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Comparison of Uncoated and Coated Carbide Inserts in End milling of Ti–6Al–4V in Terms of Surface Roughness

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Abstract

This paper compares and also optimizes the surface finish in end milling of titanium alloy Ti-6Al-4V using uncoated and PVD TiAlN coated carbide inserts under dry conditions. Response Surface Methodology (RSM) is utilized to develop an efficient mathematical model for surface roughness in terms of cutting speed, feed and axial depth of cut. For this purpose, a number of machining experiments based on factorial design of experiments method are carried out. The Center Composite Design (CCD) surface roughness models have been developed at 95% confidence level. The adequacy of the models has been verified through analysis of variance (ANOVA). Then the RSM models were further coupled with Genetic Algorithm (GA) to optimize the cutting conditions for getting achievable minimum surface roughness. The GA outcomes were further verified by experimental results. It was found that GA results matched successfully with the experimental data. Uncoated carbide insert was stumbled on as a better option than TiAlN coated carbide in terms of surface roughness.

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1. Introduction

Materials used in the manufacturing of aero-engine components generally comprise nickel and titanium base alloys. These are referred to as difficult-to-cut materials since that pose a greater challenge to manufacturing engineers due to the high temperatures and stresses that are generated during their machining. Cutting tool materials often encounter extreme thermal and mechanical stresses close to the cutting edge during machining, which usually results in plastic deformation and accelerated tool wear. A major requirement of cutting tool materials used for machining aero-engine alloys is that they must possess adequate hot hardness to withstand the elevated temperatures generated at high speed conditions of aerospace alloys. Most cutting tool materials lose their hardness at elevated temperatures resulting in the weakening of the inter-particle bond strength and consequent acceleration of tool wear which results in deterioration of surface roughness. So it is very essential to establish an adequate functional relationship between the responses (such as surface roughness, tool life) and the cutting parameters (cutting speed, feed and depth of cut). Response surface methodology (RSM) may help in establishing the relationships between surface roughness and the cutting parameters for coated and uncoated inserts. The method was introduced by G.E.P Box and Wilson [1]. The main idea of RSM is to use a set of designed experiments to obtain an optimal response with limited number of experiments to save cost and time.

RSM is a dynamic and foremost important tool of design of experiment (DOE), wherein the relationship between response(s) of a process with its input decision variables is mapped to achieve the objective of maximization or minimization of the response properties [1,2]. Many machining researchers have used response surface methodology to design their experiments and assess results. Analytical models have been created to predict surface roughness and tool life in terms of cutting speed, feed and axial depth of cut in milling steel material [3] and [4]. An effective approach has also been presented to optimize surface finish in milling Inconel 718 [5].

Kaye et al [6] used response surface methodology in predicting tool flank wear using spindle speed change. A unique model has been developed which predicts tool flank wear, based on the spindle speed change, provided the initial flank wear at the beginning of the normal cutting stage is known. Wu [7] first pioneered the use of response surface methodology in tool life testing.

Thomas et al. [8] used a full factorial design involving six factors to investigate the effects of cutting and tool parameters on the resulting surface roughness and on built-up edge formatting in the dry turning of carbon steel. The Taguchi method was used by Yang and Tarng [9] to find the optimum cutting parameters for turning operations. Choudhury and El-Baradie [10] had used RSM and 2^3 factorial design for predicting surface roughness when turning high-strength steel. Mansour et al [3] developed a surface roughness model for end milling of semi-free cutting carbon case-hardened steel. They suggested that an increase in either the feed or axial depth of cut increases the surface roughness, while an increase in the cutting speed decreases the surface roughness. S. Shrif et al. [11] used factorial design coupled with response surface methodology in developing the surface roughness model in relation to the primary machining variables such as cutting speed, feed and radial rake angle. Thiele and Malkote [12] had used a three-factor complete factorial design to determine the effects of workpiece hardness and cutting tool edge geometry on surface roughness and machining forces.

The main objective of the current work was to develop RSM models for surface roughness based on cutting speed, axial depth of cut and feed for uncoated and coated inserts and then coupling GA with the developed RSM model to optimize the cutting conditions to search out the minimum surface roughness.

2. Materials and Methods

In this work, experimental results were used for modeling using RSM. The experimental data were utilized to generate mathematical models of second-order. Then the mathematical models were taken as objective function and were optimized using a Genetic Algorithm approach to search out the machining conditions for the best surface finish.

