Crossref
Similarity Check
Powered by iThenticate

Reason- A Technical Journal
ISSN 2277-1654
Volume XX 2021

ESTIMATION OF GEOMETRY AND PROPERTIES OF WELD BEAD USING ARTIFICIAL NEURAL NETWORKS

Tapas Bera[1] and Santanu Das[2]
Department of Mechanical Engineering, Kalyani Government Engineering College,
Kalyani-741235, India
Email: [1]tapasbera6382@gmail.com, [2]sdas.me@gmail.com

Paper submitted on October 16 2021, Accepted after revision on January 26 2022
DOI:10.21843/reas/2021/46-56/212373

Abstract: Investigations on prediction or estimation of output responses in welding using artificial neural networks (ANN) have become popular among researchers. In this work, metal active gas (MAG) welding was implemented to join EN-8D medium carbon steel plates together by varying welding current, weld voltage and torch traverse speed as input parameters. Depth of penetration, reinforcement, hardness and bend angle at failure were the responses. Then the input parameters and output parameters are used to train the neural networks in this work. Feed forward network with Levenberg-Marquardt training function is implemented. 3-10-4 model of ANN is used for the prediction of depth of penetration, reinforcement, hardness and bend angle. From the regression chart, it is found that the designed model predicted the results of both replications with quite less error and hence, the effectiveness of the technique.

Keywords: GMAW; ANN; Neural network; MAG welding; Modeling; MATLAB

1. INTRODUCTION

Gas metal arc welding (GMAW) process is widely used in several industries for joining of various types of metallic materials together in a wide range of applications. The process produces high quality weld joint minimizing common problems associated with welding maintaining good productivity [1, 2]. GMAW process uses a servo motor-controlled wire electrode feeding to maintain a uniform electrode tip-workpiece distance and hence, the quality of welding. GMAW process for this reason can also be automated or robotized comfortably and is extensively used different automobile and other industries.

Metal active gas (MAG) welding is a type of GMAW process where 100% CO_2 gas is used as a shielding gas in contrast to metal active gas (MIG) welding where inert gas or gas mixture is employed to provide a protective gas shield [3]. MAG welding produces high quality of weld joint with deeper penetration and high deposition rate in steels and therefore, used widely in welding and fabrication industries at present. To guarantee good quality of weld joint, obtaining a favourable bead geometry is quite important [4, 5]. There are three weld bead geometry parameters, namely, depth of penetration, bead width and height of reinforcement. For getting desired weld bead in welding joint of two or more workpieces, depth of penetration needs be high and often a full penetration in one pass is much desired, while bead width and height of reinforcement can be as less as possible. However, if weld cladding is the requirement, then depth of penetration is be quite less to reduce dilution between the substrate and the clad layer; however, bead width and height of reinforcement are to be high to cover the substrate as much as possible [6, 7].

Many research works were performed to investigate weld bead geometry and some other weld characteristic, and the corresponding process parameters were evaluated to find out the optimal condition for meeting desired weld joint quality. While some investigators worked on different arc welding processes to join varying workpiece materials and tried to evaluate the optimum condition experimentally, many employed some optimization and/or prediction algorithms to obtain desired bead geometry. Design of experiment (DoE), regression analysis, grey relational analysis (GRA), artificial neural networks (ANN), or simply neural networks (NN), genetic algorithm (GA), the analytical hierarchy process (AHP), particle swarm optimization (PSO), etc. were resorted to by different investigators to achieve success in the respective domain.

Artificial neural networks (ANN), or simply neural networks (NN), is quite a popular algorithm and pressed into wide variety of applications. ANN was reported to have employed in tool condition monitoring of varying cutting tools using either a single sensory signal or multiple signals obtained from different sensors, while ANN was also utilized in determining the condition for esterification process in chemical industry, determining viscosity of two-phase liquid-solid particles mixture making a slurry to facilitate its transportation through long pipelines, etc. Even prediction of drilling burr formation was done successfully with the ANN.

