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Modelling on CVN Toughness of Weld Deposits

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ABSTRACT

The Charpy V Notch toughness (CVN) of steel is an important property while considering structural and heavy loading conditions. In welded structures, CVN is attributed to many variables like composition of steel, heat input of welding, pre- and post-heat treatments of the weldment, type of welding process etc. The regression analysis works accurately for three to four variables. The property of weldment is associated to more than three-four variables. So this conventional regression analysis couldn't capture associated trends among the variables due to their non-linearity. This complexity is countered well by artificial neural network (ANN) modelling. In the present work, artificial neural network approach is utilized for the prediction of CVN of ferritic steel welds, which is multi-phase complex engineering material. The multilayer perceptron (MLP) method is used for formulating the neural network models. Numerous models were made by adjusting the hyperparameters and a best model was selected having least training error. The crucial results obtained from this model where analysed from response graphs and contour plot. This (MLP) approach for formulating neural network model was proved to be efficient after validation procedure and the same model could be exploited well for predicting accurate value of CVN in a very time and cost-effective manner.

Keywords: Charpy toughness; ferritic steel; artificial neural network; multilayer perceptron

INTRODUCTION

The neural network is a non- linear regression method which is capable of capturing magnanimous complexity in the data due to its inherent flexibility and avoiding overfitting both at the same time (Dimitriu et al. 2009; Keehan et al. 2002). The ANN modelling is used ubiquitously in science in general and particularly in materials science for the understanding of complex property relationships. Apart from this, the scope of ANN has been widened to the fields of hydrological sciences, atmospheric sciences, civil engineering, process engineering and structural engineering (Carlan et al. 2004). The field of materials science essentially involves rigorous experimental characterization and mathematical modelling. This generates enormous amounts of data, which is used for analysing properties of matter, formulating and validating theories. Neural network modelling turns out to be a wonderful, amenable and promising tool, which helps in developing quantitative expressions without even compromising the known complexity of the problem (Bhadeshia et al. 1999). The present work is focused on prediction of CVN of ferritic steel with the help of ANN. The Figure 1 represents the 20 input variables and output variable- Charpy toughness.

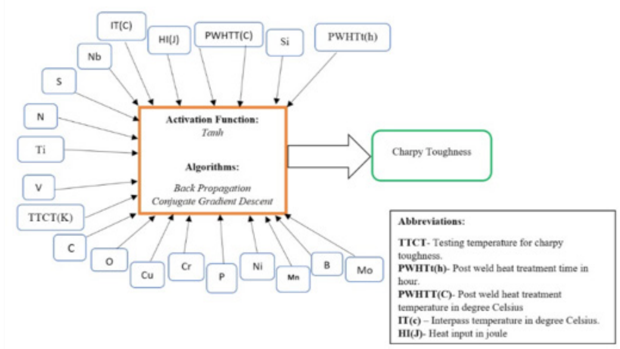

FIGURE 1. A non-linear network representation showing input nodes (input variables), hidden layer and output node (output variable).

The ferritic steel comprises majorly of ferrite phases like acicular, allotriomorphic and widmanstatten ferrite in conjunction with other microphases (pearlite, bainite and martensite) as shown below in Figure (2,3). By varying the proportions of microphases in the ferritic steel by subjecting it to heat treatments, enhances it mechanical properties. Ferritic steel is classified into three classes on the basis of their properties and applications, namely heat resistance steel, Cr-Mo steel and structural steel. They are generally characterised by high strength and toughness (Lalam et al. 2000; Bhadeshia et al. 2007).

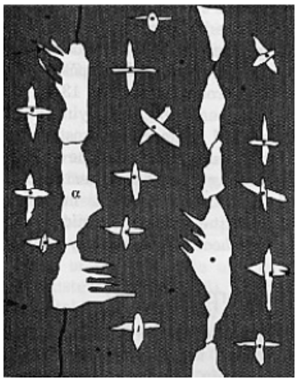

FIGURE 2. Schematic showin different components of the primary microstructure in the columnar austenite grains of ferritic steel weld (Bhadeshia 1992)

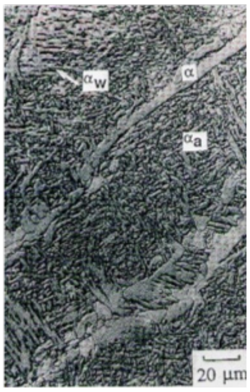

FIGURE 3. SEM micrograph of the primary microstructure of the ferritic steel weld, α- allotriomorphic ferrite, αw - Widmanstatten ferrite and αa- acicular ferrite (Honeycombe et al. 1995)

