



Multi-Response Optimization of Al/GrCp10 MMC Performance in WEDM Using Integrated TOPSIS-ANFIS Approach

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Abstract Lightweight material such as aluminum-based metal matrix composites (MMC) is extensively used in automobile, aerospace, and some other precise engineering applications. For such material, the processing is not simple due to the presence of some other material in the aluminum. To overcome this, wire electrical discharge machining (WEDM) is projected for cutting of aluminum-graphite (10%) metal matrix composite with variation in process parameters. In present work, the technique for order of preference by similarity to ideal solution (TOPSIS) and an adaptive neuro-fuzzy inference system (ANFIS) is employed to assess the WEDM of AlGrCp10 MMC. Taguchi's L_{27} orthogonal array was adopted for the experimentation. The influence of process variables, pulse on time (PON), pulse off time (POFF), the feed rate of wire

(WFR), and the tension in the wire (WT), is considered for overall performance measure. The overall performance is measured in terms of the responses such as material removal rate (MRR), overcut (OVT), and surface roughness (Ra). Analysis of variance, i.e., ANOVA, is performed to find out the most influencing process parameters. TOPSIS-ANFIS predicted results are tested for the confirmation tests which show an enhancement of overall closeness coefficient increases from 0.656793 to 0.772138. The optimum setting obtained for the overall performance is pulse on time = 112 μ s pulse off time = 56 μ s, wire feed rate = 12 m/min, and wire tension of 1.2 kg.

Keywords Al/GrCp10 MMC · ANFIS · Multi-response optimization · TOPSIS · WEDM

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Introduction

Nowadays, most of the metal cutting industries use advanced machining processes for improving product quality and the performance of an enterprise. Along with advanced and latest precise machining processes, aluminum-based metal matrix composite is also drastically increased in space, defense, and automobile industries. Hence, the effort has been made to focus on measuring the WEDM process's performance, which will help find the ease of machining aluminum with 10% graphite (by weight) MMC. In WEDM, the material is cut with a wire that follows a definite pathway to form the intricate and complicated product. Worldwide, the research will find out the new composites and their ease of machine process parameters. The impact of various WEDM process parameters during the machining of Nitinol alloy has been performed using RSM, and multi-response optimization

using desirability function has been effectively performed (Chakala et al. 2018) [1]. Chia-Chi Sun used TOPSIS for the optimization of the multiple process responses [2]. The fuzzy analytic hierarchy process is coupled with the TOPSIS technique used for analyzing the machining performance. The model developed is based on an ambiguous environment with a triangular fuzzy number. Goswami et al. have used the Taguchi approach coupled with the utility concept to optimize the WEDM process parameters of Nimonic-80 materials [3]. Huu-Phan et al. analyzed the impact of titanium powder mixed into the dielectric fluid in EDM of copper and graphite-based materials using the TOPSIS method [4]. Jenarthanani et al. investigated two responses, i.e., MRR and Ra. The investigation was done to know the optimum performance during WEDM of Inconel 600 material [5]. Kavimani et al. (2019) have examined the process and used grey relational analysis to improve the process's performance [6]. Majumdar et al. have employed multi-response techniques like general regression and ANN to get the optimized value of surface roughness and micro-hardness [7].

Numbers of experiments were conducted by considering PON, POFF, and peak current as process parameters. A comparative analysis between process parameters using molybdenum brass and zinc-coated wires in WEDM has been performed effectively to optimize WEDM process parameters (Mevada et al. 2013) [8]. Taguchi approach was used for the analysis and investigation. The optimization of process parameters for the EDM process using low-frequency vibrations for the response parameters such as surface roughness and material removal rate has been investigated. (Nguyen et al. 2020) [9]. Various soft computing techniques such as an artificial neural network (ANN), ANFIS, fuzzy grey approach during the analysis (Phate et al. 2018–2020) [10–12]. Vikas et al. have analyzed the food quality using a soft computer vision system. Computer vision systems such as ANFIS and ANN were effectively used for the analysis [13, 14]. Rao et al. (2016) investigated the influence of various parameters in WEDM of aluminum alloy on the residual stresses generated on the surface [15]. A comparative analysis of metaheuristic optimization algorithms for optimal active control of structures using soft computing techniques was performed (Katebi et al. 2019 and Sefghi et al. 2017) [16]. Vinod Kumar et al. (2015) worked on WEDM of Monel-400, i.e., nickel copper-base alloy [17]. ANOVA was performed for investigation. The experimental results showed that current (103 A), pulse on time (113 micro sec), pulse off time (37 micro sec), and the voltage (50 V) were the optimum combination. Kolli et al. (2015) used the Taguchi method to study the impact of dielectric fluid on WEDM of titanium alloy [18]. The surface modifications of the die steel using WEDM and the analysis of WEDM process

Fig. 1 Methodology for WEDM analysis using ANFIS-based TOPSIS technique

parameters such as wire speed and the servo speed have been effectively examined over the recast layer formation (Mussada et al. 2019) [19]. The authors reviewed the machining of Al/SiC MMC. AHP-TOPSIS-based method has been employed for multi-response optimization of the EDM process during the machining of cobalt-bonded tungsten carbide composite. The method was compared with the other multi-response optimization. (Nadda et al. 2018) [20]. Fuzzy logic coupled with backpropagation neural networks was adopted for the multi-response optimization of the WEDM process. This was used to check the relative importance and evaluate the performance of WEDM of aeronautics superalloy Naina et al. [21]. Parametric analysis is adopted to know the optimal parameters which minimize residual stresses on the components. A method for multi-response optimization of EDM process parameters for Al/SiC20% SiC MMC using TOPSIS has been widely employed to know the best set of process parameters (Satpathy et al. 2017) [22]. WEDM process performance is measured in MRR, Ra, and recast layer thickness (RLT) effectiveness. Tamasang et al. (2015) used an advanced technique, i.e., ANN integrated with the response surface method (RSM), to improve performance [23]. M. Phate et al. have effectively examined the EDM process for the fabricated new Al-based alloy using soft computing technique such as ANN and other modeling techniques such as dimensional analysis and response surface method (RSM) [24, 25].

