INDIAN WELDING JOURNAL Volume 55 No. 3, July 2022

On Dissimilar Welding of AISI 304 and EN 8 Steels through Metal Active Gas Welding: Part II- Estimation of Weld Characteristics Using Regression Analysis and Neural Networks

Tapas Bera[1] and Santanu Das[2]
[1]Research Scholar, Department of Metallurgical and Materials Engineering
Indian Institute Technology Kharagpur, Kharagpur, 700032, India
[2]Professor and Head, Department of Mechanical Engineering
Kalyani Government Engineering College, Kalyani-741235, India
Email: [1]tapasbera6382@gmail.com, [2]sdas.me@gmail.com

ORCID: Tapas Bera: https://orcid.org/0000-0002-7513-7234
ORCID: Santanu Das: https://orcid.org/0000-0001-9085-3450

DOI : 10.22486/iwj.v55i3.213078

Abstract

Nowadays, researchers have been using several predicting tools in the areas of defense, marketing, finance, and engineering. In the area of welding processes, estimation of response parameters is done. As a predicting tool in this investigation, artificial neural networks (ANN) and regression equations are used. Using the ANN model, predictions can be made through various learning methods possible with this algorithm. The regression equation for each response parameter is obtained from MINITAB software. Weld bead geometry, hardness, and maximum bending load of the welded zone are predicted. Sets of input and output data needed for experimental runs are obtained by joining AISI 304 and EN 8 steels together using the GMAW process. To predict weld bead geometry and mechanical properties of the weld zone of dissimilar steels, two separate prediction tools are used. The outcomes are then compared. Such research is novel in the field of predicting and comparing the output parameters of different weld joints using ANN and regression analysis (RA). It is concluded that ANN as well as regression equations have predicted the weld bead geometry, hardness, and maximum bending load with a little error. It is also found that ANN provides satisfactory predicted results with much less error than the results obtained from the regression equation.

Keywords: ANN, Regression equation, GMAW, ANOVA, MATLAB, MINITAB.

1.0 Introduction

Gas metal arc welding (GMAW) is a versatile process used to join a large variety of similar and dissimilar metallic materials. The process is applied in the automotive sector, nuclear power plants, etc. Several research studies were carried out on the joining of different metals and their alloys using GMAW. Kumar et al. [1] used Taguchi's method to investigate the parameter optimization of AISI 304 and low carbon steel weld joints utilizing GMAW process. As per signal to noise ratio and ANOVA analysis,it was calculated that current had a substantial impact on the hardness of the weld zone (52.45%). Singh et al. [2] studied how the hardness of different metals influences welding joint. With the use of filler wire of austenite stainless steel of 0.8 mm in diameter, stainless steel 304 was welded with mild steel, utilizing metal inert gas welding. Result of this examination indicated optimum value of welding current and voltage which applied to create the weld section for maximum hardness of welded mild steel and stainless steel 304 specimens. The study of tensile strength in the gas metal arc welding process was done by Chaudhari et al. [3]. From this investigation, it was concluded that tensile strength is directly proportional to the travel speed and gas flow rate. It was also concluded that tensile strength is inversely proportional to the feed rate and voltage.

Various statistical tools and algorithms are applied in different engineering applications for optimization as well as prediction purposes. Multivariate optimization techniques are mostly used to study the effects of more than one output parameter on the input parameters. Some of the most commonly used optimization methods in welding are genetic algorithms, ant colony optimization, analytical hierarchy process, grey relational analysis, etc. Linear regression equations and artificial neural networks are applied as prediction tools. Patel et al. [4] used Grey Relational Analysis for the optimization of MIG and TIG welding parameters. The techniques used to weld AISI 1020 steel plates of 5 mm thickness. Using the mentioned optimization method, the optimal parameter combination was obtained. Sabiruddin et al. [5] used the Analytical Hierarchy Process optimization technique in the GMAW of C45 medium carbon steels. Then, through the calculation of a pair-wise comparison matrix and a global matrix for alternative, the optimized condition was obtained. In the optimization of the GMAW process, Correia et al. [6] conducted a comparison of genetic algorithms and RSM. The findings revealed that both approaches capable of determining the best circumstances. Researchers further observed that genetic algorithms are an efficient approach to optimize, particularly in discontinuous experimental zones. Singh et al. [7] investigated the weld area and ultimate tensile strength of nitrogen-stimulated austenitic stainless steel in the GMAW technique. An artificial neural network was implemented to model the project. It was concluded that the prediction analysis of the ANN model was found acceptable for all the responses.Artificial Neural Network was used by Bera et al. [8] to estimate the ultimate tensile strength, elongation, and hardness of the weld joint. The 3-10-3 ANN model with Levenberg-Marquardt (LM) training function was shown to estimate experimental data with the least amount of error. Bera and Das [9] used the 3-10-4 ANN model to predict depth of penetration, reinforcement, hardness, and bend angle at failure. It was discovered that the constructed model predicted the outcomes of both replications with significantly less error, indicating the effectiveness of the technique.

