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Parametric Analysis of Turning EN24 Steel Using Grey Relational Approach

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Abstract: *Machining is the most widely used way of production for transforming a given work piece into a finished product. This research is focused upon investigating the effect of the turning parameters cutting speed, feed, depth of cut and tool material on the quality of machining, while turning EN24 steel using carbide tool. The quality characteristics taken for assessing the quality of the machined work piece are surface roughness, material removal rate and tool wear rate. The experimentation is carried out using Taguchi's L16 orthogonal array. The optimal parametric level is obtained using Grey Relation Analysis. The results are validated by running confirmation experiment with the obtained optimal set of parameters and significant improvement was found.*

Keywords: *EN24 Steel, Grey Relational Analysis, Taguchi, Tool wear rate, Orthogonal Array.*

I. Introduction

Turning process of material removal using conventional or numerically controlled lathes have been one of the primal methods of manufacturing shafts of required dimensions. Despite the amount of research done in this field, thanks to the advent of newer materials, applications and machining conditions, it still remains analluringarea for the researchers. Silva et al [1] studied the effect of the temperature at the tool-chip interface by taking three control arameters such as cutting speed, feed and depth of cut while carrying out external turning process of an AISI 1045 steel using WC TNMG 16 04 12-SF hard metal insert. And it also studies the effect of direct control on surface roughness. M. Junaid Mir and M. F. Wani [2] carried out turning process AISI D2 steel with PCBN, Mixed ceramic and coated carbide inserts to investigate the influence of cutting parameters on tool wear and surface roughness. Mathematical model was developed for each response parameters against cutting factors using a quadratic regression analysis. Lisa Toller et al [3] made a comparative study between two cutting inserts by carrying out turning operation on steel.

Two cutting inserts used during the research work are cemented carbide with a nickel-iron binder and cobalt based reference insert. From this study tool life of cemented carbide insert was found to be less than that of cobalt based reference insert.

Abhijit Saha and Himadri Majumder [4] analyzed the effect on frequency of tool, vibration and average surface roughness by using input parameters such as spindle speed, feed and depth of cut during plain turning operation through the use of process capability study. M. Hanief et al [5] investigated the effect on cutting force while carrying out the turning operation of red brass (C23000) with high speed steel (HSS) tool. The control parameters used while carrying out a turning operation was speed, depth of cut and feed rate. In order to reach the objective behavior of cutting force is modeled using two alternate approaches i.e. artificial neural network (ANN) and multiple regression analysis (MRA). Zeqing Xiao [6] aimed to develop a model by investigating the effect of cutting parameters such as spindle speed, feed rate, and depth of cut on surface roughness during the hard turning of AISI 1045 steel using YT5 tool by adopting regression analysis. M.R. Stalin John et al [7] investigated the effect of cutting parameters such as speed, burnishing force, and feed on surface roughness, residual stress, micro-hardness and out of roundness during the turning operation of D3 tool steel material by making use CNC lathe. In this research, finite element analysis method is employed to generate model for surface roughness pattern and to simulate ball burnishing process using DEFORM-2D software. D. Manivel and R. Gandhinathan [8] employed Taguchi method to optimize effect of cutting parameters such as cutting speed, feed rate and depth of cut on surface roughness and tool wear during hard turning of ADI with carbide inserts. In this research paper L18 orthogonal array was used to carry out the experiments. Adilson José de Oliveira1 et al [9] optimized cutting parameters in turning of high chromium white cast iron using two grades of PCBN tool.

