Multi Response Optimization of Hard Turning Process Parameters for OHNS Steel by Taguchi Based Grey Relational Analysis and Assignment of Weights Method

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Abstract: *The Scope of the current work is to multi optimize the hard turning parameters for OHNS (Oil Hardened Non Shrinkage) steels through taguchi based Grey Relational Analysis (GRA) and Assignment of weights method and also to identify the significant parameter influencing the output characteristics considerably. The present work considers the hard turning operation parameters such as cutting speed, feed and depth of cut to measure the output characteristics such as cutting force, material removal rate (MRR), surface roughness and tool wear. The results obtained through the experimental design matrix generated by adopting Taguchi's L_9 Orthogonal array has been considered for multi objective optimization. The research findings have shown that through Assignment of weights method the optimized parameter combination is found to be A3B3C3 and the depth of cut is the significant parameter followed by feed and cutting speed. The optimized parameter setting recommended from GRA is found to be A3B1C1 and Cutting speed is found to be the most significant parameter followed by Feed and Depth of Cut. In both the analysis methods Feed takes the second position as dominant or influencing factor out of the three parameters considered.*

Keywords: Assignment of Weights, Grey Relational Analysis, Hard Turning, Multi Response Optimization, OHNS Steels, Taguchi's Orthogonal Array

