A Comparison of Optimization Methods in Cutting Parameters Using Non-dominated Sorting Genetic Algorithm (NSGA-II) and Micro Genetic Algorithm (MGA)

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Abstract

Since cutting conditions have an influence on reducing the production cost and time and deciding the quality of a final product the determination of optimal cutting parameters such as cutting speed, feed rate, depth of cut and tool geometry is one of vital modules in process planning of metal parts. With use of experimental results and subsequently, with exploitation of main effects plot, importance of each parameter is studied. In this investigation these parameters was considered as input in order to optimized the surface finish and tool life criteria, two conflicting objectives, as the process performance simultaneously. In this study, micro genetic algorithm (MGA) and Non-dominated Sorting Genetic Algorithm (NSGA-II) were compared with each other proving the superiority of Non-dominated Sorting Genetic Algorithm over micro genetic since Non-dominated Sorting Genetic Algorithm results were more satisfactory than micro genetic algorithm in terms of optimizing machining parameters.

Keywords: Cutting Parameters, Surface Roughness, Tool life Criteria, Optimizing, NSGA-II, MGA,

1. INTRODUCTION

Proper selection of machining parameters such as depth of cut, feed rate, cutting speed and rake angle for the best process performance is still challenging matter. In workshop practice cutting parameters are selected from database or specialized hand book which is not necessarily optimum value [1]. Optimization of cutting parameters is usually a difficult job because it requires both machining operation experience and knowledge of mathematical algorithms simultaneously. The traditional methods for optimization problems include calculus-based searches, dynamic programming, random searches, and gradient methods whereas modern heuristic methods include artificial neural networks [2], Lagrangian relaxation approaches [3], and simulated annealing [3]. Some of these methods are successful in locating the optimal solution, but they are usually slow in convergence and require much computing time. Other methods may risk being trapped at a local optimum which fails to give the best solution. In multiple performance optimizations, there is more than one objective function, each of which may have a different optimal solution. Most of the time these objectives conflict with one to another. [4,5]. Rozenek and his associations used a piecework made of composite material with metal matrix composite and investigated the variation in feed rate and surface roughness led by changing the corresponding parameters [6]. Tosun and his associations used a statistical model for determining optimal parameters in order to minimize the holes led on the wire during the process [7]. Tosun and Cogun conducted a research regarding the effect of machining parameters on the rate of wire corrosion considering lessened weight from wire while being machined [8]. Wang and his associations optimized process parameters in order to achieve optimal performance using genetic algorithm (GA) with artificial neutral network (ANN). ANN is an approach used for modeling the process, where weight are updated by GA. Gen-Hunter software is used in order to find out solutions for multi-objective problems concerning optimization phase. MRR and surface roughness which are 2 output parameters are aimed here to be optimized as a process performance [9]. Su and his associations have optimized the EDM parameters, from stage of the rough cutting to the finish cutting. The relationship between the process parameters and machining performance was established using a trained neutral network. Subsequently, GA with properly defined objective functions was changed to the neutral network to find out the optimal process parameters. For transformation of MRR, surface roughness and machine tool wear into a single objective, a simple weighted method was used [10]. The generic algorithm (GA) is an evolutionary algorithm based on the mechanic of natural selection and it combines the characteristic of direct search and probabilistic selection method. It is a powerful tool for obtaining global values for multi-model and combinatorial problems [11]. The GA operates on a population of potential solutions applying the principle of survival of the fittest to produce better and better approximations to a solution. In this study, after designing and obtaining the experimental data with a use of statistical model and main effect plots, the most important parameters effective on average surface roughness (Ra) and also tool life criteria (A) will be specified. Following the models obtained the comparison between two methods of non-dominated sorting genetic algorithm (NSGA-II) and micro genetic algorithm (MGA) both will be investigated.

2. EXPERIMENTAL WORK

The work material used for the present investigation is ST-37 steel with the diameter of 45 mm and length of 400 mm. For machining operation a Russian lath machine was used and the tool material was HSS with clearance angle of 6°, back rake angle of 0°, side cutting edge angle of 90° and rake angle which was variable during machining process.

