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Investigations on Tensile Strength of Austenitic Stainless Steels Using Artificial Neural Network Model

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Abstract - This paper presents the details on the investigation and classification of various 316 grades of stainless Steel based on their mechanical properties. The results facilitate in espousing a certain grade of steel for marine applications. The different grades of 316 Stainless steel have their unique chemical composition. With the advancement in soft computing techniques, Artificial Neural Network (ANN) is used to classify the different grades of 316 Stainless Steel based on the changes in their tensile strength with respect to their chemical composition and to subsequently identify the grade of 316 stainless steel for the specified application. The twelve-different sets of the chemical composition of the various grades of stainless steel are given as input to the neural network. The mechanical properties such as Ultimate Tensile strength and Yield strength are chosen as the target. This neural network could predict the changes in the above-mentioned mechanical properties due to the changes in overall chemical composition. The neural networks are trained using the Back propagation Levenberg-Marquardt algorithm and it yielded 316L grade stainless steels as an optimal choice of marine-grade material. Knowledge on these properties is inevitable to understand its behaviour for various dynamic loading conditions when subjected to joining and machining. Based on the obtained results, validations are carried out. The outcome signifies the observance of close coherence between existing data and estimated data. Considering the vitality, the same neural network is adopted and customised for Cold Metal Transfer (CMT) joinability.

Keywords: *Ultimate Tensile strength, Yield strength, Backpropagation Levenberg-Marquardt algorithm*

INTRODUCTION

CMT is a modified Gas Metal Arc Welding (GMAW) process which is invented by the Fronius Company [1]. This welding technique is suitable for joining materials like steel, aluminium, zinc, etc. The major advantage of CMT is no-spatter, low input heat with a good deposition rate [2]. Recent, weld experiments concentrate more on the mechanical properties influences on weld quality. From the obtained test results optimal weld parameters are designated. This process not only wastes manpower, material, and financial resources, but also the experimental results are sometimes not precise. It is beneficial to examine the mechanical properties such as tensile strength and yield strength of material before welding so that better weld results could be obtained based on the material properties. In this study, for the prediction of mechanical properties, a soft computing technique is proposed. The Artificial Neural Network is one of the promising optimizing tools to analyse the mechanical characteristics of the austenitic stainless steel (ss) grade 316. The technological importance of 316 stainless steel accounts for high corrosion resistance, in addition to high toughness, good strength and oxidation resistance at wide range operating temperatures, making it a candidate material for marine applications [3]. Basic, prediction on mechanical properties of the materials using their empirical equations is considerably difficult. Therefore, the ANN technique is applicable for this purpose, provides a different approach to the material modelling techniques than numerical or statistical methods. From the available literature, it is noted that the feedforward backpropagation algorithm based neural networks are widely used to train the network due to their high reliability.

In the present study, the mechanical behaviour predictions are done for various grades of 316 austenitic stainless sheets of steel using the ANN model. Levenberg-Marquardt Backpropagation algorithm is used to train the neural network such that it predicts the Ultimate tensile strength (UTS) and Yield tensile strength (YTS) of various 316-grade austenitic stainless steel (316, 316L, 316H, 316F, 316Ti, 316J1, 316J1L, 316LN, and 316N). The material could be then implemented for Cold Metal Transfer joining process

MATERIALS AND METHODS

The materials used in this analysis are 316, 316L, 316H, 316F, 316Ti, 316J1, 316J1L, 316LN, and 316N. These grades of stainless steels are categorized by their good strength and high toughness at wide range operating temperatures and oxidation resistance. Marine-grade stainless alloys contain molybdenum to resist the corrosive effects of salt in the marine environment. The salt concentrations in the seawater vary, thus increasing the concentration due to the spray and evaporation in splash zones. The Austenitic 316 stainless steel grades are more suitable for marine environments, intermittent submersion and splash zone environments in the seawater. The chemical composition of different 316-grade steels used is given in **Table *1***. ANN model is developed using MATLAB software. In total 1080 datasets are trained in the Levenberg-Marquardt Backpropagation algorithm. The UTS and YTS of austenitic stainless steel grades are analysed.

Table 1 Chemical composition (in wt.%) of 316 stainless steel grades

Austenitic stainless steel 316	**C**	**Si**	**Mn**	**P**	**S**	**Ni**	**Cr**	**Mo**	**Cu**	**N**	**Ti**	**Fe**
SUS316	0.08	1.00	2.00	0.045	0.030	10.00-14.00	16.00-18.00	2.00-3.00	0	0-0.10	0	61.7-71.9
SUS316L	0.03	1.00	2.00	0.045	0.030	12.00-15.00	16.00-18.00	2.00-3.00	0	0-0.10	0	61.7-71.9
SUS316N	0.08	1.00	2.00	0.045	0.030	10.00-14.00	16.00-18.50	2.00-3.00	0	0.10-0.22	0	61.9-71.9
SUS316LN	0.03	1.00	2.00	0.045	0.030	10.50-14.50	16.50-18.50	2.00-3.00	0	0.12-0.22	0	61.7-71.9
SUS316Ti	0.08	1.00	2.00	0.045	0.030	10.50-13.50	16.50-18.50	2.00-3.00	0	0	0.4-0.7	61.1-70.1
SUS316J1	0.08	1.00	2.00	0.045	0.030	10.00-12.00	17.00-19.00	1.20-2.75	1.00-2.50	0	0	60.6-70.5
SUS316J1L	0.03	1.00	2.00	0.045	0.030	12.00-16.00	17.00-19.00	1.20-2.75	1.00-2.50	0	0	60.5-70.5
SUS316F	0.08	1.00	2.00	0.045	0.10	10.00-14.00	16.00-18.00	2.00-3.00	0	0	0	61.7-71.9
SUS316H	0.40	0.75	2.00	0.045	0.030	10.00-14.00	16.00-18.00	2.00-3.00	0	0	0	61.7-71.5