Ferritic steel finds its application in many fields. Ferritic steel supersedes austenitic steel in the construction of power plant. Latter is susceptible to thermal fatigue owning to tis high thermal expansion (Bhadeshia et al. 2008). The usage for nuclear applications is concerned with the least swelling of ferrite as compared to austenite when bombarded with neutrons (Bhadeshia 2007). The most unmanageable problem lies in predicting the mechanical behaviour of a weldment. This is generated due to many variables like variety of heterogeneities, chemical composition, process parameters, heat treatment, imperfections and changes occurring during service. The test is usually carried out at a variety of temperatures in order to characterise the ductile–brittle transition inherent to body–centred cubic metals (Bhadeshia 2002). The charpy toughness test encompasses the usage of square sectioned notched bar fractured under specific conditions, which yields an empirical value not suitable for engineering design, yet a useful quality control test recognised internationally. The toughness of steel depends of many variables while that of weld involves more variables due to perplexity of welding process. To predict this toughness using linear regression analysis in a conventional manner hasn't proved to be reliable. A neural network approach is rather chosen to deal with the non-linearity associated among the variables. The trained network result consists of conditioning the function, which in combination with a series of coefficients (weights), relates the inputs to output (Bhadeshia et al.1995). In present work, multilayer perceptron neural network method is used. Figure (4) shows the actual representation of the ANN model.

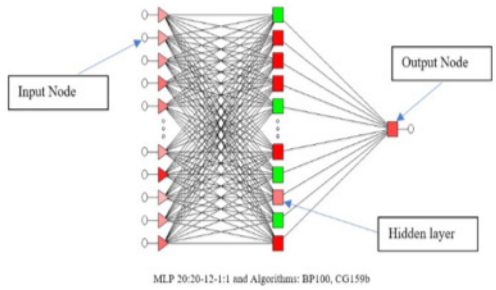

FIGURE 4. Network model illustration

MODELLING WORK

The database for the modelling work consisted of weld deposits. These were intended for minimum dilution enabling measurement of various weld metal properties. The welded joints were made using MMAW, SAW and TIG welding processes. These experimental data were collected from numerous sources like research papers, journals and handbooks (Chauhan, B. J., Personal communication to Welding Industries; Technical handbook of Bohler welding products, edition 2005; Welding consumables product catalogue, LINCOLN ELECTRIC, CC11-17-rev.0; Welding electrode booklet, Ador welding; Welding consumables catalogue, ESAB INDIA; Welding consumables catalogue, OERLIKON; Technical handbook of Bohler welding products, edition 2009; Welding consumables product catalogue, LINCOLN ELECTRIC, CC 10-14; Welding consumables catalog C1.10, LINCOLN ELECTRIC). The sole purpose of this project work is to predict CVN accurately as a function of different input variables. The data base comprises of 100 weld deposit experimental data. The data has 20 input and CVN as output variable. The statistical value of data is showed in table 1, this is indicative of the diversity in the experimental data that was used in the present work. In the present work, multilayer perceptron neural network method was used. Each MLP model entails three layers i.e., input layer, hidden and output layer. Numerous models were trained in the statistica software by adjusting crucial hyperparameters like no of hidden layers, activation function and epochs. The best model suitable for practical work was selected on the basis of least training error (Bhadeshia 1995; Chauhan et al. 2020].

TABLE 1. The statistical data of 20 input variables and output variable (CVN)

Variable	Min value	Max value	Mean	Standard Deviation
Carbon(wt%)	0.029	0.119	0.07	0.025
Silicon(wt%)	0.169	0.569	0.332	0.086
Manganese (wt%)	0.51	2.169	1.18	0.559
Sulphur(wt%)	0.004	0.0089	0.0068	0.0014
Phosphorus(wt%)	0.005	0.016	0.01	0.0026
Nickel(wt%)	0	10.8	3.71	3.87
Chromium(wt%)	0	9.1	0.73	1.95
Molybdenum(wt%)	0	1.04	0.263	0.285
Vanadium(wt%)	0	0.24	0.02	0.048
Copper(wt%)	0	0.3	0.058	0.106
Oxygen(ppmw)	249.99	642	374.08	85.568
Titanium(ppmw)	0	460	55.78	114.31
Nitrogen(ppmw)	17	459	96.23	87.956
Boron(ppmw)	0	64	2.13	7.36
Niobium(ppmw)	0	699.99	36.999	126.359
Heat input (kJ.mm-1)	1	1.39	1.15	0.156
Interpass_ temperature(C)	150	199.99	191.74	17.786
Post-weld_ heat_treatment_ temperature(C)	0	749.99	203.1	219.653
Post-weld_heat_ treatment_time(h)	0	16	6.7	7.523
Testing_ temperature_ for_Charpy_ toughness(K)	77	296.99	214.039	58.81
Charpy- Toughness/J	4.499	113.499	70.391	36.098