For simultaneous investigation of variable affection such as cutting speed, feed rate, depth of cut and rake angle the Taguchi method design of experiments with the use of MINITAB software was carried out. The machining parameters used and their levels were presented in Table1. The values of the levels were selected so that the standard values of parameters were included.

Cutting parameters	unit	symbol	Levels		
			1	2	3
Cutting speed	(m/min)	*v*	17	25	33
Feed rate	(mm/rev)	*f*	0.09	0.13	0.17
Depth of cut	(mm)	*d*	0.2	0.4	0.6
Rake angle	(degree)	*z*	0	14	-

TABLE 1: Machining parameters and their levels

Velocity of rotation for different diameters of workpiece and based on selected cutting speeds was calculated from equation1.

$$N = \frac{1000V}{\pi D} \qquad (1)$$

Where diameter (*D*) is in mm, cutting speed (*V*) is in min/m and velocity of rotation (*N*) is in rev/min.
In this study tool life is defined by the volume of the material removed so that surface finish becomes 1.5 times higher than the initial surface roughness value at the beginning of machining operation.

$$1/v = \frac{1}{\pi \times D \times d \times L \times 10^3} \qquad (2)$$

Where material removal volume (*v*) is in mm^3, diameter (*D*) is in mm, depth of cut (*d*) is in mm and length of the workpiece (*L*) is in mm which reach the tool life criterion. The experimental result for surface roughness and tool life criteria after 18 experiments is presented in table2.

S.No.	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Rake angle (degree)	Surface roughness (µm)	Tool life criteria ($1/m^3$)
1	17	0.09	0.2	0	6.53	41.176
2	17	0.13	0.4	0	7.15	37.703
3	17	0.17	0.6	0	8.1	35.295
4	25	0.09	0.2	0	7.21	44.539
5	25	0.13	0.4	0	7.05	33.087
6	25	0.17	0.6	0	6.81	29.277
7	33	0.09	0.4	0	5.79	48.179
8	33	0.13	0.6	0	6.02	43.096
9	33	0.17	0.2	0	5.71	36.868
10	17	0.09	0.4	14	5.53	53.57
11	17	0.13	0.2	14	5.49	20.607
12	17	0.17	0.2	14	6.02	75.449
13	25	0.09	0.4	14	3.21	45.714
14	25	0.13	0.6	14	4.1	37.7
15	25	0.17	0.2	14	3.55	55.698
16	33	0.09	0.6	14	2.48	70.872
17	33	0.13	0.2	14	2.25	81.907
18	33	0.17	0.4	14	2.54	61.977

TABLE 2: Experimental results

3. DATA ANALYSIS

3.1 Analysis of Surface Roughness

Regression analysis is performed to find out the relationship between factors and the average surface roughness (R_a). With MINITAB software Statistical model based on linear equation was developed for surface roughness.

$$R_a = 9.71-0.148v+4.12f+0.403d-0.199z \quad (3)$$

The normal probability plot is presented in Fig1. It is noticeable that residuals fall on a straight line. It basically shows that the errors are dispersed and the regression model completely matches the observed values.

