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Comparative Study of the Machinability Characteristics of Nimonic C-263 Super Alloy

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***Abstract*:-- Nickel base super alloy has the combined property of "high mechanical strength" and "High heat and corrosion resistance" at elevated temperature. This is the reason for which Nickel based super alloy are extremely used in Aircraft, Aerospace, Submarine and chemical industries. Machining of Nimonic C-263 has always been a challenging task owing to its hot strength, low thermal conductivity, tendency to work harden and affinity towards tool materials. Although coated tools have been used to overcome some of these challenges, selection of coated tool with appropriate deposition technique is of immense significance. The current study attempts to comparatively evaluate various performance parameters in machining of Nimonic C-263 such as surface roughness, cutting force, tool temperature and tool wear. The tool materials used for this study are cubic boron nitride(CBN), ceramic and PVD coated TiAlN. To determine the effects of parameters selection on machining using Design of Experiments (DOE), Taguchi. L9 / L27 orthogonal array design of experiments was adopted to optimize the parameters. By using Taguchi and Grey Relational Analysis / Analysis of Variance (ANOVA) etc., an optimum value or the best value of surface roughness, cutting force, tool temperature and tool wear is obtained.**

Key words: **Nimonic C-26, cubic boron nitride(CBN),ceramic and PVD coated TiAlN, Taguchi and ANOVA.**

I. INTRODUCTION

Purpose of the Work

The purpose of this work is to study the machinability characteristics of Nimonic C-263 a nickel based super alloy. The tool materials used for this study are namely ceramic tool, cubic boron nitride and PVD coated TiAlN. The input parameters are cutting speed depth of cut and feed rate while the performance parameters are tool wear, surface roughness, cutting forces and tool temperatures. Further, using the Taguchi method we will be calculating single objective optimization and will also optimize using multi objective algorithm to find the same.

Scope for the Work

Nimonic C-263 has a lot of application in aerospace industry, in submarines and chemical industry due to its extreme chemical and physical properties. Machining it has always been a difficult task because of its hot strength, low thermal conductivity and tendency to work harden. In this work we are trying to conduct a comparative study of the machining of Nimonic C-263 super alloy using three different tool material and find the optimum values of input parameters so that we can get the best surface roughness, less tool wear, less tool temperature and optimum value of cutting forces.

II. REVIEW OF LITERATURE

Ezilarasan et al. presented the experimental investigation and analysis of the machining parameters while turning the nimonic C-263 alloy, using whisker reinforced ceramic inserts. The experiments were designed using Taguchi's experimental design. The parameters considered for the experiments are cutting speed, feed rate and depth of cut. Process performance indicators, viz., the cutting force, tool wear and surface finish were measured [1]. Srinivas et al. explained that taguchi method is a statistical approach to optimize the process parameters and improve the quality of components that are manufactured. The objective of the study is to illustrate the procedure adopted in using Taguchi Method to a lathe turning operation [2].Senthil Kumar et al. studied the effects of the cutting parameters (cutting speed, feed rate and depth of cut) on the surface roughness in machining the Nimonic C-263 alloy were investigated. The experiments were conducted using Taguchi's experimental design. The effect of cutting parameters on surface roughness was evaluated and the optimum cutting conditions for minimizing the surface roughness were determined [3].Koyilada et al. attempts to comparatively evaluate various performance measures in machining of Nimonic C-263 such as surface roughness, cutting force, cutting temperature, chip characteristics, and tool wear with particular emphasis on different modes of tool failure for commercially available

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inserts with multi-component coating deposited using chemical vapour deposition (CVD) and physical vapour deposition (PVD) techniques. Influence of cutting speed (Vc) and machining duration (t) has also been investigated using both coated tools [4].Shuhokoseki et al. studied High-strength, low-conducting Ni-based super alloys require higher cutting force and cutting temperature than other materials during the machining process. To understand how the coating characteristics such as defects formation and physical and mechanical properties affect cutting performance, TiN coatings were deposited by three physical vapour deposition (PVD) methods (arc ion plating, sputtering, and hollow cathode) and chemical vapour deposition (CVD) [5].

