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Optimization of Cutting Parameters in Milling Process Using Genetic Algorithm and ANOVA (March 2020)

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KEYWORDS

Milling, cutting conditions, genetic algorithms.

ABSTRACT

In this present work use a genetic algorithm for the selection of cutting conditions in milling operation such as cutting speed, feed and depth of cut to investigate the optimal value and the effects of it on the material removal rate and tool wear. The material selected for this work was Ti-6Al-4V Alloy using H13A carbide as a cutting tool. Two objective functions have been adopted gives minimum tool wear and maximum material removal rate that is simultaneously optimized. Finally, it does conclude from the results that the optimal value of cutting speed is (1992.601m/min), depth of cut is (1.55mm) and feed is (148.203mm/rev) for the present work.

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1. INTRODUCTION

Milling operation is widely used in many enforcements such as aerospace and automobile industries. A wide variety of applications can range from very simple parts to final parts with complex geometry and shape, high level of precision and surface qualities. In general, the milling model is more complex than other types of processing operations. During the literary survey, some important journal papers published in various national and international conferences are reviewed. Mention was made of improvement of articles related to the milling process published by a various project of companies. Some standard books are referred to during this stage. Some important information, knowledge and conclusions are derived from this literary survey to enable the fundamentals of doing the work, prepared this study to increase the rate of metal removal and reduce the tool wear in the milling process where the main parameters in machining affecting on tool wear and material removal rate are cutting speed, feed, and depth of cut.

Before milling, it is necessary to adopt suitable cutting parameters to obtain better surface roughness. Through the objective function. The machine user can refer to the technical manual of the machine and it is necessary to rely on the dynamic characteristics of the tool the cutting parameters can be selected through which the tool wear. Cutting time and cutting force are reduced then produce a surface on stable conditions [1]. Ti-6Al-4V widely used in aerospace and chemistry due to its high mechanical properties and corrosion and heat resistance, titanium alloys is used as a work piece use in applications that require high cutting speed [2]. The ambit of cutting speed and feeding that provide favorable performance is very restricted according to the available records, so it needs to sort out the ranges that give good operating conditions because the choice of operating standards is very important [3]. Siddaet al. used a genetic algorithm with response surface methodology, they were linked with an effective function, which reduced surface roughness by about 44.22%. The experiments Taguchi’s L50 orthogonal array [4]. Sonmez et al. [5] manage to maximize the production rate by developing an optimal strategy through which calculates parameters of cut for multi-pass milling process like plain and face milling. Kim and Ramulu [6] considered the quality of the hole and the cost of the machines as the objective function that improved the drilling process for the graphite/titanium bismaleimide-titanium alloy. Wang et al. [7] Considered that the objective function is the production time by which to improve the cutting conditions for the plain milling.

2. MATERIALS and METHODS

I. Workpiece material

Titanium alloys (Ti-6Al-4V) due to their high corrosion resistance and low density with high strength to weight ratio are used in many applications including aerospace and chemistry, the physical properties and chemical composition are listed in TABLES I and II respectively. The experimental work was implemented on a vertical 3-axis CNC Milling machine "C-tek" type in Turning Unit, Training and Workshop Center at the University of Technology as shown in Figure 1 on Ti-6Al-4V Alloy Work piece (80mm length, 40mm width, and 20mm depth) Figure 2 using H13A carbide as a cutting tool.

TABLES I: Physical and mechanical properties OF Ti6al4v

	Densit-y g/cm3	Young's modulus Gpa	Shear modulus Gpa	Bulk modulus Gpa	Poisson 's ratio	Yield strength Mpa	Ultimate strength Mpa	Hardness Rockwell C	Unifo-rm Elongat ion %
Min	4.429	104	40	96.8	0.31	880	900	36	5
Max	4.512	113	45	153	0.37	920	950	--	18

TABLE I: The typical alchemical structure of Ti6al4v

	V	Al	Fe	O	C	N	H	Y	Ti	Remainder Each	Remainder Total
Min	3.5	5.5	--	--	--	--	--	--	--	--	--
Max	4.5	6.75	0.3	0.2	0.8	0.5	0.015	0.005	Balance	0.1	0.3

Figure 1: 3-Axis CNC milling machine "C-tek" type

Figure 2: The work piece that used in this study

II. Experimental details

The input parameter chosen for machining operation is cutting speed, feed rate, and depth of cutting its range shown in TABLE III.

