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The Effects of Cutting Speed, Depth of Cut and Rake Angle on Material Removal Rate in Cryogenic Machining of AISI 4340 Steel

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***Abstract:*-This experimental research on cryogenic turning process involves the modeling and optimization of the process parameters affecting the machining performance and value oriented sustainable manufacturing. It is most important task to select the cutting parameters for achieving high cutting performance characteristics in the cryogenic turning process. In this research work, the machining parameters namely the cutting speed, feed rate, depth of cut and rake angle are optimized for maximum material removal rate on AISI 4340 steel. The experimentation was planned using Taguchi's L9 theory. An orthogonal array (L9), the signal-to-noise (S/N) ratio, and the Qualitek-4 were employed to the study the material removal rate in the turning of AISI 4340 steel under cryogenic condition. It was observed that cutting speed, depth of cut and rake angle was the most influential factors on the material removal rate. To validate the study, confirmation experiment has been carried out at optimum set of parameters and predicted results have been found to be in good agreement with experimental findings. The results have revealed that cryogenic machining has yielded better MRR.**

Keywords: Cryogenic; Turning; Taguchi method; Qualitek4

1. INTRODUCTION

Traditionally and historically, manufacturing processes are planned and developed in order to achieve either maximum productivity or minimum cost. In contrast, present trends push manufacturers to develop new methodologies incorporating sustainability concepts [1]. Sustainable manufacturing processes are those which demonstrate improved environmental impact and energy and resource efficiency, generate minimum quantity of wastes, provide operational safety and personal health, while maintaining or improving the product quality [2]. Due to the problems in the conventional cooling system, it is necessary to use a coolant which is effective and also environmentally acceptable in the manufacturing industry. For this purpose, liquid nitrogen as a cryogenic coolant has been explored since 1950s in the metal cutting industry. Cryogenic cooling applied to metal cutting has been studied nearly for six decades; however, in the last ten years remarkable results were achieved by different methods. Cryogenic cooling is an attractive method and has been examined in the material cutting field for future applications. It is most important task to select the cutting parameters for achieving high cutting performance characteristics in the cryogenic turning process. Usually, the desired cutting parameters can be achieved by machining experts or by the use of hand book. Here, this does not ensure that the selected machining parameters from hand book would produce optimal or near optimal machining performance for all machines and environment. However, the basic experimental approaches looked upon all factors as causes of variation would be reduced and therefore, quality is to be improved. Therefore, a different approach is required if product quality is to be improved. This approach is entitled parameter design by Taguchi and is covered in this research work. Parameter design is used to dampen the effect of noise by choosing the proper levels for control factors. Furthermore, a large number of experiments have to be performed and analyzed in order to get the machining parameters with respect to the concerned machining performance characteristics. Then, an objective function with constraints is formulated to solve the optimal machining parameters using optimization techniques.

