

Prediction Analysis of Weld-Bead and Heat Affected Zone in TIG welding using Artificial Neural Networks

Shamith L Saldanha^{1,2}, V Kalaichelvi¹ and R Karthikeyan²

¹ Department of Electrical & Electronics Engineering, BITS Pilani Dubai Campus, UAE, P.O.BOX 345 055

² Department of Mechanical Engineering, BITS Pilani Dubai Campus, UAE, P.O.BOX 345 055

Corresponding Author E-mail: f20140001@dubai.bits-pilani.ac.in

Abstract. TIG Welding is a high quality form of welding which is very popular in industries. It is one of the few types of welding that can be used to join dissimilar metals. Here a weld joint is formed between stainless steel and monel alloy. It is desired to have control over the weld geometry of such a joint through the adjustment of experimental parameters which are welding current, wire feed speed, arc length and the shielding gas flow rate. To facilitate the automation of the same, a model of the welding system is needed. However the underlying welding process is complex and non-linear, and analytical methods are impractical for industrial use. Therefore artificial neural networks (ANN) are explored for developing the model, as they are well-suited for modelling non-linear multi-variate data. Feed-forward neural networks with backpropagation training algorithm are used, and the data for training the ANN taken from experimental work. There are four outputs corresponding to the weld geometry. Different training and testing phases were carried out using MATLAB software and ANN approximates the given data with minimum amount of error.

Keywords: TIG welding, artificial neural network, modelling, performance analysis

1. Introduction

Welding is an important joining process in the field of manufacturing. It is widely used in the construction of automobiles, large equipment and ship-building. Tungsten Inert Gas or TIG welding (also known as Gas Tungsten Arc Welding or GTAW) is a relatively new type of Welding [1]. It provides cleaner and stronger welds than more traditional welding processes such as standard arc welding and gas welding [1], resulting in its increasing use in various industries. For any welding technique or process used there needs to be a documented knowledge of the weld quality, strength, fatigue etc., under different practical conditions such as Weld Current, Wire feed speed, Gas flow rate and so on. This will help in deciding welding parameters to be used for a particular weld requirement, speeding up the product and manufacturing design process, and more so in the manufacture of custom products, adding to further automation in welding processes.

A common metric used in the determination of strength and fatigue characteristics of welds is the depth and width of the Weld Bead Zone and the Heat Affected Zone (HAZ) [2]. The dependence of these weld quality metrics, on adjustable parameters such as weld current and wire feed speed, are non-linear in nature and any reasonably accurate analytical method, is far too complex for practical



and commercial use [3]. Therefore useful non-linear models will have to be developed from experimental data using expert system methods [4] such as fuzzy logic, artificial neural network (ANN) and neuro-fuzzy methods, which are excellent in modelling non-linear data that does not neatly fit into traditional equations [5]. Here ANN will be used as it is good in modelling from existing data.

Narang et al in [6] determined the weld pool geometry of TIG welding using standard fuzzy logic methods. Kalaichelvi et al in [7] have determined the weld pool geometry in Gas Metal Arc Welding, also called MIG welding, using Fuzzy Rule based system tuned through Genetic Algorithm techniques. A similar success in using the ANN methods has been done by Acharjee et al [8], having used ANN techniques in the modelling of welding of thermoplastics in Laser Transmission Welding. Another inspiration for using NN-based models comes from [9].

Section 2 briefly describes TIG welding and the data set, Section 3 briefly introduces the ANN and the methodology. Section 4 depicts a successful ANN model along with the weld bead geometry. Section 5 describes the effect of variation in the ANN parameters on the welding model. Section 6 concludes the paper and its salient results.

2. TIG Welding and Associated Data Set

Welding process is a primary manufacturing process of joining two metal pieces [1]. TIG welding is a relatively modern type of welding in which electric arc is used. The electrode is non-consumable one made of tungsten metal, while inert gas, such as argon is passed over the welding surface to prevent the oxidation [3].

TIG Welding is being increasingly preferred in industry over other welds as it gives cleaner and higher quality welds. The arc can be controlled minutely and the cleaning of the joint after welding is minimal due to low spatter, and it can also be used to join dissimilar metals [10].