The present investigation focuses on prediction of weld bead geometry, hardness and maximum bending load of dissimilar metal weld joints. Gas metal arc welding is utilized to join AISI 304 stainless steel and EN 8 medium carbon steel plates. Artificial neural network and linear regression analysis are performed to predict the output parameters. Then, predicted results from both the methods are analyzed and compared.

2.0 Experimental

2.1 Joining of Dissimilar Steels

In this work, AISI 304 and EN 8 steel plates are tried to join together by using GMAW process. 100% CO_2 is utilized as a shielding gas in this process. Schematic diagram for MAG welding setup is shown in **Fig. 1**. Heat input, root gap and torch angle are preferred as input parameters, which are arranged using Taguchi's L9 orthogonal array to select treatments of the experimental work. Several destructive tests, such as the macro etch test, hardness test, and bending test, are performed. Input and output values are shown in **Table 1.**

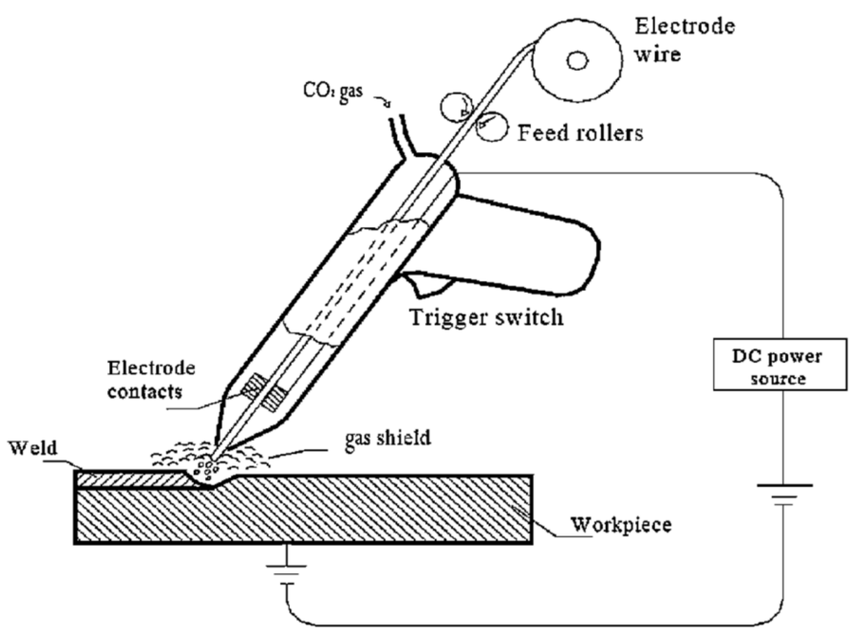


Fig. 1 : Schematic diagram of MAG welding setup

Table 1 : Input and output parameters

Sl. No.	Levels of Input parameters			Reinfor-cement (mm)	Depth of Penetration (mm)	Bead width (mm)	Rockwell hardness (Scale A)	Max. bending load (kN)
	Heat Input (kJ/mm)	Root Gap (mm)	Torch Angle (Degree)					
1	0.552	0	30	2.928	1.508	9.72	56	2.8
2	0.552	1	45	2.327	5	12.16	58	5.2
3	0.552	2	75	1.781	6	11.30	59	8.4
4	0.645	0	45	4.047	3.628	12.06	63	4.4
5	0.645	1	75	4.145	6	11.40	56	6.4
6	0.645	2	30	1.857	6	15.40	55	6
7	0.737	0	75	2.214	2.750	11.72	67	7.2
8	0.737	1	30	3.149	6	10.42	60	6.4
9	0.737	2	45	1.857	6	10.58	63	8.4

From the experimental results, it is observed that, by increasing heat input and root gap, response parameters such as depth of penetration, hardness and maximum bending load increase. But reinforcement and bead width decrease as input parameters are increased. There are combined effects of input parameters on output parameters which should be discussed by optimizing the process parameters.

