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APPLY QUALITY LOSS FUNCTION BASED GREY RELATION MULTI-OBJECTIVE TECHNIQUE TO OPTIMIZATION OF MILLING MACHINING PARAMETERS

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ARTICLE INFO **ABSTRACT** **ORIGINAL RESEARCH ARTICLE**

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Basically, this optimization procedure, whenever carried out, involves partial differentiation for the minimization of the unit cost, maximization of production rate or maximization of profit rate. It has long been recognized that conditions during cutting, such as feed rate, cutting speed and depth of cut, should be selected to optimize the economics of machining operations as assessed by productivity, total manufacturing cost per component or some other suitable criterion. These quality features are highly correlated and are expected to be influenced directly or indirectly by the direct effect of process parameters or their interactive effects create multi-objective problems. To predict this problem we take the sixteen combinations of milling machining operation. In view of the fact, that traditional Taguchi method cannot solve a multi-objective optimization problem; to overcome this limitation grey relational theory has been coupled with Taguchi method. This problem can be solved by extended Taguchi's method to convert multi objective problem into single objective problem. The developed models for different constraints have been used for the construction of an optimization programmed which can be used to obtain optimum cutting speeds, feed rates, axial depth of cut and radial depth of cut under different constraints.

1. INTRODUCTION

The response of the workpiece subjected to dynamic cutting force gives an indication the best possible speeds from the point of view of accuracy. Accuracy gives much better finished goods and reducing the machining process. This process play significant role in manufacturing market. Apart from quality, there exists another criterion, called productivity which is directly related to the profit level and also goodwill of the organization. In machining operations, achieving desired surface quality features of the machined product, is really a challenging job. Because, these quality features are highly correlated and are expected to be influenced directly or indirectly by the direct effect of process parameters or their interactive effects. To predict this problem we take the sixteen combinations of milling machining operation. Milling is the process of machining flat, curved, or irregular surfaces by feeding the work piece against a rotating cutter containing a number of cutting edges. In this process we perform end milling operation on workpiece and calculate material removal rate and surface roughness.

Milling machines are basically classified as being horizontal or vertical to indicate the axis of the milling machine spindle. These machines are also classified as knee-type, ram-type, manufacturing or bed type, and planer-type milling machines. During the last half of the nineteenth Century, milling machines gradually replaced shapers and planers which have lathe-type, single-point tool bits that move over the work in a straight line and scrape off metal one stroke at a time.

In the previous work Datta and Umesh (2009) has been optimize the optimal parameter [1] for output in turning operation by L_9 (OA). Here we discuss on milling operation parameter for optimal output by L_{16} (OA).

Another important development came in the 1930s when Rudolph Bannow and Magnus Wahlstrom brought out the Bridgeport-style vertical milling machine. This design offers versatility and economy in place of the higher metal removal rates of traditional horizontal milling machines. Because of this versatility, there are more Bridgeport-style mills in existence today than any other milling machine design. Horizontal mills are now usually reserved for production applications where high metal removal rates on identical parts are needed, not prototyping and short runs.

1.1. MATERIAL REMOVAL RATE

It is the ratio of volume removed from the work piece to a unit time. Material removal rate (MRR) [10] has been calculated from the difference of weight of work piece before and after experiment.

Terms Used:

N: RPM of Cutter

n: Number of Teeth on Cutter

W: Width of cut (may be full cutter or partial cutter)

t: depth of cut

V: cutting speed -- a Handbook value

L: Length of pass or cut

f_m: Table (machine) Feed

f_t: feed/tooth of cutter -- a Handbook value

D: Cutter Diameter

$$MRR = \frac{Vol\,Removed}{CT} = \frac{L*W*t}{CT} = W*t*f_m \quad \ldots\ldots(1)$$

When determining cutting time and MRR, care must be exercised. Ask yourself if total cutting time or time to make one pass across the part is being requested, i.e. is a single or multiple pass operation to be studied. Also, note that in the MRR equation the "cutting time" term does not include the time of partial engagement (L_A). Again, if a multi-pass operation is being employed, the appropriate width term should be used in the MRR equation.

