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Fuzzy Logic Approach for Enhancing the Performance of Grinding Process

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ABSTRACT

This analysis focuses on finding an optimum set of machining parameters in external centerless grinding process by adopting grey relational analysis, coupled with fuzzy logic approach. This hybrid technique is used to determine the grey-fuzzy reasoning grade from the calculated multi-characteristics grey relational grade of surface roughness and roundness error to reduce the fuzziness in output. Experiments are designed using Taguchi's Design of Experiments (DoE), for three parameters varied through three levels an L_9 (3^3) Orthogonal Array (OA) is selected. The optimal level values are determined from the response table and main effects plot and the individual effect of one parameter over another parameter is determined using the interaction plot. Confirmation experiment conducted with the optimum input parameters obtained from grey-fuzzy reasoning grade shows a reduction in surface roughness and roundness error values.

Keywords - Grinding parameters; Taguchi's DoE; Grey Relational Analysis; Fuzzy logic.

1. INTRODUCTION

Grinding process is dissimilar to other machining processes such as turning and milling, as the multipoint cutting edges of the grinding wheel do not have uniformity, which act differently on the work piece at each grinding. These complexities and difficulties of illustrating the grinding process also raise obstacles to the optimization of the grinding process and to the verification of the interrelationship between grinding parameters and outcomes of the process. Centerless grinding operation is best suited for mass production and is one of the key processes to ground components to close tolerances with high surface finish in automobile industries. The high quality work done on the centerless grinding machine is achieved through proper selection of grinding parameters. Improper selection of input parameters gives rise to out of roundness, poor surface finish etc. Quantification of surface roughness value and roundness error of the workpiece is necessary to determine the quality of the component grounded. The centerless grinding parameters have to be optimized in order to obtain best quality of machined component and to achieve less production cost. Fig. 1 shows the schematic representation of external centerless grinding process [1]. Garitaonandia et al. [2] presented an efficient method to solve the characteristic equation of centerless grinding process by applying root locus perspective method using simulation approach.

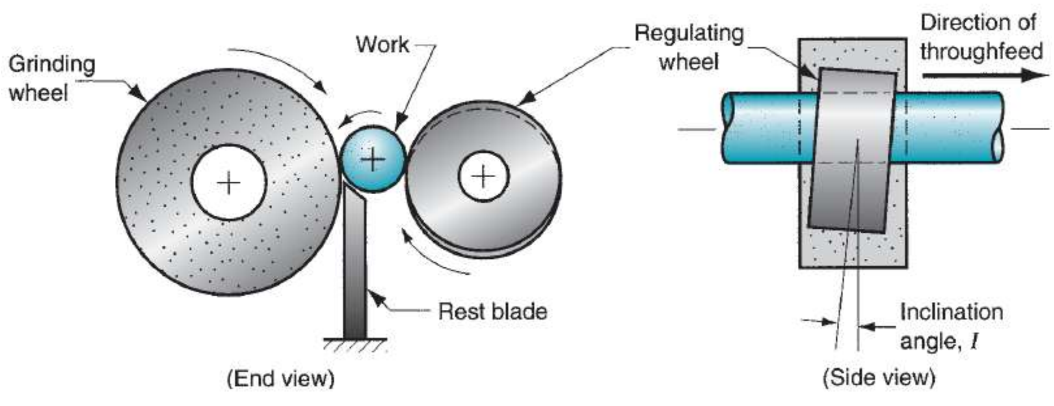

Fig. 1 Schematic External Centerless Grinding Process

Xu et al. [3] has investigated the workpiece roundness based on process parameters by both simulation and experimental analysis. Kwak et al. [4] analyzed the grinding power and surface roughness of the workpiece by response surface methodology and has developed a model to predict them. Krajnik et al. [5] minimized the surface roughness by optimizing the grinding process by response surface methodology and developed an empirical model for it. Zhou et al. [6] minimized the lobing effect by developing a stability diagram for workpiece and thereby selecting the grinding parameters. Dhavlikar et al. [7] minimized the roundness error of workpiece by applying both Taguchi and dual response methodology. Kwak [8] evaluated the effect of grinding parameters on geometric error and has developed a second-order response model for it. Senthilkumar and Tamizharasan [9] applied Taguchi's DoE to design and conduct experiments and obtained the optimal setting of input parameters for achieving better outputs within the available resources.

