ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, Vol 9(13), DOI: 10.17485/ijst/2016/v9i13/90550, April 2016 ISSN (Online) : 0974-5645

Development of an ANN Model to Predict MRR and SR during AWJM Operation for Lead Tin Alloy

K. S. Jai Aultrin and M. Dev Anand

Department of Mechanical Engineering, Noorul Islam Centre for Higher Education, Kumaracoil – 629180, Thuckalay, Kanyakumari District, Tamil Nadu, India; aultrin2010@gmail.com, anandpmt@gmail.co

Abstract

Background/Objectives: Last decades have witnessed a rapid growth in the development of harder, difficult and complexity to machine metals and alloys. AWJM is one of the most freshly built up nontraditional machining processes in processing various types of hard-to-cut materials nowadays. It is an economical method for heat sensitive materials that cannot be machined by processes that produce heat while machining. Machining parameters play a lead role in determining the economics of machine and machining quality. This paper investigates the prediction of MRR and Surface roughness on Lead Tin Alloy using the Artificial Neural Network (ANN). **Methods/Statistical analysis:** In this work, the influence of five AWJM parameters of the process on SR and MRR of an American element referred as Lead Tin Alloy which is machined by AWJM was experimentally performed and analyzed. According to RSM design, different experiments have been performed with the combination of input parameters on this American element. **Findings:** Outcome depicts the minimum error attained for data belonging to test is 1.063814%% for MRR and 0.208967018% for SR. Also the maximum error obtained is about 9.475104% for MRR and 9.070886429% for SR. By training the network deviations may occur but error is reduced because this technique is heuristic.

Keywords: Artificial Neural Network, Material Removal Rate, Response Surface Methodology, Surface Roughness

1. Introduction

AWJM is the recently built up technique. This technique is suitable for machining of brittle materials similar to ceramics, stones and glass as well as for ferrous, composite materials and non-ferrous materials. AWJM process is not as much of responsive to properties of the material since it created chatter, without heat effects, inflict stresses of minimum over the work material, and possess greater versatility in machining and much flexible[1]. In this technique, a rivelet of little abrasive particles is pioneered into the water jet and this combination of abrasive water jet is later permitted to impact on the work piece to cut it[2]. In AWJM process, few efforts has been done for modeling and also to predict and optimization of the input parameters of process. The move engaged along this track to develop numerous arithmetical equations to predict and optimize the output parameters comprise regression analysis modeling, fuzzy logics, ANOVA, Genetic Algorithm, DOE, and neural networks[3]. An ANN model is built up to predict the cutting speed to the intended cutting surface quality using AWJM[4]. Prediction of cut depth through ANN model is developed[5]. Prediction of SR in turning process through ANN model is developed[6]. Presented a work on neuro-genetic technique suggests that an ANN model to forecast cut depth is developed along the consideration of diameter of focusing nozzle, jet traverse rate, flow rate of abrasive, water pressure. ANN associated along GA, i.e. neuro-genetic technique, is projected for recommending the parameters of the process[7]. An attempt has been made by N. Ramesh Babu and D.S. Srinivasu to develop models on ANN and FL for various materials processing applications using AWJC with the consideration of diameter of focusing nozzle[8].

2. Experimental Work

2.1 Material

An American element mainly Lead Tin alloy exists in

* Author for correspondence

numerous forms namely ribbon, tube, ingot, foil, bar, rod, wire and pipe. Significant factor in choosing Lead Tin alloy is that because of their high strength to weight ratio, their resistance against corrosion by numerous chemicals, their high thermal and electrical conductivity, non-toxicity, reflectivity, and appearance, and their easiness in formability and machinability and nonmagnetic properties. Few appliance of Lead Tin alloy comprise bicycle frames, aerospace maintenance, transport, Marine fittings, brake components, valves couplings etc and has also functional in surgery, drilling paint removal, peening, turning etc. Exclusive surface finish exists and could also be anodized. Exclusive corrosion resistance towards atmospheric conditions with its density 11.035 g/ cm^3 and its Modulus of Elasticity E = 80GPa. Lead Tin alloy plate dimension place utilized in this research is 150mm x 50mm x 50mm. shown in Figure 1.

