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Research Paper

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A hybrid approach for the prediction and optimization of cutting forces using grey-based fuzzy logic§

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Abstract

This study focused on the Grey-Based Fuzzy Logic Algorithm for the prediction and optimization of multiple performance characteristics of oblique turning process. Experiments have been constructed according to Taguchi's L16 orthogonal array design matrix. Cutting speed, rate of feed and depth of cut were selected as input parameters, whereas material removal rate, cutting force and surface roughness were selected as output responses. Using grey relation analysis (GRA), grey relational coefficient (GRC) and grey relation grade (GRG) were obtained. Then, Grey based fuzzy algorithm was applied to obtain grey fuzzy reasoning grade (GFRG). Analysis of variance (ANOVA) carried out to find the significance and contribution of parameters on multiple performance characteristics. Finally, confirmation test was applied at the optimum level of GFRG to validate the results. The results also show the application feasibility of the grey based fuzzy algorithm for continuous improvement in product quality in complex manufacturing processes.

Keywords: Turning process, cutting forces, grey relation analysis, fuzzy logic algorithm, optimization.

1. INTRODUCTION

Turning is a very important machining process in which a single-point cutting tool removes material from the surface of a rotating cylindrical workpiece [1]. The cutting tool is fed linearly in a direction parallel to the axis of rotation [2,3]. As indicated in Figure 1, turning is carried out on a lathe that provides the power to turn the workpiece at a given rotational speed and to feed the cutting tool at a specified rate and depth of cut. Therefore, three cutting parameters, i.e. cutting speed (V), feed rate (F), and depth of cut (D), should be properly selected for better surface finish with lower cutting force [2,3].

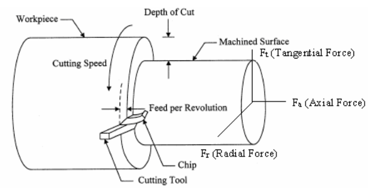

Figure 1: Schematic representation of oblique turning process [1]

In a turning operation, it is an important task to select cutting parameters for achieving high cutting performance. Usually, the desired cutting parameters are determined based on experience or by use of a handbook [1]. However, this does not ensure that the selected cutting parameters have optimal or near optimal cutting performance for a particular machine and environment. To select the cutting parameters properly, several mathematical models based on statistical regression techniques or neural computing have been constructed to establish the relationship between the cutting performance and the cutting parameters [1-8]. Then, an objective function with constraints is formulated to solve the optimal cutting parameters using optimization techniques. Therefore, considerable knowledge and experience are required for using this modern approach [1]. Furthermore, a large number of cutting experiments has to be performed and analyzed in order to build the mathematical models. Thus the required model building is very costly in terms of time and materials [1]. Basically, the grey based fuzzy logic is a powerful tool for the design of multivariable complex systems. It provides a robust systematic and efficient way in order to model the multivariable complex systems. Therefore, this study applied a Taguchi L9 orthogonal array to plan the experiments on turning process [2,3]. Three controlling factors including cutting speed (V), depth of cut (d) and feed rate (f) were selected as input parameters whereas material removal rate, cutting force

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§ This paper was presented in the IMSEC-2016 and surface roughness were selected as output responses. Using grey relation analysis (GRA), grey relational coefficient (GRC) and grey relation grade (GRG) were obtained. Then, Grey based fuzzy algorithm was applied to obtain grey fuzzy reasoning grade (GFRG). Analysis of variance (ANOVA) carried out to find the significance and contribution of parameters on multiple performance characteristics. Finally, confirmation test was applied at the optimum level of GFRG to validate the results. The results also show the application feasibility of the grey based fuzzy algorithm for continuous improvement in product quality in complex manufacturing processes [8-12].

2. EXPERIMENTAL PROCEDURE AND DETAILS

The cutting experiments were carried out on an experimental lathe setup using HSS cutting tool for the machining of AISI 1050 steel bar which is 30 mm in diameter and 80 mm in length. The mechanical properties and percent composition of workpiece material is listed in Table 1 [2,3].