2.1 RSM Mathematical Model

RSM explores the relationships between several explanatory variables and one or more response variables [2]. The following linear relationship could be considered for achieving this:

$$y = f(v, a, f) + \varepsilon$$

The surface roughness model for end milling in terms of the cutting parameters can be expressed in general terms as:

$$R_a = CV^k a^m f^l \quad (1)$$

Where R_a is the predicted surface roughness (μm), V is the cutting speed (m/min), f is the feed (mm/tooth), and a is the axial depth of cut (mm), C, k, l and m are model parameters to be estimated using the experimental results. To determine the constants and exponents, this mathematical model can be linearized by employing a logarithmic transformation and Equation (1) can be re-expressed as:

$$\ln R_a = \ln C + k \ln V + m \ln a + l \ln f \quad (2)$$

The linear model of equation (2) is:

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \quad (3)$$

Where y is the true response of surface roughness on a logarithmic scale and x_0=1(dummy variable); x_1, x_2, x_3 are logarithmic transformations of speed, depth of cut and feed, respectively; while β_0, β_0, β_0 and β_0 are the parameters to be estimated. Equation (3) can be expressed as:

$$\hat{y}_1 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \quad (4)$$

Where $\hat{y}_1$ and y are the estimated response and the measured surface roughness on a logarithmic scale respectively, ε is the experimental error and the b values are estimates of the β parameters.

The second-order model can be extended from the first-order model equation as:

$$\begin{aligned}\hat{y}_2 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_{11} x_1^2 + \\ b_{22} x_2^2 + b_{33} x_3^2 + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{23} x_2 x_3\end{aligned} \quad (5)$$

Where $\hat{y}_2$ is the estimated response based on the second order model. Analysis of variance is used to verify and validate the model.

2.2 Optimization by Genetic Algorithm

Genetic Algorithms are search algorithms for optimization, based on the mechanics of natural selection and genetics [13]. The mechanics of GA is simple, involving copying of binary strings and the swapping of the binary strings. The simplicity of operation and computational efficiency are the two main attractions of the GA approach. The GA solves optimization problem iteratively based on biological evolution process in nature (Darwin's theory of survival of the fittest) [13].

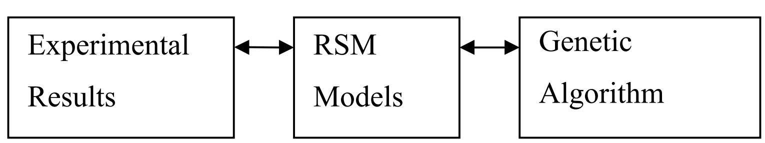


Figure 1. Interfacing of Experimental results, RSM Models and GA

The optimization problem in this study is solved by coupling the developed RSM model with the developed GA as shown in Figure 1. In the solution procedure of an optimization problem with GA begins with a set of parameter values or “chromosomes” (usually in the form of bit strings) which are randomly generated or selected. The entire set of these chromosomes comprises a “population”. The chromosomes evolve during several iterations or “generations”. New generations called “offspring” are generated using the “crossover” and “mutation” technique. Crossover involves splitting two chromosomes and then combining one-half of each chromosome with the other pair. Mutation involves flipping a single bit of a chromosome. The chromosomes are then “evaluated” using certain “fitness” criteria and the best ones are kept while the others are discarded. This process repeats until one chromosome has the best fitness and is taken as the best solution of the problem.

GA is very appealing for single and multi-objective optimizations problems. Some of its advantages are as follows: (1) as it is not based on gradient-based information, it does not require the continuity of convexity of the design space, (2) it can explore large search space and its search direction or transition rule is probabilistic, not deterministic, in nature, and hence, the chance of avoiding local optimality is more, (3) it works with a population of solution points rather than a single solution point as in conventional techniques, and provides multiple near-optimal solutions, (4) it has the ability to solve convex, and multi-model function, multiple objectives and non-linear response function problems, and it may be applied to both discrete and continuous objectives functions [14].

3. Experimental Details

End milling tests were conducted on Vertical Machining Center (VMC ZPS, Model: 1060) with full immersion cutting under dry conditions. Machining was performed with a 20 mm diameter end-mill tool holder fitted with one insert. Uncoated and TiAlN coated inserts were used in the experiments. Mitutoyo SURFTEST SV-500 was used to measure the surface roughness.

