Identification of abrasive waterjet nozzle wear based on parametric spectrum estimation of acoustic signal

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The abrasive waterjet nozzle is one of the most critical parts that influences the technical and economical performance of an abrasive waterjet system. In order to control the uniformity of cutting results in milling and cutting, it is necessary to devise a sensing system that can sense on-line the nozzle wear. This paper presents an on-line technique for monitoring the nozzle wear which is based on monitoring the acoustic signals generated by the abrasive waterjet. The autoregressive moving average (ARMA) spectra are used to estimate the nozzle wear. It has been shown that the ARMA spectra can reveal more features of the nozzle wear than the conventional fast Fourier transform (FFT) method. It was found that the amplitude of the spectra and the frequency of the spectra peaks of ARMA models have a high sensitivity to a small variation of the nozzle exit geometry. A method based on on-line acoustic signals is proposed for identification of the nozzle inside diameter.

1 INTRODUCTION

As a new manufacturing process, abrasive waterjet has been very effective in machining difficult-to-machine materials. This cutting technique is one of the most recently introduced machining methods in which an abrasive such as garnet, aluminium oxide or silicon carbide is accelerated by a thin stream of high-velocity waterjet and directed through an abrasive waterjet nozzle towards the target material. Thus the role of the nozzle in abrasive waterjet 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, the nozzle is also subjected to constant wear as machining progresses. As a result, the inside diameter of the nozzle increases gradually, which can be used as an indicator to quantify nozzle wear. The increased wear of the nozzle makes the clearance between the waterjet and nozzle larger. The result of this is incomplete mixing of the abrasive particles with the waterjet, which causes a reduction in cutting ability and tends to produce unacceptable manufacturing quality. Especially the width of cut and consequently the precision of machining is directly related to the nozzle outlet diameter and its shape. In the case of drilling and/or milling by abrasive waterjet the cutting performance (depth of penetration) declines as the nozzle diameter increases, after the optimum nozzle diameter has been passed (1, 2).

Abrasive waterjet is formed in a nozzle system as shown in Fig. 1. Pressurized water is expelled through a sapphire orifice to form a coherent, high-velocity waterjet. The waterjet and a stream of solid abrasive are introduced into a nozzle constructed of hard material. The nozzle is subjected to abrasive and erosive modes of wear (3). The initially coherent waterjet breaks into droplets that accelerate the solid particles. When the jet stream first enters the nozzle, the abrasive trajectories are different from those of the fluid motion and the abrasive hits the entrance section of the nozzle at random angles. This form of wear is called the erosion impact wear mode. A second mechanism corresponds to hydrodynamic drag forces imposed by the water phase on the solid particles. As a result of momentum transfer between the water and abrasives, a focused, high-velocity stream of abrasive passing through the nozzle will wear the nozzle itself. Once the jet stream advances through the nozzle, erosive particles travel parallel to it. During this movement the particles cause abrasive or shallow impact erosion of the wall. This form of wear is called the sliding erosion wear mode.

Automated equipment must have the ability to detect nozzle wear early before final results exceed acceptable limits. However, currently there is no reliable wear-sensing system available. A number of approaches have been investigated. Generally speaking, the methods that could be used to detect nozzle wear can be categorized as either direct or indirect. Direct methods make an assessment of nozzle wear by either measuring the inside diameter of the nozzle at its tip or measuring the material loss of the nozzle by radiometric techniques. Two direct sensing methods to measure the nozzle inside diameter have been proposed (4, 5). Unfortunately, these approaches cannot be successfully used

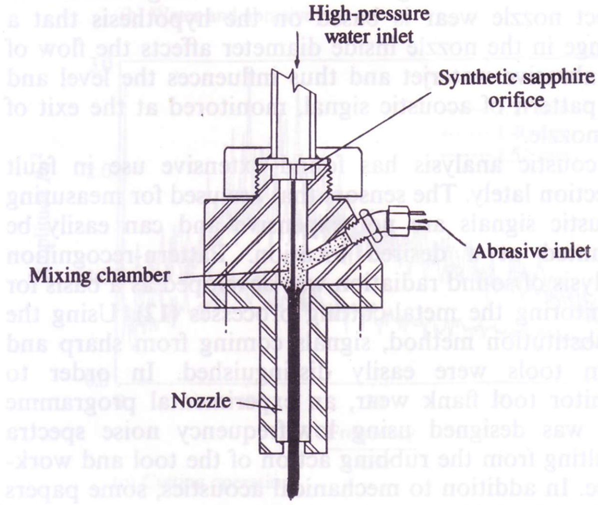

Fig. 1 Schematic presentation of abrasive waterjet cutting head

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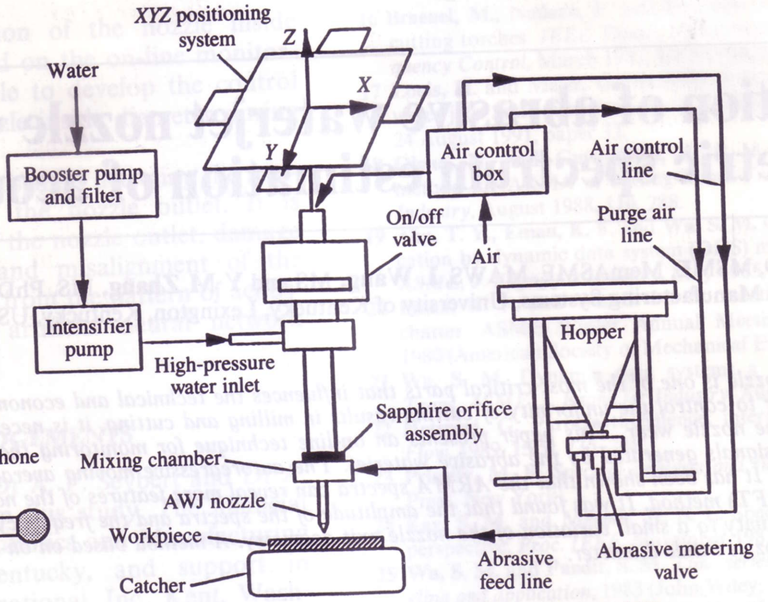


Fig. 2 A general concept of abrasive waterjet cutting system

for monitoring a continuous increase in the nozzle inside diameter. The indirect methods are promising approaches for on-line sensing of nozzle wear and compensation for the increase in the nozzle inside diameter. Indirect methods are based on the measurement of parameters that are correlated to the nozzle wear such as the change in the stream diameter at the nozzle exit or the change of the workpiece normal force generated by the impacting jet.