Along with the above-mentioned applications, ANN also served as a prediction tool in the area of welding technology for estimation of response parameters. By providing the set of input and output parameters, the network is trained. Its capacity to learn aids in obtaining superior results. In most of the ANN models, there are three layers: input layer, hidden layer(s) and output layer. Each layer is made up of a number of processing neurons. The network is deemed to be trained when the difference between ANN output and target output is reduced to a small value. Neurons, connections between them giving weights, propagation function, hyper-parameters, and many learning methods make up a neural network. Through a high degree of non-linear correlations between input and output parameters, ANN can be used for prediction, inspection, tracking, image analysis and recognition, etc. in several fields of management and engineering [4-17].

Chan et al. [4] tried to estimate weld bead geometry produced through GMAW process with the help of ANN, when Lee and Um [5] assessed the weld bead through regression analysis as well as ANN, Sreeraj et al. [6] made a comparison of the applicability of the ANN and particle swarm optimization (PSO) in predicting gas metal arc welded beads. Prediction of GMAW process parameters with the use of ANN was made by Shah and others [7], Sreeharan et al. [8], Ates [9], and many others. Strength of welded joint was tried to estimate by sensing arc signal during pulsed GMAW process by Pal et al. [10] with the ANN. On the other hand, Singh and others applied ANN in estimating bead characteristics during gas metal arc welding with nitrogen-rich austenitic stainless steel [11], while Nagesh and Dutta [12] resorted to an integrated approach by combining design of experiments, ANN and GA to predict fillet weld joint using GMAW successfully. ANN as well as regression analysis were pressed into estimation of bead geometrical properties by Csalino and others [13] to obtain some success. Nagesh and Dutta [14] further used ANN in making estimates of bead geometry in SMAW process also, when Bera and Das [15], Kanti and Rao [16] as well as Das and Das [17] predicted bead geometry obtained through some arc welding processes employing ANN. So, after the above discussion, it can be stated that ANN is having enormous ability to be applied in estimating weld bead characteristic effectively.

In the present work, back propagation type ANN algorithm is tried to estimate responses of GMAW process, such as depth of penetration, height of reinforcement, hardness of the weld bead and bend angle at failure. Based on the experimental results obtained through metal active gas welding of EN-8D medium carbon steel specimens, the ANN model is constructed and its effectiveness is tested.

2. EXPERIMENT ON WELDING OF EN 8D STEELS

Sarkar and Das [20] utilized gas metal arc welding method on a steel to determine the best conditions for obtaining a strong weld within the domain of the experimental investigation. 100% CO_2 gas was used as protecting gas in this method and hence, the process employed is known as Metal Active Gas (MAG) welding. Medium carbon steel (EN 8D) plates of thickness 6 mm were joined in the investigation. The quality of the weld zone was checked by changing process parameters. Weld current, weld voltage and torch traverse speed were taken as input parameters. They explored metallurgical properties, chemical composition, and bead shape. To check for repeatability, each experimental run was replicated twice. For both the replication's, related data are shown in Table 1 through Table 3.

Table 1. Input data (Process Parameters)

Sl. No.	Weld Current (A)	Weld Voltage (V)	Transverse Speed (mm/min)
1	130	22.5	327
2	130	25	554
3	130	30	723
4	140	22.5	554
5	140	25	723
6	140	30	327
7	160	22.5	723
8	160	25	327
9	160	30	554

Table 2. Output data for replication 1

Sl. No.	Depth of Penetration (mm)	Reinforcement (mm)	Hardness (BHN)	Bend Angle at Failure (degree)
1	2.088	3.49	200	5
2	3.303	1.728	325	4
3	3.46	2.385	342	2
4	3.093	2.33	175	7
5	2.878	1.326	335	2
6	3.025	1.655	325	15
7	3.35	3.3	140	4
8	2.005	4.047	125	4
9	3.325	1.225	200	2

