iJRASET

International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VII Month of publication: July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84423

GRA Assisted Multi-Response Optimization of Process Parameters in Sustainable Machining AISI D3 with Cutting Oil Developed from Waste Lubricating Oil

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Abstract: The global need for sustainable manufacturing processes is increasing and the need for reducing the environmental footprint of traditional petrol/chemical based cutting fluids has come into play, which makes sustainable machining an important field of research. This study proposes to investigate the multi-response optimization of the machining parameters of turning AISI D3 tool steel with a cutting oil obtained from recycled waste lubricating oil under Minimum Quantity Lubrication (MQL) conditions. The cutting oil was developed by refining used cutting oil and adding the appropriate additives which improve the properties of the oil, such as lubricating properties, anti-wear properties, corrosion resistance and resistance to oxidation. The Taguchi L18 orthogonal array was used to design turning experiments with input parameters of MQL air pressure, cutting speed, feed rate and depth of cut. The machining performance was investigated by cutting forces (Fx, Fy and Fz), surface roughness (Ra), and flank wear of the tools (Vb). Grey Relational Analysis (GRA) was applied to optimize multiple performance characteristics by converting them to a single Grey Relational Grade (GRG) and Analysis of Variance (ANOVA) was used to identify the statistical significance of the machining parameters. From the experimental results, it was observed that the best machining condition was obtained at air pressure of MQL=1 bar, cutting speed=150 m/min, feed rate=0.04 mm/rev and depth of cut=0.4 mm. The results of ANOVA showed that within the investigated range, the depth of cut has the greatest influence on the overall machining performance of the process, it has a statistically significant effect at the probability level of 99.7 percent (p = 0.003), while the effects of other factors (MQL air pressure, cutting speed and feed rate) were comparatively small. Developed waste lubricating oil-based cutting fluid has exhibited good cutting performance and the valorisation of waste with reduction of reliance on virgin petroleum-based cutting fluids. The use of recycled cutting oil with the Taguchi–Grey Relational Analysis approach represents an efficient method for multi-response optimization, and is a step towards environmentally friendly cutting oil use in machining.

Keywords: Cutting oil, waste lubricating oil, Taguchi integrated GRA, ANOVA.

I. INTRODUCTION

Sustainable manufacturing is growing in importance as it helps to reduce environmental impacts while keeping productivity and product quality high. Cutting fluids are used in significant amounts, in machining processes, especially in turning and milling which leads to high level of pollution in the environment, occupational health issues and disposal costs. Traditional mineral oil-based cutting fluids are made from non-renewable petroleum resources and are laced with harmful chemicals that can harm humans and the environment. This has turned the development of environmentally friendly cutting fluids and sustainable machining methods into an important research area in manufacturing today.

The waste lubricating oil from automobile and industrial applications is an environmental problem because of the presence of degraded hydrocarbons, heavy metals, oxidation products and other contaminants. Waste lubricating oil is a source of soil and groundwater contamination if disposed of in the wrong way, which can impact ecosystems and public health. But waste lubricating oil has significant percentage of base oil that can be recovered by proper treatment and purification. The recycling and transfer of waste lubricating oil to the production of machining cutting oil not only helps alleviate environmental pollution but also advocates the principle of resource conservation and circular economy. The use of recycled WLOS in producing cutting fluids offers a cost effective and environmentally friendly alternative to the production of cutting oil.

In the last few years, some researchers have discussed the application of vegetable oils, biodegradable lubricants, nano-enhanced cutting fluids and recycled cutting oils in sustainable machining applications. Vegetable oils have high lubricity and biodegradability and tend to have low oxidative stability and thermal performance under extreme machining conditions. With proper treatment and additives, recycled WL0 discarded from engines can be used with qualities comparable to virgin oils and will provide better lubrication properties, higher load carrying capacity and lower production costs while at the same time reducing environmental issues related to the disposal of waste. However, there is still a lack of studies focused on the study of the performance of cutting oils produced from waste lubricating oils, especially during the machining of hardened tool steels.