Here TIG welding is performed on two dissimilar metals, 316 L stainless steel and Monel alloy. This particular combination will be helpful for high-quality products in aerospace, healthcare, advanced manufacturing, automobiles etc. as such combinations produce parts that are strong, lightweight and resistant to corrosion simultaneously.

There are two main zones in the welded joint which are of interest, and from which our outputs are derived. The inner zone is called as the ‘Weld Zone’, where re-solidified metal is present. The outer zone is the ‘Heat Affected Zone’ or HAZ, which is present around the first zone and is the reheated and recrystallized metal, but which has not melted [3]. These size of these zones are useful in determining the joint strength, joint failure and other characteristics of the weld-bead joint for further modelling. The size of the Weld Bead Zone and the HAZ are determined from the microstructure of the weld-bead.

Here the 4 input parameters are the arc current, shielding gas flow rate (Argon gas), the speed of wire feed, and length of the electrode arc. The data set for the training and testing of the neural network is derived from TIG welding experiments, where the above four parameters have been adjusted to generate varying outputs. The specimens were analyzed using microscopes to get the microstructure of the weld-bead. From this weld-geometry and the outputs were obtained. A photograph of the microstructure of one of the specimens is shown in Figure 1. There are 27 data points in total. Some of the data points are given in Table 1.

The weld-bead geometry is also approximated from the ANN model output by using a cubic spline interpolation [11]. This is a reasonable approximation to the actual weld-bead geometry, and this information along with the area under the curve can help in determining joint characteristics. Two curves are generated, one for the Weld bead zone and the other for the HAZ. The “not-a-knot” condition is enforced here to facilitate the curve-fitting from a few points [11]. The area for the two zones can also be found if required for further analysis. The equation involved is the cubic polynomial, and is shown in equation (1) over an interval $[x_1, x_2]$, and with $[a, b, c, d]$ as the polynomial coefficients.