Table 3. Output data for replication 2

Sl. No.	Depth of Penetration (mm)	Reinforcement (mm)	Hardness (BHN)	Bend Angle at Failure (degree)
1	2.05	3.154	210	3
2	3.4	1.65	327	7
3	3.39	2.563	275	3
4	4.488	1.3	220	2
5	3.405	1.1	327	7
6	4.73	1.67	332	7
7	4.065	3.258	145	4
8	4.065	5.1	152	9
9	5.1	2.05	210	9

Maximum weld current was found to provide a high-quality weld joint within the range of experimentations. There are also other parameters like torch speed, weld voltage that were to choose suitably. Optimum process parameters in the investigation using 100% carbon dioxide were evaluated through grey relational analysis.

3. DETAIL OF MODELING WITH ARTIFICIAL NEURAL NETWORK

Utilizing the experimental observations made by Sarkar and Das [20], Artificial Neural Network (ANN) is used in the present work to model for the purpose of prediction or estimation. In MATLAB software, ANN is constructed.

The artificial neural network is trained by Levenberg-Marquardt (LM) training function detailed in [31]. 3-10-4 structure of ANN model is used in this work. The ANN selected consists of three layers viz., input layer with three number of nodes that are selected input welding parameters, hidden layer having ten nodes and an output layer having four nodes. Such model is formed by several trial runs. Hidden layer with a total 10 nodes provides satisfactory results. 70% of the observed data are used for training, 15% data are used for validation and 15% data are taken for testing purpose.

The network is re-trained several times to reduce the error which is the difference between target and predicted data. Weights and bias values of each network are automatically set after each run.

4. RESULTS AND DISCUSSION

The artificial neural network (ANN) is utilized to estimate response parameters during gas metal arc welding (GMAW) of EN8D low carbon steel. Table 1, 2 and 3 contain experimental datasets that are taken to generate the ANN prediction model. To evaluate network performance, the correlation coefficient (R) is observed. It also displays how close the predicted output is to the desired results. Tables 4 and 7 show the estimated values obtained using the ANN model.

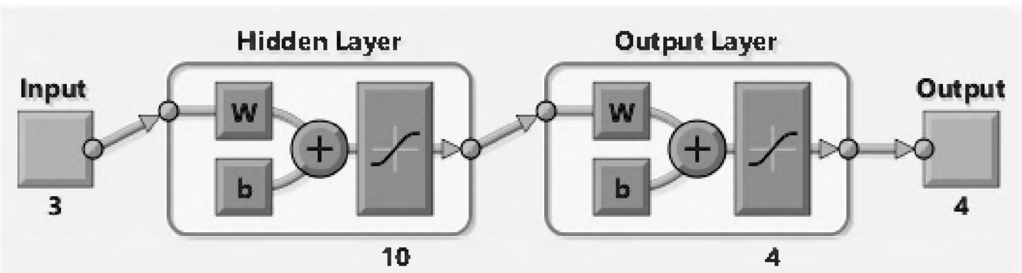


Fig. 1. Schematic view of ANN formed for both replications

Table 4. ANN predicted output parameters for replication 1

Sl. No.	Depth of Penetration (mm)	Reinforcement (mm)	Hardness (BHN)	Bend Angle at Failure (degree)
1	2.064	3.421	200	5.0
2	3.305	1.887	325	4.0
3	3.329	1.545	342	2.0
4	3.286	2.306	175	7
5	3.111	2.167	335	2.5
6	2.176	1.747	262	2.0
7	3.288	3.340	140	4
8	2.011	3.969	125	4
9	3.339	1.406	200	2.0

From the neural network of replication 1, several graphical plots of Target value with predicted value are developed which are shown in Fig. 2. The regression plot is made in MATLAB 2017a software. The value of correlation coefficient (R) is almost 1 for all the data sets. A relation between output and target value is also formed in regression chart. The comparison chart between the output or actual values and the predicted values for replication 1 is shown in Fig. 3(a) through 3(d). Except for some of the results of 'bead angle at failure' and 'reinforcement', it reveals that error is relatively low. It also shows that, the projected data line almost meets the end point of the actual or output data bar graphs. As a result, actual and predicted values are almost identical.