TABLE III: Operating parameter

Cutting speed (rpm)	500, 1500, 2000
Feed rate (mm/rev)	30, 100, 150
Depth of cut (mm)	0.4, 1.5, 2

Table IV shows the specific parameters and their levels. Where nine experiments conducted as stated by Taguchi design.

TABLE IV: Experimental results

No of exp	speed	feed	depth of cut	MRR	TW
1	500	30	0.4	3.2515	0.0884
2	500	100	1.5	26.407	0.5560
3	500	150	2.0	38.897	0.8115
4	1500	30	1.5	18.846	0.4078
5	1500	100	2.0	37.499	0.7105
6	1500	150	0.4	16.228	0.3885
7	2000	30	2.0	25.936	0.5539
8	2000	100	0.4	15.837	0.2790
9	2000	150	1.5	31.821	0.3692

The main effect plot and signal-to-noise ratio of MRR and TW are shown in Figures 3, 4, 5, and 6 respectively, and the response table for means and S/N ratio display in TABLES V, VI, VII, and VIII respectively.

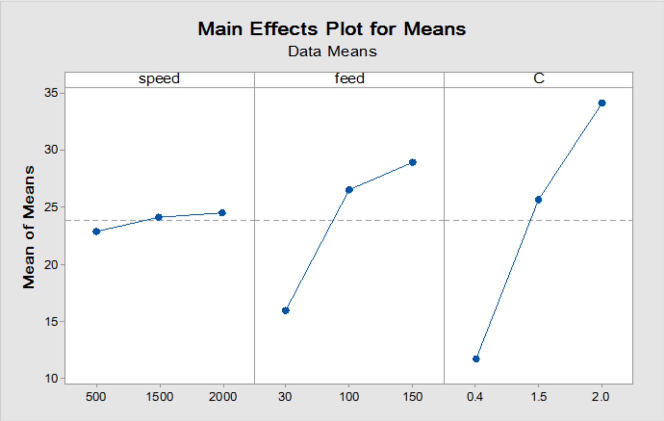

Figure 3: Main effect plot for MRR

TABLE VI: Response table for means (MRR)

Level	speed	feed	depth of cut
1	22.85	16.01	11.77
2	24.19	26.58	25.69
3	24.53	28.98	34.11
Delta	1.68	12.97	22.34
Rank	3	2	1

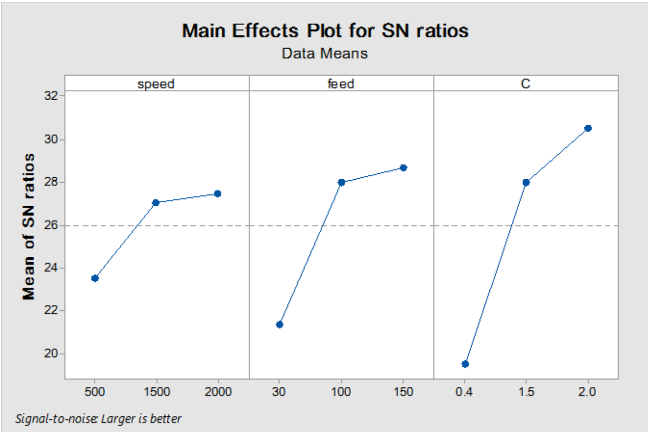

Figure 4: Signal-noise ratio for MRR

TABLE VII: Response table for signal to noise ratios larger is better (MRR)

Level	Speed	Feed	Depth of cut
1	23.49	21.34	19.48
2	27.06	27.97	28.00
3	27.44	28.69	30.52
Delta	3.95	7.34	11.04
Rank	3	2	1

Figure 5: Main effect plot for TW

TABLE VII: Response table for means (TW)

Level	speed	feed	depth of cut
1	0.4853	0.3500	0.2520
2	0.5023	0.5152	0.4443
3	0.4007	0.5231	0.6920
Delta	0.1016	0.1730	0.4400
Rank	3	2	1