The above Figure 5 constitutes graph of CVN predicted vs observed. Each point on the graph indicates the data that was used and is divided into three- training data, validation data and testing data for which blue, red and green colours are used respectively. The best model was selected from numerous trained models on the ground of least training error of 0.017966.Test error 0.182680 and validation error 0.221990 where noted. This model was utilized to fetch results in the form of response graphs and contour plots to comprehend trends among input and output variable (CVN).

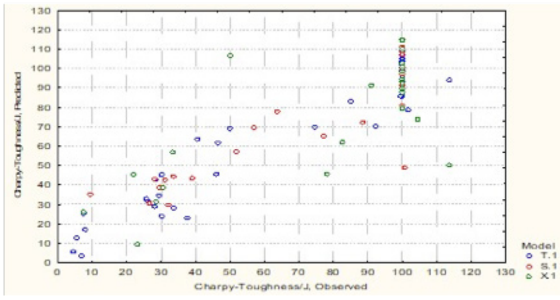

FIGURE 5. Combined training, validation and testing data of best model – CVN (J)

SIGNIFICANCE OF EACH VARIABLE

The trained model gave information (table 2) regarding the most significant variables, in accordance to its effect on CVN. This Ranking is correlated to the metallurgical aspects related to CVN variation by the variables. Vanadium(wt%) is ranked one as it is grain refiner, nitrogen(ppmw) second as it restricts the grain growth, Testing temperature(K) as third has a crucial impact on CVN whereas phosphorus(wt%), Sulphur(wt%) and interpass temperature(C) contribute least towards varying the CVN of ferritic steel welds. All variables considered in the modelling had noteworthy effect on the output, which is indicative of appropriate choice of input variables. The relevance obtained, represents the extent to which a particular input explains variation in output, rather like a particular correlation coefficient in the linear regression analysis (Lalam et al. 2000).

TABLE 2. Ranking of variables on the basis of their affect on CVN

Variable	Rank (most affecting to toughness)
Vanadium(wt%)	1
Nitrogen(ppmw)	2
Testing_temperature_for_Charpy_toughness(K)	3
Chromium(wt%)	4
Copper(wt%)	5
Post-weld_heat_treatment_time(h)	6
Nickel(wt%)	7
Boron(ppmw)	8
Carbon(wt%)	9
Molybdenum(wt%)	10
Oxygen(ppmw)	11
Heat input(kJ.mm-1)	12

continue ...

... continued

Silicon(wt%)	13
Post-weld_heat_treatment_temperature(C)	14
Titanium(ppmw)	15
Manganese (wt%	16
Niobium(ppmw)	17
Phosphorus(wt%)	18
Sulphur(wt%)	19
Interpass_temperature(C)	20

INTERPRETATION OF RESPONSE GRAPHS

Varying trends where observed in the response graphs of the input variables. Carbon, silicon, niobium, phosphorus, Post weld heat treatment temperature and Testing temperature for Charpy toughness shows an increasing trend towards CVN as shown in figures 6,7,8,9,10,11 the trends are explained as follows.

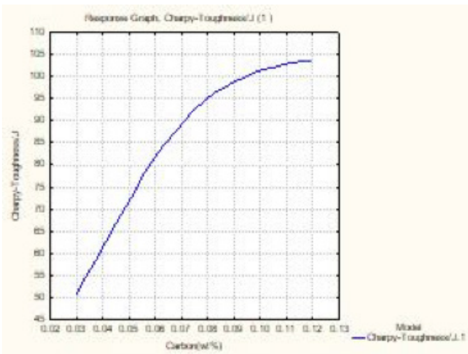

FIGURE 6. Response graph of Carbon(wt%) Vs Charpy Toughness (J)