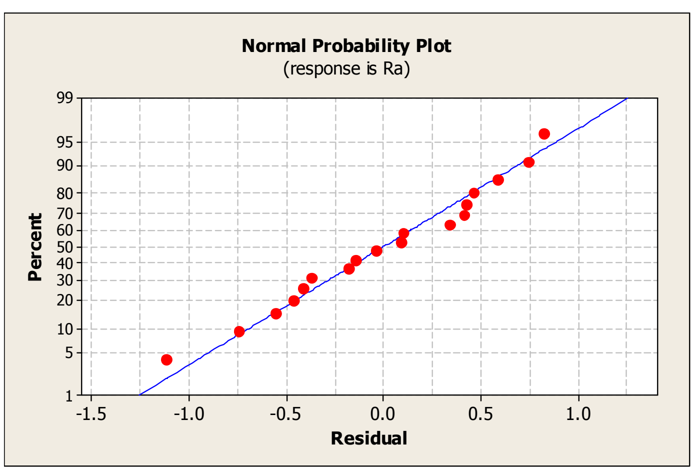

FIGURE 1: Normal probability plot for average surface roughness

Table3 shows that test results are valid. Predicted machining factors performance were compared with the actual machining performance and, subsequently, a good agreement was made. Since the amount of errors was proved to be acceptable, so these models can be selected as the best ones and use them in optimization levels.

Run	*v*	*f*	*d*	Angle	Results of model	Results of experiments	Error (%)
1	17	0.09	0.4	14	4.94	5.53	-10
2	33	0.09	0.4	0	5.35	6.02	10

TABLE 3: Results for confirmation test for Ra

The effect of factors on surface roughness is presented in Fig2. It indicates that cutting speed and rake angle have the most significant effect on surface roughness (R_a) by which increase of any of them can cause severe decrease in surface roughness But feed rate and depth of cut doesn't have significant effect on surface roughness.

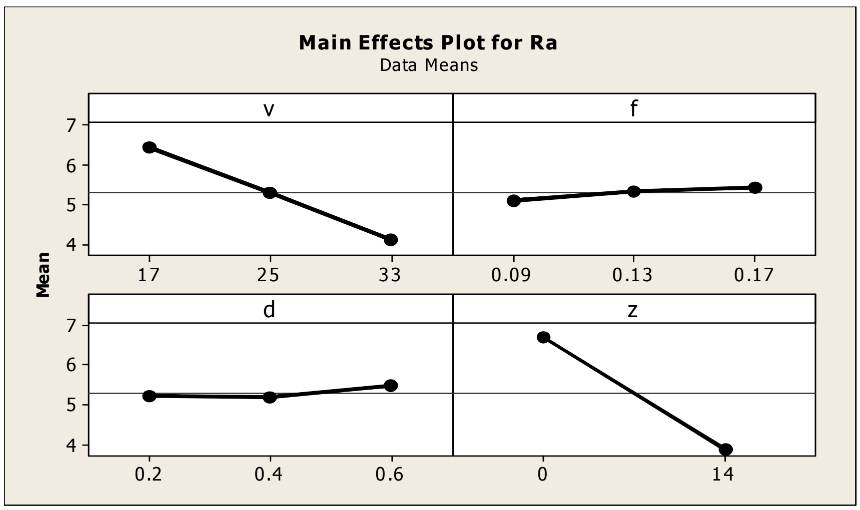

FIGURE 2: Effect of factor on surface roughness

3.2 Analysis of Tool Life Criteria

Regression analysis is performed to find out the relationship between factors and the tool life criteria (A). With MINITAB software Statistical model based on linear equation were developed for surface roughness.

$$A = 26.2+0.901v-20f-18.4d+1.17z \quad (4)$$

The normal probability of residuals for tool life criteria is presented in Fig3. It is observed that the residuals are distributed normally and in a straight line and hence the model is adequate.