AISI D3 is a high carbon, high chromium cold work tool steel that is widely used for producing dies, punches, blanking tools, shear blades, and wear resistant parts. AISI D3 is considered to be a difficult-to-machine material, due to its high amount of carbide, hardness and excellent wear resistance. AISI D3 is known to have high cutting force, high cutting temperature, wear of tool and poor surface finish when machined. Hence, the right machining parameters in combination with a suitable cutting fluid are crucial to enhance the machining performance, prolong the tool life and deliver an excellent surface integrity.

There are multiple competing responses like cutting force, surface roughness, material removal rate, and tool wear that affect the performance of a machining process. An optimized one response usually leads to the decline of another response; hence single objective optimization is not suitable for practical manufacturing applications. Thus, multi-response optimization techniques have become a hot subject of interest for exploring the optimum set of machining parameters that can achieve an optimum balance of more than one performance characteristic. Grey Relational Analysis (GRA) is one of the effective and easy-to-implement algorithms among the different optimization methods to solve multi-response optimization problems with small experimental data. GRA reduces the complexity of computation by combining multiple quality characteristics into a single Grey Relational Grade (GRG) and at the same time optimizes conflicting responses. GRA in conjunction with the Taguchi design of experiments (DOE) offers a systematic method to determine the best machining conditions using the least number of experiments.

In the current work, a cutting oil was formulated and purified from waste lubricating oil to use for sustainable machining applications by applying suitable purification and formulation processes. The Taguchi experimental design was used to perform turning experiments on AISI D3 steel under different machining process conditions. The performance of cutting, feed rate, depth of cut, cutting fluid conditions and their effects on cutting forces, surface roughness, material removal rate and tool flank wear were considered in the evaluation for the machine performance. Grey Relational Analysis was then applied to optimize the multiple performance characteristics; finally, the relative significance of the machining parameters on the Grey Relational Grade was obtained by Analysis of Variance (ANOVA).

The novelty of this research is introducing recycled waste lubricating oil-based cutting oil in conjunction with Grey Relational Analysis (GRA) for sustainable multi-response optimization in turning of AISI D3 steel. As opposed to the research works that mainly used vegetable oil-based or commercial cutting fluids, this work shows that it is possible to use recycled waste lubricating oil as an environmentally friendly cutting fluid for the machining process while at the same time optimizing various machining responses. The results afforded by this study are helpful for sustainable manufacturing, as it encourages waste valorization, cuts down on the need for petroleum-based cutting fluids, enhances machining performance and supports the principles of the circular economy.

II. LITERATURE REVIEW

Grey Relational Analysis (GRA) has been effectively applied in various machining processes to optimize performance and enhance efficiency. For instance, in CNC machining, GRA was utilized to evaluate different toolpath strategies, revealing that the Zigzag path significantly improved machining efficiency by optimizing parameters such as spindle speed and feed rate [1]. Similarly, GRA facilitated the optimization of cutting parameters for AISI 4140 and IS-2062 steels, leading to substantial improvements in performance metrics like cutting power and surface roughness [2]. In electrochemical machining (ECM), a dynamic version of GRA was employed to optimize multiple parameters, achieving optimal material removal rates while minimizing defects [3]. Furthermore, in wire electrical discharge machining (WEDM), GRA was integrated with the Taguchi method to enhance cutting rates and surface quality, demonstrating its versatility across different machining techniques [4] [5].

Multi-response optimization in machining is crucial for enhancing productivity and quality across various processes. Techniques such as the MOORA method have been effectively applied to optimize parameters like chip-tool interface temperature, cutting force, and tool wear rate in turning operations, demonstrating its flexibility in complex decision-making scenarios [6]. Similarly, the desirability approach, utilized in turning aluminium alloys, identified optimal cutting parameters that improved surface roughness and metal removal rate, showcasing its practical implications in manufacturing [7].

In Electrical Discharge Machining (EDM), fuzzy logic combined with TOPSIS and the Taguchi method has been employed to balance quality and productivity, optimizing material removal rate and surface roughness [8]. Furthermore, hybrid methods integrating Grey Relation Analysis and fuzzy logic have been proposed for CNC end milling, aiming for continuous quality improvement and effective off-line quality control [9-10]. These methodologies collectively highlight the significance of multi-response optimization in achieving efficient machining processes.