An abrasive waterjet diameter monitoring system based on a machine vision system (6) was proposed. The abrasive waterjet diameter can be directly monitored and measured by a solid state charge coupled device (CCD) matrix or linear array camera, and the actual diameter of the nozzle can be linked to the abrasive waterjet diameter. Recently, a number of experiments (7–11) have proven that the workpiece normal force generated by an abrasive waterjet can be used as an indicator of nozzle wear. With an increase in the nozzle inside diameter, the workpiece normal force will increase, keeping all other cutting variables constant; thus wear can be monitored from an early stage.

The idea of using an acoustic sensing method to detect nozzle wear is based on the hypothesis that a change in the nozzle inside diameter affects the flow of the abrasive waterjet and thus influences the level and the pattern of acoustic signal, monitored at the exit of the nozzle.

Acoustic analysis has found extensive use in fault detection lately. The sensors that are used for measuring acoustic signals are not expensive and can easily be mounted at a desired location. Pattern-recognition analysis of sound radiation was developed as a basis for monitoring the metal-cutting processes (12). Using the resubstitution method, signals coming from sharp and worn tools were easily distinguished. In order to monitor tool flank wear, an experimental programme (13) was designed using low-frequency noise spectra resulting from the rubbing action of the tool and workpiece. In addition to mechanical acoustics, some papers deal with fluid acoustics. In fact, measurement and theory of the high-speed jet noise have been investigated in aerodynamics for many years. The predictions of the theory are in good agreement with experimental work (14). In order to control the process of laser grooving, acoustic sensing was used (15). The acoustic signal is emitted from the impinging gas jet on the erosion front. Correlations between resonant frequency and hole, kerf or groove geometry were found. An automatic remote detection of nozzle wear in plasma cutting torches has been investigated (16). It was found that the amplitude and spectral structure of the resonant tone are extremely sensitive to any changes in the orifice geometry. The acoustic technique has also been proposed to analyse the state of the abrasive waterjet (AWJ) cutting in inaccessible environments like the deep sea (17).

This study is to investigate the correlation between the nozzle inside diameter and the generated level of sound. In order to analyse the relationship between the nozzle inside diameter and the generated acoustic signal, the experiments are performed when only water is forced through the nozzle and when a mixture of water and abrasive is used. In the case of abrasive waterjet, the level of sound is monitored during workpiece cutting and without cutting. The nozzle wear is expected to cause a change in the level of acoustic signal. Also, the different flow media (pure water and mixture of water and abrasive particles) passing through the different nozzle inside diameters should yield different sound characteristics.

Two of the most critical parameters related to nozzle wear are the condition of the waterjet nozzle (sapphire orifice) that creates the jet stream and the alignment of that stream concentric to the nozzle. A microscopic chip in a sapphire orifice or misalignment with the nozzle can reduce nozzle life to minutes instead of hours. It is evident that a non-uniform wear pattern of nozzle outlet, damage to the waterjet nozzle and misalignment of the nozzle will affect the pattern of acoustic signal. An investigation based on using an artificial neural network to develop a real-time nozzle wear monitoring and compensating system is undertaken by the authors. Frequency domain acoustic signals are used as input to the neural network. The ability of the artificial neural network to adapt and continuously train provides an opportunity to gradually build intelligence into the network. It is expected that the shape of the nozzle outlet, the condition of waterjet nozzle and misalignment of the waterjet could be detected from the pattern of acoustic signal by using the artificial neural network approach.

It has been reported that autoregressive moving average (ARMA) models can adequately describe the stationary stochastic process characteristic and have been widely utilized to analyse the stationary time series (**18–20**). In order to bypass the temporal influence on the system, a data-based numerical representation is suggested for the stationary stochastic process. If the ARMA model indicates appropriately, it can capture the correlation among different variables and may be used for prediction. A more detailed description about the ARMA modelling methodology can be found in reference (**21**). In this study, ARMA spectra of acoustic signals are used to estimate the nozzle wear. It is expected that the amplitude of the spectra and the peaks of the spectra will be influenced by the change in the nozzle inside diameter.

2 EXPERIMENTAL SET-UP

The experiments for the present study were conducted at the Center for Robotics and Manufacturing Systems, University of Kentucky. The experimental set-up consists of three major components:

1. A commercial abrasive waterjet cutting system is used to perform the experiments (Fig. 2). In this system, an intensifier pump is connected to the abrasive waterjet cutting head which consists of a sapphire orifice, an abrasive waterjet nozzle and a mixing chamber. The position of the cutting head is controlled by a computer numerical controlled (CNC) positioning table.
2. A 386 Compar/PC data acquisition system is used to collect and process the data. It consists of two personal computer (PC) compatible expansion boards and a custom software package that is designed to allow a PC to act as a dual-channel FFT signal analyser which controls data analysis and displays graphics.
3. A 6.35 mm condenser microphone (B&K 4135) is aimed at the nozzle's outlet to measure the acoustic signal. During the cutting operation the microphone travels with the cutting head in order to maintain a fixed distance from the nozzle outlet. Also the atmospheric pressure is measured at regular intervals during testing and frequent checks are made on the microphone calibration using B&K pistonphone (type 4220). The block diagram of this experimental set-up is shown in Fig. 2.

In order to minimize the measuring error caused by the reflection noise, an acoustic foam is utilized to cover the stand and supporting structure. The signal is preamplified before it is sent to the PC. The amplified signal is fed into a single-channel spectrum analyser, which analyses the signal using fast Fourier transform and displays the signal spectrum. A frequency range from 0 to 40 kHz is scanned. Sampling time for a single sweep of the frequency range is 10 ms.