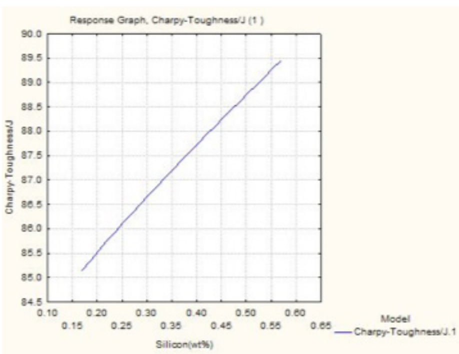

FIGURE 7. Response graph of silicon (wt%) Vs Charpy Toughness (J)

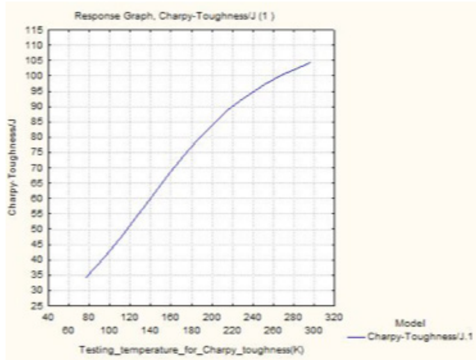

FIGURE 8. Response graph of Niobium (ppmw) Vs Charpy Toughness (J)

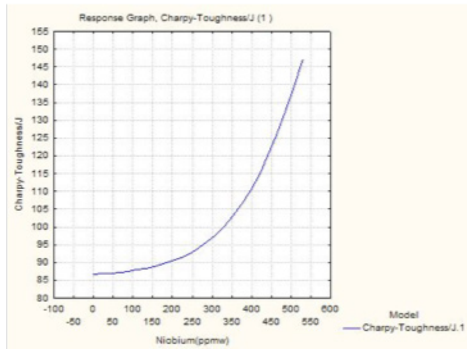

FIGURE 9. Response graph of phosphorus(wt%) Vs Charpy Toughness (J)

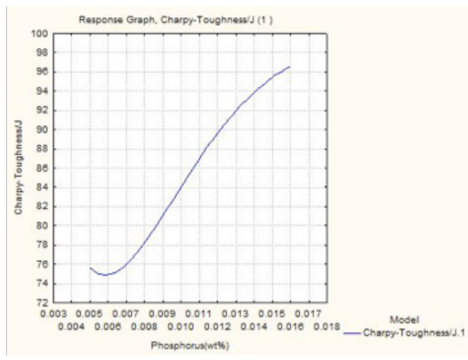

FIGURE 10. Response graph of testing temperature for Charpy toughness(k) Vs Charpy Toughness (J)

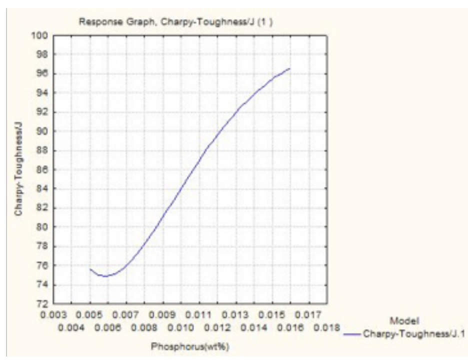

FIGURE 11. Response graph of post weld heat treatment(C) Vs Charpy Toughness (J)

Carbon increase the CVN from 51J to 104 J. The least value of CVN is observed at 0.03% carbon. And highest value of CVN is observed at 0.12% carbon. At higher concentration of carbon, favourable acicular ferrite phase is formed leading to increase in toughness (LALAM et al. 2000).The least value of CVN 85.1 J is observed at 0.17 % silicon and highest value of 89.45 J at 0.57 % silicon. The lowest value of CVN 86J is observed at 0 ppmw of niobium. The highest value 147 J is observed at 530 ppm of niobium. The least of CVN 75 J is observed at 0.006% phosphorus. Before receding to this value, at 0.005% phosphorus 75.7 J is observed. The highest value of CVN 96.8 J is observed at 0.016% phosphorus. The lowest value of CVN of 81.1J at 0 degree Celsius of post weld heat treatment temperature. Highest value of 96J of CVN at 700 degree Celsius of post weld heat treatment temperature. The least value of 35 J is observed at testing temperature of 79K. The highest value of 104.9 J is observed at testing temperature of 290.8 k. The decreasing trend in CVN is observed in manganese, chromium, molybdenum, nitrogen, vanadium, titanium, heat input and post weld heat treatment time as shown in figures 12,13,14,15,16,17,18, 19, the trends observed in this above-mentioned graph are as follows.

