

Prediction of Abrasive Water Jet Plain Milling Process Parameters Using Artificial Neural Networks

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Abstract-Technology of abrasive water jet (AWJ) is one of the most important processes for machining due to its advantages over other technologies. It has proved to be an efficient process for plain milling of various materials. The paper presents a new predictive model of AWJ milling of aluminum alloy. The model is developed to predict some interesting process parameters from process variables. As AWJ is a complicated multi input-output system, its model is developed using artificial neural network (ANN) as one of the artificial intelligent models. A feed forward neural network based on back error propagation is used. The ANN training set is generated by extensive experimental work. The tests considered four process variables, which are traverse speed, water jet pressure, stand-off distance and abrasive flow rate and three process parameters, namely; surface roughness, depth of cut and material removal rate. The study of the relation between process variables and parameters yields to eliminate the stand-off distance from the training set. Therefore, the ANN has been designed to have three input neurons for process variables and three output neurons for process parameters. The designed ANN was trained and tested. The ANN succeeded to model the AWJ process by extracting the process parameters from process variables with a regression factor above 90%. This paper is a step towards a better understanding, modeling and controlling of AWJ milling process.

Keywords- Abrasive Water Jet (AWJ); Plain Water Jet (PWJ) Milling; Controlled Depth Milling (CDM); Surface Roughness; Depth of Cut; Material Removal Rate; Artificial Neural Networks

Nomenclature

f: Jet traverse speed (m/min)
p: Jet pressure (MPa)
 m_a : Abrasive flow rate (g/min)
d: Nozzle diameter (mm)
 θ : Impingement angle (degrees)
s: Stand-off distance (mm)
i: Pass increment (mm)
 R_a : Surface roughness (μm)
MRR: Material removal rate (mm^3/min)

I. INTRODUCTION

The global economy is becoming one of the more benefit targets in the manufacturing industry. Nowadays, the need of manufacturing industry for rapid prototyping and small production batches is increasing. These trends have placed an increase on the use of new and advanced technologies for quickly turning raw materials into usable goods; with no time being required for tooling [1].

The most recent technology, which develops new non-traditional methods, is the abrasive water jet machining (AWJ). It is used in industry for material processing with many advantages such as; no thermal distortion, high machining versatility, high flexibility, quick machining and small cutting forces [2]. It can be even a more attracting technology if plain water jet (PWJ) milling is employed due to reduced running costs caused by the absence of abrasives and the elimination of surface contaminations with grit embedment [3]. AWJ is widely used in the machining of materials such as steel, stone, brass, titanium, aluminum, inconel in addition to any kind of glass and composites [4]. The intensity and the efficiency of the machining process depend on several AWJ process variables which may be classified as hydraulic, abrasive, work material and cutting variables [5, 6].

Most of the studies dispute the hydrodynamic characteristics of abrasive jets, hence achieving the influence of all operational variables on the process effectiveness including abrasive type, size and concentration, impact speed and angle of impingement. Other studies investigated the nozzle shape size and wear, jet velocity and pressure, stand-off distance (SOD). The result of these studies were the overall process performance in terms of material removal rate, geometrical tolerances and surface finishing of work pieces [7]. In order to predict the depth of cut, the experiments were conducted in varying water

pressure, nozzle traverse speed, abrasive mass flow rate and stand-off distance for cutting granite tiles using abrasive water jet cutting process [8].

Most of the work done by researchers is to study the creation of through pockets by milling with AWJ. Also other researchers investigated the milling with abrasive water jet. Recently, researchers have also started experimenting on generating blind pockets using AWJ. This process is called controlled depth milling (CDM) [9].

Depth of cut is the most investigated factor to predict the AWJM parameters. In literature, results indicated that the cut depths decreased with increasing traverse speed [10-14] and decreasing abrasive size. On the other hand, increase of the abrasive mass flow rate leads to increase in the cut depths, and the stand-off distance has no discernible effects on the cut depths [15]. Effect of stand-off distance on the depth of cut is not significant, and this is because of the small range of the stand-off distance (2 to 5 mm) [16]. Also the optimum stand-off distance is equal to 2 mm [17].

Surface roughness, which is used to determine and to evaluate the quality of a product, is one of the major quality parameters of the plain water jet (PWJ) milling product, where arithmetic mean of surface roughness, maximum roughness of profile height and mean spacing of profile irregularity are the dependent output variables [18]. In addition, the depth of cut is an important parameter which evaluates the process quality and effectiveness [12, 13, 19]. Surface roughness is influenced by traverse speed which is the most influential factor that affects surface roughness in the AWJM while stand-off distance is the least influential factor that affects surface roughness [18]. Veselko Mutavdjic et al. [20] selected Aluminum as the test in the abrasive water jet machining process. It was found that the parameter of roughness of the machined surface continuously improves (R_a decreases) when abrasive flow rate increases. They also found that the results show a greater decline in the quality of the machined surface when traverse speed is increased. M. A. Azmir et al. [11] presented a study on the effect of abrasive water jet machining (AWJM) process parameters on surface roughness (R_a) of aramid fiber reinforced plastics (AFRP) composite. Results described that increasing the traverse rate allows less overlap machining action and fewer abrasive particles to impinge the surface, increasing the roughness of the surface.

Also, a faster traverse rate increases the jet deflection which results in a higher magnitude of surface roughness.

In addition, milling time and material removal rate have been taken into consideration to evaluate the economical approach of the PWJ milling [21]. Considerable efforts have been made in understanding the influence of dynamic variables such as water jet pressure, abrasive flow rate, traverse rate, stand-off distance, and number of passes on material removal rate [15].

The literature reveals that ANNs find many applications to predict surface finish through different machining processes, but very little effort is reported on the use of ANNs in AWJ machining process. Additionally, applied experimental methods are requiring a large number of trials when the number of machining parameters increases [1]. Few researchers concentrated on modeling and optimizing AWJM through other techniques such as artificial neural network (ANN), fuzzy logic (FL), genetic algorithm, grey relational analysis, simulated annealing and artificial ant colony etc. [14].

In order to determine the relationship between machining parameters and surface roughness in AWJ machining process, an artificial neural network and multiply regression analysis were carried out based on Taguchi's orthogonal array by Ulas Caydas and et al. [1] Summarizing the mean features of the results, both the neural network and regression approaches were seen to be sufficient for estimating surface roughness in AWJ machining with a very small test error where tests were done on AA 7075 aluminum alloy.

Yiyu Lu et al. [22] applied the artificial neural network in abrasive water jet cutting to find a model that can be used to find the relationships between the process input parameters and the cutting speed. The overall results indicate that the ANN is able to learn the complicated relationships between main AWJ input parameters and cutting speed with necessary cutting surface quality. The proposed prediction model for certain AWJ systems can be used for parameter optimization and numerical simulation of AWJ cutting process.

Azlan Mohd Zain et al. [23] studied the Artificial Neural Network (ANN) and Simulated Annealing (SA) techniques, were integrated labeled as integrated ANN-SA to estimate optimal process parameters in abrasive water jet (AWJ) machining operation. In the study, the process parameters were considered as traverse speed, water jet pressure, stand-off distance, abrasive grit size and abrasive flow rate. The quality of the cutting of machined-material is assessed by looking to the roughness average value (R_a). The optimal values of the process parameters are targeted for giving a minimum value of R_a . It was found that integrated ANN-SA is giving much lower value of R_a at the recommended optimal process parameters compared to the result of experimental and ANN single-based modeling.

The estimation of appropriate values of the abrasive water jet process parameters is important to get an effective process performance. Therefore, numerous mathematical and empirical models have been developed. However, the process complexity confines the use of these models for limited operating conditions; e.g., some of these models are valid for special material combinations while others are based on the selection of only the most critical variables such as pump pressure, traverse rate, abrasive mass flow rate and others that affect the process. Furthermore, these models may not be generalized to other operating conditions. Two neural network approaches, back-propagation and radial basis function networks, are proposed. The results from these two neural network approaches are compared with that from the linear and non-linear regression models. The neural

networks provide a better estimation of the parameters for the AWJ machining process [9].

In this paper, the feed forward back-propagation network is used to develop a sufficiently accurate, reliable and intelligent numerical prediction model of AWJ milling process. Trained by experimental database for aluminum alloy, the network with definite structure and parameters can present a good approximation to complex nonlinear relationships between the input process variables and the output process parameters.

