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REAL-TIME MONITORING OF AWJ NOZZLE WEAR USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

An abrasive waterjet nozzle wear monitoring and compensating mechanism using the frequency domain acoustic signals generated by the jet exiting the nozzle, as input, is proposed. An artificial neural network which forms the critical part of this system is developed using the back-propagation algorithm. The trained network is capable of determining the nozzle diameter corresponding to any unknown sound signal, instantaneously. The proposed system can be used for continuous monitoring of nozzle wear in real-time.

1 INTRODUCTION

As a commercial system, even though it was first introduced in 1983 for cutting glass, abrasive waterjet (AWJ) cutting currently finds application for machining a wide range of metals and non-metals like cast iron, stainless steel, mild steel, aluminum, copper, titanium and its alloys, high carbon steels and tool steels, concrete, ceramic and different types of composite materials. In this process, the material removal takes place primarily through the erosive action of abrasive particles which are accelerated by a thin stream of high velocity waterjet directed through an AWJ nozzle. Thus the role of the nozzle in AWJ machining can be considered to be analogous to that of the cutting tool in traditional machining; the difference being that there is no tool-workpiece contact here. However, like a conventional cutting tool, AWJ nozzle is also subjected to constant wear as machining progresses. As a result, the inside diameter (ID) of the nozzle increases gradually which can be used as an indicator to quantify nozzle wear.

The increased wear of the AWJ nozzle makes the clearance between the abrasive waterjet mixture and the nozzle larger. This causes incomplete mixing of the abrasive particles with the high velocity waterjet which results in reduction in cutting ability and poor product quality. The width of cut increases as nozzle wear progresses, which affects the precision of machining causing undesirable changes in work geometry. The surface quality deteriorates considerably with nozzle wear. Beyond the optimum nozzle diameter, the depth of penetration of AWJ also reduces with nozzle wear. Even though proper selection of nozzle material, type of abrasive and machining conditions can reduce the rate of AWJ nozzle wear, it cannot be completely eliminated. Replacing the nozzle too often before it is worn completely will increase the downtime of the machine and prove to be very uneconomical. Hence, from process automation point of view, it is very essential to devise suitable sensing techniques to monitor the progress of AWJ nozzle wear during machining in order to ensure uniform product quality at desirable level and replacement of the worn nozzle at the right time.

There have been several investigations on AWJ nozzle wear monitoring through direct and indirect sensing techniques. The direct sensing techniques (Kovacevic, 1988) are primarily based on measuring the nozzle ID at its tip or measuring the material loss of the nozzle by radiometric techniques. Even though few of these direct sensing techniques are close to on-line, they need extensive instrumentation and set-up, prior to the experiment. Indirect sensing techniques are based on measuring some parameter such as jet diameter (Kovacevic, 1991), workpiece normal force (Kovacevic, 1989), sound energy, vibration, etc. which varies with change in nozzle ID. However, parameters like workpiece normal force can be used only in the case of AWJ turning or milling operation, as cutting through the workpiece can destroy the dynamometer (force sensor). Some preliminary studies were conducted by Merchant and Chalupnik (1987) on the AWJ sound power measurement. Recently, Kovacevic, et al. (1993) conducted extensive investigation for detection of nozzle wear using acoustic signature analysis. The results showed that there is a co-relation between the AWJ nozzle wear and auto regressive moving average (ARMA) model coefficients of the acoustic signals. Here, the time domain signals were used for analysis. Even though acoustic signals are generated on-line, considerable time need to be spent on ARMA modeling before the AWJ nozzle ID can be identified. Thus, nozzle wear monitoring cannot be executed in real-time. In the current investigation, a technique is developed for on-line monitoring of AWJ nozzle wear using artificial neural network.

