

Proceeding Paper

A Hybrid MCDM-Grey Wolf Optimizer Approach for Multi-Objective Parametric Optimization of μ -EDM Process [†]

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[†] Presented at the International Conference on Recent Advances on Science and Engineering, Dubai, United Arab Emirates, 4–5 October 2023.

Abstract: Micro-electrical discharge machining (μ -EDM) has come up as an effective material removal process for the manufacturing of miniaturized components in modern industries. The performance and quality of the μ -EDM process mainly depend on the combination of process parameters selected. This paper attempts to demonstrate the applicability of three well-known multi-criteria decision-making (MCDM) techniques, including the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), multi-attributive border approximation area comparison (MABAC), and complex proportional assessment (COPRAS) methods, separately hybridized with the grey wolf optimization (GWO) algorithm. The proposed hybrid optimization approaches are applied to find the optimal parametric setting of a μ -EDM process during machining on a stainless steel shim as the work material. Feed rate, capacitance, and voltage were selected as the machining control parameters, while material removal rate, surface roughness, and tool wear ratio were selected as the responses. The polynomial regression (PR) meta-models are observed as the inputs to these hybrid optimizers. The results obtained are further compared to the traditional weighted sum multi-objective optimization (WSMO) approach, which suggests that all the considered MCDM-PR-GWO approaches outperform traditional PR-WSMO-GWO approaches in obtaining better machining performance measures.

Keywords: μ -EDM process; MCDM; GWO; meta-model; optimization



Citation: Das, P.P. A Hybrid MCDM-Grey Wolf Optimizer Approach for Multi-Objective Parametric Optimization of μ -EDM Process. *Eng. Proc.* **2023**, *59*, 112. <https://doi.org/10.3390/engproc2023059112>

Academic Editors: Nithesh Naik, Rajiv Selvam, Pavan Hiremath, Suhas Kowshik CS and Ritesh Ramakrishna Bhat

Published: 23 December 2023



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1. Introduction

Micro-electrical discharge machining (μ -EDM) is emerging as an effective machining process for manufacturing microcomponents in present-day industry. Its working principle is based on that of the original EDM process, which employs electrical spark energy to generate heat, leading to melting and evaporating the work material. This machining is well known for its ability to produce high dimensional accuracy with a better surface finish [1]. μ -EDM is different from that of EDM with respect to the type of the pulse generator, resolution of the axis movements, plasma channel radius, and size of the electrode [2]. It finds its applications in areas like producing micro holes in fuel injection nozzles, spinnerets, micro-electro-mechanical systems (MEMS), micro-fluidic devices, cooling holes of turbine blades, etc. Like most other machining process, the μ -EDM process is also governed by several machining parameters such as gap voltage, peak current, pulse-on time, flushing pressure, pulse-off time, dielectric type, etc. To attain the best machining output, the operator should have a thorough understanding of the process parameters and their relation to several machining performance measures, such as the material removal rate (MRR), taper, overcut (OC), surface roughness (Ra), tool wear ratio (TWR), etc. [3,4]. Mostly, the selection of the optimal parametric combination relies on the operators' knowledge and expertise. However, it is usually seen that rapid tool wear, poor surface finish, slow machining, etc., result from the selection of an inappropriate parametric combination. It is thus recommended to apply suitable mathematical optimization techniques to identify the optimal parametric setting of the μ -EDM process for enhanced machining performance.

The parametric optimization of the μ -EDM process has been already studied by many past researchers. Recently, Quarto et al. [5] adopted particle swarm optimization (PSO) to identify the optimal parametric settings of peak current, voltage, and frequency while performing μ -EDM of AISI304 as the work material. Selecting capacitance, voltage, and the electrode rotational speed as the control parameters for the μ -EDM process, Nguyen et al. [6] employed the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach to optimize responses such as depth of machining, overcut, and tool wear. Das et al. [7] applied multi-criteria decision-making (MCDM) and the teaching-learning-based optimization (TLBO) approach to identify the optimal parametric mix of peak current, pulse-on time, gap voltage, and flushing pressure. Pain et al. [8] considered four process parameters including voltage, frequency, duty factor, and tool diameter and applied the grey relational analysis (GRA) method for maximizing the MRR and minimizing OC. In addition, several other methods such as data envelopment analysis-based ranking (DEAR) [9,10], the desirability function approach [11,12], non-dominated sorting genetic algorithm (NSGA) [13,14], etc. were applied to find the optimal parametric setting for the μ -EDM process.