Table 1. Chemical and mechanical properties of AISI 1050 medium carbon steel

Chemical composition %	C	P	S	Mn	Cr	Fe	Ni	Cu
	0.49	0.02	0.02	0.78	0.08	97.99	0.10	0.26
Mechanical properties	Yield strength (MPa)		Tensile strength (Mpa)		Elongation (%)		Vickers Hardness (HV)	
	365		636		24		261	

Phynix TR-100 model surface roughness tester was used to measure the surface roughness of the machined samples. Cut off length () was chosen as 0.3 for each roughness measurement. Average of six measurements of surface roughness was taken to use in the multi-criteria optimization. Also, material removal rate (MRR, mm3/min) was calculated using Eq. (1);

$$MRR = 1000Vfd \tag{1}$$

where f (mm/rev) denotes the feed rate, d (mm) describes the cutting depth and V (m/min) presents the cutting speed of the turning operation.

2.1 Process Parameters and Test Results

In full factorial design, the number of experimental runs exponentially increases as the number of factors as well as their level increases. This results huge experimentation cost and considerable time [11]. So, in order to compromise these two adverse factors and to search the optimal process condition through a limited number of experimental runs Taguchi's L9 orthogonal array consisting of 9 sets of data has been selected to optimize the multiple performance characteristics of turning process [8-12]. Experiments have been conducted with the process parameters given in Table 2, to obtain the machined surface on AISI 1050 medium carbon steel. The feasible space for the cutting parameters was defined by varying the cutting speed in the range of 110-600 m/min, the feed rate in the range of 0.2-0.6 mm/min, and the depth of cut in the range of 0.5-1.5 mm.

Table 2. Cutting parameters and their levels

Cutting Parameters	Notation	Unit	Levels of factors		
			1	2	3
cutting speed	V	m/min	110*	300	600
feed rate	f	mm/min	0.2*	0.4	0.6
depth of cut	d	mm	0.5*	1.0	1.5

*initial factor setting

In order to prevent the sudden increase of cutting forces due to the dullness of the cutting edge, the HSS tool was changed after three repetition of each experiment. Table 3 shows the selected design matrix based on Taguchi L9 orthogonal array consisting of 9 sets of coded conditions and the experimental results for the responses of F, Ra and MRR. All these data have been utilized for analysis and evaluation of optimal parameter combination required to achieve desired quality within the experimental domain [10,11].

Table 3. Orthogonal L9 array of the experimental runs and results

Run no	Parameter level			Experimental results		
	V	f	d	MRR (mm^3/min)	F (N)	R_a ()
1	1	1	1	0.11	123	0.87
2	1	2	2	0.44	179	2.33
3	1	3	3	0.99	364	6.62
4	2	1	2	0.60	166	1.98
5	2	2	3	1.80	295	3.82
6	2	3	1	0.90	255	3.96
7	3	1	3	1.80	340	0.92
8	3	2	1	1.20	218	1.22
9	3	3	2	3.60	268	5.60

3. GREY BASED FUZZY LOGIC

In this section, the constructed grey based fuzzy logic approach for oblique turning process optimization is given in details.

3.1. Grey Relational Analysis (GRA)

In Grey relational analysis, experimental data i.e., measured features of quality characteristics are first normalized ranging from zero to one. This process is known as Grey relational generation. Next, based on normalized experimental data, Grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall Grey relational grade is determined by averaging the Grey relational coefficient corresponding to selected responses [13-16]. The overall performance characteristic of the multiple response process depends on the calculated Grey relational grade (GRG) [14]. This approach converts a multiple response process optimization problem into a single response optimization situation with the objective function of overall Grey relational grade. The optimal parametric combination is then evaluated which would result highest Grey relational grade. The optimal factor setting for maximizing overall Grey relational grade can be performed by Taguchi method [13,16,17]. In Grey relational generation, the normalized F and Ra corresponding to the smaller-the-better (SB) criterion which can be expressed as given in Eq. (2) [18,19]:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{2}$$