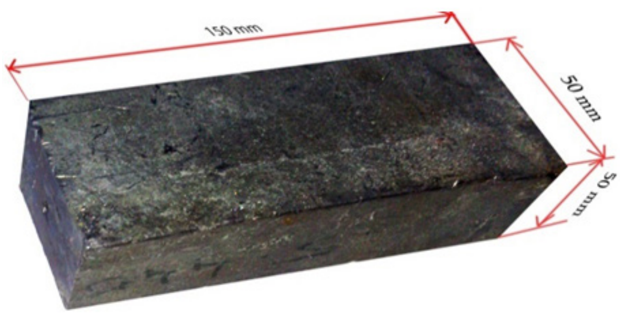

Figure 1. Lead Tin Alloy.

2.2 Response Surface Methodology

RSM is a set of arithmetical and statistical approach which seems to be helpful towards modeling and investigation of issues. In the present study[9] five process parameters are chosen and assorted in three levels as shown in Table 1.

Depending upon the retort surface methodology, Box-Behnken design 46 sets of experimental design was selected and was shown in Figure 2. The parameters and its levels have been chosen depending upon the assessment of certain journals which were acknowledged on AWJC on materials like Titanium[9], Mild Steel[10] Copper[11] and Epoxy Composite Laminate[12].

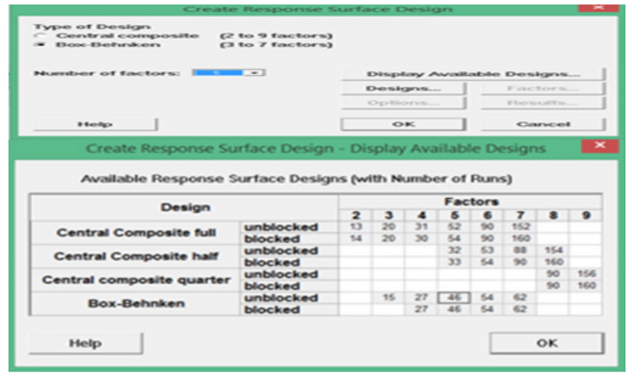

Figure 2. Selection of Box-Behnken design and selection of no of factors.

2.3 Data Collection and Experimentation

AWJC machine is used to cut the Lead Tin Alloy which is set with KMT, a pressure pump of ultrahigh along the designed pressure of 4000bar, abrasive hopper of gravity feed type, a feeder system of abrasive, a valve that is controlled pneumatically and a work piece table. Control stand holding the controller is used to adjust the SOD for different experiments. The abrasive water jet machine is programmed using numerical control code and is to change the transverse speed and manage the abrasives supplement. After the water is pumped at very high pressures resulting in greater velocity of water jet of 1000m/s as egresses off focusing nozzle cuts the preferred size and shape of the material. The KMT abrasive water jet cutting machine with its mixing chamber is shown in Figure 3.

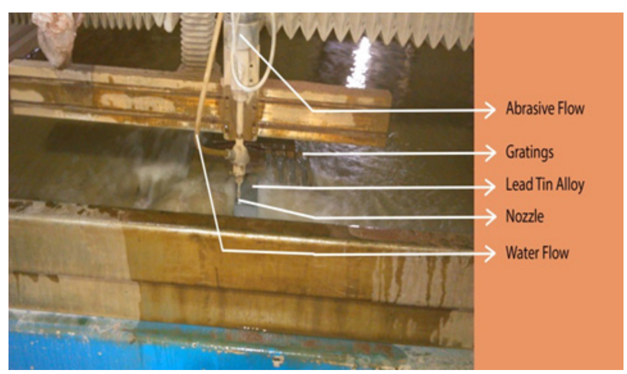

Figure 3. Experimental Setup of AWJM with mixing chamber

Table 1. Levels of parameters used in experiment

Levels	Water Pressure (P) Bar	Abrasive Flow Rate (mf) Kg/min	Orifice Diameter (do) mm	Focusing Nozzle Diameter (df) mm	Stand Off Distance (s) mm
Low	3400	0.4	0.3	0.9	1
Medium	3600	0.55	0.33	0.99	2
High	3800	0.7	0.35	1.05	3