Graphite is used due to its high thermal and electric conductivity. It also has wide applications in engineering such as nuclear, chemical, electrical, and mechanical industries. From the literature review, it has been observed that no researcher has tried the machining of aluminum with more than 5% graphite. Aluminum with 10% graphite MMCs is fabricated in the present work, and their ease of machining is examined for this novel combination. The novelty of the MMC is observed in terms of the graphite percentage. From the literature review, it is cleared that the addition of graphite beyond 8% would cause a decrease in the fluidity of the composite. In the presented work, 10% graphite is used for the preparation of the composite.

The experimental findings will help the industries to use graphite with 10% in aluminum as a healthy alternative for the various engineering applications in automobile, aerospace, defense research, and manufacturing industries.

The present work aims to fabricate the MMC with a novel combination of aluminum with 10% graphite and

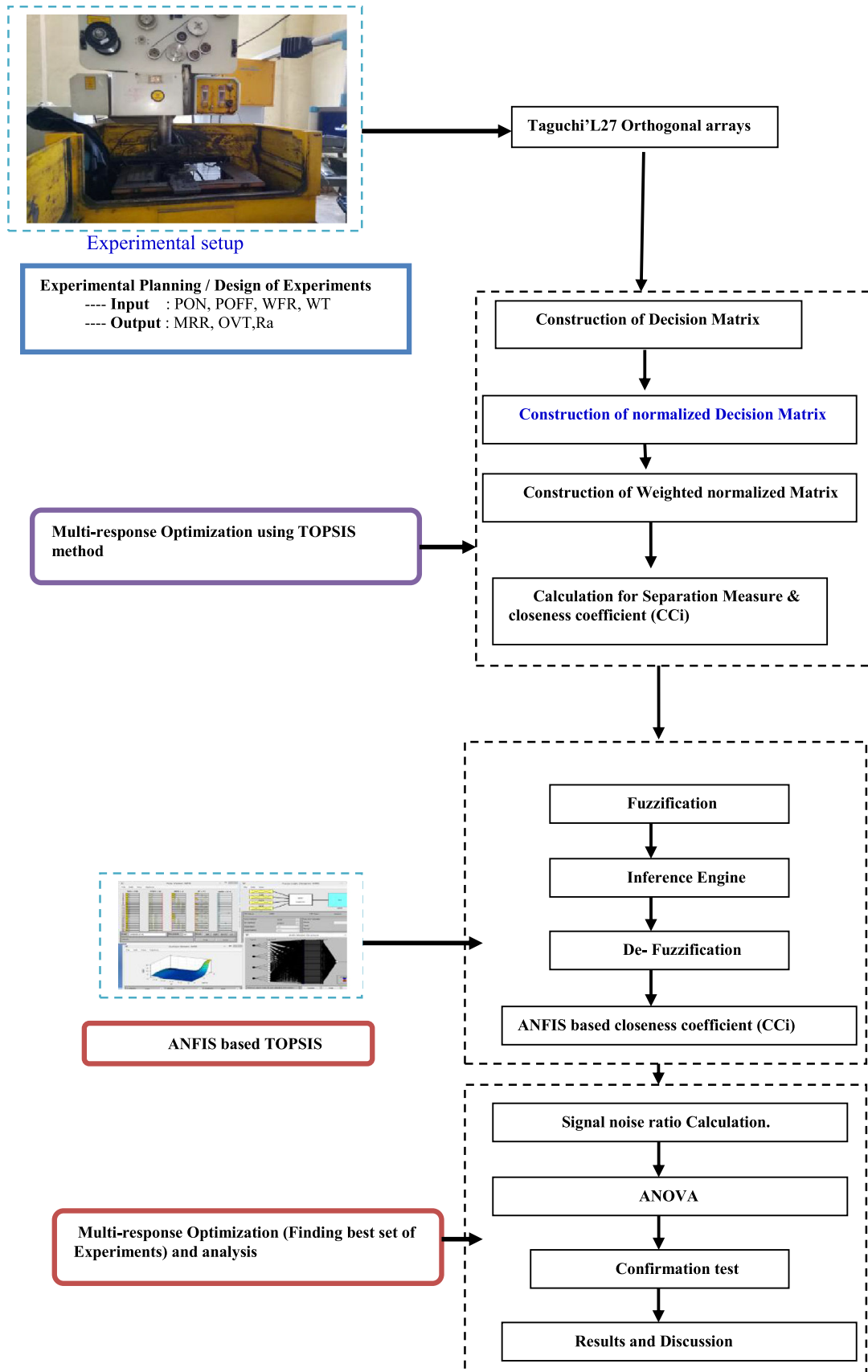


Table 1 Chemical contents of AlGr/Cp10 MMC

Component	Weight (%)	Component	Weight (%)
Al	92.2–94.7	Mn	0.3–0.9
Cr	Max 0.1	Si	Max 0.2
Cu	3.8–4.9	Ti	Max 0.15
Fe	Max 0.3	Zn	Max 0.25
Mg	1.2–1.8	Others	Max 0.15

their ease of machining to effectively be used for the various engineering applications. The present work aims to find out the best set of process parameters for multi-response optimization. From the literature review, it is observed that higher percentage of graphite would cause clustering issue. Also, it leads to increase in the viscosity in the melts. Hence, preparation and machining of the composite is really tough work. The basic objective of the work is to prepare the MMC and then to provide the ease of machining. This will help the manufacturing industry effectively machine the novel composition to minimize the surface roughness to 3.639 μ , overcut at 0.3652 μ , and maximum material removal rate at 21.234 mm³/min. PON (112 μ s), POFF (54 μ s), wire feed rate at 6 m/min, and the wire tension at 0.8 kg, respectively, are observed.