3 EXPERIMENTAL ANALYSIS FOR ACOUSTIC SIGNAL

The following is the analysis of findings for three different conditions, that is when only water is forced through the nozzle, when a mixture of water and abrasive are used during workpiece cutting and without cutting. The distance (d) between the nozzle's outlet and the microphone is 20.5 cm and the abrasive type is garnet (grains of 200 μm average diameter). It is evident that the different conditions will generate a different pattern of acoustic spectra. The aim of this analysis is to investigate under which conditions the acoustic signal will give the best information about the nozzle wear. An analysis is done on the spectral components of the acoustic signal as features for classification.

Case 1. For the purpose of simplicity, a single-phase waterjet flow is initially considered. Figure 3a shows the acoustic spectra for a waterjet without abrasive. It is found that the patterns of spectra are the same, and

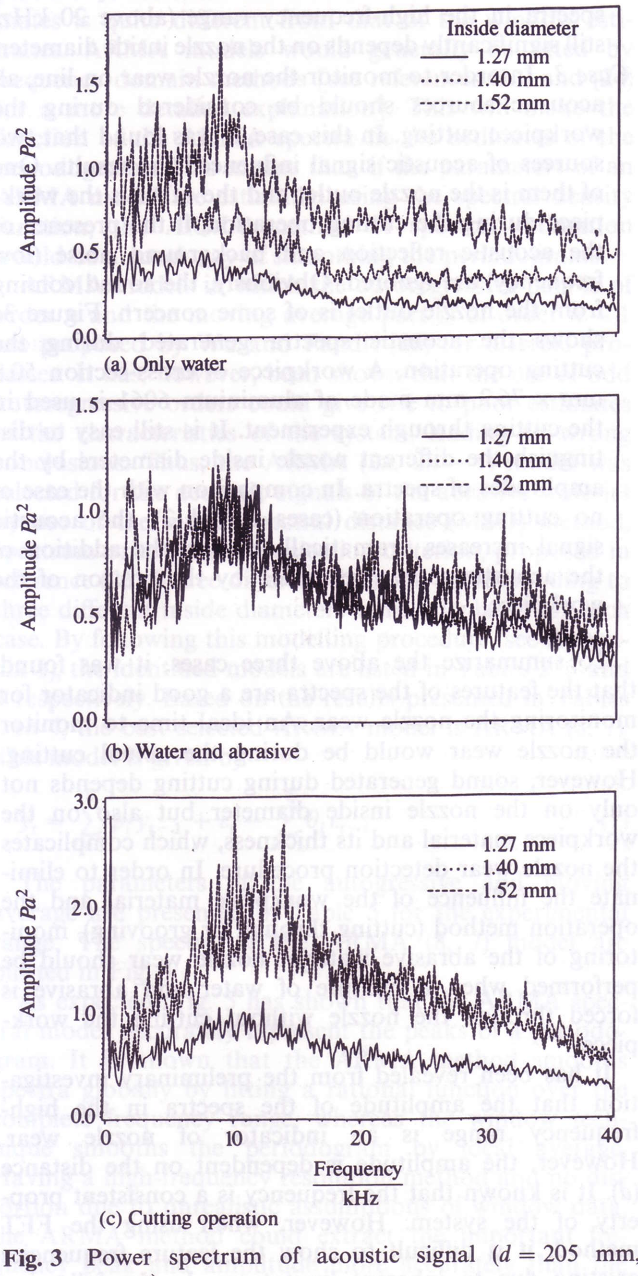


Fig. 3 Power spectrum of acoustic signal (d = 205 mm, garnet)

the amplitude of the spectra evidently increases with increasing nozzle inside diameter. The results show that with an increase of the nozzle inside diameter, the acoustic signal has the same frequency pattern for a certain length of nozzle, while the acoustic power shows an evident increase.

Case 2. It is known that three phases (water, air and abrasive) exist in the abrasive waterjet flow. The interaction between turbulent fluid flow and the particles will raise the turbulence due to wake shedding. On the other hand, the effects of particles on continuous phase turbulent properties are limited to wave numbers (**22**). The kinetic energy of the turbulence is somewhat higher in the three-phase jet, as compared to the single-phase one. Figure 3b shows the acoustic spectra for the case of the waterjet with abrasive without cutting the workpiece. All other parameters are the same as in the previous experiment. It can be seen that the fluid flow mixed with abrasive becomes more chaotic than in the case of water due to the presence of the abrasive. However, the amplitude of spectra in the high-frequency range (above 20 kHz) still significantly depends on the nozzle inside diameter.

Case 3. In order to monitor the nozzle wear on-line, all acoustic sources should be considered during the workpiece cutting. In this case, it was found that two sources of acoustic signal influenced the results. One of them is the nozzle outlet and the other is the workpiece during the cutting operation, if the presence of the acoustic reflection and background noise (low frequency) are ignored. Obviously, the sound coming from the nozzle outlet is of some concern. Figure 3c shows the acoustic spectra generated during the cutting operation. A workpiece of cross-section 50.8 mm × 76.2 mm made of aluminium 6061 is used in the cutting through experiment. It is still easy to distinguish the different nozzle inside diameters by the amplitudes of spectra. In comparison with the case of no cutting operation (cases 1 and 2), the acoustic signal increases dramatically due to the addition of the acoustic source generated by the erosion of the workpiece.

To summarize the above three cases, it was found that the features of the spectra are a good indicator for monitoring the nozzle wear. An ideal time to monitor the nozzle wear would be during the actual cutting. However, sound generated during cutting depends not only on the nozzle inside diameter but also on the workpiece material and its thickness, which complicates the nozzle wear detection procedure. In order to eliminate the influence of the workpiece material and the operation method (cutting through or grooving), monitoring of the abrasive waterjet nozzle wear should be performed when a mixture of water and abrasive is forced through the nozzle without cutting the workpiece.

It has been revealed from the preliminary investigation that the amplitude of the spectra in the high-frequency range is an indicator of nozzle wear. However, the amplitude is dependent on the distance (d). It is known that the frequency is a consistent property of the system. However, when using the FFT method, it is difficult to show the feature frequencies existing due to inherent limitations. In the following study, the authors focus on the analysis of the acoustic signal produced by a mixture of water and abrasive without cutting and attempt to distinctively sort out the important frequencies of the acoustic signal using the ARMA spectra approach. The set of data has been recorded when the distance d is 30.5 cm and the abrasive type is aluminium oxide. The diameter of the nozzle outlet is measured when each set of data is recorded. The other parameters are kept constant throughout this study for the purpose of simplicity, as shown in Table 1.

