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Experimental Analysis and Soft Computing Modeling of Abrasive Waterjet Milling of Steel Workpieces

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Abstract. Conventional machining processes such as turning, milling and drilling have long been prominent in the metalworking industry but alternative processes which do not require the use of a cutting tool in order to conduct material removal have also been proven to be sufficiently capable of achieving high efficiency in various cases. In particular, Abrasive Waterjet (AWJ) machining can be regarded as a rather appropriate choice for cutting operations, taking into consideration that it involves no heat affected zones, is able to process all material types and create a variety of complex features with success. In the present work, a comprehensive study on the effect of four process parameters, namely jet traverse speed, stand-off distance, abrasive mass flow rate and jet pressure on the width and depth of machined slots on a steel workpiece is conducted. The results are first analyzed with statistical methods in order to determine the effect and the relative importance of each parameter on the produced width and depth of the slots. Finally, these results are used to develop soft computing predictive models based on Artificial Neural Networks (ANN), which can efficiently relate the process parameters with its outcome.

1 Introduction

Abrasive Water Jet (AWJ) machining is an unconventional process used for material removal, as an alternative to traditional cutting methods. High-pressure water-abrasive cutting technology is commonly termed as cold, due to its association with the absence of a heat-affected zone on the workpiece. Although this method is used for cutting through the materials, researchers are also trying to establish the right combination of the jet pressure

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(P), stand-off distance (h), traverse speed (v_t) and the abrasive mass flow rate (m_a) in order to achieve the desired depth, when cutting is not performed through the entire workpiece. If the depth of the cut is uniform and controlled, then this process is known as AWJ Milling.

Goutham et al. [1] tried to establish a monitoring system for AWJ milling using acoustic emissions and cutting forces during a controlled depth cutting of pockets. They found that the depth of cut and the Material Removal Rate (MRR) increase as the jet pressure increases and decrease as v_t and h increases. Pal and Tandon [2] conducted a similar experiment by AWJ machining of blind pockets on different materials, including stainless steel 304 and tool steel M2 Rc 20. They investigated the milling depth, materials characteristics, surface roughness and the milling time during controlled depth milling. The experiments showed that there is a non-linear correlation between milling time and milling depth. Also, the machinability of each material influences significantly the milling time of pockets of the same depth. Akkurt et al. [3] machined AISI 1030 steel and AISI 304 stainless steel, among other materials, in order to evaluate the influence of v_t and the workpiece thickness on surface roughness. The experimental results explained that the "cutting wear" mechanism results in better surface quality than the "deformation wear" mechanism. Moreover, surface roughness was higher for the 5mm specimens than in the 20mm specimens for the steel-based materials; that could be explained as high strength materials require higher cutting forces and thus deformation is higher for the workpieces with thinner cross section. For the same stainless steel, Yuvaraj, Pavithra, and Shamli [4] carried out experiments in order to achieve surface patterns through the controlled milling. In this experimental study, a multicriteria technique was used to evaluate the effect of input parameters, namely jet pressure, traverse speed, stand-off distance and abrasive flow rate in the process. The results showed that based on selected parameters the surface morphology on stainless steel implants would be able to be predicted. On the other hand, in their investigation, Hlaváč et al. [5] tried to investigate the characteristic phenomena of the taper inside the cut during AWJ milling. This experimental research was performed also to examine the influence of brittle/ ductile behavior during liquid nitrogen cooling on plates of various steel types with thickness close to 30mm. The results were compared with the theoretical relation between the traverse speed and taper angle and difference between the inlet and outlet width of kerf up to 35.4% and 44.9% was found at lower and higher traverse speed values, respectively.