II. ARTIFICIAL NEURAL NETWORKS

One of the most important approaches in artificial intelligence is neural network, which is traditionally considered as simplified model of neural processing in the human brain. Most scientists know that the human brain is a type of computer. The origins of neural network are based on efforts to model information processing in biological systems, which may largely rely on parallel processing as well as implicit instructions based on recognition of patterns of “sensory” input from external sources [24].

Human body consists of trillions of cells. A portion of them is the nerve cells called “neurons”, which shown in Fig. 1. These neurons have different shapes and size. A neuron collects signal from others through fine structures is called dendrite. The neuron sends out spikes of electrical activity through a long, thin stand known as axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input which is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes [25].

Neural networks are systems that can acquire, store, and utilize knowledge gained from experience. An artificial neural network (ANN) is capable of learning from an experimental data set to describe the nonlinear and interaction effects with great success. It consists of an input layer used to present data to the network, output layer to produce ANN’s response, and one or more hidden layers in between. The input and output layers are exposed to the environment while hidden layers do not have any contact with the environment. Layers consist of a number of neurons. ANNs are characterized by their topology, weight vectors, and activation function that are used in hidden and output layers of the network. A neural network is trained with a set of data and tested with other set of data to arrive at an optimal topology and weights. Once trained, the neural network can be used for prediction.

During training process, the network adjusts its weights to minimize the errors between the predicted and desired outputs. Back propagation algorithm is the most common algorithm for adjusting the weights [26].

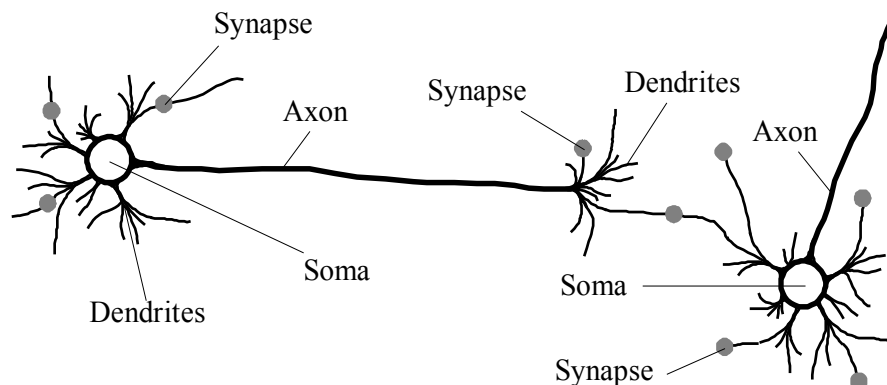


Fig. 1 Neural network biological illustration

Even though several learning methods have been developed, the back-propagation (BP) method has been proven to be successful in applications related to surface finish prediction. In the present work, back-propagation learning algorithm which has a unique learning principle is used. Fig. 2 shows back-propagation networks illustration in a schematic form [27]. In the network, each neuron receives total input from all of the neurons in the proceeding layer. A neuron in the network produces its input by processing the net input through an activation (transfer) function which is usually nonlinear. There are several types of activation functions used for back-propagation. However, the sigmoidal activation function is most utilized. The weights are dynamically updated using the back-propagation algorithm. For the purpose of minimizing error, the weights of the inter-connections are adjusted during the training procedure until the expected error is achieved. To adjust the weights of the networks, the process starts at the output neuron and works backward to the hidden layer [28].

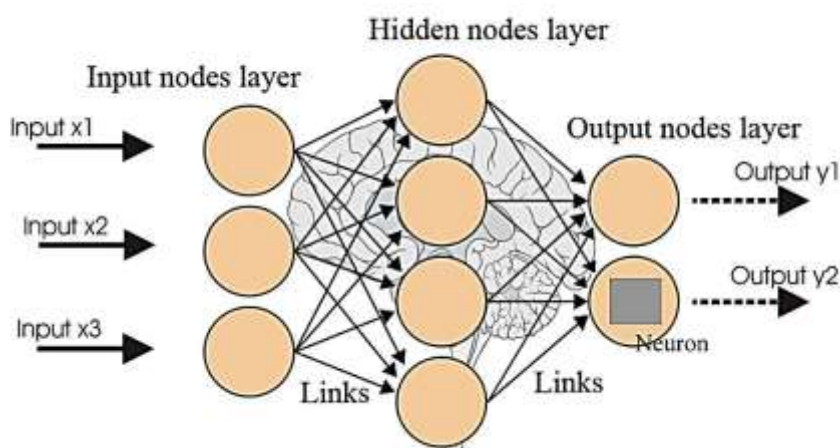


Fig. 2 Schematic illustration of artificial neural network [27]

III. AIM OF THE WORK

The aim of the present work is to investigate the plain milling of pockets using PWJ and developing an ANN pattern to predict process parameters, which are depth of cut, surface roughness and material removal rate. The investigation focuses on identifying the process variables, which influence the process parameters in interest. The considered process variables are traverse speed, jet pressure, abrasive flow rate and stand-off distance. The experimental work was applied using aluminum specimens. The experimental methodology is explained in detail in section IV. The experimental results are presented and discussed in section V, while neural network design, training and testing are shown in section VI. The conclusions are summarized in section VII.

IV. EXPERIMENTAL WORK

The main objective of the present research is to use the artificial neural network to develop a model that is capable to predict the process output parameters from certain process input variables. Therefore, experiments in different values of process variables were carried out, and measured output parameters were investigated. In this investigation, the relations of process parameters with process variables were found. Table 1 shows the cutting variables and their ranges.

TABLE 1 PROCESS VARIABLES AND THEIR RANGES

Process variable	Value	Type
Jet traverse speed, f	From 1000 to 2000 mm/min	Variable
Jet pressure, p	From 20 to 100 MPa	Variable
Abrasive flow rate, m_a	From 60 to 250 g/min	Variable
Stand-off distance, s	2, 3, 4, 5 mm	Variable
Nozzle diameter, d	1.2 mm	Fixed
Jet impingement angle	90°	Fixed
Abrasive material	As shown in table 5	Fixed
Jet increment	0.3 mm	Fixed
Path shape	Zigzag	Fixed
Work material	Aluminum alloy	Fixed

In this work, real cutting operations have been accomplished using an industrial computer numerically controlled AWJ machine [29]. Photos for the machine and the machine cutting nozzle are shown in Fig. 3. The machine general specifications are shown in table 2.

The tests were applied on Alumecc 89 [30] specimens. Alumecc 89 is a high strength aluminum alloy supplied in the form of hot rolled, heat treated plate (30×120×250 mm). The alloy properties are listed in table 3 while the chemical composition is shown in table 4. The machining operations were conducted using the abrasive material [31], where its physical properties and chemical composition are shown in table 5.



Fig. 3 AWJ machine and cutting nozzle

TABLE 2 GENERAL SPECIFICATIONS OF THE USED AWJ MACHINE

Item	Identification
Machine model	SOITAAB
Intensifier	ACCUSTREAM
Table size	2000 x 4000 mm
Nozzle diameter	1.2 mm
Jet impingement angle	90°
Max. pressure	400 MPa
Max. feed	4000 mm/min
Max. abrasive flow rate	520 g/min
Stand-off distance	More than 1mm
Vertical cut height	300 mm

TABLE 3 ALUMEC 89 ALLOY PROPERTIES

Property	Identification
Density (kg/m ³)	2830
Modulus of elasticity (GPa)	71.5
Tensile strength (MPa)	590
Yield strength (MPa)	550
Brinell hardness (BHN)	160

TABLE 4 ALUMEC 89 ALLOY CHEMICAL COMPOSITION

Element	Cu	Mn	Mg	Cr	Zn	AL
Content (%)	0.7	0.1	2.6	0.13	4.3	Rest

TABLE 5 PHYSICAL PROPERTIES AND CHEMICAL COMPOSITION OF USED ABRASIVE MATERIAL

Physical Properties	Typical chemical composition
* Color: Reddish brown * Hardness: 7.5 – 8.0 per Moh's scale * Specific Gravity: 4.0 – 4.2 * Grain Shape: Angular to sub-angular * Melting Point: ~ 1315° C * Free Crystalline Silica: < 1% * Size: # 80 mesh (U.S. standard screen)	* Silicon dioxide (SiO₂) 38% (non-crystalline) * Ferric oxide (Fe₂O₃) 29% * Aluminum oxide (Al₂O₃) 23% * Magnesium oxide (MgO) 5% * Calcium oxide (CaO) 2% * Manganese oxide (MnO) <1%

During measuring of both depth of cut and surface roughness, the pocket was divided into six planes. The distance between each two successive planes of measurements is 3 mm which yields 6 measured points. The two end planes are located from 7.5 mm away from both ends of the pocket. This is because at the start of the pocket, the jet starts with zero speed tends to accelerate to reach the selected speed then moves in constant speed, finally decelerates to reach the end of the pocket at zero

speed. The start and end distances needed for acceleration and deceleration are 7.5 mm respectively, in these regions the depth of cut and surface roughness are not constant. The selected points for measurement are illustrated in Fig. 4 (a). In order to measure the depth of cut of the milled pockets, dial indicator with a resolution of 0.001 mm was used. Fig. 4 (b) illustrates the dial indicator technique used in this work. All measuring points were averaged for 3 times of measurements.