1. INTRODUCTION

Manufacturing process of any method (Additive, Formative, and Subtractive) consists of crucial factors which has a severe impact or influence over the output characteristics of the end product. The improper selection of the manufacturing parameters results with a component or part with poor characteristics which may further lead to the rejection of the manufactured part in quality assessment. The general output characteristics associated with any subtractive manufacturing processes are high surface finish, high material removal rate, reduced tool wear, enhanced dimensional accuracy, low machining time and setup time. The above mentioned output characteristics can be achieved through proper selection of cutting parameters through the optimization of process parameters either as a single objective or multi objective manner . The optimized parameter combination obtained for one output characteristic may not provide accurate results in case of other output characteristics associated with the problem. Problems with multiple objectives prevails everywhere and techniques or methods such as Grey Relational Analysis, Desirability Function analysis, TOPSIS (Technique of Order Preference Similarity to the Ideal Solution) and many other methods have been developed in the recent decades to solve the multi objective problem in an effective manner. Raneen Abd Ali et.al[1] conducted multi response optimization study of face milling process parameters for AL-2024 alloys using grey relational analysis by varying the parameters such as cutting speed , feed , depth of cut and tool path strategy and adopted Taguchi L_{27} Orthogonal array for conducting experimental trials and found that the cutting speed has the maximum contribution with 74.72% towards the output responses and tool path strategy is found to have a significant influence over the surface roughness and topography. Rafał Swiercz et.al [2] investigated the Electric Discharge machining parameters such as Discharge current, pulse time and time interval for tool steel 55NiCrMoV7 by adopting desirability function approach for three different cases namely finishing, semi finishing and roughing operation. The authors have concluded that the factors discharge current and pulse time have significant effect over the surface roughness and white layer thickness , but the factor time interval has significant effect only over the process stability. S.Muniraj et.al [3] analysed the effect of turning parameters for micro alloyed steel by considering cutting speed, feed and depth of cut by adopting Taguchi based Grey Relational Analysis coupled with principal component analysis. Nikolaos Fountas et.al [4] studied the effect of cutting parameters while turning brass alloy by adopting taguchi based experimental design and grey wolf algorithm by considering the three major parameters cutting speed, feed and depth of cut. Doreswamy Deepak and Rajendra Beedu [5] reported about the effective parameters in turning of Al-6061 alloy by using Taguchi based Grey analysis method and concluded that Feed rate is the most significant factor that influences MRR and surface finish than cutting speed and depth of cut. Shen-Jenn Hwang and Yi-Hung Tsai [6] experimented and optimized the turn – boring process parameters such as concentration of cutting fluid, cutting fluid temperature, feed rate, depth of cut and cutting speed for 15-5PH stainless steel to understand the surface roughness roundness error and material removal rate by Taguchi based grey relational analysis. Franko Puh et.al [7] have utilized taguchi based grey relational analysis for optimizing the turning process parameters such as cutting speed , feed and depth of cut to find the optimum combination of input parameters which reduces the surface roughness and increases the material removal rate. Suha K. Shihab et.al [8] has studied the multi response optimization of hard turning process parameters by applying grey relational analysis along with principal component analysis for AISI (American Iron and Steel Institute) 52100 hard alloy using a CNC machine . The experimental results are further analysed using ANOVA (Analysis of Variance) and depth of cut is found to be the most significant factor influencing surface roughness and cutting forces. Mahadev Naik et.al [9] has conducted optimization study on turning process parameters for AISI 410 steel using taguchi's orthogonal array and ANOVA. The authors have concluded that the factor feed rate has more significant impact over the surface roughness of the specimens studied. P Raveendran and P Marimuthu [10] have studied the multiple optimization of turning parameters for glass fibre reinforced plastic composite rod using TiCN/TiN coated tool through grey relational analysis and desirability function for simultaneous evaluation of optimal conditions obtained. The authors have applied ANOVA to identify the significant parameter and stated that depth of cut has more significance towards both surface roughness and tool wear. P. C. Mishra et.al [11] studied the multi response optimization of parameters involved in turning of AA 7075/SiC composites in dry and spray cooling environments using Grey relational analysis. Parvinder Singh and A. S. Channi [12] investigated about the influencing process parameter and Multi optimal process conditions for turning of AISI D2 tool steel using weighted product approach and Taguchi's L9 Orthogonal Array for experimental design. Arun Kumar et.al [13] analysed the influence of cutting parameters such as Cutting speed , Depth of cut and feed while cutting GFRP (Glass Fibre Reinforced Plastics) material in the form of a circular bar of 40mm diameter using Taguchi's L9 orthogonal array and TOPSIS method . The authors have identified that depth of cut has a greater influence over MRR and lesser influence over surface roughness than speed and feed. B. Vijay Krishna Teja [14] investigated about the multi response optimization of milling parameters for on AISI 304 stainless steel in a CNC machine using tungsten carbide end mill by Taguchi based Grey relational analysis to evaluate the surface roughness and material removal rate of the finished work piece. Cutting speed is found to have the maximum influence. S. Ranganathan and T. Senthilvelan [15] have studied the multi response optimization of hot turning parameters for Stainless Steel (Type 316) using grey relational analysis considering the parameters cutting speed, feed, and depth of cut and temperature of the work piece using a conventional lathe. The optimization study has revealed that feed rate and cutting speed are the dominant variables in multi performance analysis for the output characteristics such as tool life, material removal rate and surface roughness. Kamaljit Singh and C S Kalra [16] studied the effect of machining parameters such as peak current, flushing pressure, pulse on time and voltage gap for OHNS steel to evaluate the material removal rate and micro hardness and they have found that current has more significance over the material removal rate and in case of micro hardness flushing pressure is found to be more significant than other parameters considered for investigation. Anil Raj et.al [17] has investigated the performance of OHNS steels during hard turning by using the two different conditions namely Minimal Quantity Lubrication and Minimum cutting fluid application as per taguchi's orthogonal array experimental design and the results of tool wear pattern were compared using SEM images with the wet and dry turning conditions. . Anshuman Das et.al [18] found that mist cooled environment is better than dry cutting for the hard turning of EN24 alloy steel by using a coated cermet tool. The authors have concluded that the chip morphology and surface finish were better in terms of mist cooled environment than dry cutting environment. Chaudhari Y D [19] investigated that the tool wear in hard turning of AISI H11 material using tool materials such as high CBN, low CBN and mixed ceramic by Taguchi's Orthogonal Array and found that hardness is the most influencing factor over tool wear with a contribution of 43.30% than other factors considered in the study. Prof. Sande A. N [20] conducted optimization study in hard turning of AISI D2 Steel by adopting Plackett-Burman design to evaluate the cutting force, residual stresses and surface roughness by considering the hard turning input variables such as Cutting speed, Feed and Depth of Cut and he has found that better surface roughness is obtained in dry turning environmental condition.

