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Enhancing efficiency in photo chemical machining: a multivariate decision-making approach

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Non-Traditional Machining (NTM) outperforms traditional processes by offering superior geometric and dimensional accuracy, along with a better surface finish. Photo Chemical Machining (PCM) represents one such NTM process, using chemical etching for material removal. PCM finds substantial application in the creation of microchannels in pharmaceutical, chemical and energy industries. Several input parameters—such as etchant concentration, etching time and etchant temperature—profoundly influence the machining's quality and efficiency. Therefore, the optimization of these parameters is crucial. This study presents a comparative analysis of five Multiple Criteria Decision Making (MCDM) techniques—Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), Additive Ratio Assessment (ARAS), Weighted aggregated sum product assessment method (WASPAS) and Multi-Attributive Border Approximation Area Comparison Method (MABAC)—for the optimization of the PCM process. Key performance metrics considered are Material Removal Rate (*MRR*), Surface Roughness (*SR*), Undercut (U_c) and etch factor (*EF*). The weights of these criteria were calculated using the Criterion-Induced Aggregation Technique (CRITIC) and was compared with other popular methods like MEREC, Entropy and equal weights. *MRR* and *EF* are seen as beneficial criteria, while *SR* and U_c are perceived as cost criteria. Optimum process parameters were identified as 850 g/L etchant concentration, 40 min etching time and 70°C etchant temperature. Two of the three employed MCDM techniques agreed on these optimal parameters, reinforcing the findings. Furthermore, a strong correlation was observed amongst the employed MCDM techniques, further validating the results.

KEYWORDS

photochemical machining, MCDM, TOPSIS, MOORA, ARAS, non-traditional machining

1 Introduction

As the demand for superior dimensional and geometric accuracy rises, various non-traditional machining processes are gaining industrial prominence. The manufacturing of microfluidic devices in pharmaceutical and biotechnological industries necessitates exceptional dimensional accuracies, achievable only through a select few non-traditional machining processes (Wangikar et al., 2019). One such process is Photo-Chemical Machining (PCM), which employs photochemical etching for material removal, enabling the machining of intricate shapes with high dimensional accuracy. PCM leverages highly accelerated yet controlled corrosion to remove material from the bulk (Wangikar et al., 2017).

TABLE 1 Weights allocated under different methods.

Weight allocation method	*EF*	*MRR*	*SR*	U_c
MEREC	0.1132	0.3095	0.4173	0.1600
CRITIC	0.2243	0.2650	0.2200	0.2907
Entropy	0.0743	0.1172	0.6376	0.1708
Equal	0.2500	0.2500	0.2500	0.2500

Recently, PCM has garnered significant interest from the scientific community due to its advantages, such as high dimensional accuracy, negligible residual stress and improved surface finish. Agrawal et al. (Agrawal et al., 2021) utilized PCM to machine SS-430 and conducted parametric optimization using Taguchi-Grey Relation Analysis to identify optimum process parameters. Their findings indicated that a lower concentration

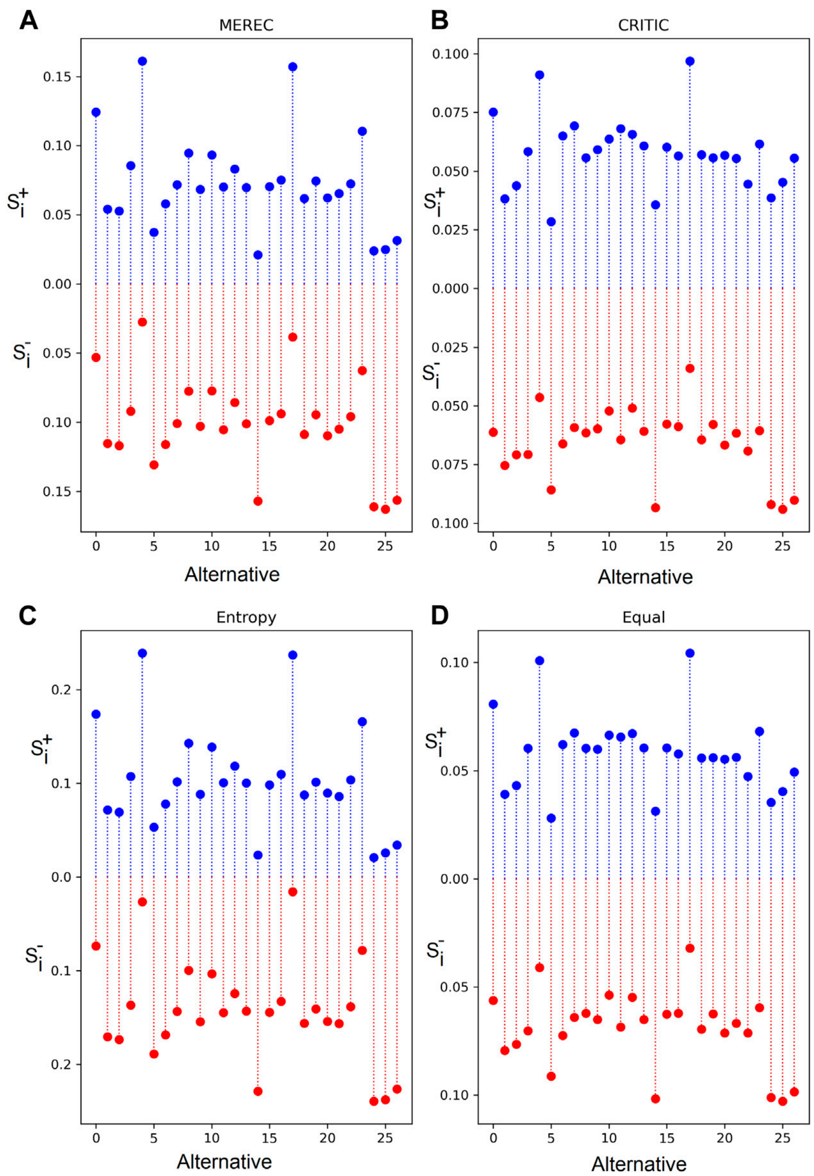

FIGURE 1
Plot of Euclidean distance versus alternatives for weights calculated by **(A)** MEREC, **(B)** CRITIC, **(C)** Entropy and **(D)** Equal weights.

