International Journal of Research in Advent Technology, Vol.5, No.9, September 2017
E-ISSN: 2321-9637
Available online at www.ijrat.org

Investigation of Optimum Cutting Parameters for End Milling ofH13 Die Steel using Taguchi based Grey Relational Analysis

O.Y. VENKATASUBBAREDDY[1], A. HEMANTHA KUMAR[2], G.SURESH BABU[3]
K. AJAYA KUMAR REDDY[4]
Assistant Professor[1, 3, 4], Associate Professor[2]
Mechanical Engineering Department[1, 2, 3, 4]
Annamacharya institute of technology and sciences, Rajmpeta
Email: vsreddy303@gmail.com[1]

Abstract-In today's industrial scenario to remain competitive in the market, manufacturers rely on their engineers to quickly and effectively set up manufacturing processes for new products to achieve good quality. Due to this surface finish & material removal rate becomes very important. In the present the study parameter optimization of end milling process for H13 die steel with multi response criteria based on the Taguchi L9 Orthogonal array with the grey relational analysis. Surface roughness and material removal rate are optimized with consideration of performance characteristics namely cutting speed, feed rate and depth of cut. A grey relational grade obtain from the grey relational analysis is be used to unravel the end milling process with the multiple performance characteristics.

Index Terms- End Milling, Taguchi Design of Experiments, Grey relational analysis.

1. INTRODUCTION

End milling is one of the important machining operations, widely used in most of the manufacturing industries due to its capability of producing complex geometric surfaces with reasonable accuracy and surface finish. The effect of cutting parameters is reflected on surface roughness, surface texture and dimensional deviations of the product. Surface roughness, which is used to determine and to evaluate the quality of a product, is one of the major quality attributes. Surface roughness and material removal rate are tribunals of the technological quality of a product and a factor that greatly influences manufacturing cost. Attempts have been made to optimize quality and productivity in a manner that these multi criterions could be fulfilled simultaneously up to the expected level. Sandeep kumar et.al cast-off the optimized vale of Input Parameters to increase the productivity & quality in end milling of H13 by Taguchi technique [16]. Upinder Kumar et.al investigated optimum values of input parameters in high speed turning of H13 in dry conditions. Taguchi's L9 orthogonal array and analysis of variance (ANOVA) are used for individual optimization [20]. J.C. Outeiro examined the residual stresses induced by dry turning of AISI H13 tool steel. He used modelling and optimization procedure based in Artificial Neural Network (ANN) and Genetic Algorithm (GA) [11]. The effects of various milling parameters such as spindle speed, feed rate, depth of cut and coolant flow on the surface roughness (Ra) of finished products were studied by Avinash A. Thakre [1].Lohithaksha M Maiyar et.al examined the parameter optimization of end milling operation for Inconel 718 super alloy with multi response criteria based on the Taguchi orthogonal array with the grey relational analysis [12].Optimization of Machining Parameters in End Milling of AISI H11 Steel Alloy was carried out by Nikhil Aggarwal and Sushil Kumar Sharma using Taguchi based Grey Relational Analysis [14]. E. Kuram discussed an application of Taguchi experimental method for investigating the influence of milling parameters and cutting fluid types on the tool wear and forces during milling of AISI 304 stainless steel [6].

Optimization of process parameters for pulsed laser milling of micro-channels on AISI H13 tool steel was studied by Daniel Teixidor et.al. These study enthusiasms on understanding the influence of laser milling process parameters on the final geometrical and surface quality of micro-channel features fabricated on AISI H13 steel [4]. From above literature we can say that input machining parameters play an important role in production and manufacturing. Selection the optimal levels of parameters can lead us to higher productivity within same set of resources. Also, there are number of optimization techniques available for generating a model which will lead us towards best output results. In the similar way present study will go step by step towards better and best results for surface finish and material removal rates.

2. EXPERIMENTAL SETUP

Major headings should be typeset in boldface with the words uppercase.

2.1. *Material*

The material used for this study is premium high grade H13 die steel. It contains strengthening agents such as vanadium and molybdenum. These steels are resistant to softening at elevated temperatures due to the presence of chromium content. Since increased hardness slows down the formation of heat checking cracks, improved tool performance can be expected. The composition of H13 is given in following table:

Table 1. Composition of H13

Alloying Elements	*C*	*Si*	*Mn*	*Cr*	*Mo*	**V**
Percentage	*0.36*	*1*	*0.4*	*5*	*1.2*	**0.9**

2.2. *Machining setup*

End milling operation was carried out on a BFW SURYA VF 30 CNC VS in wet conditions. The CNC milling machine equipped with AC variable speed spindle motor up to 6000 rpm and 3.7KW motor power was used for the present experimental work. The cutter used in this work was mechanically attached regular carbide Proton plus coated end mill cutter with dimensions 12x22x120 mm manufactured by Totem Forbes.

