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OPTIMIZATION OF MACHINING PARAMETERS IN TURNING TO STEEL USING GREY RELATIONAL ANALYSIS

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Abstract:
The present study investigated the multi-response optimization of turning using nanofluids as coolants to determine the best parametric combination for surface roughness, flank wear, and material removal rate (MRR) by employing the Taguchi method and Grey relational analysis. Eighteen experimental runs were carried out using an orthogonal array of the Taguchi method within the defined experimental domain to derive and optimize the goal functions. The selected objective functions related to the turning process parameters included the volume fraction of nanoparticles (0.04%, 0.08%), cutting speed (110, 170, and 230 m/min), feed rate (0.125, 0.15, and 0.175 mm/rev), type of nanoparticles (MoS_2, multi-walled carbon nanotubes (MWCNT), and SiO_2), and depth of cut (0.3, 0.6, and 0.9 mm). The multi-response optimization problem was addressed using the Taguchi approach in conjunction with Grey relational analysis. The significance of the factors affecting the overall quality characteristics in the Minimum Quantity Lubrication (MQL) turning of AISI 4340 with nanofluid was quantitatively evaluated through Signal-to-Noise ratio (S/N) analysis and Analysis of Variance (ANOVA) to determine the contribution of each parameter to performance outcomes. The cutting speed was identified as the most significant parameter. Verification experiments were conducted to validate the optimal results. These findings demonstrated the effectiveness of the Taguchi technique and Grey relational analysis in continuously improving product quality in the manufacturing sector.

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1. INTRODUCTION

Machining processes played a critical role in the manufacturing industry, with cutting operations being among the most essential. In these operations, cutting fluids primarily served to lubricate the interface between the cutting tool and the workpiece, facilitated chip removal from the cutting zone, and cooled both the tool and the workpiece [1,2]. To achieve high-quality machining, an effective cutting fluid was required to dissipate the heat generated during the cutting process. In this context, nanofluids emerged as a new class of advanced fluids that offered superior thermal performance compared to conventional fluids [3,4]. Nawas and Nazir [5] numerically analyzed the thermal performance of MoS_2 and $MoS_2 - SiO_2$ hybrid nanofluids in ethylene glycol (a partially ionized Carreau fluid) using finite element method (FEM). They found that hybrid nanofluids enhance thermal performance but exert higher shear stress on elastic surfaces, raising structural concerns. Hall and ion slip effects accelerate fluid flow by reducing the opposing Lorentz force. These fluids exhibited enhanced thermal conductivity and were prepared by dispersing nanoparticles into base cutting fluids, forming nanolubricants. The addition of nanoparticles improved thermal conductivity,

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stability, as well as rheological and tribological properties, without negatively affecting pressure drop, thereby resulting in improved machining performance. Numerous studies were conducted to explore the effects of nanofluids in machining applications. For instance, Roy and Amitava Ghosh investigated the use of minimum quantity lubrication (MQL) in high-speed turning of AISI 4140 steel using TiN-coated carbide inserts. They employed nanofluids based on ethylene glycol mixed with MWCNTs at concentrations of 1 vol% and 3 vol%. Their findings demonstrated that cutting forces and specific energy were significantly reduced, particularly with 3 vol% alumina and 1 vol% MWCNTs. Moreover, MWCNTs proved more effective than alumina in reducing tensile stress, thereby lowering the cutting zone temperature and extending tool life [6–8]. Nayak et al. [9] optimized the dry turning of AISI 304 stainless steel by analyzing the effects of cutting speed, feed rate, and depth of cut on MRR, cutting force, and surface roughness. Using Taguchi's L27 design and Grey Relational Analysis (GRA), they identified optimal parameters (45 m/min, 0.1 mm/rev, 1.25 mm) that improved overall performance by 88.78%. The study highlights the effectiveness of GRA in multi-response optimization for sustainable machining.