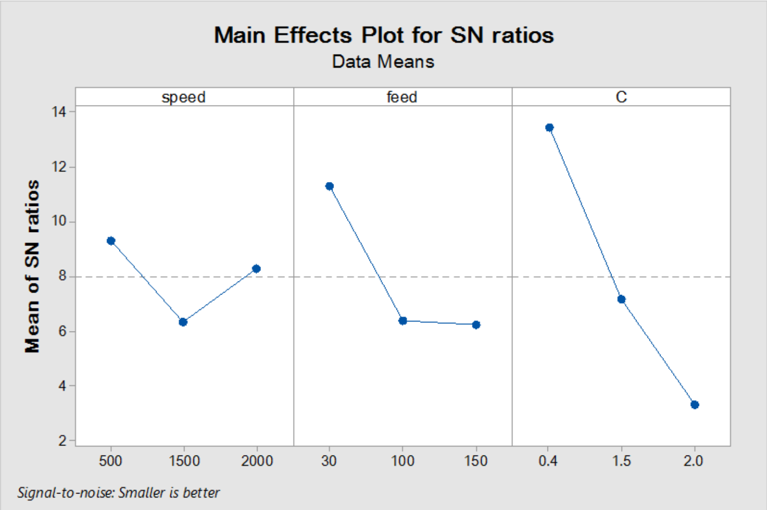

Figure 6: Signal-Noise Ratio for TW

TABLE VIII: Response table for Signal to Noise Ratios smaller is better (TW)

Level	speed	feed	depth of cut
1	9.328	11.331	13.457
2	6.324	6.385	7.181
3	8.291	6.227	3.305
Delta	3.004	5.104	10.152
Rank	3	2	1

III. Genetic Algorithm Optimizations

Genetic algorithms are used to find the best solutions to the problem based on the mechanism of natural selection and heredity (Goldberg, 1989; Deb Kalyanmony, 1991) according to Darwin's theory, the survival of the fittest. Many researchers use GA in their works Tolouei-Rad and Bidhendi [8] specified the optimum operating parameters of the milling process used in NC machines which can also be used in traditional instruments. Choudhury and Rao [9] give optimal values of speed and feed during the cutting operation that achieved through a new method for improving cutting tools. Suresh et al. [10] used a genetic algorithm to improve surface roughness as well as a surface response methodology to develop a mathematical model of the second order of operating standards that predict surface roughness.

The first step in GA that selecting a coding to specify problem parameters, a chosen worker, a crossover worker, and a mutation worker. Select population size, Crossover eventuality, and mutation eventuality. Choose a superior generation number t max. set t = 0. Figure 7 clarifies the proceedings of GA.

