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Grey relational analysis coupled with principal component analysis to optimize the machining process of ductile iron.*

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Abstract

The strict specifications for specific applications of the ductile iron casting must qualify the defined standards with limiting tensile strength and the correct material composition limits. The undesired combinations of properties are reported during casting of ductile iron components because of the graphite presence as spheroids rather than as flakes. The design specific grades of ductile Iron comprising desired matrix microstructure can be produced by controlling the matrix microstructure with alloy additions around the graphite either by heat treatment or as-cast. The present research investigates the machinability of ductile iron grade EN-GJS-500-7and the development of model and optimized design for the major machining characteristic indexes viz. metal removal rate, cutting forces and surface roughness in turning process. The cutting parameters selected are cutting speed, feed rate and depth of cut. The grey relational analysis adopting grey relational grades as performance index is used to determine the optimal combination of cutting parameters. The set of experiments on the basis of response surface methodology (RSM) are employed in preparing the objective model to study the effect of the main turning parameters. Further principal component analysis is applied to calculate the weighting values corresponding to the selected machining characteristic indexes in order to determine their relative importance during the process. The results obtained from the confirmation experiments revealed that grey relational analysis coupled with principal component analysis is an appropriate approach and thus proposed to be a useful tool to improve the cutting performance in turning process.

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1. Introduction

There are many grades of spheroidal iron or ductile iron or nodular cast iron, which can be specified and offering the engineers varying degrees of tensile strength and elongation. The various suitable grades may be achieved through a combination of alloy additions and with the adoption of specific heat treatment.

Nomenclature	
R_a	average surface roughness in micro-meter
F_c	resultant cutting force in Newton
C_t	cutting time in seconds
MRR	metal removal rate mm^3/s
RSM	response surface methodology

Considerable research has been done on the use of different tool materials for machining ductile iron (DI). Due to its high strength and ductility, cutting tools often suffer flank wear and crater wear. Therefore, cutting tools need to have high value of wear resistance. K-grade carbide tools reported to have sufficient wear resistance, but require the cutting fluids during machining. P-grade tools can be used in dry cutting. Al_2O_3 ceramics are successful for continuous cut processes. Si_3N_4 ceramics and PCBN cutting tools are not suggested for machining DI [1].Jaharah et al. [2] applied orthogonal L9 array in Taguchi method and carried out the experimental work on ductile cast iron grade FCD 500 using carbide cutting tool in dry end milling condition. The results were analyzed using analysis of variance (ANOVA) to enlighten the effect of end milling parameters on the tool life, cutting force and surface roughness.The grey system theory proposed by Deng, 1982 [3], has been proven to be suitable while dealing the problems with insufficient, uncertain and poor information. In recent years, grey relation analysis has become a powerful tool to analyze the problem having multiple performance characteristics. Pariera et al. [4] applied PCA for modelling and optimization of surface roughness using the multivariate mean square error and global index method for AISI 1045 end milling. Principal component analysis (PCA) was proposed by Pearson in 1901 and further evolved as a statistical tool by Hotteling in 1993. The PCA is a multivariate statistical tool used in explaining the variance-covariance structure of a dataset, using linear combinations of the original variables. Thus the original correlated responses are represented by new uncorrelated variables called principal components. Meenu et al. [5], attemptedTaguchi grey relational analysis to the experimental results in order to optimize the turning parameters for unidirectional GFRP composite and applied PCA to evaluate the weight corresponding to different performance characteristics. The principal component, having highest accountability proportion, was treated as single objective function for optimization (multi-response performance index). Therefore in recent times principal component analysis has been considered as an analytical tool for the optimization of a system with multiple performance characteristics [6, 7, 8].

Material under investigation is Ferritic-Pearlitic Ductile Iron Grade 80-55-06, A536. Cerium is an optional constituent in ductile iron. The present grade is specified to have a minimum tensile strength of 80 ksi (552 MPa), yield strength of 55 ksi (379 MPa) and an elongation of 6%. Applications include crankshafts, gears, rollers and body lifting brackets in automobile sector.