In this work, optimization of centerless grinding parameters regulating wheel speed, feed rate and depth of cut is performed by considering multiple responses simultaneously by applying grey relational analysis. Prediction of output responses is carried out by fuzzy logic approach which is coupled with grey analysis to reduce the fuzziness in output.

2. MATERIAL SELECTION

The workpiece material chosen for this work is AISI 1040 steel, which is used in the applications of stressed pins, shafts studs, keys etc. The chemical composition of the workpiece material is shown in Table 1.

The SEM microphotograph of workpiece material AISI 1040 steel is shown in Fig. 2. The microstructure of the matrix shows large grains of pearlite in a matrix of ferrite. The microstructure is typical of medium carbon steel that has been hot rolled and re-crystallized.

The Grinding wheel used for the experiment is an Aluminium oxide abrasive wheel, whose designation is A60-L5-V20 as per the ANSI standard B74.13-1977 [1].

2. METHODOLOGIES APPLIED

2.1 Taguchi's Design of Experiment

Taguchi method is a powerful tool in quality optimization [10-13]. Taguchi method makes use of a special design of OA to examine the quality characteristics through a minimal number of experiments [14-15]. Taguchi's DoE is used to design the OA for three parameters regulating wheel speed, feed rate and depth of cut and for each parameter three different values that are chosen is shown in Table 2.

Table 1 Chemical composition of AISI 1040 steel

Sl. No	Element	% Composition
1	Carbon	0.436
2	Silicon	0.198
3	Manganese	0.761
4	Molybdenum	0.012
5	Titanium	0.006
6	Vanadium	0.004
7	Tungsten	0.045
8	Phosphorous	0.023
9	Sulphur	0.025
10	Copper	0.056
11	Aluminium	0.045
12	Iron	98.389

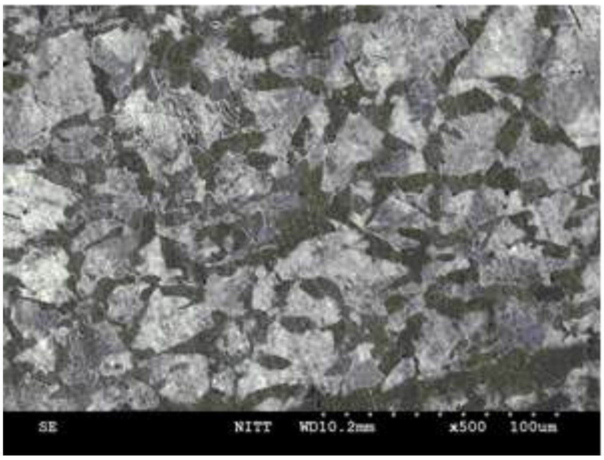

Fig. 2 SEM image of AISI 1040 steel

Table 2 Control parameters and its levels

Sl. No	Parameter / Level	Level 1	Level 2	Level 3
1	Regulating wheel Speed (m/min)	20	40	80
2	Feed rate (°)	2	4	6
3	Depth of Cut (mm)	0.02	0.04	0.06

For various combinations of control parameters and its levels, the formulated L_9 OA is shown in Table 3.

