Optimization of Cutting Conditions when End Milling Aeronautic Materials (Ti-6Al-4V) using Genetic Algorithm and Response Surface Methodology

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ABSTRACT

The present work was initiated to explore the optimum tool performance in machining of Ti-6Al-4V using Super-Nitride (SN_{TR}) coated WC-Co end mills under wet conditions. Ti-alloys, particularly α + β alloys such as Ti-6Al-4V, have been the focus of considerable research recently because of their high specific strength to weight ratio, which is even maintained at elevated temperatures, excellent fracture toughness, extensive ductility and corrosion resistance. These properties make Ti-alloys the most attractive metallic materials for metal working, aeronautic industry, chemical industry, marine environments, and biomaterials applications. The Response Surface Methodology (RSM) and Genetic Algorithm (GA) were used in finding the optimum machining conditions. It was proven that overall performance using GA delivers better results than RSM, when the experimental trials were conducted according to design of experiments (DOE).

Keywords

Optimum Tool Performance, Super-Nitride, Titanium Alloys, Response Surface Methodology, Genetic Algorithm

1. INTRODUCTION

As mentioned above, ti-alloys, particularly α + β alloys such as Ti-6Al-4V, have been the focus of considerable research recently, because of their excellent fracture toughness, extensive ductility, corrosion resistance and high specific strength to weight ratio (E/ρ), which is even maintained at elevated temperatures (250 °C – 600 °C). These properties make Ti-alloys the most attractive metallic materials for metal working, aeronautic industry, chemical industry, marine environments, and biomaterials applications [1]-[2]. On the other hand previous studies have shown that titanium alloys are considered as the difficult to machine materials because of its low thermal conductivity, its high heat capacity and high chemical reactivity, regardless of the type materials used[3]-[5]. To overcome such situation, the optimum cutting conditions play a significant role in machining of difficult to cut materials. One of the optimum cutting conditions that result in the best tool performance using RSM was reported by[6]. Another investigation were carried out by [7] and [8] using genetic algorithms for machining processes. They reported that genetic algorithm can be utilized for investigating the optimum machining conditions. None of previous studies were focused for optimizing of cutting conditions on aerospace materials using this algorithm. This challenge was taken into consideration in this study, to fill the lack of information in this field. Therefore, further investigation of utilization of a genetic algorithm, was employed for optimizing of machining conditions on titanium alloys.

2. EXPERIMENTAL SET-UP

The tests were carried out with a constant a_a (axial depth of cut) 5mm and a_e (radial depth of cut) 2mm under flood conditions with a 6% concentration of water base coolant using MAHO 700S CNC machining center for side milling operation. The grade K-30 solid carbide end mill cutters, with PVD Super Nitride coated which were prepared with different radial rake angle according to Design of Experiment (DOE), were used for experimentation

The reference workpiece material was a rectangular bar (110 x 110 x 270 mm) of Ti-6Al-4V. Tool life criteria used were $VB_{max} \geq 0.25$ mm, chipping $VB_{ave} \geq 0.20$ mm and catastrophic failure.

Tool wear was measured using a Nikon tool makers' microscope with 30x magnification. The measurements of tool wear according to ISO 8688-2 were carried out for each cutting edge at initial cut and continuously after a particular length of cut (depend on wear progressive of each tool) until the end of tool life was achieved.

The independent variables such as cutting speed, feed, and radial rake angle coded with the following equation by taking into consideration the capacity and limiting cutting conditions of milling machine.

$$x = \frac{\ln x_n - \ln x_{n0}}{\ln x_{n1} - \ln x_{n0}} \tag{1}$$

Where *x* is the coded variable of any factor corresponding to its natural x_n, x_{n1} is the natural value at the +1 level and x_{n0}, is the natural value of the factor corresponding to the base or zero level[9]. The level of independent variables and coding identification are illustrated in Table 1.

Table 1: Levels of independent variables for end milling Ti6Al4V

Independent Variable	Level in coded form				
	-α	-1	0	1	+α
V (m.mm^{-1}) x_1	124.53	130	144.22	160	167.03
f_z (mm.tooth^{-1}) x_2	0.025	0.03	0.046	0.07	0.083
γ_o (°) x_3	6.2	7.0	9.5	13.0	14.8

3.RESEARCH METHODOLOGY

The mathematical models which were built using RSM will be utilized to find the optimum cutting condition using GA. The results delivered by using GA, were compared to the results using RSM[10]. The models can be described as 3F1 and 2nd CCD mathematical model.