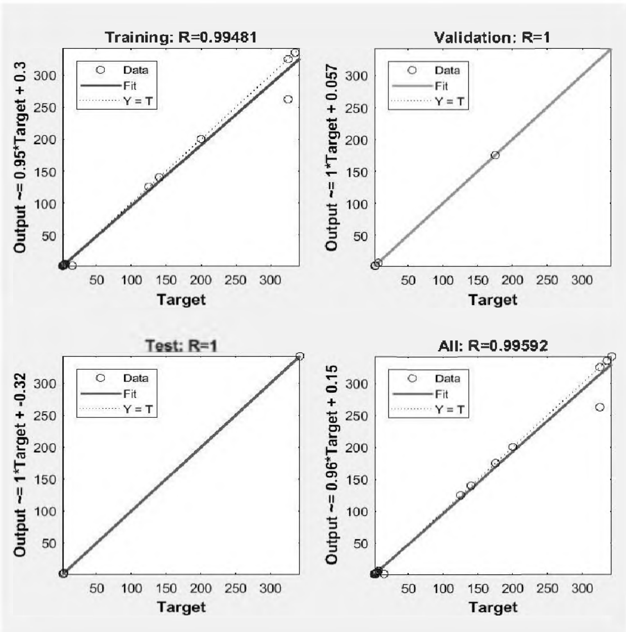
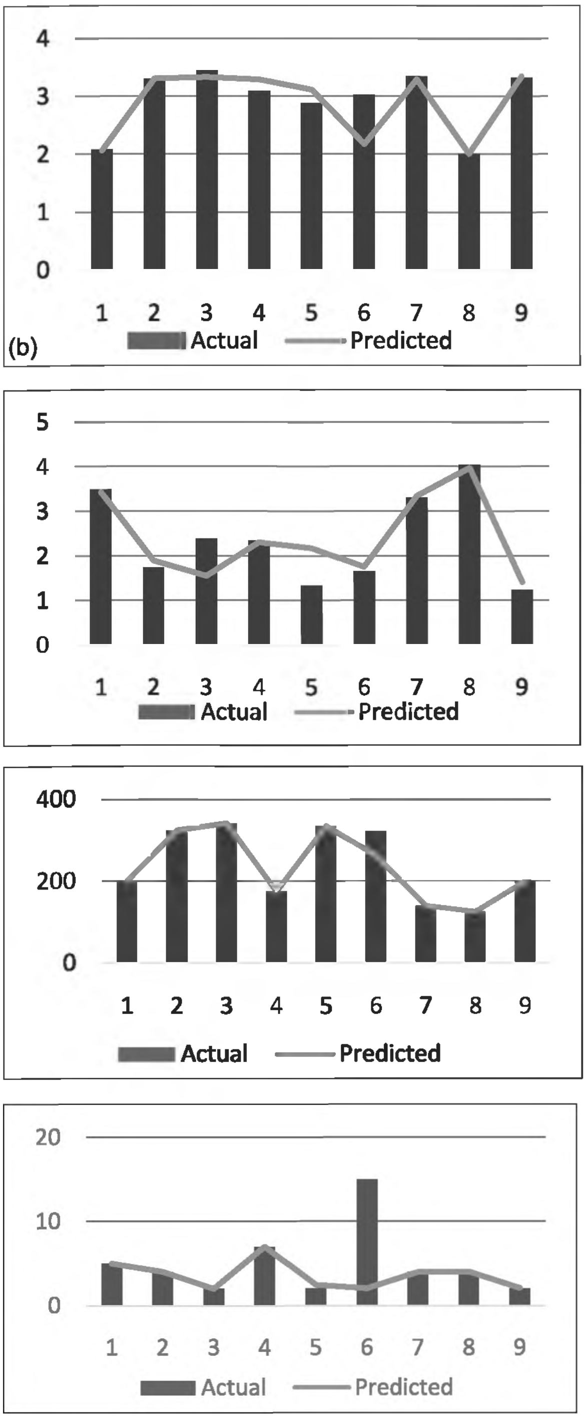


