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Research Article

STUDY OF OPTIMIZATION OF ABRASIVE WATER JET MACHINING PROCESS USING HYBRID MULTI RESPONSE TECHNIQUES

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ABSTRACT
Abrasive water jet (AWJ) is used for machining of hard and brittle materials like Glass, Granite, Marble, Ceramics, etc. However, the poor quality surfaces obtained at the jet exit side require post processing operations. Therefore, optimum selection of process parameters is important for economic and superior quality AWJ machining. The objective this paper is to optimize the parameters of Abrasive Water Jet machining process using Taguchi multi response method (Weightage Method and Principal Component Analysis) and Response surface Methodology and comparison of the results obtained by these methods. The three techniques were applied to optimize the process parameters like Transverse speed, Abrasive flow rate, Standoff distance of Abrasive Water Jet machine. The comparison of the results for MRR and Surface Roughness proposed by this technique is presented. These Optimized techniques were done using the data taken from literature.

Keywords: *Abrasive Jet Machining, Taguchi Method, Weightage Method, Principal Component Analysis, Response Surface Methodology*

INTRODUCTION
Water jet (WJM) and abrasive water jet machining (AWJM) technology has been found to be one of the most recent developed and fastest growing advanced non-traditional machining processes used in industry for material processing with the distinct advantages of no thermal distortion, high machining versatility, high flexibility and small cutting forces. It is used in a wide range of industries from automotive and aerospace to medical and the food industries. Current applications include stripping and cutting of fish, cutting of car carpets, removal of coatings from engine components, to cutting of composite fuselages for aircraft construction. The impact of the water alone is enough to machine a material, however, with the addition of abrasive, the material removal rate in the process is several orders of magnitude higher. However, AWJM has some limitations and drawbacks. It may generate loud noise and a messy working environment.

It may also create tapered edges on the kerf, especially when cutting at high traverse rates. AWJM is complicated dynamical and stochastic process with incomplete information about mechanism and side effects character. It's complicated appearance in large amount and parameters multiform determining process behaviour in large number of relations among parameters, and their interactions. Their complicacy its incomplete knowledge functioning mechanisms and large amount of factors entering to the process (Parmar *et al.*, 2014). Laser Cutting is generally economical for cutting Inconel 800H sheets up to 3mm thick and beyond 3mm thick abrasive water jet machining is often used. On the other hand, AJWM is preferred over laser cutting because of its capacity to machine the components with least slot width (Reddy *et al.*, 2014).

Nagdeve *et al.*, (2008) applied Taguchi method to find optimum process parameter for Abrasive water jet machining (AWJM). Experimental investigation were conducted to assess the influence of abrasive water jet machining (AWJM) process parameters on MRR and surface Roughness (Ra) of aluminium. Experiments are carried out using (L9) orthogonal array by varying pressure, standoff distance, Abrasive flow rate and Traverse rate respectively. Pressure is the most significant factor on MRR during AWJM. Meanwhile standoff distance, Abrasive flow rate and Traverse rate are sub significant in influencing (Badgujar and Rathi, 2014).

Badgujar and Rathi, (2006) optimized the input parameters of AWJM, such as pressure within pumping system, abrasive material grain size, stand-off distance, nozzle speed and abrasive mass flow rate for machining SS304.
The Taguchi design of experiment, the signal-to-noise ratio, and analysis of variance are employed to analyze the effect of the input parameters by adopting L27 Taguchi orthogonal array (OA). It is found that the parameter design of the Taguchi method provides a simple, systematic, and efficient methodology for the optimization of the cutting parameters (Selvan and Raju, 2011).
Reddy *et al.*, (2014) studied the effect on inconel. Because of its poor machinability to process it, among nontraditional processes abrasive water jet machining is commonly used.
The approach used is based on the analysis of variance and signal to noise ratio (SN Ratio) to optimize the AWJM process parameters for effective Material Removal Rate (MRR) and Surface Roughness (SR). Important AWJM machining parameters such as water pressure, focussing tube size, traverse speed & abrasive flow rate were predicted for optimized MRR and SR.
Sreenivasa Rao *et al.*, (2009) has conducted experimental investigation to study the effect of parameters, viz water pressure, Traverse speed, and Standoff distance, of Abrasive Water jet Machine (AWJM) for mild steel (MS) on surface roughness (SR).
Further Taguchi's method, analysis of variance and signal to noise ratio (SN Ratio) are used to optimize the considered parameters of abrasive Water Jet Machining.
In Taguchi's design of experimentation, L9 orthogonal array is formulated and it can be concluded that water pressure and transverse speed are the most significant parameters and standoff distance is sub significant parameter.
Shanmugam and Masood (2008) studied "Investigation on Kerf characteristic in abrasive water jet cutting of layered composite."
Layered composites are "difficult-to-machine" materials as it is inhomogeneous due to the matrix properties, fibre orientation, and relative volume fraction of matrix.
Abrasive water jet cutting has proven to be a viable technique to machine such materials compared to conventional machining. The effects of the different parameters Abrasive flow rate (g/s), Standoff distances (mm), Traverse Speed (mm/s), Water pressure (Mpa) on the response characteristics Kerf taper angle were explained.

