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Modelling of Elongation 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 elongation 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; Elongation; 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 elongation 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 Elongation as a function of a large number of variables, including the chemical compositions, the welding parameters and heat treatments. As a consequence, the Elongation database consists of 1827 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, 915 neurons in the first hidden layer, 2 neurons in the second hidden layer and 1 neuron in the output layer. (Figure.1)

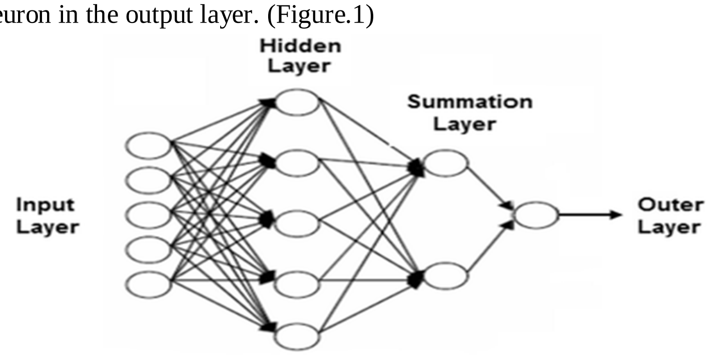

Figure 1. The architecture of Generalized Regression Neural Network

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(915), validation data set(456) (or selection dataset) and testing dataset(456) of Elongation 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 Elongation

Variables	Min	Max	Average	StDev	Variables	Min	Max	Average	StDev
C wt%	0.01	0.16	0.0688	0.0189	Cu wt%	0	2.04	0.0628	0.202
Si wt%	0.01	1.14	0.352	0.1229	O ppm	63	1650	411.2567	117.9406
Mn wt%	0.24	2.31	1.2102	0.3986	Ti ppm	0	1000	84.9978	126.1291
S wt%	0.002	0.14	0.0078	0.0049	B ppm	0	200	10.306	29.8403
P wt%	0.001	0.25	0.0101	0.0071	Nb ppm	0	1770	47.0246	139.0368
Ni wt%	0	10.66	0.5374	1.5246	HI kJ mm-1	0.55	4.8	1.2294	0.7057
Cr wt%	0	9.35	0.4452	1.1844	IPT C	20	350	203.8697	35.2603
Mo wt%	0	2.4	0.1798	0.3569	PWHTT C	20	750	319.5599	188.6206
V wt%	0	0.32	0.0151	0.0437	PWHTt h	0	32	10.3452	6.1765
ELOG %	7.4	41.1	25.6466	4.6985					

