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ORIGINAL ARTICLE

An adaptive control strategy for the abrasive waterjet cutting process with the integration of vision-based monitoring and a neuro-genetic control strategy

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Abstract This paper presents an integrated approach for the monitoring and control of abrasive waterjet (AWJ) cutting process. A machine-vision-based monitoring approach was proposed to obtain the bore diameter of the focusing nozzle from time to time. A neuro-genetic approach, proposed by Srinivasu and Ramesh Babu (Appl Soft Comput 8(1):809–819, 2008) was employed as a control strategy to modify the process parameters, such as water pressure, abrasive flow rate, and jet traverse rate, so as to maintain the desired depth of cut, with changes in the diameter of the focusing nozzle monitored with a machine vision system. By combining the monitoring and control strategies, an integrated approach for adaptive control of AWJ cutting process is realized. The effectiveness of the proposed integrated approach for adaptive control of AWJ cutting process was shown by comparing the results obtained from the experiments with the process parameters suggested by the control strategy to achieve the desired depth of cut. From the results of the study, it is seen that the proposed monitoring system is capable of monitoring the focusing nozzle diameter with a mean absolute deviation of 0.05 mm and that the neuro-genetic strategy is capable of modifying the controllable process parameters to maintain the desired depth of cut with a mean absolute deviation of 0.87 mm.

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1 Introduction

Abrasive waterjet (AWJ) cutting process is influenced by several process parameters, such as hydraulic, abrasive, mixing, and cutting parameters. Among them, the diameters of orifice and focusing nozzle are uncontrollable process parameters, since they change from time to time due to wear [1–4]. Changes in the size of orifice and focusing nozzle significantly influence the performance of the process. In general, the rate of wear on the orifice is less compared to the rate of wear on the focusing nozzle [2]. Further, the orifice is replaced when it undergoes excessive wear or breaks during the operation. On the other hand, the focusing nozzle undergoes wear during the operation and is used until it reaches a particular size [1–3, 5–9]. It was observed that an increase in the diameter of the focusing nozzle up to a certain limit increases the depth of cut. Beyond this limit, it reduces the depth of cut [10]. This is due to an inefficient entrainment of abrasives in the mixing chamber and the improper mixing of abrasives with water in the focusing nozzle. Thus, the wear on the focusing nozzle affects the process response in terms of the material removal rate, depth of cut, cutting efficiency, kerf geometry, and the roughness of the cut surface [1–3, 11–14]. Hence, it is important to know the size of the focusing nozzle from time to time for controlling AWJ cutting process accurately [1, 3–10, 15–18]. The control of the process is possible by modifying controllable process parameters according to the change in the diameter of the focusing nozzle [1, 4, 15–21]. In order to achieve this goal, it is necessary to develop: (1)

a monitoring system that can determine the diameter of the focusing nozzle and (2) a control strategy that can suggest the modifications to controllable process parameters based on the change in the diameter of the focusing nozzle observed by the monitoring system.

Attempts made to monitor the wear on the focusing nozzle include direct and indirect sensing methods. Among the direct sensing techniques, such as conductive loop and radiometric approaches, the former approach makes use of a conductive loop embedded into the tip of the focusing nozzle to monitor the diameter continuously [6]. However, this particular approach demands for a special arrangement to embed the conductive loop into the focusing nozzle tip. On the contrary, the radiometric approach is not suitable on the shop floor due to the need for special preparation of the nozzle, as well as potential hazards due to radioactivity [6]. Indirect sensing methods monitor the structure of the jet, the forces during cutting, the level of acoustic emission, etc. for the purpose of determining the condition of the focusing nozzle [7–10, 20]. Among the various methods, the vision-based system is the most simple and least expensive method that monitors the structure of the jet from which the diameter of the focusing nozzle is obtained [7]. As the structure of the jet emerging from the nozzle changes with varying diameters of focusing nozzle, one can determine the diameter of the focusing nozzle only when the relationship between the divergence of the jet and the diameter of the nozzle is established. However, under varying conditions of water pressure, this particular method is likely to indicate different diameters for the same diameter of focusing nozzle [7]. Monitoring systems based on cutting force measurement require special fixtures for mounting the material being cut by AWJ cutting process. Moreover, the jet can damage the force sensor during the cutting operation [6, 10, 19]. Acoustic-emission-based systems are more expensive and require tedious analysis procedures to identify the exact condition of the nozzle [19]. In a similar way, other monitoring systems make use of vibration sensor and ultrasonic gages for obtaining the wall thickness of the nozzle and are not very reliable, due to the nature of the scheme employed for analyzing the measured signals [5]. All of the above monitoring systems collect the data in a continuous manner, which make the analysis computationally complex. Apart from all this, some of the sensors need to be protected with great care in order to operate them in the harsh conditions of AWJ cutting, such as high-velocity abrasives, the splashing of water, etc. [19]. With the development of newer materials for nozzles, the rate of wear on the focusing nozzle is becoming less and less. Hence, one can think of a monitoring system that is less complex, insensitive to process parameters, and can be employed to monitor the diameter of the focusing nozzle at periodic intervals. As machine vision systems are being used widely for direct inspection, the present work attempts to make use of such a system for monitoring the bore diameter of the focusing nozzle.

