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MODELING OF THE END MILLING PROCESS FOR ALUMINUM ALLOY AA6061T6 USING HSS TOOL

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ABSTRACT

This study is focused to determine the optimum operating parameters for the end milling process of AA6061T6 under wet cooling conditions. A central composite design of response surface methodology is used to develop an effective analytical model for surface roughness. The primary cutting parameters, namely, speed, feed rate and depth of cut, are considered in this study. Surface roughness is measured using a perthometer. The adequacy of the model is tested using ANOVA at 95% confidence level. Significant parameters are identified in terms of the cutting parameters. The obtained results show that the most significant parameters for the machining of the mentioned alloy are feed rate and depth of cut. The resultant model is then tested for optimization using a genetic algorithm.

***Keywords*:** End mill; aluminum alloy; response surface methodology; central composite design; surface roughness; genetic algorithm.

INTRODUCTION

Milling is the most extensively used metal machining operation. Most of the finished products undergo milling processes at some stage of fabrication (King & MacDonald, 1975). The widespread use of end milling for machining parts is attributed to its ability to give a faster rate of metal removal as well as a reasonably good surface texture. End milling operations are highly adaptable for both the roughing and finishing operations for different products that can be produced with a high level of accuracy and surface finish (Sutherland, 1988). Machining productivity with good design and specifications, as well as the process economics and product quality, make the study of the milled surface vital (Hossain & Ahmad, 2012; Razak, Rahman, & Kadirgama, 2012a,b; Najiha, Rahman, Kamal, Yusoff, & Kadirgama, 2012). The machining process for producing a milled surface is affected by a number of machining parameters such as the cutting conditions and tool geometry (Razak et al., 2012a; Najiha, Rahman, Yusoff, & Kadirgama, 2012). These parameters play a key role in the final quality and finish of a milled surface. Surface texture or surface quality play a vital role in improving the fatigue strength, corrosion resistance and creep life of the machined part (Mohammed, Montasser, & Joachim, 2007).

The surface roughness parameter is an indicator of surface finish quality which in turn finally controls the process performance and the operating costs (Boothroyd & Knight, 1989). Surface roughness is affected by a number of factors including cutting parameters, tool geometry, workpiece material, chatter and cutting fluids (Lakshmi & Subbaiah, 2012). Many researches have been conducted in order to study the effects of machining parameters on the surface quality of the product in end milling operations. The axial depth of cut, radial depth of cut and feed rate are the most significant parameters in machining, affecting tool deflection and the surface (Saffar et al., 2009). Elmagrabi et al. (2008) stated that the feed rate and the depth of cut are the most significant factors affecting surface roughness. In order to investigate surface roughness under controllable and uncontrollable factors in end milling operations, an empirical approach was used (Huang & Chen, 2008). An integrated study of surface roughness was done by Oktem (2009). This study was used to model and optimize the cutting parameters when end milling AISI1040 steel material. Oktem (2009) used the PCA based Taguchi method to optimize the differing objectives of maximizing the metal removal rate and minimizing the surface roughness. In another study, research was done to investigate the effects of tool geometry on the quality of the surface (Reddy, 2005). Surface roughness affects the quality of the machined surface and plays an important role in the functional characteristics of the final product as it also affects several functional aspects of the machined part, such as light reflection, heat transmission, coating characteristics, surface friction, fatigue resistance (Moshat et al., 2010). However, the mechanism behind the formation of surface roughness is very dynamic, complicated and process-dependent; therefore it is very difficult to calculate its value through analytical formulae (Moshat et al., 2010). Surface finish can be characterized by various parameters such as average roughness (R_a), smoothening depth (R_p), root mean square (R_q), and maximum peak-to-valley height (R_t) (Hasegawa, Seireg, & Lindberg, 1976).

In addition to surface roughness, the material removal rate (MRR) is a factor that affects the machining productivity and cost. The MRR signifies the total machining time for the workpiece. It is also necessary to study the material removal rate along with surface roughness in the CNC end milling process. The surface finish of the machined surface has been identified as a quality attribute, whereas MRR has been treated as a performance index directly related to productivity (Moshat et al., 2010). Both the surface roughness and the material removal rate vary greatly with the change of cutting process parameters. That is why proper selection of cutting process parameters is also essential, along with its prediction to obtain a good surface finish (lower Ra value) and higher material removal rate in the CNC end milling process (Moshat et al., 2010). So in order to contribute towards the production cost and quality, it is essential to have a model that is able to evaluate both indices, i.e., surface roughness and material removal rate, before the machining of the part, thus helping to reduce the machining cost and time, and increasing the surface quality, hence helping to optimize the machining process.

