MATERIAL REMOVAL RATE AND SURFACE ROUGHNESS BASED CUTTING PARAMETERS OPTIMIZATION FOR TURNINING EN24 STEEL

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Abstract:- Quality and productivity play a vital role in manufacturing industries to attain profit. Manufacturing industries need improvements so as to survive technology. These improvements pave way to enhance quality and productivity of the product/process. CNC Turning machines helped in development of such technologies are used for the present study. The high strength, ductile and wear resistance steel alloy EN24 is selected for Turning. In the work, Taguchi L9 Orthogonal Array design of experiment is used for the selection of cutting parameters and a total of nine turning operations are conducted. Material Removal Rate is calculated and Surface Roughness is measured for all the nine experiments. Signal to Noise ratio (S/N) and mean values are calculated to find the influencing cutting parameter for material removal rate and surface roughness. ANOVA technique is used to calculate the optimal cutting parameters for achieving better material removal rate and surface roughness. A comparison is made between the S/N ratios and initial readings. ANOVA technique is used for analysing parameters that influence material removal rate and surface roughness.

Keywords: CNC Turning, Cutting parameters, Taguchi L9 Orthogonal Array, Signal to Noise Ratio, ANOVA Analysis of Variance.

1. Introduction

CNC Turning operation is one of the widely used machining process in industries. In turning, a single point cutting tool removes excess material from the surface of the rotating workpiece to achieve accuracy and surface roughness. Turning operation is performed on CNC ACE LT-20 Lathe machine (as shown in the figure 1) having maximum power of 30KVA and maximum spindle speed 50-4000 rpm. To achieve profits in machining, numerous researchers stated that cutting parameters play a vital role in achieving Material removal rate (MRR) and surface roughness (SR). Selection of cutting parameters for achieving MRR and SR is critical as it involves several other machining elements like stability, rigidity of machine tool, power, coolant, work holding, tool holding, Tool angles, wear of tool, etc. Industries select cutting parameters from the tool provider manuals or conducts costly trial and error experiments to achieve the desired MRR and SR. In the work, in order to reduce the costly trail experiments, Taguchi L9 orthogonal array is used to design the optimal cutting parameters to know the trend of machining on MRR and SR. A total of nine experiments are selected for performing turning operation, MRR is calculated and surface roughness of each experiment are measured using profilometer. S/N Ratios are calculated for all the cutting parameters and analysis is done for optimal cutting parameters using ANOVA Analysis of Variance. The ANOVA selected parameters are machined and a significant improvement is observed in MRR and SR.

Fig.1 CNC ACE LT-20 Lathe machine used for performing Turning operation.

CNC Turning operation is performed on steel alloy EN24 steel alloyed with nickel, chromium, and molybdenum. These alloying elements offer good strength, ductility, wear resistance and has impact properties at low temperature. It is used in the manufacturing of high strength shafts, punches, dies, gears, retaining rings, drill bushings. The chemical composition and mechanical properties are shown in table 1 and 2 respectively.

Table1: Chemical Composition of En24 Alloy Steel

Elements		Values %	Elements	Values %
Carbon		0.36-0.44	Phosphorus	0.035
Silicon		0.10-0.35	Chromium	1.00-1.40
Manganese		0.45-0.70	Molybdenum	0.20-0.35

Table2: Mechanical Properties of En24 Alloy Steel

Tensile Stress	850-1000 N/mm^2
Yield Stress	680 N/mm^2
Yield Stress	650 N/mm^2
0.2% Proof Stress	665 N/mm^2
0.2% Proof Stress	635 N/mm^2
Elongation	13%
Impact Strength	54 J
Thermal Conductivity	41.9 w/m-°C
Hardness	248-302 Brinell
Density	7840 kg/m^3
Elastic Modulus	207×10^9
Melting Point	1500°C

2. Literature survey

Muhammad et al., 2019, Present study focuses on the determination on the optimum cutting conditions leading to minimum surface roughness as well as electrostatic charge and maximum productivity. Optimization is based on the response surface methodology (RSM). Mathematical model is developed for surface roughness, electrostatic charge and material removal rate using RSM regression analysis for a rigid contact lens polymer by design expert software. RSM allowed the optimization of the cutting conditions for minimal surface roughness, electrostatic charge, and maximal material removal rate.