III. EXPERIMENTATION

In this research work, machining of AISI D3 have been performed with cutting oil developed from waste lubricating oil. L_{18} orthogonal array of Taguchi method has been used to perform the machining experiments with MQL air pressure, cutting speed, feed and depth of cut as process parameters and cutting forces, surface finish and tool wear as machining response variables.

Cutting forces in three directions (Fx, Fy and Fz) has been measured using Kistler lathe dynamometer having the provisions of a charge amplifier, data acquisition system and PC software. Tool wear has been measured by dinolight digital microscope with image analysis software. Surface finish of the machined components has been measured with Mitutoyo made surface roughness tester SJ-201P. Table 1 represents experimentation details. Cutting oil has been developed from waste lubricating oil by using IS 1115 code of cutting oil formulations. Cutting oil-water emulsion has been formed by 95 % water and 5 % base oil. Various additives like extreme pressure additives, anti-oxidants, corrosion and rust inhibitors, emulsifier, polyglycols, esters have been used to improve the service properties of the oil. Fig. 1 indicates layout of experimentation process. Fig. 2 indicates photographs of various instruments used in the experimentation process.

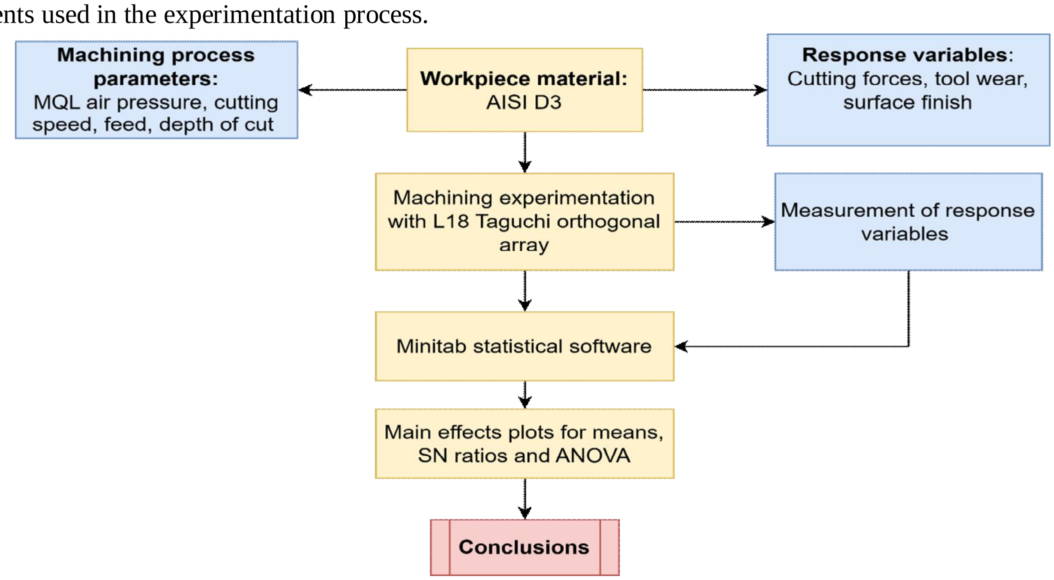
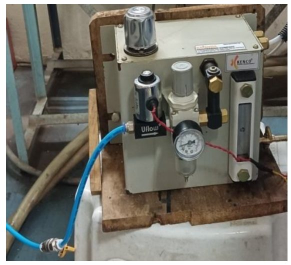


Fig.1 Layout of experimental investigation process

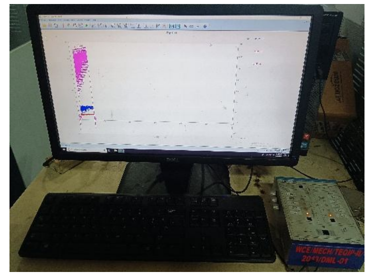
Table 1 Experimentation details

Work piece material	Alloy Steel AISI D3 (alloy of carbon, nickel, chromium and molybdenum), Applications: manufacture of dies, punches, cutting tools, and wear-resistant components
Machine tool	CNC lathe Maxturn + (made by M TAB)
Cutting tool	TNMG160408MTTT8115
Cutting fluids	Cutting oil developed from waste lubricating oil
Process parameters and their levels	1. MQL air pressure [bar] (1,2) 2. Cutting speed [m/min] (90,120,150) 3. Feed [mm/rev.] (0.04,0.07,0.1) 4. Depth of cut [mm] (0.4,0.7,1)
Machining response variables	1. Cutting forces (Fx, Fy, Fz) 2. Surface finish 3. Tool wear