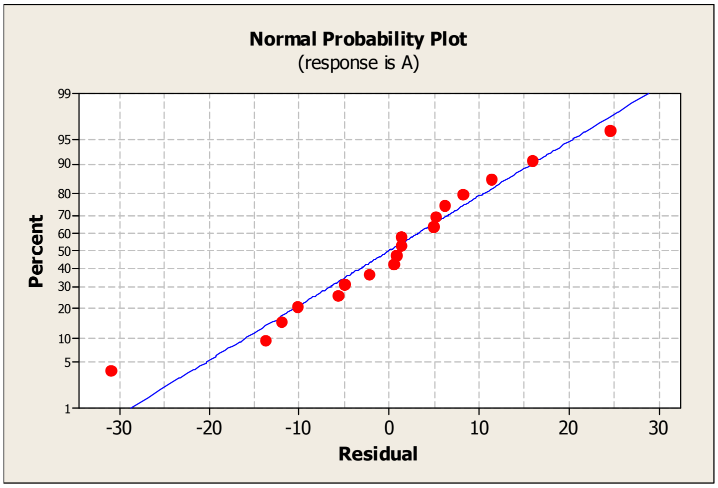

FIGURE 3: Normal probability plot for tool life criteria

Table4 shows that test results are valid. Predicted machining factors performance was compared with the actual machining performance and, subsequently, a good agreement was made. Since the amount of errors was proved to be acceptable, so these models same as previous model can be selected as the best ones and use them in optimization level.

Run	*v*	*f*	*d*	Angle	Results of model	Results of experiments	Error (%)
1	17	0.09	0.4	14	48.737	53.57	9
2	33	0.09	0.4	0	46.773	43.096	8

TABLE 4: Results for confirmation test for A

The effect of factors on tool life criteria is presented in Fig4. It indicates that all four considering parameters include cutting speed, feed rate, depth of cut and rake angle have significant effect on tool life criteria (A). But effect of cutting speed and rake angle are the most.

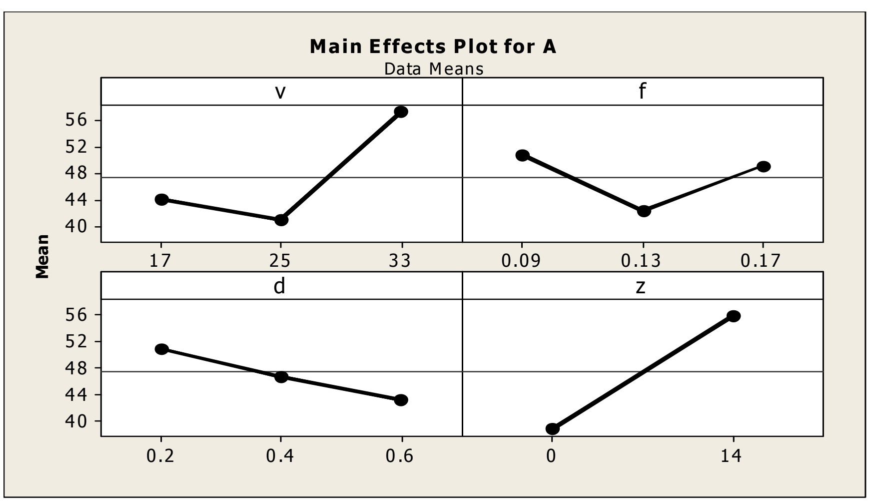

FIGURE 4: Effect of factors on tool life criteria

4. OPTIMIZATION

To optimize cutting parameters in the machining of St-38 steel two methods of optimization includes Non-dominated Sorting Genetic Algorithm (NSGA-II) and micro genetic algorithm (MGA) was used. The objectives set for both methods in the present study were as follows:

1. Minimization of tool life criteria (A)

2. Minimization of average surface roughness (Ra)

5. NSGA-II ALGORITHM

The non-dominate sorting Genetic Algorithm (NSGA-II) which was introduced by Deb [12]. It is a powerful general purpose optimization tool to solve optimizing problems in mathematics and engineering. NSGA-II deals with a possible solution regarding a population and therefore, it can have some applications in problems of multi-objective optimizations. It leads to have a number of simultaneous solutions. Despite, this algorithm is fast, but it has been as a controversial method and has been opposed due to have some difficulty and complexity when it comes to computational approach. The elitism is also disregarded in this method. The selection operator differs from simple genetic algorithm (SGA). Crowded comparison is the operator in which selections can be achieved considering ranking and crowding distance. The solution of initially parent population is checked with other solutions and eventually, solution is put into consideration to make aware of its validation using rules given below [7]:

$$Obj.1[i] \succ Obj.1[j] \text{ and } Obj.2[[i] \geq Obj.2[j] \;, \qquad (5)$$

Or

$$Obj.1[i] \geq Obj.1[j] \text{ and } Obj.2[i] \succ Obj.2[j], i \neq j \qquad (6)$$