The performance of two grades of PCBN tool was compared in term of tools' life, wear mechanisms at the tool cutting edges, roughness, and microstructure. Wojciech Zębala& Robert Kowalczyk [10] analyzed the behavior of cutting force and surface roughness by taking into consideration cutting parameters and cobalt content present in the work piece in turning of WC-CO using polycrystalline diamond (PCD) tool. The cutting parameters selected for this research paper was cutting speed, feed, depth of cut and response output was cutting force and surface roughness. Abdullah Kurt et al [11] performed dry finish turning operation to analyze the behavior of cutting stresses with respect to the cutting parameters by using AISI H13 hot work steel as work piece material and ceramic tool as cutting material. Sayak Mukherjee et al [12] investigated the effect of cutting parameters i.e. Speed, Feed and Depth of cut in turning of SAE 1020 with carbide cutting tool by employing Taguchi method. Response output used for this research is MRR. Linhu Tang et al [13] aimed to develop a model to investigate effect of cutting parameters such as the cutting speed, depth of cut, feed, work piece hardness, and nose radius on three-component cutting forces during the dry hard turning of AISI D2 tool steel with the PCBN tool using orthogonal regression methodology(ORM) and response surface methodology. M. C. Santos Jr et al [14] studied the effect of cutting parameters namely cutting speed, feed rate, and depth of cut on machining force, chip thickness ratio and chip disposal during the turning operation of aluminum alloy. Second order model was developed for cutting parameters using central composite design (CCD) of experiments. Relation between cutting parameters and response output was analyzed with the help of response methods and level curves. The cutting condition that affects the output parameters were determined using genetic algorithm method (GAM). P. Jayaramana and L. Mahesh kumar [15] studied the effect of cutting parameters namely cutting speed, feed rate and depth of cut on surface roughness, roundness and material removal rate during turning of AA 6063 T6 aluminum alloy with uncoated carbide insert. Cutting parameters were optimized with the help of orthogonal array. Grey relational analysis (GRA) was used to identify optimal level of each cutting parameters with respect to Grey relational grade (GRG).

This research work is engrossed in identifying the effect of the cutting parameters on the output characteristics while the carbide cutting tool insert is put into action for turning EN24 alloy steel.

II. Experimentation

The turning of EN24 steel using carbide tool is carried out using “AKSAR MICRONS” CNC turning machine, at Birla Institute of Technology and Science, Pilani-Goa. EN-24 steel is a popular grade of through hardening alloy steel due to its excellent machinability. EN-24 is mainly used in automotive industry which uses components like gears, shafts, studs and bolts. The composition of the material has been shown in Table 1.

The cutting tool material used for carrying out the experimentation is the carbide tool of TNMG160408UM and TNMG332UM grade. In this research, based on the literature survey, four parameters cutting speed (rpm), feed (mm/rev), depth of cut (mm) and type of tool material are considered for the investigation.

Table 1: Chemical Composition of EN 24

C	*SI*	*MN*	*S*	*P*	*Cr*	*Mo*	*Ni*
0.36/0.44	0.10/0.35	0.45/0.70	0.04 max	0.035 max	1.00/1.40	0.20/0.35	1.30/1.70

Therefore, these turning parameters and their associated levels are selected based on preliminary literature review and preliminary experimentation carried out. The levels of turning process parameters are shown in Table 2.

Table 2: Input Parameters and their levels

PARMETERS	UNIT	LEVELS	
		I	II
Cutting Speed	rpm	1500	2000
Feed	mm/rev	0.15	0.2
Depth of Cut	mm	1	2
Tool Material	Type 1/ Type 2	Type1(Uncoated)	Type 2(Coated)

The quality characteristics that are investigated are Surface roughness, Material removal rate and Tool Wear Rate.

A. Surface Roughness Measurement

The surface roughness is measured by using Mitutoyo Surf Test Ver2.00 surface roughness tester. Sampling length of 40mm was selected to determine the surface texture of the work piece. The surface roughness was measured at three locations and then the average roughness (Ra, Rq, Rz) is calculated.

B. Material Removal Rate

Material Removal Rate (MRR) is a measure of productivity, the higher the volume of chips removed, the higher the productivity of cutting. For our experimentation to calculate the MRR we had used the following formula.

$$\text{MRR} = \frac{Volume\ \ of\ material\ \ removed}{Time\ \ taken}$$

$$\text{MRR} = \frac{Initial\ \ volume\ -Final\ \ volume}{Time}$$

$$\text{MRR}=\frac{\left(\frac{\pi d_1^2 l}{4}\right)-\left(\frac{\pi d_2^2 l}{4}\right)}{t}$$

where d_1= initial diameter of workpiece in mm
d_2 = final diameter after machining of workpiece in mm
l = length in mm
t = time of machining in sec

C. Tool Wear Measurement

In order to measure the tool wear, the CNC turning machine has been embedded with a device named Renishaw. It measures the tool wear in X and Z directions. First the RP3 three axis probe of Renishaw is made to come in contact with the work piece surface in X-direction before starting machining, and the value of tool wear is recorded. After the machining, again the tool wear is measured and the difference between these values before and after the machining gives the actual tool wear. Same procedure is applied to get the tool wear in Z-direction.