2.2 Estimation of Response Parameters using Regression Analysis

With the supplied set of explanatory variables p (x_1, x_2,.....x_p), regression models are set up to predict the dependent variables (Y). Input variables of the equation are heat input, root gap and torch angle, and output characteristics are reinforcement, depth of penetration, bead width, Rockwell hardness and maximum bending load. Regression equations for output parameters are shown below.

Reinforcement, R (mm) = 3.03 + (0.35*Q) − (0.616*G) + (0.0012*A)

Depth of Penetration, P (mm) = 0.06 + (4.05*Q) + (1.686*G) + (0.0081*A)

Bead width, W (mm) = 11.91 − (0.79*Q) + (0.630*G) − (0.0077*A)

Rockwell hardness in scale A, HRA = 38.12 + (30.6*Q) − (1.50*G) + (0.0667*A)

Max bending load, P(kN) = - 4.24 + (10.07*Q) + (1.40*G) + (0.0495*A)

Where Q, G and A stands for Heat Input (kJ/mm), Root Gap (mm) and Torch Angle (degree) respectively.

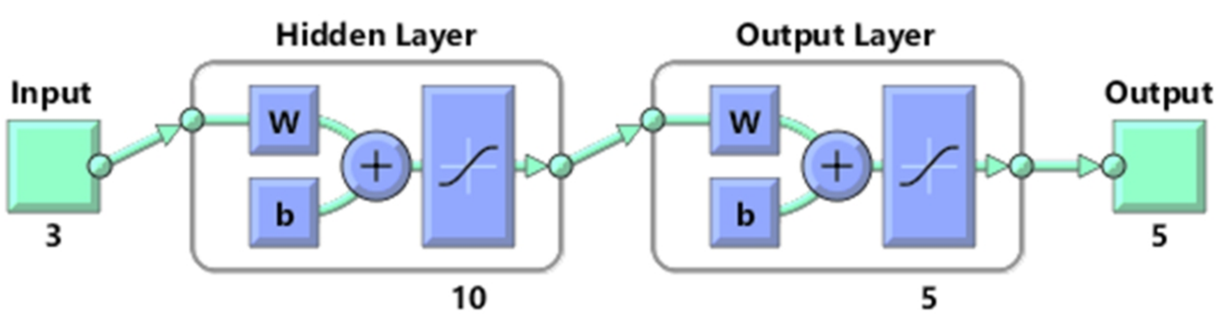


Fig. 1 : Schematic view of ANN formed

2.3 Estimation of Response Parameters using ANN

An artificial neural network (ANN) is also implemented for the prediction of output data, so that the predicted result can be compared with the predicted results obtained from the linear regression equation. The 3-10-5 model of ANN, along with the Levenberg-Marquardt (LM) training function, is used to design the network as shown in the diagram (**Fig. 1**).

3.0 Results and Discussion

3.1 Results obtained from Regression Equation and ANN

Estimation of output parameters is made using regression equations and ANN, which are shown in **Table 2** and **Table 4**. Then error values are calculated as listed in **Table 3** and **Table 5**.

