Appendix - D

ACADEMIC CONTRIBUTION
(Publications)

The following is a list of the outcomes that have been published / presented during the period of the doctoral study:

JOURNAL PAPER

- B. J. Chauhan., S. N. Soman, "Modeling of Yield Strength of Ferritic Steel Welds" *International Journal for Research in Applied Science and Engineering Technology*, Vol. 6, issue 8, August 2018, 524-531. (UGC Approved Journal, *ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887).*
- B. J. Chauhan., S. N. Soman, "Modeling of Ultimate Tensile Strength of Ferritic Steel Welds" *International Journal for Research in Applied Science and Engineering Technology*, Vol. 6, issue 10, October 2018, 21-28. (UGC Approved Journal, *ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887).*

INTERNATIONAL CONFERENCE

- B. J. Chauhan**.,** S. N. Soman, "Modeling of Charpy Toughness of Ferritic Steel Welds", *International conference on Recent Advances in Metallurgy for Sustainable Development*, Key-note lecture, IC-RAMSD 2018,1-3 February2018, Organized by The M S University of Baroda., Under the patronage of Ministry of Steel Government of India, New Delhi.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue VIII, August 2018- Available at www.ijraset.com

Modelling of Yield Strength of Ferritic Steel Welds

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Abstract: The design of ferritic steel welding alloys to match the ever desired properties of newly developed steels is not a simple task. It is traditionally achieved by experimental trial and error, modifying compositions and welding conditions until an adequate result is discovered. Savings in 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 yield strengths of ferritic steel weld deposits from their chemical composition, welding conditions and heat treatments. The development of the General regression neural network (GRNN) models is described, as is the confirmation of their metallurgical fundamentals and accuracy.
Keywords: Neural network; Ferritic Steels; Yield Strength; Welding alloys; Variables

I. INTRODUCTION

The tensile strength 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 composition, the welding parameters and any heat treatment.

There is no common fundamental or experimental model capable of estimating the tensile parameters as a function of all these variables [1,2].

The difficulty is the complexity of the nonlinear relationship between input variables and yield strength. 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 yield strength of steel weld deposits as a function of many input variables.

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 Yield Strength 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.

In the present work, a neural network method is used as a Generalised Regression Neural Network[4]. All GRNN networks have 17 inputs, 1061 neurons in the first hidden layer, 2 neurons in the second hidden layer and 1 neuron in the output layer. (Figure.1)

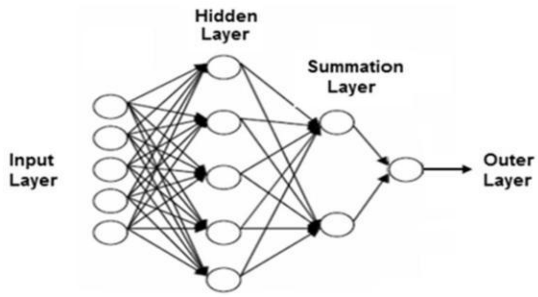

Figure 1. The architecture of Generalized Regression Neural Network

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(1061), Validation data set(530) (or Selection dataset) and testing dataset(530) of Yield Strength were compared. The lowest errors models were selected because they are best for practical applications.

Table 1 The 17 Input variables used in the analysis of the yield strength

Variables	Min	Max	Average	StDev	Variables	Min	Max	Average	StDev
C wt%	0.01	0.22	0.0708	0.0216	Cu wt%	0	2.18	0.0659	0.2062
Si wt%	0	1.63	0.3467	0.1262	Ti ppm	0	1000	78.6382	122.4481
Mn wt%	0.23	2.31	1.1959	0.4175	B ppm	0	200	9.2504	27.9733
S wt%	0.001	0.14	0.0081	0.0051	Nb ppm	0	1770	53.7704	145.3195
P wt%	0.001	0.25	0.0108	0.0075	HI kJ mm-1	0.55	7.9	1.3573	0.9931
Ni wt%	0	10.66	0.5807	1.4971	IPT C	20	375	205.4668	42.7739
Cr wt%	0	12.1	0.6243	1.5961	PWHTT C	20	780	328.1428	211.1714
Mo wt%	0	2.4	0.2001	0.3591	PWHTt h	0	50	9.4335	6.5893
V wt%	0	0.32	0.0191	0.0507	YS MPa	210	1026	535.7139	119.8611