Artificial neural networks (ANN) have been investigated for several years in the area of image processing and pattern recognition with an aim to achieve human-like performance. Due to the high computational rates provided by massive parallelism of simple processing elements ANN has proven to be very effective in process monitoring applications also. It can provide greater degree of robustness or fault tolerance compensating for minor variability in data and is capable of making weaker assumptions regarding the shape of distribution of the data due to the non-parametric nature of the network. The ability of ANN to adaptation and continuous training provides an opportunity to gradually build intelligence to the network. These advantages have motivated several investigations in tool condition

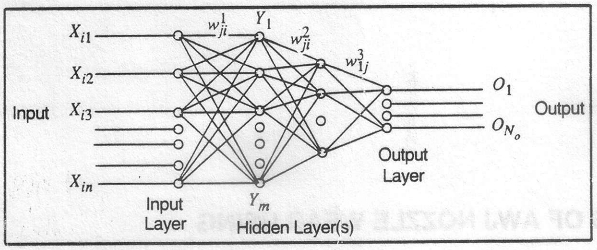

FIG. 1. NEURAL NETWORK ARCHITECTURE FOR BACK-PROPAGATION ALGORITHM

monitoring in machining operations (Rangwala et al., 1987, Jammu et al., 1993, Tansel et al., 1993). As a controlling technique, neural controlling is finding applications in various manufacturing processes (Karsai, et al., 1992, Wu, 1992, Garrett, et al., 1993, Sbarbaro, et al., 1993, Skitt, et al., 1993). ANN is used as a signal classifier in non-destructive evaluation (Damarla, et al., 1992) and GMA welding (Matteson, et al., 1992). However, until today there has been a limited application of ANN in non-traditional manufacturing arena.

Current investigation is based on the principle of AWJ nozzle wear monitoring through artificial neural network. Frequency domain acoustic signals are used as input to the neural network. This ANN is developed using the back-propagation algorithm. Initially, the neural network is trained by inputting several sets of acoustic signals and corresponding nozzle diameters as expected output. After training, the neural network is capable of determining instantaneously the nozzle diameter corresponding to any unknown acoustic signal. A real-time AWJ nozzle wear monitoring and compensating mechanism, based on artificial neural network is proposed.

2 ARCHITECTURE OF ARTIFICIAL NEURAL NETWORK

Artificial neural networks have a large set of processing nodes (or neurons) and the data is supplied parallel to the nodes in the input layer. The output nodes provide the network classification and the intermediate nodes are used for data analysis. The pre-selected signal set, known as the training set, consisting of data belonging to distinct categories, is utilized for training the ANN.

Based on the arrangement of the neurons, their interconnection and training algorithms used, ANN can be classified into different types. Among these, the most widely used network is the back propagation (BP) network (Lippmann, 1987) where the nodes are arranged in different layers. Each processing node in the intermediate layers (also known as hidden layers) makes a decision according to the training paradigms used when presented with a set of data from the input layer. The decision taken by each node in the first hidden layer is passed on to the next layer and so on, until the output layer is reached. The unknown signals are classified into different pre-defined categories by the output nodes. These types of neural networks which utilize training sets are also called supervised network.

Sufficient knowledge-base of the signals (training data) is necessary for training any supervised network. The training data consists of signals that are representative of the different classification desired. Inaccurate or incomplete knowledge-base leads to faulty classification. Hence, it is necessary to ensure that the training data consists of signals which are true representative of the various classes. Thus, selection of training data is very critical in supervised learning of the neural network.

A brief description of the back propagation algorithm adopted in this paper is given here for the sake of completeness. A detailed analysis of BP network can be found in Rumelhart, et al. (1986). Fig. 1 shows the general architecture of the neural network for back propagation algorithm. It consists of multilayer nets namely input layer, hidden layer(s) and output layer with each layer consisting of several nodes. The output of a node in BP network is usually modeled by a sigmoidal function which is given for the j th neuron in the k th layer as

$$O_j^k = \frac{1}{1 + e^{-\left(\Sigma_i w_{ji}^k O_i^{k-1} - \Theta_j^k\right)}} \tag{1}$$

where, Θ_j^k is the threshold value, and O_i^{k-1}, the output of the ith neuron in the $(k\text{-}1)th$ layer, is connected to the jth neuron through a link whose weight is w_{ji}^k.