Table 2 : Estimation of response parameters using linear regression equation

Sl. No.	Reinforcement (mm)	Depth of Penetration (mm)	Bead width (mm)	Rockwell hardness in Scale A	Max Bending load (N)
1	3.2592	2.5386	11.24292	57.0122	2.80364
2	2.6612	4.3461	11.75742	56.5127	4.94614
3	2.0812	6.2751	12.15642	57.0137	7.83114
4	3.30975	3.03675	11.05395	60.8585	4.48265
5	2.72975	4.96575	11.45295	61.3595	7.36765
6	2.05975	6.28725	12.42945	56.858	6.54015
7	3.37795	3.65235	10.75027	65.6747	6.89409
8	2.70795	4.97385	11.72677	61.1732	6.06659
9	2.10995	6.78135	12.24127	60.6737	8.20909

Table 3 : Error values obtained from linear regression prediction

Sl. No.	Reinforcement (mm)	Depth of Penetration (mm)	Bead width (mm)	Rockwell hardness in Scale A	Max Bending load (N)
1	-0.3312	-1.0306	-1.52292	-1.0122	-0.00364
2	-0.3342	0.6539	0.40258	1.4873	0.25386
3	-0.3002	-0.2751	-0.85642	1.9863	0.56886
4	0.73725	0.59125	1.00605	2.1415	-0.08265
5	1.41525	1.03425	-0.05295	-5.3595	-0.96765
6	-0.20275	-0.28725	2.97055	-1.858	-0.54015
7	-1.16395	-0.90235	0.96973	1.3253	0.30591
8	0.44105	1.02615	-1.30677	-1.1732	0.33341
9	-0.25295	-0.78135	-1.66127	2.3263	0.19091

Table 4 : Predicted results obtained from ANN

Sl. No.	Reinforcement (mm)	Depth of Penetration (mm)	Bead width (mm)	Rockwell hardness in Scale A	Max Bending load (N)
1	2.993425291	1.511248492	10.38873982	56.01733883	2.805093501
2	2.525871227	4.903395768	12.22254212	57.95240071	5.238532637
3	1.892261051	5.814239964	13.16262006	60.2170846	8.315399854
4	3.781911333	3.684707435	12.10961968	62.38055967	4.374133064
5	4.144977338	5.99989695	12.78525565	66.9974245	8.353528587
6	1.894998875	5.008178266	15.30747506	55.04450143	7.609660729
7	4.145	6	13.14183657	66.99999996	7.751320565
8	3.206980627	5.655261742	10.64637928	60.00715042	6.375983782
9	1.838064083	5.999899053	11.88150851	63.49354172	8.399968495

Table 5 : Error values obtainedfrom ANN

Sl. No.	Reinforcement (mm)	Depth of Penetration (mm)	Bead width (mm)	Rockwell hardness in Scale A	Max Bending load (N)
1	-0.065425291	-0.003248492	-0.668739822	-0.017338832	-0.005093501
2	-0.198871227	0.096604232	-0.062542121	0.047599291	-0.038532637
3	-0.111261051	0.185760036	-1.86262006	-1.217084604	0.084600146
4	0.265088667	-0.056707435	-0.04961968	0.61944033	0.025866936
5	2.27E-05	0.00010305	-1.38525565	-10.9974245	-1.953528587
6	-0.037998875	0.991821734	0.092524943	-0.04450143	-1.609660729
7	-1.931	-3.25	-1.42183657	0.0000000365	-0.551320565
8	-0.057980627	0.344738258	-0.22637928	-0.007150417	0.024016218
9	0.018935917	0.000100947	-1.301508506	-0.493541723	0.0000315

3.2 Comparison of Estimated Response obtained from Regression Analysis and ANN

All the response parameters of dissimilar welding in MAG welding are predicted by the linear regression equation as well as by the artificial neural network (ANN). Reinforcement, depth of penetration, bead width, hardness, and maximum bending load are predicted and compared with the actual values taken from the destructive testing. Line plotsare formed for each response, providing actual data, predicted data obtained from the regression equation and predicted data obtained from ANN. All the charts are shown below.

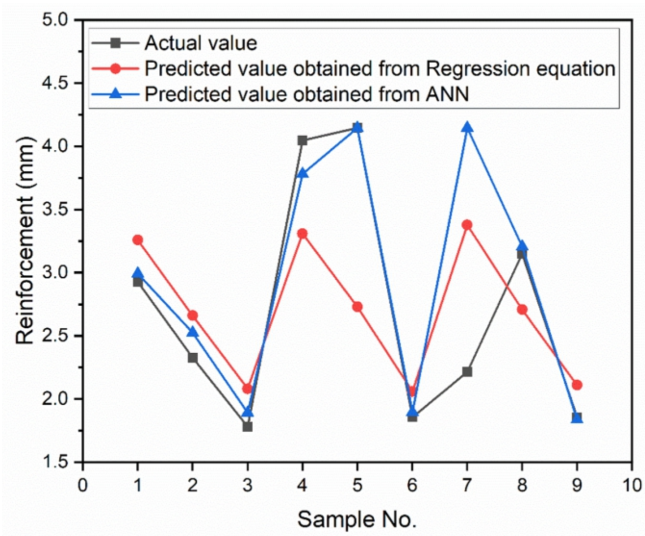


Fig. 2 : Line plot showing comparison of actual value and estimates for reinforcement