The 3F1 mathematical model can be illustrated as:

$$y = 1.3454 - 0.64798x_1 - 1.293x_2 + 0.053199x_3 - 0.23732x_1x_2 \tag{2}$$

with the following ranges of cutting speed V_c, feed per tooth $f_z$and radial rake angle γ_o: $130 \leq V_c \leq 160$m.min^{-1}; $0.03 \leq f_z \leq 0.07$mm tooth^{-1} ; and $7 \leq \gamma_o \leq 13$ (°).
while the 2nd CCD mathematical model illustrated as follow:

$$y = 1.7688 - 0.64452x_1 - 1.2860x_2 + 0.052572x_3 + 0.050453x_1^2 - 030624x_2^2 - 0.076721x_3^2 - 0.23732x_1x_2 \tag{3}$$

with the following ranges of cutting speed V_c, feed per tooth f_z and radial rake angle γ_o:$124.53 \leq V_c \geq 167.03$m.min^{-1}; $0.025 \leq f_z \geq 0.083$mm tooth^{-1} ; and $6.2 \leq \gamma_o \geq 14.8$ (°).

GA form a class of adaptive heuristics base on principles derived from the dynamic of natural population genetic. The searching process simulates the natural evaluation of biological creatures and turns out to be an intelligent exploitation of a random search.

The problem to be solved using GA is coded to binary numbers known as chromosomes. Each chromosome contains the information of a set of possible process parameters. The population of chromosomes is formed randomly. The fitness of each chromosome is then evaluated using an objective function after the chromosome has been decoded. Selected individuals are then reproduced; the selecting occurs usually in pairs through the application of genetic operator. This operator is applied to pairs of individuals with a given probability, and result in a new offspring. The offspring from reproduction are then further perturbed by mutation. These new individuals then make up the next generation. These processes of selection, reproduction and evaluation are repeated until some termination criteria are satisfied. The representing of GA is illustrated in Figure 1.

In order to optimize the present problem using GA, the following parameters such as population size, maximum number of generation, total string length, crossover probability, mutation probability, and elitism probability have to be selected to obtain optimal solution with less computational efforts.