During the learning process, the network is supplied with a set of input patterns $\{X_1, X_2, ..., X_{N_p}\}$, known as training patterns and the corresponding outputs of the network, $\{O_1, O_2, ..., O_{N_p}\}$, are compared with the desired (known) output patterns $\{d_1, d_2, ..., d_{N_p}\}$, where, N_p denotes the total number of input patterns. Each input pattern, X_i is given by $X_i = \{x_{i1}, x_{i2}, ..., x_{in}\}$, where, n denotes the number of sampling points and also determines the number of input nodes. If the number of output nodes is given by N_o, then the output vector O_i corresponding to input vector X_i is given by $O_i = \{O_{i1}, O_{i2}, ..., O_{iN_o}\}$. The network is considered to be trained if the summed square of the error, E is within the desired error limit, ε, where, E is given by,

$$E = \frac{1}{2}\sum_{p=1}^{N_p}\sum_{j=1}^{N_o}(d_{pj} - O_{pj})^2 \le \varepsilon, \quad \text{and,} \quad 0 \le \varepsilon \le 0.1 \tag{2}$$

If E is not within a specified limit, the link weights are adjusted in order to minimize the error, E. Adjustments are carried out according to a gradient search technique employing a convergence parameter, η, which is empirically determined (Lippmann, 1987). Weight adjustment at the $(t+1)th$ iteration step is given by,

$$w_{ji}^k(t+1) = w_{ji}^k(t) - \eta\frac{\partial E}{\partial w_{ji}^k} \tag{3}$$

where, $0 < \eta \le 1$. Then from equations (1) and (3),

$$w_{ji}^k(t+1) = w_{ji}^k(t) + \eta\delta_j O_i^{k-1} \tag{4}$$

where, δ_j is the error term for node j. If node j is an output node, then

$$\delta_j = O_j(1 - O_j)(d_j - O_j) \tag{5}$$

where, d_j and O_j are the desired and actual output values of the output node j, for a given input pattern. If node j is an internal node, then

$$\delta_j = O_j^k(1 - O_j^k)\sum_i^{N_{k+1}} \delta_i w_{ji}^{k+1} \tag{6}$$

where, N_{k+1} is the number of nodes in the $(k+1)th$ level.

A modified form of the above BP algorithm is adopted here, in which the training of the network is conducted by applying one pattern at a time, and the error is computed to adjust the weights before the next pattern of the training set is applied (Lippmann, 1987). Training is said to be complete if the error of all the patterns lie within the pre-defined value. It is found, in general, that signals, even though they belong to the same category, differ from each other slightly. Hence, selection of training data should ensure that a fair combination of all sets of data corresponding to that category is considered for training. Once the network is trained, the remaining signals in the test data set are applied sequentially for classification in the respective categories.

3 EXPERIMENTAL SETUP AND PROCEDURE

The experimental setup consists of an AWJ cutting system, microphone, amplifier, A/D convertor, PC/AT with suitable software and workpiece. The AWJ cutting system used for conducting the experiment consists of a high pressure intensifier pump, AWJ cutting head, abrasive metering and delivery system, abrasive hopper with garnet as abrasive, catcher tank and X-Y-Z

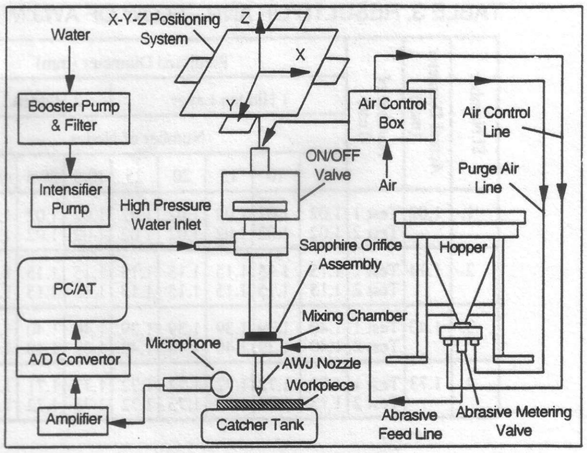

FIG. 2. SCHEMATIC OF EXPERIMENTAL SETUP

TABLE 1. PROCESS PARAMETERS

Abrasive Waterjet Cutting	
Abrasive material	- Garnet
Abrasive mesh size	- 80 (0.180 mm)
Abrasive particle shape	- angular(random)
Orifice material	- Sapphire
Orifice diameter	- 0.33 mm
Nozzle length	- 76.2 mm
Method of feed	- suction
Condition of abrasive	- dry
Angle of Jet	- 90 degrees
Waterjet Pressure	- 276 MPa
Stand-off Distance	- 6.00 mm
Traverse Speed	- 1 mm/s
Abrasive Flow Rate	- 6 g/s
Workpiece Details	
Material	- Aluminum Al 2024
Material thickness	- 25.4 mm
Length of cut	- 50.8 mm
Experimental Variables	
Range of Nozzle diameter	- 1 to 1.7 mm
Experimental Conditions	- Waterjet Flow, AWJ Flow & AWJ Cutting

positioning system controlled by a CNC controller. A schematic of the experimental setup is shown in Fig. 2.

