IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 54, No. 2, April, 2021, pp. 309-315
Journal homepage: http://iieta.org/journals/jesa

Using Artificial Neural Networks to Predict the Effect of Input Parameters on Weld Bead Geometry for SAW Process

Majid Midhat Saeed*, Ziad Shakeeb Al Sarraf

Department of Mechanical Engineering, Faculty of Engineering, University of Mosul, Mosul 00964 - 060, Iraq

Corresponding Author Email: ziadalsarraf@uomosul.edu.iq

https://doi.org/10.18280/jesa.540213

Received: 12 October 2020
Accepted: 23 February 2021

Keywords:
ANN, back propagation, welding, input process parameters, bead geometry

ABSTRACT

Based on high quality and reliability, one of the most efficient methods for joining metals is Submerged Arc Welding (SAW). In this presented work, an attempt has been successfully taken to develop a model to predict the effect of input parameters on weld bead geometry of submerged arc welding process with the help of neural network technique and analysis of various process control variables and important of weld bead parameters in submerged arc welding. The complexity non-linear relationships of input / output variables for any computational models can be addressed by using artificial neural networks (ANN). Today, ANN represents a powerful modeling technique, that depend on statistical approach, presently practiced in many fields of engineering for modeling complex relationships that other physical models cannot be explained it easily. A welding process with automatic or semiautomatic is required to complete the weld through using tubular electrode with consumable flux. Parameters such as welding current, welding speed and voltage are influenced on the quality of the joints. The work conducts many experiments; these are basically depending on many factors and levels. A selection of 2205 duplex stainless steel is carried out in this study to conduct three factors and five levels of central composite design. Neural network model structure having number of neurons layers such as (3 input layers, 1 hidden layer and 3 output layers) with back propagation algorithm has been successfully applied to extract weld bead geometry from predicting the effect of input parameters. Good agreement was obtained between predicted and experiment results, however process parameters such as speed shows opposite effect on all weld parameters. It was seen that weld height and width are proportional to the amount of input current. The prediction of the neural network model showed excellent agreement with the actual results, which indicate that the neural network is viable means for predicting of not only weld bead geometry, but also other parameters such as polarity, current type and flux geometry. This recommends setting the neural network to be applicable for real time work.

1. INTRODUCTION

One of the most important processes that are always considered to be a main demand in manufacturing industries is welding. Therefore, selection of welding process such as Shielded metal arc welding (SMAW), gas tungsten arc welding (GTAW), gas metal arc welding (GMAW), and flux cored arc welding (FCAW) …etc. is depended practically on the suitable environment of doing process. In industry for example, a fusions welding process, Flux cored arc welding developed from gas metal arc welding process to improve arc effect, metal transfer deposition and both properties and appearance of weld metal. FCAW has been specified as popular process due to good consistency and high-quality weld deposition, metal deposition can be controlled accurately, ability to weld in all position due to smooth characteristics, low spatters and minimum cost for shielding gas, high deposition rate which led to maximize productivity [1]. Selection of appropriate welding technique is very important to obtain good quality of weld bead [2]. For many applications of welding processes, a flux-cored wire performs better and faster. FCAW is suitable for low, mild and high alloy steels as well as stainless steels [3]. In industry, submerged arc welding is considered to be one of the most joining processes that are used to obtain weld quality, due to its ability to predict and monitoring of weld parameters in order to produce weld consistency. Many researches have been focused on SAW technique, first to establish the process and second to study the effect of welding variables on joint area (weld bead weld width and weld size). Start in 1986, Gupta and Parmar predict the weld bead dimension of SAW by using fractional factorial technique. After that a mathematical model are presented to reveal the geometry of flux cored weld process. Studies on weld bead width in GMAW processes were revealed to examine the effect of input parameters on weld process, later many studies on weld bead were carried out through using different analyses such as multiple regression analysis to predict the influence of process parameters on weld for the GMAW. Artificial Neural Networks were used to predict the weld bead geometry and penetration in shielded metal-arc welding. The extraction data of multiple regression technique are used in artificial neural network to determine shear wave velocity of carbonate reservoir [3, 4]. In industry, stainless steels are commonly used as a selection material due to its corrosion resistance. Classification of stainless-steel types is varied between ferritic, austenitic, martensitic, precipitation-hardening and duplex stainless steels. These steels are identified based on their micro structure and major crystal phase. It possesses potential properties such as high mechanical properties, high fatigue strength, good weld ability, low coefficient of thermal expansion and withstands corrosion [4]. These properties allow steel to be applied in different areas such as cargo tanks, pipe systems in chemical tankers, bridges, pressure vessels and heat exchangers. Generally, welding parameters can be chosen according to the previous experience or by trial-and-error method decided by welders. After conducting trial, the welds, the welds are inspected whether it meets the joint requirement or not. The above constrains have been overcome by design of experiment technique. It develops correlation between input process variables and output. Optimization of welding process is essential to achieve desired bead quality [5]. A stainless-steel clad quality is used by Kannan and Murugan [6] to study the effect of flux cored arc welding process on weld bead quality, through analyzing the input parameters. Among the input weld parameters such as current, speed and voltage were considered as significant parameters in SAW and the parameters of weld geometry such as width, height and total area were taken as output values.