Material and Method

Al/GrCp10 MMC Preparation

The experiments are conducted using EZEECUT NXG—wire-cut EDM with 320 \times 400 mm axis travel. Brass wire (ϕ 0.25 mm) and workpiece of Al/GrCp10 (dimensions 200 \times 75 \times 10 mm) are used for investigation. A flow of work in the presented research is as shown in Fig. 1. The graphite has very high intensity, higher temperature resistance, high thermal shock resistance property, very low density, and admirable commitment against corrosion and radiation performance. The sand casting process prepares

the Al/GrCp10 MMC. The chemical composition of the Al/GrCp10 MMC is tabulated in Table 1.

Plan for Experimentation

Taguchi's L₂₇ OA using experiments (DOE) is adopted for the experimentation considering four governing parameters tabulated in Table 2. Table 2 demonstrates the different levels of machining parameters and observed responses. Figure 1 shows the flow of work or methodology adopted during the analysis. The observations during the experimentation are tabulated in Table 3.

TOPSIS Methodology This is the industrial most preferred method use in industries for multi-response optimization. This method is working on the principle of shortest route method. Alternatives or choices should have the shortest distance from the ideal positive solution and the longest distance from the perfect negative solution. The basic methodology and TOPSIS are as publicized in Fig. 1. The various steps involved in the TOPSIS are:

Step 1: This is the first step in TOPSIS. The aim of this is to evaluate the 27 runs known as alternatives, and the three attributes known as responses are MRR, overcut, and surface roughness. MRR is considered as a beneficial sort of feature (maximize), while Ra and OVT are considered as non-beneficial (minimize). The general 27 \times 3 decision matrix is given by Eq. (1).

$$D = \begin{bmatrix} Y_{11} & Y_{12} & Y_{13} & \dots & Y_{1n} \\ Y_{21} & Y_{22} & Y_{23} & \dots & Y_{2n} \\ Y_{31} & Y_{32} & \vdots & \ddots & \vdots \\ \dots & \dots & \dots & \dots & \dots \\ Y_{m1} & Y_{m2} & Y_{m3} & \dots & Y_{mn} \end{bmatrix} \quad (1)$$

where 'n' is the number of the attributes, responses and 'm' is the number of alternatives.

Step 2: After constructing a 27 \times 3 decision matrix, the responses are normalized the decision matrix between the range 0 – 1. The decision matrix is normalized by using the following Eq. (2):

Table 2 List of parameters and their test points

S. no	Parameter	Symbol (Unit)	Test points(levels)		
			Lower(1)	Middle (2)	Higher (3)
1	Pulse on time	PON (μ s)	108	110	112
2	Pulse off time	POFF (μ s)	52	54	56
3	Feed rate of wire	WFR (mm/min)	6	9	12
4	Tension in wire	WT (kg)	0.8	1	1.2

Table 3 Plan for experimentation

Run	PON	POFF	WFR	WT	MRR (mm ³ /s)	Overcut (mm)	Ra (micro mm)
1	108	52	6	0.8	12.696	0.3512	3.735
2	108	52	6	0.8	13.524	0.3865	3.523
3	108	52	6	0.8	13.254	0.3685	3.354
4	108	54	9	1	10.365	0.3045	2.935
5	108	54	9	1	9.635	0.3125	3.215
6	108	54	9	1	10.254	0.3102	3.365
7	108	56	12	1.2	14.325	0.3025	3.125
8	108	56	12	1.2	13.654	0.3125	3.254
9	108	56	12	1.2	12.365	0.3025	3.056
10	110	52	9	1.2	16.325	0.3201	3.524
11	110	52	9	1.2	15.868	0.3185	3.425
12	110	52	9	1.2	16.023	0.3251	3.325
13	110	54	12	0.8	12.854	0.2985	3.102
14	110	54	12	0.8	13.021	0.2925	3.012
15	110	54	12	0.8	12.854	0.3021	3.215
16	110	56	6	1	16.356	0.3562	3.452
17	110	56	6	1	15.985	0.3485	3.356
18	110	56	6	1	15.421	0.3525	3.452
19	112	52	12	1	19.524	0.3254	3.568
20	112	52	12	1	20.524	0.3365	3.689
21	112	52	12	1	19.568	0.3452	3.758
22	112	54	6	1.2	21.521	0.3651	3.875
23	112	54	6	1.2	20.652	0.3568	3.758
24	112	54	6	1.2	21.324	0.3652	3.689
25	112	56	9	0.8	17.635	0.2985	3.564
26	112	56	9	0.8	18.325	0.3025	3.658
27	112	56	9	0.8	18.458	0.3125	3.758

$$R_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^m X_{ij}^2}} \tag{2}$$

where $i = 1, 2, 3, \dots, m$ and $j = 1, 2, 3, \dots, n$. X_{ij} represents the experimental value of the i th response to j th experimental run and R_{ij} represents the normalized value.

Step 3: After constructing the normalized matrix, the next step is to assign weightage to all responses or attributes as per the researcher’s priority. In the given case, analytic hierarchy process (AHP) is adopted for deciding the criterion weightage. The basic calculations are given below (Tables 4 and 5). The 50% weightage assign to the surface roughness, 30% weightage assign to the MRR, and the remaining 20% weightage assign to overcut were observed.

Let

1. Equal importance, 2. moderate importance, and 3. strongly important

According to AHP

Step 4: After confirming the weightage, the next step is to form the weighted normalized decision matrix. It is obtained by multiplying the normalized decision matrix by its associated weights. The weighted normalized decision matrix was constructed as per Eq. (3).

$$E_{ij} = WT_i * R_{ij} \tag{3}$$

Step 5: After the construction of the weighted normalized matrix, the step is to find out the positive ideal solution (PIS) and the negative ideal solution (NIS) by using Eq. (4).

$$\begin{aligned} E^+ (\text{PIS}) &= \text{Maximum}(E_1^+, E_2^+, E_3^+, \dots, E_n^+), \\ E^- (\text{NIS}) &= \text{Maximum}(E_1^-, E_2^-, E_3^-, \dots, E_n^-) \end{aligned} \tag{4}$$

Step 6: After deciding the ideal positive and ideal negative solution for each response, the next step is to find out the separation measure of each alternative from the ideal positive and negative solution. The separation measure is calculated by using Eq. (5).