Yuvaraj and Pradeep Kumar [6, 7] have studied the AWJ cutting of AISI D2 steel by different abrasive mesh sizes and different jet impingement angles. Grey Relationship Analysis and Analysis of Variance (ANOVA) test was performed in order to determine the influencing parameters such as pressure, jet angle and mesh size on the different response parameters, namely, the MRR, taper angle, taper ratio, surface quality and the penetration depth. The results of the aforementioned tests revealed that there was an improvement during the AWJ cutting by setting the jet angle at 70^o, jet pressure at 225MPa and by using the #100 abrasive mesh size. Finally, the purpose of the investigation of Ankush and Lalwani [8] was to explore the machinability of AISI H13 die steel by using AWJ. An ANOVA test for the surface roughness revealed that, the traverse speed is the most significant factor with contribution almost 77%, followed by the jet pressure and the stand-off distance in order to achieve smoother surfaces.

In the present work, a comprehensive experimental study on AWJ milling of steel is conducted in respect to four major process parameters, namely jet pressure, traverse speed, abrasive mass flow rate and stand-off distance in order to determine their effect on depth of penetration and kerf width. For these parameters, a relatively wide range of values is employed and after statistical analysis is conducted on the experimental outcome, Artificial Neural Network (ANN) models are developed in order to effectively establish the correlation between input parameters and responses of the AWJ milling process.

2 Methodology

AWJ milling experiments were performed on a low carbon S355 steel workpiece under three different levels of traverse speed, abrasive mass flow rate, stand-off distance and jet pressure. In each case, a straight, non-through slot was created with its depth (d) and width (w) considerably varying according to the process conditions. The experiments were designed according to Taguchi L9 orthogonal array for traverse speed, abrasive mass flow rate and stand-off distance, with each sequence of experiments repeated for three different jet pressure values; the levels for each process parameter are presented in Table 1.

Table 1. Process parameters levels.

Parameter	Level 1	Level 2	Level 3
Traverse speed (mm/min)	100	300	500
Abrasive mass flow rate (g/s)	2	5	8
Stand-off distance (mm)	1	3	5
Jet pressure (MPa)	233	317	400

The AWJ milling experiments were carried out on a H.G. RIDDER – Automatisierungs GmbH model HWE-1520 machine with 80 mesh size garnet as abrasive. In any case, the jet impingement angle was 90^0, perpendicular to the workpiece surface, focusing tube diameter was 1 mm and waterjet nozzle diameter was 0.3 mm. After the experiments were carried out, depth of penetration and kerf width were measured based on high resolution images captured on an optical microscope which were subsequently processed by ImageJ software.

The neural networks used in the present study are multi-layer perceptron (MLP) models with a single hidden layer. Two different neural network models will be created by using data from the 27 experiments, one regarding depth of penetration and one for the kerf width with different input parameters and their evaluation will be performed based on Mean Squared Error (MSE) values.

3 Results and Discussion

In order to determine the influence of process parameters to the depth of penetration and kerf width, statistical analysis of the experimental results is necessary. In Fig. 1, the main effects plot for the depth of penetration is depicted. Fig.1 reveals that a considerable drop in depth occurs when traverse speed increases, whereas an increase of abrasive mass flow rate and jet pressure leads clearly to higher depth. These trends are anticipated as the abrasive flow rate and jet pressure affect the kinetic energy of the jet [9], thus creating deeper slots at high values, whereas higher traverse speed leads to shorter time for the jet to remove material from the workpiece at a certain region. Moreover, from these graphs it can be observed that traverse speed, abrasive mass flow rate and jet pressure lead to the highest variation of depth of penetration values, whereas stand-off distance seems to have only a small effect on depth. The observations regarding the influence of each process parameter on depth are confirmed by ANOVA results, as it was found that the relative importance of v_t, m_a, h and P were 53.1%, 23.9%, 3.4% and 13.6%, respectively. All process parameters except for stand-off distance were found statistically important, indicating that they can be used to effectively regulate the depth of penetration during AWJ milling.