Table 2. Planning matrix of the experiments

Sl. No	P(Bar)	Mf (Kg/min)	do (mm)	df (mm)	S (mm)	MRR mm^3/min	SR (μm)
1.	3400	0.55	0.33	0.99	3	1709	2.45
2.	3600	0.55	0.33	0.9	1	2014.86	1.415
3.	3600	0.55	0.3	1.05	2	1970.09	1.624
4.	3600	0.55	0.33	0.9	3	1916.85	2.2
5.	3800	0.55	0.33	0.9	2	2182.26	0.788
6.	3600	0.55	0.33	0.99	2	1997.84	1.609
7.	3400	0.4	0.33	0.99	2	1688.65	2.109
8.	3600	0.7	0.35	0.99	2	1997.84	1.52
9.	3800	0.55	0.33	0.99	3	2085.98	1.201
10.	3800	0.55	0.3	0.99	2	2149.19	0.801
11.	3600	0.55	0.33	0.99	3	1896.34	2.1
12.	3400	0.55	0.33	1.05	2	1746.88	1.905
13.	3600	0.4	0.33	0.99	1	1943.11	1.887
14.	3600	0.55	0.33	0.99	2	2009.16	1.571
15.	3600	0.55	0.35	0.9	2	1948.44	1.53
16.	3600	0.55	0.3	0.9	2	2003.48	1.709
17.	3400	0.55	0.33	0.9	2	1751.19	1.9
18.	3600	0.55	0.33	0.99	2	2003.48	1.566
19.	3600	0.4	0.3	0.99	2	1842.16	1.91
20.	3400	0.55	0.35	0.99	2	1751.19	1.899
21.	3800	0.4	0.33	0.99	2	2136.25	1.211
22.	3600	0.7	0.33	0.99	3	1891.29	1.999
23.	3600	0.7	0.33	0.99	1	2055.75	1.431
24.	3600	0.4	0.35	0.99	2	1866.4	2.013
25.	3600	0.4	0.33	0.9	2	1842.16	1.945
26.	3600	0.55	0.35	0.99	3	1916.85	2.008
27.	3600	0.7	0.33	0.9	2	1970.09	1.5
28.	3400	0.55	0.33	0.99	1	1800.08	1.789
29.	3600	0.7	0.3	0.99	2	1937.8	1.699
30.	3600	0.55	0.33	1.05	1	2049.81	1.707
31.	3600	0.55	0.3	0.99	1	2009.16	1.5
32.	3800	0.7	0.33	0.99	2	2142.69	0.62
33.	3600	0.4	0.33	1.05	2	1866.4	1.934
34.	3600	0.55	0.3	0.99	3	1916.84	2.309
35.	3600	0.55	0.33	0.99	2	2014.86	1.597
36.	3800	0.55	0.33	1.05	2	2162.3	0.8
37.	3400	0.7	0.33	0.99	2	1800.08	1.9
38.	3600	0.55	0.35	1.05	2	2020.6	1.704
39.	3400	0.55	0.3	0.99	2	1768.66	2.102
40.	3600	0.4	0.33	0.99	3	1842.16	2.345
41.	3600	0.55	0.33	0.99	2	2020.6	1.64
42.	3600	0.55	0.35	0.99	1	2079.86	1.634
43.	3800	0.55	0.35	0.99	2	2162.3	0.881
44.	3600	0.7	0.33	1.05	2	1970.09	1.539
45.	3600	0.55	0.33	1.05	3	1922.04	1.997
46.	3800	0.55	0.33	0.99	1	2223.3	0.8

For performing the experiments we have to design the combination of input parameters for each experiment and how many experiments has to be done. For this purpose using Minitab software according to the Box-Behnken design of Response surface methodology design of experiments, with five input parameters, 46 experimental designs has been chosen and performed investigational and time for machining is observed for all experiments as shown in Table 2. The MRR is estimated by the formula.

