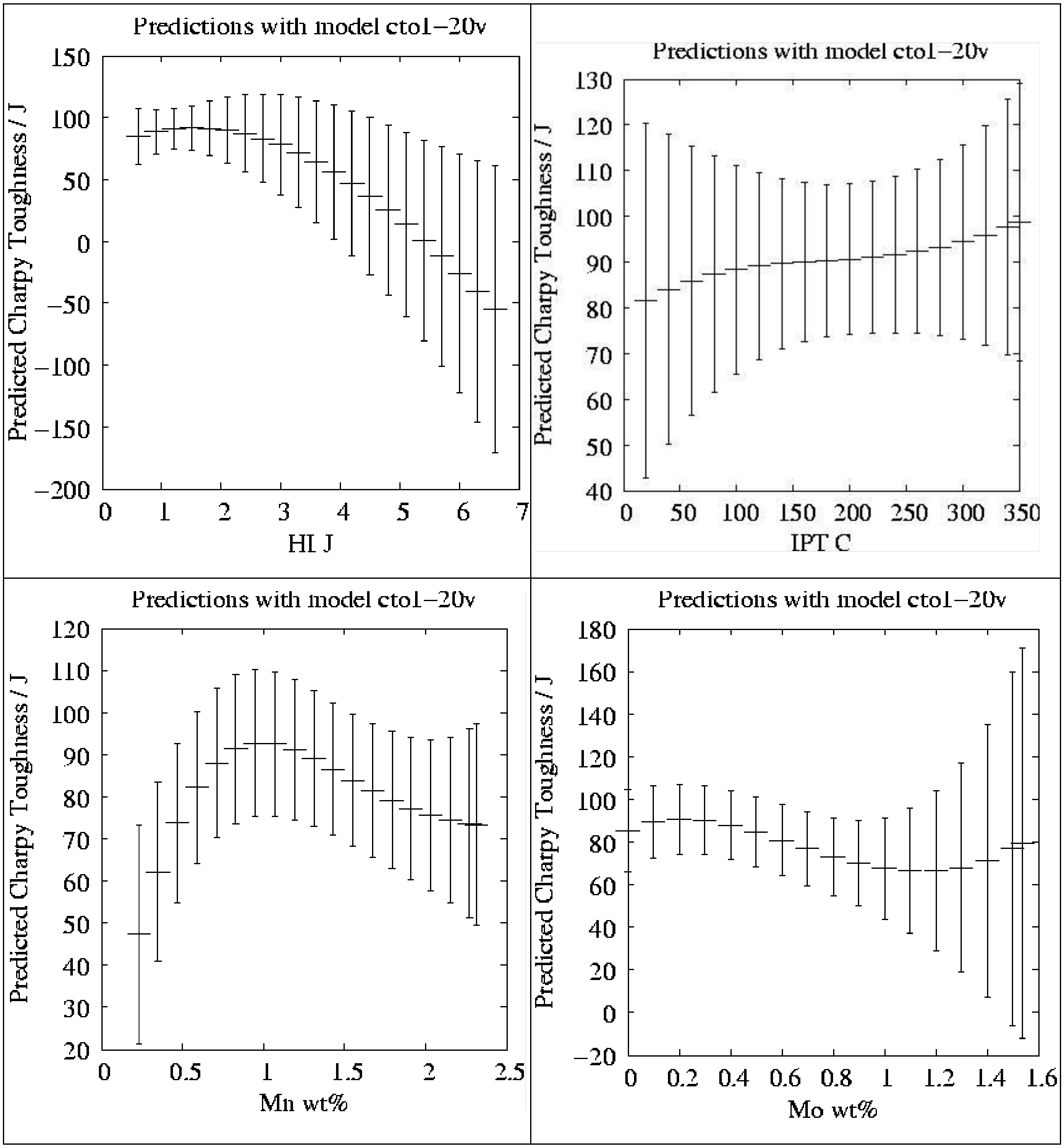
Trends of Charpy Toughness Model (BNN)