Once the diameter of the focusing nozzle is known from a suitable monitoring system, the next step is to control the process by modifying the controllable parameters so as to achieve the desired results with the current size of focusing nozzle, i.e., adaptive control of AWJ cutting process. This can be achieved with hybrid control strategies, which include suitable process models that consider the current diameter of the focusing nozzle to predict the process performance and control strategies that can suggest changes in the controllable parameters accordingly. Recent efforts on the modeling of AWJ machining processes include the application of softcomputing approaches, such as artificial neural networks (ANN), fuzzy logic, and genetic algorithms (GA), for developing the models to predict the performance of AWJ machining processes and to select process parameters in achieving the desired performance [1, 4, 15–18, 22, 23]. These methods are gaining importance since they do not require knowledge of the physical phenomenon of the process, material properties, mathematical definition of the process, assumptions regarding the process, etc. and can be built using quantitative and qualitative process knowledge in the modeling of complex processes such as AWJ cutting [1, 4, 15–18, 22, 23]. Further, softcomputing approaches offer good flexibility to upgrade the existing models to a comprehensive model, thus, becoming suitable approaches for developing process control models that are built with the continuous collection of data from the process [1, 15, 24, 25].

Recent efforts on process control include the development of neuro-genetic and neuro-fuzzy strategies for suggesting controllable process parameters, such as water pressure, abrasive flow rate, and jet traverse rate, in achieving the desired depth of cut with wear on the diameter of the focusing nozzle taken into account [1, 4, 16–18]. In the neuro-genetic process control strategy, a GA-based search approach is used to suggest modifications to process parameters, based on the change in diameter of the focusing nozzle, for the purpose of maintaining the desired depth of cut [1]. This particular approach suggested process parameters by considering the known size of the focusing nozzle. But, the exact size of the focusing nozzle needs to be known to employ this approach for adaptive control applications. As there were no attempts to combine the monitoring with control strategies for an adaptive control of AWJ cutting process, the present work attempts to develop an integrated approach by combining the machine-vision-based system for monitoring the bore diameter of the focusing nozzle with a neuro-genetic approach to control the process considering the changes in the diameter of the focusing nozzle.

2 Methodology

In Fig. 1, an integrated approach proposed for adaptive control of AWJ cutting process is shown. It consists of the following phases:

1. Monitoring of the focusing nozzle diameter using a machine-vision-based monitoring approach
2. Development of an integrated approach that combines the machine-vision-based monitoring system with the neuro-genetic control strategy to suggest modifications to process parameters for maintaining the desired depth of cut by considering the diameter of the focusing nozzle obtained from machine-vision-based monitoring system
3. Validation of the proposed integrated approach with suitable experimental studies to employ it for adaptive control of AWJ cutting process

3 Monitoring of the focusing nozzle diameter using a machine vision approach

Figure 2a shows a photograph of the setup employed for monitoring the focusing nozzle diameter using a machine vision system. The same setup is shown schematically in Fig. 2b. It contains an 8-bit monochromatic charge coupled device (CCD) camera (Pulnix model TMC6) with a pixel resolution of 768×565, a frame grabber, a circular illumination system, a PXI system, and a CRT display. For monitoring the diameter of the focusing nozzle, the image of the focusing nozzle tip is captured by bringing the cutting head to a position above the camera (Fig. 2a). The image, captured in the Labview 7.0 environment, is first converted into a binary image, which is then processed with edge-detection and feature-detection algorithms to obtain the diameter of the focusing nozzle.