III. RESULTS AND DISCUSSION

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

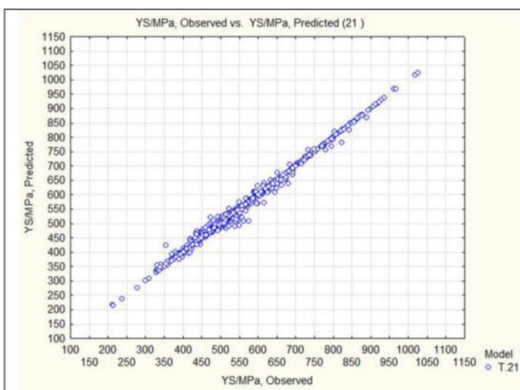

Figure a Training Data for GRNN model of Yield Strength

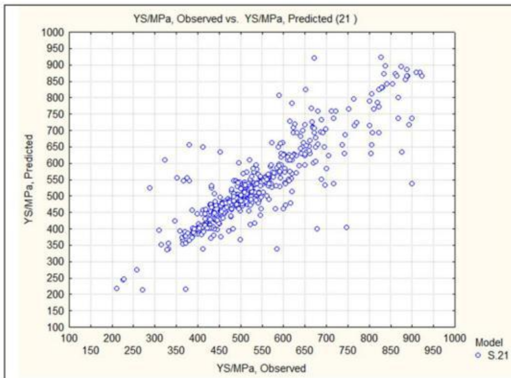

Fig b Validation Data for GRNN model of Yield Strength

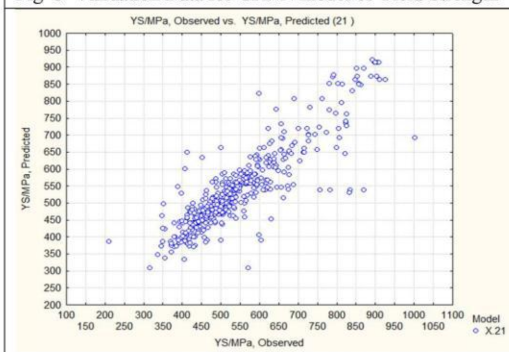

Fig c Test Data for GRNN model of Yield Strength

Figure 2 Training data, validation data and test data of the Best GRNN model for Yield Strength.

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(Yield Strength).(Figure 3)

a Yield Strength(MPa) – Carbon(wt %)

b Yield Strength(MPa) – Silicon(wt %)

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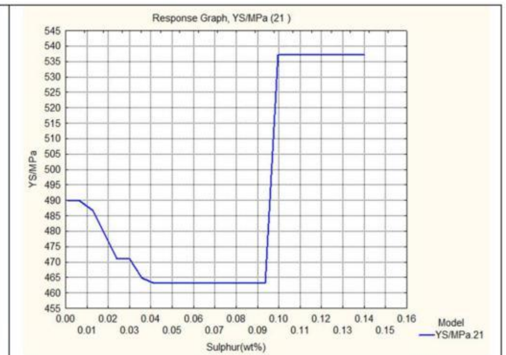
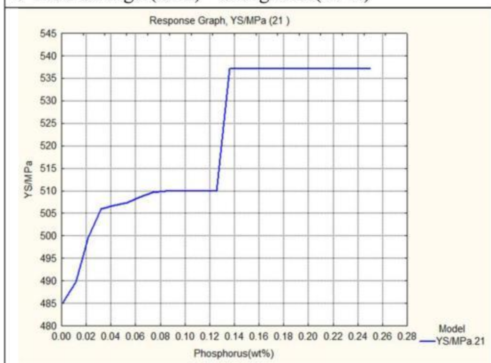
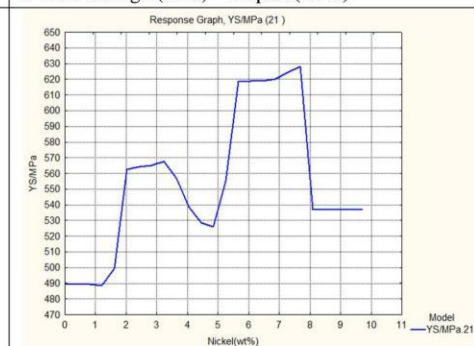
c Yield Strength(MPa) – Manganese(wt %)