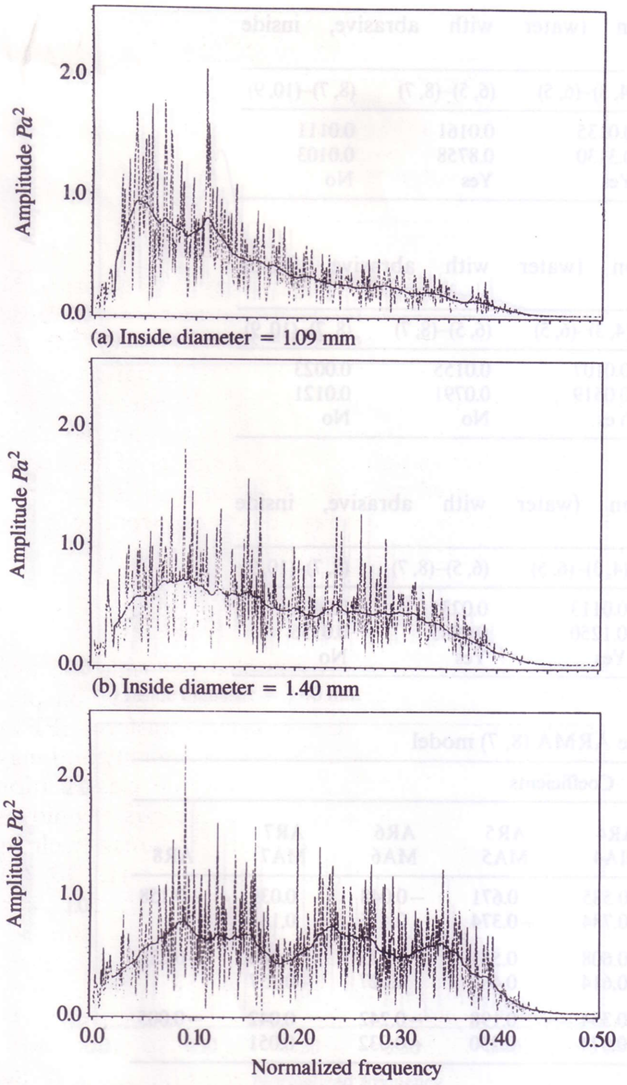
Table 1 Constant process parameters for AWJ cutting

Waterjet pressure (P)	275 MPa
Waterjet orifice size (d_n)	0.254 mm
Stand-off distance (SOD)	6.00 mm
Traverse speed (u)	0.85 mm/s
Jet angle (α_c)	90°
Abrasive flowrate (M_a)	6.05 g/s

4 RESULTS AND DISCUSSION

The spectrum of discretely sampled deterministic and stochastic processes is usually obtained based on procedures employing the fast Fourier transform (FFT), since it conveniently reveals hidden periodicity and may be efficiently used for discrimination and classification of time series data. In fact, spectral analysis techniques have found important applications in areas such as machinery diagnosis and failure prediction (**12, 13, 16**). Unfortunately, there are several inherent performance limitations. Traditionally non-parametric spectrum estimates have two major problems. Firstly, the conventional FFT approach makes an unrealistic assumption about window data. If the data are unwindowed, the estimate is probably too badly biased to be used. Problems such as limited frequency resolution, spectral distortion due to leakage and the appearance of negative power spectra are still presented in most cases. In particular, when the series is short, the spectrum is mixed or the range of the spectrum is large. Secondly, the FFT analysis of time series is based on the assumption that the signal is made up of sine and cosine waves with different frequencies. Thus, it is difficult to extract useful characteristics. In order to alleviate the limitations of the FFT approach, parametric techniques have been introduced. The parametric spectral estimation is one that can make a more realistic assumption. The function can eliminate the need for a window. As a result, the spectral estimation of parametric approaches are much better than the FFT spectral estimation. Among these approaches, a strong interest has been generated in ARMA spectral estimation because of its simplicity, better performance and parsimony.

Figure 4 shows a spectrum analysis performed on the data by means of the fast Fourier transform technique. These periodograms indicate that the residuals are not just white noise but can be decomposed into some typical frequencies which are superimposed on each other. Unfortunately, because of the large variance resulting from leakage and biasing in the estimation of the parameters, the obtained spectra do not clearly show the frequencies existing in the signal. Thus, it is difficult to identify the feature of frequency. The spectral density function estimates, which have been considered



(c) Inside diameter = 1.65 mm

Fig. 4 Comparative power spectrum signal for water and abrasive with smoothing filter and without smoothing filter (d = 305 mm, aluminium oxide)

so far, are all based on the technique of smoothing the periodograms via a suitable spectral window.

4.1 Smoothing the Fourier spectrum

Conventional periodograms lead to spectral estimates that are characterized by many 'hills and valleys'. Typically, in order to obtain the smoothed spectrum estimate, the discrete Fourier transform should be converted to the second window. The Fourier transform of the data is performed in a single segment. Then, a non-recursive second-order filter applied to the spectral estimate is computed by forming a weighted sum of the discrete unsmoothed spectral values. In this study, an average smoothing filter technique is used (**19**) (see Appendix 2).

Figure 4 shows typical spectral estimates which have used the average smoothing filter technique ($\alpha = 0.9$, $p = 20$). There are two disadvantages in using this approach. Firstly, the procedure of the moving average filter smooths the data of the 'high frequency' portion in the sense of average. This means it smooths the variance of the spectra. However, this kind of 'high frequency' is decided by the data and selection of the order p and coefficient α. If the selection is inappropriate, either the filter will smooth the peak that is of interest or the variance of the spectra is still large enough for the dominant peak in the spectra not to be found. Secondly, the moving average filter smooths the spectral estimation in the local average sense. In general, it is unable to identify the feature unless there is reason to believe that the underlying spectrum is smooth. Autocorrelation lag window or spectral window smoothing will substantially reduce the fluctuations but not eliminate them (**20**). Thus, this approach is not promising for detecting the dominant frequencies as the features of acoustic signal generated by the mixture of water and abrasive flowing through an abrasive waterjet nozzle.

