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Modelling of Utltimate 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)

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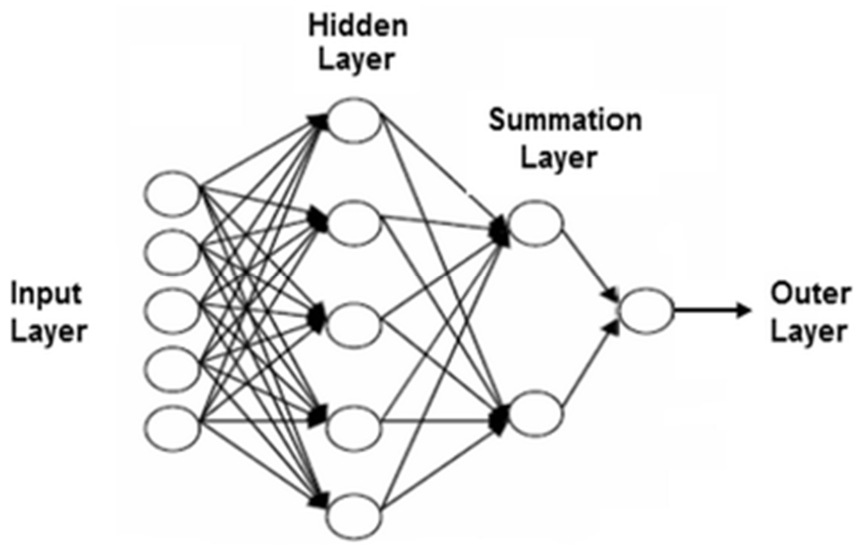

Figure 1. The architecture of Generalized Regression Neural Network

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(1047), validation data set(522) (or selection dataset) and testing dataset(522) of Ultimate Tensile Strength were compared. The lowest traning errors models were selected because they are best for practical applications.

Table 1 The 18 Input variables used in the analysis of the Ultimate Tensile Strength

Variables	Min	Max	Average	StDev	Variables	Min	Max	Average	StDev
C wt%	0.01	0.22	0.0705	0.021	Cu wt%	0	2.18	0.0597	0.1953
Si wt%	0.01	1.63	0.3477	0.1283	O ppm	0	1650	377.6982	166.9297
Mn wt%	0.23	2.31	1.1955	0.4156	Ti ppm	0	1000	80.0548	124.85
S wt%	0.001	0.14	0.008	0.0051	B ppm	0	200	9.3161	28.1533
P wt%	0.001	0.25	0.0107	0.0073	Nb ppm	0	1770	51.1751	141.6126
Ni wt%	0	10.66	0.581	1.5071	HI kJ mm-1	0.55	7.9	1.3392	0.9366
Cr wt%	0	12.1	0.5869	1.4827	IPT C	20	375	206.4539	41.9047
Mo wt%	0	2.4	0.1988	0.3606	PWHTT C	20	770	333.6054	206.2762
V wt%	0	0.32	0.0187	0.0506	PWHTt h	0	50	9.7532	6.5109
UTS MPa	273	1184	621.21	123.49					

III. RESULTS AND DISCUSSION

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

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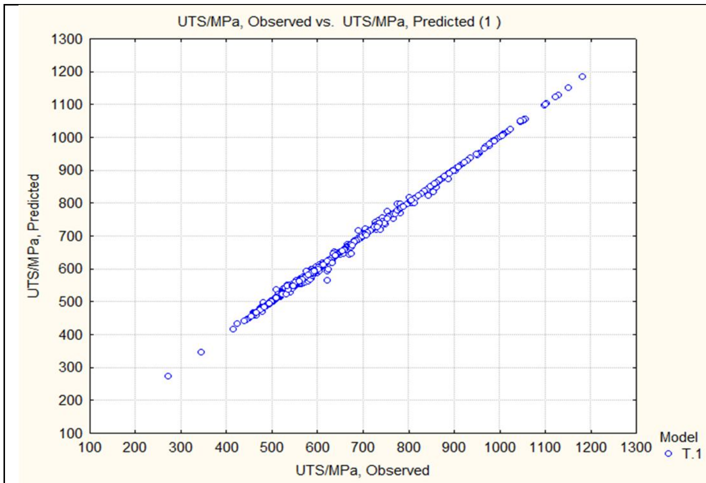

