MODELING OF ABRASIVE WATER JET MACHINING USING TAGUCHI METHOD AND ARTIFICIAL NEURAL NETWORKS

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Keywords: Abrasive Water Jet Machining (AWJM), Artificial Neural Networks (ANN), Taguchi Method, Surface Quality, Process Parameters.

Abstract: This work presents a hybrid approach based on the Taguchi method and the Artificial Neural Networks (ANNs) for the modeling of surface quality characteristics in Abrasive Water Jet Machining (AWJM). The selected inputs of the ANN model are the thickness of steel sheet, the nozzle diameter, the stand-off distance and the traverse speed. The outputs of the ANN model are the surface quality characteristics, namely the kerf geometry and the surface roughness. The data used to train the ANN model was selected according to the Taguchi's design of experiments. The acquired results indicate that the proposed modelling approach could be effectively used to predict the kerf geometry and the surface roughness in AWJM, thus supporting the decision making during process planning.

1 INTRODUCTION

The AWJM belongs to the non-conventional material removal methods and is used in industry to machine different materials ranging from soft, ductile to hard and brittle materials. This process does not produce dust, thermal defects or fire hazards. It is a good process for shaping composite materials and imparts almost no surface delamination see Momber and Kovacevic, 1997 and Wang and Wong, 1999.

The primary interests in TRIP sheet steel processing are the kerf shape (kerf width and kerf taper) and surface quality (surface roughness of cut), as well as burrs which may be formed at the jet exit (Figure 1). Kerf shape and quality in slotting sheet materials by AWJM and the resulting surface roughness have been studied in recent research works (Gudimetla, 2002; Hascalik, Ulas and Gurun 2007; Jegaraj and Babu, 2007; Valicek et al., 2007).

The innovation of the present work relies on the use of a hybrid modeling approach based on the Taguchi method and the Artificial Neural Networks (ANNs) for the modeling of surface quality characteristics in Abrasive Water Jet Machining (AWJM). The experiments were performed on two transformation induced plasticity (TRIP) steel sheets which were processed using AWJM with three different diameters of the nozzle (nozzle diameter), three different distance values between the nozzle and the sheet steel (stand-off distance) and three different traverse speeds (also known as cutting speed or travel speed). The selected inputs of the ANN model are the thickness of steel sheets, the nozzle diameter, the stand-off distance and the traverse rate (cutting speed). The outputs of the ANN model are the surface quality characteristics, namely the kerf geometry and the surface roughness. The data used to train the ANN model was selected according to the Taguchi's design of experiments (DoE).

2 EXPERIMENTAL SETUP

Details concerning the experimental procedure and the materials are given elsewhere; see Petropoulos et al., 2009 and Vaxevanidis et al., 2010; therefore only the main features are summarized below.

TRIP multi-phase steels belong to a new generation of steel grades exhibiting an enhanced combination of strength and ductility, with extensive

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applications in automotive and aerospace industry; see Olson and Azrin, (1978). The TRIP steels tested are designated as TRIP 800 HR-FH and TRIP 700 CR-FH. Specimens of both materials are of square form (10x10 cm^2) but differ in thickness, hardness and processing method.

Machining was performed on a SIELMAN HELLENIC HYDROJET industrial AWJM system.

In each specimen a slot of 3 cm in length was cut. Each slot corresponds to different machining conditions. After processing, each specimen was separated in order to allow roughness measurements to be performed on the machined surface.

The pressure at which a water jet operates is about 400 MPa, which is sufficient to produce a jet velocity of 900 m/s. Such a high-velocity jet is able to cut materials such as ceramics, composites, rocks, metals etc (Momber and Kovacevic, 1997).

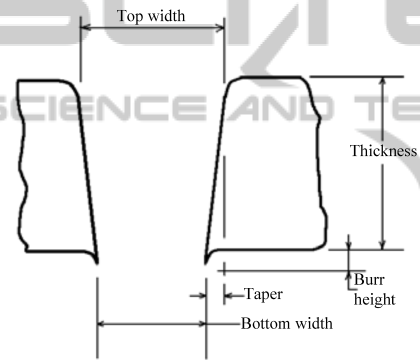

Figure 1: Schematic representation of a typical cut in AWJM.

