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Optimization of Process Parameters for Milling of Al6061-T6 Using AHP, RSM and Jaya Algorithm.

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***Abstract*-- With the widespread application of aluminium alloy Al6061-T6 mostly in automotive and aerospace industries, the machining of aluminium has become a subject of interest today. Proper understanding of behaviour of process input parameters and its optimal settings are required for improved product quality as well as for mass production. Prediction of surface roughness and material removal rate in multi-point machining process is important for engineers. However, due to the random and complex nature of multipoint machining process, with its many variables, it become difficult to formulate a realistic and accurate mathematical model. The present work here highlights the potential in application of Analytic Hierarchy process method, response surface methodology and a computational optimization algorithm, Jaya for the selection of optimal process output responses during the milling of Al6061-T6 aluminium alloy. Type of cutting, spindle speed, feed rate, depth of cut and coolant are the process input parameters considered for experimentation whereas material removal rate, surface roughness on left as well as right side, workpiece vibrations, tool vibrations, temperature of workpiece and tool while cutting and corner radius have been considered as process output parameters. Attempt has been made to identify the optimal setting of process input parameters for optimizing the aforesaid output responses, simultaneously. AHP with equal and unequal weights has been used for selection of set of process input parameters for optimized responses. In addition to this, mathematical models are solved using Jaya algorithm. Good agreement has been found in the results.**

***Keywords*— Analytical Hierarchy process method, Al6061-T6, milling, Jaya algorithm.**

I. INTRODUCTION

Nowadays aluminium alloys are widely used in many engineering fields and particularly where weight reduction is a critical factor, such as aerospace and automotive industries. A need for weight reduction has emerged and has led to the increased application of lightweight materials such as aluminium. The use of aluminium alloy offers an opportunity for vehicle weight reduction, which can lead to a reduction of fuel consumption and emission without compromising performance, comfort and safety.

Although pure aluminium is one of the most widespread elements on earth, it is too soft and ductile. Therefore it is often combined to form alloys with many different elements, such as copper (Cu), silicon (Si), magnesium (Mg), zink (Zn) and manganese (Mn). Al6061-T6 belongs to the aluminium series 6000 with silicon and magnesium as the principal alloying elements. The T6 suffix describes the heat treatment applied to the alloy. Aluminium alloys offer high corrosion resistance and good formability. In addition, the recyclability of aluminium alloys is also a considerable attraction to manufacturers. However, the use of aluminium requires not only a different approach in car design but also a different approach to manufacturing technology and joining processes [1]. Aluminium has advantage above other materials comprising a high strength/weight ratio, corrosion resistance and formability. Alloys like 6061, 7075 and 2024 are sometimes referred as aerospace alloys due to their partial applications in the aeronautics industry. These alloys are engineered to be lightweight and strong. Their ease of formability allows complex shapes and parts to be drawn, which can be further enhanced with heat treatment. Aluminium Al6061-T6 is an alloy which contains magnesium and silicon as major alloying elements and commonly serves several purposes due to the superior mechanical properties such as good hardness and good weldability[2,3] as well as the solutionized and tempered grade characteristics of this type of aluminium. Widespread applications for this type of material are found in aircraft, automotive and food packaging industry. Al6061-T6 is one of the most commonly used materials for aerospace fixtures, automotive wheel hubs, engine and hard disks and has highly favourable properties of a high strength to weight ratio, good machining properties, good weldability and corrosion resistance [4,5]. As a result many investigations into advance manufacturing processes for aluminium have been done here. A combination of high mechanical strength with low density as well as good corrosion resistance have made Al-Si-Mg alloy the target for number of structural applications in which fusion welding is often required.

