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A grey-fuzzy approach for optimizing machining parameters and the approach angle in turning AISI 1045 steel

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A B S T R A C T

The influence of the machining parameters and approach angle of carbide inserts over tool wear at the flank face, surface roughness and material removal rate are investigated experimentally in this work. The optimum conditions are found out by using a hybrid grey-fuzzy algorithm. The grey relational analysis and fuzzy logic technique are coupled to obtain a grey-fuzzy grade for evaluating multi-characteristics output from the grey relational coefficient of each response. The experiments were designed using Taguchi's design of experiments; a L_9 (3^4) orthogonal array was selected for four parameters varied through three levels. Fuzzy-based reasoning was integrated using the grey approach to reduce the degree of uncertainty. The optimal setting was found out by a response table and the influences of input parameters on the output were determined by Analysis of variance. With the help of this hybrid technique the performance characteristics of the machining process were improved, which is proved by the results from the confirmation experiment.

A R T I C L E I N F O

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1. Introduction

Traditional metal removal process such as 'turning' utilizes a hardened cutting tool to remove unwanted material from the rotating workpiece to obtain the desired shape. During the process the turning parameters viz. cutting speed, depth of cut and feed rate are provided to obtain the desired workpiece at a rapid rate, higher tool life and with producing good quality components [1]. But the chosen machining parameters vary from one workpiece to another, from one machine to another machine and from one operation to another operation such as rough turning and finish turning. Apart from the conditions chosen for machining, the cutting tool geometry also plays a vital role. Alteration in the tool geometry reduces the friction developed between the cutting tool-workpiece and between tool-generated chip, roughness produced at the surface of workpiece, contact area between tool-workpiece, cutting forces generated and heat generated. Along with these conditions, the angle at which the cutting tool approaches the workpiece for machining also influences the output responses obtained such as chip formation and magnitude of cutting forces. The approach angle normally affects the cutting edge length which is in contact with workpiece [2].

Tamizharasan and Senthilkumar [3] analyzed the material removal rate (*MRR*) and roughness in turning AISI 1045 steel using uncoated cemented carbide cutting inserts of different ISO designated cutting tool geometries by performing experiments based on Taguchi's technique.

Ramaiah et al. [4] optimized turning parameters for lower cutting forces and temperature using fuzzy approach during turning Al 6061 workpiece using CNMG cutting tool as per Taguchi experimental design. Hashmi et al. [5] developed a fuzzy logic model for selecting turning parameters in the machining process and applied it to three workpiece materials and four cutting tool materials based on the matrix system. Cabrera [6] investigated the effects of machining parameters using fuzzy model to predict the surface roughness parameters during turning composite material with cutting tools coated with TiN. The influence of temperature at cutting zone over wear at flank area is studied [7] for cutting tools of various geometries while turning AISI 1045 steel.

Raidu et al. [8] developed a fuzzy logic based model for selecting cutting parameters in turning tool and die steel with cemented carbide, ceramic and sintered PcBN cutting tool during hard turning operation. Kalaichelvi et al. [9] presented an on-line cutting tool wear detecting method during turning Al/SiC composite by measuring the spindle motor current based on fuzzy logic approach. Gupta et al. [10] applied Taguchi technique of optimization and fuzzy reasoning in high speed machining of P-20 steel with TiN coated tool for optimizing multiple outputs tool life, power, surface roughness and cutting force considering nose radius of cutting tool and cutting environment. Gokulachandran and Mohandas [11] developed model for predicting tool life based on regression model and fuzzy logic method, when end milling IS2062 steel using P30 uncoated carbide tipped tool using results obtained from experiments conducted based on Taguchi's approach and found that fuzzy model results are much closer to experimental values. Prediction of output responses by using artificial neural network in MATLAB tool is performed with experiments designed using Taguchi's DoE for varying combinations of machining parameters and cutting tool geometry [12].

Simunovic et al. [13] performed face milling experiments on aluminium alloy based on central composite design of response surface methodology and developed regression models for surface roughness and predicted it using artificial neural network model and compared it. Rajmohan et al. [14] designed experiments based on Taguchi's technique and applied grey-fuzzy technique to obtain optimum conditions during drilling aluminium matrix hybrid composites for evaluating multiple responses. Senthilkumar and Tamizharasan [15] carried out finite element simulation study in turning process and optimized the performance of carbide inserts of varying geometries using Taguchi's technique. Ramamurthy et al. [16] optimized wire-EDM parameters during machining titanium alloy by applying grey relational analysis for multiple outputs and found the significant parameters using ANOVA tool. Apart from machining process, this grey-fuzzy method is applied to other complex optimization problems involving more than one response by converting them into a grey-fuzzy reasoning grade.

1.1 Problem identification

It is understood from the literature survey, that machining parameters feed rate, cutting speed, depth of cut, tool geometries such as rake angle, nose radius, relief angle, side cutting edge angle, approach angle of cutting tool [17, 18] have an higher influence on the cutting forces, wear, chatter, surface finish and material separated as chip from the workpiece to obtain the desired shape and size. Hence, for machining a particular material for a suitable application both machining parameters [19] and geometrical parameters have to be optimized [20, 21] to attain better results. From these conditions, the chosen parameters to be analyzed in this work are turning parameters cutting speed, depth of cut and feed rate along with the approach angle with which the cutting tool approaches the workpiece for metal removing during turning AISI 1045 steel [17], a material which is mostly used in industries. The experiments are designed using Taguchi's DoE and by applying grey relational analysis, the multiple output parameters are converted into grey relational grade [22, 23]. Fuzzy logic technique [20, 24] is used to reduce the fuzziness in the output values to obtain a better optimized condition.

