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RESEARCH ARTICLE OPEN ACCESS

MULTI-OBJECTIVE OPTIMIZATION OF END MILLING PROCESS PARAMETERS FOR MINIMUM SURFACE ROUGHNESS USING MOGA

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ABSTRACT

In this paper, a multi-objective genetic algorithm (MOGA) has been used for the optimization of end milling process parameters for minimum surface roughness and machining time. The regression equation has been generated and used in the multi-objective genetic algorithm tool in MATLAB R2015a. In the present work, an experiment has been carried out on the end milling process of AISI1020 with a tungsten carbide tool by varying cutting speed, feed rate and depth of cut. The responses such as surface roughness and machining time have been measured using a Mitutoyo surface roughness tester and stopwatch, respectively. Optimize the machining parameters for minimum surface roughness and machining time. This study finds the interactive effect of input parameters such as cutting speed, feed and depth of cut on surface roughness. The result achieved by MOGA has been validated through experimentation. A good correlation has been found between MOGA and experimentation. It proves MOGA can be efficiently utilized to optimize end milling process parameters for minimum surface roughness and machining time.

I. INTRODUCTION

End milling has been used in various industries, including die-making, aerospace, automotive, and biomedical for simple to complex geometric profiles [1]. End milling operation is a very common machining operation and it removes the material fast with good quality. Surface roughness has a significant impact on production cost and quality and its estimate of a product's technological quality. Surface roughness also affects functional qualities, including fatigue resistance, surface friction, coating properties, heat transmission, etc. Surface finish is very dynamic and process dependent so it is very difficult to calculate the surface roughness through the analytical techniques. Machining time decides the completion time of the product and the productivity rate of industries. The prediction of machining time is useful for the estimation of delivery time and manufacturing cost of products in industries. When the machining time is decreased the machining cost decreases and the production rate increases [2].

The MOGA has been used to optimize end milling process parameters for minimum surface roughness and machining time. C. C. Tsao et al.[2009] has been used the grey–Taguchi method for A6061P-T651.In this paper, grey relational analysis has been used and reduce flank wear and surface roughness [3]. S. Moshat et al. [2010] have used the Taguchi method coupled with grey relational analysis for end milling operations. They calculate the weights of each response. The Entropy measurement technique has been used for the estimation of its performance characteristics [4]. J.S. Pang et al. (2014) have used the Taguchi methodology for optimization. Aluminium-based composite material has been used for end milling operations. They have selected responses such as surface roughness and cutting force [5]. S. Ajith Arul Daniel et al. [2019] have used artificial neural networks and grey Taguchi analysis for the optimization of input process parameters for the milling operation of Al5059-SiC-MoS2 [6]. Reddy Sreenivasulu et al. [2019] used Grey grey-based Taguchi approach integrated with entropy measurement for glass fiber-reinforced polymer matrix composite for optimization [7]. M. Jebaraj et al. (2019) have used TOPSIS and ANOVA for statistical analysis for optimization. They selected cutting speed, feed and cooling environment as input variables and temperature, surface roughness and cutting forces were selected as responses [8]. Jakeer Hussain

Shaik et al. (2020) have used an FEA to improve the dynamic stability of the end milling process. Study the effect of input parameters on output variables through ANOVA and artificial neural network.

They selected input parameters such as tool rotational speed, tool overhang, bearing span, tool diameter and force angle for optimum design of the spindle tool system and stable depth of cut [9]. Menderes Kam et al. (2021) have analyzed the tool vibration and surface roughness of the turning process for AISI 4340 (34CrNiMo6). They have used the Taguchi Method for analysis. Analysis of variance was used to determine the effects of machining parameters on the Vibration and surface roughness values [10]. I.A. Daniyan et al. (2021) used response surface methodology and find out the relation of end milling process parameters in terms of optimization. The experiment has been conducted on the DMU80monoBLOCK Deckel Maho 5-axis CNC milling machine for AA6063. The mathematical and optimization model has been developed based on numerical value and Physical experiment results [11].

II. METHODOLOGY

In this study, experimental results have been used for the generation of regression equations in Minitab 17. The regression equation has been used for the generation of objective functions in MOGA. Here cutting speed, feed rate and depth of cut are controllable factors that influence surface roughness. The surface roughness (µm) and machining time (Sec.) have been discovered using eq. (1) and eq. (2).