$$y = a(x - x_1)^3 + b(x - x_1)^2 + c(x - x_1) + d \quad (1)$$

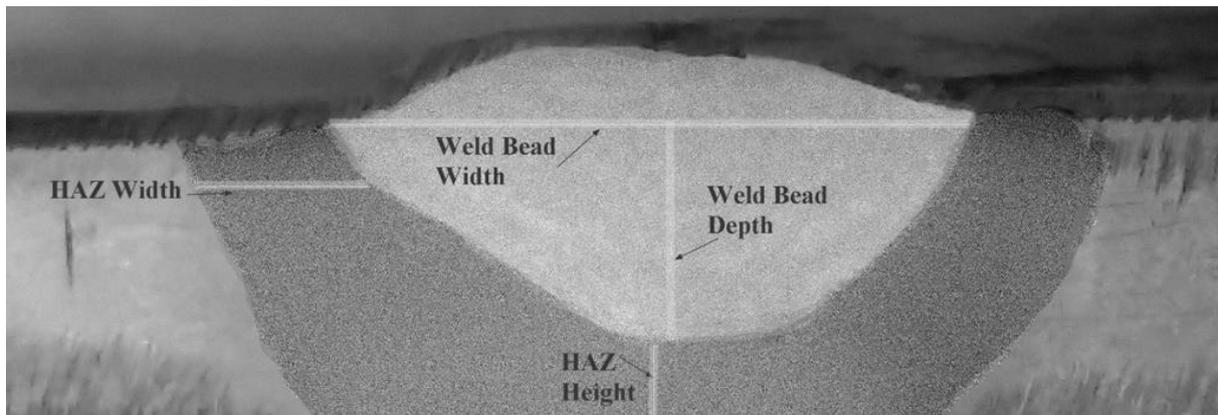


Figure 1. Weld Bead Image used for Checking Outputs

Table 1: Part of Data Sets used for Training the ANN Model

S. No.	Input Parameters				Output Parameters			
	Welding current (A)	Wire Feed Speed (mm/sec)	Arc Length (mm)	Argon Flow rate (litre /min)	Weld Bead Width (mm)	Weld Bead Depth (mm)	HAZ Width (mm)	HAZ Depth (mm)
1	80	15	2	4	6.62	1.65	1.12	1.22
2	80	15	4	6	5.72	1.78	2.44	1.52
3	80	9	4	6	5.00	1.47	2.67	1.54
4	80	24	4	6	6.47	2.14	2.25	1.51
5	120	15	2	5	7.78	1.51	1.13	1.60
6	120	24	2	5	8.81	1.81	1.04	1.59
7	120	15	3	6	7.09	1.62	1.75	1.74
8	120	9	3	6	6.20	1.33	1.91	1.76
9	120	24	4	4	7.05	2.57	1.77	1.12
10	150	15	3	4	7.27	1.94	1.43	1.25

3. Analysis using ANN

An Artificial Neural Network or ANN is a connected mathematical processing system composed of summing units with transfer functions called neurons and weighted interconnections, which can satisfy a complex and non-linear input-output relationship [5].

The ANN is also quite suitable for use in modelling of manufacturing processes [12]. An illustration of a neural network (NN) is shown in figure 2. This mathematical tool can be used to learn a pattern or a particular relationship in a given data set, especially non-linear ones. It is inspired from the mechanism of learning of the human brain, hence its name [13].

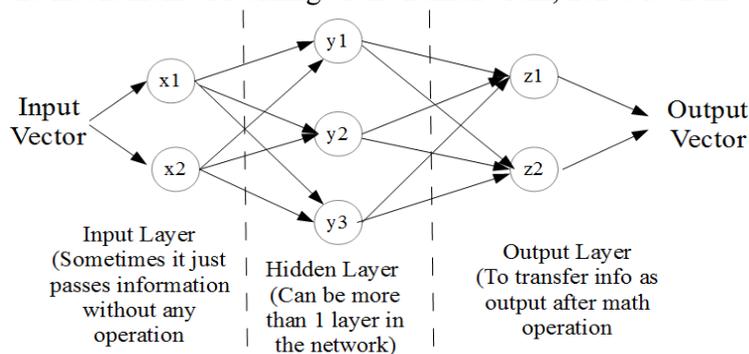


Figure 2. Feedforward Neural Network.

The type of NN used here is the Multi-layer Feed-forward Backpropagation NN, itself a sub-class of supervised learning techniques. The data set consists of the input and a target output corresponding to that input, for which the NN tries to match through modifying its weights are modified in an iterative process called training. Backpropagation is the type of training in which the error is fed back into the weights, of which there are several sub-types. The number of iterations used is called epochs and is a measure of the speed to converge to a good solution. The BPNN models well many non-linear and multi-variable processes in manufacturing having sufficient data [13].

For the NN to be useful for mechanical modelling, the network should remember the characteristics of data that was used to train. It should also be reasonably accurate in predicting results from new and unseen before data. Both of these features, respectively called memorization and generalization, are developed through the partitioning of the overall data set into training and testing data sets. Here for modelling purposes, the original data set was randomly sorted into the two sub-sets, and in different ratios. The first was used for training the network and the other for simulating the response of the NN with new fresh data. The methodology followed in this research is explained in the simple flow chart in figure 3 for easy reference.