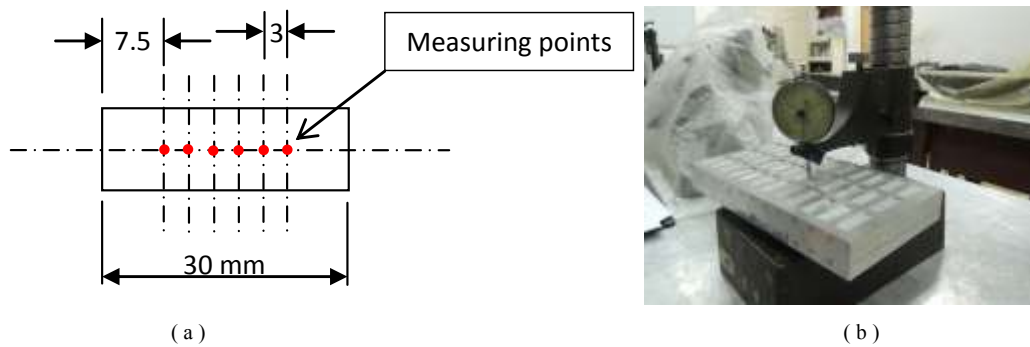


Fig. 4 (a) Schematic drawing illustrates the measuring planes in the milled pocket (b) Dial indicator during measurement of depth of cut

A “Talysurf Sutronic 3P” profilometer was used to measure the surface roughness Fig. 5(a). During the measurements, the stylus of the profilometer was located at the measuring points in the AWJ milled pocket as described before to ensure the surface uniformity. The stylus is traversed in a direction perpendicular to longitudinal tool path with cut-off length of 0.8 mm Fig. 5(b).



Fig. 5(a) Talysurf Sutronic 3P used in surface roughness measurement. (b) Measuring the pocket

The machining tests were conducted as a blind pocket milling operation. The pocket size is 10×30 mm. The pocket depth value is one of the process parameters. Fig. 6 shows the tool path configuration during the pocketing operation. The tool path type is of a rectangular zigzag with a fixed side path of 0.3 mm, which represents the jet increment in AWJ milling. Fig. 7 shows the machined pockets in the test specimens.

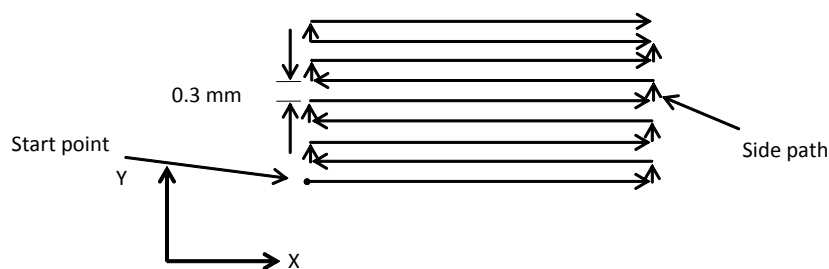


Fig. 6 Path configuration of milling pocket



Fig. 7 Machined pockets in the test specimen

V. TEST RESULTS AND DISCUSSION

The results are arranged to describe the effects of cutting variables on cutting parameters. Therefore, the test results are categorized by cutting parameters. During the tests only one variable is considered at a time while the other variables are kept fixed.

A. Depth of Cut

1) Effect of Traverse Speed on Depth of Cut

The depth of cut was measured at different traverse speeds (f), ranging from 1000 to 2000 mm/min. Tests were repeated for two abrasive flow rates of 100 and 150 g/min. Stand-off distance is 2 mm. The relation between depth of cut and traverse speed is illustrated in Fig. 8. The figure shows that depth of cut decreases with the increase of traverse speed. This is because the exposure time of the workpiece unit area to the cutting abrasive jet is reduced. The relation is of a power function form with a high regression ratio R^2 . This relation is nearly similar irrespective of the considered abrasive flow rates. Also the figure shows that the higher jet traverse speed gives lower depth of cut at the lower abrasive flow rate. This can be explained by the increases in the traverse speed that cause the number of particles impacting on the target material to decrease in the given exposure time, thus reducing the depth of cut.

It is clear that when the jet traverse speed increased twice, the depth of cut was reduced by 70 % in the used measuring range of the traverse speed. Also to get the higher regression factor R^2 , the power formula is used as shown in Fig. 8.

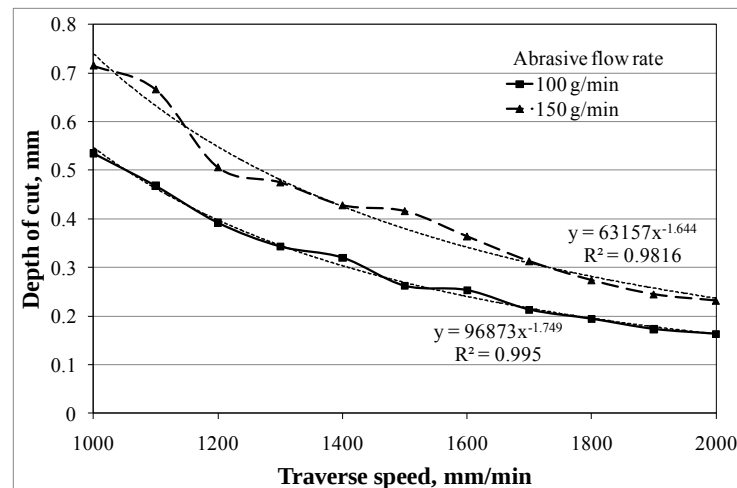


Fig. 8 Effect of traverse speed on depth of cut at different abrasive flow rates

2) Effect of Jet Pressure on Depth of Cut

The effect of jet pressure (p) on depth of cut was tested at different pressures, ranging from 20 to 100 MPa. Tests were repeated for two abrasive flow rates of 150 and 250 g/min. The relation between jet pressure and depth of cut is shown in Fig. 9. The figure shows that when the jet pressure increases, the depth of cut has slight random changes around a fixed value. This means that the jet pressure has no effect on the depth of cut in the test range.

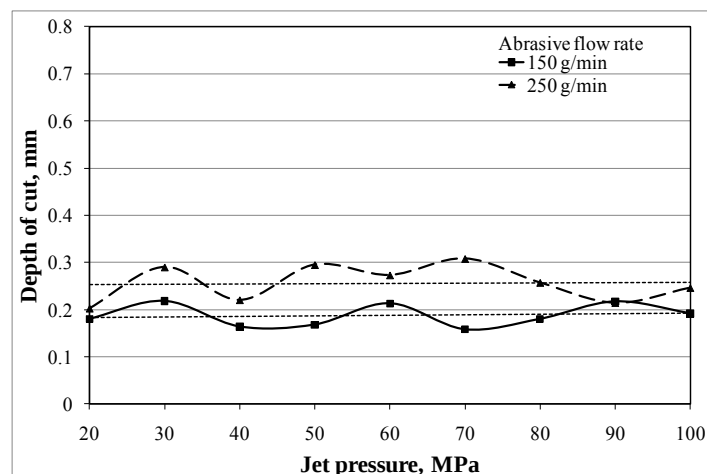


Fig. 9 Effect of jet pressure on depth of cut at different abrasive flow rates

3) Effect of Abrasive Flow Rate on Depth of Cut

The effect of abrasive flow rate (ma) on depth of cut was tested. The tests were conducted at different abrasive flow rates from 60 to 220 g/min. The tests were repeated at traverse speeds of 1600 and 2000 mm/min. Fig. 10 shows the test results and the trend curves. It is found that the increase of abrasive flow rate increases the depth of cut. The general trend of this relation is a polynomial function with high regression ratio R². When the abrasive flow rate increased 3.5 times, the depth of cut also increased about 3.8 times.

