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Parametric Analysis of Titanium Alloy For Abrasive Jet Machining Process By Using Genetic Logarithm

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Abstract— Titanium has begun to be used widely in engineering applications due to their favourable properties such as good corrosion resistance, high specific strength and the highest strength to weight ratio of any metal. It has obtained widespread use in the aerospace and biomedical fields. However Titanium is highly reactive and has high hardness at elevated temperatures. This coupled with its low thermal conductivity and elastic modulus makes it a hard to machine material. In this paper an effort has been made to study and optimize the drilling process of a hole by making use of Abrasive jet machining (AJM) on a Ti-6Al-4V composite material. The effect of process parameters such as Pressure, Abrasive flow rate, standoff distance and material thickness on Material Removal Rate (MRR) and surface roughness has been studied. The experiments were designed and conducted on the basis of Taguchi's experimental design of L16.Apart from single level optimization, multi optimization was also performed by making use of Genetic Algorithm (GA).

Keywords— Titanium Ti-6Al-4V**,** Design of experiments, Orthogonal Array, Taguchi, AJM, Genetic Algorithm

1. INTRODUCTION

Titanium Ti-6Al-4V alloys is a material possessing favorable properties such as high strength, corrosion resistance, high strength to weight ratio. Since it can withstand high temperature, Titanium alloys are used in a wide array of fields such as biomedical, aerospace, marine and automotive industries. However, the high hardness of the material makes it very hard to machine it into intricate shapes using conventional machining processes. Hence unconventional machining processes are generally used to machine Titanium alloys. Among them Electro Discharge Machining (EDM), Electro Chemical Machining (ECM) ,Abrasive jet machining (AJM) and Abrasive water jet machining(AWJM) are generally used.
AJM can be used to efficiently produce intricate shapes with minimum damage to the surface. Also by controlling the grain size of the abrasive, it is possible to achieve a good surface finish [1].

The machinability of AJM can be enhanced by investigating the process parameters involved in the machining process. In this paper we have attempted to study the effect of Pressure, Flow rate of abrasive, standoff distance and thickness of the plate against the quality characteristics namely MRR and surface roughness taken one at a time and also together.

The experimentation has been designed by making use of Taguchi based orthogonal arrays. Taguchi method has been widely used in the selection of the process parameters. Taguchi method makes use of Orthogonal Arrays (OAs) [2] for designing the experiments. The predominant advantage of this technique lies in its simplicity and adaptability. They provide the required information making use of only the least possible number of trials. However they still yield results which have good precision and are reproducible. In order to determine the performance characteristics under the optimal machining parameters, a specially designed experimental procedure is required. A full factorial experimental design will cover all the possible arrangements possible for a particular experimental setup. However as the number of factors and levels increases, the total number of experiments also increases. Making it unviable both financially and in terms of time taken. Hence Taguchi's orthogonal arrays are made use of to reduce the number of experiments required [3].

The experiment includes four process parameters where two parameters are set at 4 levels and two parameters at 2 levels. Therefore each process parameter at 4 levels will contribute 3 degrees of freedom each whereas the process parameters at 2 levels will contribute 1 degree of freedom each. Therefore there are 8 degrees of freedom in total in this experiment design [2] [5].

While selecting an Orthogonal Array it should be noted that the degrees of freedom of the Orthogonal Array must be greater than or equal to those of the process parameters. [10]. An L16 array as chosen here will have 15 degrees of freedom (i.e.: 16-1=15).It has already been specified that the process parameters used here have 8 degrees of freedom. The degree of freedom for the Orthogonal Array is less than the degrees of freedom of the process parameters. Hence it is possible to use an L16 for the experiments in this study. The experimental layout for the process parameters in terms of an L16 Array is given in Table 4.

2. MATERIAL USED AND SETUP

The material used here is Ti-6Al-4V alloy. The composition of the alloys is given in Table.