Similarly, Surya et al. [10] optimized dry and wet machining of EN19 steel by analyzing cutting speed, feed, and depth of cut on material removal rate and surface roughness using GRA. They found spindle speed and depth of cut to be the most significant factors for dry and wet machining, respectively. Today, the goal in manufacturing is to achieve high performance and economic efficiency while also meeting environmental requirements. This demands careful design and development of systems, which in turn requires extensive experimentation. The Design of Experiments (DOE), particularly when integrated with GRA, has become a powerful tool to optimize such processes effectively. Elsiti and Elmunafi [11] optimized turning process parameters using GRA for multi-response optimization. They studied cutting speed, feed rate, and depth of cut based on a three-level, two-factor factorial design with center points. Performance measures included MRR, tool life, and surface roughness. Experiments were conducted on AISI 420 martensitic stainless steel using a coated carbide tool (KC5010). The study demonstrated improved machining performance through the GRA-based multi-response optimization approach. Jadhav et al. [12] investigated the impact of cryogenic treatment on tungsten carbide inserts during dry turning of P20 tool steel. The study aimed to optimize cutting forces, a key factor affecting tool-workpiece interaction and tool life. Using Taguchi’s L27 orthogonal array and simulation tools like MATLAB and artificial neural network (ANN), the authors compared untreated and cryogenically treated inserts. Results showed that cryogenic treatment significantly reduced cutting forces under the same machining conditions, indicating improved cutting efficiency and reduced tool stress.

The objective of the present work is to identify the optimal turning conditions for hardened AISI 4340 steel using a Grey-based Taguchi approach. Signal-to-noise (S/N) ratio analysis and Grey relational analysis were applied to determine the most effective process parameters that enhance surface roughness, minimize flank wear, and maximize MRR.

2. MATERIAL AND METHODS

AISI 4340 steel was selected for the present investigation. The chemical composition of the workpiece material was as follows: C – 0.412%, Si – 0.221%, Mn – 0.61%. The preparation of the nanofluids included the use of nanoparticles such as MWCNTs, nanosilicon dioxide (SiO_2) powder, and nanomolybdenum disulfide (MoS_2) powder. Table 1 presents the properties of the nanoparticles that were added to the base fluid (ethylene glycol). Additionally, sodium dodecyl sulfate (SDS) was used as a surfactant.

Table 1. The physical properties of nanoparticles

Nanoparticle material	APS (nm)	Purity (%)	Specific surface area (m^2/g)	Volume density (g/cm^3)	Crystal form	Color
SiO_2	20	>99.99	240	0.063	Cube	White
MoS_2	20	>99.99	31.9	3.41	Hexagonal	Grey black
MWCNT	50	>99.9	120	0.30-0.45	Sphere	Black

The nanofluids were prepared by adopting A two-step method, where the nanoparticles were dispersed in base fluids. Its quantity was determined by using the law of mixtures. The weight percentage (ϕ) was calculated by applying the following equation [12].

$$\phi = \frac{M_{np}/\rho_{np}}{\frac{M_{np}}{\rho_{np}} + \frac{M_{bf}}{\rho_{bf}}} \quad (1)$$

where are: M_{bf} - mass of the base fluid (g); ϕ - volume fraction; M_{np} - mass of nanoparticle(g); ρ_{np} - density of the nanoparticle (g/L); ρ_{bf} - density of the base fluid (g/L).

The turning experiments in this study were performed on AISI 4340 alloy steel using a CNC lathe operating under MQL conditions with nanofluids as the cutting medium. The workpiece specimens were cylindrical, each measuring 400 mm in length and 80 mm in diameter. They underwent a two-stage heat treatment process to achieve a final hardness of approximately 50 HRC. Initially, the specimens were heated to 850°C, soaked for 30 minutes, and then quenched in oil. This was followed by a tempering process at 450°C for 3 hours, after which the sample was cooled in air. The nanofluids used in this study were prepared by dispersing three types of nanoparticles (MoS_2, MWCNT, and SiO_2) into a base fluid of ethylene glycol. A two-step method was applied for preparation, where SDS served as a surfactant to enhance dispersion stability. The mixture was homogenized using a LUC–410 ultrasonic mixer operating at 50 Hz and 400 W for a duration of 4 hours. Two volume fractions of nanofluids, 0.04% and 0.08%, were used for testing. Machining was conducted on a CNC lathe with a 22 kW spindle motor capable of reaching speeds up to 5000 rpm. The cutting tool used was a CNMG 120408 carbide insert with multilayer CVD coatings ($TiN/TiCN/Al_2O_3$), a nose radius of 0.8 mm, a back rake angle of -6°, a clearance angle of 5°, and an approach angle of 95°. The MQL system consisted of a sealed nanofluid reservoir, an air compressor, and a nozzle system. The nanofluid was sprayed at a rate of 60 mL/h under 4 bar air pressure, with the nozzle directed at the cutting zone approximately 30 mm from the tool tip to ensure effective cooling and lubrication.