MRR should follow the larger-the-better (LB) criterion, which can be expressed as given in Eq. (3) [18]:

$$x_j(k) = \frac{y_j(k) - \min y_j(k)}{\max y_j(k) - \min y_j(k)} \tag{3}$$

where $x_i(k)$ and $x_j(k)$ is the value after the Grey relational generation for SB and LB criterion respectively. Min $y_i(k)$ is the smallest value of $y_i(k)$ and for the kth response, and max $y_i(k)$ is the largest value of $y_i(k)$ for the kth response [18]. An ideal sequence is $x_0(k)$ (k=1,2,…,9) for the responses. The definition of Grey relational grade in the course of Grey relational analysis is to reveal the degree of relation between the 16 sequences [$x_0(k)$ and $x_i(k)$, k=1,2,…,9 and i=1,2,…,9]. The Grey relational coefficient $\xi_i(k)$ can be calculated as given in Eq. (4) [13,18]:

$$\xi_i(k) = \frac{\Delta_{\min} - \psi\Delta_{\max}}{\Delta_{0i}(k) + \psi\Delta_{\max}} \tag{4}$$

where $\Delta_{0i} = \|x_0(k) - x_i(k)\|$ is difference of the absolute value $x_0(k)$ and $x_i(k)$; ψ is the distinguishing coefficient $0 \le \psi \le 1$ (equal $\psi = 0.3$ is used); $\Delta_{\min} = \forall j^{\min} \in i \forall k^{\min} \|x_0(k) - x_j(k)\|$ is the smallest value of $\Delta_{0i}(k)$; and $\Delta_{\max} = \forall j^{\max} \in i \forall k^{\max} \|x_0(k) - x_j(k)\|$ is the largest value of $\Delta_{0i}(k)$. After averaging the Grey relational coefficients, the Grey relational grade γ_i can be computed as given in Eq. (5) [18]:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{5}$$

where n is the number of process responses. The higher value of Grey relational grade corresponds to intense relational degree between the reference sequence $x_0(k)$ and the given sequence $x_i(k)$. The reference sequence $x_0(k)$ represents the best process sequence; therefore, higher Grey relational grade means that the corresponding parameter combination is closer to the optimal [16]. The mean response for the Grey relational grade with its grand mean and the main effect plot of Grey relational grade are very important because optimal process condition can be evaluated from this plot [18].

3.2 Fuzzy Inference System (FIS) Modeling

In GRA, the use of performance characteristics such as lower-the-better, higher-the-better and nominal-the-better reflects that there is some level of uncertainty in the obtained results. This uncertainty can be effectively checked by using fuzzy logic [13,19-29]. The grey-fuzzy method was created and applied by Lin in 2004 [15]. It takes a fuzzy rules approach rather than making a traditional GRG estimation for grey relational analysis. For GRG estimation, two approaches were employed to compare output performance. One is the traditional GRG function while the other is the fuzzy inference system (FIS) [13,16,28-29].

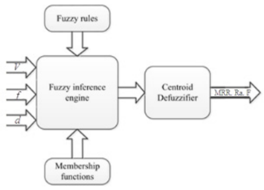


Figure 2: 3-inputs and 3-outputs fuzzy logic system

In the first step, fuzzifier uses the membership function to fuzzify inputs which are obtained before GRG calculations. Membership function is used to define how the values of the input and output are mapped to a value between 0 and 1 [14]. In the next step of the calculation, nine fuzzy rules for three inputs and one output are developed using Eq. (6) based on the results that obtained from the experiments for inference.

$$\begin{aligned}
&\text{Rule 1 : if X1 is A1; X2 is B1;and X3 is C1 then y is D1; else}\\
&\text{Rule 2 : if X1 is A2; X2 is B2;and X3 is C2 then y is D2; else}\\
&\vdots\\
&\text{Rule n : if X1 is An; X2 is Bn;and X3 is Cn then y is Dn; else}
\end{aligned} \tag{6}$$

Ai, Bi, Ci and Di are fuzzy subsets defined by the corresponding membership functions such as μA_i, μB_i, μC_i and μD_i.