2. Analysis Method

2.1. Response surface methodology (RSM)

Response surface methodology (RSM) is a collection of mathematical and statistical methodology which is useful for the modeling and analysis of problems where the response of interest is influenced by number of variables and the objective is to optimize the responses by describing the relationship between the responses and set of controllable variables [9].The second order polynomial developed for a response surface relates the selected response as a function of k input variables described by Equation 1. After the model building, the statistical approach ANOVA is employed to check its significance and validity.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_i \sum_j \beta_{ij} x_i x_j + \varepsilon \tag{1}$$

Where β_0 , β_i , β_{ii} and β_{ij} are the coefficients to be estimated by the ordinary least square algorithm.

2.2. Signal to noise ratio

Under design of experiment approach, signal to noise (S/N) ratio is used to represent a performance characteristic for parameter design and experimental planning. The larger value of S/N ratio is generally required. The three types of S/N ratio suggested by Taguchi are the lower-the-better, the higher-the-better and the nominal-the-better. For metal removal rate, higher the better and for cutting forces, surface roughness and cutting time, lower the better S/N ratio is chosen.
The S/N ratio with a lower-the-better and a higher-the-better characteristic is expressed as Equation 2 and 3 respectively.

$$\eta_{ij} = -10.\log\left(\frac{1}{n}\sum_{j=1}^{n} y_{ij}^{2}\right) \tag{2}$$

$$\eta_{ij} = -10.\log\left(\frac{1}{n}\sum_{j=1}^{n} \frac{1}{y_{ij}^{2}}\right) \tag{3}$$

Where η_{ij} is the signal to noise ratio for i_{th}experiment at the j_{th}test, n is the total number of the tests.

2.3. Grey relational analysis

Data pre-processing: Pre-processing of the data related to the group of sequences is called "grey relation generation". It is aimed to process the complicate and tedious data to gain a clear rule, which is called the whitening of a sequence of numbers. The expected goal for each influence factor is determined based on the principle of data processing. The linear data pre-processing method for the S/N ratio is calculated as per Equation 4.

$$x_i^*(k) = \frac{x_i^{(0)}(k) - \min .x_i^{(0)}(k)}{\max .x_i^{(0)}(k) - \min .x_i^{(0)}(k)} \tag{4}$$

Where $x_i^*(k)$ is the sequence after the data processing, $x_i^{(0)}(k)$ is the original sequence of S/N ratio, $\max .x_i^{(0)}(k)$ and $\min .x_i^{(0)}(k)$ are the largest and smallest value of $x_i^{(0)}(k)$ respectively, for $i = 1,2,3,..,m$ and $k = 1,2,3,..,n$.

Grey relation coefficient and grey relational grade: The grey relation coefficients can be calculated with the preprocessed sequences data. The grey relation coefficients are obtained as given by Equation (5).
$\Delta_{0i}(k)$ is the deviation of the reference sequence $x_0^*(k)$ and the comparability sequence $x_i^*(k)$ and is obtained as absolute value of the difference between reference sequence $x_0^*(k)$ and the comparability sequence $x_i^*(k)$ as given

by Equation (6). $\Delta\min$ and $\Delta\max$ are given by Equation 7 and 8 respectively.

$$\gamma((x_0^*(k).x_i^*(k)) = \frac{\Delta\min + \varsigma.\Delta\max}{\Delta o_i(k) + \varsigma.\Delta\max} \tag{5}$$

$$\Delta o_i(k) = x_0^*(k) - x_i^*(k) \tag{6}$$

$$\Delta\min = \min_{\forall i}.\min_{\forall k} \Delta o_i(k) \tag{7}$$

$$\Delta\max = \max_{\forall i}.\max_{\forall k} \Delta o_i(k) \tag{8}$$

Where $\varsigma =$ distinguishing coefficient, $\varsigma \in [0,1]$ and represent the relational degree between the reference sequence $x_0^*(k)$ and the comparability sequence $x_i^*(k)$. In present study, the distinguishing coefficient ς is set to 0.5.The grey relational grade is defined as a weighted sum of the grey relation coefficients and is obtained as given by Equation 9.The degree of influence the comparability sequence could exert over the reference sequence is indicated by grey relational grade; therefore the grey relational grade may be higher for a particular comparability sequence than others. In case when the both sequences are identical then the value of grey relational grade is equal to 1. In present study the corresponding weighting values are obtained by the principal component analysis.