Guanghui et al., 2019, Optimization method of cutting parameters considering the tool wear conditions is developed. Firstly, the quantified relationships among cutting parameters, tool wear and production indexes are analysed. Then, a multi-objective cutting parameters optimization model is established based on the above production indexes to determine the optimal cutting parameters and tools. Thirdly, a modified NSGA-II algorithm is used to resolve the proposed model. Finally, a case study is designed to demonstrate the advantages and feasibility of the proposed approach. The results show that optimal cutting parameters change with the tool wear conditions.

Milan et al.,2019, Attempted to optimize the machining parameters in dry turning operation of Inconel 825 workpiece. The cutting parameters are speed of cut, rate of feed and the coating of tool. The response parameters are roughness of machined surface and rate of material removal rate. Grey relation analysis coupled with Taguchi is used for optimization. Coated carbides tools, namely Physical Vapour Decomposition (PVD), Chemical Vapour Decomposition (CVD) are used. The material removal rate is more with CVD coated insert when compared to PVD coated insert.

Janaki Ramulu et al., 2019, Investigated the machinability of CSN 12050 carbon steel bar using carbide inset tool. Taguchi method is used to utilize the optimum cutting parameters. Experiments are performed under dry cutting condition. Signal to noise ratio tests are designed. Analysis of variance (ANOVA) is performed to determine the importance of machining parameters on the material removal rate (MRR). The results revealed that there is an improvement of optimal cutting conditions for each significant MRR response parameters.

Congbo Li et al., 2019, The paper presents an integrated approach of cutting tool and cutting parameter optimization. The proposed work is to minimize the energy footprint and production time of the face milling process. The energy footprint characteristics are analyzed by considering multiple cutting tool flexibilities and cutting parameters. Then a multi-objective integrated optimization model for minimizing energy footprint and production time is proposed and solved via a multi-objective Cuckoo Search algorithm. Finally, case studies are conducted to verify the feasibility and validity of the proposed integrated optimization approach. The results revealed from case studies, interaction effects between cutting tool and cutting parameters are revealed.

Salim Belhadi et al., 2018, Investigated the influence of cutting parameters on the output performance parameters namely surface roughness, the cutting force and power and the material removal rate during dry hard turning operation of martensitic stainless steel (AISI 420) treated at 59HRC. The machining is performed using a coated ceramic insert (CC6050) for Taguchi L25 obtained data. ANOVA and Pareto chart analysis are done to quantify the influence on the output parameters. Response surface methodology and Artificial neural networks are applied and compared for output parameters. The results indicated that surface roughness (Ra) is strongly influenced by the feed rate, depth of cut is influencing cutting force, cutting power, and material removal rate. ANN and RSM models predicted close to experimental results and the former predicted with better accuracy.

Anupam et al.,2018, In machining AISI 52100 grade steel of hardness 55 HRC a new carbide tool of 12µm thickness HSN^2 coating material is used. A relationship is built between input process parameters i.e. cutting speed, feed rate and depth of cut with output responses i.e. main cutting, radial and feed forces, surface quality of workpiece. Statistical design of experiment work is used to examine the effect of the cutting parameters on machining. The cutting parameters are optimized using response surface methodology and validated using confirmation test. It is found that cutting speed is the most effective parameter among all the output response.

Adil et al.,2018, The objective of the research is to set optimal CNC Turning parameters i.e. cutting speed, feed rate and depth of cut for obtaining material removal rate. CNC Turning operation is performed on aluminium ENAC- 43400 using a carbide tool. ANFIS model is used for optimization of MRR in CNC Turning operation. The results obtained, predicted material removal rate (MRR) are between (4125-17500 mm3/min), followed by max. material removal rate obtained (17500 mm3/min) at condition higher cutting speed (250 m/min), higher feed rate (0.07 mm/rev) and higher depth of cut (1 mm). ANFIS model technique can be effectively used for the optimization of material removal rate at the error of training data 2.255%.

Yusuf et al.,2018, The paper presents a design of experiment work related to optimization of machining factors in turning process of aluminium alloys. Carbon emission and surface quality were concurrently optimized. The experiment is carried out using Box Behnken Design and response surface methodology is applied to get the regression model for the carbon emission and surface roughness during turning process. The relationship between the factors and the responses is investigated using surface plot. Further, the desirability function method using the Response Optimizer tool in MINITAB and goal programming methodology is used to obtain the values of the parameters that achieved minimum surface roughness and a minimum quantity of carbon emission.

