Modeling of Penetration Depth in Submerged Arc Welding Using Artificial Neural Network

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Modeling of Penetration Depth in Submerged Arc Welding Using Artificial Neural Network

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Abstract

The penetration depth, which is the distance from the surface of the plate to the bottom of the pool or the bottom edge where melting took place, will have a decisive importance in the strength of the weld metal. Submerged arc welding is a manufacturing process that is directly affected by various input parameters and interactions, and these effects directly affect the penetration depth. This research used an artificial neural network with two hidden layers to find the relationship between process inputs and their effects on weld penetration depth. Arc voltage (V), electric current intensity (I), electrode stick-out (N), welding speed (S), and the thickness of the layer of nanoparticles (F) were selected as input layer neurons and penetration depth as output layer neurons. Also, the investigation of the effect of the input parameters on the penetration depth showed that the increased intensity of the electric current increases the heat input to the welding pool. This, in addition to the rise in the melting of the base metal, also increases the penetration depth. Increasing the arc voltage increases the amount of heat input to the welding pool, but the melting speed of the electrode does not change much, so the penetration depth increases slightly.

Keywords: Artificial neural networks (ANNs), Modeling and Optimization, Weld geometry, Nanoparticles, Submerged arc welding (SAW).

1. INTRODUCTION

Welding is a production method that connects two metallic or non-metallic materials and creates a continuous member. Welding with various methods has the most powerful application for connecting and integrating parts, especially in cases without disassembling them. Welding is used in multiple industrial sectors, from construction in the building sector to large and diverse industries such as automotive, aerospace, shipbuilding, and nuclear [1-5].

Submerged arc welding (SAW) is a method of connecting different parts. The arc between the electrode wire and the workpiece is submerged under a layer of powdered flux delivered in front of the electrode from a hopper [6]. SAW has several advantages over other welding processes. For example, SAW has a relatively higher material deposition rate than traditional welding methods [2]. Furthermore, SAW provides a purer and cleaner high-volume weldment, free from porosity, slag inclusions, and other defects [7]. SAW is widely used for welding thicker plates and produces less distortion than other welding processes. Also, SAW is fully automated, which increases productivity [8-11]. Overall, SAW is a versatile welding process with several advantages over other welding processes, making it suitable for various applications. On the other hand, welding parameters such as welding speed, current, and voltage can affect the welding quality. [12-14].

A significant problem today's welding engineers faces is achieving the desired quality of welded metal. Experience usually achieves this goal and requires many experimental tests that ultimately lead to finding the optimal welding parameters [15]. In this case, several studies have been done in modeling and optimizing the effective parameters of the welding process. Researchers have tried to find the optimal values of these parameters by modeling and seeing the relationship between the input and output variables to achieve the desired properties in the weld metal [16-26].

This paper investigated the impact of arc voltage, electric current intensity, electrode stick-out, welding speed, and the nano-particle layer thickness on the geometry of the created welds as influential parameters. The Central Composite Rotatable Design was used to determine the process input parameters. Then, the perceptron artificial neural network was used for modeling between input and output data and prediction of weld penetration depth.

2. ARTIFICIAL NEURAL NETWORK

This research used the artificial neural network to find the relationship between the input variables and the output value in the submerged arc welding process. Artificial neural networks (ANNs) are computational models inspired by the structure and function of the brain [27]. They are used in various applications, including object detection, solving partial differential equations, and training and testing phases [28, 29]. An artificial neural network consists of three input, intermediate and output layers, and each layer of the neural network contains a set of nodes that have the same function as the human brain's neurons. To train for it, it can be different.

The input layer receives the data and sends it to the next layer to perform various calculations. In other words, this layer does not apply any computing and processing operations to the data and is only responsible for receiving and sending data to the middle layer. As seen in Figure 1, the first or input layer has five nodes, including arc voltage, electric current intensity, electrode stick-out, welding speed, and the thickness of the layer of nanoparticles.

The layer between the input and output layers is called the middle layer. The minimum number of intermediate layers of the neural network is one layer, and based on the complexity and type of problem, it can be added to the number of intermediate layers of the network. The more intermediate layers of the network, the deeper the network and the higher its computational load. The middle layers are responsible for performing computational operations on the data received from the input layer.

