iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 8 Issue: XII Month of publication: December 2020

DOI: https://doi.org/10.22214/ijraset.2020.32428

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 8 Issue XII Dec 2020- Available at www.ijraset.com

Modelling of Charpy Toughness of Ferritic Steel Welds

B J Chauhan[1], S N Soman[2]
[1]Associate Professor, [2] Professor and Head, Department of Metallurgical and Materials Engineering, Faculty of Technology and Engineering, The M. S. University of Baroda, Vadodara, Gujarat, India.

***Abstract:** The design of ferritic steel welding alloys to fit the ever expected properties of newly evolved steels is not a very easy task. It is traditionally attained by experimental trial and error, changing compositions and welding conditions until a sufficient result is established.*

Savings in the economy and time might be achieved if the trial process could be minimised. The present work outlines the use of an artificial neural network to model the charpy toughness of ferritic steel weld deposits from their chemical compositions, welding conditions and heat treatments.

The development of the General regression neural network (GRNN) models is explained, as is the confirmation of their metallurgical principles and precision.

Keywords: Neural network; Ferritic Steels; Charpy Toughness; Welding alloys; Variables

I. INTRODUCTION

The charpy impact test provides the basic design data essential in both the specification and acceptance of welding materials. Although the measurements involved are simple, their values depend in a complicated way on the chemical compositions, the welding parameters and the heat treatments. There is no common fundamental or experimental model capable of estimating the toughness parameters as a function of all these variables [1,2].

The difficulty is the complexity of the nonlinear relationship between input variables and charpy toughness. The physical models for strengthening mechanisms are not sufficiently sophisticated [3] and the linear regression methods used traditionally are not representing the real behaviour which is far from linear when all the variables are taken into account.

The aim of this work was to use GRNN to empirically model and interpret the dependence of the charpy toughness of steel weld deposits as a function of many input variables.

The General regression neural network is capable of realising a great variety of nonlinear relationships of considerable complexity. Data are presented to the GRNN in the form of input and output parameters,. As in regression analysis, the results then consist of the regression coefficients and a specification of the kind of function which in combination with the weights relates the independent or input variables to the dependent or output variables.

The design of a model using the GRNN method requires a large database of experimental measurements was assembled for neural network analysis of ferritic steel welds.

II. MODELLING WORK

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. The data were collected from a large number of sources.(Table 1).

The aim of the neural network analysis was to predict the Charpy Toughness as a function of a large number of variables, including the chemical compositions, the welding parameters and heat treatments. As a consequence, the Charpy Toughness database consists of 3449 separate experiments with 20 input variables.

In the present work, a neural network method is used as a Generalised Regression Neural Network[4]. All GRNN networks have 20 inputs, 1725 neurons in the first hidden layer, 2 neurons in the second hidden layer and 1 neuron in the output layer. (Figure.1)

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 8 Issue XII Dec 2020- Available at www.ijraset.com

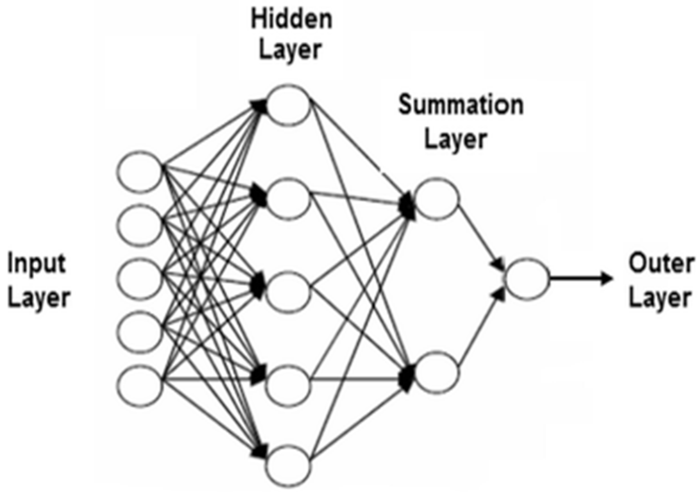


Figure 1. The architecture of Generalized Regression Neural Network

The hundred and thousand of models were trained with this neural network method in statistica software. The training errors, Validation errors (or Selection errors) and testing errors of training dataset(1725), validation data set(862) (or selection dataset) and testing dataset(862) of Charpy Toughness (CT) were compared. The lowest traning errors models were selected because they are best for practical applications.

Table 1 The 20 Input variables used in the analysis of the Charpy Toughness

Variables	Min	Max	Average	StDev	Variables	Min	Max	Average	StDev
C wt%	0.022	0.19	0.022	0.19	O ppm	63	1535	399.6638	110.6312
Si wt%	0.01	1.63	0.01	1.63	Ti ppm	0	770	96.0337	132.9401
Mn wt%	0.23	2.31	0.23	2.31	N ppm	0	979	77.5725	60.8648
S wt%	0.002	0.14	0.002	0.14	B ppm	0	200	13.1739	33.4533
P wt%	0.003	0.25	0.003	0.25	Nb ppm	0	1770	37.6917	133.0933
Ni wt%	0	10.8	0	10.8	HI kJ mm-1	0.6	6.6	1.1954	0.6596
Cr wt%	0	11.78	0	11.78	IPT C	20	350	199.0003	31.0232
Mo wt%	0	1.54	0	1.54	PWHTT C	0	760	186.1773	249.8889
V wt%	0	0.53	0	0.53	PWHTt h	0	100	3.3429	6.6257
Cu wt%	0	2.18	0.0638	0.2128	TTCT K	77	409	227.8425	38.3343
					Charpy Toughness J	0	300	72.714	42.8411

III. RESULTS AND DISCUSSION

The normal behaviour of the Predicted Charpy Toughness and Observed Charpy Toughness are observed in the Figure. 2 for Training data, Validation data and Testing data. Training of the model is excellent by GRNN method.

