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Machinability analysis and hybrid optimization during wet turning of SS304 using coated tools

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Abstract

In this work, SS304 has been machined using tungsten carbide tool inserts coated with multilayer of TiN/TiAlN under conventional wet cooling condition. Experiments have been conducted based on Taguchi robust technique with L9 orthogonal array. Effect of three important machining parameters cutting speed (CS), feed (F), and depth of cut (DC) on machinability aspects i.e. surface roughness (Ra) and material removal rate (MRR) have been investigated. Further, grey relational technique integrated with genetic algorithm (GA) was used for simultaneous optimization of MRR and Ra. It was observed that the optimized machining parameter setting for MRR and Ra is CS: 170 m/min; F: 0.2 mm/rev; and DC: 0.5 mm. The optimum values of MRR and Ra are 81.39 g/min and 3.14µm respectively.

Keywords: Coating; Machinability; Stainless Steel; Surface Roughness; Tool Wear

1. Introduction

Titanium nitride coatings have been utilized in the last 20 years in number of industrial applications. Titanium shows insufficient oxidation resistance for temperature higher than 500 °C; therefore, Aluminum is added to increase the oxidation resistance of coating upto temperature 900 °C [1, 2]. Properties of greater oxidation and good wear resistance of TiAlN coating can be prolifically used in dry cutting process [3]. The same is used for machining of austenitic stainless steel AISI 304 in the present research. Hardness and oxidation resistance of the coatings can be upgraded by using layer dimensions on nano-scale to fulfill the special application requirements. It was reported that TiN/TiAlN multilayer coating have better characteristics instead of single layer and gradient (Ti,Al)N coatings [4-6]. AISI 304 austenitic steel or stainless steel (SS) 304 is an important material for numerous industrial, domestic, scientific, biomedical, and precision applications due to superior corrosion resistance, excellent strength, and biocompatibility [7]. But, its machining is not so easy i.e. SS possesses poor machinability. It compels to explore and establish alternate ways to machine this material.

Cutting fluid plays a pivotal role in the success of machining operations. In machining, a significant portion of heat is produced due to tool-chip friction while shearing takes place [8]. Lubrication is imperative to overcome the adverse effect of heat and to protect tools and worksurface. Extreme pressure additives and other elements are mixed in cutting fluids to minimize friction and thereby reduce the heat generation and to decrease the power required for producing chips or machining.

In past, researchers have conducted many investigations to optimize the process parameters using design of experiments and other artificial intelligence techniques [8-10]. Process productivity and surface quality are two conflicting responses to determine the success of machining operations. It compels to make use of optimization techniques.

In the present work AISI 304 steel machining in wet cooling environment using multilayer coated tools has been investigated by planning and conducting experiments based on Taguchi L9 orthogonal array. Further, the machining parameters were optimized using grey relational technique integrated with genetic algorithm (GA) to secure the best values of MRR and Ra.

2. Experimental details

A total of nine experiments with two replicates each based on Taguchi L9 orthogonal array were conducted. SS304 cylindrical bar of 650 mm length and 85 mm diameter was initially used to start the machining. The machining time of six minutes was set for each experiment. The single point tungsten carbide tool inserts coated with TiAlN were used for the machining of SS304 on a conventional lathe machine tool. Figure 1 presents the experimental setup used in the present work. Cutting fluid in the form of soluble oil mixed with water mixture was used as a coolant. A flow rate of 3L/min was set during machining. The metal removal rate was measured by dividing the difference in the weight of bar before and after machining by total time of machining. The average surface roughness (Ra) was measured using TMtech make surface roughness tester set at 0.8 mm cut-off and 4.0 mm evaluation length. The input machining parameters levels (bracketed after conducting some preliminary experiments and considering machine constraints), units and notations are given in Table 1.