Table 3 Experimental L_9 Orthogonal array

Trial No.	Regulating wheel speed (m/min)	Feed rate (°)	Depth of Cut (mm)
1	20	2	0.02
2	20	4	0.04
3	20	6	0.06
4	40	2	0.04
5	40	4	0.06
6	40	6	0.02
7	80	2	0.06
8	80	4	0.02
9	80	6	0.04

2.2 Grey Relational Analysis

In order to determine the optimum condition of various input parameters to obtain the best quality characteristics, Grey Relational Analysis (GRA) is carried out [16-18]. GRA has been broadly applied in evaluating or judging the performance of a complex project with meager information. However, data to be used in grey analysis must be preprocessed into quantitative indices for normalizing raw data for another analysis. Preprocessing raw data is a process of converting an original sequence into a decimal sequence between 0.00 and 1.00 for comparison. If the expected data sequence is of the form "higher-the-better", then the original sequence can be normalized as, In order to determine the optimum condition of various input parameters to obtain the best quality characteristics, GRA is carried out [19,20]. GRA has been broadly applied in evaluating or judging the performance of a complex project with meager information. However, data to be used in grey analysis must be preprocessed into quantitative indices for normalizing raw data for another analysis. Preprocessing raw data is a process of converting an original sequence into a decimal sequence between 0.00 and 1.00 for comparison. If the expected data sequence is of the form "higher-the-better", then the original sequence can be normalized as,

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{1}$$

where x^o_i (k) is the original sequence, x^*_i (k) the sequence after the data preprocessing, max x^o_i (k) the largest value of x^o_i (k), and min x^o_i (k) implies the smallest value of x^o_i (k).When the form "smaller-the-better" becomes the expected value of the data sequence, the original sequence can be normalized as,

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{2}$$

Following data pre-processing, a grey relational coefficient is calculated to express the relationship between the ideal and actual normalized experimental results. The grey relational coefficient can be expressed as follows,

$$\zeta_i(k) = \frac{\Delta_{\min} + \zeta.\Delta_{\max}}{\Delta_{0i}(k) + \zeta.\Delta_{\max}} \tag{3}$$

where Δ_{oi}(k) is the deviation sequence of the reference sequence which is given by,

$$\Delta_{0i}(k) = \left\| x_0^*(k) - x_i^*(k) \right\| \tag{4}$$

$$\begin{aligned} \Delta_{\max} &= \max_{\forall j \varepsilon i} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|, \\ \Delta_{\min} &= \min_{\forall j \varepsilon i} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|. \end{aligned} \tag{5}$$

ζ is distinguishing or identification coefficient: $\zeta \in [0, 1]$. $\zeta = 0.5$ is generally used. After obtaining the grey relational coefficient, we normally take the average of the grey relational coefficient as the grey relational grade. The grey relational grade is defined as follows.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} {}_i\zeta_i(k) \tag{6}$$

2.3 Fuzzy Inference System

Fuzzy inference or fuzzy ruled based system consists of four parts namely a fuzzification interface, a rule base and database, a decision making unit and a defuzzification interface [21]. The functions of the fuzzy interface system is, a rule base which consists of a number of fuzzy IF-THEN rules and the related databases that defines the membership functions of the fuzzy sets which are used in the fuzzy rules, a decision making unit which performs the inference operations based on the written rules, a fuzzification interface that is used to convert the crisp inputs that have the fuzziness into degrees of match with the linguistic values and finally a defuzzification interface unit which converts the fuzzy predicted results of the inference into an improved crisp output [22].

5. RESULTS AND DISCUSSIONS

Based on the L_9 array designed using Taguchi's DoE, experiments are conducted in a centerless grinding machine. In this study, nine different workpieces were taken and for each level, a separate workpiece is used. The roundness error is calculated using a Bench center attached with a digital dial gauge and the surface roughness is measured with a Kosaka make Surfcoder-SE1200. These output quality characteristics measured were given in the Table 4.

Table 4 Inner and Outer array of Taguchi's DoE

Exp. No	Output response		Data Pre-Processing		Deviation Sequence		Grey Relational Coefficient		Grey Relational Grade
	Surface Roughness (µm)	Roundness Error (mm)	SR	RE	SR	RE	SR	RE	
1	2.825	0.020	0.05729	0.23077	0.94271	0.76923	0.347	0.394	0.370
2	2.982	0.016	1	0.53846	0	0.46154	1.000	0.520	0.760
3	1.646	0.023	0.66036	0	0.33964	1	0.595	0.333	0.464
4	2.791	0.010	0.07468	1	0.92532	0	0.351	1.000	0.675
5	2.885	0.020	0.0266	0.23077	0.9734	0.76923	0.339	0.394	0.367
6	2.024	0.010	0.46701	1	0.53299	0	0.484	1.000	0.742
7	2.166	0.013	0.39437	0.76923	0.60563	0.23077	0.452	0.684	0.568
8	2.937	0.016	0	0.53846	1	0.46154	0.333	0.520	0.427
9	2.273	0.013	0.33964	0.76923	0.66036	0.23077	0.431	0.684	0.558