4.2 Spectral estimation of the ARMA model

One promising approach to spectral estimation is using the spectral estimation of ARMA models. ARMA spectral estimation is a comprehensive approach to the parametric method. The character of the ARMA estimates is quite different from that of the window estimates. ARMA models would generally be fitted by frequency domain methods [see references (**23**) and (**24**) for a more detailed explanation]. This will make the function of the ARMA spectra fit the ordinates of the periodograms. This means that, if the parameters of an ARMA model are estimated using the spectral density function, the ARMA method of spectral estimation would be a good way of smoothing the periodograms.

ARMA models in which the autoregressive part is of order n and the moving average part is of order $n-1$ are proposed by Wu and Pandit (**25**) for discrete processes. It has, however, been shown that the use of odd autoregressive orders could give rise to poor estimates of the characteristics of the system, leading to wrong conclusions. Thus, the ARMA ($2n$, $2n-1$) model was selected for the acoustic signals of the abrasive waterjet by use of the model spectral distance (MSD) method, spectrum-oriented order selection criterion, proposed in reference (**26**). Three different data sets corresponding to three different inside diameters were calculated for each case. By following this modelling procedure (see Appendix 1), the identified models are listed in Tables 2, 3 and 4 respectively. Based on the results presented in Tables 2 to 4, the best selected ARMA model is ARMA (8, 7). This model is given by

$$y_t = \sum_{i=1}^{8} \phi_i y_{t-1} + \varepsilon_t - \sum_{i=1}^{7} \theta_i \varepsilon_{t-i} \qquad (1)$$

The parameters of the autogressive and moving average are presented in Table 5 for the experimental range. The spectra of the ARMA (8, 7) model are plotted in Fig. 5.

As expected, Fig. 5 has shown that the ARMA spectral modes accurately represent the peaks of a periodogram. It is known that the ARMA method smooths spectra globally by fitting a rational function over the complete frequency range, whereas the window technique smooths the periodogram by local average. Having a high-frequency resolution method and no distortion due to unrealistic assumptions of window data, the ARMA method could extract the important frequency peak and amplitude more accurately than the FFT method. By use of the ARMA method, two domi-

Table 2 ARMA model order selection (water with abrasive, inside diameter = 1.09 mm)

Transfer trial	(1, 0)–(2, 1)	(2, 1)–(4, 3)	(4, 3)–(6, 5)	(6, 5)–(8, 7)	(8, 7)–(10, 9)
$D_H^2 - D_L^2$	0.0019	0.0079	0.0135	0.0161	0.0111
Distance	11.195	1.9924	0.3130	0.8758	0.0103
Significance	Yes	Yes	Yes	Yes	No

Table 3 ARMA model order selection (water with abrasive, inside diameter = 1.40 mm)

Transfer trial	(1, 0)–(2, 1)	(2, 1)–(4, 3)	(4, 3)–(6, 5)	(6, 5)–(8, 7)	(8, 7)–(10, 9)
$D_H^2 - D_L^2$	0.00390	0.0065	0.0107	0.0155	0.0023
Distance	17.6930	1.29924	0.0519	0.0791	0.0121
Significance	Yes	Yes	Yes	No	No

Table 4 ARMA model order selection (water with abrasive, inside diameter = 1.65 mm)

Transfer trial	(1, 0)–(2, 1)	(2, 1)–(4, 3)	(4, 3)–(6, 5)	(6, 5)–(8, 7)	(8, 7)–(10, 9)
$D_H^2 - D_L^2$	0.0029	0.0069	0.0113	0.0235	0.0461
Distance	11.195	1.9924	0.1250	0.0985	0.0156
Significance	Yes	Yes	Yes	Yes	No

Table 5 Parameters of the ARMA (8, 7) model

Inside diameter mm	Coefficients AR1 MA1	AR2 MA2	AR3 MA3	AR4 MA4	AR5 MA5	AR6 MA6	AR7 MA7	AR8
1.09	1.174	0.132	−0.433	−0.585	0.671	−0.048	0.039	−0.158
	−0.912	1.287	1.058	−0.784	−0.374	0.415	0.184	
1.40	1.283	−1.111	0.413	−0.608	0.533	−0.475	0.186	−0.221
	−0.256	0.780	−0.740	−0.614	0.489	0.027	−0.157	
1.65	0.485	−0.537	0.380	−0.354	0.198	−0.242	0.042	−0.005
	−0.608	0.451	−0.065	0.074	0.250	0.032	0.051	

nant frequencies can be revealed to be present in the acoustic signal. Three sets of data corresponding to the inside diameters of 1.09, 1.40 and 1.65 mm respectively have shown that with an increase in the nozzle wear, the two dominant frequencies tend to shift to the higher frequency, while the amplitudes of the peak frequencies decrease. Also, amplitudes of the spectra in the high-frequency range (above 20 kHz) increase. This shows that with an increase of nozzle inside diameter, the sound energy of the high frequency increases. Thus, in addition to the amplitude of the spectra (**27**), the dominant frequencies are also a good indicator for monitoring the nozzle wear. Since the frequency is a consistent property of the system, the dominant frequencies are chosen as the indicators to identify the state of the nozzle inside diameter. Figure 6 shows two dominant frequencies and the corresponding amplitude with respect to the different nozzle inside diameters. It can be seen that there are distinctive features corresponding to the different nozzle inside diameters. In order to get a reliable approach to monitor the nozzle wear, a high sensitive feature is appreciated. For this case, the higher dominant frequency is chosen as an indicator when monitoring nozzle inside diameters in the range of 1.4–1.65 mm, while for inside diameters between 1.1 and 1.4 mm, its amplitude is used as the indicator. Thus, a suitable technique for monitoring the nozzle wear under given cutting conditions can be obtained. Based on the fact that the abrasive waterjet operation lasts only for a short period and the nozzle wear rate is low, there is no need for frequent adjustment of the waterjet pressure or cutting head position to keep the desired final results. The acoustic signals can be monitored in a given period of time when the cutting head is moved away from the workpiece to the corner of the worktable where the monitoring system is set. A proposed control scheme based on a minicomputer for the model-fitting, feature-extraction and decision-making process is shown in Fig. 7 (**28**).