Fig. 2. Plots of estimated output values with target values



(a)

(b)

(c)

(d)

Fig. 3. Comparison chart of actual data VS predicted data (replication 1) [(a) Depth of penetration (mm) (b) Reinforcement (mm) (c) Hardness (BHN) (d) Bead angle at failure(degree)]

Table 5. ANN predicted output parameters for replication 2

Sl. No.	Depth of Penetration (mm)	Reinforcement (mm)	Hardness (BHN)	Bend Angle at Failure (degree)
1	2.209	3.164	219	3.9
2	3.414	1.269	327	6.8
3	3.657	2.110	280	3.3
4	2.886	1.539	255	6.3
5	3.588	1.496	322	7
6	4.831	2.2	331	7.1
7	4.076	3.343	145	4.2
8	4.014	4.456	153	8.3
9	4.984	2.308	217	8.8

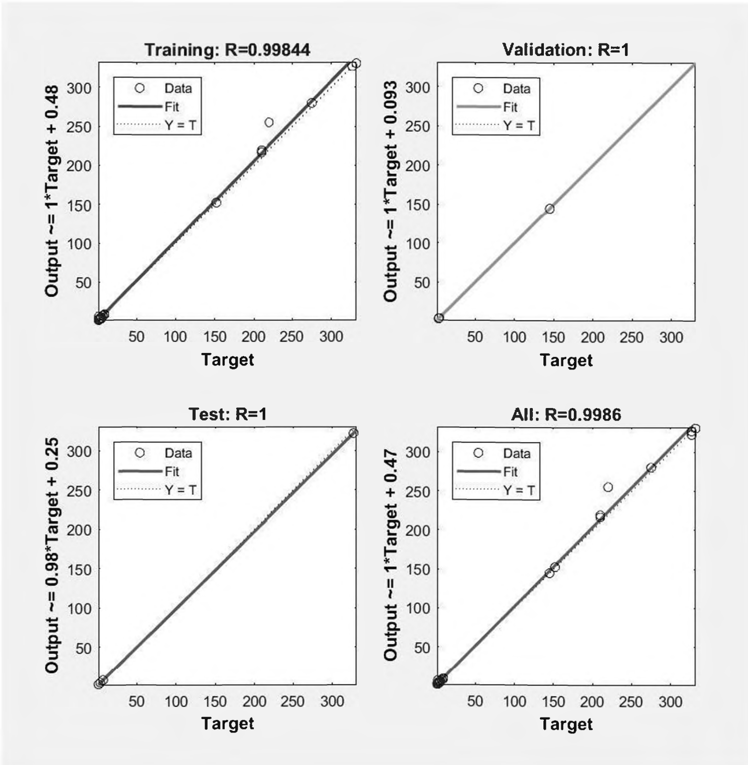


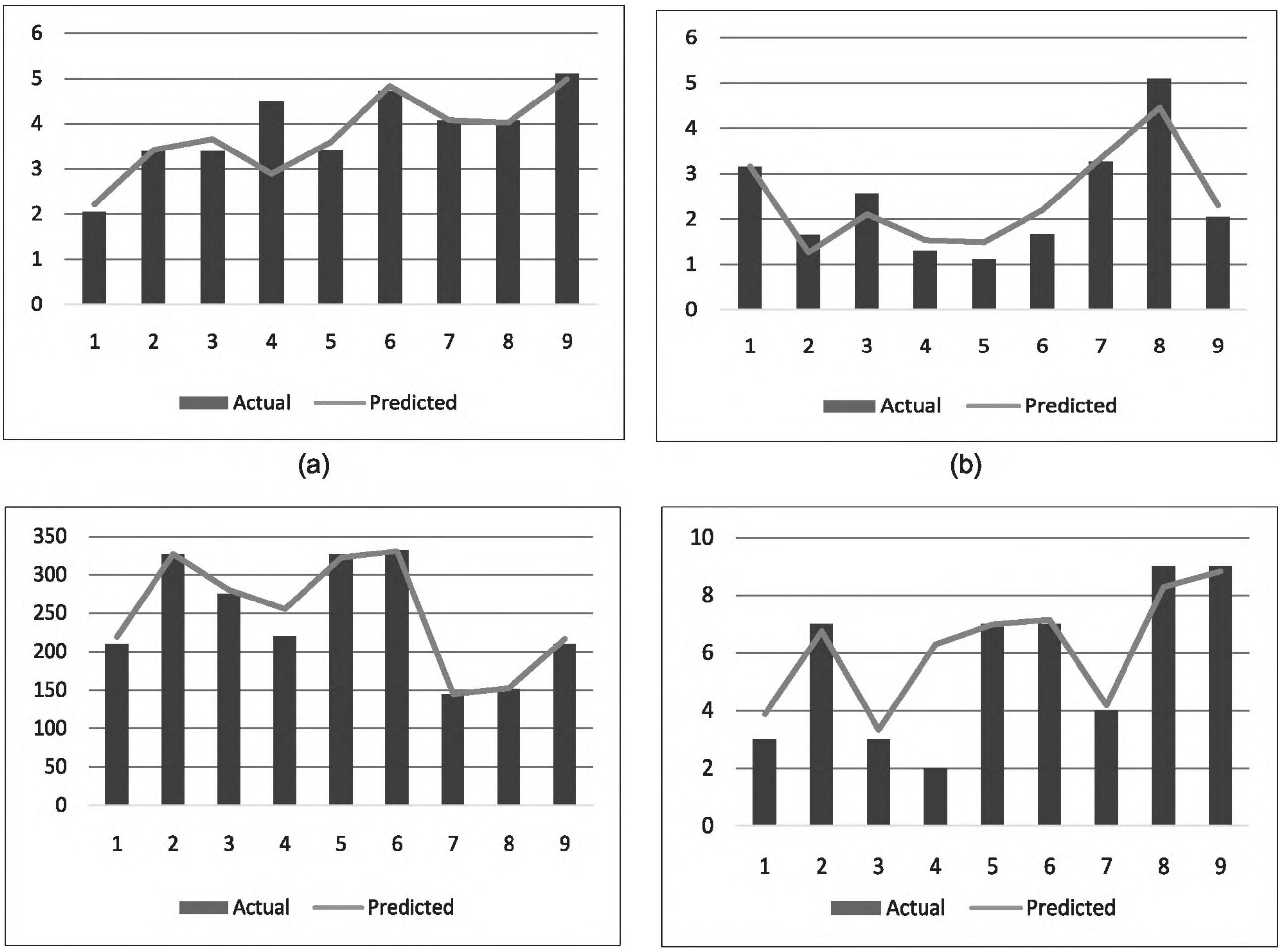
Fig. 4. Plots of estimated output values with target values

Similarly, from the neural network of replication 2, several graphical plots of Target value with predicted value are developed which are shown in Fig. 4. The regression plot is made in MATLAB 2017a software. The value of correlation coefficient (R) is found in all the regression graphs for replica 2. A relation between output and target value is also formed in regression chart. The comparison chart between the output values or actual values and the predicted values for replication 2 is shown in Fig. 5(a) through 5(d). Except for some of the results, it reveals that error is relatively low. The predicted data line graph almost reaches the end point of the actual data bar graph. As a result, it is possible to say that predicted and actual or output values are closer to each other.