In the presented work, considering the experimental dataset obtained from past research, polynomial regression (PR) models were developed and simultaneously solved for single- and multi-objective optimization using the grey wolf optimizer (GWO) algorithm. Additionally, three popular MCDM techniques, namely the TOPSIS, multi-attributive border approximation area comparison (MABAC), and complex proportional assessment (COPRAS) methods were hybridized separately with the GWO algorithm to identify the optimal parametric combination of said μ -EDM process. Three PR models were developed based on the process parameters as input and the corresponding calculated MCDM scores as the output. The MCDM-based PR metamodels were observed as the input to the GWO optimizer and are henceforth known as the TOPSIS-PR-GWO, MABAC-PR-GWO, and COPRAS-PR-GWO approaches. The results obtained were further compared to the traditional weighted sum multi-objective optimization (WSMO) approach (known as the PR-WSMO-GWO approach), which suggests that all the considered MCDM-PR-GWO approaches outperformed the traditional approaches in obtaining better machining performance measures. The flowchart for the hybrid MCDM-GWO approach is presented in Figure 1.

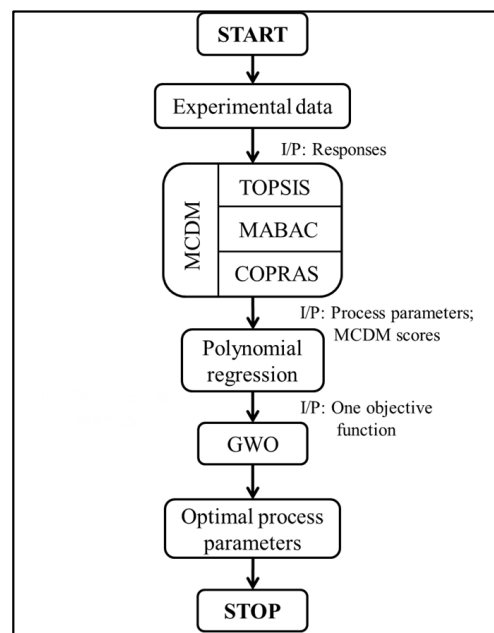


Figure 1. Flowchart of the proposed hybrid MCDM-GWO approach.

2. Methodology

2.1. PR Metamodel

A mathematical metamodel is a regression equation representing a set of input variables with a given output [15]. Typically, a metamodel can be denoted by the given expression:

$$y(x) = \hat{y}(x) + \varepsilon \tag{1}$$

where $y(x)$ is the output desired from the developed metamodel, $\hat{y}(x)$ is the estimated response, and ε represents the error. The PR metamodel is a commonly used statistical technique that represents the relationships between the input and output variables, as represented below:

$$y(x) = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=1}^n \beta_{ii} x_i^2 + \sum_{i \neq j \neq k}^n \beta_{ijk} x_i x_j x_k + \sum_{i \neq j \neq k \neq \dots \neq n}^n \beta_{ijk\dots n} x_i x_j x_k \dots x_n + \varepsilon \tag{2}$$

where $y(x)$ is the desired output, x_i is the i th input variable ($i = 1, 2, \dots, n$), β_0 is the intercept coefficient, β_i is the effect coefficient of the i th input variable, β_{ii} is the effect coefficient of the x_i^2 term, β_{ijk} is the interaction coefficient for variables i, j , and k ($i \neq j \neq k$), $\beta_{ijk\dots n}$ is the interaction coefficient for all the considered variables ($i \neq j \neq k \dots \neq n$), and ε represents the error.