III. RESULTS AND DISCUSSION

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

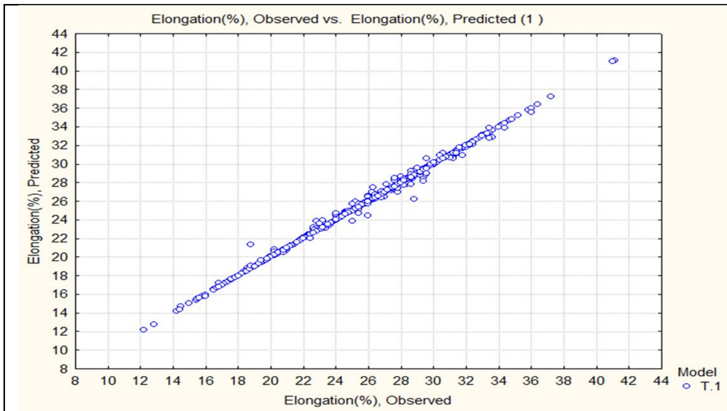

Figure a Training Data for GRNN model of Elongation

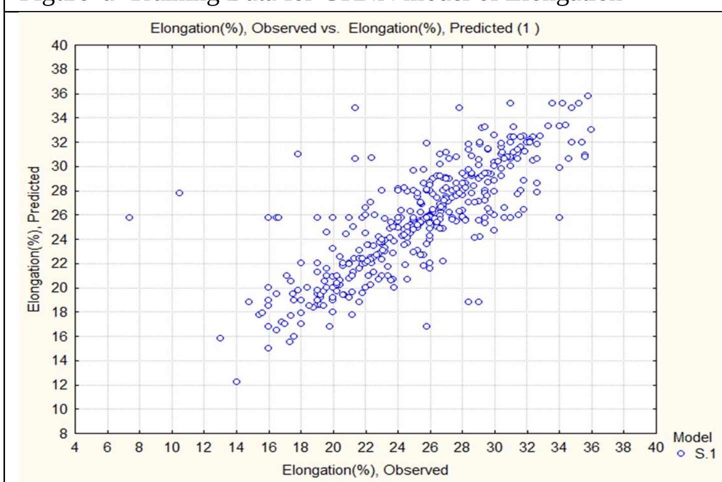

Fig b Validation Data for GRNN model of Elongation

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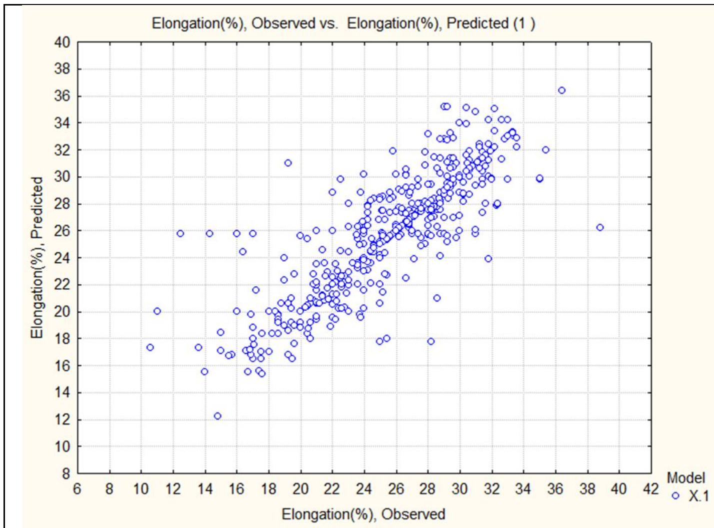
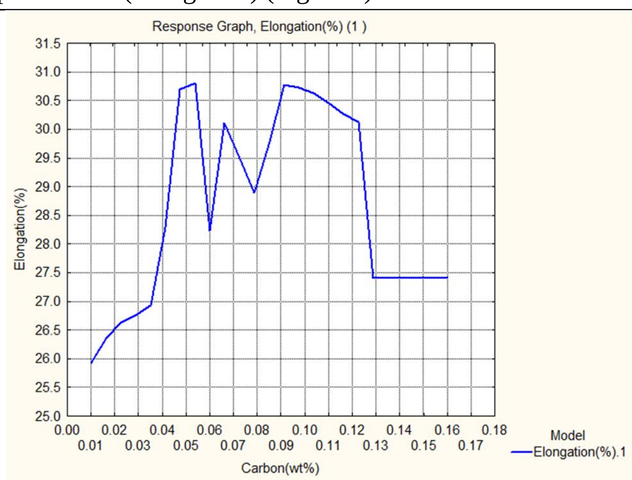


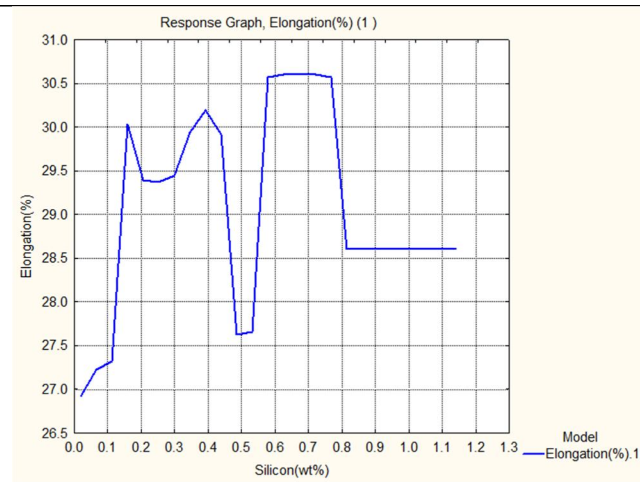
Fig c Test Data for GRNN model of Elongation