2. Material selection

The workpiece material chosen for analysis in this work is AISI 1045, medium carbon steel, with desired properties of strength and hardness and other physical properties. The applications includes component parts for vehicles, shafts, bushings, crankshafts, connecting rods and parts for the machine building and steel for axes, knives, hammers, etc. The Brinell hardness value is 280 BHN. Table 1 shows the AISI 1045 steel chemical composition.

The micrograph of the selected workpiece AISI 1045 is shown in Fig. 1, large grains of pearlite is distributed in ferrite matrix. The micrograph shows that the steel is recrystallized and hot rolled falling into the category of medium carbon steel.

The cutting tool insert chosen for turning AISI 1045 steel is uncoated cemented carbide, CNMG 120408 CT 3000 grade, TAEGUTEC make. Three cutting tool insert holders with various approach angles such as PCLNR (95°), PCBNR (75°) and PCDNR (45°) are used for analysis. The micrograph of carbide insert is shown in Fig. 2, which contains particles of predominant tungsten carbide. During compacting process, voids are present, identified as black areas. Cobalt solid solution is present in between the grain areas. Solid solution phases of TiC and WC are present in the structure.

Table 1 Chemical composition of AISI 1045 steel

Element	C	Si	Mn	Cr	Ni	Mo	S	P	W	V	Fe
% Alloying	0.451	0.253	0.780	0.336	0.040	0.001	0.009	0.011	0.160	0.004	98.406

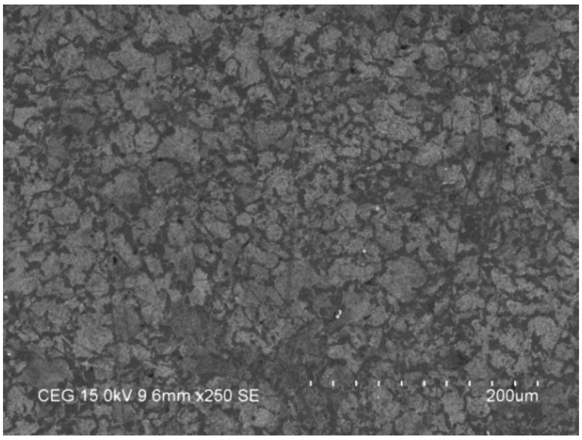

Fig. 1 Micrograph of AISI 1045 steel

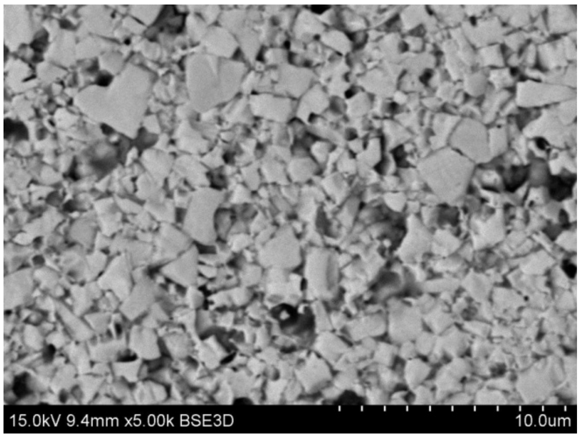

Fig. 2 Micrograph of cemented carbide insert

3. Experimental setup and methodology

Experiments are conducted on a 2-axis CNC Turning center with 350 mm swing diameter, distance between the centres is 600 mm, 4500 rpm spindle speed, 11 kW motor power. After completing the turning operation, with Tool maker's microscope of Mitutoyo make, flank wear is measured. The specification of the microscope is 67 mm working distance, 30× magnification, 13 mm field diameter and 2× objective. Surfcorder SE 3500 is used to measure surface roughness of specifications, measuring distance in X direction is 100 mm, Z is 600 μm, 0.05-2 mm measuring speed and MRR are calculated from the formula given in Eq. 1 in g/min. Fig. 3 shows the CNC turning center and measuring instruments used in this work.

$$MRR = \frac{Weight\ before\ machining - Weight\ after\ machining}{Time\ taken\ for\ machining} \tag{1}$$

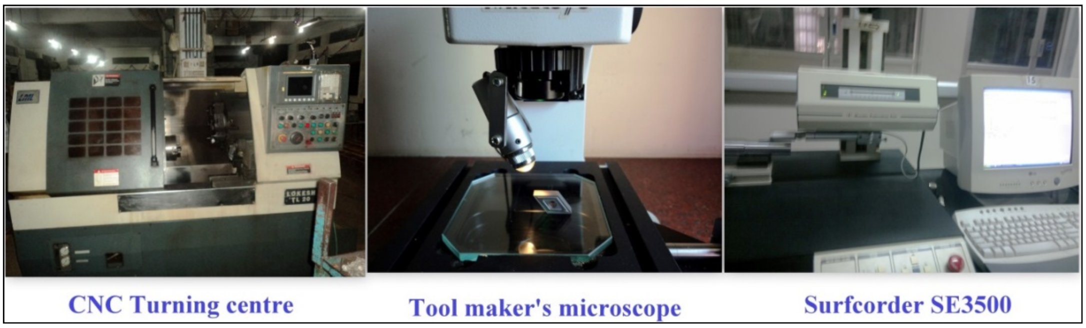

Fig. 3 Turning centre and equipment's used

3.1 Taguchi's design of experiments

Taguchi designed orthogonal arrays (OA's) of various combinations to perform experiments for different parameters and level values. In unique manner, Taguchi developed standard OA's which can be used in various experimental conditions [25-28]. In this work, Taguchi's design of experiments (DoE) is applied for designing the experimental array considering four parameters such as cutting speed, depth of cut, feed rate and approach angle of cutting tool inserts that are varied through three levels. Table 2 shows the chosen control parameters and their selected values [29] for experiments.