5 CONCLUSIONS

Through the experimental study it was shown that the acoustic signal could be successfully applied in monitoring the nozzle wear. From the results of the tests and conducted signal processing, it is proven that the ARMA spectra can be used for on-line monitoring of nozzle wear. The following conclusions can be drawn:

1. An identification of ARMA spectra is used to monitor the nozzle wear. It has been shown that the ARMA spectra can reveal more features of the acoustic signal than the conventional FFT method. Also, a smoothing technique is used. The results

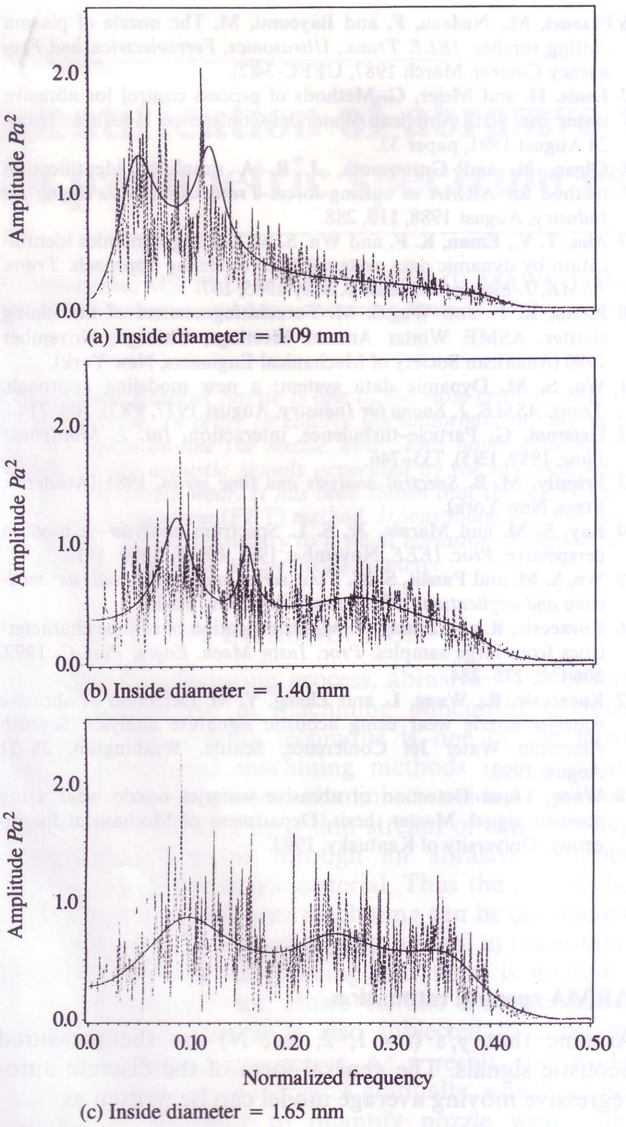


Fig. 5 Comparative power spectrum of acoustic signal for water and abrasive with conventional method and ARMA model method ($d = 305$ mm, aluminium oxide)

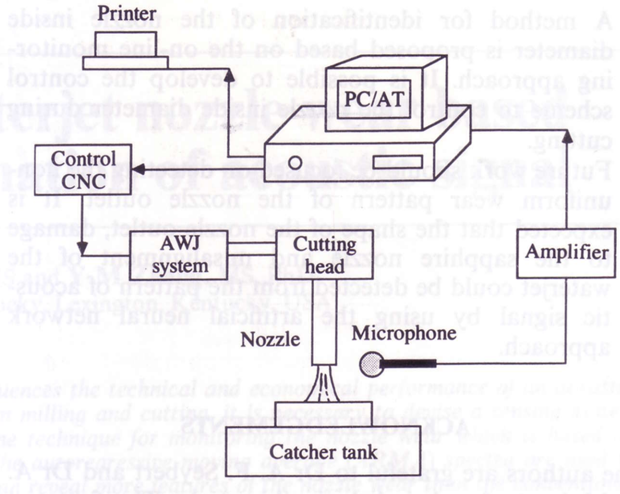


Fig. 7 A closed-loop control system for nozzle wear

show that the ARMA method is a more promising method than the non-parametric method.

2. The spectra of the acoustic signal have a high sensitivity to a small variation of the nozzle inside diameter. Under each investigated condition, the patterns of the spectra are the same during the increase of the nozzle inside diameter. Among the analysed cases, monitoring of nozzle wear is most promising when a mixture of water and abrasive is forced through the nozzle without cutting.
3. The ARMA model order was selected using the MSDC method. ARMA (8, 7) was chosen as the most desired form.
4. The ARMA spectra show that there are two dominant frequencies in the acoustic signature. With an increase of the nozzle wear, the two dominant frequencies tend to shift to the higher frequency while the amplitude of the two dominant frequencies decrease. Also, the amplitude of the acoustic signal in the high-frequency range (above 20 kHz) is a good indicator for monitoring the nozzle wear.