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

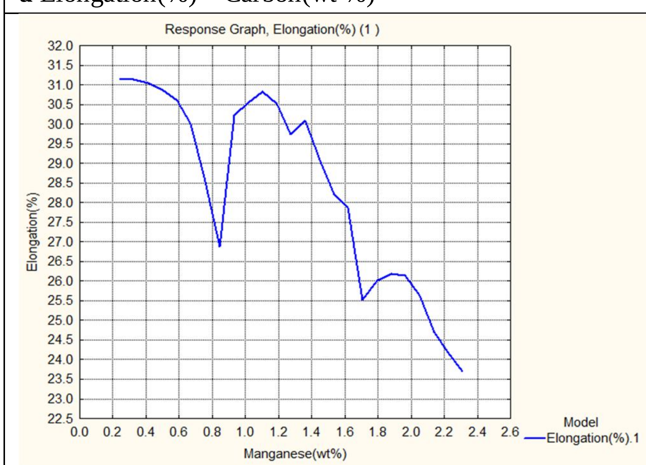
The best model of GRNN has training error 0.010208, validation error (selection error) 0.134319 and testing error 0.123726. This model is used for getting the results in form of various response graphs to understand the trend between the input variables and output variable(Elongation).(Figure 3)



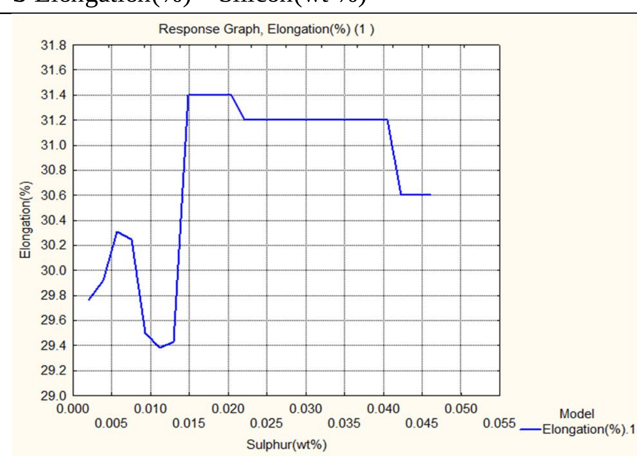
a Elongation(%) – Carbon(wt %)



b Elongation(%) – Silicon(wt %)



c Elongation(%) – Manganese (wt %)



d Elongation(%) – Sulphur (wt %)

