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Optimization of Process Parameters for Machining Marble using Abrasive Water Jet Machining through Multi Response Techniques

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Abstract

Objective: Abrasive water jet machining is a most popular non-Traditional machining technique used for machining a wide range of hard-to-cut materials and complex geometric shapes. This technique is very much preferred for machining thermally sensitive materials. In the present study, Optimization of machining parameters such as water pressure, stand-off distance (SOD) and quality of cut by were carried out by considering multiple performance characteristics such as high MRR, good surface finish (Ra) and minimum kerf Angle (K_a). **Methods:** The experiments were designed using Taguchi's Design of experiments and carried out on Marble for each combination of (L_9) orthogonal array. The optimal combinations of machining parameters were obtained using Taguchi Weightage method and principal component analysis. **Findings:** The analysis of the Taguchi method reveals that, MRR is significantly affected by stand-off distance while, surface roughness is affected by Abrasive flow rate. **Improvements:** Experimental results have shown that the output parameters have been improved using this approach.

Keywords: Abrasive Water Jet Machining, Principal Component Analysis, Taguchi's Method, Weightage Method

1. Introduction

Abrasive water jet machining is non-traditional machining process which is used for processing hard brittle materials such as Hardened metals, ceramics, and glass. Softer materials such as foam and rubbers can also be processed using this technique. A high velocity jet generated through the conversion of pressure energy present in the high pressure water into its kinetic energy along with abrasive particles is used for machining purpose. In the mixing chamber a high speed abrasive water jet is formed by suspending the abrasives through the high velocity water jet. A nozzle is used to direct the high velocity abrasive water jet onto the target in a controlled manner. The material removal occurs through combined micro-cutting action along with brittle fracture of the work material. During the course of the experimentation process the standoff distance and the impingement angle can be set desirably.

AWJM is considered to be a flexible technique in the aspect that it can be used to machine a wide range of materials such as Aluminium[3], AL-6351[5], AL 7075[7], Aluminium 6061 Alloy[11], Stainless Steel[6,9], SS304[2], Mild Steel[4], EN8[8], Copper Iron Alloy[10] and Lead Tin Alloy[10]. From commercial point of view this technique is also used to cut ceramics such as Granite, Marble etc.

Taguchi method is simple, systematic, and efficient methodology[1] for optimizing the process parameters of

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AWJM. In most of the cases parameters such as pressure, stand-off distance, transverse rate and abrasive flow rate were considered as the input variables[2-11]. These variables are varied based on the experimental design in order to achieve optimum material removal and surface finish[2-11].

The experimental results can be validated using ANNOVA[1-11] and future predictions regarding optimal process parameters can be done using Response Surface Methodology (RSM)[9], Regression Model[6], Artificial Neural Networks[10], and Adaptive Neuro Fuzzy Inference System[11].

From the past literatures it is evident that Material Removal Rate (MRR) is significantly affected by abrasive jet pressure[2] and Stand – off distance[2]. Surface roughness depends on Grain size[1,7,8] and Transverse speed[3-5,8].

Based on literature and increased usage of ceramics, in this paper an attempt has been made to optimize the key parameter for machining marble.

2. Experimental Work

2.1 Material

Through literature it was observed that many explorations are being carried out to assess the cutting performances of abrasive water jets for different kinds of materials such as steel, brass, aluminium, inconel and granite. Marble which is used in various architectural applications has led to investigation of various machining and processing technologies to improve the productivity and to reduce the costs.

The AWJM used in this research is OMAX water jet systems. The dimension of work piece is 300 mm x 300 mm x 6mm. The OMAX water jet system uses pneumatic system to control its motion axis.

Table 1. gives the specifications of AWJM used for experimentation purpose.

Table 1. Specification of AWJM

PARAMETERS	RANGE
Max. Pressure	3800 bar
Min. Pressure	1800 bar
Stand Off Distance	1.5mm
Quality of Cut	Q1 to Q5
Max. Power	30hp Direct Drive
Max. Transverse Speed	9m/min
Accuracy	±0.025
Repeatability	0.05
X Y Travel	1575mm X 1575mm
Table Size	2337mm X 2752mm
Orifice Diameter	0.35mm

The constant machining parameters that were used are as in Table 2.

Table 2. Constant machining parameters

PARAMETERS	RANGE
Abrasive type	Garnet
Abrasive size	80 Grit size
Orifice diameter	0.35mm
Material & Thickness	Marble of 6mm

Input parameters (abrasive water jet pressure, quality of cut and stand-off distance) at three levels used for experimentation are shown in Table 3.

