Analysis of Surface Roughness with Different Lubricants for En8 on CNC End Milling

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Abstract— Face milling is a very common method for metal cutting and finishing of machined parts. The input machining parameters being considered in this research is spindle speed, tool feed and type of lubricants. The Stainless steel EN8 is used as work piece. The tool used for milling operation is HSS face milling cutter. The Taguchi's L9 orthogonal array has been used to design the combinations of parameters of experiments. The surface roughness of EN8 has been measured after operations. The optimum levels of parameters have been found 2000 rpm spindle speed, 200mm/rev tool feed and using cutting oil are optimized parameters to obtained Lowest SR.

Key words: Surface Roughness, ANOVA

I. INTRODUCTION

Manufacturing is the fortitude of any industrialized nation. Today's competitive manufacturing era of high industrial development and research, is being called the age of mechanization, automation and computer integrated manufacturing. Due to new researches in the manufacturing field, the advancement has come to this extent that every different aspect of this technology has become a full-fledged fundamental and advanced study in itself. This has led to introduction of optimized design and manufacturing of new products. New developments in manufacturing areas are deciding to transfer more skill to the machines for considerably reduction of manual labor. Manufacturing systems in industrialized countries have dramatically changed as a result of advance manufacturing technologies. The development of computer aided design and manufacturing system is evolving to the phase of integrated manufacturing systems, which is oriented towards the need of 21^{st}century. Efforts are made to maintain and improve the vitality of manufacturing system. Keeping it as center stone of all economic activities and ensuring that manufacturing remains an attractive industrial area. Optimization of corporate activities in computer integrated manufacturing (CIM) and CAPP in one of the greatest targets of the system.

A. Surface Roughness

Surface roughness is defined as a group of irregular waves in the surface, measured in micro-meters (mm). It is produced by the fluctuations of short wavelengths characterized by asperities (local maxima) and valleys (local minima) of varying amplitudes and spacing. Surface roughness is defined by various characteristics of the surface profile such as Centre-line average R. peak-to-valley height Hand average roughness depth, but these have limitations. The randomness of the profile is no measured by any of these parameters. The randomness of the surface profile causes the roughness value to vary under the given cutting conditions and is caused by the random nature of the mechanism of formation of the built-up edge, side flow and tool wears.

The randomness of the profile may be assessed from the auto-correlation function of the profile. There are various simple surface roughness amplitude parameters used in industry, such as roughness average (Ra), root-mean-square (RMS) roughness (RI), maximum peak-to-valley roughness (Ry or Rm) and ten point height (R). The roughness average (Ra) is the mean arithmetic deviation of the profile from the mean line. The RMS is defined as the root mean square deviation of the profile from the mean line. The R. is the maximum height of the irregularities. The ten point height (Rz) is defined as the height of irregularities with respect to ten points. There are various methods used for the roughness measurement such as stylus profilometry, light sectioning and taper sectioning methods, scanning electron microscopy and transmission electron microscopy etc.

The parameter Ra is used in this study. The average roughness (Ra) is the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation length. Therefore, the Ra is specified by the following equation:

$$Ra = \frac{1}{L}\int_0^L |Y(x)|dx$$

Where Ra is the arithmetic average deviation from the mean line, L is the sampling length, and Y is the ordinate of the profile curve.