LEVENBERG-MARQUARDT NEURAL NETWORK MODELING

The ANN is created and trained using MATLAB software. Our input data set is divided into time steps based on the number of data samples. The three categories of time steps are Training, Validation and Testing. An optimal material in an arc welding process influences the mechanical properties of the weldment in its respective application.

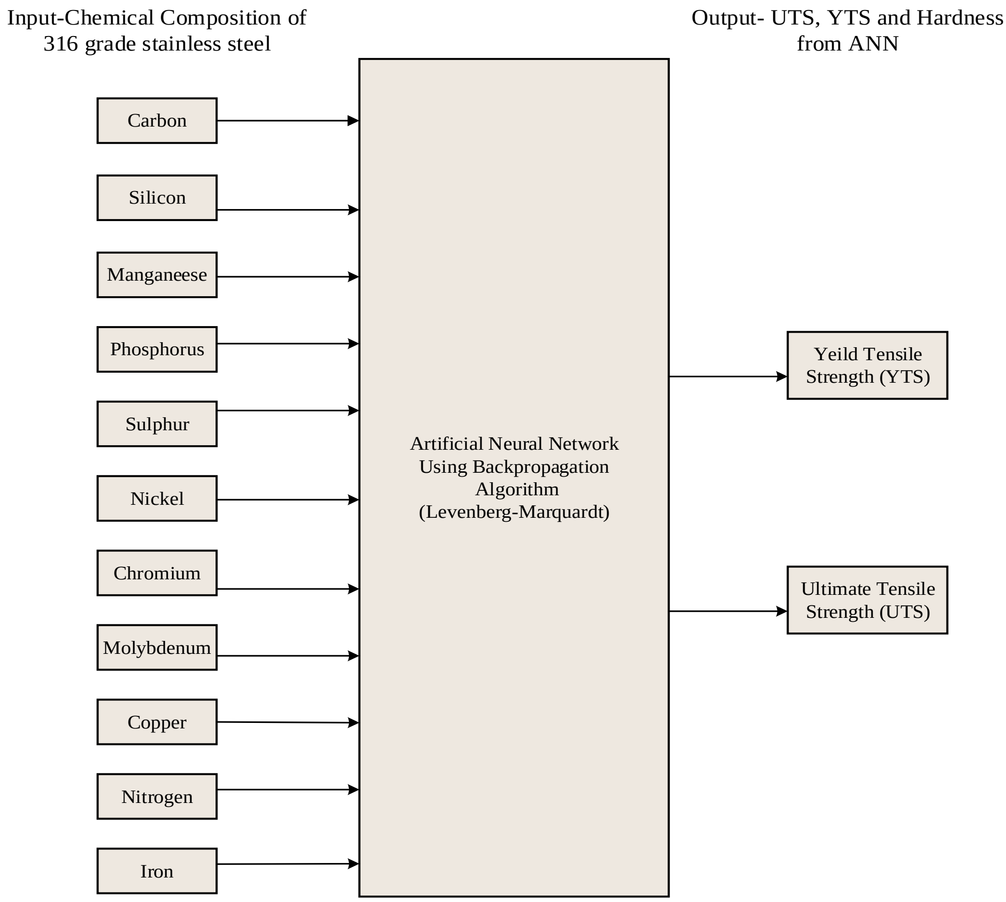

Figure. 1 ANN model for the prediction of material properties

To train the neural network, the chemical composition in the percentage of the 316 Stainless Steel comprising; Carbon (C), Silicon (Si), Manganese (Mn), Phosphorous (P), Sulphur (S), Nickel (Ni), chromium (Cr), Molybdenum (Mo), Copper (Cu), Nitrogen (N) and Iron (Fe) are fed as input data to the neural network. The mechanical properties (Minimum and maximum range) such as yield strength and ultimate tensile strength are set as a target to the neural network as shown in *Figure. 1*. The Backpropagation LM algorithm is used to train the ANN and the neural network could provide an optimal solution as the best suited marine grade material which could be welded using the CMT process. The back-propagation algorithm is widely being implemented as a learning algorithm in the feed-forward multilayer neural networks. The Levenberg-Marquardt backpropagation algorithm is used for training our neural network. The Training stops automatically when there is no improvement in the generalization, which is an indication of an increase in the Mean Square Error (MSE) of the samples [6]. Levenberg-Marquardt (LM) algorithm is a widely used optimization algorithm that provides a solution called non-linear least square minimization [7]. This iterative technique is designed to minimize the sum of the squared error function of the form shown in Eqn (1),

$$E = \frac{1}{2}\sum k(\ {e_k}^2) \ = \frac{1}{2} \parallel e \parallel^2 \tag{1}$$