The purpose of this study is to optimize the end milling process of aluminum alloy AA6061T6 under flooded lubrication conditions. Experiments have been designed using the central composite design approach. The results obtained have been used to investigate the most significant and influential parameters in end milling under flooded machining conditions. A genetic algorithm is implemented to optimize the end milling parameters. The literature survey indicates that genetic algorithms are thriving in the optimization of machining parameters (Ahmad, Tanaka, & Saito, 2004). A multi-objective genetic algorithm based approach is used in this work for an end milling operation that is assumed as a controlled optimization problem. Multi-objective optimization problems usually have many optimal solutions, known as Pareto optimal solutions (Miettinen, 1999; Goel et al., 2007). Specimen surface roughness and material removal rate are used as the objective functions in this single pass end milling constrained parameter optimization problem. Significant parameters affecting the surface roughness and material removal rate are indicated by ANOVA. The perthometer is used to obtain the average surface roughness R_a. Statistical quadratic models of surface roughness are used to fit the experimental data of the surface roughness.

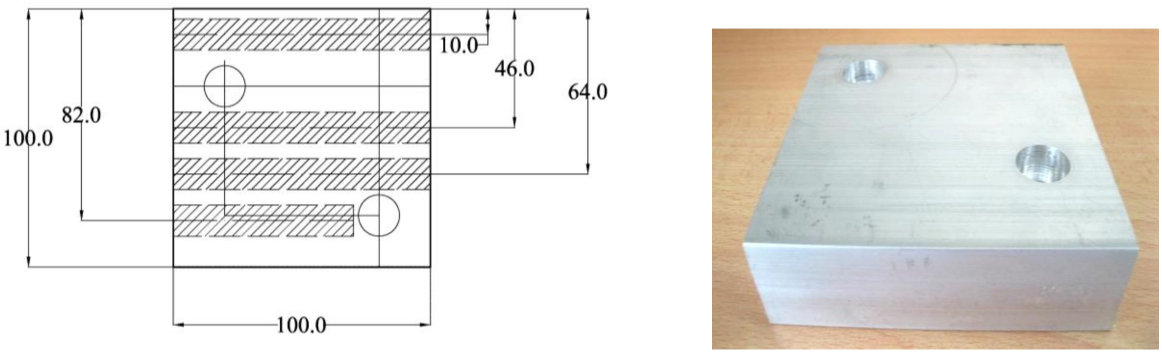
METHODOLOGY

Machining Parameters and Design of Experiments

In this research, the feed rate, speed and depth of cut are set as machining variables. In order to find the effects of parameters and the combination of the parameters, design of experiments is done. Experiments are designed according to a central composite design of response surface methodology. Machining parameters are taken as factors in the design of experiments and there are five levels for every factor, as shown in Table 1.

Table 1. Assignment of levels to factors

Factors	Levels				
	1	2	3	4	5
Cutting speed (rpm)	866	932	1037	1142	1209
Axial depth of cut (mm)	0.367	1.0	2.0	3.0	3.63
Feed rate f_z (mm/min)	79	95	120	145	161



(a) (b)

Figure 1. (a) Machining pattern on the workpiece; (b) workpiece.

Workpiece and Cutting Tool Material

AA6061T6 aluminum alloy is used as a workpiece material. This is a general purpose alloy which offers adequate machinability and gives continuous chips. The main constituents of the alloy are Si, Cu and Mg. The dimensions of the workpiece are 100 mm × 100 mm × 30 mm. Workpieces from the same batch were used in the experiments. A high speed steel end mill with two flutes is selected for the machining.

The two-flute tool is selected in order to avoid chip clogging in the tool flutes. A central composite design with a quadratic model is applied. Finally, optimization is carried out to find the best design. The significance of the input machining parameters on the response variable, i.e., surface roughness, is determined by ANOVA. Experiments are performed using a vertical CNC milling center, HAAS TM-2 machining pattern on the specimen, as shown in Figure 1.

Measurement of Parameters

Surface roughness is the response of the experiments. A perthometer is used to measure the surface profile. The average surface roughness is determined from the profile data. Surface roughness is measured in µm.