MRR = (mf – mi) / t

Where, mf = mass of the material after machining, mi = mass of the material before machining and t = Machining Time. The surface roughness for the machined Lead Tin Alloy is measured using Portable surface roughness tester in National College of Engineering, Tamilnadu, India, is shown in Figure 4.

Figure 4. Surface roughness tester.

3. Artificial Neural Networks

An ANN is defined as data-processing system comprising of huge number of extremely interrelated artificial neurons (processing elements) in an architecture inspired by the arrangement of cerebral cortex of the brain. These processing elements are usually organized into a sequence of layers. This arrangement is shown in Figure 5, where the input layer is a buffer that presents data to the network. This input layers is not a neural computing layer because the nodes have weights and no activation function. The top layer is the output layer, which present the output response for a given input. The other layer (or layers) is called the intermediate or hidden layer because it usually has no connections with the outside world.

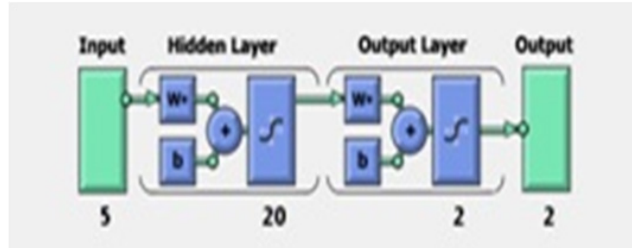

Figure 5. Neural network architecture.

3.1 Back Propagation Learning Algorithm

Back propagation is a systematic method for training multiple-layer (three or more) artificial neural networks. The elucidation of this training algorithm in 1986 by Rumelhart was the key step in making neural networks practical in many real-world situation. Based on this algorithm, the networks learns a distributed associative map between the input and output layers. This algorithm differs from others is the weights have been estimated through the network learning phase. The complexity with multilayer perceptions is estimating the hidden layers weight in a best way that results in minimal output error. When more are the hidden layers, then more complicated it come across. In order to keep informed about the weights, we should estimate the error. The error in the output layer is measured effortlessly which shows the dissimilarity among actual and desired outputs. However in the hidden layer there exists indirect examination of error, thus it is essential to use some other technique to calculate error, which is the ultimate goal.

The error back propagation algorithm can be outlined as:

Step 1: Initialize all weights to small random values.

Step 2: Choose an input-output training pair.

Step 3: Calculate the actual output from each neuron in a layer by propagating the signal forward through the network layer by layer (forward propagation).

Step 4: Compute the error value and error signals for output layer.

Step 5: Propagate the errors back ward to update the weights and compute the error signals for the preceding layers.

Step 6: Check whether the whole set of training data has been cycled once, yes – go to step 7; otherwise go to step 2.

Step 7: Check whether the current total error is acceptable; yes terminate the training process and output the field weights, otherwise initiate a new training epoch by going to step 2.

3.2 Procedure for Prediction of MRR and SR Using ANN

Initially the experimental value has been separated in two sets, one is the set to train and another is the set of data to test which has been utilized for ensuring performance of ANN model produced in order to apt a sample of 46. Chosen ratio preferred is 10:36. Following the quantity of nodes in the layers which are hidden must be found out. Due to this reason iterations were made to choose the MSE value which is least for the numerous nodes that are hidden. For application the training algorithm which has been identified to be the apt is Levenberg-Marquardt training algorithm because it will reduce the MSE value that offer enhanced accurateness to predict. The training function, the transfer function, the learning function and the performance functions utilized were logsig, traingdx, learngdx and MSE correspondingly. The least MSE Value is acquired for 20 hidden layer nodes in this research. Therefore a network of 20 hidden nodes, 2 output node and 5 input nodes has been formed, hence 5-20-2 network has been framed. So ANN model along feed forward network with Levenberg-Marqudt algorithm and back propagation algorithm has been educated for the research along collected data. Efficiency of ANN model completely relying on trial and error method. The modeling using ANNs comprises of the following factors is given in Table 3. Table 4 specifies the set of training data and Table 5 specifies the set of testing data.

