Journal of Advances in Science and Technology
Vol. 18, Issue No. 2, September–2021, ISSN 2230-9659

Yield Strength Modelling for Ferritic Steel Welds

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Abstract - Creating ferritic steel welding alloys that can keep up with the demands of modern steel production is no easy undertaking. Until an optimal composition and welding process are found, this has often been accomplished through a process of experimental trial and error. A shorter trial period could mean less money and time spent on the process overall. In this study, we describe how an artificial neural network may be used to predict the yield strengths of ferritic steel weld deposits based on the materials used, the welding parameters employed, and the post-welding heat treatments applied. It details the creation of the General regression neural network (GRNN) models and the verification of their metallurgical underpinnings and correctness..

Keywords - Neural network; Ferritic Steels; Yield Strength; Welding alloys; Variables, General regression neural network (GRNN) models

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INTRODUCTION

The tensile strength test is critical for the specification and acceptance of welding materials because it provides the fundamental design data needed for both. Measurements themselves are straightforward, but the values that result from them depend intricately on things like chemical make-up, welding parameters, and post-weld heat treatment.To estimate the tensile parameters as a function of all these factors, neither a fundamental nor an experimental model is available [1,2].

The problem arises from the intricate nonlinear connection between the input variables and the output strength, which is difficult to predict. When all the variables are considered, the true behaviour is highly nonlinear, but the physical models for strengthening mechanisms are not sophisticated enough to capture this.

To empirically model and interpret the dependence of yield strength of steel weld deposits as a function of many input variables was the goal of this work, and GRNN was the tool of choice.

Incredibly complex nonlinear relationships are within the reach of a general regression neural network. Information is fed into the GRNN through input and output parameters. The outputs are the regression coefficients, as in regression analysis, and a description of the type of function that, together with the weights, links the independent or input variables to the dependent or output variables.

For the purpose of neural network analysis of ferritic steel welds, a large database of experimental measurements was compiled for model design using the GRNN approach.

MODELLING WORK

All of the measurements were taken on weld metal characteristics, and all of the data came from weld deposits where the joint was created to limit dilution from the base metal. Tungsten inert gas welding (TIGW), submerged arc welding (SAW), and manual metal arc welding (MMAW) are the three types of electric welding techniques represented (TIG). The amount of heat used was the only indicator of the welding operation itself. Multiple sources were used to compile the data. (Table 1).

The purpose of the neural network analysis was to make predictions about the Yield Strength based on a wide range of factors, such as the chemical composition, the amount of heat applied during welding, and the presence or absence of subsequent heat treatment. This results in a total of 2121 experiments being included in the yield strength database, each with their own unique set of 17 input variables.

Generalized Regression Neural Networks[4] are utilised as a neural network technique in this paper. There are 17 nodes in every GRNN network. There are 1061 neurons in the primary obscuring layer. There are 2 hidden-layer neurons and 1 output-layer neuron. (Figure.1)

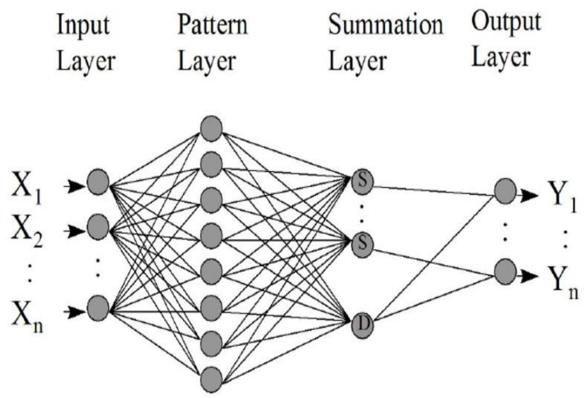

Fig. 1 Architecture of generalized regression neural network

Table 1: The Input Variables for Yield Strength Model. “p.p.m .’ corresponds to parts per million by weight.

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

RESULTS AND DISCUSSIONS

The normal behavior of the Predicted Yield Strength and Observed Yield Strength observed in fig. 2 for training data , Validation data, Training of the model is excellent by GRNN method.

