Optimisation of Surface Roughness when CNC Turning of Al-6061: Application of Taguchi Design of Experiments and Genetic Algorithm

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ABSTRACT

Surface roughness is often used as a measure to identify surface integrity of machined parts. The objective of this study was to optimise part surface roughness by investigating the effects of cutting speed, feed rate, depth of cut and tool nose radius on the surface roughness of Aluminium 6061. A five-level L_{25} *Taguchi orthogonal array was modified to accommodate a four-level process parameter. The optimization was conducted on the prediction model generated by use of Response Surface Methodology (RSM) together with Analysis of Variance (ANOVA), and confirmation test validated the predicted values obtained from the Genetic Algorithm (GA). The best combination of parameters for minimum surface roughness was found to be a cutting speed of 250 m/min, feed rate of 0.03 mm/rev, depth of cut of 0.2 mm and tool nose radius of 0.503 mm. The study proves the efficacy of the GA approach in optimisation of machining parameters for improved surface roughness.*

Keywords: *Genetic Algorithm, Optimisation, Surface Roughness, CNC Turning.*

Introduction

Surface roughness produced by machining processes is one of the important criteria to identify quality of machined parts. Improving the surface roughness produced by machining processes through optimisation of parameters has been widely and studied [1]. Turning is the most common type of machining process in the contemporary manufacturing industry. The quality of the turning process

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is generally determined by numerous measurements including surface roughness and geometrical features of products. Further, machining quality can be expressed in terms of various product attributes such as fatigue life, corrosion resistance, aesthetics, precision fit and tribology related characteristics [2]. However, surface roughness is the most common measurement for judging the quality of product.

Taguchi, Response Surface Methodology (RSM), Artificial Neural Network (ANN), Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA) have been widely recognized in the industry for optimisation of surface roughness. Out of this list of artificial intelligence techniques, ANN, PSO and GA are the most often used soft computing techniques which are amply applied in optimisation of machining processes. However, GA was used for solving constrained and unconstrained optimisation problems based on the mechanics of genetics and natural selection of the process that drives biological evolution [3]. The GA solution approach begins with a set of potential solutions referred to as chromosomes, which are randomly selected. The chromosomes evolve during several iterations and the new generations are known as offspring, which are generated by utilising the reproduction, crossover and mutation techniques. Mutation involves the flipping of a chromosome and crossover involves splitting of two chromosomes and then combining half of each chromosome with the other pair. The chromosomes are assessed using certain fitness criteria in which only the best ones are kept and the others are discarded. This is repeated until one chromosome has the best fit and is taken as the optimal solution [4].

Mondal et al. [5] applied GA for optimisation of the keyway milling process. Depth of cut, feedrate and spindle speed were investigated at three levels each. ANN and RSM techniques were used to develop a prediction model and then GA was applied to verify the study results. Sahu and Andhare [6] used RSM and GA approaches to model and optimize the productivity in the high speed milling of Ti-6Al-4V. Power consumption, material removal rate (MRR), surface roughness and tool wear were analysed and a muti-objective model was built to optimise the selected performance measures. Kumar and Sait [7] used ANN and GA to model and optimise the machining of composite pipes. The investigated parameters were feed, speed and depth of cut, while force acting on the cutting tool was selected as the performance measure. Sangwan et al. [2] coupled ANN with GA to minimise surface roughness. Additionally, cutting speed, feedrate and depth of cut have been focused in the study and feedrate was found as the main influencing parameter.

Experimental design determines the required number of experimental runs which best reflects the possible parameter combinations. When the parameters and levels involved are low, the full factorial approach could be used to investigate all parameter combinations. However as the number of parameters and levels increase, the full factorial method becomes impractical and instead orthogonal array design approach can be used. The Taguchi method has great potential in low cost experimentation and as such is widely accepted by engineers and scientists [8]. The use of orthogonal array design technique in accompanying the Taguchi model helps in reducing the model to ensure minimum experimental runs for identification of optimal parameter levels while establishing relative importance [9]. Furthermore, in the Taguchi approach, Analysis of Variance (ANOVA) could also be beneficial to investigate the influence of parameters on performance measures [10]. A modified form of the Taguchi method, often referred to as the dummy treated experimental design, allows factors with different number of levels to be accommodated in the same orthogonal array Design of Experiments (DOE) by repeating one or more of the available levels [11]. The repeated level can be chosen based on experimental data or simply whichever is easiest, cheapest, or more practical [12].