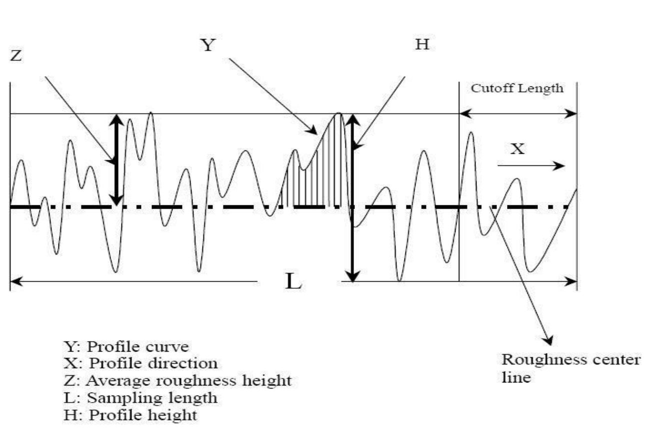


Fig. 1: Surface Roughness Graph

II. LITERATURE SURVEY

Erhan & Asadauskas (2000) studied the comparison of the lubricants made of petroleum, vegetable-based lubricants. The base stock typically contributes to more than 80% of lubricant and must meet performance criteria in such aspects as cleanliness, visco metric properties, volatility, oxidative and hydrolytic stability, deposit forming tendencies, solvency, miscibility or compatibility with system elastomers and other. For vegetable-based lubricants, oxidative stability and low temperature problems are considered the most critical. Thin film oxidation test was used to compare oxidative stabilities. Vegetable oils appear an order of magnitude less stable than mineral oils or synthetic biodegradable base stocks, such as isoalkyl adipates or poly alphaolefins. Low temperature performance of vegetable oils, namely pour points and cold storage, was also problematic. These problems can only partially be relieved by lubricant additives, thus vegetable oils have to be modified chemically to eliminate sites susceptible to oxidation and to disrupt formation of crystals at low temperatures.

Dereli et al. (2001) investigated the optimal cutting parameters, such as the number of passes, depth of cut for each pass, cutting speed and feed, which are applicable for assigned cutting tools, is one of the vital modules in process planning of metal parts, since the economy of machining operations plays an important role in increasing productivity and competitiveness. The present paper introduces system software developed to optimize the cutting parameters for prismatic parts. The system is mainly based on a powerful artificial intelligence (AI) tool, called genetic algorithms (GAs). It is implemented using C programming language and on a PC. It can be used as standalone system or as the integrated module of a process planning system called OPPS-PRI (Optimized Process Planning System for prismatic parts) that was also developed for prismatic parts and implemented on a vertical machining center (VMC). With the use of GAs, the impact and power of AI techniques have been rejected on the performance of the optimization system. The methodology of the developed optimization system is illustrated with practical examples throughout the paper.

Ghani et al. (2004) studied the outlines the Taguchi optimization methodology, which is applied to optimize cutting parameters in end milling when machining hardened steel AISI H13 with TiN coated P10 carbide insert tool under semi-finishing and finishing conditions of high speed cutting. The milling parameters evaluated is cutting speed, feed rate and depth of cut. An orthogonal array, signal-to-noise (S/N) ratio and analysis of variance (ANOVA) are employed to analyze the effect of these milling parameters. The analysis of the result shows that the optimal combination for low resultant cutting force and good surface finish are high cutting speed, low feed rate and low depth of cut. Using Taguchi method for design of experiment (DOE), other significant effects such as the interaction among milling parameters are also investigated. The study shows that the Taguchi method is suitable to solve the stated problem with minimum number of trials as compared with a full factorial design.

Zhang et al. (2007) analyzed Taguchi design application to optimize surface quality in a CNC face milling operation. Maintaining good surface quality usually involves additional manufacturing cost or loss of productivity. The Taguchi design is an efficient and effective experimental method in which a response variable can be optimized, given various control and noise factors, using fewer resources than a factorial design. This study included feed rate, spindle speed and depth of cut as control factors, and the noise factors were the operating chamber temperature and the usage of different tool inserts in the same specification, which introduced tool condition and dimensional variability. An orthogonal array of L9 was used; ANOVA analyses were carried out to identify the significant factors affecting surface roughness, and the optimal cutting combination was determined by seeking the best surface roughness (response) and signal-to-noise ratio. Finally, confirmation tests verified that the Taguchi design was successful in optimizing milling parameters for surface roughness.

Bajic et al. (2008) studied cutting parameters on surface roughness on face milling. Cutting speed, feed rate and depth of cut have been taken into consideration as the influential factors. A series of experiment have been carried out in accordance with a design of experiment (DOE). In order to obtain mathematical models that are able to predict surface roughness two different modeling approaches, namely regression analysis and neural networks, have been applied to experimentally determined data. Obtained results have been compared and neural network model gives better explanation of the observed physical system. Optimal cutting parameters have been found using simplex optimization algorithm.