Aluminium combined with various percentages of other metals to form the alloys that are used in aircraft construction. Aluminium is one of the most widely used metals in modern aircraft construction. It is vital to the aviation industry because of its high strength to weight ratio, its corrosion-resisting qualities, and its comparative ease of fabrication. This material has density one third of steel and when alloyed with proper ingredient has strength more than steel. Many researchers had worked on Al6061-T6. Ming et al. [6] presented work on machining of Al6061-T6for getting higher product quality by providing appropriate lubrication or coolant using nanoparticles of silicon dioxide in proper concentration at the machining zone to improve the tribological characteristics of the said alloy. Wang et al. [7] presented work on the heat generation on the machined surface of Al6061 aluminium alloy and presented the relationship between the heating time, heating temperature and average size of the precipitates for Al6061 alloy. Nityanandam and Radhakrishanan[8] evaluated the controlling of milling machine for Al6061 on different thicknesses such as 100 mm X 45 mm plate with 2 mm, 3 mm and 4 mm thickness. Rahmati et al. [9] presented a study on Al6061-T6 alloy to improve the product quality particularly the surface roughness by introducing correct lubrication in the form of nanoparticles of Molybdenum disuphide (MoS2). The structure, shape and size of nanoparticles play an important role in their tribological properties [10, 11]. Raju et al. [12] presented work on optimization of cutting conditions for surface roughness in CNC end milling. The authors developed the integrated study of surface roughness to model and optimize the cutting parameters for end milling of 6061 aluminium alloy. Use of HSS and carbide tool was made in wet and dry cutting conditions. Genetic algorithm supported with regression equations was utilized to determine the best combinations of cutting parameters providing roughness to the lower surface through optimization process. Yazdi and Chavisho[13] presented work on the effect of cutting parameters and machining forces on surface roughness and material removal rate of Al6061in CNC face milling operation using two different modelling techniques, regression analysis and multilayer perceptron (MLP) neural network. Sreejith[14] experimented on Al6061 aluminium alloy with minimum quantity lubrication (MQL), dry and flooded lubrication and studied the effect of different lubricant environments when Al6061 aluminium alloy was machined with diamond coated carbide tools.

In the present work an attempt is made to correlate temperature change during the cutting process for work piece as well as cutter. Also here an attempt will be made to set a relation between vibration getting induced in the work piece and cutter during the cutting process. Also for the first time effect of type of cutting, spindle speed, feed rate, depth of cut and coolant conditions will be observed on the corner radius of the work piece using weighted sum method and analytic hierarchy process and validated by response surface methodology and Jaya algorithm. Details of experimental setup are given in the following section.

II. Experimental Setup

Trials were performed on Deckel Maho DMF-180, 5 axis CNC milling machine having two cutting options- up-milling and down-milling. To mill the slots on Al6061-T6 plate, an uncoated tungsten carbide cutting tool was used having 3 flutes, 8 mm diameter and 40 mm length of flute. Maximum length of cutting tool is also 40 mm which was set with a tool pre-setter. Along with various spindle speeds, feeds and depth of cut, the machine has a facility for selecting the coolant as flooded coolant, through toll coolant and air purging. The factors and levels of input process parameters are as shown in Table 2.1.

Table 2.1:
Factors and levels for input process parameters

Symbol	Factor	Units	Level 1	Level 2	Level 3
A	Cutting	Type	Up-milling	Down-milling	-
B	Spindle speed	Rpm	7000	8000	9000
C	Cutting feed rate	mm/min	1800	2100	2400
D	Depth of cut	mm	1.0	1.5	2.0
E	Coolant	Type	Flooded	Through tool	Air purge

Reponses for analysis are material removal rate, surface roughness, temperature and vibrations. Material removal rate is calculated from the volume removed per unit time. For surface roughness, Mittutoyo surface roughness tester was used. Vibrations also affect the quality of the product in the form of chatter mark. The instrument FFT (Fast Fourier Transform) was used to measure vibrations in terms of acceleration with the help of two accelerometers. Fig 2.1shows mounting positions of the accelerometers.

Fig.2.1: Mounting position of accelerometers

Temperature of workpiece and temperature of cutting tool during process was measured with the help of laser gun. The heat generated during the cutting process should be carried away by coolant. However with different types of coolant conditions and cutting conditions temperature of workpiece as well as cutting tool gets affected. Corner radius is measured with the help of coordinate measuring machine (CMM). Output responses of the experimentation are tabulated in Table 2.2.

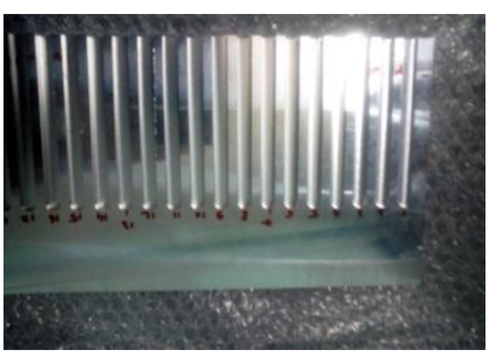

Fig. 2.2: Machined workpiece

Slots of 100 mm x 8 mm having different depth of cuts, as per design of experiment were machined. Milling operation was performed overall size of Al6061-T6 aluminium alloy of 250 mm X 150 mm x 20 mm thickness. Analysis of responses is given in the next section.