III. Data Collection And Measurement

Based on the experimental design, necessary set up were made in the machine and the machining is carried out. Table 3 shows the data collected for all the output parameters.

Table 3: Data Collected

Trial No.	CS	FEED	DOC	TM	Ra	MRR	TWR
1	1	1	1	1	0.636	358.089	37
2	1	1	1	2	1.194	340.859	28
3	1	1	2	1	0.623	665.212	96
4	1	1	2	2	0.699	685.856	34
5	1	2	1	1	0.876	527.628	101
6	1	2	1	2	0.864	529.513	33
7	1	2	2	1	0.936	1010.72	93
8	1	2	2	2	0.939	1023.42	35
9	2	1	1	1	0.564	437.104	104
10	2	1	1	2	0.734	472.658	33
11	2	1	2	1	0.637	869.711	105
12	2	1	2	2	0.898	906.491	41
13	2	2	1	1	0.907	679.825	103
14	2	2	1	2	0.909	724.035	39
15	2	2	2	1	0.94	1221.75	95
16	2	2	2	2	0.948	1373.96	36

IV. Grey Relational Analysis

A system for which the relevant information is completely known is a "white" system, while a system for which the relevant information is completely unknown is a "black" system. Any system between these limits is a "grey" system having poor and limited information.

A. Data Pre-processing

The grey relational analysis begins with the data pre-processing as the range and the units of the output characteristics data vary. It is very necessary to normalize these data to take it up to the further analysis. This normalization of the data obtained can be done under three heads depending of the nature of the variable being tested. First is the "larger the better" type of data sequence in which, the output characteristics are desired to be large or maximum. Second is the "smaller the better" type of data sequence wherein the output data should be least or minimum. The third type of data sequence is the "nominal the better" in which the data obtained should be nominal. The formulae for the above-mentioned normalization methods are shown in the Eqn. i, Eqn. ii, and Eqn. iii.

$$x_i^* \quad (k) = \frac{x_i\,(k) - \min(x_i^0(k))}{\max(x_i^0(k)) - \min x_i^0(k)} \qquad Eqn.(i)$$

$$x_i^* \quad (k) = \frac{\max(x_i\,(k)) - x_i^0(k)}{\max(x_i^0(k)) - \min(x_i^0(k))} \qquad Eqn.(ii)$$

$$x_i^*(k) = 1 - \frac{|x_i^{(0)} - \mathrm{OV}\,|}{\{\max x_i^{(0)}(k) - \mathrm{OV}, \mathrm{OV} - \min x_i^{(0)}(k)\}} \qquad Eqn.(iii)$$

where, $x_i^*(k)$ is the reference sequence and $x_i^0(k)$ is the original sequence.

B. Grey Relational Coefficient (GRC)

From the normalized values of the responses, the second stage of calculating grey relational coefficients ($\varepsilon_i(k)$) for each of the responses is performed. The Eqn. (iv) shows the formulae used for the same. This stage consists of two sub stages viz. the calculation of the deviation sequence (Δ_{oi}) and the introduction of the distinguishing coefficient (η). The value of η varies between 0 to 1and is usually taken as 0.5 in order to give equal weightage to all the responses.

$$\varepsilon_i(k) = \frac{\Delta_{\min} + \eta.\Delta_{\max}}{\Delta_{0i} + \eta.\Delta_{\max}} \, Eqn.(iv)$$

C. Grey Relational Grade (GRG)

Finally, the GRG (γ_i) of each of the trails conducted is calculated using the Eqn. v. Upon ranking the GRG, the higher the value of GRG closer it is to the optimal set of parameters.