CNC lathe machine



MQL unit



DAS of cutting force measurement

Surface roughness tester

Dinolite digital microscope for tool wear measurement

Cutting oil-water emulsion

Fig. 1 Photographs of instruments and devices used in machining experimentation

Table 3 indicates L_{18} orthogonal array with values of response variables measured during the experimentation.

Table 2. L_{18} orthogonal array with values of response variables measured

Expt. No.	MQL air pressure (Bar)	Cutting speed (m/min.)	Feed (mm/rev)	Depth of cut (mm)	Cutting force (Fx) N	Feed force (Fy) N	Thrust force (Fz) N	Surface roughness (Ra)	Tool flank wear (Vb) mm
1	1	90	0.04	0.4	95.714	99.354	0.491	0.59	0.177
2	1	90	0.07	0.7	174.80	154.41	55.20	0.78	0.24
3	1	90	0.1	1	289.85	185.02	141.96	0.906	0.146
4	1	120	0.04	0.4	93.18	406.60	12.93	1.08	0.35
5	1	120	0.07	0.7	168.83	173.88	70.10	1.64	0.297
6	1	120	0.1	1	259.88	209.24	134.76	1.11	0.379
7	1	150	0.04	0.7	146.27	147.01	54.11	1	0.204
8	1	150	0.07	1	243.68	166.51	143.70	1.96	0.18
9	1	150	0.1	0.4	115.31	134.87	8.60	0.686	0.267
10	2	90	0.04	1	224.33	188.99	103.08	0.99	0.309
11	2	90	0.07	0.4	141.56	167.98	10.41	1.52	0.161
12	2	90	0.1	0.7	231.44	214.73	76.99	1.13	0.387
13	2	120	0.04	0.7	155.45	158.47	24.80	1.24	0.199
14	2	120	0.07	1	228.35	171.31	81.90	1.72	0.181
15	2	120	0.1	0.4	116.74	132.75	14.24	1.28	0.173
16	2	150	0.04	1	189.60	165.59	61.28	1.22	0.233
17	2	150	0.07	0.4	110.41	130.41	18.87	0.693	0.212
18	2	150	0.1	0.7	188.69	176.76	33.28	1.15	0.175

IV. MULTI-RESPONSE OPTIMIZATION BY USING GREY RELATIONAL ANALYSIS

Grey Relational Analysis (GRA) method is a multiple-response optimization method based on Grey System Theory, which was proposed by Deng Julong. It is commonly applied in manufacturing and machining to minimize several performance parameters simultaneously, especially if data from experiments is scarce, or not complete. The multiple responses are transformed into a single Grey Relational Grade (GRG) by GRA and the best combination of process parameters is identified. Grey Relational Analysis (GRA) is a statistical decision-making technique which rates the similarity or closeness between an ideal (reference) sequence and the responses from experiments. It converts the multiple quality characteristics into a single performance index (Grey Relational Grade (GRG)), which is then utilized to find the optimum process parameters.

In the Taguchi–Grey Relational Analysis approach, the optimization procedure generally consists of the following steps:

1) Design experiments using a Taguchi orthogonal array.
2) Conduct machining experiments and measure all response variables.
3) Normalize the experimental data according to the desired quality characteristic (smaller-the-better, larger-the-better, or nominal-the-best).
4) Calculate the Grey Relational Coefficient (GRC) for each response.
5) Determine the Grey Relational Grade (GRG) by averaging the GRC values.
6) Analyse the GRG using Taguchi analysis and ANOVA to identify the optimum parameter levels and the significance of each factor.
7) Perform a confirmation experiment to validate the predicted optimum conditions.

The parameter combination corresponding to the highest Grey Relational Grade is considered the optimum because it represents the best overall compromise among all the selected performance characteristics.