2.2. Grey Wolf Optimizer

Grey wolves usually live and hunt in groups. The GWO technique takes into account the leadership and hunting techniques of grey wolves. Almost half the iterations of the original GWO are engaged for exploration and the next half for exploitation. The solutions derived from the GWO are divided into four groups, namely alpha (α), beta (β), delta (δ), and omega (ω), representing the best, second-best, third-best, and remaining solutions, respectively. The practice of hunting by grey wolves is mainly divided into five components [16,17], i.e., (a) social hierarchy, (b) tracing, pursuing, and nearing the prey, (c) following, surrounding, and distressing the prey until it halts moving, (d) attacking the prey (exploration), and (e) searching for new prey (exploitation). This is mathematically represented as

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{W}(t) \right| \tag{3}$$

$$\vec{W}(t + 1) = \vec{W}_p(t) - \vec{A} \cdot \vec{D} \tag{4}$$

where iteration number is t , $\vec{W}_p(t)$ and $\vec{W}(t)$ indicate the location vectors of the prey and the grey wolf, respectively, for iteration t , $\vec{W}(t + 1)$ is the new location of the grey wolf, and the coefficient vectors \vec{A} and \vec{C} can be calculated as:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{5}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{6}$$

where \vec{r}_1 and \vec{r}_2 are vectors usually taken within 0 and 1. The value of the \vec{a} vector decreases linearly from 2 to 0 with each iteration and is specified by:

$$\vec{a}(t) = 2 - \frac{2t}{t_{\max}} \tag{7}$$

where t_{\max} represents the maximum number of iterations.

After surrounding the prey, a grey wolf starts the hunt (finding the best solutions). At this stage, the best wolf (α , β , and δ) candidates have superior information about the prey location. At the same time, the remaining wolf candidates (ω wolves) alter their positions

in accordance with the locations of the best wolf candidates. The hunting pattern of grey wolves can be denoted mathematically as follows:

$$\vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{W} \right| \tag{8}$$

$$\vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{W} \right| \tag{9}$$

$$\vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{W} \right| \tag{10}$$

$$\vec{W}_1 = \vec{W}_\alpha - \vec{A}_1(\vec{D}_\alpha) \tag{11}$$

$$\vec{W}_2 = \vec{W}_\beta - \vec{A}_2(\vec{D}_\beta) \tag{12}$$

$$\vec{W}_3 = \vec{W}_\delta - \vec{A}_3(\vec{D}_\delta) \tag{13}$$

$$\vec{W}(t + 1) = \frac{\vec{W}_1(t) + \vec{W}_2(t) + \vec{W}_3(t)}{3} \tag{14}$$

The hunting process ends with the grey wolves attacking the prey when it stops moving. Mathematically, this is represented by decreasing the value of \vec{a} . \vec{a} is also responsible for decreasing the fluctuation range of \vec{A} in the interval $[-a, a]$. When the value of \vec{A} is $[-1, 1]$, the subsequent location of the search agent can be somewhere between its present location and the location of the prey. A value of $|A| < 1$ will make the wolves attack, and $|A| > 1$ will make the grey wolves deviate from the prey to search for a better prey location. After the hunt of the prey, the grey wolves begin exploration for new prey in subsequent iterations. The process of exploration ends when the termination condition is satisfied.

