OPTIMIZATION OF PROCESS PARAMETERS IN TURNING OF MAGNESIUM AZ91D ALLOY FOR BETTER SURFACE FINISH USING GENETIC ALGORITHM

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Highlight
Optimization of machining parameters using genetic algorithm.

Abstract
This research examined at the optimum cutting parameters for producing minimum surface roughness and maximum Material Removal Rate (MRR) when turning magnesium alloy AZ91D. Cutting speed (m/min), feed (mm/rev), and cut depth (mm) have all been considered in the experimental study. To find the best cutting parameters, Taguchi's technique and Response Surface Methodology (RSM), an evolutionary optimization techniques Genetic Algorithm (GA) and Non-dominated Sorting Genetic Algorithm-II (NSGA-II) were employed. GA gives better results of 34.04% lesser surface roughness and 15.2% higher MRR values when compared with Taguchi method. The most optimal values of surface roughness and MRR is received in multi objective optimization NSGA-II were 0.7341 µm and 9460 mm^3/min for the cutting parameters cutting speed at 140.73m/min, feed rate at 0.06mm/min and 0.99mm depth of cut. Multi objective NSGA-II optimization provides several non-dominated points on Pareto Front model that can be utilized as decision making for choice among objectives.

Keywords
genetic algorithm; magnesium alloy; turning; optimization; pareto front; RSM.

Introduction

Magnesium alloys are advanced and lighter materials used extensively in industries like automobile, aerospace, engine block casing etc. They possess excellent strength to weight ratio which is a significant factor in modern industrial products [1]. In machining of magnesium alloy surface roughness and MRR have become significant factors in terms of quality and economy characteristics. As a result, experimental methods must be used to optimize machining parameters for newer materials [2]. Numerous optimization techniques which include Fuzzy Logic, Taguchi optimization, Ant colony optimization, and simulated annealing gives solutions for various optimization problems. Noticeably, genetic algorithm optimization is a modern method and it additionally determined to be better in arriving at optimized solution for complicated real worldwide problems [3,4]. Many academics and businesses are currently interested in improving manufacturing strategies in order to save costs, improve quality [5], and gain from increased efficiency.

Boostani et al. [6] have investigated AISI 304 austenitic stainless steel in order to improve cutting quality and productivity while lowering power consumption. Surface roughness was assessed in a short period of time using a surface roughness tester; this could be influenced by machine vibration, tool and material type, and coolant supply. Cutting parameter optimization focuses primarily on cutting force, surface quality, and processing cost, according to Su's study [7]. It also claims that the impact of cutting parameters on energy

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consumption is neglected in the multi-objective cutting operation of cutting parameters using the RSM approach. Kavimani et al. [8] have investigated the influence of machining parameters on wire electrical discharge machining performance in magnesium composite, they have reported that the MRR and surface roughness are significant towards parameter involvement. Kuntolu et al. [9] investigated the modelling of cutting parameters and tool geometry for multi-criteria optimization of surface roughness and vibration using response surface methodology. They found that feed rate is the most important contributing factor to surface roughness, and that the interaction of cutting speed and tool coating has a minor impact.

Lamentably, in multi variable trouble characteristic most computational techniques for complicated machining systems require significant computational resources to assess each parameter. No method presently consequences inside the same levels of efficiency for all process. The prevailing work interests to apply the surface roughness values and MRR as multi objective capabilities, as an efficient approach for identifying the exceptional parameters for traits, via GA and NSGA-II. GA is a technique seeking out optimum combinations and solutions over the traditional optimization strategies. The stairs usually followed in GA are reproduction, crossover and mutation. There are various algorithms and techniques of solving multi-objective optimization hassle exist [10]. Therefore, multi-objective optimization is pondered as a utility of single-objective optimization for conduct a couple of goals. NSGA gives the higher maximum extraordinary solution for each objective function in terms of solutions [11]. NSGA-II based multi-objective optimization for MRR, and Surface roughness has been completed on this machining for magnesium alloy. Multi objective optimization GA (MOGA) toolbox of MATLAB has been utilized in this paper.