Figure a Training Data for GRNN model of Ultimate Tensile Strength

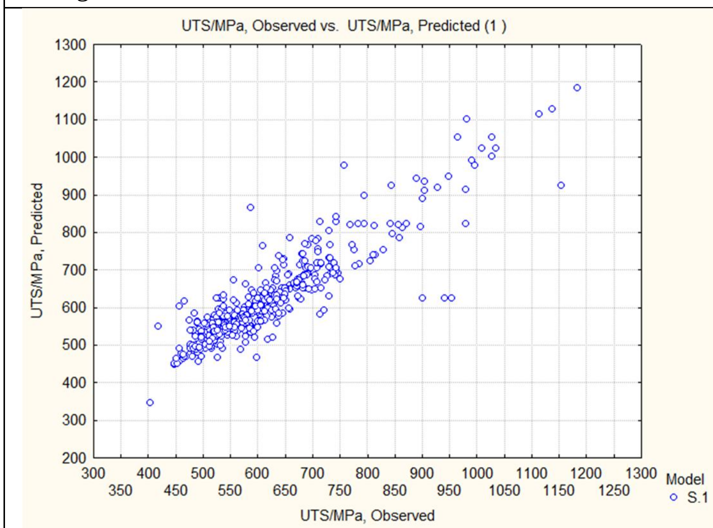

Fig b Validation Data for GRNN model of Ultimate Tensile Strength

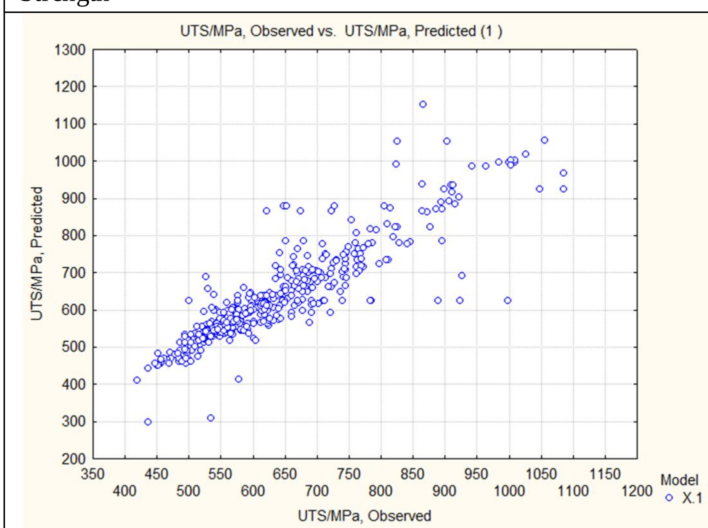

Fig c Test Data for GRNN model of Ultimate Tensile Strength

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

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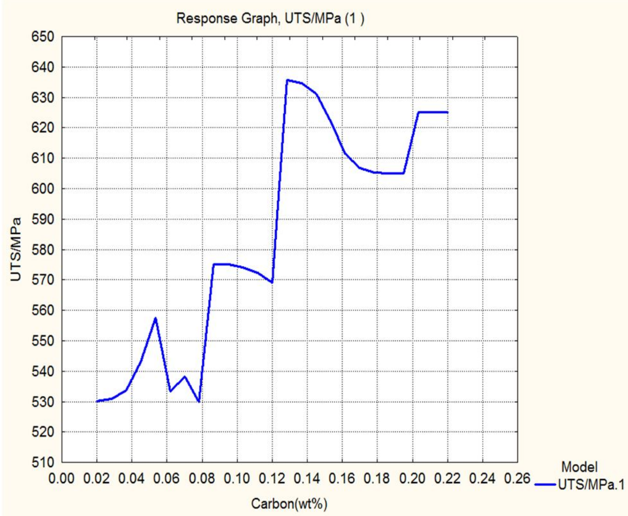
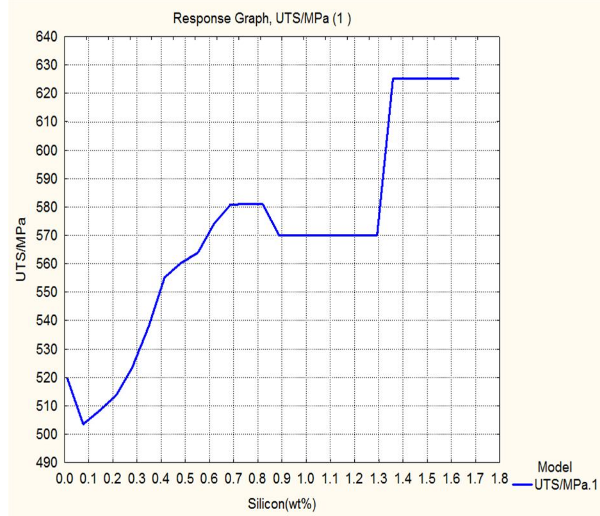
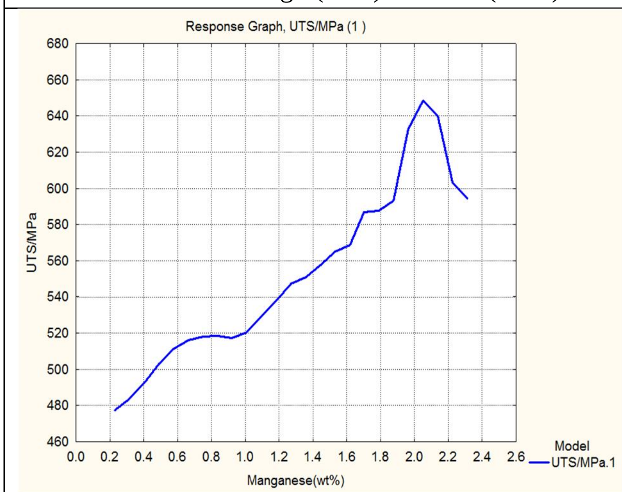
The best model of GRNN has training error 0.011404, validation error (selection error) 0.018101, and testing error 0.018669. This model is used for getting the results in form of various response graphs to understand the trend between the input variables and output variable(Ultimate Tensile Strength).(Figure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



