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ORIGINAL ARTICLE

Parameter estimation for abrasive water jet machining process using neural networks

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Abstract The abrasive water jet machining process, a material removal process, uses a high velocity jet of water and an abrasive particle mixture. The estimation of appropriate values of the process parameters is an essential step toward an effective process performance. This has led to the development of numerous mathematical and empirical models. However, the complexity of the process confines the use of these models for limited operating conditions; e.g., some of these models are valid for special material combinations while others are based on the selection of only the most critical variables such as pump pressure, traverse rate, abrasive mass flow rate and others that affect the process. Furthermore, these models may not be generalized to other operating conditions. In this respect, a neural network approach has been proposed in this paper. Two neural network approaches, backpropagation and radial basis function networks, are proposed. The results from these two neural network approaches are compared with that from the linear and non-linear regression models. The neural networks provide a better estimation of the parameters for the abrasive water jet machining process.

Keywords Abrasive water jet machining process · Backpropagation network · Neural networks · Radial basis function network

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1 Introduction

High-pressure water jets have been in continuous development since the beginning of the 20th century. Preliminary applications of this technology included washing out valuable materials like gold by excavating the soft gold bearing rocks, industrial machining, and others. Some of the alternate non-traditional machining techniques such as laser machining (LM), electric discharge machining (EDM), electro chemical machining, ultrasonic machining (USM), abrasive water jet machining (AWJM) and others were employed to overcome the limitations of water jets [15]. Amongst all the machining techniques, AWJM has the advantage of achieving the same quality of cut without any micro-cracking and thermal weakening when compared to other processes. The AWJM process can virtually cut through any material (most suited for hard and brittle materials) with a relatively lower machining cost. The key is the abrasive materials that are contained in the jet of water for the process. The major drawback of this process is its low material removal rate, tapering effect, unavoidable flaring of abrasive jets, and embedding of abrasives on the work-piece. These drawbacks have been the driving factors for the continual interest in the research and manufacturing community toward the use of AWJM as an effective machining process.

1.1 The AWJM process

An abrasive water jet is a jet of water that contains some abrasive material. Abrasives are particles of special materials like aluminum oxide, silicon carbide, sodium bicarbonate, dolomite and/or glass beads with varying grain sizes. Usually the water exits a nozzle at a high speed and the abrasive material is injected into the jet stream. This process is sometimes known as entrainment in that the abrasive particles become part of the moving water much as passengers become part of a moving train. The added abrasives drastically increase the range of materials that can be cut with a water jet. Materials like super alloys, ceramics, glass, and refractory material are typically machined by this process. This process aids in achieving higher traverse speeds, machining of thicker materials, and better edge quality.

The use of the abrasive water jet for machining or finishing purposes is based on the principle of erosion of the material upon which the jet hits. Each of the two components of the jet; i.e., the water and the abrasive material, have both a primary purpose and a secondary purpose. It is the primary purpose of the abrasive material within the jet stream to provide the erosive forces. It is the primary purpose of the jet to deliver the abrasive material to the work-piece for the purpose of erosion. However, the jet also accelerates the abrasive material to a speed such that the impact and change in momentum of the abrasive material can aid it in performing its function (secondary purpose). In addition, it is a secondary purpose of the water to carry both the abrasive material and the eroded material clear of the work area so that additional processing can be performed [2]. In one way or another in any machining process the spent material must be gotten out of the way and the water jet provides that mechanism.

The abrasive water jet-cutting process is characterized by a large number of process parameters that determine the efficiency, economy and quality of the entire process. In general, the parameters in the abrasive water-jet cutting process can be divided into four categories [10]:

1. Hydraulic parameters
   - Pump pressure (p)
   - Water-orifice diameter (d_o)
   - Water flow rate (m_w)
2. Mixing and acceleration parameters
   - Focus diameter (d_f)
   - Focus length (l_f)
3. Cutting parameters
   - Traverse rate (v)
   - Number of passes (n_p)
   - Standoff distance (x)
   - Impact angle (ϕ)
4. Abrasive parameters
   - Abrasive mass flow-rate (m_a)
   - Abrasive particle diameter (d_p)
   - Abrasive particle size distribution ($f(d_p)$)
   - Abrasive particle shape
   - Abrasive particle hardness (H_p)

Figure 1 schematically shows the working of the AWJM process along with some of the process parameters, where d_c denotes the depth of cut required on the work-piece material. AWJM has been successful applied to industrial cleaning, surface preparation, rock fragmentation, demolition, manufacturing operations, and rock and soil drilling etc. [10].