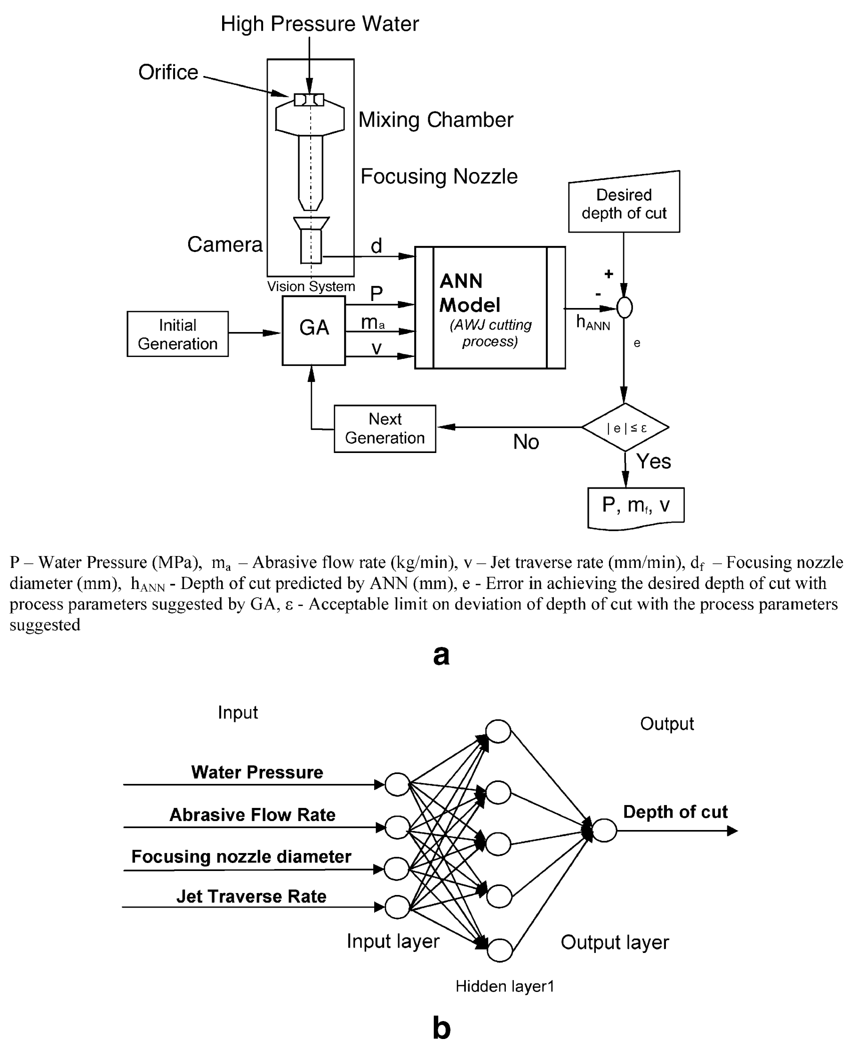

Fig. 1a, b Schematic of an integrated approach for adaptive control of abrasive waterjet (AWJ) cutting process. **a** Integration of the vision-based monitoring of the focusing nozzle diameter and the neuro-genetic approach for parameter selection of the control strategy. **b** Feed-forward artificial neural network (ANN) model with 4-5-1 structure for the prediction of the depth of cut in AWJ cutting

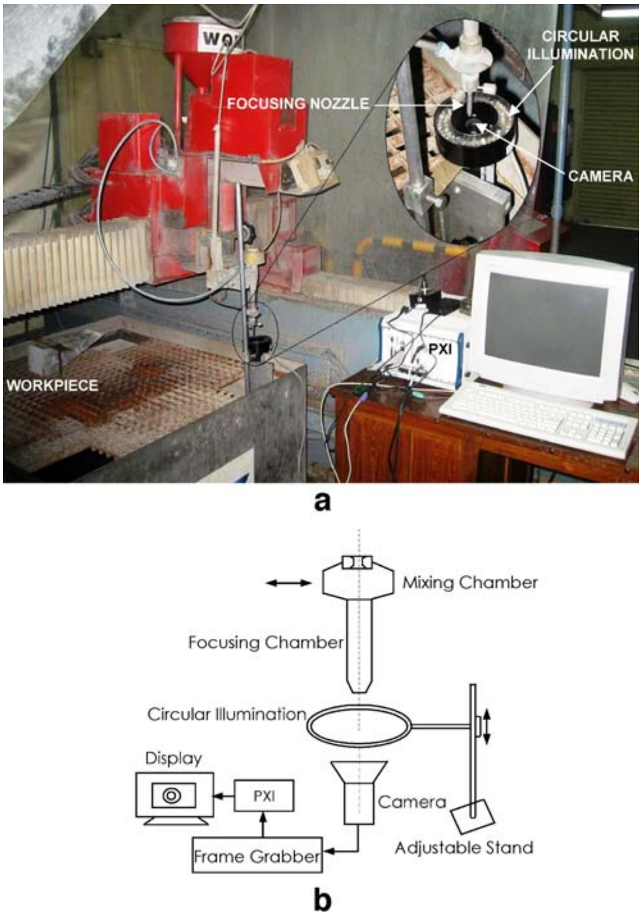

Fig. 2 **a** Photograph of the vision-based system for monitoring the focusing nozzle bore diameter. **b** Schematic diagram showing the arrangement of different units of the vision-based monitoring system