Surface roughness (µm)

$$= -0.1803 - 0.000302 * Vc + 2.573 *f + 0.0473 *d \quad (1)$$

Machining time (Sec.)

$$= 6.695 - 0.01570 * Vc - 10.047 *f + 0.033 *d \quad (2)$$

III. EXPERIMENTATION

In this study we considered 3 factors such as cutting speed, feed and depth of cut. The range of input variables are shown in Table 1.

Table 1: Factors and level combination.

Factors	**Cutting Speed**	**Feed**	**DOC**
Levels	5	5	5
Values	140, 150, 160, 170, 180	0.12, 0.15, 0.18, 0.21, 0.24	0.2, 0.4, 0.6, 0.8, 1

Source: Authors, (2025).

Based on the design of the experiment we carried out a total of 25 experiments. All the experiments have been carried out on JYOTI CNC vertical milling center. The experimental setup is shown in Fig. 1.

Figure 1: Experimental set-up of end milling operation.
Source: Authors, (2025).

AISI1020 steel is selected as a workpiece material because it is easily available and low price. The chemical composition of AISI1020 is shown in Table 2.

Table 2: AISI1020 chemical composition.

Elements	**P**	**Mn**	**C**	**S**	**Fe**
Composition in %	0.026	0.565	0.197	0.039	99.100

Source: Authors, (2025).

Solid carbide end mill cutters have been selected as a cutting tool with 12 mm diameter and 4 flutes [12]. During the experimentation total of 25 work specimens (100 x 50 x 10) have been prepared for 25 datasets. The work specimen before the experimentation is shown in Figure 2.

Figure 2: Work Specimen before the operation.
Source: Authors, (2025).

The work specimens after the end milling operation are shown in Figure 3.

Figure 3: Work Specimen after the operation.
Source: Authors, (2025).

The experimental values of surface roughness have been measured through the MITUTOYO Surface texture tester shown in Fig. 4. The machining time has been measured through a stopwatch.

Figure 4: Surface roughness measurement.
Source: Authors, (2025).

The experimental results of 25 data sets are shown in Table 3.

Table 3: Experimental Results of 25 data set.

Sr. No.	Cutting speed (m/min)	Feed rate (mm/tooth)	Depth of cut (mm)	Surface roughness (µm)	Machining Time (Sec.)
1	140	0.24	0.2	0.30	2.10
2	140	0.24	0.4	0.46	2.19
3	140	0.24	0.6	0.44	2.34
4	140	0.24	0.8	0.44	2.10
5	140	0.24	1	0.48	1.80
6	150	0.12	0.2	0.12	3.10
7	150	0.12	0.4	0.12	3.23
8	150	0.12	0.6	0.11	3.31
9	150	0.12	0.8	0.11	3.25
10	150	0.12	1	0.13	3.39
11	160	0.15	0.2	0.18	2.40
12	160	0.15	0.4	0.17	2.76
13	160	0.15	0.6	0.15	2.56
14	160	0.15	0.8	0.17	2.40
15	160	0.15	1	0.20	2.51
16	170	0.18	0.2	0.26	2.30
17	170	0.18	0.4	0.26	2.29
18	170	0.18	0.6	0.25	2.23
19	170	0.18	0.8	0.24	2.22
20	170	0.18	1	0.29	2.33
21	180	0.21	0.2	0.30	1.70
22	180	0.21	0.4	0.35	1.75
23	180	0.21	0.6	0.38	1.82
24	180	0.21	0.8	0.31	1.86
25	180	0.21	1	0.35	1.93

Source: Authors, (2025).

III.1 MULTI-OBJECTIVE OPTIMIZATION

Here multi-objective genetic algorithm has been used for optimization with MATLAB R2015a. The developed regression equation achieved through Minitab17 has been utilized for the MOGA tool. In MOGA, three main subordinates reproduction, crossover and mutation have been used for optimization. The objective functions for minimizing the surface roughness and machining time are shown in eq. (3) and eq. (4).

To minimize:

Surface roughness,

$$Ra = -0.1803 - 0.000302\times Vc + 2.573\times f + 0.0473\times d \tag{3}$$

Machining time,

$$Tc = 6.695 - 0.01570\times Vc - 10.047\times f + 0.033\times d \tag{4}$$

The constraint function of responses is shown in eq. (5).

$$C = [(-0.1803 - 0.000302\times Vc + 2.573\times f + 0.0473\times d) - 0.48] \tag{5}$$

The selected upper and lower bound of cutting speed is 140 and 180, for feed rate is 0.12 and 0.24 and for depth of cut is 0.2 and 1. Multi-objective genetic algorithm processing parameters and their values are shown in Table 4.