To evaluate machining performance, three key responses were measured: surface roughness (*Ra*), flank wear (*VB*), and MRR. Surface roughness was measured using a Mitutoyo SJ-301 surface tester, while flank wear was assessed using an optical microscope equipped with a digital imaging system. The MRR was calculated using the difference between the initial and final weights of the workpiece, divided by the product of material density and machining time, as shown in Fig. 1.

Fig. 1 Sequential stages of the experimental procedure

To compute the MRR, the following Eq.2 was used [13]:

$$\mathrm{MRR} = \frac{w_i - w_f}{\rho \cdot t_m} \quad (2)$$

where are: *MRR* - Removal Rate of Material (mm^3/min); w_i and w_f - Initial and final weight, respectivily of the specimens (g); ρ - Density (kg/m^3); t_m - Machining time (min).

3. TAGUCHI-BASED GREY RELATIONAL ANALYSIS

The GRA was preferred for handling incomplete and uncertain information. Taguchi-based Grey relational analysis was employed to effectively evaluate the complex interrelationships among multiple performance characteristics [14,15]. Experimental data used in the analysis to assess quality characteristics were first normalized within the range of zero to one, a process referred to as "grey relational generation." The correlation between the desired and actual experimental outcomes was then determined by calculating the Grey Relational Coefficient (GRC). Subsequently, the Grey relational score was calculated by averaging the GRCs for a selected set of responses. The resulting Grey relational score represented the overall performance characteristic of the multi-response process. This method converted a multi-response optimization problem into a single-response optimization scenario, where the objective function was defined by the overall Grey relational grade [15]. The normalized surface roughness and flank wear values in grey relational generation that meet the smaller-the-better (SB) criterion are as follows:

$$X_i(K) = \frac{\max y_i(K) - y_i(K)}{\max y_i(K) - \min y_i(K)} \quad (3)$$

where are: $x_i(K)$ - is the value after the Grey relational generation; *min* $y_i(K)$ - is the smallest value of $y_i(K)$ for the k^{th} response; *max* $y_i(K)$ - is the largest value of $y_i(K)$ for the k^{th} response.

An ideal sequence is (x_0(K)=1,2,3 …….. 18) for the responses [12]. The definition of Grey Relational Grade (GRG) is to reveal the degree of relation between the 18 sequences. The GRC is calculated as:

$$\zeta(\mathrm{k}) = \frac{\Delta\mathrm{min} + \psi\Delta\mathrm{max}}{\Delta_{0\mathrm{i}}(\mathrm{k}) + \psi\Delta\mathrm{max}} \tag{4}$$

$$\Delta_{0\mathrm{i}} = /\mathrm{x}_0(\mathrm{K}) - \mathrm{x}_\mathrm{i}(\mathrm{K}) \tag{5}$$

where is: ψ - is the distinguishing coefficient [11]. After averaging the GRC, the Grey relational grade can be computed as:

$$\gamma_\mathrm{i} = \frac{1}{\mathrm{n}}\sum_{\mathrm{K}=1}^{\mathrm{n}} \zeta\mathrm{i}(\mathrm{k}) \tag{6}$$