2. LITERATURE REVIEW

Zhou et al. (1995) [3] investigated on tool life criteria in cryogenic turning. A new tool-life criterion depending on a pattern-recognition technique was proposed and neural network and wavelet techniques were used to realize the new criterion. The experimental results showed that this criterion was applicable to tool condition monitoring in a wide range of cutting conditions. Lin et al. (2001) [4] adopted an abdicative network to construct a prediction model for surface roughness and MRR. Once the process parameters: cutting speed, feed rate and depth of cut were given; the surface roughness and MRR could be predicted by this network. Regression analysis was also adopted as second prediction model for surface roughness and MRR. Feng and Wang (2002) [5] investigated for the prediction of surface roughness in finish cryogenic turning operation by developing an empirical model through considering working parameters: work piece hardness (material), feed, cutting tool point angle, depth of cut, spindle speed, and cutting time. Data mining techniques, nonlinear regression analysis with logarithmic data transformation were employed for developing the empirical model to predict the surface roughness. Suresh et al. (2002) [6]focused on machining mild steel by TiN-coated tungsten carbide(CNMG) cutting tools for developing a surface roughness prediction model by using Response Surface Methodology (RSM). Genetic Algorithms (GA) used to optimize the objective function and compared with RSM results. It was observed that GA program provided minimum and maximum values of surface roughness and their respective optimal machining conditions. Lee and Chen (2003) [7] highlighted on artificial neural networks (OSRR-ANN) using a sensing technique to monitor the effect of vibration produced by the motions of the cutting tool and work piece during the cutting process developed an on-line surface recognition system. The authors employed tri-axial accelerometer for determining the direction of vibration that significantly affected surface roughness then analyzed by using a statistical method and compared prediction accuracy of both the ANN and SMR. Choudhury and Bartarya (2003) [8] focused on design of experiments and the neural network for prediction of tool wear. The input parameters were cutting speed, feed and depth of cut; flank wear, surface finish and cutting zone temperature were selected as outputs. Empirical relation between different responses and input variables and also through neural network (NN) program helped in predictions for all the three response variables and compared which method was best for the prediction. Kirby et al. (2004) [9] developed the prediction model for surface roughness in turning operation. The regression model was developed by a single cutting parameter and vibrations along three axes were chosen for in-process surface roughness prediction system. By using multiple regression and Analysis of Variance (ANOVA) a strong linear relationship among the parameters (feed rate and vibration measured in three axes) and the response (surface roughness) was found. The authors demonstrated that spindle speed and depth of cut might not necessarily have to be fixed for an effective surface roughness prediction model. Proposed a new approach, for the parametric optimization of cryogenic turning process based on L_{18} (21×37) orthogonal array using Taguchi's robust design. The machining parameters namely speed, feed, depth of cut, rake angle are optimized with consideration performance characteristics MRR improving the machining efficiency. Mathematical and Artificial Neural Network models has been developed relating the machining performance and process parameters. Developed an Artificial Neural Network(ANN) by using Inconel 718 as a work material to predict the performance characteristics namely MRR and surface roughness based on Taguchi's L_9 orthogonal array. The response by optimized concurrently using multi-response-signal-to-noise (MRSN) ratio in addition to Taguchi's parametric design approach. ANOVA was employed to identify the level of importance of machining parameters on the multi performance characteristics. From the literature, it is observed that researchers have already worked in the area of cryogenic turning technology. To the best of the knowledge of the authors of this work, any published paper of optimizing multiple performance characteristics of cryogenic turning using Taguchi's L_9 orthogonal array coupled with ANOVA is not work found. Keeping this consideration in view, the author has made an attempt to solve a problem for the optimization of multiple performance characteristics using S/N ratio with Taguchi's parameters design to achieve better MRR.

In recent years, along with other types of steels, AISI 4340 steel has also emerged as an important material for industrial applications. Despite extensive research on cryogenic turning process, determining the desirable operating conditions during cryogenic turning of AISI 4340 steel, in industrial setting, still relies on the skill of the operators and trial-and-error methods. So the aim of the present work is to obtain the optimum machining conditions for cryogenic turning of AISI 4340 steel, for minimizing the surface roughness based on Taguchi technique. Experiments were carried out to study the effect of various parameters viz. speed, feed, depth of cut and rake angle on the material removal rate. The levels of significance on the surface roughness were statistically evaluated by using Qualitek-4.

3. EXPERIMENT

The experimental studies were performed on a High power rigid lathe machine tool. The composition of AISI 4340 steel work-piece material used for experimentation in this work is a given in table 1. HSS T-42, S-400 (CT) 3/8″x 3″ single point turning tool was used in the experiments. The parameters, selected for different settings of speed, feed, depth of cut and rake angle were used in the experiments (Table 2). The photographic view of the machining zone has been shown in fig.1. The other details of the experimentation have been shown in Table 3.