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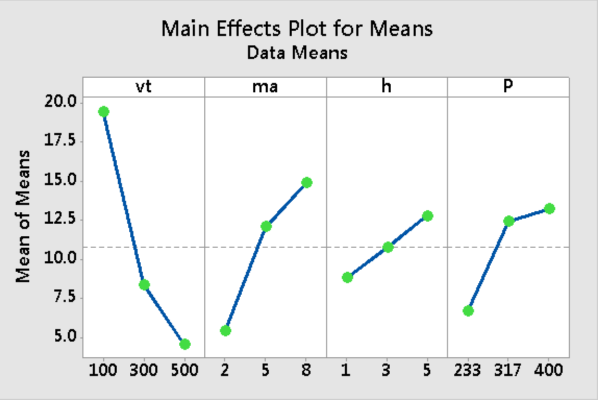

Fig. 1. Main effects plot for depth of penetration.

In Fig.2, the main effects plot for kerf width is presented, in which stand-off distance is shown to have the most noticeable impact on kerf width, clearly increasing it with increasing values. Kerf width is also positively affected by abrasive flow rate, negatively affected by traverse speed and a small positive effect is caused by the jet pressure. Higher stand-off distances lead to a larger divergence of the jet above the workpiece [9] and larger dispersion of the abrasive particles, which remove material at larger distances. Moreover, higher abrasive mass flow rate leads to more intense impact of the particles with the surface and higher traverse speed does not allow for widening of the slot due to shorter time of impact of the jet with the workpiece surface [10]. ANOVA results again confirm the observations on Fig.2, as stand-off distance is proven to be most important factor with 56.8% relative importance, whereas traverse speed and abrasive mass flow rate follow with 20.1% and 14.6%, respectively. For the selected range of jet pressure values, this parameter is considered statistically not important for kerf width with a relative importance of 1.13%.

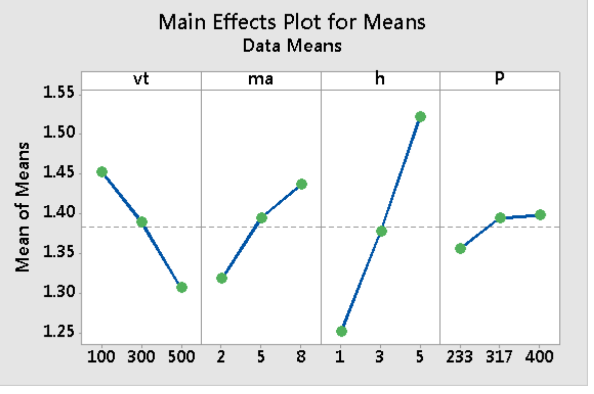

Fig. 2. Main effects plot for kerf width.

After the experimental results were analyzed with statistical methods, soft computing models using Artificial Neural Networks are developed in order to predict depth of penetration and kerf width in respect to process parameters. ANN were selected, as they have been proven to be capable to predict the outcome of even highly non-linear processes with high accuracy compared to other traditional methods, such as regression models. As the depth of penetration is not fixed during AWJ milling, it is important to be able to predict it for any desired combination of process parameters. Furthermore, kerf width considerably higher than the desired value is a defect of the AWJ milling process and it is crucial to select process conditions that lead to acceptable values of kerf width.

Different MLP models will be developed for each response and in each model only the statistically significant parameters are employed, as depicted in Fig.3a and b. Given the amount of available data pairs and number of input and output neurons, the number of the neurons in the hidden layer will be varied between 2 and 8. Each network will be tested 50 times and the optimum network architecture will be determined according to MSE values during training and test procedures.

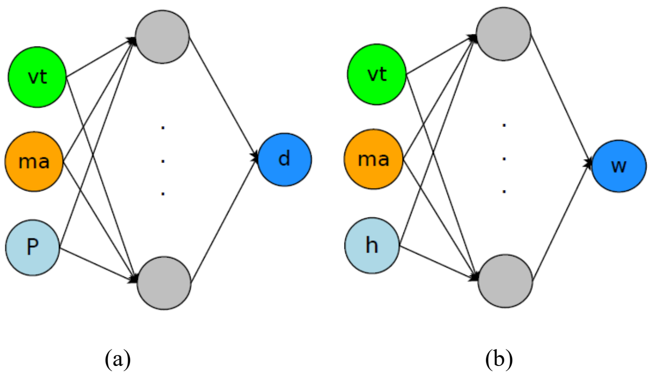

Fig. 3. Schematic of ANN models for (a) depth of penetration, (b) kerf width.