Bhattacharya et al. [12] used a modified Taguchi orthogonal array in investigating the optimal parameter settings for rough and finish machining of die steels in powder-mixed electrical discharge machining (EDM). Five of the seven input parameters were varied at three levels, while the remaining two were varied at two levels. It was calculated that twenty degrees of freedom (DOF) were needed for the experimental design so an L_{27} orthogonal array was used, with the dummy treatment being used for the third level of the two-level factors. The dummy treated DOE was effective in this research study since the extra six DOF were used to measure experimental error which increased the accuracy of the results.

This paper presents an experimental investigation on optimisation of surface roughness in turning of aluminium 6061 alloy (Al-6061) by physical vapour deposition (PVD) coated carbide tool inserts and joint application of Taguchi approach. Further, from a comprehensive review of literature it was found that several pioneers in the area of research have attempted successfully the application of GA for optimisation of surface roughness by involving various machining parameters such as cutting speed, feedrate and depth of cut. These parameters are by no means exhaustive, it represents our understanding of, and opinion about the application of GA. Thus, in addition to the list, in the current study, we selected tool nose radius what we believed to be the most relevant parameter for improvement of surface roughness and that has not been given much attention by the academia. Furthermore, the reason for selection of Al-6061 as workpiece material is due to its high strength to weight ratio, high surface finish, excellent corrosion resistance and good workability [13], [15] and [16]. Moreover, typical applications for Al-6061 include aircraft and aerospace components, marine fittings, transport, bicycle frames, camera lenses, drive shafts, electrical fittings and connectors, brake components, valves and couplings. In addition, in this paper, experiments were performed using L_{25} Taguchi orthogonal array method. Additionally, ANOVA technique was used to determine the optimum process parameters for minimising surface roughness in conjunction with GA approach. Confirmation test was conducted to validate the predicted values using the Boxford CNC Lathe and Mitutoyo surface roughness tester.

Research Methodology

The research methodology employed in this study is summarised in Figure 1. The steps followed to conduct the experiments are explained in the following sections.

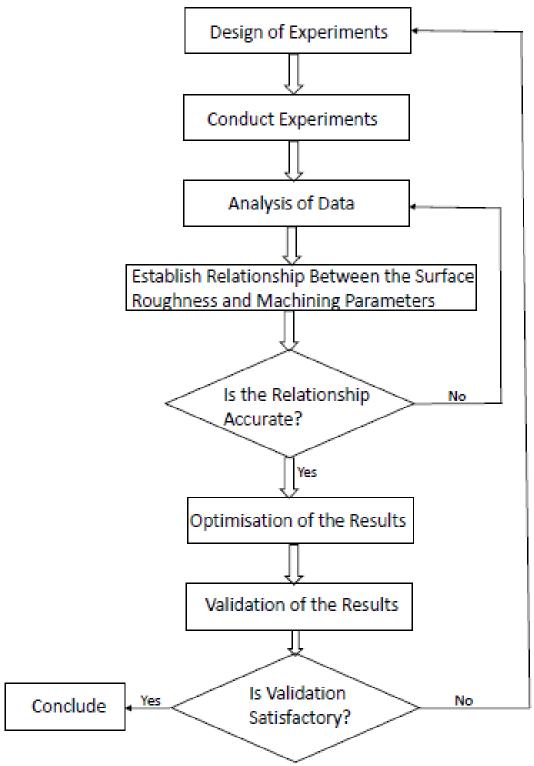


Figure 1: Research Methodology Followed in the Study

Design of Experiments

Taguchi L_{25} orthogonal array of experimental design with four factors and five levels was employed to conduct the study. The dummy level approach as used in previous researches [11] - [14] was followed for the tool nose radius parameter that consisted of only four levels. Level 4 was repeated in experiments where a level 5 setup was required, based on the assumption that surface roughness increases with increase in tool nose radius [15]. The machining parameters used and their levels are summarised in Table 1. These levels were selected based on a previous research study on Al-6061 and carbide tools [13].