3.1 Determining the geometry of the focusing nozzle bore diameter using the Hough transform

The boundaries of the image are detected by means of a well-known canny edge-detection algorithm [26]. In order to obtain the bore diameter of the nozzle from this image, the well-known Hough transform technique was applied [27]. The Hough transform is a shape analysis method which uses a constraint equation relating the points in a feature space to the parameters that represent the shape. If a circle is parameterized by its center co-ordinates (a, b) and its radius, r, then an arbitrary point (x_i, y_i) will be transformed into a surface in the a–b–r parameter space defined by:

$$(x_i - a)^2 + (y_i - b)^2 = r^2 \quad (1)$$

This method considers each point, i.e., edge point, on the feature space and determines the votes for different combinations of parameters, i.e., a, b, and r, satisfying the relation given in Eq. 1. At the end of the voting or accumulation process, those elements of the array containing a large number of votes indicate the strong evidence for the presence of the shape with corresponding parameters. Using this procedure, the diameter of the focusing nozzle is determined.

4 Development of an integrated approach for adaptive control of AWJ cutting

In order to develop an integrated approach for adaptive control of AWJ cutting process, the present work attempts to use the neuro-genetic approach proposed for the selection of process parameters in AWJ cutting considering the variation in the diameter of the focusing nozzle [1]. Before describing the integrated approach for adaptive control of AWJ cutting process, a brief description on the neuro-genetic strategy is covered in the following section for the sake of completeness.

4.1 Neuro-genetic control strategy for the selection of process parameters considering the variation in the diameter of the focusing nozzle

For maintaining the desired process response, i.e., adaptive control of AWJ cutting, the neuro-genetic approach suggests modifications to the controllable process parameters [1]. This approach includes: (1) an ANN model for the prediction of process performance by considering the change in the diameter of the focusing nozzle and (2) a strategy for modifying controllable process parameters based on the change in the diameter of the focusing nozzle.

4.1.1 Artificial neural network model for the prediction of the depth of cut

In order to build a suitable model for predicting the performance of AWJ cutting process with any size of focusing nozzle, the data was collected by using different sizes of focusing nozzles, i.e., 0.76 mm, 1.2 mm, and 1.6 mm. Different controllable process parameters, such as water pressure, abrasive flow rate, and jet traverse rate were varied at three levels with each size of focusing nozzle. This has resulted in full-factorial experimentation with 81 (3^4) experiments. Various parameters employed for conducting the experiments are shown in Table 1. The experiments were conducted on a trapezoidal-shaped 6063-T6 aluminum alloy workpiece. This particular cross section was chosen in order to determine the maximum penetration of the jet into the material with different combinations of process parameters. The maximum penetration of jet into the material was determined by the relation [22]:

$$h = L \sin 25^\circ \quad (2)$$

Table 1 Process parameters chosen for abrasive waterjet (AWJ) cutting experiments conducted for process monitoring and modeling studies

Parameters	Range
Fixed parameters	
Stand-off distance (mm)	4
Type and size of abrasive	Garnet, 120 mesh
Diameter of orifice (mm)	0.25
Number of passes	1
Variable parameters	
Diameters of focusing nozzle (mm)	0.76, 1.00, 1.2, 1.60
Water pressure (MPa)	100, 170, 240
Abrasive mass flow rate (kg/min)	0.07, 0.11, 0.33
Jet traverse rate (mm/min)	30, 90, 150

where L is the slant length of the cut. The data collected from the experiments was used to develop the ANN model for predicting the depth of cut with known parameters, such as water pressure, abrasive flow rate, jet traverse rate, and diameter of the focusing nozzle. Figure 1b shows the structure of the ANN model developed for the prediction of the depth of cut. For the development of the ANN model, the total experimental data was divided into training, validation, and testing data sets. From the total experimental data, 70% of the data was selected for training the model, 10% of the data for validation, and remaining 20% of the data for testing the developed model. Apart from this, the capability of the ANN model in predicting the performance of the process with any other size of focusing nozzle, i.e., different from the sizes of focusing nozzles used for building the model, was examined by means of separate testing data. This data was generated from the experiments conducted with a focusing nozzle of diameter 1.0 mm and water pressures of 135 MPa and 205 MPa, abrasive flow rates of 0.027 kg/min and 0.04 kg/min, and jet traverse rates of 60 mm/min and 120 mm/min (Table 4).