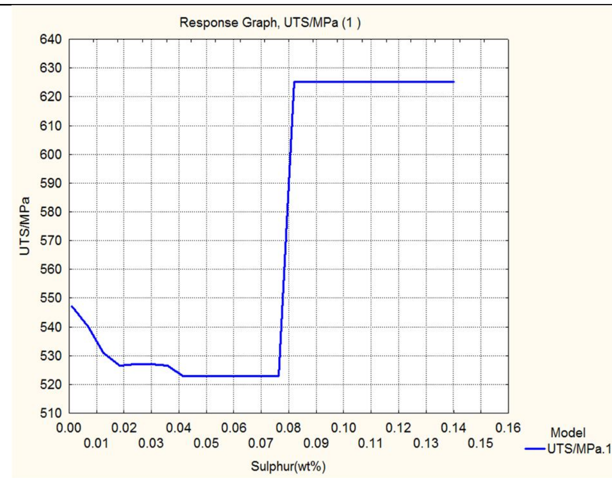
a Ultimate Tensile Strength(MPa) – Carbon(wt %)



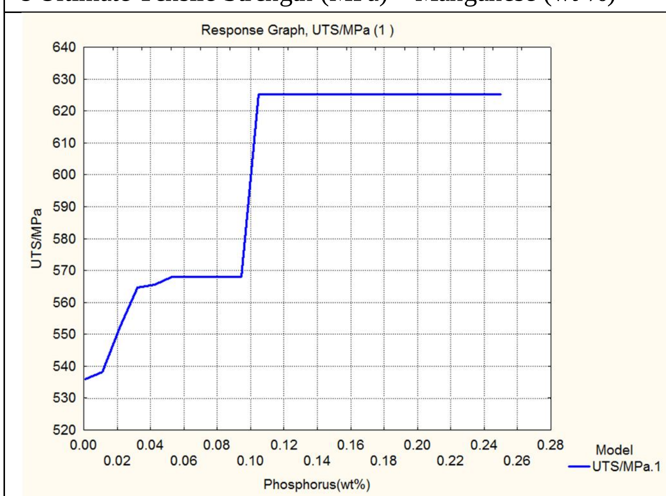
b Ultimate Tensile Strength(MPa) – Silicon(wt %)



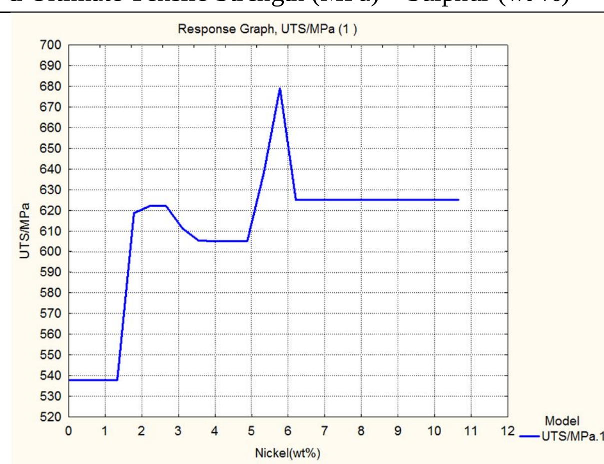
c Ultimate Tensile Strength (MPa) – Manganese (wt %)



d Ultimate Tensile Strength (MPa) – Sulphur (wt %)



e Ultimate Tensile Strength (MPa) – Phosphorus(wt %)



f Ultimate Tensile Strength (MPa) – Nickel(wt %)