The inference engine then performs fuzzy reasoning on fuzzy rules by taking max–min inference (Eq. (7)) to generate a fuzzy value [14].

$$\begin{aligned}
&\mu_{C_0}(Y) = (\mu_{A_1}(X_1) \wedge \mu_{B_1}(X_2) \wedge \mu_{C_1}(X_3) \wedge \mu_{D_1}(Y) \ \vee \ldots \\
&\mu_{A_n}(X_1) \wedge \mu_{B_n}(X_2) \wedge \mu_{C_n}(X_3) \wedge \mu_{D_n}(Y)
\end{aligned} \tag{7}$$

Where $\wedge$ is the minimum operation and, $\vee$ is the maximum operation. Finally, in this study, centroid defuzzification method was used in order to convert the fuzzified values. The centroid defuzzification method is given in Eq. (8).

$$Y_0 = \frac{\sum Y \mu_{C_0}(Y)}{\sum \mu_{C_0}(Y)} \tag{8}$$

The flowchart adopted in the present study to determine the optimal combination of ball turning parameters for the multi response optimization is shown in Figure 3.

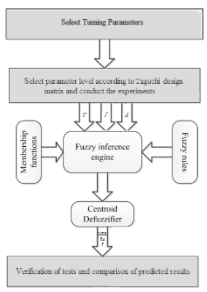


Figure 3: Flowchart of the proposed grey based fuzzy logic method

The methodology consists of a six forward step approach given below [14]:

Step 1: Selecting the Turning input parameters and their levels as given in Table 2. Perform the experiments according to the Taguchi's orthogonal design matrix given in Table 3.

Step 2: Normalize all of the responses using Eqs. (2) and (3). Calculate the grey relational coefficients using Eq. (4), and followed by calculation of grey relational grade (GRG) using Eq. (5).

Step 3: Fuzzify the grey relational coefficients obtained from each response and the overall grey relational grade using membership function. Also, establish the fuzzy rules in linguistic form relating the grey relational coefficient and the overall grey relational grade using Eq. (6).

Step 4: Using max-min interface operations given in Eq. (7), calculate the value of fuzzy multi response output (), and follow by calculating the grey-fuzzy reasoning grade Y0 using centroid defuzzification method given in Eq. (8).

Step 5: Select the optimal combination of parameters through response table and response graph obtained from grey-fuzzy optimization. Find out the contribution of each factor and their interactions on the multi response output using analysis of variance (ANOVA) Table.

Step 6: Carry out the confirmation tests to verify the results obtained and compare the results determine the improvements and percentage error.

4. RESULTS AND DISCUSSION

The pre-processed data of the normalized experimental results, grey relational coefficients and the overall grey relational grade for each combination of parameters is tabulated in Table 4, Table 5 and Table 6. The grey-fuzzy reasoning grade is obtained by using MATLAB v7.10.0 (R2010a) fuzzy logic tool box.

Table 4. Grey relational generation of each performance characteristics

Run no	MRR	F	Ra
	Larger-the-better	Smaller-the-better	Smaller-the-better
Ideal sequence	1.000	1.000	1.000
1	0.000	1.000	1.000
2	0.095	0.768	0.746
3	0.252	0.000	0.000
4	0.140	0.822	0.807
5	0.484	0.286	0.487
6	0.226	0.452	0.463
7	0.484	0.100	0.991
8	0.312	0.606	0.939
9	1.000	0.398	0.177

Table 5. Evaluation of Δ_{0i} for each of the responses

Run no	MRR	F	Ra
Ideal sequence	1.000	1.000	1.000
1	1.000	0.000	0.000
2	0.905	0.232	0.254
3	0.748	1.000	1.000
4	0.860	0.178	0.193
5	0.516	0.714	0.513
6	0.774	0.548	0.537
7	0.516	0.900	0.009
8	0.688	0.394	0.061
9	0.000	0.602	0.823

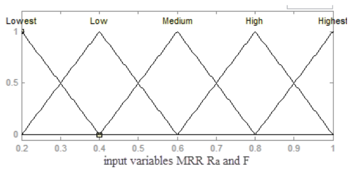
Table 6 shows the calculated Grey relational coefficients (with the weights of $\psi_{MRR} = 0.3$, $\psi_F = 0.3$ and $\psi_R = 0.3$) of each performance characteristic using Eq. (4).