Table 4: Processing parameters of MOGA.

Operation and parameter	Functions and values
Number of input variable constraint	3
Number of objective function	2
Population size	50
Tournament size	2
Selection function	Tournament
Crossover function	Single point
Mutation function	Adaptive feasible
Creation function	Feasible population
Distance measure function	Distance crowding
Function tolerance	1e-4
Constraint tolerance	1e-3
Cross over fraction	0.8
Migration fraction	0.2

Source: Authors, (2025).

Here Figure. 5 indicates the average distance between individuals. In this graph, all of the distances between the individuals are shown between 0 to 16.

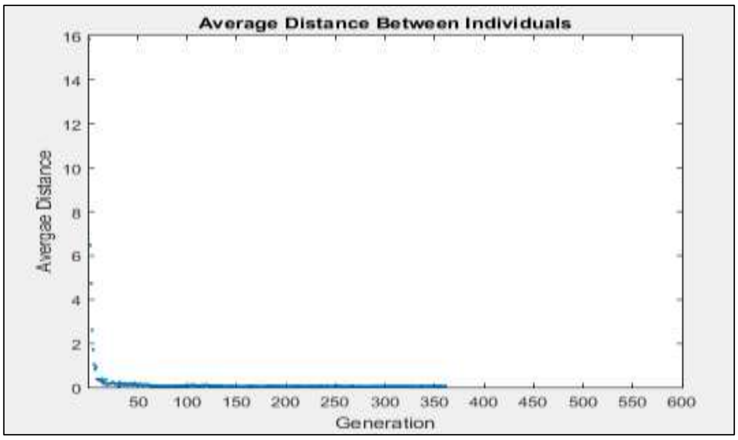

Figure 5: Average distance between individuals.
Source: Authors, (2025).

Fig. 6 gives information about the individuals and their distance. Here distance is 0 to 0.6 and the individuals is 0 to 50 showing the relation between the distances of the individual's value. Fig. 7 shows the average spread is 0.145034 has the maximum spread with given generations.

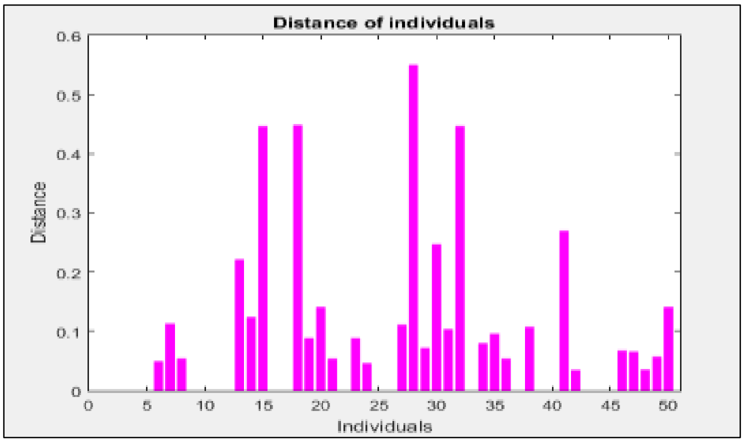

Figure 6: Distance of individuals.
Source: Authors, (2025).

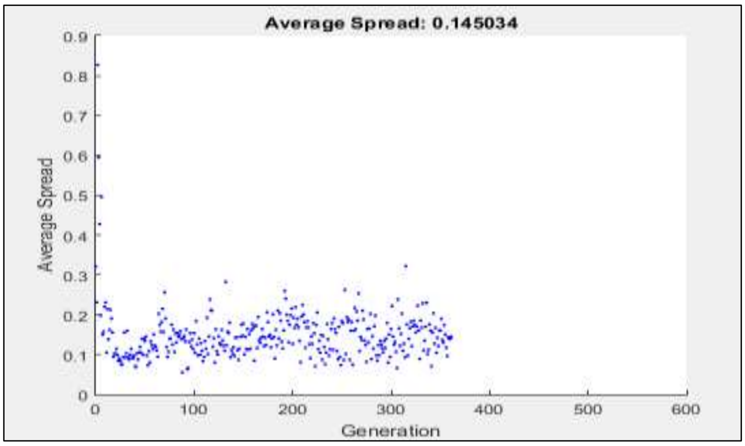

Figure 7: Average spread with generation.
Source: Authors, (2025).