The experiment is conducted by varying the nozzle diameter keeping all other parameters constant. The constant process parameters are given in Table 1. A 6.35 mm condenser microphone is utilized to measure the generated sound signal. The microphone is kept at about 10 cm from the tip of the nozzle and is directed towards the nozzle exit. During the cutting process, the microphone also travels along with the cutting head so that it is always at the same distance from the cutting head. In order to investigate the feasibility of nozzle wear monitoring using the sound generated by the flow of waterjet or abrasive waterjet mixture or during cutting, separately, the experiments were conducted at three different conditions. The first set of measurements were taken when pure waterjet was forced through the nozzle (without cutting). The second set of measurements were taken when the mixture of abrasive waterjet was forced through the nozzle (without cutting). For the third set of experiments, linear cuts were made on an aluminum plate and the generated acoustic signal is measured using the microphone as the cut progresses. The frequency of the measured sound signals range from 0 to 40 KHz at an interval of 100 Hz. Thus the sampling time for a single sweep of the frequency range was 10 ms. The amplified signal is analyzed using an FFT spectrum analyzer. Twelve (12) data sets were used for averaging in the frequency domain. For each experiment, ten (10) sets of averaged frequency domain data corresponding to each nozzle diameter were acquired for analysis. The measurements were repeated until the AWJ nozzle was worn up to 70%.

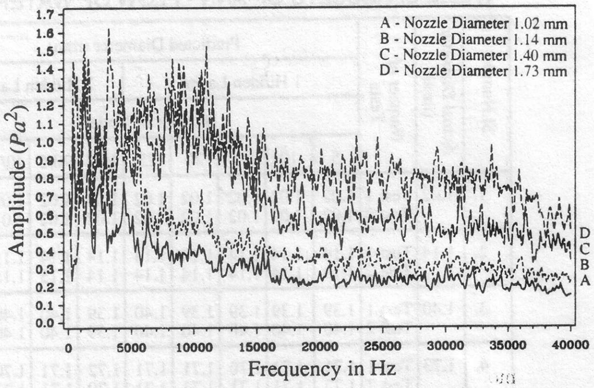

FIG. 3. TYPICAL FREQUENCY DOMAIN SIGNAL - FLOW OF WATERJET

4 RESULTS AND DISCUSSION

The frequency domain acoustic signals obtained for three different experimental conditions namely with the flow of high velocity waterjet, with the flow of abrasive waterjet mixture and during AWJ cutting are analyzed separately. The effectiveness of nozzle wear monitoring system developed using the acoustic signals generated under each experimental condition is evaluated for relative comparison. The accuracy of the neural network in predicting the nozzle diameter when the test data is applied to the input layer, is quantified in terms of the relative error. It should be noted that the results obtained using the signals generated by the flow of waterjet or abrasive waterjet mixture are general in nature i.e. independent of the workpiece material and method of machining; whereas that of the acoustic signals generated during cutting depends upon the type of cutting (i.e. whether it is through cutting or milling) and workpiece material. However, once the experimental conditions and details of workpiece material are known, a few set of training data are sufficient for developing the network.

An artificial neural network is developed for each set of experimental condition using the back propagation algorithm as described in section 2. Among the ten sets of averaged frequency domain data per nozzle ID, eight sets were used for training the neural network and two sets were used as test data. As there are 400 data points per input acoustic signal (at an interval of 100 Hz), the input layer of the ANN consists of 400 nodes. All the data points corresponding to 0 to 40 KHz frequency range were used for designing the network. The output layer of the neural network consists of a single node which gives the nozzle diameter corresponding to the respective input signal. After the network is trained using the training data, once the error measure is within the specified limit (1% of the corresponding nozzle ID), the effectiveness of the network is evaluated using the test data. The number of nodes in the hidden layer and the number of hidden layers are varied and the results are evaluated to determine the optimum design of the ANN. The results corresponding to the different experimental conditions are given in Table 2, 3 and 4. The number of nodes adopted for each hidden layer is also given. For example, a figure of "10/3" indicates that there are 10 nodes for the first hidden layer and 3 nodes for the second.