where is: i^{th} alternative in GRA. In this equation, γ_i denotes the GRG, reflecting how closely the i^{th} alternative aligns with the ideal or reference sequence. The term n indicates the total number of performance characteristics or criteria considered in the analysis. The variable $\zeta i(k)$ represents the GRC for the i^{th} alternative with respect to the k^{th} performance characteristic, measuring the degree of closeness between the alternative and the reference value for that criterion. The summation calculates the total of these coefficients across all criteria, and the factor 1/n normalizes this total to compute the average GRC. Thus, the GRG provides a single comparative index that can be used to rank alternatives based on their overall performance across multiple criteria. The higher value of GRG corresponds to an 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. Consequently, a higher Grey relational score indicated that the corresponding parameter combination was closer to the optimal condition. The mean response for the GRG, along with its overall average and the main effect plot of the GRG, were essential for evaluating the optimal process conditions [15]. The optimal parametric combination was then identified as the one yielding the highest GRG. The optimal settings for maximizing the overall Grey relational grade were determined using the Taguchi method. Taguchi's S/N ratio was utilized to obtain the optimal results based on the selected parameters. The Signal-to-Noise ratio was calculated using the following equation:

Larger the Better (LTB) for grey relational grade [16-20].

$$\frac{\mathrm{S}}{\mathrm{N}} = -10\mathrm{log}101/\mathrm{n}\sum_{Y=1}^{n}[1/\mathrm{Y}_\mathrm{i}^2] \tag{7}$$

where are: Y_i - results of grey relational grade; N - Number of trials of repetitions; S - the variance.

4. DESIGN OF EXPERIMENT

The working ranges of the parameters were selected for the subsequent design of experiments based on Taguchi's L18 orthogonal array (OA) design. In the present study, five controllable variables, namely, volume fraction of nanoparticles (%), cutting speed (v), feed rate (f), type of nanoparticles, and depth of cut (d), were considered as the primary cutting parameters. The selected parameters and their corresponding levels are presented in Table 2.

Table 2. Factors and their levels used in the experiments

Symbol	Control factors	Levels			Unit
		I	II	III	
A	Volume fraction of nanoparticles	0.04%	0.08%	-	-
B	Cutting speed (*v*)	110	170	230	m/min
C	Feed (*f*)	0.125	0.15	0.175	mm/rev
D	Depth of cut (*d*)	0.3	0.6	0.9	mm
E	Nano particles type	MoS_2	MWCNT	SiO_2	-

5. RESULT AND DISCUSSION

Experimental results, together with normalized values of response, deviation values, values of grey coefficient, values of grey relational grade and s/n ratio for grey relational grade, are given in Tables 3 and 4.

Table 3. Measured data of responses and normalized values of responses

Measured data									Normalized values		
Run	A	B	C	D	E	Flank wear (mm)	Ra (µm)	MRR (mm^3/min)	Flank wear	Ra	MRR
1	1	1	1	1	1	0.035	1.055	3178.23	0.868	0.448	0.012
2	1	1	2	2	2	0.052	0.725	4585.23	0.547	0.773	0.171
3	1	1	3	3	3	0.032	1.51	3617.28	0.925	0	0.062
4	1	2	1	1	2	0.043	0.615	3126	0.717	0.882	0.006
5	1	2	2	2	3	0.056	0.723	4707.69	0.472	0.775	0.185
6	1	2	3	3	1	0.045	1.31	4248	0.679	0.197	0.133
7	1	3	1	2	1	0.055	0.778	6198	0.491	0.721	0.354
8	1	3	2	3	2	0.081	0.596	11527.08	0	0.9	0.958
9	1	3	3	1	3	0.028	1	3072.66	1	0.502	0.000
10	2	1	1	3	3	0.04	1.098	4843.56	0.774	0.406	0.201
11	2	1	2	1	1	0.04	0.544	5084.85	0.774	0.952	0.228
12	2	1	3	2	2	0.042	1.087	5946.06	0.736	0.417	0.326
13	2	2	1	2	3	0.04	0.815	4915.23	0.774	0.685	0.209
14	2	2	2	3	1	0.075	0.676	10326	0.113	0.822	0.822
15	2	2	3	1	2	0.036	0.616	6254.61	0.849	0.881	0.361
16	2	3	1	3	2	0.066	0.585	11893.32	0.283	0.911	1.000
17	2	3	2	1	3	0.058	0.495	8292.75	0.434	1	0.592
18	2	3	3	2	1	0.048	0.726	6108	0.623	0.772	0.344