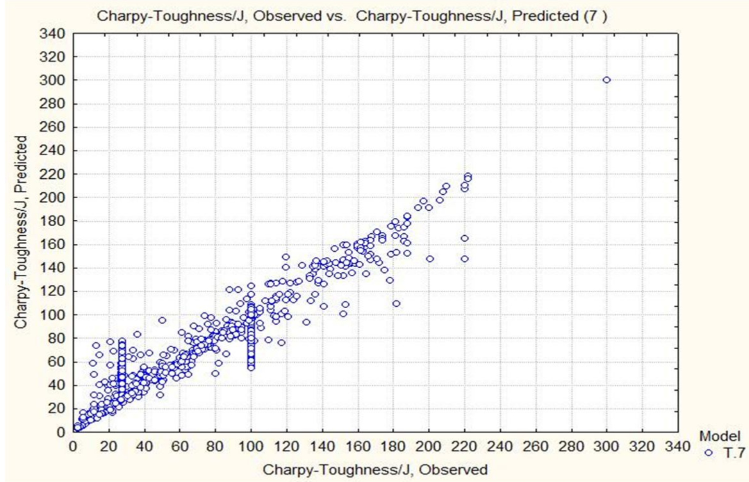


Figure a Training Data for GRNN model of Charpy Toughness

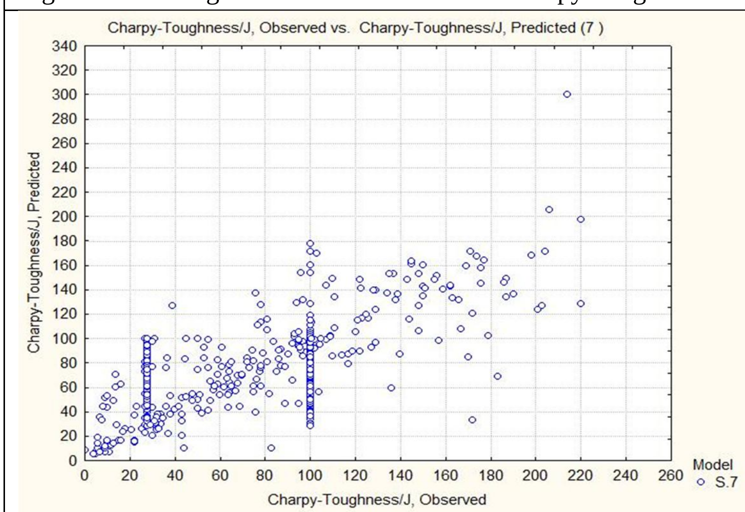


Fig b Validation Data for GRNN model of Charpy Toughness

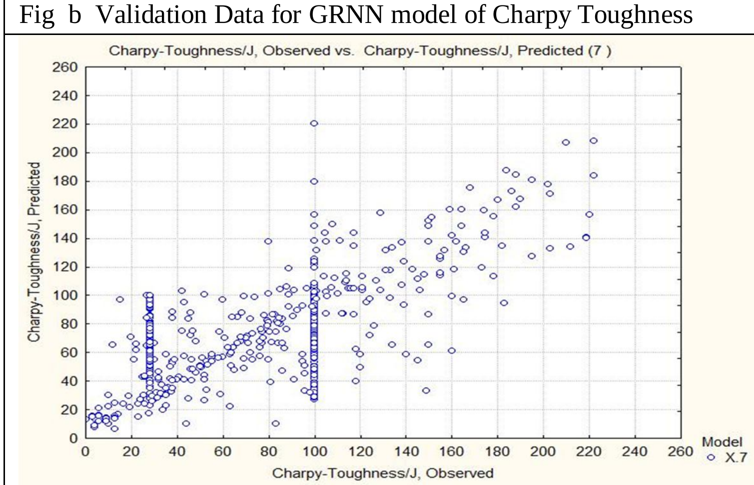
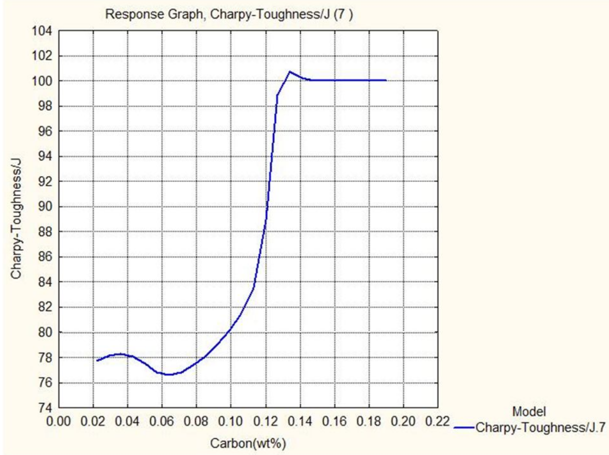


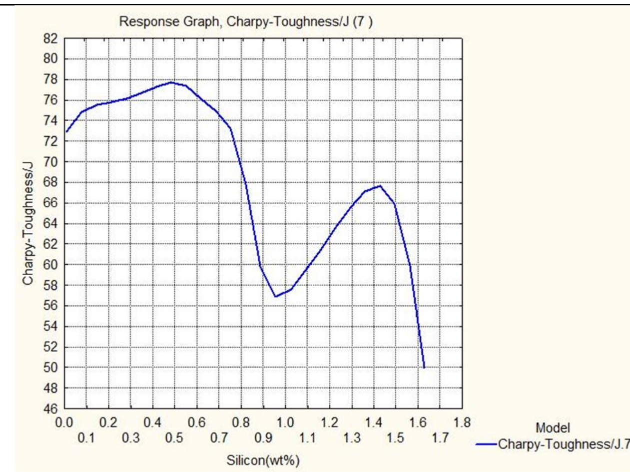
Fig c Test Data for GRNN model of Charpy Toughness

Figure 2 Training data, validation data and test data of the Best GRNN model for Charpy Toughness.