Table 4 Comparative weightage assign to the various criterion

	Ra	MRR	OVT
Ra	1	2	3
MRR	0.5	1	2
OVT	0.33333333	0.5	1
Sum	1.83333333	3.5	6

$$S_i^+ = \sqrt{\sum_{j=1}^m (E_{ij} - E_j^+)^2}$$

$$S_i^- = \sqrt{\sum_{j=1}^m (E_{ij} - E_j^-)^2} \quad (5)$$

Step 7: The last step is the TOPSIS algorithm. From each calculated separation measure from ideal positive and ideal negative solution, find out the closeness coefficient of each alternatives using Eq. (6).

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (6)$$

The first rank is assigned to the alternative which has the highest value of closeness coefficient.

Results and Discussion

Optimization Using TOPSIS

The experimental data collected in the previous as per the selected plan optimize with the help of the ANFIS-based TOPSIS approach. There are three responses, i.e., MRR, overcut, and Ra. These responses are normalized by using

Eq. (1), and tabulated in Table 7. Different priorities are given to all responses. The weightage for the response MRR, overcut, and the Ra is 0.3:0.2:0.5. The relative weighted normalized matrix is constructed using selected weightage. The weights are multiplied to get the normalized weighted matrix using (2) as tabulated in Table 7. The ideal positive and negative solution for all responses is as published in Table 7.

The separation count of each alternative to the ideal positive and negative solutions calculates using Eq. (4), shown in Tables 4, 5, and 7. Finally, the relative closeness coefficient (CC_i) for each WEDM process alternative calculates using (5). S/N ratio of closeness coefficient values is as shown in Table 5. Table 5 shows that the impact of pulse on time (PON) is the most influencing. The optimal levels of all parameters, as in Fig. 2. The best sets of input parameters for WEDM are at level 3 to maximize the MRR and minimize the Ra and the overcut. ANOVA and the impact of process parameters tabulate in Table 16. It observes that the influence of pulse on-time is highest as compared to the others. Figure 3 shows that the residuals lie very close to a straight line, which implies the normal distribution of error. Figure 4 shows the contribution of each parameter.

ANFIS-Based TOPSIS Method

ANFIS is a mixed projecting model consisting of a neural network and fuzzy logic to create a relationship between various parameters. Combining fuzzy logic and neural network gives an augment to the implementation of the hybrid approach. The neural network can identify the pattern and agree to match the changing surrounding. On the other side, the fuzzy logic system uses human knowledge and performs effective decision making [14]. In the

Table 5 Calculation for criterion weightage using AHP

	Ra	MRR	OVT	Criterion weightage	Final weightage
Ra	0.54555374	0.57142857	0.5	0.538994103	0.5
MRR	0.27277687	0.28571429	0.33333333	0.297274829	0.3
OVT	0.18166939	0.14285714	0.16666667	0.163731068	0.2

Table 6 Ideal positive & ideal negative solution for all the response variables

S. no	Response	Objectives	Ideal Positive	Ideal negative
1	MRR	Beneficial (maximization)	0.07759	0.03474
2	OVT	Non-beneficial (minimization)	0.03415	0.04512
3	Ra	Non-beneficial (minimization)	0.08199	0.1082

Table 7 TOPSIS calculation matrix

Run	Normalized data			Weighted normalized matrix						
	MRR	OVT	Ra	MRR (0.3)	OVT (0.2)	Ra (0.5)	Si +	Si–	CCi	S/N CCi
1	0.1525	0.205	0.208	0.0457	0.0410	0.1043	0.039	0.0124	0.2390	–12.43
2	0.1625	0.225	0.196	0.0487	0.0451	0.0984	0.034	0.0171	0.3287	–9.663
3	0.1593	0.215	0.187	0.0477	0.0430	0.0936	0.033	0.0196	0.3715	–8.598
4	0.1245	0.177	0.163	0.0373	0.0355	0.0819	0.040	0.0280	0.4109	–7.725
5	0.1158	0.182	0.179	0.0347	0.0364	0.0898	0.043	0.0203	0.3181	–9.946
6	0.1232	0.181	0.188	0.0369	0.0362	0.0940	0.042	0.0169	0.2854	–10.88
7	0.1721	0.176	0.174	0.0516	0.0353	0.0873	0.026	0.0286	0.5193	–5.690
8	0.1641	0.182	0.181	0.0492	0.0364	0.0909	0.029	0.0241	0.4478	–6.978
9	0.1486	0.176	0.170	0.0445	0.0353	0.0853	0.033	0.0267	0.4462	–7.007
10	0.1962	0.186	0.196	0.0588	0.0373	0.0984	0.025	0.0271	0.5190	–5.696
11	0.1907	0.185	0.191	0.0572	0.0371	0.0956	0.024	0.0269	0.5210	–5.662
12	0.1925	0.189	0.185	0.0577	0.0379	0.0928	0.022	0.0286	0.5546	–5.119
13	0.1544	0.174	0.173	0.0463	0.0348	0.0866	0.031	0.0265	0.4567	–6.805
14	0.1565	0.170	0.168	0.0469	0.0341	0.0841	0.030	0.0291	0.4869	–6.249
15	0.1544	0.176	0.179	0.0463	0.0352	0.0898	0.032	0.0239	0.4257	–7.415
16	0.1965	0.207	0.192	0.0589	0.0415	0.0964	0.024	0.0271	0.5235	–5.620
17	0.1921	0.203	0.187	0.0576	0.0406	0.0937	0.024	0.0274	0.5326	–5.471
18	0.1853	0.205	0.192	0.0556	0.0411	0.0964	0.027	0.0243	0.4713	–6.533
19	0.2346	0.189	0.199	0.0703	0.0379	0.0996	0.019	0.0373	0.6567	–3.651
20	0.2466	0.196	0.206	0.0740	0.0392	0.1030	0.022	0.0400	0.6450	–3.807
21	0.2351	0.201	0.209	0.0705	0.0403	0.1049	0.024	0.0362	0.5933	–4.533
22	0.2586	0.213	0.216	0.0775	0.0426	0.1082	0.027	0.0429	0.6083	–4.317
23	0.2482	0.208	0.209	0.0744	0.0416	0.1049	0.024	0.040	0.6208	–4.140
24	0.2562	0.213	0.206	0.0768	0.0426	0.1030	0.022	0.0425	0.6513	–3.723
25	0.2119	0.174	0.199	0.0635	0.0348	0.0995	0.022	0.0318	0.5855	–4.648
26	0.2202	0.176	0.204	0.0660	0.0353	0.1021	0.023	0.0333	0.5886	–4.602
27	0.2218	0.182	0.209	0.0665	0.0364	0.1049	0.025	0.033	0.5635	–4.982