Table 1: The Selected Parameters and Levels of the Study

Parameter	Unit	Level				
		1	2	3	4	5
Cutting Speed (X_1)	m/min	150	175	200	225	250
Feedrate (X_2)	mm/rev	0.03	0.06	0.09	0.12	0.15
Depth of Cut (X_3)	mm	0.2	0.4	0.6	0.8	1.0
Tool Nose Radius (X_4)	mm	0.1	0.2	0.4	0.8	-

Conduct of Experiments

The experiments were conducted using Al-6061 material of 25.4 mm in diameter and 100 mm in length on Boxford CNC lathe 250 PC. A snapshot of the machine setup used to conduct the experiments can be seen in Figure 2(a). The cutting tool selected as carbide coated with titanium aluminium nitride (TiAlN) and chromium oxide tips as shown in Figure 2(b). A soluble oil coolant was used and coolants flow rate was kept as constant. As CNC machines utilize numerical control (NC) programming codes, simulations and dry runs were performed to ensure proper communication to the machine. Snapshots of the selected workpiece profile as well as a simulated finished specimen are given in Figure 3(a) and Figure 3(b) respectively.

The surface roughness of the machined samples was measured by using Mitutoyo surface roughness tester (SJ 410 series). Initially, the roughness tester was calibrated and then roughness values were measured at three different locations of the workpiece minor diameter (neck) at 120° incidence from each other, i.e. 0°, 120° and 240°, and the average of the three values was taken as an arithmetic surface roughness (R_a). The surface roughness values and profiles were obtained by using SURFPAK software. The measured values of surface roughness are listed in Table 2. With the use of Minitab software, the analysis of results was performed by means of ANOVA tool. In addition, residual, interaction and main effects plots were generated with the use of the Minitab software. Then by the use of MATLAB software, optimisation of the results was carried. Finally, a confirmation run was organised for validation of the optimal results.

Figure 2(a): Boxford CNC Lathe Machine Setup Used in the Study

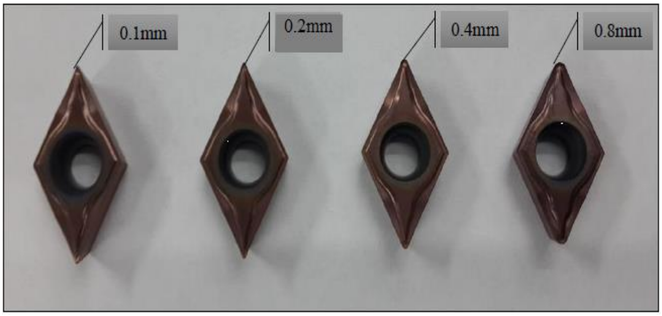


Figure 2(b): Tool Inserts Used to Conduct Experiments

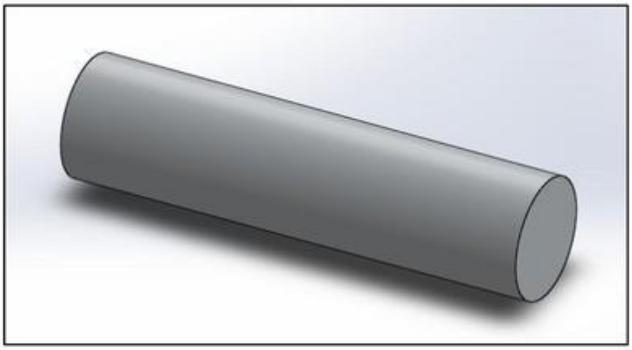


Figure 3(a): A Snapshot of the Selected Workpiece Profile
(Material: Al-6061; 25.4mm diameter x 100mm length)