1.2. SURFACE ROUGHNESS

Surface roughness of texture is the measure if the finer surface irregularities in the surface texture and is composed of three components: roughness, waviness and form. These are the result of the manufacturing process employed to create the surface. Surface roughness average (Ra), also known as arithmetic average (AA) is rated as the arithmetic average deviation of the surface valleys and peaks expressed in micro inches or micro meters. ISO standards use the term CLA (Center Line Average). Both are interpreted identical.

Where Ra is the arithmetic average value or departure from profile front eh center line, the equation for four as-measured values:

$$Ra = CLA = AA = \frac{M1 + M2 + M3 + M4}{4} \ldots.(2)$$

Where:

Mx = measure value

Root Mean Square (RMS / Rq / Rs) can be calculated by:

$$RMS = \sqrt{\frac{M1 + M2 + M3 + M4}{4}} \ldots\ldots(3)$$

The ability of a manufacturing operation to produce a specific surface roughness depends on many factors. For example, in end mill cutting, the final surface depends on the rotational speed of the end mill cutter, the velocity of the traverse, the rate of feed, the amount and type of lubrication at the point of cutting, and the mechanical properties of the piece being machined. A small change in any of the above factors can have a significant effect on the surface produced.

2. LITERATURE REVIEW

Umesh Khandey (2009), discussed on the view of the fact, that traditional Taguchi method cannot solve a multi-objective optimization problem; to overcome this limitation grey relational theory has been coupled with Taguchi method. Furthermore to follow the basic assumption of Taguchi method i.e. quality attributes should be uncorrelated or independent [1].

Jaya Krishna. Nagallapati (2008), present the principal component analysis (PCA) based neural networks for predicting the surface roughness in CNC end milling of P20 mould steel. For training and testing of the neural network model, a number of experiments have been carried out using Taguchi's orthogonal array in the design of experiments (DOE) [2].

Moshat et al. (2010) present study highlights optimization of CNC end milling process parameters to provide good surface finish as well as high material removal rate (MRR). The surface finish and material removal rate have been identified as quality attributes and are assumed to be directly related to productivity. An attempt has been made to optimize aforesaid quality attributes in a manner that these multi-criterions could be fulfilled simultaneously up to the expected level. This invites a multi-objective optimization problem which has been solved by PCA based Taguchi method [3].

Wang and Lan (2008) used Orthogonal Array of Taguchi method coupled with grey relational analysis considering four parameters viz. speed, cutting depth, feed rate, tool nose run off etc. for optimizing three responses: surface roughness, tool wear and material removal rate in precision turning on an ECOCA-3807 CNC Lathe. The MINITAB software was explored to analyze the mean effect of Signal-to-Noise (S/N) ratio to achieve the multi-objective features [4].

According to previous studied the grey–Taguchi method was adopted to optimize the milling parameters such as cutting speed, feed and depth of cut. In this study, the cutting speed, feed rate, axial depth of cut and radial depth of cut are given parameter to evaluate optimum output in terms of surface roughness and material removal rate restricted with some practical constraints of milling operations, are expressed in terms of variables which satisfy minimum production cost or maximum production rates of milling operations.

3. MATERIALS AND METHODS

3.1. MACHINING TEST

Preparing milling machine for milling tests were conducted on Vertical Machining Center. Machining was performed with a 20 mm diameter end-mill tool holder for investigating the effect of four factors (cutting speed, feed, axial and radial depth of cut) on the cutting force generated when end milling of CVD coated carbide tools have been used. The tool inserts were made by Kennametal and had an ISO catalogue number of SPCB120308 (KC735M). The detail of tool is given below.

Cutter diameter = 8mm
Overall length = 108 mm
Fluted length = 38 mm
Helix angle = 300
Hardness = 1570 HV
Density = 14.5 g/cc
Transverse rupture strength =3800 N/mm2

The workpiece used in this study was P20 mould steel of flat work pieces of 100 mm ×100mm ×10mm and the density of the material in metric units is 7.8 g / cc hardened to 310 HB. The end mill can be equipped with two square inserts whose all four edges can be used for cutting.