Where e_k is the error, e is a vector with element e_k. When the difference between previous weight and new weight is small, the error vector is expanded using Taylor's series into a first-order equation as shown in Eqn (2),

$$\mathrm{e}\ (\mathrm{j}+1) \ = \mathrm{e}(\mathrm{j})\ \frac{\delta e_k}{\delta w_i}(\mathrm{w}(\mathrm{j}+1) - \mathrm{w}(\mathrm{j})) \tag{2}$$

$$E \ = \ \frac{1}{2} \parallel e(j) + \frac{\delta e_k}{\delta w_i}\ (\mathrm{w}(\mathrm{j}+1) - \mathrm{w}(\mathrm{j})) \parallel^2 \tag{3}$$

The error function is expressed in Eqn (3),

EXPERIMENTAL VALIDATIONS

The desired set of input and output data is fed into the neural network. In this work, NARX (Nonlinear autoregressive with external input) neural networks are used which can learn to predict one-time series data when given with past values of the same time series, along with the feedback input [8]. The neural network is created and trained using the Levenberg-Marquardt (LM) algorithm in the open-loop form initially [9], [10], [11]. Here, open-loop (single-step) is highly efficient than closed-loop (multi-step) training. The Open-loop training allows the user to feed the network with past outputs while it is being trained to result in the correct present outputs. Once the training is complete, the network can be converted to closed-loop form or any form depending on the application and requirement. After training, the mean squared error (MSE) and Regression R can be seen in the training window [12]. The Mean Squared Error (MSE) is the average squared difference between the targets and neural network outputs. Low values of MSE are better [13]. Zero MSE indicates is no error. The Regression Analysis R is done to measure the correlation between targets and neural network outputs. The experimental implementation is shown in the following workflow Figure. *2*

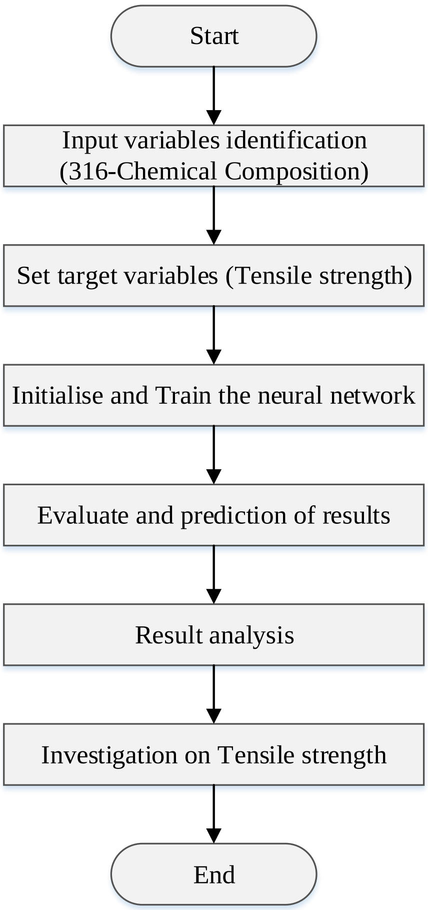

Figure. 2 Work Flow

RESULTS AND DISCUSSION

This section presents the various results and inferences investigated in the study.

5.1 Artificial Neural Network Modelling

The input data of the first neural network (training set) consists of 1080 datasets of which each has twelve input variables which are the concentration of C, Si, Mn, P, S, Ni, Cr, Mo, Cu, N, Ti, Fe. The output variables are ultimate tensile strength (UTS) and yield tensile strength (YTS). The objective of this study is to classify the input data and develop an ANN model for predicting the accurate UTS and YTS. The optimal values of UTS and YTS are represented in Figure. *3* and Figure. *4* respectively for each grade.

