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SWARA-CoCoSo method-based parametric optimization of green dry milling processes

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Abstract

Attaining green environment for various machining processes has now caught the attention of many manufacturing industries. The input parameters involved in those machining processes are mainly responsible for achieving the desired performance as they are directly related to the process outputs. Hence, proper selection of the input process parameters becomes vital for having sustainable machining environment. In this paper, an integrated application of step-wise weight assessment ratio analysis (SWARA) and combined compromise solution (CoCoSo) methods is presented to identify the optimal parametric combinations of two green dry milling processes. In the first example, cutting speed, depth of cut, feed rate and nose radius are treated as the input parameters, while power factor, electric consumption and surface roughness are the responses. On the other hand, in the second example, cutting speed, feed rate, depth of cut and width of cut, and surface roughness, active cutting energy and material removal rate are respectively considered as the input parameters and responses. Instead of considering equal weights, SWARA method assigns relative subjective importance to the responses based on the preference set by the decision-makers, while CoCoSo ranks the experimental trials from the best to the worst. The derived optimal parametric settings are finally analyzed using the developed regression equations. It is observed that SWARA-CoCoSo method outperforms the other popular optimization techniques in identifying the best parametric intermixes for the green dry milling processes for having improved machining performance with minimal environmental effect.

Keywords: Green dry milling, SWARA, CoCoSo, Optimization, Milling parameter, Response

Introduction

Green machining represents an eco-friendly material removal process, in which the prime focus is to reduce its environmental impacts, safeguard operators' health, and decrease power consumption [1, 2]. In conventional machining processes, like turning, drilling, milling, and shaping, material is removed from the workpiece in the form of chips with the help of a sharp-edged cutting tool having direct contact with the workpiece surface. In a wet machining process, liquid lubricant is employed to carry away the heat generated in the machining zone as well as to evacuate the metal chips removed during the cutting operation. This involves additional machining cost along with poor environmental impacts, such as emission of toxic gases to the surrounding. Alternatively, dry machining with almost no or minimum lubricant requirement has gained much popularity as a cost-effective eco-friendly machining process having less detrimental effects on the environment. With continuously rising public awareness for environmental-related impacts and to enforce environmental protection laws for occupational safety and health regulations, dry machining has emerged out as a crucial area for deployment of sustainable manufacturing decisions. It helps in minimizing use of liquid lubricants which can indirectly cause air and water pollutions.

Dry milling is a process of removing material from the workpiece by pressing forward a rotating cutter against the work material with no or minimal liquid lubricant requirement. The effects of different operating parameters of dry milling processes on the machining outputs have been explored by many researchers [3, 4]. Influences of these process parameters are highly correlated with the technological outputs of milling operation. The corresponding parametric values need to be carefully selected as an improper selection may result in deterioration of milling performance with poor product quality and may also lead to various adverse consequences, such as temperature rise, tool fracture, and fatigue in work material. Several mathematical techniques have already been adopted by the previous researchers to overcome human interventional errors and identify the best parametric combinations in milling processes for having improved machining conditions [5]. Taguchi methodology [6], genetic algorithm (GA) [7], non-dominated sorting genetic algorithm (NSGA-II) [8], particle swarm optimization (PSO) [9], teaching-learning-based optimization algorithm [10], grey relational analysis (GRA) [11, 12], GRA combined with fuzzy logic [13], multi-objective optimization based on ratio analysis (MOORA) [14], graph theory and matrix approach [15], technique for order of preference by similarity to ideal solution (TOPSIS) [16, 17], desirability function approach [18], etc. are among the popular mathematical techniques deployed for attaining the most desired responses in various milling operations.

More recently, the trade-off between quality of cutting and power consumption during machining operation has been explored by many researchers. Continuous rise in demand of energy along with various constraints associated with increased carbon emission has significantly influenced the manufacturing industries to save energy [19]. Selection of the optimal parametric combination for a machining process may too play a key role in this direction. Researchers have shown keen interest in adopting various optimization techniques to select the optimal parametric settings of various machining processes to reduce energy consumption (EC), and decrease emission of toxic gases and harmful substances to the environment [20–23]. Dry milling also consumes a significant amount of electrical energy during removal of material from the workpeice. Hence, possibilities must be searched out for saving energy which indirectly lead to reduction in carbon emission produced by various power plants for electric energy generation. Well-known optimization techniques, like GRA [24], response surface methodology (RSM) [25], GA [26, 27], adaptive simulated annealing [28], and desirability function approach [29], have been adopted to determine the optimal milling parameters resulting in less energy consumption during material removal process. Although, these methodologies are quite capable of providing optimal or near-optimal solutions while solving parametric optimization problems, their complex application procedure, higher computational time and effort, dependency of different algorithm-specific parameters, assignment of equal priorities to the considered responses by the decision-makers, etc. may hinder their widespread applications. Hence, an urgent need arises to explore this area to overcome the above-mentioned drawbacks.

This paper proposes the combined application of step-wise weight assessment ratio analysis (SWARA) and combined compromise solution (CoCoSo) methods to solve parametric optimization problems for two green dry milling process based on past experimental data. In conventional parametric optimization problems for machining operations, it is noticed that equal importance is usually assigned to all the responses, mainly to ease out the calculation steps. But, in real-time machining scenario, based on the end product requirements and to fulfill customers' demands, one particular response (quality characteristic) may be preferred over the others. Thus, those responses may have different priority weights. The SWARA method, developed by Keršuliene et al. [30], allows the decision-makers (or a group of experts) to opine on the importance of one attribute over the other based on a significance ratio scale while assigning unequal weights to the considered attributes (responses). Its extremely simple computation procedure makes it a popular choice among the research community to calculate criteria weights [31–33]. On the other hand, CoCoSo is a newly developed multi-criteria decision-making (MCDM) technique leading to a compromise solution based on simple additive weighting and weighted product models [34]. Since its inception, this method has been gaining popularity in solving various complex decision-making problems, like security evaluation [35], sustainable supplier selection [36], optimization of drilling performance [37], cache placement strategy selection [38] etc. In this paper, CoCoSo method is applied to determine the optimal mixes of two green dry milling process parameters based on the past experimental dataset. It would finally lead to enhanced milling performance with minimal harmful effects while achieving green sustainable machining environment.

Materials and methods

Green milling process

A traditional milling process helps in removing material from a workpiece in the form of chips by moving forward a rotating multi-point cutting tool against the workpiece. During its operation, a large amount of electrical energy is consumed which mainly depends on the combination of various milling parameters. A green dry milling can be categorized as a metal removal process with minimum energy and liquid lubricant requirements while maintaining the quality of the machined components. The interrelationship between various input parameters and outputs in a green milling process can be illustrated through an input-output model, as shown in Fig. 1. The inputs to this process are different machining parameters, workpiece, tool, and electric power, while the outputs are finished product, heat, noise, vibration, and metal chips. To attain green machining environment, the manufacturer should take into account two main aspects, i.e., manufacturing aspect and environmental aspect. The decision-making model for a green milling process thus consists of material removal rate (MRR), surface roughness (in the form of average surface roughness (Ra)), tool wear, etc., as the manufacturing aspects, and power factor (PF), EC, temperature rise, noise, etc., as the environmental

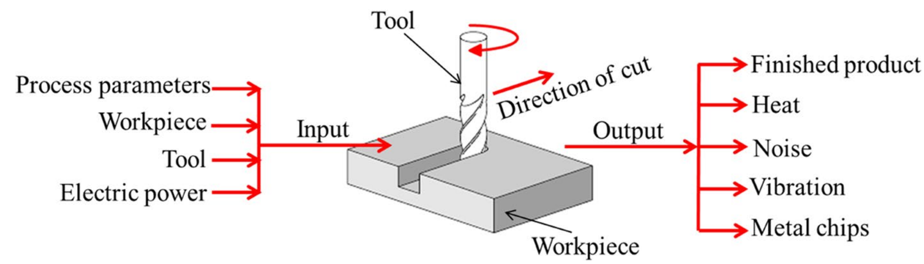

Fig. 1 Input-output model for a green dry milling process

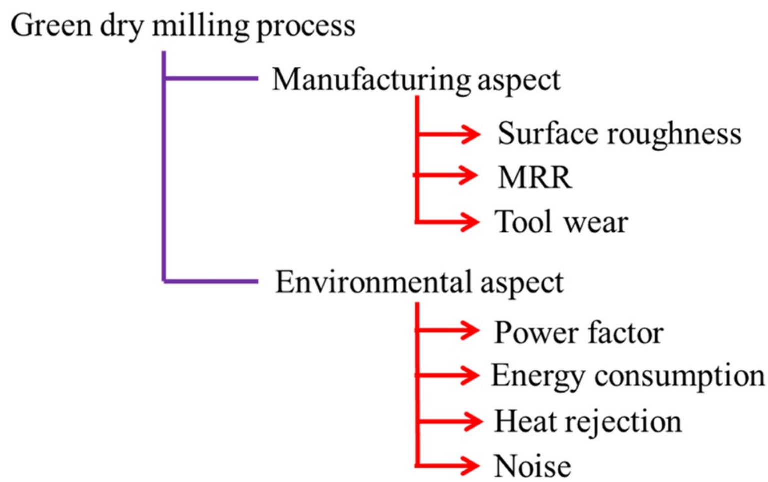

Fig. 2 Manufacturing and environmental aspects of a green dry milling process

aspects. Figure 2 presents a schematic diagram illustrating the manufacturing and environmental aspects of a green milling process.

SWARA method

The computational steps involved in SWARA method are provided as below [30, 39]:

Step 1: defining and ranking of the decision criteria

In this step, the concerned decision-makers define the decision criteria and rank them from the best to the worst based on their expertise and knowledge. These criteria can be denoted as C_j ($j = 1,2,\ldots n$), where C_1 and C_n respectively represent the best and the worst criteria sorted according to their assigned ranks.

Step 2: determination of the comparative importance of each criteria

The average value of comparative importance (s_j) of each criterion is now determined based on the corresponding rank. It basically describes how criterion C_j is more important than criterion C_{j+1}.

Step 3: estimation of the coefficient (k_j) of each criterion

The coefficient of each criterion can be obtained as follows:

$$k_j = \left\{ \begin{array}{ll} 1 & \text{if } j = 1 \\ s_j + 1 & \text{if } j > 1 \end{array} \right\} \tag{1}$$

Step 4: determination of the recalculated weight (q_j) of each criterion

The recalculated weight of each criterion can now be estimated using Eq. (2).

$$q_j = \left\{ \begin{array}{ll} 1 & \text{if } j = 1 \\ \frac{q_{j-1}}{k_j} & \text{if } j > 1 \end{array} \right\} \tag{2}$$

Step 5: calculation of the relative weight (w_j)

The final weight of each criterion can be computed while dividing the weight obtained in the previous step by the sum of the weights.

$$w_j = \frac{q_j}{\sum\limits_{j=1}^{n} q_j} \tag{3}$$

CoCoSo method

This method is an integrated approach based on simple additive weighting and weighted product models. Its procedural steps are enumerated as below [40]:

Step 1: development of the initial decision matrix

The corresponding decision matrix is first formulated considering m alternatives (number of experimental trials) and n criteria (number of responses).

$$X = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix}$$

where x_{ij} is the performance measure of ith alternative with respect to jth criterion.

Step 2: normalization of the decision matrix

Depending on the type of the criterion considered, the initial decision matrix is now normalized employing the following equations [41]:

For beneficial (higher-the-better) criterion:

$$n_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \left(i = 1, 2 \ldots, m; j = 1, 2 \ldots, n\right) \tag{4}$$

For non-beneficial (lower-the-better) criterion:

$$n_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{5}$$

where n_{ij} is the normalized value of x_{ij}.

Step 3: calculation of the power of weighted (P_i) and sum of weighted (S_i) comparability sequence scores

The power of weighted comparability and sum of weighted comparability sequence scores are computed for each of the alternatives.

$$P_i = \sum_{j=1}^{n} \left(n_{ij}\right)^{wj} \tag{6}$$

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

where w_j is the weight assigned to jth criterion.

Step 4: estimation of the appraisal scores

The appraisal scores of each alternative can now be calculated using the following three aggregation strategies:

$$a_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{8}$$

$$a_{ib} = \frac{P_i}{\min_i P_i} + \frac{S_i}{\min_i S_i} \tag{9}$$

$$a_{ic} = \frac{\lambda \times P_i + (1-\lambda) \times S_i}{\lambda \times \max_i P_i + (1-\lambda) \times \max_i S_i} (0 \le \lambda \le 1)\left(\lambda = 0.5 \text{ by default}\right) \tag{10}$$

Step 5: calculation of the final appraisal score (A_i)

The final appraisal score for each alternative is estimated using Eq. (11).

$$A_i = (a_{ia} \times a_{ib} \times a_{ic})^{\frac{1}{3}} + \frac{1}{3}(a_{ia} \times a_{ib} \times a_{ic}) \tag{11}$$

The alternative with the highest appraisal score is identified as the best option for final selection. The flowchart exhibiting application of this integrated SWARA-CoCoSo method for parametric optimization of green dry milling processes is portrayed in Fig. 3.

In this paper, the parametric optimization problems of two green dry milling processes are solved using SWARA-CoCoSo approach which has several advantages over the other integrated MCDM techniques. At first, in SWARA method, based on the preference of the participating stakeholders (manufacturers, machine operators, and end users), different weight sets for the considered responses can be determined while evaluating their influences on final rankings of the alternative experimental trials. It has also extremely simple computational steps. On the other hand, in CoCoSo

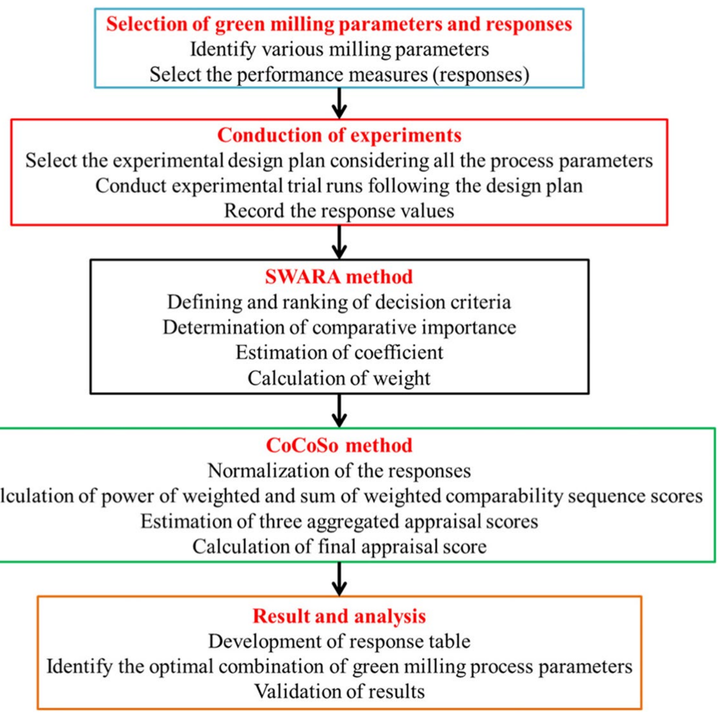

Fig. 3 Application of SWARA-CoCoSo method for parametric optimization of green dry milling processes

Table 1 Green milling parameters and their levels for example 1 [29]

Parameter	Unit	Level		
		− 1	0	+ 1
Cutting speed (*V*)	m/min	60	110	160
Depth of cut (*a*)	mm	0.2	0.6	1.0
Feed rate (*f*)	mm/z	0.04	0.08	0.12
Nose radius (*r*)	mm	0.2	0.4	0.8

method, power of weighted and sum of weighted comparability sequences are aggregated together to determine the composite performance scores of the experimental runs. This integrated approach has minimum dependency on algorithm-specific parameters. Its superiority in identifying the optimal parametric intermixes for green milling processes is also contrasted against desirability function approach and GRA technique. Thus, it can be employed as an efficient multi-objective optimization tool for solving parametric optimization problems of green dry milling processes.

Results and discussion

Example 1

Green dry milling is an eco-friendly machining operation which aims in reducing the environmental impacts, minimizes EC and protects operator's health. Nguyen et al. [29] performed dry milling operation in a computer numerical control Spinner U620 machining center on stainless steel 304 work material having dimensions 350 mm × 150 mm ×

25 mm. Four milling parameters, i.e., cutting speed (V), depth of cut (a), feed rate (f), and nose radius (r) were considered with three level variations, as presented in Table 1. Based on Box-Behnken design plan, 25 combinations of experiments were conducted with PF, EC (in kJ), and Ra (in μm) as the responses (process outputs). The measured values of all the considered responses and the experimental design plan are provided in Table 2. The value of PF can be derived as the ratio of active power consumption with respect to apparent power consumption. Higher value of PF is practically desired as it assures that the milling setup would generate more active power necessary for the machining operation. On the other hand, EC is the power in the form of electrical energy consumed while removing material from the workpiece. Finally, Ra measures the micro-undulations of a given workpiece surface both in horizontal and vertical directions. It actually denotes the quality of a machined surface. Among these three responses, PF is the only higher-the-better quality characteristic, while EC and Ra are lower-the-better type of quality characteristics. For this green dry milling process, applying desirability function approach, Nguyen et al. [29] suggested the optimal parametric condition as $V = 160$ m/min, $a = 0.42$ mm, $f = 0.09$ mm/z and $r = 0.8$ mm.

It has already been mentioned that in order to simplify the calculations involved in any of the MCDM techniques, equal weights are usually allotted to all the criteria (responses). But, in real-time machining environment, these relative weights may vary

Table 2 Parametric combinations and measured responses for example 1 [29]

Exp. no.	*V* (m/min)	*a* (mm)	*f* (mm/z)	*R* (mm)	PF	EC (kJ)	Ra (μm)
1	110	0.2	0.04	0.4	0.518	50.33	0.45
2	110	0.6	0.12	0.8	0.867	25.46	1.08
3	110	0.6	0.08	0.4	0.652	31.56	0.85
4	60	0.6	0.08	0.2	0.611	53.66	1.34
5	160	0.6	0.12	0.4	0.851	18.42	0.95
6	60	0.6	0.12	0.4	0.736	42.6	1.47
7	110	0.2	0.12	0.4	0.690	21.99	1.14
8	60	0.6	0.08	0.8	0.685	59.13	0.78
9	60	1.0	0.08	0.4	0.703	61.68	1.31
10	110	1.0	0.12	0.4	0.868	26.72	1.49
11	110	1.0	0.08	0.2	0.732	35.41	1.42
12	160	0.6	0.08	0.2	0.719	22.84	0.89
13	160	1.0	0.08	0.4	0.835	27.26	0.79
14	60	0.2	0.08	0.4	0.547	48.96	0.82
15	160	0.6	0.04	0.4	0.690	44.62	0.47
16	110	0.6	0.04	0.2	0.566	54.03	0.98
17	60	0.6	0.04	0.4	0.529	94.95	0.82
18	110	1.0	0.04	0.4	0.659	63.82	1.06
19	160	0.2	0.08	0.4	0.671	22.07	0.41
20	110	0.6	0.12	0.2	0.752	23.74	1.55
21	110	0.6	0.04	0.8	0.648	62.35	0.52
22	160	0.6	0.08	0.8	0.862	26.68	0.36
23	110	0.2	0.08	0.2	0.576	28.23	0.91
24	110	0.2	0.08	0.8	0.681	32.95	0.48
25	110	1.0	0.08	0.8	0.843	39.02	0.89

based on manufacturer's or customer's requirements. The SWARA method has the capability to estimate varying sets of criteria weights depending on the opinions of the concerned decision-makers. In this paper, three decision-makers are considered having their dissimilar judgments on the relative importance of the responses. The first decision-maker (one of the customers) has assigned maximum importance to Ra and the corresponding preference order is Ra→EC→PF. On the other hand, the second decision-maker (manufacturer) has set the preference order of the responses as EC→Ra→PF. Finally, for the last decision-maker (the machine operator), the responses are preferred as PF→Ra→EC. Thus, the decision-makers have separately ranked the responses depending on their level of importance. The average values of comparative importance (s_j) of all the responses are calculated based on the ranks assigned by the participating decision-makers. Now, utilizing Eqs. (1)–(3), the final weights of the responses are estimated using SWARA method for the three decision-makers, as shown in Tables 3, 4, and 5, respectively.

Following the procedural steps of CoSoSo method and based on the type of quality characteristic, the response values, provided in Table 2, are linearly normalized, applying Eqs. (4) and (5). These normalized values are provided in Table 6. The power of weighted comparability sequence and sum of weighted comparability sequence for each of the alternative experimental trials are also calculated considering weight set 1 (based on the preference of decision-maker 1) in Table 6. Using the three aggregation strategies of Eqs. (8)–(10), the corresponding appraisal scores are computed for all the experimental trials. Finally, these appraisal scores are transformed into a final appraisal score, employing Eq. (11). The computed values of these appraisal scores for all the experimental trials for criteria weight set 1 are exhibited in Table 7. From this table and Fig. 4, it can be noticed that among the 25 experiments, trial number

Table 3 Weight set for responses for decision-maker 1

Response	s_j	k_j	q_j	w_j
Ra		1	1	0.3872
EC	0.15	1.15	0.8696	0.3367
PF	0.22	1.22	0.7128	0.2760

Table 4 Weight set for responses for decision-maker 2

Response	s_j	k_j	q_j	w_j
EC		1	1	0.3640
Ra	0.07	1.07	0.9346	0.3402
PF	0.15	1.15	0.8127	0.2958

Table 5 Weight set for responses for decision-maker 3

Response	s_j	k_j	q_j	w_j
PF		1	1	0.3689
Ra	0.08	1.08	0.9259	0.3416
EC	0.18	1.18	0.7847	0.2895

Table 6 Normalized responses and comparability sequence measures for weight set 1

Exp. no.	PF	EC	Ra	P_i	S_i
1	0	0.5830	0.9244	1.8039	0.5542
2	0.9971	0.9080	0.3950	2.6651	0.7339
3	0.3829	0.8283	0.5882	2.5200	0.6123
4	0.2657	0.5395	0.1765	2.0169	0.3233
5	0.9514	1	0.5042	2.7534	0.7945
6	0.6229	0.6840	0.0672	2.1091	0.4283
7	0.4914	0.9534	0.3445	2.4679	0.5900
8	0.4771	0.4681	0.6471	2.4346	0.5398
9	0.5286	0.4347	0.2017	2.1320	0.3704
10	1	0.8915	0.0504	2.2766	0.5957
11	0.6114	0.7780	0.1092	2.2163	0.4730
12	0.5743	0.9422	0.5546	2.6342	0.6905
13	0.9057	0.8845	0.6387	2.7732	0.7951
14	0.0829	0.6009	0.6134	2.1729	0.4627
15	0.4914	0.6577	0.9076	2.6535	0.7085
16	0.1371	0.5347	0.4790	2.1399	0.4033
17	0.0314	0	0.6134	1.2124	0.2462
18	0.4029	0.4068	0.4118	2.2260	0.4076
19	0.4371	0.9523	0.9580	2.7630	0.8122
20	0.6686	0.9305	0	1.8709	0.4978
21	0.3714	0.4260	0.8655	2.4567	0.5811
22	0.9829	0.8921	1	2.9575	0.9588
23	0.1657	0.8718	0.5378	2.3503	0.5475
24	0.4657	0.8101	0.8992	2.7011	0.7495
25	0.9286	0.7308	0.5546	2.6755	0.7171

22 with parametric combination as $V = 160$ m/min, $a = 0.6$ mm, $f = 0.08$ mm/z, and $r = 0.8$ mm, and having the maximum appraisal score of 3.1583 is the most preferred choice for attaining the target response order as set by the first decision-maker.

To validate the optimal combination of the dry milling process parameters derived using SWARA-CoCoSo method for weight set 1, the related response table is developed in Table 8 based on the calculated final appraisal scores for the alternative trials. These values are obtained while considering the average of the final appraisal scores at the corresponding parametric levels of the experimental trials. The highest average appraisal scores (shown in bold face) in Table 8 indicate that to attain green manufacturing environment and satisfy the requirements of decision-maker 1, the parametric condition must be set as $V = 160$ m/min, $a = 0.2$ mm, $f = 0.08$ mm/z, and $r = 0.8$ mm for this milling process. A similar parametric setting is also obtained in Table 9 for criteria weight set 2. However, for weight set 3, the parametric combination (shown in Table 10) is attained as $V = 160$ m/min, $a = 1$ mm, $f = 0.08$ mm/z, and $r = 0.8$ mm, and it is different from the earlier derived setting. The response graph of Fig. 5 clearly highlights the optimal settings of different milling parameters for three different weighting scenarios. Compared to the observations of Nguyen et al. [29], the optimal parametric settings deriving using SWARA-CoCoSo method differ with respect to depth of cut and feed rate.

Table 7 Aggregated scores for weight set 1

Exp. no.	a_{ia}	a_{ib}	a_{ic}	A_i
1	0.0321	3.7389	0.6021	1.8740
2	0.0462	5.1789	0.8679	2.6232
3	0.0426	4.5656	0.7998	2.3404
4	0.0318	2.9768	0.5976	1.5859
5	0.0482	5.4981	0.9059	2.7724
6	0.0345	3.4790	0.6479	1.8139
7	0.0416	4.4321	0.7808	2.2754
8	0.0404	4.2007	0.7595	2.1721
9	0.0340	3.2627	0.6390	1.7258
10	0.0390	4.2973	0.7334	2.1873
11	0.0366	3.7492	0.6867	1.9456
12	0.0452	4.9773	0.8489	2.5330
13	0.0485	5.5166	0.9111	2.7834
14	0.0358	3.6717	0.6730	1.9058
15	0.0457	5.0662	0.8584	2.5737
16	0.0346	3.4032	0.6494	1.7867
17	0.0198	2.0000	0.3724	1.0428
18	0.0358	3.4915	0.6725	1.8379
19	0.0486	5.5779	0.9129	2.8076
20	0.0322	3.5651	0.6048	1.8117
21	0.0413	4.3865	0.7757	2.2543
22	0.0532	6.3338	1.0000	3.1583
23	0.0394	4.1623	0.7399	2.1422
24	0.0469	5.2719	0.8811	2.6683
25	0.0461	5.1194	0.8663	2.5997

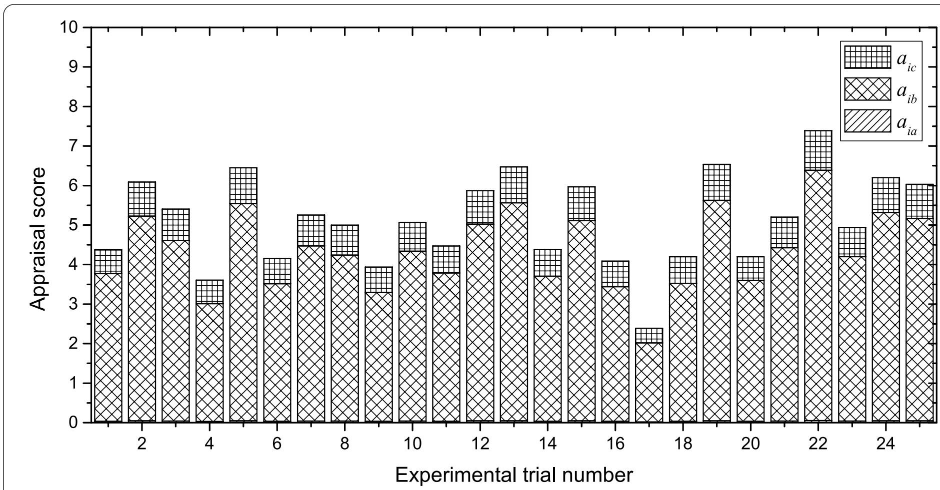

Fig. 4 Ranking of the alternative trials for weight set 1 for example 1

To justify the superiority of SWARA-CoCoSo method as an effective multi-objective optimization tool, three RSM-based equations (considering only the statistically significant terms) are developed in Eqs. (12)–(14) correlating the considered milling

Table 8 Response table for final aggregation score for weight set 1

Parameter	Level		
	−1	**0**	**+1**
Cutting speed	1.7077	2.1805	**2.7714**
Depth of cut	**2.2789**	2.1899	2.1800
Feed rate	1.8949	**2.3360**	2.2473
Nose radius	1.9675	2.1493	**2.5793**

Table 9 Response table for final aggregation score for weight set 2

Parameter	Level		
	−1	**0**	**+1**
Cutting speed	1.7923	2.3147	**2.9369**
Depth of cut	**2.3888**	2.3162	2.3371
Feed rate	1.9558	**2.4698**	2.4374
Nose radius	2.0973	2.2741	**2.7199**

Table 10 Response table for final aggregation score for weight set 3

Parameter	Level		
	−1	**0**	**+1**
Cutting speed	1.7975	2.3123	**2.9487**
Depth of cut	2.3380	2.3240	**2.3830**
Feed rate	1.9552	**2.4680**	2.4536
Nose radius	2.0660	2.2750	**2.7610**

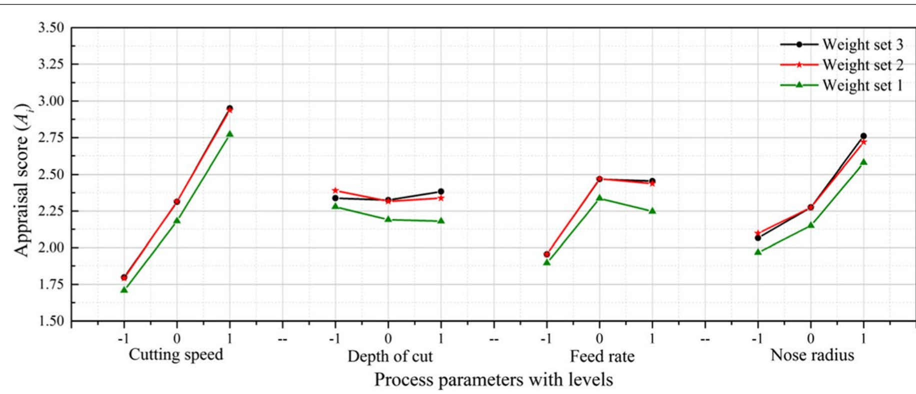

Fig. 5 Response graph for final aggregation score for example 1

parameters and responses. Based on these equations, the corresponding response values are predicted at the optimal parametric combinations derived using criteria weight sets 1, 2, and 3. The estimated response values are provided in Table 11 and are also subsequently compared with those obtained by Nguyen et al. [29]. It can be observed from this table that the response values estimated at the parametric settings for weight sets 1

Table 11 Comparison of response values at different parametric combinations for example 1

Optimal parametric setting	*V*	*a*	*f*	*r*	PF	EC	Ra
Desirability function approach [29]	160	0.42	0.09	0.8	0.8360	20.6300	0.3500
SWARA-CoCoSo (weight sets 1 and 2)	160	0.2	0.08	0.8	0.8695	19.9288	0.2947
Improvement (%)					4.0115	3.3989	15.7897
SWARA-CoCoSo (weight set 3)	160	1	0.08	0.8	0.9830	19.9288	0.3921
Improvement (%)					17.5885	3.3989	-12.0229

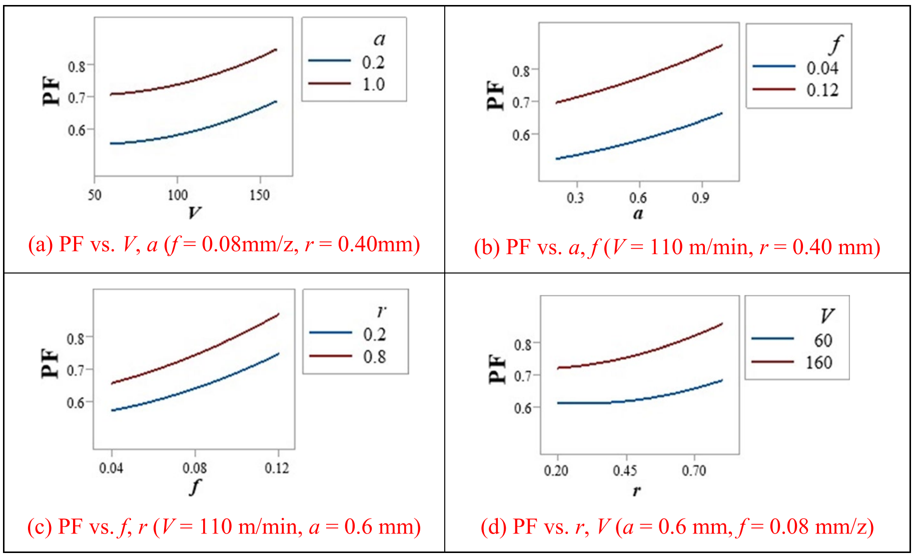

Fig. 6 Effects of different green milling parameters on PF. **a** PF vs. *V*, *a* ($f = 0.08$ mm/z, $r = 0.40$ mm. **b** PF vs. *a*, *f* ($V = 110$ m/min, $r = 0.40$ mm). **c** PF vs. *f*, *r* ($V = 110$ m/min, $a = 0.6$ mm). **d** PF vs. *r*, *V* ($a = 0.6$ mm, $f = 0.08$ mm/z)

and 2 derived using SWARA-CoCOSo clearly outperform those as attained by Nguyen et al. [29]. At the proposed optimal settings of the green dry milling parameters for criteria weight sets 1 and 2, 4.01, 3.40, and 15.79% improvements in the values of PF, EC, and Ra are respectively achieved against the past observations. The parametric combination for weight set 3 achieves 17.59 and 3.40% improvements in the values of PF and EC respectively, but the Ra is worsened by 12.02% as compared to its previous value.

$$\begin{aligned} \mathrm{PF} = {} & 0.4927 - 0.001129 \times V - 0.3011 \times r + 0.000011 \times V^2 + 0.0797 \times a^2 + 11.95 \\ & \times f^2 + 0.2828 \times r^2 - 0.000575 \times V \times f + 0.0016 \times V \times r + 0.578 \times a \times f \\ & + 0.772 \times f \times r \end{aligned} \tag{12}$$

$$\mathrm{EC} = 184.3 - 1.277 \times V - 1594 \times f + 0.003383 \times V^2 + 5767 \times f^2 + 3.3 \times r^2 + 3.269 \times V \times f \tag{13}$$

$$\begin{aligned} \mathrm{Ra} = {} & 1.013 + 0.842 \times a - 2.327 \times r - 0.000023 \times V^2 + 0.2422 \times a^2 + 87.5 \times f^2 \\ & + 1.766 \times r^2 - 0.001375 \times V \times a - 0.002125 \times V \times f - 4.062 \times a \times f \end{aligned} \tag{14}$$

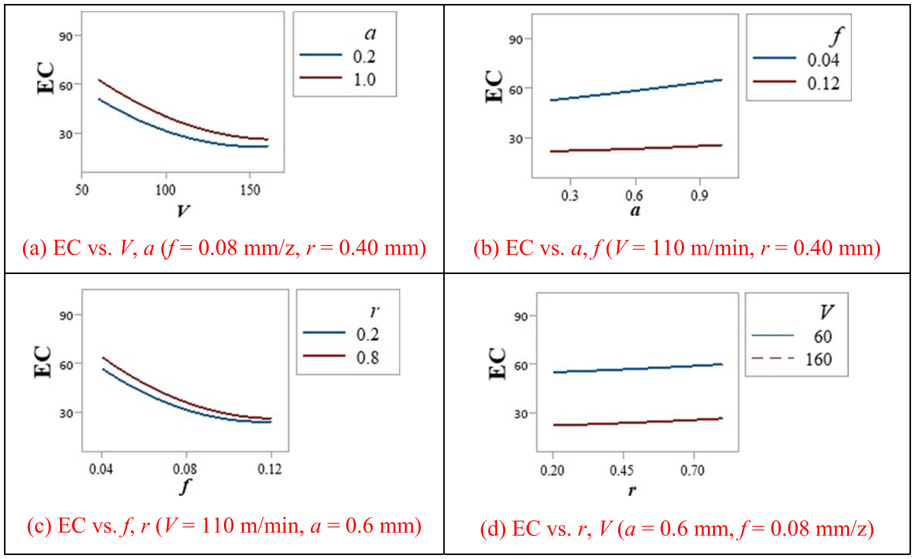

Fig. 7 Effects of milling parameters on EC. **a** EC vs. *V*, *a* (*f* = 0.08 mm/z, *r* = 0.40 mm). **b** EC vs. *a*, *f* (*V* = 110 m/min, *r* = 0.40 mm). **c** EC vs. *f*, *r* (*V* = 110 m/min, *a* = 0.6 mm). **d** EC vs. *r*, *V* (*a* = 0.6 mm, *f* = 0.08 mm/z)

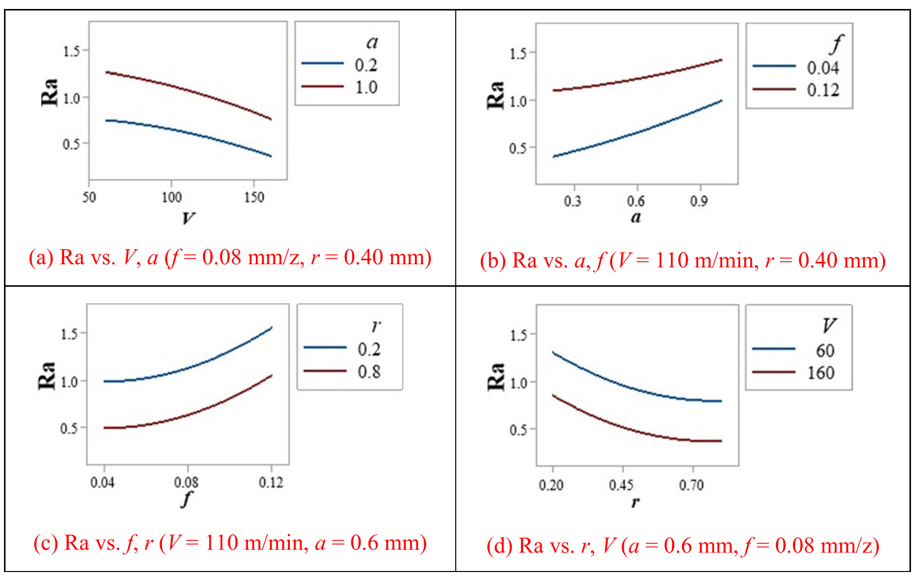

Fig. 8 Effects of milling parameters on Ra (**a**) Ra vs. *V*, *a* (*f* = 0.08 mm/z, *r* = 0.40 mm). **b** Ra vs. *a*, *f* (*V* = 110 m/min, *r* = 0.40 mm). (c) Ra vs. *f*, *r* (*V* = 110 m/min, *a* = 0.6 mm). **d** Ra vs. *r*, *V* (*a* = 0.6 mm, *f* = 0.08 mm/z)

Based on the developed RSM-based equations for the three responses, the corresponding interaction plots are now generated, as shown in Figs. 6, 7, and 8. These plots basically demonstrate the effects of the considered dry milling parameters on the responses. They would further help the process engineers in clearly understanding and selecting the best combination of milling parameters to fulfill the target requirements. As compared to desirability function approach [29], the application of SWARA-CoCoSo method suggests lower settings for both depth of cut and feed rate for weight sets 1 and 2 to attain sustainable machining performance with quality responses. It can be justified that at lower values of depth of cut and feed rate, cutting force required for removal of material from the workpiece would be much lower, thus reducing consumption of energy. On the other, lower vibration at smaller values of depth of cut and feed rate indirectly helps in improving surface quality of the machined components.

It can be noticed from Fig. 6 that higher values of cutting speed increase power consumption due to higher motor speed required to meet the increased value of spindle speed. This ultimately increases the active power, i.e., useful power resulting in increase in PF. With increasing values of both depth of cut and feed rate, the undeformed chip section increases. It is responsible for an increase in motor load to remove higher amount of material resulting in an increase in active power along with PF. Increase in nose radius also causes an increase in the power required to overcome frictional resistance, consuming more power. Thus, at higher nose radius, increase in active power causes PF to increase.

In the similar direction, increase in cutting speed triggers rise in temperature at the cutting zone reducing hardness and strength of the work material. In this condition, the cutting force required for material removal gets reduced, causing reduction in the value of EC, as depicted in Fig. 7. At lower depth of cut, requirement of cutting force is also low with decreased value of EC. Higher feed rate reduces the cutting time which is indirectly responsible for lower value of EC. Increasing nose radius would make the cutting tool blunt, resulting in more power consumption to overcome friction.

As mentioned earlier, at higher cutting speed, temperature at the cutting zone increases, thus reducing strength and hardness of the work material. This leads to less cutting force required for material removal, reducing the Ra value, as noticed in Fig. 8. At lower depth of cut and feed rate, reduced vibration during the cutting operation indirectly helps in improving the value of Ra. Higher nose radius increases the contact area between the tool and the workpiece, leading to generation of better surface quality with decreased Ra value.

Example 2

Based on Taguchi's orthogonal array, Khan et al. [12] conducted 27 green face milling experiments on AISI 1045 steel to investigate the influences of cutting speed (V), feed rate (f), depth of cut (a) and width of cut (w) on MRR, Ra, and active cutting energy (ACE). During the experiments, each of the considered milling parameters was varied at three different operating levels. The detailed experimental design plan and values of the measured responses are provided in Table 12. Using GRA technique, Khan et al. [12] determined the optimal parametric combination for the said face milling process as $V =$ 1200 rev/min, $f = 320$ mm/min, $a = 0.5$ mm, and $w = 15$ mm. This experimental dataset is now considered here as the second example to prove the effectiveness of SWARA-CoCoSo approach in solving parametric optimization problems of green dry milling processes.

Following the procedural steps of SWARA method, weights of all the responses are calculated for the three participating decision-makers. For the first decision-maker, maximum importance is allotted to MRR with the corresponding preference order of

Table 12 Experimental design plan and responses for example 2 [12]

Exp. no.	*V* (rev/min)	*f* (mm/min)	*a* (mm)	*w* (mm)	MRR (mm^3/min)	Ra (μm)	ACE (kJ)
1	1200	220	0.3	5	330	3.30	535.802
2	1200	220	0.4	10	880	2.95	184.929
3	1200	220	0.5	15	1650	1.41	88.519
4	1200	270	0.3	5	405	3.83	426.109
5	1200	270	0.4	10	1080	3.87	146.050
6	1200	270	0.5	15	2025	1.68	69.823
7	1200	320	0.3	5	480	3.97	361.832
8	1200	320	0.4	10	1280	3.53	122.976
9	1200	320	0.5	15	2400	2.29	53.988
10	1700	220	0.3	10	660	1.81	337.042
11	1700	220	0.4	15	1320	1.13	142.727
12	1700	220	0.5	5	550	3.47	299.031
13	1700	270	0.3	10	810	2.85	269.604
14	1700	270	0.4	15	1620	1.41	113.648
15	1700	270	0.5	5	675	3.91	238.476
16	1700	320	0.3	10	960	2.55	213.559
17	1700	320	0.4	15	1920	1.39	92.551
18	1700	320	0.5	5	800	4.12	193.109
19	2200	220	0.3	15	990	1.76	244.303
20	2200	220	0.4	5	440	3.33	425.797
21	2200	220	0.5	10	1100	2.36	165.620
22	2200	270	0.3	15	1215	1.17	193.939
23	2200	270	0.4	5	540	3.72	338.579
24	2200	270	0.5	10	1350	2.58	131.343
25	2200	320	0.3	15	1440	1.41	160.886
26	2200	320	0.4	5	640	3.86	286.850
27	2200	320	0.5	10	1600	2.76	108.147

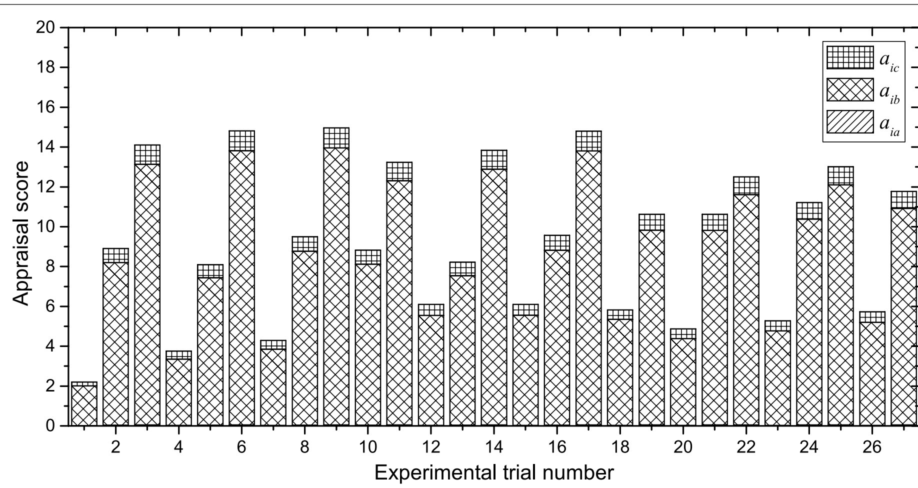

Fig. 9 Ranking of the experimental trials for weight set 1 for example 2

Table 13 Response table for final aggregation score for the three weight sets for example 2

Parameter	Weight set 1			Weight set 2			Weight set 3		
	Level			Level			Level		
	1	2	3	1	2	3	1	2	3
Cutting speed	3.5669	**3.8295**	3.7969	3.5287	**3.8313**	3.7911	3.8491	**4.1165**	4.0642
Feed rate	3.5252	3.7151	**3.9529**	3.5347	3.7017	**3.9146**	3.7551	4.0026	**4.2721**
Depth of cut	3.2452	3.7348	**4.2133**	3.2553	3.7237	**4.1720**	3.4387	4.0329	**4.5583**
Width of cut	1.9998	3.8491	**5.3444**	2.0346	3.8456	**5.2708**	2.1850	4.1702	**5.6747**

Table 14 Comparison of responses at different parametric combinations for example 2

Optimal parametric setting	*V*	*f*	*a*	*w*	MRR	Ra	ACE
GRA [12]	1200	320	0.5	15	2400	2.2900	53.9800
CoCoSo method (weight sets 1, 2, and 3)	1700	320	0.5	15	2400	1.9434	52.7740
Improvement (%)						15.1354	2.2342

the responses set as MRR (0.4000)→Ra (0.3333)→ACE (0.2667). Similarly, the preference order of the responses for the second decision-maker is set as Ra (0.3548)→MRR (0.3379)→ACE (0.3072). The preference order of the responses for the third decision-maker is considered as ACE (0.3574)→Ra (0.3437)→EC (0.2989). Likewise the first example, based on the application steps of CoCoSo method, the experimental data is normalized depending on the type of the responses. The power of weighted comparability sequence, sum of weighted comparability sequence, appraisal score and final appraisal score for each of the experimental trials are subsequently computed. Figure 9 plots these appraisal scores for all the alternative experiment trials for weight set 1. This figure reveals that experiment run number 9 ($V = 1200$ rev/min, $f = 320$ mm/min, $a = 0.5$ mm, and $w = 15$ mm) with the maximum appraisal score of 5.8832 is the most suitable parametric intermix for the green face milling operation at weight set 1 (when maximum importance is assigned to MRR). This observation exactly matches with that of Khan et al. [12].

In Table 13, average values of the final appraisal scores at the corresponding parametric levels of the experimental trials for all the considered weight sets are provided. In this table, the maximum values of the average appraisal scores are marked in bold face. It can be interestingly noticed that for the three different weight sets, $V = 1700$ rev/min, $f = 320$ mm/min, $a = 0.5$ mm, and $w = 15$ mm emerge out as the optimal parametric combination for the green face milling operation. This intermix of the milling parameters differs from that derived by Khan et al. [12] only with respect to cutting speed. A lower cutting speed was suggested by Khan et al. [12], whereas, SWARA-CoCoSo method-based analysis recommends a moderate setting of cutting speed. Although a lower cutting speed would provide better surface quality of the machined components along with consumption of minimum active energy, but the achievable MRR (which is proportional to machining/production rate) would decrease. On the other hand, higher cutting speed would lead to higher MRR, but it has a detrimental effect on surface quality with increased consumption of active energy. Thus, the adopted approach suggests a moderate setting of cutting speed leading to simultaneous optimization of all the responses under consideration.

Using the RSM-based equations developed taking into account only the statistically significant terms, the corresponding response values at the SWARA-CoCoSo method-based parametric combination are now derived, as shown in Table 14. This table also provides the response values as obtained by Khan et al. [12] while solving this problem using GRA technique. It can be noticed that although the optimal parametric intermix derived using SWARA-CoCoSo method predicts the same MRR value, but there are respectively 15.13 and 2.23% improvements in the values of Ra and ACE. This again proves the applicability and potentiality of SWARA-CoCoSo approach in solving parametric optimization problems of green dry milling processes. For this problem, interaction plots (not shown here due to paucity of space) can also be developed to depict influences of different milling parameters on the considered responses.

Conclusions

This paper proposes an integrated application of SWARA and CoCoSo methods for solving parametric optimization problems for two green dry milling process leading to sustainable manufacturing environment. Based on the detailed analysis, the following conclusions can be drawn:

a) Instead of assigning equal weights to the considered responses, SWARA method allocates different weight sets to those responses keeping in mind varying requirements of all the stakeholders. This may lead to different parametric intermixes for fullest exploration of the machining capability of the said process.
b) In the first example, the optimal parametric condition as $V = 160$ m/min, $a = 0.2$ mm, $f = 0.08$ mm/z, and $r = 0.8$ mm for weight sets 1 and 2 would result in 4.01, 3.40, and 15.79% improvements in the values of PF, EC, and Ra respectively against the past observations.
c) On the other, for the first example, the parametric mix as $V = 160$ m/min, $a = 1$ mm, $f = 0.08$ mm/z, and $r = 0.8$ mm for weight set 3 achieves 17.59 and 3.40% improvements for PF and EC respectively, but the Ra value is worsened by 12.02% as compared to the past findings.
d) In the second example, the optimal parametric intermix as $V = 1700$ rev/min, $f = 320$ mm/min, $a = 0.5$ mm and $w = 15$ mm for all the weight sets provides 15.13 and 2.23% improvements in the values of Ra and ACE respectively, but the MRR value remains the same.
e) The interaction plots would help in studying the influences of the milling parameters on the responses.
f) Thus, this integrated method, being simple, easy to implement and free from any complex calculation, can act as an effective multi-objective optimization tool for identifying the optimal parametric mixes for various machining processes.

In this paper, as all the analyses are performed based on past experimental data, there is no scope for validation of the derived results using confirmatory trials. Involvement of different stakeholders (manufacturers, machine operators, and end users) while assigning varying importance to the responses, aggregation of power of weighted and sum of weighted comparability sequences, easily understandable mathematical steps, minimum dependency on algorithm-specific parameters etc. may make this approach as an effective multi-objective optimization tool for solving parametric optimization problems of diverse machining processes. The potentiality of other subjective criteria weighting techniques, like pivot pairwise relative criteria importance assessment (PIPRECIA) and best worst method, may be explored for assigning relative importance to the responses. As a future scope, SWARA method may also be combined with other yet to be popular MCDM techniques, like multi-attributive border approximation area comparison (MABAC) and multi-attributive real-ideal comparative analysis (MARICA) for solving parametric optimization problems for green and sustainable machining processes.

Abbreviations

ACE: Active cutting energy; CoCoSo: COmbined COmpromise SOlution; EC: Energy consumption; MOORA: Multi-Objective Optimization based on Ratio Analysis; NSGA-II: Non-dominated Genetic Algorithm-II; PSO: Particle Swarm Optimization; GA: Genetic Algorithm; PIPRECIA: PIvot Pairwise RElative Criteria Importance Assessment; GRA: Grey relational analysis; PF: Power factor; MRR: Material removal rate; Ra: Average surface roughness; MABAC: Multi-Attributive Border Approximation area Comparison; RSM: Response Surface Methodology; MCDM: Multi-criteria decision-making; SWARA: Step-wise weight assessment ratio analysis; MARICA: Multi-attributive real-ideal comparative analysis; TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution.

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Authors' contributions

PPD: data collection, mathematical analysis, and draft writing. SC: literature review and technical editing. The authors read and approved the final manuscript.

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Declarations

Competing interests

The authors declare that they have no competing interests.

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