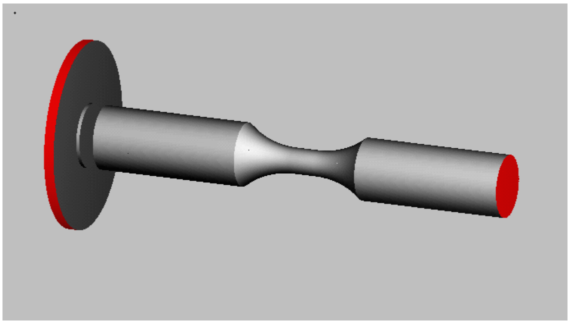


Figure 3(b): A Snapshot of the Simulated Finished Specimen

Analysis of Data

Development of the Prediction Model

A prediction model was established for determination of surface roughness using the selected process parameters cutting speed, feedrate, depth of cut and tool nose radius. The experimental results, as given in Table 2, were analysed by using Minitab software. A stepwise iterative process was performed to reduce as many insignificant or combination of terms from the resultant equation. The resultant prediction model is given in Equation (1). The validity of the prediction model was tested by observing its deviation from the actual results of the experimentation process. Figure 4 shows a comparison of deviations between measured and predicted surface roughness values. From Figure 4, it can be observed that there was a general consistency in the mean of the deviations.

$$R_a = 1.200 - 0.00132X_1 + 10.37X_2 + 0.006X_3 - 4.07X_4 + 34.1X_2^2 + 4.60X_4^2 - 18.51X_2X_4 \quad (1)$$

Analysis of Variance

In order to specify both significant and non-significant effect of experimental parameters, Analysis of Variance (ANOVA) was performed by using the established prediction model (Equation 1) and the results are presented in Table 3. To determine whether the interaction effect is statistically significant or not, the P (importance/probability) value was selected to test the hypothesis. If 95% confidence interval is considered, then a $P < 0.05$ (5% importance value) indicates that the parameter is significant. P for the selected parameters can be seen in Table 3. Accordingly, the effective parameters for R_a are observed as feedrate and tool nose radius that show a P value < 0.05, while depth of cut was witnessed as the least significant parameter with a value of 0.978.