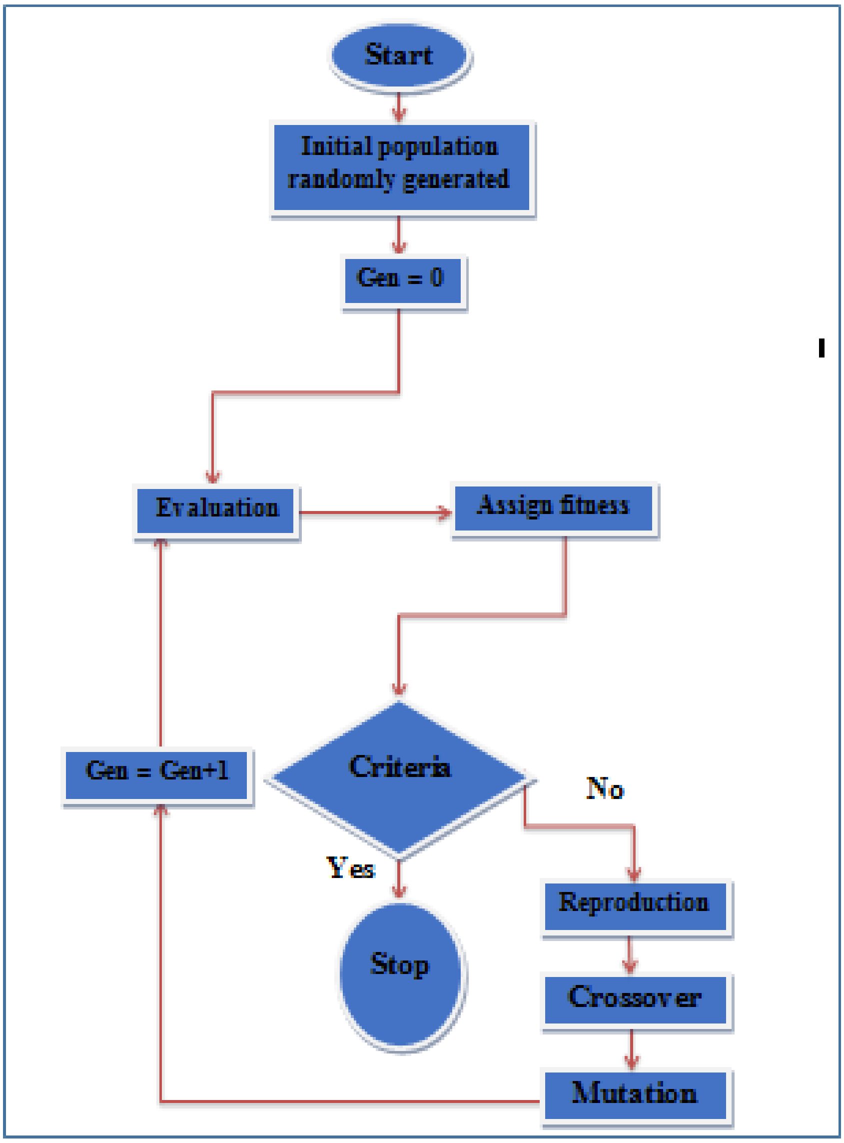

Figure 7: Genetic algorithm proceedings

IV. Fitness Function Equations

This work aimed to find the optimum value of operating parameters that gives topmost material removal rate (MRR) and minimum tool wear (TW), material removal rate is represented as follows:

$$\text{MRR} = (1000)*(v)*(f)*(d) \tag{1}$$

Where the tool wear represents in Eq. (2).

$$\text{TWR} = 0.44539V^{0.23904}f^{0.249125}d^{0.17987} \tag{2}$$

Where, V is cutting speed (m/min), f is feed rate (mm/rev), and d is the depth of cut (mm)
For this work, the fitness function represented as follows:

$$\text{Fitness function} = (\text{TWR}) + (\text{MRR}) \tag{3}$$

V. GA Information

In this work as shown in Figure 8, the values entered in the MATLAB program were: population size (60), the total length of the of bit strings (18), the chromosome length is (6), the probability for a crossover (0.85), single-point operator, the probability for mutation is (0.02) and fitness parameter (MRR, tool wear).

Where the lower and upper bounds for operating parameters:

Upper bounds =500 for Speed, lower bounds =2000

Upper bounds =30 for Feed , lower bounds =150

Upper bounds =0.4 for depth of cut lower bounds =2

Figures 8 and 9 show the program that finalizes after inserting the fitness function then inserts whole data in GA.