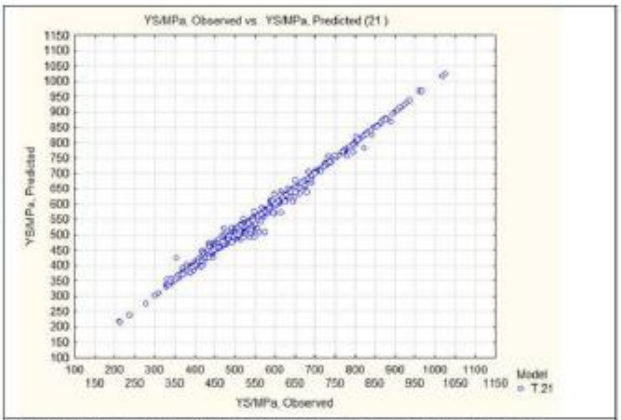

Figure a Training Data for GRNN model of Yield Strength

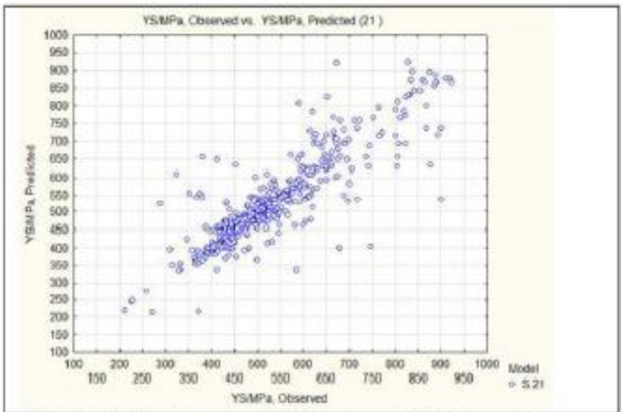

Fig b Validation Data for GRNN model of Yield Strength

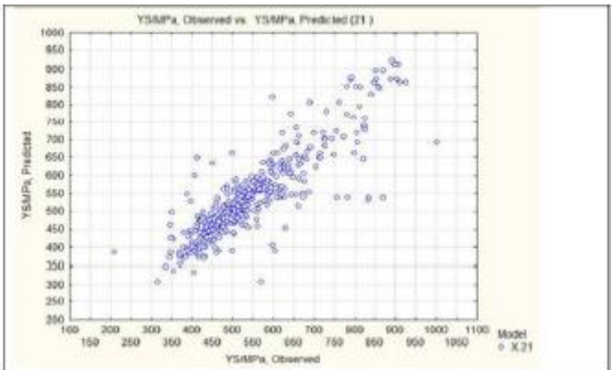

Fig c Test Data for GRNN model of Yield Strength

Fig. 2 for training data , Validation data, Training of the model is excellent by GRNN method.

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). Fig. 3

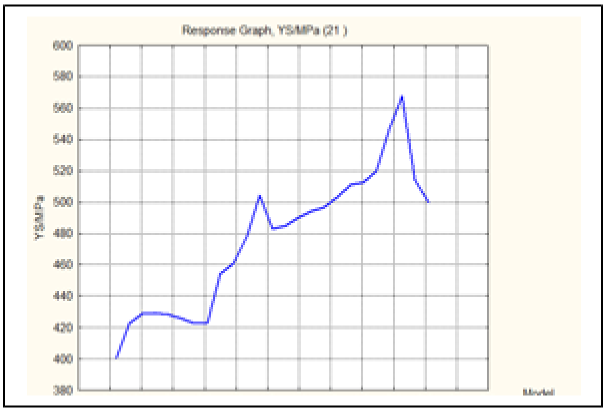

Fig. c Response Graph of Yield Strength MPa and Manganese(wt%)

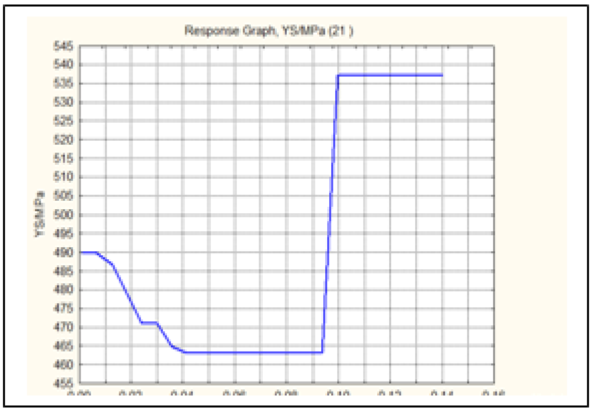

Fig. d Response Graph of Yield Strength MPa and Sulphur(wt%)