Table-1 Chemical composition of AISI D3 steel (wt %)

AISI 4340 C-0.382, S-0.022, P-0.026, Si-0.228, Mn-0.609, Cr-0.995, Ni- 1.514, Mo- 0.226, Fe-95.998

Table-2 Machining settings used in the experiments

Values in coded form	Spindle Speed (N) RPM	Feed(f) mm/rev	Depth of Cut (d) mm	Rake Angle
1	45	0.045	0.2	4
2	180	0.08	0.4	8
3	280	0.1	0.6	12

Table-3 fixed parameters

Workpiece	AISI 4340 steel rod
Coolant	Liquid Nitrogen

Fig 1:- Machining zone

3.1 Design of experiment based on Taguchi method

To evaluate the effects of cutting parameters of cryogenic turning process in terms of cutting performance characteristics such as Surface Roughness a Taguchi method used here to model the cryogenic turning process. In this study, Taguchi method, a powerful tool for parameter design of performance characteristics, for the purpose of designing and improving the product quality [10, 11]. In the Taguchi method, process parameters which influence the products are separated into two main groups: control factors and noise factors. The control factors are used to select the best conditions for stability in design or manufacturing process, whereas the noise factors denote all factors that cause variation. According to Taguchi based methodology, the characteristic that the larger value indicates the better machining performance, such as Surface roughness is addressed as the-smaller-the-better type of problem. The S/N Ratio, i.e. η, can be calculated as shown below: Larger-the-better

$$n = -10 \log_{10} [\text{mean of sum squares of reciprocal of measured data}]$$

This case has been converted to SMALLER-THE-BETTER by taking the reciprocals of measured data and the taking the S/N ratios as in the smaller-the –better case.

4. RESULTS AND DISCUSSION

The experimental results are collected for material removal rate and 9 experiments were conducted using Taguchi (L9) experimental design methodology and there are two replicates for each experiment to obtain S/N values. In the present study all the designs, plots and analysis have been carried out using Minitab statistical software. Larger amount of material removal rate show the high productivity of cryogenic turning. Therefore, larger the better are applied to calculate the S/N ratio of material removal rate respectively. Regardless of category of the performance characteristics, a greater η value corresponds to a better performance. Therefore, optimal level with the greatest η value. By applying Eqs. (1) The η values for each experiment of L9 (table 2) was calculated in Table 4. The optimal machining performance for MRR was obtained as 280 rpm cutting speed (Level 3), 0.1 mm/rev feed rate (Level 3), 0.6 mm depth of cut (Level 3) and 4^0rake angle (Level 1) settings that give the maximum MRR.

Table 4:-Experimental design using L_9 orthogonal array

Exp no	Factor Assignment N	f	D	α	MMR(mm3/min)	S/N ratio db
1	1	1	1	1	37.85	31.5613
2	1	2	2	2	133.45	42.5064
3	1	3	3	3	249.37	47.9369
4	2	1	2	3	300.27	49.5502
5	2	2	3	1	798.01	58.0402
6	2	3	1	2	336.46	50.5387
7	3	1	3	2	698.26	56.8803
8	3	2	1	3	418.71	52.4383
9	3	3	2	1	1037.98	60.3238

Table 5: S/N ratio response table for MRR

Factors /Levels	Level 1	Level 2	Level 3	Delta	Rank
N	40.67	52.71	56.55	15.88	1
f	46.00	50.99	52.93	6.94	3
d	44.85	50.79	54.29	9.44	2
α	49.98	49.98	49.98	0.00	4

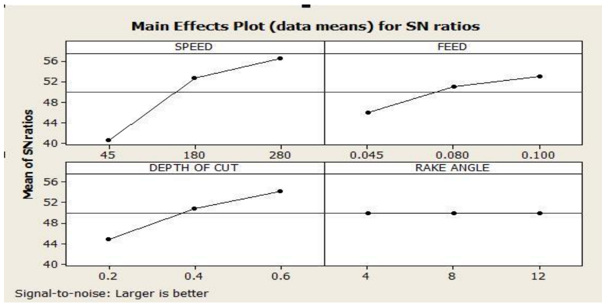

Figure 6.1: Main effect plot for the MRR (LN2)