Taguchi Multi Response Method

Taguchi method is not suitable enough to be used as such to optimize the multi-response problems. However, we can collect the observed data for each response using Taguchi's designs and the data can be analyzed by different methods developed by various researchers. 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 optimal levels for each response. Usually the general approach in these problems is to combine the multi responses into single statistic (response) and then obtain the optimal levels.
The assignment of weights and principal component method is used to find the optimum levels for the values as shown in the Table 1.

Assignment of Weights

In assignment of weights, the multi-response problem is converted into single response problem. Suppose we have two responses in a problem. Let W1 be the weight assigned to, say the first response R1 and W2 be the weight assigned to the second response R2. The sum of the weighted response (W) will be single response, where

W = W1 + W2

This W is termed ad Multi Response Performance Index (MPRI) as shown in the Table 1. Using this MRPI, the problem is solved as a single response problem. In the multi response problem, each response can be original observed data or its transformation such as S/N ratio. In this approach is the method of determining of weights.

Table 1: Output Responses and Determination of MRPI

S No	Traverse Speed (mm/min) (S)	Abrasive Flow Rate (grams/min) (R)	Standoff Distance (mm) (H)	MRR (grams/min)	W_{MRR}	SR (µm)	W_{SR}	MRPI
1	160	500	2	4.58	0.100732	2.80	0.103636	0.747505
2	160	600	3	4.82	0.107389	2.42	0.120909	0.809941
3	160	700	4	5.03	0.111826	2.31	0.127272	0.853784
4	200	500	3	4.67	0.101842	2.66	0.107474	0.757633
5	200	600	4	5.02	0.110051	2.47	0.117008	0.836034
6	200	700	2	5.01	0.11227	2.57	0.111608	0.858266
7	225	500	4	5.23	0.117151	2.69	0.106684	0.908738
8	225	600	2	5.29	0.116929	3.06	0.096727	0.906398
9	225	700	3	5.41	0.121811	2.70	0.108682	0.95892

Figure 1 gives effect of Process parameters on MRPI

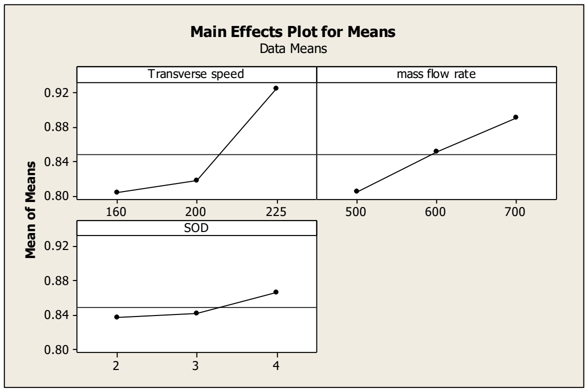

Figure 1: Effect of Process Parameters on MRPI

Principal Component Analysis

Principal Component Analysis (PCA) is the general name for a technique which uses sophisticated underlying mathematical principles to transforms a number of possibly correlated variables into a smaller number of variables called principal components. The origins of PCA lie in multivariate data analysis, however, it has a wide range of other applications, as we will show in due course. PCA has been called, one of the most important results from applied linear algebra and perhaps its most common use is as the first step in trying to analyze large data sets. Some of the other common applications include; de-noising signals, blind source separation, and data compression.

In general terms, PCA uses a vector space transform to reduce the dimensionality of large data sets. Using mathematical projection, the original data set, which may have involved many variables, can often be interpreted in just a few variables (the principal components). It is therefore, often the case that an examination of the reduced dimension data set will allow the user to spot trends, patterns and outliers in the data, far more easily than would have been possible without performing the principal component analysis.

The principal component analysis (PCA) is an effective multivariate statistical method that selects a small number of components to account for the variance of original multi responses. In PCA, the original data set of MQC is converted into PC which is a linear combination of multi-responses obtained in an experimental trial. By using PCA, a set of correlated variables (quality characteristics) are transformed into a set of uncorrelated principal components (PC). A weighting factor for a PC is determined based on its contribution percentage to total variance. The TPCI for each experimental run is used to find out the average factor effect at each level. The parameter levels corresponding to the maximum TPCI value is also found out. TPCI is calculated and given in the table 2.