$$\Gamma \cdot \left(x_0^*, x_i^*\right) = \sum_{k=1}^{n} \varphi_k . \gamma\left(x_0^*(k), x_i^*(k)\right) \tag{9}$$

$\Gamma \cdot \left(x_0^*, x_i^*\right)$ is the grey relational grade and represents the level of correlation between reference sequence $x_0^*(k)$ and the comparability sequence $x_i^*(k)$. φ_k represents the weighted value of the k_{th} performance characteristic.

2.4. Principal component analysis

This technique is introduced by Hotelling, although the origins are in orthogonal adjustments by least squares that is introduced by Pearson and later developed by Eckart [10]. Principal component analysis is considered as a multivariate data analysis that seeks to reduce the dimensionality of the study. The procedure proposed in present study is described as follows [11].

The original multiple performance characteristic array is described as given by Equation 10.

$$X = \begin{pmatrix} x_1(1) & \dots & x_1(n) \\ \vdots & \vdots & \vdots \\ x_m(1) & \cdots & x_m(n) \end{pmatrix} \tag{10}$$

Where x is the grey relation coefficient for each quality performance characteristics, m is the number of experiments, n is the number of the quality performance characteristics. The value of $m = 17, n = 3$ is considered in present study.Correlation coefficient array is evaluated and described as Equation 11.

$$R_{jl} = \frac{Cov(x_i(j)\ x_i(l))}{\sigma x_i(j) \times \sigma x_i(l)}, j = 1, 2, ..., n \quad \& l = 1, 2, ..., n \tag{11}$$

Where $Cov\ x_i(j), x_i(l)$ is the covariance of sequence $x_i(j)$ and $x_i(l)$; $\sigma_{x_i}(j)$ is the standard deviation of sequence $x_i(j)$; $\sigma_{x_i}(l)$ is the standard deviation of sequence $x_i(l)$.

The eigen values and eigen vectors evaluated from the correlation coefficient array are given by Equation 12.

$$(R - \lambda_k I_m)V_{ik} = 0 \tag{12}$$

Where λ_k is eigen values; $V_{ik} = [a_{k1}a_{k2} \cdots .a_{kn}]^T$ are eigen vectors corresponding to the eigen values λ_k and $\sum_{k=1}^{n} \lambda_k = n, k = 1, 2, ..., n$.

The uncorrelated principal components is thus evaluated as given by Equation 13.

$$Y_{mk} = \sum_{i=1}^{n} x_m(i).V_{ik} \tag{13}$$

Where Y_{m1}, Y_{m2} ,. . . Y_{mn} are the first, second and so on, the principal componentsin decreasing order of variance.

3. Experimental procedure

High power precision lathe NH22, HMT, India with specially designed experimental setup (Figure.1) was used to conduct the experiments. In order to increase the rigidity and robustness during the experiments cylindrical workpiece are held between three jaw chucks and tailstock using revolving center so that tool overhang is restricted to minimum possible value of 20 mm [12]. The cutting operation is performed on the selected grade of ductile iron work pieces of sizes 40 mm diameter and 300 mm length. The mechanical and chemical properties of spheroidal cast iron(EN-GJS-500-7) are listed in Table 1. Figure 2, represents the validation of weight and atomic percentage using energy dispersive X-ray spectroscopy (EDX). The carbide inserts (supplied by WIDIA) wereselected with the designation ISO codes CNMG-431-TN-1000, chip-breaker on two sides, corner radius (R_c) 0.040 mm, insert cutting edge length 12.896 mm, relief angle 0°, shape rhomboid mounted on a commercial tool.To obtain the statistical significant data, surface roughness is measured at four equally spaced locations around the circumference of the workpiece using the Mitituyoto, model SURFTEST SJ-210. The cutting forces were measured using strain gauge based sensor turning tool dynamometer bearing capacity 3 kN, serial no. 108/2015, Medilab (India), Model LTD-300. The dynamometer is mounted on special design fixture with holding dimension of 25 x 25 mm shank size cutting tool. The LABVIEW based software is used for data acquisition with DAQ speed of 10 MHz and the sampling rate of 100 samples /second. Cutting experiments were planned using the central composite design (CCD). Central composite designs consist of a factorial or fractional factorial design with center points, augmented with a group of axial (or star) points that allow estimation of curvature. Therefore, the 17 experiments comprises of three factors at two levels (2k = 23 = 8 tests), six axial points (2k =6) and three center points (3 tests). The value of axial distance, α = 1.5 is considered. The machining tests are conducted by considering three machining parameters: cutting speed (v), feed (f) and depth of cut (d). Ranges are selected based on the shop floor and recommendation by the tool supplier. Table 2 presents the factor- level data defined for input machining conditions.

