Optimization of Cutting Parameters in High Speed Turning by Grey Relational Analysis

Upinder kumar*, Deepak Narang**
*(M.Tech Student, P.C.E.T., Lalru (Punjab) - India)
** (Assistant Professor, P.C.E.T., Lalru (Punjab) – India)

Abstract:

Medium Carbon Steel AISI 1045 has a wide variety of applications in vehicle component parts & machine building industry. Surface roughness and Material Removal Rate are the main quality functions in high speed turning of medium carbon steel in dry conditions. In this study, the optimization of two response parameters (Surface roughness and Material Removal Rate) by three machining parameters (cutting speed, feed rate and depth of cut) is investigated in high speed turning of H13 in dry conditions. Taguchi's L'9 orthogonal array and analysis of variance (ANOVA) are used for individual optimization. The simultaneous optimization is done by Grey Relational Analysis approach. The different levels of all machining parameters are used and experiments are done on HMT STALLION-100 HS CNC lathe machine. Material Removal Rate is investigated. The optimum condition for combined effects was found V2-F1-D3 and the optimal value of the surface roughness (Ra) comes out to be 1.007 (µm) and of MRR is 465.08 (mm³/sec). The optimum results are also verified with the help of confirmation experiments.

Keywords: ANOVA, CNC Turning, Grey Relational Analysis, MRR, Optimization, Surface Roughness, Taguchi Method.

1. Introduction

Quality plays a major role in today's manufacturing market. From Customer's viewpoint quality is very important because the quality of product affects the degree of satisfaction of the consumer during usage of the product. It also improves the goodwill of the company.

High speed turning is a machining operation which is done on CNC lathe. The quality of the surface plays a very important role in the performance of dry turning because a good quality turned surface surely improves fatigue strength, corrosion resistance and creep life. Surface roughness also affects on some functional attributes of parts, such as, contact causing surface friction, wearing, light reflection, ability of distributing and also holding a lubricant, load bearing capacity, coating and resisting fatigue.

As we know in actual machining, there are many factors which affect the surface roughness i.e. cutting conditions, tool variables and work piece variables. Cutting conditions include speed, feed and depth of cut and also tool variables include tool material, nose radius, rake angle, cutting edge geometry, tool vibration, tool overhang, tool point angle etc. and work piece variable include hardness of material and mechanical properties. It is very difficult to take all the parameters that control the surface roughness for a particular manufacturing process. In a turning operation, it is very difficult to select the cutting parameters to achieve the high surface finish. This study would help the operator to select the cutting parameters.

The work material used for the present study is AISI 1045 medium carbon steel of composition { Carbon (0.43-0.50)%, Silicon (0.2-0.3)%, Magnesium (0.60-0.90)%, Phosphorus (0.05)% Sulphur (0.05)% }. Its tensile strength is (620- 850) Mpa. This Carbon steel is suitable for shafts and machinery parts. It is mostly used in Automobile parts, in gears and machine building industry.

This paper is about experimentally investigating and optimizing the machining parameters for Material Removal Rate (MRR) and Surface Roughness in CNC turning by taguchi method and Grey Relational Analysis. Taguchi's orthogonal arrays are highly fractional designs, used to estimate main effects using few experimental runs only. These designs are not only applicable for two level factorial experiments, but also can investigate main effects when factors have more than two levels. Designs are also available to investigate main effects for some mixed level experiments where the factors included do not have the same number of levels. For example, a four-level full factorial design with five factors requires 1024 runs while the Taguchi orthogonal array reduces the required number of runs to 16 only.

David et al. (2006) described an approach for predicting Surface roughness in a high speed end-milling process and used artificial neural networks (ANN) and statistical tools to develop different surface roughness predictors.

Akhyar, G. et al. (2008) has used the application of taguchi method in optimization of cutting parameters for surface roughness in turning Ti-6%Al-4%V extra low interstitial with various tool grades coated and uncoated cemented carbide tools under dry cutting condition and high cutting speed. The analysis of results show that the optimal combination of parameters are at cutting speed of 75 m/min, feed rate of 0.15 mm/min, depth of cut of 0.10 mm and tool grade of KC9225.