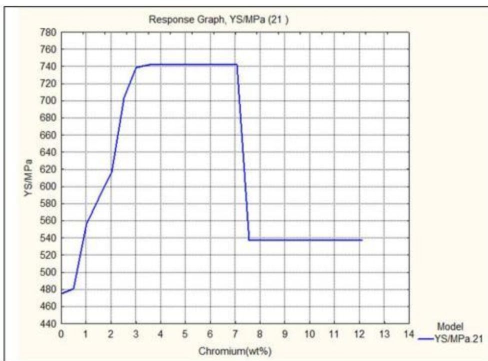
d Yield Strength(MPa) – Sulphur(wt %)



e Yield Strength(MPa) – Phosphorus(wt %)



f Yield Strength(MPa) – Nickel(wt %)



g Yield Strength(MPa) – Chromium(wt %)

h Yield Strength(MPa) – Molybdenum(wt %)

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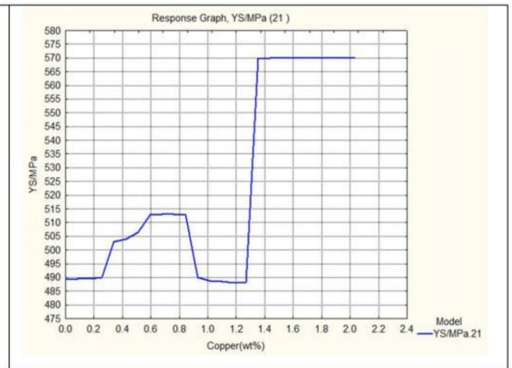
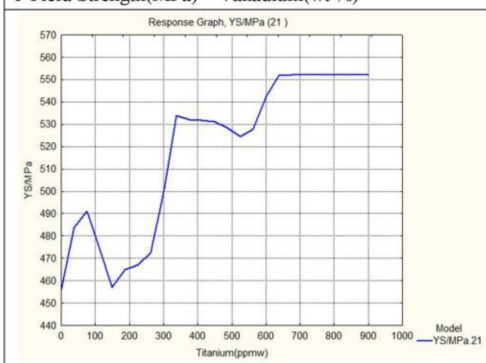
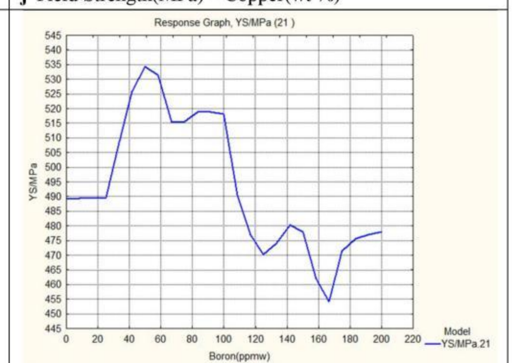
i Yield Strength(MPa) – Vanadium(wt %)



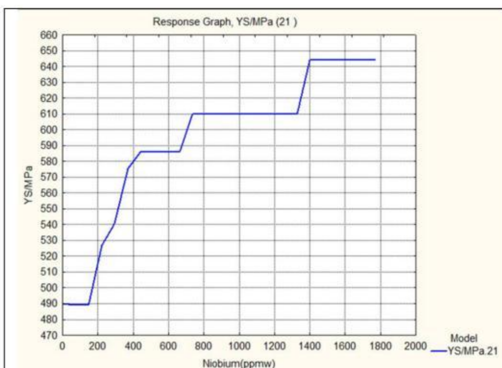
j Yield Strength(MPa) – Copper(wt %)



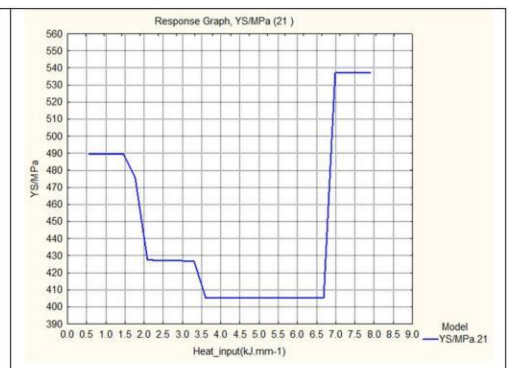
k Yield Strength(MPa) – Titanium(ppmw)



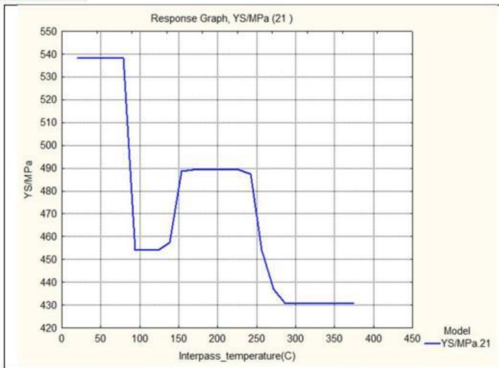
l Yield Strength(MPa) – Boron(ppmw)