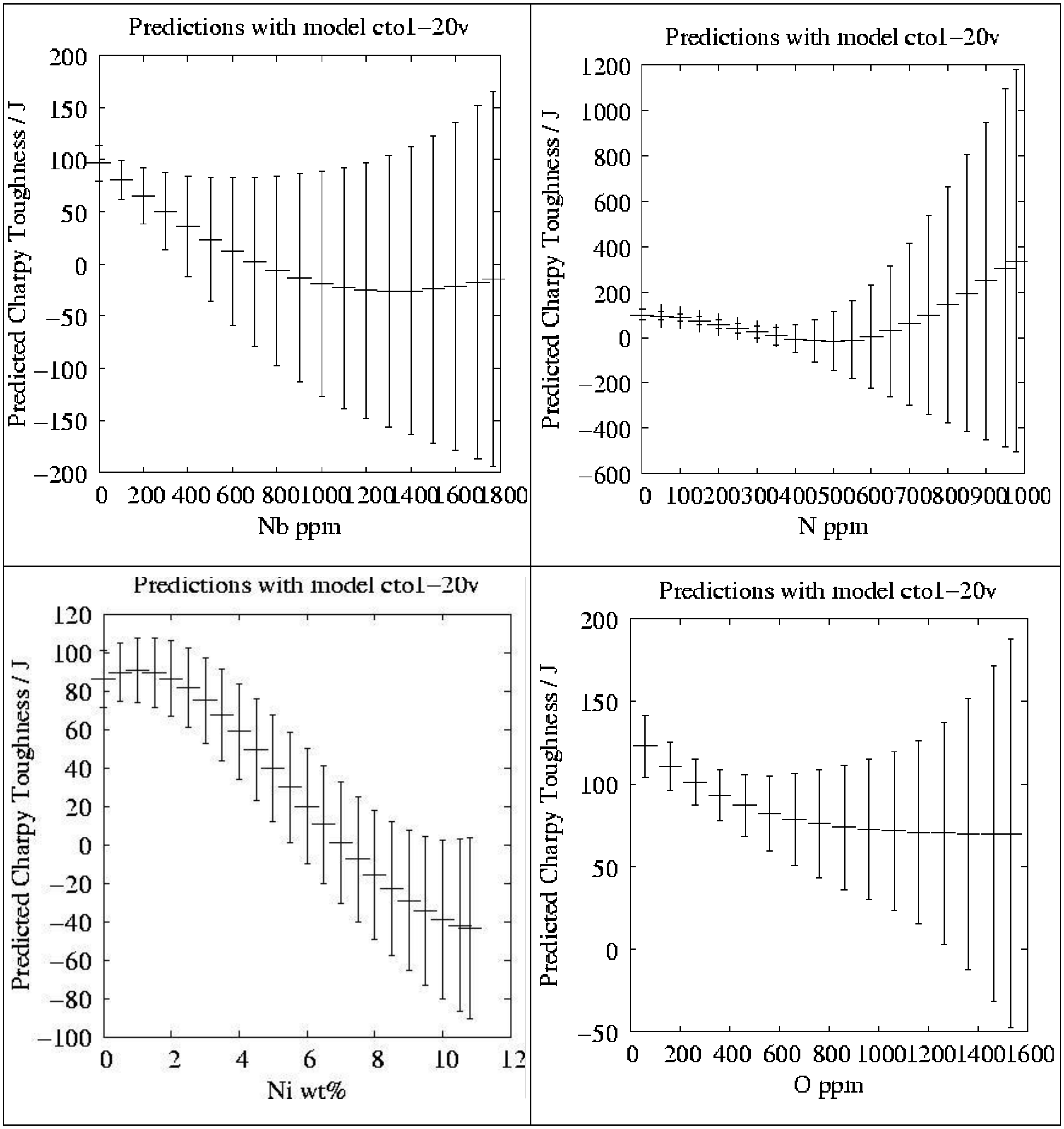


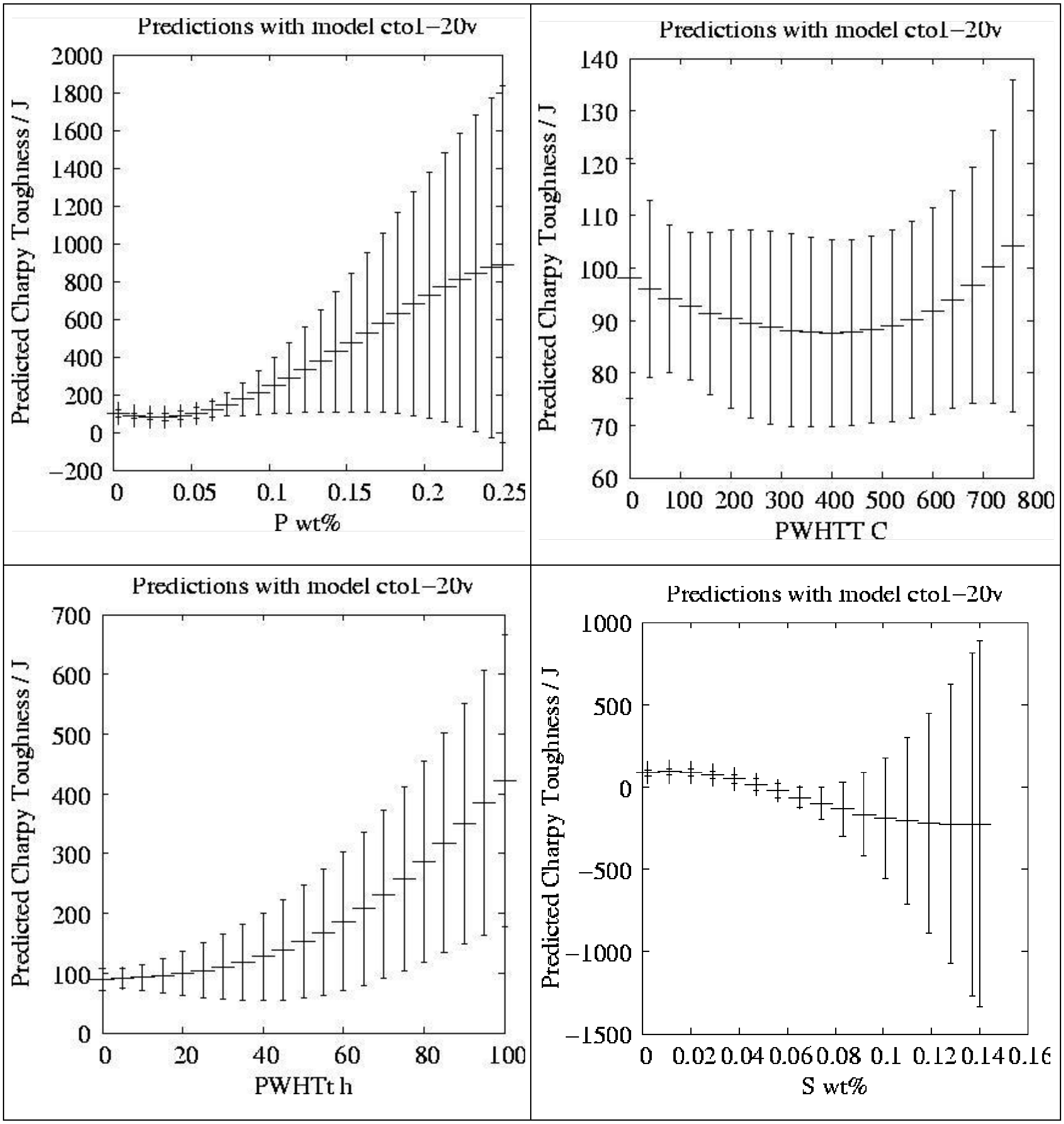







Predictions with model cto1−20v
Predicted Charpy Toughness / J
HI J
Predictions with model cto1−20v
Predicted Charpy Toughness / J
IPT C
Predictions with model cto1−20v
Predicted Charpy Toughness / J
Mn wt%
Predictions with model cto1−20v
Predicted Charpy Toughness / J
Mo wt%


Predictions with model cto1−20v
Predicted Charpy Toughness / J
Nb ppm
Predictions with model cto1−20v
Predicted Charpy Toughness / J
N ppm
Predictions with model cto1−20v
Predicted Charpy Toughness / J
Ni wt%
Predictions with model cto1−20v
Predicted Charpy Toughness / J
O ppm



Predictions with model cto1−20v
Predicted Charpy Toughness / J
P wt%
Predictions with model cto1−20v
Predicted Charpy Toughness / J
PWHTT C
Predictions with model cto1−20v
Predicted Charpy Toughness / J
PWHTt h
Predictions with model cto1−20v
Predicted Charpy Toughness / J
S wt%