Table 1.Mechanical and chemical properties of spheroidal cast iron(EN-GJS-500-7)

Mechanical properties		Chemical composition confirmed by EDX		
Tensile strength (R_m), N/mm^2	500	Element	Weight%	Atomic%
0.2 % proof strength ($R_{p0,2}$), N/ mm^2	320	F K	79.58	86.66
Elongation at fracture A, %	7	Si K	15.70	11.56
Brinell hardness, HB	170-230	Mn K	4.72	1.78
Modulus of elasticity (E_o), kN/ mm^2	169	Totals	100.00	

Figure 1. The experimental set inclusive of lathe tool dynamometer, data acquisition, surface roughness tester, inserts and tool holder.

Table 2. Cutting parameters and their levels

Levels	*v (m/min.)*	*f(mm/min)*	*d (mm)*
-1.5	180	0.07	0.53
-1	220	0.08	0.7
0	240	0 .1	0.95
+1	340	0.12	1.2
+1.5	380	0.13	1.37

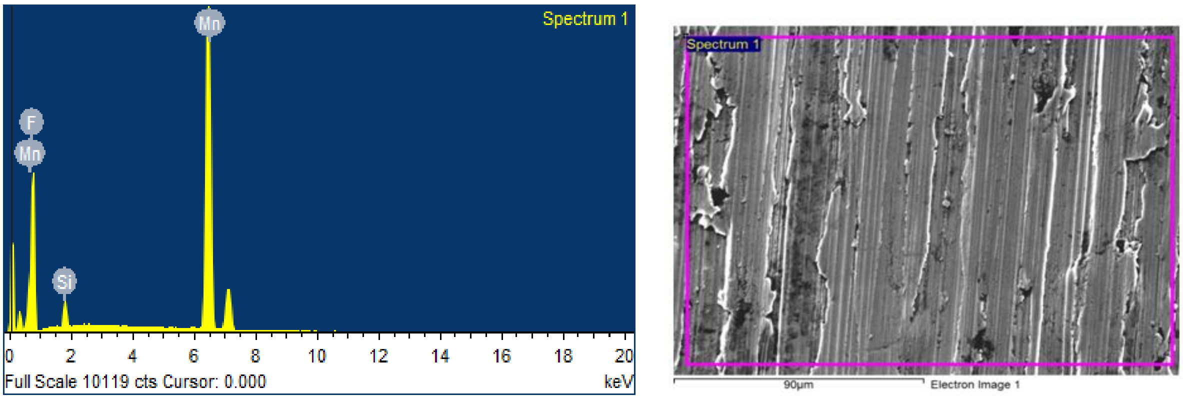

Figure. 2. (a) EDX ; (b) SEM of EN-GJS 500-07.

4. Analysis and discussions

Table 3 represents the experimental design matrix with the calculated S/N ratios for desired result towards the best performance with the smallest variance using Equations 2 and 3. The stepwise procedure adopted is as follows.

(1) Conversion of experimental design into relevant S/N values.

(2) Normalization of S/N ratios.

(3) Calculations for the corresponding grey relational coefficients.

(4) Calculation of grey relational grades using PCA.

(5) Performing ANOVA for statistical analysis of data.