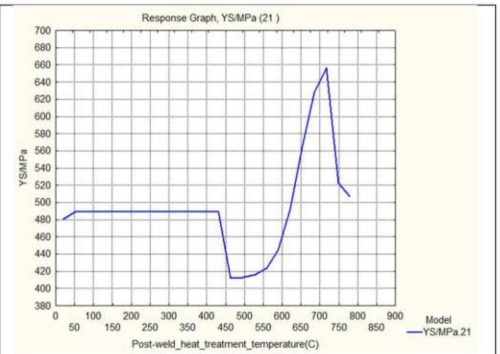
m Yield Strength(MPa) – Niobium(ppmw)



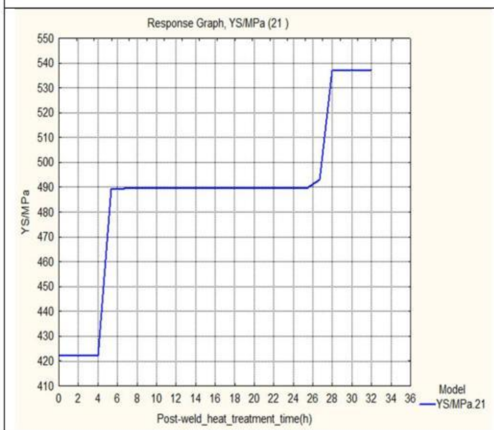
n Yield Strength(MPa) – Heat input (kJ mm-1)



o Yield Strength(MPa) – Interpass temperature (C)



p Yield Strength(MPa) – Post-weld heat treatment temperature (C)



q Yield Strength(MPa) – Post-weld heat treatment time (h)

Figure 3 Response graphs(a to q) of Input variables and Yield Strength of Ferritic Steel Welds

The influence of each of the variables on the yield strength of welding alloys which is discussed here. The carbon increases the yield strength up to 522 MPa with 0.05% then drop to 477 MPa at 0.1%. After 0.15% C, yield strength increases to 536 MPa than decrease to 519 MPa at 0.2% C. In the case of silicon between 0.1% to 0.2%, there is a drop of the 440 MPa to 431 MPa in yield strength and then increases to 505 MPa at 0.45%. At 0.8%, yield strength is 515 MPa and decreases between 1.0% to 1.2% from 515 MPa to 504 MPa. The trend of manganese shows the increase in the Mn% the value of the yield strength is also increased from 400 MPa to 563 MPa. At various points, 0.8%, 1.1%, 2.1% the decrease in yield strength is observed. The sulphur shows the first decrease in the yield strength from 490 MPa to 464 MPa. At slightly more than 0.09%, it is increased from 464 MPa to 537 MPa. The Phosphorus gives the increase in yield strength from 485 MPa to 537 MPa. The nickel has the maximum yield strength of 629 MPa at 7.8% and minimum 490 MPa at 1%. In figure. It shows at 4.9% the yield strength value drop to 528 MPa. More than 7.8 %i Ni gives a further drop in yield strength 539 MPa. The Chromium has a maximum yield strength of 740 MPa between 3% to 7%. More than 7% Cr reduces the yield strength to 539 MPa. Increase in the yield strength from 479 MPa to 740 MPa only by the gradual addition of chromium up to 3%. Molybdenum increases the yield strength from 490 MPa to 730 MPa at 1.98%. At 0.8% Mo gives yield strength 719 MPa. More than 1.98% Mo decreases yield strength from 730 MPa to 539 MPa. Vanadium increases the yield strength from 492 MPa to 600 MPa at 0.15%. At 0.22% V, yield strength decreases to 538 MPa. Copper increases the yield strength from 490 MPa to 513 MPa at 0.6%. At 1.2% Cu, yield strength decreases to 488 MPa. Cu gives maximum yield strength of

570 MPa when it is more than 1.27%. Titanium gives a minimum yield strength of 457 MPa to maximum 553 MPa. At 700 ppm yield strength is the highest. In between some range of Titanium from 90 ppm to 630 ppm, up and down in yield strength. Boron shows maximum yield strength of 535 MPa at 50 ppm. More than 50 ppm decreases the yield strength to 454 MPa. Niobium has a trend of increase in yield strength from 490 to 644 MPa with an increase from 180 to 1400 ppm.