Srikanth and Kamala (2008) proposed a real coded genetic algorithm (RCGA) for finding optimum cutting parameters and explained various issues of RCGA and its advantages over the existing approach of binary coded genetic algorithm (BCGA).

Roy, R. K. (2001). the very intention of Taguchi Parameter Design is for maximizing the performance of a naturally variable production process by modifying the controlled factors.

Hassan, K. et al. (2012) [11] has done the experimental investigation of material removal rate (MRR) in cnc turning of C34000 using taguchi method using L‟27 array. When the MRR is optimized alone the MRR comes out to be 8.91. The optimum levels of process parameters for simultaneous optimization of MRR have been identified. Optimal results were verified through confirmation experiments. It was concluded that MRR is mainly affected by cutting speed and feed rate.

2. Design of Experiment:

Experiments were designed using Taguchi method so that effect of all the parameters could be studied with minimum possible number of experiments. Using Taguchi method, Appropriate Orthogonal Array has been chosen and experiments have been performed as per the set of experiments designed in the orthogonal array. Signal to Noise ratios are also calculated for analyzing the effect of parameters more accurately. Results of the experimentation were analyzed analytically and also graphically using ANOVA. ANOVA used to determine the percentage contribution of all factors upon each response individually.

3. Taguchi method

Traditional experimental design methods are very complicated and difficult to use. Additionally, these methods require a large number of experiments when the number of process parameters increases. In order to minimize the number of tests required, Taguchi experimental design method, a powerful tool for designing high-quality system, was developed by Taguchi. This method uses a design of orthogonal arrays to study the entire parameter space with small number of experiments only. Taguchi recommends analyzing the mean response for each run in the inner array, and he also suggests to analyze variation using an appropriately chosen signal-to-noise ratio (S/N). There are 3 Signal-to-Noise ratios of common interest for optimization of static problems:

(I) SMALLER-THE-BETTER:

$$\eta = -10\log\left(\frac{(\sum Yi^2)}{n}\right)$$

(II) LARGER-THE-BETTER:

$$\eta = -10\log(\sum \frac{1}{yi^2})/n)$$

Where, η - Signal to Noise(S/N) Ratio,
Yi - ith observed value of the response,
n - no. of observations in a trial,
y - average of observed values (responses).

Regardless of category of the performance characteristics, the higher S/N ratio corresponds to a better performance. Therefore, the optimal level of the process parameters is the level with the highest S/N value. The statistical analysis of the data is performed by analysis of variance (ANOVA) to study the contribution of the various factors and interactions and to explore the effects of each process on the observed values.

4. Experimental Plan and details:

In this study, three machining parameters were selected as control factors, and each parameter was designed to have three levels, denoted 1, 2, and 3 (Table 1). The experimental design was according to an L'9 array based on Taguchi method, while using the Taguchi orthogonal array would markedly reduce the number of experiments. A set of experiments designed using the Taguchi method was conducted to investigate the relation between the process parameters and response factor. Minitab 16 software is used to optimization and graphical analysis of obtained data

Table 1 Turning parameters and levels

Symbol	Turning parameters	Level 1	Level 2	Level 3
V	**Cutting speed(m/min)**	150	188	226
F	**Feed rate(rev/min)**	0.1	0.2	0.3
D	**Depth of cut(mm)**	0.5	1.0	1.5

Medium Carbon Steel (AISI 1045) of Ø: 24 mm, length: 70 mm were used for the turning experiments in the present study. The turning operation is performed in 3 steps of 17 mm length each over the total length of varying depth of cut. The chemical composition of AISI 1045 sample can be seen in Tables 2.

Table 2 Chemical composition of Medium Carbon Steel (AISI 1045)

Element	Percentage
Carbon	(0.43-0.50)%
Silicon	(0.2-0.3)%
Magnesium	(0.60-0.90)%
Phosphorus	(0.05)% max.
Sulphur	(0.05)% max.