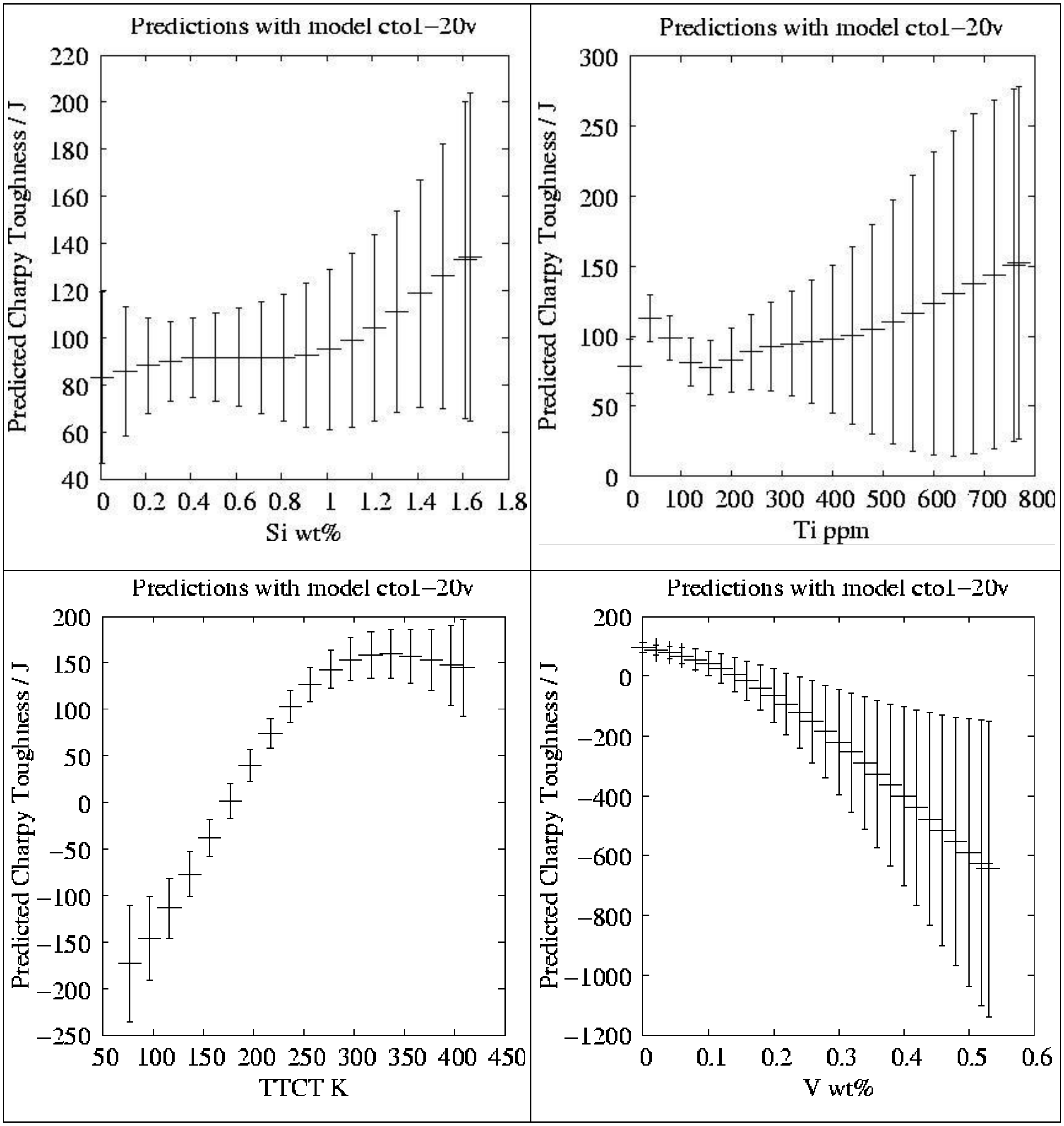


Figure.3 Predicted Charpy Toughness/J and 20 input variables

Figure.3 shows the predicted Charpy Toughness trends with 20 input variables. Charpy Toughness values are negative when large error bars present.(more data required in these input spaces and more research required in input spaces).These graphs are useful to know the trends of both variables and useful in design of welds and understand the character of each input variable with output variable.

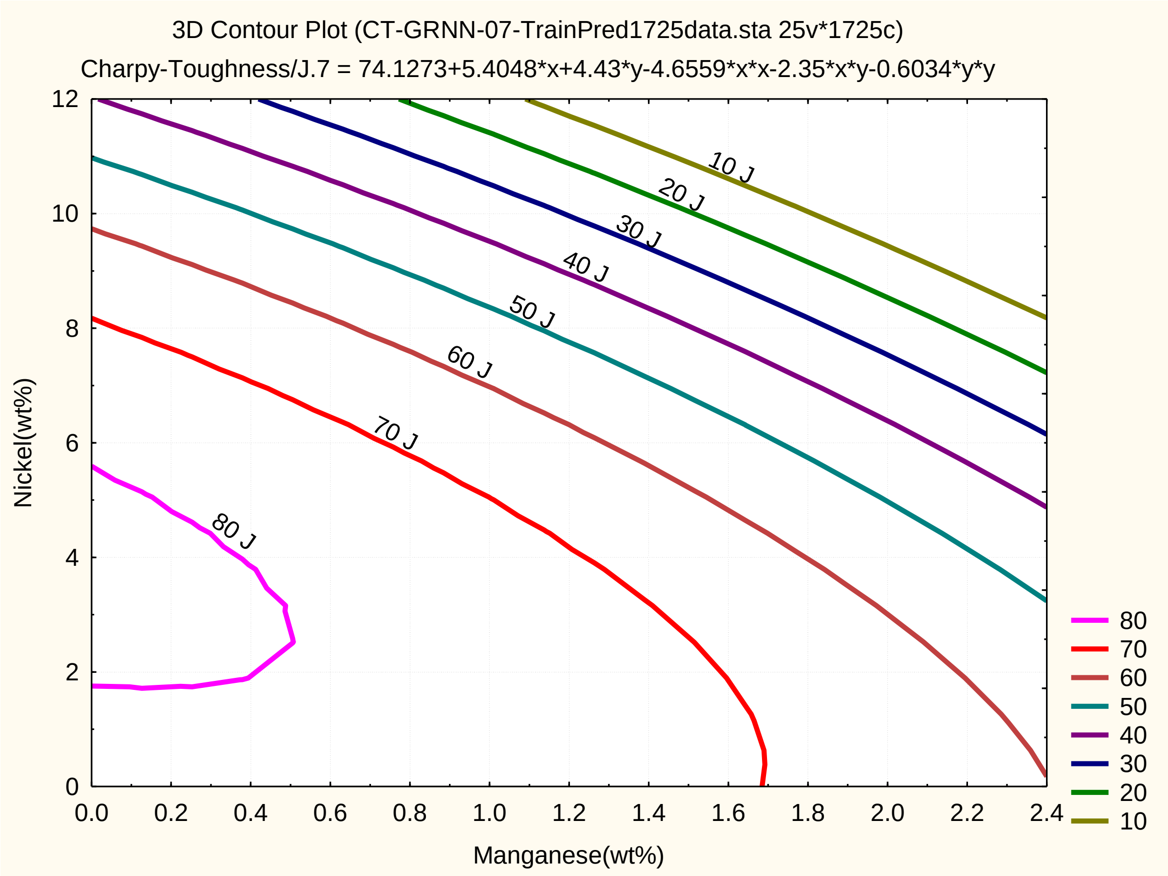


Figure.4 3D Contour Plot of Charpy Toughness, Nickel and Manganese (GRNN)

3D contour Plot gives the relations between the two input variables and one output variable. Figure.4 shows the relations between Nickel, Manganese and Charpy Toughness by GRNN. Graph gives the information about how these two Nickel and Manganese control the Charpy Toughness from 10J to 80J. Traditionally in alloy design it is known that increase the Nickel increase the Toughness. In Figure.4, it is very critical to maintain the toughness with Nickel and Manganese. To achieve a 80J and more, the compositions of **Nickel** must be maintained in range of **1.9 to 5.6 wt%** and **Manganese** must be maintained maximum **0.4 wt%.** In literature, these values are **6 to 8 wt% Nickel** and **0.8 wt% Manganese.(BNN was used)**