Table 3.1 Process variables and their limits

S No.	Cutting Speed (V) m/min	Feed Rate (f) mm/tooth	Axial Depth of cut (D) mm	Radial Depth of Cut (d) mm
1	80	0.125	0.5	0.3
2	85	0.15	0.75	0.4
3	90	0.175	1	0.5
4	95	0.2	1.5	0.6

Then surface roughness and surface profile have been measured precisely with the help of a portable stylus-type profilometer (Tomlinson Roughness Meter). The results of the experiments have been shown in Table. Analysis has been made based on those experimental data which is shown in table 1. Optimization of surface roughness and material removal rate has been made by PCA and Taguchi method coupled with grey relational analysis. Confirmatory tests have also been conducted finally to validate optimal results.

Table 3.2 Experimental data

S No.	Cutting Speed (V) m/min	Feed Rate (f) mm/ tooth	Axial Depth of cut (D) mm	Radial Depth of Cut (d) mm	Surface roughness R_a µm	MRR mm^3/min
1	80	0.125	0.5	0.3	0.96	0.0187
2	80	0.15	0.75	0.4	1.18	0.045
3	80	0.175	1	0.5	1.12	0.0875
4	80	0.2	1.5	0.6	0.84	0.18
5	85	0.125	0.75	0.5	0.82	0.0468
6	85	0.15	0.5	0.6	1.44	0.045
7	85	0.175	1.5	0.3	0.74	0.0787
8	85	0.2	1	0.4	0.92	0.08
9	90	0.125	1	0.6	1.08	0.075
10	90	0.15	1.5	0.5	1.1	0.1125
11	90	0.175	0.5	0.4	1.18	0.035
12	90	0.2	0.75	0.3	0.84	0.045
13	95	0.125	1.5	0.4	0.56	0.075
14	95	0.15	1	0.3	0.48	0.045
15	95	0.175	0.75	0.6	0.58	0.0787
16	95	0.2	0.5	0.5	0.56	0.05

4. RESULT AND DISCUSSION

4.1. NORMALIZATION

When the range of the series is too large or the optimal value of a quality characteristic is too enormous, it will cause the influence of some factors to be ignored. The original experimental data must be normalized to eliminate such effect. The data normalization according to whether NB (nominal-the-best) [9]. The normalization is taken by the following equations.

$$X_i = \frac{(y)_i - \min(y)_i}{\max(y)_i - \min(y)_i} where i = 1,2 \ldots..n \quad \ldots..(4)$$

Table 4.1 Normalized value

S No.	R_a	MRR
Ideal sequence	1.0000	1.0000
1	0.5000	1.0000
2	0.4068	0.4167
3	0.4286	0.2143
4	0.5714	0.1042
5	0.5854	0.4000
6	0.3333	0.4167
7	0.6486	0.2380
8	0.5217	0.2344
9	0.4444	0.2500
10	0.4364	0.1667
11	0.4068	0.5357
12	0.5714	0.4167
13	0.8571	0.2500
14	1.0000	0.4167
15	0.8276	0.2380
16	0.8571	0.3750

4.2. CHECKING FOR CORRELATION BETWEEN TWO QUALITY CHARACTERISTICS

It is the normalized series of the *i th* quality characteristic. The correlation coefficient between two quality characteristics is calculated by Mintab software and the following equation (5).

$$C = \frac{cov(A_i B_i)}{\delta A_i * \delta B_i} \ldots \ldots.(5)$$

Table 4.2 Correlated value

S. No.	Correlation between responses	Pearson correlation coefficient (C)	Comment
1	R_a and MRR	0.078	Both are correlated

C=0 *There is no correlation*

C≠0 There no correlation

4.3. CALCULATION OF THE PRINCIPAL COMPONENT

- Calculate the Eigen value and the corresponding eigenvector from the correlation matrix formed by all quality characteristics.
- Calculate the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

Table 4.3 Eigen values, eigenvectors, (AP) and (CAP) computed for the responses

	A	B
Eigen Value	1.0779	0.9221
Eigen vector	0.707 0.707	0.707 -0.707
AP	0.539	0.461
CAP	0.539	1.000