The turning tests were carried out to determine the Material Removal Rate and Surface Roughness under various turning parameters. A HMT STALLION-100 HS CNC lathe machine is used for experimentation. Roughness is measured using stylus type surface roughness tester „Surftest SJ-201 made of Mitutoyo, Japan. The turning length was 40 mm for each measurement. An average of 5 measurements of the surface roughness was taken to use in the multi-criteria optimization. The Material Removal Rate, MRR (mm^3/ min) was calculated using formula:

$$MRR = \frac{W_i - W_f}{\rho_s\, t} mm^3/sec$$

Where, Wi = Initial weight of work piece in gm
Wf= Final weight of work piece in gm
t = Machining time in seconds
ρs= Density of mild steel
= (7.8×10^{-3} gm/mm^3).

5. Experimentation and Calculation:

In high speed turning operation, surface roughness is an important criterion. The purpose of the analysis of variance (ANOVA) is to investigate which design parameter significantly affects the surface roughness. Based on the ANOVA, the relative importance of the machining parameters with respect to surface roughness was investigated to determine the optimum combination of the machining parameters.

The Material Removal Rate calculations and experimental results of the surface roughness for turning of AISI 1045 with different turning parameters are shown in Table 3 and Table 4.

Table 3 Design of experiment and calculations

S. No.	Weight before turning (*Wi*) (kg)	Weight after turning (*Wf*) (kg)	Machining Time (*t*)(secs)	Means of MRR (mm^3/sec)
1	0.252	0.237	16.1	119.44
2	0.257	0.227	9.3	413.56
3	0.254	0.214	7.2	712.25
4	0.251	0.221	13.2	291.37
5	0.258	0.218	7.3	702.49
6	0.256	0.241	6.9	278.70
7	0.253	0.213	12.2	420.34
8	0.255	0.240	7.2	267.09
9	0.258	0.228	6.3	610.50

Table 4 Design of experiment and calculations

Ex. No.	CS (m/min)	F (mm/rev)	D (mm)	MRR (mm^3/sec)	Ra (µm)
1	150	0.1	0.5	119.44	1.46
2	150	0.2	1.0	413.56	2.20
3	150	0.3	1.5	712.25	3.15
4	188	0.1	1.0	291.37	1.09
5	188	0.2	1.5	702.49	1.76
6	188	0.3	0.5	278.70	3.14
7	226	0.1	1.5	420.34	0.95
8	226	0.2	0.5	267.09	1.80
9	226	0.3	1.0	610.50	2.95

Table 5 ANOVA Table for means of MRR

Source	DF	SS	MS	P	C
CS	2	463	231	0.974	0.13 *
FR	2	105079	52540	0.140	29.88 **
DOC	2	229038	114519	0.069	65.13 ***
Error	2	17049	8525		4.84
Total	8	351630			

Table 6 Response Table for MRR

Level	Cutting Speed	Feed Rate	Depth of Cut
1	415.1	277.1	221.7
2	424.2	461.0	438.5
3	**432.6**	**533.8**	**611.7**
Delta	17.6	256.8	389.9
Rank	3	2	1

Table 7 ANOVA Table for Surface Roughness

Source	DF	SS	MS	P	C
CS	2	0.2209	0.1104	0.045	3.77 **
FR	2	5.5739	2.7869	0.002	95.17 ***
DOC	2	0.0512	0.0256	0.169	0.87 *
Error	2	0.0104	0.0052		0.17
Total	8	5.8566			

Table 8 Response Table for Surface Roughness

Level	Cutting Speed	Feed Rate	Depth of Cut
1	2.270	**1.167**	2.133
2	1.997	1.920	2.080
3	**1.900**	3.080	**1.953**
Delta	0.370	1.913	0.180
Rank	2	1	3

Where,
V-Variable, CS-Cutting Speed,
F-Feed Rate, D-Depth Of Cut,
SR-Surface Roughness, E-Error,
T-Total, DF-Degree of Freedom,
SS-Sum of Squares, MS-Mean of Squares,
F-a statistical parameter, P-Percentage,
C-Contribution.