3.1 Cutting Tool

Two typed of carbide inserts were used in this study. One was uncoated carbide insert (model: R390-17 04 08E-NL H13) and the other was TiAlN coated carbide (model R390-11 T3 08E-ML2030) from Sandvick coromill. These two inserts were selected from Sandvik Coromant tool catalogue [15].

3.2 Cutting Conditions

Cutting parameter values i.e. cutting speed, axial depth of cut, feed were selected within specific ranges. These independent variables were then coded taking into consideration the limitation and capacity of the cutting tools. Levels of independent cutting variables and coding identification for the experiment using uncoated and coated inserts are presented in Table 1.

The independent variables were then coded to the levels using the following transformation equation:

$$x = \frac{\ln x_n - \ln x_{n0}}{\ln x_{n1} - \ln x_{n0}} \qquad (6)$$

Where x is the coded value of any factor corresponding to its natural value x_n, while x_{n1} is the +1 level and x_{n0} is the natural value of the factor corresponding to the base of zero level.

Table 1. Coding identification of independent variables

Levels	Lowest	Low	Center	High	Highest
Coding	$-\sqrt{2}$	-1	0	$+1$	$+\sqrt{2}$
x_1 Cutting speed, V(m/min)	30.59	39	70.1	126	160.6
x_2 axial depth of cut, a (mm)	0.5	0.61	1	1.65	2.03
x_3 Feed, f (mm/tooth)	0.05	0.06	0.088	0.128	0.15

3.3 Experimental Design

In the experiment, full central composite design (CCD) was used to develop the first order and second order models. The analysis of mathematical models was carried out using Design of Expert 6.0.8 package for both the first and second order models.

4. Results and Model Developments

Cutting conditions and the measured surface roughness values for all the cutting tests are shown in the Table 2. From the results it was found that the surface roughness values for the coated inserts were in most cases inferior compared to those obtained with the uncoated.

Table 2 Cutting conditions in coded form and surface roughness results

Exp. No.	Coding of Level			R_a, Surface roughness (μm)	
	x_1	x_2	x_3	UNCOATED	COATED
1	-1.00	-1.00	-1.00	0.17	0.22
2	1.00	-1.00	-1.00	0.33	0.31
3	-1.00	1.00	-1.00	0.38	0.24
4	1.00	1.00	-1.00	0.33	0.45
5	-1.00	-1.00	1.00	0.33	0.44
6	1.00	-1.00	1.00	0.41	0.64
7	-1.00	1.00	1.00	0.37	0.59
8	1.00	1.00	1.00	0.4	0.69
9	0.00	0.00	0.00	0.19	0.32
10	0.00	0.00	0.00	0.24	0.35
11	0.00	0.00	0.00	0.23	0.33
12	0.00	0.00	0.00	0.27	0.39
13	-1.41	0.00	0.00	0.23	0.30
14	1.41	0.00	0.00	0.61	0.62
15	0.00	-1.41	0.00	0.2	0.41
16	0.00	1.41	0.00	0.23	0.48
17	0.00	0.00	-1.41	0.17	0.25
18	0.00	0.00	1.41	0.5	0.76

Figure 2 shows the comparison between these two sets of surface roughness data. Though the roughness values are higher in case of coated inserts but the trend of the graph for both the coated and uncoated are similar. This similar fashion of the graphs implies that the effects of the independent cutting variables are similar.