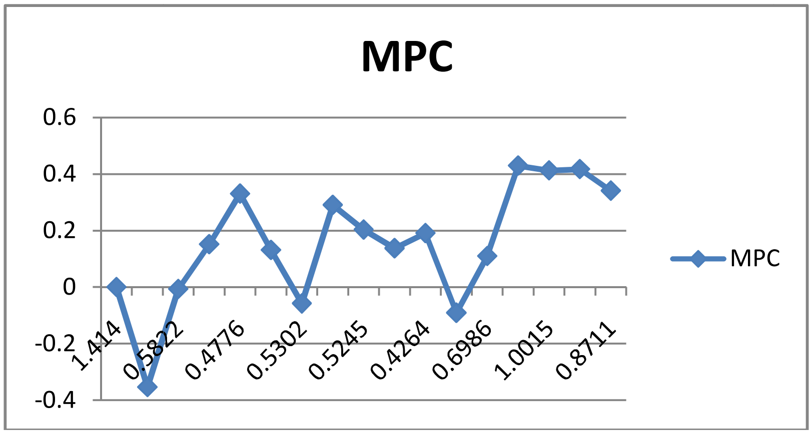

Fig 4.1 Principal components of R_a and MRR in all L_{16} experimental observations

4.4. QUALITY LOSS ESTIMATES $L_{AB}(k)$ (FOR PRINCIPAL COMPONENTS)

It can be calculated by difference between ideal and actual Q_k & Q_{AB}.
Where Q_k =ideal principle component, and Q_{AB}=actual principle component.

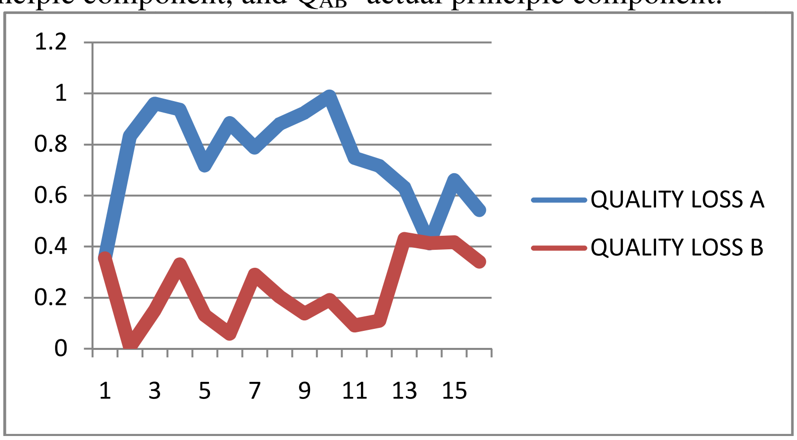

Fig 4.2 Quality loss of R_a and MRR

4.5. CALCULATION OF THE INDIVIDUAL GREY RELATIONAL GRADES

After the calculation of the grey relational coefficient and the weight of each quality characteristic, the grey relational grade [10] is determined by:

$$G_i = \frac{L_{min} + \varepsilon L_{max}}{L_i + \varepsilon L_{max}} i = 1,2 \ldots \ldots \ldots . . n \qquad \ldots \ldots . . (6)$$

Where,
L_{min}= Minimum quality loss in component.
L_{max} = maximum quality loss in component.
ε = distinguish coefficient (0.5)
L_i = quality loss at present

