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Application of Artificial Neural Networks in Abrasive Water Jet Milling

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Abstract

In the present study, Artificial Neural Networks (ANN) is used to predict the geometrical characteristics of a micro-channel fabricated through Abrasive Water Jet Machining (AWJM) technique. The process parameters considered are abrasive size, traverse speed, abrasive flow rate and standoff distance respectively. The quality of the micro-channel can be assessed in terms of its width, depth, taper and surface roughness. The optimum values of the process parameters are used to predict the response parameters. The impact force of the abrasive water jet and the jet vibrations are considered as additional input to the process parameters. The ANN predicted values are 99% in agreement with the experimental results.

Keywords: geometry, force, vibration, artificial neural networks

1. Introduction

Any component manufactured and the corresponding geometrical parameters obtained measure the performance of the concerned manufacturing process. Maintaining close dimensional tolerances throughout the process is well established in most of the conventional machining processes because of its large data base available. Unconventional manufacturing processes which were developed over the past few decades lack in achieving the required dimensional tolerances even after the major technological advancements. AWJM is one such process which needs to be elaborately studied. This process is gaining its popularity due to its added advantages over other unconventional processes like minimum heat affected zone, unchanged material characteristics after machining, faster material removal, etc.

The basic mechanism of material removal in AWJM process is erosion where the mechanical energy is used for the material removal to take place. The process has the capability to cut variety of materials ranging from soft like rubber, leather, etc. to very hard materials like titanium, Inconel, etc. which are mostly used in all engineering sectors. AWJM process is a highly complex phenomenon that does not allow pure analytical or physical modeling due its sensitiveness to a large set of process parameters. Thus, experimental and analytical models are developed by using conventional approaches such as regression modeling, etc. Although statistical regression modeling may be acceptable for process modeling, but such techniques may not precisely describe the underlying non-linear relationship between the input and response parameters.

A process model is a mathematical function that relates the process parameters and its performance. In general, models are categorized in three forms namely, experimental, analytical and Artificial Intelligence (AI) based models. Experimental and analytical models can be developed using conventional approaches like Statistical Regression techniques. While, AI based models are developed using non-conventional approaches such as ANN, Fuzzy, Genetic Algorithm (GA), etc. An ANN technique is a mathematical or

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computational method which is a massively parallel, distributed processor having capability of storing experimental knowledge. Initially ANN learns by experience and then it stores the information in the form of synaptic weights. Modern neural networks are non-linear statistical data modeling tools to model complex relationships between inputs and outputs and also find patterns in the given data. The advantages of using ANN for model prediction are; ANN is able to handle nonlinear models that learns how to map input to output; ANN is successful in terms of speedy, simplicity to learn from the minimum input data; does not need any preliminary assumptions unlike in a conventional modeling process; the behavior of the experimental results are easy to understand from the neuron models; the performance of the predicted ANN model can be improved by defining more levels from the input process parameters. The neural network toolbox in MATLAB is very easy to understand and is used for training and testing the experimental data.

A review on the application of ANN to predict surface roughness in a conventional machining process is elaborated by Zain, et al. [2009]. The usage of ANN for unconventional machining processes is not enough matured based on the available literature and its application for AWJM in particular is very much limited. Reports on prediction of surface roughness [2] and jet speed [3] for a given pressure, abrasive flow rate, and thickness of the target material are available. ANN provides a better method of process parameter estimation based on the selection of most critical and optimal values of the parameters [4]. The reports by Yang et al. [2005] gives the cutting ability for several engineering materials with AWJM technique that can be assessed with ANN based numerical models. The reports on granite machining by Chakravarthy [1997, 2000] gives analysis of the experimental results through empirical modeling and the process parameters optimization through hybrid approach. The use of ANN has been attempted to measure the performance of the abrasive water jet machining process [9]. A review on the use of non-conventional machining processes gives an insight of use of neural networks for abrasive water jet machining [10]. The present paper discusses about the usage of ANN for predicting the micro-channel characteristics by machining at very high traverse rates. The innovative method of the work apart from the accomplished work is considering the force and vibrations of the jet as a part of the control parameters along with the process parameters.

Nomenclature

v	$Traverse\ Speed$
h	$Standoff\ distance$
$\dot{m}_a$	$abraive\ flow\ rate$
d	$abrasive\ diameter$
F	$Impact\ force$
g	$Jet\ vibration$

2. Experimentation

In the present work, micro-channels are fabricated on SS304 material with varying process parameters. The input parameters, ranges and values at the corresponding levels are mentioned in Table 1. The process parameters range is selected based on the machine limiting conditions and the available literature. Considering each parameter at 3-levels, a full factorial experimental set is generated with MINITAB software which leads to 81 (3^4) runs. All the trials are conducted on a SS304 plate using a CNC operated Abrasive Water Jet Machining Center (Model No. OMAX 2626, USA). The schematic of the experimental setup shown in Fig. 1, consists of a force dynamometer on which the test material is fixed which is further mounted on the machine bed. The jet vibrations are measured using an accelerometer having a magnetic base is placed on the flat face of the mixing chamber. Figure 2 shows the plate on which the micro-channels are fabricated. Figure 3 illustrates the schematic of the channel geometry in which measurements are made as per the standard procedures. A typical sectioned geometry of the fabricated channels with # 160 size abrasive is shown in Fig. 4. The partial set of input parameters and the corresponding responses are given in Appendix A. The response parameters targeted in the present work are width, depth, taper and surface roughness. In this work, the impact force and jet vibrations are considered as additional input variables.

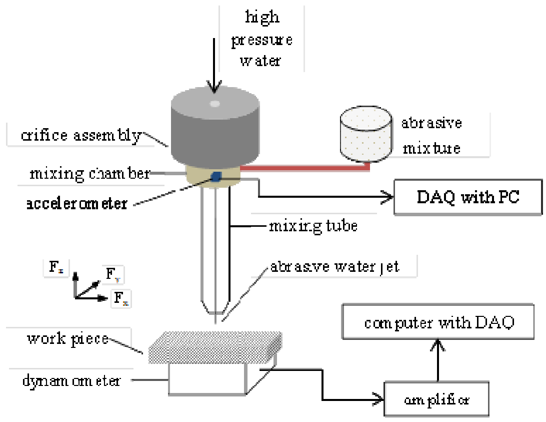

Fig. 1. Schematic of the experimental setup

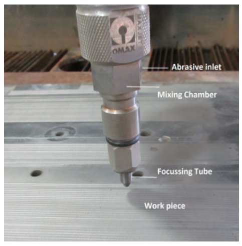

Fig. 2. Experimental setup

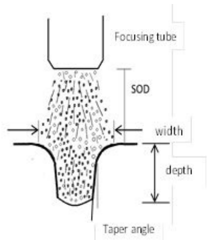

Fig. 3. Channel schematic

Table 1: Range of process parameters

Process parameter	Level 1	Level 2	Level 3
Traverse speed (mm/min)	3000	3500	4000
Abrasive flow rate (kg/min)	0.27	0.38	0.49
Standoff distance (mm)	3	4	5
Abrasive mesh size (#)	80	120	160