Table 1. Machining process parameters

Sr. No	Process parameter	Units	Level 1	Level 2	Level 3
1	Cutting speed (CS)	m/min	70	120	170
2	Feed (F)	mm/rev	0.1	0.15	0.20
3	Depth of Cut (DC)	mm	0.5	1.0	1.5

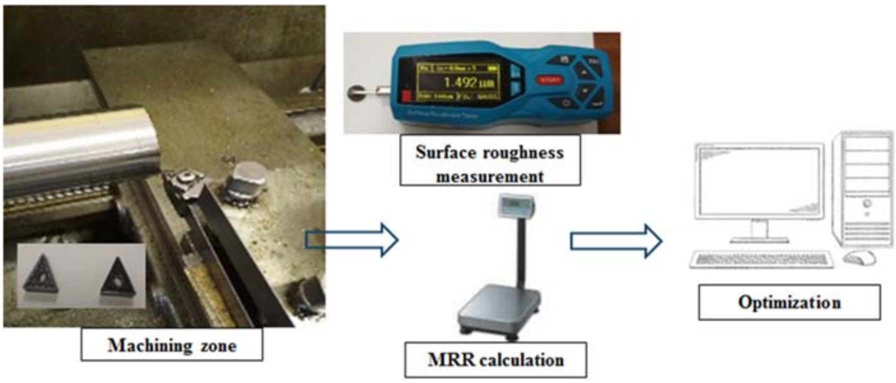


Fig. 1 Experimental setup

3. Results and discussion

Table 2 presents the values of machinability indicators i.e. MRR and Ra considered in the present work. The average of two replications is used as the final value corresponding to each experimental run.

Table 2. Experimental combinations with corresponding results

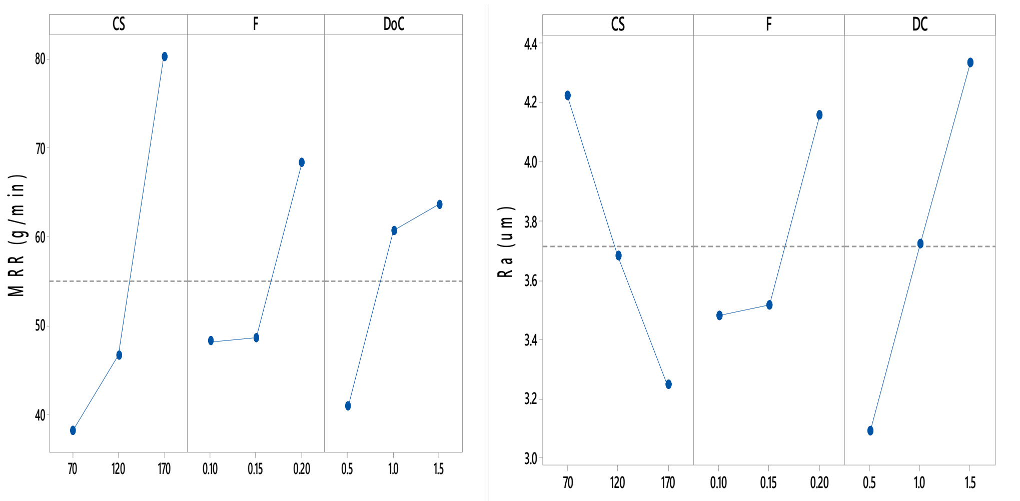
Expt No.	CS (m/min)	F (mm/rev)	DC (mm)	MRR	R_a
1	70	0.1	0.5	19.71	3.41
4	70	0.15	1	35.33	3.96
8	70	0.2	1.5	59.67	5.29
7	120	0.1	1	45.12	3.47
2	120	0.15	1.5	51.33	4.15
5	120	0.2	0.5	43.67	3.43
6	170	0.1	1.5	79.78	3.56
9	170	0.15	0.5	59.25	2.44
3	170	0.2	1	101.55	3.74

Table 3 presents the result of ANOVA for MRR and Ra mean values. It reveals that CS has the maximum influence on the MRR. The percentage influence of CS is 62.939% preceeded by DC (19.526%) and F (16.845%). The L9 orthogonal array has eight degree of freedom (DF), however the DF of each process parameter is two due to three levels of each parameter. SS in Table 3 contributes to evaluate the percentage influence of each parameter by dividing the SS of each parameter to the total SS. The P-value smaller than 0.05 signifies the influence of process parameter on the response characteristic for a confidence interval of 95%. In the present work, all three input parameters show a P-value less than 0.05. It is also clear from Table 3 that DC has the maximum influence of 49.989% followed by CS (30.905%) and F (18.638%). P-values (<0.05) for all the three input signify their influence on Ra.