III. GAPS IDENTIFIED

From the literature reviewed for the purpose of this work it was observed that the tool material used for the evaluation of machinability characteristics were limited to only PVD and CVD coated inserts. Also, tool temperature and cutting forces were not considered as performance parameters in many of them.

IV. METHODOLOGY

Experimental Procedure

A heavy-duty lathe machine was used for the purpose of conducting experiments. A round bar of Nimonic C-263 with 40 mm diameter and 110 mm length was used as the work piece. Chemical composition of Nimonic C-263 in wt.% is 52.49Ni, 20.79Cr, 19.12Co, 5.71Mo, 0.23Mn, 0.2Fe, 1.91Ti, 0.19Al, 0.09Cu, 0.02Si, 0.05C, 0.005S, 0.001Pb, 0.19Al and 0.001B. Commercially available ceramic, PVD coated carbide inserts and cubic boron nitride were used and their performance were compared. Surface roughness was measured using a roughness test at three different locations for each run and then average value was taken. A tool-work thermocouple was used to approximately measure cutting temperature. Cutting force was measured using dynamometer. Stereo zoom microscope was used to measure the average flank wear of both the coated tools after each run of experiment. The turning operation was carried out with three different cutting speeds (Vc), i.e. 300, 450 and 600 rpm. Three different feed (f) of 0.059, 0.103, 0.147 mm/rev and depth of cut (ap) of 0.5, 0.75, 1 mm were used to carry out the experiment. Each experimental run was continued for 20 mm length after which the tool was disengaged and surface roughness and tool wear were subsequently evaluated prior to next experimental run. At the end of the experimental run the values of all the parameters were calculated and noted for subsequent discussion.

Single Objective Optimization - Taguchi's Method

Dr Genichi Taguchi developed an engineering method of quality improvement referred as Quality Engineering in Japan and Robust Design in the West. According to the philosophy of Dr Taguchi, deviation from intended value in any of the product feature causes losses to customer, manufacturer and to the society. Therefore, emphasis is given on minimizing the losses by reducing the deviation. In this method, emphasis is given on concept selection and parameter optimization to make the robust product(s) and/or process (es). Robustness is attained by reducing the measured variation of key quality characteristics and ensuring that those quality characteristics can be easily adjusted onto the nominal value or target. Minimizing variation or making the system less sensitive to variation not only reduces the cost but also improves the quality of the product/process. Dr Taguchi created unique metrics, called as signal-to-noise ratios, to analyze a system's robustness. These metrics help us to take decisions regarding optimization of product/process concepts. The quality of the product/process (i.e. its performance) can vary due to many reasons. The causes of the variability are called noise factors. Noise factors are responsible for deviation of response or functional characteristics from its target value. Signal-to-noise ratio basically reflects the variability in the response of a system caused by noise factors (Khoei et al., 2002). There are varieties of S/N ratio characteristics, the selection of which is problem specific. The commonly used S/N ratio characteristics in quality engineering are as below (Phadke, 1989; Roy, (1990) :

Larger-the-better characteristics

$$\text{S/N Ratio} = -10\log_{10}(1/n)\sum_{i=1}^{n}\frac{1}{y_{ij}^2} \qquad \text{........(3.2.1)}$$

Smaller-the-better characteristics

$$\text{S/N Ratio} = -10\log_{10}(1/n)\sum_{i=1}^{n}y_{ij}^2 \qquad \text{........(3.2.2)}$$

Nominal-the-better characteristics

$$\text{S/N Ratio} = -10\log_{10}\left(\frac{\bar{y}}{S_y^2}\right) \qquad \text{.........(3.2.3)}$$

Where Yi is the experimentally observed value and n is the repeated number of each experiment.

$\bar{y}$ is the average of observed data and $\mathbf{S_y^2}$ is the variance of y. For each type of characteristics, with the above S/N transformation, the higher the S/N ratio the better is the result.