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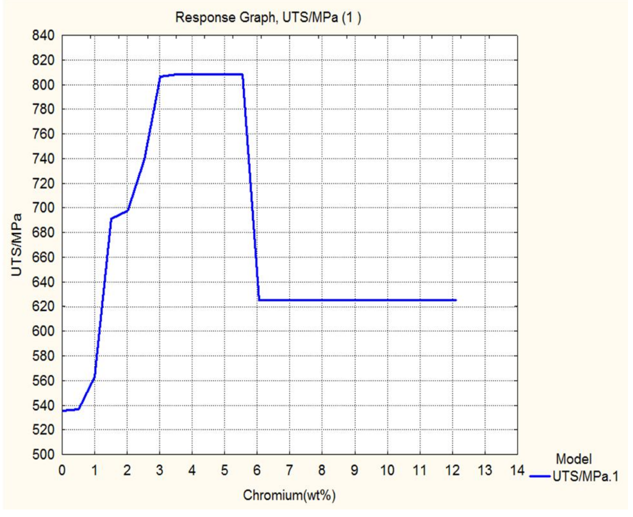
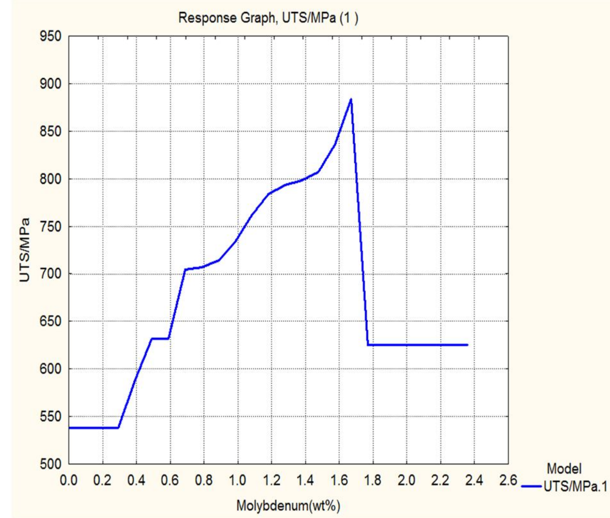
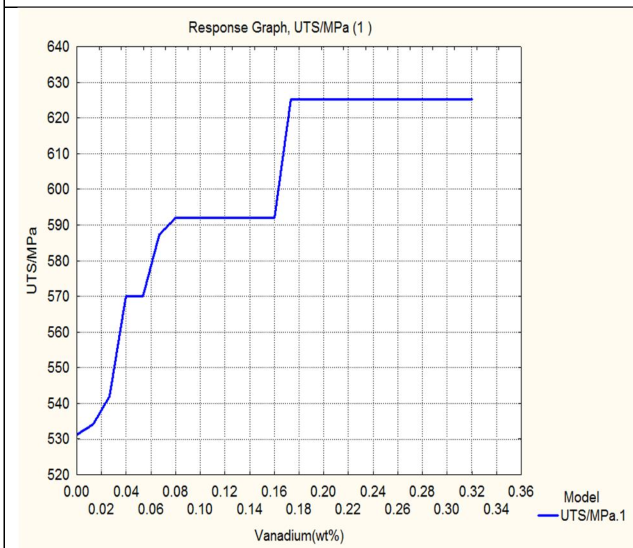


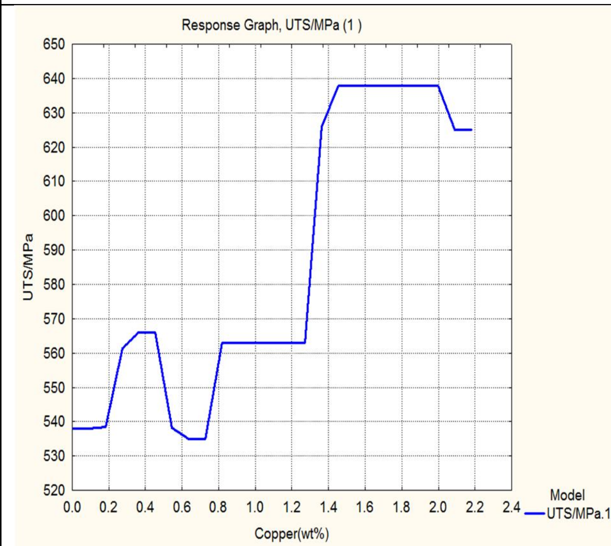
g Ultimate Tensile Strength (MPa) – Chromium(wt %)