From the above line plot (**Fig. 2**) of reinforcement, it isobserved that predicted data obtained from ANN is quite close to actual data sets in almost all cases. Also, the predicted data obtained from the regression equation provides satisfactory results.

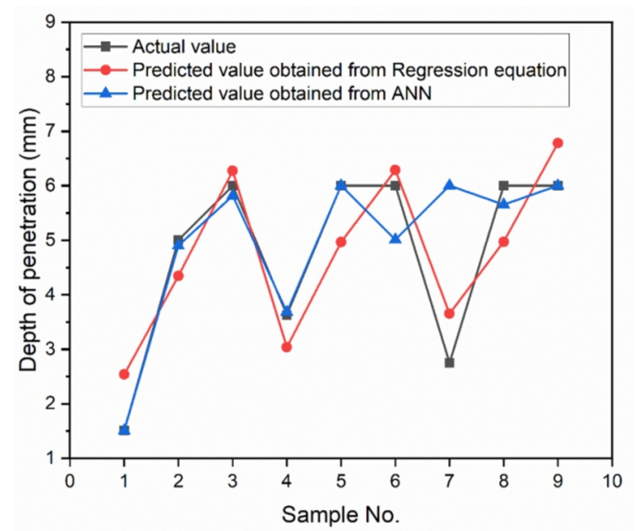


Fig. 3. Line plot showing comparison of actual value and estimates for Depth of penetration

A similar kind of trend is found in the results of the depth of penetration (**Fig. 3**). It is observed that predicted data obtained from ANN are quite close to actual data sets in almost all cases except for a few points. The predicted data obtained from the regression equation resemble the actual data with less error.

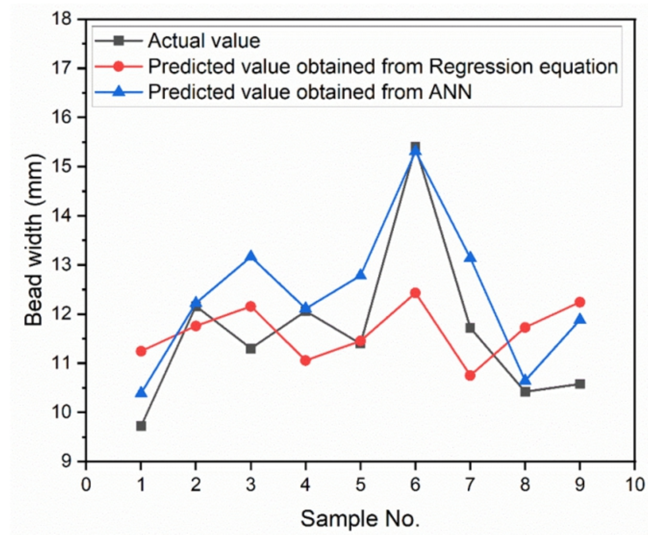


Fig.5 : Line plot showing comparison of actual value and estimates for Rockwell hardness

The predictions made by both methods are close to the actual values as shown in **Fig. 5**. But, if the comparison is made, then ANN shows better results in the estimation of Rockwell hardness with negligible deviation.