Table 3. Modeling by artificial neural network

Sl. No.	Factors	Description
1.	Tool Used	MATLAB Software
2.	Tool Box Used	Nftool Tool Box
3.	Architecture Used	Feed Forward Architecture
4.	Learning System Used	Supervised Learning
5.	Algorithm Followed	Back Propagation Levenberg Marquardt Algorithm
6.	Activation Function	Sigmoid
7.	Total Number of Layers	3 Layers
8.	Number of Hidden Layers	20

Table 4. Set of training data

Sl. No	P (Bar)	Mf (Kg/min)	do (mm)	df (mm)	s (mm)	MRR m^3/min)	SR
1.	3400	0.55	0.33	0.99	3	1709	2.45
2.	3600	0.55	0.33	0.9	1	2014.86	1.415
3.	3600	0.55	0.3	1.05	2	1970.09	1.624
4.	3600	0.55	0.33	0.9	3	1916.85	2.2
5.	3800	0.55	0.33	0.9	2	2182.26	0.788
6.	3600	0.55	0.33	0.99	2	1997.84	1.609
7.	3400	0.4	0.33	0.99	2	1688.65	2.109
8.	3600	0.7	0.35	0.99	2	1997.84	1.52
9.	3800	0.55	0.33	0.99	3	2085.98	1.201
10.	3800	0.55	0.3	0.99	2	2149.19	0.801
11.	3600	0.55	0.33	0.99	3	1896.34	2.1
12.	3400	0.55	0.33	1.05	2	1746.88	1.905
13.	3600	0.4	0.33	0.99	1	1943.11	1.887
14.	3600	0.55	0.33	0.99	2	2009.16	1.571
15.	3600	0.55	0.35	0.9	2	1948.44	1.53

16.	3600	0.55	0.3	0.9	2	2003.48	1.709
17.	3400	0.55	0.33	0.9	2	1751.19	1.9
18.	3600	0.55	0.33	0.99	2	2003.48	1.566
19.	3600	0.4	0.3	0.99	2	1842.16	1.91
20.	3400	0.55	0.35	0.99	2	1751.19	1.899
21.	3600	0.55	0.3	0.99	1	2009.16	1.5
22.	3800	0.7	0.33	0.99	2	2142.69	0.62
23.	3600	0.4	0.33	1.05	2	1866.4	1.934
24.	3600	0.55	0.3	0.99	3	1916.84	2.309
25.	3600	0.55	0.33	0.99	2	2014.86	1.597
26.	3800	0.55	0.33	1.05	2	2162.3	0.8
27.	3400	0.7	0.33	0.99	2	1800.08	1.9
28.	3600	0.55	0.35	1.05	2	2020.6	1.704
29.	3400	0.55	0.3	0.99	2	1768.66	2.102
30.	3600	0.4	0.33	0.99	3	1842.16	2.345
31.	3600	0.55	0.33	0.99	2	2020.6	1.64
32.	3600	0.55	0.35	0.99	1	2079.86	1.634
33.	3800	0.55	0.35	0.99	2	2162.3	0.881
34.	3600	0.7	0.33	1.05	2	1970.09	1.539
35.	3600	0.55	0.33	1.05	3	1922.04	1.997
36.	3800	0.55	0.33	0.99	1	2223.3	0.8

Table 5. Test data for predicting the MRR and SR

Sl. No	P (Bar)	Mf (Kg/min)	Do (mm)	Df (mm)	S (mm)	MRR mm³/min	SR (µm)
1.	3800	0.4	0.33	0.99	2	1959.220	1.307647
2.	3600	0.7	0.33	0.99	3	1994.945	2.06760
3.	3600	0.7	0.33	0.99	1	2114.8914	1.560804
4.	3600	0.4	0.35	0.99	2	1977.9930	2.008793
5.	3600	0.4	0.33	0.9	2	1896.8314	1.886104
6.	3600	0.55	0.35	0.99	3	2033.3524	1.993245
7.	3600	0.7	0.33	0.9	2	1835.424	1.592554
8.	3400	0.55	0.33	0.99	1	1665.3577	1.900651
9.	3600	0.7	0.3	0.99	2	2121.4085	1.796605
10.	3600	0.55	0.33	1.05	1	2028.0038	1.842619