present work, the fuzzy inference system has four inputs and one output. ANFIS structure consists of various layers, and each layer consists of several nodes.

The rule sets used for the analysis are as shown in Fig. 2. The surface viewer is used to know the influence of various parameters on performance. The surface viewer plot is as shown in Fig. 3.

Rules: Collection of If–then statements (Fig. 5).

In the present case, let us denote X_1, X_2 and X_3 are the response which is considered as an input to the ANFIS network and one output, i.e., ANFIS TOPSIS CCI (Y). The following set of rules is used for the analysis:

- **Rule 1:** If X_1 is Low, X_2 is Low, X_3 is Low and X_4 is Low, **then Y** is very Low
- **Rule 2:** If X_1 is Low, X_2 is Low, X_3 is Low and X_4 is Medium, **then Y** is Low

- **Rule 3:** If X_1 is Low, X_2 is Low, X_3 is Low and X_4 is Low, **then Y** is medium
- **Rule 4:** If X_1 is Low, X_2 is Low, X_3 is medium and X_4 is Low, **then Y** is high
-
-
-
-
-
-
- **Rule 80:** If X_1 is high, X_2 is high, X_3 is high, and X_4 is medium, **then Y** is high
- **Rule 81:** If X_1 is high, X_2 is high, X_3 is high, and X_4 is Lo high w, **then Y** is very high

In ANFIS, an artificial neural network (ANN) takes the fuzzy rules from the input and the fuzzy membership

Fig. 2 ANFIS rule viewer

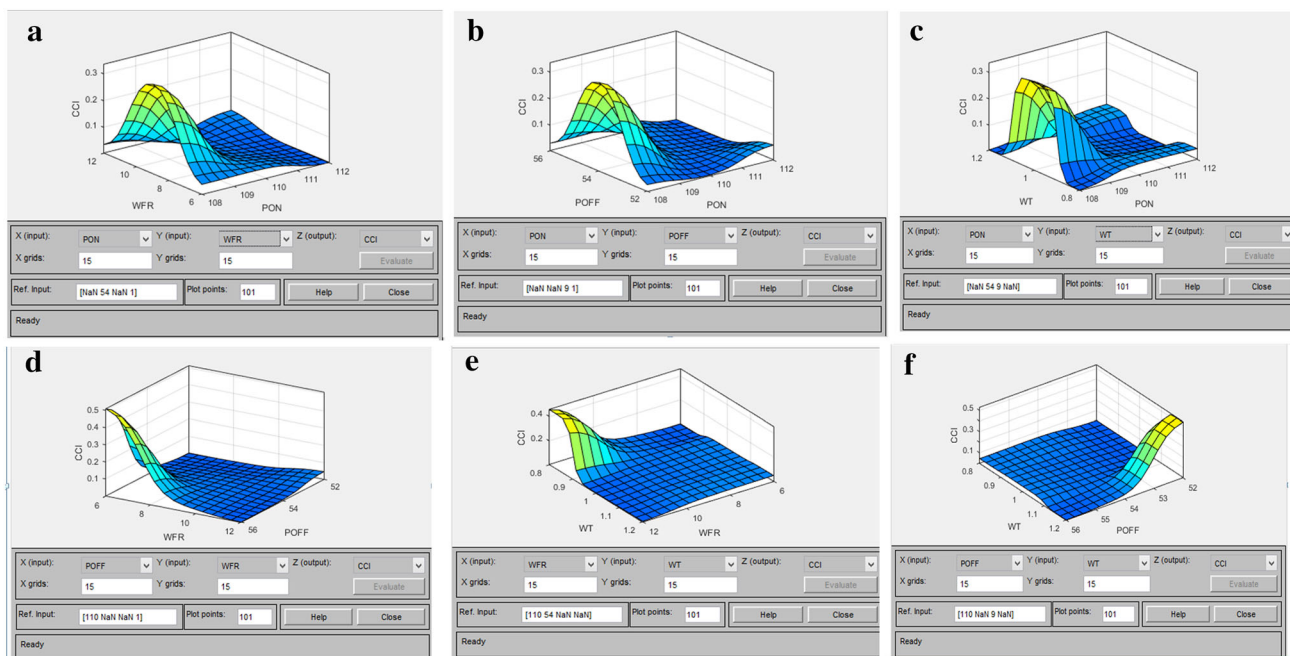
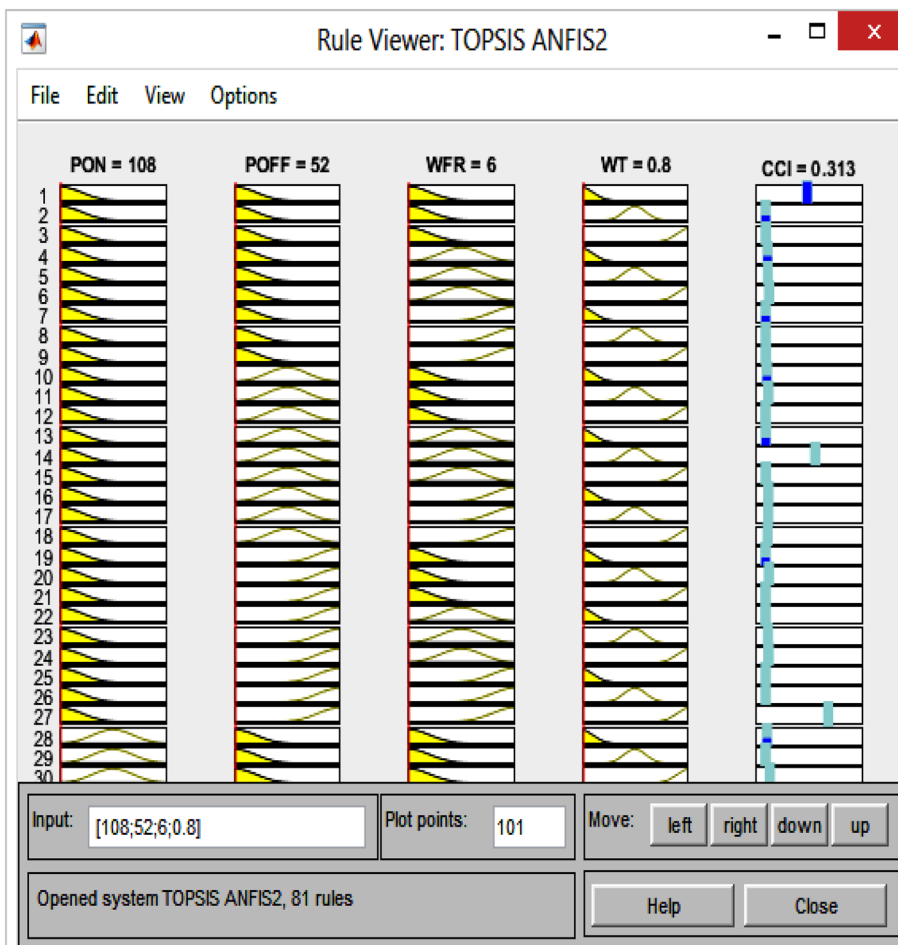