Materials and methods

Taguchi approach and RSM

The design of experiments has been taken using Taguchi methodology, it is an effective method in producing robust design. It provides a simple and methodical qualitative optimum design at a minimal cost. It has a collection of orthogonal arrays which can be used to study into the effectiveness of different process parameters. Genechi proposed the signal-to-noise (S/N) ratio, which took both means and variability into account and the influence of process characteristics on the performance measure is indicated by S/N ratios in ANOVA [12,13].
In Taguchi approach three levels of performance characteristics are followed in the analysis of S/N ratio that is “Smaller the better”, “Larger the Better” and “Nominal the Better”. Based on the criteria, different S/N ratios can be selected. The main objective of the analysis of variance is to evaluate the cutting parameters that significantly affect surface quality characteristics. Effective parameter is determined by F-test value and compared with standard F- table value. RSM [14] is a statistical method for modeling and analysis, which deals different variables and responses. RSM is used to develop a model for suitable approximation for relationship between the response variables and independent variables as followed by Equation (1).

$$\eta = \beta_o + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_i \sum_j \beta_{ij} X_i X_j \quad (1)$$

GA approach- Single objective optimization

GA is an evolutionary optimization approach for solving problems involving the application of evolutionary biology principles [15]. Genetic inheritance, natural selection, mutation, and crossover are all biologically inspired approaches used by GAs. GAs are used to model the process of biological evolution and Darwin's hypothesis of survival of the fittest. A set of ability solutions or chromosomes within the character of bit strings that are randomly picked are used to solve an optimization with GA. A population is made up of the full set of these chromosomes. The chromosomes evolve for the duration of numerous iterations or generations. New generations (offspring) are generated making use of the crossover and mutation method. Crossover is the process of separating two chromosomes and then combining one-half of each pair with the other. A single chromosomal bit is spun during a mutation. The chromosomes are then assessed against a set of fitness requirements, with the best ones being kept and the rest being destroyed. This approach is repeated until one chromosome exhibits high-quality fitness and is deemed the best answer to the challenge [16,17].

Multi-Objective Optimization with NSGA-II

The Non-dominated Sorting GA (NSGA) became proposed through Srinivas and Deb [18], and is based on several layers of classifications of the individuals and it is prominent algorithm for multi-objective optimization. Before selection is carried out, the population is ranked on the premise of domination the usage of Pareto the front.

NSGA become developed for this study to reap optimum cutting parameters in terms of population, cross over, mutation and crowding distance parameters applied [19]. Figure 1 depicts the flow chart for the implementation of the NSGA-II algorithm.

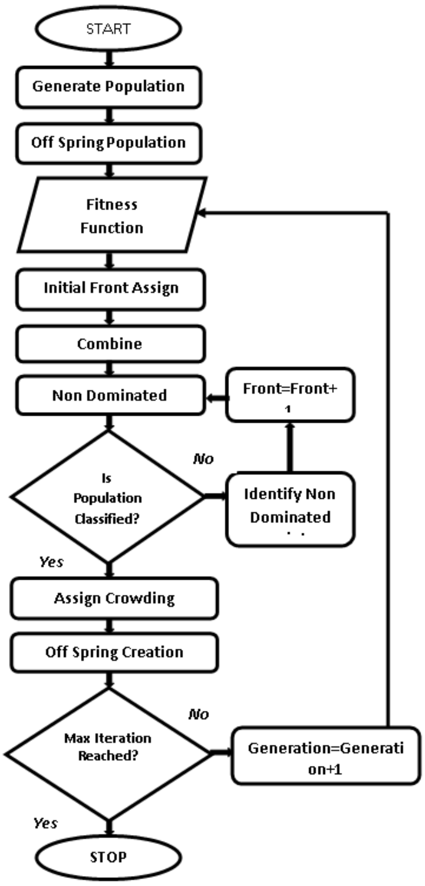

Figure 1. NSGA-II Process Flow Chart.