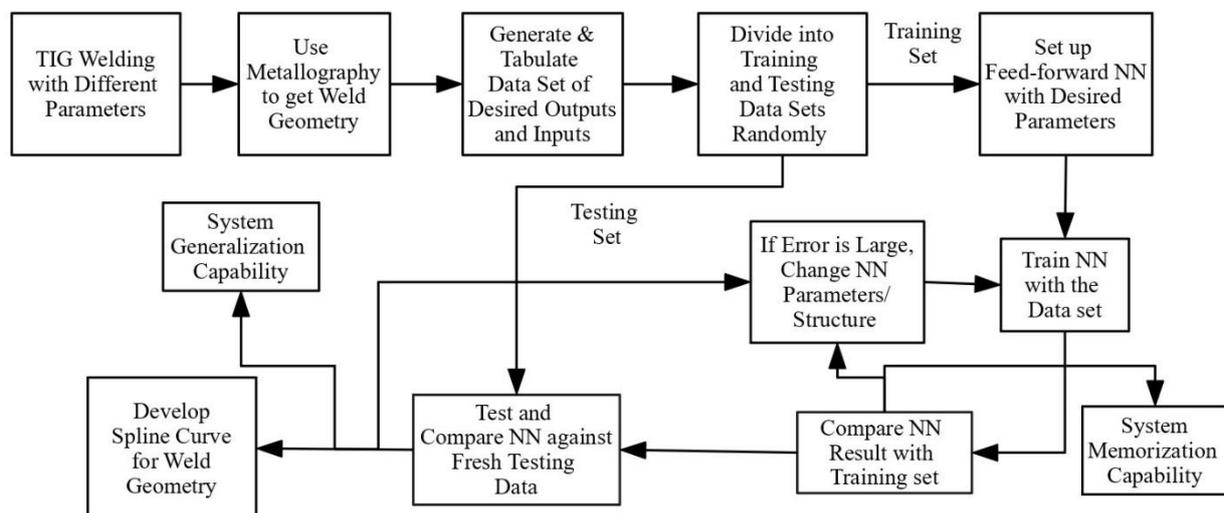


Figure 3. Flowchart of ANN Modelling for Welding System

4. ANN Model and Error Analysis

Feed forward neural networks of the type as shown in figure have been developed for the 4 outputs separately. Each has the same properties and each network has the same inputs. They are fed with the same training data, as in each network is trained with all the data points of the 4 inputs and its output relevant to that network. MATLAB with its Neural Network Toolbox was used for the creation, training and analyzing the neural networks.

The modelling was done using a 3 layer network as shown in figure 4, in which there are 2 hidden layers and one output layer. The transfer function in all the layers are purely linear in nature. The backpropagation algorithm is the Levenberg-Marquardt (or LM) algorithm [14], which trains the network faster and more efficiently in these types of uses [15]. The neural network performance is trained till the minimum acceptable gradient is reached. Figure 5 shows the accuracy for the training data alone (memorization testing) for the NN modelling Weld-Bead Depth. The other outputs show similar accuracies.

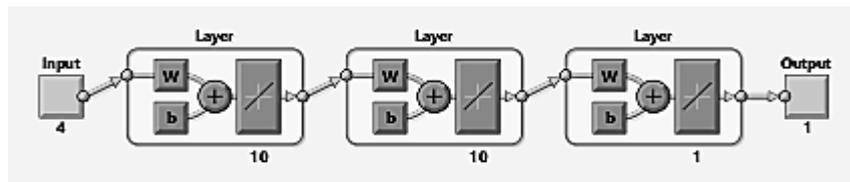


Figure 4. Network used in Training and Testing of the Weld-Bead geometry

Moreover the 4 outputs of the network, after training have been further processed to generate spline curves that represent the actual geometry of the weld-bead zone and the HAZ, given just the four outputs of the ANN model. The two spline curves shown are for the weld bead zone and for the heat affected zone and is shown in figure 6.

In figure 7, the generalization ability of the ANN modelling is shown through the use of a regression-type comparison, made by testing the NN against the separate testing data.