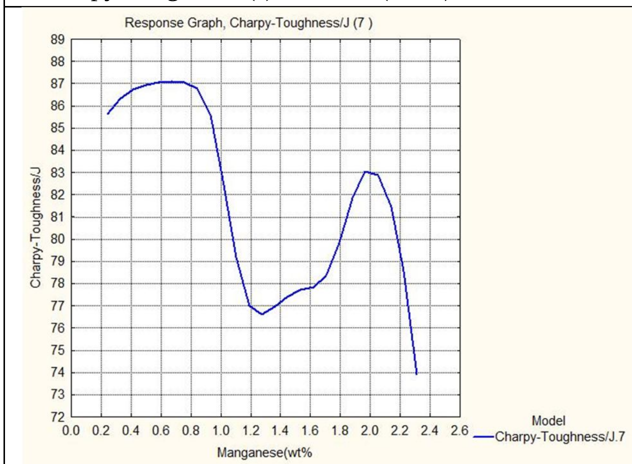
The best model of GRNN has training error 0.011404, validation error (selection error) 0.018101, and testing error 0.018669. This model is used for getting the results in form of various response graphs to understand the trend between the input variables and output variable(Charpy Toughness).(Figure 3)



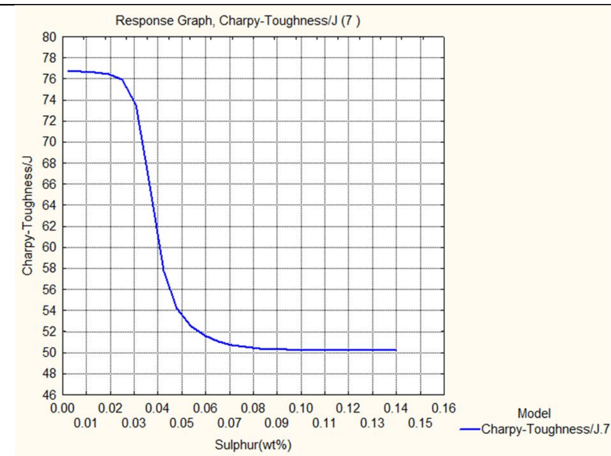
a Charpy Toughness (J) – Carbon(wt %)



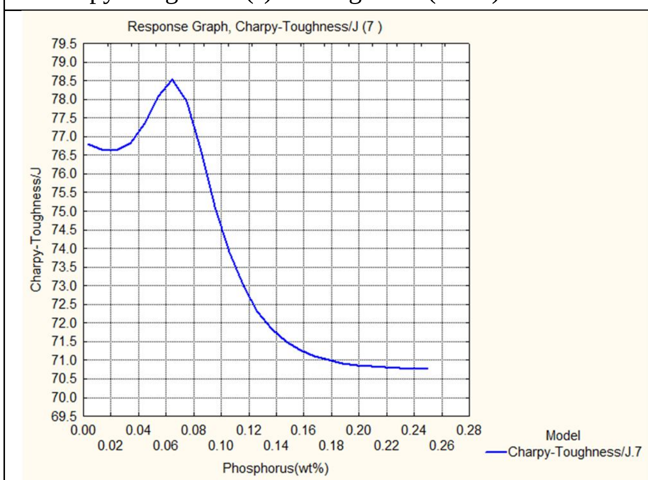
b Charpy Toughness (J) – Silicon(wt %)



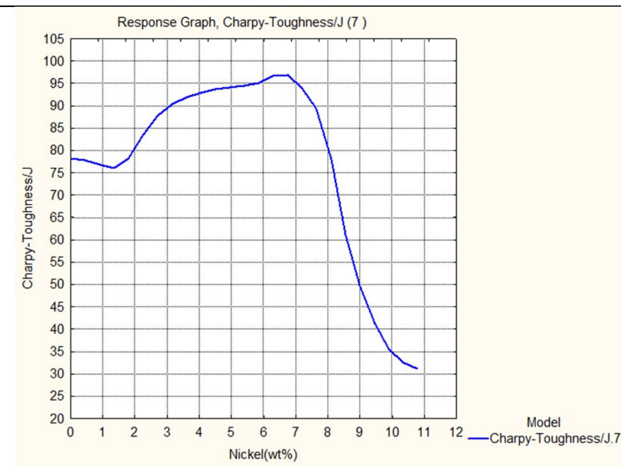
c Charpy Toughness (J) – Manganese (wt %)



d Charpy Toughness (J) – Sulphur (wt %)

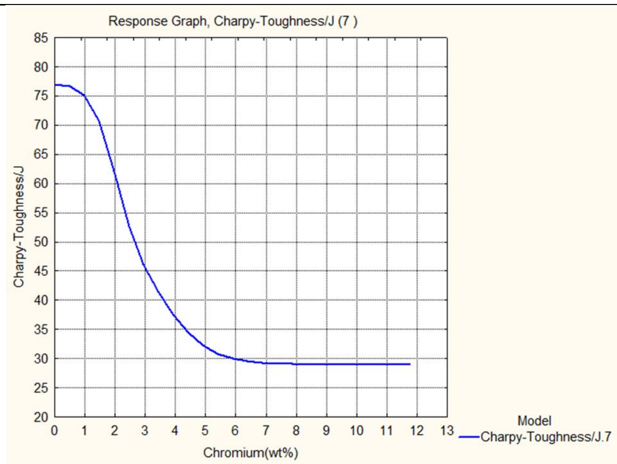


e Charpy Toughness (J) – Phosphorus(wt %)