Experimental Design

The chemical composition of Magnesium AZ91D alloy is shown in Table 1 and the turning experiment was carried out in size of 50 mm diameter and 70 mm length workpiece. In this turning operation CVD coated carbide tool insert of triangular shape was used and the standard code of cutting tool TNMG 16 04 08 was chosen. The CNC turn master was chosen for cutting operation. Cutting parameters Cutting Speed *v* (m/min), Feed rate *f* (mm/rev) and depth of cut *d* (mm) were considered in this machining process and its levels are presented in Table 2. The machining of magnesium alloy was carried out in dry condition. The surface roughness measurement was conducted with Mitutyo Surftest 211. The turning experiment was carried out in 50 mm diameter and 70 mm length of 5 work pieces and shown in Figure 2. The roughness values were taken on the work piece circumference in three different places and the average value is presented in Table 3. The MRR (*Q)* is an important parameter in industrial economy and quality factor. In this work the MRR calculated by using standard Equation 2. MRR is calculated in each level of machining process and the data are presented in Table 3.

$$Q = v \times f \times d \ (mm^3/min) \quad (2)$$

Table 1. Chemical Composition of Magnesium AZ91D Alloy.

Element	Al	Mn	Zn	Si	Fe	Cu	Ni	Mg
Weight %	8 7-10.5	0.15-0.4	0.35-1.0	0.3	0.05	0.15	0.01	Balance

Table 2. Cutting parameters and their levels.

Factor	Unit	Level-1 (Low)	Level-2 (Medium)	Level-3 (High)
v	m/min	80	110	150
f	mm/rev	0.05	0.10	0.15
d	mm	0.5	0.75	1.0

The Taguchi orthogonal array L27 was chosen for machining experiments. The signal to noise ratios for surface roughness Ra and MRR obtained using Taguchi's approach are shown in Table 3. A lower surface roughness value is usually desirable in metal cutting. The S/N ratio was determined using the smaller-is-better methodology for the aforementioned responses. Regardless of the category of performance criteria, the higher the S/N ratio, the better the performance. The highest value of the S/N ratio indicates the optimum value for each level of process parameter.

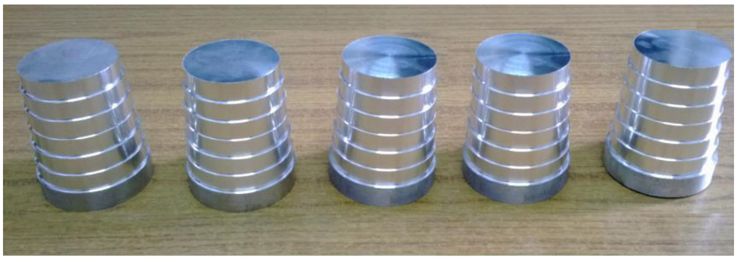

Figure 2. Machined Work pieces.

Results and Discussion

Taguchi approach- Main effect analysis

To investigate the effects of cutting parameters on surface roughness and MRR, Minitab® is used to construct a primary effect plot for various S/N ratios. The main effect graph shows a visualization of the main response values of the S/N ratio at each level of factor. Cutting speed has an impact on surface roughness, as shown in Figure 3. Increasing cutting speed reduces surface roughness in level 2 and then increases. The most essential factor is the feed rate; as the feed rate increases, the surface roughness increases to level 2, and then decreases as the depth of cut increases.

Figure 4 depicts the effects of factors on MRR values. It indicates that MRR increases as cutting speed, feed rate, and depth of cut increase. Taguchi methodology implies optimum cutting parameters of 110m/min cutting speed (level 2), 0.05mm/rev feed rate (level 1), 1mm depth of cut (level 3) to attain minimum surface roughness of 0.63µm and 150m/min cutting speed (level 3), 0.15mm feed rate (level 3), 1mm depth of cut (level 3) to reach maximum MRR of 19550 mm^3/min and shown in Table 4.

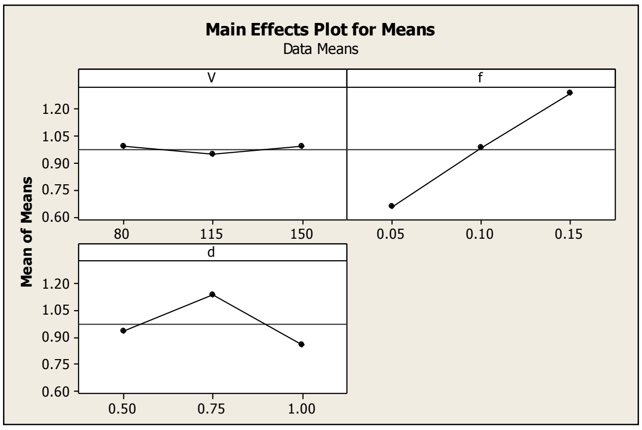

Figure 3. Main effect plot for surface roughness.