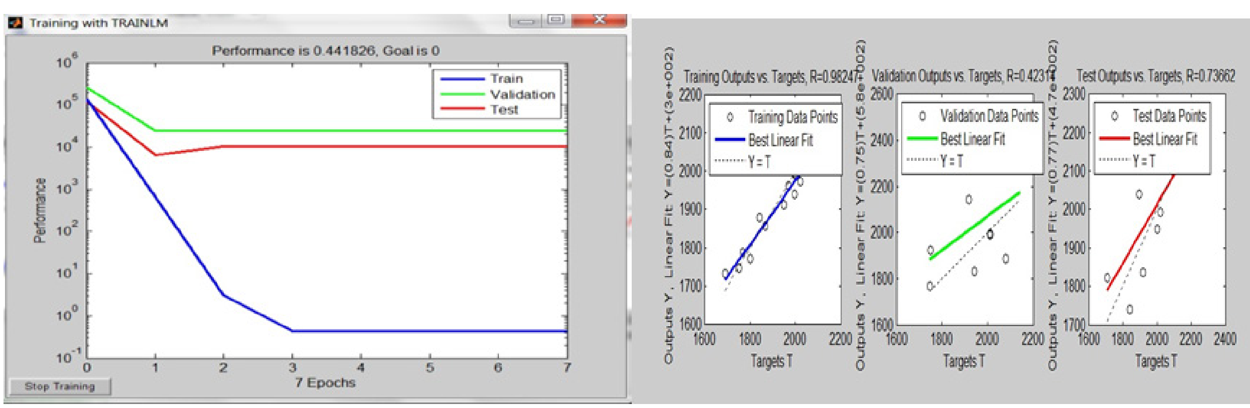

Figure 6. Plot of data regression i.e, Training, Testing and Validation.

Table 6. Error between actual and predicted MRR and SR

Sl. No	Actual MRR(mm3/min)	Predicted MRR (mm3/min)	Percentage of Error	Actual SR (µm)	Predicted SR (µm)	Percentage of Error
1.	2136.25	1959.22	8.286	1.211	1.307647064	7.980764963
2.	1891.29	1994.94	5.480	1.999	2.067	3.431976993
3.	2055.75	2114.89	2.876	1.431	1.560	9.070886429
4.	1866.4	1977.99	5.979	2.013	2.008	0.208967018
5.	1842.16	1896.83	2.967	1.945	1.88	3.028065408
6.	1916.85	2033.35	6.077	2.008	1.993	0.734784907
7.	1970.09	1835.42	6.835	1.500	1.592	6.170303532
8.	1800.08	1665.35	7.484	1.789	1.900	6.240987747
9.	1937.8	2121.40	9.47	1.699	1.796	5.744851927
10.	2049.81	2028.00	1.06	1.707	1.8424	7.944895376

4. Results and Discussions

The results illustrate that the data from training and forecasted values have reached very close to each other. Regression plot to train, test and validate the ANN model is depicted in Figure 6 which exhibits the network targets corresponding to outputs to train, validate, and test sets. To fit best, the data must fall along 45 degree dash line, making targets the network output. In this work the aptness is satisfactory corresponding to all sets of data with the values of R for every scenario. Assessment against forecasted and investigational values of MRR and SR using ANN is depicted in Figures 7 and 8 and Table 6 and found that the predicted values are very closer to the experimental values and also the percentage of error is acceptable..