Table 3 ANOVA results for MRR and Ra

Source	DF	MRR			R_a		
		SS	%	P	SS	%	P
CS	2	2953.46	62.939	0.011	1.4260	30.905	0.015
F	2	790.45	16.845	0.039	0.8600	18.638	0.025
DC	2	916.26	19.526	0.034	2.3066	49.989	0.009
Res. Error	2	32.39	0.690		0.0216	0.468	
Total	8	4692.55			4.6142		

It is desirable to achieve high productivity and thus high MRR in machining operations. Therefore, MRR is considered as higher the better type characteristic. Fig. 2a depicts the variation of MRR mean value at various levels of input machining parameters.



(a) (b)

Fig. 2. Variation of (a) MRR, (b) Ra, with machining parameters

It was found that with the increase in CS, the MRR increases from 38.24 g/min (at level 1) to 80.19g/min (at level 3). With the increase in the CS value in the same machining duration, more material was removed. ‘F’ is the movement of tool towards the work-piece in a single rotation of work-piece. Thus, a high value of feed corresponds to the high distance travelled by the tool towards the work-piece, which finally removes more material from the work-piece. A high value of feed more than the permissible value results into the failure of tool (or breakage of cutting edge). Therefore, increase in ‘F’ value ammeliorate the MRR value from 48.20g/min to 68.30g/min. DC is the the value given initially at the start of machining process and is expressed in mm. It is the movement of tool into the work-piece. If tool moves by 1mm in the work-piece, then the diameter reduced in one complete experiment is 2mm (in case of turning). Hence, high value of DoC corresponds to the higher MRR from 40.88 g/min to 63.59 g/min (Table 4). Fig.

2b shows that high value of CS (170m/min), low value of F (0.1mm/rev) and DC (0.5mm) produce least Ra, which is desired for better surface quality. The reason for low Ra at high CS is the removal of build-up edges as the time of machining reduces. Also, the chip fracture reduces at high speed, which helps to reduce the Ra value. With the increase of F and DC, friction and cutting force increases that finally result in work surface deterioration and higher roughness i.e. Ra value. Table 4 gives the response values at different levels of input parameters.

Table 4 Responses for mean data

Level	MRR			Ra		
	CS	F	DC	CS	F	DC
1	38.24	48.20	40.88	4.22	3.48	3.09
2	46.71	48.64	60.67	3.68	3.51	3.72
3	80.19	68.30	63.59	3.24	4.15	4.33
Delta	41.96	20.09	22.72	0.98	0.67	1.24
Rank	1	3	2	2	3	1

4. Optimization

Grey relational is a statistical technique to convert all responses into a single response having normalized value in between 0 to 1. There are four steps for the evaluation of grade values i.e. (i) data pre-processing (Table 5), (ii) deviational sequence (Table 5), (iii) grey relational coefficient (GRC) (Table 6), (iv) grade values (Table 6). These values are computed as per the evaluation made by Deng [11]. After the computation of grade, the regression analysis is performed to find out the regression coefficients of empirical model (Eq. 1). This empirical model is solved further using genetic algorithm (GA) and the limits were selected from Table 1.

Table 5 Data pre-processing and deviational sequence

Sl. No.	Data Pre-processing		Deviational Sequence	
	MRR	R_a	MRR	R_a
1	0.0000	0.6596	1.0000	0.3404
2	0.1909	0.4667	0.8091	0.5333
3	0.4883	0.0000	0.5117	1.0000
4	0.3105	0.6386	0.6895	0.3614
5	0.3864	0.4000	0.6136	0.6000
6	0.2928	0.6526	0.7072	0.3474
7	0.7340	0.6070	0.2660	0.3930
8	0.4831	1.0000	0.5169	0.0000
9	1.0000	0.5439	0.0000	0.4561