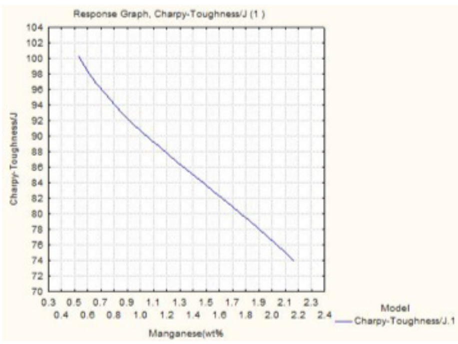

FIGURE 12. Response graph of manganese(wt%) Vs Charpy Toughness (J)

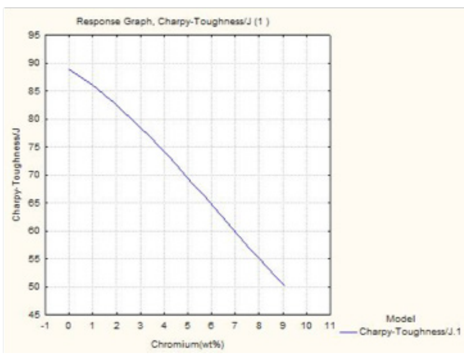

FIGURE 13. Response graph of chromium(wt%) Vs Charpy Toughness (J)

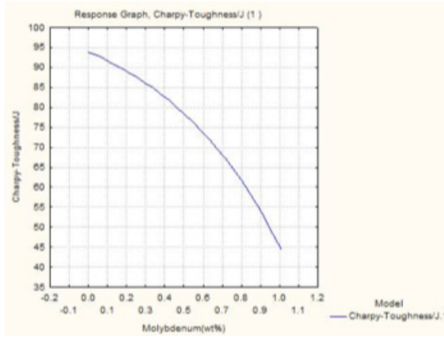

FIGURE 14. Response graph of molybdenum(wt %) Vs Charpy Toughness (J)

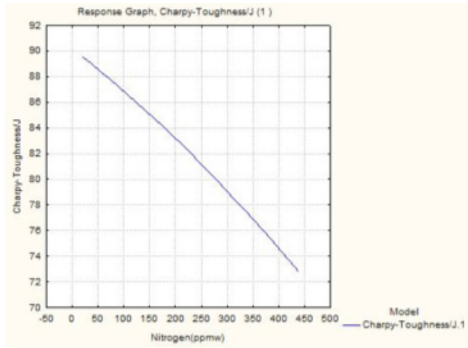

FIGURE 15. Response graph of nitrogen (ppmw) Vs Charpy Toughness (J)

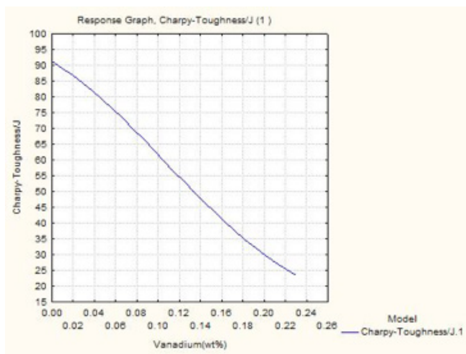

FIGURE 16. Response graph of vanadium (wt%) Vs Charpy Toughness (J)

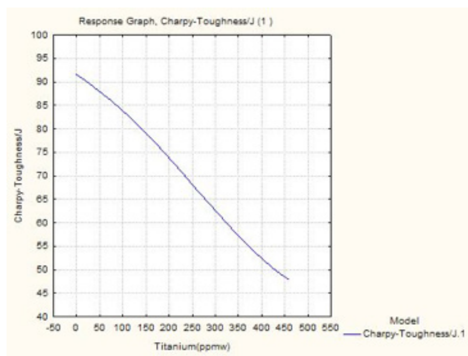

FIGURE 17. Response graph of titanium(ppmw) Vs Charpy Toughness (J)

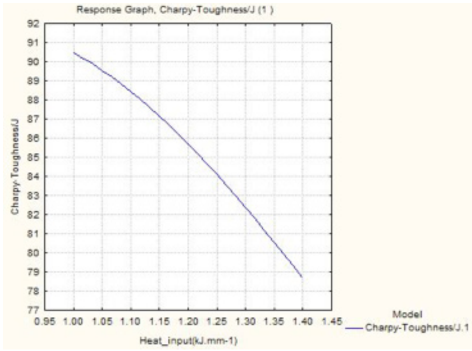

FIGURE 18. Response graph of heat input(KJ.mm) VosbCshearrvpeydTfourgshunlepshsu(Jr)