Table 3 shows the different combinations of turning parameters and cutting insert approach angle, based on which experiments are conducted as per Taguchi's DoE.

Table 2 Input parameters and their level values

Parameter / Level	Symbol	Level 1	Level 2	Level 3
Cutting speed (m/min)	A	227	256	285
Feed rate (mm/rev)	B	0.432	0.318	0.203
Depth of cut (mm)	C	0.30	0.45	0.60
Approach angle (°)	D	95	75	45

Table 3 Inner array of Taguchi's L_9 orthogonal array

Trial No.	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Approach angle (°)
1	227	0.432	0.30	95
2	227	0.318	0.45	75
3	227	0.203	0.60	45
4	256	0.432	0.45	45
5	256	0.318	0.60	95
6	256	0.203	0.30	75
7	285	0.432	0.60	75
8	285	0.318	0.30	45
9	285	0.203	0.45	95

The approach angle of the cutting tool insert, approaching the workpiece during turning is altered by changing the tool holder nomenclature. The nomenclature of the cutting tool holder used for varying the cutting insert approach angle is shown in Fig. 4.

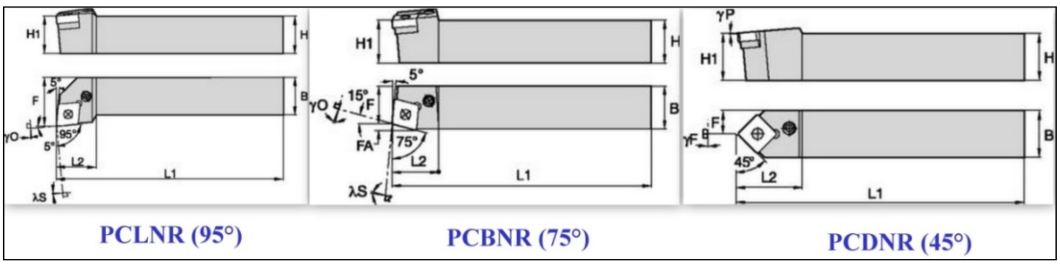

Fig. 4 Cutting tool holders with various approach angles

3.2 Grey relational analysis

For multi-response optimization, Grey relational analysis (GRA) is applied for determining the optimum conditions of various input parameters considered to obtain the best quality characteristics considering single and multiple responses [30-32]. In complex processes having meagre information, for judging or evaluating the performance GRA is applied. Raw data cannot be used in grey analysis, but the data should be pre-processed in a quantitative way for normalizing data for subsequent analysis. For comparison and evaluation, the original sequence is converted between 0.00 and 1.00, in which no information or full information is available. For "Higher-the-better" condition of optimization, the original sequence is normalized as

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

where $x_i^0(k)$ is original sequence, x_i^* (k) sequence after data pre-processing, max $x_i^0(k)$ largest value of $x_i^0(k)$, and min $x_i^0(k)$ smallest value of $x_i^0(k)$. For "Smaller-the-better" condition, the original sequence is normalized as

$$x_i^*(k) = \frac{max\, x_i^0(k) - x_i^0(k)}{max\, x_i^0(k) - min\, x_i^0(k)} \tag{3}$$

Grey relational coefficient is calculated after data pre-processing, to express the relationship between actual and ideal normalized experimental values. Deviation sequence is determined by finding the maximum of the normalized values regardless of response variables, trials and replications. Let this maximum value be R, which is known as reference value which is given as

$$R = Max(X_{ijk}) \tag{4}$$

Find the absolute difference between each normalized value and the reference value (R), regardless of the response variables, trials and replications. Let it be Δ_{ijk}, where, i = 1,2,3,..., p and j = 1, 2, 3,..., q and k = 1, 2, 3,..., r.

$$\Delta_{ijk} = X_{ijk} - R \tag{5}$$

Grey relational coefficient is expressed as

$$\zeta_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \tag{6}$$

where $\Delta_{oi}(k)$ is deviation sequence of reference sequence, given by

$$\Delta_{oi}(k) = \| \; x_0^*(k) - x_i^{*0}(k) \; \| \tag{7}$$

$$\begin{aligned} \Delta_{max} &= \max max \; \| \; x_0^*(k) - x_j^{*0}(k) \; \| \\ \Delta_{min} &= \min min \; \| \; x_0^*(k) - x_j^{*0}(k) \; \| \end{aligned} \tag{8}$$

ζ is known as distinguishing or identification coefficient. Generally ζ = 0.5 is used ζ ϵ [0, 1]. Grey relational grade is calculated by taking the average of the determined grey relational coefficient of responses. The grey relational grade is calculated as

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} i\, \zeta_i(k) \tag{9}$$

3.3 Fuzzy inference system

Fuzzy inference or fuzzy ruled based system constitutes four models; fuzzification interface, rule base and database, decision making unit and finally a defuzzification interface [33]. Membership functions of the fuzzy sets are defined by the database, which are used in fuzzy rules, inference operation on the framed rules is performed by the decision making unit. Conversion of inputs into degrees of match with linguistic values are carried out by fuzzification interface; defuzzification interface converts the fuzzy results of the inference into crisp output [34]. The fuzzy rule base is driven by if-then control rules with the two inputs and one output i.e.,

- Rule 1: if x_1 is A_1 and x_2 is B_1 then y is C_1 else
- Rule 2: if x_1 is A_2 and x_2 is B_2 then y is C_2 else

  ...
- Rule n: if x_1 is A_n and x_2 is B_n then y is C_n

A_i, B_i and C_i are fuzzy subsets which are defined by the corresponding membership functions, i.e., μA_i, μB_i and μC_i. Fig. 5 shows the schematic illustration of the fuzzy inference system, based on which prediction is carried out.

