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GRA and CoCoSo Based Analysis for Optimal Performance Decisions in Sustainable Grinding Operation

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Abstract
Currently, researchers are continually thinking of intelligent and sustainable manufacturing methods. Surface grinding is the finishing machining process performed for dimensional accuracy and surface smoothness. The heat caused during grinding hinders these responses, leading to poor quality and rejection of the workpiece, which has been produced to its entire value. So, optimizing the surface grinding input parameters controlling the output responses is crucial. This is generally achieved using Taguchi and other optimization methods. In the case of multiple responses, equal weightage is considered for all the responses to get an optimized input parameter setting. This gives less flexibility for the decision-maker to choose the grinding parameters following his priorities for the responses. The issue is addressed with two effective Multi-Attribute Decision-Making (MADM) methods, namely Grey Relational Analysis (GRA) and Combined Compromise Solution (CoCoSo). This paper focuses on applying the above MADM methods for ranking the grinding input parameters settings obtained from the Taguchi analysis of the selected case study, surface grinding of EN8 steel plates using a Cashew Nut Shell Liquid (CNSL), a green Cutting Fluid (CF). Two sets of weights are considered for the dual responses of the selected study to obtain the ranking of the grinding parameters to aid the decision-maker in making flexible decisions. The ranking correlation studies showing high correlation and statistical significance are also presented. Both the GRA and CoCoSo approaches are efficient, relatively simple to comprehend, and provide a flexible strategy for the decision-maker to make intelligent decisions, avoiding trial and error.

Keywords- Sustainable grinding, Green cutting fluid, Cashew nut shell liquid/oil (CNSL), Multi-attribute decision making (MADM), Grey relational analysis (GRA), Combined compromise solution (CoCoSo).

Abbreviations

AHP	Analytical Hierarchy Process
CF	Cutting Fluid
CNSL	Cashew Nut Shell Liquid/Oil
CoCoSo	Combined Compromise Solution method
COPRAS	COmplex PRoportional ASsessment
DEA	Data Envelopment Analysis
DOC	Depth of Cut
DOE	Design of Experiments
GRA	Grey Relational Analysis
GRC	Grey Relational Coefficient
GRG	Grey Relational Grade
GWG	Grinding Wheel Grade
GWS	Grinding Wheel Speed
MADM	Multi-Attribute Decision-Making Methods
MRR	Material Removal Rate
Ra	Surface Roughness
SAW	Simple Additive Weighing
Temp	Grinding Temperature

TODIM	TOmada de Decisao Interativa Multicriterio
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UNGA	United Nations General Assembly
VIKOR	VIšekriterijumsko KOmpromisno Rangiranje
WS	Work Speed

1. Introduction

United Nations General Assembly (UNGA), in a resolution 2030 Agenda (September 2015), formulated and adopted seventeen Sustainable Development Goals, also known as Global Goals, which are roadmaps for the well-being of people and the planet. Goal number twelve is to ensure responsible or sustainable consumption and production. Sustainable production deals with safeguarding the environment with efficient use of resources and the least impact due to the manufacturing processes (Cf, 2015; Jamwal et al., 2022).

Currently, engineers and researchers continually think of intelligent, sustainable, and eco-friendly production and machining methods (Ajay et al., 2023b; John et al., 2021). The researchers found that smart manufacturing and Industry 4.0 have eight dimensions, including technology, human resources, processes, goods, and services, where processes play an essential role (Kumar et al., 2023). The machining process is a very important and integral part of production, to manufacture most of the varied products such as tools, components, equipment, etc., having high precision and surface quality (Goindi and Sarkar, 2017). Surface grinding is a crucial finishing process of machining performed to achieve dimensional and geometric accuracy and create a high-quality surface finish for a workpiece (Garcia et al., 2020). The increased temperatures involved in grinding cause deterioration of dimensional accuracy, surface integrity, and surface texture of the workpiece, including a reduction in tool life due to wear. The tool and the job experience thermal deformation due to the intricate thermal stresses also brought on by these higher temperatures (Ravi et al., 2021; Weiss et al., 2015). This extreme heat generated during the process significantly hinders the workpiece's quality (Sinha et al., 2023). This is highly disadvantageous because the workpiece has already been produced to its entire value, and scrapping it costs money (de Martini Fernandes et al., 2019). Also, Surface Roughness (*Ra*) is a crucial quality characteristic that directly impacts the tribological performance, wear resistance, and useful life of many parts and components (Ghosh et al., 2019).

The use of Cutting Fluid (CF) is one of the solutions for keeping the above-mentioned problems associated with grinding in control (Gajrani and Sankar, 2020; Gugulothu and Pasam, 2019; Irani et al., 2005; Pervaiz et al., 2018). Mineral oil with petroleum as a base and synthetic oils are two primary categories of CFs that are used most frequently in the market (Sankaranarayanan et al., 2021). These traditionally used CFs made from petroleum and chemicals pose a serious menace to the ecosystem and are also dangerous to the health of humans (Hassan et al., 2023). Also, tough regulations have been laid down by regulatory agencies regarding the use of traditionally used harmful CFs (Lee et al., 2017). These issues compelled researchers to focus on CFs as a significant area of their concern and to investigate and find better eco-friendly substitutes to replace the harmful, toxic CFs that are being used presently for machining (Katna et al., 2020). Numerous studies demonstrate that vegetable oil-based (natural oil) CFs can replace conventional petroleum-based CFs with all necessary competing qualities. They are highly biodegradable, low, or nontoxic, leading to more environmentally friendly and sustainable manufacturing processes. They thus rank as one of the most popular options (Debnath et al., 2014).

The surface grinding input variables, Grinding Wheel Grade (GWG), CF, Grinding Wheel Speed (GWS), Work Speed (WS), and Depth of Cut (DOC), significantly impact the other responses along with the Grinding Temperature (*Temp*), such as *Ra*, Material Removal Rate (MRR), and tool wear, etc. Therefore, to obtain the intended workpiece quality, the input parameters must be set correctly (Ajay and Mittal, 2020; Usgaonkar and Prabhu Gaonkar, 2023b; Kumar et al., 2018; Kumar and Gulati, 2019). Usually, this is performed by applying the Taguchi technique, Design of Experiments (DOE), and other optimization techniques like Response Surface Methodology (RSM), evolutionary algorithms like genetic algorithms, particle swarm optimization, etc., and Artificial Neural Networks (ANN), among others (Chandrasekaran et al., 2010; Kumar et al., 2020). The most common method for optimizing the experimental input parameters is the DOE with the Taguchi technique (Bose and Pain, 2018; Dowey and Matthews, 1998). In the case of multiple responses, equal weightage is considered for all the responses to get an optimized input parameter setting (Das et al., 2022). This gives less flexibility for the decision-maker to choose the grinding parameters following his priorities for the responses and sometimes forces him to adopt a trial-and-error strategy. The use of Multi-Attribute Decision-Making (MADM) methods can be thought of to find the solution to the above problem (Chaube et al., 2024). In this study, this problem is very well tackled by using two effective Multi-Attribute Decision Making (MADM) methods, Grey Relational Analysis (GRA) and Combined Compromise Solution (CoCoSo) in this current study.

The GRA was developed from the grey systems theory proposed by Professor Julong Deng (Sifeng and Yingjie, 2015), which emphasizes analyzing issues with small samples and insufficient data. It handles uncertain systems with partially known information. The incomplete and undetermined is termed “Grey.” Grey relations are those that involve incomplete information. So, GRA deals with systems with uncertainty and incompletely known information to generate, excavate, and extract data from partially available information. The GRA is one of the potent tools for analyzing processes with multiple responses. The complicated multiple response optimization problem in GRA is brought down to optimizing a single response Grey Relational Grade (GRG), based on this ranking and optimum parameter setting levels are identified (Jozić et al., 2015). CoCoSo is a novel method that combines simple additive weight and the exponential weight product model of MADM. The approach offers potential compromise options for the decision-maker to consider. It ranks the alternatives on relative performance scores (Yazdani et al., 2019). Both the methods, GRA and CoCoSo, are adopted to rank and determine the best grinding input parameter combination that would give the optimal performance of the responses. Two sets of weightings have been considered for ranking the output responses in both these methods. Correlation and statistical significance studies are also presented.

The paper is set up as follows: The literature study with a literature summary table is presented in Section 2. A short explanation regarding the implementation of both the ranking methods, GRA and CoCoSo, is given in Section 3. Section 4 highlights the case study selected for the analysis. The application of both methods to the selected experimental study with detailed analysis and results and their comparison have been discussed in Section 5, along with the results of the correlation and statistical significance studies. Section 6 concludes the study, followed by the list of references at the end.

2. Literature Review

In their experimental investigation of surface grinding EN8 steel considering Cashew Nut Shell Liquid (CNSL) as a green CF, Usgaonkar and Prabhu Gaonkar (Usgaonkar and Prabhu Gaonkar, 2023a) took into consideration the CF used, rotational speed, and grade of the grinding wheel, as well as DOC and table speed, as significant grinding parameters that can influence the output variable, surface finish. They used the DOE and half-fraction factorial methods for analysis. Jozić et al. (2015) applied Taguchi's DOE approach with GRA to optimize multiple objectives of input constraints and machining conditions for end milling operations. Cooke et al. (2007) optimized the input variables of the electric wire arc spray method to coat the sugarcane mill rollers with ferrous-based material to improve their wear properties. Segu et al. (2013) used Laser surface texturing in combination with solid lubrication to improve tribological properties. The tribological tests were performed on a pin-on-disc tribometer, and the analysis was done using the Taguchi method. Rathod et al. (2023) optimized the input variables to turn AISI 304 stainless steel, applying Taguchi, GRA, and Principal Component Analysis techniques to extend tool life, reduce machining times, and enhance surface finish. Das et al. (2022) applied the GRA technique along with the Taguchi method to obtain the optimum face milling parameters for the Ti6Al4V metal matrix composite. Rajan et al. (2021) used the GRA approach to analyze surface texture, flank wear, and machining power to determine the ideal input parameters for turning Ti-6Al-4V ELI alloy. Chakraborty et al. (2022) conducted a study of the wire electrical discharge method with powder for machining Ti6Al4V alloy to improve the machining efficiency. Optimal solutions are obtained and compared from different methods, such as the responsive surface method, GRA, and particle swarm optimization. Jeyaraj and Sivasakthivel (2022) optimized the process input parameters using GRA, which were then validated by performing confirmation experiments in the experimental study to electrodeposit nickel and chromium composite using a nickel plating bath.

Yazdani et al. (2019) were the first to introduce this CoCoSo algorithm. The steps of the algorithm are discussed in detail, along with the advantages and its comparison with the other established methods of MADM. A real-life case study has been taken up and compared with other methods by performing sensitivity analysis to validate the proposed algorithm of CoCoSo. They claim that the results are very close to the other existing methods. The newly proposed CoCoSo method is advantageous in accurate decision decision-making and can help the industry achieve its goals. Kharwar et al. (2022) applied the CoCoSo method for multi-response optimization of competing outcomes: surface texture, torque, and thrust force to drill epoxy composites with multiwall carbon nanotube reinforcement. This CoCoSo method was one of the other methods used by Nguyen et al. (2023) who conducted an experimental study of friction stir welding of distinct aluminium alloys to optimize control variables like the tool spin rate, travel velocity, plunging depth, and tilting angle to reduce the energy consumed in welding time and increase the ultimate tensile strength and percent elongation. They have used an adaptive neuro-based fuzzy inference system approach for optimization, GRA for deciding weights for responses, and CoCoSo for deciding the best alternative solution. The experimental outcomes of tool steel 90CrSi cylindrical workpieces milled using powder-mixed electrical discharge machining were used by Bui et al. (2023) to apply the CoCoSo approach in addition to other MCDM approaches. The output response focused is MRR and Ra. They inferred that the CoCoSo method results are equally efficient compared to other methods applied. Kumar and Verma (2021) optimized output machining variables of surface finish in terms of Ra and Rz values and circularity error using the CoCoSo method and found it to have potential.

The literature summary is as shown in **Table 1**.

Table 1. Summary of the literature studies.

Sr. No.	Authors	Machining operation	Eco-friendly CF	Optimization method	Ranking & ranking method	Varying the weights of responses
1.	Kumar and Gulati (2019)	Single Point Incremental sheet metal Forming	Yes	Taguchi, DOE, ANOVA	No	No
2.	Usgaonkar and Prabhu Gaonkar (2023b)	Surface Grinding	Yes	Taguchi, Regression Analysis	No	No
3.	Cooke et al. (2007)	Electric wire arc spray process	No	Taguchi	No	No
4.	Segu et al. (2013)	Laser surface texturing, Tribological experiments on pin-on-disc tribometer	No	Taguchi	No	No
5.	Das et al. (2022)	Turning	YES	Taguchi, ANOVA	NO	NO
6.	Sifeng and Yingjie (2015)	No	No	GRA	Yes, GRA	Yes
7.	Jozić et al. (2015)	End Milling Operation	Yes	Taguchi, GRA	Yes, GRA	No
8.	Yazdani et al. (2019)	No	No	CoCoSo	Yes, CoCoSo	No
9.	Rathod et al. (2023)	Turning	NO	Taguchi, ANOVA, GRA, Principle Comp. Analysis	Yes, GRA	NO
10.	Rajan et al. (2021)	Turning	YES	Taguchi, GRA	Yes, GRA	NO
11.	Chakraborty et al. (2022)	Powder mixed Wire Electrical Discharge Machining	NO	Response Surface Methodology, GRA, Particle Swarm Optimization	Yes, GRA	NO
12.	Jeyaraj and Sivasakthivel (2022)	Electrodeposition technique	NO	Taguchi, GRA	Yes, GRA	NO
13.	Kharwar et al. (2022)	Drilling	NO	Response Surface Methodology, Principal Components Analysis, CoCoSo	Yes, CoCoSo	NO
14.	Nguyen et al. (2023)	Friction Stir Welding	YES	Adaptive Neuro-based Fuzzy Inference System Approach, GRA, CoCoSo	Yes, GRA, CoCoSo	NO
15.	Bui et al. (2023)	Powder-Mixed Electrical Discharge Machining	NO	Taguchi, CoCoSo, MARCOS, SPOTIS	Yes, CoCoSo, MARCOS, SPOTIS	NO
16.	Kumar and Verma (2021)	Drilling	NO	Response Surface Methodology, ANOVA, Principal Component Analysis, CoCoSo	Yes, CoCoSo	no
17.	Do and Nguyen (2022)	Turning	NO	Taguchi, CoCoSo, MABAC, MAIRCA, EARM, TOPSIS	Yes, CoCoSo, MABAC, MAIRCA, EARM, TOPSIS	YES
18.	Present Paper	Surface Grinding	YES	Taguchi, GRA, CoCoSo	Yes, GRA, CoCoSo	YES

The following points and gaps are observed from the literature reviewed:

- The traditionally used hazardous petroleum and chemical-based CFs are required to be replaced urgently as they pose a threat to humans as well as the environment.
- Using environment-friendly non-edible bio-CFs is one of the alternatives.
- The selection of the right machining or grinding parameters setting with the right CF will lead to better quality of the workpiece with lesser costs.
- In addition to the CF selection, other input parameters such as GWG, GWS, WS, and DOC, also affect the surface grinding output responses such as *Ra*, *Temp*, etc. It is therefore essential that these input parameters are configured correctly to achieve the desired workpiece quality.
- The Taguchi method is the most commonly used method to optimize the machining or grinding input parameters to get optimized responses.
- In the case of multiple responses, the Taguchi method and the other optimization methods consider equal weightage to the responses and provide a single input machining or grinding parameter setting for

response optimization (Das et al., 2022). These methods do not provide alternative solutions considering differential weightages to the multiple responses as per the need and priorities of the design.

- The MADM methods like GRA and CoCoSo are capable of optimizing and ranking the input machining and grinding parameter settings obtained from Taguchi DOE considering differential weightages to the multiple responses. There are numerous MADM methods proposed such as R- method, BHARAT, Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Simple Additive Weighing (SAW), TOmada de Decisao Interativa Multicriterio (TODIM), Data Envelopment Analysis (DEA), COmplex PRoportional ASsessment (COPRAS), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR) etc. including GRA and CoCoSo (Rao, 2024).
- GRA is an established method and many researchers have used this method for optimizing machining parameters as reported in the literature. The method CoCoSo is also reported as a stable method when compared to the other methods and has been applied to the machining process (Do and Nguyen, 2022). It was thought to try these two methods for the present study and compare the results with the Taguchi analysis of the selected study.
- Using Taguchi DOEs in combination with MADM methods such as GRA, CoCoSo, etc. will provide a flexible strategy to the decision maker in deciding the input machining or grinding parameter settings for multi-response optimization with differential weightages to the responses. This will save the time, money, and energy of the decision maker avoiding trial and error methods.
- The above was the motivation for the current study. The experimental case study selected for the present work is surface grinding of EN8 steel using CNSL and traditional synthetic CF (Usgaonkar and Prabhu Gaonkar, 2023b). The use of CNSL, which is environment-friendly, and bio-degradable obtained from waste cashew nut shells will enhance sustainability (Ajay et al., 2023a). Nineteen experiments were conducted applying Taguchi's Orthogonal Array along with validation experiments wherein input parameters considered are GWG, CF, GWS, WS, and DOC. Output responses of interest were the *Ra* and the *Temp*. This paper analyses the optimal performance of the grinding operation in terms of identifying optimal settings of the input parameters and ranking them. Two effective MADM methods, GRA and CoCoSo, are applied to the experimental data which provide optimized input grinding parameter settings considering differential weightages to the responses *Ra* and *Temp*.

3. The Research Methodology

3.1 The GRA Method

In a "grey system," just a portion of the data is known while the remaining portion is unknown; because of this ambiguity, it will provide a variety of solutions. The GRA is one of the potent tools for analyzing processes with multiple responses. In GRA, the intricate multiple response optimization challenges are reduced to the optimization of a single response GRG based on which ranking and optimum parameter setting levels are identified (Jozić et al., 2015).

3.1.1 Steps in the GRA Method

The stepwise procedure of the GRA method (Jozić et al., 2015) is as follows

***Step* I: Arrange the data of response variables in tabular form**

Arrange the experimental results regarding input and response variable values in tabular form.

***Step* II: Data preprocessing and normalizing**

Data of response variables is preprocessed to change the original sequence to a sequence that can be compared. The most crucial part of the GRA is a linear normalization of the response variables. Linear normalization is typically required as the response variable range and units differ. According to the type of quality characteristics of the response variable, either larger-the-better or smaller-the-better, the initial sequence is transferred to a sequence that can be compared by normalizing the response variable data between zero and one using the Equation (1) & Equation (2) (Jozić et al., 2015) given below. In this study, for normalizing the values of surface finish and grind temperature, which are required to be smaller-the-better, Equation (1) (Jozić et al., 2015) is used.

$$b_{ij} = \frac{max\,(a_{ij}) - (a_{ij})}{max\,(a_{ij}) - min\,(a_{ij})} \tag{1}$$

For normalizing the response variable performance characteristic larger-the-better Equation (2) can be used.

$$b_{ij} = \frac{(a_{ij}) - min\,(a_{ij})}{max\,(a_{ij}) - min\,(a_{ij})} \tag{2}$$

where, a_{ij} are original data and b_{ij} are normalized data.

***Step* III: Determining the deviation sequence**

From the values obtained using Equation (1), if any setting value is equal to 1 or close to 1, then that setting *i* is taken as the top for the response *j*. The reference sequence a_0 is demarcated as (a_{01}, a_{02}, …, a_{0j}, …, a_{0n}) which is equal to (1, 1, …, 1, …, 1), with a_{0j} being the reference value for the *j*th response and which determines the setting with the comparability sequence nearest to the reference sequence. i.e. $\Delta_{ij} = \left|a_{0j} - a_{ij}\right|$ (Jozić et al., 2015).

***Step* IV: Calculation of grey relational coefficient (GRC) (Jozić et al., 2015)**

The GRC is determined by Equation (3) (Jozić et al., 2015). GRA tells us how close a_{ij} is to a_{0j}. The larger the GRA, the closer the a_{ij} and a_{0j}.

$$\gamma\left(a_{0j}, a_{ij}\right) = \frac{(\Delta_{min} + \xi\Delta_{max})}{(\Delta_{ij} + \xi\Delta_{max})} \tag{3}$$

for i = 1, 2, 3, ………, *m and j* = 1, 2, 3, ………, *n* where, $\gamma\left(a_{0j}, a_{ij}\right)$ is the GRC between a_{ij} and a_{0j},

$\Delta_{ij} = \left|a_{0j} - a_{ij}\right|$ (Jozić et al., 2015)

$\Delta_{min} = min\left\{\Delta_{ij},\ for\ i = 1, 2, 3, \dots\dots\dots, m\ and\ j = 1, 2, 3, \dots\dots\dots, n\right\}$

$\Delta_{max} = max\left\{\Delta_{ij}, for = 1, 2, 3, \dots\dots\dots, m\ and\ j = 1, 2, 3, \dots\dots\dots, n\right\}$

ξ - distinguishing coefficient, $\xi \in (0, 1)$.

***Step* V: Determining the GRG**

The GRA is quantified in terms of GRG. The GRG is a weighted sum of the GRCs, determined using Equation (4) (Jozić et al., 2015).

$$\Gamma(A_0, A_i) = \sum_{j=1}^{n} W_j(a_{0j}, a_{ij}) \tag{4}$$

for i = 1, 2, 3, ………, *m* where, $\sum_{j=1}^{n} W_{ij} = 1$.

$\Gamma(A_0, A_i)$ is the GRG between comparability sequence A_i and reference sequence A_0. The weightage of response variable *j* is W_j and the decision maker can decide it based on his priorities. The GRG shows the similarity between the comparison and reference sequences.

***Step* VI: Ranking the experiments based on the GRG**

The ranks are allocated for experiments in decreasing order of the GRG, the highest GRG experiment taking the rank 1, and so on.

3.2 The CoCoSo Method

CoCoSo is a novel method combining additive weight and the exponential weight product model of MADM. This technique presents potential compromise alternatives that the decision-maker may consider. It ranks the alternatives on relative performance scores (Yazdani et al., 2019).

3.2.1 Steps in the CoCoSo Method

Following are the steps to implement the CoCoSo technique (Yazdani et al., 2019).

***Step* I: Prepare the decision table**

Arrange the experimental results in terms of input and response variable values in a table (**Table 2**) shown below (Yazdani et al., 2019).

Table 2. Decision table (Do and Nguyen, 2022).

		CRITERIA			
SOLUTIONS	Sr. No.	R_1	R_2	R_j	R_n
	T_1	t_{11}	t_{12}	t_{ij}	t_{1n}
	T_2	t_{21}	t_{22}	t_{2j}	t_{2n}
	T_i	t_{i1}	t_{i2}	t_{ij}	t_{in}
	T_m	t_{m1}	t_{m2}	t_{mj}	t_{mn}

m- the number of solutions, n- the number of the criteria, T_i- the solution i, R_j- the criterion j, t_{ij}- the value of criterion j at the solution i. $i = 1; 2; ...; m$ and $j = 1; 2; ...; n$.

***Step* II: Normalize the data**

Normalize the data using Equation (5) (Yazdani et al., 2019) for condition smaller-the-better & Equation (6) (Yazdani et al., 2019) for condition larger the better as given below:

$$n_{ij} = \frac{max\,(t_{ij}) - (t_{ij})}{max\,(t_{ij}) - min\,(t_{ij})} \tag{5}$$

$$n_{ij} = \frac{(t_{ij}) - min\,(t_{ij})}{max\,(t_{ij}) - min\,(t_{ij})} \tag{6}$$

***Step* III: Compute the Si and Pi**

The S_i and P_i are to be calculated using Equation (7) and Equation (8) (Yazdani et al., 2019).

$$S_i = \sum_{j=1}^{n} (w_j n_{ij}) \tag{7}$$

$$P_i = \sum_{j=1}^{n} (n_{ij})^{w_j} \tag{8}$$

where, S_i is the total of the weighted comparability sequence, P_i is the sum of the power weight of comparability sequences, and w_j is the weight of the criterion j. The CoCoSo methodology has the provision for selecting the value for w_j depending upon the priorities and the significance of the response criteria.

***Step* IV: Compute the relative weights for the alternatives**

The CoCoSo methodology uses three appraisal score strategies, K_{ia}, K_{ib}, and K_{ic}, to generate relative weights. K_{ia}, K_{ib}, and K_{ic} are calculated using Equations (9), (10), and (11), respectively (Yazdani et al., 2019), which are given below:

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)} \tag{9}$$

$$K_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{10}$$

$$K_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\lambda \max_i S_i + (1-\lambda)\max_i P_i}\ ; 0 \le \lambda \le 1 \tag{11}$$

The value of λ decides the weightages of S_i, the total of the weighted comparability sequence and the P_i, the sum of the power weight of comparability sequences. It is the measure of distinguishability and $0 \le \lambda \le 1$. Distinguishability increases as λ decreases. The value for λ is usually taken as λ = 0.5, but the method provides the flexibility to the decision maker to keep it in the range of 0 and 1. In this analysis, the λ is taken as 0.5 (Yazdani et al., 2019).

***Step* V: Rank the alternatives**
The alternatives are finally ranked by determining k_i using Equation (12) (Yazdani et al., 2019). The highest value of K_i becomes the best option.

$$K_i = (K_{ia} K_{ib} K_{ic})^{\frac{1}{3}} + \frac{1}{3}(K_{ia} + K_{ib} + K_{ic}) \tag{12}$$

4. The Case Study: Surface Grinding of EN 8 Steel

In an experimental study of surface grinding EN8 steel, Usgaonkar and Prabhu Gaonkar (2023b) compared the performance of environmentally friendly non-edible CNSL and the conventional chemical synthetic CF to optimize the grinding responses, *Ra*, and *Temp* making use of the L_{16} Orthogonal Array and 2^5 Taguchi design. EN 8 steel flat plates measuring 150 mm × 25 mm × 10 mm were the workpiece of the experiment. The grinding operation was performed on the SFW1 HMT LIMITED surface grinder. The run orders were randomly selected for the experimentation with every run being replicated five times and the average value was considered for the analysis. Before grinding, the grinding wheel was dressed regularly from time to time. The workpiece was thoroughly cleaned after grinding using Carbon Tetrachloride. The SurfTest SJ-210 Mitutoyo recorded the *Ra* with a cut-off length of 0.8 mm and a sampling length of 4 mm. For every workpiece and run, five readings for *Ra* were taken along the lay at various places and the average value was used for the analysis as entered in **Table 3**. FLUKE Ti10 Thermal Imager was used to record the *Temp*. Each run recorded five temperature readings, with the average value being considered for analysis, as entered in **Table 3**. The input parameters with two levels focused were the CF type (Synthetic, CNSL), GWG (A46K5V10- G46, A60K5V10- G60), GWS (1500 RPM, 3000 RPM), DOC (10 µm, 20 µm) and WS (10 m/ min, 15 m/ min). Minitab software was used to conduct the investigation. The optimization results were also confirmed by conducting validation experiments. The authors inferred that the CNSL performed well in comparison to the synthetic CF, and it is obtained from waste cashew nut shells and can be thought of as a potential eco-friendly bio-CF, to substitute the harmful traditionally used CFs. This was a motivation to select this case study to improve further. So, the data from all the performed experiments were chosen for the current investigation, as shown in **Table 3**. Some optimized results of Taguchi analysis were falling outside the L_{16} Orthogonal Array of 2^5 Taguchi design, they have been validated by conducting validation and confirmation experiments separately. The DOE data are from Sr. No. 1 to 16, and the validation experiment data are from Sr. No. 17 to 19 as entered in **Table 3** (Usgaonkar and Prabhu Gaonkar, 2023b). Arranging the data in a tabular form called a decision table (**Table 3**), is the first step (Step I) of both the methods, GRA & CoCoSo.

Step I: Arrange the data in tabular form/ Prepare the decision table

The Step I for the GRA method (Section 3.1.1, Step I) and the CoCoSo method (Section 3.2.1, Step I) is the same. Accordingly, the experimental results regarding input and response variable values are arranged in tabular form to prepare the decision table as shown in **Table 3**.

Table 3. Decision table (experimental results of surface grinding EN8 steel) (Usgaonkar and Prabhu Gaonkar, 2023b).

Sr. No.	Grinding input parameters (Alternate optimal solutions)					Objectives (responses)	
	CF	GWS (RPM)	GWG	DOC (μm)	WS (m/min)	*Ra* (μm)	*Temperature* (^{O}C)
1.	Synthetic	1500	G46	10	10	0.126	38.7
2.	Synthetic	1500	G46	20	15	0.110	39
3.	Synthetic	1500	G60	10	15	0.185	35.8
4.	Synthetic	1500	G60	20	10	0.141	37.5
5.	Synthetic	3000	G46	10	15	0.097	37
6.	Synthetic	3000	G46	20	10	0.121	38.5
7.	Synthetic	3000	G60	10	10	0.137	35.2
8.	Synthetic	3000	G60	20	15	0.102	39
9.	CNSL	1500	G46	10	15	0.202	**34**
10.	CNSL	1500	G46	20	10	0.199	36
11.	CNSL	1500	G60	10	10	0.114	**34**
12.	CNSL	1500	G60	20	15	0.095	36.5
13.	CNSL	3000	G46	10	10	0.090	36
14.	CNSL	3000	G46	20	15	0.093	38.5
15.	CNSL	3000	G60	10	15	0.083	35
16.	CNSL	3000	G60	20	10	0.116	37.5
17.	CNSL	3000	G60	20	15	**0.055**	38.8
18.	Synthetic	1500	G60	10	10	0.147	35.9
19.	**CNSL**	**3000**	**G60**	**10**	**10**	**0.073**	**34.5**

5. Analysis and Discussion

5.1 Using GRA

Step II: Data preprocessing and normalizing (refer to Table 4)

Data preprocessing brings the responses with different units to one comparable unit. The response data normalization is performed and brought between zero and one. The normalized original data of responses *Ra* and *Temperature*, with the smaller-the-better condition, is as entered in **Table 4**, using Equation (1) (Section 3.1.1, Step II), as the responses *Ra* and *Temperature* are required to be minimized (Usgaonkar and Prabhu Gaonkar, 2023b; Jozić et al., 2015). Here, the maximum value of a_{ij} for *Ra* is 0.202 μm, with a minimum value of 0.055 μm. Similarly, the maximum value for a_{ij} of *Temperature* is 39^{0}C, and the minimum is 34^{0}C (refer to **Table 3**).

Step III: Determining the deviation sequence

Table 5 shows the deviation sequence determined as per Section 3.1.1, Step III.

Step IV: Calculation of GRC

The GRC is determined using Equation (3) (Section 3.1.1, Step IV) as entered in **Table 6**. The distinguishing coefficient ξ is the measure of distinguishability and $\xi \in (0, 1)$. Distinguishability increases as distinguishing coefficient ξ decreases. The distinguishing coefficient ξ is taken as 0.5 in this analysis (Jozić et al., 2015).

Step V: Determining the GRG & _Step_ VI: Ranking the experiments based on the GRG

The GRG is determined using Equation (4) (Section 3.1.1, Step V), and the grades are ranked with the highest grade, taking the rank 1 and so on (**Table 7**). **Table 7** shows the ranking for two combinations of weights. i.e. 1). When *Ra* and *Temp* have been allotted the equal weightage as 0.5.2). When the weightage for *Ra* is taken as 0.6 and *Temp* as 0.4.

Table 4. Normalized data.

Sr. No.	Data		Normalization	
	Ra **(µm)**	***Temp*** **(°C)**	***Ra*** **(µm)**	***Temp*** **(°C)**
1.	0.126	38.8	0.5145	0.0500
2.	0.110	**39.0**	0.6236	**0.0000**
3.	0.186	35.9	0.1089	0.6250
4.	0.142	37.5	0.4102	0.3000
5.	0.098	37.0	0.7102	0.4000
6.	0.122	38.5	0.5462	0.1000
7.	0.138	35.3	0.4375	0.7500
8.	0.102	**39.0**	0.6773	**0.0000**
9.	**0.202**	**34.0**	**0.0000**	**1.0000**
10.	0.199	36.0	0.0162	0.6000
11.	0.114	**34.0**	0.5966	**1.0000**
12.	0.096	36.5	0.7224	0.5000
13.	0.091	36.0	0.7555	0.6000
14.	0.093	38.5	0.7409	0.1000
15.	0.083	35.0	0.8068	0.8000
16.	0.117	37.5	0.5782	0.3000
17.	**0.055**	38.8	**1.0000**	0.0400
18.	0.147	35.9	0.3727	0.6200
19.	0.073	34.5	0.8773	0.9000

Table 5. Deviation sequence.

Sr. No.	***Ra*** **µm**	***Temp*** **°C**
1.	0.4855	0.9500
2.	0.3764	**1.0000**
3.	0.8911	0.3750
4.	0.5898	0.7000
5.	0.2898	0.6000
6.	0.4538	0.9000
7.	0.5625	0.2500
8.	0.3227	**1.0000**
9.	**1.0000**	**0.0000**
10.	0.9838	0.4000
11.	0.4034	**0.0000**
12.	0.2776	0.5000
13.	0.2445	0.4000
14.	0.2591	0.9000
15.	0.1932	0.2000
16.	0.4218	0.7000
17.	**0.0000**	0.9600
18.	0.6273	0.3800
19.	0.1227	0.1000

Table 6. The GRC.

Sr. No.	GRC	
	***Ra* µm**	***Temp* °C**
1.	0.5074	0.3448
2.	0.5705	0.3333
3.	0.3594	0.5714
4.	0.4588	0.4167
5.	0.6331	0.4545
6.	0.5242	0.3571
7.	0.4706	0.6667
8.	0.6077	0.3333
9.	0.3333	1.0000
10.	0.3370	0.5556
11.	0.5535	1.0000
12.	0.6430	0.5000
13.	0.6716	0.5556
14.	0.6587	0.3571
15.	0.7213	0.7143
16.	0.5424	0.4167
17.	1.0000	0.3425
18.	0.4435	0.5682
19.	0.8029	0.8333

Table 7. The GRG and Ranks allotted with different weights.

Sr. No.	W_j= (0.5, 0.5)		W_j= (0.6, 0.4)	
	Grade	**Rank**	**Grade**	**Rank**
1.	0.4261	19	0.4424	17
2.	0.4519	15	0.4757	14
3.	0.4654	14	0.4442	16
4.	0.4377	18	0.4420	18
5.	0.5438	9	0.5617	8
6.	0.4407	17	0.4574	15
7.	0.5686	8	0.5490	9
8.	0.4705	13	0.4980	11
9.	0.6667	5	0.6000	6
10.	0.4463	16	0.4244	19
11.	0.7767	2	0.7321	3
12.	0.5715	7	0.5858	7
13.	0.6136	6	0.6252	5
14.	0.5079	10	0.5381	10
15.	0.7178	3	0.7185	4
16.	0.4796	12	0.4921	13
17.	0.6712	4	0.7370	2
18.	0.5059	11	0.4934	12
19.	0.8181	1	0.8151	1

5.2 Using CoCoSo

Step II: Normalize the data

The original data is normalized using Equation (5) (Section 3.2.1, Step II), which is for cost criteria, the smaller-the-better, as the responses are *Ra* and *Temp*, both of which are required to be minimized. Since the formula of normalization for both the methods GRA and CoCoSo is the same (refer to Equation (1), Section 3.1.1, Step II & Equation (5), Section 3.2.1, Step II), **Table 4** may be referred for normalized data (Jozić et al., 2015; Yazdani et al., 2019). The maximum and minimum values of t_{ij} for surface texture *Ra* is 0.202 µm and 0.055 µm respectively. Similarly, the maximum value of t_{ij} for *Temp* is 39 ^{0}C, and the minimum value is 34 ^{0}C (refer to **Table 4**).

Step III: Compute the values of Si & Pi

The *Si* and *Pi* values are calculated using Equation (7) & Equation (8) (Section 3.2.1, Step III) and entered in **Table 8**. The *Ra* and *Temp* have been allotted equal weightage as 0.5 for this case.

Table 8. The *Si and Pi* values

Sr. No.	*Si*	*Pi*
1.	0.2823	0.9409
2.	0.3118	0.7897
3.	0.3669	1.1205
4.	0.3551	1.1882
5.	0.5551	1.4752
6.	0.3231	1.0553
7.	0.5938	1.5275
8.	0.3386	0.8230
9.	0.5000	1.0000
10.	0.3081	0.9020
11.	0.7983	1.7724
12.	0.6112	1.5571
13.	0.6778	1.6438
14.	0.4205	1.1770
15.	0.8034	1.7927
16.	0.4391	1.3081
17.	0.5200	1.2000
18.	0.4964	1.3979
19.	0.8886	1.8853

Step IV: Compute the relative weights of the alternatives & _Step_ V: Rank the alternatives

The relative weights. K_{ia}, K_{ib}, $K_{ic,}$ and the final weight K_i are calculated using Equation (9), Equation (10), Equation (11) & Equation (12) (Section 3.2.1, Step IV), respectively, as entered in **Table 9**. The value for λ is taken as λ = 0.5. The final ranking is done by referring to K_i values with the highest value with rank 1 and so on (Section 3.2.1, Step IV, **Table 9**).

Table 9. The values of $K_{ia,}$ $K_{ib,}$ $K_{ic,}$ K & Ranks.

λ = 0.5			**Weights (0.5, 0.5)**		
Sr. No.	K_{ia}	K_{ib}	K_{ic}	**Sr. No.**	K_{ia}
1.	0.0358	2.1915	0.4410	1	0.0358
2.	0.0323	2.1047	0.3971	2	0.0323
3.	0.0436	2.7188	0.5362	3	0.0436
4.	0.0452	2.7627	0.5564	4	0.0452
5.	0.0595	3.8346	0.7319	5	0.0595
6.	0.0404	2.4810	0.4969	6	0.0404
7.	0.0621	4.0377	0.7647	7	0.0621
8.	0.0340	2.2418	0.4188	8	0.0340
9.	0.0439	3.0376	0.5407	9	0.0439
10.	0.0354	2.2338	0.4362	10	0.0354
11.	0.0753	5.0725	0.9267	11	0.0753
12.	0.0635	4.1370	0.7816	12	0.0635
13.	0.0680	4.4826	0.8369	13	0.0680
14.	0.0468	2.9799	0.5759	14	0.0468
15.	0.0760	5.1162	0.9359	15	0.0760
16.	0.0512	3.2122	0.6299	16	0.0512
17.	0.0504	3.3617	0.6201	17	0.0504
18.	0.0555	3.5286	0.6829	18	0.0555
19.	0.0812	5.5355	1.0000	19	0.0812

Table 10 shows the ranking for two combinations of weights. i.e. 1). When *Ra* and *Temp* have been allotted the same weightage as 0.5.2). When the weightage for *Ra* is taken as 0.6 and *Temp* as 0.4.

Table 10. The ranking with different weights.

Sr. No.	Weights			
	(0.5, 0.5)			
	K		K	
1.	1.2153	1	1.2153	1
2.	1.1445	2	1.1445	2
3.	1.4985	3	1.4985	3
4.	1.5325	4	1.5325	4
5.	2.0926	5	2.0926	5
6.	1.3739	6	1.3739	6
7.	2.1982	7	2.1982	7
8.	1.2155	8	1.2155	8
9.	1.6237	9	1.6237	9
10.	1.2275	10	1.2275	10
11.	2.7322	11	2.7322	11
12.	2.2507	12	2.2507	12
13.	2.4300	13	2.4300	13
14.	1.6323	14	1.6323	14
15.	2.7567	15	2.7567	15
16.	1.7673	16	1.7673	16
17.	1.8158	17	1.8158	17
18.	1.9336	18	1.9336	18
19.	2.9717	19	2.9717	19

5.3 Comparing GRA, CoCoSo and Taguchi Results

Table 11 shows the optimized settings obtained from the Taguchi analysis of the case study.

Table 11. Optimized settings of Taguchi analysis (Usgaonkar and Prabhu Gaonkar, 2023b).

Sr. No.	CF	GWS RPM	GWG	DOC µm	WS m/min	*Ra*		*Temp*		Remarks
						Expt. µm	Pred. µm	Expt. °C	Pred. °C	
1.	CNSL	3000	G60	20	15	0.055	0.058	38.8	39.7	When only *Ra* is optimized
2.	CNSL	1500	G60	10	10	0.114	0.112	34	33.9	When only *Temp* is optimized
3.	CNSL	3000	G60	10	10	0.073	0.072	34.5	34.4	When both *Ra* and *Temp* are optimized

Sr. No. 1 is the setting when only *Ra* is optimized, Sr. No. 2 is the setting when only *Temp* is optimized, and Sr. No. 3 is the setting when both *Ra* and *Temp* are optimized together. **Table 12** shows the comparison of ranking done for the experimental results by both the methods, GRA & CoCoSo, for the combinations of weights (0.5, 0.5), (0.6, 0.4), (1, 0), & (0, 1). These weight combinations are selected to compare the best solution obtained by both methods to the optimal solutions obtained from the Taguchi analysis. In Taguchi analysis, when both the responses *Ra* and *Temp* are considered equal weightage, then (0.5, 0.5) weight is considered for the GRA and CoCoSo analysis and when only one response either *Ra* or *Temp* is optimized, then the combination (1, 0) and (0, 1) is selected respectively. The combination of weights for responses *Ra* and *Temp* (0.6, 0.4) is selected as it is the combination obtained from the R-method of MADM. Out of the two responses, *Ra* and *Temp*, *Ra* is given top priority, followed by *Temp* in second position. By using the R-method, the weightage obtained for *Ra* is 60% and 40% for *Temp*. For deciding the weights for the responses, the decision-maker can use his intuitive experience or preference, or he may use some weight-determining methods like the R-method, AHP, entropy method, standard deviation method, equal weights, rank exponent, rank sum, rank reciprocal and centroid weights, etc. (Rao and Lakshmi, 2021).

Table 12. Comparison of ranking for the surface grinding outcomes by GRA and CoCoSo.

Sr. No.	Grinding input parameters (Alternate optimal solutions)					Objectives (responses)		GRA ranks				CoCoSo ranks			
	CF	GWS RPM	GWG	DOC μm	WS m/min	*Ra* μm	*Temp* °C	(0.5, 0.5)	(0.6, 0.4)	(1, 0)	(0, 1)	(0.5, 0.5)	(0.6, 0.4)	(1, 0)	(0, 1)
1.	Synthetic	1500	G46	10	10	0.126	38.7	19	17	13	16	18	16	13	16
2.	Synthetic	1500	G46	20	15	0.110	**39**	15	14	9	18	19	18	10	18
3.	Synthetic	1500	G60	10	15	0.185	35.8	14	16	17	6	14	15	17	6
4.	Synthetic	1500	G60	20	10	0.141	37.5	18	18	15	12	13	12	15	12
5.	Synthetic	3000	G46	10	15	0.097	37	9	8	7	11	7	6	7	11
6.	Synthetic	3000	G46	20	10	0.121	38.5	17	15	12	14	15	13	12	14
7.	Synthetic	3000	G60	10	10	0.137	35.2	8	9	14	5	6	7	14	5
8.	Synthetic	3000	G60	20	15	0.102	39	13	11	8	18	17	17	8	18
9.	CNSL	1500	G46	10	15	**0.202**	**34**	5	6	19	1	12	14	19	1
10.	CNSL	1500	G46	20	10	0.199	36	16	19	18	8	16	19	18	9
11.	CNSL	1500	G60	10	10	0.114	**34**	2	3	10	1	3	3	9	1
12.	CNSL	1500	G60	20	15	0.095	36.5	7	7	6	10	5	5	6	10
13.	CNSL	3000	G46	10	10	0.090	36	6	5	4	8	4	4	4	8
14.	CNSL	3000	G46	20	15	0.093	38.5	10	10	5	14	11	11	5	14
15.	CNSL	3000	G60	10	15	0.083	35	3	4	3	4	2	2	3	4
16.	CNSL	3000	G60	20	10	0.116	37.5	12	13	11	12	10	10	11	12
17.	CNSL	3000	G60	20	15	**0.055**	38.8	4	2	1	17	9	8	1	17
18.	Synthetic	1500	G60	10	10	0.147	35.9	11	12	16	7	8	9	16	7
19.	**CNSL**	**3000**	**G60**	**10**	**10**	**0.073**	**34.5**	1	1	2	3	1	1	2	3

The comparison of the optimization results of the Taguchi analysis of the selected case study (Usgaonkar and Prabhu Gaonkar, 2023b) and the results of the top five Ranks, each by GRA and CoCoSo are displayed in **Table 13**.

Table 13. Comparison of the top five ranks, each by GRA and CoCoSo.

Sr. No. (Table 12)	CF	GWS RPM	GWG	DOC μm	WS m/min	*Ra* μm	*Temp* °C	0.5, 0.5		0.6, 0.4		1, 0		0, 1	
								GRA	CoCoSo	GRA	CoCoSo	GRA	CoCoSo	GRA	CoCoSo
9.	CNSL	1500	G46	10	15	**0.202**	**34**	5	12	6	14	19	19	1	1
11.	**CNSL**	**1500**	**G60**	**10**	**10**	**0.114**	**34**	**2**	**3**	**3**	**3**	**10**	**9**	**1**	**1**
12.	CNSL	1500	G60	20	15	0.095	36.5	7	5	7	5	6	6	10	10
13.	CNSL	3000	G46	10	10	0.090	36	6	4	5	4	4	4	8	8
14.	CNSL	3000	G46	20	15	0.093	38.5	10	11	10	11	5	5	14	14
15.	CNSL	3000	G60	10	15	0.083	35	3	2	4	2	3	3	4	4
17.	**CNSL**	**3000**	**G60**	**20**	**15**	**0.055**	**38.8**	**4**	**9**	**2**	**8**	**1**	**1**	**17**	**17**
19.	**CNSL**	**3000**	**G60**	**10**	**10**	**0.073**	**34.5**	**1**	**1**	**1**	**1**	**2**	**2**	**3**	**3**

When both the responses *Ra* and *Temp* are optimized considering equal weightage, then the optimized parameter setting obtained from the Taguchi analysis is at Sr. No. 3 (**Table 11**) and Sr. No. 19 (**Table 12** & **Table 13**) i. e. CF- CNSL, GWS- 3000, GWG- G60, DOC- 10 µm, WS- 10 m/min with *Ra*- 0.073 µm and *Temp*- 34.5 ^{0}C. The same setting is allotted as Rank 1 by GRA and CoCoSo for the weightages (0.5, 0.5) and (0.6, 0.4) (refer **Table 12** & **Table 13**, Sr. No. 19). When *Ra* alone is optimized, the setting obtained from the Taguchi analysis is at Sr. No. 1 (**Table 11**) and Sr. No. 17 (**Table 12** & **Table 13**) i. e. CF- CNSL, GWS- 3000, GWG- G60, DOC- 20 µm, WS- 15 m/min with *Ra*- 0.055 µm and *Temp*- 38.8 ^{0}C. The same setting is allotted as Rank 1 by GRA and CoCoSo for the weightage (1, 0) (refer to **Table 12** & **Table 13**, Sr. No. 17). Also, when *Temp* alone is optimized, the setting obtained from the Taguchi analysis is at Sr. No. 2 (**Table 11**) and Sr. No. 11 (**Table 12** & **Table 13**) i. e. CF- CNSL, GWS- 1500, GWG- G60, DOC- 10 µm, WS- 10 m/min with *Ra*- 0.114 µm and *Temp*- 34 ^{0}C. The same setting is allotted as Rank 1 by GRA and CoCoSo for the weightage (1, 0) (refer to **Table 12** & **Table 13**, Sr. No. 11). From the above discussion it is seen that the optimized reading obtained from all the three methods Taguchi, GRA and CoCoSo agree with each other.

Also, it is observed that in some places the ranks allotted by GRA and CoCoSo do not agree with each other (refer to **Tables 12** & **13**). For example, in ranks at Sr. No. 2 & Sr. No. 11 when only *Ra* is optimized GRA allots the ranks 9 & 10 and CoCoSo allots the ranks 10 & 9 respectively. If we arrange the responses *Ra* for (1, 0) from **Table 12** in ascending order and rank, then the ranking given by GRA matches and CoCoSo there is little variation especially when the responses are very close (Sr. No.2- *Ra* is 0.110 µm and Sr. No. 11- *Ra* is 0.114 µm). It appears that the method CoCoSo is a little less sensitive than the method GRA especially when the responses are very close to each other.

Figure 1 shows the comparison of rankings by GRA & CoCoSo for the weightages (0.5, 0.5) and (0.6, 0.4) in graphical form. The X-axis shows the alternate optimal solutions from $\mathbf{s_1}$ to $\mathbf{s_{19}}$, with the Y-axis showing the ranks.

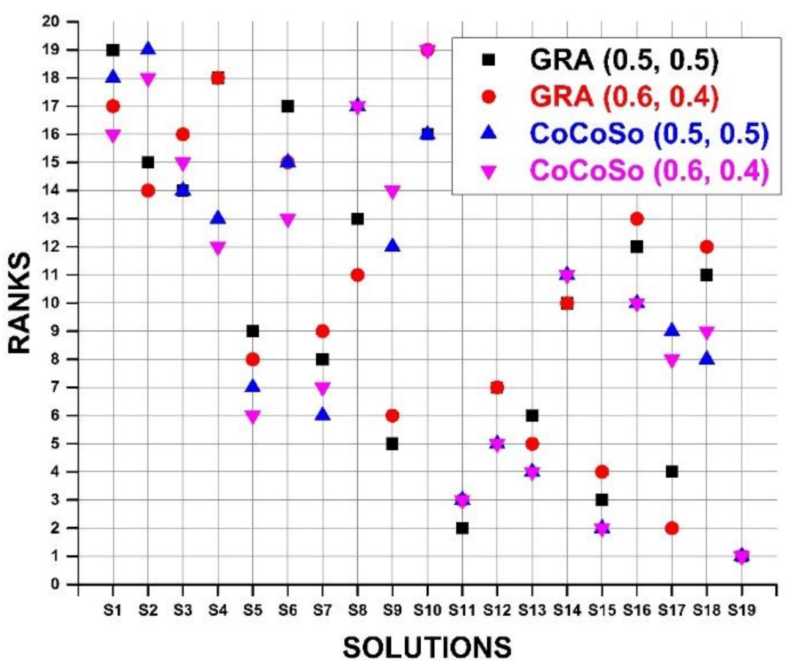

Figure 1. The comparison of the solutions of GRA and CoCoSo for the weightages (0.5, 0.5) and (0.6, 0.4).

Also, **Figure 2** shows the comparison of the top five solutions of GRA and CoCoSo for the weightages (0.5, 0.5), (0.6, 0.4), (1, 0), and (0, 1) in graphical form. It can be observed that the lower ranks proposed by both methods coincide at some of the places and the ranking obtained from both methods is quite close with very little variation indicating a strong correlation between both the methods GRA and CoCoSo.

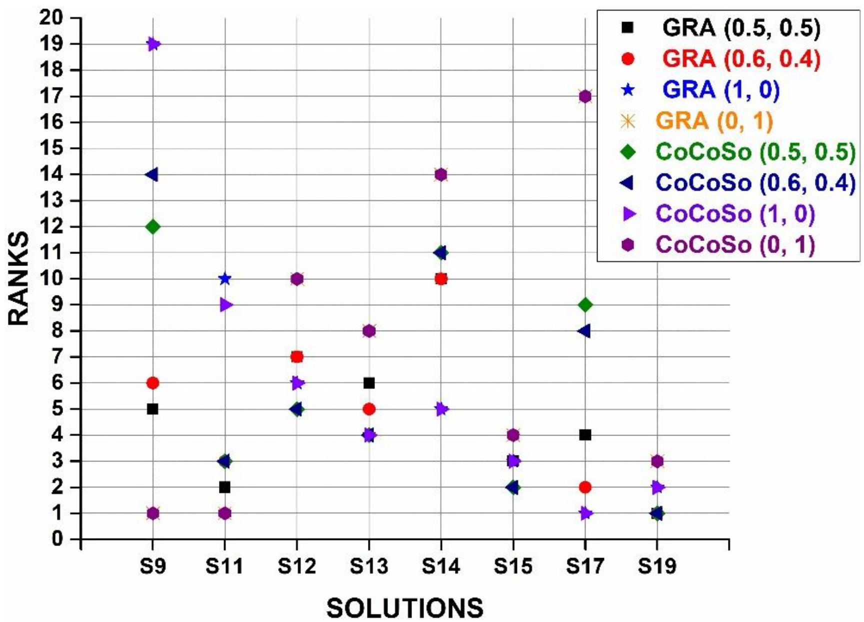

Figure 2. The comparison of the top five solutions of GRA and CoCoSo.

To check the correlation and statistical significance between the ranking pairs, (*Ra*- 0.5, *Temp*- 0.5) and (*Ra*- 0.6, *Temp*- 0.4) for GRA & CoCoSo, the Spearman rank correlation test and Kendall's rank correlation method are performed, as shown in **Table 14**. For the two pairs mentioned above, the derived Spearman Rank Coefficients are 0.8526 and 0.7982, respectively, establishing a very strong connection (Leclezio et al., 2015). The Z values produced by the Kendall's Tau Test performed for the two pairs mentioned above are larger than 1.96, and the p-values are less than 0.05, pointing to a statistically significant correlation between the respective pairs (refer **Table 14**).

Table 14. Tests of correlation and statistical significance for GRA and CoCoSo.

	Sr. No.	1	2
	Test Pair (weights)	(0.5, 0.5)	(0.6, 0.4)
Spearman Rank Correlation Test	**The sum of Squares of Rank Differences**	168	230
	Rank Coefficient (r)	0.8526	0.7982
	Critical Value for Spearman Rank (for n = 19, alpha = 0.05) (v)	0.391	0.391
	Check	r > v	r > v
	Comment	Highly correlated	Highly correlated
Kendall's Rank Correlation Method	**The sum of the Number of Concordances (C)**	144	140
	The sum of the Number of Discordances (D)	27	31
	Kendall's Tau Value	0.6842	0.6374
	Z Value	4.0933	3.8134
	Check	Z > 1.96	Z > 1.96
	p Value	4.25505E-05	0.000137115
	Check	p < 0.05	p < 0.05
	Comment (at alpha level 0.05)	Statistically significant correlation	Statistically significant correlation

6. Conclusion

The study covered the step-by-step application of the GRA & CoCoSo approach. The optimization results of the selected experimental study obtained from the Taguchi analysis agree with the outcomes of both the GRA and CoCoSo methods. The ranking proposed by both methods is almost the same with very little variation especially when the responses are very close. In such cases, GRA is more sensitive and accurate as compared to the method CoCoSo. The Spearman Rank Correlation Test and Kendall's Rank Correlation Method establish strong correlation and statistical significance between the ranking pairs proposed by both methods.

The decision-makers flexibility to change the weights of the objectives based on their priorities and needs to achieve the ranking for an alternative optimal solution is a particularly intriguing feature of both the GRA and CoCoSo methodologies. Also, the novelty and contribution of the current research work is that these MADM methods of GRA and CoCoSo are successfully applied to a vital machining operation like surface grinding. Here, the decision maker is provided with an efficient, relatively simple to comprehend, and flexible strategy to aid him in decision-making in the limited time and capacity he has and to pay attention to and process the information and choose the optimal input parameters setting based on their ranking, by deciding the weights of the responses as per his need. This study will significantly benefit the industry's design, process planning, and production departments.

There is a broad scope in the future to extend these GRA and CoCoSo techniques to other machining areas, such as turning, milling, etc., with more input parameters and responses. The present study proposes that the weights assigned to the responses should be as per the decision-maker's tastes and priorities based on the job's requirements and specifications. Some more novel MADM methods can be thought of to aid the decision maker in deciding the weights to be assigned to the responses. Also, the study can be extended by studying more methods in the area of MADM for ranking and comparing their efficiency. It will also be interesting to try combining these MADM methods with the latest predictive tools like ANN, etc., for predicting the ranked optimal input parameter settings and the weights.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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