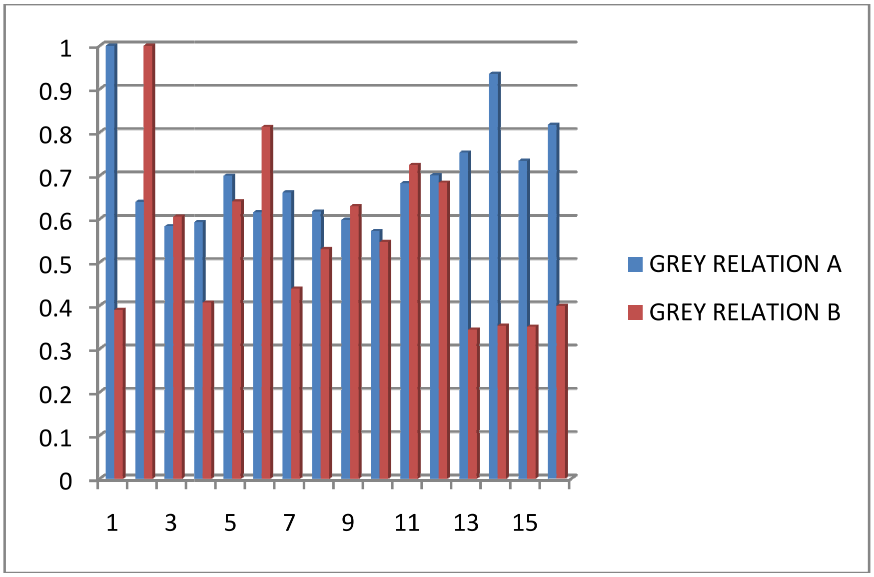

Fig 4.3 Individual grey relational grades of R_a and MRR

4.6. Calculation of overall grey relational grade

In this section, the multiple quality characteristics are combined into one grey relational grade, thus the traditional Taguchi method can be used to evaluate the optimal parameter combination. Finally the anticipated optimal process parameters are verified by carrying out the confirmatory experiments. The grey relational grade is determined by:

$$\nabla = \sum_{k=1}^{n} w_k G_{o,i}(k) i = 1, \ldots\ldots m \qquad \ldots\ldots (7)$$

Table 4.4 Overall grey relational grade and S/N ratio

S No.	overall grey relational grade	S/N ratio
1	0.6949	-3.16155
2	0.8196	-1.72796
3	0.5940	-4.52427
4	0.4994	-6.03103
5	0.6702	-3.47591
6	0.7138	-2.92847
7	0.5501	-5.19117
8	0.5736	-4.82782
9	0.6136	-4.24229
10	0.5592	-5.04866
11	0.7035	-3.05472
12	0.6922	-3.19537
13	0.5477	-5.22915
14	0.6441	-3.82093
15	0.5424	-5.31361
16	0.6081	-4.32050

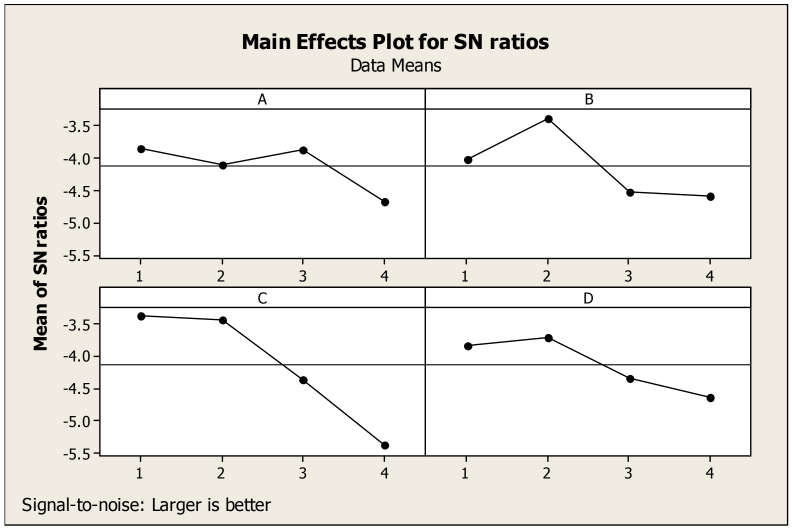

Fig 5.1 Signal to Noise

Table 5.1 Result

	Optimal setting	
	Prediction	**Experimented**
Level of factor	$A_1B_2C_1D_2$	$A_1B_2C_1D_2$
S/N ratio	-1.92642	-1.90486

5. CONCLUSION

1. Here we conclude that all 16 operations we performed and take its output but better output we found in one combination factor by extended Taguchi's method as shown in table5.1.
2. Grey relation theory has been converting the multi objective problem into single objective problem. Thus the single objective problem can be solving by Taguchi's method.
3. Here I obtain the optimize result by Taguchi method which will give better output in all 16 combinations of variable. PCA and grey relation grade result is extremely closed to experimented results which indicate this optimization can be effectively used to minimize the number of operations.

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