5. CONCLUSIONS

After obtaining the results from joining of EN 8D steel plates, the Artificial Neural Network is furnished. Then the target values and predicted values are compared to check the validation of the network. The following outcomes are gathered from the experiment.

- Artificial Neural Network can be used as a prediction tool in welding technologies.



(a) (b)

(c) (d)

Fig. 5. Comparison chart of actual data VS predicted data (replication 2)
[(a) Depth of penetration (mm) (b) Reinforcement (mm) (c) Hardness (BHN) (d) Bead angle at failure (degree)]

- For both the replications, ANN with Levenberg-Marquardt training function is successfully utilized.
- Regression chart is obtained from both the replications. In case of replication 1, the correlation coefficient values for training, testing, validation and that comprising of all datasets are found out to be 0.995, 1, 1, 0.996 respectively. Similarly in case of replication 2, the correlation coefficient values for training, testing, validation and that comprising of all datasets are found out to be 0.998, 1, 1, 0.999 respectively.
- As the correlation coefficient is found to be almost 1 in all the datasets, the predicted results and target results are quite close to each other indicating effectiveness of the ANN model developed.

REFERENCES

[1] Khanna, O. P., A Text Book of Welding Technology, Dhanpat Rai Publications, New Delhi, 2001.

[2] Nadkarni, S.V., Modern Arc Welding Technology, Oxford & IBH Publishing Co. Pvt. Ltd., New Delhi.

[3] Bera, T., The History of Development of Gas Metal Arc Welding process, Indian Science Cruiser, Vol 34, No 4, pp. 64-66, 2020.

[4] Chan, B., Pacey, J. and Bibby, M., Modelling Gas Metal Arc Weld Geometry Using Artificial Neural Network Technology, Journal of Canadian Metallurgical Quarterly, Vol. 38, pp. 43-51, 1999.

[5] Lee, J. and Um, K., 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, Vol. 34, pp. 149-158, 2000.

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

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

[8] Sreeharan, B.N., Kannan, T. and Aravind, P., Process Optimization of GMAW over AA6351 Aluminium Alloy Using ANN, Vol. 8, pp. 208-218, 2017.

[9] Ates, H., Prediction of Gas Metal Arc Welding Parameters Based on Artificial Neural Networks, Materials and Design, Vol. 28, pp. 2015-2023, 2007.

[10] Pal, S., Pal, S.K. and Samantaray, A.K., Artificial Neural Network Modeling of Weld Joint Strength Prediction of a Pulsed Metal Inert Gas Welding Process Using Arc Signals, Journal of Materials Processing Technology, Vol. 202, pp. 464-474, 2008.

[11] Singh, V., Chandrasekaran, M. and Thiruganananasambandam, M., Artificial Neural Network Modelling of Weld Bead Characteristics during GMAW of Nitrogen Strengthened Austenitic Stainless Steel, AIP Conference Proceedings, 2128, 020024, 2019.

[12] Nagesh, D.S. and Datta, G.L., Modeling of Fillet Welded Joint of GMAW Process: Integrated Approach Using DOE, ANN and GA, International Journal on Interactive

Design Manufacturing, Vol. 2, pp. 127-136, 2008.

[13] Casalino, G., Hu, S.J. and Hou, W., Deformation Prediction and Quality Evaluation of the Gas Metal Arc Welding Butt Weld, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, Vol. 217, No. 11, pp. 1615–1622, 2003.

[14] Nagesh, D.S. and Datta, G.L., Prediction of Weld Bead Geometry and Penetration in Shielded Metal-Arc Welding Using Artificial Neural Networks, Journal of Materials Processing Technology, Vol. 123, No. 2, pp. 303-312, 2002.

[15] Bera, T. and Das, S., Application of Artificial Neural Networks in Predicting Output Parameters of Gas Metal Arc Welding of Dissimilar Steels, Indian Science Cruiser, Vol. 35, No. 3, pp. 26-30, 2021.