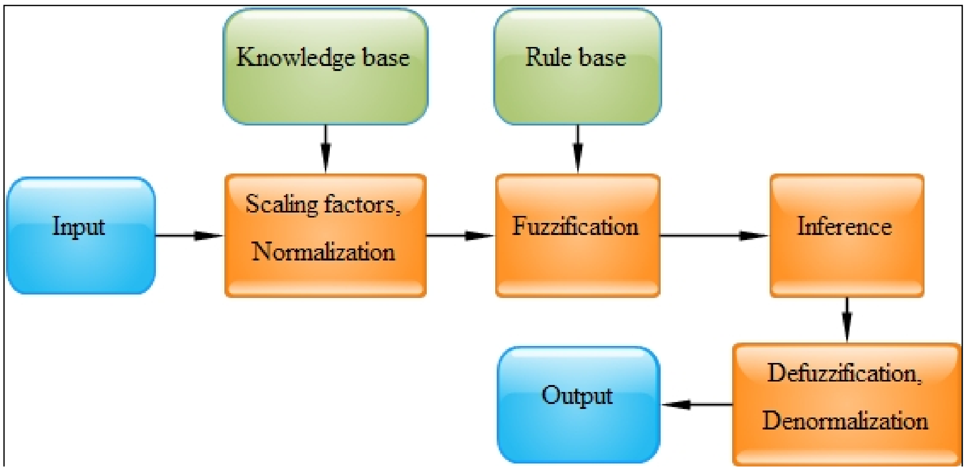

Fig. 5 Fuzzy inference systems

3.4 Analysis of variance

A statistical technique applied to evaluate the difference among the available set of scores is Analysis of variance (ANOVA) [35]. ANOVA is applied to quantity the contribution of chosen input parameters over the output responses [36]. Inferences from ANOVA table can be used to identify the parameters responsible for the performance of the selected process and can control the parameters for better performance. Data analysis is not possible with ANOVA but variance of the data can be evaluated with this statistical tool.

4. Results and discussion

With the formulated L_9 OA designed using Taguchi's DoE, experiments are conducted in CNC turning center. In this study, nine different workpieces are taken and for each level a separate workpiece is used. Using the measuring instruments, the output responses wear at flank face of cutting insert and surface roughness at workpiece surface are measured and using the formulae given in Eq. 1 *MRR* is calculated, which are given in the Table 4.

Table 4 Output quality characteristics measured

Trial No.	Flank wear (mm)	Surface roughness (μm)	Material removal rate (g/min)
1	0.228	1.2	0.368
2	0.301	2.5	0.26
3	0.179	2.1	0.433
4	0.099	1.9	0.341
5	0.098	2.7	0.218
6	0.115	0.6	0.311
7	0.329	3.4	0.207
8	0.222	1.7	0.312
9	0.350	1.6	0.209

The observations made from the output characteristics shows that, when cutting speed is increased from 227 to 256 m/min, flank wear reduces by 55.39 %, surface roughness by 10.35 % and *MRR* by 18.08 %. An increase in flank wear by 188.46 % and surface roughness by 28.85 % is noticed along with a decrease in *MRR* by 16.21 % when cutting speed is further changed from 256 m/min to 285 m/min. A reduction in flank wear by 3.72 %, *MRR* by 17.30 % is observed with an increase in surface roughness by 60.5 % when feed rate is increased from 0.203 mm/rev to 0.318 mm/rev. While feed rate is further increased to 0.432 mm/rev from 0.318 mm/rev, flank wear increases by 5.8 %, *MRR* by 15.97 % with a reduction in surface roughness by 5.78 %.

When depth of cut is changed from 0.3-0.45 mm, flank wear increases by 32.98 %, surface roughness by 71.38 % with a reduction in *MRR* by 18.18 % is obtained. A reduction in flank wear by 19.20 % and increase in surface roughness by 36.65 % and *MRR* by 5.93 % are observed when depth of cut is changed from 0.45-0.6 mm. When approach angle is altered from 45° to 75°, flank wear and surface roughness increases by 48.50 % and 14.05 % respectively with a decrease in *MRR* by 28.45 %. With further increase in approach angle from 75° to 95°, flank wear and surface roughness are reduced by 9.27 % and 15.41 % with an increase in *MRR* by 2.32 %.

In analysing the data, smaller-the-better concept of normalizing is selected while flank wear and surface roughness are considered, since these two responses have to be minimized. But higher-the-better concept is considered for *MRR* since this response should be maximized. Table 5 shows the normalized data of responses after pre-processing and deviation sequence of GRA.

After determining the deviation sequence, grey relational coefficient of each individual response is calculated, which are tabulated in Table 6. For multi-characteristics optimization, which considers all the output responses simultaneously, grey relational grade is derived by considering equal weightages to grey relational coefficient of individual responses. Based on the obtained grey relational grade, ranking is given as shown to identify the best input combination.

From ranking, it is observed that the sixth experiment has the highest grey relational grade of 0.787. Higher grey relational grade obtained indicates that the input parameters chosen for that experiment are considered as the best combination for performing the experiment to obtain better performance characteristics.