The last layer of the neural network is the output layer, which calculates the output values of the neural network. In other words, the output layer receives inputs from the middle layer, performs calculations, and produces the network output. In this research, the middle layer had three nodes, and the output layer had one node (penetration depth).

3. Experimentation and data collection

In this paper, the experiments were performed by submerged arc welding process with DC reverse polarity on St37 steel with a size of 15×50×150 mm^3 by welding of PARS CAT P2310 semi-automatic robot with PARC ARC 1203T power supply with constant voltage curve (The chemical composition of the welding wire and consumed flux is shown in Table 1). Arc voltage (V), electric current intensity (I), electrode stick-out (N), welding speed (S), and the thickness of the layer of nanoparticles (F) have been considered input parameters. The maximum and minimum ranges were set for each parameter according to the implementation of several experiments based on one variable at a time and checking the weld quality in welded samples. Then the parameters arc voltage, electric current intensity, electrode stick-out, welding speed, and the thickness of the layer of nanoparticles in five-level (-2, -1, 0, +1, and +2) were determined by Central Composite Rotatable Design. The design matrix and the results are presented in Table 2. Then the artificial neural network was used for modeling between input and output data. The Developed structure of the artificial neural network model is shown in Figure 1.

Table 1- Chemical composition of the welding wire and consumed flux.

Chemical composition of the welding wire				
Element	C	Mn	Si	Fe
%W	0.04-0.08	0.9-1.3	0.5-0.8	Balance

Chemical composition of the consumed flux		
$SiO_2 + TiO_2$	Al_2O_3 + MnO	CaF_2
% 5	% 55	% 30

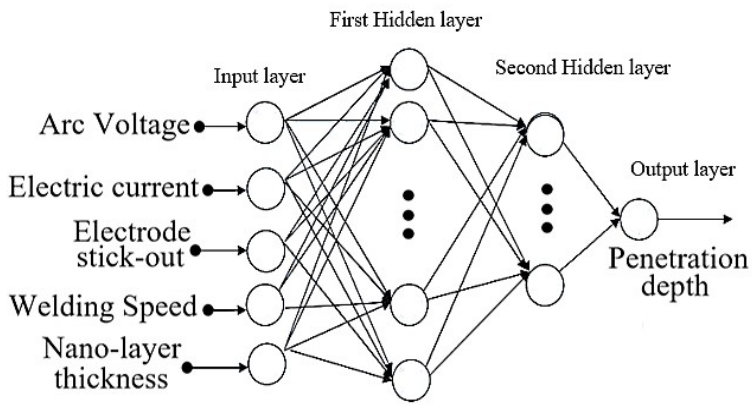

Figure 1. Developed structure of artificial neural network model.

Table 2- Input parameters and their ranges

Std.	V	I	N	S	F	Penetration depth	Error
1	0	0	0	0	0	7.01	-0.24
2	0	0	0	-2	0	8.14	0.40
3	-1	1	-1	1	1	7.65	0.17
4	1	1	1	-1	-1	9.28	0.36
…	…	…	…	…	…	…	…
51	0	0	0	0	0	7.12	-0.13205
52	-1	1	1	1	-1	7.48	0.227065
53	2	0	0	0	0	8.10	-0.49463

4. Results and discussion

This study was carried out to achieve the maximum penetration depth, so the neural network structure with five neurons in the input layer and one neuron in the output layer was used to model between input parameters and output variables. Considering the effects of each parameter on the depth of weld penetration and to achieve optimal welding conditions with the most significant penetration depth of weld, the regression equation was investigated and evaluated with the help of the artificial neural network. The input layer contains five neurons, including arc voltage, electric current intensity, electrode stick-out, welding speed, and the thickness of the layer of nanoparticles, and the output layer has one neuron, including penetration depth.