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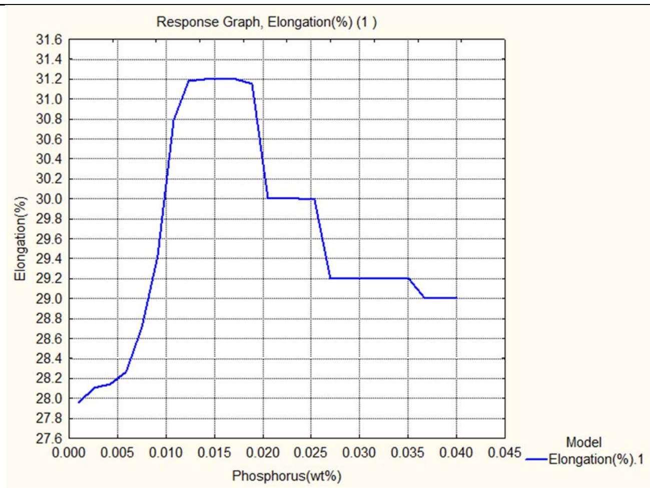
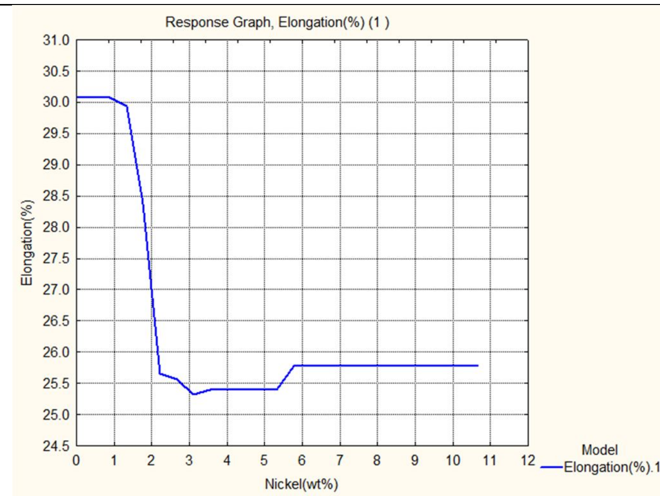
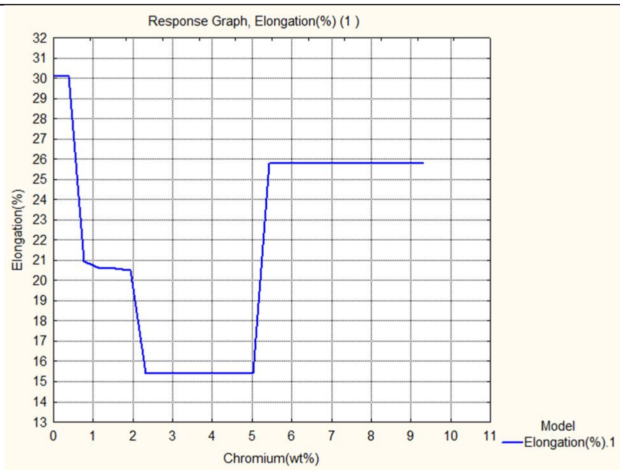


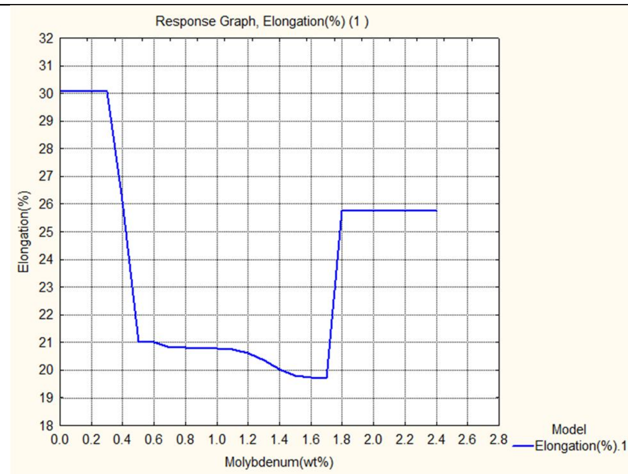
e Elongation(%) – Phosphorus(wt %)



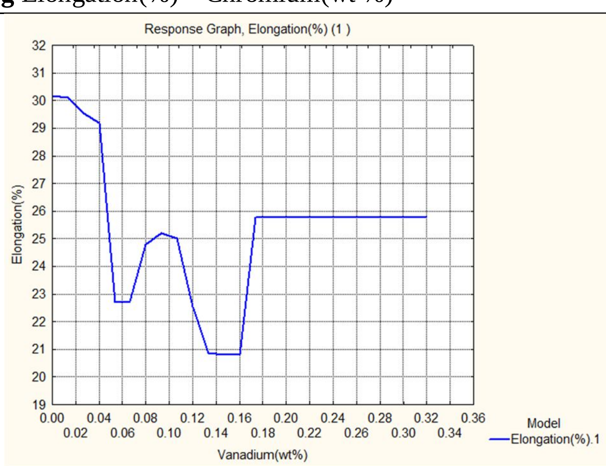
f Elongation(%) – Nickel(wt %)