Table 5 Normalizing sequence and deviation sequence of GRA

Trial No.	Normalized sequence			Deviation sequence		
	Flank wear	Surface roughness	Material removal rate	Flank wear	Surface roughness	Material removal rate
1	0.484	0.786	0.712	0.516	0.214	0.288
2	0.194	0.321	0.235	0.806	0.679	0.765
3	0.679	0.464	1.000	0.321	0.536	0.000
4	0.996	0.536	0.593	0.004	0.464	0.407
5	1.000	0.250	0.049	0.000	0.750	0.951
6	0.933	1.000	0.460	0.067	0.000	0.540
7	0.083	0.000	0.000	0.917	1.000	1.000
8	0.508	0.607	0.465	0.492	0.393	0.535
9	0.000	0.643	0.009	1.000	0.357	0.991

Table 6 Grey relational coefficient and grey relational grade

Trial No.	Grey relational coefficient			Grey relational grade	Rank
	Flank wear	Surface roughness	Material removal rate		
1	0.492	0.700	0.635	0.609	4
2	0.383	0.424	0.395	0.401	8
3	0.609	0.483	1.000	0.697	2
4	0.992	0.519	0.551	0.687	3
5	1.000	0.400	0.345	0.582	5
6	0.881	1.000	0.481	0.787	1
7	0.353	0.333	0.333	0.340	9
8	0.504	0.560	0.483	0.516	6
9	0.333	0.583	0.335	0.417	7

The fuzzy logic technique of prediction identifies the uncertainties in output responses that are vague, incomplete information and problem imprecision [37, 38]. Reduction of uncertainty present in the grey relational grade can be performed by developing a fuzzy reasoning grade using fuzzy logic approach [39-41]. The fuzzy logic approach is performed to a single grey-fuzzy reasoning grade than considering complicated multiple outputs. Input data and defuzzified output are compared to achieve good prediction accuracy. These fuzzified data's are used by expert systems to answer vague and imprecise questions and describe the ways of assigning functions to fuzzy variables or membership values. Mamdani's inference method is chosen from different techniques available for obtaining membership function values using fuzzy implication operations, known as max-min reference method used for yielding aggregation of fuzzy rules. The defuzzification approach used is centroid method, which is more appealing and prevalent of all available methods [42, 43]. The fuzzy logic technique produces an improved lesser uncertain grey-fuzzy relational grade than the normal grey relational approach, providing a greater value of grey-fuzzy reasoning grade with reduction in fuzziness of data's.

For fuzzifying grey relational coefficient of each response, triangular membership function and fuzzy rules are established. Three fuzzy subsets are assigned for each output response grey relational grade as shown in Fig. 6, by using triangular membership function with three membership functions as Low, Medium and High as shown in Fig. 7.

In fuzzy logic approach, to formulate the statement for predictions, If-Then rule statements are used, which have three grey relational coefficients such as flank wear, surface roughness and *MRR* with one output as grey-fuzzy reasoning grade. The fuzzy subsets that are applied to the multi-response output and the fuzzy subset ranges are presented in Table 7.

Fuzzy logic tool in MATLAB software is used for this grey-fuzzy technique. The grey-fuzzy output is segregated into five membership functions. For activating the fuzzy inference system (FIS) a set of rules are written and to predict the reasoning grade FIS is evaluated for all the 9 experiments. Fig. 8 shows the rule editor in fuzzy environment for predicting the grey-fuzzy reasoning grade, for a given input values of flank wear, surface roughness and *MRR*.

The influence of flank wear, surface roughness and *MRR* based on the if-then rules framed for three membership functions of input functions and five membership functions of output function; grey-fuzzy reasoning grade are given in the surface plot as shown in Fig. 9.