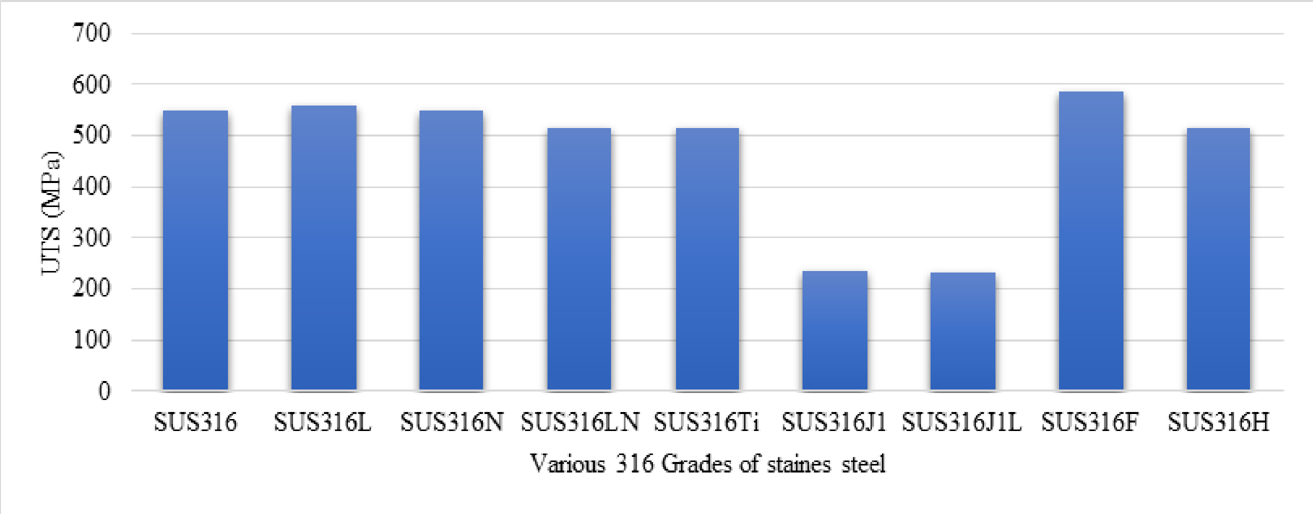

Figure. 3 UTS for various 316 grades of stainless steel

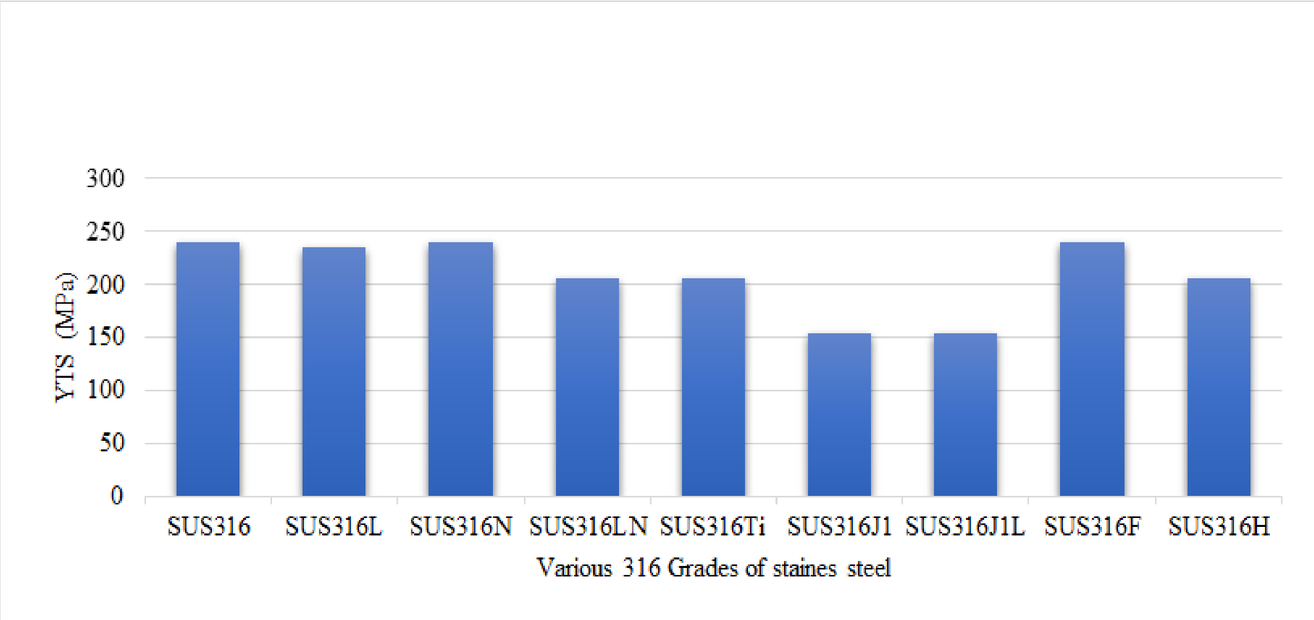

Figure. 4 YTS for different 316 grades of stainless steel

5.2 Performance of ANN

The performance validation of the neural network in predicting the UTS and YTS are shown in the performance plots Figure. *5* and Figure. *6*.