Table 4. The Deviation Sequences, Grey Relation Coefficient, grade and S/N for grade results

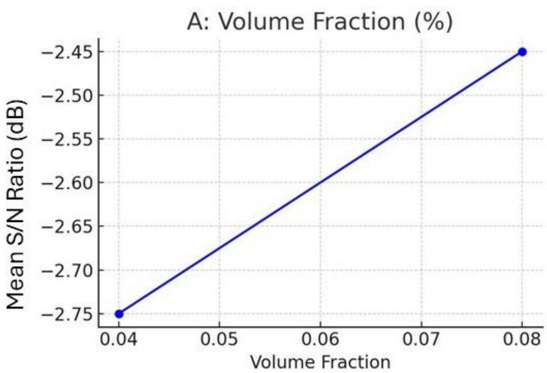
Deviations values				Grey Relation Coefficient					
Run	Flank wear	Ra	MRR	Flank wear	Ra	MRR	grade	s/n-grade	Rank
1	0.132	0.552	0.988	0.883	0.644	0.503	0.670	-3.474	14
2	0.453	0.227	0.829	0.688	0.815	0.547	0.678	-3.381	12
3	0.075	1.000	0.938	0.930	0.500	0.516	0.672	-3.453	13
4	0.283	0.118	0.994	0.779	0.894	0.502	0.733	-2.699	6
5	0.528	0.225	0.815	0.654	0.817	0.551	0.669	-3.487	15
6	0.321	0.803	0.867	0.757	0.555	0.536	0.607	-4.336	18
7	0.509	0.279	0.646	0.663	0.782	0.608	0.679	-3.361	11
8	1.000	0.100	0.042	0.500	0.909	0.960	0.790	-2.049	2
9	0.000	0.498	1.000	1.000	0.668	0.500	0.701	-3.089	9
10	0.226	0.594	0.799	0.815	0.627	0.556	0.655	-3.680	17
11	0.226	0.048	0.772	0.815	0.954	0.564	0.724	-2.799	7
12	0.264	0.583	0.674	0.791	0.632	0.597	0.663	-3.570	16
13	0.226	0.315	0.791	0.815	0.760	0.558	0.700	-3.100	10
14	0.887	0.178	0.178	0.530	0.849	0.849	0.742	-2.594	5
15	0.151	0.119	0.639	0.869	0.893	0.610	0.781	-2.152	3
16	0.717	0.089	0.000	0.582	0.919	1.000	0.831	-1.603	1
17	0.566	0.000	0.408	0.639	1.000	0.710	0.779	-2.171	4
18	0.377	0.228	0.656	0.726	0.815	0.604	0.707	-3.007	8

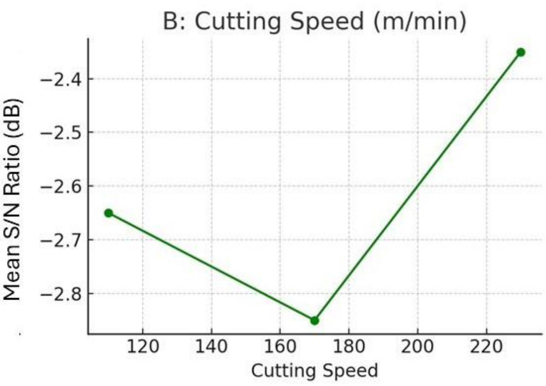
5.1 S/N Ratios Analysis of Grey Relational Grade