(6) Selection of optimal level of cutting parameters.

(7) Conducting confirmation experiments.

Using equation 4, normalization of S/N ratios is done. The larger value of the normalized outcome equal to 1 indicates the best performance. The deviation sequences $\Delta o_i(k)$ for i = 1-17, in order to obtain the values of $\Delta\max(k)$ and $\Delta\min(k)$ is calculated based on equation 6.

Table 3. Experimental design and signal to noise ratio

Experiment No.	Process parameters			Performance Characteristics				S/N ratios			
	v	f	d	R_a	F_c	C_t	MRR	SNR_a	SNF_c	SNC_t	SNMR
1	280	0.07	0.95	1.85	184.6	1.92	18.58	114.657	45.325	43.637	25.382
2	340	0.08	1.2	2.2	178.6	1.39	32.57	113.152	45.038	39.913	30.258
3	220	0.12	1.2	1.82	230.8	1.43	31.62	114.799	47.265	40.257	29.998
4	220	0.08	1.2	2.22	173.2	2.14	21.08	113.073	44.771	42.542	26.476
5	280	0.1	0.95	2.26	155.8	1.35	26.55	112.918	43.851	39.554	28.480
6	280	0.1	0.53	1.68	128.2	1.35	14.81	115.494	42.158	39.554	23.411
7	280	0.1	0.95	2.23	176.2	1.35	26.55	113.034	44.920	39.554	28.480
8	280	0.1	1.37	2.8	240.2	1.35	38.28	112.765	47.611	39.554	31.660
9	340	0.12	1.2	2.24	250.5	0.92	48.86	112.995	47.976	39.276	33.779
10	180	0.1	0.95	1.9	133.4	2.09	17.07	114.425	42.503	42.212	24.643
11	340	0.12	0.7	1.84	168.4	0.92	28.50	114.704	44.527	39.276	29.098
12	340	0.08	0.7	1.65	98.2	1.39	19.00	115.650	39.842	39.913	25.576
13	280	0.1	0.95	2.32	164.6	1.35	26.55	112.690	44.329	39.554	28.480
14	380	0.1	0.95	2.08	190.8	0.99	36.03	113.639	45.612	39.913	31.133
15	220	0.08	0.7	1.36	109.4	2.14	12.30	117.329	40.780	42.542	21.795
16	280	0.13	0.95	1.85	230.2	1.04	34.51	114.657	47.242	36.124	30.759
17	220	0.12	0.7	1.78	171.88	1.43	18.44	114.992	44.705	40.257	25.317

Based on Equation 5, the grey relation coefficients for 17 comparability sequences are calculated as follows:

$$\gamma((x_0^*(1).x_1^*(1)) = \frac{0.000+(0.5)1.000}{0.5761+(0.5)1.000} = 0.4646 \quad (11)$$

$$\gamma((x_0^*(2).x_1^*(2)) = \frac{0.000+(0.5)1.000}{0.3260+(0.5)1.000} = 0.6053 \quad (12)$$

$$\gamma((x_0^*(3).x_1^*(3)) = \frac{0.000+(0.5)1.000}{0.000+(0.5)1.000} = 1.000 \quad (13)$$

$$\gamma((x_0^*(4).x_1^*(4)) = \frac{0.000+(0.5)1.000}{0.7007+(0.5)1.000} = 0.4164 \quad (14)$$