Heat Input has stated of the yield strength of 490 MPa, then drops in between 1.5 to 6.6 kJ mm-1 to 406 MPa. The highest value of yield strength 537 MPa is obtained at and more than 6.7 kJ mm-1. When the Interpass temperature is less than 70 C, the yield strength is 538 MPa. More than 70 C decrease in yield strength is observed to 470 MPa and further increase to 490 MPa at 150 C. Minimum yield strength is 430 MPa at 270 C. Post weld heat treatment temperature increases up to 425 C shows yield strength 480 MPa and 490 MPa. More than 455 C, the yield strength increases to maximum 655 MPa at 710 C then drop to 510MPa. Post weld heat treatment time has a trend of increase in yield strength from 420 to 490 MPa between 4 to 5 hours. More than 25 hours, it increases maximum yield strength to 538 MPa.

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

The GRNN model has good accuracy in prediction of yield strength of ferritic steel welds on unseen data which is excellent for the design of welds.(Table.2) The predicted yield strength for the unseen data of three weld alloys are compared with measured values of yield strength 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 yield strength by GRNN model for unseen data of three ferritic weld deposits

Variable	Weld alloy 1	Weld alloy 2	Weld alloy 3
Carbon(wt%)	0.041	0.049	0.081
Silicon(wt%)	0.30	0.35	0.24
Manganese(wt%)	0.62	1.37	0.59
Sulphur(wt%)	0.007	0.007	0.009
Phosphorus(wt%)	0.010	0.013	0.012
Nickel(wt%)	2.38	1.06	10.8
Chromium(wt%)	0.03	0.03	1.17
Molybdenum(wt%)	0.005	0.005	0.300
Vanadium(wt%)	0.012	0.012	0.006
Copper(wt%)	0.03	0.03	0.30
Titanium(ppm)	55	55	00
Boron(ppm)	2	2	1
Niobium(ppm)	20	20	10
Heat_input(kJ.mm-1)	1.0	1.0	1.2
Interpass_temperature(C)	200	200	150
Postweld_heat_treatment_temperature(C)	250	250	250
Post-weld_heat_treatment_time(h)	14	14	14
Measured YS/MPa	466	498	896
Predicted YS/MPa	466	497	913

IV. CONCLUSIONS

General Regression Neural Network is the best for capturing trends of input variables and output variables in weld alloys which is 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 yield strength. It is now possible, therefore, to estimate the yield strength 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 steels 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 yield strength of weld alloys for real applications in industries.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue VIII, August 2018- Available at www.ijraset.com

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

Modelling of Ultimate Tensile Strength of Ferritic Steel Welds

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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 ultimate tensile strength 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; Ultimate Tensile Strength; Welding alloys; Variables

I. INTRODUCTION

The tensile strength 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 tensile parameters as a function of all these variables [1,2].

The difficulty is the complexity of the nonlinear relationship between input variables and ultimate tensile strength. 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 ultimate tensile strength 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 Ultimate Tnsile Strength as a function of a large number of variables, including the chemical compositions, the welding parameters and heat treatments. As a consequence, the Ultimate Tnsile strength database consists of 2091 separate experiments with 18 input variables.

In the present work, a neural network method is used as a Generalised Regression Neural Network[4]. All GRNN networks have 18 inputs, 1047 neurons in the first hidden layer, 2 neurons in the second hidden layer and 1 neuron in the output layer. (Figure.1)

INTERNATIONAL CONFERENCE

ON

RECENT ADVANCES IN METALLURGY FOR SUSTAINABLE DEVELOPMENT

(IC-RAMSD 2018)

FEBRUARY 1-3, 2018

This is to certify that Dr./Mr./Ms.

B. J. CHAUHAN

from METALLURGICAL AND MATERIAL ENGINEERING DEPARTMENT has presented Plenary/Key-~~Note~~/Special/Technical paper titled MODELLING OF TOUGHNESS OF THE FERRITIC STEEL WELDS

in the International Conference on RECENT ADVANCES IN METALLURGY FOR SUSTAINABLE DEVELOPMENT (IC-RAMSD 2018) organized by the Department of Metallurgical and Materials Engineering, Faculty of Technology and Engineering, The M.S. University of Baroda under the patronage of Ministry of Steel, Government of India, New Delhi on February 1-3, 2018 held at Faculty of Technology & Engineering, The Maharaja Sayajirao University of Baroda, Vadodara.

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