2 Process parameter estimation

Determining the optimal process parameters by testing/experimentation is a time consuming and cost ineffective procedure. The knowledge of a mathematical function that relates the cutting parameters to the cutting results is necessary for a computer controlled cutting process. An important aspect is to estimate some of the most crucial output process parameters using the input parameters. One of the critical input parameters is the depth of cut (d_c), which reflects the thickness of the work-piece material to be removed. The important operating variables influencing the depth of cut are pump pressure (p), traverse rate (v), abrasive flow-rate (m_a), grit type and size, and water jet and orifice diameter [12].

A number of semi-empirical equations for estimating the abrasive jet cutting process parameters and its performance have been developed [1, 10]. Some of these models are based on theories related to volume-displacement, energy-conservation, regression and kinetic energy equations.

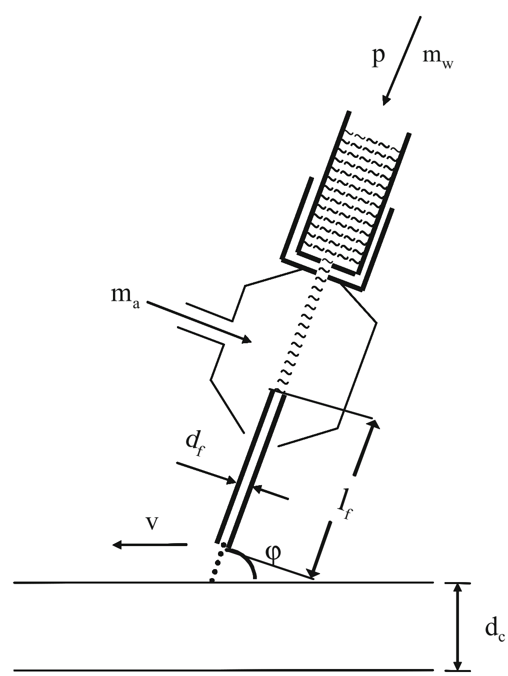

Fig. 1 Schematic drawing of abrasive water jet machining process

Numerical models have also been developed on few occasions for modeling specific aspects of this process. A good discussion regarding some of the models developed for this process is given in [10]. Jain and Jain [5] provide a comprehensive review of analytical material removal models and some semi-empirical/empirical material removal models for different mechanical type advanced machining processes. With a view of developing a knowledge base on building strategies for adaptive control of the AWJM process, Jegaraj and Babu [6] employ a full-factorial experimentation approach. They analyze the effect of changes in the dimensions of orifice and focusing nozzle on depth of cut, material removal rate, cutting efficiency, kerf geometry, and cut surface topography. Based on their experiments they suggest that maintaining the orifice sizes in the range of 0.25–0.3 mm and maintaining the focusing nozzle sizes in the range of 0.76–1.2 mm with the ratio of focusing nozzle size to orifice size in between 3 and 4.5 is required to maintain the quality and efficiency of the machining process. Lemma et al. [8] present a semi-empirical model for predicting the maximum depth of cut in both oscillation and normal AWJ cutting processes. Through an experimental study they show that for ductile materials processing oscillating the nozzle during cutting at relatively small angle and high frequencies of oscillation increases the efficiency of the erosion process.

It should be noted that most of analytical models proposed in the literature are governed by an approximated or estimated behavior of system variables during processing. The number of parameters considered has almost always been restricted to only a manageable few either due to the lack of knowledge of the behavior or limitations of the analytical models. Unfortunately, the process is too complex to neglect the rest of the parameters. These parameters, under certain conditions, may drastically affect the machining process and yield unacceptable outputs. For example, the effect of abrasive particle hardness, particle shape, standoff distance, and impact angle, have not been considered by many of the mathematical or empirical models employed. These parameters may affect the process significantly. To account for all these parameters and possibly other parameters is a difficult task for these models. A comprehensive model, analytical or other types of models, considers most of the significant parameters and sufficiently represents the system is desired.

In this respect, Singh [13] developed an expert system for this process. The expert system takes input variables like intensifier (or pump) ratings, material to be cut, material thickness, cut quality and flow constraints and recommends values for system settings such as pressure, abrasive flow rate and nozzle and focusing tube bore diameters. This system too inherently implements the same analytical models that exhibit the aforesaid inadequacies. Just recently, some effort has been made to use fuzzy control for this application. Fuzzy control has been investigated on two occasions [7, 14] for selecting optimal process parameters. The earlier approach estimates the process parameters such as abrasive mass flow rate, traverse rate and others using an iterative approach based on the given depth of cut. The latter approach predicts the depth of cut achievable with a given set of process parameters via a genetic algorithm and a fuzzy model. The fuzzy rule base was obtained partly through expert knowledge and partly through the knowledge gained from the experimental values of input-output data. Unlike fuzzy control strategies, neural networks are more flexible in incorporating new input or output parameters via online training [18]. Instead of undergoing the rigorous task of devising appropriate membership functions and generating the rule base, it would be straightforward to simply use the input-output data values to formulate a model that represents the abrasive water jet machining process.