4.1 Flow of Waterjet

Typical frequency domain signals obtained when high pressure waterjet is forced through nozzle for four different diameters are given in Fig. 3. For single phase flow it is known (Lush, 1971) that sound power is proportional to the square of the inside diameter of the nozzle. Hence it is natural to expect that sound pressure level will increase with the nozzle diameter which is indicated by Fig. 3. However, this trend is more obvious for frequencies between 20 KHz and 40 KHz. Artificial neural networks of different designs are obtained by varying the number of hidden layers and their nodes. The results obtained for the various trials are given in Table 2. From this table it could be concluded that the relative error of the predicted nozzle diameter is less than 2% for all the designs of the neural network. Hence, the frequency domain acoustic signals generated by the flow of waterjet in the nozzle is very effective for nozzle wear monitoring.

TABLE 2. RESULTS OF ANN - FLOW OF WATERJET

Sl.Number	Actual Diameter (mm)	Number of Tests	Predicted Diameter (mm)								
			1 Hidden Layer					2 Hidden Layers			
			Number of Nodes								
			5	10	15	20	25	10/3	20/5	40/10	50/10
1.	1.02	Test 1	1.02	1.02	1.02	1.02	1.02	1.03	1.02	1.02	1.02
		Test 2	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.01	1.01
2.	1.14	Test 1	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.15	1.15
		Test 2	1.14	1.14	1.14	1.14	1.14	1.14	1.15	1.15	1.15
3.	1.40	Test 1	1.39	1.39	1.39	1.39	1.40	1.39	1.40	1.40	1.40
		Test 2	1.40	1.40	1.40	1.40	1.40	1.39	1.40	1.40	1.40
4.	1.73	Test 1	1.71	1.71	1.70	1.71	1.71	1.72	1.71	1.70	1.71
		Test 2	1.72	1.71	1.71	1.71	1.71	1.70	1.71	1.71	1.72

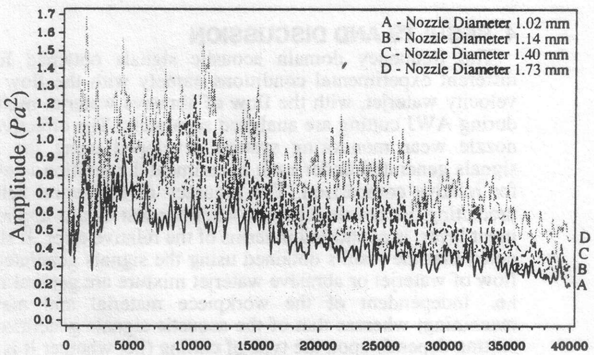

FIG. 4. TYPICAL FREQUENCY DOMAIN SIGNAL - FLOW OF AWJ MIXTURE

4.2 Flow of Abrasive Waterjet Mixture

A three phase flow exists in the abrasive waterjet (water, abrasive and air) which creates a turbulence while passing through the nozzle. This flow generates sound while exiting from the AWJ nozzle. The pattern of this generated acoustic signal can be expected to vary with nozzle diameter. From Fig. 4, it can be noted that sound pressure level gradually increases with increase in nozzle diameter which is more prominent at frequencies between 20 KHz and 40 KHz. These signals (0 to 40 KHz) were used to design the neural network. The results of the various designs of the network are given in Table 3. From this table, it can be noted that the neural network is capable of predicting the nozzle diameter with an accuracy of 97% and above indicating that acoustic signal generated by the flow of abrasive waterjet mixture can also be used for nozzle wear monitoring.