2. WELDING PARAMETERS

The welding process variables are totally affected on weld quality [7]. Therefore, obtaining weld bead geometry of high strength and good quality will depend on how to match between input parameters [8]. Arc welding as many welding processes, uses most of these common variables such as AC or DC current, speed, voltage, electrode dimensions, type and dimension of flux layer and polarity as input variables. The extent of base metal fusion is directly influenced by welding current, while both shape depth of penetration are affected by the type of electrode diameter. As shown in Figure 1, the diameter of the weld bead consisting of bead width (W) and reinforcement height (H). The weld exhibits more brittleness compared with the parent materials, so it is necessary that the weld bead be large enough so that a distance which is measured from the root to outside weld is shortest through the parent materials not through the weld bead. However, minimum bead width is recommended due to reducing wastage of the weld electrode and thereby consuming more time.

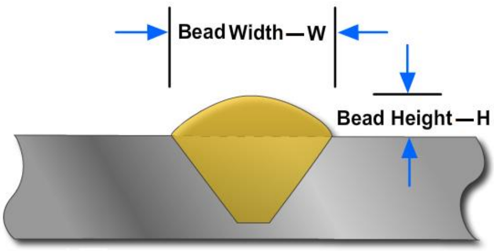

Figure 1. Weld bead (width and height)

3. THE TECHNIQUE OF ARTIFICIAL NEURAL NETWORK

Nowadays, artificial neural network (ANN) is considered to be one of the most adaptable intelligent techniques consisting of simple elements operating in parallel, which are specifically adapted by human nervous systems trained to perform a sub particular function by adjusting the values of the weights to be connected between elements and then create a complex input/output relationship. In addition to linearity, this technique has ability to create nonlinear mapping and then performing continuous nonlinear functions, which can be used to model welding process. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics. In artificial neural network, several techniques can be performed to model welding process such as multilayer perception (MLP), radial basis function (RBF), and self-organizing map (SOM), however the most common is the multilayer perception (MLP) [9]. The last technique of ANN requires proper output values in order to learn, which allow this technique to be a supervised network. With back propagation algorithm, MPL is widely used because of its simplicity and great forecast ability in the weld modeling [10]. The goal for this type of network is to create a model based on historical data to continuously correct maps and to produce the desired unknown values. The final adjustments of weight parameters can be identified by ANN through iterative training of theses parameters. Many artificial intelligence methods can be efficiently performed as a key technique for monitoring and controlling of welding process, such as ANN, fuzzy logic …etc. Examining weld strength due to pulsed metal inert gas welding have carried out by Sukhomay Pal et al. [10], which the process parameters with the root mean square (RMS) measurements of welding current and voltage, were used as input variables of the model and the ultimate tensile strength of the weldment plate was considered as the output value. A multilayer neural network was developed to estimate the ultimate tensile strength in weld plates. They compared the output obtained from multiple regression analysis with the developed artificial neural networks models and concluded the powerful of ANN model against multiple regression analysis. Another work to study the weld bead geometry and penetration through considering current, voltage, speed and electrode dimensions as process parameters was done by using ANN model in order to study the influence factors for electric arc welding [11].