Table 1: Composition of Material

Element	Composition
Al	6.321%
V	3.714%
C	0.006%
Fe	0.091%
Si	0.010%
Mn	0.005%
Cr	0.021%
Sn	0.001%
Ti	Remaining

This α-β Titanium is used primarily in biomedical applications.
From initial pilot experiments it was observed that a significant change in the response parameters is observed at 4 levels for pressure and abrasive flow whereas at only 2 levels for standoff distance and thickness of the work piece. Hence we make use of a mixed level setup of an L16 orthogonal array. The experimental arrangement of the array is displayed in Table 3.

Table 2: Process parameters and their levels

Notation	**Factor**	**Level 1**	**Level 2**	**Level 3**	**Level 4**
A	Pressure	3300	3500	3700	3900
B	Abrasive flow rate	0.45	0.50	0.55	0.60
C	Stand off distance	1.5	2	-	-
D	Thickness of work piece	22	29	-	-

Table 3: Experimental design using L16 array

Experiment Number	Pressure (Bar)	Abrasive flow rate (kg/min)	Standoff distance (mm)	Thickness (mm)
1	3300	0.45	1.5	22
2	3300	0.50	1.5	29
3	3300	0.55	2	22
4	3300	0.60	2	29
5	3500	0.45	2	29
6	3500	0.50	2	22
7	3500	0.55	1.5	29
8	3500	0.60	1.5	22
9	3700	0.45	1.5	29
10	3700	0.50	1.5	22
11	3700	0.55	2	29
12	3700	0.60	2	22
13	3900	0.45	2	22
14	3900	0.50	2	29
15	3900	0.55	1.5	22
16	3900	0.60	1.5	29

The diameter of the orifice is 0.250 mm and the abrasive used here is Garnet with a mesh size of 40.
The two response parameters so analyzed here are material removal rate (MRR) and surface roughness (SR).

3. RESULTS AND DISCUSSIONS

The experimental results obtained are given below in table 4.Table 4: Experimental results

Experiment	MRR (gm/sec)	Surface roughness(µm)
1	56	2.68
2	195	2.51
3	69	2.4
4	154	2.32

5	71.3	2.3
6	97.9	2.95
7	106	2.92
8	13.3	2.87
9	58.5	2.32
10	64.3	2.56
11	62.9	2.78
12	93.7	2.9
13	77.5	3.65
14	66.9	2.3
15	41.7	3.75
16	97	2.73

The data collected from experiments pertaining to output responses, MRR and SR from training data set table are used to implement the proposed methodology. The need in developing the mathematical relationships is to relate the machining responses to the cutting parameters thereby facilitating the optimization of the machining process.
Regression analysis is a simple statistical tool used to find the mathematical relation between the control variables and the responses. Multiple regression is made use of here.

For MRR the regression equation was calculated to be

MRR = -2750 + 0.509A + 495B +120.3C - 0.02278A*B - 18.82 C*D

Surface Roughness = -18.85 + 0.00645A +0.722D - 0.000218A*D

The generated regression equation was used to predict the values of MRR and SR for various settings and is compared with the experimental results. A graph was plot using x-axis as experiment number and y-axis for respective responses. According to the graph no high differences or errors are seen. These indicate that the developed models satisfactorily represent the outputs. The comparison graphs are shown below

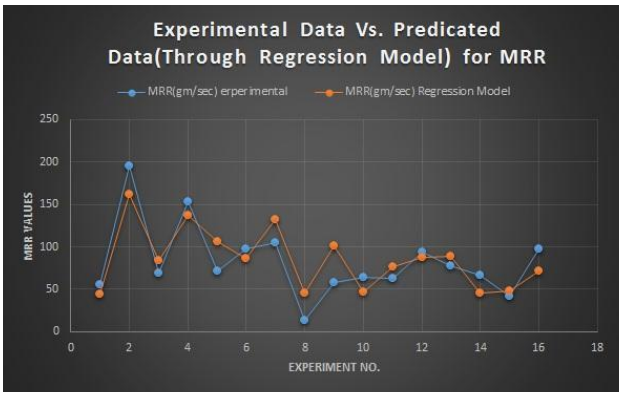
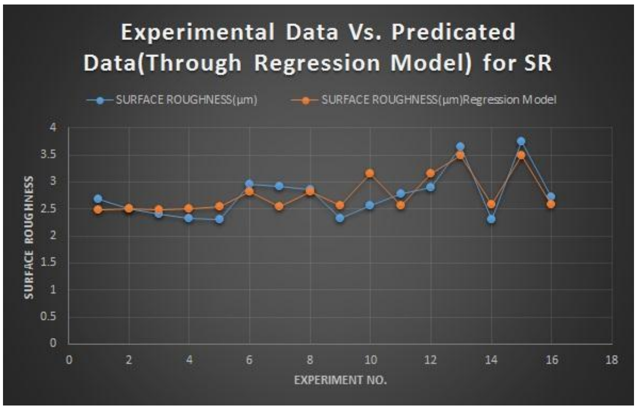