Thus $\gamma((x_0^*(k).x_1^*(k)) =$ (0.4646, 0.6053,1.000,0.4164), where k = 1- 4. In order to determine the corresponding weighting values for each performance characteristic principle component analysis is especially introduced. The data representing the grey relational coefficient for each performance characteristic is used to evaluate the correlation coefficient matrix and by using Equation 9 the corresponding eigen values are calculated. The first principal component has variance (eigen value) 2.5334 and accounts for 63.3% of the total variance. The second and third principal component has variance 0.7353 and 0.6162 which accounts for 18.4% and 15.4% respectively of the data variability. Thus, most of the data structure is reduced to two or three underlying dimensions. The remaining principal components account for a very small proportion of the variability and are probably unimportant.The eigen factor corresponding to each eigen valueand its square representing the contribution of the corresponding performance characteristic to the principal component is listed in Table5. Table 6 shows that the contributions of average surface roughness, cutting force, cutting time and metal removal rate to be 0.1989, 0.2960, 0.1584and 0.3457 respectively. The variance contribution for the first principal component characterizing the four performance characteristics is found to be 63.3%. Hence for this study, the squares of its corresponding eigen vectors are selected as the weighting values of the related performance characteristic and the coefficients $\varphi_1, \varphi_2, \varphi_3$ *and* φ_4 in Equation 6, are thereby set as 0.1989, 0.2960, 0.1584 and 0.3457 respectively.Based on equation.6 and the data obtained, the grey relational grade is illustrated as following.

$$\Gamma \cdot \left(x_0^*, x_1^*\right) = 0.1989(0.4646) + 0.296(0.6053) + 0.1584(1.000) + 0.3457(0.4164) = 0.5737$$

The same procedure is adopted to determine grey relational grades of the comparability sequences for $i = 1 – 18$ and are listed in Table 4. Thereby the optimization design is performed with respect to a single grey relational grade rather than complicated performance characteristics.

Table 4.The sequence after data pre-processing, grey relational coefficient and grades

No.					Grey relational coefficient				Grey relation grades
Reference sequence	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	
Comparability sequence	R_a	F_c	C_t	MRR	R_a	F_c	C_t	MRR	
1	0.4239	0.6740	1.0000	0.2993	0.4646	0.6053	1.0000	0.4164	0.5737
2	0.0994	0.6387	0.5043	0.7061	0.3570	0.5805	0.5022	0.6298	0.5401
3	0.4545	0.9125	0.5501	0.6845	0.4782	0.8511	0.5264	0.6131	0.6424
4	0.0825	0.6059	0.8543	0.3906	0.3527	0.5592	0.7743	0.4507	0.5140
5	0.0491	0.4929	0.4566	0.5578	0.3446	0.4965	0.4792	0.5307	0.4749
6	0.6044	0.2847	0.4566	0.1349	0.5583	0.4114	0.4792	0.3663	0.4353
7	0.0741	0.6243	0.4566	0.5578	0.3507	0.5710	0.4792	0.5307	0.4981
8	0.0162	0.9552	0.4566	0.8232	0.3370	0.9177	0.4792	0.7387	0.6700
9	0.0657	1.0000	0.4195	1.0000	0.3486	1.0000	0.4628	1.0000	0.7845
10	0.3739	0.3271	0.8103	0.2376	0.4440	0.4263	0.7250	0.3961	0.4661
11	0.4340	0.5759	0.4195	0.6094	0.4691	0.5411	0.4628	0.5614	0.5209
12	0.6381	0.0000	0.5043	0.3155	0.5801	0.3333	0.5022	0.4221	0.4395
13	0.0000	0.5516	0.4566	0.5578	0.3333	0.5272	0.4792	0.5307	0.4817
14	0.2045	0.7093	0.5043	0.7792	0.3859	0.6323	0.5022	0.6936	0.5833
15	1.0000	0.1153	0.8543	0.0000	1.0000	0.3611	0.7743	0.3333	0.5436
16	0.4239	0.9097	0.0000	0.7480	0.4646	0.8471	0.3333	0.6649	0.6259
17	0.4961	0.5978	0.5501	0.2939	0.4981	0.5542	0.5264	0.4145	0.4898

Table 5. The Eigen values and explained variation for principal components

Principal component	Eigen values	Explained variation (%)
First	2.5334	63.3
Second	0.7353	18.4
Third	0.6162	15.4
Fourth	0.115	2.9

The response table (Table 7) is made in order to calculate the average grey relational grade for each cutting parameter level. The calculation involves sorting the grey relational grades corresponding to different levels of the cutting parameter in each column of the experimental matrix and taking an average of those under same level. For example for 0-level of cutting speed (v_3), the grey relation grade of experiment No.1, No.5, No.6, No.7, No.8, No.13, No.16 in Table 3 are averaged. Therefore there average is the average grey relational grade for v_3,and is calculated as:

$$\overline{v_3} = (0.5737 + 0.4749 + 0.4353 + 0.4981 + 0.6700 + 0.4817 + 0.6259)/7 = 0.537$$