TABLE 2 TOPSIS rank under various weight.

Sr. No.	MEREC		CRITIC		Entropy		Equal	
	CC_i	Rank	CC_i	Rank	CC_i	Rank	CC_i	Rank
1	0.2996	25	0.4487	24	0.2970	25	0.4105	25
2	0.6808	7	0.6635	5	0.7044	7	0.6703	5
3	0.6892	6	0.6181	7	0.7148	6	0.6400	7
4	0.5182	20	0.5478	9	0.5601	19	0.5377	13
5	0.1453	27	0.3373	26	0.0990	26	0.2890	26
6	0.7781	5	0.7509	1	0.7800	5	0.7647	2
7	0.6671	8	0.5045	16	0.6840	8	0.5382	12
8	0.5840	16	0.4609	22	0.5849	16	0.4867	21
9	0.4502	23	0.5248	13	0.4108	23	0.5071	20
10	0.6009	12	0.5026	17	0.6360	11	0.5204	15
11	0.4536	22	0.4500	23	0.4266	22	0.4473	24
12	0.6002	13	0.4860	21	0.5897	14	0.5107	18
13	0.5073	21	0.4363	25	0.5122	21	0.4491	23
14	0.5923	14	0.4997	18	0.5876	15	0.5182	17
15	0.8820	1	0.7233	2	0.9067	2	0.7649	1
16	0.5843	15	0.4896	20	0.5950	13	0.5090	19
17	0.5556	19	0.5096	15	0.5473	20	0.5190	16
18	0.1962	26	0.2598	27	0.0621	27	0.2348	27
19	0.6379	10	0.5304	11	0.6403	10	0.5545	10
20	0.5596	18	0.5099	14	0.5807	17	0.5271	14
21	0.6383	9	0.5399	10	0.6318	12	0.5630	9
22	0.6158	11	0.5265	12	0.6452	9	0.5432	11
23	0.5699	17	0.6088	8	0.5714	18	0.6007	8
24	0.3616	24	0.4956	19	0.3207	24	0.4662	22
25	0.8709	2	0.7044	3	0.9199	1	0.7410	3
26	0.8683	3	0.6751	4	0.9025	3	0.7181	4
27	0.8324	4	0.6184	6	0.8688	4	0.6664	6

of etchant combined with high temperature and etching time yielded optimum results. Misal et al. (Misal et al., 2017) employed ferric chloride as an etchant to machine Inconel 718 using the PCM process, observing that the etchant's temperature and etching time significantly influenced surface roughness.

Given PCM's diverse applications, it is crucial to select optimum process parameters directly impacting machining quality. Multi-Criteria Decision Making (MCDM) techniques are widely used in various fields of study for process parameter optimization. Das and Chakraborty (Das and Chakraborty, 2022) applied a Grey Correlation-based EDAS technique for PCM, Laser-Assisted Jet Electro-Chemical Machining and Abrasive Water Jet Drilling process optimization. They accurately predicted optimum process parameters and confirmed these using regression equations. Chakraborty et al. (Chakraborty et al., 2020) used the Multi-Attributive Border Approximation Area Comparison Method (MABAC) approach to select the best non-traditional machining process. They successfully tested the method's validity through two different scenarios, concluding that rough numbers could be effectively used with the MABAC technique for MCDM problems. Deosant et al. (Deosant et al., 2021) integrated the AHP with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to select suitable non-traditional micro-machining processes. Their study highlighted electrical discharge machining as the most effective technique among the various techniques considered.

Kalita et al. (Kalita et al., 2022) conducted a comparative study of various MCDM techniques for milling process optimization. They

TABLE 3 Ranking using MOORA.

Sr. No.	MEREC		CRITIC		Entropy		Equal	
	y_i	Rank	y_i	Rank	y_i	Rank	y_i	Rank
1	0.1131	3	0.0596	3	0.1728	3	0.0678	3
2	0.0459	24	0.0242	27	0.0701	21	0.0275	26
3	0.0435	25	0.0279	26	0.0664	22	0.0260	27
4	0.0691	9	0.0364	19	0.1055	9	0.0414	13
5	0.1562	1	0.0824	1	0.2387	1	0.0936	1
6	0.0399	26	0.0342	22	0.0518	23	0.0322	24
7	0.0463	23	0.0522	8	0.0708	20	0.0449	11
8	0.0629	13	0.0533	6	0.0962	13	0.0458	8
9	0.0931	5	0.0491	9	0.1422	5	0.0557	5
10	0.0556	17	0.0322	24	0.0849	17	0.0333	22
11	0.0896	6	0.0473	10	0.1369	6	0.0537	6
12	0.0622	14	0.0549	5	0.0951	14	0.0472	7
13	0.0754	7	0.0398	16	0.1152	7	0.0452	10
14	0.0632	12	0.0436	12	0.0966	12	0.0379	18
15	0.0481	22	0.0412	15	0.0204	26	0.0388	16
16	0.0621	15	0.0395	17	0.0949	15	0.0372	20
17	0.0702	8	0.0370	18	0.1073	8	0.0421	12
18	0.1541	2	0.0813	2	0.2355	2	0.0923	2
19	0.0547	18	0.0428	14	0.0835	18	0.0368	21
20	0.0648	11	0.0342	21	0.0990	11	0.0388	17
21	0.0561	16	0.0440	11	0.0857	16	0.0379	19
22	0.0543	19	0.0309	25	0.0830	19	0.0325	23
23	0.0674	10	0.0355	20	0.1029	10	0.0404	15
24	0.1083	4	0.0571	4	0.1654	4	0.0649	4
25	0.0379	27	0.0333	23	0.0196	27	0.0306	25
26	0.0504	21	0.0431	13	0.0251	25	0.0407	14
27	0.0510	20	0.0530	7	0.0311	24	0.0456	9

used entropy weight calculation with six MCDM techniques and compared the ranks obtained, suggesting that objective weight calculation performs better with robust data. Shanmugasundar et al. (Shanmugasundar et al., 2022) utilized Method Based on the Removal Effects of Criteria (MEREC) weight calculation with various MCDM techniques for industrial robot selection, presenting a comparative study among various MCDM techniques to identify the drawbacks and advantages of the techniques used. Kumari and Acherjee (Kumari and Acherjee, 2022) applied a Criterion-Induced Aggregation Technique (CRITIC)—COmbinative Distance-based ASsessment (CODAS)-based technique to select the best non-conventional machining process among eight processes based on six different criteria. Their method's comparison with established methods demonstrated good performance. Pathapalli et al. (Pathapalli et al., 2020) developed an aluminium composite using the stir casting process and optimized turning process parameters using Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) and weighted aggregated sum product assessment method (WASPAS) techniques. A comparative study revealed that both techniques work well for turning parameter optimization. Goswami et al. (Goswami et al., 2021) used an Additive Ratio Assessment (ARAS)-TOPSIS hybrid MCDM technique for robot selection among twelve industrial robots based on five contrasting criteria, suggesting that objective weight determination techniques are free from decision-maker biases and, thus, superior to subjective methods.