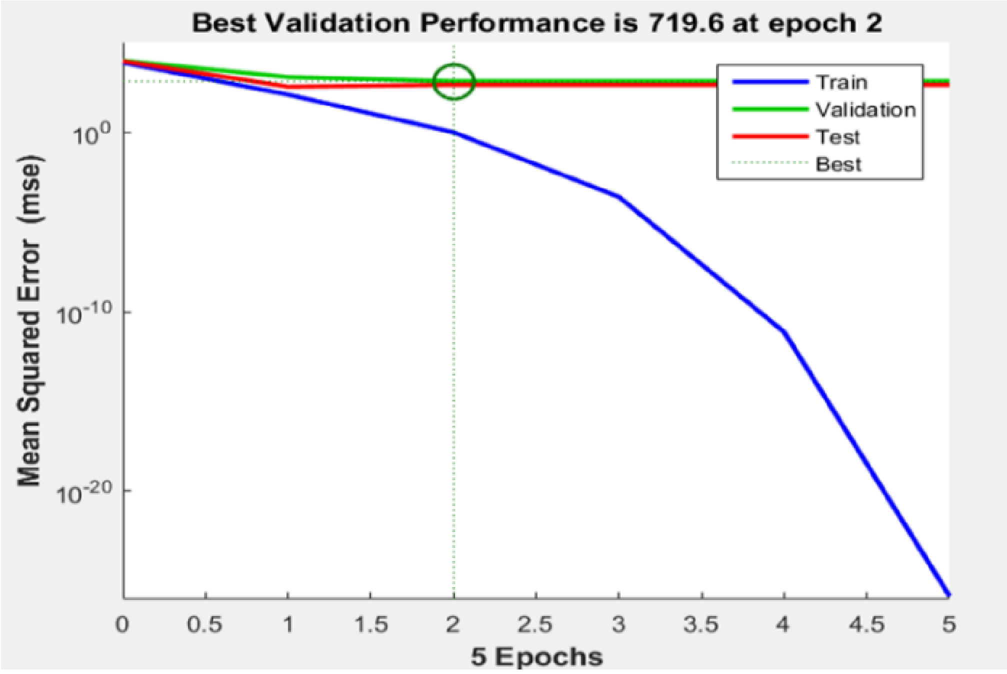

Figure. 5 Performance of ANN while predicting UTS

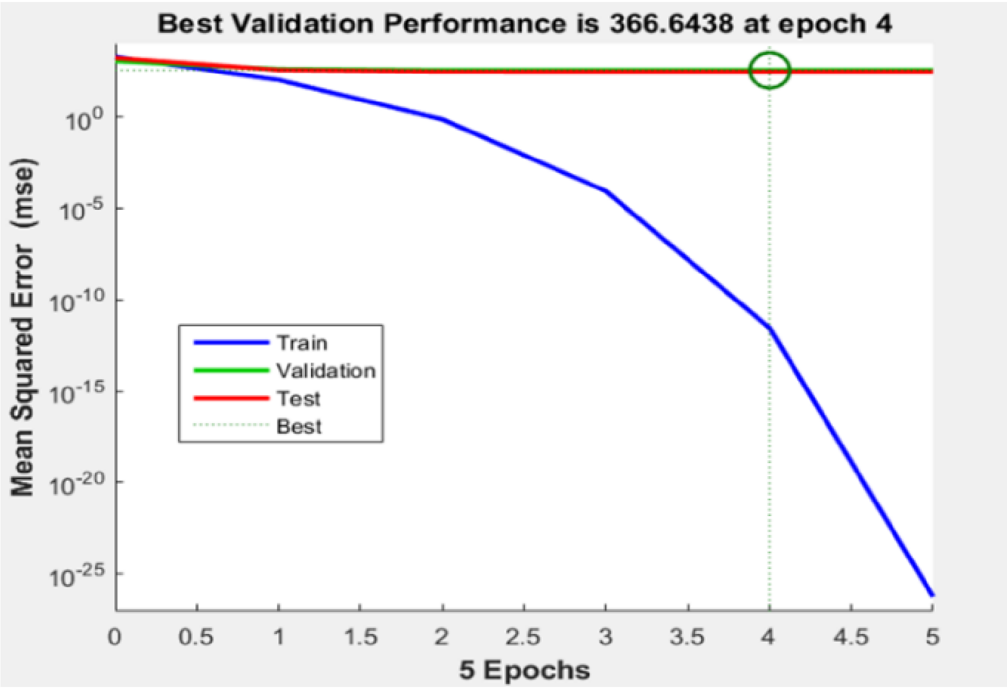

Figure. 6 Performance of ANN while predicting YTS

5.3 Regression Plot analysis

The regression plots while predicting the UTS and YTS are shown in the following *Figure. 8* and Figure. *8*. The accuracy is prediction increases when the regression coefficient R is close to 1.