Here *** & ** represents most significant and significant parameters and * as less significant.

6. Grey Relational Analysis

In the Grey relational analysis the quality characteristics are first normalized, ranging from zero to one. This process is known as Grey Relational Generation. Then the Grey Relational Coefficient based on normalized experimental data is calculated to represent the correlation between the desired and the actual experimental data. Then overall Grey Relational Grade (GRG) is determined by averaging the Grey relational coefficient corresponding to selected responses.

The overall performance characteristic of the multiple response process depends on the calculated GRG. This Grey relational approach converts a multiple response process optimization problem into a single response optimization problem. The optimal parametric combination is then evaluated, which would result in the highest Grey relational grade. The optimal factor setting for maximizing the overall Grey relational grade can be performed using the Taguchi method.

In Grey relational generation, the normalized MRR should follow the larger-the-better (LB) criterion, which can be expressed as:

$$x_j(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

The normalized Ra should follow the smaller-the-better (SB) criterion which can be expressed as:

$$x_j(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

where, $x_i(k)$ and $x_j(k)$ are the value after Grey Relational Generation for LB and SB criteria. Max $y_i(k)$ is the largest value of $y_i(k)$ for k^{th} response and min $y_i(k)$ is the minimum value of $y_i(k)$ for the k^{th} response.

The Grey relational coefficient $\xi_i(k)$ can be calculated as:

$$\xi_i(k) = \frac{\Delta\min - \Psi\,\Delta\max}{\Delta\, o_i(k) + \Psi\,\Delta\max}$$

And

$$\Delta\, o_i = \| x_o(k) - x_i(k) \|$$

Where $\Delta\, o_i$ is the difference between absolute value $x_o(k)$ and $x_i(k)$. Ψ is the distinguishing coefficient $0 \le \Psi \ge 1$. Δ min and Δ max are the minimum and maximum value among the $\Delta\, o_i$ for corresponding k^{th} response.

Now the Grey Relational Grade (GRG) can be calculated as:

$$\gamma i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k)$$

Where n - number of process responses.

The higher value of the GRG corresponds to a relational degree between the Reference Sequence $x_o(k)$ and the given sequence $x_i(k)$. The Reference Sequence $x_o(k)$ represents the best process sequence. Therefore, a higher GRG means that the corresponding parameter combination is closer to the optimal. The mean response for the GRG and the main effect plot of the GRG are very important because the optimal process condition can be evaluated from this plot.

S.No.	Mean Values		S/N Ratios	
Xo	MRR	Ra	MRR	Ra
1	119.44	1.46	41.5430	-3.287
2	413.56	2.20	52.3308	-6.848
3	712.25	3.15	57.0526	-9.966
4	291.37	1.09	49.2889	-0.748
5	702.49	1.76	56.9328	-4.910
6	278.70	3.14	48.9027	-9.938
7	420.34	0.95	52.4720	0.445
8	267.09	1.80	48.5332	-5.105
9	610.50	2.95	55.7137	-9.396
Max.	**712.25**	**3.15**	**57.0526**	**0.445**
Min.	**119.44**	**0.95**	**41.5430**	**-9.966**

Table 9: S/N Ratio Calculation for MRR and Ra

Table 10: Grey Relational Analysis Calculations

S. No.	GRGC		RSDC		GRCC	
	MRR	Ra	MRR	Ra	MRR	Ra
(Xo)	1.000	1.000	1.000	1.000	1.000	1.000
1	0.000	0.768	1.000	0.232	0.333	0.683
2	0.496	0.431	0.504	0.569	0.498	0.467
3	1.000	0.000	0.000	1.000	1.000	0.333
4	0.290	0.936	0.710	0.064	0.413	0.886
5	0.983	0.631	0.017	0.369	0.967	0.575
6	0.255	0.004	0.745	0.996	0.401	0.334
7	0.507	1.000	0.493	0.000	0.503	1.000
8	0.249	0.613	0.751	0.387	0.400	0.563
9	0.828	0.090	0.172	0.910	0.744	0.354