3. Results and Discussion

Parametric Optimization of μ -EDM Process

To demonstrate the applicability of the proposed hybrid MCDM-GWO approach, the experimental observations of Natarajan et al. [18] are considered in this paper. The experiments were conducted in a multipurpose micromachine tool fixed with a tungsten electrode (tool) of 300 μm diameter on a stainless steel shim (workpiece). A schematic diagram of the μ -EDM process setup is shown in Figure 2. Considering a central composite design with 32 experimental design points including 5 center points, Natarajan et al. [18] conducted 32 sets of experiments. For the machining control parameters, feed rate (A) in $\mu\text{m/s}$, capacitance (B) in nF, and voltage (C) in V were selected and varied. Other machining parameters were kept fixed, such as spindle speed = 2000 rpm, drilling depth = 500 μm , synthetic oil as the dielectric fluid, and the threshold value taken as 30. For measuring the machining performance, MRR in mm^3/min , Ra in μm , and TWR were selected as responses. The MRR was calculated as the reduction in volume of the material before and after machining with respect to machining time. The Ra on the machined profiles was measured by using a white light interferometer microscope. TWR is the ratio of the volume of tool material removed with respect to the volume of workpiece material removed. The experimental plan and the measured responses are provided in Table 1. Using the desirability function approach, Natarajan et al. [18] concluded that a parametric setting of feed rate = 4.31 $\mu\text{m/s}$, capacitance = 0.1 nF, and voltage = 120 V results in optimum response values of MRR = 0.016 mm^3/min , Ra = 0.49 μm , and TWR = 1.08.

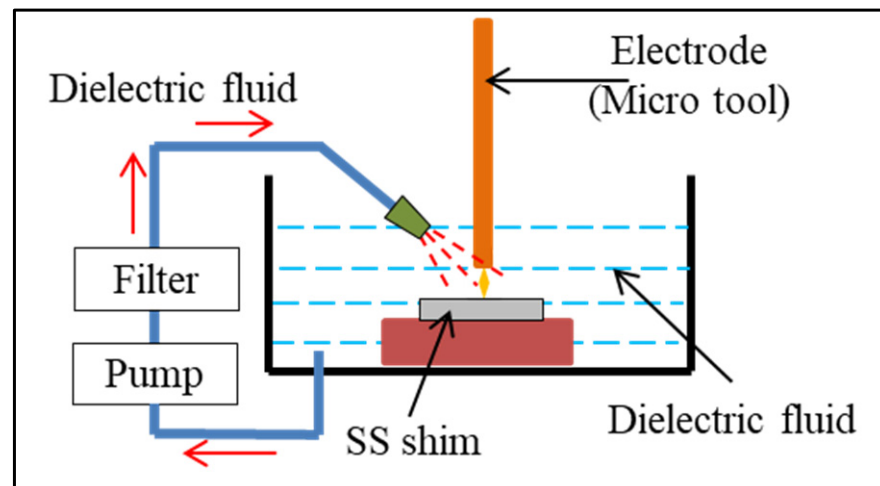


Figure 2. Schematic diagram of the μ -EDM process setup.

Table 1. Experimental plan and measured responses [18].

Exp. no.	A ($\mu\text{m/s}$)	B (μm)	C (V)	MRR (mm^3/min)	Ra (μm)	TWR
1	2	0.1	80	0.003	0.36	1.64
2	4	0.1	80	0.008	0.38	0.54
3	6	0.1	80	0.01	0.38	1.78
4	2	0.1	100	0.004	0.41	2.38
5	4	0.1	100	0.008	0.45	1.32
6	6	0.1	100	0.008	0.52	2.32
7	2	0.1	120	0.007	0.42	2.68
8	4	0.1	120	0.017	0.45	0.89
9	6	0.1	120	0.012	0.54	1.92
10	2	1	80	0.004	1.1	2.23
11	4	1	80	0.01	1.2	1.32
12	6	1	80	0.01	1.2	2.35
13	2	1	100	0.007	1.9	2.68
14	4	1	100	0.018	1.82	1.28
15	6	1	100	0.016	1.88	2.62
16	2	1	120	0.008	1.9	2.88
17	4	1	120	0.038	1.82	1.19
18	6	1	120	0.018	1.82	2.23
19	2	10	80	0.007	3.8	2.46
20	4	10	80	0.011	3.7	1.23
21	6	10	80	0.013	3.7	2.78
22	2	10	100	0.01	4.2	2.92
23	4	10	100	0.036	4.8	1.82
24	6	10	100	0.012	4.4	2.82
25	2	10	120	0.022	5.2	3.16
26	4	10	120	0.046	5.9	1.58
27	6	10	120	0.014	4.8	3.12
28	4	1	100	0.009	1.88	1.2
29	4	1	100	0.052	1.86	1.48
30	4	1	100	0.024	1.65	1.38
31	4	1	100	0.014	1.74	1.36
32	4	1	100	0.022	1.7	1.54

Next, based on the experimental dataset presented in Table 1, three PR models were developed for the three considered responses using Minitab 19.1 software. These PR models represent mathematical relationships of the output performance measures with the input

machining parameters. These models were first solved for traditional single-objective optimization followed by multi-objective optimization for the said μ -EDM process.

$$Y(MRR) = -0.0479 + 0.0244 \times A + 0.0027 \times B + 0.00001 \times C - 0.00296 \times A^2 - 0.000693 \times B^2 + 0.000001 \times C^2 + 0.00078 \times A \times B + 0.00001 \times A \times C + 0.00006 \times B \times C - 0.00001 \times A \times B \times C \quad (15)$$

$$Y(Ra) = -3.65 + 0.288 \times A + 1.048 \times B + 0.0624 \times C - 0.033 \times A^2 - 0.1006 \times B^2 - 0.000272 \times C^2 + 0.0145 \times A \times B - 0.00011 \times A \times C + 0.00394 \times B \times C - 0.000184 \times A \times B \times C \quad (16)$$

$$Y(TWR) = -2.63 - 2.039 \times A + 0.513 \times B + 0.1482 \times C + 0.3153 \times A^2 - 0.03688 \times B^2 - 0.000592 \times C^2 - 0.0246 \times A \times B - 0.00541 \times A \times C - 0.00097 \times B \times C + 0.000318 \times A \times B \times C \quad (17)$$

For the single-objective optimization, each of the developed PR models was solved separately using the GWO algorithm in the Matlab R2016a software, considering the specified ranges of the machining parameters ($2 \mu\text{m/s} \leq A \leq 6 \mu\text{m/s}$, $0.1 \text{ nF} \leq B \leq 10 \text{ nF}$, and $80 \text{ V} \leq C \leq 120 \text{ V}$) as the constraints. The GWO-specific parameters were set as the number of search agents (grey wolves) = 500, the maximum number of cycles/generations = 150, and the number of iterations = 100. The results obtained for the single-objective optimization by solving each PR model are given in Table 2. It can be seen from the table that the single-objective optimization produced dissimilar results, which are not possible to maintain in a single machining setup. To overcome this drawback, a single combination of machining parameters should be derived through multi-objective optimization using the PR-WSMO-GWO approach. The following equation has been developed.

$$\text{Minimize } Z = -w_1 \times \frac{Y(MRR)}{MRR_{\max}} + w_2 \times \frac{Y(Ra)}{Ra_{\min}} + w_3 \times \frac{Y(TWR)}{TWR_{\min}} \quad (18)$$

where $Y(MRR)$, $Y(Ra)$, and $Y(TWR)$ are the developed PR models for the three considered responses, $MRR_{\max} = 0.047143 \text{ mm}^3/\text{min}$, $Ra_{\min} = 0.16287 \mu\text{m}$, and $TWR_{\min} = 0.63627$, and w_1 , w_2 , and w_3 are the weights assigned to MRR, Ra, and TWR, respectively. In this paper, the CRITIC method [19,20] was employed to estimate the weights of MRR, Ra, and TWR as 0.3425, 0.2722, and 0.3853, respectively. Thus, by applying the PR-WSMO-GWO approach and solving Equation (18), the corresponding values of MRR, Ra, and TWR were obtained as $0.0126 \text{ mm}^3/\text{min}$, $0.3892 \mu\text{m}$, and 0.7042 , respectively, at the machining parametric intermix of feed rate = $3.55 \mu\text{m/s}$, capacitance = 0.158 nF , and voltage = 80 V .