Fig 1: Comparison of MRR

The graphs show the experimental and the regression modeled results to be fairly in sync.



The experimental values of MRR and SR were tested using MATLAB by first training the software with the data set i.e. the experimental values.

In the process of optimization the aim is to maximize the quality.

MRR is achieved at the expense of SR, similarly better SR is obtained at the cost of MRR. This is due to the conflicting effect of the process control parameters on MRR and SR.

This machining problem is formulated as a multi objective optimization problem in which SR is minimized and MRR is maximized simultaneously subject to the feasible bounds of process control parameters.

The feasible bounds of the variables listed in the formulation of the problem are :-

Maximum:

MRR = -2750 + 0.509A + 495B +120.3C - 0.02278A*B - 18.82 C*D

Minimum:

MRR = -2750 + 0.509A + 495B +120.3C - 0.02278A*B - 18.82 C*D

Subject to

$$3300 \le A \le 3900$$
$$0.45 \le B \le 0.60$$
$$1.50 \le C \le 2.00$$
$$22 \le D \le 29$$

Once the optimization problem is formulated, then it is solved using the evolutionary algorithm called genetic algorithm[5].

Evolutionary Algorithms are generally robust to variations of control parameters. Tests with populations of different sizes of 250, 350 and 500 were performed. In all cases, the best results were achieved with the large populations. However, it was noted during the runs that there was increase in computation times with increasing the population sizes. Thus, a reasonable size of 60 was considered. GA, being probabilistic by nature, it is possible that it will land at differing approximate solutions every time. In order to exploit this intrinsic variation, multiple runs are performed.

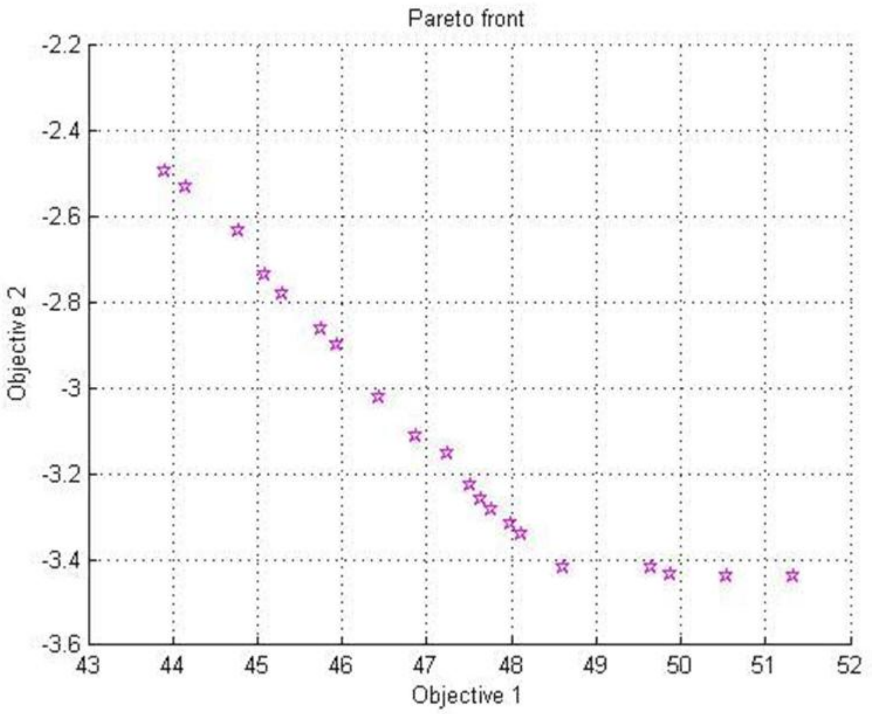
Table 5: GA control parameters

Population size	60
Number of generations (Maximum)	60
Crossover probability %	85
Mutation probability %	5
Reproduction probability %	10
Selection method	Tournament
Fitness measure	R^2