Table 2: Determination of TPCI

S. No.	PC1	PC2	TPCI
1	-0.17826	0.178262	-1.1E-16
2	-0.33784	0.814923	0.477084
3	-0.31948	1.094738	0.775262
4	-0.23203	0.308701	0.076674
5	-0.15797	0.822476	0.66451
6	0.134305	0.675034	0.809339
7	0.30974	0.814816	1.124555
8	0.553758	0.553758	1.107517
9	0.407032	1.007182	1.414214
Mean			0.716573

Figure 2 gives effect of Process parameters on TPCI

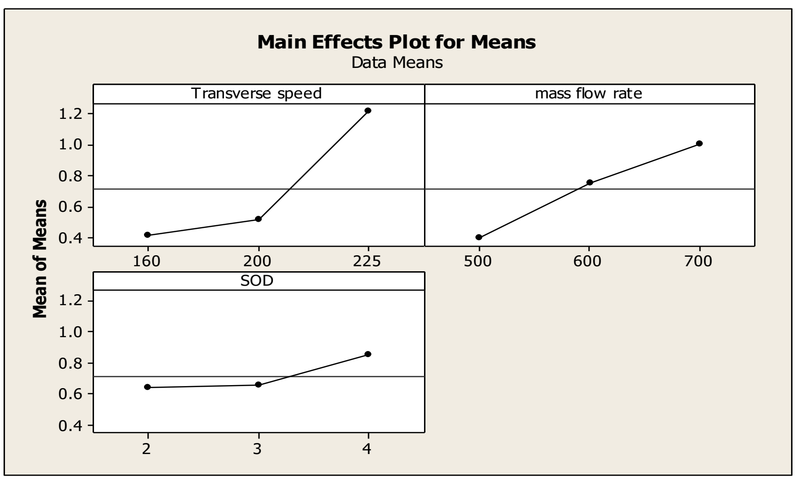

Figure 2: Effect of Process Parameters on Tpci

MATERIALS AND METHODS

Response Surface Methodology

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response.

A second-order model can be constructed efficiently with central composite designs (CCD) (Montgomery, 1997). CCD are first-order (2*N*) designs augmented by additional centre and axial points to allow estimation of the tuning parameters of a second-order model. Figure 3 shows a CCD for 3 design variables.

The design involves 2*N* factorial points, 2*N* axial points and 1 central point. CCD presents an alternative to 3*N* designs in the construction of second-order models because the number of experiments is reduced as compared to a full factorial design (15 in the case of CCD compared to 27 for a full-factorial design). Using MATLAB simulation, MRR and SR is predicted by ANN given in the Table 3.

Table 3: Predicted MRR and SR using ANN

S	R	H	Predicted MRR	Predicted SR
192.5	600	3	5.019969	2.582363
137.8417	600	3	3.580713	2.397921
192.5	768.1793	3	5.108187	2.467381
225	700	2	5.126621	2.811094
160	500	4	4.600654	2.399195
225	500	4	5.209338	2.644819
160	700	2	3.925161	2.523881
192.5	431.8207	3	4.639514	2.71372
192.5	600	3	5.019969	2.582363
160	500	2	4.516209	2.681069
192.5	600	3	5.019969	2.582363
225	500	2	4.88588	2.681069
192.5	600	4.681793	4.971722	2.391276
192.5	600	3	5.019969	2.582363
160	700	4	5.002689	2.376618
192.5	600	3	5.019969	2.582363
192.5	600	3	5.019969	2.582363
192.5	600	1.318207	5.080256	2.791426
247.1583	600	3	6.235247	2.744841
225	700	4	6.381314	2.578756

Using MINITAB 16 optimized values are predicted for RSM is shown in the figure 4.

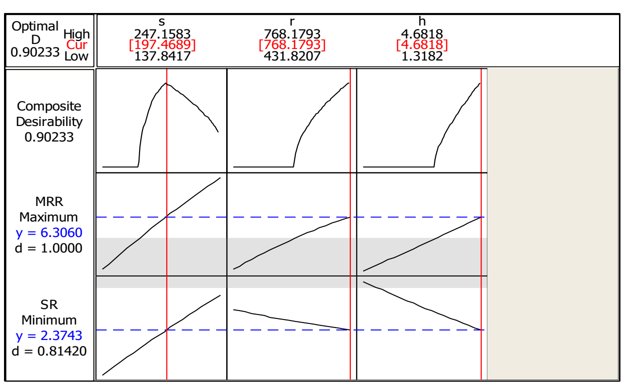

Figure 3: Response Surface Optimizer

Regression Equation

The Estimated Regression Equation for MRR and SR using data is given by

$$MRR = -0.0111913\ S - 0.0120393\ R - 1.60870\ H - 3.24628E\text{-}05\ S*S - 4.63554E\text{-}06\ R*R + 0.00743367\ H*H + 6.16050E\text{-}05\ S*R + 0.00160068\ S*H + 0.00240540\ R*H + 9.65851$$