2. MATERIALS AND METHODS

2.1 OHNS Steels

The present work considers OHNS steel as the work piece material with a hardness of 48HRC for turning under different combination of process parameters of hard turning such as Cutting speed, Feed and Depth of Cut. The material of the work piece is OHNS steel which is a general purpose tool steel with very low shrinkage and used in applications where the alloy steels are found to be incapable to provide the expected hardness, strength and wear resistance. World association of steels have listed around 3600 grades of steel which are used in industrial, commercial and other applications. OHNS steel are found to be used as a raw material to manufacture blanking and stamping dies , reamers , rotary shear blades , milling cutters and so on. The hardening temperature of OHNS steel lies between 7900 °C and 8200 °C. The various elements such as Carbon, Manganese, Silicon, Chromium and Vanadium are present and their chemical composition for the OHNS steels are shown in Table 1

Table - 1 Percentage Composition of Elements for OHNS Steel

Elements	Carbon	Manganese	Silicon	Chromium	Vanadium
% Composition	0.94	1.2	0.30	0.50	0.15

2.2 Hard Turning

Becoming a competitor to the grinding process, hard turning is considered to be a fast growing technology in machining materials with hardness value ranging between 45 HRC to 65 HRC. The potential benefits of hard turning over grinding process includes low setup time, machining complex structures both internal and external surfaces, single part clamping and so on. Such potential benefits of hard turning process has attracted the researchers in considering this process as a competitor to grinding process which generally has a higher setup time and few other disadvantages associated . Hard turning of materials can be machined in a conventional or numerical controlled lathe.

3. Experimental Work

A nine experimental trial, three different input variables varying at three levels forms the experimental design matrix obtained through MINITAB 17.0 software as per Taguchi's orthogonal array. The input parameters such as cutting speed, Feed and Depth of cut has been considered to vary at three levels and the output responses considered are Material Removal Rate, Cutting Force in Z direction, Tool wear and Surface roughness. As per the variables and levels selected in this work L_9 and L_{27} Orthogonal array (OA) can be considered for the preparation of experimental plan. L_{27} Orthogonal array consists 27 experiments and it is full factorial design and L9 consists only 9 experiments which is fractional factorial experiment which can provide results with good agreement. The Table 2 shows the different input variables that have been varied during machining the work piece and Table 3 shows the different output responses considered for further evaluation through optimization techniques.

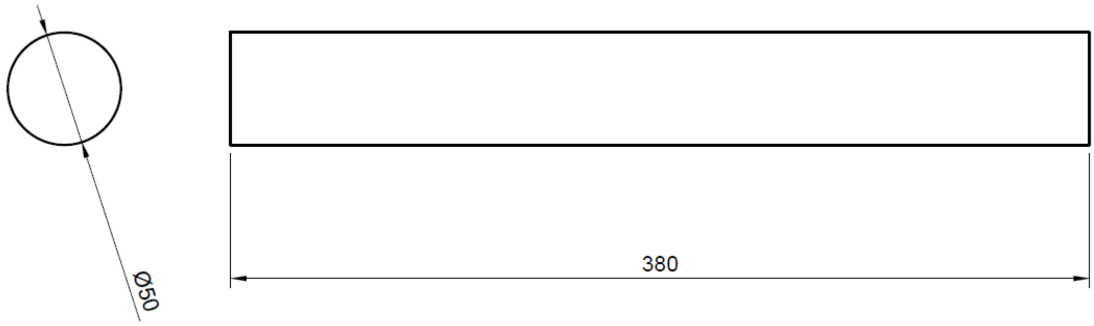
Table - 2 Hard Turning Input Parameters and their Varying Levels

Input Parameters	S.I Unit	Symbol	Level 1	Level 2	Level 3
Cutting Speed	mm/min	A	80	90	100
Feed Rate	mm/rev	B	0.07	0.08	0.09
Depth of Cut	mm	C	0.3	0.6	0.9

Table - 3 Output Responses for Measurement

Output Responses	S.I Unit	Symbol
Surface Roughness	mm	R1
Cutting Force	N	R2
Tool Wear	mm	R3
Material Removal Rate	mm^3/min	R4