Various steps involved in the development of the ANN model include the selection of a network configuration, suitable learning algorithm, learning rate parameter, momentum constant, and the number of epochs. The back propagation learning algorithm was used for training the network. In order to select the optimum/near-optimum values for the initial weights, each ANN was initialized with different random initializations for ten times. Among them, the initial weights of the ANN that gives the minimum error in the prediction of the depth of cut is selected as the network with optimum initialized weights. As the number of hidden layers in the network increases, the computational complexity increases. Further, a single-hidden-layer network is sufficient to form an arbitrarily close approximation to any nonlinear decision boundary [28]. Thus, the present work considered an ANN with a single hidden layer. The number of hidden nodes in the hidden layer was changed incrementally from 1 to 50 and the number of nodes that gave the minimum error in the prediction of the depth of cut while training and validating the network was selected. Similarly, the learning rate and momentum constants and the number of epochs were also selected randomly based on the minimum error prediction criterion with both training and validation data sets.

4.1.2 Selection of process parameters considering variations in the diameter of the focusing nozzle

For the selection of process parameters for controlling the process results, a neuro-genetic approach is employed, which is the same as that shown in Fig. 1. A neuro-genetic approach considers the desired depth of cut as an input. The GA randomly generates a set of real coded chromosomes containing the process parameters, such as water pressure, abrasive flow rate, and jet traverse rate. As very small and very large size populations lead to premature and slow rates of convergence of the GA, the population size of 30 is selected [29]. Each chromosome in the initial population containing the process parameters, such as water pressure, abrasive flow rate, and jet traverse rate, is fed to the ANN model, along with the diameter of the focusing nozzle obtained from the monitoring system for predicting the depth of cut. The deviation in the depth of cut from the desired depth of cut is chosen as an objective function. The fitness value for each chromosome in the population is estimated using the fitness function (F), where E is the objective function [30]:

$$F = \frac{1}{1+E} \tag{3}$$

The chromosomes with large fitness values in the population are selected by the reproduction operator. The primary objective of the reproduction operator is to make more copies of good solutions and to eliminate bad solutions in any population. Among the various methods adopted for reproduction, such as tournament selection, roulette wheel selection, and ranking selection, the tournament selection procedure was adopted, since it gives better or equivalent convergence and less computational complexity compared to other reproduction operators [31]. As the reproduction operator can only increase the copies of existing good solutions in the population, the crossover operation is performed to create the new solutions. In order to create effective new solutions from the parent solutions, a specialized crossover, known as the simulated binary crossover (SBX), with a crossover probability of 0.9 was selected [32]. In order to avoid the convergence to local minima and to explore the total parameter space, the strings are subjected to mutation operation. For this purpose, a polynomial distribution with a mutation probability of 0.01 was used to create a solution in the vicinity of a parent solution [33]. The above steps complete one generation and the resulting population becomes the new population. This procedure is continued for several generations until the deviation in the prediction of the depth of cut is less than the specified limit of error, i.e., 0.01 mm.

4.2 Integration of vision-based monitoring and the neuro-genetic control strategy

The proposed integrated approach for adaptive control of AWJ cutting process combines the vision-based monitoring of the focusing nozzle diameter with a neuro-genetic control strategy for parameter selection (Fig. 1). To measure the diameter of the focusing nozzle at periodic intervals, the cutting head is brought to a position above the machine vision system. By employing the procedure outlined in Sect. 3, the diameter of the focusing nozzle is determined. This particular diameter of focusing nozzle is fed to the neuro-genetic control strategy. The neuro-genetic control strategy considers the diameter of the focusing nozzle and the desired depth of cut as inputs and suggests the modified process parameters. After a certain period of operation, the procedure is repeated to monitor the changes in the focusing nozzle diameter that occur due to its wear during the operation. Now, the neuro-genetic strategy considers the current diameter of the focusing nozzle to suggest modifications to the process parameters so as to maintain the desired depth of cut. This process of monitoring and determination of the diameter of the focusing nozzle with a machine vision system and the suggestion of modified process parameters with the neuro-genetic control strategy is continued until the completion of AWJ cutting in order to keep the process under control.