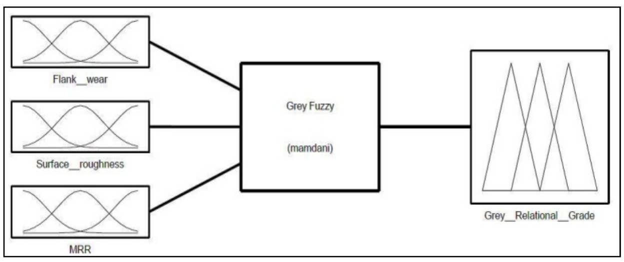

Fig. 6 Fuzzy editor in Fuzzy inference system

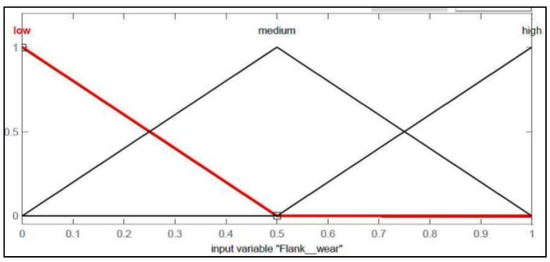

Fig. 7 Triangular membership function applied in FIS

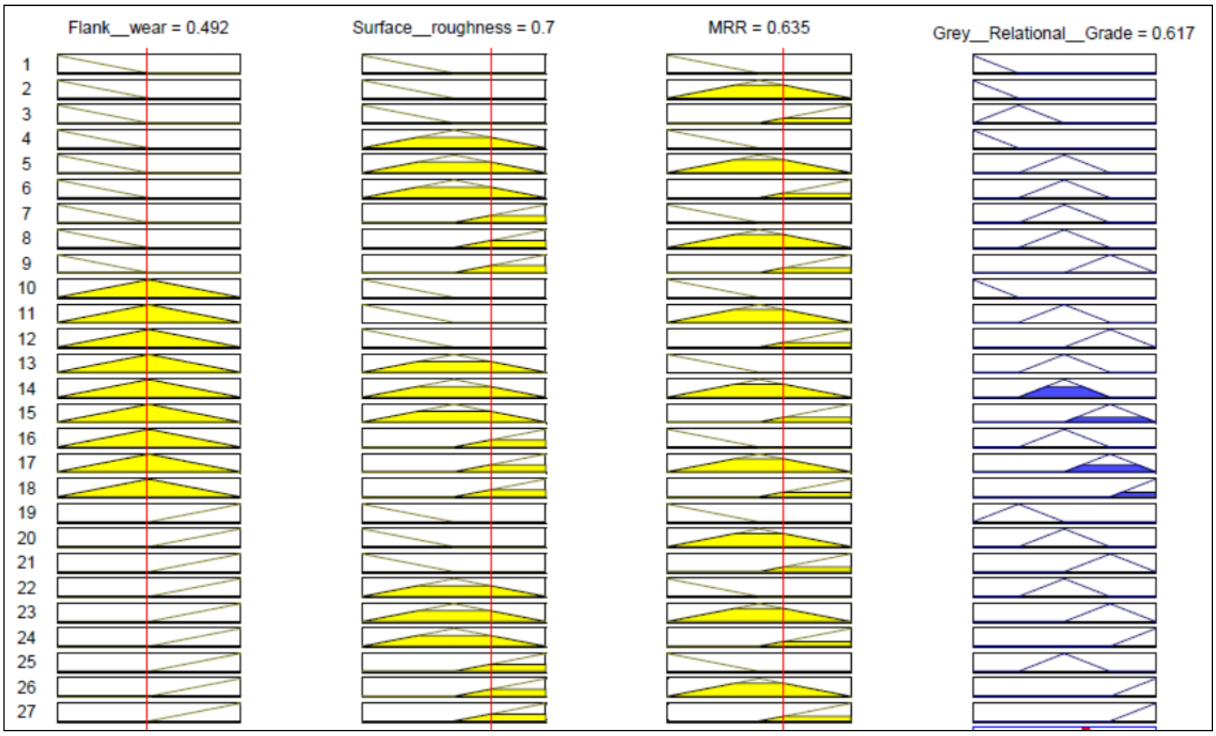

Fig. 8 Rule editors in fuzzy environment

Table 7 Range of fuzzy subsets for grey-fuzzy reasoning grade

Sl. No.	Range of values	Condition	Membership function
1	[-0.25 0 0.25]	Very low (VL)	
2	[0 0.25 0.50]	Low (L)	
3	[0.25 0.5 0.75]	Medium (M)	Triangular function
4	[0.5 0.75 1]	High (H)	
5	[0.75 1 1.25]	Very high (VH)	

Table 8 indicates the determined grey fuzzy reasoning grade from fuzzy logic output and its ranking obtained from the predicted values of FIS. Results of grey relational grade and grey-fuzzy reasoning grade are compared, which shows an improvement in the values of grey-fuzzy reasoning grade, reducing the uncertainty and fuzziness. It is confirmed from the results that the experiment no. 6 has the best combination of machining parameters and approach angle.

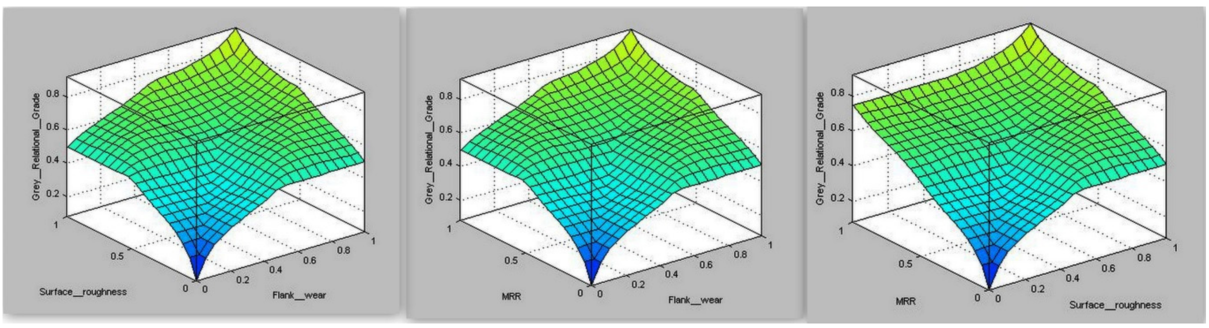

Fig. 9 Influence of output responses on grey-fuzzy reasoning grade

Table 8 Grey-fuzzy reasoning grade

Trial No.	Grey relational grade	Grey-fuzzy reasoning grade	% Improvement	Order
1	0.609	0.617	1.31	4
2	0.401	0.434	8.23	8
3	0.697	0.757	8.61	2
4	0.687	0.746	8.59	3
5	0.582	0.591	1.55	5
6	0.787	0.808	2.67	1
7	0.340	0.404	18.82	9
8	0.516	0.539	4.46	6
9	0.417	0.460	10.31	7

The comparison between the obtained grey relational grade and grey-fuzzy reasoning grade obtained from fuzzy technique is shown in Fig. 10. An improvement in the grey-fuzzy reasoning grade can be observed as compared to the grey relational grade value.

The best level values of various input control parameters are determined from the average values of grey-fuzzy reasoning grade as shown in Table 9, from which the optimal level of each parameter is determined.

From the grey-fuzzy reasoning grade response table, the best level of parameters are identified as cutting speed of 256 m/min, feed rate as 0.203 mm/rev, depth of cut as 0.30 mm and approach angle of 45°, represented as $A_2B_1C_1D_1$. Main effects plot of grey-fuzzy reasoning grade is drawn from the response table, as shown in Fig. 11. It is obvious that the steep slope of cutting speed, feed rate and approach angle shows that they are the most influencing parameters that the other input parameter depth of cut.