Kromanis and Krizbergs (2008) studied a technique to predict a surface roughness of part to be machined according to technological parameters. Such technique could be achieved by making mathematical model of machining. In this study as machining process a milling process is chosen, especially end milling. Additionally to the study, one of the key factors, which differ from similar studies, is that as surface parameters the 3D surface parameters are used. In this study all the surface parameters are expressed as 3D parameters. 3D surface parameters give more precise picture of the surface; therefore it is possible more precisely to evaluate the surface parameters according to technological parameters. In result of the study, the mathematical model of end-milling is achieved and qualitative analysis is maintained. Achieved model could help technologists to understand more completely the process of forming surface roughness.

III. EXPERIMENTAL SETUP

A scientific approach to plan the experiments was a necessity for efficient conduct of experiments. In this experiment the whole work is done by a CNC VMC model CNC VMC 640 from Ambala College of Engineering & Applied Research, Devsthali, Ambala Cantt. The En8 was work piece.

Fig. 2: CNC Milling Machine

A. Stainless Steel En8

EN8 is a medium carbon steel usually and has good tensile strength. EN8 is a very popular grade and is readily machinable in any condition. It can be further surface-hardened to produce components with enhanced wear resistance. The chemical composition of En8 is given in table 1.1 below.

Constituent	% Composition
C	0.4535
Mn	0.8196
P	0.04846
S	0.04717
Si	0.3308

Table 1: Chemical Composition of EN8

The chemical composition of En8 shown in table 1 but these can change according to use. The mechanical, physical and electrical properties of EN8 as shown in table 2

Tensile Strength (MPa)	660
Yield Strength (MPa)	465
Hardness(HV)	208

Table 2: Mechanical, Physical and Electrical properties

En8 provides the best combination of wear resistance and corrosion resistance and is used in refineries, oil and gas industries and chemical plants.

Applications En8 is as below:

1) Shafts and Gears
2) Bolts and Studs
3) General-purpose axles

B. Vegetable-Based Cutting Fluid

Vegetable oils consist of triacylglycerides (triglycerides) which are glycerol molecules with three long chain fatty acids attached at the hydroxyl groups via ester linkages. Long polar fatty acid chains provide high strength lubricant films. This film interacts strongly with metallic surfaces and reduces both friction and wear.

In this study, vegetable based cutting fluid (VBCF) is prepared with both base oil and a mixture of surfactants in different ratios. Properties of surfactants used are shown in table 3.3. The ability of a surfactant to form oil in water emulsion is defined in terms of hydrophilic–lyophilic balance (HLB) value which can be estimated by stirring into water and observing the mixture.

Name of surfactant	Surfactant composition	Class	Density
Tween 80	Polyoxyethylene (80) Sorbitanmonooleate	Non-ionic	1.07
Peg 400	Polyethylene glicol ester	Non-ionic	1.13

Table 3: Properties of surfactants

Base oil	% of Tween 80	% of Peg 400
Canola oil	20 %	5 %
Vegetable oil	20 %	5 %

Table 4: Composition of lubricant

Fig. 3: Canola oil and Vegetable (sunflower) oil & Peg 400 and Tween 80

1) Design of Experiment

The present chapter gives the application of the Taguchi experimental design method. The objective of this research work is to study machining parameters for optimization of SR and MRR the design variable can be summarized as follows:

1) Three level of spindle speed have been used.
2) Three level of spindle tool feed to be used.
3) Three types of lubricant to be used.

Controllable factor	Level 1	Level 2	Level 3
Spindle Speed(rpm)	1000	1500	2000
Tool Feed(mm/rev)	200	400	600
Lubricant	Cutting oil	Vegetable Oil	Canola Oil

Table 5: Selected Factors and levels

Run	Spindle Speed(rpm)	Tool Feed(mm/rev)	Lubricant
1	1000	200	Cutting Oil
2	1000	400	Vegetable Oil
3	1000	600	Canola Oil
4	1500	200	Vegetable Oil
5	1500	400	Canola Oil
6	1500	600	Cutting Oil
7	2000	200	Canola Oil
8	2000	400	Cutting Oil
9	2000	600	Vegetable Oil