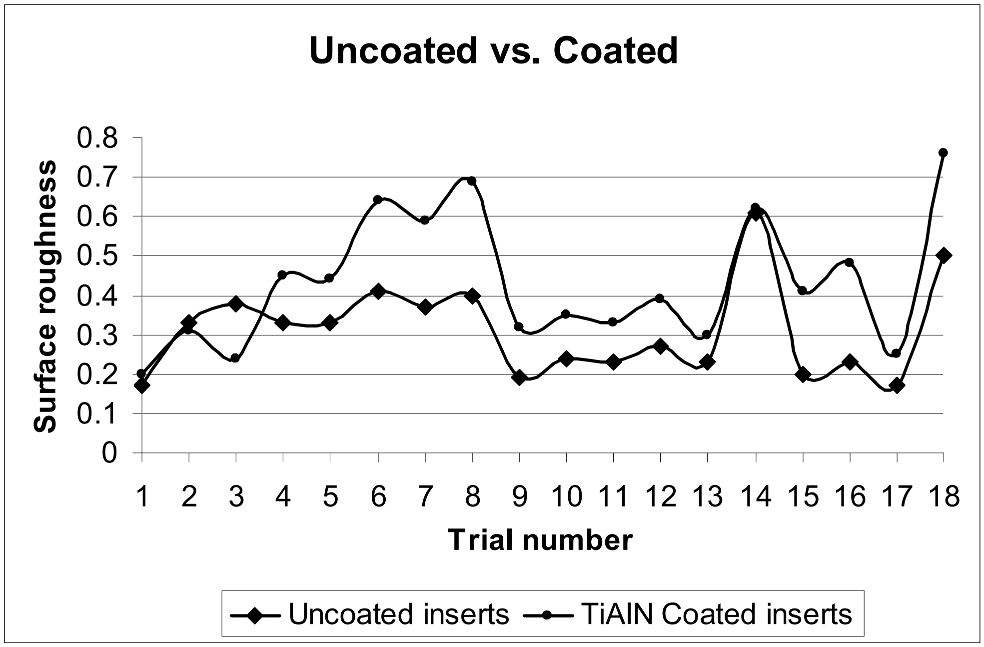


Figure 2. Comparison between surface roughness values using coated and uncoated carbide inserts

4.1 Development of first-order model

The surface roughness prediction model for *uncoated carbide inserts* was been formulated by utilizing the experimental results in Table 2. The developed first-order CCD model in coded form is:

$$\hat{y}_{1uncoated} = -1.24 + 0.18x_1 + 0.083x_2 + 0.21x_3 \tag{7}$$

By substituting the values of x from the transformation Equation (6) into Equation (7) the following equation for R_a for uncoated carbide inserts is generated:

$$R_{a\_uncoated} = 0.3065\, V^{0.307} a^{0.1657} f^{0.560} \tag{8}$$

ANOVA was used to verify the adequacy of the proposed first-order CCD model and the results are shown in the Table 3. The Model F-Value of 4.071 implies that the model is significant. There is only 3.05% chance that a “Model F-Value” this large could occur due to noise. The “lack of Fit F-value” of 5.363 implies that the lack of fit is not significant relative to the pure error. There is a 9.68% chance that a “Lack of Fit F-Value” this large could occur due to noise. Non- significant lack of fit is good. Therefore, we can use the model to navigate the response surface.

Table 3. ANOVA for first order model using uncoated insert

Source	SS [a]	DF [b]	MS [c]	F Value	Prob > F	
Block	0.002	1	0.002			
Model	1.135	3	0.378	4.071	0.0305	significant
x_1	0.442	1	0.442	4.759	0.0481	
x_2	0.093	1	0.093	1.005	0.3345	
x_3	0.599	1	0.599	6.448	0.0247	
Residual	1.208	13	0.093			
Lack of Fit	1.144	10	0.114	5.363	0.0968	not significant
Pure Error	0.064	3	0.021			
Cor Total	2.345	17				

[a] Sum of Squires

[b] Degree of Freedom

[c] Mean Square

For TiAlN coated carbide inserts the first-order surface roughness prediction model was also developed by using the experimental results in Table 2 which, in coded form, is:

$$\hat{y}_{1coated} = -0.89 + 0.21x_1 + 0.087x_2 + 0.34x_3 \tag{9}$$

By substituting the values of x from the transformation Equation (6) into Equation (9) the following equation for R_a for coated carbide inserts is found:

$$R_{a\_coated} = 0.813V^{0.358}a^{0.174}f^{0.904} \tag{10}$$

Again ANOVA is utilized for the verification of the developed model of surface roughness using TiAlN coated carbide and the results are revealed in the Table 4. The model F-Value of 57.4092 indicates the model is significant. There is only a 0.001% chance that a "Model F-Value" this large could arise due to noise. The "lack of Fit F-value" of 1.9943 insinuates the lack of fit is not significant relative to pure error. There is a 31.03% chance that a "Lack of Fit F-Value" this large could occur due to noise.

The first-order CCD models of both uncoated and coated one in Equation (8) and Equation (10) respectively revealed that feed has the most significant effect on surface roughness, followed by cutting speed and axial depth of cut. The trend is the same for both the uncoated and coated inserts.