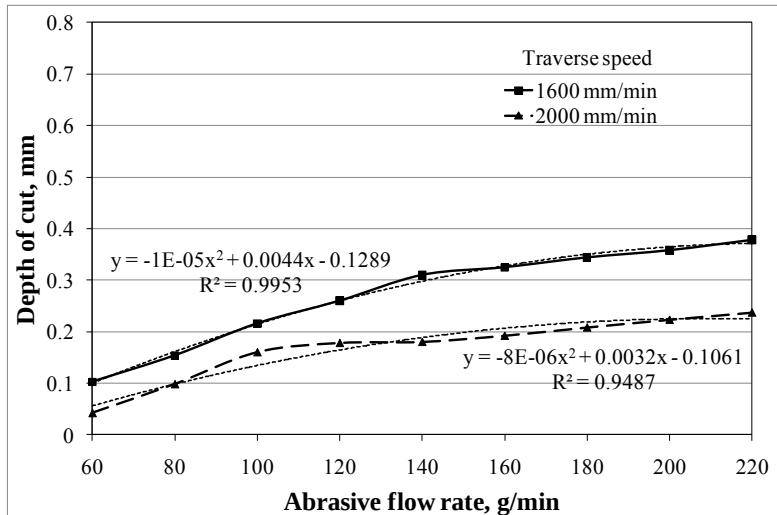


Fig. 10 Effect of abrasive flow rate on depth of cut at different traverse speed

4) Effect of Stand-off Distance on Depth of Cut

The effect of stand-off distance on depth of cut was tested. The test was conducted at four different stand-off distances and repeated at three abrasive flow rate values. The results are illustrated in Fig. 11. The depth of cut values change barely with the increase of the stand-off distance. Therefore, it is concluded that the stand-off distance has no effect on depth of cut in the range of the tests.

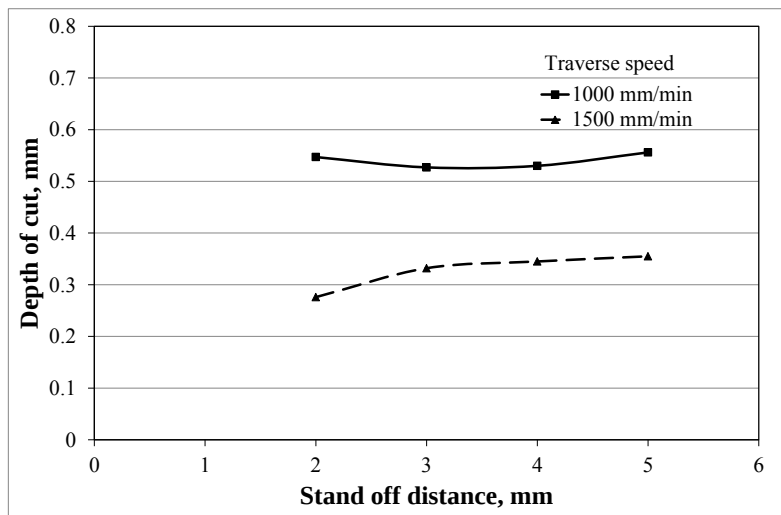


Fig. 11 Effect of stand-off distance on depth of cut at different traverse speeds

B. Material Removal Rate (MRR)

1) Effect of Traverse Speed on MRR

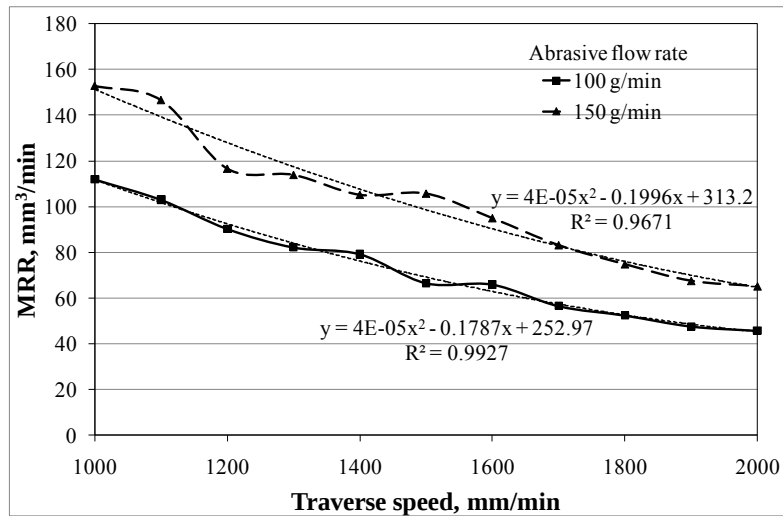


Fig. 12 Effect of traverse speed on MMR at different abrasive flow rates

2) Effect of Jet Pressure on MRR

The effect of jet pressure on MMR was tested in range of pressures from 20 to 100 MPa. In this range, it was found that when the jet pressure increased, the MRR was almost of a fixed value. The tests were repeated at two abrasive flow rates. Therefore, it is concluded that jet pressure has no effect on MMR in the test range. Fig. 13 shows the test results of the effect of jet pressure on the MMR at different abrasive flow rates.

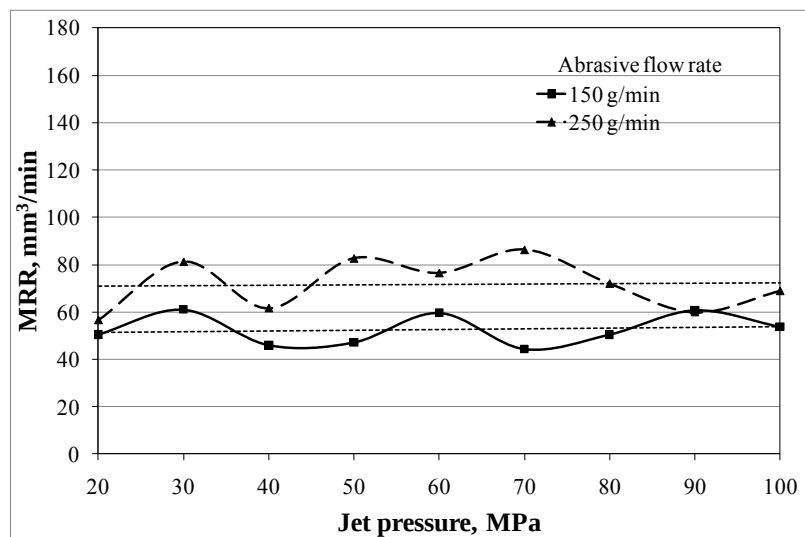


Fig. 13 Effect of jet pressure on MMR at different abrasive flow rates

3) Effect of Abrasive Flow Rate on MRR

A number of experiments were carried out to find the relation between the abrasive flow rate and MRR. During these tests, the abrasive flow rate varied from 60 to 220 g/min, and the testes were repeated for two traverse speeds 1600 mm/min and 2000 mm/min. Fig. 14 shows the test results with their trend curves. It shows that MRR increases with the increase of abrasive flow rate. The trend is of a polynomial function with high regression ratio R^2 . When the abrasive flow rate increased 3.5 times, the MRR was increased 3 times.