From the aforementioned literature, it is clear that MCDM techniques are widely used for selecting optimum process

TABLE 4 Rank Calculation using ARAS.

Sl. No.	MEREC		CRITIC		Entropy		Equal	
	K_i	Rank	K_i	Rank	K_i	Rank	K_i	Rank
1	3.1932	12	2.0379	24	5.4508	4	2.1792	21
2	2.5375	23	2.0565	23	3.3205	22	2.0907	23
3	2.6082	21	2.1742	21	3.3797	21	2.1791	22
4	2.4145	25	1.7280	27	3.7915	18	1.8141	27
5	4.2585	2	2.6062	6	7.3384	2	2.7626	4
6	2.6877	18	2.3081	16	3.1157	23	2.3277	16
7	2.9408	16	2.4411	13	3.7971	17	2.3772	13
8	3.2796	8	2.5989	7	4.4636	10	2.5503	8
9	3.7655	4	2.7394	3	5.4017	5	2.8067	2
10	2.6113	20	2.0343	25	3.7189	19	2.0253	25
11	3.6807	5	2.6926	4	5.3287	6	2.7149	5
12	3.4629	6	2.7640	2	4.5642	8	2.7125	6
13	3.1993	11	2.3937	14	4.6656	7	2.3890	12
14	3.2359	9	2.5239	9	4.3750	11	2.4968	10
15	2.4158	24	2.3038	17	2.3163	25	2.2544	19
16	3.0039	14	2.3380	15	4.1831	13	2.3210	17
17	3.2799	7	2.5059	10	4.5507	9	2.5095	9
18	4.9003	1	3.2256	1	7.8854	1	3.2919	1
19	3.0770	13	2.4702	11	4.0460	16	2.4397	11
20	2.9117	17	2.2909	18	4.1807	14	2.3134	18
21	3.2309	10	2.5925	8	4.1856	12	2.5615	7
22	2.6505	19	2.0798	22	3.7008	20	2.0745	24
23	2.9815	15	2.2690	20	4.1729	15	2.3317	15
24	3.8471	3	2.6910	5	5.8198	3	2.8011	3
25	2.0255	27	2.0020	26	1.8579	27	1.9397	26
26	2.3465	26	2.2808	19	2.1475	26	2.1974	20
27	2.5730	22	2.4596	12	2.5579	24	2.3633	14

parameters in multi-objective problems. Although these techniques have been extensively applied across various domains, the optimization of PCM process parameters using MCDM techniques remains underexplored. Moreover, a comparative study of various MCDM techniques in the PCM process using objective weight determination methods has yet to be conducted. The current study attempts to bridge this gap by comparing five MCDM techniques—TOPSIS, MOORA, ARAS, WASPAS, and MABAC—using four different objective weight determination techniques namely, CRITIC, MEREC, Entropy along with equal weights to optimize PCM process parameters. Additionally, a correlation analysis is presented to elucidate the similarities and differences between the techniques employed.

2 Materials and methods

2.1 Experimental procedure

The experimental data for this study were derived from Agarwal and Kamble (Agrawal and Kamble, 2019). Stainless Steel-304 (SS-304) was selected as the substrate material for the PCM process. The etchant was prepared by dissolving ferric chloride in water, with precise weighing of ferric chloride to ensure the desired concentration. Prior to the application of the photoresist coating, the specimen was thoroughly cleaned with acetone and water. The coated material and phototool were then exposed to UV light. The portions not covered by the phototool and exposed to UV light remained unetched post-machining.

TABLE 5 Rank calculation using WASPAS.

Sl. No.	MEREC		CRITIC		Entropy		Equal	
	Q_{WASPAS}	Rank	Q_{WASPAS}	Rank	Q_{WASPAS}	Rank	Q_{WASPAS}	Rank
1	1.1487	25	1.3471	10	1.4392	23	1.2842	10
2	1.7259	6	1.4929	6	2.3152	6	1.5082	6
3	1.7035	7	1.3873	8	2.3015	7	1.4203	7
4	1.3775	16	1.4123	7	1.8604	13	1.3770	9
5	0.9557	26	1.0889	24	1.0931	26	1.0464	26
6	2.1055	5	1.7097	5	2.8347	5	1.7533	5
7	1.5822	8	1.1891	15	2.0904	8	1.2248	15
8	1.3599	18	1.0804	25	1.7064	19	1.1010	23
9	1.2876	21	1.2485	12	1.4759	22	1.2401	13
10	1.3943	15	1.1384	20	1.8798	12	1.1538	21
11	1.2128	24	1.0950	23	1.4208	24	1.0952	24
12	1.4212	13	1.1331	21	1.7440	16	1.1560	20
13	1.2239	22	1.0409	26	1.5329	21	1.0474	25
14	1.3976	14	1.1422	19	1.7434	17	1.1585	19
15	4.0787	3	2.5674	3	6.2574	3	2.7672	3
16	1.3658	17	1.1224	22	1.7532	15	1.1380	22
17	1.3504	19	1.1629	18	1.6612	20	1.1725	18
18	0.9210	27	0.8940	27	0.9755	27	0.8808	27
19	1.5068	10	1.2069	14	1.9252	10	1.2316	14
20	1.3394	20	1.1680	17	1.7384	18	1.1841	17
21	1.5217	9	1.2269	13	1.9074	11	1.2515	12
22	1.4450	12	1.1867	16	1.9328	9	1.2034	16
23	1.4655	11	1.3852	9	1.8394	14	1.3796	8
24	1.2223	23	1.2803	11	1.3911	25	1.2567	11
25	6.9396	1	3.9391	1	11.4063	1	4.3407	1
26	6.0844	2	3.4833	2	9.7714	2	3.8277	2
27	3.7577	4	2.3030	4	5.7128	4	2.4909	4