Salman et al.,2018, The objective of study is to determine optimum machining parameters during high speed turning of Al 6061 T1 alloy. The machining parameters optimize the trade-off between three competing responses i.e. cutting energy, material removal rate and surface roughness. The multi-objective function is optimized using regression analysis and response surface optimization. ANOVA results revealed that cutting speed to be the most significant parameter affecting multi-objective function.

Alkan et al., 2018, The paper presents effects of cutting parameters on cutting forces and surface roughness based on Taguchi experimental design method is determined. Taguchi L9 orthogonal array is used to investigate the effects on machining parameters. Signal to Noise ratio is calculated by average surface roughness and cutting force. The material investigated is 625 steel for two cases with heat treatment and without heat treatment. Predicted and calculated values with measurements are very close to each other. Confirmation results showed that Taguchi method is successful in the optimization of machining parameters for maximum surface roughness and cutting forces in the CNC turning process.

Qinge Xiao et al., 2018, The paper generalizes the energy-aware parametric optimization for multiple machining configurations. Proposed a two-stage knowledge driven method by integrating data mining (DM) techniques and fuzzy logic theory. In the first stage, a modified association rule mining algorithm is developed to discover empirical knowledge, based on which a fuzzy inference engine is established to achieve preliminary optimization. In the second stage, an iterative fine-tuning process is carried out to realize Pareto optimization of turning parameters for minimizing specific energy consumption and processing time. The simulation results show that the method has a high potential for enhancing energy efficiency and time efficiency in turning system.

Miroslav Radovanovic, 2018, Studied optimization of turning operation consisting multi-pass roughing and single-pass finishing AISI 1064 steel with carbide cutting tool, in terms of material removal rate and machining cost. For multi-pass roughing, optimization problem with two objectives (material removal rate and machining cost), three factors (depth of cut, feed and cutting speed), and five machining constraints (cutting force, torque, cutting power, tool life, and cutting ratio) is studied. For single-pass finishing, optimization problem with two objectives (material removal rate and machining cost), four factors (tool nose radius, depth of cut, feed, and cutting speed), and three machining constraints (surface roughness, tool life, and cutting ratio) is studied. Optimization problem is solved using three techniques: iterative search method, multi-objective genetic algorithm (MOGA), and genetic algorithm (GA). The optimal solution is determined by using the weighted-sum-type objective function, with a genetic algorithm.

3. Experimentation

Design of experiments is considered as one of the most comprehensive approach in product or process development. It is a statistical approach that attempts to provide a predictive knowledge of a complex, multi-variable process with few trails. We selected Taguchi method for the stated experiments. To know the present trend and to reduce production time and cost L9 Orthogonal Array is selected for the present study. Designed experiments are often carried in four phases planning, screening, optimization and verification.

(i) Taguchi Design of Experiments: The traditional experimental design method is too much complex and time consuming. To overcome limitations of traditional method, Taguchi method is used. The advantages of implementing Taguchi technique is: To find out significant factors in a shorter time period, to decrease the cost, decrease the experimental time. Taguchi is mostly used to design the best process parameter to minimize the variation. Taguchi method is based on certain steps of planning, conducting, and evaluating the results of matrix experiments to determine the best level of control parameters. Taguchi steps are as follows:

- Determine the factors and identify the text conditions.
- Selection of proper Orthogonal Array.
- Assignment of factors and interactions.
- Conduct an experiment.
- Analysis of the data, predict the optimum control factor levels and the performances.
- Verify the experiment.

(ii) Control Factors: In the present experimental study cutting speed, feed and depth of cut has been considered as process variables. The process variables with their notations and units are listed in the Table3.

Table3: Process Parameters and their levels

Sl.No	Process Parameters		
	Cutting Speed (m/min) [A]	Feed (mm/rev) [B]	Depth of Cut (mm) [C]
1	130	0.05	0.3
2	150	0.1	0.5
3	170	0.15	0.7

(iii) Selection of Orthogonal Array: All the experiments have been carried out using Taguchi L9 Orthogonal Array (OA) and is proposed by Melesse (2019) et. al., [4] is as shown in the Table4.

Table4: Taguchi L9 runs for experimental design

Run Order	Cutting Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

(iv) Conducting the Matrix Experiment: In accordance with the above orthogonal array, experiments are conducted with their factors and their levels. The experimental design with the selected values of the factors are shown in table5. Each of the above nine experiments are conducted. As per Taguchi experimental design philosophy, a set of three levels assigned to each process parameters have two degrees of freedom (D0F) and for two level process parameter, one degree of freedom. This gives a total of 8 degrees of freedom for 9 experiments selected for three process parameters in this work. Taguchi L9 Orthogonal array is shown in the below table 4.

