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EDM PROCESS PARAMETER OPTIMIZATION FOR EFFICIENT MACHINING OF INCONEL-718

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Abstract. *In the present work, multi-response optimization of electro-discharge machining (EDM) process is carried out based on an experimental analysis of machining superalloy Inconel-718. The study aims at optimizing and determining an optimal set of process variables, namely discharge current (I_p), pulse-on duration (T_{on}) and dielectric fluid-pressure (F_p) for achieving optimal machining performance in EDM. Nine independent experiments based on L9 orthogonal array are carried out by using tungsten as the electrode. The productivity performance of the EDM process is measured in terms of material removal rate (MRR) and its cost parameter is measured in terms of tool wear rate (TWR) and electrode wear rate (EWR). The TOPSIS is used in conjunction with five different criterion weight allocation strategies— (namely, mean weight (MW), standard deviation (SDV), entropy, analytic hierarchy process (AHP) and Fuzzy). While MW, SDV and entropy are based on the objective evaluation of the decision-maker (DM), the AHP can model the DM's subjective evaluation. On the other hand, the uncertainty in the DM's evaluation is analyzed by using the fuzzy weighing approach.*

Key Words: *EDM, Parameter Optimization, MCDM, TOPSIS, Criteria Weight*

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1. INTRODUCTION

Over the past two decades, an increasing demand for quality finishing and intricate shapes of high strength materials has led to global interest in non-traditional machining. Electrical discharge machining (EDM), one of the popular non-traditional machining approaches, is at the forefront and perhaps most robust in modern-day machining technology [1]. It is widely used in industries for cutting intricate shapes, grooving patterns, micro-holes, boring, craters in alloys and superalloys like Inconel, haste alloy, etc. Unlike the traditional machining approaches, EDM is a non-contact metal removal process that works on the principle of thermo-electrical erosion which is controlled by high-frequency pulses generated in a dielectric medium. It has a unique ability to eliminate mechanical stresses, chatter and vibration issues without being in contact with the working material. In general operation, it develops a significant potential difference between an electrode (tool) and the workpiece, resulting in melting, vaporization and removal of work material debris [2].

EDM is advanced machining; hence it is highly preferred for materials difficult to cut like superalloys. Though a significant amount of work has been carried out on machining of superalloys with MCDM approaches in EDM and Wire-EDM, optimization analysis related to its machining efficiency with different electrodes and dielectric has not been adequately explored. Inconel-718, one of the toughest materials is a Ni-based superalloy with a chemical composition of C0.8%, Mn0.35%, Ni54%, Cr20%, Ti0.75%, and Fe [3, 4]. It is extensively used in making gas turbine blades, jet engine parts, ballistic missiles and automotive applications. Its ability to retain the same texture and hardness throughout various temperatures makes it suitable for robust engineering structures. Despite being rich in carbides, abrasive contents and high resistance properties, Inconel-718 displays sparse heat dissipation and shows poor machinability, resulting in blur formation and rough surface finish while machining in EDM. This can be attributed to poor thermal conductivity and rapid work-hardening of Inconel. These challenges make it extremely hard to machine even in EDM and thus raises concern regarding the usage of a proper electrode, dielectric as well as optimized process parameters. This is where multi-criteria decision-making (MCDM) approaches come handy.