Agarwal and Kamble (Agrawal and Kamble, 2019) identified three input variables that were of prime significance following an extensive literature survey. These three input parameters: concentration of etchant, etching time and temperature of the etchant were varied between three levels to conduct 27 experimental runs based on Taguchi orthogonal array experimental design. Concentration of etchant was measured in gm/ltrs and denotes the strength of etchant, etching time was measured in minutes and denotes the time for which the material was exposed to the etchant. Etchant was also used in an elevated temperature to expedite the process of chemical etching and the temperature was measured in °C. Three levels of all these factors are presented in Table A1. The Material Removal Rate (MRR), Surface Roughness (SR), Etch Factor (EF) and Undercut (U_c) were measured and documented (Table A2).

2.2 Multi criteria decision making

Five MCDM techniques namely, TOPSIS, MOORA, ARAS, WASPAS, and MABAC methods were used to identify the compromise optimum values of responses variables. Weight of the response variables were calculated using CRITIC, MEREC and Entropy methods and a comparison was made with the case when equal weights are assigned to all criteria. All the MCDM techniques used in the current work are discussed in detail in the

TABLE 6 Rank calculation using MABAC.

Sl. No.	MEREC		CRITIC		Entropy		Equal	
	S_i	Rank	S_i	Rank	S_i	Rank	S_i	Rank
1	−0.1945	25	−0.0127	14	−0.1428	25	−0.0341	17
2	0.1021	6	0.1564	7	0.1484	6	0.1565	8
3	0.0737	8	0.0830	10	0.1179	7	0.0891	10
4	−0.0853	23	0.0249	11	0.0260	11	0.0117	12
5	−0.2810	27	−0.0915	22	−0.3333	26	−0.1184	23
6	0.2555	3	0.3086	1	0.2459	4	0.3180	1
7	0.0031	16	−0.1100	23	0.0171	13	−0.1033	22
8	−0.0354	18	−0.1301	25	−0.0504	21	−0.1258	24
9	0.0653	10	0.1633	6	−0.0215	20	0.1596	7
10	−0.0820	22	−0.1229	24	−0.0045	15	−0.1280	25
11	−0.0274	17	−0.0140	16	−0.0865	24	−0.0189	16
12	0.0333	12	−0.0586	19	−0.0210	19	−0.0521	19
13	−0.0979	24	−0.1345	26	−0.0851	23	−0.1394	26
14	0.0098	15	−0.0502	18	−0.0113	17	−0.0507	18
15	0.3060	1	0.2570	2	0.3091	1	0.2739	2
16	−0.0412	20	−0.0891	21	−0.0203	18	−0.0905	21
17	0.0127	13	0.0029	13	−0.0107	16	0.0012	13
18	−0.2479	26	−0.1960	27	−0.3923	27	−0.2115	27
19	0.0393	11	−0.0193	17	0.0305	10	−0.0163	15
20	−0.0407	19	−0.0134	15	−0.0001	14	−0.0081	14
21	0.0773	7	0.0219	12	0.0406	9	0.0260	11
22	−0.0444	21	−0.0746	20	0.0196	12	−0.0785	20
23	0.0730	9	0.1683	5	0.0772	8	0.1660	4
24	0.0105	14	0.1722	3	−0.0669	22	0.1653	5
25	0.2322	4	0.1504	8	0.2968	2	0.1623	6
26	0.2801	2	0.1704	4	0.2930	3	0.1862	3
27	0.2300	5	0.0996	9	0.2299	5	0.1203	9

following sections. It should be noted here that for all the methods discussed, in an MCDM problem having m alternatives and n criteria, the decision matrix is a matrix $X = [x_{ij}]_{mxn}$; where x_{ij} is the performance value associated with the i th alternative under j th criterion.

2.2.1 CRITIC weight calculation

CRITIC was proposed by Diakoulaki et al. (Diakoulaki et al., 1995) in 1995 as an objective weight determination method. The primary advantage of objective weighting method is that it omits any preferences that the decision maker might have with respect to any criteria. The internal contrasts within a criterion and conflict intensity between criteria are assessed to assign weights to them using CRITIC method. Steps involved in CRITIC method are as follows:

Step 1: Formulation of the decision matrix.

Step 2: Decision matrix is normalized using Eq. 1,

$$r_{ij} = \frac{x_{ij}-x_j^{worst}}{x_j^{best}-x_j^{worst}} \tag{1}$$

Step 3: Pearson Correlation Coefficient is used to determine the degree of correlation. It is calculated using Eq. 2

$$CF_{jk} = \frac{\sum_{i=1}^{m}\left(r_{ij}-\bar{r}_j\right)\left(r_{ik}-\bar{r}_k\right)}{\sqrt{\sum_{i=1}^{m}\left(r_{ij}-\bar{r}_j\right)^2\sum_{i=1}^{m}\left(r_{ik}-\bar{r}_k\right)^2}} \tag{2}$$

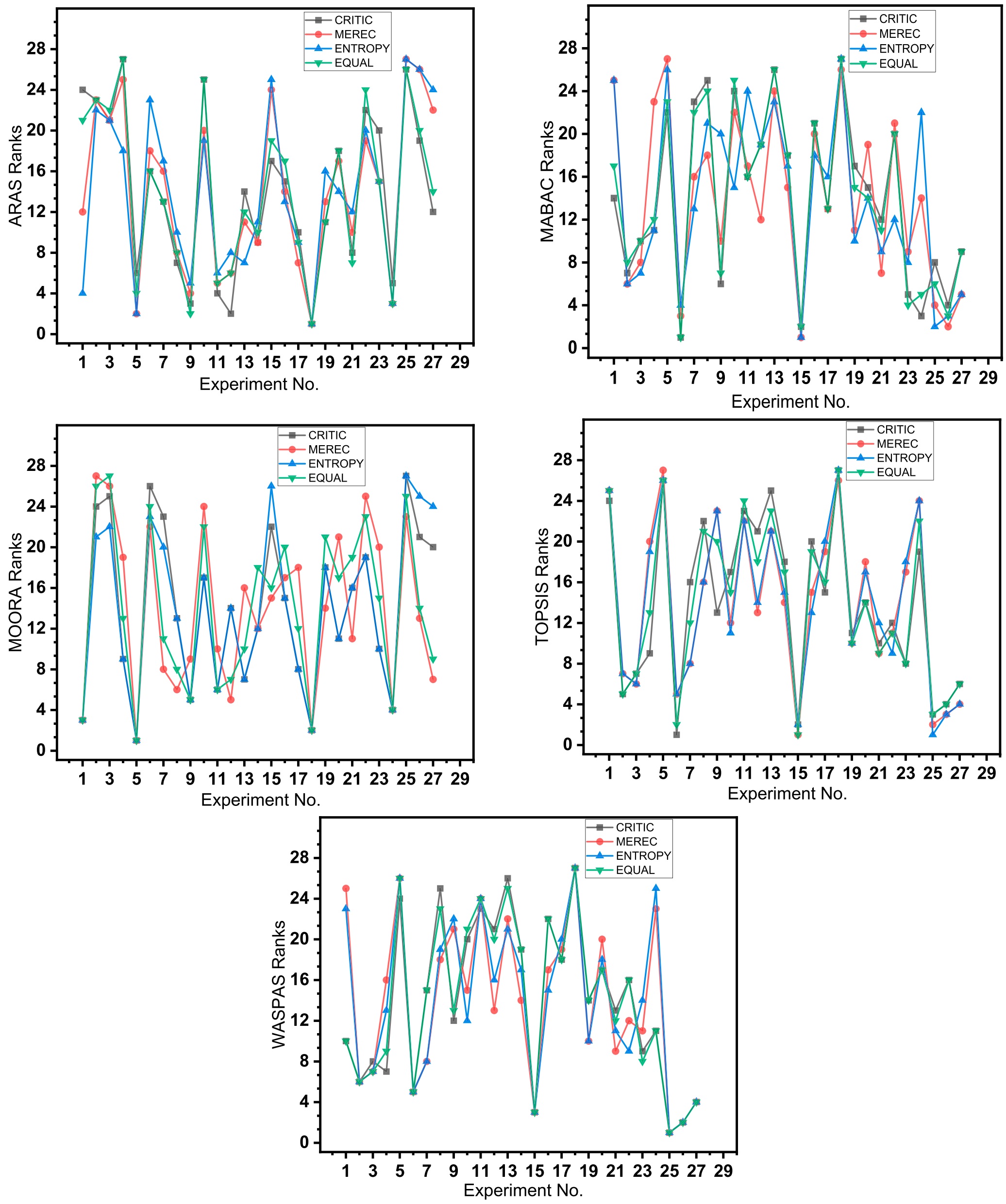

FIGURE 2
Ranks Comparison among various weights.

Step 4: Weights of the criteria is calculated using Eqs 3, 4,

$$c_j = \sigma_j \sum_{k=1}^{n} 1\text{-}CF_{jk} \tag{3}$$

$$w_j = \frac{c_j}{\sum_{j=1}^{n} c_j} \tag{4}$$

w_j is the weight of the j th criteria.

2.2.2 MEREC weight calculation

MEREC is a weight evaluation method developed in 2019 by Ghorabaee et al. (Keshavarz-Ghorabaee et al., 2021) to assess weights based on deviation of performance ratings on removal of a criteria. The weights reflect the effect it has on performance rating if the criteria were omitted from the decision-making process. The procedural steps involved in this method are as follows.

Step 1: A normalized decision matrix P is formulated from the matrix X wherein each element of the matrix P is defined as in Eq. 5

$$p_{ij} = \frac{\min(x_{kj})}{x_{ij}} \; if \; j\epsilon B$$
$$p_{ij} = \frac{x_{ij}}{\max(x_{kj})} \; if \; j\epsilon C \tag{5}$$

Step 2: An index S_i is calculated which signifies the overall performance of the alternatives in a logarithmic scale using Eq. 6

$$S_i = ln\left(1 + \left(\frac{1}{m}\sum_j \left|ln\left(p_{ij}^x\right)\right|\right)\right) \quad (6)$$

Step 3: Similarly, an index S'_{ij} is calculated which signifies the overall performance of the alternatives by excluding the criteria in a logarithmic scale using Eq. 7,

$$S'_{ij} = ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j} \left|ln\left(p_{ik}^x\right)\right|\right)\right) \quad (7)$$

Step 4: Absolute deviation D is calculated by subtracting one performance rating with other. Absolute value of the difference is taken as the deviation. It can be mathematically represented as in Eq. 8,

$$D_j = \sum\left|S'_{ij} - S_i\right| \quad (8)$$

Step 5: Weights of each alternative is calculated using Eq. 9,

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (9)$$

2.2.3 Entropy weight calculation

Entropy weights was adopted into MCDM problems from the concept of Shannon entropy developed by Shannon in 1948 as a concept in probabilities. This method works on the premise that the higher weight should be assigned to the criteria that carries the maximum information in a decision-making process. The procedural steps involved in this method are as follows:

Step 1: The decision matrix is normalized using Eq. 10,

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (10)$$

Step 2: Entropy is then calculated as in Eq. 11,

$$\mathrm{e_j} = -\frac{\sum_{i=1}^{m} p_{ij} \log p_{ij}}{\log m} \quad (11)$$

Step 3: The weight from the Entropy value is calculated using Eq. 12,

$$w_j = \frac{1 - e_j}{\sum_{i=1}^{n}\left(1 - e_j\right)} \quad (12)$$

where $1 - e_j$ is called divergence value.