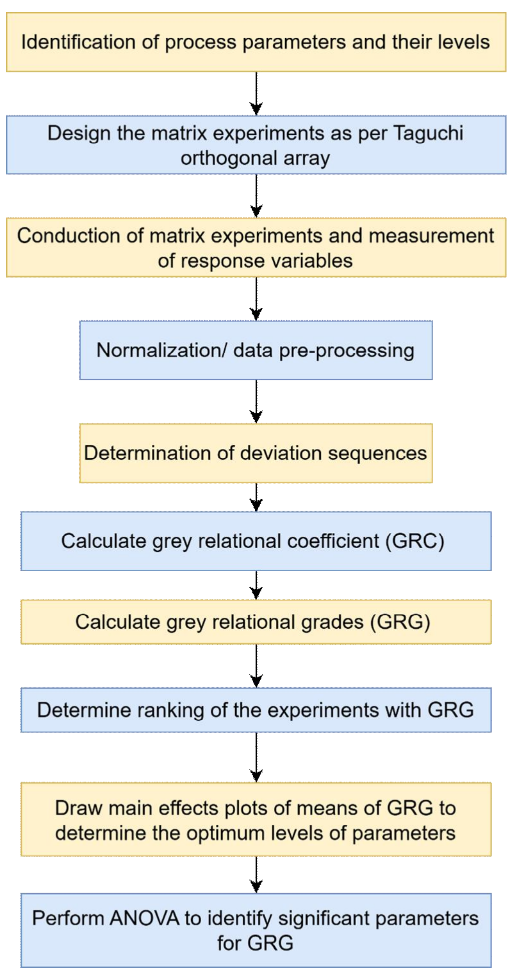


Fig. 2 Steps in grey relational analysis method

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

1) *Data pre-processing*

Pre-processing raw data is the process of converting an original sequence into decimal sequence between 0.00 to 1.00 for comparison. When the form **"Smaller-the-better** "becomes the expected value of the data sequence, the original sequence can be normalized as,

$$Xi(K) = \frac{\max Xi(K) - Xi\ (K)}{\max Xi\ (K) - \min Xi\ (K)}$$

Table 3 Data pre-processing/normalization

Expt. No.	Fx	Fy	Ft	Ra	Vb
1	0.987	1.000	1.000	1.000	0.871
2	0.585	0.821	0.618	0.861	0.610
3	0.000	0.721	0.012	0.769	1.000
4	1.000	0.000	0.913	0.642	0.154
5	0.615	0.757	0.514	0.234	0.373
6	0.152	0.642	0.062	0.620	0.033
7	0.730	0.845	0.626	0.701	0.759
8	0.235	0.781	0.000	0.000	0.859
9	0.887	0.884	0.943	0.930	0.498
10	0.333	0.708	0.284	0.708	0.324
11	0.754	0.777	0.931	0.321	0.938
12	0.297	0.624	0.466	0.606	0.000
13	0.683	0.808	0.830	0.526	0.780
14	0.313	0.766	0.432	0.175	0.855
15	0.880	0.891	0.904	0.496	0.888
16	0.510	0.784	0.576	0.540	0.639
17	0.912	0.899	0.872	0.925	0.726
18	0.514	0.748	0.771	0.591	0.880
Min	0	0	0	0	0
Max	1	1	1	1	1

2) *The deviation sequence of the reference sequence is given by,*

$$\mathbf{Xi(K) = 1 - \frac{Xi\ (K) - Xi}{\max Xi\ (K) - Xi}}$$

Table 4 Determination of deviation sequences

Expt. No.	**Fx**	**Fy**	**Ft**	**Ra**	**Vb**
1	0.013	0.000	0.000	0.000	0.129
2	0.415	0.179	0.382	0.139	0.390
3	1.000	0.279	0.988	0.231	0.000
4	0.000	1.000	0.087	0.358	0.846
5	0.385	0.243	0.486	0.766	0.627
6	0.848	0.358	0.938	0.380	0.967
7	0.270	0.155	0.374	0.299	0.241