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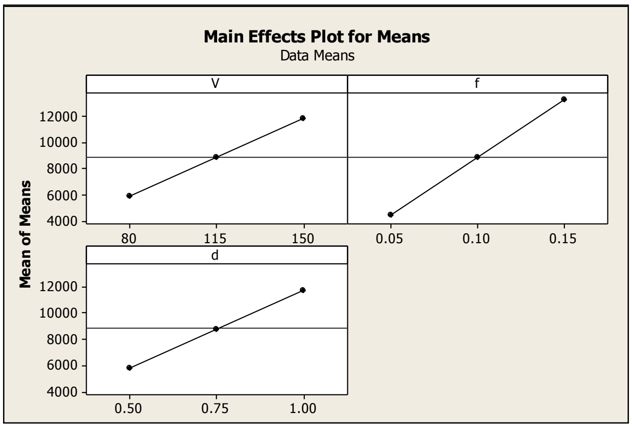

Figure 4. Main Effect Plot for MRR.

Table 3. Experimental Data with S/N ratio.

Trail No	Cutting Speed (m/min) v	Feed Rate (mm/rev) f	Depth of Cut (mm) d	Ra (µm) Ra	MRR (mm3/min) Q	Surface roughness S/N Ratio	MRR S/N Ratio
1	80	0.05	0.5	0.45	1963	6.93575	65.85619
2	80	0.05	0.75	0.88	2944	1.110347	69.37802
3	80	0.05	1	0.64	3925	3.876401	71.87679
4	80	0.1	0.5	0.86	3925	1.310031	71.87679
5	80	0.1	0.75	1.25	5888	-1.9382	75.39862
6	80	0.1	1	0.79	7850	2.047458	77.89739
7	80	0.15	0.5	1.45	5888	-3.22736	75.39862
8	80	0.15	0.75	1.48	8831	-3.40523	78.92044
9	80	0.15	1	1.12	11775	-0.98436	81.41922
10	115	0.05	0.5	0.57	2944	4.882503	69.37802
11	115	0.05	0.75	0.67	4416	3.478504	72.89984
12	115	0.05	1	0.62	5888	4.152166	75.39862
13	115	0.1	0.5	0.85	5888	1.411621	75.39862
14	115	0.1	0.75	1.23	8831	-1.7981	78.92044
15	115	0.1	1	0.82	11775	1.723723	81.41922
16	115	0.15	0.5	1.35	8831	-2.60668	78.92044
17	115	0.15	0.75	1.40	13247	-2.92256	82.44227
18	115	0.15	1	0.99	17663	0.087296	84.94104
19	150	0.05	0.5	0.63	3925	4.013189	71.87679
20	150	0.05	0.75	0.77	5888	2.270185	75.39862
21	150	0.05	1	0.70	7850	3.098039	77.89739
22	150	0.1	0.5	0.81	7850	1.8303	77.89739
23	150	0.1	0.75	1.17	11775	-1.36372	81.41922
24	150	0.1	1	1.06	15700	-0.50612	83.91799
25	150	0.15	0.5	1.42	11775	-3.04577	81.41922
26	150	0.15	0.75	1.37	17663	-2.73441	84.94104
27	150	0.15	1	0.99	19550	0.087296	87.43982

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Table 4. Response table for data means

Level	**Surface Roughness (Ra)**			**MRR(Q)**		
	v	f	d	v	f	d
1	0.9911	0.6589	0.9322	5888	4416	5888
2	0.9444	0.9822	1.1356	8831	8831	8831
3	0.9911	1.2856	0.8589	11775	13247	11775
Rank	3	1	2	2.5	1	2.5

ANOVA and RSM

The findings of the analysis of variance for surface roughness and MRR are shown in Tables 5 and 6 respectively. Surface roughness and MRR are both influenced by the feed rate than by cutting depth and cutting speed. RSM is used to develop the correlation between cutting parameters and responses in terms of second order equations. The Equations (3) and (4) are the quadratic response surface model impacting surface roughness and MRR with turning factors v, f, and d.