5 Results and discussion

5.1 Monitoring of the focusing nozzle using a machine vision system

To examine the effectiveness of the proposed vision-based monitoring system in determining the diameter of the focusing nozzle, seven focusing nozzles of different diameters were chosen. These nozzles are labeled as 1 to 7 and their diameters are shown in Table 2. All of these nozzles were used in AWJ cutting for a certain period. The diameter of the worn out focusing nozzles was measured by using a machine vision system. To detect the boundaries of the image with a canny edge-detection algorithm, a threshold value of 0.6 was selected. Figure 3a shows an image of the tip of the focusing nozzle, labeled as 7, captured with the vision system and Fig. 3b shows the image after subjecting the original image to the edge-detection process. In Fig. 3b, two concentric circles can be seen. The outer circle corresponds to the outer diameter of the focusing nozzle and the inner circle corresponds to bore of the focusing nozzle. Figure 3c presents the count of the points falling on the circles with different radius. Usually, one peak will be observed in the case of a single circle having the highest number of points sharing a single radius. But, in the present case, two dominated peaks, as observed in Fig. 3c, correspond to the outer diameter and the bore diameter of the focusing nozzle. In order to evaluate the effectiveness of the vision system, the diameters of the focusing nozzle determined with the vision system are compared with the diameters measured by a Vidicom-Qualifier-688, a non-contact coordinate measuring machine (CMM). The results obtained with both of the methods for different diameters of focusing nozzles are presented in Table 2. From the results, it can be observed that the proposed machine-vision-based monitoring system can determine the diameter of the focusing nozzle with a mean absolute error of 0.05 mm. This error can be attributed to

Table 2 Measured diameters of focusing nozzle with a non-contact co-ordinate measuring machine (CMM) and the machine vision system

Nozzle no.		1	2	3	4	5	6	7
Diameter of focusing nozzle, d_f (mm)	Original diameter of the focusing nozzle (mm)	0.76	0.76	1.0	1.0	1.0	1.2	1.6
	After a certain period of operation							
	Measured with a non-contact CMM (d_1) (mm)	0.852	0.901	1.043	1.066	1.175	1.313	1.690
	Measured with a machine vision system (d_2) (mm)	0.812	0.860	1.002	1.008	1.140	1.220	1.640
	Deviation (d_1–d_2) (mm)	0.040	0.041	0.041	0.058	0.035	0.093	0.050
Mean absolute error (MAE) (mm)=0.05								

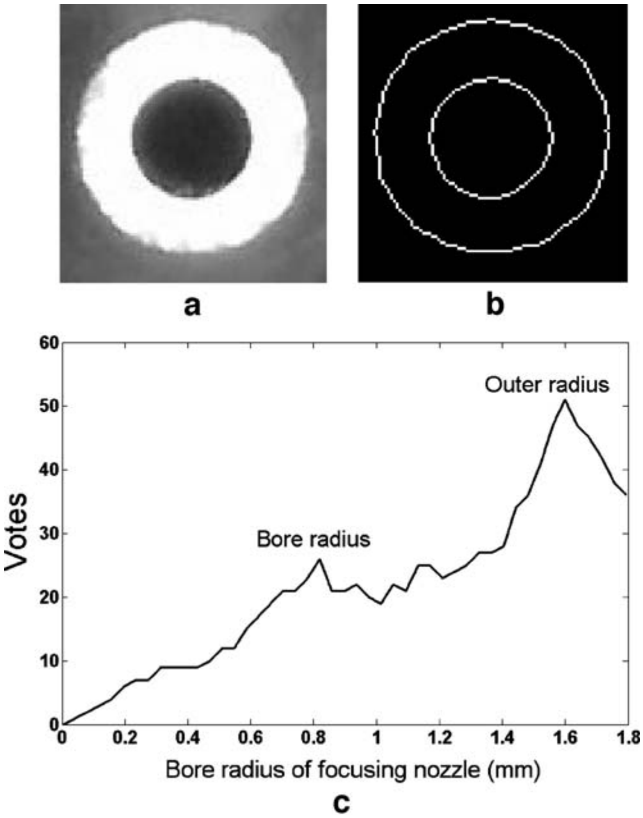

Fig. 3 **a** Image of the tip of the focusing nozzle with a bore diameter of 1.6 mm. **b** Inner and outer boundaries of the focusing nozzle obtained by an edge-detection algorithm. **c** Plot of radius versus votes

the resolution of the camera and the quality of the image acquired with the illumination system.