The interaction plot or interdependence plot between the input parameters over the calculated grey-fuzzy reasoning grade is shown in Fig. 12. For a cutting speed of 285 m/min, in between cutting speed and feed rate a considerable interaction effect is observed. For all level values of depth of cut and approach angle, a significant interaction exists between cutting speed and depth of cut, and in between cutting speed and approach angle. A higher level of interaction exists between feed rate and depth of cut, and in between feed rate and approach angle for all values. For a depth of cut of 0.30 mm, a noticeable interaction effect is observed between depth of cut and approach angle.

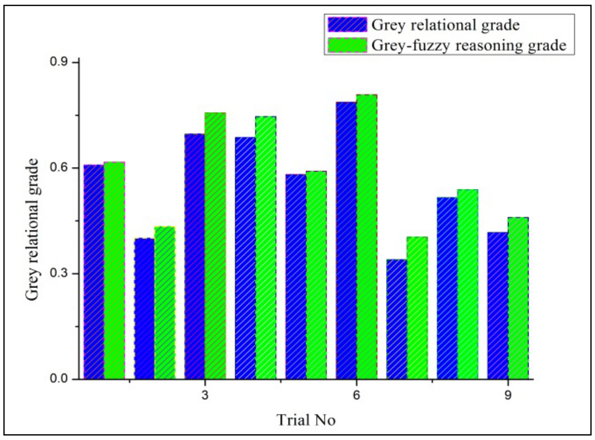

Fig. 10 Comparison between grey relational and grey-fuzzy reasoning grade

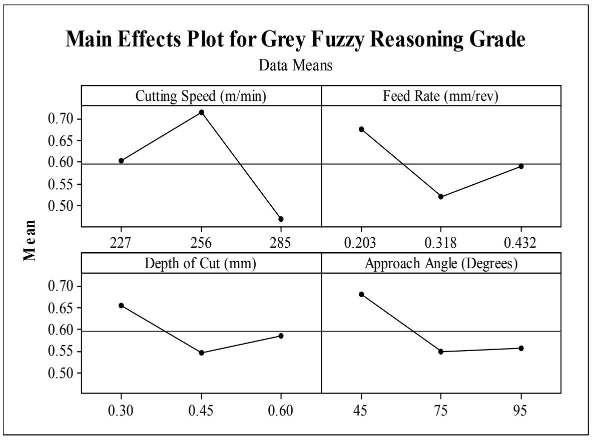

Fig. 11 Main effects plot for grey-fuzzy reasoning grade

Table 9 Grey-fuzzy reasoning grade response table

Level / Parameter	Cutting speed	Feed rate	Depth of cut	Approach angle
Level 1	0.603	0.675	0.655	0.681
Level 2	0.715	0.521	0.547	0.549
Level 3	0.468	0.589	0.584	0.556
Max – Min	0.247	0.154	0.108	0.132
Rank	1	2	4	3

For an approach angle of 45°, a significant interaction is observed between approach angle and depth of cut. In between approach angle and feed rate and in between depth of cut and feed rate, a significant interaction effect is observed for all level values. For an approach angle of 75°, a noticeable interaction effect is observed between approach angle and cutting speed.

To reveal the significance of input parameters the grey-fuzzy reasoning grade obtained is subjected to ANOVA. The ANOVA table shown in Table 10 does not provide enough data's since the degrees of freedom for residual error is zero. This happens when four input parameters with three level values are considered and an L_9 OA is chosen for analysis. Hence ANOVA pooling is to be performed.

Pooling is the process of ignoring an insignificant factor once its contribution is less, which is done by combining the influence of the insignificant factor with the error term. Pooling is a common practice of revising and re-estimating ANOVA results. Pooling is recommended, for two reasons. First, when a number of factors are included in an experiment, the laws of nature make it probable that half of them would be more influential than the rest. Second, in statistical predictions, which encounters two types of mistakes: alpha and beta mistakes. An alpha mistake is calling something important when it is not. A beta mistake is the opposite of an alpha mistake: significant factors are mistakenly ignored. A factor is pooled when it fails the test of significance. Unfortunately, the test of significance can be done only when the error term has nonzero DoF. Pooling is started with the factor that has the least influence. In this analysis, depth of cut is having the least influence; hence it is pooled as shown in Table. 11.