8	0.765	0.219	1.000	1.000	0.141
9	0.113	0.116	0.057	0.070	0.502
10	0.667	0.292	0.716	0.292	0.676
11	0.246	0.223	0.069	0.679	0.062
12	0.703	0.376	0.534	0.394	1.000
13	0.317	0.192	0.170	0.474	0.220
14	0.687	0.234	0.568	0.825	0.145
15	0.120	0.109	0.096	0.504	0.112
16	0.490	0.216	0.424	0.460	0.361
17	0.088	0.101	0.128	0.075	0.274
18	0.486	0.252	0.229	0.409	0.120
Min	**0**	**0**	**0**	**0**	**0**
Max	**1**	**1**	**1**	**1**	**1**

3) *Thus, the grey relational coefficient can be expressed as,*

$$\xi\,(K) = \frac{\Delta\min + \xi.\ \Delta\max}{\Delta\, Oi + \xi.\ \Delta\max}$$

$$\Delta Oi\ (K) - Xo(K) - Xi(K)$$

where $\Delta 0i$ (k) is the deviation sequence of the reference sequence
ζ is distinguishing or identification coefficient: $\zeta \in [0, 1]$. $\zeta = 0.5$ is generally used
The grey relational grade is defined as,

$$\gamma i = \frac{1}{n}\sum_{k=1}^{n} \omega k \zeta i(k)$$

Table 5 Determination of grey relational coefficient, grey relational grade and ranking of the experiments

Expt. No.	**Grey relation coefficient**					**Grades**	**RANK**
	Fx	**Fy**	**Ft**	**Ra**	**Vb**		
1	0.9749	1.0000	1.0000	1.0000	0.7954	**0.954051**	**1**
2	0.5465	0.7362	0.5669	0.7829	0.5618	0.638828	9
3	0.3333	0.6420	0.3361	0.6843	1.0000	0.599142	11
4	1.0000	0.3333	0.8520	0.5830	0.3713	0.627929	10
5	0.5652	0.6733	0.5071	0.3948	0.4438	0.516849	14
6	0.3710	0.5830	0.3478	0.5685	0.3409	0.442235	18
7	0.6494	0.7632	0.5718	0.6256	0.6751	0.657015	7
8	0.3952	0.6958	0.3333	0.3333	0.7799	0.50752	15
9	0.8163	0.8122	0.8982	0.8771	0.4990	0.780559	3
10	0.4285	0.6315	0.4111	0.6313	0.4250	0.505493	16
11	0.6702	0.6912	0.8784	0.4241	0.8893	0.710657	5
12	0.4156	0.5711	0.4835	0.5592	0.3333	0.472543	17
13	0.6123	0.7221	0.7466	0.5131	0.6945	0.657712	6
14	0.4211	0.6810	0.4680	0.3774	0.7749	0.544484	13
15	0.8067	0.8214	0.8389	0.4982	0.8169	0.756439	4
16	0.5049	0.6987	0.5409	0.5209	0.5807	0.569227	12
17	0.8509	0.8318	0.7958	0.8693	0.6461	0.798781	2
18	0.5073	0.6649	0.6859	0.5502	0.8060	0.642865	8