Where, chromosome numbers can be shown as i and j, respectively. Subsequently, it can be noticeable that the selected solution is validated by rules introduce. It makes it be marked as dominated. If the rule doesn't satisfy, it will be marked as non-dominated. In order to the solutions, the corresponding process must continues until all solution selected are ranked. Fitness which is as equal as its non-dominated level assigns to each solution. There is no result to demonstrate none of the solutions is better compared with other solutions. Solutions are considered as part of a special rank or non-dominated level. The crowding distance is considered to be as an average distance between two points on both sides of selected solution point along each objectives function. Each objective function's boundary solution with largest and smallest values is assigned an infinity value. The algorithm flowchart is illustrated in Fig5. For solving optimization problem using GA, fitness value is required. it connects the objective with decision variable. In the present investigation objective are minimization of average surface roughness (R_a) and minimization of tool life criteria which are function of decision variables namely, cutting speed, feed rate, depth of cut and rake angle.

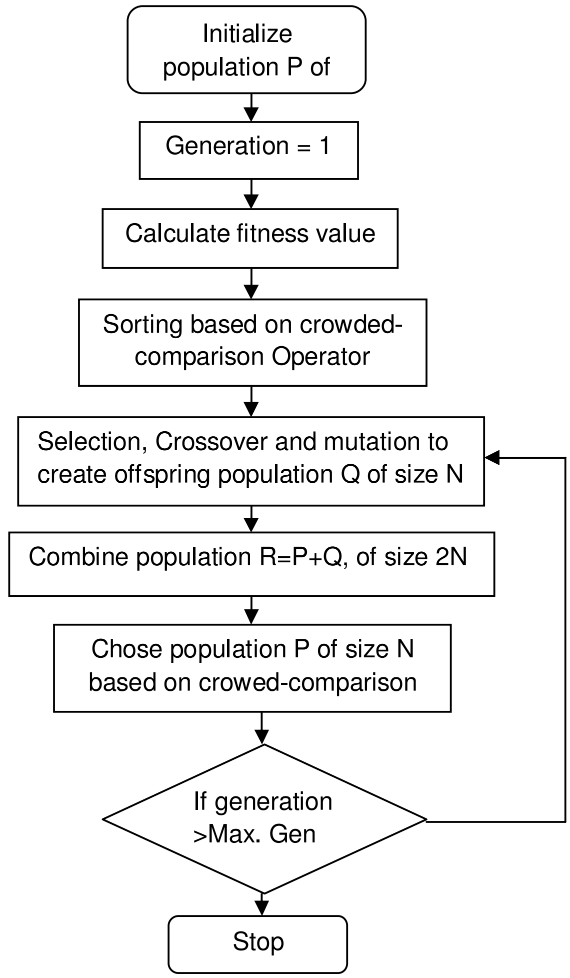

FIGURE 5: Flow chart for the NSGA-II algorithm [7]

6. MICRO GENETIC ALGORITHM (MGA)

MGA operates on a population, of designs similar to the simple genetic algorithm (SGA). However, unlike the SGA, the mechanics of the MGA allow for a very small population size, *npop*. The MGA can be outlined in the following way:

1. A micro-population of five designs is generated randomly.
2. The fitness of each design is determined and the fittest individual is carried to the next generation (elitist strategy).
3. The parents of the remaining four individuals are determined using a tournament selection strategy. In this strategy, designs are paired randomly and adjacent pairs compete to become parents of the remaining four individuals in the following generation [13]
4. Convergence of the μ-population is checked. If the population is converged, go to step 1, keeping the best individual and generating the other four randomly. If the population has not converged, go to step 2.

Note that mutations are not applied in the MGA since enough diversity is introduced after convergence of a micro-population. In addition, [13] and [14] have shown that MGAs reach the optimum in fewer function evaluations compared to an SGA for their test functions. The flow chart of the above algorithm is shown in Fig6.