Table 5. ANOVA for Surface Roughness

Source	**DF**	**SS**	**MS**	**F**
v	2	0.01307	0.00653	0.38
f	2	1.76780	0.88390	51.45
d	2	0.36980	0.18490	10.76
Error	20	0.34360	0.01718	
Total	2	2.49427		

Table 6. ANOVA for MRR

Source	**DF**	**SS**	**MS**	**F**
v	2	155981953	77990977	23.82
f	2	350959395	175479697	53.60
d	2	155981953	77990977	23.82
Error	20	65473906	3273695	
Total	2	728397207		

$$Ra=-1.95365-0.00757143\times v+16.4071\times f+6.45714\times d+0.000038095\times v^2-4\times f^2-3.84000\times d^2\ 0.0190476\times v\times f+0.000952381\times v\times d-9.53333\times f\times d \tag{3}$$

$$Q=9672.32-84.10\times v-96723\times f-12896\times d+841.071\times v\times f+112.143\times v\times d+117750\times f\times d \tag{4}$$

Single objective genetic algorithm

50 population size, 1 crossover rate, 0.1 uniform distribution mutation rate, bit number 16 for each variable, and 1500 iterations were used in this investigation. For single objective optimization, the optimal cutting parameters for surface roughness and MRR were calculated using RSM Equations (3) and (4). Cutting speeds of 80 to 200 m/min, feed rates of 0.05 to 0.2 mm, and depth cuts of 0.5 to 2 mm were used for the optimization study. The optimal value of cutting parameters resulted in the minimizing of surface roughness and maximum MRR through GA optimization as shown in Figure 5. From this optimization the results for surface roughness and MRR are shown in Table 7. Single objective optimization study carried out separately on surface roughness and MRR yields optimal parameter values as 0.4789(µm) and 23059 (mm^3/min) respectively. For optimizing both objective, multi-objective optimization technique is preferable.

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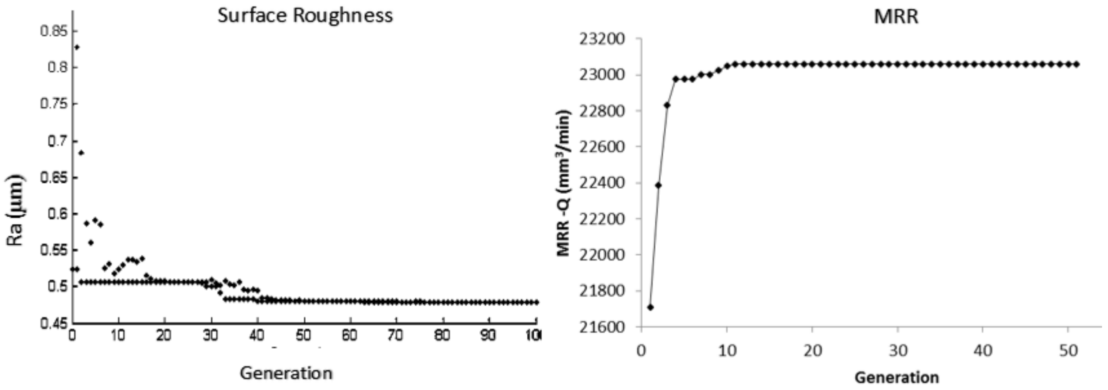

Figure 5. GA Single objective approach.

Table 7. Optimized cutting parameter in single objective GA algorithm.

Response	**v (m/min)**	**f (mm/min)**	**d (mm)**	**Optimized Value**
Ra	127	0.05	0.5	0.4789(μm)
MRR	148	0.15	1	23059 (mm^3/min)

<u>Non-dominated Sorting Genetic Algorithm-II</u>
In this multi objective optimization study, population size of 50, crossover rate of 1.0, and 0.1 mutation rate were utilized for 2500 iterations. Solve XL and MATLAB mathematical software's are used in this research to intensify NSGA-II and Pareto front analysis and the most efficient cutting parameters has been selected to attain minimal surface roughness with maximum metal removal rate. Figure 6 represents Pareto Front analysis, which indicate that while increase of MRR tends to increase the surface roughness of material. In graph, curve A to B shows lesser values of MRR with the increase of surface roughness when compared with curve C to D. MRR value achieved at points B and D are 8000 mm^3/min and 23000 mm^3/min respectively. Through NSGA-II optimal values of surface roughness and MRR are attained between point B and C as shown in Table 8. The most optimal value achieved in curve B to C is 0.7341 μm surface roughness and 9460 mm^3/min MRR for the cutting parameters of 140.73m/min cutting speed, 0.06 mm/min feed rate and 0.99 mm depth of cut.