Table5: Orthogonal Array for the present work

Experiment Run Order	Cutting Speed (m/min)	Feed (mm/rev)	Depth of Cut (mm)
1	130	0.05	0.3
2	130	0.1	0.5
3	130	0.15	0.7
4	150	0.05	0.5
5	150	0.1	0.7
6	150	0.15	0.3
7	170	0.05	0.7
8	170	0.1	0.3
9	170	0.15	0.5

(v) Experimentation: The experiments are conducted as per Taguchi Design of Experiments. In the experiments, the measurable parameters are surface roughness and material removal rate. The results are shown in the Table 6.

Table6: Experimental results

Experiment Run Order	Cutting Speed (m/min)	Feed (mm/rev)	Depth of Cut (mm)	Surface Roughness (μm)	Material Removal Rate (mm^3/min)
1	130	0.05	0.3	1.45	15.78
2	130	0.1	0.5	0.92	26.30
3	130	0.15	0.7	0.90	47.34
4	150	0.05	0.5	0.95	27.81
5	150	0.1	0.7	0.65	47.13
6	150	0.15	0.3	1.10	15.95
7	170	0.05	0.7	0.71	47.51
8	170	0.1	0.3	0.77	14.98
9	170	0.15	0.5	0.83	27.09

The experiments were conducted to study the effect of process parameters over the output response characteristics with the process parameters given in the table 3. The experiments result for the material removal rate and surface roughness and signal to noise ratio are given in the table6 and table7. The experiments are repeated to obtain the S/N values. In the present study, all the design and plots have been carried out.

4. **Performance analysis:**

(i) SIGNAL TO NOISE RATIO (S/N RATIO): Taguchi experiments usually use two step optimization process. In step one, use the signal to noise ratio to identify those control factors that reduces variability. In step two, identify the control factor that move mean to target and have a small or no effect on the signal to noise ratio. The signal to noise ratio measures how the response varies relative to the nominal or target value under different conditions. Usually there are three categories of performance characteristic in the analysis of S/N ratio.

1) Taguchi S/N ratio for Smaller-the-better

n = -10 Log_{10} [mean of sum of squares of measured data]

This is usually the chosen S/N ratio for all undesirable characteristics for which the ideal value is zero. But when the ideal value is zero, the difference between measured data and the ideal value is expected to be small as possible. The generic form of S/N ratio becomes:

n = -10 Log_{10} [mean of sum of squares of {measured – ideal}]
2) Taguchi S/N ratio for Larger-the-better

n = -10 Log_{10} [mean of sum of reciprocal of measured data]
Taking the reciprocals of measured data and taking the value of S/N ratio as in the smaller-the better case, convert it into smaller-the-better case.

(ii) ANALYSIS OF VARIANCE (ANOVA): ANOVA is a statistical method for determining the existence of differences among several population means. Since there are a large number of variables controlling the process, some mathematical models are required to represent the process. These models are to be developed using only the significant parameters influencing the process rather than including all the parameters. In order to achieve this, statistical analysis of the experimental results will have to be processed using the analysis of variance (ANOVA).

(iii) Material Removal Rate: MRR being 'higher the better' type of machining quality characteristic, the S/N for this type of response is used and given below the table7.

η= -10log$_{10}$[MSD], are MSD $= \frac{1}{n}\sum_{i=0}^{n} \frac{1}{(yi)2}$ --------- (1)
are, S/N = Signal to Noise Ratio,

n = No of measurements,

y = Measured values

The S/N ratios were calculated using equation (1) for each of the 9 trails and the values are reported in the table6.

(iv) Surface Roughness: SR being 'lower the best' type of machining quality characteristic, the S/N for this type of response is used and given below the table7.

η = -10 log$_{10}$[MSD], are MSD $= \frac{1}{n}\sum_{i=0}^{n}(yi^2)$ ----------- (2)

are, S/N = Signal to Noise Ratio,

n = No of measurements,

y = Measured Values

The S/N ratios were calculated using equation (2) for each of the 9 trails and the values are reported in the table7.