$SR = - 0.00328433\ S - 0.00237305\ R - 0.195371\ H - 3.17451E\text{-}06\ S*S + 3.42437E\text{-}07\ R*R + 0.00370739\ H*H + 9.37412E\text{-}06\ S*R + 0.000617496\ S*H - 7.68463E\text{-}05\ R*H + 3.88446$

RESULTS AND DISCUSSIONS

From Taguchi Multi-response method, in Assignment of Weight and Principal Component Analysis the optimized response for MRR and SR is S3R3H3.

The Optimized MRR and SR predicted by Taguchi Multi-response method is 5.6211 grams/min and 2.55111 µm.

In Response Surface Methodology, for centre cubic design, the output responses like MRR and SR are predicted by Artificial Neural Network using Back propagation technique. From Response Surface Methodology, the predicted optimized response for MRR and SR is S197.4689 R768.1713 H4.6818. The optimized MRR and SR from RSM are 6.3060 grams/min and 2.3743 µm.

Conclusion

In Taguchi multi response method analysis of various parameters using Weightage method and principal component analysis on the basis of experimental results taken from the literature, analysis of variance (ANOVA), F-test; the following conclusions AWJM process as follows

i. Traverse rate and Abrasive flow rate are the most significant control factors on MRPI and standoff distance is the sub- significant parameter on MRPI. Hence, the optimum recommended parametric combination for optimum MRR and surface Roughness is S3R3H3.

ii. Similarly, Traverse rate and Abrasive flow rate are the most significant control factors on TPCI and standoff distance is the sub- significant parameter on TPCI. Hence, the optimum recommended parametric combination for optimum MRR and surface Roughness is S3R3H3.

In Response Surface Methodology, for centre cubic design, the output responses like MRR and SR are predicted by Artificial Neural Network using Back propagation technique. From Response Surface Methodology, the predicted optimized response for MRR and SR is S197.4689 R768.1713 H4.6818. The output responses MRR and SR optimized by RSM are maximized as compared to Taguchi Multi-response methods like Assignment of Weights and Principal Component Analysis.

REFERENCES

Badgujar P and Rathi MG (2014). Taguchi Method Implementation in Abrasive Water jet Machining Process Optimization *International Journal of Engineering and Advanced Technology* (IJEAT) ISSN: 2249 – 8958 **3**(5).

Jurkovic Z, Perinic M and Maricic S (2012). Application of Modeling and Optimization Methods in Abrasive Water Jet Machining *Journal of Trends in the Development of Machinery and Associated Technology* **16**(1) ISSN 2303-4009 (online) 59-62.

Nagdeve L, Chaturvedi V & Vimal J (2012). Implementation of Taguchi Approach for Optimization of Abrasive Water Jet Machining Process Parameters, *International Journal of Instrumentation, Control and Automation* (IJICA) ISSN: 2231-1890 **1**(3, 4).

Nagdeve L, Chaturvedi V & Vimal J (2012). Parametric Optimization of Abrasive Water Jet Machining Using Taguchi Methodology, *International Journal of Research in Engineering & Applied Sciences* **2** 23-32.

Parmar CM, Yogi PK and Parmar TD (2014). Optimization of Abrasive Water Jet Machine Process Parameter for Al-6351 Using Taguchi Method *International Journal of Advance Engineering and Research Development* (IJAERD) **1**(5) e-ISSN: 2348 - 4470, print-ISSN: 2348-6406.

Patel VB and Prof Patel VA (2012). Parametric Analysis of Abrasive Water Jet Machining of En8 Material *International Journal of Engineering Research and Applications* (IJERA) ISSN: 2248-9622 **2**(3) 3029-3032.

Reddy DS, Kumar AS and Rao MS (2014). Parametric Optimization of Abrasive Water Jet Machining of Inconel 800H Using Taguchi Methodology *Universal Journal of Mechanical Engineering* **2**(5) 158-162.

Selvan MCP and Raju NMS (2011). Assessment of Process Parameters in Abrasive Water jet Cutting of Stainless Steel *International Journal of Advances in Engineering & Technology* **1**(3) 34-40.

Sreenivasa Rao M, Ravinder S & Seshu Kumar S (2014). Parametric Optimization of Abrasive Water jet Machining for Mild Steel: Taguchi Approach, *International Journal of Current Engineering and Technology* E-ISSN 2277 – 4106, P-ISSN 2347 – 5161 (special Issue 2).