The Multi objective Genetic algorithm generates a graph called Pareto chart, where the decision for selecting optimum control values can be taken. The algorithm found the Pareto Optimal Front of the conflicting objective functions with good diversity of the solutions as shown in Graph 1 below. The optimal input variables and their corresponding objective function values are presented in Table 6.

By analysing the Pareto's front, some decisions could be taken, depending upon specific requirements of the process. For instance, at point 1, a component can be machined with the best surface quality but with maximum MRR. On the other extreme of the front, the highest material removal rate can be achieved but it will be of the worst surface quality. All the other points are in-between cases.

As it can be observed from the graph, no solution in the front is better than any other. The choice of a solution has to be made purely based on production requirements. For example, if one chooses to machine a component with a surface quality of -4.914 µm, he can select the set of input variables from Table 6 accordingly; he would achieve the max MRR and fine Surface Quality.



Graph 1: Pareto chart for multi objective optimization

Table 6: Optimized values through GA

Exp No	MRR (gm/sec)	SR (µm)	Pressure (Bar)	Abrasive flow rate kg/min)	Stand off distance (mm)	Thickness (mm)
1	43.912	-2.492	3300	0.5999	1.5	22
2	50.543	-3.439	3872.734	0.5101	1.5264	22.00016805
3	48.608	-3.416	3858.867	0.5769	1.5184	22.00004423
4	49.875	-3.436	3870.639	0.5127	1.5009	22.00015819
5	47.629	-3.259	3763.678	0.5939	1.5021	22.00029866
6	47.993	-3.317	3797.894	0.5991	1.5008	22.00002713
7	44.159	-2.529	3321.956	0.5729	1.5022	22.00218131
8	48.112	-3.338	3811.966	0.5649	1.5001	22.00009809
9	45.299	-2.781	3474.510	0.5942	1.5361	22.00006582
10	51.325	-3.439	3872.736	0.4913	1.5002	22.00057209
11	45.078	-2.733	3445.384	0.5718	1.5167	22.00024336
12	49.654	-3.418	3859.241	0.5491	1.5011	22.00021573
13	45.750	-2.859	3521.909	0.5842	1.5003	22.00008675
14	46.875	-3.111	3674.092	0.5924	1.5025	22.00018816
15	47.248	-3.151	3698.660	0.5238	1.5012	22.00013883
16	45.935	-2.897	3544.886	0.5926	1.5001	22.00042597
17	47.757	-3.284	3778.822	0.5747	1.5019	22.00202567
18	44.769	-2.633	3385.678	0.5524	1.5004	22.00003777
19	46.437	-3.018	3618.480	0.5932	1.5003	22.00003777
20	47.519	-3.225	3743.323	0.5940	1.5014	22.00161073
21	43.912	-2.4922	3300	0.5999	1.5	22

4. CONCLUSIONS

1. From the Pareto chart, highest MRR obtained was 50.54 gm/sec with least surface roughness value as 3.43µm when cutting conditions were set to a pressure of 3872.7 Bar, abrasive flow rate of 0.51kg/min, standoff distance of 1.52mm and thickness 22mm.
2. The results show that regression is a promising tool for mathematical modelling as high values for correlation are obtained here.
3. Material removal rate and surface roughness are selected as they are important considerations for manufacturing the components with high accuracy and surface quality.
4. Genetic Algorithm was applied for Multi-Objective Optimization of the conflicting performance measures to find multiple sets of optimal solutions. The generated Pareto-optimal set gives a very clear picture to the manufacturing engineer to choose a particular optimal set of input variables depending upon his requirements.
5. The optimal values obtained by the proposed methodology could serve as a ready-reckoner to operate the specific machine with great ease to achieve the quality and the production rate as demanded by the consumers.

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