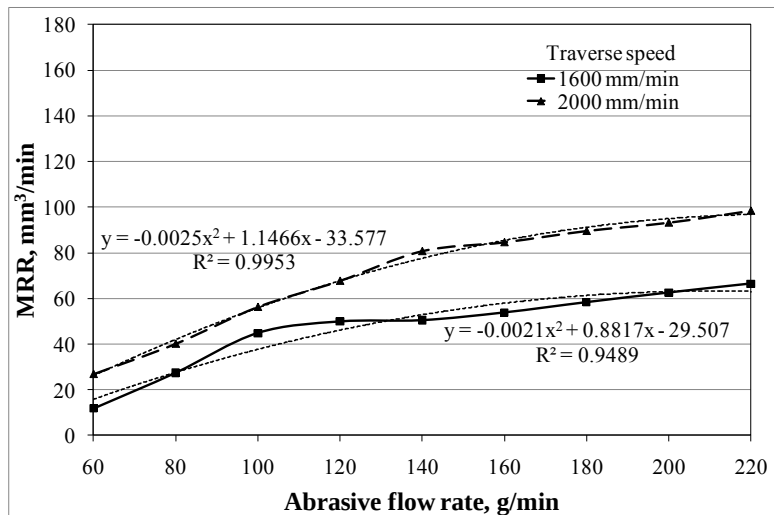


Fig. 14 Effect of abrasive flow rate on MRR at different traverse speed

4) Effect of Stand-off Distance on MRR

The MRR values were tested at four different stand-off distances. The tests were repeated at two different traverse speeds 1000 mm/min and 1500 mm/min. The test results are illustrated in Fig. 15. The tests show that the MRR values are nearly constant at different stand-off distances. Therefore, it is concluded that the stand-off distance has no effect on MRR value.

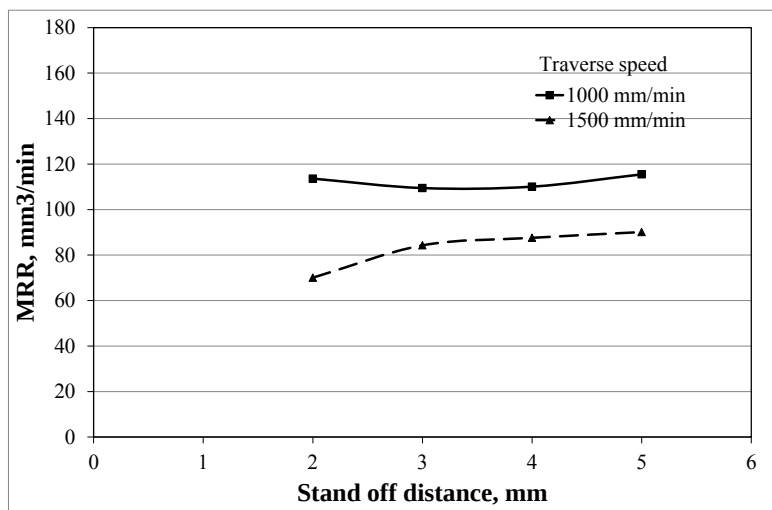


Fig. 15 Effect of stand-off distance on MRR at different traverse speeds

C. Surface Roughness

1) Effect of Traverse Speed on Surface Roughness:

The surface roughness R_a parameter values were measured at different traverse speeds in the range from 1000 to 2000 mm/min. This test was repeated for two different abrasive flow rates 100 g/min and 150 g/min. The test results show that with the increase of traverse speed, surface roughness decreases. Increasing of the traverse speed twice yields a decrease in the surface roughness twice. The relation trend is of a power function with medium regression ratio R^2 . Fig. 16 shows the test results and their trend curves. This is due to the fact that a higher traverse speed allows less overlap machining action and fewer particles to impact on the target material for a given exposure time.

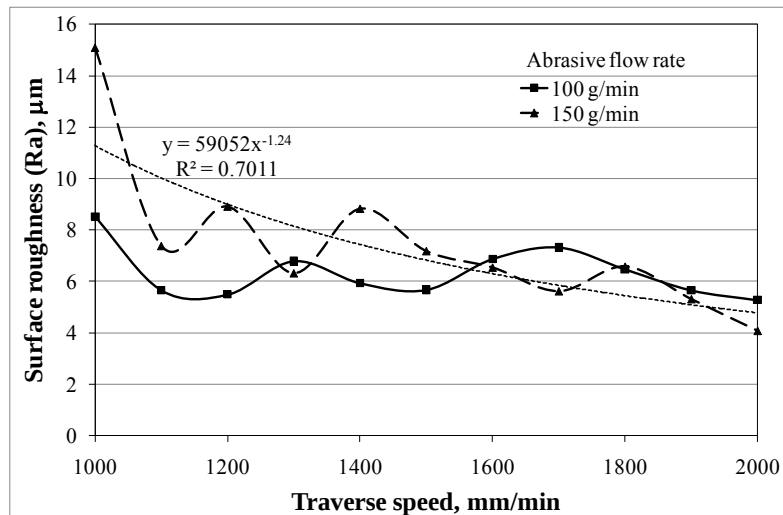


Fig. 16 Effect of traverse speed on surface roughness at different abrasive flow rates

2) Effect of the Jet Pressure on the Surface Roughness:

The effect of jet pressure on surface roughness Ra parameter was tested under ranges of pressures from 20 to 100 MPa. In this range, it was found that when the jet pressure increased, the surface roughness Ra parameter was almost of a fixed value. The tests were repeated at two abrasive flow rates 150 g/min and 250 g/min. Therefore, it is concluded that jet pressure has no effect on surface roughness Ra parameter in the test range. Fig. 17 shows the test results of the effect of jet pressure on the surface roughness Ra parameter at different abrasive flow rates.

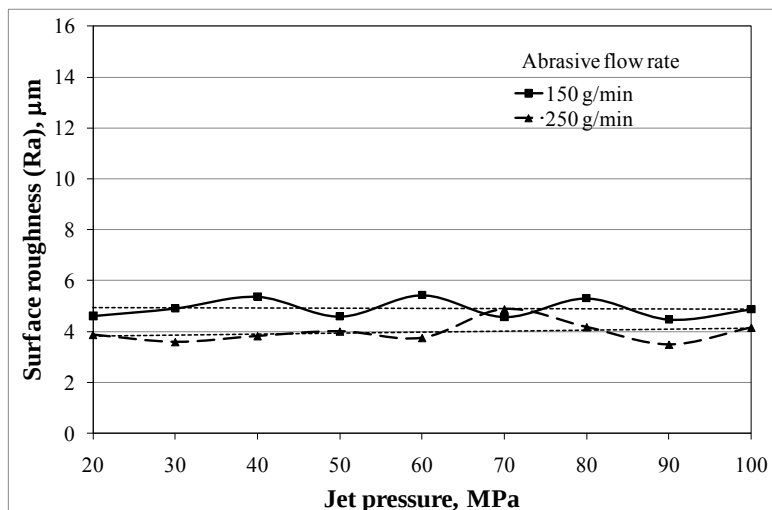


Fig. 17 Effect of jet pressure on surface roughness at different abrasive flow rates

3) Effect of Abrasive Flow Rate on Surface Roughness:

The surface roughness Ra parameter values were tested at a range of abrasive flow rates from 60 to 220 g/min. The tests were repeated at two different traverse speeds 1600 mm/min and 2000 mm/min. The test results are illustrated in Fig. 18. The tests show that the surface roughness Ra values are slightly decreasing as the abrasive flow rate increases. Increasing of abrasive flow rate 3.5 times leads to decrease the surface roughness 25% at traverse speed of 1600 mm/min and 45% at traverse speed of 2000 mm/min. An increase in the abrasive flow rate allows more particles to impinge on the surface and produce a smoother surface.

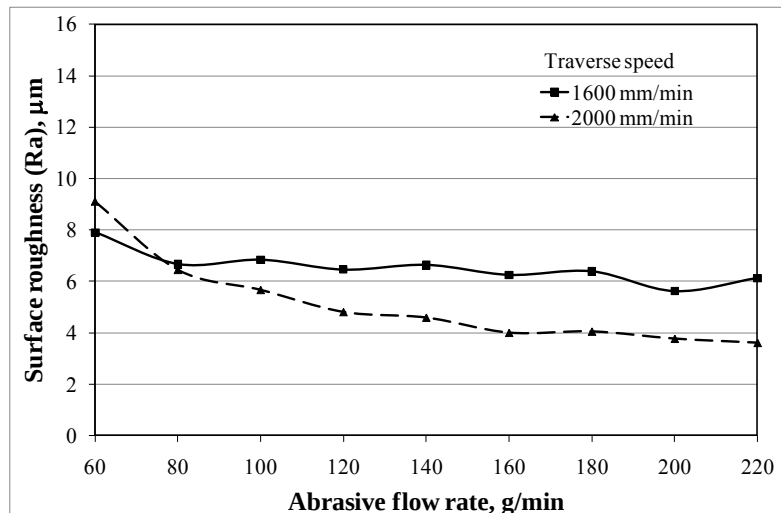


Fig. 18 Effect of abrasive flow rate on surface roughness at different traverse speeds

4) Effect of the Stand-off Distance on the Surface Roughness:

The effect of stand-off distance on the surface roughness was tested. The test was conducted at four different stand-off distances and repeated at two traverse speeds 1000 mm/min and 1500 mm/min. The results are illustrated in Fig. 19. The surface roughness parameter R_a values barely change with the increase of the stand-off distance. Therefore, it is concluded that the stand-off distance has no effect on depth of cut in the range of the tests.