Table 2.2:
Output responses of the experimentation.

Run No.	MRR mm3/sec	SRLH µm	SRR Hµm	VW/P g	VTOOL g	TW/P °C	TTOOL °C	CR mm
1	201.51	1.861	1.629	0.0626	0.0064	26.3	26.1	0.0295
2	366.23	4.238	3.526	0.0600	0.0260	27.2	26.3	0.0520
3	536.91	1.801	2.581	0.0447	0.0077	26.8	27.2	0.0778
4	219.58	3.532	3.530	0.0765	0.0318	26.4	26.2	0.0389
5	373.83	3.134	3.593	0.0791	0.0143	25.2	26.4	0.0692
6	562.06	2.694	3.531	0.0782	0.0058	25.5	25.5	0.0666
7	345.16	3.200	4.040	0.1883	0.0054	25.2	25.3	0.0701
8	461.54	4.002	4.159	0.1870	0.0133	26.1	25.5	0.0649
9	270.57	7.209	2.598	0.1533	0.0023	25.5	25.9	0.0535
10	477.14	2.181	4.544	0.0701	0.0016	25.3	25.8	0.0819
11	279.07	1.774	2.201	0.0655	0.0021	24.9	25.4	0.0473
12	425.53	3.010	4.447	0.0658	0.0039	25.9	25.0	0.0693
13	360.00	4.640	4.206	0.0750	0.0011	24.4	26.1	0.0650
14	484.85	3.989	3.901	0.0744	0.0034	24.7	25.6	0.0705
15	274.60	1.898	2.753	0.0752	0.0093	25.6	25.2	0.0601
16	426.29	5.216	3.679	0.1810	0.0109	25.6	25.5	0.0560
17	268.16	4.087	2.222	0.1830	0.0021	23.8	26.1	0.0625
18	372.67	4.024	4.230	0.1557	0.0036	25.3	25.9	0.0705

To choose the optimum process parameter from this data set, it is a multiple attribute decision making (MADM) task. This MADM task can be solved with weighted sum method. Weighted sum method is also called as Simple additive weighting (SAW) method and is the simplest and widely used MADM method. First step in this method is to assign weights to all attributes i.e. responses such that sum of all weights is 1. Here equal weights, 0.125 is assigned to all attributes. As the attributes have different units of measurements, normalization of data is essential. Applying the weights to the normalized data and the scores are calculated. Thus rank 1 is obtained by run#11 from the set of experiments. Hence input process parameters in run#11 setting, A2-B1-C2-D1-E1 are the optimum parameter from the considered set of parameters for given responses. Table 3.3 show optimum set of factors and its levels.

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III. Analytic Hierarchy Process

It is one of the most popular analytical techniques for complex decision making problems. Saaty [14] developed this method, which decomposes a decision making problem into a system of hierarches of objectives, attributes and alternatives. The main procedure of AHP using the radical root method or geometric mean method and its stepwise implementation is as follows. Step 1: Determine the objective and evaluation attributes. There are ten objectives in this experimentation. Step 2: Determine the relative importance of different attributes with respect to the objectives. Construct a pairwise comparison matrix using the scale of relative importance. Unequal weights are used for different attributes. The relative normalized weight of each attribute are obtained by calculating the geometric means of rows in the comparison matrix. Find maximum Eigen value λmax, calculate consistency index CI, using M as number of objectives and consistency ratio CR = CI / RI, where RI is Random index value. As CR < 0.1, the weights are acceptable. Applying these weights to the normalized data find the normalized scores and ranks for each run in the experimentation. Thus highest normalized weighted score is obtained by run#3 and marked as rank 1.The input process parameters used in run#3, A1-B1-C3-D3-E3 are the optimum process parameters from the parameters considered for the study.

IV. Mathematical Modelling And Data Analysis

The regression equations are formulated for each response using all input parameters (Here A, B, C, D, E are referred to as X1, X2, X3, X4 and X5) and interaction between the input parameters (X1*X2, X1*X3 and so on).