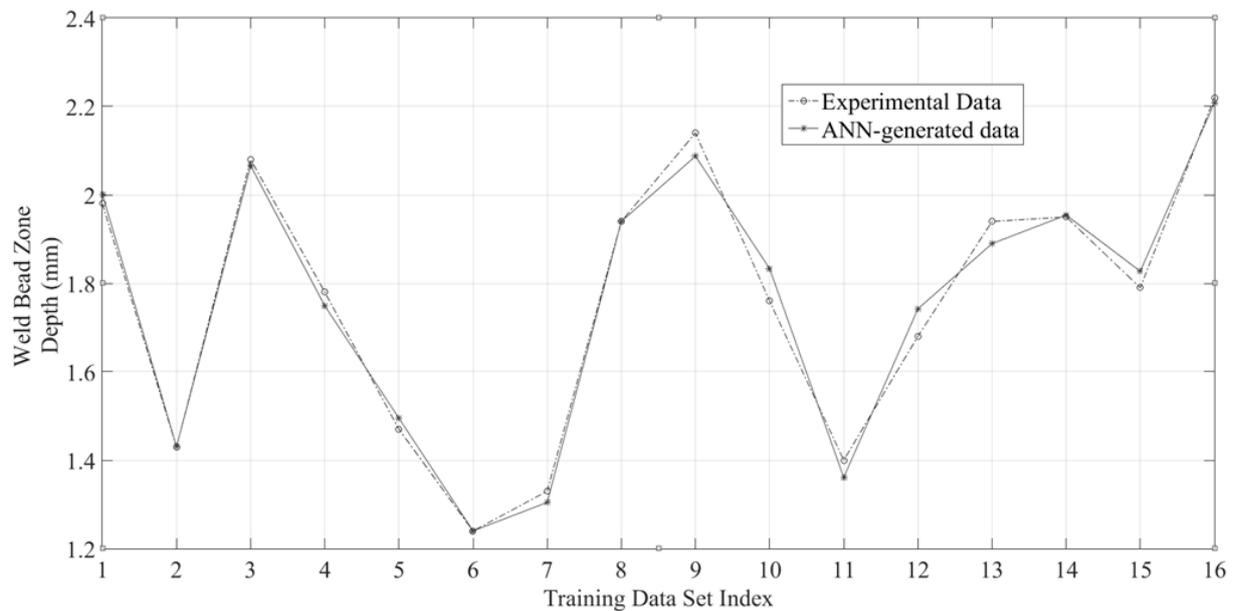


Figure 5. Comparison between Experimental and ANN Generated Data Sets for Weld Bead Depth

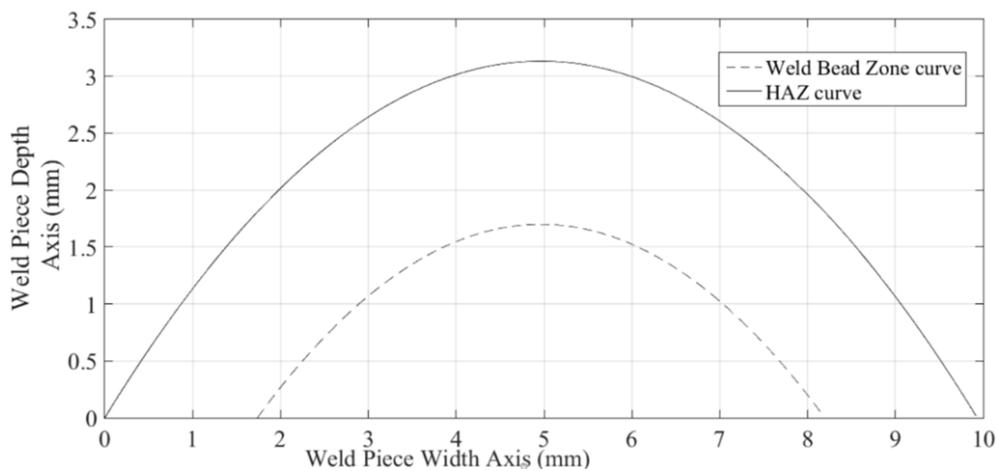


Figure 6. Spline Curve Showing the Approximate Weld Geometry of the Weld bead zone and HAZ as a Transverse Cross Section of the Weld-Piece.

5. Results and Discussion

The effect on the system modelling on the variation of ANN parameters is useful for optimising the modelling and for developing similar models in further research. A common metric to be used in this comparison is the root-mean-square-error (RMS error), as it is an unbiased yet convenient comparison metric. The RMS error is compiled for the training and testing data separately. The average of the RMS errors of the outputs as a whole for each data sub-set is used for comparison.

Changing the ratio of training to testing data, in the overall data set fed into the NN is shown in figure 8. However, the ratio of training to testing data should not be reduced too low otherwise generalization errors may occur. Therefore the optimum ratio here would be 60/40 for training and testing respectively.