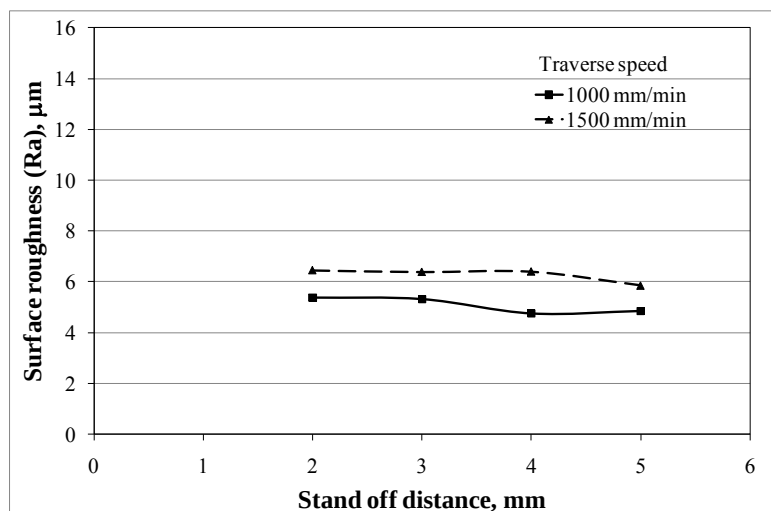


Fig. 19 Effect of stand-off distance on surface roughness at different traverse speeds

Results mentioned above are summarized in Table 6. Initially, stand-off distance investigation was carried out to determine which stand-off distances will be used in the plan of the experiments. The results show that stand-off distance has no effect on process parameters which yields to select any distance in the experimental work which was selected as 2 mm. This leads to select only three variables as inputs for the neural network which are jet speed, jet pressure and abrasive flow rate.

TABLE 6 SUMMARY OF THE EFFECTS OF AWJ PROCESS VARIABLES ON PROCESS PARAMETERS

Process variable	Process variable range	Effect of variable increase on process parameters		
		Depth of cut	MRR	Surface roughness
Traverse speed	From 1000 to 2000 mm/min	Decrease	Decrease	Decrease of R_a
Jet pressure	From 20 to 100 MPa	No effect	No effect	No effect
Abrasive flow rate	From 60 to 220 g/min	Increase	Increase	Decrease of R_a
Stand-off distance	2, 3, 4, 5 mm	No effect	No effect	No effect

VI. ARTIFICIAL NEURAL NETWORK

A. Network Topology, Training and Testing

A generalized feed forward network is used for developing artificial neural network (ANN) model. These networks are used for a generalization of the multi-layer perceptron so that connections can jump over one or more layers. The network has

three inputs of traverse speed, jet pressure and abrasive flow rate and output of surface roughness Ra, depth of cut and material removal rate. The size of hidden layers is one of the most important considerations when solving actual problems using multi-layer feed forward network. Three hidden layers were adopted for the present model. Attempts have been made to study the network performance with a different number of hidden neurons. A number of networks are constructed, each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The training has been accomplished by trainlm, which is able to obtain lower mean square errors than any of the other algorithms tested. The general network is supposed to be 3-n-3, which implies 3 neurons in the input layer, 3 neurons in the hidden layer and 3 neurons in the output layer. Fig. 20 illustrates the developed artificial neural network model which was designed in this work. Using a neural network package developed in Matlab software, different network configurations with different number of hidden neurons were trained, and their performance is checked.

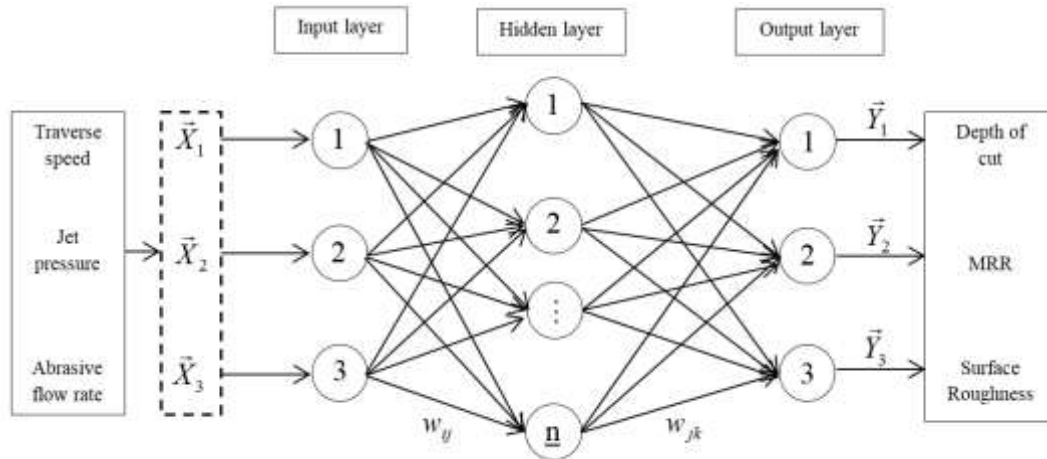


Fig. 20 Schematic illustration of artificial neural network model for the depth of cut, material removal rate and surface roughness

Data were input to ANN model as a matrix of six columns. The first three columns are the jet traverse speed, jet pressure and the abrasive flow rate respectively. While the second three columns are the resulted roughness, depth of cut and material removal rate respectively. All input data were first normalized and randomized. The 65 different process variables were set as input data. Also another 15 different values of variables are used to test the pattern performance after the ANN was structured.

Neural network pattern is adjusted to use 70% of input data to learn, 15% to validate, and final 15% to test. table 7 illustrates some of the input data set.

TABLE 7 DATA SET FOR ANN

No.	Feed (mm/min)	Pressure (bar)	Abrasive flow rate (g/min)	Roughness (μm)	Depth (mm)	MRR (mm^3/min)
1	500	250	70	6.109	0.471	45.715
2	750	250	70	6.703	0.263	37.02
3	1000	250	70	7.629	0.194	40.293
4	1250	250	70	8.16	0.139	32.253
5	1500	250	70	8.62	0.103	26.372
6	500	250	110	4.113	1.092	105.989
7	750	250	110	4.589	0.533	75.025
8	1000	250	110	6.112	0.369	76.639
9	1250	250	110	6.728	0.271	62.881
10	1500	250	110	7.103	0.207	53

B. Neural Network Results

Neural network was developed to get a pattern that can be used to predict depth of cut, surface roughness and material removal rate for the AWJ milling using Aluminum alloy. The result shows that the pattern is able to predict the three process parameters set in the work scope with high accuracy. Fig. 21 illustrates the pattern performance of the developed ANN. This figure shows that the best performance of the model is 0.007 at epoch 307. Also this figure does not indicate any major problems with the training. The validation and test curves are very similar with a mean squared error of 10-2. This result leads to ensure that the over-fitting problem has occurred.