The data were randomly selected, and the Levenberg-Marquardt algorithm was used in the neural network. Training data presented to the network during training and adjusted according to its error was chosen equal to 70%. Validation data used to measure network generalization and halt training when generalization stops improving was selected equal to 20%. Testing data that do not affect the activity and provide an independent measure of network performance during and after training was chosen to equal 10%. The regression coefficients of experimental data and neural network training data to achieve the maximum penetration depth are shown in Figure 2. The error histogram between the outputs and the target, which shows the degree of belonging of each data group for different errors, is shown in Figure 3. The values of the errors measured by the neural network compared to the actual values of the laboratory measurement data are displayed in Table 2. The neural network performance calculation index was Mean Squared Error (MSE). MSE is the average squared difference between outputs and targets. Lower values are better, and zero means no error. Regression R-Values measure the correlation between outputs and targets. An R-value of 1 indicates a close relationship, and 0 represents a random relationship. MSE and R-Values are shown in Figure 4. Also, the performance plot related to test, validation, and train data is shown in Figure 4, and point 29 is chosen as the optimal point. Since the validation check was six and no improvement has been observed, the network is stopped.

Also, the effect of Arc voltage, electric current intensity, electrode spacing from the nozzle, welding speed, and nano-particles layer thickness was investigated on the penetration depth. The results show that the electric current's intensity significantly affects the welding geometry, increasing the welding penetration depth by increasing the melting speed of the base metal and the welding wire. On the other hand, excessive current will lead to loss of energy and welding wire [30-33]. As shown in Figure 5, the current increased from 500 to 700 Amps, the heat entering the workpiece grew, and a higher amount of the base metal melted and thus increasing the penetration depth. Welding voltage differs between the welding wire potential and the molten metal's surface area. A higher welding voltage can cause a slight increase in the penetration depth [30,33]. Although by increasing the arc voltage from 24 to 32 volts, the heat input into the workpiece rose, the melting rate of the electrode did not change very much. Therefore, the weld's penetration increased by a small amount, and the effect of the discharge voltage on the increase in penetration depth was much less than the effect of the welding current. Too long nozzle distance from the workpiece causes the improper protection of the welding pool and the melt to be exposed to the atmosphere. On the other hand, the very short distance of the nozzle causes the tip of the nozzle to burn due to the high heat of the boiling pool, and with the increase of the electrode distance, the penetration depth decreases. [34,35]. By increasing the electrode spacing from the nozzle from 30 to 40 mm, the heat flux concentration of the workpiece decreased, and the amount of heat entering the workpiece was reduced. Therefore, the amount of melting of the substrate and the penetration depth was subsequently reduced. As the welding speed increases, the heat input to the welding area decreases; therefore, the penetration depth increases [32-36]. The results indicate that the heat input into the workpiece decreased by increasing the welding speed from 300 to 500 mm/min. The nano-particles used in this study can introduce large amounts of manganese oxide and alumina into the boiling pool. Because the thermal conductivity of nanoparticle powder is lower than the base metal, increasing the thickness of the nanoparticles reduces the penetration depth.

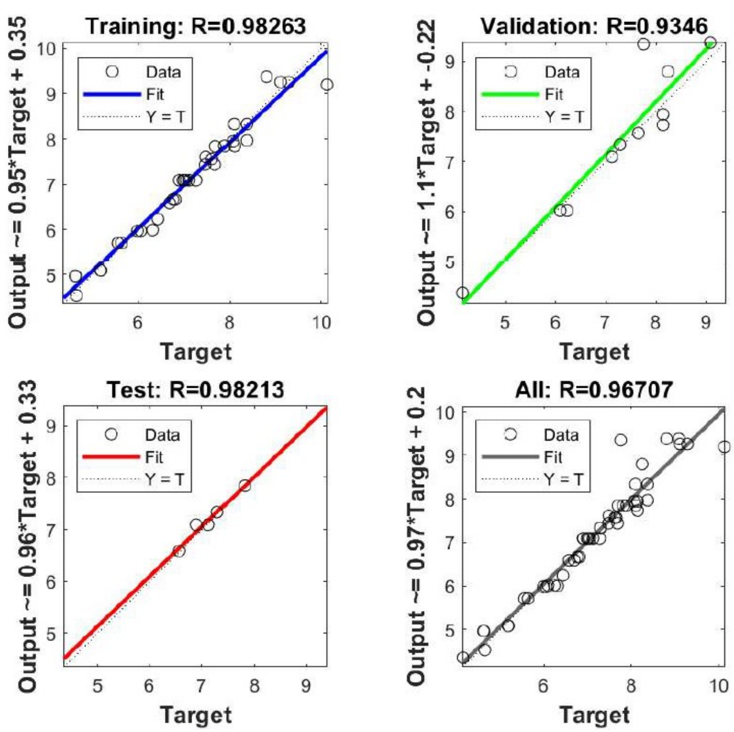

Figure 2. The regression coefficients of experimental data and neural network training data.