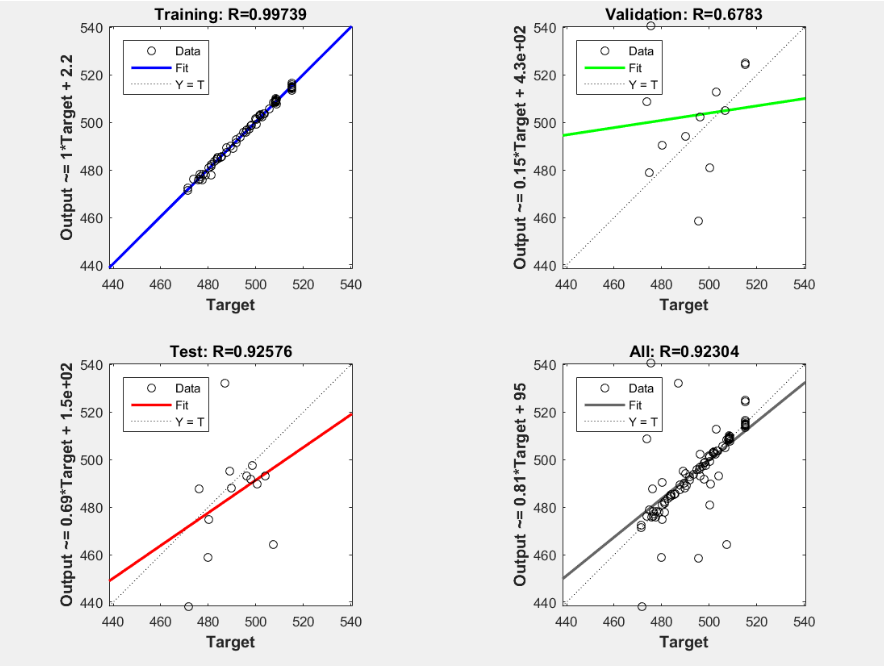

Figure. 7 Regression plot while predicting UTS

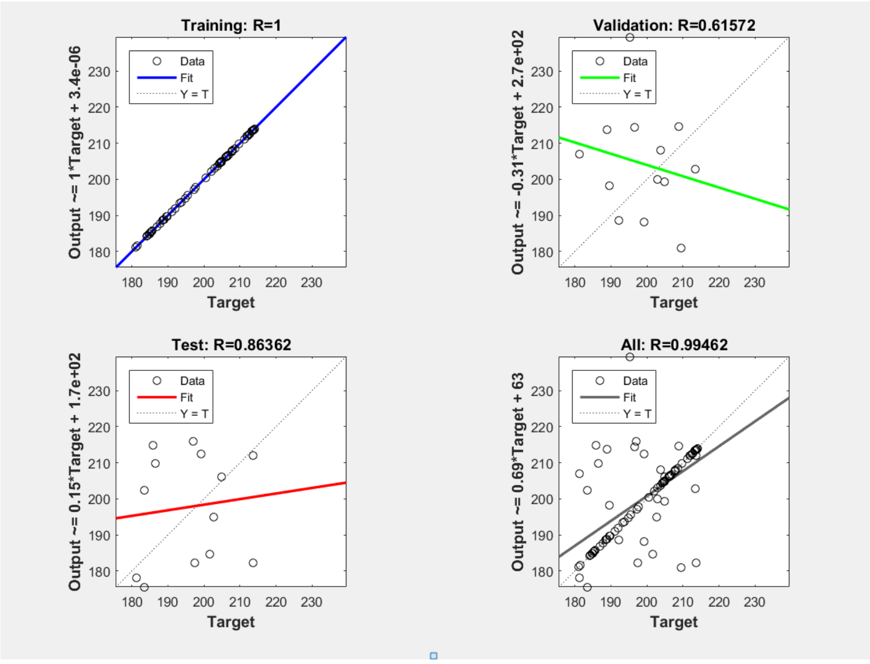

Figure. 8 Regression plot while predicting YTS

5.4 Prediction Plot analysis

The predicted UTS and YTS are shown in Figure. *9* and Figure. *10*. The x-axis is split into equal 10 readings where 0-10 indicates class1, 10-20 indicates class 2, and 20-30 indicates class 3. Likewise, till 80-90 indicating class 9. The prediction errors observed are ±10%.