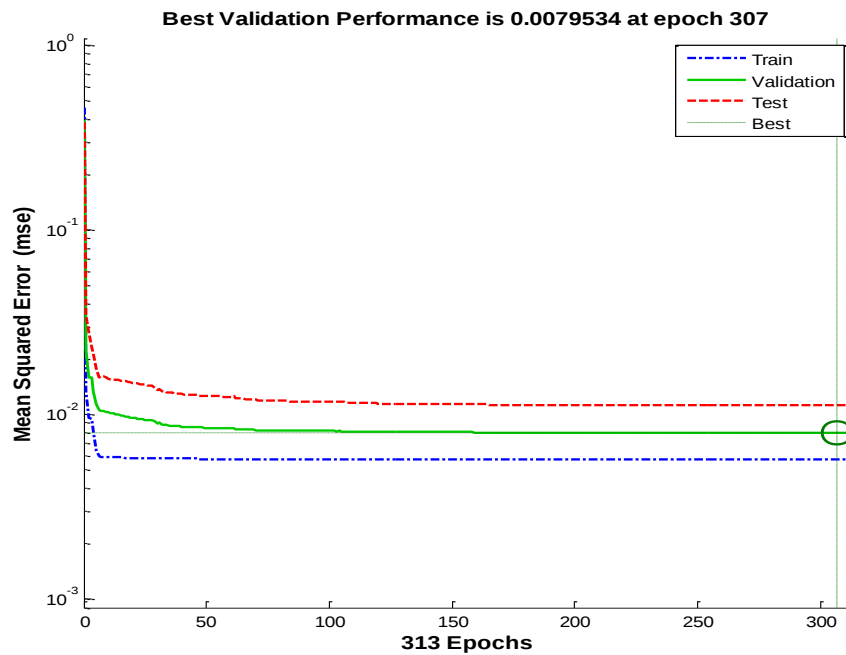


Fig. 21 Validation performance of the ANN pattern

Fig. 22 illustrates the result error in this pattern. In this figure the large center peak indicates very small errors or output that is very close to the targeted values. Also small outliers of data are indicated which leads to verify that the data are sufficient to train and learn the network.

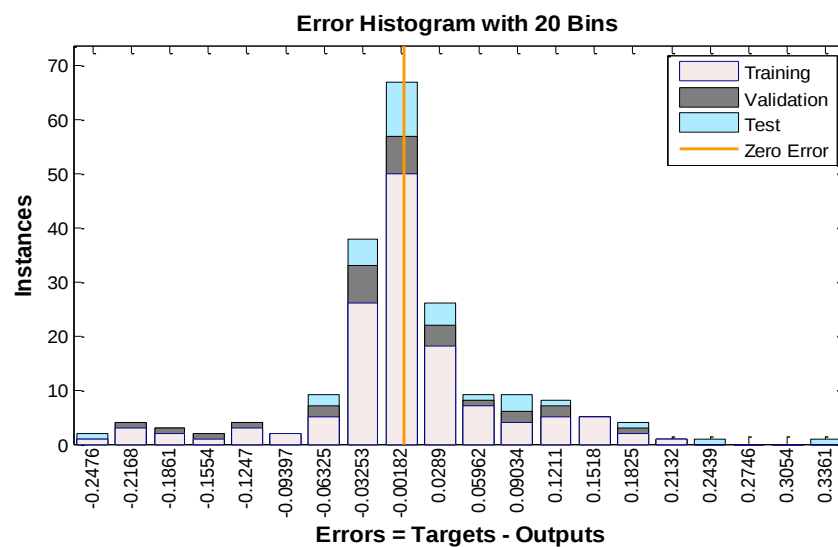


Fig. 22 Error histogram of the ANN pattern

The next step in validating the network is to create a regression plot, which shows the relationship between the outputs of the network and the targets. Fig. 23 and Fig. 24 illustrate the regression plots of training, validation, and testing data of the developed ANN model. The dashed line in each plot represents targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If $R = 1$, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets [32]. For this result, the training data indicates a good fit. The validation and test results also show R values greater than 0.9. The scatter plot is helpful in showing that certain data points have poor fits.

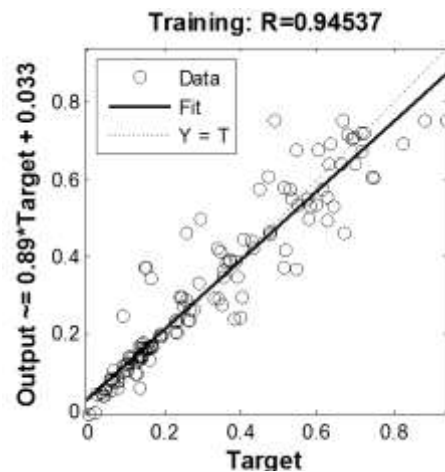


Fig. 23 Regression analysis of the ANN pattern for training regression factor

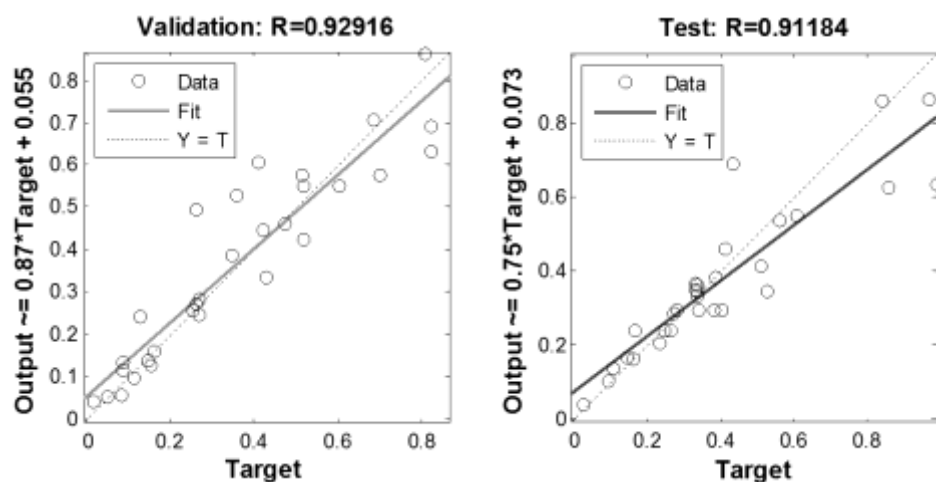


Fig. 24 Regression analysis of the ANN pattern for validation and test regression factors

In addition the ANN pattern was tested by 15 different cases of the input variables. These variables, observed parameters and predicted parameters by the ANN pattern were listed in the table 8. In addition, the table shows the percentage of difference between the observed and predicted parameters. Fig. 25 to Fig. 27 illustrates the observed and predicted parameters at every experiment.

TABLE 8 INPUT VARIABLES AND OUTPUT PARAMETERS AS MEASURED AND RESULTED FROM THE ANN PATTERN

Ex. No.	Input variables			Output parameters								
				Roughness R_a μm			Depth of cut mm			MRR mm^3/min		
	Feed mm/min	Pressure bar	Abrasive flow rate g/min	Observed	Predicted	Error %	Observed	Predicted	Error %	Observed	Predicted	Error %
1	500	1000	110	5.434	4.224	22.3	1.153	1.138	1.3	111.909	116.624	4.3
2	750	1000	110	5.752	5.125	10.9	0.562	0.589	4.8	79.107	79.291	0.3
3	1000	1000	110	6.381	6.02	5.7	0.347	0.411	18.5	72.07	68.897	4.5
4	1250	1000	110	6.633	6.799	2.6	0.268	0.345	29	62.185	65.823	5.9
5	1500	1000	110	6.644	7.402	11.5	0.213	0.208	2.5	54.536	56.382	3.4
6	500	1000	150	4.189	3.85	8.1	1.787	1.735	3	173.445	178.975	3.2
7	750	1000	150	4.987	4.604	7.7	0.798	0.974	22.2	112.326	122.496	9.1
8	1000	1000	150	5.368	5.474	2	0.547	0.592	8.3	113.608	95.116	16.3
9	1250	1000	150	6.114	6.33	3.6	0.354	0.451	27.5	82.14	85.517	4.2
10	1500	1000	150	6.454	7.067	9.6	0.276	0.327	18.6	70.666	76.609	8.5
11	500	1000	250	3.946	3.813	3.4	2.804	1.951	30.5	272.153	263.452	3.2
12	750	1000	250	4.726	4.06	14.1	1.461	1.449	0.9	205.648	216.541	5.3
13	1000	1000	250	5.3	4.52	14.8	0.864	0.93	7.8	179.447	171.408	4.5
14	1250	1000	250	5.663	5.182	8.5	0.563	0.562	0.2	130.634	139.713	7
15	1500	1000	250	5.937	5.977	0.7	0.447	0.384	14.2	114.448	123.458	7.9