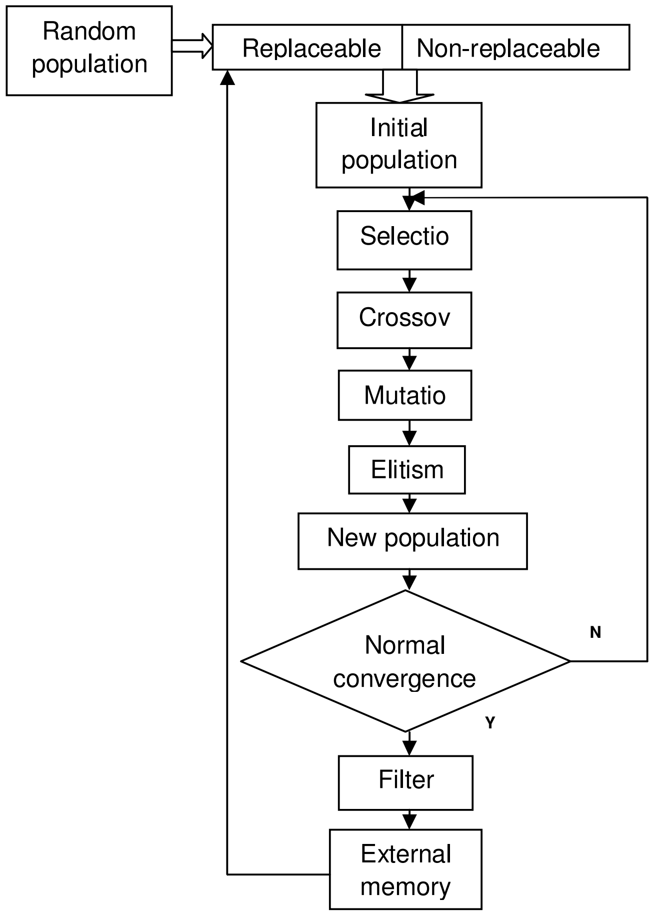

FIGURE 6: Flow chart for the micro genetic algorithm

7. DISCUSSION

In this study comparison of two different optimization methods include Non-dominated Sorting Genetic Algorithm (NSGA-II) and micro genetic algorithm (MGA) for turning process of ST-38 steel was investigated.

First, the control parameters in NSGA-II were adjusted to obtain the best performance. The parameters used are: probability of crossover = 0.8, mutation probability = 0.2 and population size = 100. It was found that the above control parameter produces better convergence and distribution of optimal solutions. The 100 generations were generated to acquire the true optimal solution. A sample of 40 out of 100 sets was presented in Table 5. The non-dominated solution set obtained over the entire optimization is shown in Fig7. This figure shows the formation of the Pareto front leading to the final set of solutions.

Second, micro genetic algorithm (MGA) is applied to optimize of cutting parameters, using VIDUAL BASIC programming according to the flow chart shown in Fig6. The extracted results from corresponding methods are shown in Fig 8. Since none of the solutions in both NSGA-II and MG methods is absolutely better than any other, any one of them is the “better solution”. As the best solution can be selected based on individual product requirements, the process engineer must therefore select the optimal solution from the set of available solutions. If the engineer desires to have a better surface finish, or less tool life criteria a suitable combination of variables can be selected.