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V. DESIGN OF EXPERIMENT

A classical full factorial design considers all the possible combination of parameters. This increases the number of experiments and the time taken to do them. Under cost and time constraints, these many experiments cannot be conducted. That is why orthogonal arrays are considered for our project work. It is a special standard design that requires the minimum number of experiments to find the effects of parameters. The minimum number of experiments to be conducted in orthogonal designs is given by:

$N_{Taguchi} = 1 + N_v (L-1)$

$N_{Taguchi}$ = Number of experiments to be conducted

N_v = Number of variables

L = number of Levels

Run	Factors			
	Tool Material	Speed	Feed	Depth Of Cut
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table: L_9 orthogonal design

Multi Objective Optimization - Taguchi -Grey Relational Analysis:

Genichi Taguchi, a Japanese scientist, developed a technique based on orthogonal array (OA) of experiments. This technique has been widely used in different fields of engineering to optimize the process parameters. The integration of DOE with parametric optimization of process can be achieved in the Taguchi method. An orthogonal array (OA) provides a set of well-balanced experiments, and Taguchi's Signal-to-Noise(S/N) ratios, which are logarithmic functions of the desired output, serve as objective functions for optimization. It helps to learn the whole parameter space with a small number (minimum experimental runs) of experiments.

Orthogonal array (OA) and S/N ratios are used to study the effects of control factors and noise factors and to determine the best quality characteristics for particular applications. The optimal process parameters obtained from the Taguchi method are insensitive to the variation of environmental conditions and other noise factors. However, originally, Taguchi method was designed to optimize single-performance characteristics. Optimization of multiple performance characteristics is not straight forward and much more complicated than that of single-performance characteristics. To solve the multiple performance characteristics problems, the Taguchi method is coupled with grey relational analysis (GRA). This method was first proposed by Deng in 1982 to fulfill the crucial mathematical criteria for dealing with poor, incomplete, and uncertain system. This Grey based Taguchi technique has been widely used indifferent fields of engineering to solve multi-response optimization problems.

Normalization of S/N Ratio

It is the first step in the grey relational analysis; a normalization of the S/N ratio is performed to prepare raw data for the analysis where the original sequence is transferred to a comparable sequence. Linear normalization is usually required since the range and unit in one data sequence may differ from the others. A linear normalization of the S/N ratio in the range between zero and unity is also called as the grey relational generation. Further analysis is carried out based on these S/N ratio values. If the target value of original sequence is infinite, then it has a characteristic of the "higher is better". Maximization of the quality characteristic of interest can be expressed as

Higher is better". The original sequence can be normalized as follows:

$$x^*_i(k) = \frac{x^o{}_i(k) - \min x^o{}_i(k)}{\max x^o{}_i(k) - \min x^o{}_i(k)} \quad \text{... ... ...} \quad (3.3.1)$$

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

$$x^*_i(k) = \frac{\max x^o{}_i(k) - x^o{}_i(k)}{\max x^o{}_i(k) - \min x^o{}_i(k)} \quad \text{... ... .} (3.3.2)$$

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

$$x^*_i(k) = 1 - \frac{|\, x^o{}_i(k) - x^o |}{\max x^o{}_i(k) - x^o} \quad \text{.... . ...} \quad (3.3.3)$$

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

$$x^*_i(k) = \frac{x^o{}_i(k)}{x^o{}_i(1)} \quad \text{... ... ...} \quad (3.3.4)$$

Where $i = 1..., m; k = 1..., n$. m is the number of experimental data items and n is the number of parameters. $x^o{}_i(k)$ Denotes the original sequence, $x^*{}_i(k)$ the sequence after the data pre-processing, max $x^o{}_i(k)$ the largest value of

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$x^o{}_i(k)$, min $x^o{}_i(k)$ the smallest value of $x^o{}_i(k)$, and x^o is the desired value.