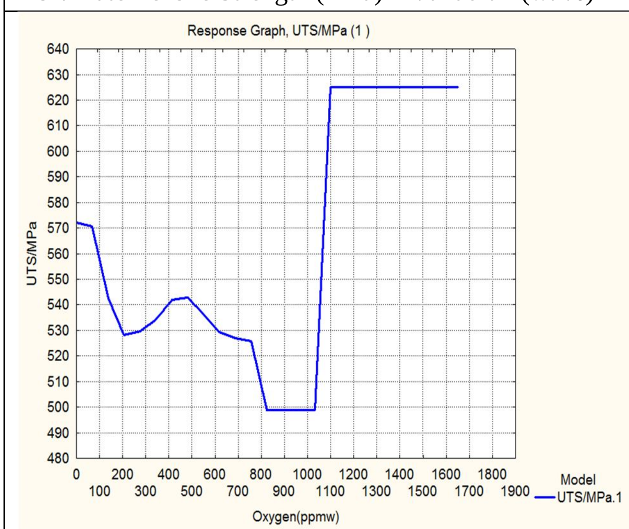
h Ultimate Tensile Strength (MPa) – Molybdenum(wt %)



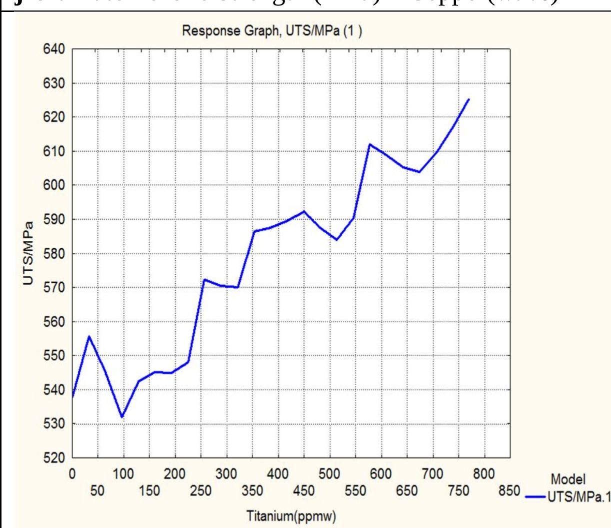
i Ultimate Tensile Strength (MPa) – Vanadium(wt %)



j Ultimate Tensile Strength (MPa) – Copper(wt %)



k Ultimate Tensile Strength (MPa) – Oxygen(ppm)



l Ultimate Tensile Strength (MPa) – Titanium(ppm)

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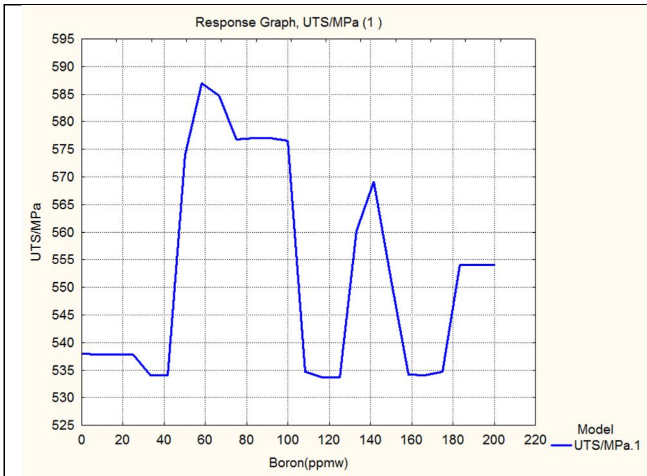
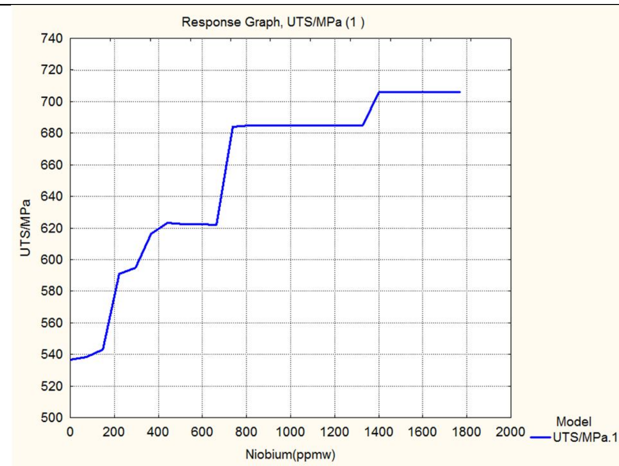
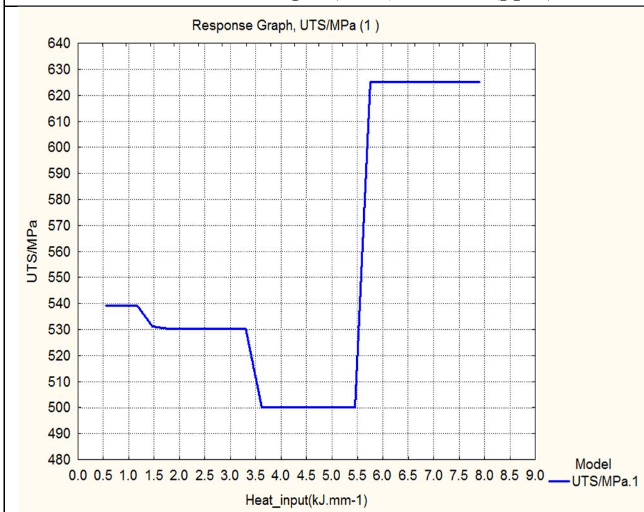