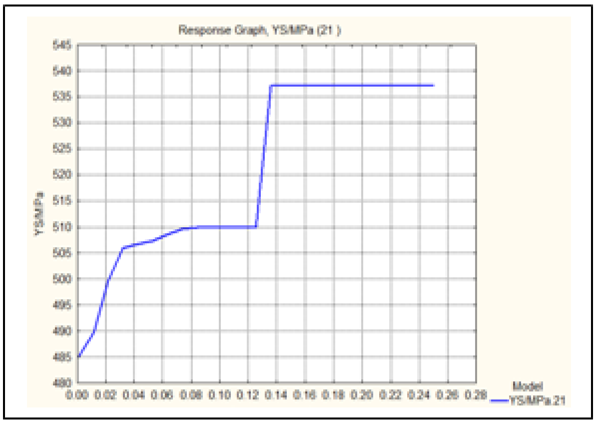

Fig. e Response Graph of Yield Strength MPa and Phosphorus(wt%)

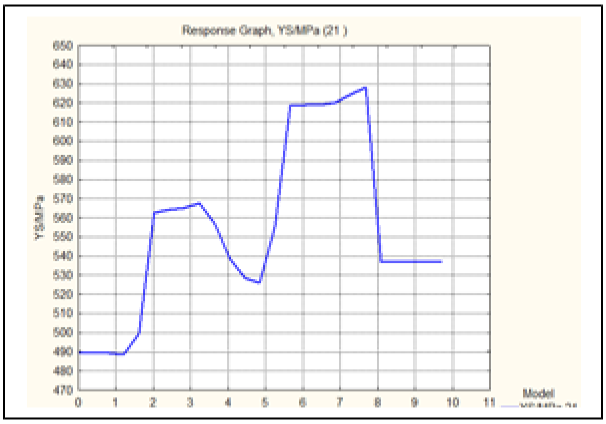

Fig. f Response Graph of Yield Strength MPa and Nickel(wt%)

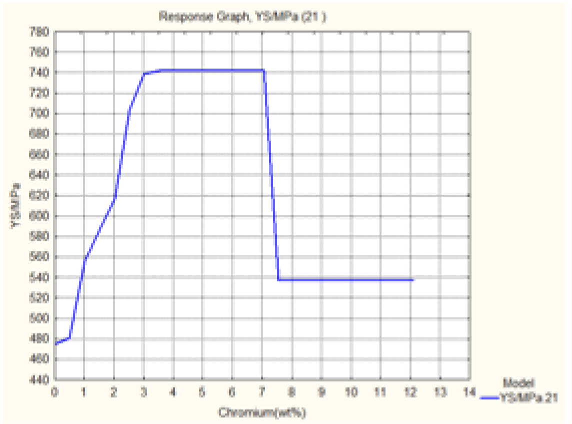

Fig. g Response Graph of Yield Strength MPa and Chromium(wt%)

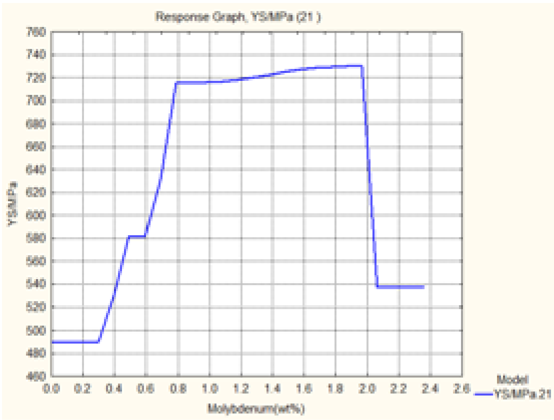

Fig. h Response Graph of Yield Strength MPa and Molybdenum(wt%)

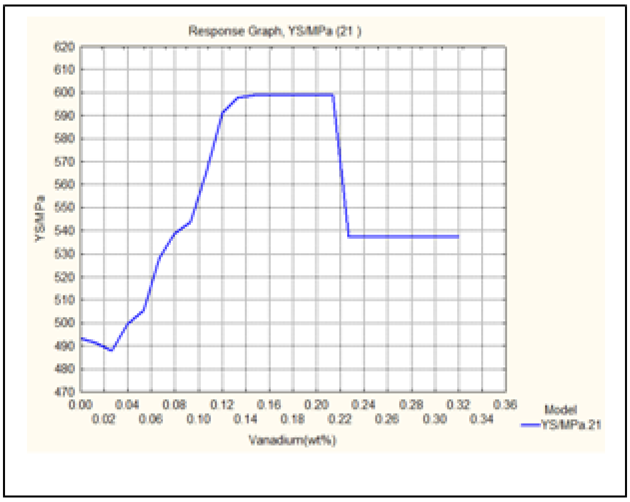

Fig. i Response Graph of Yield Strength MPa and Vanadium(wt%)