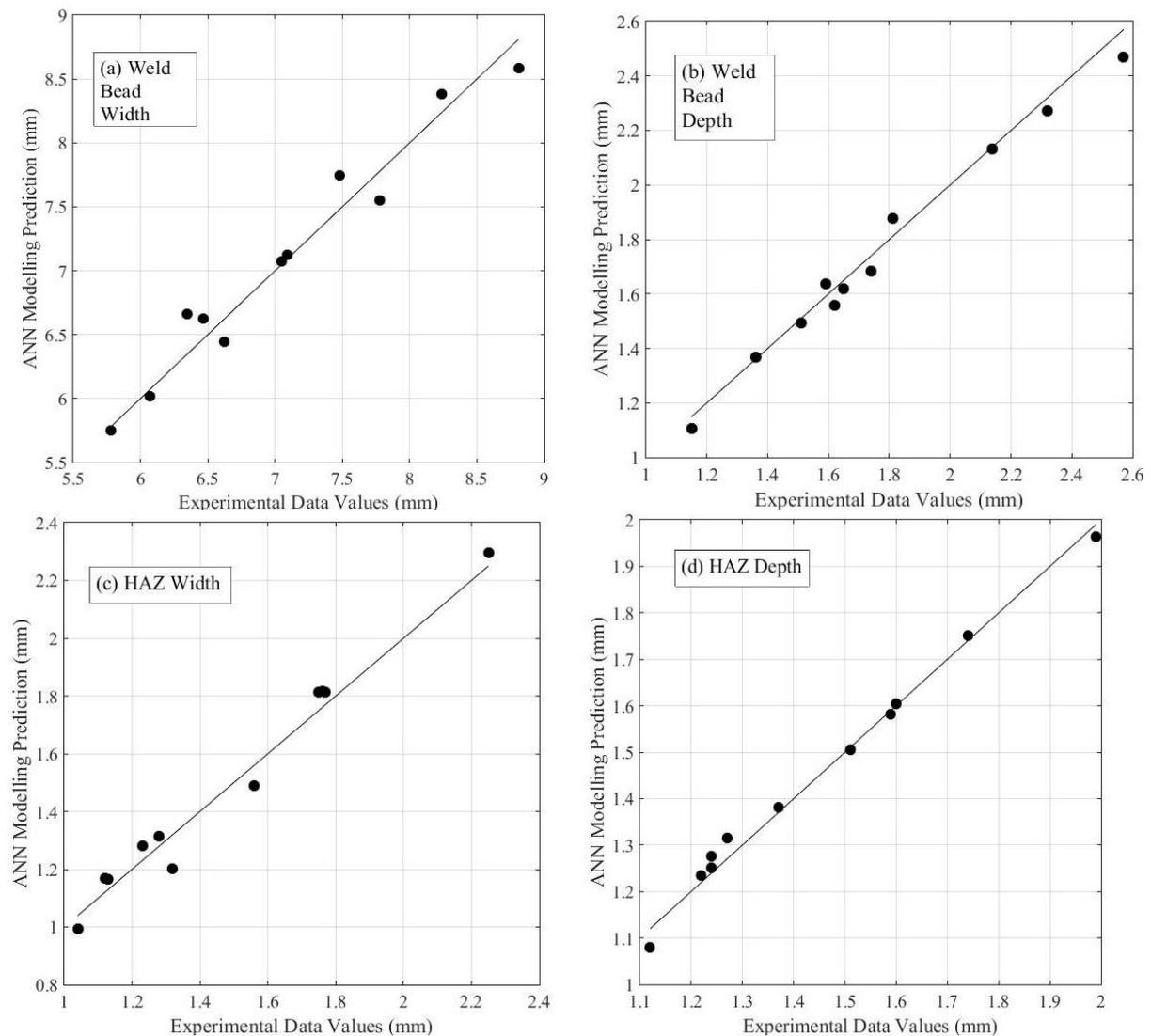


Figure 7. Performance using Regression Analysis for the Testing Data Sets of Four Outputs

The training algorithm is checked next. The train/test ratio is fixed at 60/40, while the different training algorithms such as Levenberg-Marquadt (LM), Scaled Conjugate Gradient (SCG) and Resilient backpropagation (RP) are tried. The number of epochs (or iterations) to reach a satisfactory solution is shown in Figure 9. The figure shows that the LM method converges to a good solution in the least number of iterations, therefore taking the least time. The actual RMS errors are the same for all three algorithms.