IV. RESULTS AND DISCUSSIONS

The interactive effect of input parameters such as cutting speed, feed and depth of cut on the surface roughness was analyzed, which is helpful for the selection of input process parameters for a better surface finish. The MINITAB 17 has been used to find the interactive effect of input parameters on surface roughness. The interactive effect of cutting speed, feed and depth of cut on the surface roughness is shown in Fig.8. It is observed that the surface roughness decreases when the cutting speed increases and the feed rate and depth of cut decrease simultaneously.

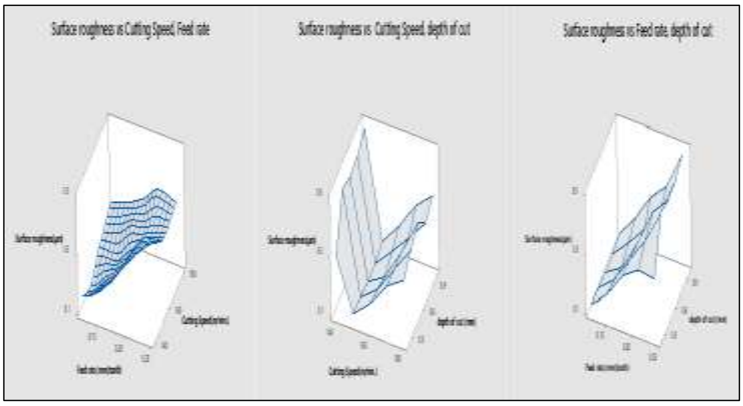

Figure 8: Interactive effect of process parameters on surface roughness
Source: Authors, (2025).

Here MOGA tools have been used for multi-objective optimization. The optimum combination of end milling process parameters of eighteen non-dominated Pareto optimal solutions achieved through MOGA is shown in Table 5.

Table 5: Non-dominated Pareto optimal solution

Sr No.	Cutting speed(m/min)	Feed rate (mm/tooth)	DOC (mm)	MOGA Surface roughness (µm)	MOGA Machining time (Sec.)
1	180.00	0.24	0.2	0.39	1.46
2	180.00	0.14	0.2	0.14	2.45
3	180.00	0.18	0.2	0.23	2.11
4	180.00	0.12	0.2	0.08	2.67
5	180.00	0.14	0.2	0.14	2.45
6	180.00	0.21	0.2	0.31	1.80
7	180.00	0.21	0.2	0.31	1.77
8	180.00	0.13	0.2	0.11	2.59
9	180.00	0.19	0.2	0.26	1.96
10	180.00	0.15	0.2	0.16	2.36
11	180.00	0.18	0.2	0.23	2.11
12	180.00	0.24	0.2	0.39	1.46
13	180.00	0.16	0.2	0.19	2.24
14	180.00	0.12	0.2	0.08	2.67
15	180.00	0.23	0.2	0.37	1.54
16	179.99	0.22	0.2	0.34	1.68
17	179.99	0.22	0.2	0.33	1.70
18	180.00	0.16	0.2	0.20	2.23

Source: Authors, (2025).

The relation between the number of individuals and the score is shown in Fig. 9 which gives the range of minimum and maximum values of surface roughness and machining time related to the constraint function.

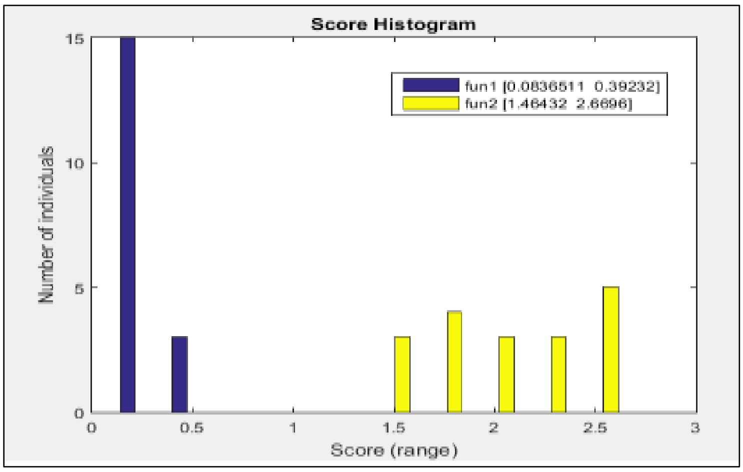

Figure 9: Score Histogram chart.
Source: Authors, (2025).