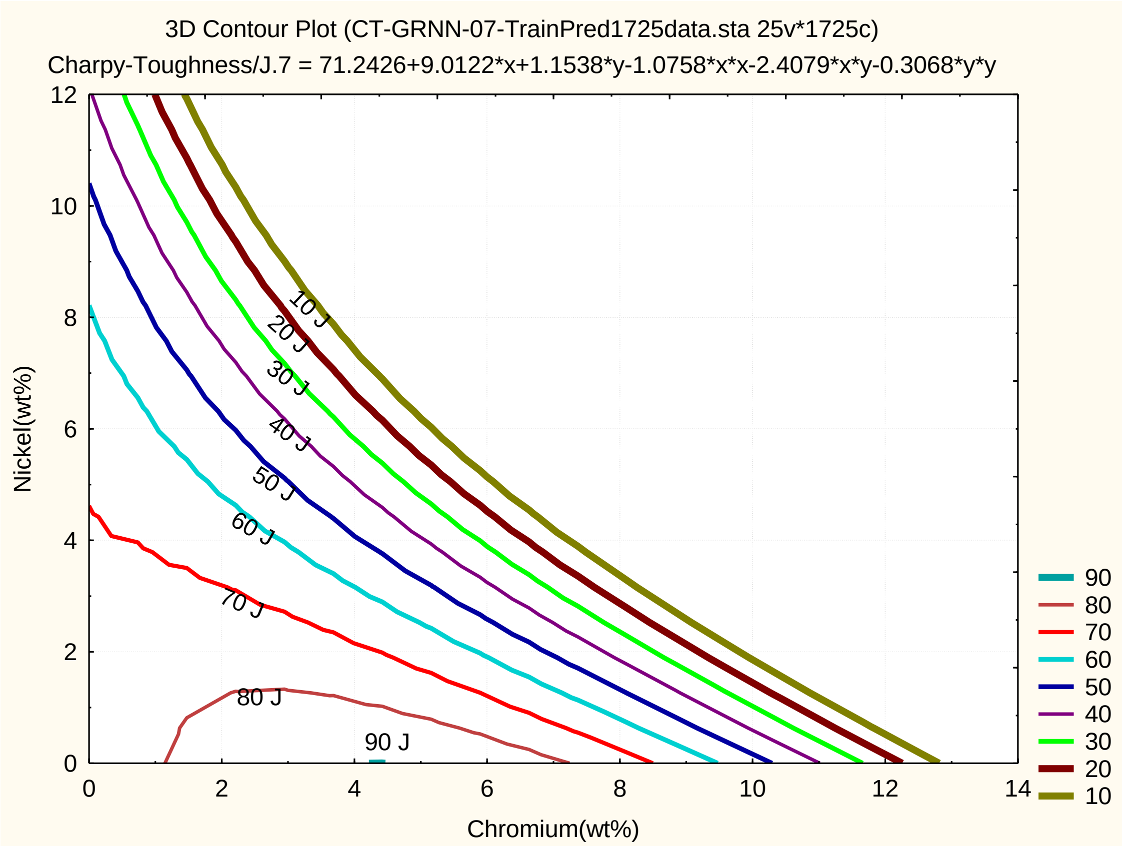


Figure.5 3D Contour Plot of Charpy Toughness, Nickel and Chromium (GRNN)

3D contour Plot gives the relations between the two input variables and one output variable. Figure.5 shows the relations between Nickel, Chromium and Charpy Toughness by GRNN. Graph gives the information about how these two Nickel and Chromium control the Charpy Toughness from 10J to 80J. Traditionally in alloy design it is known that increase the Nickel increase the Toughness. In Figure.5, it is very critical to maintain the toughness with Nickel and Chromium. To achieve a 80J and more, the compositions of Nickel must be maintained maximum 1.6 wt% and Chromium must be maintained in range of 1.6 to 7.0 wt%.

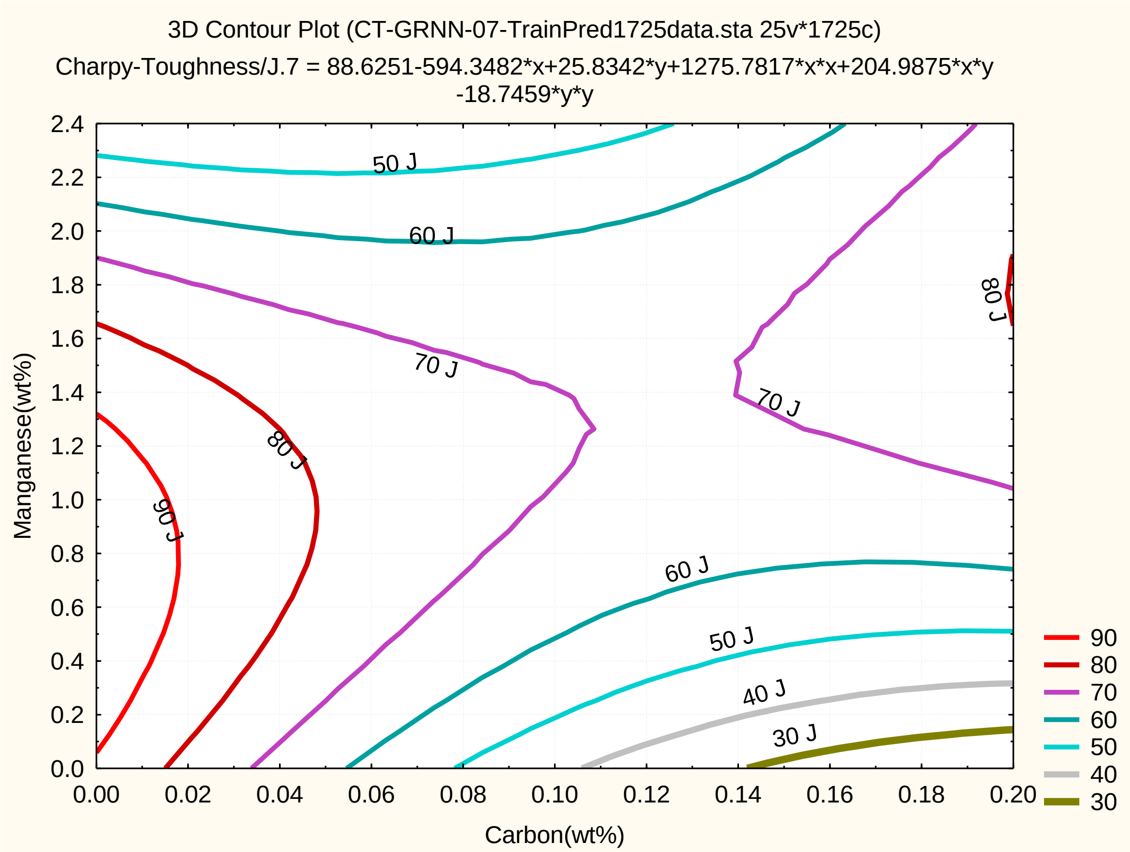


Figure.6 3D Contour Plot of Charpy Toughness, Manganese and Carbon (GRNN)

3D contour Plot gives the relations between the two input variables and one output variable. Figure.6 shows the relations between , Manganese, Carbon and Charpy Toughness by GRNN. Graph gives the information about how these two Manganese and Carbon control the Charpy Toughness from 30J to 90J. Traditionally in alloy design it is known that increase the Manganese decrease the Toughness. In Figure.6, it is very critical to maintain the toughness with Manganese and Carbon. To achieve a 90J and more, the compositions of Manganese must be maintained in range of 0.1 to 1.3 wt% and Carbon must be maintained less than 0.02 wt%.