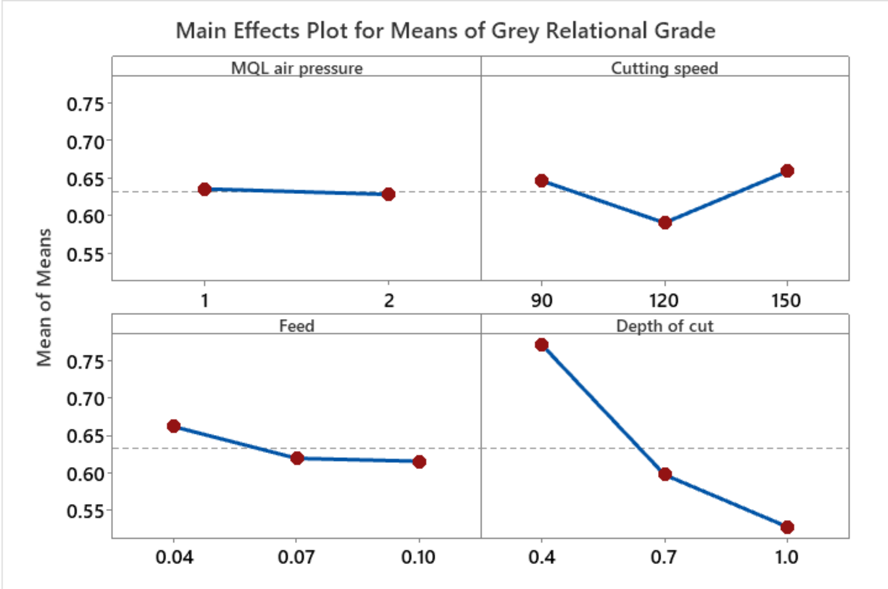


Fig.3 Main effects plots for means of GRG

The main effects plot for the Grey Relational Grade (Fig. 3) shows that the best overall machining performance occurs at 1 bar MQL air pressure, 150 m/min cutting speed, 0.04 mm/rev feed rate and 0.4 mm depth of cut. The deepest cutting parameter, depth of cut, has the greatest mean GRG variation among all the parameters of the machining process, which indicates that it is the most influential parameter in affecting the responses. As the depth of cut increases, the Grey Relational Grade significantly decreases, which reflects a worsening of cutting forces, surface roughness and tool wear. The cutting speed also has a significant influence with the best GRG achieved at 150 m/min. The effects of air pressure used in MQL are not significant within the range of the investigated cutting speeds.

4) Analysis of Variance for GRG

Table 6 ANOVA for GRG

Source	DF	Adj SS	Adj MS	F-Value	P-Value
MQL air pressure	1	0.000241	0.000241	0.03	0.868
Cutting speed	2	0.015905	0.007953	0.96	0.416
Feed	2	0.007906	0.003953	0.48	0.635
Depth of cut	2	0.188557	0.094278	11.36	**0.003**
Error	10	0.083006	0.008301		
Total	17	0.295616			

From ANOVA results (Table 6) it is found that the depth of cut is the most influential machining parameter which has significant contribution to the simultaneous optimization of cutting forces, surface roughness and tool flank wear. With the increase of depth of cut, the significant decrease in the Grey Relational Grade is due to the increase in cutting loads, contact between cutting tool and workpiece, rising cutting temperatures, and more tool wear, which all have negative impact on machining performance. However, the Grey Relational Grade is not greatly affected by the changes of MQL air pressure, cutting speed, and feed rate in the conditions of the investigated machining range. These parameters show trends in the main effects plot, but do not show up in the statistical analysis when compared to the experimental variability. The main effects plot from the Taguchi method and the ANOVA results agree, and a low depth of cut (0.4 mm) is effective for attaining better overall machining performance. Therefore, the best combination as per the Taguchi–Grey Relational Analysis is found to be 1 bar MQL air pressure, 150 m/min cutting speed, 0.04 mm/rev feed rate and 0.4 mm depth of cut, which gives the optimum compromise among all the selected performance characteristics.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
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Volume 14 Issue VII July 2026- Available at www.ijraset.com

It can be seen that the depth of cut is the most significant factor, followed by the cutting speed, feed rate and MQL air pressure, as shown on the contour plots. The best Grey Relational Grades are always achieved at: • MQL air pressure: 1 bar • Cutting speed: 150 m/min • Feed rate: 0.04 mm/rev • Depth of cut: 0.4 mm In these conditions, the optimum combination of the parameters (A_1–B_3–C_1–D_1) determined by Taguchi–Grey Relational Analysis (GRG) is the best. The contour plots also show that contour lines are rather close together and equally spaced, suggesting that there are low interaction effects between the machining parameters, and their individual effects dominate overall machining performance. The low depth of cut from a machining view point provides the following advantages: Low cutting force, low tool loading, low cutting temperature and low vibration, which is all to gain all at once. Likewise, using a lower feed rate will result in better surface finish and lower cutting forces, and a higher cutting speed will create smoother chip formation under MQL. Changes of MQL air pressure result in small changes of the Grey Relational Grade in the examined range.