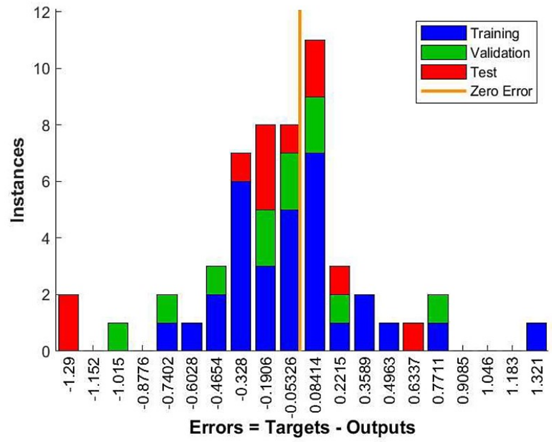

Figure 3. The error histogram between outputs and target.

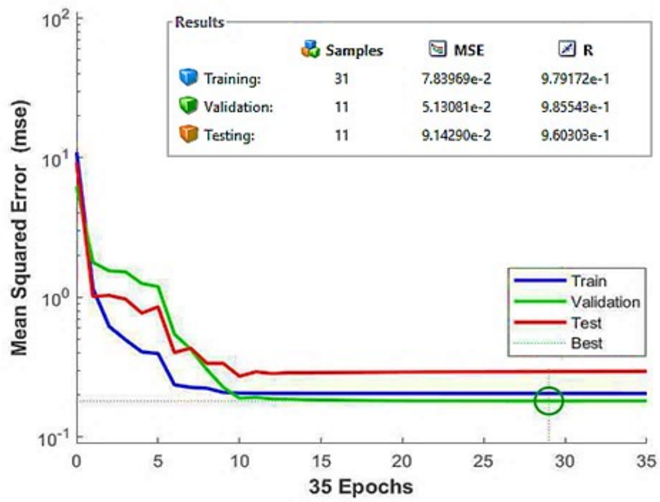

Figure 4. Performance plot- the Mean Squared Error and R-Values between outputs and target.

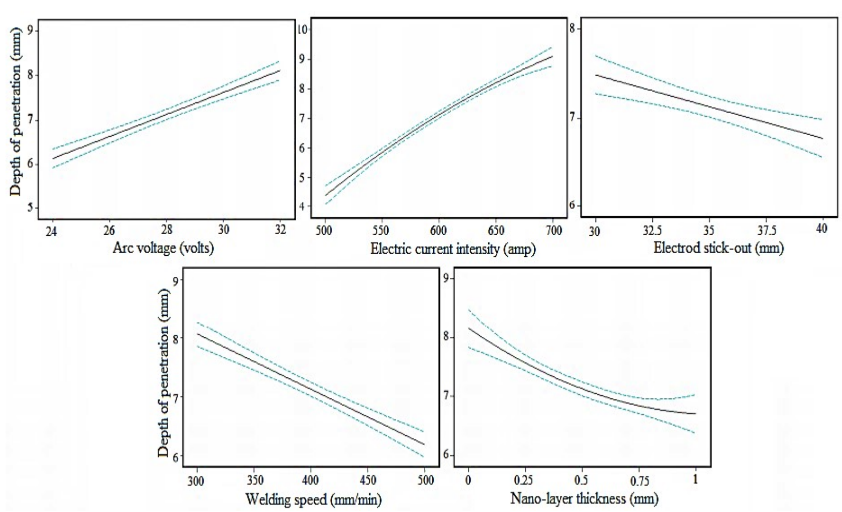

Figure 5. The effect of input parameters on the penetration depth

5. CONCLUSIONS

Welding is a production method that connects two metallic or non-metallic materials and creates a continuous member. Welding is used in various industrial sectors, from construction in the building sector to large and diverse industries such as automotive, aerospace, shipbuilding, and nuclear. In this research, an artificial neural network with two hidden layers was used to find the relationship between the input parameters of the submerged arc welding process and their effect on penetration depth. Arc voltage, electric current intensity, electrode stick-out, welding speed, and the thickness of the layer of nanoparticles were selected as input layer neurons and penetration depth as output layer neurons. Also, the investigation of the effect of the input parameters on the penetration depth showed that:

• Increasing the electric current intensity to 700 amps increases the heat input to the welding pool, melting the base metal and increasing the penetration depth.
• By increasing the arc voltage from 24 to 32 volts, the heat entering the welding pool increases, but the melting rate of the electrode does not change much. As a result, the penetration depth increases slightly.
• Increasing the thickness of the layer of nanoparticles had significant effects on the geometry of the welding.

6. ACKNOWLEDGMENTS

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7. REFERENCES

1. M.I. Khan, Welding Science, and Technology, (2007), “New Age International (P) Limited”.
2. R.W. Messler Jr, (2008), “Principles of welding: process, physics, chemistry, and metallurgy”, John Wiley & Sons.
3. P.T. Houldcroft, R. John, (2001), “Welding and Cutting: A Guide to Fusion Welding and Associated Cutting Processes”, Elsevier.
4. D. Paniagua-Mercado, Tl, S. David, (2003), “Physical processes in fusion welding”, Reviews of modern physics, **67**, 85.
5. Rahmati, Farhad, and Amir Ghandehariun, (2023), “Sustainability Development and Life Cycle Assessment of Welding Processes: Focus on SMAW and GMAW”, The 8th International and 19th National Conference on Manufacturing Engineering ICME2023.
6. S. Kou, (2003), “Welding Metallurgy New Jersey”, USA, vol. **431**, no. 446, pp. 223–225.
7. Patel, H. N., Chauhan, V. D., & George, P. M., (2021), “Effect of process parameters on submerged arc welding: A review”, In AIP Conference Proceedings, Vol. **2317**, No. 1, p. 050011.
8. L. H. S. Barbosa, P. J. Modenesi, L. B. Godefroid, and A. R. Arias, (2019), “Fatigue crack growth rates on the weld metal of high heat input submerged arc welding”, International Journal of Fatigue, vol. **119**, pp. 43–51.
9. N. D. Jadhav, B. Diwakar, and P. Shinde, (2018), “Parametric optimization of submerged arc welding process using Response Surface Methodology”, International Research Journal of Engineering and Technology (IRJET), vol. **5**, no. 8.

10. A. Biswas, S. Bhoumik, and A. Bhowmik, (2015), "Study of Microstructure of Weldment Obtained by Submerged Arc Welding (SAW) on IS 2062 Grade B Mild Steel Plate at Zero Degree Celsius", Paris France Jan, 23-24, 13(01).

11. A. Choudhary, M. Kumar, and D. R. Unune, (2019), "Experimental investigation and optimization of weld bead characteristics during submerged arc welding of AISI 1023 steel", Defence Technology, vol. **15**, no. 1, pp. 72–82.

12. M. Sailender, G. C. M. Reddy, and S. Venkatesh, (2016), "Parametric Design for Purged Submerged Arc Welding on the Strength of Low Carbon Steel", European Journal of Engineering and Technology Research, vol. **1**, no. 3, pp. 1–6.

13. J. Roy, B. D. Barma, J. D. Barma, and S. C. Saha, (2013), "Optimization of process parameters for submerged arc welding by weighted principal component analysis based Taguchi method", in Advanced Materials Research, vol. **622**, pp. 45–50.

14. C. Ankush, M. Kumar, and D. R. Unune, (2018), "Parametric modeling and optimization of the novel water-cooled advanced submerged arc welding process", The International Journal of Advanced Manufacturing Technology, vol. **97**, no. 1–4, pp. 927–938.

15. Ridings, G. E., Thomson, R. C., & Thewlis, G, (2002), "Prediction of multiwire submerged arc weld bead shape using neural network modeling", Science and technology of welding and joining, **7(5)**, 265-279.

16. Dey, Vidyut, Dilip Kumar Pratihar, and Gauranga Lal Datta, (2008), "Prediction of weld bead profile using neural networks", first international conference on emerging trends in engineering and technology, IEEE.