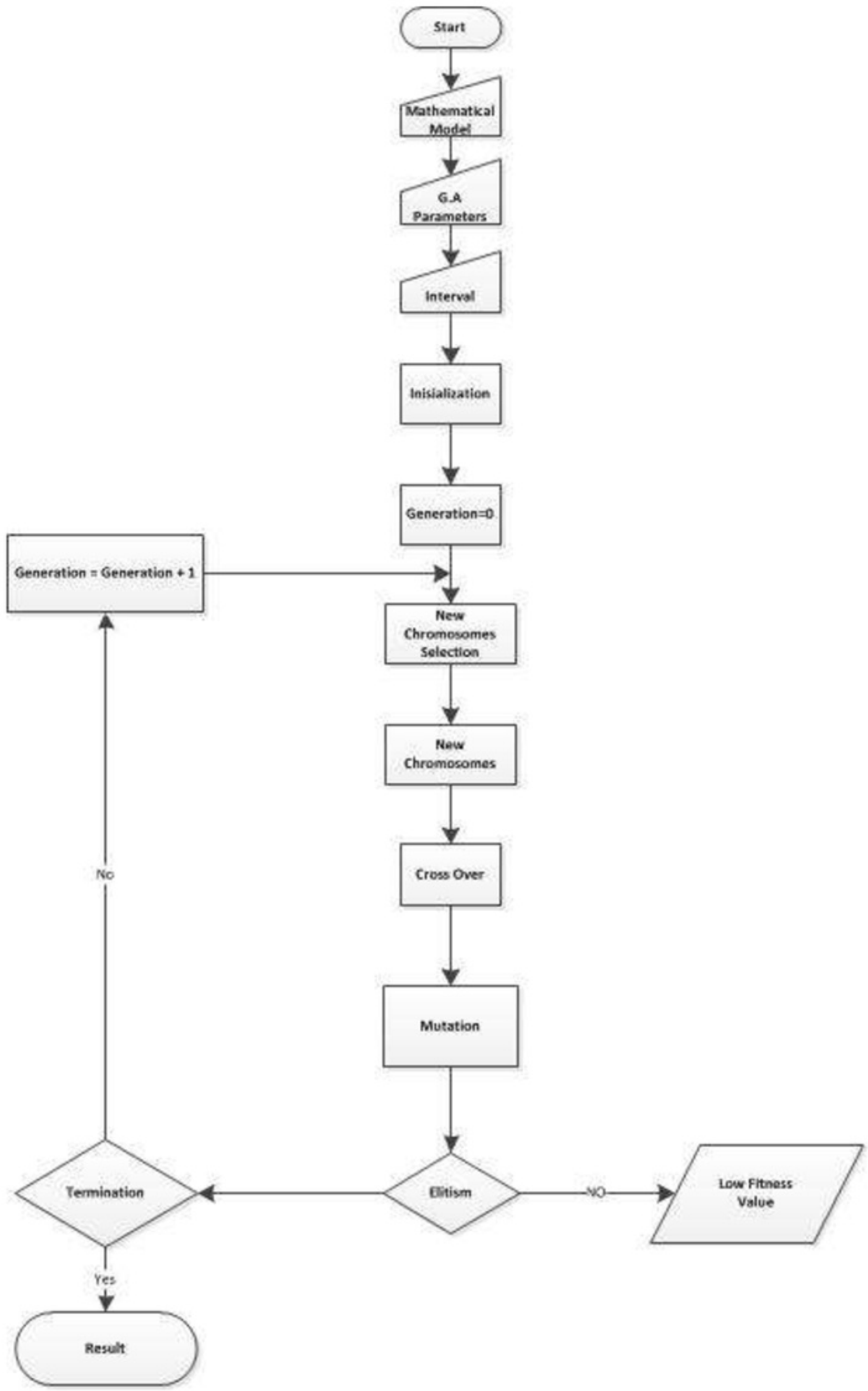

Figure 1: Flow chart of GA methodology approach.

4. RESULTS AND DISCUSSION

Tool life experimental results for SN_{TR} coated carbide tools are illustrated in Table 2These results are used to validate the comparison between the optimization using RSM and GA.

Table 2: Tool life result for SN_{TR} coated carbide tools

Std Order	Type	Cutting speed V [m/min]	Feed rate fz [mm/th]	Radial Rake angle γ[°]	Tool Life [min]
1	Factorial	-1	-1	-1	20.09
2	Factorial	1	-1	-1	8.85
3	Factorial	-1	1	-1	2.41
4	Factorial	1	1	-1	0.41
5	Factorial	-1	-1	1	22.2
6	Factorial	1	-1	1	9.68
7	Factorial	-1	1	1	2.72
8	Factorial	1	1	1	0.46
9	Center	0	0	0	5.77
10	Center	0	0	0	6.04
11	Center	0	0	0	5.69
12	Center	0	0	0	5.94
13	Axial	-1.4142	0	0	16.12
14	Axial	-1.4142	0	0	15.95
15	Axial	1.4142	0	0	2.56
16	Axial	1.4142	0	0	2.70
17	Axial	0	-1.4142	0	16.44
18	Axial	0	-1.4142	0	16.03
19	Axial	0	1.4142	0	0.44
20	Axial	0	1.4142	0	0.43
21	Axial	0	0	-1.4142	4.94
22	Axial	0	0	-1.4142	4.43
23	Axial	0	0	1.4142	5.55
24	Axial	0	0	1.4142	5.29

Table 3: The optimization results using RSM and GA

Std Order	Experimental Results (min)	Response Surface Methodology (min)	Genetic Algorithm (min)
1	20.09	20.02	20.09
2	8.85	8.78	8.88
3	2.41	2.43	2.28
4	0.41	0.41	0.53
5	22.2	22.27	22.12
6	9.68	9.76	9.94
7	2.72	2.70	2.73
8	0.46	0.46	0.50
9	5.77	3.84	3.82
10	6.04	3.84	3.82
11	5.69	3.84	3.82
12	5.94	3.84	3.82
13	16.12	16.14	15.64
14	15.95	16.14	15.64
15	2.56	2.61	2.58
16	2.7	2.61	2.58
17	16.44	19.59	15.38
18	16.03	19.59	15.38
19	0.44	0.52	0.43
20	0.43	0.52	0.43
21	4.94	4.67	4.55
22	4.43	4.67	4.55
23	5.55	5.42	5.27
24	5.29	5.42	5.27

Table 4: Comparison between RSM and GA validated using the experimental results.