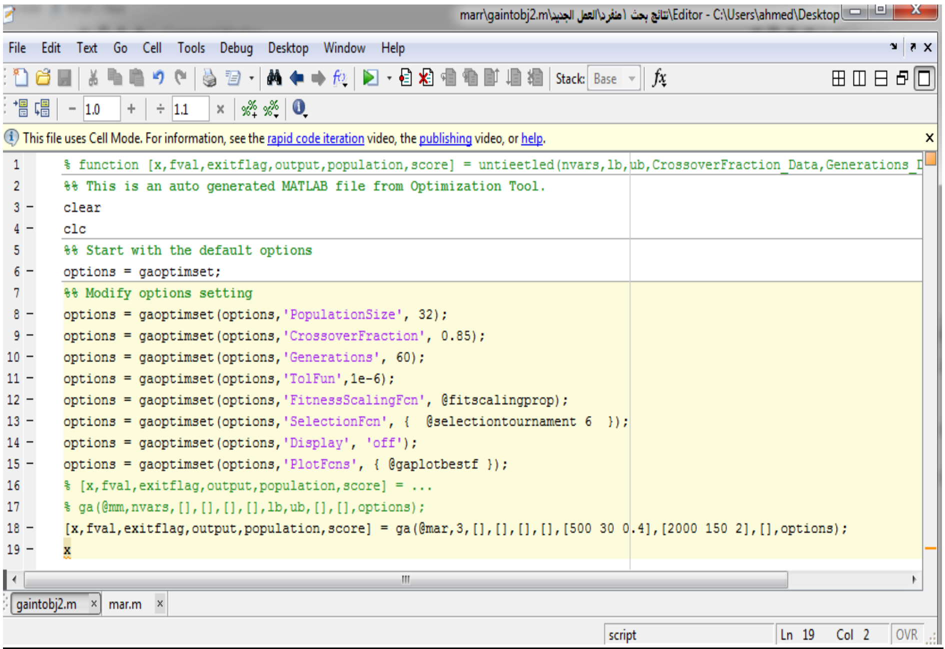

Figure 8: Initialization program

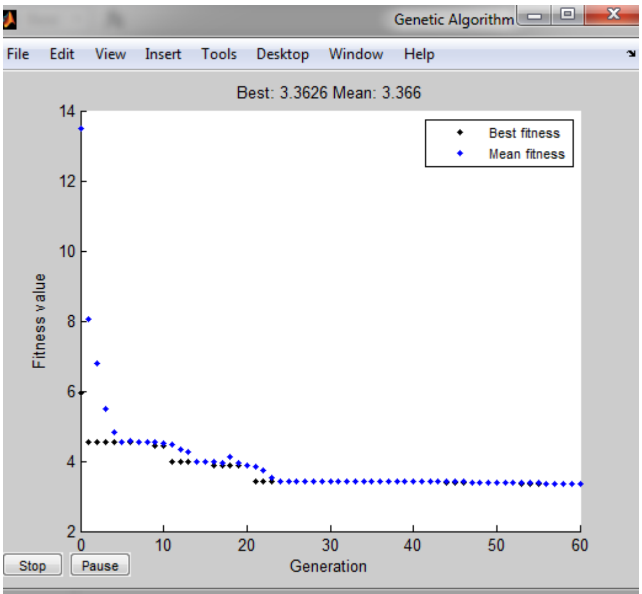

Figure 9: The implemented data on GA

Providing better reproductive opportunities through offspring gives more possible solutions so Table 9 shows that the increase in the crossover value caused improvement in the results until to reach the optimal values, where reading No (20) in Table X shows the best fitness (3.3626) and mean fitness (3.366) which was evident in Figure 9 which represents the implementation of the program.

TABLE X: The optimum solution for several values of GA parameters

Number of iteration	Crossover	Mutation	Optimal solution	
			Best	Mean
1	0.5	0.04	0.056321	0.056453
2	0.5	0.05	0.066012	0.067432
3	0.5	0.06	0.069412	0.073211
4	0.5	0.07	0.077213	0.077631
5	0.5	0.08	0.078231	0.078912
6	0.6	0.04	0.065221	0.066321
7	0.6	0.05	0.072132	0.072322
8	0.6	0.06	0.075423	0.076421
9	0.6	0.07	0.079543	0.082311
10	0.6	0.08	0.094352	0.096432
11	0.7	0.04	0.653211	0.662132
12	0.7	0.05	0.663214	0.673421
13	0.7	0.06	0.554231	0.564326
14	0.7	0.07	0.674325	0.684321
15	0.7	0.08	0.732154	0.754234
16	0.85	0.04	1.453678	1.497654
17	0.85	0.05	1.674385	1.687542
18	0.85	0.06	2.734226	2.764239
19	0.85	0.07	2.834216	2.863143
20	0.85	0.08	3.362600	3.366000

The optimal solution obtained at different values in the case of crossover and mutation, Table XI shows cutting parameter that created for 15 generations and first population =60 by using crossover eventuality (0.85) and mutation eventuality (0.02) .

TABLE XI: parameters of cut for 15 generation & first populations = 60 in crossover & mutation operator

	Crossover					mutation				
No of generation	V	F	D	MRR	TWR	V	F	D	MRR	TWR
1	500	30	0.4	3.2515	0.0883	500	35	0.4	3.7919	0.1007
2	1000	50	0.45	6.1249	0.1578	600	45	0.5	6.2907	0.1529
3	1200	60	0.5	7.9156	0.1985	700	50	0.6	8.2489	0.1939
4	1400	70	0.55	9.7063	1.7255	800	60	0.7	10.748	0.2467
5	1500	80	0.6	11.499	0.2783	900	70	0.75	12.538	0.2857
6	1800	90	0.65	13.288	0.3208	1000	100	0.8	16.489	0.3720
7	2000	100	0.7	15.078	0.3615	1100	125	1	22.027	0.4877
8	500	110	0.75	16.859	0.3733	1200	150	1.5	31.816	0.6859
9	100.00	120	0.8	18.651	0.4192	1400	50	2	28.094	0.5909
10	1200	125	0.85	19.902	0.4481	1500	70	0.45	8.2897	0.2135
11	1400	130	0.9	21.152	0.4771	1800	75	0.85	14.501	0.2579
12	1500	135	1	23.110	0.5181	2000	80	0.55	10.791	0.2731
13	1800	140	1.5	30.738	0.6725	1120	90	0.65	13.284	0.3092
14	2000	145	1.8	35.532	0.7702	1440	40	0.9	11.424	0.2654
15	500	150	2	44.541	0.8115	950	145	2	38.359	0.8073

Optimal results were getting after the pick of the fitness function for the overall length of the string 18 and then relocate to the MATLAB (R2017b) after initialization GA parameters and symbolize these results in Table XII.