Finally, solving complex and difficulty issues can be overcome by the capability of ANN, as this approach apply successfully to investigate the weld geometry of titanium alloy [12]. A study which adopted multiple regression analysis with back propagation was done through modeling of bead height for metal arc welding process. The result indicates that the back propagation neural network considerably more accurate than multiple regression [13]. On the other hand, most of studies are reported that artificial networks are efficient technique which can be performed for analysis and modeling of weld bead geometry, penetration in arc welding [14, 15]. In present work, ANN models have been used by many researchers to understand and predict their targeted information [14, 15]. In the presented work, artificial neural network (ANN) was selected to develop and predict of the weld bead geometry in submerged arc weld (SAW) for welding of 2205 duplex stainless steel. A neural network algorithm linked with back propagation has been performed effectively to associate the input parameters with the weld bead geometry.

4. PREPARATION AND SET-UP OF WELD PROCESS

First, the samples were prepared to be conducted for experiments, which are selected from 2205 duplex stainless steel and were cut by means of electrical wire cut machine, which it shapes and dimensions should match the general standardization of preparing pieces. The dimensions are 150 mm length and 50 mm width, while thickness of piece is 6 mm. The cutting process of the desired length is obtained with the help of oxy-acetylene flame. After proper cut, the pieces were leaved to cool for a couple of hours, then the pieces were put in the position to be weld in pairs so that they remain together during the experiment. By the end of arc weld, the joint parts were welded have V- groove form. The actual range of weld parameters were proposed based on focus external observation of the weld bead. This was carried out by using visual inspection to observe bead smoothness, absence of porosity, undercut, HAZ, penetration etc. The upper and lower limits (1.68 and -1.68) of variables were specified by coding their values, while the intermediate values were determined based on selected suitable equation $X_i=1.68\ [2X-(X_{max}+X_{min})] / (X_{max}-X_{min})$, where Xi is the coded value of the variable of X, which X is considered as a mid value between maximum and minimum values of X [13]. Table 1 shows levels of process parameters.

Table 1. Selected process parameters in SAW

Factor Levels	Welding Process Parameters (units)		
	Welding Current (I) (Amp)	**Welding Speed (S) (cm/min)**	**Voltage (V) (Volts)**
-1.68	170	25	28
-1	182	27	30
0	200	31	32
1	218	35	34
1.68	230	37	36

In the present work, 2205 duplex stainless steel plates were joined successfully by SAW process, through using filler wire. The experiments were conducted by set three factors with five levels central composite rotatable design. The data of weld were recorded in the form of a design matrix as shown in Table 2. A full replication of factorial design was applied with six centre and starting points at a distance of 1.68 units measured from the centre point. This result indicates that 10 rows were match up the factorial portion, while 11-18 rows were matched to the axial portion, and the remaining 12 rows corresponds to the central portion. Hence, the experimental design consists of 30 successful trials however few numbers were repeated or neglected. In order to develop mathematical models, many attempts were conducted relating to the relationship between process parameters and weld bead geometry. Response surface method was also conducted to design five levels of experiments, which the effect of process (input) parameters on weld bead geometry was clearly identified. Also, a 30 number of experiments allow to study and explore the effect of butt weld process on weld bead geometry, and permit the values to be used as an input command to the artificial network model of weld process. This paper presents a neural network model in order to predict weld bead geometry for input process parameters in 2205 duplex stainless steel butt weld deposited by SAW. The selected input parameters were welding current, welding speed and circuit voltage. The chosen output parameters were weld bead width, reinforcement and total area. The design simulation of weld was done after developed of forward neural network trained by back propagation algorithm.

5. EXPERIMENT WORK

As shown in Figure 2, the experimental part was setup which consists of a power source of MEMCO 600 MMR semiautomatic welding equipment with constant voltage rectifier, filler wire (type E2209T1-4/1) feeding unit (wire feeder controller) with shielding gas flow control, welding gun and a manipulator which guides to deposit the filler metal on the selected area. The work table which is equipped by two independent controllers of two axes is connected in order to help for locating the right position of welding region.