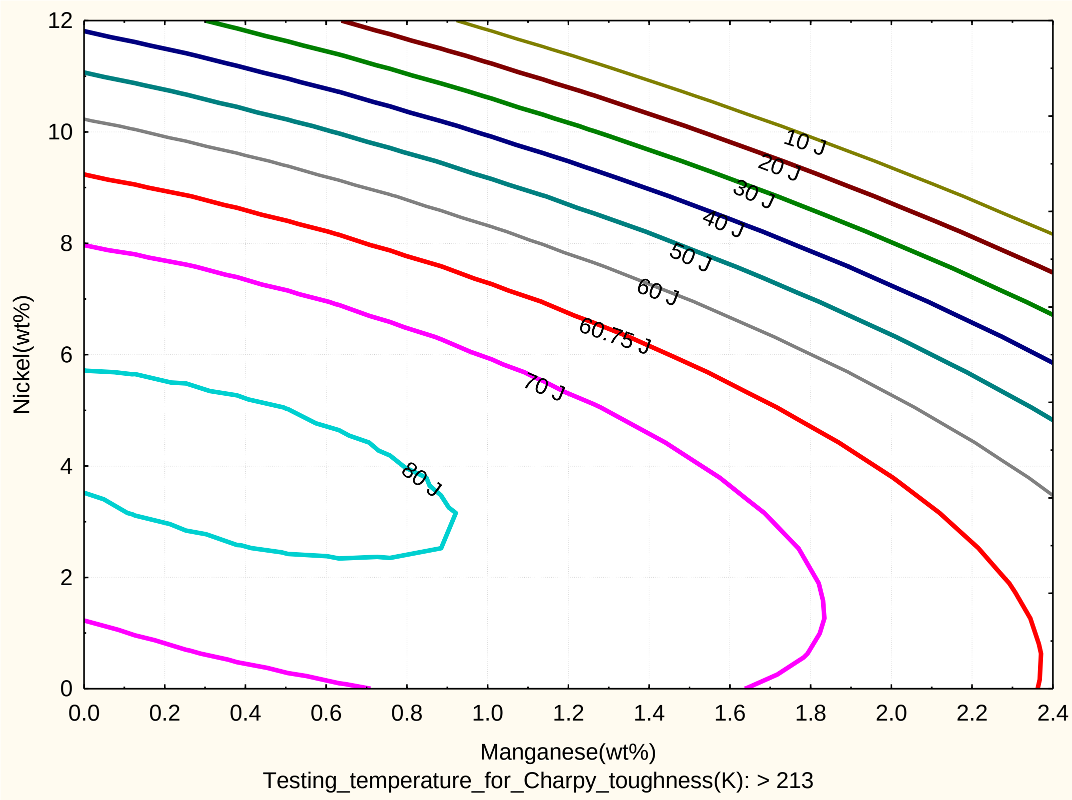


Figure.7 3D Contour Plot of Charpy Toughness, Nickel Manganese and Testing Temperaturecfor Charpy toughness > 213K (-60C) (GRNN)

3D contour Plot gives the relations between the three input variables and one output variable. Figure.7 shows the relations between Nickel, Manganese and Testing Temperaturecfor Charpy toughness > 213K (-60C) and Charpy Toughness by GRNN. Graph gives the information about how these three Nickel, Manganese and Testing Temperaturecfor Charpy toughness > 213K control the Charpy Toughness from 10J to 80J. Traditionally in alloy design it is known that increase the Nickel increase the Toughness. In Figure.7, it is very critical to maintain the toughness with Nickel, Manganese and Testing Temperaturecfor 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%.** In literature, to these values are **6 to 10.8 wt% Nickel** and **0.6 wt% Manganese**.(BNN)

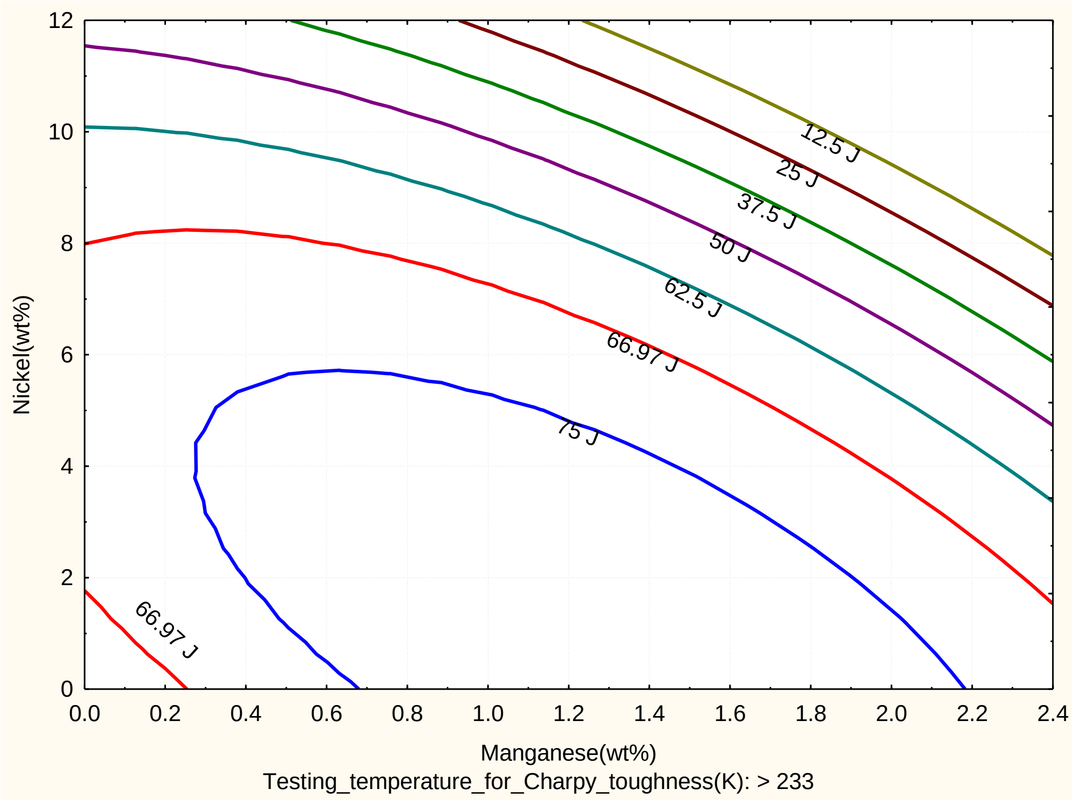


Figure.8 3D Contour Plot of Charpy Toughness, Nickel Manganese and Testing Temperaturec for Charpy toughness > 233K (-40C) (GRNN)