Similarly the average grey relational grade for feed rate and depth of cut at level 0 are calculated as:

$$\overline{f_3} = (0.4749 + 0.4353 + 0.4981 + 0.6700 + 0.4661 + 0.4817 + 0.5833)/7 = 0.516$$

$$\overline{d_3} = (0.5737+0.4749+0.4981+0.4661+0.4817+0.5833+0.6259)/7 = 0.529$$

Table 6. The eigen vectors for principal components and contribution of each individual quality characteristic for the first principal component

Quality characteristics	Eigen vector				Contribution
	I PC	II PC	III PC	IV PC	
Average surface roughness	0.446	-0.188	0.873	0.053	0.1989
Cutting Force	-0.544	0.378	0.398	-0.634	0.2960
Cutting Time	0.398	0.899	-0.02	0.182	0.1584
Metal removal rate	-0.588	0.116	0.28	0.75	0.3457

Using the same method, calculations are performed for each cutting parameter level and the response table is constructed. Basically the larger the grey relational grade, the better, the corresponding multiple performance characteristic. Accordingly, the level that gives the largest average response is selected. From the response table shown in Table 7, the best combination of the cutting parameters is the set with cutting speed (v_5= 380 m/min.), feed rate (f_5=0.13 mm/min.) and depth of cut (d_5=1.37 mm). After the evaluation of optimal parameter level settings, the prediction and verification of optimized result is carried out using confirmation experiments. Table 8 shows the results after confirmatory experiments.

Table 7. Response table for the grey relational grade

Symbol	Cutting parameter	Level 1	Level 2	Level 3	Level 4	Level 5	Max-Min
v	Cutting speed	0.466	0.547	0.537	0.571	0.583	0.117
f	Feed rate	0.574	0.547	0.516	0.609	0.626	0.110
d	Depth of cut	0.435	0.498	0.529	0.620	0.670	0.235

Mean Grey relational grade = 0.5461

Table 8. Confirmation tests

Trial runs	R_a	F_c	C_t	MRR
Trial 1	1.58	328.2	0.80	67.0
Trial 2	1.56	332.4	0.78	66.5
Trial 3	1.52	320.0	0.78	66.5
Trial 4	1.50	318.2	0.80	67.5
Average	1.54	324.7	0.79	66.875

The MINITAB 17 statistical software is finally used to determine which parameter significantly affects the performance characteristics considering the grey relation grades as variables. The result of ANOVA for the grey relational grades are shown in Table 9, indicating the sources of variation, their degrees of freedom, the total sum of squares, the mean squares, *F-statistics* and *p-values*. The *p-value* is used to determine whether a factor is significant. If the *p-value* is lower than 0.05, then the factor is significant. The *p-values* are obtained significant at alpha = 0.05

significance level.Table 10, shows the model summary. The R^2 value indicates that the predictors explain 95.56% of the variance among grey relational grade. The adjusted R^2 is 89.85%, which accounts for the number of predictors in the model. Both values indicate that the model fits the data well. The predicted- R^2 value is obtained close to the R^2 and adjusted R^2 values i.e. 88.84%, therefore, the model does not appear to be over fit and has adequate predictive ability. The obtained confirmatory experimental results are compared with the predicted optimal process characteristics using the regression equations based on the obtained regression coefficients by the response surface methodology as shown in table 11.