Table 3. Process control parameters and levels

S. No.	PARAMETER	LEVEL 1	LEVEL 2	LEVEL 3
1	Pressure (MPa)	140	170	200
2	Quality of cut	Q3	Q4	Q5
3	Stand-off distance (mm)	1.5	2.5	3.5

The initial parameters as per the TOA settings were: Water jet pressure–100MPa, Quality of cut-3, and Stand-off distance-1.5 mm.

For each experimental trial, the process parameters as given by orthogonal array were set. The total degree of freedom (dof) which is used in selecting an appropriate TOA for experiments is computed as follows.

dof = [(N - 1) for each process parameter + $(N - 1)^2$ for each interaction + 1], Where N → Number of levels

Thus, dof = (3-1) *3 +1 = 7 (Assuming no interaction).

Hence, a standard L9 OA is obtained and used for carrying out present experimental work. The L9 OA is as shown in Table 4.

Analysis of the experimental data (Table 5) of the selected material reveals that the three basic parameters, i.e., pressure, stand-off distance and quality of cut have significant impact on surface roughness (Ra), material removal rate and Kerf Angle (Ka). The effects of each of these parameters were studied while keeping the other parameters as constants. Surface roughness and Kerf Angle were measured using surfcoder and vision measuring system.

Table 4. L9 orthogonal array

WATER PRESSURE	QUALITY OF CUT	SOD
A	**B**	**C**
140	Q3	1.5
140	Q4	2.5
140	Q5	3.5
170	Q3	2.5
170	Q4	3.5
170	Q5	1.5
200	Q3	3.5
200	Q4	1.5
200	Q5	2.5

Table 5. Output responses for L9OA

A	B	C	MRR(g/s)	Ra(µm)	Ka(degree)
140	Q3	1.5	8.103836	4.642	0.751167
140	Q4	2.5	6.167907	3.288	0.794833
140	Q5	3.5	5.521818	3.717	0.931167
170	Q3	2.5	7.676633	5.268	0.981667
170	Q4	3.5	5.212639	3.877	0.962333
170	Q5	1.5	3.439654	6.618	0.890333
200	Q3	3.5	5.066533	4.111	1.053333
200	Q4	1.5	2.745013	5.548	0.851167
200	Q5	2.5	1.873413	6.786	0.869333

2.2 Signal-to-Noise (S/N) Ratio

The S/N ratio articulates the deviation of the output from the required value. In general, larger-the-better, nominal-the-better and smaller-the-better characteristics are used to find the deviation.

$$\frac{S}{N} = -10\log\left(\frac{1}{n} x \sum \frac{1}{y^2}\right)$$

$$\frac{S}{N} = -10\log\left(\frac{y^2}{s^2}\right)$$

$$\frac{S}{N} = -10\log\left(\frac{1}{n} x \sum y^2\right)$$

Where y is average of output data, y^2 is variance of output data, and n is number of observations.

In the present design, as we intend to maximize MRR we use larger-the-better category for it and smaller-the-better condition is used for both surface roughness and Kerf Angle as the aim is to minimize both of them. Table 6 gives signal to noise ratio for output responses.

Table 6. S/N ratio for output responses

MRR- Larger the better	Ra- Smaller the better	Ka-Smaller the better
18.17381	-13.3341	2.4853
15.80276	-10.3386	1.9945
14.84164	-11.4039	0.6194
17.70342	-14.4329	0.1607
14.34115	-11.7699	0.3335
10.7303	-16.4145	1.0090
14.09422	-12.2789	-0.4513
8.770887	-14.8827	1.3997
5.452672	-16.6323	1.2163

3. Taguchi Multi Response Method

Taguchi method is not suitable enough to be used as such to optimize the multi-response problems. Most of the literature published on Taguchi method application deals with single response. In multi response problems if we try to determine optimum levels for the factors based on one response at a time, we may get different set of optimality for other responses. Generally in order to avoid this, the multi – responses are combined into single response from which we can conclude the optimal parameters. In this attempt for such a conversion, assignment of weights and principal component methods were used to find the optimum parameters.