5.2 Neuro-genetic approach for process control

5.2.1 Prediction of the depth of cut with artificial neural networks

With the procedure outlined earlier in Sect. 4, an ANN with a 4-5-1 structure, i.e., a single hidden layer with five hidden nodes, was found to perform well in predicting the depth of cut and is as illustrated in Fig. 1b. Table 3 shows the depth of cut predicted with the ANN model for different combinations of process parameters with different sizes of focusing nozzle. From the results, it can be noticed that the ANN model can predict the depth of cut with a mean absolute error of 1.66 Finally, by performing the *t*-test, the model was accepted with a 0.05 level of significance. These statistical measures show the effectiveness of an ANN model in capturing the complex and non-linear nature of the AWJ cutting process. The effectiveness of the ANN model for predicting the depth of cut with worn out focusing nozzles was shown by considering the experimental data collected with a 1.0-mm diameter focusing nozzle. The results of this study are presented in Table 4. From the results, it can be seen that the ANN model can predict the depth of cut with a mean absolute error of 0.73. By

Table 3 Performance of the artificial neural network (ANN) model in predicting the depth of cut with the process parameters used for the testing experiments

Sl. no.	P (MPa)	v (mm/min)	m_f (kg/min)	d_f (mm)	Depth of cut, h (mm)		Deviation (mm)
					ANN	Experimental	
1	170	150	0.03	0.8	6.47	6.77	0.30
2	100	150	0.03	0.8	3.29	2.83	0.46
3	240	30	0.03	1.6	18.98	20.09	1.11
4	240	90	0.11	1.6	24.57	21.84	2.72
5	100	90	0.11	0.8	6.87	8.29	1.41
6	100	90	0.11	1.6	6.48	5.02	1.46
7	240	150	0.03	1.2	6.59	5.89	0.70
8	170	90	0.07	0.8	21.11	16.81	4.30
9	240	150	0.11	0.8	24.85	23.58	1.27
10	170	90	0.11	1.6	14.36	13.1	1.26
11	240	150	0.07	0.8	16.78	19.00	2.21
12	240	90	0.07	0.8	28.94	28.17	0.77
13	170	30	0.03	1.2	15.82	19.00	3.18
14	100	30	0.03	0.8	15.85	11.35	4.50
15	170	90	0.03	1.6	3.77	3.49	0.28
16	170	150	0.07	1.2	8.89	8.29	0.60
MAE=1.66							

P=water pressure; v=jet traverse rate; m_f=abrasive flow rate; d_f=focusing nozzle diameter; Deviation=error in the prediction of the depth of cut by the ANN

Table 4 Comparison of the depth of cut predicted by the ANN with experimental results considering a focusing nozzle diameter of 1.0 mm

Sl. no.	P (MPa)	v (mm/min)	m_f (kg/min)	d_f (mm)	Depth of cut, h (mm)		Deviation (mm)
					ANN	Experimental	
1	135	60	0.027	1.0	8.15	6.49	1.66
2	205	60	0.027	1.0	14.78	14.00	0.77
3	135	120	0.027	1.0	4.25	3.38	0.87
4	205	120	0.027	1.0	7.18	7.61	0.43
5	135	60	0.04	1.0	11	11.83	0.83
6	205	60	0.04	1.0	19.48	19.86	0.38
7	135	120	0.04	1.0	5.91	5.49	0.42
8	205	120	0.04	1.0	9.24	9.72	0.48
MAE=0.73							

performing the t-test, the model was accepted with a 0.05 level of significance. These statistical studies show the generalization capability of the proposed ANN model for the worn-out condition of the focusing nozzle that is different from the original condition of the focusing nozzle.

5.2.2 Selection of process parameters with the neuro-genetic approach

This section covers the studies conducted on: (1) the selection of process parameters for a desired depth of cut and (2) the suggestion of modified process parameters in maintaining the desired depth of cut with variations in the diameter of the focusing nozzle by a neuro-genetic control strategy:

1. Selection of process parameters to achieve any desired depth of cut

The neuro-genetic strategy considers the initial diameter of the focusing nozzle as 0.76 mm in selecting the process parameters for achieving the desired depth of cut of 20 mm. In this strategy, the GA generates several combinations of process parameters to realize the desired depth of cut. After 1,000 generations, the process parameters are converged to a set of process parameters, i.e., water pressure of 168.56 MPa, jet traverse rate of 112.64 mm/min, and abrasive flow rate of 0.103 kg/min for realizing the desired depth of cut of 20 mm with a 0.76-mm-diameter focusing nozzle. The experimental depth of cut achieved with these process parameters is 18.54 mm, thus, giving a deviation of 1.46 mm.

