ISSN: 0974-2115
www.jchps.com Journal of Chemical and Pharmaceutical Sciences

Prediction of Quality Response by AWJM Process for Aluminium 6061 Alloy Using ANN

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ABSTRACT

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 recently developed nontraditional machining process in processing various kinds 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 the lead role in determining the machine economics and quality of machining. In this study the consequence of five AWJM process parameters on MRR and SR of an American element named Aluminium 6061 alloy which is machined by AWJM was experimentally performed and analyzed. According to RSM design, different experiments were conducted with the combination of input parameters on this American element. This paper investigates the prediction of MRR and Surface roughness on Aluminium 6061 alloy using the Artificial Neural Network (ANN).

KEY WORDS: Response Surface Methodology, Artificial Neural Network, Material Removal Rate, Surface Roughness.

1. INTRODUCTION

AWJC is the recently developed processes. This technique is suitable for machining of brittle materials similar to glass, ceramics and stones as well as for composite materials and ferrous and non-ferrous materials. From the literature review of Momber and Kovacevic (1992) consider that the AWJM process is very less sensitive to material properties since it do not cause chatter, no thermal effects, require minimal stresses on the work material, and have high machining versatility and flexibility. Hashish (1989) reviewed that in this type of process, a flow of little abrasive particles is introduced into the waterjet and this combination abrasive water jet is then allowed to impact on the work piece to cut it. A few efforts has been done to model, predict and optimize the input process parameters in AWJC process. The approaches used in this direction to develop various mathematical equations for predicting and optimizing the output parameters include DOE, regression analysis modeling, ANOVA, Genenic Algorithm, fuzzy logics and neural networks. An ANN model is developed for predicting the cutting speed to the desired cutting surface quality using AWJ cutting is developed by Lu (2005). Prediction of Depth of cut through ANN model is developed by Srinivasu (2005). Prediction of Surface roughness in turning process through ANN model is developed by Naveen (2013). Srinivasu (2005) presented a paper on neuro-genetic technique suggests that an artificial neural network model for prediction of depth of cut is developed with the consideration of diameter of focusing nozzle, jet traverse rate, abrasive flow rate, water pressure. ANN combined with GA, i.e. neuro-genetic approach, is proposed to suggest the process parameters. An attempt has been made by Srinivasu (2005) to develop models on ANN and FL for various materials processing applications using AWJC with the consideration of diameter of focusing nozzle.

2. EXPERIMENTAL WORK

2.1. Material: Aluminium 6061 alloy, an American element is a precipitation hardening Aluminium Alloy which is available in several forms such as tube, ingot, ribbon, wire, foil, bar, pipe and rod. It is one of the cheapest American element alloy. The important factor in selecting Aluminum 6061 alloy is their high strength to weight ratio, appearance, and their nonmagnetic properties. Some of the applications of Aluminium 6061 alloy include marine fittings, aerospace maintenance, transport, bicycle frames, brake components, valves couplings etc. It is also applied in paint removal, surgery, peening, drilling turning etc. It has good surface finish and can be anodized. Its density is 2.7 g/cm3 and it's Modulus of Elasticity E = 80GPa. The dimension chosen to cut the Aluminium 6061 alloy for this study is 150mm x 50mm x 50mm.

2.2. Response Surface Methodology: RSM is a set of mathematical and statistical techniques which are useful for modeling and investigation of problems. In the present study five process parameters are chosen and varied in three levels as shown in Table 1.

Based on response surface methodology, Box-Behnken design 46 sets of experimental design was selected and was shown in Fig.1. The parameters and its levels were selected based on the review of certain journals that have been acknowledged on AWJC on materials like Titanium, Mild Steel, Copper, and Epoxy Composite Laminate.