Figure 2. Welding machine and their equipment

A total of 30 experimental trials follows with 5 factors, 3 levels, 1 center point design of experiments were performed in order to establish the effects of arc welding parameters on weld bead geometries. The size of each plate was 150×50×6 mm_3, which these plates were joined using butt weld with a root gap of 2 mm using flux cored 2205 duplex stainless steel wire of 1.2 mm diameter. Shielding gas containing 75% Argon, 2% Oxygen plus 23% CO_2 with a gas flow rate of 20 per minute was maintained. Plates were welded on both sides keeping electrode-to-work angle as 900. The temperature at inside weld was maintained at 150ºC and it was measured by infrared non-contact digital thermometer. To reduce systematic error that can be expected to set up into the system, a random welding trial was conducted relating to the design matrix. All experiments (30 trials) were cross-section cut at their mid-point and specimen of size 10x10x6 mm^3 was obtained from each welded plate. A typical cross sectional view of a weld bead is shown in Figure 3. During tests, the process parameters of weld were seen regularly to avoid any change could be happened during test. After end of weld process and prior to cool state, the slag was removed to leave weld in pure condition. Weld width and reinforcement height were measured using accurate caliper of least count 0.02 mm, then total area of designed matrix was calculated and recorded as tabulated in Table 2. By using a stop watch and weighting machine, the metal deposition rate was also calculated.

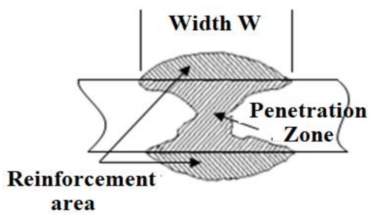

Figure 3. Weld bead cross-sections

Table 2. Process parameters, experimental and predicted data for weld bead geometry

Trial No.	Process Parameters			Width (mm)		
	I	S	V	Exp.	Pred.	% Err
1	180	25	32	12.61	12.58	0.24
2	205	25	32	12.40	12.36	0.32
3	185	34	32	11.25	11.21	0.36
4	210	34	32	12.95	12.90	0.39
5	182	28	34	13.50	13.48	0.15
6	215	28	34	15.65	15.68	-0.19
7	182	28	34	13.35	13.31	0.30
8	218	34	34	12.95	12.93	0.15
9	190	32	32	12.59	12.54	0.40
10	220	32	32	15.34	15.46	-0.78
11	210	27	32	14.85	14.88	-0.20
12	210	37	32	14.20	14.15	0.35
13	210	33	29	13.65	13.40	1.83
14	210	33	29	14.01	13.85	1.14
15	210	31	29	14.10	14.32	-1.56
16	210	31	30	13.78	13.75	0.22
17	210	31	30	13.88	13.60	2.02
18	210	31	30	13.45	13.65	-1.49
19	210	31	30	14.37	14.30	0.49
20	210	31	30	12.48	12.60	-0.96
21	215	29	28	11.85	11.90	-0.42
22	215	29	28	14.80	14.82	-0.14
23	215	29	28	14.20	14.15	0.35
24	215	28	28	13.65	13.40	1.83
25	208	28	28	13.61	13.58	0.22
26	208	28	28	12.40	12.36	0.32
27	205	28	28	11.25	11.21	0.36
28	205	26	28	12.95	12.90	0.39
29	190	26	28	12.61	12.58	0.24
30	190	26	28	12.40	12.36	0.32

Trial No.	Process Parameters			Reinforcement (mm)		
	I	S	V	Exp.	Pred.	% Err
1	180	25	32	2.38	2.36	0.84
2	205	25	32	2.88	2.85	1.04
3	185	34	32	1.85	1.83	1.08
4	210	34	32	2.25	2.24	0.44
5	182	28	34	2.27	2.22	2.20
6	215	28	34	2.45	2.41	1.63
7	182	28	34	2.30	2.36	-2.61
8	218	34	34	1.98	1.93	2.53
9	190	32	32	1.75	1.79	-2.29
10	220	32	32	2.40	2.43	-1.25
11	210	27	32	2.35	2.34	0.43
12	210	37	32	1.90	1.92	-1.05
13	210	33	29	2.15	2.18	-1.40
14	210	33	29	1.95	1.96	-0.51
15	210	31	29	1.84	1.86	-1.09
16	210	31	30	1.92	1.90	1.04
17	210	31	30	1.82	1.86	-2.20
18	210	31	30	2.05	2.10	-2.44
19	210	31	30	2.19	2.20	-0.46
20	210	31	30	2.18	2.19	-0.46
21	215	29	28	2.20	2.22	-0.91
22	215	29	28	2.35	2.36	-0.43
23	215	29	28	1.90	1.92	-1.05
24	215	28	28	2.15	2.18	-1.40
25	208	28	28	2.38	2.36	0.84
26	208	28	28	2.88	2.85	1.04
27	205	28	28	1.85	1.83	1.08
28	205	26	28	2.25	2.24	0.44
29	190	26	28	2.38	2.36	0.84
30	190	26	28	2.88	2.85	1.04