Fig. 3 (a–f) ANFIS surface viewer to know the impact of various process parameters on ‘CCI’

Fig. 4 Comparison between measured values and predicted ANFIS CCI values for **a** Training and **b** Testing Data

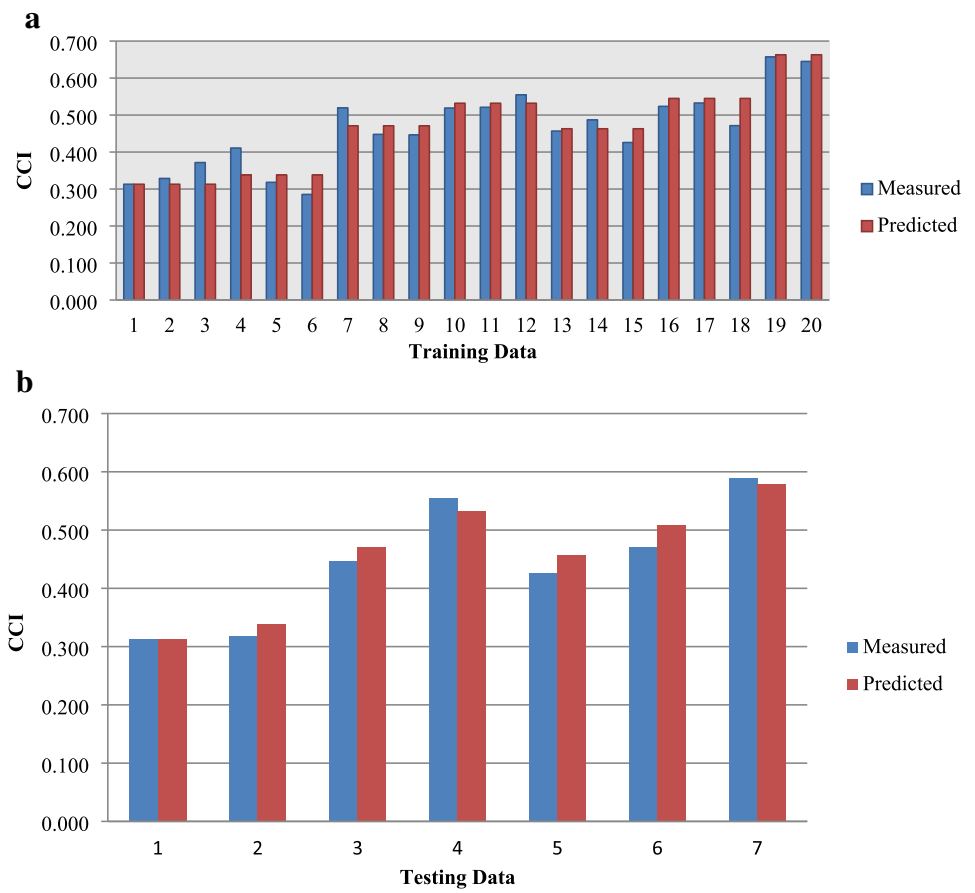


Fig. 5 Main effect plot for S/N ratios for CCI

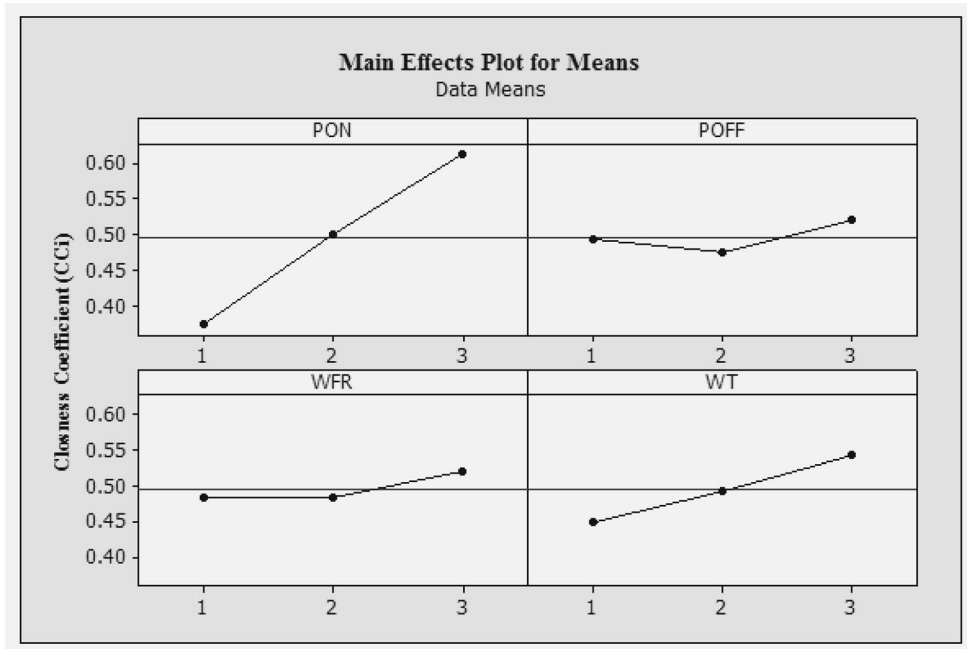


Table 8 S/N ratio for all process parameters

S. no	Parameter	Mean S/N ratio Level 1	Level 2	Level 3	Delta	Rank
1	PON	−8.952	−6.084	−4.277	4.675	1
2	POFF	−6.686	−6.876	−5.750	1.127	3
3	WFR	−6.837	−6.653	−5.822	1.015	4
4	WT	−7.380	−6.542	−5.390	1.991	2

Total S/N ratio = −4.27755625

Table 9 ANOVA table for CCI

S.no	Source	DOF	Statistical terms			
			Squ. SS	Adj. SS	Squ. MS	% Contribution
1	PON	2	0.2560	0.2560	0.128033	74.676364
2	POFF	2	0.0096	0.0096	0.004832	2.8185977
3	WFR	2	0.0081	0.0081	0.004058	2.366863
4	WT	2	0.0394	0.0394	0.019728	11.506528
5	Error	18	0.0295	0.0295	0.001644	8.6319374
6	Total	26	0.2560	0.2560	0.128033	100.00%

S = 0.0405510R -Sq = 91.37% R-Sq(adj) = 87.53%

function use during the analysis process. There are 551 nodes, 256 linear parameters, 32 nonlinear parameters, total parameters 288, training data pairs 24, and 256 fuzzy rules set was used during the ANFIS network training.

The fuzzy membership function is a technique to analyze real-life problems by experience than knowledge. This is based on real experience; hence, it gives a very realistic solution to the problem under investigation. The fuzzy logic that can be used to define represents the fuzziness in the issue. This fuzziness is mostly characterized by the

fuzzy membership function (MF). These are the representation of real nature in fuzzy logic. These functions are employed in fuzzification and defuzzification. In the present work, the Gaussian membership function is employed in the ANFIS. FLS is work in the three segments such as:

- Fuzzification: Where the precise, realistic inputs convert into fuzzy inputs. It converts crisp input into linguistic inputs. This is achieved by assuming all the crisper data as uncertain and nondeterministic. These uncertainties might have due to certain vagueness and imprecision in the data. These processes translate the accurate, crisp input into linguistic variables that are represented by the fuzzy sets.

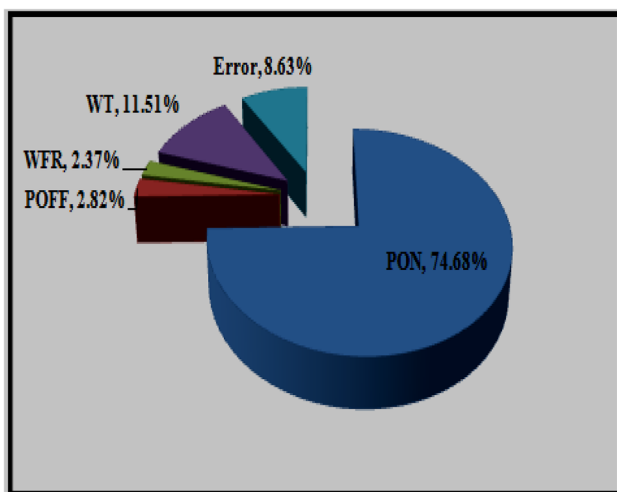


Fig. 6 Percentage contribution of each parameter in CCI analysis

Table 10 Results of confirmation test for CCI

Terms	Initial Process Parameters (PON-POFF-WFR-WT)	Optimum Process Parameters (PON-POFF-WFR-WT)
Levels	3–1 to 3–2	3–2 to 1–3
MRR	19.524	20.637
OVT	0.3254	0.3126
Ra	3.568	3.365
CCi	0.6567	0.7721

Result: Closeness Coefficient (CCi) is improved by 0.115345 (i.e., 17.5574%)

Table 11 Experimental findings

S. no	Input parameters	Initial value	Final value	Response			
				MRR	Ra	OVT	CCi
1	PON	108	110	22.40392↑	1.0045↑	1.25038↓	33.37787↑
		110	112	31.7969↑	11.57324↑	3.21185↑	22.74093↑
2	POFF	52	54	10.0794↓	5.4442↓	5.52793↓	3.71876↓
		54	56	7.60769↑	1.67064↓	0.60015↑	9.72984↑
3	WFR	6	9	11.8209↓	4.4117↓	13.7320↓	No change
		9	12	4.33310↑	3.21732↓	0.481386↑	7.6190↑
4	WT	0.8	1	3.73134↑	0.43655↓	2.719407↑	9.65253↑
		1	1.2	10.5297↑	0.78924↓	0.78299↓	10.1825↑

- **Inference Engine:** This is also known as a fuzzy rule base system. It contains a rule base consists of ‘if–then’ rules set. It also includes a database consists of various membership functions used in fuzzy rule. So the part of these is to convert given inputs into the targeted output. This process involves membership functions, set of if–then rules, and various fuzzy logic operators.
- **Defuzzification:** It converts fuzzy outputs into crisp numerical production. It is a process of mapping which creates a non-fuzzy control action. It can convert a fuzzy set into a crisp background. The centroid method mostly use in this process.