Table7: Experimental Results for Material Removal Rate

Experiment Number	Cutting Speed (m/min)	FEED (mm/rev)	Depth of Cut (mm)	Material Removal Rate (mm^3/min)	S/N Ratio
1	130	0.05	0.3	15.78	23.9621 (η_1)
2	130	0.1	0.5	26.30	28.3991 (η_2)
3	130	0.15	0.7	47.34	33.5045 (η_3)
4	150	0.05	0.5	27.81	28.8840 (η_4)
5	150	0.1	0.7	47.13	33.4659 (η_5)
6	150	0.15	0.3	15.95	24.0552 (η_6)
7	170	0.05	0.7	47.51	33.5357 (η_7)
8	170	0.1	0.3	14.98	23.5102 (η_8)
9	170	0.15	0.5	27.09	28.6561 (η_9)

Table8: Experimental Results for Surface Roughness

Experiment Number	Cutting Speed (m/min)	FEED (mm/rev)	Depth of Cut (mm)	Surface Roughness (R_a)	S/N Ratio
1	130	0.05	0.3	1.45	3.2273 (η_1)
2	130	0.1	0.5	0.92	0.7242 (η_2)
3	130	0.15	0.7	0.90	0.9151 (η_3)
4	150	0.05	0.5	0.95	0.4455 (η_4)
5	150	0.1	0.7	0.65	3.741 (η_5)
6	150	0.15	0.3	1.10	0.8278 (η_6)
7	170	0.05	0.7	0.71	2.9748 (η_7)
8	170	0.1	0.3	0.77	2.2701 (η_8)
9	170	0.15	0.5	0.83	1.6184 (η_9)

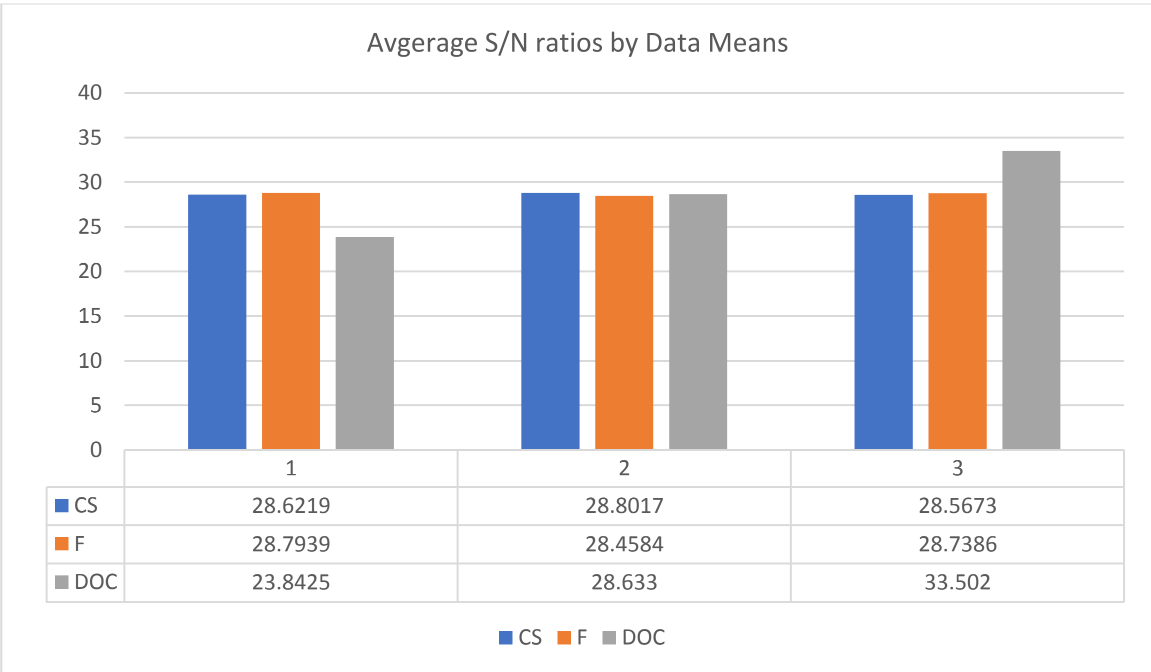
The effect of different process parameters on material removal rate and surface roughness are calculated and plotted as the process parameters change from one level to another. The average value of S/N ratio has been calculated to find out the effects of different parameters and their levels. The use of both S/N ratio approach and ANOVA technique makes it easy to analyse the results and hence, make it fast to reach the conclusion.