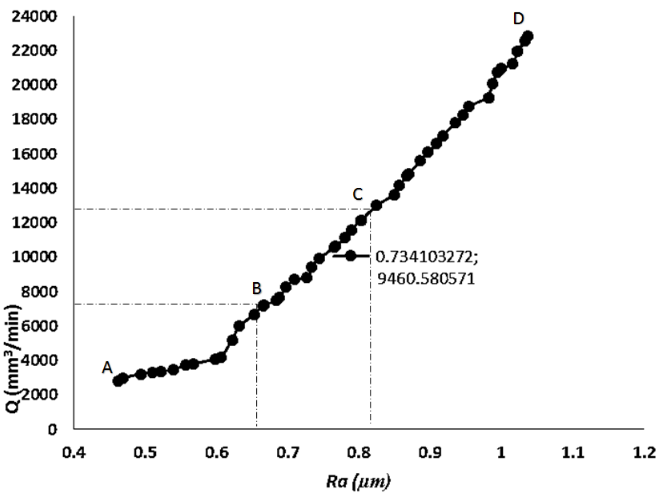

Figure 6. Pareto Front Model.

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Table 8. B to C Region Values in Pareto Front Model

S. No	v	f	d	Ra	Q
1	119.12	0.0625	0.99976	0.68822	7691.3957
2	136.29	0.0565	0.99988	0.69830	8267.28214
3	131.30	0.0628	1	0.71002	8713.91085
4	147.24	0.0548	0.99878	0.72770	8829.47595
5	140.74	0.0627	0.99976	0.73410	9460.58057
6	136.05	0.0689	0.99976	0.74446	9916.49345
7	143.90	0.0689	0.99976	0.76593	10591.1772
8	143.90	0.0693	1	0.76690	10649.4953
9	146.28	0.0712	1	0.78121	11136.4851
10	136.05	0.0814	1	0.79010	11613.8588
11	141.64	0.0814	1	0.80357	12153.2902

Impact

Furthermore, the GA technique suggested the optimal combination of parameters to achieve an improved surface finish and MRR. Therefore, this experimental study proved, based on the aforementioned observations, that the proposed methodologies can determine the optimum machining parameters which would be significantly beneficial in the manufacturing industries.

Conclusion

The cutting parameters in the turning of the magnesium alloy AZ91D were optimized using evolutionary techniques in this experiment. Through single and multi-objective GA, the RSM quadratic model has been constructed to forecast and evaluate mathematical solutions for achieving optimal cutting parameters. The following conclusions were derived using an evolutionary approach.

- Taguchi methodology implies optimum cutting parameters of 110m/min cutting speed, 0.05mm/rev feed rate, 1mm depth of cut to attain minimum surface roughness of 0.63µm and 150m/min cutting speed, 0.15mm feed rate, 1mm depth of cut to reach maximum MRR of 19550 mm^3/min.
- The minimum surface roughness attained was 0.4789m by optimized cutting parameters of 127m/min cutting speed, 0.05mm/rev feed rate, 0.5mm depth of cut, and the maximum MRR of 23059 mm3/min was attained by optimized cutting parameters of 148m/min cutting speed, 0.15mm feed rate, and 1mm depth of cut with a single objective GA approach.
- GA yields better results of about 34.04% lesser surface roughness and 15.2% higher MRR values when compared with Taguchi method.
- The most optimal values achieved in multi objective optimization NSGA-II are 0.7341 µm surface roughness and 9460 mm^3/min MRR for the cutting parameters of 140.73 m/min cutting speed 0.06 mm/min feed rate and 0.99 mm depth of cut.
- Multi objective NSGA-II optimization provides several non-dominated points on Pareto Front model that can be utilized as decision making for choice among different objectives.

Conflict of interest

There is no conflict of interest to declare.

Acknowledgments

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