Table 9. Results of the analysis of variance

Source	Degree of freedom	Adj SS	Adj. MS	F- value	P-value	Significance
Model	9	0.130353	0.014484	16.73	0.001	Significant
V	1	0.006228	0.006228	7.20	0.031	< 0.05
F	1	0.018321	0.018321	21.17	0.002	< 0.05
D	1	0.056970	0.056970	65.82	0.000	< 0.05
V*V	1	0.001330	0.001330	1.54	0.255	Not significant
F*F	1	0.017185	0.017185	19.85	0.003	< 0.05
D*D	1	0.004934	0.004934	5.70	0.048	< 0.05
V*F	1	0.007883	0.007883	9.11	0.019	< 0.05
V*D	1	0.007270	0.007270	8.40	0.023	< 0.05
F*D	1	0.014893	0.014893	17.21	0.004	< 0.05
Error	7	0.006059	0.000866	-	-	-
Lack-of-fit	5	0.005773	0.001155	8.09	0.114	Not significant
Pure error	2	0.000286	0.000143	-	-	-
Total	16	0.136412				

Table 10. Model summary

S	R-sq	R-sq(adj.)	R-sq (pred)
0.0294204	95.56%	89.85%	88.84%

Table 11. Regression coefficients obtained by response surface method

Regression coefficients	R_a	F_c	C_t	MRR
β_0	-8.78	261	8.705	26.55
β_1	0.01419	.39	.021397	0.0948
β_2	110.3	-5676.00	57.93	-265.5
β_3	6.13	31.00	.044	-27.94
β_{12}	.0219	2.29	.0525	0.9481
β_{13}	0.00042	.331	0.00	0.09980
β_{23}	24.25	-80.00	0.00	279.4
β_{11}	0.000028	0.00144	0.000019	0.00
β_{22}	462.1	32160.0	142.5	0.00
β_{33}	1.568	44.6	.0234	0.00
p- value	0.002	.006	0.000	0.000
Adj. R^2 *(%)*	86.18	79.83	99.92	99.89

From Table 12, the absolute percentage error is obtained by comparing experimental and predicted optimal process parameters and are found to be 0.32%, 1.65%, 1.89% and 0.88% for the listed responses under optimal setting (v_5, f_5, d_5). The results shows that the highest level of all machining parameters resulting to the increase of cutting force but all the other performance characteristics are minimized in order to obtain the high productivity. Nevertheless, the data obtained by response surface methodology and the proposed optimization by grey relation analysis coupled with the principal component analysis is found to be suitable to obtain the optimized design considering major machining characteristic indexes viz. metal removal rate, cutting forces and surface roughness in turning process of spheroidal graphite cast iron grade EN-GJS-500-7.

Table 12. Comparison between experimental and predicted optimal process parameters for optimal setting (v_5, f_5, d_5)

Performance characteristics	Predicted (by RSM)	Experimental	Absolute percentage error (%)
R_a	1.535	1.54 μm	0.32%
F_c	319.324	324.7 N	1.65%
C_t	0.805	0.79	1.89%
MRR	66.286	66.875	0.88%

4. Conclusions

This paper presents an application of grey relational analysis coupled with principle component analysis as an alternate to optimize manufacturing processes with multiple correlated responses using central composite experimental design. The cutting parameters are selected as per the recommendation of tool supplier, for turning of spheroidal graphite cast iron grade EN-GJS-500-7 at various factor level combinations. The results are summarized as follows;

1 .The central composite design (CCD) under response surface methodology is introduced for the experimental plan.

2. The principle component analysis used to determine the corresponding weighting values of each performance characteristic while applying grey relational analysis to present problem with multiple performance characteristics is proven to be capable of objectively reflecting the relative importance for each performance characteristic.

3. Based on analysis of variance, the major controllable factors significantly affecting the multiple performance characteristics are cutting speed, feed rate and depth of cut with a total of 97.1% contribution.

4. The optimal combination of the cutting parameters obtained with reference to the response table for the grey relational grade is cutting speed (v_5= 380 m/min.), feed rate (f_5= 0.13 mm/min.) and depth of cut (d_5= 1.37 mm). The corresponding confirmation tests show that R_a, F_c, C_t, and MRR for the suggested optimal combination is 1.54 μm, 324.7 N, 1 min 39 seconds and 66.875mm^3/s respectively.

5. The proposed technique presented in this work has been effective to the optimization of spheroidal graphite cast iron grade EN-GJS-500-7 turning operation, and it needs to be tested in other processes. Therefore it is suggested for future research works that this technique may be applied and verified in other machining or manufacturing operations like milling, welding, casting, etc.

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