In the case of depth of penetration model, the values of MSE for each model during test procedure are depicted in Fig. 4a. Usually during the development of an ANN model, training can lead to overfitting, especially when an unnecessary large number of hidden neurons is employed, which causes a lack of generalization abilities, something that can be evaluated during test procedure. Thus, from the results of Fig. 4a, it becomes obvious that the network with 5 hidden neurons is the best performing one as it has the lowest MSE test value of 1.26×10^{-4} and at the same time, it has a sufficiently low MSE train value of 7.35×10^{-5}. In the case of kerf width model, the MSE test values for each employed network are displayed in Fig. 4b. The results of Fig. 4b indicate that the model with 6 hidden neurons is the most suitable in this case as it exhibits the lowest MSE test value of 1.52×10^{-4} and its training performance is also acceptable with MSE value of 1.63×10^{-4}. Thus, it was proven that in both cases, involving highly non-linear correlations, the ANN models which were selected exhibited sufficient accuracy and generalization capabilities.

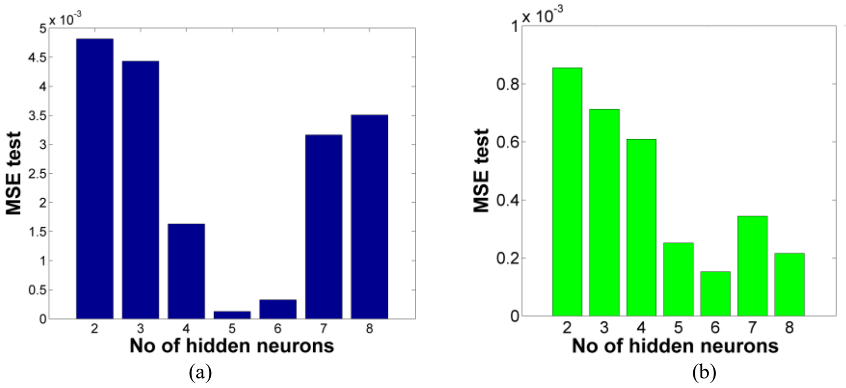

Fig. 4. MSE test values for different ANN models regarding: (a) depth of penetration, (b) kerf width.

4 Conclusions

In the present work, the effect of process parameters during AWJ milling of steel was investigated through experiments and statistical analysis, whereas the correlation between process parameters and its outcome, namely depth of penetration and kerf width was established by the use of artificial neural network models. From this work, various conclusions were drawn.

At first, the contribution of different parameters on depth of penetration was determined. Traverse speed was identified as the dominant factor, with a relative importance of over 50%, followed by abrasive mass flow rate and jet pressure. Depth of penetration can be increased with lower traverse speed values, as it leads to a longer interaction time between jet and workpiece; also, increased abrasive mass flow rate and jet pressure lead to higher depth as the jet impacts the workpiece with higher kinetic energy.

Then, the effect of process parameters on kerf width was investigated. In this case, the stand-off distance was shown to play a major role, whereas traverse speed and abrasive mass flow rate followed. The reduction of kerf width was shown to be achieved at lower stand-off distance, higher traverse speed and lower abrasive mass flow rate values.

Finally, ANN models were developed in order to establish the correlation between process parameters and the two responses of the experiment. After an investigation regarding the number of hidden neurons in the ANN models was carried out, the best performing models, exhibiting both high accuracy and generalization capability, for depth of penetration and kerf width prediction were determined, having 6 and 5 neurons, respectively, in a single hidden layer.

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