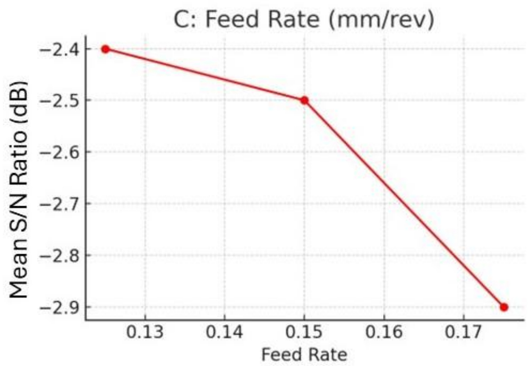
The effects plot for the S/N ratios of the Grey relational grade, as shown in Fig. 2 and Table 5, illustrates the influence of key turning parameters on overall machining performance when nanofluids were used as lubricants. It was observed that increasing the volume fraction of nanoparticles from 0.04% to 0.08% resulted in a slight improvement in the S/N ratio, indicating a minor enhancement in thermal and lubrication properties. A significant increase in the S/N ratio was noted as the cutting speed increased from 110 m/min to 230 m/min, suggesting that higher speeds enhanced chip removal and reduced tool-workpiece adhesion, thereby resulting in improved machining quality. In contrast, the S/N ratio decreased with increasing feed rate, indicating that higher feed rates resulted in greater surface deterioration and increased tool wear. Regarding the type of nanoparticles, the use of MWCNTs produced the highest S/N ratio compared to MoS_2 and SiO_2, due to their superior thermal conductivity and lubrication characteristics. Additionally, a slight decrease in the S/N ratio was observed with increasing depth of cut, which was attributed to the generation of more heat and mechanical stresses at greater depths. Overall, the analysis confirmed that cutting speed and nanoparticle type were the most influential factors in optimizing turning performance, while higher feed rates and greater depths of cut negatively impacted the Grey relational grade.

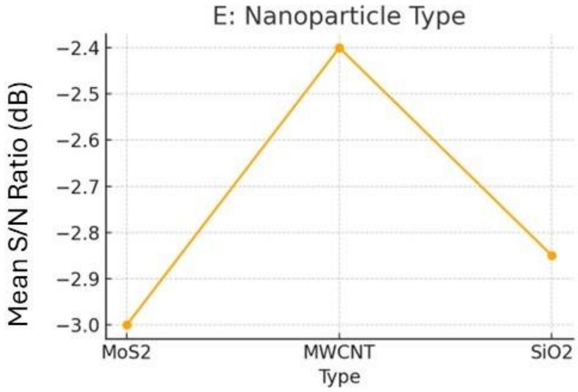
Table 5. Responses for S/N ratio –Grey relational grade

Level No.	Factor A	Factor B	Factor C	Factor D	Factor E
Level1	-3.259	-3.393	-2.986	-2.731	-3.262
Level2	-2.742	-3.061	-2.747	-3.318	-2.576
Level3	--------	-2.547	-3.268	-2.952	-3.163
Delta	0.517	0.846	0.521	0.587	0.686
Rank	5	1	4	3	2









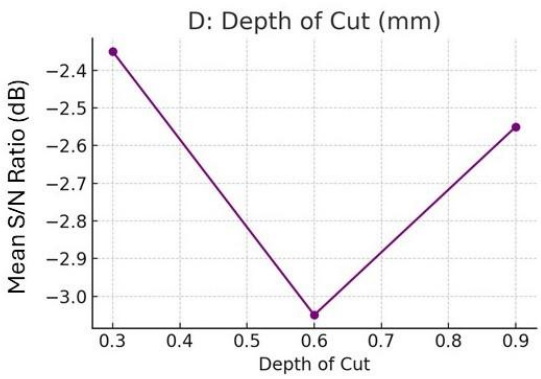


Fig. 2. Response graph for (S/N) ratio of grey relational grades; (A) Higher volume fraction improves the S/N ratio; (B) S/N ratio improves at higher cutting speeds; (C) Lower feed rate leads to better S/N ratio; (D) Shallow and deep cuts are preferable over medium depth; (E) MWCNT yields the highest S/N ratio among nanoparticle types

5.2 Analysis of Variance (ANOVA) for Grey Relational Grade

To diagnose and assess the assumption of normality for the residuals generated in the Grey relational grade analysis, a normal probability plot was prepared. The blue points represented the actual residuals plotted against the expected values from a normal distribution. Ideally, if the residuals were normally distributed, they would align closely along the solid red center line, which represented the theoretical normal distribution fit. Additionally, two dashed red lines were included, indicating the

95% confidence bounds—the Upper Confidence Limit (UCL) and the Lower Confidence Limit (LCL). These bounds provided a reference range within which most residuals were expected to lie if the normality assumption held.