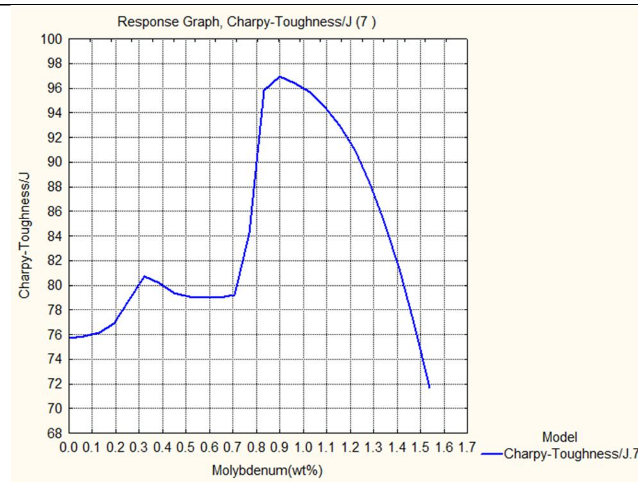


f Charpy Toughness (J) – Nickel(wt %)

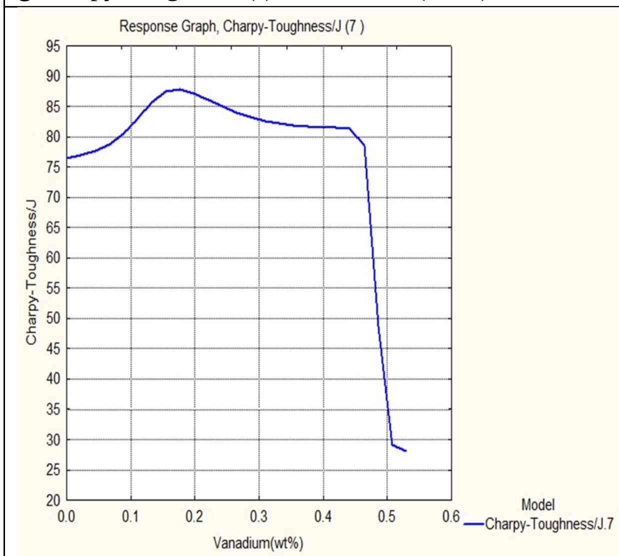
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 8 Issue XII Dec 2020- Available at www.ijraset.com



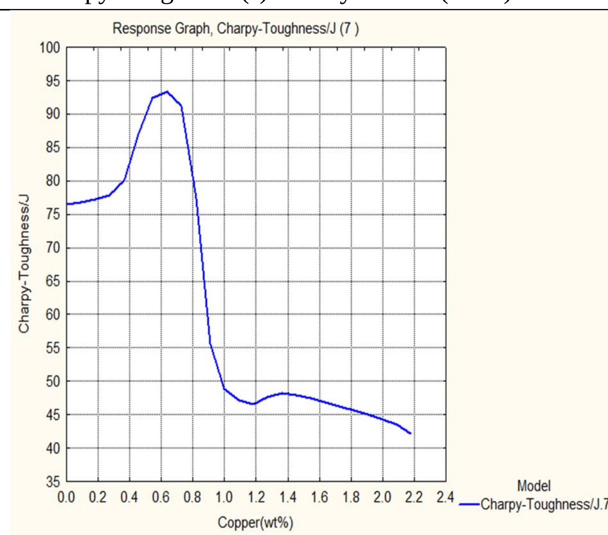
g Charpy Toughness (J) – Chromium(wt %)



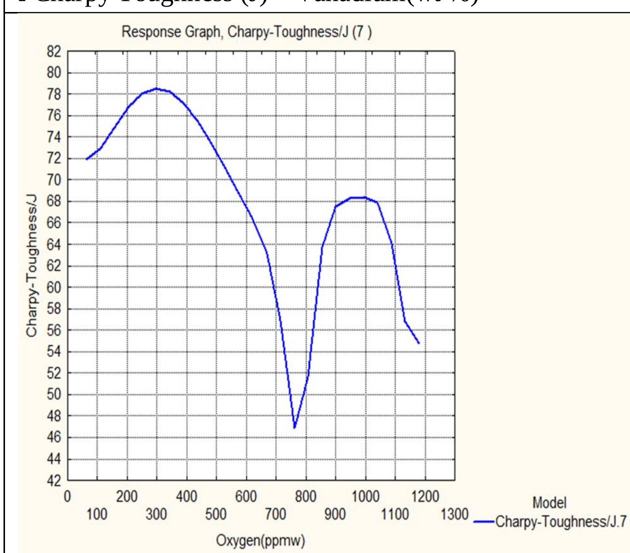
h Charpy Toughness (J) – Molybdenum(wt %)



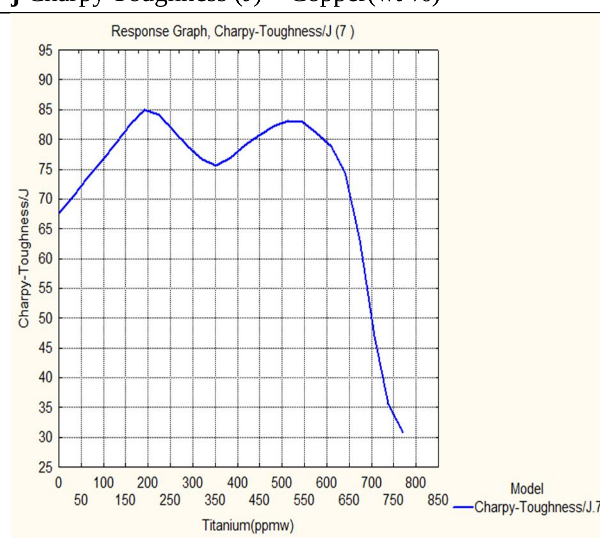
i Charpy Toughness (J) – Vanadium(wt %)