Table9: RESPONSE TABLE FOR MATERIAL REMOVAL RATE

LEVEL	Cutting Speed (m/min)	FEED (mm/rev)	Depth of Cut (mm)
1	28.6219	28.7939	23.8425
2	28.8017	28.4584	28.6330
3	28.5673	28.7386	33.5020
Delta	0.2344	0.3355	9.6595
Rank	3	2	1

The graph showing optimum level of different control factors for Material Removal Rate

Graph1: Average S/N ratio for Material Removal Rate



Analysis of Variance for Material Removal Rate:

Table10: ANALYSIS OF VARIANCE (ANOVA) FOR MATERIAL REMOVAL RATE

FACTORS	DEGREE OF FREEDOM	SUM OF SQUARES	MEAN SQUARE	F- RATIO	% RATIO	RANK
CUTTING SPEED	2	0.0902	0.0451	0.635≈1	0.0643%	3
FEED	2	0.1940	0.097	1.366≈2	0.1383%	2
DEPTH OF CUT	2	139.9261	69.98	985.6≈1000	99.79%	1
ERROR	5					
POOLED ERROR	4	0.2842	0.071			
TOTAL	8				100%	

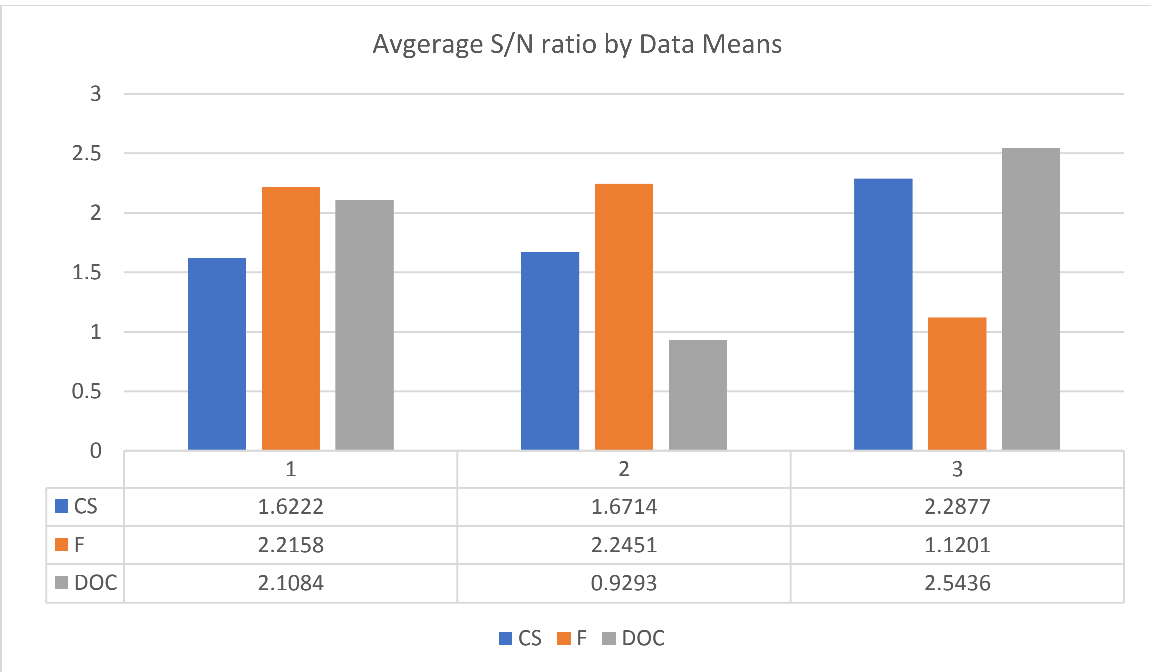
The rank indicates the relative importance of each factor to the response. The rank and the delta values show that depth of cut have the greatest factor effect on material removal rate followed by feed rate and cutting speed in that order. As MRR is the "higher the better" type quality characteristic therefore it goes the following order like (A3) third level of cutting speed, (B2) second level of feed rate and (C1) first level of depth of cut which gives maximum values of MRR.