Table.1.levels of parameters used in experiment

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

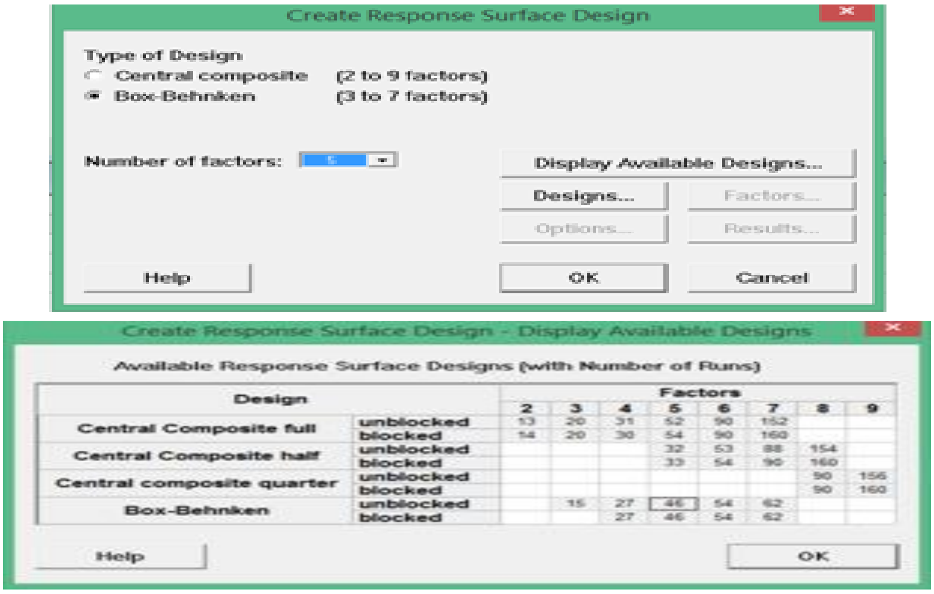

Fig.1.Selection of Box-Behnken Design and Selection of No of Factors

2.3. Data Collection and Experimentation: The machine used to cut the American element Aluminium 6061 alloy was the AWJC machine is set with KMT ultrahigh pressure pump with the designed pressure of 4000bar, gravity feed type of abrasive hopper, an abrasive feeder system, a pneumatically controlled valve and a work piece table. The controller fixed in the control stand is used to adjust the SOD for different experiments. The abrasive water jet machine is programmed using numerical control code is to change the transverse speed and manage the supplement of abrasives. After the water is pumped at very high pressures resulting in high velocity of water jet of 1000 m/s as it comes out of focusing nozzle cuts the materials of the desired size and shape. The KMT abrasive water jet cutting machine with its mixing chamber is shown in Fig.2.

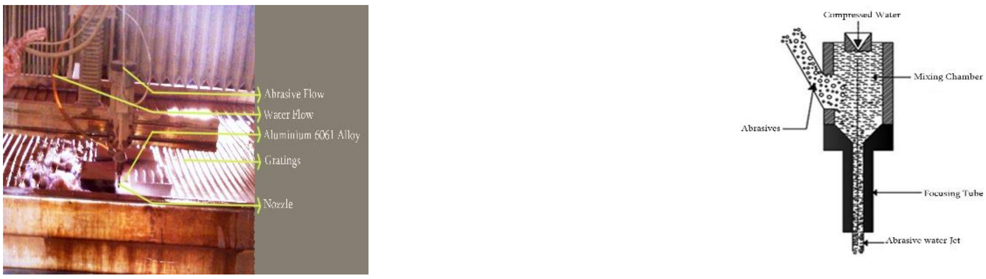

Fig.2.Experimental Setup of AWJM with Mixing Chamber

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 is selected and performed experimentally and machining time is observed for all experiments as shown in Table.2. The MRR is calculated by the formula;

$$MRR = (m_f - m_i) / t$$

Where, m_f = mass of the material after machining, m_i = mass of the material before machining and t = Machining Time. The surface roughness for the machined Aluminium 6061 alloy is measured using Portable surface roughness tester.