3.1 Assignment of Weights

Each of the output response is assigned a weightage values, say W1 be the weightage value assigned to the first response R1 and W2 be the weightage value assigned to the second response R2 and so on. The multi response is converted into single response known as multi response performance index (W), where

W = W1 + W2

The multi response problem is solved as a single response problem using MRPI. In the multi response problem, each response can be original observed data or its transformation such as S/N ratio. MRPI Table for Marble is shown in Table 7

Table 7. Determination of MRPI

S. No.	W_{MRR}	W_{Ra}	W_{Ka}	MRPI
1	0.176911	0.109988	0.131561	2.043046
2	0.134649	0.155305	0.067293	1.411544
3	0.120544	0.137381	0.069059	1.246667
4	0.167585	0.096933	0.166711	1.867532
5	0.113795	0.131711	0.131114	1.174215
6	0.075089	0.07716	0.087099	0.839326
7	0.110605	0.124214	0.165215	1.141429
8	0.059925	0.092041	0.10393	0.74554
9	0.040898	0.07525	0.081873	0.657663

3.2 Principal Component Analysis

Principal Component Analysis (PCA) uses complicated fundamental mathematical concepts to transform a number of correlated variables into a smaller number of variables called principal components.

The principal component analysis (PCA) is an effective statistical tool that selects a small number of components to account for the variance of original multi-responses. The response factors are ranked based on the weightage of their contribution to the total variance.

The stepwise procedure of PCA is as follows:

- The S/N ratio of each quality response obtained from TM is normalized using:

$$x_i^*(k) = \frac{x_i(k) - \min(x_i(k))}{\max[(x]_i(k)) - \min[(x]_i(k))}$$

Where $x_i^*(k)$ is the normalized S/N ratio for *k*th quality response in *i*th experiment, $x_i(k)$ is the S/N ratio for the *k*th quality response in the *i*th experiment, i min(x (k)) is the minimum and i max(x (k)) is the maximum of S/N ratios for the *k*th quality response in all the experiment.

The normalized multi-response array for m quality response and n experiments can be represented by matrix x* is shown below.

$$x^* = \begin{pmatrix} x_1^*(1) & x_1^*(2) & x_1^*(3) & \dots & x_1^*(m) \\ x_2^*(1) & x_2^*(2) & x_2^*(3) & \dots & x_2^*(m) \\ \dots & \dots & \dots & \dots & \dots \\ x_n^*(1) & x_n^*(2) & x_n^*(3) & \dots & x_n^*(m) \end{pmatrix}$$

- The correlation coefficient array (R_{jk}) corresponding to matrix x* is computed as follows.

$$R_j ji = (\mathrm{cov}(x_j i^{T*}(k), x_j i^{T*}(1)))/((_j(x_j i^{T*}(k)) \times (_j(x_j i^{T*}(1)))$$

Where, k =1, 2..., m., i =1, 2......,m.

- The eigen values and eigen vectors of matrix Rki are computed as follows.

$[R - ë(q)I_m)]V_q(q) = 0$

Where, ë (q) is the *q*th eigen value and $V_q(q) = [V_{q1}, V_{q2}, \ldots, V_{qn}]^T$ are the eigen vectors corresponding to the eigen value ë (q).

- The principal component (PC) is computed as follows.

$$\widehat{pc_i}(q) = \sum_{k=1}^{n} x_i^*(j) \times V_q(k)$$

Where, $pc_i(q)$ is the *q*th PC corresponding to the *k*th experimental run.

- The total principal component index (p_i) corresponding to the *k*th experiment is computed as follows and given in the Table 8.

$$\widehat{p_i} = \sum_{q=1}^{m} p_i(q) \times \lambda_i(q)$$

$$\lambda_i(q) = \frac{\lambda(q)}{\sum_{q=1}^{m} \lambda(q)}$$

Table 8. Determination of TPCI

PC1	PC2	PC3	TPCI
1.263708	−0.40681	−0.1044	0.7525
1.207283	0.449443	0.049361	1.706087
1.056483	0.345616	0.00873	1.41083
1.219374	−0.74639	−0.07462	0.398366
1.210568	−0.29738	0.26787	1.181061
0.407899	−0.25024	−0.15869	−0.00104
1.225109	−0.55816	0.328195	0.995146
0.508729	−0.29461	0.171078	0.385195
0.066859	−0.18858	0.081841	−0.03988

The TPCI for each output response is used to determine the average factor effect at each level. The parameter levels corresponding to the maximum TPCI value are also found out.

4. Results and Discussions

MRPI is obtained from assignment of weights. Analysis of variance for MRPI is given in the Table 9 and Figure 1 gives effect of Process parameters on MPRI.