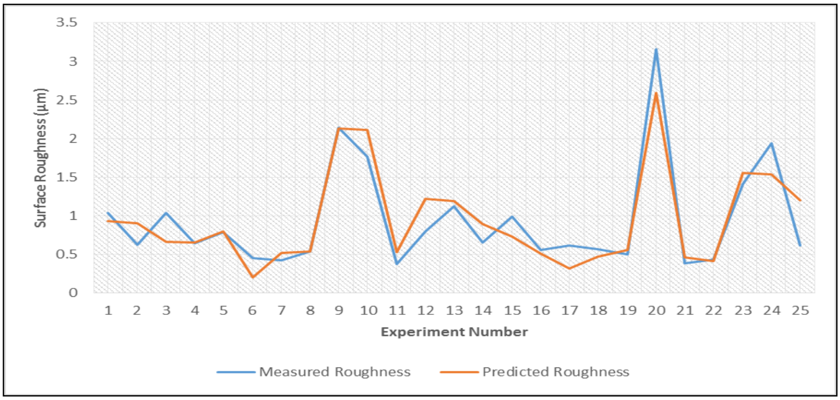


Figure 4: Measured versus Predicted Surface Roughness

Table 2: Experimental Results

Expt. No.	X_1 (m/min)	X_2 (mm/rev)	X_3 (mm)	X_4 (mm)	R_{a1}^{*} (µm)	R_{a2}^{**} (µm)	R_{a3}^{***} (µm)	Mean R_a (µm)
1	150	0.03	0.2	0.1	0.934	1.109	1.063	1.035
2	150	0.06	0.4	0.2	0.618	0.670	0.569	0.619
3	150	0.09	0.6	0.4	1.043	1.041	1.026	1.037
4	150	0.12	0.8	0.8	0.649	0.598	0.669	0.639
5	150	0.15	1.0	0.8	0.771	0.771	0.806	0.783
6	175	0.03	0.4	0.4	0.466	0.452	0.443	0.454
7	175	0.06	0.6	0.8	0.444	0.376	0.438	0.419
8	175	0.09	0.8	0.8	0.593	0.444	0.561	0.533
9	175	0.12	1.0	0.1	2.165	2.193	2.057	2.138
10	175	0.15	0.2	0.2	1.755	1.750	1.806	1.770
11	200	0.03	0.6	0.8	0.426	0.341	0.367	0.378
12	200	0.06	0.8	0.1	0.843	0.797	0.759	0.800
13	200	0.09	1.0	0.2	1.104	1.135	1.138	1.126
14	200	0.12	0.2	0.4	0.555	0.762	0.637	0.651
15	200	0.15	0.4	0.8	0.971	0.930	1.066	0.989
16	225	0.03	0.8	0.2	0.543	0.560	0.575	0.559
17	225	0.06	1.0	0.4	0.638	0.599	0.595	0.611
18	225	0.09	0.2	0.8	0.537	0.562	0.601	0.567
19	225	0.12	0.4	0.8	0.496	0.521	0.487	0.501
20	225	0.15	0.6	0.1	3.000	3.207	3.271	3.159
21	250	0.03	1.0	0.8	0.370	0.433	0.336	0.380
22	250	0.06	0.2	0.8	0.440	0.451	0.404	0.432
23	250	0.09	0.4	0.1	1.502	1.475	1.243	1.407

24	250	0.12	0.6	0.2	2.126	1.771	1.921	1.939
25	250	0.15	0.8	0.4	0.614	0.622	0.603	0.613

Note: *Average Surface Roughness at first point (0°); **Average Surface Roughness at second point (120°); ***Average Surface Roughness at third point (240°)

Table 3: ANOVA Results for Al-6061

Estimated Coefficients for Ra (Uncoded Units)		
Predictor	Coefficient	P value
Constant	1.2	0.005
X_1	-0.00132	0.502
X_2	10.37	0.000
X_3	0.006	0.978
X_4	-4.07	0.000
X_2^2	34.1	0.427
X_4^2	4.6	0.004
X_2X_4	-18.51	0.004

Analysis of Variance					
Source	**DF**	**Adj SS**	**Adj MS**	**F**	**P**
Model	7	9.1941	1.31344	13.14	0.0000
Linear	4	7.9919	1.99798	19.98	0.0000
Square	2	1.1573	0.57865	5.79	0.0120
Interaction	1	1.1441	1.14415	11.44	0.0040
Error	17	1.6999	0.09999		
Total	24	10.8939			

Analysis of Results

Statistical plots were generated from the experimental data. Figure 5 represents the normal probability plot of the residuals for surface roughness. It can be observed that the residuals fall on the straight line denoting that the errors are normally distributed and supports the adequacy of least-squares fit. Figure 6 shows the interaction plots for feedrate and tool nose radius, which conquers with the recent study [3]. These plots take into consideration the interaction effects a parameter has on the other. Moreover, it can be observed that the surface roughness decreases with decrease in feedrate and increase in tool nose radius. Additionally, the highest surface roughness value of 3.159 µm occurred when the feedrate was at its highest value of 0.15 mm/rev and tool nose radius at its lowest value of 0.1 mm. The combination that gave the lowest surface roughness values was feedrate of 0.03 mm/rev and tool nose radius of 0.8 mm. The lower feed rates allow the tool to adequately clear the material and hence prevent rapid movements, which can result in feed marks. In addition, lower feeds offer more contact time for tool-workpiece interaction. Similarly, the increase in tool nose radius allows the tool to be in greater contact with the workpiece thus benefitting the material removal process.