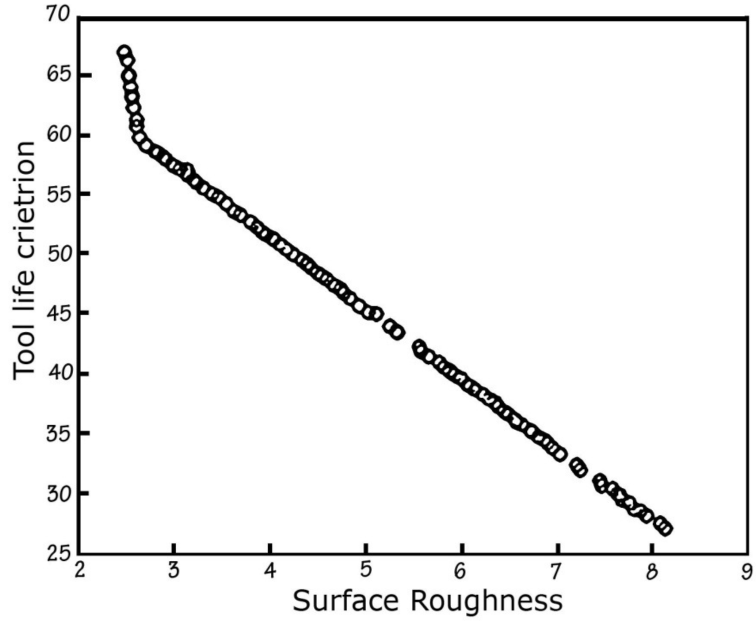

FIGURE 7: Pareto optimal front using NSGA-II for 2 objectives

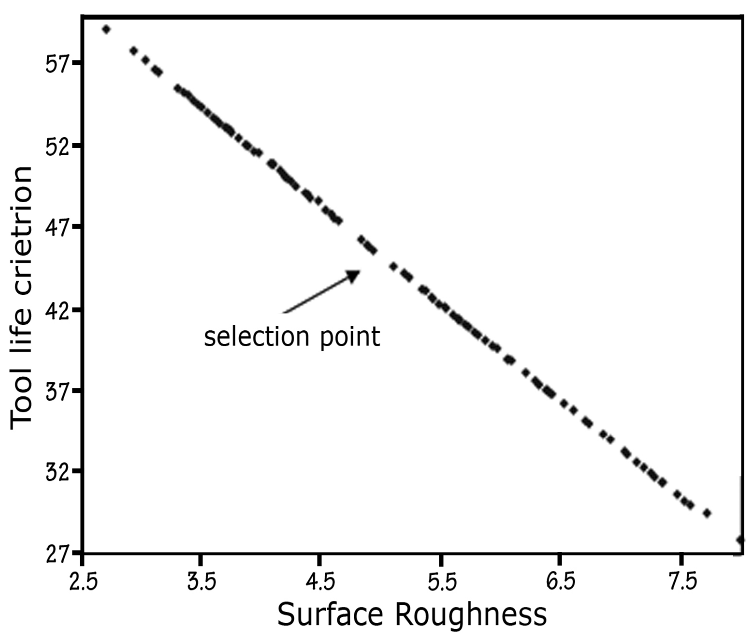

FIGURE 8: Pareto optimal front using MGA for 2 objectives

S.No.	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Rake angle (degree)	Surface roughness (μm)	Tool life criterion ($1/m^3$)
1	17	0.17	0.6	0	8.136	27.077
2	33	0.09	0.2	14	2.491	66.833
3	29.374	0.091	0.599	12.971	3.397	55.002
4	17	0.126	0.6	3.074	7.345	31.544
5	29.042	0.109	0.525	10.77	3.929	53.133
6	32.300	0.093	0.579	12.91	2.976	57.897
7	24.325	0.131	0.596	7.21	5.454	42.976
8	30.396	0.099	0.593	12.94	3.284	55.833
9	25.322	0.128	0.580	7.43	5.247	44.456
10	24.162	0.134	0.592	6.43	5.645	41.919
11	21.295	0.145	0.567	3.99	6.592	36.711
12	27.950	0.110	0.596	10.83	4.112	50.891
13	23.653	0.137	0.597	6.00	5.820	40.804
14	17.589	0.161	0.600	0.26	7.958	28.101
15	17.862	0.162	0.600	0.83	7.810	28.988
16	24.170	0.090	0.587	8.040	5.140	44.733
17	19.769	0.157	0.595	2.25	7.224	32.550
18	27.209	0.113	0.600	10.37	4.327	49.545
19	22.668	0.090	0.600	9.656	5.046	45.081
20	33.000	0.090	0.338	14.00	2.547	64.297
21	29.550	0.109	0.591	11.88	3.661	53.662
22	33.000	0.090	0.501	14.00	2.613	61.303
23	29.709	0.110	0.569	9.05	4.196	50.880
24	24.040	0.090	0.600	8.960	4.992	45.453
25	25.758	0.126	0.528	8.47	4.945	47.080
26	23.093	0.140	0.598	5.49	6.015	39.644
27	20.660	0.157	0.586	3.60	6.819	35.100
28	31.796	0.091	0.592	14.00	2.833	58.510
29	20.660	0.157	0.586	3.60	6.819	35.100
30	22.697	0.142	0.597	5.10	6.160	38.803
31	18.477	0.163	0.591	1.75	7.539	30.752
32	20.035	0.155	0.599	3.20	6.987	33.881
33	22.745	0.149	0.591	6.25	5.951	40.152
34	20.168	0.153	0.599	2.23	7.154	32.896
35	18.357	0.157	0.600	1.04	7.675	29.777
36	26.231	0.122	0.595	9.38	4.702	47.429
37	32.607	0.092	0.583	13.78	2.755	59.140
38	33.000	0.090	0.591	14.00	2.649	59.647
39	17.079	0.163	0.600	0.00	8.097	27.284
40	31.067	0.102	0.584	12.07	3.364	55.546

TABLE 5: Optimal machining parameters for the machining of ST-37steel

For comparison of the two optimization methods, the experimental results for 2 points are shown in the table 6. Considering the experimental results shown in the Table 2, the parameters of trial number 10 resulted to surface roughness of 5.53 (μm) and tool life criteria of 53.57 (1/m3). After optimizing machining parameters through NSGA-II and micro genetic algorithm, considering NSGAII the value of