The relative importance of the machining parameters with respect to the MRR was investigated to determine more accurately the optimum combinations of the machining parameters by using Qualitek-4. The results of Qualitek-4 for the machining outputs are presented in Tables 5 and 6.Statistically, F-test provides a decision at some confidence level as to whether these estimates are significantly different. Larger F-value indicates that the variation of the process parameter makes a big change on the performance characteristics. F-values of the machining parameters are compared with the appropriate confidence Table 6. Result of Qualitek-4 for:-

Table 6: Analysis of variance for mean data for MRR

Source	Df	Seqss	Adjss	Adjms	F	P
N	2	506086	506086	253043	-	57.84
f	2	57602	57602	28801	-	6.58
d	2	160349	160349	80175	-	18.33
α	2	150869	150869	75435	-	17.25
ERROR	0					
TOTAL	8	874906				100

At least 95% confidence

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Table 7: Pooled ANOVA for MRR

Source	Df	Seqss	Adjss	Adjms	F	P
N	2	506086	506086	253043	8.78	55.26
f	(2)	POOLED	-	-	-	-
d	2	160349	160349	80175	2.78	14.74
α	2	150869	150869	75435	2.61	15.65
ERROR	0	57602	57602	28801		14.35
TOTAL	8	874906				100

According to F-test analysis, the significant parameters on the SR are speed and depth of cut. The percent contributions of the machining parameters on the SR are shown in Table 7. Speed is found to be the major factor affecting the MRR (55.26%). The percent contribution of depth of cut and rake angle on the SR are 14.74%, 15.65% respectively.

4.1 Confirmation experiment

The confirmation experiment is performed by conducting a test using a specific combination of the factors and levels previously evaluated. The sample size of confirmation experiment is larger than the sample size of any specific trial in the previous factorial experiment. The final step of the Taguchi's parameter design after selecting the optimal parameters is to be predict any verify the improvement of the performance characteristics with the selected optimal machining parameters [12]. The predicted S/N ratio using the optimal levels of the machining parameters can be calculated with the help of following prediction equation:

$$\eta opt = \eta m + \sum_{j=1}^{k} (\eta j - \eta m)$$

Here, ηopt is the predicted optimal S/N ratio, ηm is the total mean of the S/N ratios, ηj is the mean S/N ratio of at optimal levels and k is the number of main design parameters that affect the quality characteristics. The results of experimental confirmation using optimal machining parameters are shown in Tables 8. From the above observations, it can be interpreted that the obtained.

Table-8 Confirmation experiment result for MRR Optimum machining parameters

Exp no	Optimum machining parameters (3331)				S/N ratio for MRR (db)	
	N	f	D	α	Predicted	Experiment
1	280	0.1	0.6	4	63.66	65.81
					Error =3.26	

MRR has reasonable accuracy for resulting model because an error of 3.26% for S/N ratio of MRR is measured.

5. CONCLUSION

This paper described the optimization of the cryogenic turning process using parametric design of Taguchi methodology. It was observed that the Taguchi's parameter design is a simple, systematic, reliable, and more efficient tool for optimization of the machining parameters. The effect of various machining parameter such as cutting speed, feed rate, depth of cut and rake angle has been studied though machining of AISI 4340 steel.

[1] It was identified that the cutting speed rake angle and depth of cut have influenced more than the other parameters considered in this study.

[2] The confirmation experiment has been conducted. Result shows that the error associated with MRR is only 3.26 %.

[3] The selection of optimum values is essential for the process manufacturing system. Thus the optimized condition, not only makes the cryogenic turning a more commercially viable process for industrial applications, but also turns a spotlight on cryogenic turning process as a promising field for further advancements.

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