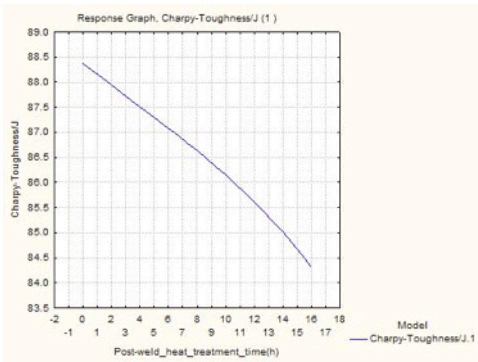

FIGURE 19. Response graph of post weld heat treatment time(h) Vs Charpy Toughness (J)

Maximum CVN of 100 J is observed at 0.53% manganese and least value of 74 J at 2.6% manganese. Very low manganese concentration lead to poor microstructure while very high leads to more strength. So there is always an optimum combination of these two needed for required toughness value (LALAM et al. 2000) **.**The highest value of CVN 89 J at 0% chromium. The lowest value of CVN 50 J is observed at 9.1% chromium. The highest value of 94.8 J is achieved at 0% molybdenum. The lowest value of 44.9 J at 1.1 % molybdenum. The highest value of 89.2 J is observed at 25 ppm of nitrogen. The lowest value of 72.8 J at 440 ppm of nitrogen. The highest value of CVN of 91 J is observed at 0% vanadium. The lowest value of CVN of 24 J is observed at 0.23% vanadium. The highest value of 92 J is observed at 0 ppwm of titanium. Least value 48 J is observed at 460 ppwm of titanium. The highest value of CVN 90.4 J at 1.00 KJ.mm-1. The lowest value of 78.8 J at 1.40 KJ.mm-1 heat input. The highest value of CVN of 88.4 J at 0-hour post weld heat treatment time. The lowest value of CVN of 84.4 J at 16 hours of post weld heat treatment time. Other graphs showed different trends wherein there was increasing and decreasing in value of CVN as value of input variable increases. This was observed for sulphur, nickel, copper, oxygen, boron and interpass temperature as shown in Figure 20,21,22,23,24 and 25, the trends as above mentioned is discussed here as follows.

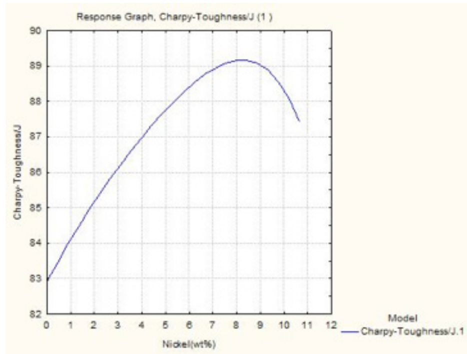

FIGURE 20. Response graph of sulphur (wt%) Vs Charpy Toughness (J)

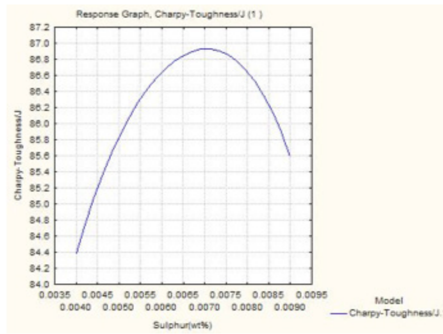

FIGURE 21. Response graph of nickel (wt%) Vs Charpy Toughness (J)

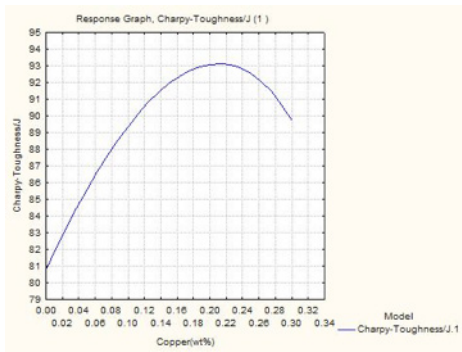

FIGURE 22. Response graph of copper (wt%) Vs Charpy Toughness (J)