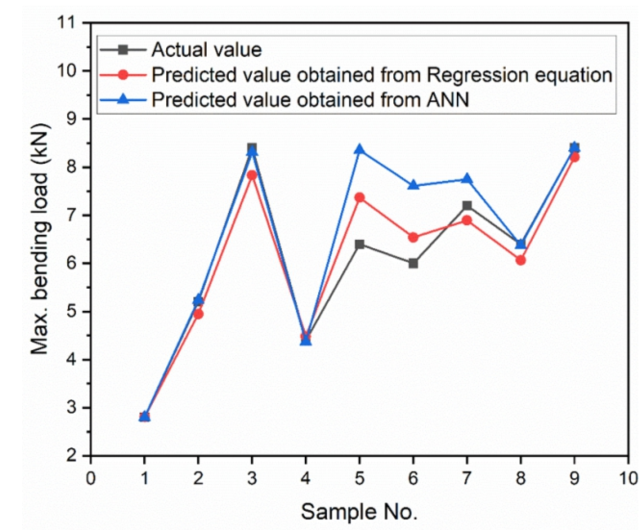


Fig. 6 : Line plot showing comparison of actual value and estimates for Maximum bending load

From **Fig. 6** it is depicted that, the predictions made by both methods are close to the actual value. But ANN provides better results in the prediction of maximum bending load than the regression equation, by a small amount.

4.0 Conclusion

Prediction of output parameters are done using linear regression equation and artificial neural network. It is observed that both the methods provide satisfactory prediction of the output parameters with negligible deviation. Reinforcement, depth of penetration, bead width, Rockwell hardness and maximum bending load are predicted. In case of estimation of bead width, error value is higher than other predicted parameters. Predictions would be more accurate by increasing a greater number of datasets. Although, it is found that ANN provides satisfactory predicted results with much less error than the results obtained from the regression equation.

References

[1] Kumar R, Kundu S and Kumar P (2015); Parameters Optimization for Gas Metal Arc Welding of Austenitic Stainless Steel (AISI 304) and Low Carbon Steel using Taguchi's Technique, International Journal of Engineering and Management Research, 5(5), pp.342-347.

[2] Singh S and Gupta N (2016); Analysis of Hardness in Metal Inert Gas Welding of Two Dissimilar Metals, Mild Steel & Stainless Steel, International Organization of Scientific Research Journal of Mechanical and Civil Engineering, 13(3), pp.94-113.

[3] Chaudhari PD and More NN (2014); Effect of Welding Process Parameters on Tensile Strength, IOSR Journal of Engineering, 4(5), pp.01-05.

[4] Patel CN and Chaudhary S (2013); Parametric Optimization of Weld Strength of Metal Inert Gas Welding and Tungsten Inert Gas Welding by Using Analysis of Variance and Grey Relational Analysis, International Journal of Research in Modern Engineering and Emerging Technology, 1(3), pp.48-56.

[5] Sabiruddin K, Bhattacharya S and Das S (2013); Selection of appropriate process parameters for gas metal arc welding of medium carbon steel specimens, International Journal of the Analytic Hierarchy Process, 5(2), pp.252-267.

[6] Correia DS, Goncalves CV, da Cunha SS and Ferraresi VA (2005); Comparison between genetic algorithms and response surface methodology in GMAW optimization, Journal of Materials Processing Technology, 160, pp.70-76.

[7] Singh V, Chandrasekaran M and Thiruganana-sambandam M (2019); Artificial Neural Network Modelling of Weld Bead Characteristics during GMAW of Nitrogen Strengthened Austenitic Stainless Steel, AIP Conference Proceedings 2128, 020024 (2019).

[8] Bera T and Das S (2021); Application of Artificial Neural Networks in Predicting Output Parameters of Gas Metal Arc Welding of Dissimilar Steels, Indian Science Cruiser, 35(3), pp.26-30.

[9] Bera T and Das S (2021); Estimation of Geometry and Properties of Weld Bead Using Artificial Neural Networks, Reason- A Technical Journal, 20, pp.46-56.

[10] Chan B, Pacey J and Bibby M (1999); Modelling gas metal arc weld geometry using artificial neural network technology, Journal of Canadian Metallurgical Quarterly, 38(1), pp.43-51.

[11] Sarkar A and Das S (2016); Selection of appropriate process parameters for gas metal arc welding of a Steel under 100% carbon dioxide gas shield, Indian Welding Journal, 49(4), pp.61-70.

[12] Saha MK, Das S, Bandyopadhyay A and Bandyopadhyay S (2012); Application of L6 orthogonal array for optimal selection of some process parameters in GMAW process, Indian Welding Journal, 45(4), pp.41-50.