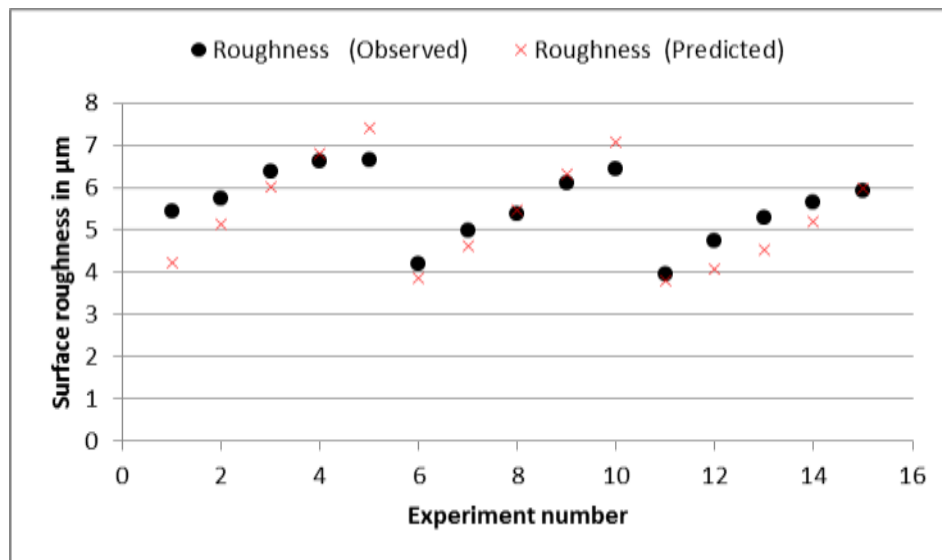


Fig. 25 Comparison of experimental and ANN output for surface roughness

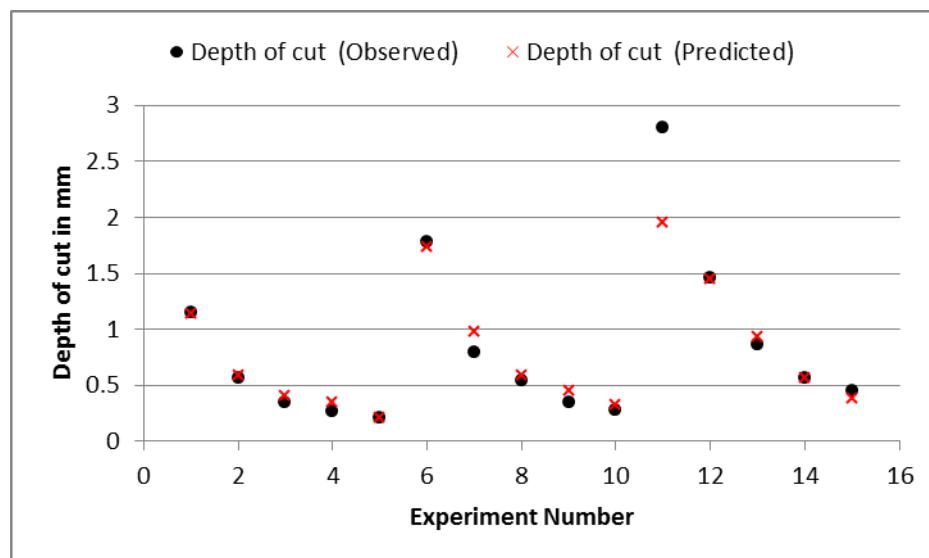


Fig. 26 Comparison of experimental and ANN output for depth of cut

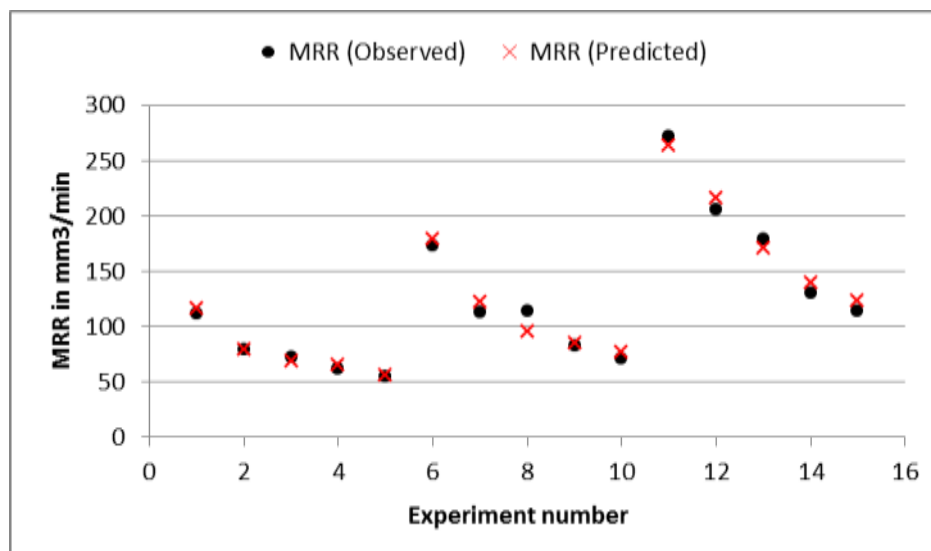


Fig. 27 Comparison of experimental and ANN output for MRR

The results show that the mean of observed surface roughness R_a is $5.57 \mu\text{m}$ with standard deviation of samples equals

0.84 μm , while the predicted of the pattern is 5.36 μm with standard deviation of samples equals 1.19 μm with mean error of 8.37 % and of standard deviation 5.62%. Also the test shows that the mean of observed depth of cut 0.83 mm with standard deviation of samples equals 0.72 mm while the predicted of the pattern gives depth of cut mean is 0.74 mm with standard deviation of samples equals 0.55 mm with mean error of 12.62 % and of standard deviation 10.62%. In addition, the test shows that the mean of observed material removal rate is 122.3 mm³/min, with standard deviation of samples is 61.3 mm³/min while the predicted of the pattern gives material removal rate mean equals 124 mm³/min with standard deviation of samples equals 60.43 mm³/min with mean error of 5.84 % and of standard deviation 3.58%.

These results yield that the pattern is able to predict the depth of cut and the material removal rate in small variations, but it is also able to predict the surface roughness in variability more than depth of cut and material removal rate.

VII. CONCLUSIONS

This paper is a step towards better understanding for AWJ pocketing operations. The objectives of the present paper are to illustrate the effect of the water jet pocketing variables on the resulting process parameters and developing an artificial neural network pattern to predict surface roughness, depth of cut and material removal rate for AWJ milling in Aluminum alloy. The considered process parameters are depth of cut, metal removal rate and surface roughness. The considered process variables are traverse speed, jet pressure, abrasive flow rate and stand-off distance. The results show that the increase of traverse speed decreases depth of cut, MRR and surface roughness. This leads to longer machining time operation but more surface quality. Moreover, depth of cut and material removal rate (MRR) depend on abrasive flow rate. Increasing abrasive flow rate increases both of depth of cut and MRR, where more abrasive particles yield more impinging and erosion of the material. This reduces the machining operation time. Moreover, increasing the abrasive flow rate has no significant effect on the surface roughness and consequently the surface quality, where the unit surface area will be completely impinged by a certain number of the abrasive particles, so more of the particles have no chance to impinge this surface area. However, increasing abrasive flow rate means more material cost.

The above summary shows that some process variables have no effect on the considered process parameters. This yields to discard these variables in any process control operation, which targets this parameter in the considered process variable range. In addition, this result has an important effect on selecting or designing AWJ machines for pocketing operations. As the jet pressure has no effect on the considered AWJ pocketing process parameters, low pressure water system including pump and valves can be used instead of the intensifier system which is more complicated and expensive. Moreover, since the stand-off distance has no noticeable effect on process parameters, it is better to select a longer value to prevent the nozzle front from being damaged by the reflection of the water stream and abrasive.

The results of the artificial neural network pattern show that the pattern can predict both depth of cut and material removal rate in more accuracy than predicting the surface roughness. Therefore the ANN pattern can be used to predetermine the process parameters for certain variables. Also the regression factor for learning, validation, testing and overall is above 90% which yields that the network works in high regression.

The summary of all results yield that the AWJ is a good machining process that can be used for milling, referring to the advantages of the AWJ. Also the ANN is a good tool that can be used for predicting the process parameters from certain variables which leads to a beneficial control of surface roughness, depth of cut and material removal rate in AWJ milling.

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