4.3 Abrasive Waterjet Cutting

The acoustic signal generated during AWJ cutting is more realistic for on-line monitoring, as this signal can be measured without affecting the production process. The frequency domain acoustic signals obtained for cutting the aluminum plate is given in Fig. 5. This, being a cutting operation, the microphone measures the total sound generated from the workpiece and the nozzle. As a result, the amplitude of the sound pressure level is higher in this case compared to the previous two cases (without cutting) which is reflected in Fig. 5. Here also the sound pressure level increases with increase in nozzle ID. Interestingly, this trend is noticeable at all frequencies. The peak amplitude for all the cases is observed at around 10 KHz. The results obtained from the various trained neural networks are given in Table 4. From this table it could be concluded that, in this case, the relative error in predicting the nozzle diameter is less than 4% for all the neural network designs. Thus, frequency domain acoustic signal generated during AWJ cutting process is a very reliable parameter for on-line monitoring of nozzle wear.

TABLE 3. RESULTS OF ANN - FLOW OF AWJ MIXTURE

Sl.Number	Actual Diameter (mm)	Number of Tests	Predicted Diameter (mm)								
			1 Hidden Layer					2 Hidden Layers			
			Number of Nodes								
			5	10	15	20	25	10/3	20/5	40/10	50/10
1.	1.02	Test 1	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02
		Test 2	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.01	1.02
2.	1.14	Test 1	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15
		Test 2	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15
3.	1.40	Test 1	1.40	1.39	1.39	1.39	1.39	1.40	1.40	1.41	1.40
		Test 2	1.40	1.39	1.40	1.40	1.40	1.39	1.40	1.40	1.40
4.	1.73	Test 1	1.72	1.72	1.72	1.72	1.72	1.73	1.71	1.71	1.71
		Test 2	1.73	1.72	1.72	1.73	1.72	1.73	1.72	1.72	1.71

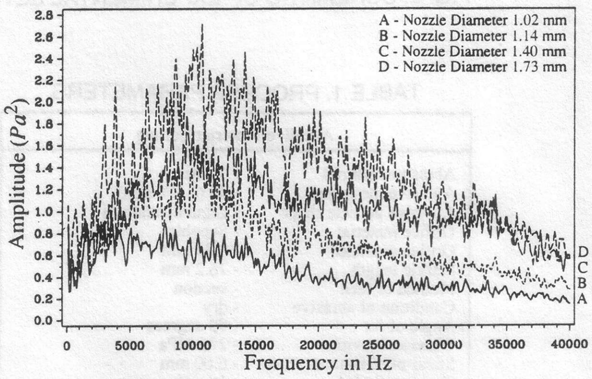

FIG. 5. TYPICAL FREQUENCY DOMAIN SIGNAL - AWJ CUTTING

TABLE 4. RESULTS OF ANN - AWJ CUTTING

Sl.Number	Actual Diameter (mm)	Number of Tests	Predicted Diameter (mm)								
			1 Hidden Layer					2 Hidden Layers			
			Number of Nodes								
			5	10	15	20	25	10/3	20/5	40/10	50/10
1,	1.02	Test 1	1.03	1.03	1.01	1.00	1.01	1.01	1.01	1.01	1.00
		Test 2	1.02	1.01	1.03	1.02	1.02	1.03	1.04	1.03	1.04
2.	1.14	Test 1	1.11	1.16	1.15	1.15	1.15	1.15	1.13	1.12	1.12
		Test 2	1.13	1.17	1.15	1.15	1.16	1.15	1.17	1.13	1.17
3.	1.40	Test 1	1.36	1.37	1.38	1.40	1.41	1.38	1.36	1.38	1.38
		Test 2	1.40	1.40	1.40	1.40	1.40	1.40	1.39	1.38	1.44
4.	1.73	Test 1	1.68	1.68	1.69	1.70	1.68	1.69	1.74	1.66	1.72
		Test 2	1.71	1.70	1.70	1.70	1.70	1.70	1.73	1.67	1.70

4.4 AWJ Nozzle Wear Monitoring and Compensating Mechanism

Using the neural network developed for the case of cutting by AWJ, an AWJ nozzle wear monitoring and compensating system is proposed. A closed-loop controls the AWJ nozzle position by compensating for the wear of nozzle ID. The closed-loop control system (shown in Fig. 6) consists of the AWJ cutting system, microphone, amplifier, A/D convertor, a computer which includes a signal processor and the trained neural network, and a piezo-electric actuator which is connected to the AWJ cutting head. The sound generated by the flow of waterjet or AWJ mixture or during cutting can be used for monitoring. This acoustic signal is measured using the microphone. It is amplified and sent to the computer through the A/D convertor. The acoustic signal is analyzed using the signal processor and the averaged frequency domain signal is inputted to the trained ANN. The neural network