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. $\gamma(x_0(k), x_i(k))$ can be expressed by Eq. 3.3.5 .

$$\gamma(x_0(k), x_i(k)) = \frac{\Delta \min + \xi \Delta \max}{\Delta_{0i}(k) + \xi \Delta \max} \qquad ....(3.3.5)$$

Where, $\Delta_{\min}$ is the smallest value of $\Delta 0_i(k) = \min_i \min_k \left| x_0^*(k) - x_i^*(k) \right|$ and $\Delta_{\max}$ is the largest value of $\Delta 0_i(k) = \max_i \max_k \left| x_0^*(k) - x_i^*(k) \right|$, $x_0^*(k)$ is the ideal normalized S/N ratio, $x_i^*(k)$ is the normalized comparability sequence, and ζ is the distinguishing coefficient. The value of ζ can be adjusted with the systematic actual need and defined in the range between 0 and 1, ζ ∈ [0, 1]. It will be 0.5 generally [15].

Determination of Grey Relational Grade (GRG)

The overall evaluation of the multiple performance characteristics is based on the grey relational grade. The grey relational grade [5] is an average sum of the grey relational coefficients which is defined as follows:

$$\gamma(x_0, x_i) = \frac{1}{m} \sum_{i=1}^{m} \gamma(x_0(k), x_i(k)) \qquad .... (3.3.6)$$

Where $\gamma(x_0, x_i)$ the grey relational grade for the jth experiment and '*m*' is the number of response characteristics

If the two sequences agree at all points, then their grey relational coefficient is 1 everywhere and therefore, their grey relational grade is equal to 1. In view of this, the relational grade of two comparing sequences can be quantified by the mean value of their grey relational coefficients and the grey relational grade. The grey relational grade also indicates the degree of influence that a 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.

Single Objective Optimization For Tool Temperature

Tool material	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	Tool temp (^{0}C)
CERAMIC	300	0.059	0.5	76
CERAMIC	450	0.103	0.75	60
CERAMIC	600	0.147	1	57
PVD COATED	300	0.103	1	92
PVD COATED	450	0.147	0.5	96
PVD COATED	600	0.059	0.75	54
CUBIC BORON NITRIDE	300	0.147	0.75	64
CUBIC BORON NITRIDE	450	0.059	1	80
CUBIC BORON NITRIDE	600	0.103	0.5	91

Table 1: Experimental Reading

Level	Tool material	speed	feed	Depth of cut
1	-36.10	-37.67	-36.78	-38.81
2	-37.86	-37.76	-38.01	-35.44
3	-37.79	-36.32	-36.96	-37.49
Delta	1.76	1.44	1.23	3.37
Rank	2	3	4	1

Table 2: Response Table for Signal to Noise Ratios of tool temperature

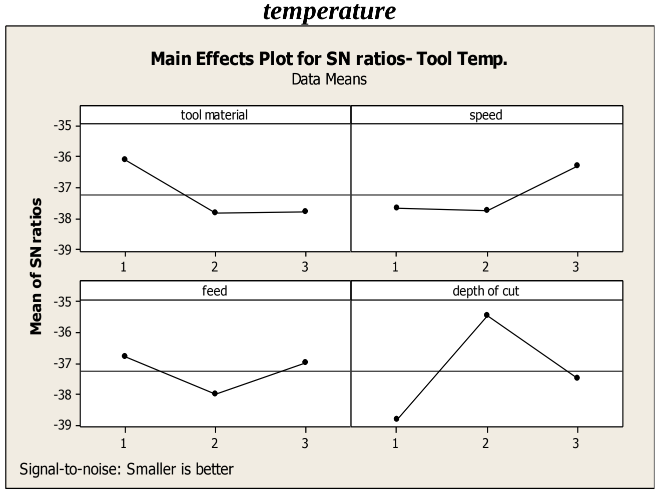

Figure 1: SN Ratio graph for tool temperature with different input parameters.