2.3. *Surface roughness measurement*

Surface roughness is defined as the finer irregularities of the surface texture that usually form nucleation sites for cracks or corrosion. Surface roughness of the machined samples was measured with Mitutoyo make Surface roughness tester (SJ-210). An average of 3 measurements of the surface roughness was taken to use in the multi-criteria optimization.

2.4. *Metal Removal Rate Calculation*

The Material Removal Rate, MRR (mm^3/ min) was calculated using formula:

$$MRR = W \times t \times f_m$$

Where, W = Width of cut

t = Depth of cut

f_m= Table (machine) Feed

2.5. *Selection of cutting parameters and their levels*

From the literature review and industrial survey, most influential parameters affecting on surface roughness and MRR are selected. Their levels for experimentation were selected from carrying out OVAT (one variable at a time) analysis. The results and selected levels of parameters are shown in table below:

Table 2: levels with parameters

Parameters	*Levels*		
	A	*B*	*C*
Speed (rpm)	*2500*	*3000*	*3500*
Feed (rev/min)	*0.3*	*0.4*	*0.5*
Depth of cut (mm)	*0.6*	*0.9*	*1.2*

3. Design of Experiment

3.1. *Taguchi method of DOE*

Experiments are designed using Taguchi method so that effect of all the parameters could be studied with minimum possible number of experiments. Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments. Signal to Noise (S/N) ratios are also calculated for analyzing the effect of machining parameters more accurately. Based on Taguchi design L9 orthogonal array has been selected for the experiments in MINITAB 14. All these data are used for the analysis and evaluation of the optimal parameters combination. The selected L9 orthogonal array is shown below:

Table 3: Experimental plan

speed	**feed**	**depth of cut**	**MRR**	**Ra**
2500	0.3	0.6	1.2	0.2557
2500	0.4	0.9	2.4	0.2715
2500	0.5	1.2	4	0.28
3000	0.3	0.9	1.8	0.2665
3000	0.4	1.2	3.2	0.271
3000	0.5	0.6	2	0.272
3500	0.3	1.2	2.4	0.255
3500	0.4	0.6	1.6	0.278
3500	0.5	0.9	3	0.365

4. GREY RELATIONAL ANALYSIS

In the grey relation analysis, experiment data, i.e., measured responses are first normalized in the range of 0 to 1. This process is called normalization or grey relation generation. Based on this data, grey relation coefficients are calculated to represent the correlation between the ideal (best) and the actual normalized experimental data. Overall, grey relation grade is then determined by averaging the grey relation coefficient corresponding to selected responses. The overall quality characteristics of the multi-response process depend on the calculated grey relation grade.

4.1. *Normalization*

Normalization of the signal to noise ratio is performed to prepare raw data for the analysis where the original sequence is transformed to a comparable sequence. Linear normalization is usually required since the range and unit in one data sequence may differ from the others. There are three different types of data normalization according to the requirement of Lower the Better (LB), Higher the Better (HB), or Nominal the Best (NB) criteria.

If the target value of original sequence is infinite, then it has a characteristic of the "higher is better". The original sequence can be normalized as follows:

$$x_i^* = \frac{x_i^o(k) - \min x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \quad (1)$$

When the "Smaller is better" is a characteristic of the original sequence, then the original sequence should be normalized as follows:

$$x_i^* = \frac{\max x_i^o(k) - x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \quad (2)$$

However, if there is a definite target value (desired value) to be achieved, the original sequence will be normalized in form:

$$x_i^* = 1 - \frac{|x_i^o(k) - x^o|}{x_i^o(k) - x^o} \quad (3)$$

Or, the original sequence can be simply normalized by the most basic methodology, i.e. let the values of original sequence be divided by the first value of the sequence:

$$x_i^* = \frac{x_i^o(k)}{x_i^o(1)} \quad (4)$$

Where i = 1 . . . m; k = 1. . . n. m is the number of experimental data items and n is the number of parameters. $x_i^o(k)$ denotes the original sequence, x_i^* the sequence after the data pre-processing, max $x_i^o(k)$ the largest value of $x_i^o(k)$, $\min x_i^o(k)$ the smallest value of $x_i^o(k)$ and x^o is the desired value.