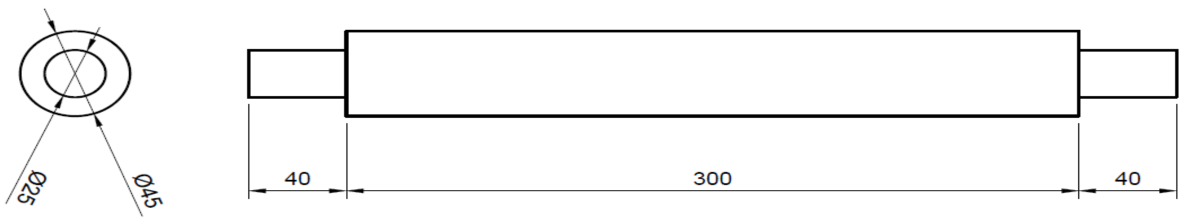
The work piece considered for machining is a circular rod of 380mm in total length and 50 mm in diameter made out of OHNS steel. Both the ends of the bar are machined to 25mm diameter for a length of 40mm and the remaining 300m length is machined to 45 mm diameter throughout. The Figure 1 and 2 shows the 2D diagram and solid model of the raw material for machining and Figure 3 and 4 shows the 2D diagram and solid model of the finished workpiece after machining. The machining of the workpiece is done in a master lathe and the tool selected for the hard turning process consists a multicoated hard metal inserts with sculptured rake face geometry with the specification SNMG 120408 MT TT5100 from Taegu Tec coated with TiC and TiCN. The tool holder has dimensions as 25 mm x 25 mm x 145 mm. The Table 4 represents the experimental design matrix or plan for the current study and it consists a total of nine experimental trials by mixing the input parameters with the defined levels.



(All Dimensions are in mm)

Figure - 1 2D Drawing of the Raw material for Machining

Figure - 2 3D Solid Model of the Raw material



(All Dimensions are in mm)

Figure - 3 2D Drawing of the Workpiece after Machining

Figure - 4 3D Solid Model of the Machined Workpiece

Table - 4 Taguchi's Experimental Design Matrix with Coded and Uncoded Values

Sl. no	Coded Values			Uncoded Values		
	A (mm/min)	B (mm/rev)	C (mm)	A (mm/min)	B (mm/rev)	C (mm)
1	1	1	1	80	0.07	0.3
2	1	2	2	80	0.08	0.6
3	1	3	3	80	0.09	0.9

4	2	1	3	90	0.07	0.9
5	2	2	1	90	0.08	0.3
6	2	3	2	90	0.09	0.6
7	3	1	2	100	0.07	0.6
8	3	2	3	100	0.08	0.9
9	3	3	1	100	0.09	0.3

Table - 5 Experimental Results of Various Output Parameters

Sl. no	A	B	C	Surface roughness, Ra	Cutting Force, Fz	Tool Wear	MRR
	(mm/min)	(mm/rev)	(mm)	(mm)	(N)	(mm)	mm^3/min
1	80	0.07	0.3	1.163	270.2	0.047	1.68
2	80	0.08	0.6	1.175	279.4	0.057	3.84
3	80	0.09	0.9	1.158	275.3	0.068	6.48
4	90	0.07	0.9	0.994	241.6	0.043	5.67
5	90	0.08	0.3	0.924	225.8	0.031	2.16
6	90	0.09	0.6	1.162	264.3	0.062	4.86
7	100	0.07	0.6	0.635	225.4	0.036	4.2
8	100	0.08	0.9	0.952	255.6	0.048	7.2
9	100	0.09	0.3	0.783	242.3	0.042	2.7

The Table 5 represents the output values obtained post to the experimental work. The output characteristic Material Removal Rate can be obtained directly from the product of cutting speed, feed and depth of cut. The other parameters such as surface roughness, tool wear and Cutting force have been measured using standard equipment or device after completing the machining work as per the experimental plan. The results obtained are further utilized for conducting the multi objective optimization.

MRR = Cutting Speed x Feed Rate x Depth of Cut (1)

4. GREY RELATIONAL ANALYSIS

Grey Relational Analysis (GRA) is a technique which is used to solve the interrelationships among the multiple responses. The method is also known as Deng's Grey Incidence Analysis model developed by a Chinese professor during 2002. The analysis consists of three major steps to attain the optimized parameter setting by normalizing the experimental data as the starting step. The procedure of normalization is nothing but a transformation performed on a single input to distribute the data evenly and scale it into acceptable range for further analysis. The normalization the procedure gets continued in finding out the values of deviation sequence and grey relation coefficient in one step and finding out the grey relational grade will be the closing one of the analysis procedure. The Grey Relational Grade obtained will be considered as MRPI (Multi Response Performance Index) for obtaining the optimized parameter setting by calculating the MRPI values for individual levels of the input parameters considered.