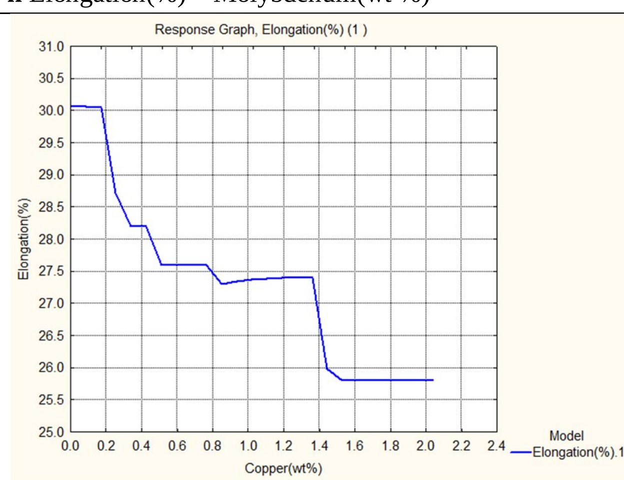
g Elongation(%) – Chromium(wt %)



h Elongation(%) – Molybdenum(wt %)



i Elongation(%) – Vanadium(wt %)



j Elongation(%) – Copper(wt %)

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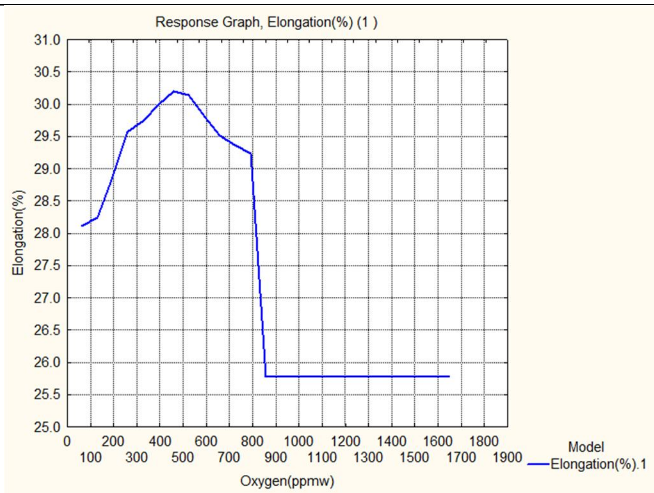
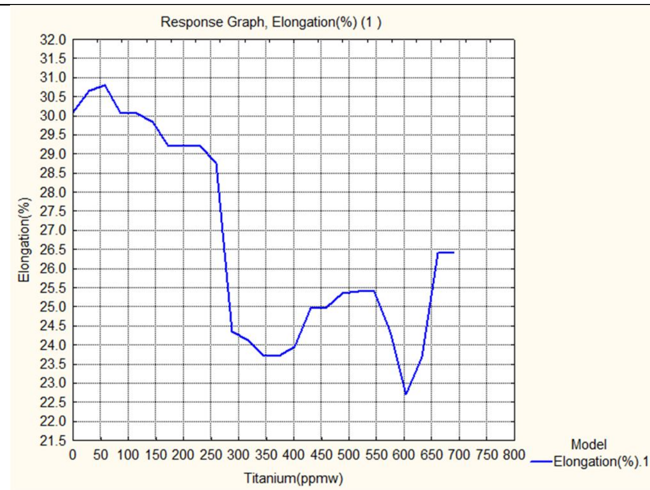
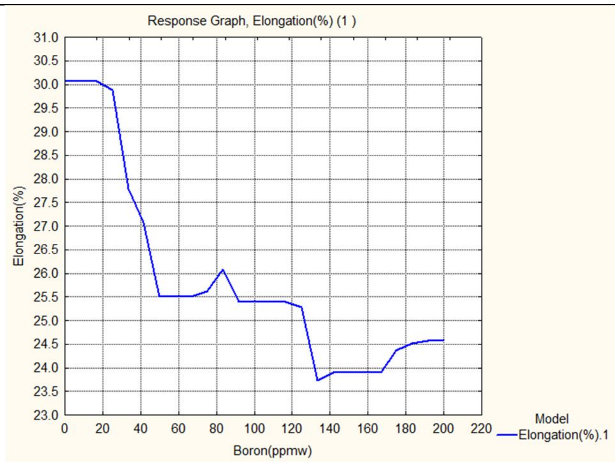