TABLE XII: (GA) that accomplish in MRR, tool wear

Speed	Feed	Depth of cut	MRR	TWR	Rank
511.026	30.16	0.41	3.4106	0.70884	1
623.064	45.73	0.45	5.6610	0.67867	1
773.113	60.29	0.54	8.5113	0.63545	1
942.641	85.13	0.63	12.437	0.35097	1
1015.543	100.30	0.72	15.388	0.28919	1
1495.612	120.43	0.72	17.567	0.27297	1
1832.721	135.72	0.83	20.780	0.15132	1
1992.601	148.203	1.55	36.335	0.00917	1

TABLE XII: Continued

Speed	Feed	Depth of cut	MRR	TWR	Rank
583.228	35.74	1.83	24.169	0.70323	1
644.310	50.53	0.42	5.7549	0.60567	1
864.214	70.62	0.53	9.4866	0.59867	1
1513.621	90.31	0.64	13.177	0.31475	1
1646.342	111.26	1.2	23.379	0.2358	1
1254.603	122.64	0.78	18.655	0.2534	1
1725.325	122.64	1.56	29.712	0.1923	1
1802.614	137.21	1.87	35.680	0.13728	1
1827.604	105.31	1.93	33.083	0.13231	1
884.23	105.31	1.93	12.7343	0.13201	1

3. RESULTS and DISCUSSION

The program has been displayed as shown in Figure 8. The population size was selected by created a random solution space at limits of operating parameters, the implemented of the GA program shown in Figure 9. The results in TABLE XIII demonstrate the effectiveness of the proposed GA approach for predicting the influence of machining Parameters on MRR, TWR Model variables are represented as a binary string the length of the chromosome is 6bit asset of binary-coded 18 populations generated, crossover, and Mutation are completed. After completing a single-point crossover and bitwise mutation on the chromosomes, the optimum solution is stored for all generation and the steps continue to reach convergence after sundry runs of GA, the MRR and TWR acquired at 0.85 crossovers and 0.02 mutation, the evaluated optimal values of the variable that obtained by GA for each machining status Located Within the range of variables of real machining conditions and also found that the best fitness for MRR and TWR is obtained if optimal parameters are used, the final results show in Table XII.

Table 11 shows that the population size was 18, the input parameters as speed, feed and depth of cut while the output parameters were MRR and TWR. The results in Table 11 showed that the genetic algorithm has given significant improvement in order to reach the optimal values where note the increase in the material removal rate as well as a decrease in tool wear, wherein Table XII speed was (511.026), feed (30.16), depth of cut (0.41) in the first reading that gives MRR (3.4106) and TWR (0.70884), the genetic algorithm made a clear improvement in the results, which led to an increase in the material removal rate and reducing tool wear. Generations were randomly generated to reach optimum values. where the reading No (8) gave the highest value of the material removal rate, and in return, the value of tool wear was small with increasing both of feed and depth of cut, that means the most influencing factor on results was feed and depth of cut, It is clear that the value of MRR influence by the depth of cut, MRR increases as the depth of cut increases at depth of cut (0.41) the MRR was (3.4106mm3/min), and the feed influence on the value of TWR its value was (0.70884μ) at feed (30.16), the optimum values were acquired at depth of cut (1.55), feed (148.203), speed (1992.601), MRR was (36.335mm3/min), TWR was (0.00917μ).