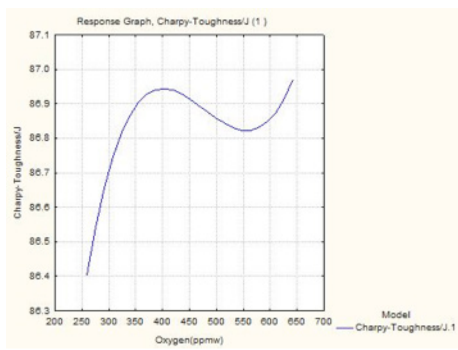

FIGURE 23. Response graph of oxygen (ppmw) Vs Charpy Toughness (J)

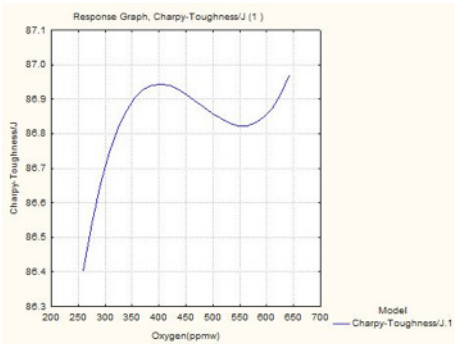

FIGURE 23. Response graph of oxygen (ppmw) Vs Charpy Toughness (J)

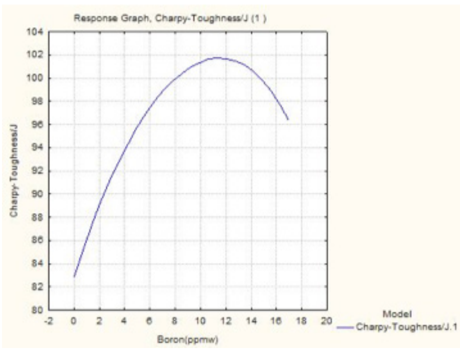

FIGURE 24. Response graph of boron (ppmw) Vs Charpy Toughness (J)

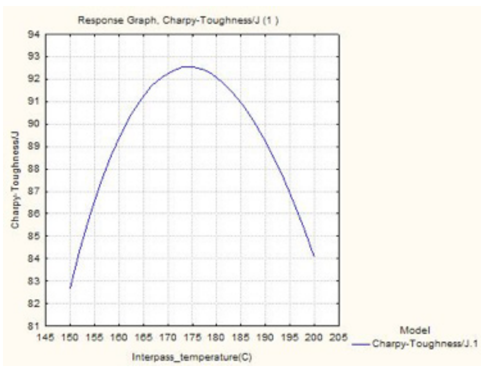

FIGURE 25. Response graph of Interpass temperature (C) Vs Charpy Toughness (J)

Least value of CVN 84.4 J is observed at 0.0040 % sulphur. The maximum value of 86.9 J at 0.0070% sulphur. The other lower value of CVN 85.6 J is observed at 0.0090 % sulphur. The least value of CVN of 83 J is observed at 0% nickel. Highest value of 89.2 J is observed at 8% nickel. Other lower value of 87.4 J is observed at 10.6 % nickel. Nickel is known to enhance CVN up to a certain limit, but this is highly determined by concentration of manganese, as both increase hardenability and strength of weld deposit (LALAM et al. 2000). The least value of CVN of 80.9 J is observed at 0% copper. Highest value of 93.1 J is observed at 0.21 % copper. Other lower value of 89.8 J is observed at 0.30 % copper. Least value of 86.4 J is observed at 260 ppwm of oxygen. A Higher value of 86.94 J is observed at 400 ppwm of oxygen. A lower value of 86.83 J is observed at 550 ppwm of oxygen. The highest value of 86.96 J is observed at 640 ppwm of oxygen. Oxide inclusions are sight of nucleation for acicular ferrite which enhances CVN value (BAILEY, N .1994).

The least value of CVN of 83 J is observed at 0 ppwm of boron. Highest value of 101.9 J is observed at 11 ppwm of boron. A lower value of 96.4 J is observed at 17 ppwm of boron. First there is increase then there is decrease in the trend. The least value of 82.8J is observed at Interpass temperature of 150 C. the highest value of 92.6 J is observed at Interpass temperature of 175 C. A lower value of 84 J is observed at Interpass temperature of 200 C. The trends observed in the above response graphs are generalised within the data set considered in modelling.