Table 6. Grey relational coefficient and grey relational grade of each performance characteristics

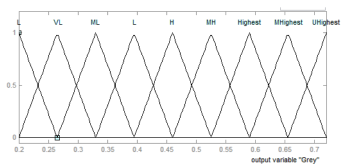
Run no	MRR	F	Ra	Grey relational grade
Ideal sequence	1.000	1.000	1.000	
1	0.248	1.000	1.000	0.711
2	0.267	0.587	0.565	0.468
3	0.306	0.248	0.248	0.264
4	0.277	0.649	0.631	0.513
5	0.390	0.316	0.391	0.362
6	0.299	0.376	0.380	0.348
7	0.390	0.268	0.974	0.538
8	0.324	0.456	0.844	0.536
9	1.000	0.354	0.286	0.541

The Grey relational coefficients, given in Table 6, for each response have been accumulated by using Eq. (4) to evaluate Grey relational grade, which is the overall representative of all the features of cutting process quality. Thus, the multi-criteria optimization problem has been transformed into a single equivalent objective function optimization problem using the combination of Taguchi approach and Grey relational analyses. Higher is the value of Grey relational grade, the corresponding factor combination is said to be close to the optimal [3,10,11].

Triangular shaped membership function, shown in Figure 4(a), is used for fuzzy modeling of the input and output data. The five linguistic membership functions such as LOWEST, LOW, MEDIUM, HIGH and HIGHEST are used to represent the GRC of the input variables.



(a)



(b)

Figure 4: Constructed membership functions for (a) input parameters, (b) output parameter

GRG is represented by the nine membership functions such as LOWEST (L), VERY LOW (VL), MEDIUM LOW (ML), LOW, HIGH (H), MEDIUM HIGH (MHIGH), HIGHEST (H), MEDIUM, HIGHEST (MH) and ULTRA-HIGHEST (UH). Also, the triangular shaped membership function used for GRG as shown in Figure 4(b).The values of GFRG and GRG obtained for nine experiments are shown in Table 7. It is evident that the experiment number 1 and 9 exhibit the best multiple performance characteristics with the highest GFRG. Based on the grey-fuzzy calculations, the absolute average percentage error between the GRG and GFRG was calculated as 6.05%. Also, as shown in Figure 5 high correlation coefficient of R2=0.987 indicates the close relationship between GRG and GFRG.

Table 7. Comparison of GRG and GFRG

Experiment no	Grey relational grade (GRG)	Grey-fuzzy reasoning grade (GFRG)	Rank	Absolute Error %
1	0.711	0.699	1	1.755
2	0.468	0.444	6	5.440
3	0.264	0.286	9	7.746
4	0.513	0.460	5	11.522
5	0.362	0.325	7	11.323
6	0.348	0.319	8	9.064
7	0.538	0.525	3	2.476
8	0.536	0.525	4	2.095
9	0.541	0.525	2	3.048
			Average percentage error=6.05%	

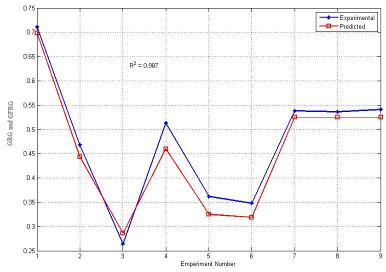


Figure 5: Comparison of experimental and fuzzy predicted GRG and GFRG

Table 8 shows the response table for the mean of GFRG. Higher is the value of GFRG, the corresponding factor combination is said to be close to the optimal [13,14]. Analysis of the means is performed for the GRFG. Based on the max-min statistics the multiple performance response is listed in Table 8. The response graph of the oblique turning parameters is plotted in Figure 8. Greater the slope of the response graph larger is the effect of the parameter on the multiple performance response [14].