Figure10 displays the influence of MRR by the depth of cut, MRR increase while depths of cut increase. The Max value of MRR was (36.335 mm^3/min) that appeared at depth (1.55mm) in reading (8), Figure 11 displays the influence of depth of cut on Tool wear, the rises in depth of cut it causes a decrease in Tool wear. The optimum value for TWR was (0.00917μ)

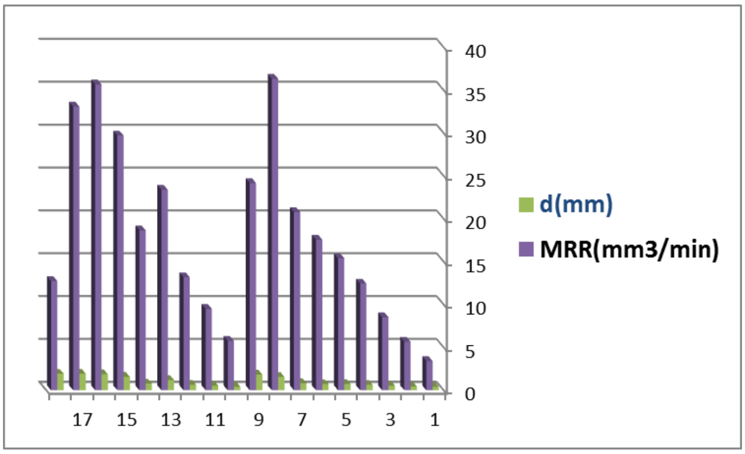

Figure 10: The influence of depth of cut on MRR

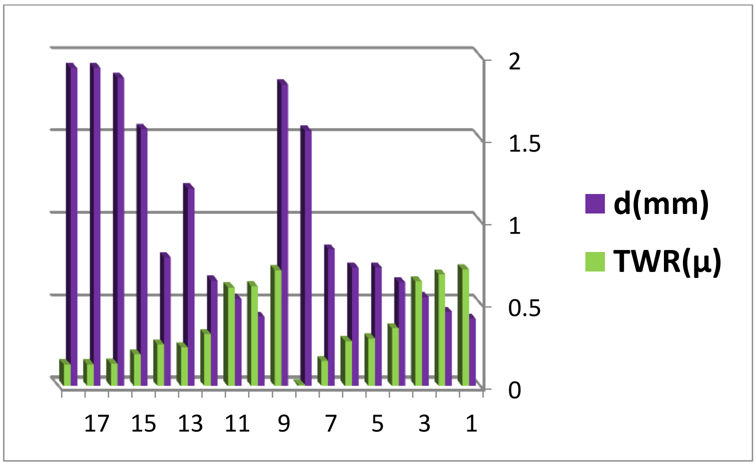

Figure 11: The influence of depth of cut on TWR

4. ANALYSIS of VARIANCE (ANOVA)

To display the influence of operating parameters on the results. Was used minitab17 program and Analysis of Variance (ANOVA) to found the important operation variables and measure their effects on the MRR & TWR, the results displayed on the Tables XIII and XIV.

TABLE 12: The results of ANOVA for MRR

Source of variance	DOF	Adj SS	Adj MS	F-Value	P-Value
Cutting speed	1	156.34	156.335	10.75	0.005
Feed	1	4.22	4.218	0.29	0.599
Depth of cut	1	416.04	416.044	28.60	0.000
Error	14	203.69	14.549		
Total	17	1854.87			

The greatest value of the F ratio among the variables was for the depth of cut was (28.60) as seen in Table XIII. Accordingly, the most effected variable on MRR is the depth of cut, which is about twice about cutting speed (10.75). The feed rate has less influence on the F ratio (0.29).

Model Summary

S	R - sq	R – sq (adj)	R – sq (pred)
0.0689641	92.79%	91.25%	82.39%

TABLE XIV: ANOVA results for TWR

Source of variance	DOF	Adj SS	Adj MS	F-Value	P-Value
Cutting speed	1	0.000120	0.000120	0.03	0.876
Feed	1	0.132622	0.132622	27.88	0.000
Depth of cut	1	0.021907	0.021907	4.61	0.049
Error	14	0.066585	0.004756		
Total	17	0.923584			

On the other hand, Table XIV display the most influential parameter at TWR is the feed with F ratio (27.88) and the depth of cut with F ratio (4.61) the cutting speed has a less influence with F ratio (0.03)

S	R - sq	R -sq(adj)	R - sq(pred)
0.0689641	92.79%	91.25%	82.39%

Regression Equations for the results are:

MRR = -5.49 + 0.01355 V (rpm) - 0.0305 F(mm/rev) + 9.63 d(mm)
TWR= 0.9454 - 0.000012 V (rpm) - 0.00540 F(mm/rev) - 0.0699 d(mm)

Figures 12 and 13 display plot for the operating parameter individually, Figure 12 displays the optimum speed of cut is (1992.601m/min), depth of cut is (1.55mm) and feed is (148.203mm/rev). While Figure 13 displays the optimum value for MRR (36.335mm3/min) With the lowest value of tool wear (0.00917μ).