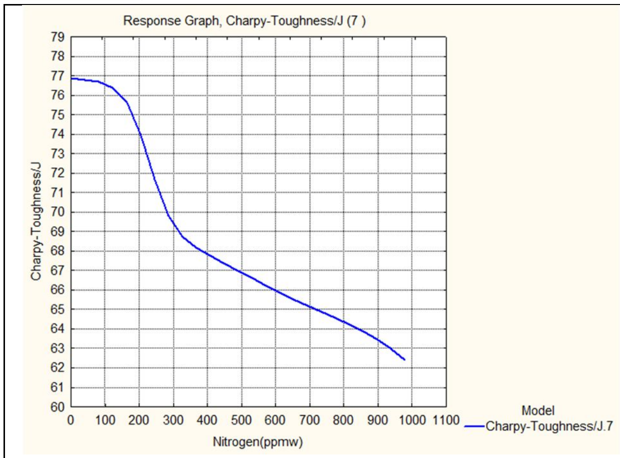
j Charpy Toughness (J) – Copper(wt %)



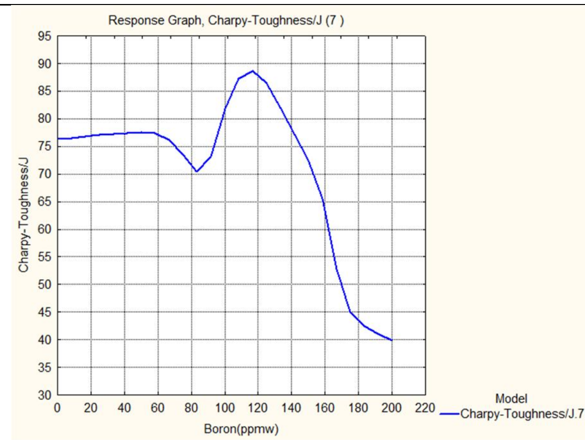
k Charpy Toughness (J) – Oxygen(ppm)



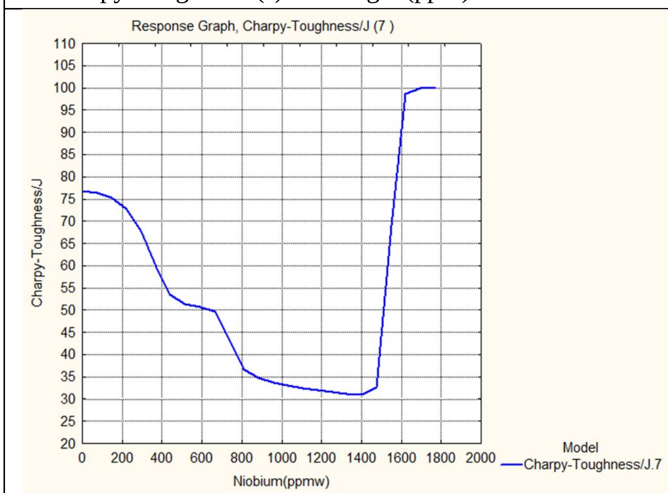
l Charpy Toughness (J) – Titanium(ppm)



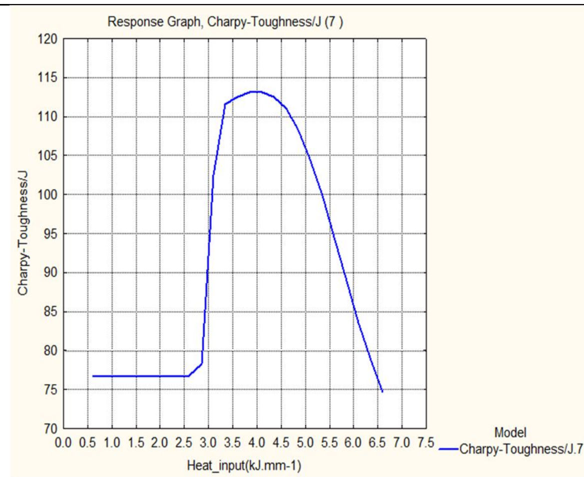
m Charpy Toughness (J) – Nitrogen(ppm)



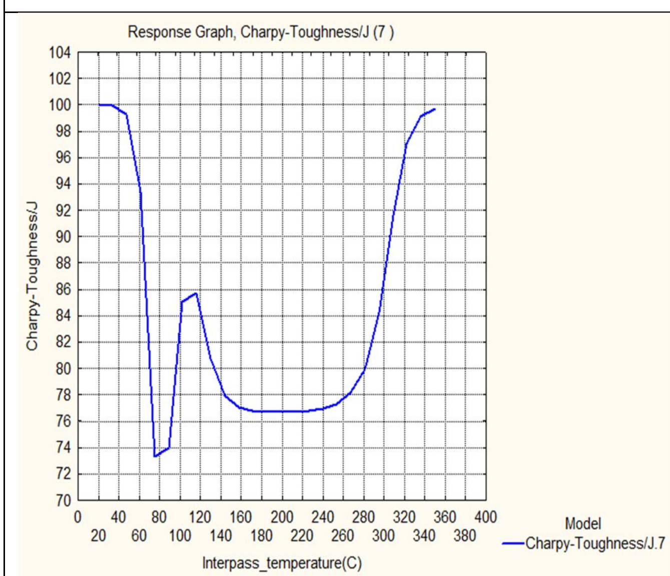
n Charpy Toughness (J)– Boron(ppm)