The roundness error and surface roughness of the workpiece has to be lower for a given set of input parameters. Hence the smaller-the-better condition is chosen as in Equ. 2. Table 4 shows the normalized sequence after data pre-processing and deviation sequences. The grey relational coefficient of surface roughness and roundness error is calculated, which are given in Table 4. In order to convert these individual responses into a combined multi-response [23], a grey relational grade is determined, which is the average of the grey relational coefficient of surface roughness and roundness error [24].

For obtaining the grey fuzzy output MATLAB software is used. The uncertainty in the evolved grey relational grade is improved by the fuzzy approach and a fuzzy reasoning of multiple outputs is developed, termed as grey-fuzzy reasoning grade. In this work, mamdani's implication method of inference for obtaining membership function is used as shown in Fig. 3. Centroid method of defuzzification is carried out in this analysis.

Triangular membership function is adopted for grey coefficient for surface roughness and roundness error with five membership functions. The output of grey-fuzzy reasoning grade is divided into five number of membership functions as shown in Fig. 4. The fuzzy inference system (FIS) is activated with a set of written rules and is evaluated to predict the grey-fuzzy reasoning grade for all nine experiments as shown in Fig. 5. When comparing the obtained results with the grey relational grade, an improvement in the value of grey-fuzzy reasoning grade is observed as given in Table 5. It is confirmed that the experiment no. 2 has the best combination of input grinding parameters. Fig. 6 shows the comparison of grey relational grade and grey-fuzzy reasoning grade. From the graph, it is visualized that the fuzziness is reduced towards the reference value 1.