2. Selection of process parameters with variation in the diameter of the focusing nozzle

When the diameter of the focusing nozzle is changed from 0.76 mm to 1.0 mm, the same neuro-genetic strategy suggested a set of process parameters, such as water pressure of 172.2 MPa, jet traverse rate of 74.46 mm/min, and abrasive flow rate of 0.068 kg/min, for achieving the desired depth of cut of 20 mm. The depth of cut achieved with these process parameters was 20.56 mm, thus, giving a deviation of 0.56 mm from the desired depth of cut. If the initially selected process parameters, i.e., water pressure of 168.56 MPa, jet traverse rate of 112.64 mm/min, and abrasive flow rate of 0.103 kg/min, chosen with the focusing nozzle diameter of 0.76 mm, were employed when the diameter is altered from 0.76 mm to 1.0 mm during cutting, these process parameters

Table 5 Parameters suggested by the neuro-genetic approach in maintaining the depth of cut of 10 mm with different sizes of focusing nozzle monitored

Sl. no.	Diameter of focusing nozzle, d_f (mm)		Process parameters obtained with the neuro-genetic approach			Depth of cut, h (mm)	
	Initial	Monitored	P (MPa)	m_f (kg/min)	v (mm/min)	Experimental	Deviation
1	0.76		179	0.042	106	11.63	1.63
		0.812	206	0.035	125	11.37	1.37
2	1.00		168	0.056	118	10.32	0.32
		1.22	165	0.071	122	10.00	0
3	1.60		180	0.098	133	9.54	0.46
		1.64	157	0.1	109	11.44	1.44
MAE							0.87

produced a depth of cut of 15.91 mm, giving an error of 4.09 mm. This illustrates the suitability of the proposed neuro-genetic approach for the adaptive control of AWJ cutting under varying conditions of the focusing nozzle.

5.3 Integrated approach of monitoring and control of AWJ cutting

The application of the proposed integrated approach for the monitoring and control of AWJ cutting process is illustrated with the following example. Initially, the cutting head is fitted with a focusing nozzle diameter of 0.76 mm. With this diameter and the desired depth of cut of 10 mm, the neuro-genetic strategy suggested a water pressure of 179 MPa, abrasive flow rate of 0.042 kg/min, and jet traverse rate of 106 mm/min. Table 5 presents the process parameters suggested by the neuro-genetic approach for maintaining a depth of cut of 10 mm with different sizes of focusing nozzle monitored. After a certain period of operation, the diameter of the focusing nozzle was monitored with the help of a vision-based monitoring system and the diameter of the focusing nozzle was observed as 0.852 mm. To achieve the same depth of cut of 10 mm with this particular diameter of 0.852 mm, the proposed approach suggested a water pressure of 206 MPa, abrasive flow rate of 0.035 kg/min, and jet traverse rate of 125 mm/min. With these process parameters, the depth of cut of 11.37 mm was achieved, thus, giving a deviation of 1.37 from the desired depth of cut of 10 mm. It may be relevant to note that the vision-based monitoring system gave the diameter of the worn out nozzle as 0.812 mm, in contrast to the diameter of 0.852 mm observed with a non-contact CMM. This particular diameter was fed to the neuro-genetic approach to obtain the modified parameters for process control. This deviation in the monitored diameter with the vision-based system could have resulted in the deviation of the achieved depth of cut with a nozzle diameter of 0.852 mm whose size could be 0.812 mm, as observed with a non-contact CMM.

The effectiveness of the proposed approach for controlling the depth of cut under varying conditions of focusing nozzle is demonstrated by considering the worn out focusing nozzles of different diameters shown in Table 5. The initial diameters of focusing nozzles are 0.76 mm, 1.0 mm, and 1.6 mm. When these nozzles have undergone changes due to wear, their diameters are increased to 0.852 mm, 1.313 mm, and 1.69 mm, respectively. In order to achieve the desired depth of cut of 10 mm, the proposed approach suggested modifications to the originally chosen process parameters, which controlled the depth of cut with a mean absolute error of 0.87 mm. This clearly demonstrates the effectiveness of the proposed approach for adaptive control of the AWJ cutting process under varying conditions of focusing nozzle that are monitored with a vision-based system.

6 Conclusions

The present work suggested an integrated approach that combined a machine-vision-based monitoring system with a neuro-genetic control strategy for the adaptive control of abrasive waterjet (AWJ) cutting process. The diameter of the focusing nozzle is monitored at regular intervals using a vision-based monitoring system. The size of the focusing nozzle monitored is considered by the neuro-genetic strategy to modify the process parameters for maintaining the desired depth of cut. The offline vision-based monitoring system can monitor the condition of the focusing nozzle at periodic intervals without much loss of production and tedious instrumentation. With the proposed monitoring system, it is possible to measure the bore diameter of the focusing nozzle with a mean absolute error of 0.05 mm. Feasibility of the proposed approach for adaptive control is demonstrated by monitoring the conditions of the focusing nozzle with the monitoring system and by achieving the desired depth of cut with a mean absolute error of 0.87 mm using the parameters suggested by the neuro-genetic strategy. Thus, the proposed integrated approach can be easily applied to the adaptive control of the AWJ cutting process without making any changes to existing AWJ cutting systems.

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