Table 4. ANOVA for first order model using PVD TiAlN coated insert

Source	SS	DF	MS	F Value	Prob > F	
Block	0.0604	1	0.0604			
Model	2.3099	3	0.7700	57.409	< 0.0001	significant
x_1	0.5819	1	0.5819	43.386	< 0.0001	
x_2	0.1035	1	0.1035	7.7141	0.0157	
x_3	1.6245	1	1.6245	121.13	< 0.0001	
Residual	0.1744	13	0.0134			
Lack of Fit	0.1516	10	0.0152	1.9943	0.3103	not significant
Pure Error	0.0228	3	0.0076			
Cor Total	2.5447	17				

The first-order models of Equation (7) and Equation (9) are utilized to draw the graph of actual and predicted surface roughness values for the uncoated and coated carbide inserts which is shown in Figure 3. It is found from Figure 3 that the predicted values from the first order model of the coated carbide are closer to the actual values and the model performs better than the uncoated one.

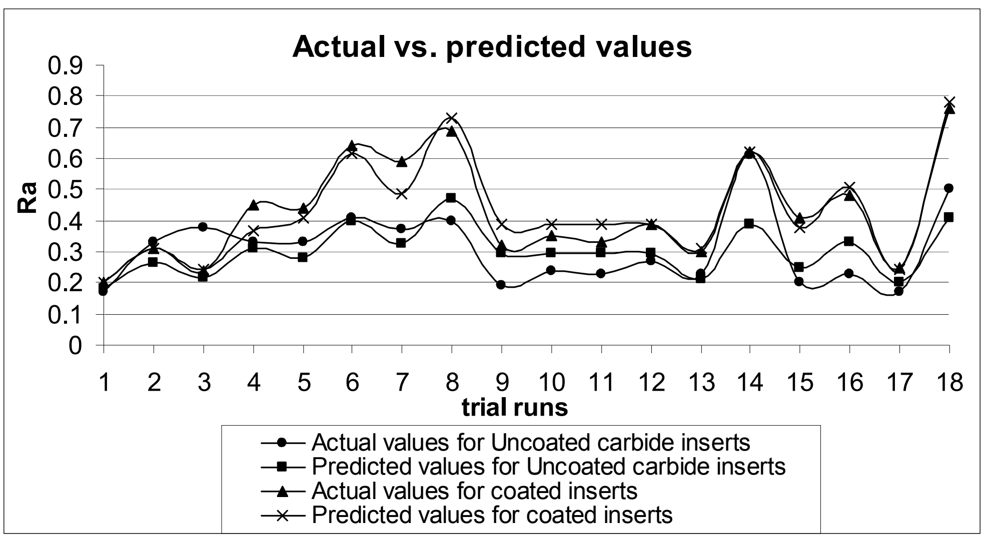


Figure 3. Actual Vs. Predicted values of surface roughness from first order model for coated and uncoated inserts.

4.2 Development second-order model

The second-order surface roughness model was also developed by utilizing the experimental results in Table 2 and employing the Center Composite Design of Response Surface Methodology. The second-order model for the *uncoated* *carbide inserts* is given as:

$$\hat{y}_{2uncoated} = -1.53 + 0.18x_1 + 0.083x_2 + 0.21x_3 + 0.21x_1^2 + 0.018x_2^2 + 0.13x_3^2 - 0.12x_1x_2 - 0.028x_1x_3 - 0.089x_2x_3 \quad (11)$$

To verify the adequacy of the proposed second order CCD model, ANOVA was employed and the results are shown in the table 5. The model F-Value of 4.1183 entails the model is significant. There is only 3.77% chance that a "Model F-Value" this large could happen due to noise. The "Lack of Fit F-Value" of 3.6119 makes it not significant relative to pure error and there is a 15.99% chance that a "Lack of Fit F-Value" this much could occur due to noise.

Table 5. ANOVA for second-order model for uncoated insert

Source	SS	DF	MS	F Value	Prob > F	
Block	0.0022	1	0.0022			
Model	1.9705	9	0.2189	4.1183	0.0377	significant
x_1	0.4423	1	0.4423	8.3190	0.0235	
x_2	0.0934	1	0.0934	1.7560	0.2267	
x_3	0.5991	1	0.5991	11.269	0.0121	
x_1^2	0.5529	1	0.5529	10.400	0.0146	
x_2^2	0.0037	1	0.0037	0.0693	0.7999	
x_3^2	0.1907	1	0.1907	3.5875	0.1001	
x_1x_2	0.1113	1	0.1113	2.0930	0.1912	
x_1x_3	0.0065	1	0.0065	0.1214	0.7378	
x_2x_3	0.0638	1	0.0638	1.2009	0.3094	
Residual	0.3721	7	0.0532			
Lack of Fit	0.3082	4	0.0770	3.6119	0.1599	not significant
Pure Error	0.0640	3	0.0213			
Cor Total	2.3448	17				