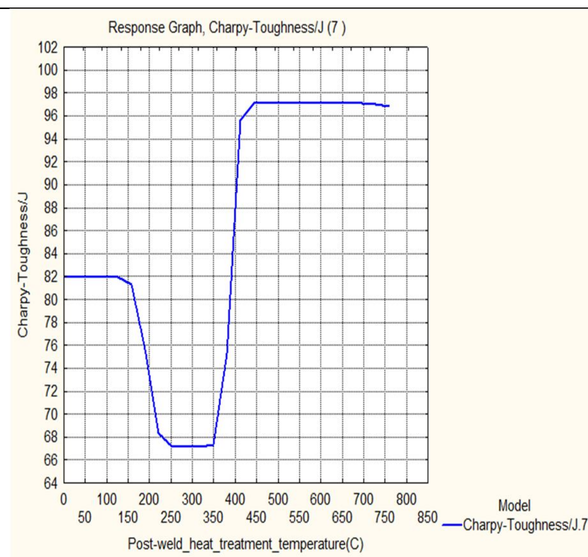
o Charpy Toughness (J) – Niobium(ppm)



p Charpy Toughness (J) – Heat Input(kJ mm-1)



q Charpy Toughness (J)– Interpass temperature(C)



r Charpy Toughness (J – Post-weld heat treatment(temperatureC)

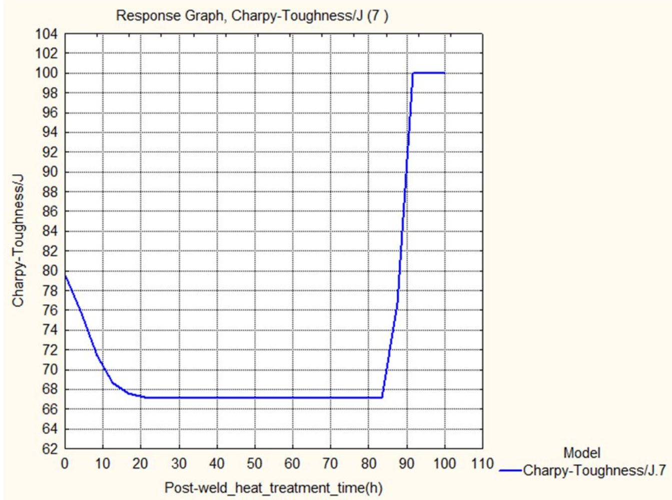
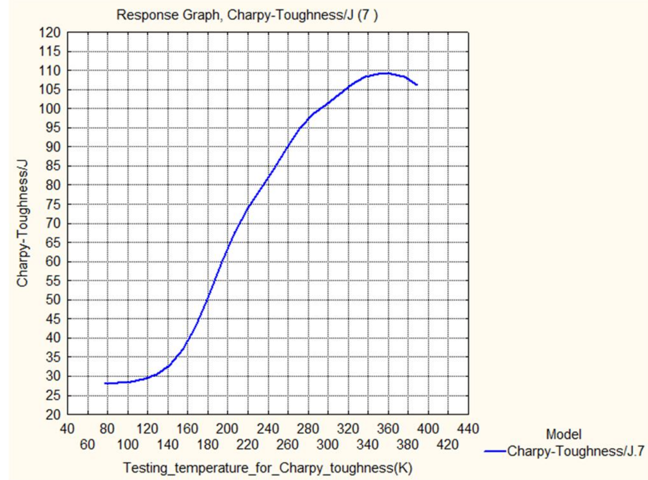
	
s Charpy Toughness (J) – Post-weld heat treatment time(h)	**t** Charpy Toughness (J) – Testing temperature for Charpy toughness(K)

Figure 3 Response graphs(a to t) of Input variables Charpy Toughness of Ferritic Steel Welds

The influence of each of the variables on the Charpy toughness of welding alloys, which is discussed here. The Charpy toughness, initially decrease from 78.1 J to 76.8 J, between the 0.02% C to 0.065% C. The Carbon concentration of the welds in between 0.065% to 0.0134%, the Charpy toughness increases very high from 76.8 J to 100.9 J. Between 0.0134% C to 0.19% C, the Charpy Toughness is a constant value of 100 J after a slight increase of 0.9 J. In the case of silicon between more than 0.0% to 0.75%, there is an increase of the 73 J to 77.8 J in the Charpy toughness and then maximum 77.8 J at 0.48% Si. Between 0.75% to 0.95% Si, the Charpy toughness decreases from 73 J to 57 J. At 1.43%, the Charpy toughness increases to 67.8 J and then decreases to 50 J at 1.62% Si. The trend of manganese shows the increase in the Mn% from 0.22% to 0.9%, the value of the Charpy toughness is also increased from 85.6 J to 87.1 J.