In the observed plot, the residual points are closely aligned along the center line, with only minor deviations at the extreme ends. This behavior indicated that the residuals were approximately normally distributed, with no significant departures from normality, such as heavy tails, skewness, or outliers. The slight deviations at the ends were considered typical in experimental data and did not pose serious concerns.

Maintaining the normality of residuals was essential, as it validated the application of the Taguchi method and Grey relational analysis in this study. It ensured that the estimates of model coefficients, results of hypothesis testing, and predictions remained statistically reliable. Therefore, the probability plot provides strong evidence that the developed model is robust, and the optimization of machining parameters based on this model is reliable, as illustrated in Fig. 3.

It was observed from Table 6 that the volume fraction of nanoparticles, cutting speed, feed, depth of cut, and type of nanoparticles influenced the grey relational grade, where the P-values for all parameters were less than 0.05. Therefore, from a statistical perspective, these values were significant. The ANOVA table showed that cutting speed, with a contribution of 25.1033%, was the most significant parameter affecting the grey relational grade, followed by the volume fraction of nanoparticles (21.4331%), then feed (16.1433%), next depth of cut (15.8058%), and lastly the type of nanoparticles, which had the lowest effect (14.0188%). The pooled error related to the ANOVA table accounted for approximately 7.4972% of the grey relational grade variability. It is known that the coefficient of determination (R^2) represents the ratio of explained variation to total variation and serves as an indicator of the degree of fit. For this model, the R^2 value was 0.925, which is very close to unity and considered acceptable. This demonstrated that 92.5% of the variability in the data could be explained by the model. As a result, the model provided a reasonably good explanation of the relationship between the independent factors and the response, as shown in Table 7.

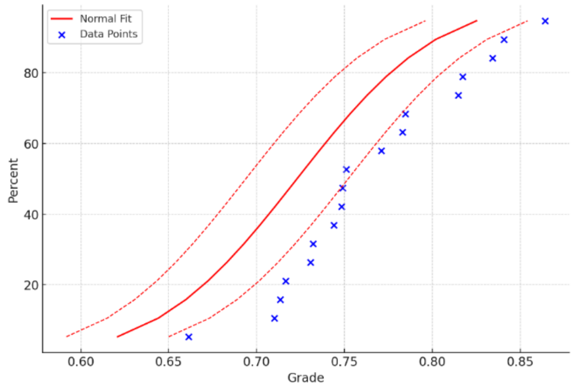


Fig. 3. Normal probability plot of residuals of grade normal distribution-90%CL

Table 6. Results of the (ANOVA)-Grey relational grade

Source	DF	AdjSS	Adj MS	F-Value	P-Value	% of contribution
A	1	0.01448	0.014477	22.87	0.0014	21.4331
B	2	0.01696	0.008478	13.39	0.0028	25.1033
C	2	0.0109	0.005452	8.61	0.0101	16.1433
D	2	0.01068	0.005338	8.43	0.0107	15.8058
E	2	0.00947	0.004734	7.48	0.0147	14.0188
Error	8	0.00506	0.000633	-------	--------	7.4972
Total	17	0.06755	------------	-------	--------	100

Table 7. Model summary of Grey relational grade

S	R-sq	R-sq(adj)	R-sq(pred)
0.0251593	0.925	0.8407	0.6205

5.3 Multiple Linear Regression Model for Grey Relational Grade

It was necessary to model the turning responses and the process variables to gain practical, predictive quantitative relationships. In the present study, mathematical models were developed based on the machining experimental results, as shown in Table 3. The experimental results were used to model the multi-response variables (surface roughness, flank wear, and MRR) using grey relational analysis. The observed data for surface roughness, flank wear, and MRR were utilized for this purpose. The regression equations developed for the Grey relational grade were illustrated in the following equation:

GRG = 0.72297 - 0.02836 A_0.04 + 0.02836 A_0.08 - 0.02907 B_110 - 0.01337 B_170+ 0.04245 B_230 - 0.00501 C_0.125 + 0.03234 C_0.15 - 0.02732 C_0.175+ 0.03197D_0.3 - 0.02707 D_0.6 - 0.00490 D_0.9 - 0.01318 E_MoS_2 + 0.03226 E_MWCNT-0.01908 E_SiO_2