Std Order	Experimental Results (min)	RSM (min)	GA (min)	Error of RSM	Error of GA
1	20.09	20.02	20.09	0.0043	0.0000
2	8.85	8.78	8.88	0.0054	0.0011
3	2.41	2.43	2.28	0.0003	0.0159
4	0.41	0.41	0.53	0.0000	0.0140
5	22.2	22.27	22.12	0.0053	0.0060
6	9.68	9.76	9.94	0.0066	0.0662
7	2.72	2.70	2.73	0.0004	0.0001
8	0.46	0.46	0.50	0.0000	0.0014
9	5.77	3.84	3.82	4.0815	4.1811
10	6.04	3.84	3.82	4.0815	4.1811
11	5.69	3.84	3.82	4.0815	4.1811
12	5.94	3.84	3.82	4.0815	4.1811
13	16.12	16.14	15.64	0.0106	0.1564
14	15.95	16.14	15.64	0.0106	0.1564
15	2.56	2.61	2.58	0.0005	0.0021
16	2.7	2.61	2.58	0.0005	0.0021
17	16.44	19.59	15.38	11.2526	0.7328
18	16.03	19.59	15.38	11.2526	0.7328
19	0.44	0.52	0.43	0.0065	0.0001
20	0.43	0.52	0.43	0.0065	0.0001
21	4.94	4.67	4.55	0.0002	0.0188
22	4.43	4.67	4.55	0.0002	0.0188
23	5.55	5.42	5.27	0.0000	0.0230
24	5.29	5.42	5.27	0.0000	0.0230
MSE (Mean Square Error)				1.620391906	0.778974202
RMSE (Root Mean Square Error)				1.272946152	0.882595152

The optimization results using RSM and GA are shown in Table 3. The Mean Square Error (MSE) of both methods are figured out in Table 4. From this table, it can be concluded that the optimization using GA delivered better results than that using RSM. It can be recognized from the value of MSE of each approach.

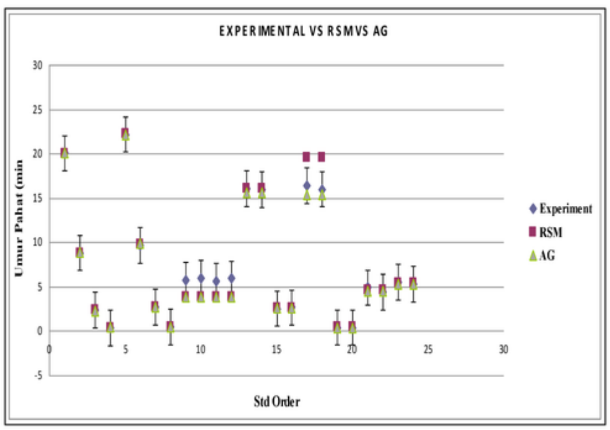

Figure 2: Error Distribution of both optimization methods validated by experimental results.

To provide easier observation of errors, the occured errors was represented and visualized in Figure 2. Finally, it can be concluded from the optimization results that GA has the ability and is suitable for achieving the best possible tool life when end milling Ti-64 in combination of cutting speed, feed rate, and radial rake angle.

5. CONCLUSIONS

1) The better overall performance in finding the optimum cutting conditions was delivered by GA compared to RSM. This can be recognized from its accuracy using the validation tests.

2) The best results of GA was produced using following parameters:
   - Population size : 80
   - Number of generation : 5
   - Total string length : 34
   - Crossover probability (Pc) : 0.8
   - Mutation probability (Pm) : 0.03
   - Elitism probability : 0.5
3) Even GA delivers better results than RSM, the difference between them was not significant.
4) It was found that GA can only give better results when the optimum parameters were taken in the iterations.

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