Table 6: L9 Orthogonal array for experiment

C. Conduct the Experiment

Run	Spindle speed(rpm)	Tool Feed(mm/rev)	Lubricant	Surface roughness in μm			Surface roughness mean
				R_1	R2	R3	
1	1000	200	Cutting Oil	2.345	2.202	2.319	2.288667
2	1000	400	Vegetable Oil	3.7	3.218	3.648	3.522
3	1000	600	Canola Oil	4.925	4.847	4.804	4.858667
4	1500	200	Vegetable Oil	1.544	1.941	1.653	1.712667
5	1500	400	Canola Oil	2.553	2.697	2.996	2.748667
6	1500	600	Cutting Oil	2.827	3.052	2.944	2.941
7	2000	200	Canola Oil	1.694	1.735	1.879	1.769333
8	2000	400	Cutting Oil	2.097	2.214	2.179	2.163333
9	2000	600	Vegetable Oil	2.32	2.488	2.814	2.540667

Table 7: L9 Orthogonal array of surface roughness

9 experiments are conducted for L9 experimental design. The result of each experiments is repeated three times it means for every experiment there is three values of SR and calculated mean SR as shown in the table 7.

Run	Spindle speed(rpm)	Tool Feed(mm/rev)	Lubricant	Surface roughness in µm			S/N ratio
				R_1	R2	R3	
1	1000	200	Cutting Oil	2.345	2.202	2.319	-7.19486
2	1000	400	Vegetable Oil	3.7	3.218	3.648	-10.9521
3	1000	600	Canola Oil	4.925	4.847	4.804	-13.7308
4	1500	200	Vegetable Oil	1.544	1.941	1.653	-4.71479
5	1500	400	Canola Oil	2.553	2.697	2.996	-8.80197
6	1500	600	Cutting Oil	2.827	3.052	2.944	-9.37414
7	2000	200	Canola Oil	1.694	1.735	1.879	-4.96492
8	2000	400	Cutting Oil	2.097	2.214	2.179	-6.7047
9	2000	600	Vegetable Oil	2.32	2.488	2.814	-8.12716

Table 8: Signal to Noise ratio of response for surface roughness

9 experiments are conducted for L9 experimental design. The result of each experiments is repeated three times it means for every experiment there is three values of SR and calculated S/N ratio for SR as shown in the table 8.

IV. RESULT AND ANALYSIS

A. Analyze The Result and Determine Optimum Factor Level Combination

To study the effect of output responses on the surface finish and material removal rate using ANOVA, the data analyzed to better condition of the work. It is necessary which parameter gives better surface finish.

The average effect response table for raw data and S/N ratio for **surface roughness** shown below.

Level	Spindle Speed(A)	Tool Feed(B)	Lubricant (C)
1	3.556	1.924	2.464
2	2.467	2.811	2.592
3	2.158	3.447	3.126
Delta (Δ)	1.399	1.523	0.661
Rank	2	1	3

Table 9: Average effect response table for raw data

Level	Spindle Speed(A)	Tool Feed(B)	Lubricant (C)
1	-10.626	-5.625	-7.758
2	-7.630	-8.820	-7.931
3	-6.599	-10.411	-9.166
Delta (Δ)	4.027	4.786	1.408
Rank	2	1	3

Table 10: Average effect response table for S/N ratio

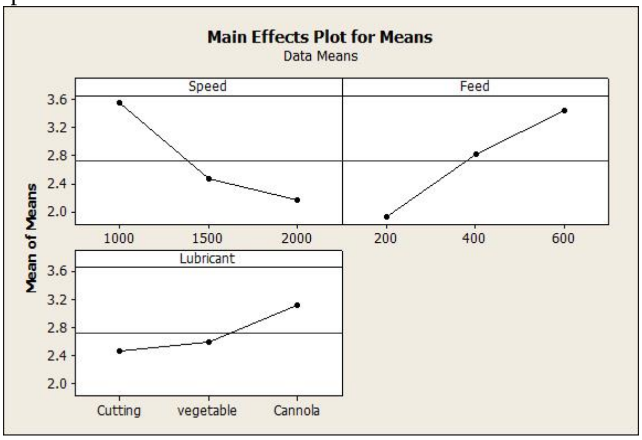
Source	DF	SS	MS	F
Spindle speed	2	3.2381	1.6190	14.44
Tool feed	2	3.5121	1.7561	15.66
Lubricant	2	0.7384	0.3692	3.29
Error	2	0.2243	0.1121	
Total	8	7.7129		