The variation of the error with different activation functions within each layer for a 3-layer network is shown in figure 10, where for example, LS+PL+PL means that the first layer has a binary sigmoidal activation followed by a purely linear activation in the next two layers. Here surprisingly, the purely linear function performs the best overall. The non-linearity of having multiple layers suffices for the modelling purpose. The non-linear sigmoidal function (either bipolar or binary) seems to drastically reduce the training error, while showing large errors for testing data, in a phenomenon called overfitting [15], putting into question its effectiveness for modelling future data.

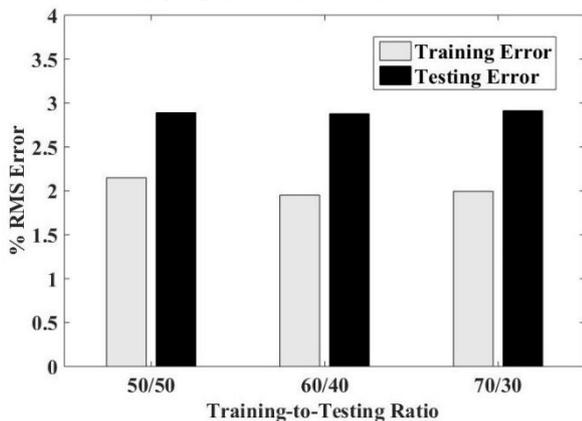


Figure 8. Effect of Variation in Training/Testing Ratio

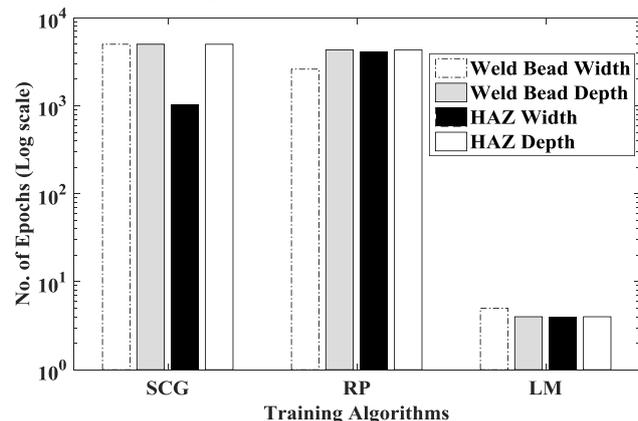


Figure 9. Number of Epochs for Different Training Algorithms

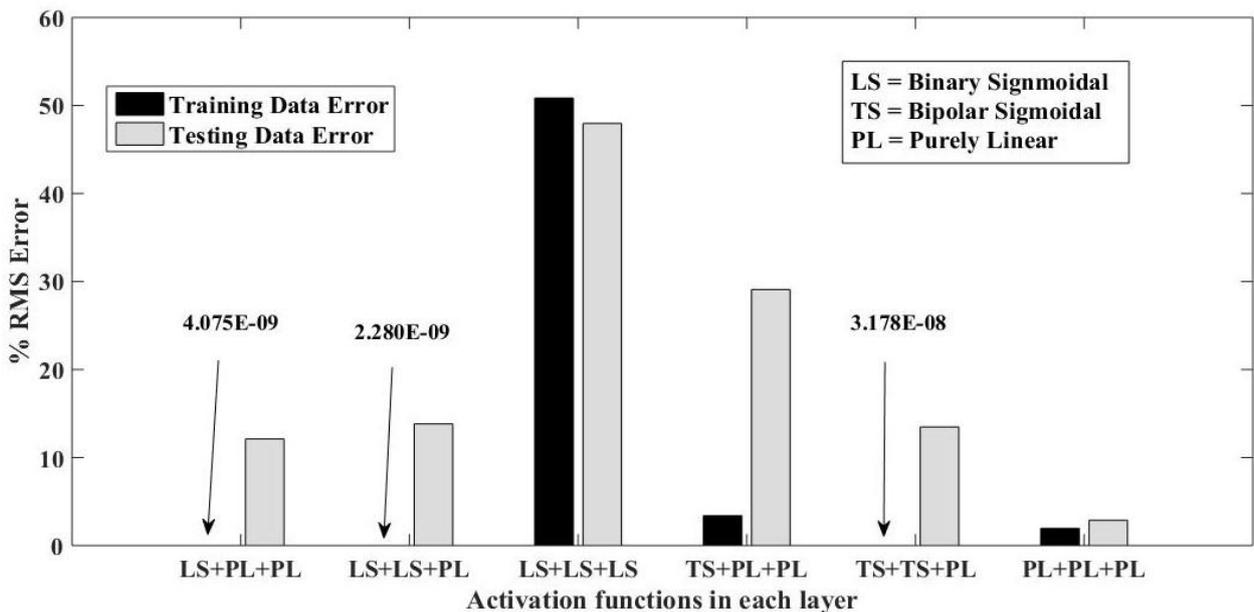


Figure 10. Mean Error for Different Activation Functions

6. Conclusions

In this work, a modelling of the dependence of the weld-bead geometry on four controllable parameters using artificial neural networks has been performed with reasonable accuracy, with the help of previously existing workshop data. Backpropagation algorithm was used for training. The NN showed low error in both memorization and generalization capability. Further improvement can be done through the use of Neuro-Fuzzy techniques. It is hoped that this work will help in facilitating the

development of an accurate system model of the welding process, which will be useful in the optimization of industrial welding processes and in the automation of welding.

References

- [1] Cary H and Helzer S 2005 *Modern Welding Technology* (Upper Saddle River: Pearson/Prentice Hall)
- [2] Hicks J 1999 *Welded Joint Design* (Cambridge: Woodhead Publishing)
- [3] Ghosh A, Mallik AK 2015 *Manufacturing Science* (New Delhi: Affiliated East-West Press Private Limited) p 306