Table 2. Results of single- and multi-objective optimization.

Condition	Output	A ($\mu\text{m/s}$)	B (μm)	C (V)	Optimal Value
Single-objective	MRR (mm^3/min)	3.9045	5.9608	120	0.047143
	Ra (μm)	2	0.1	80	0.16287
	TWR	3.9195	0.1	80	0.63627
Multi-objective	MRR (mm^3/min)				0.0126
	Ra (μm)	3.55	0.158	80	0.3892
	TWR				0.7042

As stated above, this paper solves the multi-objective parametric optimization problem based on two approaches, i.e., PR-WSMO-GWO and MCDM-PR-GWO (TOPSIS-PR-SWO, MABAC-PR-SWO, and COPRAS-PR-SWO). For the PR-WSMO-GWO approach, Equation (18) was solved to identify the optimal parametric combination for the said μ -EDM process. On the other hand, for the MCDM-PR-GWO approach, the 32 experimental observations presented in Table 1 were first considered as the initial decision matrix to be solved by the three MCDM methods (TOPSIS, MABAC, and COPRAS). The MCDM scores were calculated for all 32 experimental trials and provided in Table 3. For all the considered MCDM methods, the weights calculated by the CRITIC method were taken into account. Next, for the development of corresponding PR models, the 32 experimental combinations

presented in Table 1 were taken as the independent variables, and the measured MCDM scores as the dependent variables. Thus, three MCDM-PR metamodels were developed as $Y(TS)$, $Y(MS)$, and $Y(CS)$ for the three measured MCDM scores, i.e., the TOPSIS score, MABAC score, and COPRAS score, respectively.

$$Y(TS) = 0.453 + 0.335 \times A - 0.0556 \times B - 0.0132 \times C - 0.04524 \times A^2 - 0.00052 \times B^2 + 0.000064 \times C^2 + 0.0099 \times A \times B + 0.000409 \times A \times C + 0.00054 \times B \times C - 0.000116 \times A \times B \times C \tag{19}$$

$$Y(MS) = -0.039 + 0.4564 \times A - 0.108 \times B - 0.0248 \times C - 0.06544 \times A^2 + 0.00553 \times B^2 + 0.000106 \times C^2 + 0.0084 \times A \times B + 0.000873 \times A \times C + 0.000372 \times B \times C - 0.000105 \times A \times B \times C \tag{20}$$

$$Y(CS) = 0.1031 + 0.0406 \times A - 0.01448 \times B - 0.0027 \times C - 0.005002 \times A^2 + 0.001057 \times B^2 + 0.000013 \times C^2 - 0.000145 \times A \times B + 0.000009 \times A \times C + 0.000029 \times B \times C \tag{21}$$

Table 3. Calculated performance scores for the considered MCDM techniques.

Exp No.	TOPSIS Score	MABAC Score	COPRAS Score
1	0.4161	-0.5082	0.0313
2	0.4913	-0.3125	0.0751
3	0.449	-0.4809	0.034
4	0.3887	-0.6125	0.0235
5	0.455	-0.4306	0.0395
6	0.407	-0.5811	0.0261
7	0.392	-0.6361	0.0234
8	0.5439	-0.3045	0.058
9	0.4505	-0.4953	0.0324
10	0.365	-0.6243	0.0214
11	0.4421	-0.4535	0.0329
12	0.3881	-0.605	0.0244
13	0.3204	-0.7089	0.0188
14	0.4884	-0.4222	0.0346
15	0.3882	-0.6361	0.0253
16	0.3185	-0.7313	0.0188
17	0.7263	-0.2691	0.0492
18	0.4304	-0.5619	0.0284
19	0.2174	-0.7699	0.0159
20	0.3546	-0.5561	0.0226
21	0.2523	-0.7701	0.0195
22	0.187	-0.8362	0.0166
23	0.5235	-0.5222	0.0358
24	0.1997	-0.8173	0.0179
25	0.2822	-0.8367	0.0235
26	0.5721	-0.471	0.0417
27	0.1927	-0.8671	0.0184
28	0.416	-0.4762	0.0288
29	0.8128	-0.2159	0.0561
30	0.5524	-0.3866	0.0388
31	0.4501	-0.4579	0.0316
32	0.5187	-0.4265	0.0358

The developed MCDM-PR metamodels were then solved individually using the GWO algorithm in the Matlab R2016a software. In all three cases, the maximum values of the MCDM scores are desirable. Hence, the objective was to maximize all the MCDM-PR metamodels. The results obtained are provided in Table 4. In this table, the obtained optimal parametric values were substituted in Equations (15)–(17) to estimate the corresponding values of MRR, Ra, and TWR. It can be seen from Table 4 that compared to the PR-WSMO-GWO approach, the MABAC-PR-GWO and COPRAS-PR-GWO approaches superseded the response values in two out of the three considered responses, whereas the TOPSIS-PR-

GWO approach provided better response values as compared to PR-WSMO-GWO for all three responses. Also, the computational time required by each metamodel was calculated, as shown in Table 4. It can be observed that all three MCDM-PR-GWO approaches take computationally less time compared to that of the PR-WSMO-GWO approach.

Table 4. Comparative analysis between PR-WSMO-GWO and MCDM-PR-GWO approaches.

Method	A ($\mu\text{m/s}$)	B (μm)	C (V)	MRR (mm^3/min)	Ra (μm)	TWR	Comp. Time (s)
PR-WSMO-GWO	3.55	0.158	80	0.0126	0.3892	0.7042	1.03886
TOPSIS-PR-GWO	3.9578	0.1	80	0.0134	0.3245	0.6367	1.02534
Improvement %	-	-	-	6.35	16.62	9.58	1.3
PR-WSMO-GWO	3.55	0.158	80	0.0126	0.3892	0.7042	1.03886
MABAC-PR-GWO	3.8578	0.1	80	0.01232	0.3224	0.6375	1.00352
Improvement %	-	-	-	-2.22	17.16	9.47	3.4
PR-WSMO-GWO	3.55	0.158	80	0.0126	0.3892	0.7042	1.03886
COPRAS-PR-GWO	3.8578	0.1	80	0.01232	0.3224	0.6375	1.01936
Improvement %	-	-	-	-2.22	17.16	9.47	1.88

To compare the three considered MCDM-PR-GWO variants and PR-WSMO-GWO, the predicted response values obtained in Table 4, along with the measured responses provided in Table 1, were first normalized together and finally added for each variant separately. The results obtained are given in Table 5. It is clearly revealed that the highest sum of normalized scores (2.1749) for the TOPSIS-PR-GWO approach outperforms the other MCDM-PR-GWO and PR-WSMO-GWO variants in identifying better response values for the said μ -EDM process. Thus, based on the TOPSIS-PR-GWO approach, the optimal parametric combination can be identified as feed rate = 3.9578 $\mu\text{m/s}$, capacitance = 0.1 nF, and voltage = 80 V for simultaneous improvement of the μ -EDM performance measures. The moderately higher value of the feed rate is suggested, as MRR and TWR are directly related to the feed rate. However, with higher values of feed rate, the MRR reduces with the formation of high voltage as it erodes the tool material, reducing the removal of material from the workpiece. An increase in capacitance and voltage produces stronger sparks, resulting in erosion of both the workpiece and tool material. This causes the formation of unwanted debris increasing the Ra. The convergence diagram illustrated in Figure 3 also suggests that compared to other MCDM variants, the TOPSIS-PR-GWO approach converges to the optimal solution at a much faster rate.

Table 5. Comparative analysis between MCDM-PR-GWO variants.

Method	Parametric Combination			Normalized Response Values			Sum
	A	B	C	MRR	Ra	TWR	
PR-WSMO-GWO	3.55	0.158	80	0.1959	0.988	0.9373	2.1212
TOPSIS-PR-GWO	3.9578	0.1	80	0.2122	0.9996	0.9631	2.1749
MABAC-PR-GWO	3.8578	0.1	80	0.1902	1	0.9628	2.153
COPRAS-PR-GWO	3.8578	0.1	80	0.1902	1	0.9628	2.153

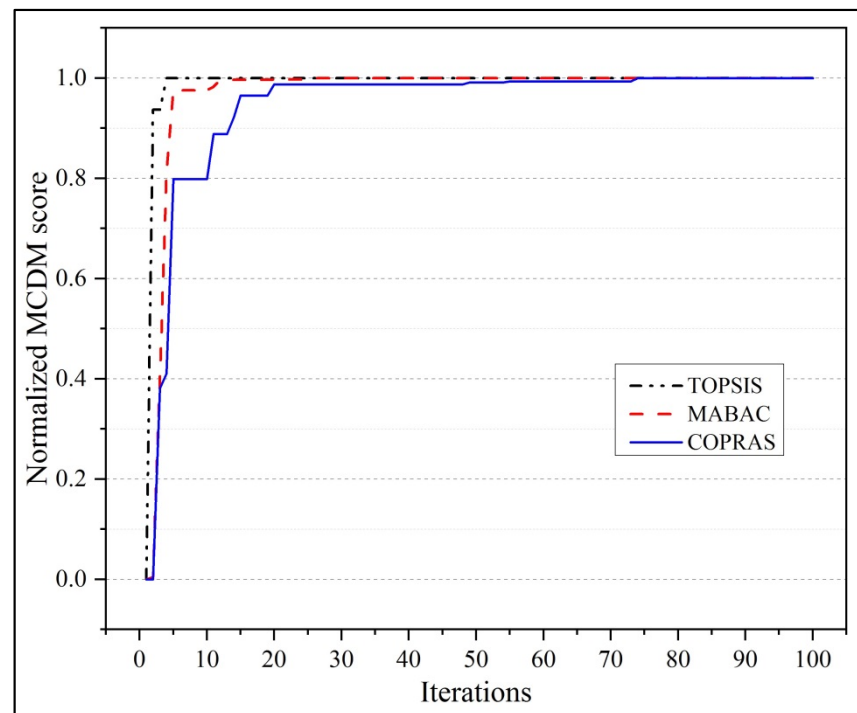


Figure 3. Convergence diagram for MCDM-PR-GWO variants.

4. Conclusions

In this paper, an attempt was made to demonstrate the applicability of hybrid MCDM-GWO (TOPSIS-PR-GWO, MABAC-PR-GWO, and COPRAS-PR-GWO) approaches in identifying the optimal parametric combination for the μ -EDM process. The results obtained are further compared to the traditional PR-WSMO-GWO approach, which suggests that all the considered MCDM-PR-GWO approaches outperform the traditional approach in obtaining better machining performance measures. Also, among the three MCDM-PR-GWO approaches, the TOPSIS-PR-GWO approach provides superior results while converging at a much faster rate as compared to the others. Based on the TOPSIS-PR-GWO approach, the optimal parametric combination is identified as feed rate = 3.9578 $\mu\text{m/s}$, capacitance = 0.1 nF, and voltage = 80 V, which results in optimal response values of $\text{MRR} = 0.0134 \text{ mm}^3/\text{min}$, $\text{Ra} = 0.3245 \mu\text{m}$, and $\text{TWR} = 0.6367$. It is also observed that the MCDM-PR-GWO approaches take computationally less time than the PR-WSMO-GWO approach. As a future scope, the work can be further explored by including other MCDM approaches hybridized with different meta-heuristic algorithms applied toward identifying the optimal parametric combination of various machining processes. One of the major limitations of hybrid MCDM-GWO approaches is the dependency of the results on the developed PR-based metamodels to define the condensed information into usable GWO objective functions. An inappropriate PR model can produce inaccurate results.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No data associated with the article.

Conflicts of Interest: The author declares no conflict of interest.

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