For the output responses with Larger the Better Case of Normalization

$$Z_{ij} = \frac{Y_{ij} - Min\,Y_{ij}}{Max\,Y_{ij} - Min\,Y_{ij}} \quad (2)$$

For the output responses with Smaller the Better Case of Normalization

$Z_{ij} = \frac{Max\, Y_{ij} - Y_{ij}}{Max\, Y_{ij} - Min\, Y_{ij}}$ (3)

Z_{ij} = *Normalized value for the ith experiment/trial for the jth dependent variable /response*

For Calculation of Deviation Sequence

$\Delta_{0i} = X_{0k} - X_{ik}$ (4)

For Calculating Grey Relational Coefficient

$GC_{ij} = \frac{\Delta_{min} + \lambda \Delta_{max}}{\Delta_{0i} + \lambda \Delta_{max}}$ (5)

For Calculating the Grey Relational Grade

$G_i = \frac{1}{m} \sum GC_{ij}$ (6)

m – No of output responses

Table - 6 Normalized Values of Output Responses

Normalized Values			
Surface roughness, Ra	**Cutting Force, Fz**	**Tool Wear**	**MRR**
(mm)	**(N)**	**(mm)**	**mm^3/min**
0.0222	0.1704	0.5676	0.0000
0.0000	0.0000	0.2973	0.3913
0.0315	0.0759	0.0000	0.8696
0.3352	0.7000	0.6757	0.7228
0.4648	0.9926	1.0000	0.0870
0.0241	0.2796	0.1622	0.5761
1.0000	1.0000	0.8649	0.4565
0.4130	0.4407	0.5405	1.0000
0.7259	0.6870	0.7027	0.1848

Table - 7 Deviation Sequence Values of Output Responses

Deviation Sequence			
Surface roughness, Ra	**Cutting Force, Fz**	**Tool Wear**	**MRR**
(mm)	**(N)**	**(mm)**	**mm^3/min**
0.9778	0.8296	0.4324	1.0000
1.0000	1.0000	0.7027	0.6087
0.9685	0.9241	1.0000	0.1304
0.6648	0.3000	0.3243	0.2772
0.5352	0.0074	0.0000	0.9130
0.9759	0.7204	0.8378	0.4239

0.0000	0.0000	0.1351	0.5435
0.5870	0.5593	0.4595	0.0000
0.2741	0.3130	0.2973	0.8152

Table - 8 Grey Relational Coefficient Values for Output Responses

Grey Relational Coefficient			
Surface roughness, Ra	**Cutting Force, Fz**	**Tool Wear**	**MRR**
(mm)	**(N)**	**(mm)**	**mm^3/min**
0.5056	0.5466	0.6981	0.5000
0.5000	0.5000	0.5873	0.6216
0.5080	0.5197	0.5000	0.8846
0.6007	0.7692	0.7551	0.7830
0.6514	0.9926	1.0000	0.5227
0.5061	0.5813	0.5441	0.7023
1.0000	1.0000	0.8810	0.6479
0.6301	0.6413	0.6852	1.0000
0.7849	0.7616	0.7708	0.5509

Table - 9 Grey Relational Grade or MRPI Index with Ranking

Trial No	**GRG**	**Rank**
1	0.5626	8
2	0.5522	9
3	0.6031	6
4	0.727	4
5	0.7917	2
6	0.5834	7
7	0.8822	1
8	0.7392	3
9	0.7171	5

Table - 10 Level Totals of MRPI Values

Input Variables	**Level 1**	**Level 2**	**Level 3**	**Difference**
Cutting Speed	1.7179	2.1021	**2.3384**	**0.6205**
Feed	**2.1718**	2.0831	1.9036	0.2682
Depth of Cut	**2.0713**	2.0179	2.0692	0.0534

The Table 6 shows the normalized values of output responses as per equation 2 and 3. Table 7 shows the values of deviation sequence and Table 8 grey relational coefficient as per equation 4 and 5. The values of Grey Relational Grade (MRPI) calculated as per equation 6 and its rankings are shown in Table 9. The level totals of MRPI values of the input variables is shown in Table No 10 and it has shown that the parameter setting A3B1C1 will yield a higher material rate with less tool wear, surface roughness and cutting force. Cutting speed is the most significant parameter than other parameters such as feed and depth of cut.

5. ASSIGNMENT OF WEIGHTS METHOD

In assignment of weights method, the multi response problem is converted in to a single response problem The present work has four different output characteristics namely cutting force, Material Removal Rate (MRR), Surface Roughness and Tool wear respectively. The output characteristic Material Removal Rate is considered to have an attribute of Larger the Better case and other parameters are considered to have smaller the better case. The weights for the individual trials need to be found for calculating the MRPI (Multi Response Performance Index) value and calculation of weights vary for the larger the better and smaller the better characteristics.