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The single objective optimization solution for tool temperature with respect to different input parameters as found from the Taguchi's DOE is as follows:

Input parameters	Optimized value
Tool material	PVD coated tool insert
Cutting speed	450 rpm
Feed rate	0.103 mm/rev
Depth of cut	0.5 mm

Table 3: Optimized values for input parameters for tool temperature

Source	DF	SS	MS	F	P	%
tool material	2	468.22	234.111	0.66	0.566	22.08
speed	2	230.22	115.111	0.32	0.741	10.85
feed	2	201.56	100.778	0.58	0.602	9.51
depth of cut	**2**	**1220.22**	**610.111**	**3.49**	**0.133**	**57.55**
Error	0	0				
Total	8	2120.22	1060.11			
99.99						

ANOVA: tool temp. Vs tool material, speed, feed, depth of cut

Among various objectives of input parameters DEPTH OF CUT has maximum influence on tool temperature by analysing S-N ratio graph, the quality characteristic of tool temperature. In accordance that smaller is better and yields optimum quality with minimum variance, lower the depth of cut lower the tool temperature.

Similarly Tool Forces(Fx, Fy, Fz), Surface Roughness, Tool Wear and Material Removal Rate are analysed.

Multi Objective Optimization- Grey Relational Analysis
In the following analysis:
A is Tool Material
B is Speed
C is Feed
D is Depth of Cut

A	B	C	D	TC	Fx	Fy	Fz	Ra	Nose	Crater	Flank	MRR	GRG	Rank
1	1	1	1	76	88.51	244.30	193.4	0.511	547.61	799.59	305.69	18.303	0.477774	5
1	2	2	2	60	115.00	409.60	309.1	0.791	1002.60	720.05	829.99	71.440	0.610371	2
1	3	3	3	57	142.30	284.80	333.3	1.074	525.53	667.21	444.60	180.107	0.581686	4
2	1	2	3	92	86.00	135.90	175.0	1.051	132.04	526.77	172.96	63.098	0.443723	7
2	2	3	1	96	53.79	121.70	151.2	1.304	121.88	496.01	111.72	68.406	0.455878	6
2	3	1	2	54	59.72	93.63	95.9	2.214	132.04	259.54	152.55	54.560	0.401519	9
3	1	3	2	64	134.30	233.30	215.0	0.881	416.26	315.02	121.88	67.970	0.404664	8
3	2	1	3	80	331.70	661.90	284.1	2.360	670.33	436.85	335.52	54.216	0.674402	1
3	3	2	1	91	46.21	373.30	137.4	0.826	924.30	639.94	934.46	63.900	0.586488	3

Table 3: Grey Relational Grading

According to the above Table, we infer that the 8th experiment is the best according to the statistical analysis using Grey Relational Analysis.
Response Table for Signal to Noise Ratios
Larger is better

Level	A	B	C	D
1	-5.137	-7.110	-5.921	-5.958
2	-7.269	-4.844	-5.327	-6.691
3	-5.305	-5.756	-6.462	-5.062
Delta	2.132	2.266	1.136	1.629
Rank	2	1	4	3

Table 4: Taguchi Analysis: GRG versus A, B, C, and D
From the above Table, we can conclude that Spindle Speed is the most influential factor among all the input parameters.

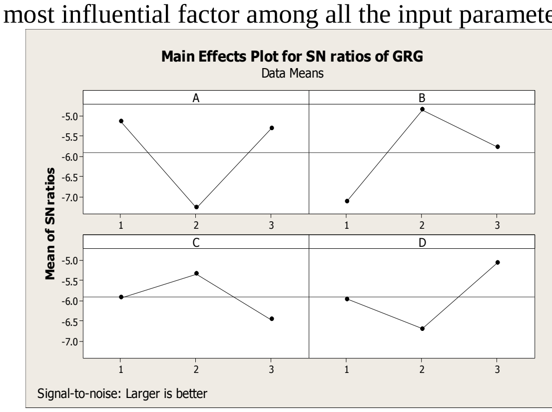

Figure 2: SN ratio graph for GRG with different input parameters

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Source	DF	SS	MS	F	P
A	2	0.0298643	0.0149322	2.94	0.164
B	2	0.0289262	0.0144631	2.85	0.170
C	2	0.0065909	0.0032955	0.22	0.809
D	2	0.0136941	0.0068470	0.47	0.658
Error	0	0	0		
Total	8	0.0790755			