Table 9. ANOVA for MRPI

Factor	DF	Adj SS	Adj MS	F-Value	P-Value	PC(%)
Pressure	2	0.77141	0.38570	16.33	0.058	43.31
Quality of cut	2	0.93420	0.46710	19.78	0.048	52.45
SOD	2	0.02836	0.01418	0.60	0.625	1.59
Error	2	0.04723	0.02361	-	-	2.65
Total	8	1.78120	-	-	-	100

Table 10. ANOVA for TPCI

Factor	DF	Adj SS	Adj MS	F-Value	P-Value	PC (%)
Pressue	2	1.3001	0.65006	11.74	0.078	42.75
Quality of cut	2	0.6100	0.30501	5.51	0.154	20.06
SOD	2	1.0204	0.51018	9.21	0.098	33.55
Error	2	0.1107	0.05537	-	-	3.64
Total	8	3.0413	-	-	-	100

From Assignment of Weights the optimized response for maximized MRR, minimized SR and Kerf Angle is A1B1C2.

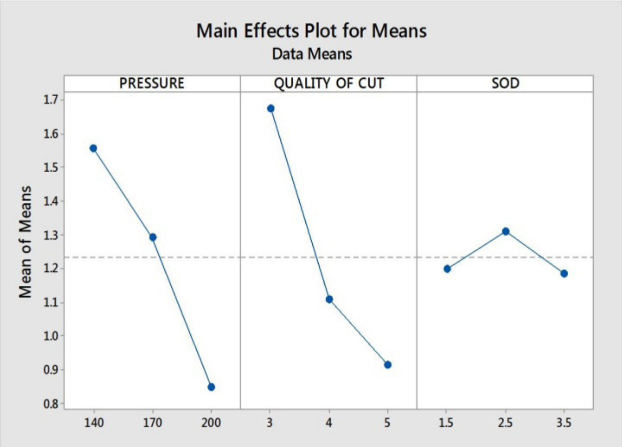

Figure 1. Effect of Process Parameters on MRPI.

TPCI is obtained from principal component analysis and analysis of variance for TPCI is given in the Table 10.

Table 11. Confirmation test

Technique	MRR(g/s)	R_a(µm)	K_a(degree)
Initial settings	8.103836	4.642	0.751167
Assignment of weights	8.60674	3.92444	0.704352
PCA	8.39394	2.27611	0.676008

Figure 2 gives effect of Process parameters on TPCI. From Principal component analysis, the optimized response for Maximized MRR, Minimized SR and Kerf Angle is A1B2C3.

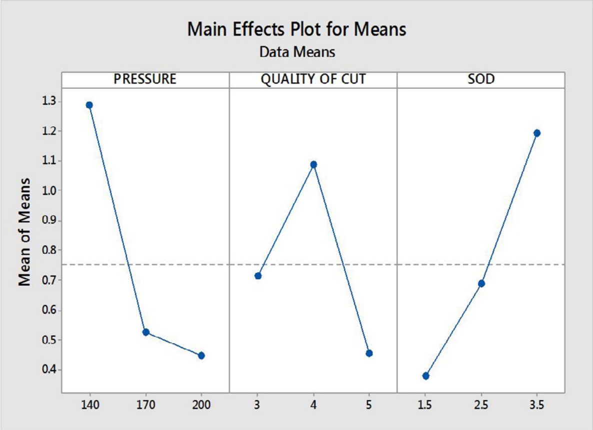

Figure 2. Effect of Process Parameters on TPCI.

The confirmation test is carried out and result obtained for responses are shown in the Table 11.

5. Conclusion

Based on the experimental analysis the following were concluded.

i. The most significant control factors on MRPI were quality of cut and pressure. Standoff distance has lesser impact on MRPI. Hence based on MRPI the recommended combination of parameter for optimal material removal and surface roughness is A1B1C2.

ii. The most significant control factors on TPCI were quality of cut and pressure. Standoff distance has lesser impact on MRPI. Hence based on TPCI the recommended parametric combination for optimal material removal and surface roughness is A1B2C3.

iii. With increase in quality of cut the MRR decreases and surface roughness increases. This is because the quality of cut has inverse impact on transverse feed rate. So the optimum value for MRR, SR and kerf angle is normalized by multi response method.

iv. From the confirmation test it is evident that MRR, surface roughness and kerf has been improved by 6.2%, 15.45% and 6.23% by assignment of weight and 3.58%, 50.96% and 10.01% by PCA.

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