Table.2.Planning Matrix of the Experiments

S.No	P (Bar)	m_f (Kg/min)	d_o (mm)	d_f (mm)	S (mm)	MRR mm^3/min	SR (μm)
1	3400	0.55	0.33	0.99	3	48.6111	3.57
2	3600	0.55	0.33	0.9	1	53.6399	2.08
3	3600	0.55	0.3	1.05	2	51.8519	2.21
4	3600	0.55	0.33	0.9	3	50.8352	2.55
5	3800	0.55	0.33	0.9	2	62.2222	1.90
6	3600	0.55	0.33	0.99	2	51.8519	2.19
7	3400	0.4	0.33	0.99	2	45.7516	3.20
8	3600	0.7	0.35	0.99	2	53.6399	1.80
9	3800	0.55	0.33	0.99	3	61.2423	2.07
10	3800	0.55	0.3	0.99	2	62.2222	2.05
11	3600	0.55	0.33	0.99	3	51.1696	2.54
12	3400	0.55	0.33	1.05	2	47.7164	3.08
13	3600	0.4	0.33	0.99	1	50.1792	1.99
14	3600	0.55	0.33	0.99	2	52.9101	2.17
15	3600	0.55	0.35	0.9	2	54.3901	2.08
16	3600	0.55	0.3	0.9	2	51.8519	2.79
17	3400	0.55	0.33	0.9	2	48.6111	3.30
18	3600	0.55	0.33	0.99	2	52.9101	2.19
19	3600	0.4	0.3	0.99	2	47.7164	2.36
20	3400	0.55	0.35	0.99	2	48.3092	2.95
21	3800	0.4	0.33	0.99	2	58.4785	1.89
22	3600	0.7	0.33	0.99	3	54.7731	2.25
23	3600	0.7	0.33	0.99	1	56.3607	1.68
24	3600	0.4	0.35	0.99	2	49.2264	2.29
25	3600	0.4	0.33	0.9	2	48.9168	2.36
26	3600	0.55	0.35	0.99	3	51.1696	2.50
27	3600	0.7	0.33	0.9	2	55.9552	2.14
28	3400	0.55	0.33	0.99	1	49.2264	2.65
29	3600	0.7	0.3	0.99	2	56.7721	2.18
30	3600	0.55	0.33	1.05	1	50.8352	1.90
31	3600	0.55	0.3	0.99	1	51.8519	1.99
32	3800	0.7	0.33	0.99	2	64.8148	1.70
33	3600	0.4	0.33	1.05	2	48.6111	2.40
34	3600	0.55	0.3	0.99	3	52.1999	2.68
35	3600	0.55	0.33	0.99	2	52.9101	2.20
36	3800	0.55	0.33	1.05	2	59.8291	1.99
37	3400	0.7	0.33	0.99	2	51.8519	2.80
38	3600	0.55	0.35	1.05	2	51.1696	2.34
39	3400	0.55	0.3	0.99	2	48.9168	3.23
40	3600	0.4	0.33	0.99	3	48.3092	2.69
41	3600	0.55	0.33	0.99	2	53.2725	2.18
42	3600	0.55	0.35	0.99	1	52.5526	1.80
43	3800	0.55	0.35	0.99	2	59.3724	1.82
44	3600	0.7	0.33	1.05	2	56.7721	2.03
45	3600	0.55	0.33	1.05	3	51.1696	2.73
46	3800	0.55	0.33	0.99	1	61.2423	1.72

2.4. Artificial Neural Network: An ANN is defined as data-processing system comprising of large number of highly interconnected 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 Fig. 3, where the input layers is a buffer that present 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.

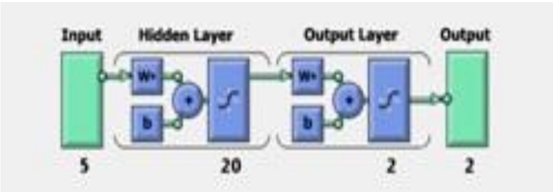

Fig.3.Neural Network Architecture

2.5. Back propagation Learning Algorithm: Back propagation is a systematic method for training multiple-layer (three or more) artificial neural networks (Swingler 1996; Tsoukalas & Uhrig 1996, Schalkoff, 1997). The elucidation of this training algorithm in 1986 by Rumelhart was the key step in making neural networks practical in many real-world situations. 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 are calculated through the learning phase of the network. The difficulty with multilayer perceptions is calculating the weights of hidden layers in a best way that results in least output error. If the hidden layers are more, then more difficult it come across. In order to update the weights, we must calculate the error. The error in the output layer is easily measured. This is the difference between actual and desired outputs. However in the hidden layer there is no direct 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 step7; 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.

2.6. Procedure for Prediction of Material Removal Rate and Surface Roughness Using ANN: Initially the experimental data is separated in two sets, one is the training set and other is the test data set. The test data is used to ensure the performance of ANN model produced to fit a sample of 46. The preferred ratio chosen is 10:36. Following the No of nodes in the hidden layers must be found out. For this reason iterations are made to choose the least MSE value for the no of hidden nodes. For application the training algorithm which was found to be the best fit is Levenberg-Marquardt training algorithm because it will reduce the MSE value that provide better accurateness of prediction. The transfer function, the training function, the learning function and the performance functions used are logsig, traingdx, learngdx and MSE respectively. In this study the lowest MSE Value is acquired for 2 hidden layer nodes. Therefore a network of 3 input nodes, 2 hidden nodes and 1 output node is formed, hence 3-2-1 network is structured. So artificial neural network model with feed forward network with back propagation algorithm and Levenberg-Marqudt algorithm was trained for the experiment with collected data. The effectiveness of ANN model fully depends on trial and error method. The modeling using Artificial Neural Networks comprises of the following factors is given in Table 3. Table 5 specifies the set of training data and Table 6 specifies the set of testing data.