TABLE11: RESPONSE TABLE FOR SURFACE ROUGHNESS

LEVEL	Cutting Speed (m/min)	FEED (mm/rev)	Depth of Cut (mm)
1	1.6222	2.2158	2.1084
2	1.6714	2.2451	0.9293
3	2.2877	1.1204	2.5436
Delta	0.6655	1.1247	1.6143
Rank	3	2	1

The graph showing optimum level of different control factor for Surface Roughness

Graph2: Average S/N ratio for Surface Roughness



Analysis of Variance for Surface Roughness

TABLE12: ANALYSIS OF VARIANCE (ANOVA) FOR SURFACE ROUGHNESS

FACTORS	DEGREE OF FREEDOM	SUM OF SQUARES	MEAN SQUARE	F- RATIO	% RATIO	RANK
CUTTING SPEED	2	0.8250	0.4125	0.5014≈1	11%	3
FEED	2	2.4656	1.2328	1.4985≈2	32.98%	2
DEPTH OF CUT	2	4.1847	2.0923	2.5434≈3	55.9%	1
ERROR	5					
POOLED ERROR	4	3.2906	0.8226			
TOTAL	8				100%	

The rank indicates the relative importance of each factor to the response. The rank and the delta values of each parameters shows that the depth of cut has the greatest effect on the surface roughness followed by feed rate and cutting speed in that order. As surface roughness is the "lower the best" type quality characteristic, it goes the following order like (A3) third level of cutting speed, (B2) second level of feed rate and (C1) the first level of depth of cut which results in minimum value for surface roughness.

(iv)Confirmation Experiment

In order to validate the results obtained, two confirmation results are conducted for each of the response characteristic (MRR, SR) at optimal levels of the process variables. The initial reading of factors obtained from S/N ratio, the optimum results obtained from the ANOVA are improved in both Material Removal Rate and Surface Roughness. It is to be pointed that the optimum values are within the specified range of the process variables. Table 12 and 13 show the confirmation result for material removal rate and surface roughness along with the highest and minimum combination of material removal rate and surface roughness.

Table13: Confirmation for Material Removal Rate

FACTORS	INITIAL READINGS OF FACTORS	OPTIMUM RESULT OBTAINED FROM ANOVA	IMPROVEMENT IN S/N RATIO
LEVEL	A3B1C3	A3B2C1	34.107 – 33.5357 = 0.571
MRR	47.51	50.74	
S/N RATIO	33.5357	34.107	

Table14: Confirmation for Surface Roughness

FACTORS	INITIAL READINGS OF FACTORS	OPTIMUM RESULT OBTAINED FROM ANOVA	IMPROVEMENT IN S/N RATIO
LEVEL	A2B2C3	A3B2C1	4.5829 – 3.7410 = 0.8419
SURFACE ROUGHNESS	0.65 (lower the best)	0.59	
S/N RATIO	3.741	4.5829	

5. CONCLUSIONS

Taguchi design of experiments is applied for turning parameters to obtain the optimal material removal rate and surface roughness. In the work, three turning parameters namely: cutting speed, feed rate and depth of cut [A], [B], [C], are selected for three levels. Experiments are conducted using L9 Orthogonal Array. Material removal rate and surface roughness are measured for each and every experiment. S/N ratios are calculated for all nine experiments to check the influencing cutting parameter for Material removal rate and Surface roughness. These ratios are calculated with consideration of performance characteristics: Higher-the-better, as the material removal rate is requested to be high and for Lower-the-best, as the surface roughness is requested to be low.

The initial reading of factors is obtained from Signal-to-Noise ratios (S/N) for both Material Removal Rate and Surface Roughness. The best combinations are obtained using ANOVA prediction. Cutting speed dominantly affects material removal rate, followed by feed rate and depth of cut in turning of EN24 alloy steel. It is concluded from the results that input parameter setting of cutting speed at 170 rpm, feed rate 0.1 mm/rev and depth of cut 0.8 mm, gives the optimum results for MRR. The percentage contribution of cutting speed (0.0643%), is followed by feed rate (0.1383%) and depth of cut (99.79%) in affecting the material removal rate. From the results, it is found that cutting speed is the most influencing parameter in affecting the surface roughness. The results revealed that minimizing surface roughness, the optimal cutting parameter is cutting speed 170 rpm, feed rate 0.1 mm/rev, and depth of cut 0.3 mm. The percentage contribution of cutting speed (11.0363%), is followed by feed rate (32.9832%) and depth of cut (55.9803%) in affecting surface roughness. In the present experiment there is an improvement in the S/N ratio in both the response variables that is Material Removal Rate (MRR) and Surface Roughness (R_a).

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