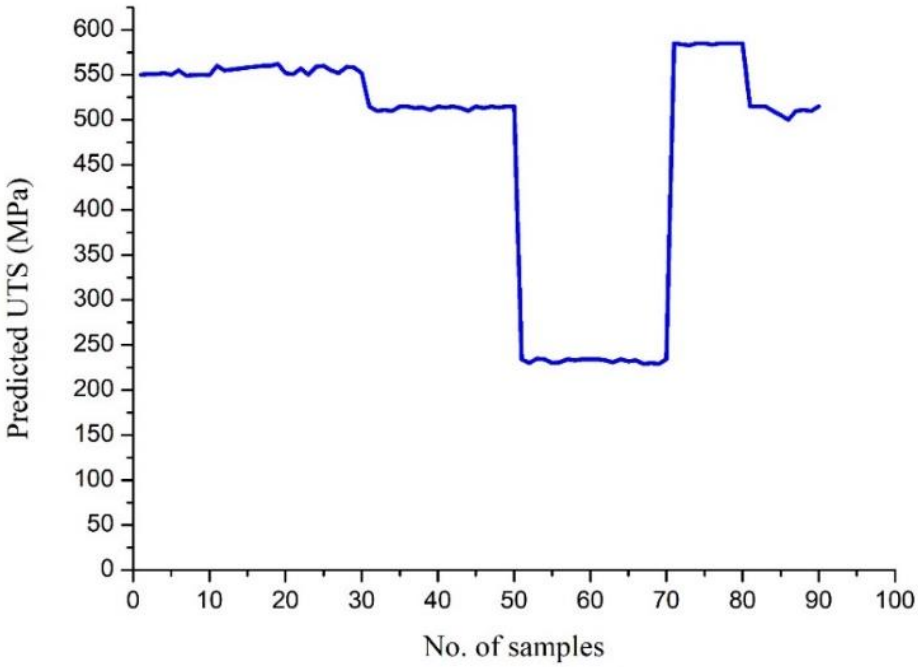

Figure. 9 Prediction plot for UTS

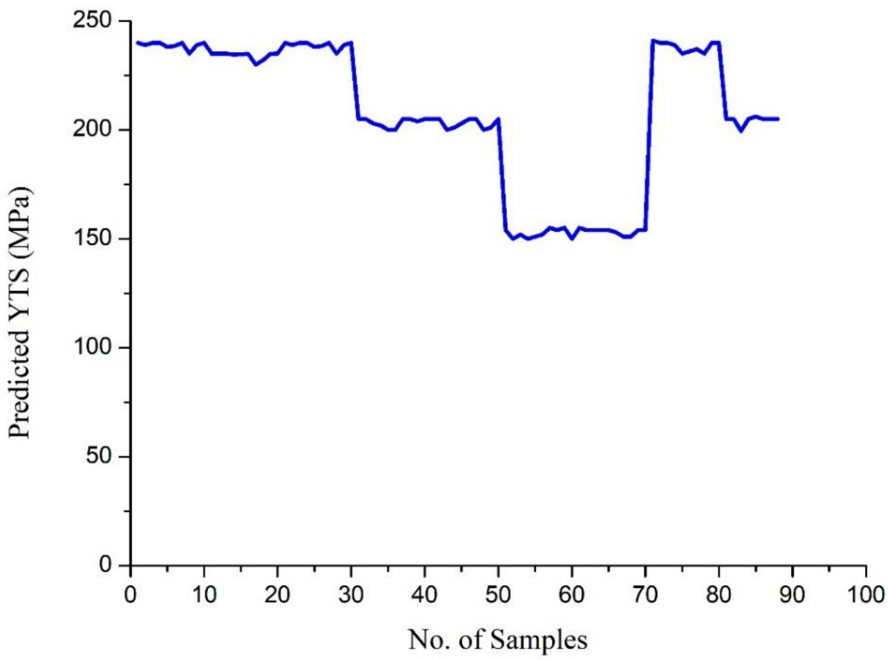

Figure. 10 Prediction plot for YTS

5.5 Interpretation

The mechanical properties of the chosen grades of the 316-stainless steel are classified as low, moderate and high after predicting the tensile properties.

Table 2. Classification of 316-grade stainless steel based on mechanical properties

Grades of SS	UTS	YTS
SUS316	High	Moderate
SUS316L	High	High
SUS316N	Moderate	High
SUS316LN	Moderate	Moderate
SUS316Ti	Moderate	Moderate

SUS316J1	Low	Low
SUS316J1L	Low	Low
SUS316F	High	Moderate
SUS316H	Moderate	Moderate

From the **Table *2***, it is observed that the 316L grade stainless steel has higher values of UTS, and YTS when compared with that of the other 316 stainless steel grades depending on the variations in chemical composition.

5.6 Experimental validation

After performing a tensile test on the various grades of stainless steel (as explained in section), the Strain-Strain curve was plotted which indicates their tensile test (as shown in Figure 11)

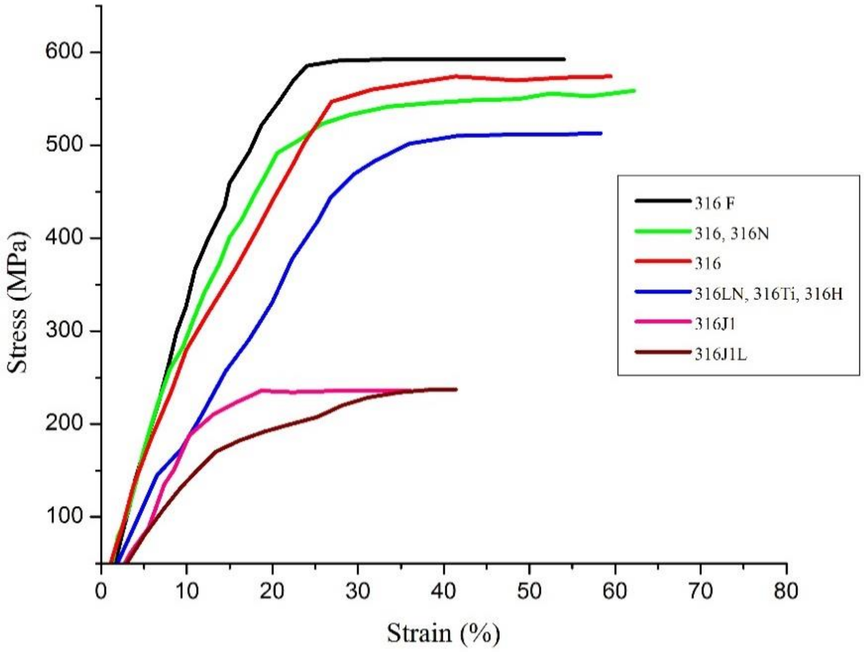

Figure 11 Experimental Validation of tensile strength

The UTS and YTS are significant parameters requiring high values to make the material best suited for a specific application. Thus, 316L could be an optimal material for marine applications. Thus, 316L could be an optimal grade of stainless steel for marine applications. The 316L grade stainless steel material was then welded using Cold Metal Transfer process as per the experimental runs shown in ***Table 3*** and the welding setup and weldment sample are shown in

Figure **12** and *Figure 13* respectively.

Table 3 Experimental Parameters

Trial No	Weld Current (Amps)	Voltage (Volts)	Travel Speed (mm/min)	Wire Feed Rate (m/min)	Weld Time (Sec)	Heat Input (J/mm)
1	90	16.9	400	3.1	14	228.15
2	90	16.9	450	3.1	13.3	202.8
3	90	16.9	500	3.1	12	182.52
4	85	16.8	400	2.9	14	214.2
5	85	16.8	450	2.9	13.3	190.4
6	85	16.8	500	2.9	12	171.36
7	80	16.5	400	2.6	14	198
8	80	16.5	450	2.6	13.3	176
9	80	16.5	500	2.6	12	158.4