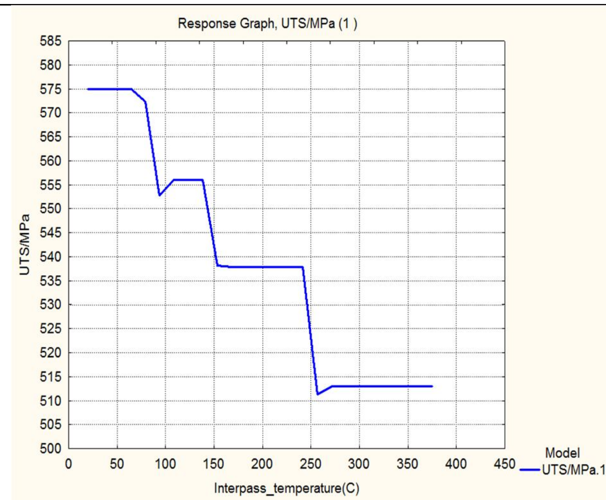
m Ultimate Tensile Strength (MPa) – Boron(ppm)



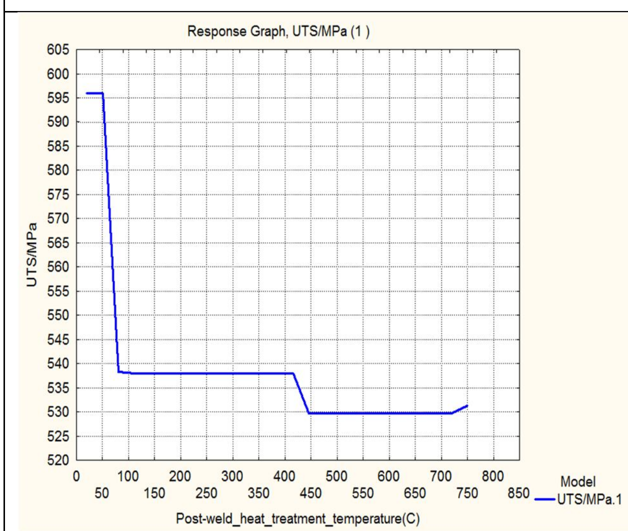
n Ultimate Tensile Strength (MPa) – Niobium(ppm)



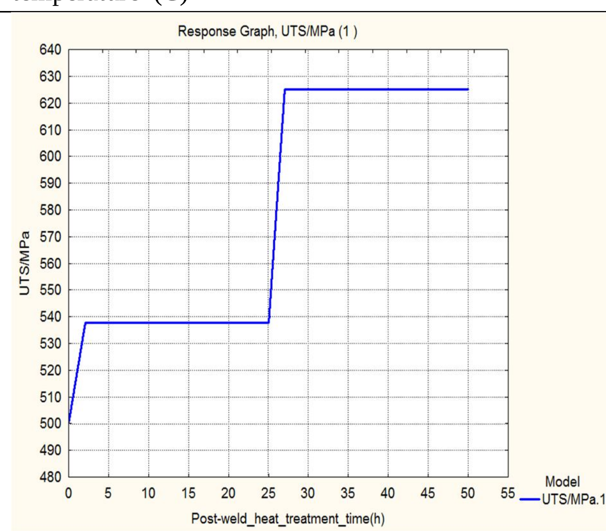
o Ultimate Tensile Strength (MPa) – Heat input (kJ mm-1)



p Ultimate Tensile Strength (MPa) – Interpass temperature (C)



q Ultimate Tensile Strength (MPa) – Post-weld heat treatment temperature (C)



r Ultimate Tensile Strength (MPa) – Post-weld heat treatment time (h)

Figure 3 Response graphs(a to r) of Input variables Ultimate Tensile Strength of Ferritic Steel Welds

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The influence of each of the variables on the ultimate tensile strength of welding alloys, which is discussed here. The carbon increases the ultimate tensile strength up to 635 MPa near to 0.13%, and the minimum at 530 MPa at 0.02%. Overall %C increases between 0.02% to 0.22%, give a general increase in the ultimate tensile strength.