4.2. *Determination of deviation sequences Δ0i(k) :*

The deviation sequence, Δ0i(k) is the absolute difference between the reference sequence x0*(k) and the comparability sequence xi*(k) after normalization. It is determined using equation:

$$\Delta 0i(k) = |x_0^*(k) - x_i^*(k)| \quad (5)$$

4.3. *Calculation of grey relational coefficient (GRC)*

GRC for all the sequences expresses the relationship between the ideal (best) and actual normalized S/N ratio. If the two sequences agree at all points, then their grey relational coefficient is 1. The grey relational coefficient ξi(k) for the kth performance characteristics in the ith experiment can be expressed as :

$$\xi_i(k) = \frac{x_i^o(k\Delta\min + \zeta\Delta\max)}{\Delta O_i(k) + \zeta\Delta\max} \quad (6)$$

Where ΔOi is the deviation sequence of the reference sequence and $x_0^*(k)$ is the comparability sequence. ζ is distinguishing or identification coefficient: ζ ∈ [0, 1] (the value may be adjusted based on the actual system requirements). A value of ζ is the smaller and the distinguished ability is the larger. ζ = 0.5 is generally used. Grey relational coefficient for 27 comparability sequences.

4.4. *Calculation of grey relational grade (GRG)*

After the grey relational coefficient is derived, it is usual to take the average value of the grey relational coefficients as the grey relational grade. The grey relational grade is defined as follows:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi i(k) \quad (7)$$

However, in a real engineering system, the importance of various factors varies. In the real condition of unequal weight being carried by the various factors, the grey relational grade was extended and defined as above. The grey relational grade γi represents the level of correlation between the reference sequence and the comparability sequence. If the two sequences are identical, then the value of grey relational grade is equal to 1. The grey relational grade also indicates the degree of influence that the comparability sequence could exert over the reference sequence. Therefore, if a particular comparability sequence is more important than the other comparability sequences to the reference sequence, then the grey relational grade for that comparability sequence and reference sequence will be higher than other grey relational grades.

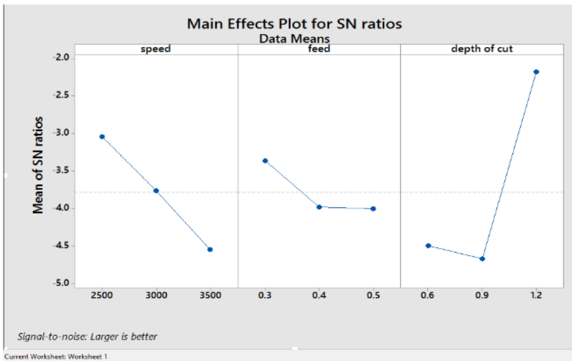
5. ANALYSIS AND DISCUSSION OF EXPERIMENTAL RESULTS

The grey relational grade γi represents the level of correlation between the reference sequence and the comparability sequence.

Table-4: Weighted grey relational grade

Experiment number	*Weighted grey relational grade*
1.	*0.6591*
2.	*0.6409*
3.	*0.8286*
4.	*0.6162*
5.	*0.7381*
6.	*0.6001*
7.	*0.7705*
8.	*0.5357*
9.	*0.5050*

The weighted grey relational grade calculated for each sequence is taken as a response for the further analysis. The larger-the-better quality characteristic was used for analyzing the GRG, since a larger value indicates the better performance of the process. The number of repeated test is one, since only one relational grade was acquired in each group for this particular calculation of S/N. The grey relation grades are now analyzed with Taguchi in Minitab17 software. This result shows that the best processing condition is the (A3, B1, C1, D2, and E1).



Graph 1. Main effects plot of S/N ratios for grey grades

Table 4: Optimum conditions

	SPEED	***FEED***	***DEPTH OF CUT***
Level	***A1***	***B1***	***C3***
Values	***2500***	***0.3***	***1.2***

After determining the optimum conditions, confirmation test is to be done to check the responses obtained from the optimum conditions. The obtained optimum values are

$$MRR = 2.62$$
$$Ra = 0.24$$

6. CONCLUSION

The present work has successfully demonstrated the application of Taguchi based grey relational analysis for multi response optimization of process parameters in End milling of H13 die steel. The important conclusions drawn from the present work are summarized as follows:

1) Multi-response problem was successfully converted into single response problem i.e. grey grade successfully which helped in optimization of both parameters simultaneously.

2) The optimal cutting parameters for the machining process lies at 2500 rpm for cutting speed, 0.3 mm/revolution for feed rate and 1.2 mm for depth of cut.

REFERENCES

[1] Avinash A. Thakre, "Optimization of Milling Parameters for Minimizing Surface Roughness Using Taguchi„s Approach," International Journal of Emerging Technology and Advanced Engineering, Volume 3, Issue 6,June 2013.