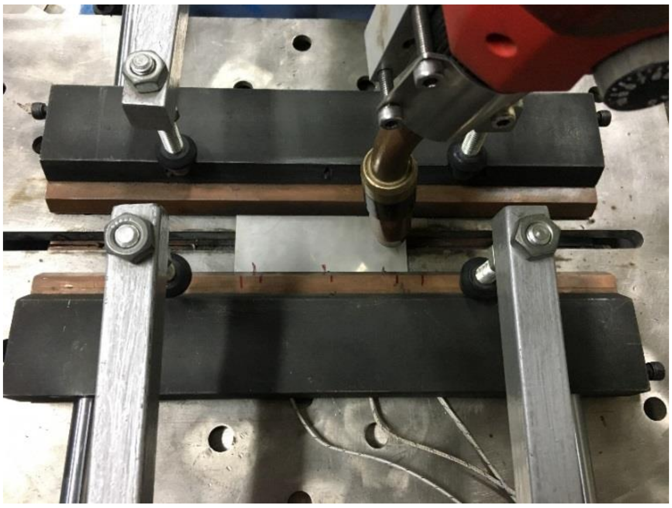

Figure 12 Welding setup

Figure 13 Welded sample of 316L using CMT

CONCLUSION

This study emphasizes the requirement of optimal material selection for a joining process. The cold metal transfer (CMT) process is an advanced Gas Metal Arc Welding process (GMAW) that enables material transfer with reduced power consumption and material wastage. The final weldment depends on the quality of the material and its corresponding mechanical properties which necessitates choosing an optimal material from the available grades. Direct or indirect choosing is possible. Direct methods like visual inspection, trial and error procedures are tedious resulting in time, energy and material wastage. With the evolution of soft computing techniques like Artificial Neural Networks (ANN), optimization of the welding parameters have become easier. The inferences drawn from this study are:

- The exploration of ANN in the CMT processes being limited, paved a way for us to extend this optimisation tool for the CMT process of Stainless steel welding.
- The mechanical properties investigated in this work are Ultimate tensile strength (UTS) and Yield tensile strength (YTS) of all 316 grades of stainless steel.
- After the training of the ANN using the Back Propagation LM Algorithm, the neural network predicted the mentioned mechanical properties accurately based on the variations in their chemical compositions. This is assured since the regression plots of all the grades indicated that the R-value is close to 1.
- From the obtained network output, the properties are classified into three grades namely; low, moderate and high. Hence, the developed ANN model has proven to be an effective nonlinear regression analysis method in identifying material behavioural trends and suggested 316L grade as an optimal material for marine application.
- The experimental validation results also agree with the predicted results thereby making 316L a favourable marine-grade application based on the mechanical properties; UTS and YTS.

REFERENCES

[1] Dilthey, U. and Stein, L., 2006. Multimaterial car body design: challenge for welding and joining. Science and Technology of Welding and Joining, 11(2), pp.135-142.

[2] Pickin, C.G., Williams, S.W. and Lunt, M., 2011. Characterisation of the cold metal transfer (CMT) process and its application for low dilution cladding. Journal of Materials Processing Technology, 211(3), pp.496-502.

[3] Desu, R.K., Krishnamurthy, H.N., Balu, A., Gupta, A.K. and Singh, S.K., 2016. Mechanical properties of Austenitic Stainless Steel 304L and 316L at elevated temperatures. Journal of Materials Research and Technology, 5(1), pp.13-20.

[4] Mandal, S., Sivaprasad, P.V., Venugopal, S. and Murthy, K.P.N., 2009. Artificial neural network modeling to evaluate and predict the deformation behavior of stainless steel type AISI 304L during hot torsion. Applied Soft Computing, 9(1), pp.237-244.

[5] Vasudevan, M., 2009. Soft computing techniques in stainless steel welding. Materials and Manufacturing Processes, 24(2), pp.209-218.

[6] Sapna, S., Tamilarasi, A. and Kumar, M.P., 2012. Backpropagation learning algorithm based on Levenberg Marquardt Algorithm. Comp Sci Inform Technol (CS and IT), 2, pp.393-398.

[7] Ranganathan, A., 2004. The levenberg-marquardt algorithm. Tutoral on LM algorithm, 11(1), pp.101-110.

[8] da Luz, F.S., Pinheiro, W.A., Monteiro, S.N., Candido, V.S. and da Silva, A.C.R., 2020. Mechanical properties and microstructural characterization of a novel 316L austenitic stainless steel coating on A516 Grade 70 carbon steel weld. Journal of Materials Research and Technology, 9(1), pp.636-640.

[9] Saha, M.K., Hazra, R., Mondal, A. and Das, S., 2019. Effect of heat input on geometry of austenitic stainless steel weld bead on low carbon steel. Journal of The Institution of Engineers (India): Series C, 100(4), pp.607-615.

[10] Kumar, S., Menaka, M. and Venkatraman, B., 2019. Simulation and experimental analysis of austenitic stainless steel weld joints using ultrasonic phased array. Measurement Science and Technology, 31(2), p.024005.

[11] Banik, S.D., Kumar, S., Singh, P.K., Bhattacharya, S. and Mahapatra, M.M., 2021. Distortion and residual stresses in thick plate weld joint of austenitic stainless steel: Experiments and analysis. Journal of Materials Processing Technology, 289, p.116944.

[12] Pandya, D., Badgujar, A. and Ghetiya, N., 2021. Effect of hydrogen additions to shielding gas on activated TIG austenitic stainless steel weld. Materials Today: Proceedings.

[13] Barla, N.A., Ghosh, P.K., Kumar, V., Paraye, N.K., Anant, R. and Das, S., 2021. Simulated stress induced sensitization of HAZ in multipass weld of 304LN austenitic stainless steel. Journal of Manufacturing Processes, 62, pp.784-796.