Table 11: Analysis of variance table for SR

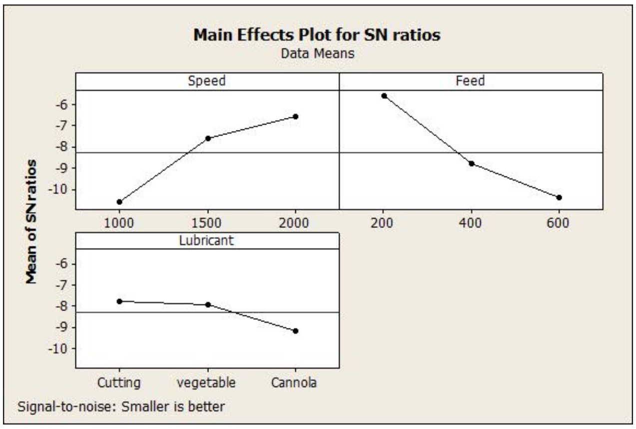
The results are analyzed using ANOVA for identified the significant factor affecting the performance measure. The ANOVA for SR is taken at 95 % of confidence level. The principal of F test is that larger the F values for a particular parameter, greater the effect on performance characteristics due to change in process parameters. Table 2.1 shows F value 14.44 for spindle speed, 15.66 for tool feed and 3.29 for lubricant used. It is analyzed that tool feed is most significant parameter than spindle speed and lubricant.

B. Determine Optimum Factor-Level Combination

Graph 1 shows three graphs, each of which contains a curve representing the mean and a curve representing the S/N ratio. The values of graphs are from average effect response tables 7 and 8 for the mean and S/N ratio. The S/N ratio indicates the degree of the predictable performance of a product or process in the presence of noise factors. Machining parameter setting with the highest S/N ratio always yield the optimum quality with minimum variance. The level that has a higher value determines the optimum level of each factor. For example, in Graph 2, level three for spindle speed (A3=2000 rpm) has the highest S/N ratio value, which indicated that machining performance at such level produced minimum variation of surface roughness. In addition, the lower surface roughness value had a better machining performance. Furthermore, level three of spindle speed (A3=2000 rpm) has indicated the optimum situation in terms of mean value. Similarly, the level one of tool feed (B1=200 mm/rev) and the level one of lubricant (C1= cutting oil) have also indicated the optimum situation in terms of S/N ratio and mean value.



Graph 1: Response Graph of three machining parameters for mean for SR



Graph 2: Response Graph of three machining parameters for S/N ratio for SR

C. Effect of Various Input Parameters On Output Characteristic (Surface Roughness)

The average value of surface roughness (µm) at each parameter (spindle speed, feed rate, depth of cut) is computed and the results are tabulated, similarly the result obtained for S/N data (db) is given. The main effect along with the corresponding S/N ratio value is plotted.

1) Effect of Spindle Speed On SR

The higher the cutting speed lesser will be the surface roughness. Surface roughness is minimum at the higher level of spindle speed.

2) Effect of Feed Rate On SR

With the decrease of feed rate, surface roughness also decreases. It is observed that the minimum surface roughness value obtained at the first level (200m/min). Higher the feed rate, higher will be the tool wear thus increases the value of surface roughness.

3) Effect of Lubricant On SR

It is observed that with the use of cutting oil, surface finishing improves.

The Graph 1 and 2 shows that the highest value of cutting speed, lower value of feed rate and cutting oil gives the better surface finish (lower surface roughness). Therefore, the optimum cutting condition will be cutting speed 2000 rpm (A3), feed rate 200mm/rev (B1), and cutting oil lubricant (C1).

V. Conclusion

In this study the optimal machining condition for face milling operation of EN8 is determined by varying parameters by Taguchi technique. The important conclusion from the present work is summarized in this chapter.

Taguchi's robust design method is suitable to analyze the metal cutting problem as described in the present work.

In face milling, increase in spindle speed, decrease in feed rate and using cutting oil lubricant will decreases the surface roughness within specified test range.

In face milling, use of higher spindle speed (2000 rpm), low feed rate (200mm/rev) and using cutting oil are optimized parameters to obtained better surface finish for the specific test range in an EN8 material.

From this investigation it has been analyzed that tool feed is most significant factor which affect the SR.

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