The plotted curves in Fig. 4 illustrate the comparison between actual and predicted grey relational grades across 18 experimental trials, each corresponding to different combinations of machining parameters. The grey relational grade served as a comprehensive performance index derived from multiple response variables, including surface roughness, flank wear, and MRR. The actual values, obtained experimentally, were represented by the blue curve with diamond markers, while the red curve with square markers denoted the grades predicted by the developed model. Overall, both curves exhibited a similar trend, indicating that the predictive model closely aligned with the experimental outcomes. Minor deviations were observed in certain experiments, particularly in runs 2, 8, and 11, which may have been attributed to variations in experimental conditions or measurement uncertainties. The highest grey relational grade appeared in experiment 17, suggesting that this parameter combination achieved the most favorable machining performance. Conversely, the lowest grades occurred around experiments 5 and 6, indicating less effective parameter settings. The close agreement between the actual and predicted grades highlighted the robustness and reliability of the prediction model in capturing the influence of turning parameters under nanofluid-based cooling conditions.

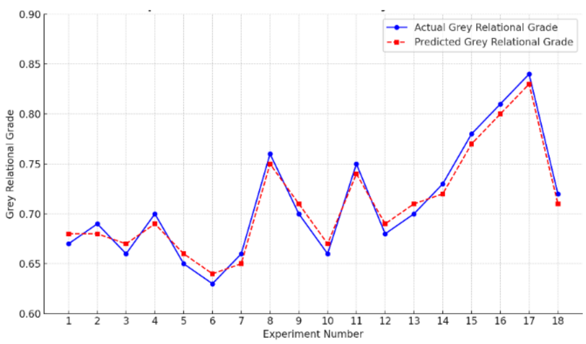


Fig. 4. The comparison plot for the grey relational grade of the experiment and prediction using a multiple linear regression model for the grey relational grade

5.4 Confirming Results

The next step, after evaluating the optimal parameter settings, was to predict and verify the improvement of quality characteristics through the optimal parametric combination. The estimated Grey relational grade using the optimal level of the design parameters was computed as shown in [16–18]:

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{z}(\gamma_i - \gamma_m) \tag{8}$$

where are: γ_m - is the total mean Grey relational grade; γ_i - is the mean Grey relational grade at the optimal level; z - is the number of the main design parameters that affect the quality characteristics.

Optimal grade = 0.722972 + (0.751-0.722972) + (0.765-0.722972) + (0.755-0.722972) + (0.755-0.722972) + (0.755-0.722972) = 0.889112

Table 8 indicates the comparison of the predicted resultant grey relational grade with those of the actual values using the optimal conditions. A good agreement was achieved between the actual and predicted results. Additionally, it was found that the calculated grey relational grade for these optimal performance characteristic values was higher than the grey relational grades observed among the eighteen experiments.

Table 8. The comparison between actual and predicted results of grey relational grade

Taguchi optimal factor settings			
Status	Factors Levels	S/N (dB)	Mean
Prediction	A2B3C2D1E2	-1.1717	0.8738
Experiment	A2B3C2D1E2	-1.0208	0.8891

6. CONCLUSION

The Taguchi-based grey relational analysis method was successfully applied to determine the optimal conditions of turning AISI 4340 steel using nanofluids as coolants for an optimal parametric combination to surface roughness, flank wear and MRR using the Grey relational analysis and Taguchi method. From S/N ratio analysis the optimal conditions of Grey relational grade can be summarized as follows: cutting speed 230 m/min, type of nanoparticles (MWCNT), depth of cut 0.3 mm, feed 0.15 mm/rev and volume fraction of nanoparticles 0.08% had the least influence on the grey relational grade.

The ANOVA for grey relational grade to obtain optimal surface roughness, flank wear and MRR clearly indicates that the cutting speed is the majorly contributor of 25.103%, followed by volume fraction of nanoparticles of 21.43%, then feed 16.143%, depth of cut 15.805% and lastly type of nanoparticles of 14.018%.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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