The regression equation for material removal rate is

MRR = 372.54 - 0.21 X1 –8.57 X2 + 28.15 X3 +112.34 X4 -9.97 X5 -9.37 X1*X2-8.60 X1*X3 -4.78 X1*X4 +2.36 X1*X5 -15.05 X2*X3 -22.43 X2*X4 + 8.68 X2*X5 +8.40 X3*X4 -14.18 X3*X5 +2.33 X4*X5. -- --- --- -- -- -- --- --- -- --- --- -- --- --- ---- -- Eqn. (1)

R-Square = 99.90% and R-Square (adjusted) = 99.81%

The regression equation for SR-LH is

SR = 3.47–0.03 X1 +0.54 X2 + 0.27 X3 -0.58 X4+0.51 X5 +0.01 X1*X2-0.68 X1*X3 +0.76 X1*X4 - 0.11 X1*X5 - 0.01 X2*X3 +0.82 X2*X4-0.46 X2*X5 -0.08X3*X4 +0.12 X3*X5 –1.03 X4*X5. - - - - - Eqn. (2)

R-Square = 91.31% and R-Square (adjusted) = 83.38%

The regression equation for SR-RH is

SR-RH = 3.41–0.01 X1 -0.05 X2 + 0.02 X3 + 0.24 X4 +0.36 X5 -0.34 X1*X2+ 0.29 X1*X3 + 0.29 X1*X4 +0.01 X1*X5 -0.15 X2*X3 +0.40 X2*X4-0.70X2*X5-0.54 X3*X5 - 0.44 X4*X5. ----- -- -- -- -- -- Eqn. (3)

R-Square = 97.48% and R-Square (adjusted) = 95.04%

The regression equation for V-WP is

V-WP = 0.10–0.02 X1 + 0.09 X2 + 0.04 X4 -0.03 X5 +0.03 X1*X3 + + 0.00 X1*X5 -0.03 X2*X3 -0.06 X2*X4+0.08 X2*X5 -0.03X3*X4 -0.03 X3*X5 +0.07 X4*X5. -- -- --- --- -- --- - -- -- - - - -- --- --- Eqn. (4)

R-Square = 98.04% and R-Square (adjusted) = 96.12%

The regression equation for V-Tool is

V-Tool = 0.009 - 0.007 X1 -0.004 X2 -0.005 X3 -0.005 X4 +0.004 X5 + 0.003 X1*X2+ 0.002 X1*X3 - 0.000X1*X4 - 0.003X1*X5 - 0.004 X2*X3 +0.005 X2*X4-0.004 X2*X5 - 0.003 X3*X4 - 0.007 X3*X5 -0.006 X4*X5. -- --- --- -- --- --- --- -- --- --- Eqn. (5)

R-Square = 91.58% and R-Square (adjusted) = 83.87%

The regression equation for T-WP is

T-WP = 25.539–0.728 X1 -0.241 X2 + 0.562 X3 + 0.114 X4 +0.023 X5 +0.281 X1*X2+ 0.236 X1*X3 + 0.424 X1*X4 + 0.106 X1*X5 - 0.385 X2*X3 +0.172 X2*X4+ 0.091 X2*X5 - 0.423 X3*X4 - 0.311X3*X5 + 0.547 X4*X5. -- --- --- - --- --- -- --- --- -- --- --- Eqn. (6)

R-Square = 91.45% and R-Square (adjusted) = 83.64%

The regression equation for T-Tool is

T-Tool = 25.833 - 0.041 X1 -0.097X2 -0.248 X3 -0.095 X4 +0.286 X5 +0.286 X1*X2-0.162 X1*X3 -0.130 X1*X4 - 0.246 X1*X5 +0.251 X2*X3 - 0.048 X2*X4 - 0.278 X2*X5+0.330 X3*X4 + 0.181X3*X5 -0.092 X4*X5. -- -- --- --- -- --- -- --- --- -- --- --- Eqn. (7)

R-Square = 99.77% and R-Square (adjusted) = 99.55%

The regression equation for CR is

CR = 0.061 - 0.004 X1 -0.000X2 -0.001 X3 +0.009 X4 +0.003 X5 -0.003 X1*X2+0.002 X1*X3 -0.005 X1*X4 - 0.001 X1*X5 +0.003 X2*X3 - 0.006 X2*X4 - 0.007 X2*X5+ 0.000 X3*X4 + 0.003X3*X5 -0.004 X4*X5. -- -- - --- -- --- --- -- --- --- -- --- --- --- - --- --- Eqn. (8)