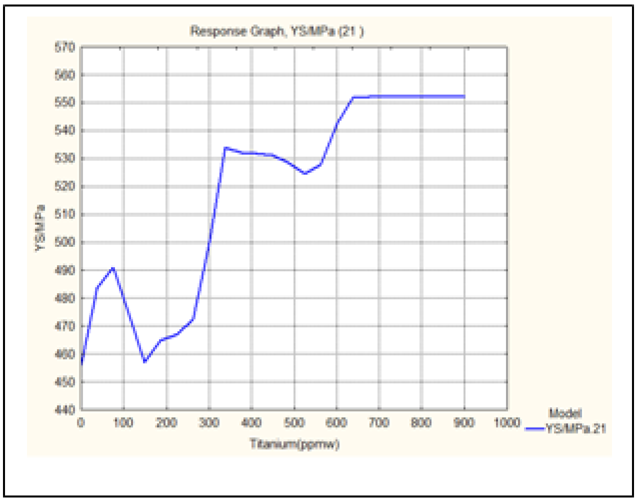

Fig. k Response Graph of Yield Strength MPa and Titanium(ppmw)

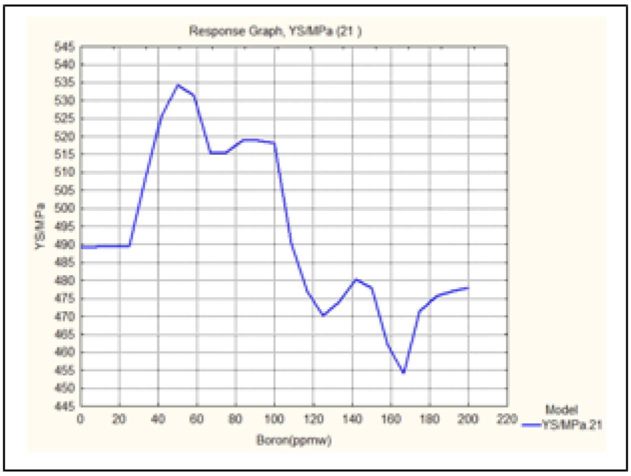

Fig. l Response Graph of Yield Strength MPa and Boron(ppmw)

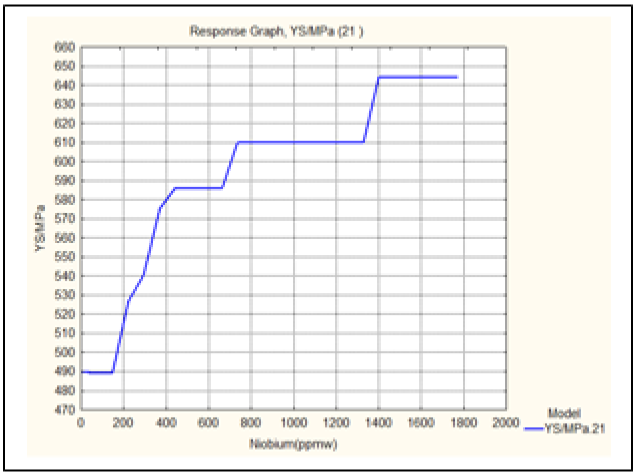

Fig. m Response Graph of Yield Strength MPa and Niobium(ppmw)