Table 6 Grey relational coefficients and grade evaluation

Sl. No.	GRC		GRG
	MRR	R_a	
1	0.3333	0.5950	0.4642
2	0.3819	0.4839	0.4329
3	0.4942	0.3333	0.4138
4	0.4203	0.5804	0.5004
5	0.4490	0.4545	0.4518
6	0.4142	0.5901	0.5021

7	0.6527	0.5599	0.6063
8	0.4917	1.0000	0.7459
9	1.0000	0.5229	0.7615

$$\textbf{Grade} = 0.248 + 0.002676\times \text{CS} + 0.355\times\text{F} - 0.0801\times\text{DC} \tag{1}$$

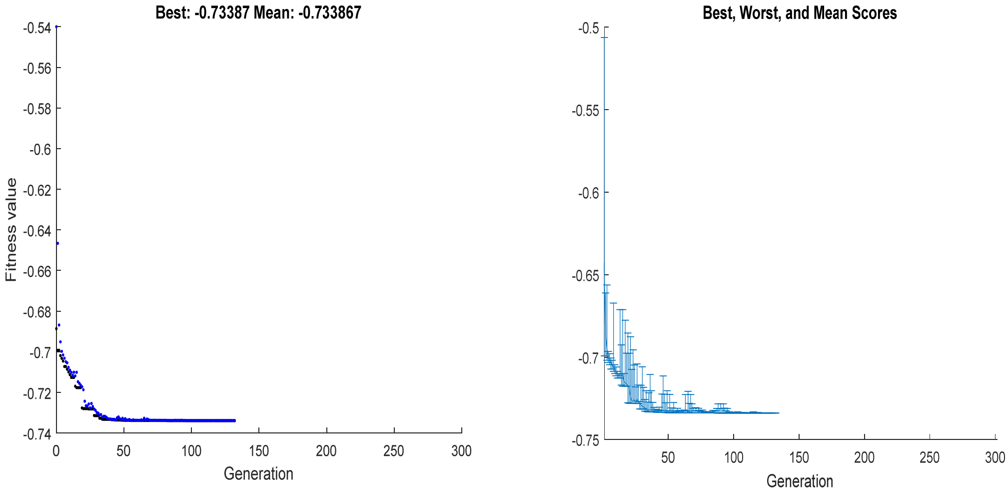


Fig. 3a Best fitness value plot

Fig. 3b Range of the grade values

Fig. 3 GA Parameters

Fig. 3a and Fig. 3b depict the best fitness value of grade and the range of grade value reduction with the increase of generations obtained by GA. It was observed that initially the range is high and converge to a single value at the end of simulation. Table 5 shows the validation experiments conducted at the suggested optimal setting. It was found that the experimental results are comparable to the predicted values in case of single as well as multiple response characteristics.

Table 7 Validation experiments at optimal setting

Responses	MRR (g/min)	R_a (µm)	GRT-GA	
			MRR (g/min)	Ra (µm)
Suggested optimal setting	$(CS)_3(F)_3(DC)_3$	$(CS)_3(F)_1(DC)_1$	$(CS)_3(F)_3(DC)_1$	
Predicted value	101.992	2.38	79.27	3.06
Experimental value (average of three values)	103.76	2.32	81.39	3.14

5. Conclusions

This paper presents the analysis of the results obtained for SS304 machining using coated carbide tools under wet cooling environment. Effects of machining parameters, statistical analysis of the data, and optimization by grey relation integrated GA technique have mainly been reported in this paper. The following conclusions can be drawn from this research work-

1. The maximum MRR was obtained at CS: 170m/min; F: 0.2mm/rev; DC: 1.5mm. Moreover, the ANOVA reveals that CS has maximum influence of 62.939% preceded by DC (19.526%) and F (16.845%).

2. The minimum Ra was obtained at CS: 170m/min; F: 0.1mm/rev; DC: 0.5mm. It was found by ANOVA that DC has maximum contribution of 49.989% followed by CS (30.905%) and F (18.638%).

3. The hybrid approach of grey relational and genetic algorithm resulted in optimum machining parameter setting CS: 170m/min; F: 0.2mm/rev; DC: 0.5 mm, and machinability indicators MRR: 81.39 g/min and Ra: 3.14 µm.

Acknowledgements

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