[13] Nagesh DS and Datta GL (2008); Modeling of fillet welded joint of GMAW process: integrated approach using DOE, ANN and GA, International Journal on Interactive Design Manufacturing, 2, pp.127-136.

[14] Shah J, Patel G and Makwana J (2017); Optimization and Prediction of MIG Welding Process Parameters Using ANN, International Journal of Engineering Development and Research, 5, pp.1487-1491.

[15] Ramos-Jaime D and Lopez-Juarez I (2010); ANN and linear regression model comparison for the prediction of bead geometrical properties in automated welding, 1st International Congress on Instrumentation and Applied Science, pp.1-10.

[16] Addamani R, Ravindra HV and Gayathri devi SK (2020); Estimation and Comparison of Welding Performances for ASTM A 106 Material in P-GMAW Using GMDH and ANN, Journal of Critical Reviews, 7(14), pp.2606-2613.

[17] Sreeraj P, Kannan T and Maji S (2013); Simulation and Parameter Optimization of GMAW Process Using Neural Networks and Particle Swarm Optimization Algorithm, International Journal of Mechanical Engineering and Robotic Research, 2(1), pp.131-146.

[18] Sreeraj P and Kannan T (2015); Modelling and Prediction of Stainless Steel Clad Bead Geometry Deposited by GMAW Using Regression and Artificial Neural Network Models, Advances in Mechanical Engineering, 4, pp.1-12.

[19] Gunaraj V and Murugan N (1999); Application of response surface methodology for predicting weld bead quality in submerged arc welding of pipes, Journal of Materials Processing Technology, 88, pp.266-275.

[20] Lee J and Um K (2000); A comparison in a back-bead prediction of gas metal arc welding using multiple regression analysis and artificial neural network, Journal of Optics and Lasers in Engineering, 34, pp.149-158.

[21] Bera T, Santra S and Das S (2022); Performance Measure of Resistance Spot Welding of Similar and Dissimilar Triple Thin Sheets by Using AHP-ANN Hybrid Network, Indian Science Cruiser, 36(2), pp.35-41.

WELD OVERLAY : Save costs, reduce bottlenecks

Abnormal delays in fabrication of pressure vessels and other equipment take place as the final assembly awaits certain components that need to have overlay/cladding done.

In house facilities for most customers are limited for pipes and piping components.

Teekay, a leading manufacturer of pipe fittings and gaskets offers you solutions towards your needs including pipe lengths up to 6.5m.

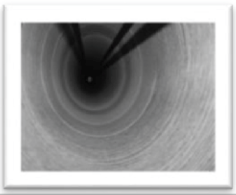
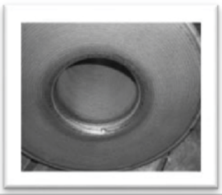
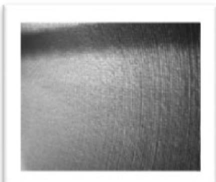
The entire weld overlay/cladding process is PLC controlled and consistency and uniformity in weld deposits is ensured. World renowned power sources ensure that the quantity parameters remain intact.

Additionally, design engineers could think of substituting solid special alloy pipes with cladding on a carbon / low alloy base to add to the growing pool of our customers who are already doing so.

Adequate testing facilities including dye penetrant, ultrasound, magnetic particle and a specially designed machine for internal ultrasound and dye penetrant testing of pipes is also available.

Some jobs done by Teekay include:-

Base Material	Overlay deposit	Base material	Overlay deposit
4" 40 SS321H Finned tubing	Inconel 625	Shell (weighing 6.5 tonnes), Domes & Floating Heads A106-B for Heat Exchanger	SS309L/347
16" X 8" Sch 160/140 WPHY-65 Red. Tee	Inconel 625	16" x 30mm thk. WP22 Cl.3 pipe	SS309L/347
8" 40 WP11 Eq. Tee	Hastelloy C-276	18" 1500# F22 flanges	SS309L/347
36" XS A106 Gr.B Pipe 36" XS WPB 90 Deg LR Elbow	Inconel 625		


Contact for further details at (Tel. 91-8108010033/44/55/66 ; Mob.91-9930517453 or sales@teekay.co.in
Registered Office: 315/317, Navratan Building, 69 P. D'Mello Road, Mumbai – 400 009