The Charpy toughness has a maximum value of 87.1 J between 0.58% Mn to 0.74% Mn. After 1.96% Mn, there is a reduction in the Charpy toughness from 83J to 74J at 2.3 Mn. The sulphur shows a maximum value of the Charpy toughness 76.6 J, upto 0.02%S. After 0.02% S, increase in sulphur decreases in the Charpy toughness from 76.6 J to 50.3 J at 0.09% S. Morethan 0.09% S gives constant Charpy toughness 50.3 J. The Phosphorus gives the maximum Charpy toughness 78.5 J at 0.064% P and increase in Phosphorus decreases the Charpy toughness to 70.7 J at 0.24% P. The nickel has the maximum 90 J to 97 J Charpy toughness between 6% Ni to 7% Ni. Between 2% Ni to 8% Ni, the charpy toughness is maintain minimum 80 J to maximum 97 J. Morethan 8% Ni reduces the Charpy toughness to 32 J at 10.8% Ni. The Chromium has a maximum Charpy toughness 77 J to 75 J up to 1% Cr. Morethan 1% Cr reduces the value of the Charpy toughness to 28 J at 8% Cr. The Charpy toughness is constant value of 28 J after 8% Cr. Molybdenum increases the Charpy toughness from 75.8 J to 80.8 J at 0.33%. At 0.9% Mo, the Charpy toughness is the highest 97 J. Increase more than 0.9% Mo the charpy toughness is reduced to 71.9 J at 1.53% Mo. Vanadium increases the Charpy toughness from a minimum 76.5 J to a maximum 87.5 J at 0.16V%. At 0.44% V, the Charpy toughness reduces and at 0.53% V, it is 27.5 J. Copper increases the Charpy toughness from 77 J to 93 J at 0.62%. Between 0.62% to 1.2% Cu, the Charpy toughness decreases from 93 J to 46.5 J. At 2.19% Cu, rhe Charpy toughness is the loweast 42.5 J. Oxygen increases the Charpy toughness from 72 J to 78.3 J at 300 ppm and it reduces to 47 J at 760 ppm. Further increases to 68.2 J at 940ppm Oxygen and then drops to 54.3 J at 1180ppm Oxygen. Titanium gives a minimum Charpy toughness of 67.5 J to maximum 85 J at 180ppm. At 350ppm Ti, the Charpy toughness has a value of 76 J. Between 500 ppm Ti to 550 ppm Ti, the Charpy toughness is 82.5 J. Morethan 550 ppm Ti, the Charpy toughness decreases from 82.5 J to 31.5 J at 770ppm Ti. Nitrogen shows a decrease in the Charpy toughness from 76.9 J to 62.3 J with an increase in a Nitrogen ppm. Boron gives a little increase in the Charpy toughness from 76.5 J to 77.5 J between greater than 0 ppm to 58 ppm. Boron shows maximum Charpy toughness of 88 J at 118 ppm. More than 118 ppm Boron, there is a decrease in the Charpy toughness to 40 J at 200 ppm Boron. Niobium has a trend of a decrease in the Charpy toughness from 76.5 J to 31.5 J with an increase from a greater than 0 ppm Nb to 1400 ppm Nb. Between 1470 ppm Nb to 1780 ppm Nb, the Charpy toughness increases and attains the highest vaule of 100 J.

Heat Input has stated that the maximum Charpy toughness of 113 J at 4.0 kJ mm-1. Between 0.5 kJ mm-1 to 2.5 kJ mm-1, the Charpy toughness is a constant 76.5 J. More than 2.8 kJ mm-1 to 4.0 kJ mm-1 Heat Input increases the Charpy toughness from 77.5 J to 113 J. Higher than 4.0 kJ mm-1 Heat Input, the Charpy toughness reduces from 113 J to minimum 74.9 J at 6.5 kJ mm-1. When the Interpass temperature is in range of 20 C to 75 C, the Charpy toughness decreases from 100 J to 73.5 J. Between 80 C to 118 C, the Charpy toughness increases from 74 J to 85.9 J and further it reduces to76.8 J at 170 C and constant 76.8 J up to 220 C. Morethan 220 C Interpass temperature, the Charpy toughness value increases to 99.9 J at 350 C. Post weld heat treatment temperature increases from 50 C to 750 C, shows the Charpy toughness is 82 J up to 125 C then it decreases to 67.2 J between 250 C to 350 C.Between 350 C to 500 C, the Charpy toughness increases from 67.2 J to 97.2 J. More than 500 C Post weld heat treatment temperatute, the Charpy toughness is almost constant 97.2 J upto 700 C. A Little decrease, from 97.2 J to 96.8 J is observed between 700 C to 750 C Post weld heat treatment temperature. Post weld heat treatment time has a trend of a decrease in the Charpy toughness from 79.2 J to 67.2 J at 22 hours. Between 22 to 83 hours, post weld heat treatment time, the Charpy toughness is a constant 67.2 J. More than 83 hours, it increases a maximum Charpy toughness to 100 J at 91 hours, Post weld heat treatment time and a constant till 100 hours. Testing Temperature of Charpy toughness shows the trend towards of an increase in the Charpy toughness from 28 J to 109 J with an increase in Testing Temperature of Charpy toughness from 80 K to 360 K and then a little reduction from 109 J to 106 J between 360 K to 390 K.

The relationship between the input variables and the Charpy Toughness is a nonlinear as seen above in response graphs (Figure 3).

The GRNN model has good accuracy in prediction of Charpy Toughness of ferritic steel welds on unseen data which is excellent for the design of welds. (Table.2) The predicted Charpy Toughness of the unseen data of three weld alloys are compared with measured values of Charpy Toughness shows the prediction capacity of the GRNN model. This GRNN model can be used for practical applications, research and development of ferritic steel alloys.

Table 2 Predicted Charpy Toughness by GRNN model for unseen data of three ferritic weld deposits

Variable	Weld alloy 1	Weld alloy 2	Weld alloy 3
Carbon(wt%)	0.037	0.033	0.03
Silicon(wt%)	0.3	0.3	0.04
Manganese(wt%)	0.65	2.17	0.61
Sulphur(wt%)	0.009	0.008	0.009
Phosphorus(wt%)	0.011	0.012	0.01
Nickel(wt%)	3.5	6.54	6.11
Chromium(wt%)	0.03	0.44	0.16
Molybdenum(wt%)	0.005	0.62	0.38
Vanadium(wt%)	0.012	0.021	0.018
Copper(wt%)	0.03	0.02	0.02
Oxygen(ppm)	440	320	340
Titanium(ppm)	55	0.0	0.0
Nitrogen(ppm)	69	139	129
Boron(ppm)	2.0	1.0	1.0
Niobium(ppm)	20	10	10
Heat_input(kJ.mm-1)	1.0	1.3	1.3
Interpass_temperature(C)	200	200	200
Postweld_heat_treatment_temperature(C)	580	0.0	0.0
Post-weld_heat_treatment_time(h)	2.0	0.0	0.0
Testing Temperature CT (K)	210	293	293
Measured CT (J)	100	41.5	123
Predicted CT (J)	100	39	113.5

IV. CONCLUSIONS

The General Regression Neural Network is the best for capturing trends of input variables and output variables in weld alloys which are nonlinear. A neural network method based within a General regression neural network has been used to rationalize an enormous quantity of published experimental data on the Charpy Toughness. It is now possible, therefore, to estimate the Charpy Toughness as a function of the chemical composition, welding conditions and a variety of heat treatment parameters.