3D contour Plot gives the relations between the three input variables and one output variable. Figure.8 shows the relations between Nickel, Manganese and Testing Temperaturec for Charpy toughness > 233K (-40C) and Charpy Toughness by GRNN. Graph gives the information about how these three Nickel, Manganese and Testing Temperaturecfor Charpy toughness > 233K control the Charpy Toughness from 10J to 80J. Traditionally in alloy design it is known that increase the Nickel increase the Toughness. In Figure.8, it is very critical to maintain the toughness with Nickel, Manganese and Testing Temperaturec 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%. In literature, to these values are 6 to 8 wt% Nickel and 0.8 wt% Manganese.(BNN)

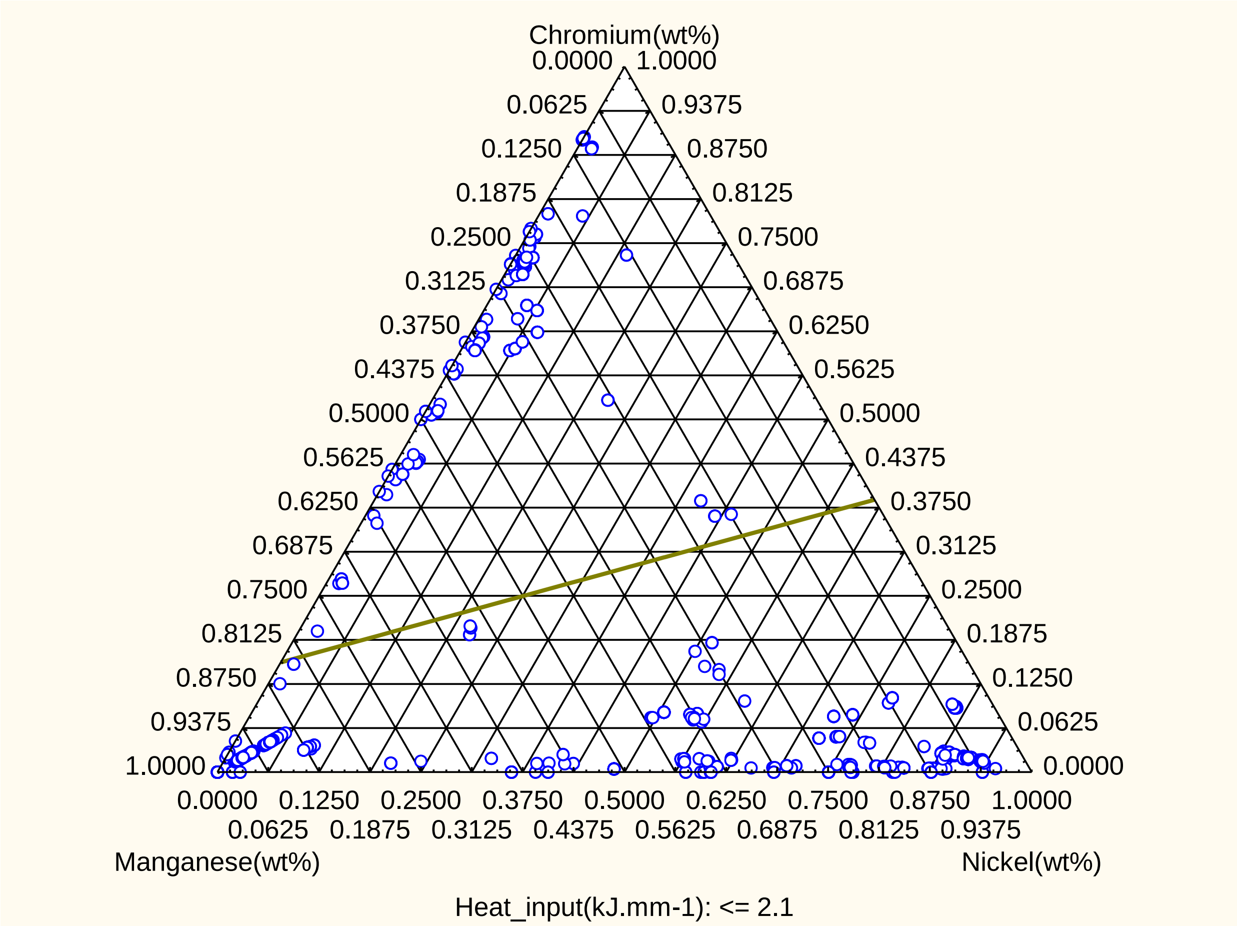


Figure.9 Ternary Categorized Graph of Chromium, Manganese, Nickel, **Heat Input** and Charpy Toughness (See Page.No.23a, 23b for Scale 0 to 1 conversion into wt%)

325 J
300
275
250
225
200
175
150
125
100
93.7362
75
69.7317
50
25 J

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Variables	0	0.0625	0.125	0.1875	0.25	0.313	0.38	0.4375	0.5	0.5625	0.625	0.6875	0.75	0.8125	0.875	0.9375	1
2	C	0	0.0119	0.0238	0.0356	0.05	0.059	0.07	0.0831	0.1	0.1069	0.119	0.1306	0.14	0.1544	0.166	0.1781	0.19
3	Si	0	0.1019	0.2038	0.3056	0.41	0.509	0.61	0.7131	0.82	0.9169	1.019	1.1206	1.22	1.3244	1.426	1.5281	1.63
4	Mn	0	0.1444	0.2887	0.4331	0.58	0.722	0.87	1.0106	1.15	1.2994	1.444	1.5881	1.73	1.8769	2.021	2.1656	2.31
5	S	0	0.0088	0.0175	0.0263	0.04	0.044	0.05	0.0613	0.07	0.0788	0.088	0.0963	0.11	0.1138	0.123	0.1313	0.14
6	P	0	0.0156	0.0313	0.0469	0.06	0.078	0.09	0.1094	0.13	0.1406	0.156	0.1719	0.19	0.2031	0.219	0.2344	0.25
7	Ni	0	0.675	1.35	2.025	2.7	3.375	4.05	4.725	5.4	6.075	6.75	7.425	8.1	8.775	9.45	10.125	10.8
8	Cr	0	0.7362	1.4725	2.2087	2.94	3.681	4.42	5.1537	5.89	6.6262	7.362	8.0987	8.83	9.5712	10.31	11.044	11.8
9	Mo	0	0.0963	0.1925	0.2888	0.39	0.481	0.58	0.6738	0.77	0.8663	0.963	1.0588	1.16	1.2513	1.348	1.4438	1.54
10	V	0	0.0331	0.0663	0.0994	0.13	0.166	0.2	0.2319	0.27	0.2981	0.331	0.3644	0.4	0.4306	0.464	0.4969	0.53
11	Cu	0	0.1363	0.2725	0.4088	0.55	0.681	0.82	0.9538	1.09	1.2263	1.363	1.4988	1.64	1.7713	1.908	2.0438	2.18
12	O	0	95.938	191.88	287.81	384	479.7	576	671.56	768	863.44	959.4	1055.3	1151	1247.2	1343	1439.1	1535
13	Ti	0	48.125	96.25	144.38	193	240.6	289	336.88	385	433.13	481.3	529.38	578	625.63	673.8	721.88	770
14	N	0	61.188	122.38	183.56	245	305.9	367	428.31	490	550.69	611.9	673.06	734	795.44	856.6	917.81	979
15	B	0	12.5	25	37.5	50	62.5	75	87.5	100	112.5	125	137.5	150	162.5	175	187.5	200
16	Nb	0	110.63	221.25	331.88	443	553.1	664	774.38	885	995.63	1106	1216.9	1328	1438.1	1549	1659.4	1770
17	HI	0	0.4125	0.825	1.2375	1.65	2.062	2.47	2.8875	3.3	3.7125	4.125	4.5375	4.95	5.3625	5.775	6.1875	6.6
18	IPT	0	21.875	43.75	65.625	87.5	109.4	131	153.13	175	196.88	218.8	240.63	263	284.38	306.3	328.13	350
19	PWHTT	0	47.5	95	142.5	190	237.5	285	332.5	380	427.5	475	522.5	570	617.5	665	712.5	760
20	PWHTT	0	6.25	12.5	18.75	25	31.25	37.5	43.75	50	56.25	62.5	68.75	75	81.25	87.5	93.75	100
21	TTCT	0	25.563	51.125	76.688	102	127.8	153	178.94	205	230.06	255.6	281.19	307	332.31	357.9	383.44	409
22	CharTou / J	0	18.75	37.5	56.25	75	93.75	113	131.25	150	168.75	187.5	206.25	225	243.75	262.5	281.25	300