Trial No.	Process Parameters			Total area (mm^2)		
	I	S	V	Exp.	Pred.	% Err
1	180	25	32	700.25	700.15	0.01
2	205	25	32	850.40	855.93	-0.65
3	185	34	32	675.10	679.55	-0.66
4	210	34	32	735.56	733.88	0.23
5	182	28	34	755.98	755.09	0.12
6	215	28	34	1015.1	1013.1	0.20
7	182	28	34	877.49	873.88	0.41
8	218	34	34	805.11	810.02	-0.61
9	190	32	32	740.20	742.52	-0.31
10	220	32	32	955.22	936.41	1.97
11	210	27	32	915.34	905.22	1.11
12	210	37	32	860.40	840.12	2.36
13	210	33	29	810.78	795.17	1.92
14	210	33	29	765.69	770.39	-0.61
15	210	31	29	790.85	799.15	-1.05
16	210	31	30	820.39	822.41	-0.24
17	210	31	30	799.96	810.39	-1.30
18	210	31	30	778.39	786.93	-1.10
19	210	31	30	753.29	748.98	2.62
20	210	31	30	752.35	750.85	0.20
21	215	29	28	756.23	750.15	0.80
22	215	29	28	915.35	905.20	1.11
23	215	29	28	860.42	840.18	2.35
24	215	28	28	810.18	812.10	-0.24
25	208	28	28	705.25	710.15	-0.69
26	208	28	28	860.40	850.93	1.10
27	205	28	28	675.10	679.55	-0.66
28	205	26	28	735.56	733.88	0.23
29	190	26	28	840.40	845.93	-0.66
30	190	26	28	780.40	785.93	-0.71

6. PROPOSED ARTIFICIAL NEURAL NETWORK MODEL

As mentioned before, a neural network model is used to build a map and set of input patterns to a corresponding set of output patterns by the concept of learn, based on previous input/output data examples related to each other. In industrial and manufacturing fields, traditional linear models are found to be inadequate when it performed modeling data contains non linear characteristics. Therefore, using neural network is a key solution to have ability to represents both linear and non linear relationships, also has capability to learn these relationships directly from data being modeled. This gives advantage to the ANN technique to be simple, low cost effective and high ability to learn from many industrial applications. In general purpose, the developed model by ANN should include a collection of database, pre-process and post process of input/output data, simulation and train of neural system for prediction demand [16]. One of the issues faced by neural network model is how to choose optimum network architecture. This can be overcome by makes proper arrangement of neurons into layer and connect pattern between these layers, as the network structure consist of input, hidden and output layers. Input layers receive weld process parameters and the output layers obtaining and providing the values of bead geometry, while hidden layers between the input and output is considered as block box [17]. Designing an architecture structure with a no of hidden layers having neurons inside these layers will reflect the performance of the neural network. Hence, optimal design structure can be confirmed due to many attempts that carried out based on the number of hidden layers. To accommodate the convergence error, trial and error method was used to conduct the required hidden layers and neurons of the design model and then to get an appropriate structure of the weld bead geometry [13]. The feed forward neural network structure was modelled, which include three neurons in the input layer, one hidden layer and three neurons in output layer using MATLAB Neural network toolbox [18, 19]. With the aid of back propagation (BP) algorithm, the model was trained to represents an approximation of regression non linearity. It is important to know here, that most researches are implemented their models by using (BP) in order to predict weld parameters of neural network processes. It was trained with help of back propagation (BP) algorithm. BP is essentially stochastic approximation to nonlinear regression. Several researchers were used BP to model welding processes and to predict welding parameters using neural network (NN). Figure 4 indicates the steps of back propagation algorithm that used in this work; the steps were arranged as mentioned in flow chart.