- [4] Bingül Z, Cook GE and Strauss AM 2000 Application of fuzzy logic to spatial thermal control in fusion welding, *IEEE transactions on Industry Applications* **36**(6) 1523-30.
- [5] Rojas R 2013 *Neural Networks: A Systematic Introduction* (Berlin: Springer Science & Business Media)
- [6] Narang HK, Singh UP, Mahapatra MM and Jha PK 2011 Prediction of the weld pool geometry of TIG arc welding by using fuzzy logic controller *International Journal of Engineering, Science and Technology* **3**(9) 77-85.
- [7] Kalaichelvi V, Karthikeyan R and Sivakumar D 2013 Analysis of Gas Metal Arc Welding Process using GA Tuned Fuzzy Rule based System *Journal of Intelligent and Fuzzy Systems* **25** 429-40
- [8] Acherjee B, Mondal S, Tudu B and Misra D 2011 Application of Artificial Neural Network for Predicting Weld Quality in Laser Transmission Welding of Thermoplastics *Applied Soft Computing Journal* **11**(2) 2548–55.
- [9] Huang SH, Zhang HC 1994 Artificial neural networks in manufacturing: concepts, applications, and perspectives *IEEE Transactions on Components, Packaging, and Manufacturing Technology* **17**(2) pp 212-28
- [10] Muncaster PW 1991 *Practical TIG (GTA) Welding: A Survey of the Process and Equipment* (Cambridge: Woodhead Publishing)
- [11] De Boor C 1978 *A Practical Guide to Splines* (New York: Springer-Verlag)
- [12] Bhanot S 2010 *Process Control Principles and Applications* (Chennai: Oxford University Press)
- [13] Karyiannis NB, Ventsanopoulos AN 1993 *Artificial Neural Networks : Learning Algorithms, Performance Evaluation, and Applications* (New York: Springer Science & Business Media)
- [14] Hagan MT, Menhaj M 1999 Training feed-forward networks with the Marquadt algorithm *IEEE Transactions on Neural Networks* **5**(6) 989-93
- [15] Elleithy K 2007 *Advances and Innovations in Systems, Computing Sciences and Software Engineering* (Dordrecht: Springer Science & Business Media) p 54