Table.3.Modeling by Artificial Neural Network

Factors	Description
Tool Used	MATLAB Software
Tool Box Used	nftool Tool Box
Architecture Used	Feed forward architecture
Learning System Used	Supervised learning
Algorithm Followed	Back propagation Levenberg Marquardt Algorithm
Activation Function	Sigmoid
Total Number of Layers	3 Layers
Number of Hidden Layers	2

Table.4.Set of training data

S.No.	P(Bar)	m_f (Kg/min)	d_o (mm)	d_f (mm)	S (mm)	MRR mm^3/min	SR (µm)
1	3400	0.55	0.33	0.99	3	48.6111	3.57
2	3600	0.55	0.33	0.9	1	53.6399	2.08
3	3600	0.55	0.3	1.05	2	51.8519	2.21
4	3600	0.55	0.33	0.9	3	50.8352	2.55
5	3600	0.55	0.33	0.99	2	51.8519	2.19
6	3400	0.4	0.33	0.99	2	45.7516	3.2
7	3600	0.7	0.35	0.99	2	53.6399	1.8
8	3800	0.55	0.33	0.99	3	61.2423	2.07
9	3600	0.55	0.33	0.99	3	51.1696	2.54
10	3400	0.55	0.33	1.05	2	47.7164	3.08
11	3600	0.4	0.33	0.99	1	50.1792	1.99
12	3600	0.55	0.33	0.99	2	52.9101	2.17
13	3600	0.55	0.3	0.9	2	51.8519	2.79

14	3400	0.55	0.33	0.9	2	48.6111	3.3
15	3600	0.55	0.33	0.99	2	52.9101	2.19
16	3600	0.4	0.3	0.99	2	47.7164	2.36
17	3800	0.4	0.33	0.99	2	58.4785	1.89
18	3600	0.7	0.33	0.99	3	54.7731	2.25
19	3600	0.7	0.33	0.99	1	56.3607	1.68
20	3600	0.4	0.35	0.99	2	49.2264	2.29
21	3600	0.55	0.35	0.99	3	51.1696	2.5
22	3600	0.7	0.33	0.9	2	55.9552	2.14
23	3400	0.55	0.33	0.99	1	49.2264	2.65
24	3600	0.7	0.3	0.99	2	56.7721	2.18
25	3600	0.55	0.3	0.99	1	51.8519	1.99
26	3800	0.7	0.33	0.99	2	64.8148	1.7
27	3600	0.4	0.33	1.05	2	48.6111	2.4
28	3600	0.55	0.3	0.99	3	52.1999	2.68
29	3800	0.55	0.33	1.05	2	59.8291	1.99
30	3400	0.7	0.33	0.99	2	51.8519	2.8
31	3600	0.55	0.35	1.05	2	51.1696	2.34
32	3400	0.55	0.3	0.99	2	48.9168	3.23
33	3600	0.55	0.33	0.99	2	53.2725	2.18
34	3600	0.55	0.35	0.99	1	52.5526	1.8
35	3800	0.55	0.35	0.99	2	59.3724	1.82
36	3600	0.7	0.33	1.05	2	56.7721	2.03

Table.5.Test Data for Predicting the MRR and SR

S.No	P (Bar)	m_f (Kg/min)	d_o (mm)	d_f (mm)	S (mm)	MRR mm^3/min	SR (µm)
1	3800	0.55	0.33	0.9	2	62.2222	1.90
2	3800	0.55	0.3	0.99	2	62.2222	2.05
3	3600	0.55	0.35	0.9	2	54.3901	2.08
4	3400	0.55	0.35	0.99	2	48.3092	2.95
5	3600	0.4	0.33	0.9	2	48.9168	2.36
6	3600	0.55	0.33	1.05	1	50.8352	1.90
7	3600	0.55	0.33	0.99	2	52.9101	2.20
8	3600	0.4	0.33	0.99	3	48.3092	2.69
9	3600	0.55	0.33	1.05	3	51.1696	2.73
10	3800	0.55	0.33	0.99	1	61.2423	1.72