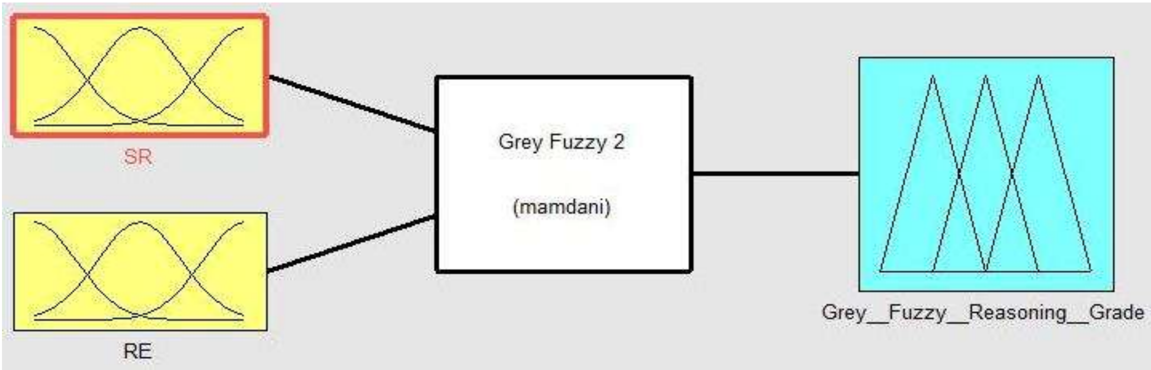

Fig. 3 Fuzzy Inference system

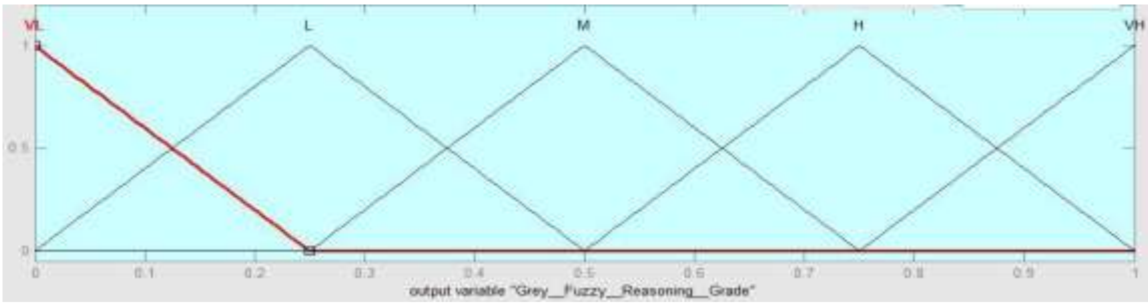

Fig. 4 Membership function of output

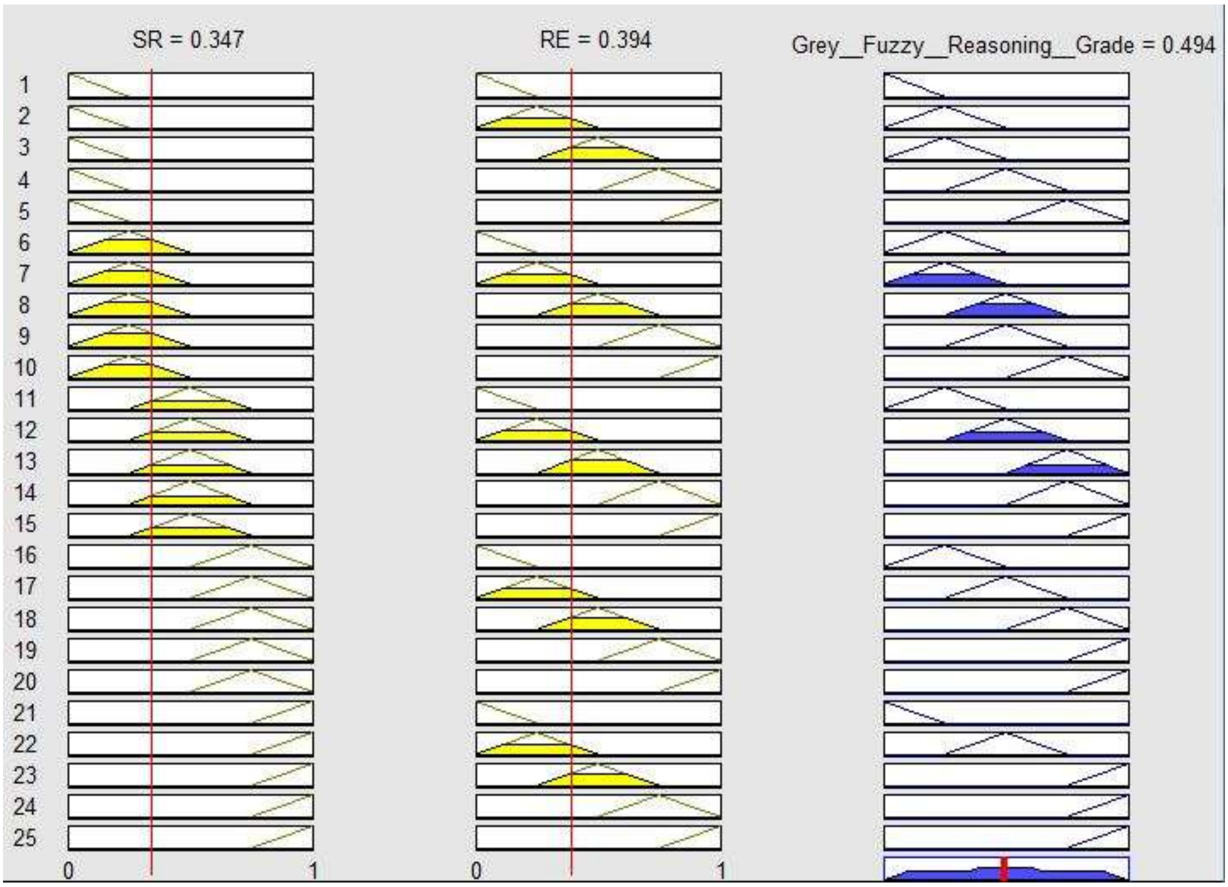

Fig. 5 Computation of Grey-Fuzzy reasoning grade

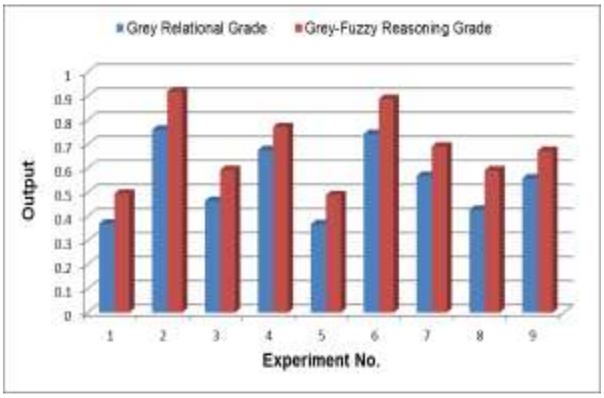

Fig. 6 Grey relational and grey-fuzzy grade

Based on the framed rule, a surface plot between surface roughness, roundness error and the output grey-fuzzy reasoning grade is drawn as shown in Fig. 7.

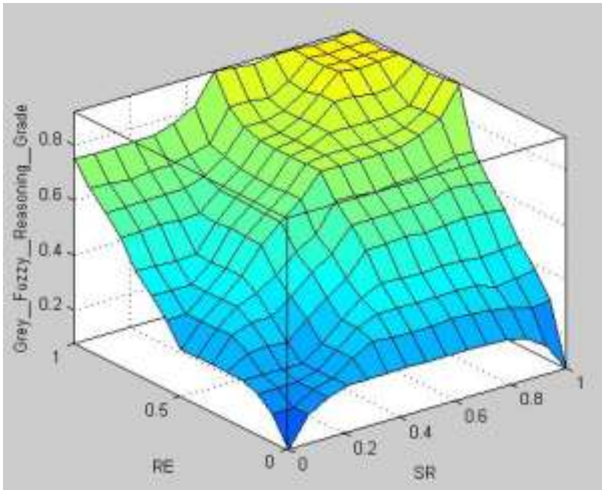

Fig. 7 Fuzzy inference surface plot

From the average value of grey-fuzzy reasoning grade for all level values of the input grinding parameters, the response table and main effects plot are obtained to find the optimal grinding parameters.

The best levels of various parameters are identified by calculating the average values of weighted grey relational grade, corresponding to each and every level of parameters and are consolidated in Table 6.

From the response table of weighted grey relational grade, the optimal parameter levels are identified as, regulating wheel speed of 40 m/min, feed rate as 6° and depth of cut as 0.04 mm. From the response table of surface roughness, the main effects plot is drawn, as shown in Fig. 8.

Table 5 Grey-fuzzy reasoning grade and % improvement

Exp. No	Grey Relational Grade	Grey-Fuzzy Reasoning Grade	% Improvement	Rank
1	0.370	0.494	33.42%	8
2	0.760	0.919	20.92%	1
3	0.464	0.593	27.69%	6
4	0.675	0.771	14.15%	3
5	0.367	0.488	33.10%	9
6	0.742	0.888	19.67%	2
7	0.568	0.690	21.43%	4
8	0.427	0.591	38.52%	7
9	0.558	0.672	20.53%	5

Table 6 Response table for Grey-fuzzy grade

Level / Parameter	Regulating Wheel Speed	Feed rate	Depth of cut
Level 1	0.669	0.652	0.658
Level 2	0.716	0.666	0.788
Level 3	0.652	0.718	0.590

The interaction effects of three factors are shown in Fig. 9. In between regulating wheel speed and feed rate a higher level of interaction exists for a speed of 20m/min and for a feed rate of 4°. For all level values of regulating wheel speed and depth of cut a considerable amount of interaction exists between them. For all level values of depth of cut a significant interaction exists between depth of cut and feed rate, but for a feed rate of 6° only a moderate interaction exists between feed rate and depth of cut.