Figure 7 depicts the main effects plots, which display the difference between means for the selected process parameters and consider one parameter at a given time relative to the response. From Figure 7 it is clear that the surface roughness decreased slightly with increase in cutting speed. This observation coincides with the study performed by Ranganath et al. [16]. Further, the surface roughness increased with increase in feedrate. According to the ANOVA results, feedrate is a dominant factor which supports the results obtained. It can also be seen that there was no significant relationship between depth of cut and surface roughness. Moreover, it is observed that the inverse relationship between the tool nose radius and surface roughness was coherent with the study findings of Gupta and Diwedi [15].

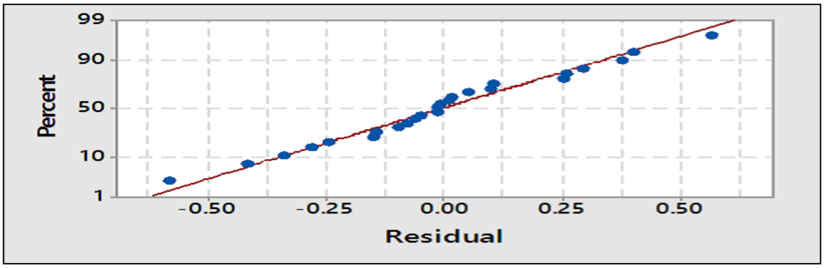


Figure 5: Normal Probability Residual Plot

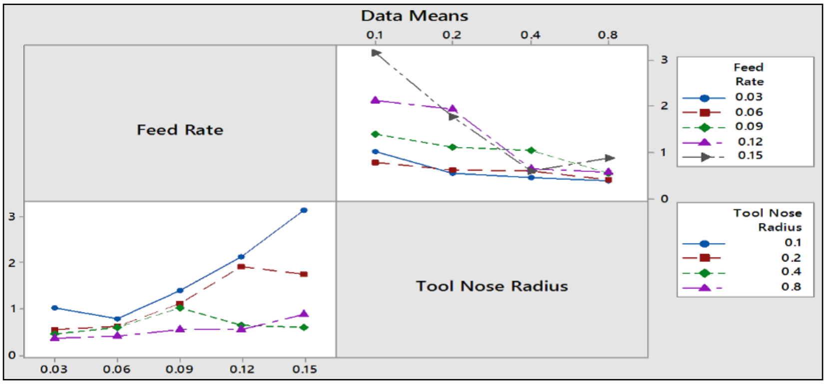
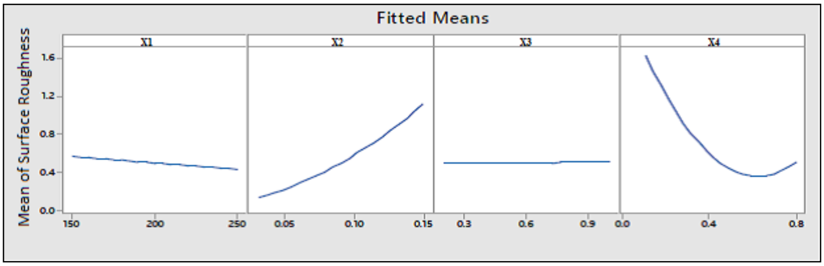


Figure 6: Interaction Plots for Feedrate and Tool Nose Radius



Note: X_1 – Cutting speed; X_2 – Feedrate: X_3 – Depth of cut; X4 – Tool nose radius

Figure 7: Main Effect Plots

Optimisation of the Results

GA Optimisation Setup

The aim of the GA optimisation is to determine the optimal values of the parameters that contribute to the minimum surface roughness. In this regard, the previously established prediction model was taken as the fitness function and the optimisation problem was formulated and given as follows:

$$\text{Minimise } R_a (X_1, X_2, X_3, X_4) = \min (1.200 - 0.00132\, X_1 + 10.37\, X_2 + 0.006\, X_3 - 4.07\, X_4 + 34.1\, X_2^2 + 4.60\, X_4^2 - 18.51\, X_2 X_4) \quad (2)$$