The selection of the input and output parameters for this research (see Table 1) was largely based on the studies carried out by Momber & Kovacevic [10], Sitarama & Ramesh Babu [14], and Singh [13]. These studies show that the orifice diameter, the depth of cut, the workpiece-abrasive material, and the combination factor are the critical parameters that govern the material removals in the abrasive water jetting machining process. Unlike the models in Momber & Kovacevic [10], this research uses two additional input parameters; i.e., the workpiece-abrasive material combination factor (F) and the orifice diameter. The workpiece-abrasive material combination factor is defined as the ratio of workpiece machinability number to the abrasive material hardness number (Mohr's scale). The orifice diameter, fixed for a particular nozzle design, is a surrogate variable for the different nozzle heads that the AWJM process employs. The fuzzy models in Sitarama & Ramesh Babu [14] were presented only for a particular workpiece-abrasive combination. A comprehensive strategy that considers all workpiece-abrasive combinations is desired (see Fig. 2).

Table 1 Input and output parameters for AWJM process

Input parameters	Output parameters
Orifice diameter (d_o) in mm	Abrasive mass flow-rate (m_a) in g/s
Depth of cut (d_c) in mm	Focus diameter (d_f) in mm
Workpiece-abrasive material combination factor (F)	Traverse rate (v) in mm
	Pump Pressure (p) in Mpa

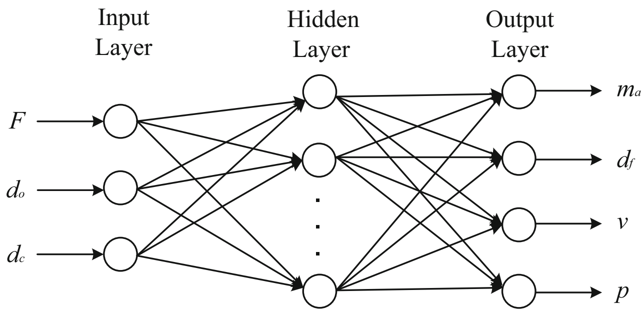

Fig. 2 The neural network strategy

3 Neural network approaches

Neural networks (NNs) are empirical machine learning strategies. It is appealing to a wide range of applications, which include functional approximation, pattern recognition, time series forecasting and others [3]. As a *universal approximator* [4, 11] it can model any nonlinear input-output relationship to any degree of precision, given appropriate network architecture, parameter selection, and sufficient amount of data. This research considers the back propagation network (BPN) and the radial basis function network (RBFN) for estimating the process parameters for the AWJM process. These paradigms were selected because of their successes in function approximation problems in the literature and their universal approximation properties.

The BPN is a supervised learning algorithm. It uses the input-output data to train the internal weights via an iterative process. The weights are adjusted using gradient descent to minimize the error on the network outputs. Some of the design parameters in a BPN include the number of hidden layers, number of hidden neurons in each hidden layer, activation function for each neuron, learning rate, momentum rate, etc. The sigmoid function, $f_{sig}(x) = \frac{1}{1+e^{-x}}$, is typically used as an activation function for the neurons in a BPN.

The training process of a RBFN begins with an unsupervised clustering phase followed by a supervised learning phase using a gradient descent approach [16]. The RBFN performs curve fitting to the input-output data in a high dimensional space [3]. The RBFN is a two-layer network; i.e., a network that has two layers of weights. The RBFN typically employs the Gaussian kernel function, $f_{Gauss}(x) = e^{-\frac{-\|x-\mu\|^2}{\sigma^2}}$, at the hidden layer.

4 Neural network development and result discussions

Seventy-eight input-output data values for three inputs and four outputs, based on an empirical analysis conducted by Momber & Kovacevic [10] on an abrasive water jet machine, were employed in this research. The dataset had five different levels of workpiece-abrasive material combination factor, two different orifice diameters, and various depths of cut. Experiments were conducted to fine-tune the network parameters for the BPN and the RBFN. The final BPN is a 3-4-4 network that has 3 input units, one hidden layer with 4 hidden units, and 4 output units. The BPN used a constant learning rate of 0.1, a momentum term of 0.4, and was trained for 500 epochs. The RBFN is a 3-100-4 network that has 3 input units, 100 radial basis function units in the hidden layer, and 4 output units. The RBFN used a constant learning rate of 0.3, a momentum term of 0.7, and was trained for 300 epochs.

The BPN and the RBFN were validated using a six fold cross validation (SFCV) technique [17]. The SFCV is a computationally expensive validation approach compared to the traditional train-and-test approach. The SFCV allows the construction of the final network using all the available data and validates the final network via multiple validation networks. In this research, the entire dataset of 78 data values was divided into six disjoint sets of 13 data values each. Each validation network was trained on five sets of the data (i.e., 65 data values in total) and tested on the left-out set (13 data values). This procedure was repeated six times such that each of these six sets was *left out* once. The final network, trained on the entire set of 78 data values, is referred to as the application network. The application network is the network that would be ultimately applied to the AWJM process. Table 2 summarizes the validation results of the BPN and the RBFN.