Table 4 The normalized scale of Ternary Plot 0 to 1 First row red colour converted to Actualscale of variables

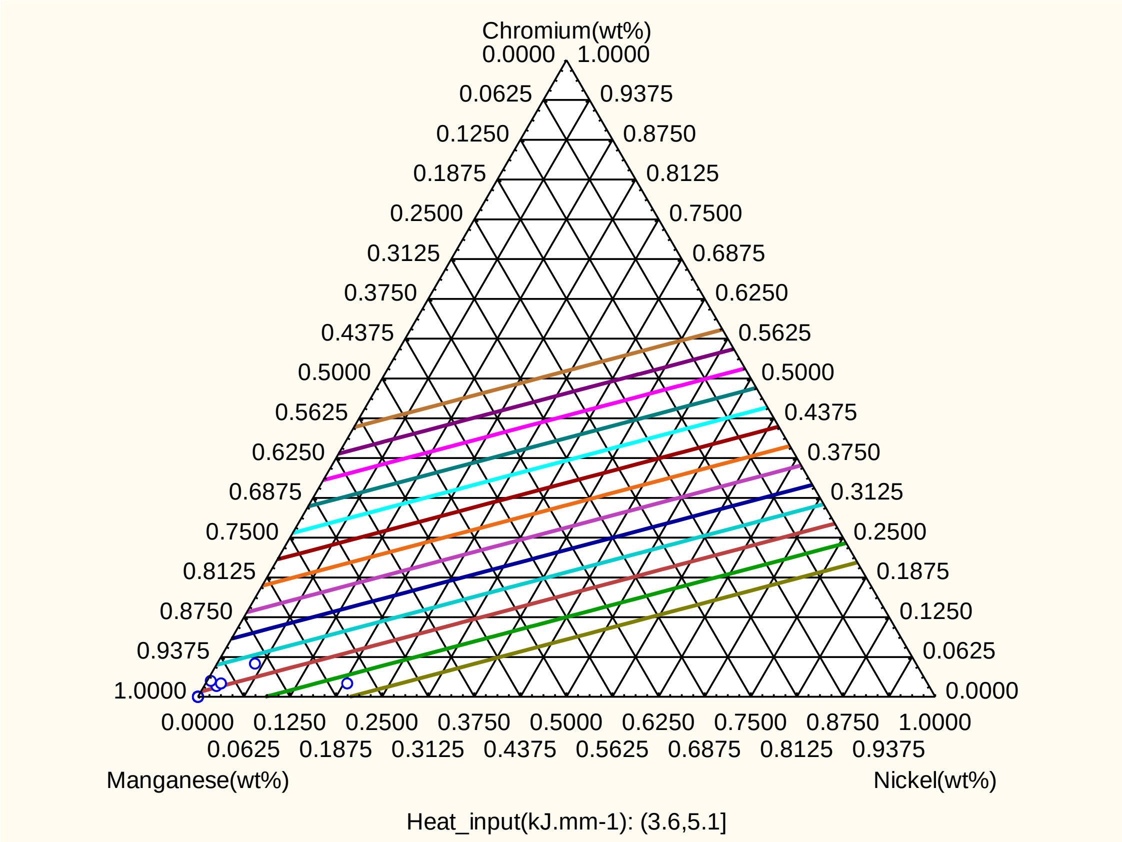


Figure.10 Ternary Categorized Graph of Chromium, Manganese, Nickel**, Heat Input** and Charpy Toughness

Ternary Categorized Graph gives the relations between the four input variables and one output variable. Figure.9, Figure.10 and Figure.11 show the relations between Chromium, Manganese, Nickel**,** Heat Input and Charpy Toughness by GRNN. Graphs gives the information about how these four Chromium, Manganese, Nickel**,** and Heat Input control the Charpy Toughness from 25J to 325J. Figure.9, and Figure.10 indicate the criticality to maintain the toughness with Chromium, Manganese, Nickel**,** and Heat Input. In Figure.9 and Figure.10 with Heat Input value <= 2.1 kJ mm-1,the toughness is achieved 25J and Heat Input 3.6 to 5.1 kJ mm-1 gives Toughness 25J to 275J. In Figure.10 shows that to increase the toughness increase Chromium, increase in Manganese and decrease in Nickel. There are number of combinations of alloying elements available for one value of Toughness. Figure.10 gives more flexibility for alloy design or weld design.