For Larger the Better case

$W_j = \frac{y_{ij}}{\Sigma y_n}$ (7)

For Smaller the Better case

$W_j = \frac{(1/y_{ij})}{(1/\Sigma y_n)}$ (8)

Where *Wj and* y_{ij} represents the Weight of the jth response / dependent variable and Observed data of the ith trial/experiment under jth response

Σy_n = Sum of yij of all the trials conducted

$(MRPI)_i = W_1 Y_{11} + W_2 Y_{12} + \ldots\ldots\ldots\ldots + W_{ij} Y_{ij} Y_{ij}$ (9)

Table - 11 Weight Calculation of Output Responses and MRPI Values

Trial No	R1 (mm)	W_{SR}	R2 (N)	W_{CF}	R3 (mm)	W_{TW}	R4 mm3/min	W_{MRR}	MRPI	Rank
1	1.163	7.6922	270.2	8.4378	0.047	9.2340	1.68	0.04222	2289.35	9
2	1.175	7.6136	279.4	8.16	0.057	7.6140	3.84	0.09651	2289.65	6
3	1.158	7.7254	275.3	8.2815	0.068	6.3824	6.48	0.16285	2290.34	2
4	0.994	9	241.6	9.4367	0.043	10.0930	5.67	0.1425	2290.09	3
5	0.924	9.6818	225.8	10.097	0.031	14.0000	2.16	0.05428	2289.40	8
6	1.162	7.6988	264.3	8.6262	0.062	7.0000	4.86	0.12214	2289.87	4
7	0.635	14.0882	225.4	10.1149	0.036	12.0556	4.2	0.10555	2289.72	5
8	0.952	9.3971	255.6	8.9198	0.048	9.0417	7.2	0.18095	2290.58	1
9	0.783	11.4253	242.3	9.4094	0.042	10.3333	2.7	0.06786	2289.46	7

Table - 12 Level Totals of MRPI Values

Input Variables	**Level 1**	**Level 2**	**Level 3**	**Difference**
Cutting Speed	6869.33	6869.35	**6869.76**	0.43
Feed	6869.16	6869.63	**6869.67**	0.51
Depth of Cut	6868.21	6869.24	**6871**	**3**

The calculation of respective weights for Material removal rate as Larger the Better characteristic is done as per equation 7 and for the weight calculation of other parameters such as tool wear, cutting force and surface roughness which falls under the category of smaller the better characteristic is done from equation 8. The Multi Response Performance Index is obtained from equation 9.Table 11 represents the calculation of weights for various parameters based upon their characteristic and MRPI value and their rankings. Table 12 represents the Level totals of MRPI values of input parameters. From the MRPI level totals the multi response optimized parameter setting is found to be A3B3C3 and Depth of cut is found to be the most influencing factor with top ranking and followed by Feed and cutting speed.

6. CONCLUSIONS

The concluding remarks about the present work may be detailed herewith for better understanding of the above study conducted.

1. The machining work carried out using OHNS steel for the calculation of output characteristic with varying attributes (Larger the better and Smaller the better) has been done and the experimental data is further analysed through two different multi response optimization techniques such as Grey Relational Analysis and Assignment of Weights method.
2. The analysis of experimental output data through Grey Relational Analysis has shown that the optimized parameter setting A3B1C1 (Higher Cutting Speed, Low Feed Rate and Low Depth of Cut) may yield results with maximized material removal rate and reduced tool wear, surface roughness and cutting force during machining the steel.
3. The Factor Cutting speed is found to be more significant over the measured output characteristics followed by feed rate and depth of cut as per GRA.
4. The Optimized parameter setting obtained through Assignment of Weights method shows that the all the three factors namely cutting speed , feed and depth of cut has to be taken at higher levels (A3B3C3) for achieving the maximum material removal rate and other outputs with low values.
5. Depth of Cut ranks top in case of the analysis done by using Assignment of Weights method and it is followed by feed and cutting speed.
6. As a similarity from both the analysis methods Feed ranks second in case of influencing factor consideration.
7. Confirmation tests may be done for validating the optimized parameter setting obtained from both the methods and to understand the accuracy in prediction of the parameter combination.

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