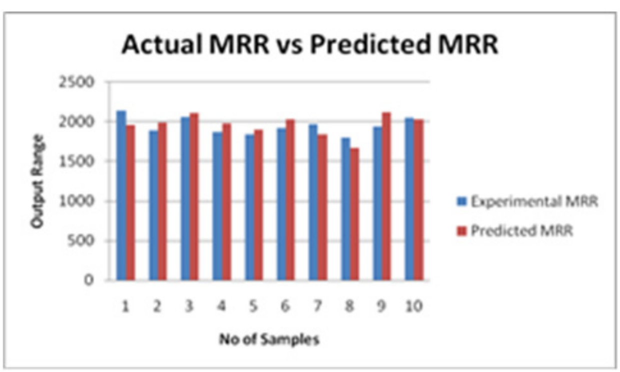

Figure 7. Comparison of Experimental MRR Vs Predicted MRR Using ANN (Test Data).

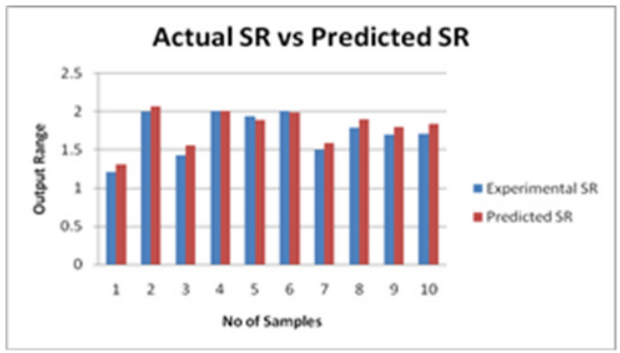

Figure 8. Comparison of Experimental SR Vs Predicted SR Using ANN (Test Data).

5. Conclusion

In this paper, the prediction of MRR and SR for Lead Tin Alloy by cutting through AWJM process by the tool named ANN using back propagation algorithm for training the data and testing the data is done which illustrates that the actual values are closer to predicted values. Outcome depicts the minimum error attained for data belonging to test is 1.063814%% for MRR and 0.208967018% for SR. Also the maximum error obtained is about 9.475104% for MRR and 9.070886429% for SR. By training the network deviations may occur but error is reduced because this technique is heuristic. This paper concludes that model for MRR and SR shall be enhanced to modify numerous layers and nodes existing along the ANN structure hidden layers, mostly to predict value of the surface roughness performance measure and material removal rate.

6. References

1. Momber AW, Kovacevic R. Principles of abrasive water jet machining. Springer Verlag Limited: London; 1992.
2. Hashish M. A model for abrasive water jet machining. Transactions of ASME Journal of Engineering Materials and Technology. 1989; 111(S2):154-62.
3. Kovacevic R, Fang M. Modeling of the influence of the abrasive water jet cutting parameters on the depth of cut based on fuzzy rules. International Journal Machine Tools Manufacture. 1994; 34(1):55-72.
4. Lu Y, Li X, Jiao B, Liao Y. Application of artificial neural networks in abrasive water jet cutting process. International Symposium on Neural Networks. Chongqing, China. 2005. p. 877-82.
5. Srinivasu DS, Ramesh BN, Srinivasa YG, Louis H, Peter D, Versemann R. Genetically evolved artificial neural networks built with sparse data for predicting depth of cut in abrasive water jet cutting. Proceedings American Water Jet Conference. Houston, Texas. 2005. p. 1-16.
6. Narayanan N, Yeldose B. Prediction of surface roughness using ANN in turning. International Journal of Emerging Technology and Advanced Engineering. 2013; 3(S4):709-13.
7. Srinivasu DS, Ramesh BN. A Neuro-Genetic approach for selection of process parameters in abrasive water jet cutting considering variation in diameter of focusing nozzle. International Journal of Applied Soft Computing. 2008; 8(1):809-19.
8. Srinivasu DS, Ramesh BN, Srinivasa YG. Neuro-Genetic approach for automatic selection of process parameters in abrasive water jet cutting considering the variation in bore diameter of focusing nozzle. Proceedings 21st All India Manufacturing Technology Design and Research Conference, Vellore, India. December 2004. p. 887-93.
9. Nithyanandam J, SushilLal D, Palanikumar K. Influence of cutting parameters in machining of titanium alloy. Indian Journal of Science and Technology. April 2015; 8(S8). p. 556-62.