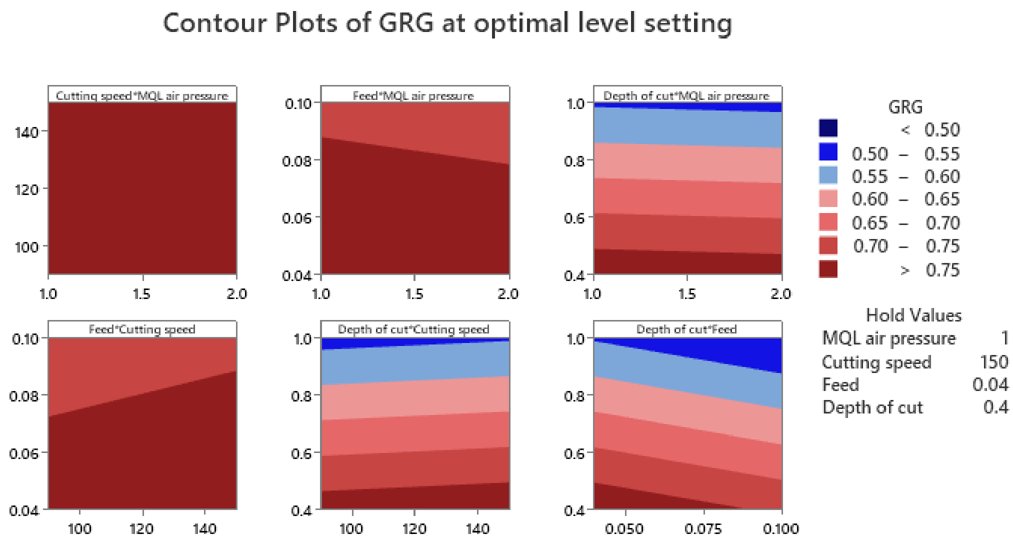

Fig.4 Contour plots for GRG

V. CONCLUSIONS

In this study, the multi-response optimization of machining parameters during turning of AISI D3 tool steel under Minimum Quantity Lubrication (MQL) conditions has been carried out using cutting oil that was synthesized using recycled waste lubricating oil. The use of Grey Relational Analysis (GRA) method coupled with Taguchi method proved to be successful for optimizing multiple machining responses such as cutting forces, surface roughness and tool flank wear. This study's key findings include:

A treated waste lubricating oil has been treated to successfully develop a sustainable cutting oil by the incorporation of suitable additives following IS 1115 specifications. The developed cutting fluid was suitable for the machining AISI D3 steel under MQL condition, which can lead to resource recovery and sustainable manufacturing.

The Taguchi–Grey Rel relational Analysis approach was used to convert several machining responses to a single Grey Rel relational Grade (GRG) in order to optimize the cutting force, surface roughness and tool flank wear by conducting a few number of experiments.

The optimum machining parameter combination which was obtained from Grey Relational Grade analysis was 1 bar MQL air pressure, 150 m/min cutting speed, 0.04 mm/rev feed rate and 0.4 mm depth of cut (A_1–B_3–C_1–D_1), which gave the optimum overall machining performance. Analysis of Variance (ANOVA) showed that the machining parameter Depth of Cut has the most significant influence on the Grey Relational Grade and is statistically significant for the combined optimization of the machining responses ($F = 11.36$, $p = 0.003$).

On the other hand, the air pressure, cutting speed and feed rate of the MQL showed no statistically significant effects in the range of the investigated parameters. Based on the results of the main effects analysis and contour plot analysis, it is concluded that the greater the depth of cut, the greater were the cutting forces, cutting temperature, tool loading and tool wear, which led to the reduction of the Grey Relational Grade of the machining performance. Lower feed rate and higher cutting speed resulted in better surface finish and reduced surface roughness.

The Taguchi response analysis results are shown to be in close agreement with the ANOVA results, which further proves the reliability of the Grey Relational Analysis technique for multi-response optimization in sustainable machining applications. The results show that oil formulation using recycled waste lubricating oil can be used as an alternative to petroleum based cutting fluids to achieve the same machining performance while being environmentally friendly. The suggested method offers waste valorization, decreases environmental pollution, follows the principles of the circular economy and offers a practical model for the sustainable optimization of the machining process of difficult-to-machine materials.

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