[2] Ch SrinivasRao, Reddy Sreenivasulu, "Application of grey relational analysis for surface roughness and roundness error in drilling of Al 6061 alloy," *Internationaljournal of lean thinking*, vol 3, issue 2, 2012.

[3] Chintan. H. Patel, Chirag. P. Patel, "Parametric Optimization of End Milling Of AISI 1018 Mild Steel by Various Lubricants with Solid Carbide End Mills," International Journal of Engineering Research and Applications, Vol. 3, Issue 4, Jul-Aug 2013, pp.728-732.

[4] Daniel Teixidor, Ine´s Ferrer, Joaquim Ciurana, Tugrul Ozel, "Optimization of process parameters for pulsed laser milling of micro-channels on AISI H13 tool steel," Robotics and Computer-Integrated Manufacturing, Vol. 29, June 2012, pp. 209–218

[5] Dhole N.S., Naik G.R, Prabhawalkar M.S., "Optimization of milling process parameters of EN33 using Taguchi parameter design approach," Journal of Engineering Research and Studies, Vol.III, Issue I, 2012.

[6] E. Kuram, B. T. Simsek, B. Ozcelik, E. Demirbas, and S. Askin , "Optimization of the Cutting Fluids and Parameters Using Taguchi andANOVA in Milling" , Vol II, 2010

[7] Emel Kuram, Babur Ozcelik, "Multiobjective optimization using Taguchi based grey relational analysis for micro-milling of Al 7075 material with ball nose end mill," Measurement 46,2013.

[8] G. Tamil Kumaran, R. John Stephen, "Optimization of Machining Parameters for Face Milling Operation using NOVA," Journal of Mechanical and Civil Engineering, e-ISSN: 2278-1684, pp. 81-87

[9] Ilhan Asilturk, Harun Akkus, "Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method," Measurement 44, 2011.

[10] J.A. Ghani a, I.A. Choudhury, H.H. Masjuki, "Performance of P10 TiN coated carbide tools when end milling AISI H13 tool steel at high cutting speed," Journal of Materials Processing Technology, 2004.

[11] Jose OUTEIRO, "Optimization of Machining Parameters for improved Surface Integrity of AISI H13 Tool Steel", Machines et Usinage á Grande Vitesse (MUGV) 2012, Oct 2012, France pp.1-10.

[12] Lohithaksha M Maiyara, Dr.R.Ramanujamb, K.Venkatesanc , Dr.J.Jeraldd, "Optimization of Machining Parameters for End Milling of Inconel 718 Super Alloy Using Taguchi Based Grey Relational Analysis," Procedia Engineering 64, 2013.

[13] M. S. Harne, Manish M. Dandge, "OVAT Analysis for Surface Finish in CNC Turning", International Journal of Innovative Technology and Exploring Engineering, Volume-4 Issue-3, August 2014.

[14] Nikhil Aggarwal and Sushil Kumar Sharma, "Optimization of Machining Parameters in End Milling of AISI H11 Steel Alloy by Taguchi based Grey Relational Analysis," International Journal of Current Engineering and Technology, Vol.4, No.4, Aug 2014.

[15] Samir K. Khrais, Y.J. Lin, "Wear mechanisms and tool performance of TiAlN PVD coated inserts during machining of AISI 4140 steel," Wear 262, 2007.

[16] Sandeep Kumar and Jagdeep Kaliraman, "Optimization of Cutting Parameters of AISI H13 with Multiple Performance Characteristics", International Journal on Emerging Technologies, July 2014

[17] Surasit Rawangwonga, Jaknarin Chatthonga, Worapong Boonchouytana, and Romadorn Burapaa, "An Investigation of Optimum Cutting Conditions in Face Milling Aluminum Semi Solid 2024 Using Carbide Tool," Energy Procedia 34, 2013.

[18] Turgay Kivak, "Optimization of surface roughness and flank wear using the Taguchi method in milling of Hadfield steel with PVD and CVD coated inserts," Measurement 50, 2014.

[19] Umesh Khandey, "Optimization of surface roughness, material removal rate and cutting tool flank wear in turning using extended Taguchi approach," A thesis submitted in partial fulfillment of the requirements for the degree of Master of Technology In Production Engineering, Under the guidance of Dr. Saurav Datta.

[20] Upinder kumar and Deepak Narang, "Optimization of Cutting Parameters in High Speed Turning by Grey Relational Analysis", International Journal of Engineering Research and Applications (IJERA), Vol. 3, Issue 1, January - February 2013, pp.832-839

[21] Y.S. Liaoa, H.M. Linb, J.H. Wang, "Behaviors of end milling Inconel 718 superalloy by cemented carbide tools," Journal of materials processing technology, 2008.