The model formulated has been applied towards the understanding of ferritic steel alloys used in welding for various equipment construction in industries (eg. Power plants, Submarines, Liquid Gas Storage Tanks..etc.) It has been used successfully on unseen data on ferritic steel welds for various applications.

The design of the ferritic weld alloys become easier, accurate, economical and time-saving with the help of the GRNN modelling. The control of the effective input variables gives the desired Charpy Toughness of weld alloys for real applications in industries.

REFERENCES

[1] H.K.D.H. Bhadeshia and L.-E. Svensson, in H. Cerjak and K.E. Easterling (eds.), Mathematical Modelling of Weld Phenomena, Institute of Materials, London, 1993, pp. 109-192.

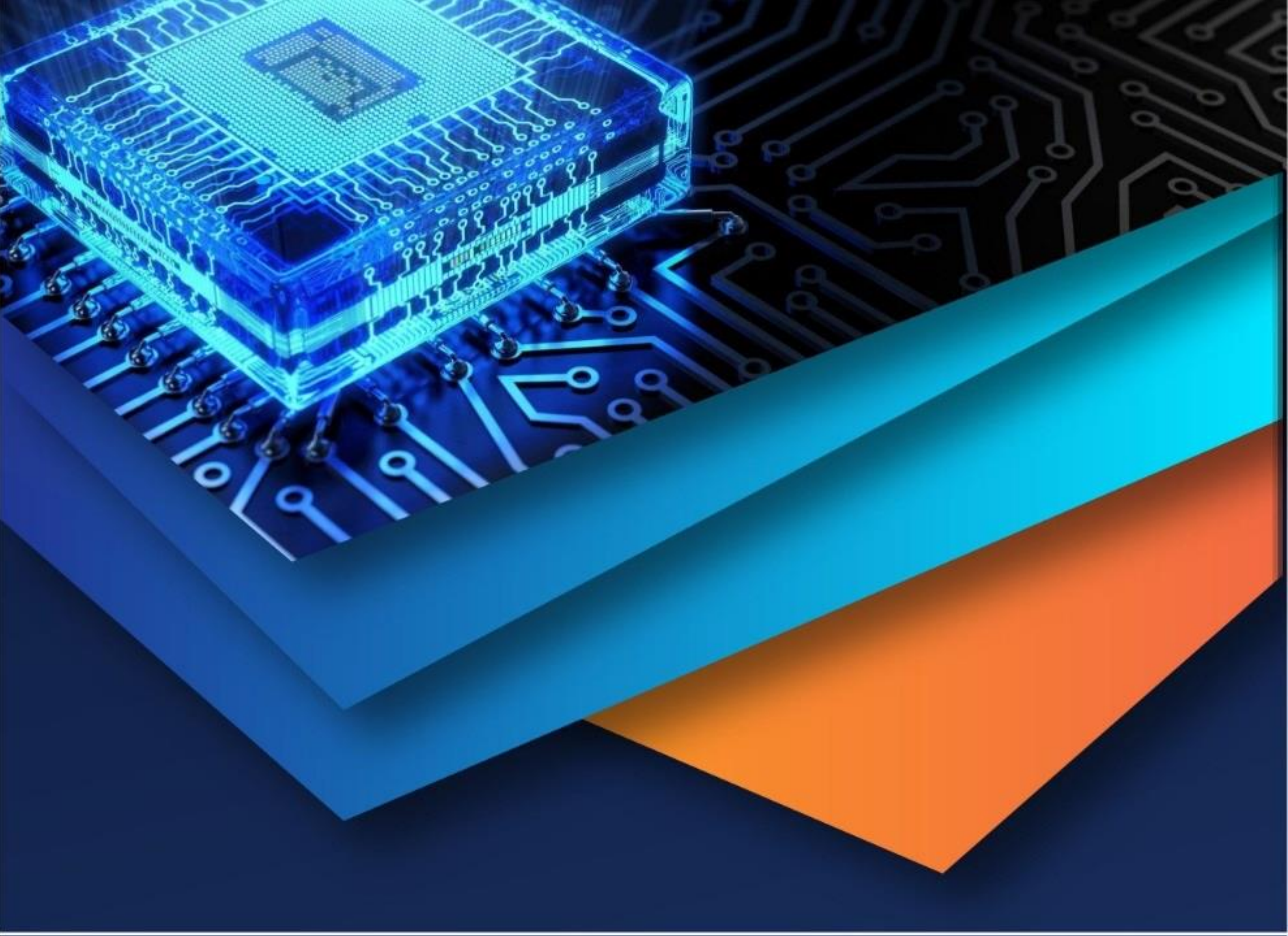
[2] H. K. D. H. BHADESHIA: in 'Mathematical modelling of weld phenomena 3', (ed. H. Cerjak), 229 – 284; 1997, London, The Institute of Materials

[3] L. E. Svensson, Control of Microstructure and Properties in Steel Arc Welds, CRC Press, London, 1994, pp. 188.

[4] Speckt, D.F. (1991). A Generalized Regression Neural Network. IEEE Transactions on Neural Networks 2 (6), 568-576.

[5] B J Chauhan and S N Soman, Modelling of Yield Strength of Ferritic Steel Welds, Volume 6 Issue VIII, August 2018,pp.521-531

[6] B J Chauhan and S N Soman, Modelling of Ultimate Tensile Strength of Ferritic Steel Welds, IJRASET, Volume 6 Issue X, Oct 2018,pp.21-28



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY