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RESEARCH ARTICLE

Evaluation and Performance Improvement of Environmentally Friendly Sustainable Turning of 6063 Aluminum Alloy in Dry Conditions Using Grey Relational Analysis

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ABSTRACT – Sustainable machining has gained importance in recent years due to its environmental, economic, and societal implications. Aluminium (Al) 6063 alloy involves turning operation to make it suitable for various applications. The work's novelty is assessing the machining characteristics along with sustainability indicators. This study aims to find the best-turning parameters for machining Al 6063 alloy. The turning parameters considered were cutting speed, feed rate, and depth of cut. A cutting speed of 200 m/min, feed rate of 0.05 mm/rev, and depth of cut of 0.25 mm were the best parameter combinations for achieving a good machining response. From the response value of mean grey relational grade (GRG) and analysis of variance (ANOVA), the depth of cut ranks one with 34.38%, which is the most dominating parameter in achieving the sustainable machining of Al 6063 alloy. Through grey relational analysis, optimized machining parameters resulted in a 72.84 percent reduction in carbon emissions, 72.82 percent reduction in energy consumption, 18.58 percent reduction in cutting power, and 6.83 percent reduction in surface roughness considering the initial parameter settings and best machining parameters. The enhancement in total GRG was 0.1702, indicating improvement in the desired responses. As a result of this study, it is clear that appropriate machining parameter selection aids sustainable machining of Al 6063 alloy.

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1.0 INTRODUCTION

Environment-friendly manufacturing is the production of goods over an energy-inexpensive and eco-friendly approach to safeguarding environmental and community benefits. Achieving sustainability in the turning process is directly connected with the cutting parameters, materials, and cutting fluid application [1]. Dry machining is the most suitable form of sustainable machining. Eco-friendly machining aims to improve approaches and procedures that deliver scientific performance to the organization in terms of cost efficiency while reducing energy consumption and resources available in nature, thus reducing the negative impact on the environment. Machining comprises many special machines like a planer, miller, shaper, driller, and turner. Here, the turning process is one of the oldest and most extensively used machining operations through which many cylinder-shaped components are machined under various machining parameters [2]. Turning is a machining process widely used to produce products like shafts, screws, threaded rods, bushings, and pins [3].

According to ISO 14000 environmental management system principles, manufacturing organizations are accountable for reducing their aggressive effect on the clean environment [4]. The stringent rules from the policymakers, possibly a government to reduce environmental pollution also without compromising the excellent quality engineering products expected by the customers, that is, both the government's stricter policy and customer demand together forced the manufacturing industries to switch over from traditional production approaches and to move on to sustainable machining methods [4]. The swing in the manufacturing industry results from increased awareness among the manufacturers, the customers, and the end users [5]. So, awareness is already realized by the manufacturing industry and is still increasing and widespread about sustainable machining operations in recent times for discovering ecological manufactured goods production through sustainable machining.

Recently, manufacturing industries have moved towards sustainable machining to produce all components to achieve cost-effectiveness and improve the three pillars of sustainability (financial, ecological, and societal) [6]. Warsi et al. [7] studied that 90% of the environmental burden in machining is due to electrical energy consumption. The increased manufacturing cost and consciousness about preserving the environment and reducing electrical energy consumption provide good potential for economic and environmental benefits. During machining, the cutting insert removes excessive material as a tiny chip, and the energy expended during a turning operation is sometimes referred to as SCE and is expressed in J/mm^3. Specific cutting energy comprises the energy spent removing the chips along the shear plane, chip flow against the cutting tool face rubbing, creating a new surface, and adjusting the variation in momentum energy [7]. For many years, researchers have studied the manufacturing of aluminum alloys, focusing on conventional machining characteristics, like accuracy, surface roughness, machinability, cutting force, MRR, etc. Conventional machining focuses

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on increased component dimensional accuracy, good surface finish, and production output. However, in recent times, an investigation that mixes conventional machining characteristics with important ecological factors is gaining significance [2]. This is attributed to researching cleaner production. In a vision toward protecting operators, industrial work, and a clean environment, traditional cutting fluids used during wet machining are gradually being replaced by dry machining [2]. The negative impacts of conventional cutting fluids and machinist's health are valid reasons to seek alternatives. MQL can produce oil mist, aerosol, and tiny liquid droplets, which can easily contaminate the environment and produce harmful dust, microorganisms, and bacteria, thus harming the health of machine operators. Using cryogenic coolants may lead to excessive carbon emission, which is also not sustainable. The production process of cryogenic coolants is not environmentally friendly [1]. Cryogenic liquids must be handled and stored in an insulated storage vessel as a safety measure [4]. Nanoparticles added with vegetable oil can be claimed as sustainable machining conditions. However, the disposal of nanofluids is not biodegradable [1].

Rusdi Nur et al. [6] conducted a study on machining modified Al-11% Si alloy using carbide-coated inserts at different machining parameters for less power consumption and good surface finish through optimization. Warsi et al. [7] carried out a study to optimize the machining parameters of the turning process in high-speed machining conditions. The workpiece material used was T6 heat-treated aluminum 6061 alloys. The maximum cutting speed was 1500 m/min. The experiment was carried out to optimize the cutting factors while machining AISI 1040 carbon steel with CNMG 12012 TF aluminum tungsten nitride coated insert and CNMG 120412 MP tungsten nitride coated insert for different machining parameters. The results obtained from this study suggested that the machining condition and cutting insert type influenced the power consumption while machining AISI 1040 [5].

Bhattacharya et al. [8] conducted a comparative analysis to predict responses in a sustainable dry-turning operation. In this study, they executed 27 trials based on the L_{27} experiment design. Also, the machining in dry conditions resulted in less energy consumption and production cost, thus ultimately leading to sustainable machining. Dry machining is efficient and environmentally friendly due to its characteristics, such as no air or water pollution.

Statistical Method for Research Workers was the reference book for Design of Experiments (DOE) written by Ronald A. Fisher [9]. The DOE was adopted in only 20% of manufacturing sectors, with 3% of the manufacturing industries using DOE frequently. It was also discovered that DOE's theoretical inexperience with actual uses and unwillingness to find a methodology to simplify its application were the main reasons for its lack of usage in manufacturing industries [9].

Multi-objective optimization (MOO) is an extensively used investigation technique that can be used for complex engineering problems like manufacturing processes. Multi-objective optimization looks compromised amid several manufacturing norms such as machining force, surface finish, cutting time, material removal rate, energy consumption, cutting power, and carbon emission [7]. Warsi et al. [7] carried out the work to reduce power consumption and surface roughness reduction simultaneously, using GRA with equal weightage procedure in multiple objective function optimizations of production factors in machining operation.

Panda et al. [10] conducted the turning experiment on AISI52100 bearing steel using a multilayered carbide insert under dry machining conditions. Machining characteristics such as flank wear, surface roughness, and chip morphology were investigated. Taguchi-based GRA was employed to perform the parametric optimization of multi-objective problems. Najiha et al. [11] studied the machinability of Al 6061-T6 alloy using two different cutting tools, namely a TiAlN-coated insert and a TiAlN/TiN-coated insert, to investigate the surface finish. The cooling/lubrication action was performed using the MQL method. Experimental results reveal that the TiAlN+TiN coated insert outperformed the TiAlN coated insert in terms of producing products with a good surface finish.

Al 6063 alloy has the ultimate tensile strength of 241 MPa and yield strength of 214 MPa. The turning process of the Al 6063 alloy has found special consideration in recent times due to its excellent strength-to-weight fraction robustness, corrosion-resistant property, and good surface finish, which are appropriate for the production of aluminum-based engineering products in several applications like automotive, storage tanks, heat sinks, tubing in the irrigation field, piping, and building products that are being made mainly by turning process [12]. As an observation from the literature, minimal studies were reported in terms of assessment of the machining characteristics (MRR, cutting force, and surface roughness) along with sustainability indicators (carbon emission, energy consumption, and cutting power) in the turning of Al 6063 alloy in dry condition. Based on this gap in the literature, the present work emphasizes the impact of all turning parameters on sustainability indicators and machining characteristics in the turning of Al 6063 alloy.

In a nutshell, in the present study, dry machining condition was considered, and an effort was put forth to find the best turning parameters for finding the optimum input parameter that will produce the components with the reduction in energy consumption, reduction in carbon emission, less power consumption with good surface finish without compromising the material removal rate.

2.0 MACHINE TOOL AND PARAMETERS

The following section presents input cutting parameters, machine tools and measuring instruments, dry machining conditions, cutting tool materials, and output responses to be measured during the machining process.

2.1 Machining Process - Turning Operation

In metal cutting, turning is the oldest and most effective production method. Turning helps manufacture many products, such as cams, bearings, gears, and other engineering components [2, 9]. Many factors are present in the machining operations, which disturb the technical specification of the end products. Turning parameters, hardness of the workpiece material, tool material, and tool shape are the most essential and well-known influencing factors [13]. The workpiece was made of commercially available Al 6063 alloy in the current study. The standard diameter of the workpiece readily available was 60 mm. The length of 320 mm was decided based on the capacity of the lathe. For all experiments, the machining length of the Al 6063 alloy bar was 30 mm.

Table 1. Turning parameters and details

Turning parameters	Step/Range	Units
Cutting Speed (V_C)	100, 150, 200	meters per minute
Feed Rate (f)	0.05, 0.075, 0.1	millimeter per revolution
Depth of Cut (d)	0.25, 0.5, 1	millimeter
Machining insert tool	Tungsten carbide uncoated inserts of Sandvik make according to ISO requirement HN SNMG08	
Tool holder	DBSNR2020K 12 for turning operation	
Workpiece material	Al 6063 alloy (Length L=320mm and Diameter D=60mm)	
Machining condition	Dry machining condition	

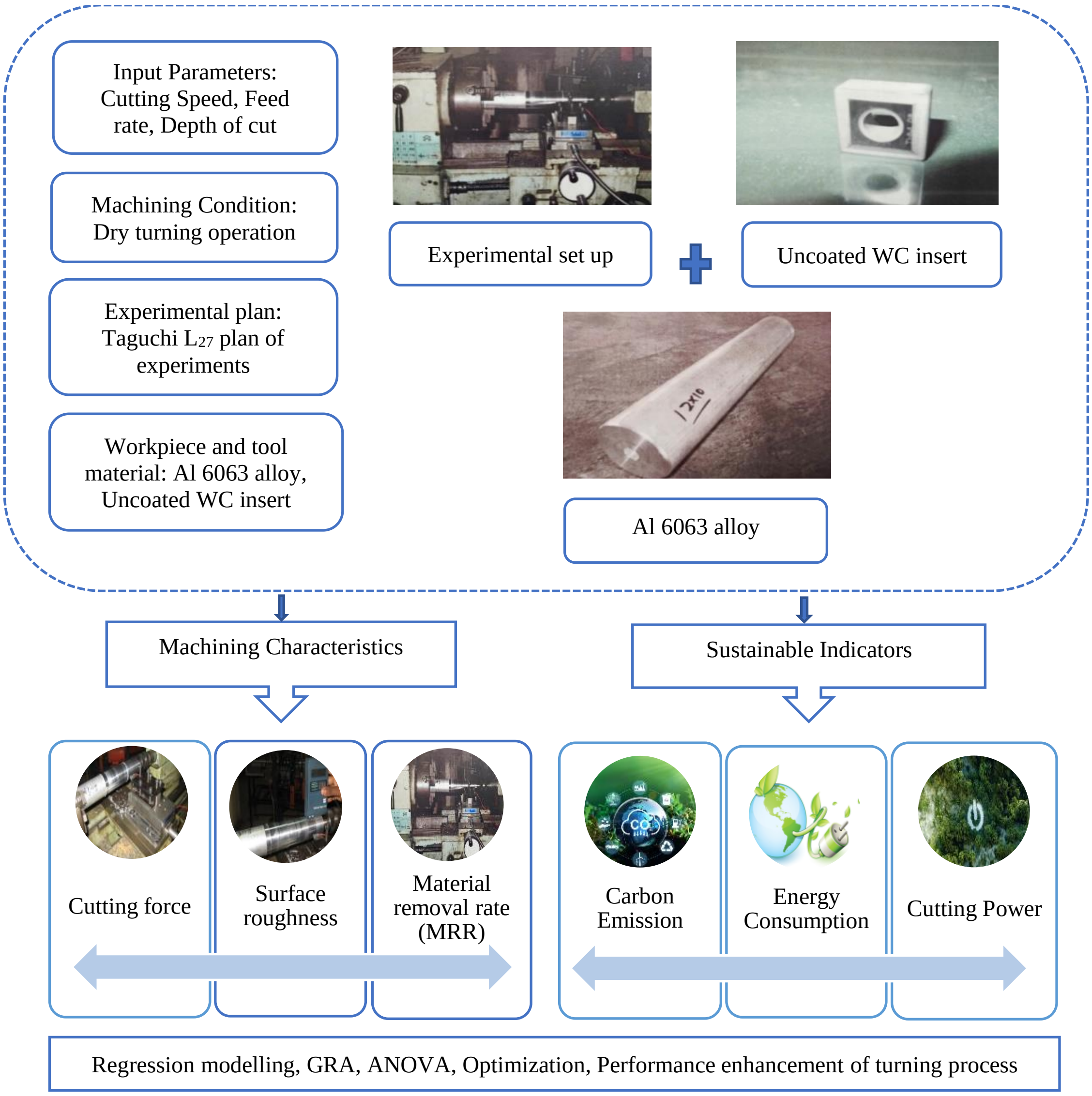

Figure 1. Schematic illustration of the experimental methodology

Sandvik's uncoated tungsten carbide inserts made as per ISO specification HN SNMG08 were used as cutting tool inserts. As per the tool manufacturer's recommendations, available tool holder, cutting parameters, and machine tool capacity uncoated tungsten carbide insert was employed for machining the commercially available Al 6063 alloy. The details of turning parameters and conditions are listed in Table 1. The ranges of these turning parameters were carefully set following the appropriate ISO standard, tool manufacturer's specifications, machine tool capacity and information from the existing literature [14]. All 27 turning trails were conducted through dry machining as a sustainable machining approach [7]. The sequence of the events involved in the present study is presented in Figure 1, and it was followed to complete the current study.

2.2 Experimental Work

Kirloskar Turnmaster-35 all-geared lathe was utilized in the present study. The distance between the two centers of the Turnmaster-35 was 800mm. The vertical height of the lathe center is 175mm. The power of the lathe machine used was 2.2 kW. "A Kistler quartz three-axis force dynamometer (Type 9215A1, standardized range: FX.0±5000 N, FY.0±5000 N, and FZ.0±3000 N) in combination with three charge amplifiers of Kistler make (Type5070), was utilized to change the dynamometer output signal into a voltage signal suitable for the data acquisition system, and a computer was utilized to measure, monitor and record the machining forces. The TR-100 surface roughness tester was utilized in the present study to measure the surface roughness. Three kinds of λ values may be specified, and the lambda denotes the distance to be moved all through the finished surface with the stylus probe [15]. Figure 2 shows the experimental setup. The material removal rate demonstrating the production was determined using Eq. (1) [9], [16–19].

$$MRR = Depth\ of\ cut \times Feed\ rate \times Cutting\ speed \tag{1}$$

where MRR is measured in cm^3/min, the feed rate is given in mm/rev, the depth of cut is given in mm, and the cutting speed is given in m/min [9].

Figure 2. Kirloskar Turnmaster-35 all-geared lathe for turning process

2.3 Estimation of Energy Consumption

The energy consumption analysis of any machine gives more information to deal with their electrical energy consumption. One of the key reasons to estimate energy consumption is to account for electrical energy, which is 50% of total production costs. The world is continually looking for new energy sources, while carbon emission from energy consumption affects the environment. Practically, part of the manufacturing cost is due to energy consumption. Here, energy consumption (E_C) was estimated through Eq. (2) [1], [20].

$$E_C = \frac{F_C\ (N) \times\ V_C\ \ \left(\frac{m}{min}\right) \times Machining\ time\ (min)}{1000} \tag{2}$$

Here, F_C is the cutting (turning) force (N) measured by the cutting tool dynamometer, V_C denotes the machining speed in m/min, and E_C denotes the cutting energy in kJ. According to one estimate, the various industry sectors account for about 31% of all energy consumption, and the manufacturing sector alone is responsible for around 60% of the energy the industry uses. Also, it was discussed that energy efficiency is not at the required level since the energy used in actual production corresponds to only 15% of the total energy consumption. So, decreasing energy consumption in machining activities will lead to cleaner production in machining processes [1].

2.4 Estimation of Carbon Emission Values

Negative environmental impact was considered the most critical problem among the industries. Manufacturing industries have started to pay much attention to reducing this negative impact on the environment only in recent decades

[1]. Using fossil fuels as an energy input for manufacturing many engineering products will contribute to CO_2 emissions, adding density to the formation of greenhouse gases. Also, the main reason for heat waves and climate change is the presence of CO_2 in the greenhouse gases in the atmosphere. So, the CO_2 emission to the atmosphere should be reduced to the maximum possible extent [1]. To decrease this, we need to look for the production of alternative energy sources and their uses in actual practice. The carbon emission can be predicted with the help of Eq. (3).

$$C_{ee} = E_C \times F_e \tag{3}$$

where, C_{ee} is carbon releases formed in kg-CO_2, E_C is electrical energy consumption, and Fe is the carbon release factor used in the case of electrical energy consumption [1],[20].

2.5 Estimation of Cutting Power

The cutting power required for turning operation was estimated by Eq. (4) [18], [21].

$$P_C = \frac{F_Z \times \ V_C}{60} \tag{4}$$

where, F_Z denotes the primary cutting (turning) force (N), and V_C denotes the (machining) speed (m/min).

2.6 Design of Experiments

The turning experiments were planned according to the L_{27} Taguchi orthogonal array plan of experiments [22]–[26]. Twenty-seven tests were conducted using three process parameters at three levels [15], [24]–[26]. In the current study, each combination of input parameters was analyzed thrice, and the average value of the associated response data was recorded. For each trial, a new insert was used to eliminate the effect of tool wear [27], [28]. Table 2 demonstrates the experimental design and responses using the L_{27} orthogonal array.

Table 2. Experiments with the L_{27} orthogonal array and the results

Runs	Cutting Speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Surface Roughness (µm)	Cutting Force (N)	MRR (cm^3/min)	Carbon Emission (kg-CO_2)	Energy Consumption (kJ)	Cutting Power (W)
1	100	0.050	0.25	1.024	51.59	1.25	2.43	5.74	85.98
2	100	0.050	0.50	1.064	134.74	2.50	6.23	14.73	224.57
3	100	0.050	1.00	1.035	184.69	5.00	8.24	19.50	307.82
4	100	0.075	0.25	1.194	88.27	1.88	2.67	6.32	147.12
5	100	0.075	0.50	1.234	163.99	3.75	4.84	11.44	273.32
6	100	0.075	1.00	1.205	217.86	7.50	6.08	14.37	363.10
7	100	0.100	0.25	1.314	161.87	2.50	3.45	8.16	269.78
8	100	0.100	0.50	1.354	243.06	5.00	5.04	11.91	405.10
9	100	0.100	1.00	1.325	291.45	10.00	5.69	13.46	485.75
10	150	0.050	0.25	1.137	56.15	1.88	2.24	5.29	140.38
11	150	0.050	0.50	1.770	146.74	3.75	5.67	13.42	366.85
12	150	0.050	1.00	1.147	186.74	7.50	6.77	16.02	466.85
13	150	0.075	0.25	1.307	98.72	2.81	2.44	5.77	246.80
14	150	0.075	0.50	1.347	179.91	5.63	4.30	10.17	449.78
15	150	0.075	1.00	1.317	220.87	11.25	4.93	11.66	552.18
16	150	0.100	0.25	1.427	172.32	3.75	2.95	6.98	430.80
17	150	0.100	0.50	1.467	253.51	7.50	4.19	9.92	633.78
18	150	0.100	1.00	1.437	295.47	15.00	4.53	10.72	738.68
19	200	0.050	0.25	0.954	21.00	2.50	0.66	1.56	70.00
20	200	0.050	0.50	0.994	102.19	5.00	3.09	7.32	340.63
21	200	0.050	1.00	0.965	150.59	10.00	4.20	9.93	501.97
22	200	0.075	0.25	1.124	41.56	3.75	0.79	1.88	138.53
23	200	0.075	0.50	1.164	135.36	7.50	2.48	5.87	451.20
24	200	0.075	1.00	1.135	183.76	15.00	3.08	7.27	612.53
25	200	0.100	0.25	1.244	127.77	5.00	1.65	3.91	425.90
26	200	0.100	0.50	1.284	208.96	10.00	2.58	6.11	696.53
27	200	0.100	1.00	1.355	241.78	20.00	2.70	6.38	805.93

3.0 TURNING FACTORS OPTIMIZATION USING GREY RELATIONAL ANALYSIS (GRA)

Warsi et al. [7] already indicated the values of responses at best and worst settings of turning parameters. So, the response variables such as surface roughness, material removal rate, cutting force, energy consumption, and cutting power have been optimized using the grey relational analysis (GRA) method. Table 3 details the output values at turning parameters' best and worst conditions.

Table 3. Response values at their best and worst settings of turning parameters

Various output responses	Response values at their best and worst conditions		Turning parameters and their levels		
			Cutting Speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)
Surface roughness (μm)	Best	0.954	200	0.050	0.25
	Worst	1.770	150	0.050	0.50
Cutting force (N)	Best	21.00	200	0.050	0.25
	Worst	295.47	150	0.100	1.00
Material removal rate (cm^3/min)	Best	20.00	200	0.100	1.00
	Worst	1.25	100	0.050	0.25
Energy consumption (kJ)	Best	1.56	200	0.050	0.25
	Worst	19.50	100	0.050	1.00
Cutting power (W)	Best	70.00	200	0.050	0.25
	Worst	805.93	200	0.100	1.00
Carbon Emission kg-CO_2	Best	0.66	200	0.050	0.25
	Worst	8.24	100	0.050	1.00

The output response values were analyzed to evaluate the behavior of the chosen machining characteristics and sustainability indicators. However, Table 3 shows that turning parameters need various cutting conditions to attain reasonable measures of surface roughness, cutting force, material removal rate, energy consumption, and cutting power, thus requiring multi-objective optimization [7].

3.1 Application of GRA for Multi-objective Complex Turning Process

Optimization of a multi-objective complex engineering problem shall be carried out effectively through grey relational analysis (GRA) [7], [29]. The succeeding steps must be followed to perform GRA to find the optimal value [7], [29]. The measured readings of all responses are standardized from 0 to 1. The process of standardization is termed grey relational standardization. Standardization is vital, as the collection and measurement of the physical SI unit of one response value will vary with the physical unit of another [29]. If the requirement of an objective function is to be maximized, then the "larger-the-better" condition is to be considered, and the calculation for standardization is Eq. (5).

$$xi*(k) = \frac{xi(k) - min\ xi(k)}{\max xi(k) - \min xi(k)} \tag{5}$$

If the requirement of an objective function is to be minimized, then the "lower-the-better" condition is to be considered, and the calculation for standardization is Eq. (6).

$$xi*(k) = \frac{max\ xi(k) - xi(k)}{\max xi(k) - \min xi(k)} \tag{6}$$

Here, xi*(k) and xi (k) are the standardized and experimental data, respectively, for ith number of experiments by using the kth response [29]. Afterward, the grey relational coefficient (GRC) can be calculated using Eq. (7).

$$\xi i(k) = \frac{\Delta min + \zeta \Delta max}{\Delta i(k) + \zeta \Delta max} \tag{7}$$

Here, Δi (k) is the absolute value of contrast between xi^0 (k) and xi*(k) and Δi (k) =| xi^0(k) - xi*(k) |. The value of xi^0 is 1. Δmax and Δmin are the universal supreme and universal least values in different data series [29]. The unique, distinctive co-efficient value (ζ) lies among 0 and 1, which is for extending or for contracting the range of grey relational coefficient (GRC), commonly kept, (ζ) = 0.5, if all the process parameters have equal weightage [29]. As the final step, the averaging of the grey relational coefficient (GRC) corresponds to every performance appearance to find the grey relational grade (GRG) using Eq. (8).

$$\gamma i = \frac{1}{n}\sum_{k=1}^{n} \xi i(k) \tag{8}$$

where 'n' is the number of process yield responses.

3.2 Computing the GRC and GRG Values

The value of already standardized data of the complete investigational outcomes, GRC, and GRG for each experiment combination are listed in Tables 4 and 5. A higher material removal rate that straightaway represents the machining efficiency or yield is desirable. Hence, the "higher-the-better" condition is considered the objective function. The ''lower-the-better'' condition is selected as the objective function for all remaining responses. The highest value of the GRG is expected to be the best value nearer to the optimal result. The maximum grey relational grade value for trial 19 is 0.8914, as shown in Table 5. This method allows anyone to select the parameters at the levels that deliver the maximum average output value [29]. It was understood from Table 6 that the highest value GRG was found at level 3 in cutting speed, level 1 in feed rate, and level 1 in the depth of cut. Thus, the turning parameters (v3, f1, d1) are the optimal combination that finds better values in attaining sustainability while machining the Al 6063 alloy.

Table 4. Normalized data of the experimental results

Run	Surface roughness	Cutting force	Material removal rate	Carbon emission	Energy consumption	Cutting power
1	0.914	0.889	0.000	0.767	0.767	0.978
2	0.865	0.586	0.067	0.265	0.266	0.790
3	0.901	0.404	0.200	0.000	0.000	0.677
4	0.706	0.755	0.033	0.734	0.735	0.895
5	0.657	0.479	0.133	0.449	0.449	0.724
6	0.692	0.283	0.333	0.285	0.286	0.602
7	0.559	0.487	0.067	0.632	0.632	0.729
8	0.510	0.191	0.200	0.423	0.423	0.545
9	0.545	0.015	0.467	0.336	0.337	0.435
10	0.776	0.872	0.033	0.792	0.792	0.904
11	0.000	0.542	0.133	0.339	0.339	0.597
12	0.763	0.396	0.333	0.194	0.194	0.461
13	0.567	0.717	0.083	0.765	0.765	0.760
14	0.518	0.421	0.233	0.520	0.520	0.484
15	0.555	0.272	0.533	0.437	0.437	0.345
16	0.420	0.449	0.133	0.698	0.698	0.510
17	0.371	0.153	0.333	0.534	0.534	0.234
18	0.408	0.000	0.733	0.489	0.489	0.091
19	1.000	1.000	0.067	1.000	1.000	1.000
20	0.951	0.704	0.200	0.679	0.679	0.632
21	0.987	0.528	0.467	0.533	0.533	0.413
22	0.792	0.925	0.133	0.982	0.982	0.907
23	0.743	0.583	0.333	0.760	0.760	0.482
24	0.778	0.407	0.733	0.681	0.681	0.263
25	0.645	0.611	0.200	0.869	0.869	0.516
26	0.596	0.315	0.467	0.747	0.747	0.149
27	0.509	0.196	1.000	0.731	0.731	0.000

Table 5. GRC and GRG of the Experimental Data

	Grey relational co-efficient (GRC)						GRG	RANK
Run	Surface roughness	Cutting force	Material removal rate	Carbon emission	Energy consumption	Cutting power		
1	0.854	0.818	0.333	0.682	0.682	0.958	0.7212	3
2	0.788	0.547	0.349	0.405	0.405	0.704	0.5329	13
3	0.834	0.456	0.385	0.333	0.333	0.607	0.4915	18
4	0.630	0.671	0.341	0.653	0.653	0.827	0.6291	5
5	0.593	0.490	0.366	0.476	0.476	0.644	0.5074	17
6	0.619	0.411	0.429	0.412	0.412	0.557	0.4731	20
7	0.531	0.493	0.349	0.576	0.576	0.648	0.5289	14
8	0.505	0.382	0.385	0.464	0.464	0.523	0.4539	24
9	0.524	0.337	0.484	0.430	0.430	0.470	0.4455	25

Table 5. (cont.)

Run	Grey relational co-efficient (GRC) Surface roughness	Cutting force	Material removal rate	Carbon emission	Energy consumption	Cutting power	GRG	RANK
10	0.690	0.796	0.341	0.706	0.706	0.839	0.6799	4
11	0.333	0.522	0.366	0.431	0.431	0.553	0.4393	27
12	0.679	0.453	0.429	0.383	0.383	0.481	0.4679	22
13	0.536	0.638	0.353	0.681	0.681	0.675	0.5940	8
14	0.509	0.463	0.395	0.510	0.510	0.492	0.4800	19
15	0.529	0.407	0.517	0.470	0.470	0.433	0.4712	21
16	0.463	0.476	0.366	0.623	0.623	0.505	0.5093	16
17	0.443	0.371	0.429	0.518	0.518	0.395	0.4455	26
18	0.458	0.333	0.652	0.495	0.495	0.355	0.4646	23
19	1.000	1.000	0.349	1.000	1.000	1.000	0.8914	1
20	0.911	0.628	0.385	0.609	0.609	0.576	0.6196	6
21	0.974	0.514	0.484	0.517	0.517	0.460	0.5777	11
22	0.706	0.870	0.366	0.966	0.966	0.843	0.7859	2
23	0.660	0.545	0.429	0.675	0.676	0.491	0.5794	10
24	0.693	0.457	0.652	0.611	0.611	0.404	0.5713	12
25	0.585	0.562	0.385	0.792	0.792	0.508	0.6040	7
26	0.553	0.422	0.484	0.664	0.664	0.370	0.5260	15
27	0.504	0.383	1.000	0.650	0.650	0.333	0.5870	9

Table 6. Mean value of GRG

Turning parameters	GRG values (Low) Level 1	(Medium) Level 2	(High) Level 3	(max-min)	Rank
Cutting Speed	0.532	0.506	**0.638***	0.1323	2
Feed Rate	**0.602***	0.566	0.507	0.0952	3
Depth of Cut	**0.660***	0.509	0.506	0.1549	1

Total Mean GRG (γm) = 0.558

Table 6 shows that depth of cut (d) is the critical turning parameter (Rank 1) that affects multi-objective optimization, followed by cutting speed (V_C, Rank 2) and feed rate (f, Rank 3). Table 6 revealed the best-turning parameters through *optimal GRG concentrations (v3, f1, d1).

3.3 Confirmation Test

Following the optimum parameter combination evaluation, the next step is to predict and check the improvement of quality characteristics using the optimum parametric condition. As per the existing literature [30, 31], run 1 (v1f1d1) was considered as the reference or initial parameter settings among the selected experimental design plan. Also, run 1 consists of the lowest range of all the three input parameters. Hence, run 1 can be considered as the initial parameter setting to evaluate the improvement in the quality characteristics of the turning process. The estimated GRG can be calculated with the help of optimum parameter combination by using Eq. (9).

$$\gamma = \gamma m + \sum_{i=1}^{0} (\gamma i - \gamma m) \tag{9}$$

where γ_m = overall mean GRG, γ_i = average GRG at the best level, and 0 is the number of the main input parameters that affect the quality characteristics. The sample calculation is as follows,

$\gamma = 0.558 + [0.638 - 0.558] + [0.602 - 0.558] + [0.660 - 0.558]$, $\gamma = 0.7848$. The outcomes of the confirmation test are shown in Table 7.

Table 7. Confirmation test

Parameters and their levels	Initial parameter settings [30, 31]	Best (optimal) turning settings	
		Prediction	Experiment
	v1f1d1		v3f1d1
Surface roughness, Ra (μm)	1.024		0.954
Cutting force, F (N)	51.59	v3f1d1	21
Material removal rate, MRR (cm^3/min)	1.25		2.50
Carbon emission, CE (kg-CO_2)	2.43		0.66
Energy consumption, EC (kJ)	5.74		1.56
Cutting power, CP (W)	85.98		70
Overall GRG	0.7212	0.7848	0.8914

Overall, the grey relationship grade has improved = 0.1702

The improvement in overall grey relational grade was obtained through the difference between the GRG values at the optimum experimental settings and the GRG value of initial parameter settings. From Table 6, the optimal input parameter combination found through the mean value of GRG is v3f1d1. The experiment was already conducted for this input parameter (Run 19), and the corresponding output responses were recorded. Hence, in the confirmation test, an experimental run considered was v3f1d1. Run 1 combination consists of the lowest range of input parameters considered in the present study. Hence, the time taken for the initial parameter settings (Run 1, v1f1d1) was 1.11 min. Also, the time taken for the optimal parameter settings (Run 19, v3f1d1) was 0.37 min which is three times less than run 1. Since the cutting speed (v3) was kept at the maximum range, the MRR value is almost two times higher than the initial run. The cutting tool and workpiece contact time is less in (Run 19, v3f1d1) due to higher cutting speed and less machining time than (Run 1, v1f1d1). Higher cutting speed will result in a good surface finish. Less contact time between the tool and workpiece will result in less cutting force. Here, the cutting force is directly related to energy consumption and cutting power. Carbon emission is directly related to energy consumption. So, the other responses, such as surface roughness, cutting force, carbon emission, and cutting power recorded, were lesser at the optimal parameter settings.

3.4 Error Analysis

The difference between the predicted and experimental values of GRG at the optimum parameter was 0.1066. The error percentage is 11.95, which is very small for the response GRG representing the multiobjective function in the present study. The results of a similar trend were observed in the existing literature [32].

3.5 GRG at Different Machining Parameters and Optimal Conditions

The GRG value at different turning parameters and the optimum parameter conditions are given below. Figures 3, 4, 5, and 6 show GRG's contour and surface plots at various turning parameters. A higher GRG value is required in the grey relational analysis. From Figure 3 to 6, we can understand the variation of GRG value for different tuning parameters. The combination of lower cutting speed, feed rate, and depth of cut resulted in a GRG value around 0.7, and the same trend was observed for cutting speed in the medium range along with feed rate up to 0.08 mm/rev and depth of cut 0.25 mm. The lowest value of GRG occurred in the cutting speed ranging from 100 m/min to 175 m/min and a depth of cut of 0.5mm along with a feed rate of 0.05 mm/rev. As demonstrated in the graphs, the value of GRG is highest at the maximum cutting speed, low feed rate, and low level of depth of cut. The highest GRG value at the optimum cutting condition was 0.8914.

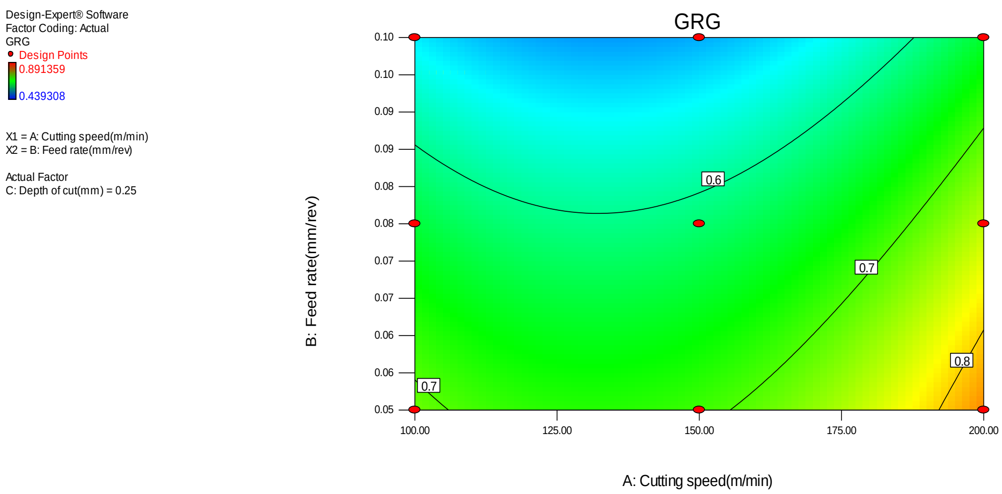

Figure 3. Contour graph of GRG vs cutting speed and feed rate

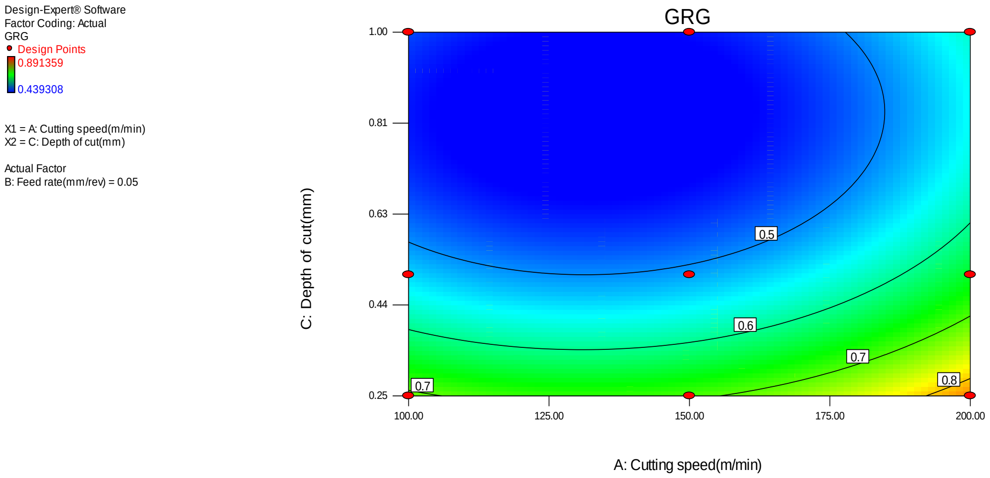

Figure 4. Contour graph of GRG vs cutting speed and depth of cut

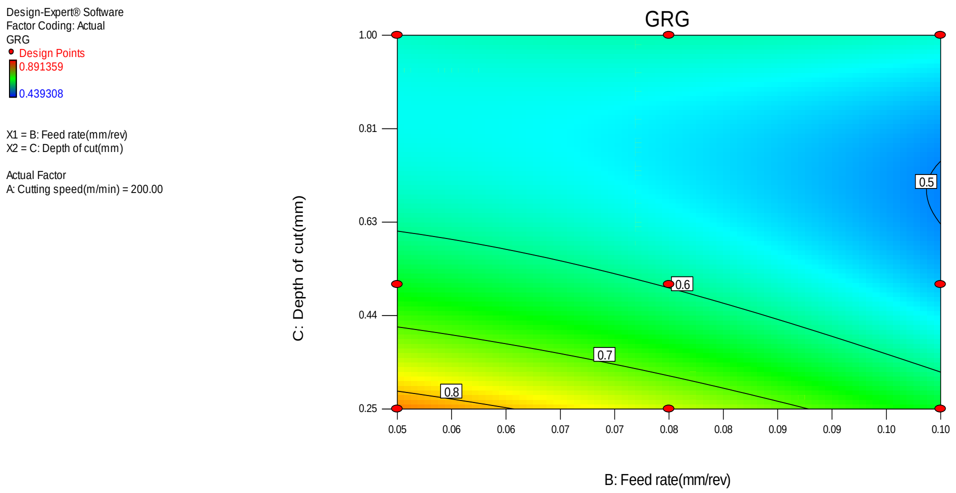

Figure 5. Contour graph of GRG vs feed rate and depth of cut

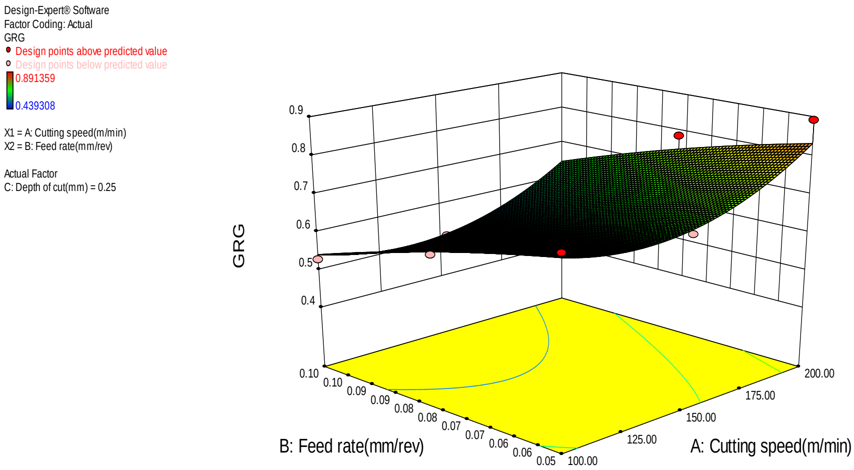

Figure 6. Response surface graph of GRG vs cutting speed and feed rate

The predicted versus the actual value of GRG is shown in Figures 7 and 8. From Figure 7, the curve nearly follows a straight line, indicating that the inaccuracy detected can be neglected. Also, from Figure 8, it is understood from the radar graph that good agreement is developed among the values of predicted and experimental results of GRG. This small error implies that the predicted and actual values are not significantly different; therefore, the generated regression model given in Equation 10 is acceptable.

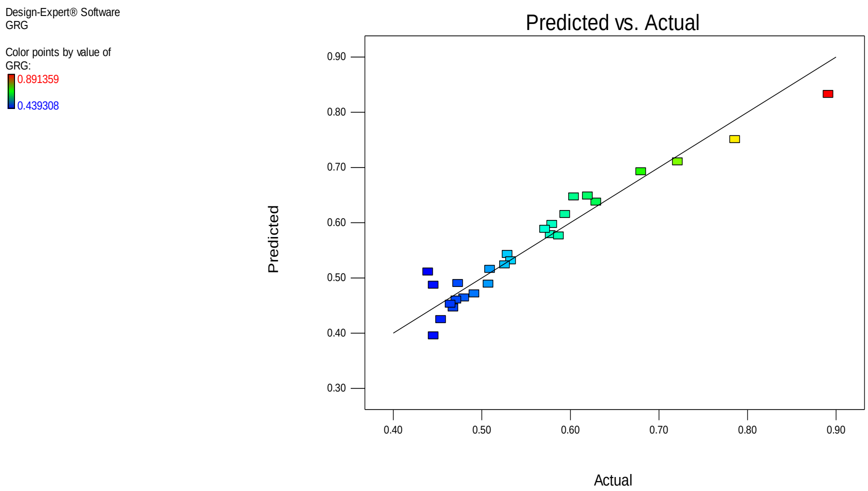

Figure 7. Predicted versus actual value of GRG

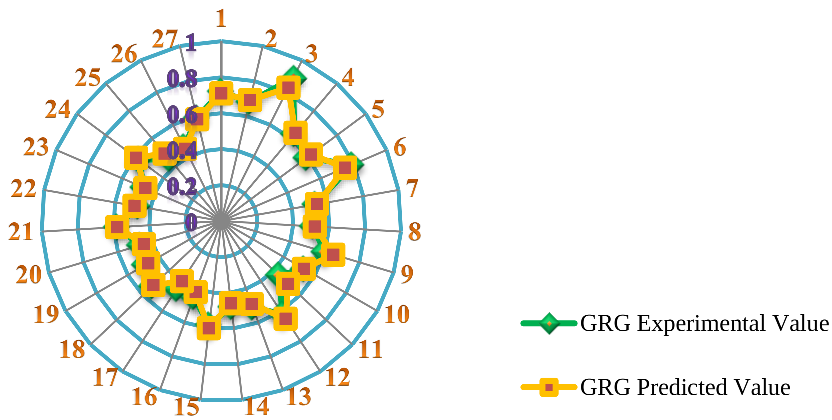

Figure 8. Radar graph of predicted versus experimental value of GRG

3.6 Regression Modelling of GRG

Response surface methodology's second-order polynomial model is quite versatile and can produce a well-fitting regression model for a turning process [7]. A mathematical model is established using the quadratic equation to correlate the independent input parameters with the dependent output responses. The efficiency of the established mathematical model is justified through adjusted R-squared, R-squared, and predicted R-squared and good precision values [33]. The confidence level fixed to investigate the predicted model is a 95% level of significance [34]. Regarding actual parameters, the equation [35] for GRG based on response surface methodology is given as Eq. (10).

$$\begin{aligned}\mathrm{GRG} = \; & 1.61728 - 0.00803172\, V_C - 1.58965\,\mathrm{f} - 1.53793\,\mathrm{d} - 0.00362136\, V_C \times \mathrm{f} - 0.000199701\, V_C \times \mathrm{d} \\ & + 4.89051\,\mathrm{f} \times \mathrm{d} + 0.0000316168\,\mathrm{Vc}^2 - 17.49027\,\mathrm{f}^2 + 0.79567\,\mathrm{d}^2\end{aligned} \tag{10}$$

The above-established model is only relevant for the circumstances used in this study, explicitly, for turning parameters given in Eqs. 11, 12, 13, cutting, workpiece, and machine tool.

$$100\ \mathrm{m/min} \le V_C \le 200\ \mathrm{m/min} \tag{11}$$

$$0.050\ \mathrm{mm/rev} \le \mathrm{f} \le 0.100\ \mathrm{mm/rev} \tag{12}$$

$$0.25\ \mathrm{mm} \le \mathrm{d} \le 1.00\ \mathrm{mm} \tag{13}$$

Summary: Adj R-Squared=89.74%; Pred R-Squared=81.92%; Adeq Precision=20.272. R-Squared = 93.29%; The "Pred R-Squared" of 0.8192 reasonably agrees with the "Adj R-Squared" of 0.8974. The Adequate Precision value considers the signal-to-noise ratio. It is desirable to have a ratio of more than four. The signal-to-noise ratio of 20.272 indicates a good signal. This model can assist practitioners in fixing the experiments.

3.7 Analysis of Variance

The correctness of the established regression equation and the impact of the turning parameters were determined using ANOVA. Table 8 demonstrates that depth of cut is the critical and most dominating parameter, contributing 34.38 %, followed by cutting speed, 15.31 %, and feed rate, 10%. Also, from the ANOVA results, it was understood that all three input parameters significantly influenced the turning process. The square terms of cutting speed and depth of cut were found to be significant, with percentage contributions of 11.56 % and 17.81 %, respectively. Furthermore, with a percentage contribution of 8.13 %, the interaction of feed rate and depth of cut has a notable influence on the turning process. Based on the above findings, all three input parameters are equally significant and should be considered necessary during the turning process to comprehend the turning characteristics and sustainability indicators fully.

Table 8. ANOVA for GRG

Source	Sum of Squares	df	Mean Square	F-Value	p-value Prob > F	% Contribution
Model	0.300	9	0.033	26.27	< 0.0001	significant
A-Cutting speed (m/min)	0.049	1	0.049	39.30	< 0.0001	15.31
B-Feed rate (mm/rev)	0.032	1	0.032	25.41	0.0001	10.00
C-Depth of cut (mm)	0.110	1	0.110	85.90	< 0.0001	34.38
AB	2.46E-04	1	2.46E-04	0.20	0.6638	0.08
AC	1.75E-04	1	1.75E-04	0.14	0.7141	0.05
BC	0.026	1	0.026	20.81	0.0003	8.13
A^2	0.037	1	0.037	29.83	< 0.0001	11.56
B^2	7.17E-04	1	7.17E-04	0.57	0.4604	0.22
C^2	0.057	1	0.057	45.54	< 0.0001	17.81
Residual	0.021	17	1.26E-03			6.56
Cor Total	0.320	26				100.00

3.8 Optimum Machining Condition

The performance improvement in percentage was estimated by comparing the reference values and the corresponding optimal values, as seen in Table 9.

Table 9. Optimum parameters and their response values

Responses at optimum conditions	Response Values			Optimum parameters of turning process		
	Reference (Initial factor settings)	Optimum values	Performance Improvement	Cutting Speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)
Surface roughness (μm)	1.024	0.954	6.83%	200	0.050	0.25
Cutting force (N)	51.590	21.00	59.29%			
Material removal rate (cm^3/min)	1.250	2.50	100%			
Carbon Emission (kg-CO_2)	2.430	0.66	72.84%			
Energy consumption (kJ)	5.740	1.56	72.82%			
Cutting power (W)	85.980	70.00	18.58%			

The sustainability of a turning process can be quantified in terms of three sustainability pillars. They are environmental, economic, and social aspects of sustainability. Reduction in carbon emission and energy consumption leads to a positive environmental impact. Improvement in surface finish and material removal rate leads to quality products and reduced rework, thereby improving economic efficiency. Reducing machining costs and improving operators' health has a positive social impact.

4.0 CONCLUSIONS

In the present work, an attempt was carried out to understand the turning of Al 6063 alloy with sustainability aspects of machining under dry conditions. The machining characteristics analyzed were MRR, surface roughness, and cutting force. The sustainability indicators evaluated were carbon emission, energy consumption, and cutting power. The conclusions obtained from the findings of the above study are listed below.

a) GRA efficiently predicted the optimum level of parameter combinations for getting the desired output per the objective function. The parameter combinations are: v3 = 200 m/min, f1 = 0.05 mm/rev, d1 = 0.25 mm.
b) Considering the initial parameter sets and best-turning parameters, optimized values resulted in a 72.84 % reduction in carbon emission, a 72.82 % reduction in energy consumption, an 18.58 % reduction in cutting power, and a 6.83 % reduction in the surface roughness, was determined through grey relational analysis.
c) From the response Table 6 of mean GRG, ranking for the selected independent cutting parameter was identified. The most significant turning parameter influencing multi-objective function was found to be the depth of cut (Rank 1), followed by cutting speed (Rank 2) and feed rate (Rank 3).
d) Through ANOVA results, it can be identified that the depth of cut is the most dominant factor (34.38 % contribution), trailed by cutting speed (15.31 % contribution) and feed rate (10 % contribution). So, it is evident that all three input parameters significantly affect the sustainable turning process.
e) The established regression model has significantly predicted the output response values where R-squared values drawn are near unity.

Overall, it was identified that the machining performance of Al 6063 alloy is favorable under a dry-cutting environment, which is a sustainable way of machining. In addition, the study can be further extended to use sustainable machining environments such as MQL and NMQL to contribute more towards sustainability.

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