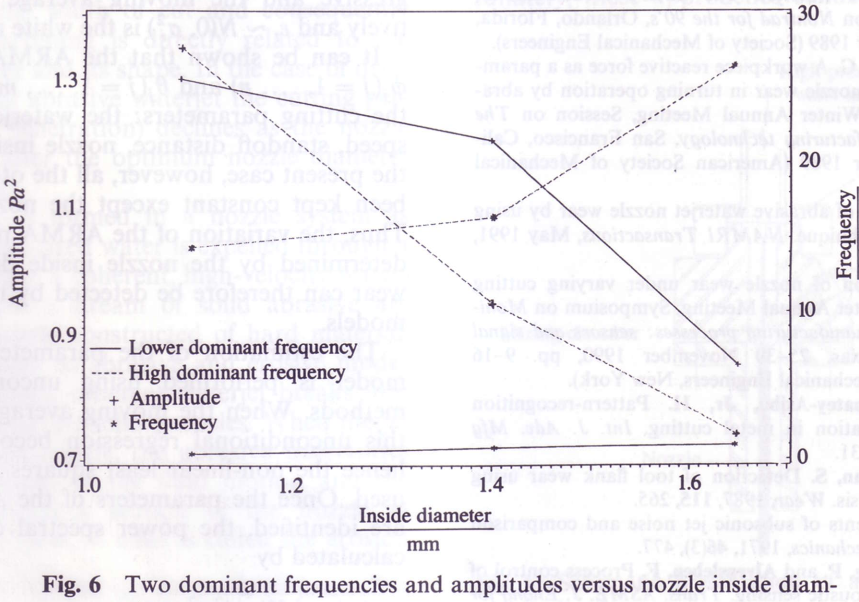


Fig. 6 Two dominant frequencies and amplitudes versus nozzle inside diameters

5. A method for identification of the nozzle inside diameter is proposed based on the on-line monitoring approach. It is possible to develop the control scheme to control the nozzle inside diameter during cutting.
6. Future work should be focused on detecting the non-uniform wear pattern of the nozzle outlet. It is expected that the shape of the nozzle outlet, damage to the sapphire nozzle and misalignment of the waterjet could be detected from the pattern of acoustic signal by using the artificial neural network approach.

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REFERENCES

1 **Hashish, M.** Pressure effects in abrasive-waterjet (AWJ) machining. *J. Engng Mater. Technol.*, July 1989, **111**.

2 **Kovacevic, R.** Monitoring the depth of abrasive waterjet penetration. *Int. J. Mach. Tools Mf.*, 1992, **32**(5).

3 **Hashish, M.** Wear characteristics of abrasive-waterjet tool materials. In *Tribological aspects in manufacturing*, 1991, PED-Vol. 54/TRIB-Vol. 2 (American Society of Mechanical Engineers, New York).

4 **Kovacevic, R.** Sensor for detecting the nozzle wear in abrasive waterjet cutting systems. Invention Disclosure, Syracuse University, New York, March 1988.

5 **Kovacevic, R.** A new sensing system to monitor abrasive waterjet nozzle wear. *J. Mater. Processing Technol.*, 1991, **28**, 117–225.

6 **Kovacevic, R.** Development of opto-electronic sensor for monitoring the abrasive waterjet nozzle wear. ASME's Winter Annual Meeting, Symposium on *Sensors, controls, and quality issues in manufacturing*, Atlanta, Georgia, 1–6 December 1991 (American Society of Mechanical Engineers, New York).

7 **Kovacevic, R.** and **Evizi, M.** Nozzle wear detection in abrasive waterjet cutting systems. *Mater. Evaluation*, March 1990, **48**, 348–353.

8 **Kovacevic, R.** and **Beardsley, H. E.** Nozzle wear sensing in turning operation with abrasive waterjet. The SME's Nontraditional Machining Conference on *Nontrad for the 90's*, Orlando, Florida, 30 October–2 November 1989 (Society of Mechanical Engineers).

9 **Kovacevic, R.** and **Chen, G.** A workpiece reactive force as a parameter for monitoring the nozzle wear in turning operation by abrasive waterjet. ASME's Winter Annual Meeting, Session on *The high energy beam manufacturing technology*, San Francisco, California, 14–17 December 1989 (American Society of Mechanical Engineers, New York).

10 **Kovacevic, R.** Detection of abrasive waterjet nozzle wear by using time series modeling technique. *NAMRI Transactions*, May 1991, pp. 96–100.

11 **Kovacevic, R.** Estimation of nozzle wear under varying cutting condition. ASME's Winter Annual Meeting, Symposium on *Monitoring and control for manufacturing processes: sensors and signal processing*, Dallas, Texas, 25–30 November 1990, pp. 9–16 (American Society of Mechanical Engineers, New York).

12 **Traeisi, E.** and **Kannatey-Asibu, Jr, H.** Pattern-recognition analysis of sound radiation in metal cutting. *Int. J. Adv. Mfg Technol.*, 1991, **6**, 220–231.

13 **Sadat, A. B.** and **Raman, S.** Detection of tool flank wear using acoustic signature analysis. *Wear*, 1987, **115**, 265.

14 **Lush, P. A.** Measurements of subsonic jet noise and comparison with theory. *J. Fluid Mechanics*, 1971, **46**(3), 477.

15 **Chryssolouris, G., Sheng, P.** and **Alvensleben, F.** Process control of laser grooving using acoustic sensing. *Trans. ASME, J. Engng for Industry*, August 1991, **113**, 268.

16 **Braeuel, M., Nadeau, F.** and **Bayoumi, M.** The nozzle of plasma cutting torches. *IEEE Trans., Ultrasonics, Ferroelectrics, and Frequency Control*, March 1987, **UFFC-34**(2).

17 **Louis, H.** and **Meier, G.** Methods of process control for abrasive water jets. Sixth American Water Jet Conference, Houston, Texas, 24 August 1991, paper 32.

18 **Olgac, N.** and **Guttermuth, J. R.** A simplified identification method for ARMA of cutting force. *Trans. ASME, J. Engng for Industry*, August 1988, **110**, 288.

19 **Ahn, T. Y., Eman, K. F.** and **Wu, S. M.** Cutting dynamics identification by dynamic data system (DDS) modeling approach. *Trans. ASME, J. Engng for Industry*, May 1985, **107**.

20 **Eman, K. F.** and **Wu, S. M.** Forecasting control of machining chatter. ASME Winter Annual Meetings, Chicago, November 1980 (American Society of Mechanical Engineers, New York).

21 **Wu, S. M.** Dynamic data system: a new modeling approach. *Trans. ASME, J. Engng for Industry*, August 1977, **99**(3), 708–714.

22 **Hetsroni, G.** Particle–turbulence, interaction. *Int. J. Multiphase Flow*, 1989, **15**(5), 735–746.

23 **Priestly, M. B.** *Spectral analysis and time series*, 1981 (Academic Press, New York).

24 **Kay, S. M.** and **Marple, Jr, S. L.** Spectrum analysis—a modern perspective. *Proc. IEEE*, November 1981, **69**(11), 1380–1418.

25 **Wu, S. M.** and **Pandit, S. M.** *Time series and system analysis: modeling and application*, 1983 (John Wiley, New York).