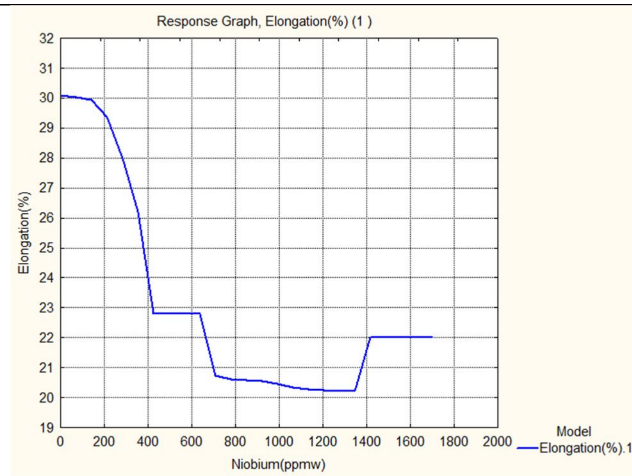
k Elongation(%) – Oxygen(ppm)



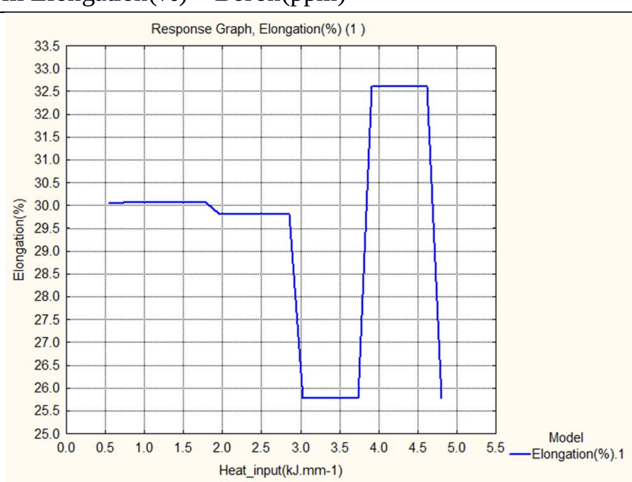
l Elongation(%) – Titanium(ppm)



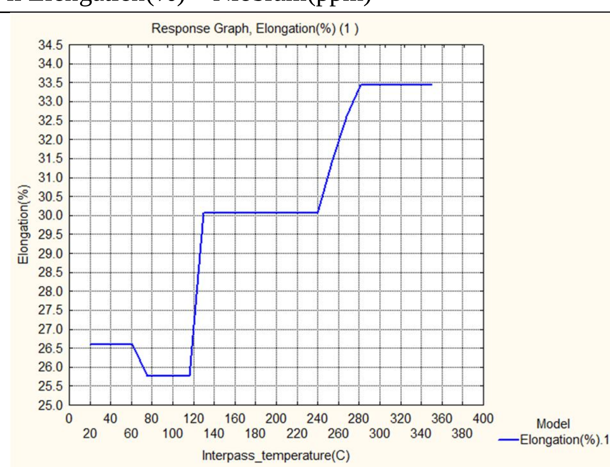
m Elongation(%) – Boron(ppm)