Statistical Modeling

In order to optimize the surface roughness, a statistical model of surface roughness is needed that constructs a relationship between the cutting parameters and the response variable, i.e., surface roughness. The measured values of average surface roughness (R_a) and material removal rate obtained for the design of experiments are listed in Table 2. The statistical modeling of the data obtained is done with the help of MATLAB.

Table 2. Measured values of average surface roughness

Speed (RPM)	Feed rate (mm/min)	Depth of cut (mm)	Surface roughness (µm)	MRR (mm^3/min)
932	95	1.00	1.52	1140
932	145	3.00	1.47	5220
1037	120	2.00	0.94	2880
1142	145	1.00	0.97	1740
1037	120	2.00	1.21	2880
1142	95	3.00	0.87	3420
1037	120	2.00	1.10	2880
1037	120	2.00	0.97	2880
932	145	1.00	1.68	1740
1142	95	1.00	1.30	1140
1142	145	3.00	1.70	5220
932	95	3.00	0.96	3420
1037	79	2.00	0.95	1900
1037	120	3.63	0.96	5232
1209	120	2.00	1.26	2880
1037	120	0.37	1.44	528.0
1037	120	2.00	0.82	2880
866	120	2.00	0.75	2880
1037	120	2.00	0.94	2880
1037	161	2.00	1.98	3860
932	95	1.00	1.52	1140
932	145	3.00	1.47	5220
1037	120	2.00	0.94	2880
1142	145	1.00	0.97	1740
1037	120	2.00	1.21	2880
1142	95	3.00	0.87	3420

The estimated regression coefficients, the analysis of variance for the surface roughness and the effects or significance of the regression terms are summarized in Table 3. The Analysis of Variance table summarizes the linear terms, the squared terms, and the interactions. The statistical significance of variables is indicated by the *p*-value of the variables. This is the probability of obtaining a test statistic that is at least as extreme as the actual calculated value (Jiang et al., 2010). It is the level of trivial significance within a statistical hypothesis test, representing the probability of the occurrence of a given variable. In this research, the level of significance is set at a standard cut-off value of $\alpha = 0.05$. The small *p*-values for the main ($p = 0.026$), linear ($p = 0.048$) and squared terms ($p = 0.054$) imply that there is curvature in the response surface. According to the regression analysis, the statistical model contains three two-way interactions (speed x feed rate, speed x depth of cut, feed rate x depth of cut). The *p*-value of 0.039 for the feed rate by depth of cut interaction is less than 0.05, which is a significant interaction effect. That is, the effect of the depth of cut on the surface roughness depends on the feed rate. The model contains three squared effects (depth of cut × depth of cut, feed × feed and speed × speed). Squared terms are used to assess whether there is curvature (quadratic effect) in the response surface.

Table 3. Estimated regression coefficients for surface roughness

Source	Coefficient	$p-$value	Significant* (at $\alpha = 0.05$)
Regression	-	0.026	yes
Linear	-	0.048	yes
Square	-	0.054	yes
Interaction	-	0.091	no
Constant	9.99288	0.217	no
Speed	0.00472	0.710	no
Feed rate	0.07163	0.104	no
Depth of cut	2.69197	0.015	yes
Speed x speed	0.00000	0.798	no
Feed rate x feed rate	0.00030	0.012	yes
Depth of cut x depth of cut	0.09002	0.178	no
Speed x feed rate	0.00001	0.815	no
Speed x depth of cut	0.00128	0.123	no
Feed rate x depth of cut	0.00759	0.039	yes

The squared terms are identified as significant in the analysis of variance table ($p = 0.048$). The *p*-values for squared effects (feed rate × feed rate = 0.012) are less than 0.05. Therefore, there are significant quadratic effects from the feed rate. The relationship between feed and surface roughness follows a curved line, rather than a straight line. The *p*-value for the linear terms is also less than the standard $\alpha = 0.05$ value, as shown in the analysis of variance table (*p*-value = 0.048). This depicts that the linear effects of some of the variables are also significant. The *p*-value for the depth of cut is 0.015, i.e., it also has a significant linear effect on the model. The quadratic model for surface roughness can be expressed as follows:

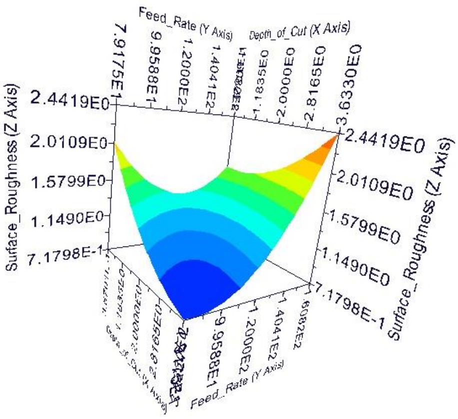
$$\begin{aligned} R_a &= 9.99288 - 0.00472 \times Speed - 0.07163 \times Feed\ rate - 2.69197 \times doc \\ &- 0.00001 \times Speed \times Feed\ rate + (0.00128 \times Speed \times doc + 0.00759 \times Feed\ rate \times doc \\ &+ 0.00000 \times Speed \times Speed + 0.00030 \times Feed\ rate \times Feed\ rate + 0.0002 \times doc \times doc \end{aligned} \quad (1)$$

where

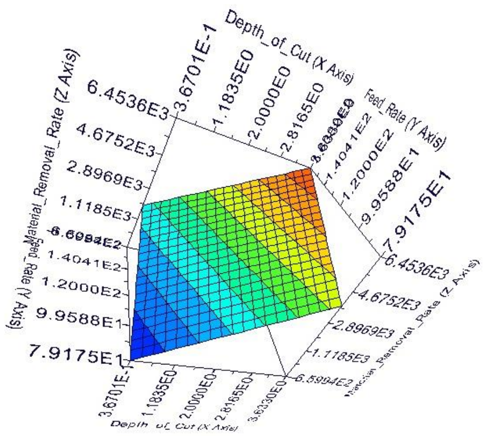
R_a	= Average surface roughness measured, μm
Speed	= Spindle speed measured, RPM
Feed rate	= Feed rate measured, mm/min
doc	= Depth of cut measured, mm.

Response Surface Charts and Function plots

A 3-dimensional response surface perspective plot and a 2-dimensional contour plot give a pictorial representation of the response surfaces, showing the combined effects of the input variables. Response surface plots showing the mutual effect of feed rate and depth of cut on the surface roughness and material removal rate are shown in Figure 2. Function plots for the surface roughness against the feed rate and depth of cut are shown in Figure 3. Function plots for the surface roughness against the feed rate and depth of cut are shown in Figure 4.

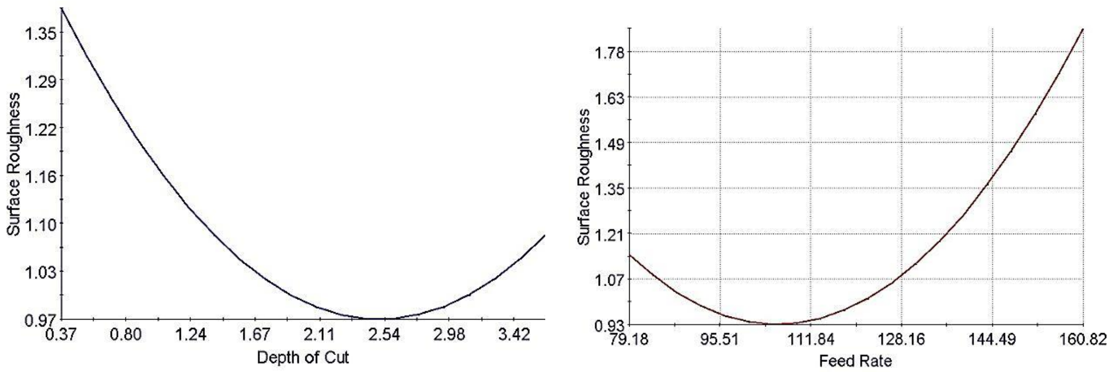


(a)