The minimum and maximum values of surface roughness are 0.0836511 and 0.39232. The minimum and maximum values of machining time are 1.46432 and 2.6696. The Pareto optimal front chart for surface roughness and machining time is shown in Fig.10.

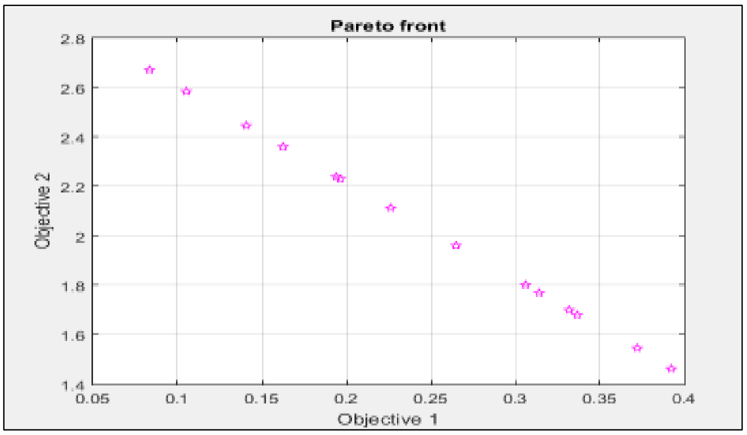

Figure 10: Pareto optimal front chart.
Source: Authors, (2025).

The achieved one set of optimized cutting parameters shown in serial numbers 3 and 11 in Table 5 gives better results of responses so that it is validated through experimentation. One set of experiments has been conducted for validation of the MOGA results. It has been found the percentage of error for surface roughness is 4.17% and the machining time is 3.65%. Fig.11 indicated a good agreement between MOGA and experimental results.

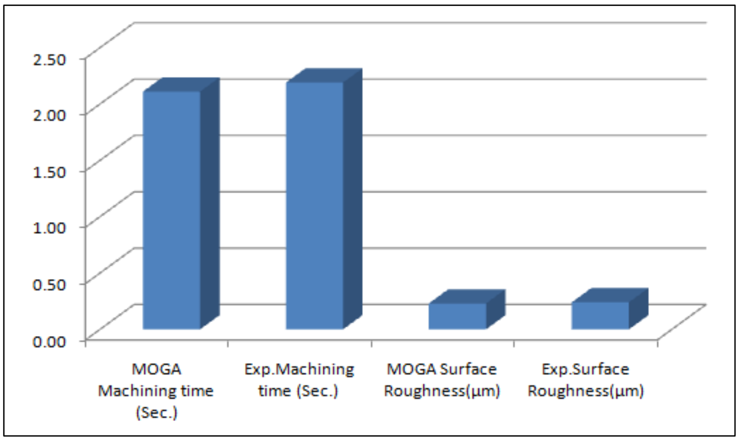

Figure 11: Multi-objective genetic algorithm Vs. Experimental result
Source: Authors, (2025).

These multi-objective optimization approaches provide the optimum cutting conditions for consequent values of responses. It has been observed that all the solutions generated by the MOGA tool are good. The preference for the selection of Pareto optimal solutions depends upon the needs of industries.

V. CONCLUSIONS

The multi-objective genetic algorithm approaches utilized for multi-objective optimization based on regression equations, have been found very useful techniques in industries. Multi-objective genetic algorithm based Pareto optimal designs approach gave the optimal solution with minimum surface roughness and machining time. It has been found average accuracy of 95.83% for surface roughness and 96.35% for machining time. Good concurrence has been found between multi-objective optimization results with experimentation. This indicates that a multi-objective genetic algorithm can be effectively used to find the optimum combination of machining parameters for end milling operation. The results of this study are to improve the productivity of products and very helpful in manufacturing industries to reduce the cost, time and number of trials.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Methodology: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Investigation: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Discussion of results: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Writing – Original Draft: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Writing – Review and Editing: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Resources: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Supervision: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.
Approval of the final text: Jignesh G. Parmar, Komal G. Dave and Mehul G. Mehta.

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