Table 8. Response table for the mean Grey relational grade

Factors	Grey fuzzy relational grade			
	Level 1	Level 2	Level 3	max-min
V	0.48	0.37	0.52	0.15
f	0.56	0.43	0.38	0.18
d	0.51	0.48	0.38	0.13
Total mean Grey fuzzy relational grade= 0.46				

As indicated in Figure 6, above the mean grey fuzzy relational grade which is shown by dashed line, the optimal condition for the turning process obtained as V3f1d1.

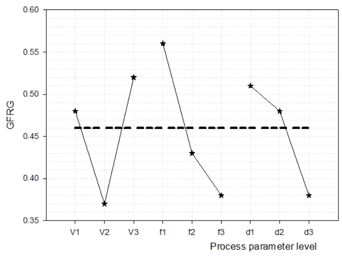


Figure 6: Response graph of GFRG for turning parameters

Analysis of variance analysis (ANOVA) is carried out to investigate which oblique turning parameters significantly affect the performance characteristic [13]. The results of ANOVA are shown in Table 9. The analysis is done at a significance level of $\alpha = 0.05$ (confidence level of 95%). Also, the statistical testing for the experimental data was carried out using Fisher's F test for ANOVA [19]. Larger the F-value shows that the change of process parameter have more strong influence on the performance characteristic [14,25]. According to the contribution effect of the parameters, feed rate (39.13%) is found to be the major factor affecting multiple performance responses, whereas cutting speed (28.20%) and depth of cut (21.01%) are found to be the second and third ranking factor on the surface roughness, material removal rate and cutting force respectively. Also, the same contribution order is seen from the F test column of the Table 9.

Table 9. ANOVA results for GFRG

Parameter	Degree of Freedom	Sum of Square	Mean Square	F	Contribution (%)
V	2	0.039	0.019	2.39	28.20
f	2	0.054	0.027	3.34	39.13
d	2	0.029	0.015	1.82	21.01
Error	2	0.016	0.008		11.59
Total	8	0.138			100

After evaluating the optimal parameter settings, the next step is to predict and verify the enhancement of quality characteristics using the optimal parametric combination. The estimated grey-fuzzy reasoning grade $\hat{\gamma}$ using the optimal level of the design parameters can be calculated as: given in Eq. (9) [13,14].

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{o} (\bar{\gamma}_i - \gamma_m) \quad (9)$$

where γ_m is the total mean GFRG, $\bar{\gamma}_i$ is the GFRG at the optimal level, and o is the number of the main design parameters that affect the quality characteristics of turning process. Table 10 summarizes the results of confirmation test and optimum levels.

Table 10. Confirmation test results

	Initial factor settings	Optimal process condition	
		Prediction	Experiment
Factor levels	V1f1d1	V3f1d1	V3f1d1
MRR (mm3/min)	0.11		0.30
F (N)	123		115
Ra (μm)	0.87		0.65
Grey fuzzy reasoning grade (GFRG)	0.64	0.68	0.70
Improvement in grey fuzzy reasoning grade=0.06			

At the optimal setting (V3f1d1) the estimated GFRG is 0.68 and that obtained from the experiment is 0.70 which is also larger than the GFRG result of initial factor setting (0.64). Thus, a gain of 0.02 in GFRG means that the grey fuzzy logic can be successfully utilized for multi characteristics optimization problems of all the machining process [13,14].

5. CONCLUSIONS

This study has concentrated on the grey based fuzzy logic multi response optimization in the oblique turning process. The following conclusions can be drawn from this study.

- The grey-fuzzy algorithm is suitable for optimizing the complicated multi response machining processes,
- Output turning parameters such as surface roughness, material removal rate and cutting force are greatly improved by using grey based fuzzy logic optimization,
- ANOVA analysis showed that, table feed rate has the highest contribution (39.13%) on the multiple performance characteristics followed by the cutting speed (28.20%) and depth of cut (21.01%),
- The grey fuzzy optimization results of parameters for turning process of AISI 1050 medium carbon steel are summarized as 600 m/min cutting speed, 0.2 mm/min feed rate and 0.5 mm depth of cut.

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