The performance of the two application networks was compared using the percent mean absolute error (PMAE). The PMAE was calculated as the mean absolute error divided by the average of the target values for each of the output parameters. The results indicated that the BPN performed marginally better than the RBFN except for pump pressure. Overall, the average PMAE (averaged error across all four output variables) for the two networks was comparable at 30% approximately. The relatively high PMAE for the networks are perhaps attributed to a few outlier cases in the original dataset. Neural networks often train to the dominant portion of the training data and generally have degraded performance on the outlier cases.

Table 2 The PMAE for validating the BPN and the RBFN

	m_a	d_f	v	p	Average
BPN	17.18	7.73	59.90	30.53	28.84
RBFN	20.39	9.02	66.90	23.49	29.95

4.1 Focused training on outlier cases

The outlier cases in the original dataset were artificially duplicated to increase their share in the training set. Thirty duplicated input-output data values, which consists of outlier cases and data values that the networks failed to provide reasonable outputs, were added to the original 78 input-output data values for the three input and four output variables. Additional network experiments were conducted on this "new" dataset. The network parameters for the BPN and the RBFN remained the same as the two final network architectures that are discussed previously. A SFCV approach (each fold has 18 data values) was used to validate the two networks and the results are provided in Table 3.

Comparing the validation results of the two networks, the RBFN clearly performs better than the BPN with an improvement of a PMAE of 6% across all four outputs. With focused training performed on the RBFN, the PMAE for the four variable estimates (m_a, d_f, v, and p) are 16.69%, 6.98%, 50.06% and 15.08%, respectively. As for the BPN, its performance was not improved with focused training. Further experimentation on the BPN with an increased network complexity (i.e., an increase in the number of hidden neurons and/or the number of hidden layers) hardly made any significant improvement.

5 Statistical regression modeling for AWJM

Two types of regression models were developed to contrast with the neural network approaches. A system of linear regression models and a system of a second order regression models were constructed using the same 108 data values (with focused training in the neural network section). Both systems of regression models were validated using a SFCV approach for the four output variables.

For the linear regression models, each of the four outputs (i.e., abrasive mass flow-rate, focus diameter, traverse rate, and pump pressure) was estimated via a stepwise approach using a linear combination of the input variables (i.e., orifice diameter, depth of cut, and workpiece-abrasive material combination factor). In the case of the second order regression models, six additional non-linear terms; i.e., the squared terms $(F^2, d_o^2, \mathit{and}\, d_c^2)$ and the cross product terms $(F \cdot d_o^2, F \cdot d_c^2, \mathit{and}\, d_o^2 \cdot d_c^2)$ were included for the stepwise approach. All the stepwise regression models were conducted using a significance level of 0.05 for the entering and leaving variables. Table 4 summarizes the performance of the two systems of regression models.

The results indicate that the linear regression models were not able to model the AWJM process well. This clearly reveals the non-linearity in the function that relates the given set of inputs to the outputs. This non-linearity was to some extent captured by the second order regression models. Though the second order regression models marginally perform better than the linear regression models, its performance is inferior to the RBFN trained with focused training.

6 Conclusions and future work

An approach towards estimating the abrasive water jet machining process parameters using neural networks has been proposed. This approach is an outcome of some inadequacies in the existing analytical models and of the simplicity involved compared to the fuzzy control models. Moving one step further from the existing models, the current approach considers the effect of two additional parameters; i.e., the workpiece-abrasive material combination and the orifice diameter as inputs to the system. Two neural networks, BPN and RBFN, were implemented through a series of experiments. The results of both networks were compared with two systems of regression models. The results show that the RBFN trained with focused training can model the AWJM relationship more accurately than the BPN and the regression models. This research demonstrates the potential of this approach for the estimation of the process parameters for the AWJM. The estimation errors could further be improved using a larger set of input-output data values collected by performing a set of controlled experiments during the AWJM process. Furthermore, a separate neural network can be constructed for each of the output parameters. This approach, despite its computational expense, may provide better network performance.

Table 3 The PMAE for validating the BPN and the RBFN with focused training

	m_a	d_f	v	p	Average
BPN	19.50	8.23	57.85	28.50	28.52
RBFN	16.69	6.98	50.06	15.08	22.20

Table 4 The PMAE for validating the linear and 2nd order regression models with focused training

	m_a	d_f	v	p	Average
Linear regression	28.21	8.69	58.00	30.77	31.42
2^{nd} order regression	18.96	9.86	57.12	29.49	28.86

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