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

There are a number of factors that can affect the yield strength of welding alloys, and each one is covered below. There is a steep decline in yield strength after adding 0.1% of carbon, from 522 MPa at 0.05% to 477 MPa at 0.1%. The yield strength improves to 536 MPa at 0.15% C, before dropping to 519 MPa at 0.2% C. Silicon's yield strength decreases from 440 MPa to 431 MPa between 0.1% and 0.2%, before rising to 505 MPa at 0.45%. Yield strength is 515 MPa at 0.8%, and it drops to 504 MPa across a range of 1%-1.2 % from 1% to 0.8%. As the manganese percentage rises, the yield strength rises alongside it, going from 400 MPa to 563 MPa. Loss of yield strength is seen at 0.8%, 1.1%, and 2.1%. In sulphur, yield strength drops from 490 MPa to 464 MPa, the first sign of a weakening material. The pressure has been raised from 464 MPa to 537 MPa, an increase of slightly more than 0.09%. The phosphorus contributes to a rise in yield strength from 485 MPa to 537 MPa. The maximum yield strength of nickel is 629 MPa at 7.8 percent and the minimum is 490 MPa at 1 percent. Meant literally. The graph demonstrates a decline in yield strength to 528 MPa at a value of 4.9%. The yield strength drops to about 539 MPa when the Ni content is more than 7.8%i. The yield strength of chromium ranges from 3% to 7%, with a high of 740 MPa. The yield strength drops to 539 MPa at a Cr content of more exceeding 7%. Addition of up to 3% chromium causes a jump in yield strength from 479 MPa to 740 MPa. Molybdenum's 1.98% yield strength improvement boosts the material from 490 MPa to 730 MPa. Yield strength is 719 MPa at 0.8% Mo. The yield strength drops from 730 MPa to 539 MPa for additions of Mo more than 1.98 percent. By adding vanadium, the yield strength can go from 492 MPa to 600 MPa, a gain of 15%. The yield strength drops to 538 MPa at 0.22% V. Yield strength is improved by 0.6% due to the addition of copper, from 490 MPa to 513 MPa. There is a drop in yield strength to 488 MPa at 1.2% Cu. When the copper content is greater than 1.27 percent, the yield strength increases to 570 MPa. As for yield strength, titanium provides between 457 and 553 MPa. The maximum yield strength is achieved at 700 ppm. Titanium yield strength can vary between 90 and 630 parts per million. At 50 parts per million (ppm), the yield strength of boron is 535 MPa, which is the highest value ever recorded. In the presence of more than 50 ppm, the yield strength drops to 454 MPa. The yield strength of niobium tends to rise from 490 MPa to 644 MPa as its concentration rises from 180 ppm to 1400 ppm.

The yield strength is stated to be 490 MPa for Heat Input, with a subsequent decrease to 406 MPa between 1.5 and 6.6 kJ mm-1. More than 6.7 kJ mm-1 is needed to attain the maximum yield strength of 537 MPa. The yield strength of Interpass is 538 MPa at temperatures below 70 C. A decline in yield strength to 470 MPa is seen at temperatures more than 155 degrees Celsius, while this strength is seen to increase to 490 MPa at temperatures of 150 degrees Celsius. The minimum yield strength is 4.3 MPa at 270 degrees Celsius. Yield strength improves to 480 MPa and 490 MPa after post-weld heat treatment is carried out at temperatures as high as 425 C. When heated over 455 degrees Celsius, the yield strength climbs to a peak of 655 MPa at 710 C, before gradually decreasing to 510 MPa. There is a correlation between post-weld heat treatment duration and yield strength, with a rise from 420 MPa to 490 MPa over the course of 5 hours. If you leave it on for longer than 25 hours, the maximum yield strength will rise to 538 MPa.

Figure 4.2 (a-q) shows that the connection between the input factors and yield strength is nonlinear.

The GRNN model is great for the design of welds due to its high accuracy in predicting the yield strength of ferritic steel welds from unseen data.

It is demonstrated that the GRNN model has prediction capacity by comparing the anticipated yield strength for unseen data of three weld alloys with measured values of yield strength. The GRNN model presented here can be put to use in ferritic steel alloys research and development. Studies of creep-exposed T91–T23 DMWs revealed the unfavourable microstructural changes that occur in these welded joints when subjected to service conditions. The dissolution of carbides in the carbon-depleted zone resulted in a partial recrystallization of the weld metal microstructure. In addition, on the side of the weld that contains the more highly alloyed Grade 91 base metal, finely distributed carbides were discovered to correlate to a substantial increase in hardness immediately adjacent to the fusion line. Good agreement was found between the computational simulations and the creep experiments after an examination and comparison with the data accumulated with 1-dimensional diffusion simulations. It was also demonstrated that familiarity with the materials and their precise microstructural properties, specifically their inherent precipitate phases, is important for enhanced outcomes from the computational simulations.

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

CONCLUSIONS

Due to the nonlinear nature of the relationship between input and output variables in weld alloys, the best neural network for capturing these trends is the generalised regression neural network. To make sense of the vast amount of available experimental data on yield strength, researchers have turned to a neural network approach based within a General regression neural network. The yield strength can now be estimated in relation to the material type, welding parameters, and heat treatment conditions. In order to better understand ferritic steel alloys used in welding for the construction of various types of equipment in industries, the model developed has been put to use. Several applications have used it successfully with blind data on ferritic steel welds. GRNN modelling makes it simpler, more accurate, more cost-effective, and quicker to design ferritic weld alloys. Weld alloys with the desired yield strength can be produced for practical use in industries thanks to careful manipulation of the most important input variables.

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