2.2.4 Technique for order of preference by similarity to ideal solution (TOPSIS)

TOPSIS was initially presented by Yoon and Hwang (Yoon and Hwang, 1981) in 1981 and is among the most popular MCDM technique that has been applied in various areas of study. Distance from the ideal best and ideal worst solution in the Euclidean scale is used to identify the best alternative in this method. Steps involved in TOPSIS method are presented below:

Step 1: Decision matrix is normalized using Eq. 13,

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (13)$$

Step 2: Weighted normalized matrix is calculated by multiplying the normalized decision matrix by their corresponding criteria weights using Eq. 14.

$$r_{ij} = n_{ij} \times w_j \quad (14)$$

Step 3: Euclidean distances from the ideal best and ideal worst solutions are calculated using Eqs 15, 16,

$$S_i^+ \sqrt{\sum_{j=1}^{n}\left(r_{ij} - A_j^+\right)^2}{}'; A_j^+ \begin{cases} \max\left(r_{ij}\right) \text{ for benefit criteria} \\ \min\left(r_{ij}\right) \text{ for cost criteria} \end{cases} \quad (15)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(r_{ij} - A_j^-\right)^2}; A_j^- \begin{cases} \max\left(r_{ij}\right) \text{ for cost criteria} \\ \min\left(r_{ij}\right) \text{for benefit criteria} \end{cases} \quad (16)$$

Step 4: Closeness coefficient is calculated using Eq. 17 and the alternatives are ranked based on CC_i in descending order.

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (17)$$

2.2.5 Multi-objective optimization on the basis of ratio analysis method (MOORA)

MOORA was used by Chakraborty (Chakraborty, 2011) to solve decision making problem for various applications in different manufacturing environments. Brauers et al. (Brauers et al., 2008) compared various ratios and suggested that the best choice as denominator is the square root of sum of squares which is considered in MOORA. The steps involved in MOORA is same as TOPSIS until the weighted normalized decision matrix is obtained. The steps after that are as follows

Step 1: After obtaining the weighted normalized decision matrix following Step 1 and Step 2 of TOPSIS, performance score is calculated as

$$y_i = \sum_{j=1}^{g} r_{ij} - \sum_{j=g+1}^{n} r_{ij} \quad (18)$$

where criteria 1 to criteria "g" are the beneficial criteria

Step 2: Rank the criteria based on performance score in descending order. The highest performance score will be ranked first.

2.2.6 Additive ratio assessment (ARAS)

ARAS method was presented by Zavadskas and Turskis (Zavadskas and Turskis, 2010) in the year 2010 as an MCDM technique that is simple and effective. ARAS method assumes that the effectiveness of an alternative is directly proportional to performance value under a criteria and weight of the criteria. This is the underlying principle behind the working of this technique. The steps in the ARAS method are as follows-

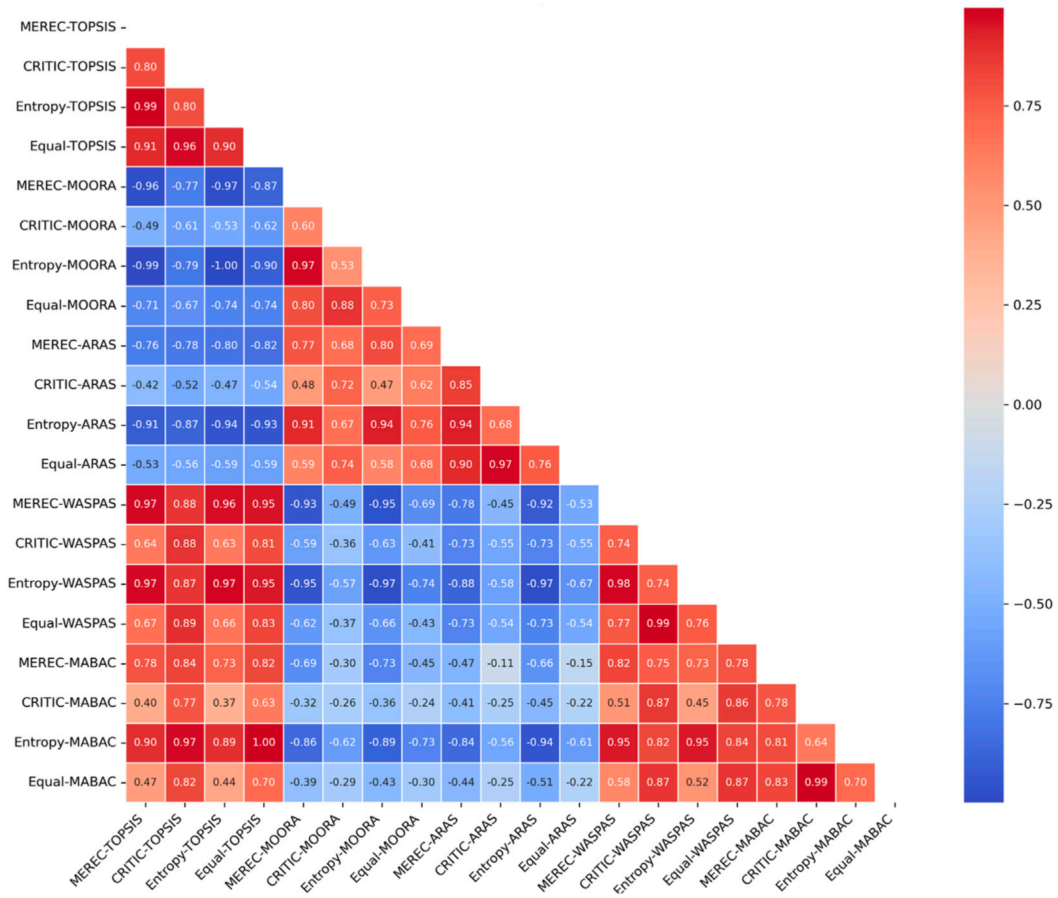

FIGURE 3
Correlation heatmap of all methods.