Table 4: Grey Relational Analysis

Trial No.	Normalized Values			Δ Values			GRC			GRG	Ranking Order
	Ra	MRR	TWR	Ra	MRR	TWR	Ra	MRR	TWR		
1	0.8857	0.0167	0.4921	0.1143	0.9833	0.5079	0.8140	0.3371	0.4961	0.5490	10
2	0.0000	0.0000	0.6349	1.0000	1.0000	0.3651	0.3333	0.3333	0.5780	0.4149	15
3	0.9063	0.3140	0.1429	0.0937	0.6860	0.8571	0.8422	0.4216	0.3684	0.5441	11
4	0.7857	0.3339	0.9841	0.2143	0.6661	0.0159	0.7000	0.4288	0.9692	0.6993	2
5	0.5048	0.1808	0.0635	0.4952	0.8192	0.9365	0.5024	0.3790	0.3481	0.4098	16
6	0.5238	0.1826	1.0000	0.4762	0.8174	0.0000	0.5122	0.3795	1.0000	0.6306	5
7	0.4095	0.6484	0.1905	0.5905	0.3516	0.8095	0.4585	0.5871	0.3818	0.4758	13
8	0.4048	0.6607	0.9683	0.5952	0.3393	0.0317	0.4565	0.5957	0.9403	0.6642	4
9	1.0000	0.0932	0.0159	0.0000	0.9068	0.9841	1.0000	0.3554	0.3369	0.5641	8
10	0.7302	0.1276	1.0000	0.2698	0.8724	0.0000	0.6495	0.3643	1.0000	0.6713	3
11	0.8841	0.5119	0.0000	0.1159	0.4881	1.0000	0.8119	0.5060	0.3333	0.5504	9
12	0.4698	0.5475	0.8730	0.5302	0.4525	0.1270	0.4854	0.5249	0.7975	0.6026	6
13	0.4556	0.3281	0.0317	0.5444	0.6719	0.9683	0.4787	0.4267	0.3405	0.4153	14
14	0.4524	0.3709	0.9048	0.5476	0.6291	0.0952	0.4773	0.4428	0.8400	0.5867	7
15	0.4032	0.8527	0.1587	0.5968	0.1473	0.8413	0.4559	0.7724	0.3728	0.5337	12
16	0.3905	1.0000	0.9524	0.6095	0.0000	0.0476	0.4506	1.0000	0.9130	0.7879	1

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \varepsilon_i \qquad \text{Eqn. (v)}$$

The Table 4 shows the calculated values of the GRC and GRG along with its ranking order.

D. Response Table

The inferences of the grey relational analysis can be found by forming the response table. The response table is formed by taking the average of the grey relational grades of each of the input variables for each level. The maximum of the values present at each input factor shows the optimal level of the parameters to be chosen. From the Table 5 the optimal levels of the parameters are found out to be $A_2\,B_1\,C_2\,D_2$. The machining done with these set of parameter levels will fetch optimal results.

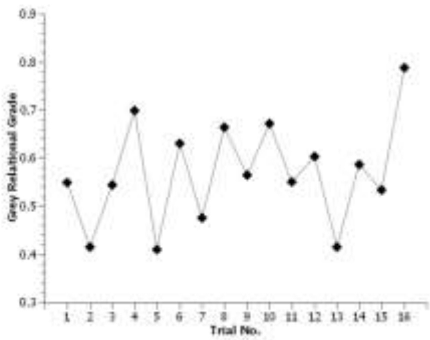

Fig .1: Scatter Plot for Grey Relational Grades

Table 5: Response Table

Parameter	Cutting Speed	Feed	Depth of Cut	Tool Material
Symbol	**A**	**B**	**C**	**D**
Level 1	0.5485	0.5745	0.5302	0.5053
Level 2	0.5890	0.5630	0.6072	0.6322
Main Effect	0.0405	0.0115	0.0770	0.1269

E. Confirmation Experiment

The optimal parametric set for achieving the lowest surface roughness, highest material removal rate and lowest tool wear rate is $A_2 B_1 C_2 D_2$ i.e. a cutting speed of 2000 rpm, feed of 0.15 mm/rev., depth of cut of 2 mm and type 2 coated tool. The confirmation experiment results show that the experiment carried out using the optimal set of parameters gives the lowest surface roughness of 0.565 microns, highest material removal rate of 1028.56 mm^3/sec and a lowest tool wear rate of 30 microns.

V. Conclusion

This research was done with an objective of getting an optimal set of turning parameters while machining EN24 steel using carbide tool. The following conclusions were arrived:

i. The trial no. 16 has got the highest value of grey relational grade, which indicates the levels of the parameters close to the optimal values.
ii. From the main effect row of the response table, the order of relevance to the output characteristics is found to be Tool Material > Depth of Cut > Cutting Speed > Feed.
iii. The optimal set of the parametric levels are $A_2 B_1 C_2 D_2$ i.e. a cutting speed of 2000 rpm, feed of 0.15 mm/rev., depth of cut of 2 mm and type 2 coated tool.

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