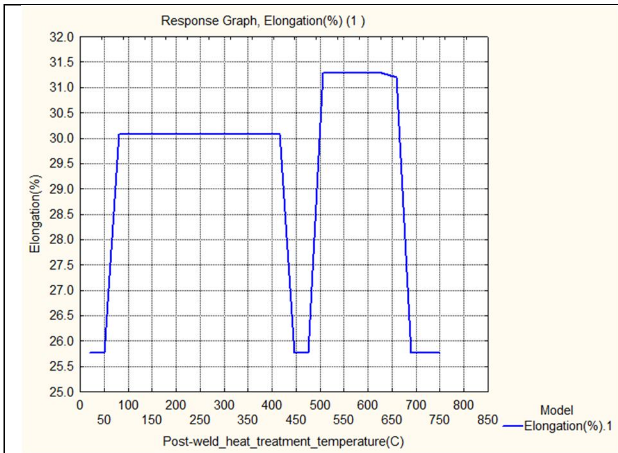
n Elongation(%) – Niobium(ppm)



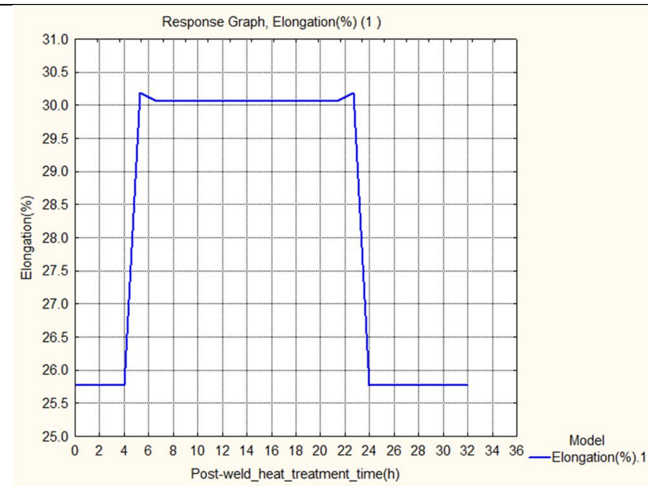
o Elongation(%) – Heat input (kJ mm-1)



p Elongation(%) – Interpass temperature (C)



q Elongation(%) – Post-weld heat treatment temperature (C)



r q Elongation(%) – Post-weld heat treatment time (h)

Figure 3 Response graphs(a to r) of Input variables Elongation of Ferritic Steel Welds