The ANOVA table for the overall response measured in the form of closeness coefficient (CCi) given in.

Table 9 Form the ANOVA results; observes that ‘PON’ and ‘WT’ have a considerable impact on the overall response compared to the other terms. Similarly, the signal/noise ratio is calculated for the general performance parameter (CCi). According to their influence on the overall performance, the process parameter’s rank is tabulated (Table 8). Table 8 shows that the parameter, such as ‘PON’ and the ‘WT,’ significantly influences parameters compared to the other two parameters. The ranks are given as per their influence on overall performance.

The surface plots showing the impact of various process input parameters on the overall response (CCi) (considering two parameters at a time and hold other parameters at their mean value) are as shown in Fig. (3a–f). Figure 3a–f observes that with an increase in the value of ‘PON’ and ‘WT,’ there is an improvement in the overall performance (CCi). This may be due to the change in spark energy which causes the rise in temperature and results in the melting of materials. Figure 4a and b shows the comparison between actual calculated ‘CCi’ and the ANFIS-based ‘CCi. The main effect plot showing the influence and contribution to the overall performance’s overall performance is shown in Figs. 5 and 6.

After identifying the best set of input parameters of WEDM, the final step is to check performance improvement. Table 10 demonstrates a comparison of initial CCi with optimal CCi. The enhancement of the ‘CCi’ value of the initial level to the optimal is 0.115345. From the experimental data, following observation has been made (Table 11):

When PON increases from 108 to 110 μs, OVT reduces by 1.25038%, MRR, Ra, and CCi increases by 22.40392, 1.0045, and 33.37787%, respectively. Similarly, when the PON increases from 110 to 112 μs, OVT increases by 3.211859%, MRR, Ra, and CCi increase by 31.79693, 11.57324, and 22.74093%, respectively. When POFF increases from 52 to 54 μs, OVT reduces by 5.52793%, MRR, Ra, and CCi reduces by 10.0794%, 5.44429%, and 3.71876%, respectively. Similarly, POFF increases from 54 to 56 μs, OVT increases by 0.60015%, MRR, Ra, and CCi increase by 7.607696, 1.670644, and 9.729844%, respectively.

When WFR increases from 6 to 9 m/min, OVT reduces by 13.732%, MRR, Ra reduce by 11.8209 and 4.411711%, and there is no change in the closeness coefficient (CCi). Similarly, when WFR increases from 9 to 12 m/min, Ra

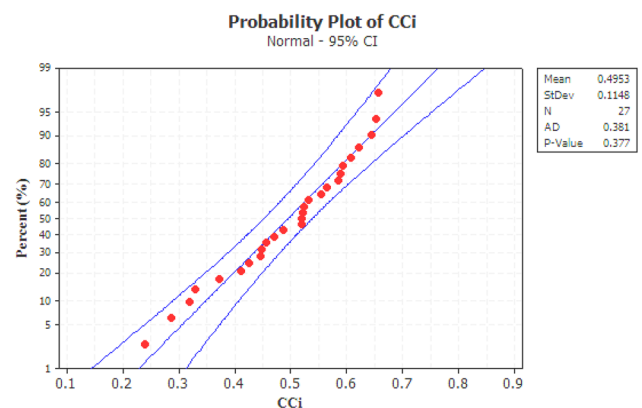


Fig. 7 Probability plot for closeness coefficient (CCi)

reduces by 3.21732%, and MRR, OVT, and CCI increase by 4.333108, 0.481386, and 7.619048%, respectively.

When WT increases from 0.8 to 1 kg, Ra reduces by 0.43655%, MRR, OVT, and the CCI increase by 3.731343, 2.719407, and 9.652530%, respectively. Similarly, When WT increases from 1 to 1.2 kg, OVT reduces by 0.78229%, MRR, Ra, and CCI increase by 10.52976, 0.789243, and 10.18256, respectively. The Al/Gr/CP10 MMC is used in various automotive valves to control low-pressure pneumatic bladders in the car seat, aerospace, defense research, and manufacturing industries. This work presents the effective use of ANFIS-based TOPSIS method to find out the optimistic process parameters, which will provide the ease of machining.

Conclusions

In this study, an attempt was made to investigate the impact of various EDM process parameters on the Al/GrCp10 MMC using ANFIS-based TOPSIS method. The following conclusions are made from the above study.

1. ANFIS-based TOPSIS method is very effectively used for multi-response optimization and for improving the process parameters' overall performance.
2. ANOVA results indicate the effect of process parameters like 'PON' and the 'WT' found to be more significant compared to the other two parameters, 'POFF' and 'WFR,' on the overall performance parameter (CCI).

The analysis observed that the 'PON' and the 'WT' significantly affect CCI. The most important parameters are 'PON' with a 74.68% contribution, followed by the wire tension 'WT' with a contribution of 8.63%. The parameters such as 'POFF' and

1. 'WFR' shows the most negligible impact on the overall performance.
2. The use of ANFIS-based TOPSIS method enhancement of closeness coefficient (CCI) from initial level combination 3–1 to 3–1 to the optimal 3–2 to 1–3 is 0.115345. It provided the optimal values for input parameters PON (112 μ s)-POFF(54 μ s)-WFR (6 m/min)- WT (1.2 kg), respectively, that enhance the overall performance of the WEDM process.
3. The novelty of the MMC is observed in terms of the graphite percentage. The addition of graphite beyond 8% would cause a decrease in the fluidity of the composite. In the presented work, 10% graphite is used for the preparation of the composite. Experimental findings provide the ease of machining, which will

help worldwide researchers to optimize the use of graphite in various industrial applications.

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Declarations

Conflict of interest The Authors declare that there is no conflict of interest.

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