The second-order model for the *coated carbide inserts* was also generated by utilizing the results in the Table 2 which is as below:

$$\hat{y}_{2coated} = -1.02 + 0.21x_1 + 0.087x_2 + 0.34x_3 + 0.05x_1^2 + 0.06x_2^2 + 0.054x_3^2 - 0.00347\,x_1x_2 - 0.067\,x_1x_3 - 0.023\,x_2x_3 \quad (12)$$

Then the developed second-order RSM model in Equation (12) for surface roughness using TiAlN coated carbide inserts was verified by the ANOVA test. The results of that ANOVA test are given in Table 6. The model F-Value of 30.3458 means the model is significant and the chance that a "Model F-Value" this high could happen due to noise is only 0.01%.The "Lack of Fit F-Value" is 1.2923 which is not significant relative to pure error and there is a 43.38% possibility that "Lack of Fit F-Value" this large could occur due to noise.

Table 6. ANOVA for second-order model for PVD TiAlN coated insert

Source	SS	DF	MS	F-Value	Prob > F	
Block	0.0604	1	0.0604			
Model	2.4221	9	0.2691	30.3458	< 0.0001	significant
x_1	0.5819	1	0.5819	65.6116	< 0.0001	
x_2	0.1035	1	0.1035	11.6657	0.0112	
x_3	1.6245	1	1.6245	183.176	< 0.0001	
x_1^2	0.0298	1	0.0298	3.3654	0.1092	
x_2^2	0.0430	1	0.0430	4.8467	0.0636	
x_3^2	0.0345	1	0.0345	3.8922	0.0891	
x_1x_2	0.0001	1	0.0001	0.0109	0.9199	
x_1x_3	0.0359	1	0.0359	4.0433	0.0843	
x_2x_3	0.0043	1	0.0043	0.4898	0.5066	
Residual	0.0621	7	0.0089			
Lack of Fit	0.0393	4	0.0098	1.2923	0.4338	not significant
Pure Error	0.0228	3	0.0076			
Cor Total	2.5447	17				

Second-order surface roughness models of Equation (11) and Equation (12) are exploited to draw the contours of actual and predicted surface roughness values for the uncoated and coated carbide inserts which is shown in Figure 4. It is found from Figure 3 and Figure 4 the second-order models have a better performance if compared with the first-order models in terms of prediction accuracy.

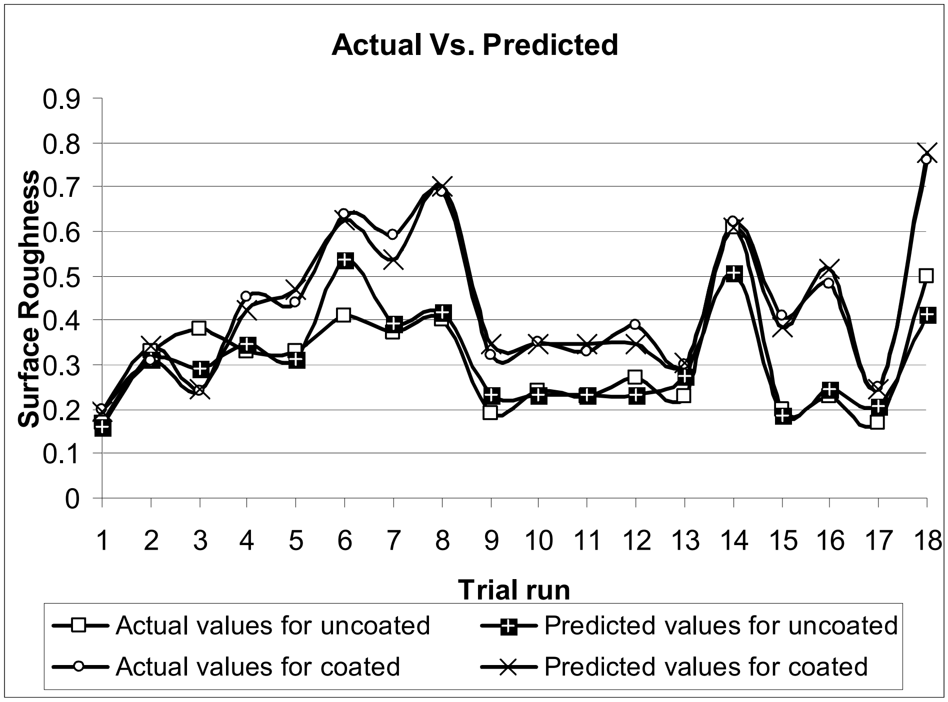


Figure 4. Actual Vs. Predicted values of surface roughness from second-order model for coated and uncoated inserts.