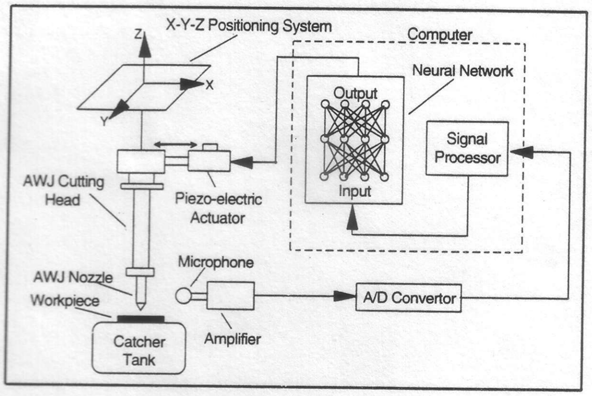

FIG. 6. AWJ NOZZLE WEAR MONITORING AND COMPENSATING MECHANISM USING ARTIFICIAL NEURAL NETWORK

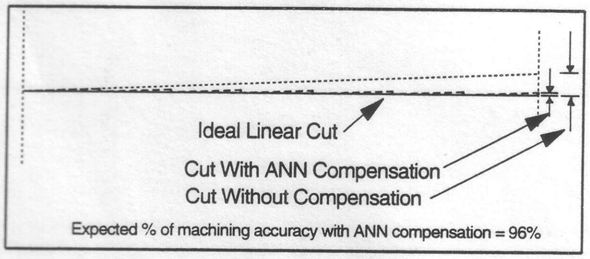

FIG. 7. LINEAR CUTS PRODUCED WITH AND WITHOUT ANN COMPENSATION

instantaneously determines the corresponding nozzle ID and this information is used to control the position of the AWJ cutting head using the piezo-electric actuator. Thus, the closed-loop is completed.

Nowadays, several standard software packages are available which are capable of doing the FFT of time domain signals very quickly. Once the neural network is trained, it can be used to determine the nozzle diameter while the machining operation is taking place (on-line monitoring). The piezo-electric actuator is also capable of responding very fast. The improvement in the machining accuracy depends upon the accuracy of the trained neural network in predicting the nozzle diameter which is 96%. The paths expected to be traced by AWJ nozzle with and without nozzle wear compensation are given in Fig. 7. It can be noted that AWJ cutting with nozzle wear compensation using the ANN is very close to the desired path, whereas without compensation it produces a tapered cut. Thus, the proposed AWJ nozzle wear monitoring and compensating mechanism is very effective for continuous monitoring in real-time. Even though discrete nozzle diameters are chosen for training the neural network and evaluating the effectiveness of this mechanism, the proposed system is capable of measuring gradual nozzle wear by interpolating the intermediate diameters. Ability to respond faster and provide repeatable performance are the other advantages offered by this system.

5 CONCLUSIONS

Frequency domain acoustic signals generated during the flow of waterjet or abrasive waterjet mixture through the nozzle or during AWJ cutting are very reliable parameters for AWJ nozzle wear monitoring. The flow of waterjet and flow of AWJ mixture generates acoustic signals which vary sharply with the change in nozzle diameter. This variation is more prominent in the ultrasonic frequency range of 20 KHz to 40 KHz. Whereas for AWJ cutting this trend is noticeable for all frequencies.

The developed artificial neural network based on back-propagation algorithm which uses the above acoustic signals as inputs, is capable of predicting the AWJ nozzle diameter with an accuracy of 96% and above for all the designs of the network considered here. Thus, the ANN is a very useful tool for this application as it can predict the nozzle diameter from the unknown acoustic signal very quickly and accurately.

An AWJ nozzle wear monitoring and compensating mechanism based on artificial neural network is proposed. This mechanism, as a closed-loop control of the nozzle position, is very promising for accurate machining by AWJ. The proposed system can ensure continuous monitoring of nozzle wear in real-time. It is also capable of responding fast and providing repeatable performance.

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