26 **Kovacevic, R.** and **Zhang, Y. M.** Identification of surface characteristics from large samples. *Proc. Instn Mech. Engrs, Part C*, 1992, **206**(C4), 275–284.

27 **Kovacevic, R., Wang, L.** and **Zhang, Y. M.** Detection of abrasive waterjet nozzle wear using acoustic signature analysis. Seventh American Water Jet Conference, Seattle, Washington, 28–31 August 1993.

28 **Wang, Liqun** Detection of abrasive waterjet nozzle wear using acoustic signal. Master thesis, Department of Mechanical Engineering, University of Kentucky, 1993.

APPENDIX 1

ARMA spectral estimation

Assume that y_t's ($t = 1, 2, \ldots, N$) are the measured acoustic signals. The general form of the discrete autoregressive moving average model can be written as

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_n y_{t-n} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_m \varepsilon_{t-m} \quad (2)$$

where $\phi_1, \phi_2, \ldots, \phi_n$ and $\theta_1, \theta_2, \ldots, \theta_m$ are the autoregressive and the moving average parameters respectively and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$ is the white noise.

It can be shown that the ARMA model coefficients $\phi_j (j = 1, \ldots, n)$ and $\theta_j (j = 1, \ldots, m)$ are determined by the cutting parameters: the waterjet pressure, traverse speed, standoff distance, nozzle inside diameter, etc. In the present case, however, all the other parameters have been kept constant except the nozzle inside diameter. Thus, the variation of the ARMA model will be mainly determined by the nozzle inside diameter. The nozzle wear can therefore be detected by the on-line identified models.

The estimation of the parameters of the stochastic model is performed using unconditional regression methods. When the moving average section is present, this unconditional regression becomes non-linear and hence the non-linear least squares method needs to be used. Once the parameters of the ARMA (n, m) model are identified, the power spectral density of y_t can be calculated by

$$p(\omega) = |H(\omega)|^2 \sigma_\varepsilon^2 \quad (3)$$

where

$$H(\omega) = \frac{1}{\sqrt{(2\pi)}} \frac{1 + \theta_1 \exp(-i\omega) + \cdots + \theta_m \exp(-im\omega)}{1 + \phi_1 \exp(-i\omega) + \cdots + \phi_n \exp(-in\omega)} \tag{4}$$

and the estimate of $p(\omega)$ is obtained by substituting estimates of the parameters $(\theta_1, \ldots, \theta_m, \phi_1, \ldots, \phi_n)$ and σ_ε^2.

Theoretically, ARMA spectral estimation should have the highest possible accuracy. However, this may not be the case when the model order is inappropriate. The order selection is therefore a fundamental step in identification of ARMA models. Many approaches have been proposed to select the order of an ARMA model. However, each approach is based on a specific application. No approach can be regarded as being the most appropriate for all applications. The application-oriented approaches are greatly appreciated. The spectrum is of primary concern in this work. Unfortunately, until now only a few criteria have been designed for the application of spectral estimation. A spectrum-oriented order selection criterion is proposed based on the concept of the model spectral distance (MSD) (**26**), in order to improve the estimation of ARMA model spectra. The MSD is regarded as a measure of the difference between two given models in the foregoing discussion. It may be employed to measure the parameter estimation accuracy. Thus, it can be shown that the significance of order increase will be determined through a comparison of possible accuracy improvement and loss. Application-oriented optimal orders should therefore be more suitable than the consistent orders in the special application.

Assume that ARMA $(p + \Delta p,\ q + \Delta q)$ $(\Delta p \geqslant 0, \Delta q \geqslant 0)$ is a higher order ARMA model than ARMA (p, q). $H^{(2)}(\omega)$ and $H^{(1)}(\omega)$ are the estimated spectra corresponding to ARMA $(p + \Delta p, q + \Delta q)$ $(\Delta p \geqslant 0, \Delta q \geqslant 0)$ and ARMA (p, q). The model spectral distance (MSD) from $H^{(2)}$ to $H^{(1)}$ can be defined as

$$D(H^{(2)} \to H^{(1)}) = \sqrt{\left(\frac{1}{2\pi} \int_{-\pi}^{\pi} |d|^2 \, d\omega\right)} \tag{5}$$

where

$$d^2(H^{(2)}(\omega) \to H^{(1)}(\omega)) \equiv \left| \frac{H^{(1)}(\omega) - H^{(2)}(\omega)}{H^{(1)}(\omega)} \right|^2 \tag{6}$$

Substituting equations (3) and (5) into equation (4) gives

$$D^2(\hat{H} \to H) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left| \frac{\Delta\hat{\theta}(e^{-j\omega})}{\hat{\theta}(e^{-j\omega})} - \frac{\Delta\hat{\phi}(e^{-j\omega})}{\hat{\phi}(e^{-j\omega})} \right|^2 d\omega \tag{7}$$

Thus, MSD can be regarded as a measure between possible models. There are two problems involved in the order selection. The MSD from ARMA (p, q) to ARMA $(p + \Delta p, q + \Delta q)$ can be considered as a possible accuracy improvement. On the other hand, the contribution of parameter estimation to the modelling error increases as the order increases. The model spectral distance criterion (MSDC) tends to select an optimal model which produces the minimum spectral estimate error among possible models. If the possible error increase is larger than the possible accuracy improvement, the order increase will not be proper. Otherwise, the order increase is proper. A model distance from the estimated model to the real model can also be estimated using the parameter estimated covariance matrix. By comparing these two types of MSD, this distance can be recognized as a possible accuracy loss due to an order increase.

APPENDIX 2

An average smoothing filter technique

A moving average of a series $[I(\omega_i), i = 1, \ldots, n]$ is a series $[\hat{f}_\omega(\omega_i)]$ defined by

$$\hat{f}_\omega(\omega_i) = \frac{1}{A} \sum_{j=-p}^{p} a_j I(\omega_{i+j}), \quad i = p + 1, \ldots, n - p \tag{8}$$

where

$$A = \sum_{j=-p}^{p} a_j$$

and

$$a_j = a_{-j} = \alpha^{|j|}$$

The order (p) and coefficient (α) should be selected. Normally, $\alpha = 0.95, 0.9, 0.8, 0.7$ and $p = 8, 10, 15, 20$ are chosen.