5. Optimization of cutting conditions

The aim of the optimization is to achieve the minimum possible surface roughness value. This can be achieved efficiently by adjusting cutting conditions with the help of an appropriate numerical optimization method. For this, minimization of surface roughness problem must be formulated in the standard mathematical format as below:

Find: v, a, f

Minimize: $R_a(v,a,f)$

Within ranges:

$$39 \le V \le 126; 0.61 \le a \le 1.65; 0.06 \le f \le 0.128$$

Table 7. Selected values of the critical parameters of GA

Subject	Values
Population size	80
Scaling function	Rank
Selection of function for mating	Stochastic uniform
Crossover function	Scattered
Crossover fraction	0.8
Mutation Function Scale Shrink	 Gaussian 1.0 1.0
Stopping criteria Generation	 250

The second-order quadratic RSM models for surface roughness was chosen as a fitness function for Genetic Algorithm (GA) for both uncoated and coated carbide inserts because it was found the developed second-order RSM model had a better performance than the first-order

5.1 Optimization by GA

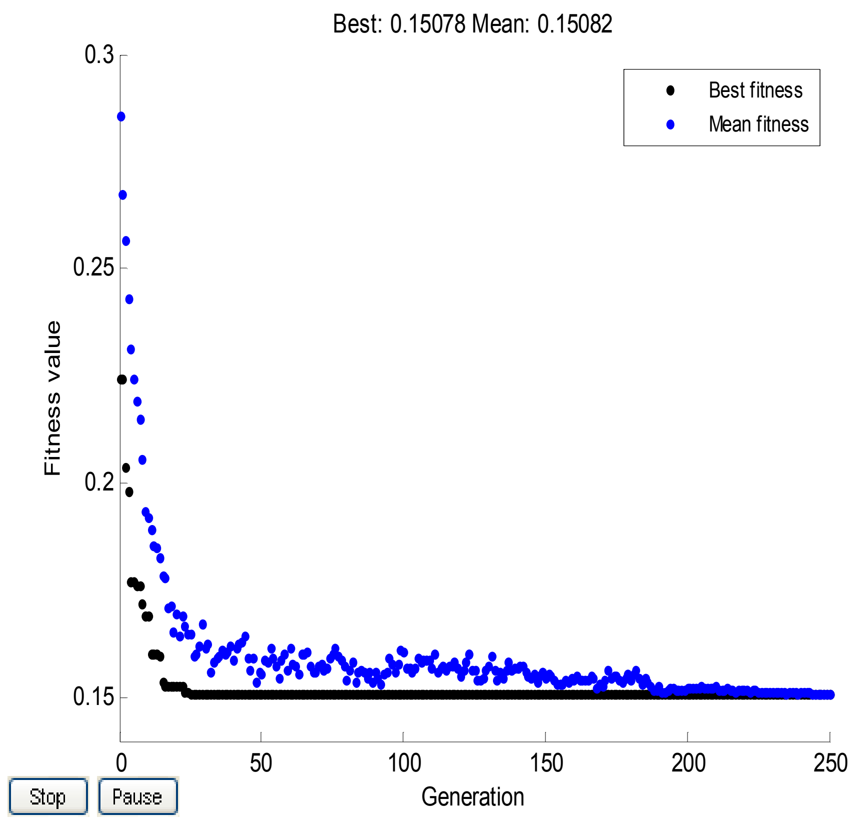
In this work, MATLAB version 7.4.0.287 (R2007a) Toolbox for GA is utilized to develop the GA program [16]. The critical parameters in GA are the size of the population, mutation, number of generations etc. The values of these parameters which were selected for this problem are given in Table 7. The developed quadratic CCD models of Equation (11) and Equation (12) are used as fitness functions for the GA. The GA program written is MATLAB programming language selects chromosomes based on the objective values.