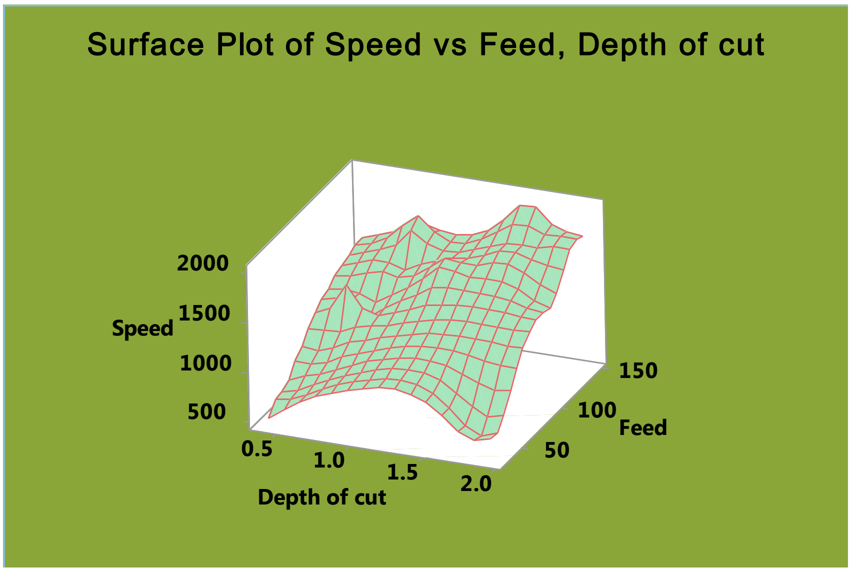

Figure 12: Surface plot of speed with feed, depth of cut

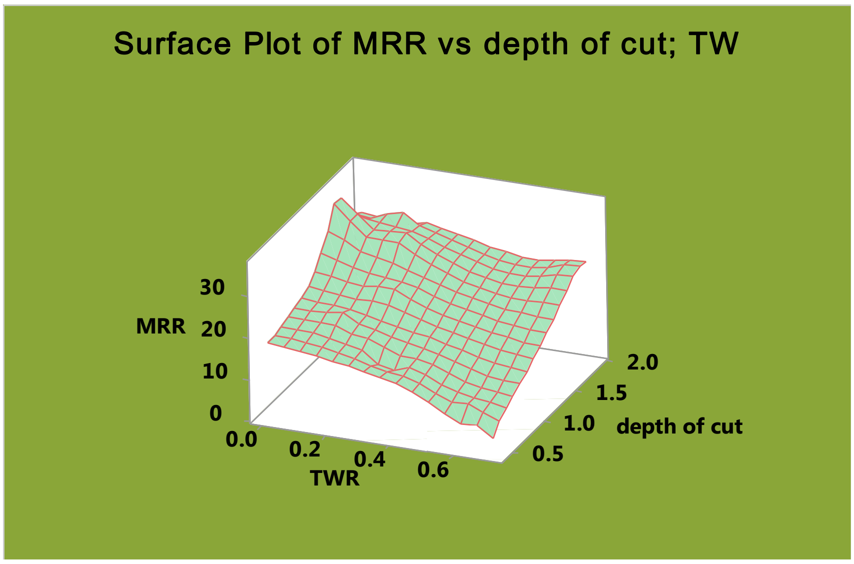

Figure 13: Surface plot of MRR with tool wear, depth of cut

5. CONCLUSIONS

In the milling process to getting the best selection for cutting parameters and study their impact on the process is resorting to optimization processes that make the model more realistic by taking into account several important operational constraints that can be summarized in our study with the following points.

i. The genetic algorithm has shown the main factors affecting the rate of metal removal and tool wear for Ti-6Al-4V Alloy.

ii. The best target function was selected, through which we were able to increase the metal removal rate to its maximum value and reduce tool wear to the minimum value.

iii. The results were speeding (1992.601m/ minute), feed (148.203mm/ rev) & depth of cut (1.55mm).

iv. Analysis of variance shows that the most effective factors were the depth of cut with an F ratio (28.60) for MRR and the feed for TWR with F ratio (27.88).

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