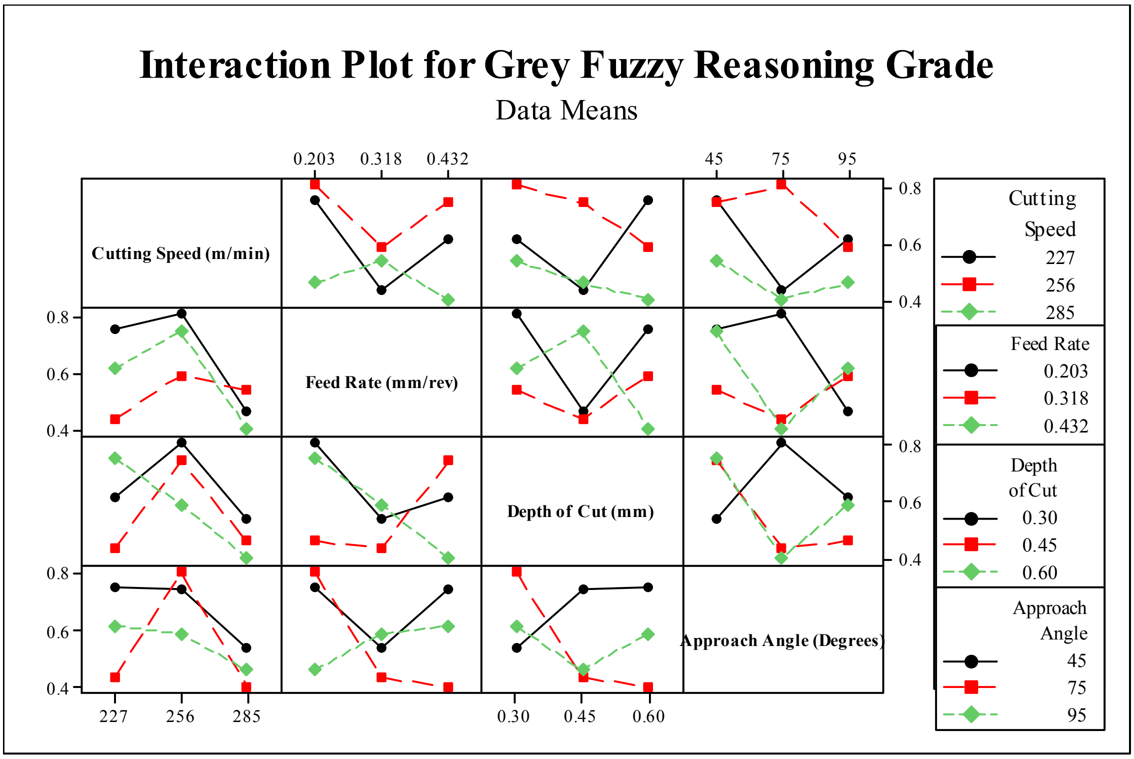

Fig. 12 Interaction plot for grey-fuzzy reasoning grade

Table 10 Analysis of variance for grey-fuzzy reasoning grade (before pooling)

Source	DOF	Seq SS	Adj MS	F	P	% Contribution
Cutting speed	2	0.092018	0.046009	*	*	*
Feed rate	2	0.035588	0.017794	*	*	*
Depth of cut	2	0.018052	0.009026	*	*	*
Approach angle	2	0.033020	0.016510	*	*	*
Residual error	0	*	*			*
Total	8	0.178677				

Table 11 Analysis of variance for grey-fuzzy reasoning grade (after pooling)

Source	DOF	Seq SS	Adj MS	F	P	% Contribution
Cutting apeed	2	0.092018	0.046009	5.10	0.164	51.50
Feed rate	2	0.035588	0.017794	1.97	0.337	19.92
Approach angle	2	0.033020	0.016510	1.83	0.353	18.48
Residual error	2	0.018052	0.009026			10.10
Total	8	0.178677				100.00

From the pooled ANOVA table, it is obvious that the cutting speed is the most influencing parameter that contributes towards the grey-fuzzy reasoning grade by 51.50 %, which is followed by feed rate by 19.92 % and approach angle by 18.48 %. The 'S' value of ANOVA is 0.095 and R^2 value is 89.90 %, which brings a better result.

4.2 Confirmation experiment

After obtaining the best level of machining parameters and approach angle, in order to verify the improvement of output quality characteristics, a confirmation test is performed. The grey-fuzzy reasoning grade estimated is expressed from the output of confirmation experiment. The grey-fuzzy reasoning grade can be estimated using the formulae given in Eq. 10.

$$\mu_{predicted} = V_{2m} + f_{1m} + d_{1m} + A_{1m} - 3\mu_{\text{mean}} \tag{10}$$

where V_{2m}, f_{1m}, d_{1m} and A_{1m} are the individual mean values of the fuzzy-grey reasoning grade with optimum level values of each parameters and μ_{mean} is the overall mean of fuzzy-grey reasoning grade. The predicted mean ($\mu_{\text{predicted}}$) at optimal setting is found to be 0.941.

From the confirmation experiment performed with the same experimental setup, the flank wear decreases from 0.228 to 0.102 mm, surface roughness reduces to 0.92 from 1.2 µm and MRR increases from 0.368 to 0.381 g/min. Thus the experimental grey-fuzzy reasoning grade is 0.772, which shows an improvement by 26.77 %.

Table 12 Initial and optimal level performance

	Initial setting	Optimal level	
		Prediction	Experiment
Setting level	$V_1f_1d_1A_1$	$V_2f_1d_1A_1$	$V_2f_1d_1A_1$
Flank wear (mm)	0.228	-	0.102
Surface roughness (µm)	1.20	-	0.92
Material removal rate (g/min)	0.368	-	0.381
Grey-Fuzzy reasoning grade	0.609	0.941	0.772
% Improvement	-	54.52 %	26.77 %

5. Conclusion

The conclusions derived from the grey-fuzzy logic approach in optimizing machining parameters and approach angle in turning AISI 1045 steel are as follows.

- Experiments are performed based on L_9 (3^4) OA chosen using Taguchi's DoE and analysis is done using grey relational analysis and fuzzy logic approach for optimizing multiple performance characteristics viz. flank wear, surface roughness and *MRR*.
- Grey-fuzzy reasoning grade is acquired to evaluate the multiple responses with the available 27 sets of framed rules, which shows an improvement when compared with the obtained grey relational grade, thereby reducing the fuzziness.
- The optimum level of input control parameters obtained are cutting speed of 256 m/min, feed rate as 0.203 mm/rev, depth of cut as 0.30 mm and approach angle of 45°.
- Interaction plot shows that, a significant level of interaction exists between all the input parameters over each other.
- ANOVA results after pooling shows that the most significant parameter that contributes towards the grey-fuzzy reasoning grade is cutting speed, contributing by 51.50 %, feed

rate by 19.92 % and approach angle by 18.48 %. It is proved that by varying the approach angle of the carbide tool, performance can be improved.
- Improvement in grey-fuzzy reasoning grade from 0.609 to 0.772 confirms the improvement in the turning process with change in turning parameters and approach angle.
- The considerable improvements in the values flank wear; surface roughness and MRR are obtained from the confirmation experiment shows the effectiveness of this grey-fuzzy approach.

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