Step 1: Normalization of the decision matrix is done using one of the two equations depending on whether the criteria is beneficial or cost

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}; \text{for beneficial criteria} \tag{19}$$

$$n_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}}; \text{for cost criteria} \tag{20}$$

Step 2: Weighted normalized decision matrix is calculated using Eq. 21,

$$r_{ij} = n_{ij} \times w_j \tag{21}$$

Step 3: Optimality function is calculated as follows

$$S_i = \sum_{j=1}^{n} r_{ij} \tag{22}$$

Step 4: Degree of utility is computed using Eq. 23 and alternatives are ranked in the descending order of the obtained value.

$$K_i = \frac{S_i}{S_0} \tag{23}$$

2.2.7 Weighted aggregated sum product assessment method

WASPAS method was suggested by Zavadskas et al. (Zavadskas et al., 2012) in 2012 as a hybrid MCDM technique that combined two pre-existing techniques. The accuracy of WASPAS was seen to be better than its parent techniques (Zavadskas and Turskis, 2010). Combined effect of weighted sum and product is calculated and the final index is used to rank the alternatives in this method. The steps involved in this method are discussed below:

Step 1: Normalization of the decision matrix is done using Eqs 24, 25,

$$n_{ij} = \frac{x_{ij}}{\max_i (x_{ij})} \text{ for benificial criteria} \tag{24}$$

$$n_{ij} = \frac{\min_i (x_{ij})}{x_{ij}} \text{ for cost criteria} \tag{25}$$

Step 2: Relative importance of alternative using the sum approach is calculated as follows

$$Q_{WAS} = \sum_{i=1}^{n} x_{ij} \times w_j \tag{26}$$

Step 3: Relative importance of alternative using the product approach is also calculated using the following equation

$$Q_{WAP} = \prod_{i=1}^{n} x_{ij}^{w_j} \tag{27}$$

Step 4: Combined importance of alternatives is calculated using the following Eq. 28,

$$Q_{WASPAS} = \alpha \times Q_{WAS} + (1-\alpha) \times Q_{WAP} \tag{28}$$

α is the factor that decides the weightage of each index. It is chosen as 0.5 commonly.

2.2.8 Multi-attributive border approximation area comparison method

MABAC method was proposed by Pamucar and Cirovic (Pamučar and Ćirović, 2015) in 2015 to solve MCDM problems and the comparison with few other MCDM techniques was also presented to validate the accuracy and consistency of the method. It works by calculating the distance of normalized performance values from the border approximation area (BAA). The alternatives with greater value of BAA is the better alternative using this method. The steps involved in ranking of alternatives using MABAC method are presented as under

Step 1: Elements of normalized decision matrix is computed from the decision matrix using the following Eq. 29,

$$n_{ij} = \frac{x_{ij} - x_i^{worst}}{x_i^{best} - x_i^{worst}} \tag{29}$$

Step 2: Weighted normalized matrix is calculated from the normalized decision matrix using the formula presented below in Eq. 30

$$V = \left[v_{ij}\right]_{m \times n}; where\ v_{ij} = w_j\left(n_{ij} + 1\right) \tag{30}$$

Step 3: BAA matrix $G = [g_j]_{1\times n}$ is defined where g_i is calculated as in Eq. 31

$$g_j = \left(\prod_{i=1}^{m} v_{ij}\right)^{\frac{1}{m}} \tag{31}$$

Step 4: Distance from this BAA is calculated for all the alternatives using Eq. 32,

$$Q = V - G \tag{32}$$

Step 5: Ranking of the alternatives is done using the overall score computed as

$$S_i = \sum_{j=1}^{n} q_{ij} \tag{33}$$

Ranking is done in the descending order of S_i.

3 Results and discussion

The response values for MRR, SR, EF and U_c are recorded as shown in Table A1. TOPSIS, MOORA, ARAS, WASPAS and MABAC methods are used to select the best alternatives among the 27 experiments. MRR and EF are treated as beneficial criteria because greater value of these criteria is desirable while U_c and SR are considered as cost criteria. Results obtained by various MCDM techniques are individually presented in Section 3.1. A comparative analysis and correlation coefficients are also presented in Section 3.2.

3.1 MCDM results

3.1.1 Weight determination

In the current work, criteria weight determination for all the MCDM techniques considered is done using four objective weight allocation methods. The steps involved in all the weight determination strategies is elucidated in earlier section. The discussed process has been religiously followed to calculate weights of various criteria in the selected MCDM problem. Weights of all the criteria obtained is presented in Table 1. It is worth noting here that while MEREC is heavily skewed in favor of surface roughness, other methods allocate weights to all criteria in close proximity with each other.

3.1.2 TOPSIS

Weights of all criterion obtained using the four weight allocation methods was used to obtain weighted normalized matrix using Eq. 14 after the normalized matrix is obtained using Eq. 13 discussed in Section 2.2.2. The distances from positive ideal and negative ideal solutions are calculated using Eqs 15, 16 respectively. Figure 1 shows the Euclidean distance from the best and the worst ideal solution. Selection of best alternative is based on the fact that the best alternative is the one that is the closest to the positive ideal but the farthest from the negative ideal point. Closeness coefficient measures how far the solution is from the ideal worst and how near a solution is to the ideal best. Ranks obtained using TOPSIS is presented in Table 2. It can be observed from Table 2 that alternative 15 can reliable be considered to be the optimal solution to the current MCDM problem which is ranked best by two of the methods and second best by the remaining two. Similarly, experiment 18 and experiment 5 are among the worst performing alternatives by TOPSIS among the 27 experiments considered.

3.1.3 MOORA

Decision matrix was normalized using Eq. 13 and weight obtained using all the methods considered were multiplied according to Eq. 14 to obtain weighted normalized decision matrix for MOORA method. Following Eq. 18, weighted normalized performance values under MRR and EF are added together and the sum of weighted normalized performance values for SR and Uc is subtracted from it to calculate the performance score. This score is used to rank the alternatives as shown in Table 3. Experiment 25 is ranked as the best alternative in two of the four weights considered. Experiment 3 and 4 and also among the better performing alternatives that are ranked first by the other two methods. Experiment 1 is again suggested to be the worst alternative among the 27 experiments.

3.1.4 ARAS

For ARAS method, a different normalization procedure is followed using Eq. 19 for MRR and EF and Eq. 20 for SR and Uc. Normalized decision matrix is multiplied with the weight of each criteria following Eqs 21, 22 based on the nature of criteria to obtain weighted normalized decision matrix. Sum of performance values under all the criteria is calculated following Eq. 23 to calculate the optimality function for an alternative. Degree of utility is calculated using Eq. 24 and the alternatives are ranked in the descending order of degree of utility as shown in Table 4. ARAS suggests that the experiment 25 is the best alternative followed by experiment 26. The worst alternative suggested by ARAS is experiment number 13.