Some points are observed to decrease maximum up to 27 MPa at 0.08%C and 25 MPa at 0.198%C. In the case of silicon between 0.1% to 0.8%, there is an increase of the 505 MPa to 580 MPa in the ultimate tensile strength and then constant to 570 MPa between 0.9% to 1.3% Si with drop in 10MPa at0. 82% Si.

At 1.35%, the ultimate tensile strength is maximum 625 MPa. The trend of manganese shows the increase in the Mn% from 0.2% to 2.08%, the value of the ultimate tensile strength is also increased from 478 MPa to 648 MPa. After 2.08% Mn, there is reduced to 592 MPa at 2.4% Mn.

The sulphur shows the first decrease in the ultimate tensile strength from 548 MPa to 523 MPa.

At 0.08%, it is increased from 523 MPa to 625MPa. The Phosphorus gives the increase in the ultimate tensile strength from 536 MPa to 625 MPa. The nickel has the maximum ultimate tensile strength of 680 MPa at 5.8% and minimum 538 MPa at 1.3%. In the figure, it shows at 2.5% the ultimate tensile strength value drops from 622 MPa to 605 MPa. More than 5.8 %i Ni gives a further drop in ultimate tensile strength 625 MPa.

The Chromium has a maximum ultimate tensile strength of 809 MPa between 3% to 5.5%. More than 5.5% Cr reduces the ultimate tensile strength to 623 MPa. Increase in the ultimate tensile strength from 538 MPa to 809 MPa only by the gradual addition of chromium up to 4%. Molybdenum increases the ultimate tensile strength from 547 MPa to 880 MPa at 1.68%. At 1.68% Mo gives a maximum ultimate tensile strength 880 MPa.

More than 1.68% Mo decreases ultimate tensile strength from 880 MPa to 625 MPa.

Vanadium increases the ultimate tensile strength from a minimum 532 MPa to a maximum 626 MPa at 0.17%. At 0.17% V, ultimate tensile strength is constant to 626 MPa. Copper increases the ultimate tensile strength from 538 MPa to 638 MPa at 1.45%. Between 0.48% to 0.74% Cu, the ultimate tensile strength decreases to 535 MPa. Cu gives maximum tensile strength of 638 MPa when it is in range, from 1.45% to 2.0%. Oxygen lowers the ultimate tensile strength of 570 MPa to 500 MPa when it is in the range of 820 ppm to 1020 ppm Oxygen content.

Higher than 1020ppm Oxygen, there is an increase in the ultimate tensile strength from 500 MPa to 625 MPa. Titanium gives a minimum ultimate tensile strength of 539 MPa to maximum 625 MPa. At 775 ppm ultimate tensile strength is the highest. In between some range of Titanium from 40 ppm to 675 ppm, up and down in range of 5 MPa to 20MPa in the ultimate tensile strength.

Boron shows maximum ultimate tensile strength of 587 MPa at 58 ppm. More than 58 ppm, there is an up and down in ultimate tensile strength between the difference of 50MPa to 20 MPa. Niobium has a trend of increase in ultimate tensile strength from 542 MPa to 708 MPa with an increase from 180 to 1400 ppm.

Heat Input has stated that the maximum ultimate tensile strength of 625 MPa at 5.5 kJ mm-1. Between 0.5 kJ mm-1 to 5.5 kJ mm-1 reduces from 540 MPa to 500 MPa.

When the Interpass temperature is less than 70 C, the ultimate tensile strength is 575 MPa. More than 70 C, a decrease in ultimate tensile strength is observed to 513 MPa with increase in Interpass temperature up to 270 C. Post weld heat treatment temperature increases from 50 C to 750 C, shows ultimate tensile strength decrease from 596 MPa to 530 MPa. Post weld heat treatment time has a trend of increase in ultimate tensile strength from 500 to 539 MPa between 2 to 25 hours. More than 25 hours, it increases maximum ultimate tensile strength to 625 MPa.

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

The GRNN model has good accuracy in prediction of ultimate tensile strength of ferritic steel welds on unseen data which is excellent for the design of welds.

(Table.2) The predicted ultimate tensile strength of the unseen data of three weld alloys are compared with measured values of ultimate tensile 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.