The influence of each of the variables on the elongation of welding alloys, which is discussed here. The % elongation starts increasing from 26% at 0.01% C up to 30.7 % near to 0.055% C. Up and down of % elongation is maximum 2.5%, between the 0.055%C to 0.09%C. There is a decrease in %elongation after 0.09% C and it goes to 27.4 % at 0.0129% C. . In the case of silicon between 0.01% to 1.14%, there is an increase from the 26.9% to 30% (at 0.16%Si) in the elongation and then further decrease to 29.4% Elongation in the range of 0.2% to 0.3% Si.At near to 0.4% Si, Elongation is 30.2%. Reduction of the Elongation of 27.7% is observed near to 0.5% Si in the graph. Highest value of 30.7% Elongation is observed between the 0.58% Si to 0.78% Si.The drop in Elongation to 28.7% at 0.8% Si and then, it remains constant. The trend of manganese shows the increase in the Mn% from 0.24% to 2.3%, the value of the elongation also decreases from 31.2% to 23.7%. Between 0.24% Mn to 0.84% Mn, there is decrease in % elongation to 26.8% and further increases to 30.8% at 1.1% Mn. Over 1.1% Mn, there is generally decreased in %Elongation with increase in %Mn, with little fluctuation of 0.6% Elongation at 1.9% Mn. The sulphur shows the first increase in the Elongation from 29.79% to 30.3%, between 0.002%S to 0.006%S. Between 0.006%S to 0.012%S, Elongation is decreased from 30.0% to 29.4%. After 0.012%S, it starts increasing to a maximum 31.4%, at 0.015%S. The only reduction in 0.8% Elongation is observed between 0.02 %S to 0.045%S. The Phosphorus gives the increase in the Elongation from 27.95% to 31.2% in the range of 0.001%P to 0.0175%P. Reduction in the Elongation from 31.2% to 29.2% is observed with increase in amount of Phosphorus up to 0.04%. The nickel has the maximum Elongation of 30% at 0.85% and decrease with increase in %Ni more than 0.85%. In the figure, it shows at 0.85% the Elongation value drops from 30% to 25.3%. More than 5.8 % Ni gives a constant value of the Elongation 25.8%. The Chromium has a maximum Elongation of 30.1% at less than and equal to 0.4% Cr. More than 0.4% Cr reduces the Elongation to 21%. Further increase in %Cr between 0.7% to 5%, the Elongation drop from 21% to 15.4%. More than 5% Cr the Elongation increases of 25.8% and constant up to a maximum 9.3% Cr. Molybdenum has a maximum Elongation 30.1% at less than and equal to 0.3% concentration. More than 0.3% Mo decreases the Elongation from 30.1% to 21% at 0.5% Mo. At 1.7% Mo, the value of Elongation is a minimum to 20.7%. More than 1.7% Mo increases Elongation up to 25.7% and then it is constant till 2.4% Mo. Vanadium decreases the Elongation from a maximum 30.2% to a minimum 22.. 7% between 0.01% to 0.068%. At 0.092% V, the Elongation is 25.2%, then decrease to 20.8% between 0.131% V to 0.16% V. More than 0.16% V increases the Elongation from 20.8% to 25.8% and 25.8% is constant up to a concentration of 0.32% V. Copper decreases the Elongation from 30.2% to 25.8% between more than 0% Cu to 2.05% Cu. Oxygen increases the Elongation of 28.15% to 30.2% when it is in the range of 50 ppm to 450 ppm. Higher than 450ppm Oxygen, there is a decrease in the Elongation from 30.2% to 25.75%. At 850 ppm Oxygen, the Elongation is 25.75% and remains constant up to maximum 1650 ppm Oxygen. Titanium gives a minimum the Elongation of 22.7% to maximum 30.8%. At 60 ppm the Elongation is the highest. In between the range of Titanium from 60 ppm to 340 ppm, the Elongation reduces from 30.8% to 23.7%. In the Elongation approximately 3.7% variation is observed between 350 ppm and 685 ppm Titanium. Boron shows the maximum Elongation of 30.1% in between 0 ppm to18 ppm. More than 18 ppm to , there is a reduction in the Elongation from 30.1% to 23.75% (at 134 ppm Boron) and the increase in 0.5% is observed at 84 ppm Boron and 200 ppm Boron. Niobium has a trend of decrease in the Elongation from 30.1% to 20.3% with an increase from 0 to 1350 ppm. More than 1420 ppm to 1700ppm, the Elongation is a constant value of 22%

Heat Input has stated that the maximum Elongation of 32.65% between 3.8 kJ mm-1 to 4.65 kJ mm-1. Heat Input between 2.7 kJ mm-1 to 3.8 kJ mm-1 reduces the Elongation from 29.7% to 25.75%. Heat Input starts from 0.5 kJ mm-1 with 30.1% an Elongation. The Elongation has a little change of 0.3% between 0.5 kJ mm-1 to 2.7kJ mm-1. When the Interpass temperature is 20^0C, the Elongation is 26.6%. More than 60^0C, a decrease in the Elongation is observed to 25.8%. To increase in Interpass temperature more than 119^0C, there is an increase in the Elongation from 25.8% at 72^0C to 33.45% at 350^0C. Post weld heat treatment temperature increases from 50^0 C to 750^0 C, shows the Elongation has higher values, 30.1% and 31.3%. Reduction in the Elongation, 28.5% is observed between 420^0C to 470^0C and more than 660^0C. Post weld heat treatment time has a trend of increase in the Elongation from 25.75% to 30.1% between 2 to 22.8 hours. More than 22.8 hours PWHTt, it decreases to minimum Elongation of 25.75%.

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

The GRNN model has good accuracy in prediction of elongation of ferritic steel welds on unseen data which is excellent for the design of welds. (Table.2) The predicted elongation of the unseen data of three weld alloys are compared with measured values of elongation 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 Elongation 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%)	0.300	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 Elongation %	31	13	11
Predicted Elongation %	31	19	13

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

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