Where,
GRGC- Grey Relational Generation Calculation,
RSDC- Reference Sequence Definition Calculation,
GRCC- Grey Relational Coefficient Calculation

Table 11: Grey Relational Grade (GRG) calculation

S.No.	Grey Relational Grade (GRG)		Rank
	Mean	S/N Ratio	
1	0.508	-5.882	6
2	0.482	-6.339	7
3	0.666	-3.530	3
4	0.649	-3.755	4
5	0.771	-2.258	1
6	0.367	-8.706	9
7	0.751	-2.487	2
8	0.481	-6.357	8
9	0.549	-5.208	5

Table 12: Analysis of Variance of means of Grey Relational Grade

Source	DF	SS	MS	P	C
CS	2	0.003647	0.001823	0.736	2.45 *
FR	2	0.017740	0.008870	0.364	11.92 **
D	2	0.117252	0.058626	0.080	78.80 ***
E	2	0.010158	0.005079		6.82
T	8	0.148796			

Table 13: Response Table for means of GRG

Level	CS	F	DOC
1	0.5520	0.6360	0.4520
2	0.5957	0.5780	0.5600
3	0.5937	0.5273	0.7293
Delta	0.0437	0.1087	0.2773
Rank	3	2	1

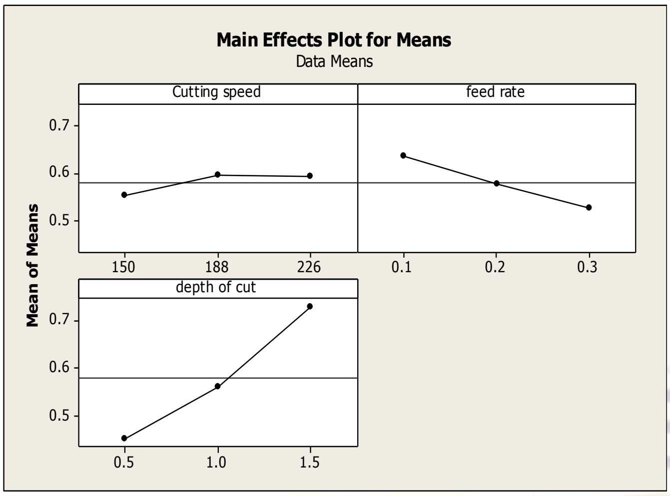

Fig 2: Main effect plot for S/N ratios of GRG

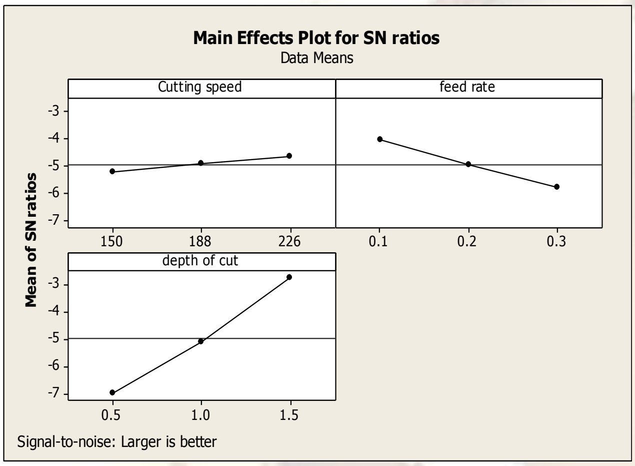

Fig 2: Main effect plot for S/N Ratio of GRG

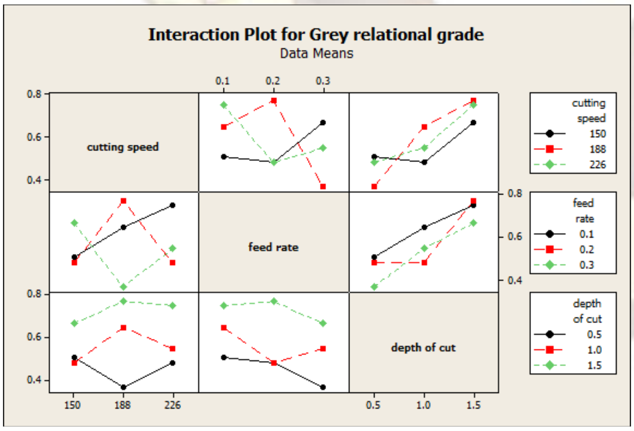

Fig 3: Interaction plot for means of GRG

7. Determination of Optimum Condition

Both the response and S/N ratio are used to derive the optimum conditions. Since for quality characteristic, Grey Relational Grade larger the better approach is desirable, the largest is the ideal level for a parameter. The S/N ratio is always highest at the optimum condition. The graphs of Figures 2 and 3 are used to determine the optimum process parameters combination. The optimum combination is therefore *V5-F2-D3*.

7.1 Predictive Equation and Verification

The predicted values of GRG, MRR and Ra at the optimal levels are calculated by using the relation:

$$\check{n} = nm + \sum_{i=1}^{o}(nim - nm)$$

Where,
ň - Predicted response value after optimization,
nm – Total mean value of quality characteristic,
nim – Mean value of quality characteristic at optimum level of
each parameter and
o – Number of main machining parameters that affect the response parameter.

Applying this relation, predicted values of GRG, MRR and Ra at the optimum conditions
are calculated as:

1. **ň(GRG)** = 0.801
2. **ň(MRR)** = 1.007 mm^3/sec
3. **ň(Ra)** = 1.0828 µm

The robustness of this parameter optimization is verified experimentally. This requires the confirmation run at the predicted optimum conditions. The experiment is conducted twice at the predicted optimum conditions.

Verifications:

1. **For Material Removal Rate (MRR):** The calculated value of MRR at the optimum condition *(V2-F1-D3)* is 485.3 mm^3/sec. The error in the predicted optimum value (465.08) and the calculated value (485.3) is only 4.3%.
2. **For Surface Roughness (Ra):** The calculated value of Surface Roughness at the optimum condition *(V2-F1-D3)* is 1.04 µm. The error in the predicted optimum value (1.007) and the calculated value (1.04) is only 4%.

Hence, so good agreement between the actual and the predicted results is observed. Since the percentage error is less than 5%, it confirms excellent reproducibility of the results. The results show that using the optimal parameter setting *(V2-F1-D3)* a higher material removal rate is achieved with lower surface roughness.

8. Results

The effect of three machining parameters i.e. Cutting speed, feed rate and depth of cut and their interactions are evaluated using ANOVA and with the help of MINITAB 16 statistical software. The purpose of the ANOVA in this study is to identify the important turning parameters in prediction of Material Removal Rate and Surface roughness. Some important results come from ANOVA and plots are given as below.

Table 14 shown below shows that optimal values of surface roughness and material removal rate that lie between the optimal ranges.

Table 14 Optimal values of machining and response parameters

CP	OV	OL	POV	EOV	OR
CS F D	188 0.1 1.5	V2- F1- D3	MRR= 465.08 Ra= 1.007	MRR= 485.3 Ra= 1.04	465.08 <MRR> 485.3 1.007 < Ra > 1.04

Where,

CP-Cutting Parameters
OV-Optimal Values of Parameters
OL-Optimum Levels of Parameters
POV-Predicted Optimum value
EOV-Experimental Optimum Value
OR-Optimum Range of MRR and Surface Roughness

9. Conclusion

In this study, the Grey relational based Taguchi method was applied for the multiple performance characteristics of turning operations. A grey relational analysis of the Material removal rate and the surface roughness obtained from the Taguchi method reduced from the multiple performance characteristics to a single performance characteristic which is called the grey relational grade. Therefore, the optimization of the complicated multiple performance characteristics of the processes can be greatly simplified using the Grey relational based Taguchi method. It is also shown that the performance characteristics of the turning operations, such as the material removal rate and the surface roughness are greatly enhanced by using this method.