INTERPRETATION OF CONTOUR PLOT

Figure 26 shows relations between carbon, manganese and CVN.The CVN values varies from 0J to 100 J across the graph in a nonlinear way where darker colour hues indicate more value of CVN and vice-versa. The higher values of toughness are observed at two locations in the graph, first between 0.7- 1.6 % manganese and carbon range of 0.02- 0.06 % carbon and second between 1.3-1.8 % manganese and carbon range of 0.12-0.14 % carbon. In the other regions there is a general decrease in CVN across the graph. The above response graphs and counter plots suggested that the association between the input variables and CVN is nonlinear in nature.

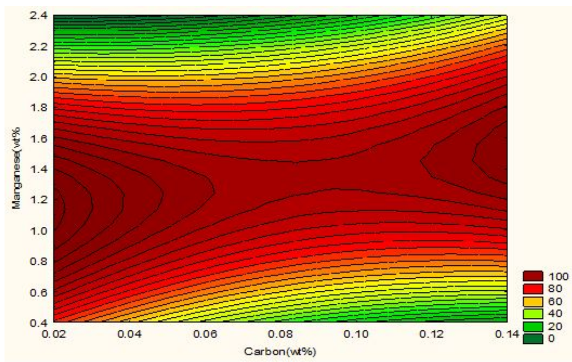

FIGURE 26: Predicted variations in charpy toughness(J) as a function of carbon and manganese concentrations.

VALIDATION THROUGH THE OPTIMISED MODEL

MLP model had a good accuracy in predicting the value of CVN of ferritic steel welds. The MLP model was used for predicting the CVN of unseen weld deposits of ferritic steel weld (Chauhan, B. J., Personal communication to Welding Industries; Technical handbook of Bohler welding products, edition 2005; Welding consumables product catalogue, LINCOLN ELECTRIC, CC11-17-rev.0; Welding electrode booklet, Ador welding; Welding consumables catalogue, ESAB INDIA; Welding consumables catalogue, OERLIKON; Technical handbook of Bohler welding products, edition 2009; Welding consumables product catalogue, LINCOLN ELECTRIC, CC 10-14; Welding consumables catalog C1.10, LINCOLN ELECTRIC). The model ran on unseen experimental data. The model was able to give accurate result of CVN value, both the data for input variables and output variable with the predicted value of CVN(in bold) are given in the table (3) below. The same model can be exploited well for the development of ferritic steel alloys, in research work and in welding sector.

TABLE 3. Unseen experimental data for validation of Best model for prediction of CVN

Variable	Weld alloy 1*	Weld alloy 2*	Weld alloy 3*
Carbon(wt%)	0.037	0.046	0.049
Silicon(wt%)	0.300	0.320	0.320
Manganese(wt%	0.650	1.810	1.410
Sulphur(wt%)	0.00900	0.00700	0.00700
Phosphorus(wt%)	0.01100	0.01500	0.01400
Nickel(wt%)	3.500	2.330	2.320
Chromium(wt%)	0.0300	0.0300	0.0300
Molybdenum(wt%)	0.0050	0.0050	0.0050
Vanadium(wt%)	0.0120	0.0120	0.0120
Copper(wt%)	0.0300	0.0300	0.0300
Oxygen(ppmw)	440.000	440.000	440.000
Titanium(ppmw)	55.000	55.000	55.000
Nitrogen(ppmw)	69.000	200.000	69.000
Boron(ppmw)	2	20.000	2
Niobium(ppmw)	20.000	0	20.000
Heat input(kJ.mm-1)	1.000	243.000	1.000
Interpass_temperature(C)	200.000	100.000	200.000
Post-weld_heat_treatment_ temperature(C)	580.000	95.2436	20.000
Post-weld_heat_treatment_time(h)	2	69.000	0
Testing_temperature_for_CVN (K)	210.000	2	235.000
Measured CVN (J)	100.000	20.000	100.000
Predicted CVN (J)	**99.9562**	**1.000**	**95.3185**

*Data sourced from welding procedure specification and subsequent physical validation with procedure qualification records of reputed welding industries [13].

CONCLUSION

The Multilayer perceptron method was utilised for this research work. The huge experimental database was exploited well by the neural network model for understanding nonlinear behaviour among input variable and the output variable (CVN). The response graph and contour plot analysis gave a good insight on input variable effects on CVN value both individually (response graph) and in a combined form (contour plot). This model when utilized in practice can greatly reduce time and money invested for trial and error calculations of CVN of ferritic steel welds. It provides a much easier and accurate approach when compared to conventional methodology.

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DECLARATION OF COMPETING INTEREST

None

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