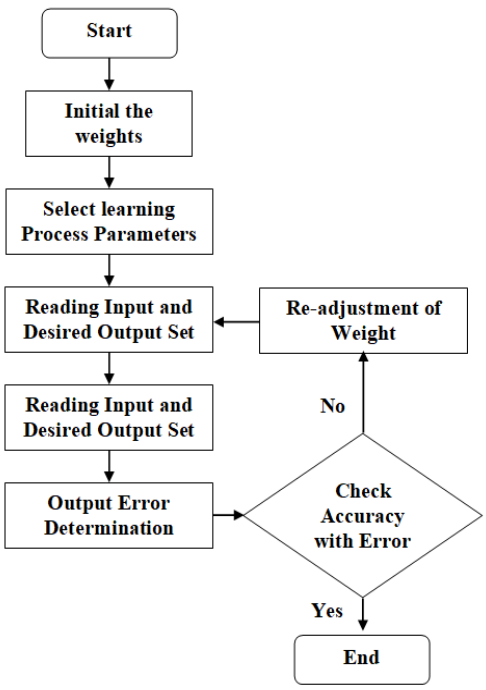

Figure 4. Basic flow chart of (BP) neural network

Based on MATLAB simulation, the developing models and training of networks were successfully completed. The train is essential to obtain balancing for process parameters to become more feasible neurons and then to reach normalized condition. Under preprocessing and to get more feasible, the parameters were normalized and transformed within a specified range varied from 0 to 1 [20]. Since, the normalized value for each raw input/output data set were converted using the following equation as follows:

$$X_n = \frac{[X - X_{min}]}{[X_{max} - X_{min}]} \tag{1}$$

where, X_n is denoted by normalize value and X is referred to input/output value, while X_{min} and X_{max} are minimum and maximum values of input and output respectively. The design model of neural networks structure was addressed to compose of 3 neurons input layer, 5 neurons in hidden layer and 3 neurons output layer. Figure 5 shows a proposed feed forward architecture model that was simulated by neural network. The difficulty prediction for operating process parameters of a non-linear model has some obstacle and may not be able to indicate the reality in determining values, while the use of neural network technique will help to predict the non-linear models due to its highly efficient tool [20]. With learning rate of 0.6, the developed models of neural network were trained based on back propagation algorithm that successfully applied to set 25 data, and with up to 10000 iterations. The trained network was necessary in order to reduce the percentage error. The network is trained for 10000 iterations and the developed was tested out of testing dataset. As listed in Table 2; the percentage error was also calculated between the experimental and predicted value. The results indicate that the percentage error is ranging between ±2.62. At the end of this training process, it was concluding that the developed neural network model, have high accuracy and more reliability for predicting of weld bead geometry.

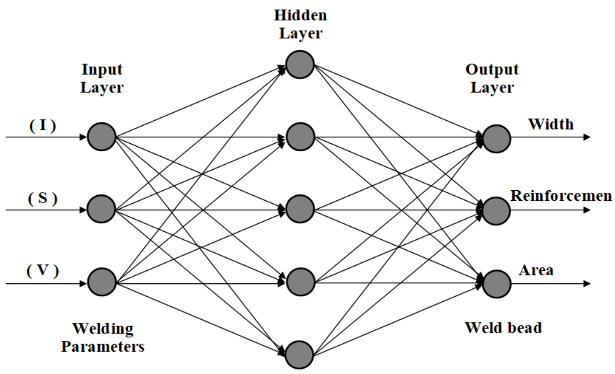

Figure 5. Predicting of weld bead geometry by proposed neural network architecture

7. RESULTS AND DISCUSSION

Study the effect of parameters on weld bead geometry was investigated experimentally and plotted on the figures. Figures 6, 7 and 8 shows the measured weld bead width, reinforcement and total area from the experiment and then predicted output values using ANN in the form of feed forward neural network model with back propagation algorithm. The results were predicted from the best architecture of neural network, so the predicted values were very close to experimental values. It can be observed from the convergence between predict and experiment values that the percentage errors determined between them are low and within acceptable condition as listed in Table 2, hence the ANN was able to predict the weld bead geometry with good accuracy.