3. RESULTS AND DISCUSSIONS

The results illustrates that the training data and predicted values have come very close to each other. The regression plot for training, testing and validating the ANN model is depicted in Fig. 4. The plots exhibit the network targets with respect to outputs for training, validation, and test sets. For best fit, the data must fall along 45 degree dash line, where the network outputs are the targets. In this work the fit is satisfactory for all sets of data with the values of R for each case. The Comparison between Predicted and Experimental values of MRR and SR using ANN is depicted in Fig. 5 and 6 and Table 6 and found that the predicted values are very closer to the experimental values and also the percentage of error is acceptable.

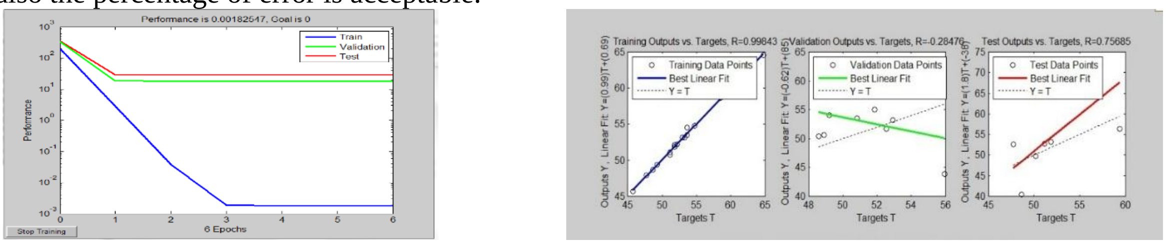

Fig.4.Plot of Data Regression i.e, Training, Testing and Validation

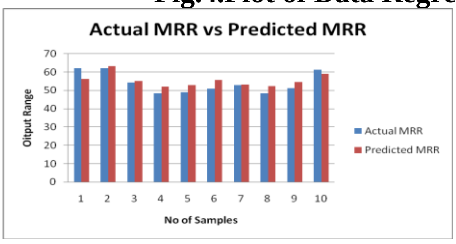

Fig.5.Comparison of Experimental MRR Vs Predicted MRR Using ANN (Test Data)

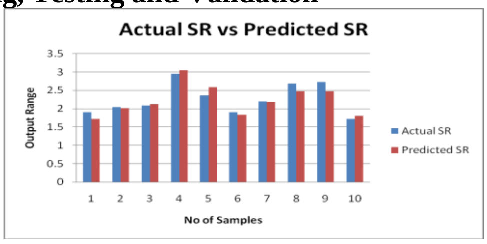

Fig.6.Comparison of Experimental SR Vs Predicted SR using ANN (Test Data)

Table.6.Error between Actual and Predicted MRR and SR

S.No.	Actual MRR	Predicted MRR	% of Error	Actual SR	Predicted SR	% of Error
1	62.2222	56.28920738	9.53517	1.90	1.723958	9.265352
2	62.2222	63.39076666	1.878054	2.05	2.017202	1.599895
3	54.3901	55.11371255	1.330412	2.08	2.133523	2.573210
4	48.3092	52.04339223	7.729775	2.95	3.045341	3.231911
5	48.9168	52.84270219	8.025673	2.36	2.593326	9.886695
6	50.8352	55.60362954	9.380173	1.90	1.838989	3.211130
7	52.9101	53.1777775	0.50591	2.20	2.185366	0.665179
8	48.3092	52.37363357	8.413374	2.69	2.482054	7.730350
9	51.1696	54.62831711	6.75932	2.73	2.480608	9.135234
10	61.2423	59.00703562	3.64987	1.72	1.811436	5.316057

4. CONCLUSION

In this paper, the prediction of MRR and SR for Aluminium 6061 alloy by cutting through Abrasive water jet machining 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. From the results it is seen that the minimum error obtained for test data is 0.50591%% for MRR and 0.665179% for SR. Also the maximum error obtained is about 9.53517% for MRR and 9.886695% 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 improved by modifying number of layers and nodes in the hidden layers of ANN structure, mostly for predicting value of the material removal rate and surface roughness performance measure.

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