References

[1] David V, Rubén M, Menéndez C, Rodríguez J, Alique R . Neural networks and statistical based models for surface roughness prediction. International Association Of Science and Technology for Development, Proceedings of the 25th IASTED international conference on Modeling, indentification and control, (2006) pp. 326-331.
[2] Srikanth T, Kamala V . A Real Coded Genetic Algorithm for Optimization of Cutting Parameters in Turning. IJCSNS Int. J. Comput. Sci. Netw. Secur,, (2008),8(6):189-193.
[3] Roy, R. K. (2001). Design of experiments using the Taguchi approach: 16 steps to product and process improvement. New York: Wiley.
[4] Arbizu IP, Pérez CJL (2003). Surface roughness prediction by factorial design of experiments in turning processes. J. Mater. Process. Technol., 143-144: 390-396.
[5] Tsao CC, Hocheng H (2008). Evaluation of the thrust force and surface roughness in drilling composite material using Taguchi analysis and neural network. J. Mater. Process. Technol., 203(1-3): 342-348.
[6] Gopalsamy B.M., Mondal B. and Ghosh S., "Taguchi method and ANOVA: An approach for process parameters optimization of hard machining while machining hardened steel", Journal of Scientific and Industrial Research, vol. 68, (2009), pp. 686-695.
[7] Cayda U., "Machinability evaluation in hard turning of AISI 4340 steel with different cutting tools using statistical techniques ", Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, (2010).
[8] Thamizhmanii S., Saparudin S. and Hasan S, "Analysis of Surface Roughness by Using Taguchi Method", Achievements in Materials and Manufacturing Engineering, (2007), Volume 20, Issue 1-2, pp. 503-505.
[9] Lan T.-S., Lo C. Y., Wang M.-Y. and Yen A-Y, "Multi Quality Prediction Model of CNC Turning Using Back Propagation Network", Information. Proceeding of American society of mechanical engineers, (2008).
[10] Palanikumar K. and Karunamoorthy L., "Optimization of Machining Parameters in Turning GFRP Composites Using a Carbide (K10) Tool Based on the Taguchi Method with Fuzzy Logics", metals and materials International, Vol. 12, No. 6 (2006), pp. 483-491.
[11] Dhavamani C. and Alwarsamy T., "review on optimization of machining", international journal of academic research, (2011), Vol. 3. No. 3. May, II Part.
[12] Yang, W. H., & Tarng, Y. S. (1998). Design optimization of cutting parameters for turning operations based on the Taguchi method. Journal of Materials Processing Technology, 84, 122-129.
[13] Lin, C. L. (2004). Use of the Taguchi method and grey relational analysis to optimize turning operations with multiple performance characteristics. Materials and Manufacturing Processes, 19(2), 209-220.

[14] Akhyar, G. et al. (2008), "Application of Taguchi method in the optimization of turning parameters for surface roughness", International Journal of Science Engineering and Technology, vol.1, no.3, pp. 60-66.
[15] Hassan, K. et al. (2012) "Experimental investigation of Material removal rate in CNC turning using Taguchi method" International Journal of Engineering Research and application, vol. 2, no. 2, pp. 1581-1590
[16] Raju Shrihari pawde and Suhas. S. Joshi,"Multiobjective optimization of surface roughness and cutting forces in high speed turning of Inconel 718 using taguchi grey relational analysis (TGRA)" International Journal of Advance Manufacturing technology, vol.2011, pp. 56:47-62
[17] D. Chakradhar and A. Venu Gopal,"Multi-objective optimization of electrochemical machining of en31 steel by grey relational analysis" International Journal of Modeling and optimization, vol. 1, No.2, June 2011 pp. 113-117