17. Dhas, J. Edwin Raja, and S. Jenkins Hexley Dhas, (2012), "A review on optimization of the welding process", Procedia Engineering, **38**, 544-554.

18. Mladenov, Georgi, and Elena Koleva, (2009), "Electron beam weld characterization, and process parameter optimization, Proceedings of the VI international conference", beam technologies & laser applications, St.-Petersburg.

19. De, A., J. Jantre, and P. K. Ghosh, (2004), "Prediction of weld quality in pulsed current GMAW process using artificial neural network", Science and technology of welding and joining, **9.3**, 253-259.

20. Al-Faruk, Abdullah, et al., (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.

21. Bhattacharya, A. B. P. K. A., Batish, A., & Kumar, P., (2012), "Experimental investigation for multi-response optimization of bead geometry in submerged arc welding using grey analysis", Journal of The Institution of Engineers (India), Series C, **93**, 123-132.

22. Kumanan, S., Dhas, J., & Gowthaman, K., (2007), "Determination of submerged arc welding process parameters using the Taguchi method and regression analysis".

23. Saha, A., & Mondal, S. C., (2014), "Optimization of process parameters in submerged arc welding using multi-objectives Taguchi method", In Advances in Material Forming and Joining: 5th International and 26th All India Manufacturing Technology, Design, and Research Conference, AIMTDR 2014, pp. 221-232.

24. Vedrtnam, A., Singh, G., & Kumar, A., (2018), "Optimizing submerged arc welding using response surface methodology", regression analysis, and genetic algorithm. Defense Technology, **14(3)**, 204-212.

25. Da Silva, M. M., Batista, V. R., Maciel, T. M., dos Santos, M. A., & Brasileiro, T. L., (2018), "Optimization of submerged arc welding process parameters for overlay welding", Welding International, **32(2)**, 122-129.

26. Choudhary, A., Kumar, M., & Unune, D. R., (2019), "Experimental investigation and optimization of weld bead characteristics during submerged arc welding of AISI 1023 steel", Defence Technology, **15(1)**, 72-82.

27. Schrimpf, M., Kubilius, J., Hong, H., Majaj, N. J., Rajalingham, R., Issa, E. B., ... & DiCarlo, J. J., (2018), "Brain-score: Which artificial neural network for object recognition is most brain-like? BioRxiv", 407007.

28. Anitescu, C., Atroshchenko, E., Alajlan, N., & Rabczuk, T., (2019), "Artificial Neural Network Methods for the Solution of Second Order Boundary Value Problems. Computers", Materials & Continua, **59(1)**.

29. Zhao, D., Wang, Y., Liang, D., & Ivanov, M., (2020), "Performances of regression model and artificial neural network in monitoring welding quality based on power signal", Journal of materials research and Technology, **9(2)**, 1231-1240.

30. I. S. Kim, J. S. Son, I. G. Kim, J. Y. Kim, and O. S. Kim, (2003), "A study on the relationship between process variables and bead penetration for robotic CO2 arc welding", Journal of Materials Processing Technology, vol. **136**, no. 1–3, pp. 139–145.

31. E. Karadeniz, U. Ozsarac, and C. Yildiz, (2007), "The effect of process parameters on penetration in gas metal arc welding processes", Materials \& design, vol. **28**, no. 2, pp. 649–656.

32. Karaoğlu, Serdar, and Abdullah Secgin, (2008), "Sensitivity analysis of submerged arc welding process parameters", Journal of materials processing technology, 202.1-3, 500-507.

33. E. B. Dasgupta and S. Mukherjee, (2013), "Optimization of weld bead parameters of nickel-based overlay deposited by plasma transferred arc surfacing", Int. J. Mod. Eng. Res., vol. **3**, no. 3, pp. 1330–1335.

34. V. Gunaraj and N. (1999), "Murugan, Application of response surface methodology for predicting weld bead quality in submerged arc welding of pipes", Journal of materials processing technology, vol. **88**, no. 1–3, pp. 266–275.

35. D. S. Nagesh and G. L. Datta, (2002), "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.

36. M. Nouri, A. Abdullah-Zadeh, and F. Malek, (2007), "Effect of welding parameters on dilution and weld bead geometry in the cladding", Journal of materials science & Technology, vol. **23**, no. 6, 2007, p. 817.