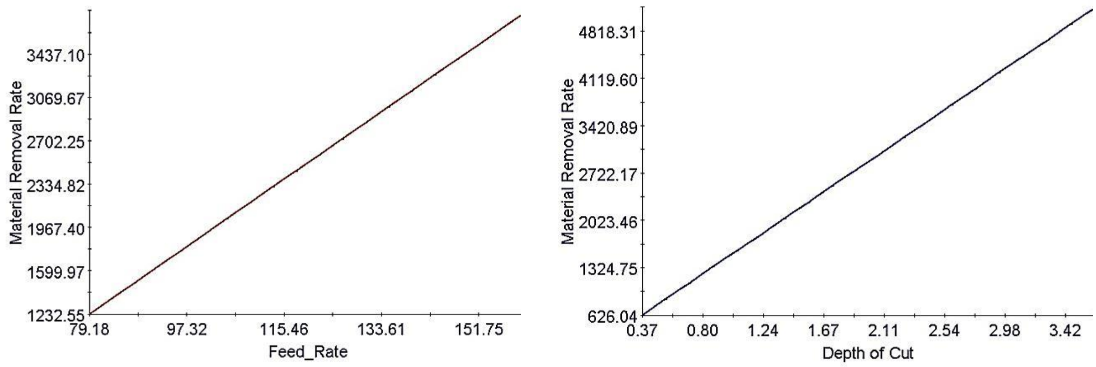
(b)

Figure 2. Surface contour plots against (a) surface roughness; (b) material removal rate.



(a) (b)

Figure 3. Function plots for surface roughness (μm) versus (a) feed rate (mm/min); (b) depth of cut (mm).



(a) (b)

Figure 4. Function plots for material removal rate (mm^3/min) vs (a) feed rate (mm/min), (b) depth of cut (mm).

OPTIMIZATION MODELING

Objective Functions

In order to optimize an operation, the objective functions have to be defined. In this research, average surface roughness, R_a and material removal rate are set as objective functions. While the MRR is a quantitative measure of productivity, surface roughness defines the quality of the machining. These two objectives are conflicting, i.e., one has to be compromised in order to achieve a gain in the other. The two objective functions, namely, the surface roughness and the material removal rate, along with the input variables, are listed in Table 3 in the earlier section.

Machining Constraints

Machining constraints are defined by the process capabilities and the final product requirements. The constraints are defined by the experimental range. The boundary conditions are defined by Eq. (3) through Eq. (8).

Minimize surface roughness, $Ra = fn(Speed,\ Feed\ rate,\ doc,\ MQL\ flow\ rate)$;

Maximize material removal rate, $MRR = fn(\text{diameter of tool},\ Feed\ rate,\ doc)$;

subject to:

1. $Speed_{\min} \le Speed \le Speed_{\max}$ (3)
2. $Feed\ rate_{\min} \le Feed\ rate \le Feed\ rate_{\max}$ (4)
3. $doc_{\min} \le doc \le doc_{mac}$ (5)
4. $MQL\,Flow\ rate_{\min} \le MQL\,Flow\ rate \le MQL\,Flow\ rate_{\max}$ (6)

while

5. $Ra_{\min} \le Ra \le Ra_{\max}$ (7)
6. $MRR_{\min} \le MRR \le MRR_{\max}$ (8)

A two-step optimization was performed based on the genetic algorithm strategy. Genetic algorithms have been used in function optimization since their inception, optimizing large poorly understood problems that arise in many areas of science and engineering (Adeli & Cheng, 1994). Optimization was carried out using two-step process optimization. The first optimization step was performed to identify the feasible designs and the second optimization was done to find the optimal design. In the first optimization step, three machining parameters (speed, feed rate, depth of cut) were defined as input variables while the measured surface roughness and material removal rate were selected as the response variables. The objectives were to minimize the surface roughness and maximize the material removal rate. The two objectives were bound by the constraints defined from the experimental scope. The multi-objective optimization managed by the multi-objective optimization genetic algorithm (MOGA), was stopped after 100 generations, and 239 Pareto designs were selected to find the optimum design. In the current study, 239 Pareto designs were obtained. The set of all Pareto optimal points is known as the Pareto frontier. The Pareto frontier for the current designs is presented in Figure 5. Starting from the design considerations obtained from the primary optimization, a second optimization was performed in order to find the most optimal design point.

From the statistical model of surface roughness, the most significant factors are identified. According to the statistical model obtained for the surface roughness and material removal rate, feed rate and the depth of cut appear to be the most significant factors, which is in complete agreement with the earlier research (Jiang et al., 2010). A two-step optimization was performed. The first step was performed in order to determine the range of parameters for feasible designs. The second optimization was done to focus on finding the final optimal design. In the first step of optimization, the selected cutting parameters were used as input variables while the response variables, i.e., surface roughness and the material removal rate, were taken as output. The main objectives selected were in conflict with each other, i.e., to minimize the surface roughness and to maximize the material removal rate. Constraints were applied to the problem within the experimental scope. In order to initialize the algorithm, a set of 20 designs obtained from the central composite designs was used. In the first step of optimization, 100 generations were run which resulted in 2625 feasible designs. From these feasible designs, 239 Pareto designs were selected for the second optimization. The reason for doing a second optimization was to help the algorithm converge and find the optimum design point. The constraints were selected from the range of variables from the Pareto designs.