Subjected to the following boundary conditions:

$$150 \text{ m/min} \leq X_1 \leq 250 \text{ m/min} \quad (3)$$
$$0.03 \text{ mm/rev} \leq X_2 \leq 0.15 \text{ mm/rev} \quad (4)$$
$$0.2 \text{ mm} \leq X_3 \leq 1.0 \text{ mm} \quad (5)$$
$$0.1 \text{ mm} \leq X_4 \leq 0.8 \text{ mm} \quad (6)$$

The optimisation exercise was performed using the GA tool available in MATLAB software with Equation 2 as fitness function, Equations (3)-(6) as the boundary conditions, and with the GA parameters settings as listed in Table 4. The GA optimisation results are sumarised in Table 5.

While performing the GA optimisation, the population type was selected as double vector. In addition, the creation, crossover and mutation functions were selected as constraint dependent. The scaling and selection functions were chosen as rank and stochastic uniform respectively. No hybrid function was used and the augmented Lagrangian function was selected for constraint handling.

The major criteria influencing the GA optimisation results are the initial population size, the type of selection function, the crossover rate and the mutation rate [17]. The parameter settings for these criteria are obtained by the trial and error approach, as there is no set guideline that can be used to come up with the best combination of settings [17].

Table 4: GA Parameter Settings

Parameter	**Set Value**
Population size	20
Number of generations	200
Mutation rate	2
Crossover rate	0.8

Table 5: GA Optimized Results

Parameter	**Optimum Value**
Cutting Speed, X_1 (m/min)	250
Feedrate, X_2 (rev/mm)	0.03
Depth of Cut, X_3 (mm)	0.2
Tool Nose Radius, X_4 (mm)	0.503
Surface Roughness (μm)	0.050

Validation of the Results

The GA optimal results were validated using the Boxford CNC Lathe 250 PC and Mitutoyo surface roughness tester. A confirmation test was performed using the 0.4 mm tool insert, which produced surface roughness of 0.302 µm and the corresponding surface roughness profile is shown in Figure 8. From the predicted and experimental results, the average deviation when using the 0.4 mm tool can be seen as 0.350 μm. Taking this average deviation into consideration, the lower limit of the predicted surface roughness value can be noted as 0.048 μm. It is clear that the actual value is close to the optimal value hence the confirmation test result of 0.302 µm can be taken as acceptable. Therefore, this study proves that the developed prediction model generated acceptable process parameter values that ensure the minimum surface roughness.

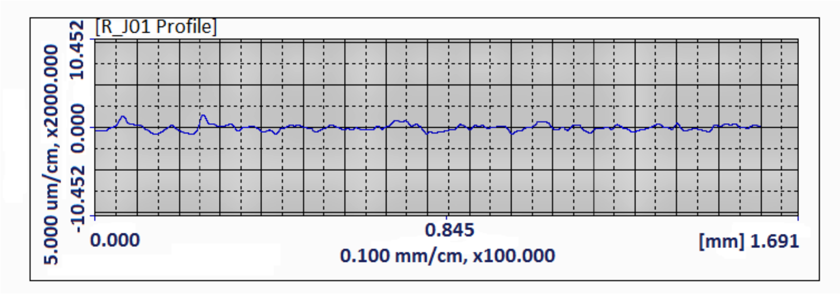


Figure 8: Surface Roughness Profile Obtained for the Confirmation Test

Conclusion

In this study, a pragmatic approach for minimisation of surface roughness using GA optimisation tool coupled with Taguchi design and ANOVA techniques was followed. The critical process parameters under investigation were cutting speed, feedrate, depth of cut and tool nose radius. Confirmation experiments show good agreement between the predicted and experimental values. The optimal combination of parameters for minimum surface roughness when machining Al-6061 were found as cutting speed of 250 m/min, feedrate of 0.03 mm/rev, depth of cut of 0.2 mm and tool nose radius of 0.503 mm. It was observed that surface roughness increases with increase in feedrate while it decreases with increase in cutting speed and tool nose radius. Depth of cut had little impact on the surface roughness.

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