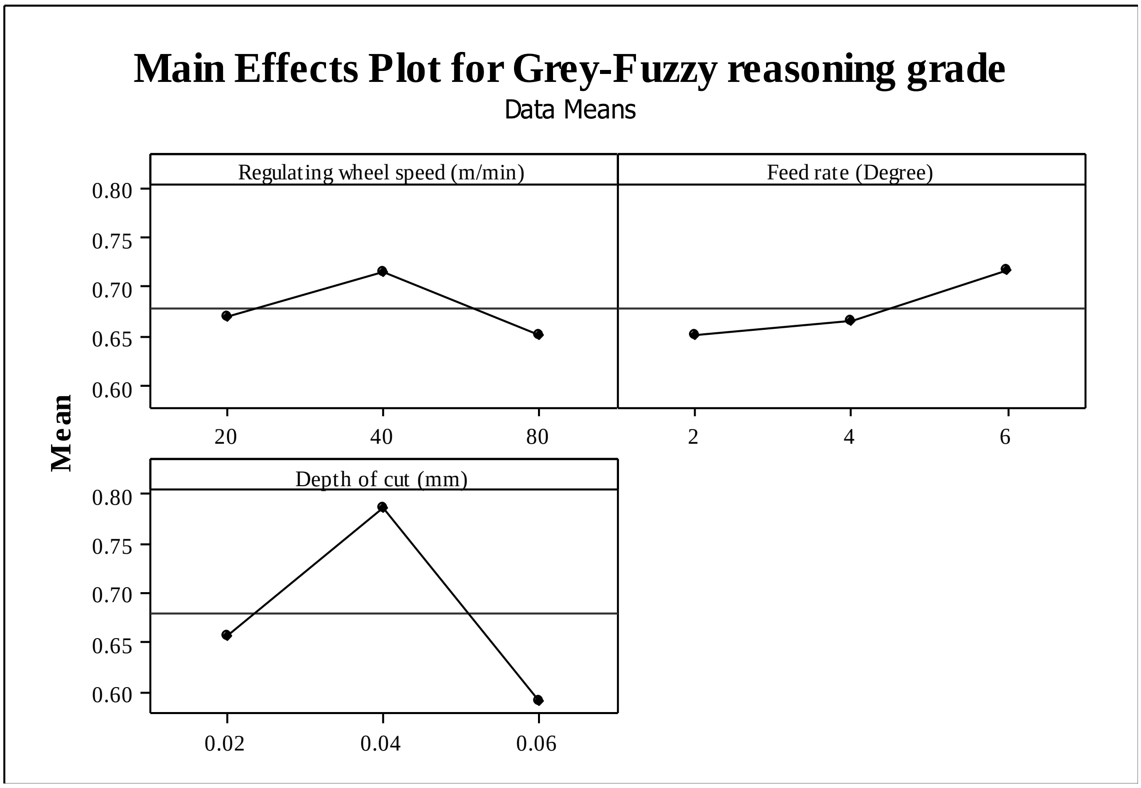

Fig. 8 Main Effects plot of grey-fuzzy reasoning grade

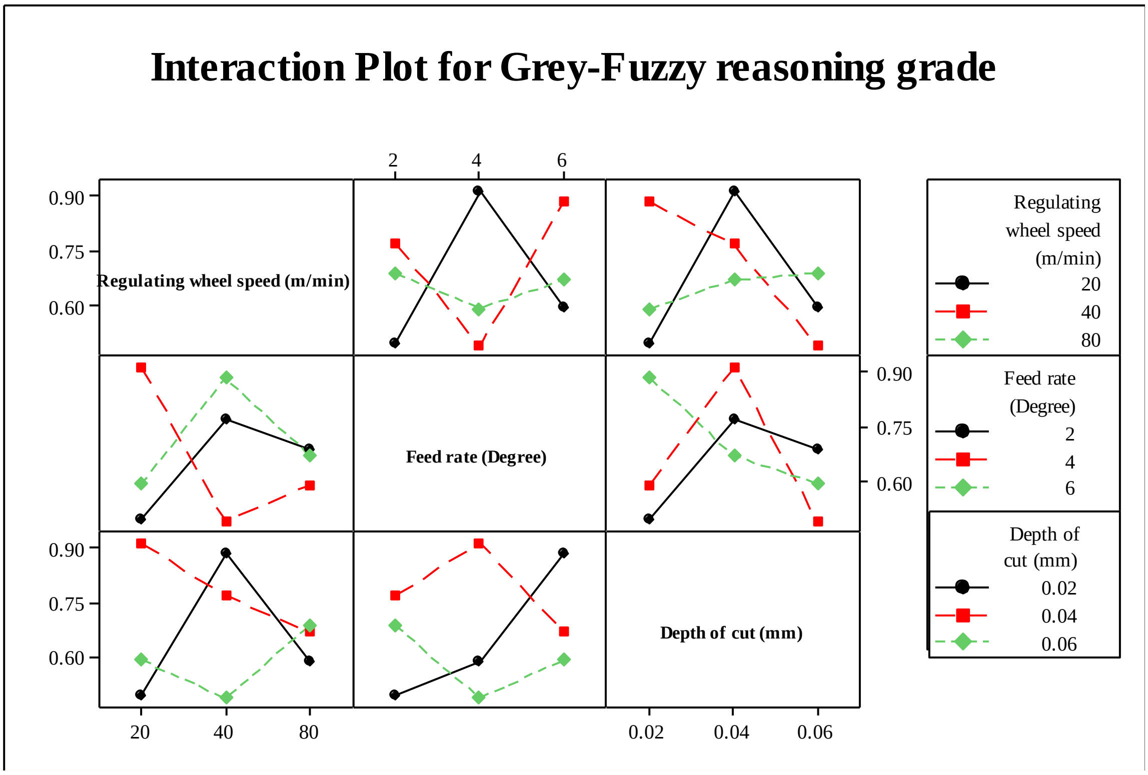

Fig. 9 Interaction plot of grey-fuzzy reasoning grade

A validation experiment is conducted based on the optimum condition obtained and the obtained quality characteristics are shown in Table 7. It is observed that the surface roughness is reduced by 16.75% and roundness error is reduced by 23.40% proving the efficiency of the hybrid grey-fuzzy approach.

Table 7 Predicted and Experimental grey-fuzzy grade

Initial grinding parameter		Optimum condition	
		Prediction	Experimental
	$v_1f_1d_1$	$v_2f_3d_2$	$v_2f_3d_2$
Surface roughness	2.825	-	2.084
Roundness error	0.202	-	0.012
Grey fuzzy reasoning grade	0.494	0.866	0.712
Improvement	-	0.372	0.218

5. CONCLUSION

In this work, a hybrid Grey relational analysis and fuzzy logic technique is applied to optimize the grinding parameters regulating wheel speed, feed rate and depth of cut. From the grey-fuzzy reasoning grade obtained, it is concluded that,

- Based on Taguchi's DoE, an L_9 orthogonal array is chosen for designing the experiments.
- Multi-response characteristics are evaluated using grey relational analysis coupled with fuzzy logic approach by determining the grey-fuzzy reasoning grade to reduce the fuzziness in the output values.
- For grey-fuzzy reasoning grade, the optimum condition obtained is regulating wheel speed of 40 m/min, feed rate of 6º and depth of cut of 0.04 mm based on grey-fuzzy reasoning grade.
- For all level values of regulating wheel speed and depth of cut and in between depth of cut and feed rate, a significant level of interaction exists between them.
- Prediction of grey-fuzzy reasoning grade shows an improvement from the initial setting values and the experimental values based on the optimum condition evolved.
- Confirmation experiment performed with the optimum level values shows a reduction in surface roughness by 16.75% and roundness error is reduced by 23.40% proving the efficiency of the hybrid grey-fuzzy approach.

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