3.1.5 WASPAS

WASPAS method is also used to identify the best alternative among the 27 experimental runs. Normalization of the decision matrix is done using Eqs 24, 25 depending on the type of criteria. Performance index for weighted aggregate sum and weighted aggregate product are calculated using Eqs 26, 27 respectively. The value of α is taken as 0.5 for the present work. The aggregate performance score is calculated using Eq. 28 and alternatives are ranked based on the score. Stepwise rank calculation is shown in Table 5 below. Experiments 25 and 26 are selected as the best and the second-best alternatives using WASPAS method. Experiment 18 is suggested to be the worst experiment by WASPAS method.

3.1.6 MABAC

In MABAC method, initial decision matrix is normalized using Eq. 21. It should be noted here that the best performance value for beneficial criteria is the maximum value while for the cost criteria it is the minimum value. Vice versa is true for worst value. For the weighted normalized matrix, Eq. 22 is used as mentioned in Section 2.2.6. BAA matrix G is then calculated using Eq. 23. Distance from this BAA matrix is calculated for all the alternatives under each criteria using Eq. 24. Eq. 25 is used to convert the Q matrix to a single performance score for each alternative. Ranks obtained using this score is tabulated in Table 6 below. It can be observed that MABAC chooses 6th experiment as the best alternative using CRITIC and equal weights are used while the 15th experiment is chosen as the best alternative when other two weights are used. 18th Experiment is chosen as the worst alternative by MABAC for most weights.

3.2 Comparative study

Figure 2 shows the plot of ranks obtained by different MCDM techniques. It can be clearly observed that the experiments no. 15 and 26 are ranked among the best four alternatives. Similarly experiment 10 and 13 are also ranked among the worst performing alternatives by all the techniques considered. It can be seen that ARAS and MOORA have significant overlap and TOPSIS, WASPAS and MABAC have significant overlap among each other for all the weights that were considered. Weights seem to play very little role as the overlap among the weights considered is significantly high for TOPSIS, WASPAS and MABAC. However, for ARAS and MOORA, the overlap among the weights considered and with other MCDM techniques considered seems very low.

Correlation analysis was also done to check the overlap between the ranks obtained by the MCDM techniques considered. Spearman rank correlation coefficient is selected as the measure for correlation between ranks in the current work (Figure 3). The most significant observation is that selection of appropriate weights is crucial to enhance the reliability of MCDM results as the correlation can be seen changing among MCDM techniques when weight allocation methods are different. While TOPSIS, WASPAS, and MABAC are quite similar, the differences in the approaches towards decision making might be the reason behind low correlation coefficient between ARAS and TOPSIS or ARAS and MOORA. Correlation coefficients also reflect that ARAS and MOORA are very closely related with each other.

4 Conclusion

This work compares TOPSIS, MOORA, ARAS, WASPAS, and MABAC using four different objectiive weight determination process, focusing on the widely used machining technique for crafting intricate shapes in microfluidic devices, specifically, the PCM process. A 27-alternative 4-criteria MCDM problem was constructed using an L27 Taguchi experimental design array and four response parameters: MRR, SR, Uc, and EF. The 15th, 25th, 26th, and 27th experimental runs emerged as better performing alternatives across all the MCDM techniques utilized in this study.

Correlation analysis between the techniques reveals that the ranks obtained using ARAS and MOORA closely correlate, while those obtained using TOPSIS, WASPAS and MABAC show close correlation among each other. There is a division between these two groups of MCDM techniques, which may be due to the normalization procedure followed in the processes. While TOPSIS, WASPAS and MABAC use the same approach to select the best alternative irrespective of the criteria's nature post-normalization, ARAS and MOORA distinguish between the benefit and cost criteria in the process of selecting the best alternative. This study's primary contribution is to elucidate this difference clearly using the example of PCM process parameters optimization.

The impact of the weight determination technique has also been studied. The most significant result in the comparison of weights is that the correlation among MCDM techniques is hugely dependent on the weight determination technique used. Therefore, weights play a significant role in reliability of MCDM tools and a careful selection of weight allocation technique is paramount in interpreting MCDM results. This work, however does not implement new age mathematical tools like fuzzy sets, soft sets and rough sets which can be integrated with the existing MCDM techniques to enhance their robustness in application.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

GS: Data curation, Formal Analysis, Investigation, Validation, Writing–original draft. RG: Writing–original draft, Writing–review and editing, Methodology. RČ: Conceptualization, Funding acquisition, Methodology, Supervision, Writing–review and editing. GS: Conceptualization, Formal Analysis, Methodology, Validation, Writing–review and editing. JSC: Formal Analysis, Investigation, Methodology, Writing–review and editing. KK: Conceptualization, Methodology, Software, Visualization, Writing–review and editing.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

TABLE A1 Input variables of experiment (Agrawal and Kamble, 2019).

Factors	Level 1	Level 2	Level 3
Concentration of Etchant (gm/lit)	650	750	850
Time of Etching (min)	30	40	50
Temperature of Etchant (°C)	50	60	70

TABLE A2 Experimental data (Agrawal and Kamble, 2019).

Sl. no.	Ra (μm)	Uc (mm)	MRR (mm^3/min)	EF	Sl. no.	Ra (μm)	Uc (mm)	MRR (mm^3/min)	EF
1	1.683	0.0270	3.140	1.48	15	0.202	0.0710	8.910	1.71
2	0.741	0.0473	6.044	1.62	16	0.968	0.0770	6.672	1.10
3	0.707	0.0623	6.280	1.52	17	1.082	0.0725	7.457	1.31
4	1.066	0.0304	3.297	1.41	18	2.258	0.0850	7.693	1.15
5	2.287	0.0413	4.553	1.40	19	0.864	0.0811	7.771	1.22
6	0.573	0.0523	7.928	1.93	20	1.006	0.0670	5.479	1.47
7	0.747	0.0930	7.614	1.03	21	0.884	0.0827	8.478	1.30
8	0.980	0.0944	7.771	1.04	22	0.859	0.0661	5.700	1.10
9	1.402	0.0573	7.928	1.76	23	1.042	0.0460	6.280	1.73
10	0.877	0.0677	5.338	1.00	24	1.615	0.0462	6.829	1.89
11	1.354	0.0736	7.693	1.33	25	0.098	0.0691	7.693	1.41
12	0.970	0.0964	8.870	1.17	26	0.117	0.081	9.184	1.44
13	1.155	0.0772	6.410	1.04	27	0.218	0.094	9.263	1.40
14	0.984	0.0821	7.879	1.14					