Table 8. Results of GA with experimental measurements

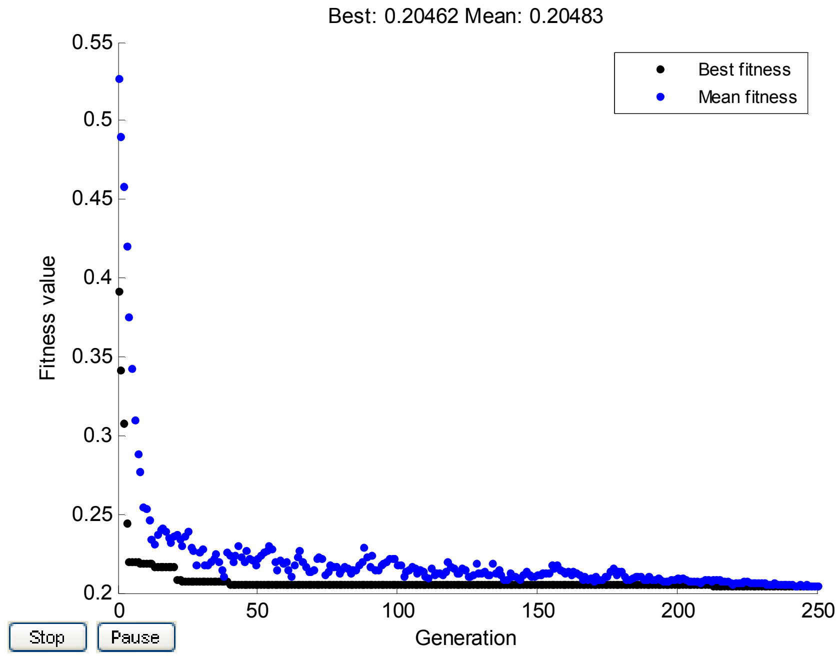
Type of insert	Optimum cutting conditions by GA		Surface Roughness (R_a)	
Uncoated carbide	Cutting Speed (m/min)	44.33	GA Predicted 0.150 μm	Experimental Measurement 0.138 μm
	Axial DoC (mm)	0.61		
	Feed (mm/tooth)	0.0605		
TiAlN coated carbide	Cutting Speed (m/min)	39.08	GA Predicted 0.204 μm	Experimental Measurement 0.197 μm
	Axial DoC (mm)	0.622		
	Feed(mm/tooth)	0.0605		

5.2 Optimization results and discussions

The optimization problem was solved for both the uncoated and coated carbide insert. The best and mean fitness values for all the iterations of 250 generations for uncoated and coated insert are given in Figure 5(a) and Figure 5(b) respectively. The optimum cutting conditions and the predicted surface roughness generated by GA is given in Table 8. If we compare the results of GA with the minimum surface roughness values in the initial cutting conditions in Table 2 we find that for uncoated carbide insert GA reduced the surface roughness from 0.17 μm to 0.15 μm by about 12% and for coated insert it reduced from 0.22 μm to 0.204 by more than 9%. Then the results of GA were further verified by experimental tests. It was found the experimental results closely resembled the predicted one. For the uncoated carbide insert the difference between the predicted and the experimental result was 8% but for coated carbide insert it was less that 3.5%.



(a)



(b)

Figure 5. Best and Mean fitness values of GA for (a) uncoated carbide insert and (b) TiAlN coated carbide insert.

6. Conclusion

Based on the statistical models developed in the work following concluding remarks can be made:

1. The full CCD second-order quadratic model has been proved to be a successful technique to predict the surface roughness produced in end-milling of titanium alloy Ti-6Al-4V using coated and uncoated carbide inserts under dry conditions.
2. The first and second order CCD model developed by RSM using Design Expert package was able to provide accurately predicted values of surface roughness close to actual values found in the experiments. The equation was checked for their adequacy with a confidence level 95%.
3. The models (for both coated and uncoated inserts) indicate that the feed has the most significant influence on surface roughness, followed by cutting speed and axial depth of cut.
4. Interaction effect between cutting speed and feed also has a high effect on surface roughness values.
5. The surface roughness values of the coated inserts were higher than the

uncoated one. This may be due to the presence of built up edge (BUE) which forms on the TiAlN coated tool.

6. The developed second-order RSM models were interfaced with GA to find the optimum cutting conditions leading to the least surface roughness values within the ranges. GA improved the surface roughness by about 12% for uncoated and 9% for coated insert. The predicted optimum cutting conditions were verified with experimental measurements and it was found that GA prediction correlates successfully with the experimental results. This establishes the optimization methodology proposed in this study by interfacing the developed RSM model and the GA is an effective tool to optimize the cutting conditions.

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