The reason for selecting these constraints was to ensure that the algorithm, while trying to optimize the two conflicting objectives, leads to a design not too far from the original one, so as to not break the constraint. In doing two optimizations, the advantage can be observed as in the first optimization phase; at the beginning the algorithm reaches the best region as a compromise between the objectives, while in the second one there is a refinement or convergence in order to identify the best designs. As initial designs, 239 Pareto designs were chosen to start the optimization. After 100 generations, the algorithm stopped and a convergence was obtained for the best optimal design within the Pareto designs range. After the second optimization, the optimization algorithm converged to a design with a spindle speed of 866 rpm, feed rate of 119.5 mm/min, depth of cut value 3.64 mmm and the compromise values of the surface roughness and material removal rate were 0.752 µm and 5231 mm^3/min respectively.

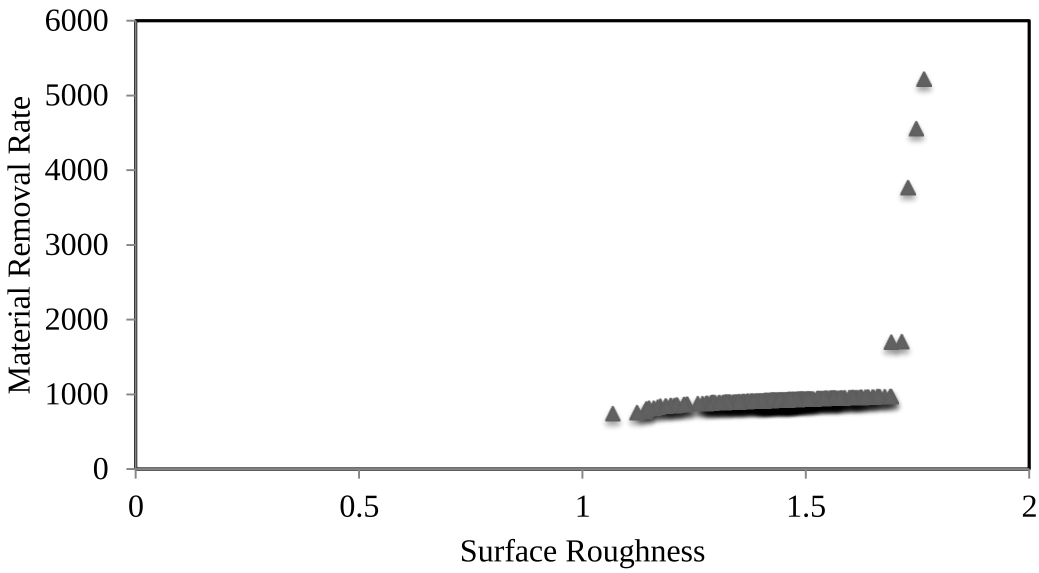


Figure 5. Pareto frontier for the output variables.

CONCLUSION

The foregoing study deals with the multi-objective optimization of a CNC end milling operation by applying a genetic algorithm. For carrying out the optimization, mathematical modeling of the surface roughness was performed using RSM. Design of experiment was made using a central composite design approach resulting in 20 designs. From the modeling of the response, it is clear that surface roughness is more sensitive to feed rate and depth of cut. The quadratic model was used for fitting experimental data. Multi-objective optimization based on the Pareto optimal designs approach was used for the selection of optimal designs within the experimental scope. This approach has many advantages. Since the Pareto designs are selected from the feasible designs, the feasibility of the optimal design is ensured. All the constraints considered were selected from the real experimental conditions. The optimization was performed in two steps. Firstly, the algorithm converged to a set of feasible designs after

100 generations. In the second step of optimization, the algorithm converged to the best optimal Pareto design. The best design obtained was the design at 866 rpm, feed rate of 119.5 mm/min and a depth of cut of 3.64 mm. The optimum values for the two objectives, i.e., surface finish and material removal rate, were found to be 0.752 µm and 5231 mm^3/min respectively.

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