[16] Kanti, K.M. and Rao, P.S., Prediction of Effect of Welding Process Parameter of MIG Process on Weld Bead Geometry, Journal of Materials Processing Technology, Vol. 200, No. 1-3, pp. 300-305, 2008.

[17] Das, A. and Das, S., Prediction of Bead Geometry of Gas Metal Arc Welded Workpiece Using Artificial Neural Networks, Proceedings of the National Seminar on 'Welding Science and Technology- Present Status & Future Direction' (NSWEST 2021), July 23-24 2021, pp.79-80, 2021.

[18] Saha, M.K., Dhara, L.N. and Das, S., Variation of Bead Geometry of 316 Austenitic Stainless Steel Weld with Varying Heat Input Using Metal Active Gas Welding, Recent Advances in Mechanical Engineering, 2021.

[19] Saha, M.K., Hazra, R., Mondal, A. and Das, S., Effect of heat input on geometry of austenitic stainless steel weld bead on low alloy steel, Journal of the Institution of Engineers (India), Series C, Vol.100, No.4, pp. 607-615, 2019.

[20] Sarkar, A. and Das, S., Selection of Appropriate Process Parameters for Gas Metal Arc Welding of a Steel under 100% Carbon Dioxide Gas Shield, Indian Welding Journal, Vol.49, No.4, pp.61-70, 2016.

[21] Ramos-Jaime, D. and Lopez-Juarez, I., 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, 2010.

[22] Sabiruddin, K., Das, S. and Bhattacharya, A., Application of the analytic hierarchy process for optimisation of process parameters in GMAW, Indian Welding Journal, Vol.42, No.1, pp.38-46, 2009.

[23] Das, A. and Das, S., Tungsten Arc Welded Workpiece Using Artificial Neural Networks, Proceedings of the National Welding Meet (NWM 2021), Tiruchirapalli, October 07-08 2021.

[24] Das, S., Roy R. and Chattopadhyay, A.B., Evaluation of Wear of Turning Carbide Inserts Using Neural Networks, International Journal of Machine Tools and Manufacture, Vol.36, No.7, pp.789-797, 1996.

[25] Das, S., Bandyopadhyay, P.P. and Chattopadhyay, A.B., Neural-Networks-Based Tool Wear Monitoring in Turning Medium Carbon Steel Using a Coated Carbide Tool, Journal of Materials Processing Technology, Vol.63, No.1-3, pp.187-192, 1997.

[26] Das, S., On Wear Monitoring of TiN Coated Tools- Part II: With Neural Networks, Proceedings of the 14th International

Conference on Robotics and Factories of the Future (CAR & FOF 1998), Coimbatore, India, pp.645-653, 1998.

[27] Mukherjee, A. and Das, S., A Simple Online Tool Condition Monitoring System Using Artificial Neural Networks, IOP Conf. Series: Materials Science and Engineering, Vol.1080, No.012021, 2021.

[28] Kartik, C.S., Suryaganesh, G., Joshi, N.R., Ghanta, K.C. and Das, S., Application of Neural Networks to an Esterification Process, Proceedings of the IIChE Golden Jubilee Congress (CHEMCON-1997), New Delhi, pp.1019-1029, 1997.

[29] Ghanta, K.C. and Das, S., Neural Networks Based Modeling of Viscosity for Facilitating Transportation of Magnetite Ore-Water Slurry, Journal of the Association of Engineers, India, Vol.83, No.2, pp.43-54, 2013.

[30] Misra, D., Das, S., Mondal, N. and Saha, P.P., Estimation of Drilling Burr Formation with Artificial Neural Network Analysis, Indian Science Cruiser, Vol.34, No.3, pp.23-31, 2020.

[31] Lera, G. and Pinzolas, M., Neighborhood Based Levenberg-Marquardt Algorithm for Neural Network Training, IEEE Transactions on Neural Networks, Vol. 13, No. 5, pp. 1200-1203, 2002.