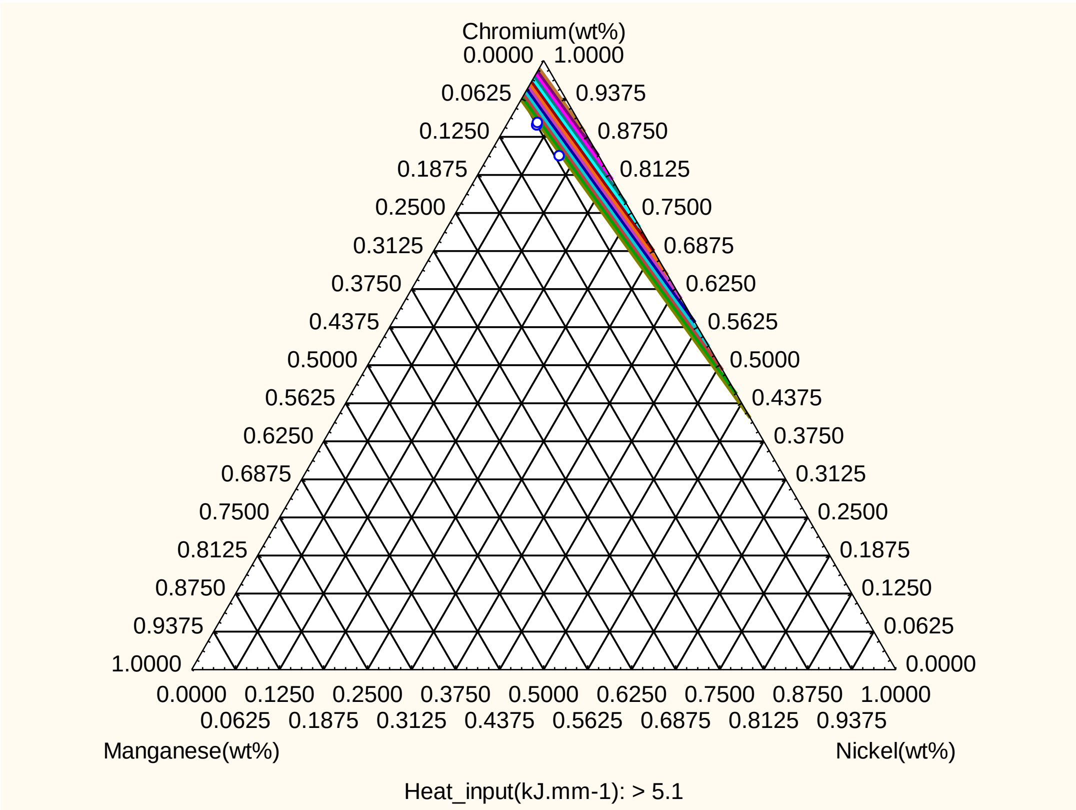


Figure.11 Ternary Categorized Graph of Chromium, Manganese, Nickel, **Heat Input** and Charpy Toughness

Figure.11 show the relations between Chromium, Manganese, Nickel**,** Heat Input and Charpy Toughness by GRNN. Graphs gives the information about how these four Chromium, Manganese, Nickel**,** and Heat Input control the Charpy Toughness from 50J to 325J. At High Heat Input > 5.1 kJ mm-1 can give wide range of Toughness, 25J to 325J. 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%. Figure.11 indicates more difficulty for alloy design or weld design because very small region available for input variable selection.

Prediction of unseen data:

Select input variables and give to the best neural network model for the prediction of output variable, it will calculate Immediately. For the design of new alloys, these neural network models are very valuable tools. If the alloy design is carried out traditionally, it will takes months or years. It also requires material, manpower, characterization etc. Alloys design for welds is very flexible, easy, economical and accurate. The range of errors in prediction of Charpy Toughness is 0.43J to 20.13J by BNN method.(See Page. No. 26a, 26b, 26c)

All mechanical properties can be studied with wide number of combinations of Neural Network Methods, and various type of Graphs. This study gives knowledge to understand the design of ferritc steel weld deposits.

C	Si	Mn	S	P	Ni	Cr	Mo	V	Cu	O	Ti	N	B	Nb	HI	IPT	PWHTT	PWHTt	TTCT	CharpyTough/J	Prediction	Error
0.037	0.3	0.65	0.009	0.011	3.5	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	580	2	210	100	83.11	-16.89
0.033	0.29	2.17	0.008	0.012	6.54	0.44	0.62	0.021	0.02	320	0	139	1	10	1.3	200	0	0	253	33.33	34.12	0.79
0.046	0.32	1.81	0.007	0.015	2.33	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	243	100	91.12	-8.88
0.033	0.29	2.17	0.008	0.012	6.54	0.44	0.62	0.021	0.02	320	0	139	1	10	1.3	200	0	0	293	41.5	42.49	0.99
0.049	0.32	1.41	0.007	0.014	2.32	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	235	100	102.9	2.9
0.033	0.29	2.17	0.008	0.012	6.54	0.44	0.62	0.021	0.02	320	0	139	1	10	1.3	200	0	0	173	18	13.85	-4.15
0.044	0.31	0.96	0.006	0.013	2.38	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	214	100	97.54	-2.46
0.033	0.29	2.17	0.008	0.012	6.54	0.44	0.62	0.021	0.02	320	0	139	1	10	1.3	200	0	0	213	25	24.55	-0.45
0.041	0.3	0.62	0.007	0.01	2.38	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	223	100	112.98	12.98
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	250	16	253	117.67	110.58	-7.09
0.053	0.35	1.83	0.007	0.012	1.06	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	234	100	105.58	5.58
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	250	16	293	137.5	130.5	-7
0.049	0.35	1.37	0.007	0.013	1.06	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	215	100	81.1	-18.9
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	250	16	173	47	45.94	-1.06
0.043	0.33	1	0.006	0.013	1.1	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	218	100	88.73	-11.27
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	250	16	213	93.33	81.68	-11.65
0.038	0.31	0.63	0.007	0.012	1.09	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	235	100	111.1	11.1
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	0	0	253	112.67	108.3	-4.37
0.045	0.33	1.85	0.007	0.016	0	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	235	100	112.4	12.4
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	0	0	293	123	114.43	-8.57
0.044	0.35	1.43	0.007	0.014	0	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	220	100	79.87	-20.13
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	0	0	173	60	55.63	-4.37
0.037	0.31	1.03	0.007	0.014	0	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	225	100	80.07	-19.93
0.03	0.4	0.61	0.009	0.01	6.11	0.16	0.38	0.018	0.02	340	0	129	1	10	1.3	200	0	0	213	88.33	87.91	-0.42
0.037	0.3	0.65	0.008	0.012	0	0.03	0.005	0.012	0.03	440	55	69	2	20	1	200	20	0	245	100	107.46	7.46

Min Error	0.42
Max Error	20.13

Conclusions:

The design of ferritic steel weld metals is very complex. There are wide variety of parameters each having their own individual effect or combined effect on the final mechanical properties. The nonlinear relationship between parameters involved in design of ferritic steel welds is solved by Neural Network Methods efficiently.

For best result of Neural Network Modelling, large data is required.

GRNN is the best method with least error in prediction and give accurate trends between the inputs and output variables.

BNN is the best with a committee model. It gives prediction as a group of models in a committee model. Compare to the past work in this field, the number of models are very less in present work only 28 , in literature it was 68, in a committee model . This gives less errors, little computational time and accurate prediction.

Large Error bars indicates that more data are required for accurate predictions in that region.

All input variables are important with respect to their significance for output variables. The various graphs become a valuable tools to design ferritic steel welds. The Ternary Catogerial graphs give informations about the relations of four input variables effect on one output variable which helps to solve some complex problems of ferritic steel welds.

Traditionally in alloy design it is known that increase the Nickel increase the Toughness. Present work shows that Toughness increases with Chromium increase and Heat Input increase which is new finding for Design of Ferritic steel Welds. The new findings about the character of variables in ferritic welds exist in present work.

Design of Ferritic steel welds is very easy, simple and economical with the help of best trained neural network model. Best trained neural network model can be used for welding industries, research and development very effectively.

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