The standard L_{18} (2^1x3^7) orthogonal design of experiments (DoE) technique was applied (Kechagias, 2007; Kechagias et al., 2010; Pappas et al., 2011). Columns 1, 2, 3, and 4 are assigned to steel sheet thickness (A, mm), nozzle diameter (B, mm), stand-off distance (C, mm), and traverse speed (D, mm/min), respectively. The other columns were left vacant (Table 1).

The measured quality indicators were the arithmetic mean surface roughness (R_a,) and the mean kerf width.

R_a measurements were performed with a Surtronic 3+ stylus profilometer supported by Talyprof® software. The cut-off length selected was 0.8 mm and the measurements were undertaken in the direction of the cut. The parameter values appear as averages of five measurements on each surface at the medium area of the cut.

Table 1: Matrix Experiment.

	Process Parameters							Performance measures	
No of Exp.	A	B	C	D	Vacant			kerf (mm)	R_a (μm)
1	0.9	0.95	20	200				0.978	4.5
2	0.9	0.95	64	300				1.155	6.2
3	0.9	0.95	96	400				1.082	7.1
4	0.9	1.2	20	200				1.351	6.2
5	0.9	1.2	64	300				1.423	7.3
6	0.9	1.2	96	400				1.447	8.8
7	0.9	1.5	20	300				1.464	7.0
8	0.9	1.5	64	400				1.792	8.7
9	0.9	1.5	96	200				1.802	9.1
10	1.25	0.95	20	400				0.858	5.9
11	1.25	0.95	64	200				1.113	6.0
12	1.25	0.95	96	300				0.952	6.3
13	1.25	1.2	20	300				1.176	6.3
14	1.25	1.2	64	400				1.151	6.6
15	1.25	1.2	96	200				1.448	6.9
16	1.25	1.5	20	400				1.385	5.8
17	1.25	1.5	64	200				1.501	6.7
18	1.25	1.5	96	300				1.560	6.8

As it is illustrated in Figure 1 the kerf is of tapered form and to evaluate this characteristic, the semi-sum of the upper area width and the lower area width were measured by a stereoscope (Petropoulos et al., 2009).

3 MODELING FRAMEWORK

An ANN model was constructed that can predict mean kerf diameter and mean surface roughness (R_a), for every possible combination of values for the four studied input parameters, namely the thickness of steel sheet, the nozzle diameter, the stand-off distance and the traverse speed. However, the prediction capability of the model is more efficient while the values of the parameters are inside the valid ranges, which can be extracted from the values summarized in Table 2.

Table 2: Parameter Design.

Process Parameters		Units	Levels		
			1	2	3
A	steel sheet thickness	mm	0.9	1.25	-
B	nozzle diameter	mm	0.95	1.2	1.5
C	stand-off distance	mm	20	64	96
D	traverse speed	mm/min	200	300	600

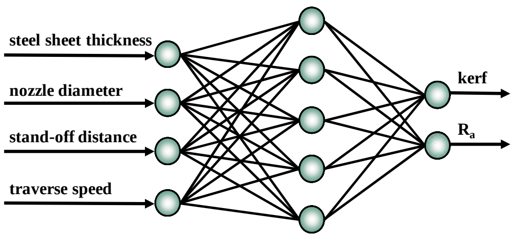

Figure 2: Architecture of the neural network model.

The model was created with the use of the Neural Network Fitting Tool of Matlab®, which is used for data fitting problems (Demuth and Beale, 2001). In fitting problems, neural network is used to map between a data set of numeric inputs (independent variables) and a set of numeric targets (response variables).

A two-layer feed-forward network with five (5) sigmoid hidden neurons and two (2) linear output neurons was used in the frame of this modelling approach. The network was trained with Levenberg-Marquardt backpropagation algorithm. The neural network architecture is presented in Figure 2.

The input data that was fed to the ANN model is an 18x4 matrix, representing eighteen (18) samples (number of experiments) of four (4) elements (steel sheet thickness, nozzle diameter, stand-off distance and traverse speed), while the target data is an 18x2 matrix, representing eighteen (18) samples of two (2) elements (kerf and R_a).

These 18 samples were randomly divided into three subsets, namely the training, the validation and the testing samples. The training subset that uses the 70% of the data (12 samples) is presented to the network during training, and the network is adjusted (define weight factors and bias) according to its error. The validation subset that contains the 15% of the data (3 samples) is used to measure network generalization, and to halt training when generalization stops improving. The testing subset that uses the 15% of the data (3 samples) has no effect on training and so provides an independent measure of network performance during and after training. This subset is used to compare output (simulated data) and target (experimental data).

Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. Mean Squared Error (MSE) is the average squared difference between outputs and targets. Lower values are better. Zero means no error. The MSE of training of the created ANN was equal to 0.0425 and its training took 12 epochs to complete. The best validation performance is 0.10429 at epoch 6.

Regression values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. The regression analysis of the created ANN model resulted to R values for training, validation and testing, which were very close to 1, means a very close relationship between the output (simulated values) and the target (experimental values).

4 MODELING RESULTS

Based on the design variables for AWJM modeling presented in Table 1, the performance measures (surface quality characteristics) are tabulated in Table 3. In the same Table the simulated results obtained by the created ANN model as well as the deviation between experimental (measured) and simulated by ANN values are presented.

The correlation between experimental and simulated data (neural network output) for kerf and R_a is shown in Figure 3 and 4 respectively.

A good correlation between experimental data and simulated data (neural network output) both for kerf and R_a (R^2 close to 0.7) is evident.

Table 3: Experimental and simulated by ANN values of the performance measures (kerf and R_a).

No of Exp	Experimental		Simulated		Deviation	
	kerf (mm)	R_a (μm)	kerf (mm)	R_a (μm)	kerf (mm)	R_a (μm)
1	0.978	4.5	1.231	6.9	0.253	2.4
2	1.155	6.2	0.946	6.0	-0.209	-0.2
3	1.082	7.1	1.035	7.5	-0.047	0.4
4	1.351	6.2	1.155	6.4	-0.196	0.2
5	1.423	7.3	1.391	7.5	-0.032	0.2
6	1.447	8.8	1.485	8.3	0.038	-0.5
7	1.464	7.0	1.525	7.0	0.061	0.0
8	1.792	8.7	1.734	8.8	-0.058	0.1
9	1.802	9.1	1.842	9.0	0.040	-0.1
10	0.858	5.9	1.092	6.4	0.234	0.5
11	1.113	6.0	0.865	5.6	-0.248	-0.4
12	0.952	6.3	1.094	6.4	0.142	0.1
13	1.176	6.3	1.217	6.2	0.041	-0.1
14	1.151	6.6	1.300	6.6	0.149	0.0
15	1.448	6.9	1.223	6.8	-0.225	-0.1
16	1.385	5.8	1.321	5.9	-0.064	0.1
17	1.501	6.7	1.516	6.5	0.015	-0.2
18	1.560	6.8	1.467	7.6	-0.093	0.8

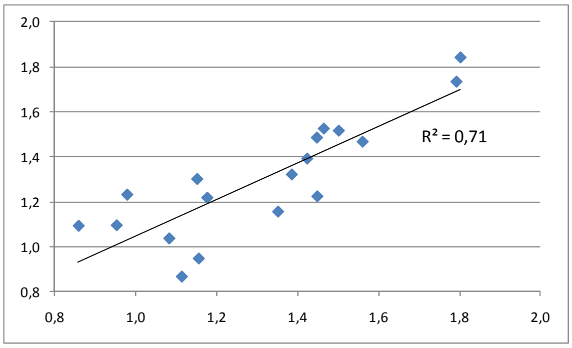

Figure 3: Correlation between experimental data and simulated data (neural network output) for kerf.

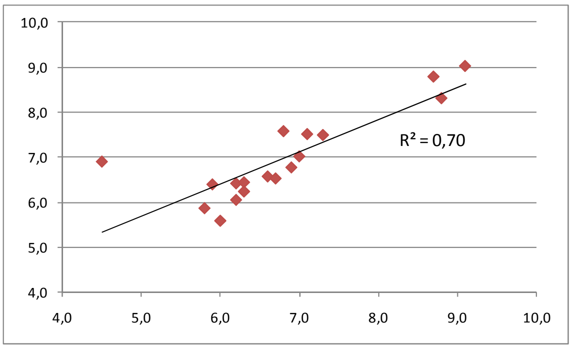

Figure 4: Correlation between experimental data and simulated data (neural network output) for R_a.

5 CONCLUSIONS

The proposed hybrid approach based on Artificial Neural Networks and Taguchi methodology was used for AWJM mean kerf width and surface roughness modelling purpose.

The Taguchi approach was used in order to optimize the experimental effort whitout loosing the prediction accuracy of the ANN model.

The acquired results indicate that the proposed modelling approach could be effectively used to predict the kerf geometry and the surface roughness in AWJM, thus supporting the decision making during process planning.

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