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Table 2 Predicted Ultimate Tensile 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	0.088	0.11
Silicon(wt%)	0.3	0.35	0.28
Manganese(wt%)	0.62	0.54	0.6
Sulphur(wt%)	0.007	0.007	0.007
Phosphorus(wt%)	0.010	0.009	0.016
Nickel(wt%)	2.38	7.0	10.62
Chromium(wt%)	0.03	0.15	1.13
Molybdenum(wt%)	0.005	0.4	0.3
Vanadium(wt%)	0.012	0.016	0.006
Copper(wt%)	0.03	0.01	0.3
Oxygen(ppm)	440	290	290
Titanium(ppm)	55	0.0	0.0
Boron(ppm)	2.0	1.0	1.0
Niobium(ppm)	20	10	10
Heat_input(kJ.mm-1)	1.0	1.4	1.4
Interpass_temperature(C)	200	150	200
Postweld_heat_treatment_temperature(C)	250	250	250
Post-weld_heat_treatment_time(h)	14	16	16
Measured UTS/MPa	538	972	1194
Predicted UTS/MPa	538	978	1183

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 Ultimate Tensile strength. It is now possible, therefore, to estimate the Ultimate Tensile 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 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 Ultimate Tensile strength of weld alloys for real applications in industries.

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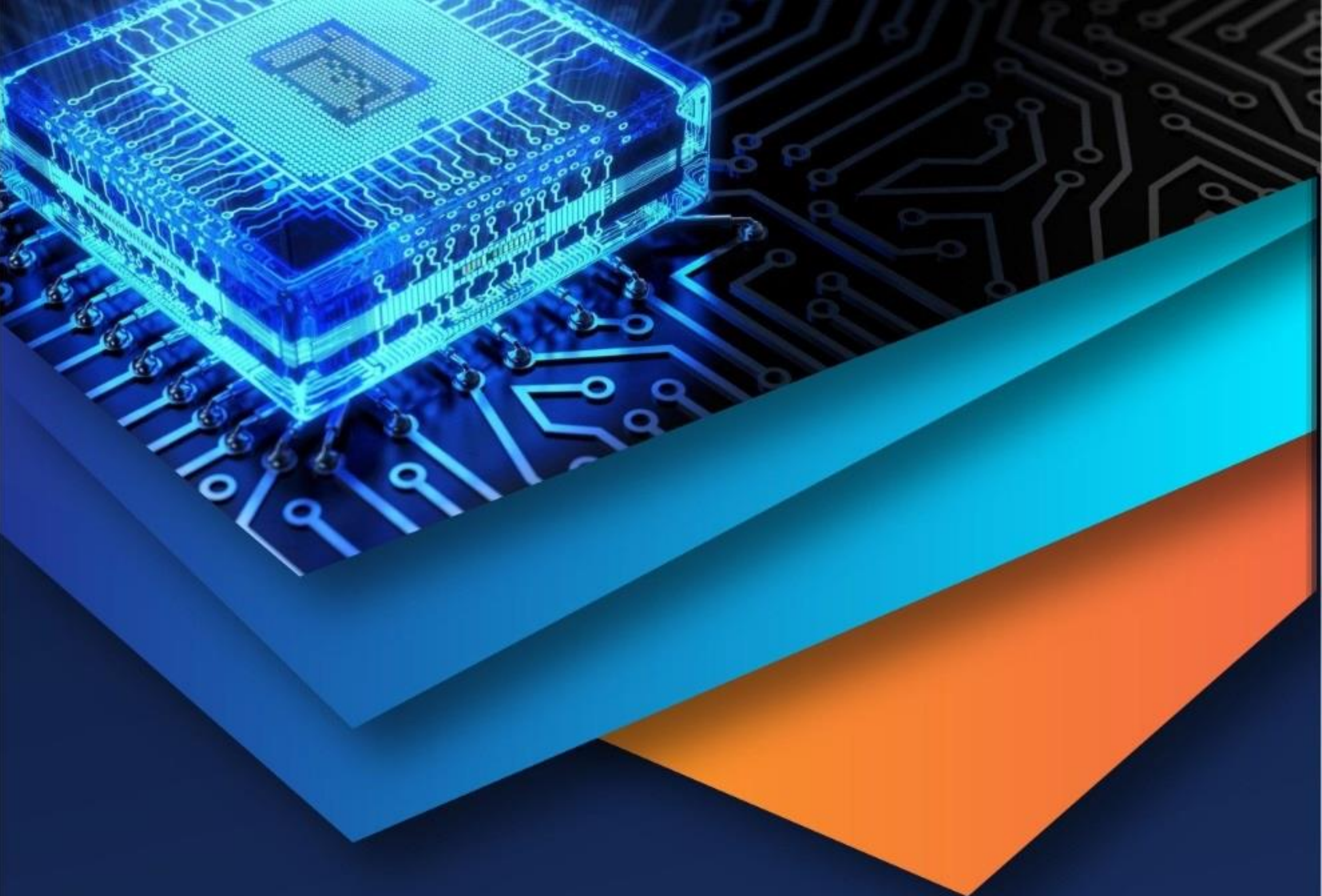

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