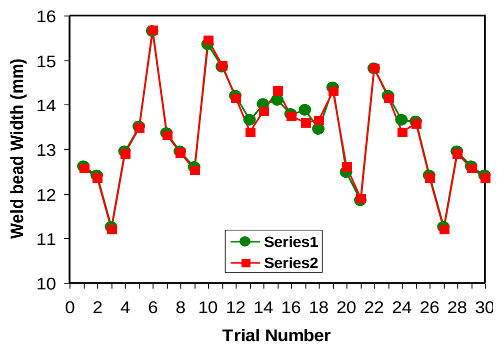

Figure 6. Comparison between predicted and experimental weld bead width vs. the number of trials network model

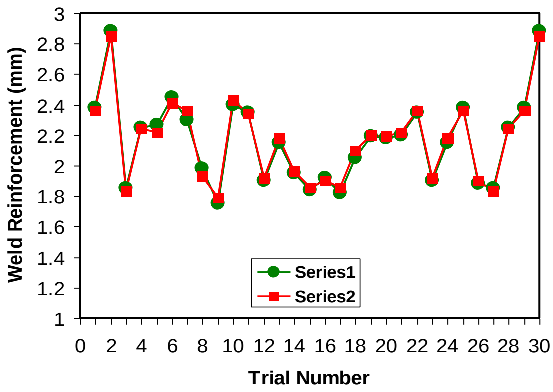

Figure 7. Comparison between predicted and experimental weld bead reinforcement vs. the number of trials network model

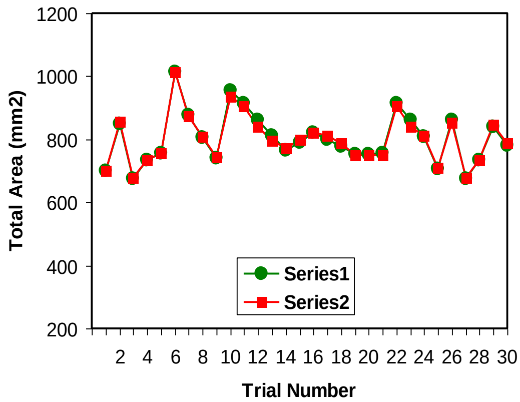

Figure 8. Comparison between predicted and experimental weld bead areas vs. the number of trials network model

8. CONCLUSION

An ANN based on neural network model with back propagation algorithm has been successfully set up to simulate the influence of weld parameters as an input values and study their effect on weld bead geometry of 2205 duplex stainless steel sheet in submerged arc welding (SAW). The simulation model of the welding process was carried out based on feed forward artificial neural network structure (3-5-3) to extract weld bead geometry from predicting the effect of input parameters. A multiple set of data were used to train the network in order to predict the geometry of weld, minimize the percentage error that can be initiated during tests and to benefit from artificial neural network to predict the quality of weld. In general, the predicted results and the results from experiments are compared, which show good agreement. However, process parameters such as speed have opposite effect on all weld parameters. In experiments, increasing speed substantially reduce heat, lower burn off rate and minimum the deposition at weld joint so affect weld bead parameters. It was seen that weld height and width are proportional to the amount of input current, which means that input high current leads to increase in height but decrease in width. Also, it was observed that the weld bead become wider as received high amount of voltage. At end this work shows that it is possible to use neural network in order to predict the weld bead geometry. The proposed neural network has the modeling competence with average accordance ratio of 93.5%, which allow the ANN to have powerful and alternate technique to predict weld bead geometry, and hence permit it to include other parameters such as polarity, type of current and flux geometry. Furthermore, it was recommended to set the neural network as a technique used for real time work.

ACKNOWLEDGMENT

The authors would like to express their thanks to the materials laboratory in department of mechanical engineering for their funding, the University of Mosul for the sponsorship under its research and development program, also for supporting of the research.

REFERENCES

[1] Sathiya, P., Aravindan, S., Soundararajan, R., Haq, A.N. (2009). Effect of shielding gases on mechanical and metallurgical properties of duplex stainless-steel welds. Journal of Materials Science, 44(1): 114-121. https://doi.org/10.1007/s10853-008-3098-8

[2] Missori S., Murdolo, F., Sili, A. (2004). Single pass laser beam welding of clad steel plate. Weld Journal, 83(2): 65-71. https://doi.org/10.29391/2019.98.006

[3] Flux Cored Welding, Welding Procedures and Techniques. 23 of June 2006.