R-Square = 97.14% and R-Square (adjusted) = 94.37%

ANOVA test is performed to indicate the percentage contribution of input process parameters on each output process parameters. This analysis is done at 95% confidence level. Larger F-value indicates that the variation of input process parameters makes big change on the performance of the process. . The most significant factor for MRR is Depth of cut, the percentage contribution of DOC to MRR is 88.80% for surface roughness LH it is Spindle speed, the percentage contribution of Spindle speed to SR-LH is 41.74%, the percentage contribution of DOC to SR-RH is 61.17%, the most significant factor is Spindle speed, the percentage contribution of Spindle speed to V-WP is 98.43%, the most significant factor to V-TOOL is Coolant having the percentage contribution 37.74%. Similarly the most significant factor is cutting type to T-WP at 35.32% and the most significant factor to T-TOOL is coolant at 96.68.

Validation of Mathematical models are used to predict the output parameters. The predicted output parameters are compared with that of experimental output parameters for all 18 runs. Error is calculated by taking absolute difference between experimental and predicted output parameters, average percentage error is found out to be 4.8494.

V. VALIDATION USING JAYA ALGORITHM

The mathematical model equations for MRR, SR-LH, SR-RH, V-WP, V-TOOL, T-WP, T-Tool and CR are solved using Jaya algorithm [15] for optimization of process output parameters within the considered input process parameters. Each run of JA gives optimal conditions and the corresponding output response values are produced. In the present experimentation, maximum MRR obtained using JA is 559.2021mm3/sec at up-milling type of cutting, spindle speed: 8000 rpm, feed rate: 2400 mm/min, depth of cut: 2.0 mm and type of coolant is flooded. Likewise results for all responses obtained by JA for different output responses are shown in Table 2.3.

Table 2.3:
Optimum responses obtained by solving the mathematical model equation by Jaya Algorithm.

Output responses	Optimal process input parameters				
	Type of cutting	Spind speed rpm	Feed rate Mm/r	Dept of cu mm	Coolant
MRR = 559.2021 mm3/sec	Up-milling	8000	2400	2.0	Flooded
SR-LH = 1.6449	Down-milling	7000	2100	1.0	Flooded
SR-RH = 1.6749	Up-milling	7000	1800	1.0	Flooded
V-WP = 0.0379 m/sec2	Up-milling	7000	2100	1.5	Through tool
V-TOOL = 0.000938 m/sec2	Down-milling	7000	1800	2.0	Air purging
T-WP = 22.8134	Down-milling	9000	2100	1.0	Air purging
T-TOOL= 24.896 °C	Up-milling	9000	2100	2.0	Through tool
CR = 0.0282 mm	Up-milling	7000	1800	1.0	Flooded

VI. CONCLUSION

The present experimentation focused on the optimization of machining performance characteristics (such as material removal rate, surface roughness (LH), surface roughness (RH), vibrations (WP), vibrations (Tool), Temperature (WP), temperature (Tool) and corner radius) during milling operation of Al6061-T6 aluminium alloy on a Dekel Maho CNC milling machine. Taguchi's L18 orthogonal array design had been used herein to determine the process input parameters combinations for conducting the experiment and to obtain multiple process output responses with less number of experimental runs. The process input parameters considered are: type of cutting, spindle speed, feed rate, depth of cut and coolant.

EXPLORING RESEARCH AND INNOVATIONS

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The process output parameters considered are: material removal rate, surface roughness (LH), surface roughness (RH), vibrations (WP), vibrations (Tool), Temperature (WP), temperature (Tool) and corner radius. The AHP method is used to select the optimum set of input process parameters using both equal and unequal weights of importance of the input process parameters and the process planner may make use of these results. Furthermore, the mathematical models are developed for prediction of all responses (i.e. process output parameters) which are expressed as functions of input process parameters. The mathematical models are found to be satisfactory showing maximum average percentage error as 4.85. Furthermore the mathematical models are solved by Jaya Algorithm, which is simple and easy to apply in practical optimization domain. Results obtained by RSM and JA are very close, MRR by RSM it is 559.202 mm3/sec whereas using JA it is 559.2021 mm3/sec, similarly SR-LH by RSM is 1.64489796 µm whereas with JA it is 1.6449 µm.

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