surface roughness and tool life criteria decrease to 5.102 (μm) and 44.600 (1/m3) respectively. However, regarding to micro genetic algorithm these mentioned values decrease to 5.102 (μm) and 44.723 (1/m3), respectively. Thus, considering the data given, as feed rate is kept constant, by changing cutting speed, depth of cut and rake angle, it can be observed that lower surface roughness and tool life criteria can be achieved which both are more desirable. It is noticed that results in two mentioned algorithms better results were achieved with use of NSGA-II. The reason why use of NSGA-II is better is that despite both algorithms lead in same values for surface roughness, but for tool life criteria values of 44.60 and 44.723 (1/m3) were attributed to NSGA-II and micro genetic algorithm, respectively, demonstrating superiority of NSGA-II over micro genetic algorithm.

	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Rake angle (degree)	Surface roughness (μm)	Tool life criteria $1/m^3$
Experimental result(Table 2, trial no.10)	17	0.09	0.40	14	5.53	53.57
NSGA-II	17.40	0.09	0.60	13.30	5.102	44.600
MGA	17.62	0.09	0.60	13.12	5.102	44.723

TABLE 6: Example of optimized values derived from NSGA-II and MGA

8. CONCLUSION

The experiments were conducted on a lathe machine for the machining of ST-37 steel. The tool used for the machining operation is a HSS tool. The responses studied average surface roughness and tool life criteria. The first-order polynomial models were developed for tool life criteria and average surface roughness, and were used for optimization. In this study two multi-objective evolutionary algorithms based on efficient methodology, NSGA-II and MGA was utilized to optimize machining parameters in the machining of ST-37steel. The emphasis must be put on providing a preferred solution for the process engineer in the short period of the time. The choice of one solution over other ones is dependent on the requirements of process engineer [15]. In conclusion, by comparison of micro genetic algorithm and NSGA-II it was noticed that in spite of the fact, both algorithms have good results in optimization issues, but it was shown that NSGA-II had slightly superiority over micro genetic algorithm whereas NAGA-II results were more satisfactory than micro genetic algorithm in terms of optimizing machining.

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