Table 5:Two-way ANOVA: GRG versus A, B, C, D Predictor

Predictor Constant	Coef	SE Coef	T	P
	0.4127	0.2071	1.99	0.117
A	-0.00071	0.05072	-0.01	0.989
B	0.04059	0.05072	0.80	0.468
C	-0.01858	0.05072	-0.37	0.733
D	0.02995	0.05072	0.59	0.587

Table 6: Regression Analysis: GRG versus A, B, C, D

S = 0.07121 R-Sq = 74.35% R-Sq(adj) = 48.69%

Regression Analysis: GRG versus A, B, C, D

The regression equation is

GRG = 0.413 - 0.0007 A + 0.0406 B - 0.0186 C + 0.0299 D

S = 0.124234 R-Sq = 21.9% R-Sq(adj) = 0.0%

Table 7: Analysis of Variance

Source	DF	SS	MS	F	P
Regression	4	0.01734	0.00433	0.28	0.877
Residual Error	4	0.06174	0.01543		
Total	8	0.07908			

Source	DFSeq	SS
A	1	0.00000
B	1	0.00988
C	1	0.00207
D	1	0.00538

CONCLUSION

- We performed single objective optimization using Taguchi design of experiments methodology. Further, multi-objective optimization using Grey Relational Analysis was also performed for better results. Following are the conclusions:
- In order to improve Tool Temperature response characteristics using Taguchi analysis, depth of cut must be adjusted as it has the highest impact on it. Feed rate has the least impact on the process.
- In order to improve tool force Fx response characteristics using Taguchi analysis, depth of cut must be adjusted as it has the highest impact on it. Feed rate has the least impact on the process.
- In order to improve tool force Fy response characteristics using Taguchi analysis, tool material must be adjusted as it has the highest impact on it. Depth of cut has the least impact on the process.
- In order to improve tool force Fz response characteristics using Taguchi analysis, tool material must be adjusted as it has the highest impact on it. Depth of cut has the least impact on the process.
- In order to improve Surface Roughness response characteristics using Taguchi analysis, tool material must be adjusted as it has the highest impact on it. Feed rate has the least impact on the process.
- In order to improve Nose Wear response characteristics using Taguchi analysis, tool material must be adjusted as it has the highest impact on it. Depth of cut has the least impact on the process.
- In order to improve Crater Wear response characteristics using Taguchi analysis, tool material must be adjusted as it has the highest impact on it. speed has the least impact on the process.
- In order to improve Flank Wear response characteristics using Taguchi analysis, tool material must be adjusted as it has the highest impact on it. speed has the least impact on the process.
- In order to improve MRR response characteristics using Taguchi analysis, feed rate must be adjusted as it has the highest impact on it. Tool material has the least impact on the process.

- Optimal combination of parameters using Taguchi methodology for lowest tool temperature is 2-2-2-1.
- Optimal combination of parameters using Taguchi methodology for lowestFx is 3-2-1-3.
- Optimal combination of parameters using Taguchi methodology for lowest Fy is 3-2-2-3.
- Optimal combination of parameters using Taguchi methodology for Fz is 1-2-3-3.
- Optimal combination of parameters using Taguchi methodology for Sourface Roughness is 2-2-1-3.
- Optimal combination of parameters using Taguchi methodology for lowest Nose Wear is 1-2-2-1.
- Optimal combination of parameters using Taguchi methodology for lowest Crater Wear is 1-2-2-1.
- Optimal combination of parameters using Taguchi methodology for lowest Flank Wear is 1-3-2-1.
- Optimal combination of parameters using Taguchi methodology for largest MRR is 1-3-3-3.
- Grey Relational Analysis was used for multi-objective optimization of the process. The recommended optimal setting for the process after optimization is 3-2-1-3.

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