[4] Ezuber, H.M., El-Houd, A., El-Shawesh, F. (2007). Effects of sigma phase precipitation on seawater pitting of duplex stainless steel. Desalination, 207(1-3): 268-275. https://doi.org/10.1016/j.desal.2006.05.021

[5] Benyounis, K.Y., Olabi, A.G. (2008). Optimization of different welding processes using statistical and numerical approaches-A reference guide. Advances in Engineering Software, 39(6): 483-496. https://doi.org/10.1016/j.advengsoft.2007.03.012

[6] Kannan, T., Murugan, N. (2006). Effect of flux cored arc welding process parameters on duplex stainless steel clad quality. Journal of Material Processing Technology, 176(1-3): 230-239. https://doi.org/10.1016/j.jmatprotec.2006.03.157

[7] Kang, M.J., Kim, Y., Ahn, S., Rhee, S. (2003). Spatter rate estimation in the short circuit transfer region of GMAW. Weld Journal (Miami, Florida), 82(9): 238-247.

[8] Ureña, A., Otero, A., Utrilla, M.V., Munez, C.J. (2007). Weldability of a 2205 duplex stainless steel using plasma arc welding. Journal of Material Processing Technology, 182(1-3): 624-631. https://doi.org/10.1016/j.jmatprotec.2006.08.030

[9] Kim, I.S., Lee, S.H., Yarlagadda, P.K.D.V. (2003). Comparison of multiple regression and back propagation neural network approaches in modelling top bead height of multipass gas metal arc welds. Science and Technology of Welding and Joining, 8(5): 347-352. https://doi.org/10.1179/136217103225010998

[10] Nagesh, D.S., Datta, G.L. (2002). Prediction of weld bead geometry and penetration in shielded arc welding using artificial neural networks. Journal of Materials Processing Technology, 123(2): 303-312. https://doi.org/10.1016/S0924-0136(02)00101-2

[11] Al-Faruk, A., Hasib, A., Ahmed, N., Das, U.K. (2010). Prediction of weld bead geometry and penetration in electric arc welding using artificial neural networks.

International Journal of Mechanical & Mechatronics Engineering, 10(4): 19-24. https://doi.org/10.1016/S0924-0136(02)00101-2

[12] Khorram, A., Yazdi, M.S., Ghoreishi, M., Moradi, M. (2010). Using ANN approach to investigate the weld geometry of Ti 6Al 4V Titanium Alloy. International Journal of Engineering and Technology, 2(5): 491.

[13] Palani, P.K., Murugan, N. (2006). Selection of parameters of pulsed current gas metal arc welding. Journal of Materials Processing Technology, 172(1): 1-10. https://doi.org/10.1016/j.jmatprotec.2005.07.013

[14] Pal, S., Pal, S.K., Samantaray, A.K. (2008). 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, 202(1-3): 464-474. https://doi.org/10.1016/j.jmatprotec .2007.09.039

[15] Ghosh, A., Mukherje, S., Chattopadhyaya, S., Sarker, P.K. (2007). Weld bead parametric estimation of SAW process through neural network. Indian Welding Journal, 40(4): 33-43. https://doi.org/10.22486/iwj.v40i4.178436

[16] Yousif, Y.K., Daws, K.M., Kazem, B.I. (2008) Prediction of friction stir welding characteristic using neural network. Jordan Journal of Mechanical and Industrial Engineering, 2(1): 151-155.

[17] Chang, W.S., Na, S.J. (2001). Prediction of laser-spot-weld shape by numerical analysis and neural network. Metallurgical and Materials Transactions B, 32(4): 723-731. https://doi.org/10.1007/s11663-001-0126-3

[18] Demuth, H., Bcalc, A.M. (2000). Neural Networks Toolbox User`s guide, version 4. The mathworks Inc.

[19] Rajasekaran, S., Pai, G.V. (2003). Neural networks, fuzzy logic and genetic algorithm: Synthesis and applications (with cd). PHI Learning Pvt. Ltd.

[20] Jeng, J.Y., Mau, T.F., Leu, S.M. (2000). Prediction of laser butt joint welding parameters using back propagation and learning vector quantization networks. Journal of Materials Processing Technology, 99(1-3): 207-218. https://doi.org/10.1016/S0924-0136(99)00424-0