Several researchers over the past few years have tested different materials for tools and dielectrics for EDM operations. While a number of them have made use of metaheuristic approaches like genetic algorithm (GA), particle swarm optimization (PSO) etc., others have made use of MCDM approaches like TOPSIS (technique for order performance by similarity to ideal solution), PSI (preferential selection index), and WSM (weighted-sum method) in order to improve EDM response parameters. Mohanty et al. researched Inconel 781 using copper, graphite and brass tools in EDM. In their study, they observed that the tool material, discharge current and pulse on-time affect machinability of Inconel on a wide range. Further, they showed experimentally that MRR increases monotonically while using a graphite tool followed by copper and brass [5]. Lin et al. investigated the effect of tungsten carbide tool on process parameter optimization of Inconel 718 using grey–relation and grey-Taguchi MCDM technique [6]. Kumar et al. studied the effect of brass wire EDM on Inconel 718 using Taguchi L27 with a multi attributed simulated annealing (SA) algorithm. They found that pulse-on time and gap voltage have a more considerable influence on kerf and MRR of material. Vikas et al. [7] studied the MCDM methods to optimize process parameters of Inconel-718 using the Cu-Cadmium tool in EDM. They applied Taguchi L9 to the design variable dataset and used TOPSIS and PROMETHEE to compare the responses based on ranking. Rahul et al. [8] carried out a research study to determine the appropriate setting of process parameters like gap voltage, discharge current, and flushing pressure for optimal machining of Inconel 718 in EDM. They used Taguchi L25 orthogonal array with PCA-TOPSIS to measure performance characteristics, i.e., MRR, EWR, surface roughness, SCD and WLT. They found that the peak current plays the most significant role while the flushing parameter is of least interest in machining optimization. Huang and Liao [9] performed an experimental study in order to optimize machining parameters of wire-EDM using grey relation and statistical analysis. Using Taguchi L18 orthogonal array, they found that the feed rate has a significant effect on MRR while the gap width and surface roughness were influenced by pulse on-time. Joy et al. [10] performed process parameter optimization using Taguchi L9 and PROMETHEE approach for Inconel 718 in EDM. MCDM method was found to be successful in the combined optimization of MRR & TWR. Singaravel et al. [11] performed the turning process optimization of EN25 steel using Taguchi and TOPSIS MCDM approach. Chakraborty and Das [12] used a multivariate quality loss function approach to optimize several non-traditional machining processes. They also used a superiority and inferiority ranking method to identify the best parametric combination of a green EDM process [13]. Chakraborty et al.[14] used TOPSIS to optimize EDM and WEDM process of Inconel 718 machining.

Farshid [15] carried out an experimental study on Inconel 718 in EDM and used an artificial neural network (ANN) in conjunction with GA to predict machining conditions and optimize the EDM process. He found that MRR is more influenced by the process conditions as compared to surface roughness. Both current and pulse on-time are effective for MRR enhancement but the gap voltage is highly influential for MRR. Implementation of ANN-NSGA (artificial neural network-non-sorting genetic algorithm) can efficiently optimize the process conditions. Mandeep and Hari [16] experimentally studied machining of Inconel X-750 using Wire-EDM. Taguchi and grey relation methods were used to optimize the process variables.

Though the above literature survey shows that a significant amount and a diverse quality of work have been done so far in order to optimize the process parameters for Inconel-718 with MCDM, considerable lacuna still remains.

- Relatively very few studies have been conducted with Shannon entropy distribution and improved-AHP with TOPSIS for predicting accurate results.
- No comparative study on the application of various subjective and objective weights to experimental data is seen.
- Very few papers on the comparative assessment of the ranking performance of TOPSIS on the application of fuzzy weights and non-fuzzy weights are seen.

Therefore, in this paper, an attempt is made to determine an optimal combination of process variables (namely, discharge current, pulse on-time, and dielectric effect) that would effectively increase the MRR while decreasing the TWR and EWR. TOPSIS as a widely known and preferred MCDM approach is used in this research as it uniquely converts multiple responses into a single performance criterion at a low computational cost. Though the conventional TOPSIS is reliable and easy to implement, it is susceptible to uncertainty and personal influences. Entropy and AHP weights are competent in improving the TOPSIS performance through decision/weight matrix *via* discrete probability distribution and pairwise relative comparison matrix, respectively. These weighted distributions avoid biasing at each level, i.e. experimental/personal and converge the data with consistency and a high degree of accuracy when combined with general TOPSIS steps. This research covers two crucial objectives— (1) experimental evaluation of suitable process parameters using an L9 orthogonal array with performance measures being MRR (higher the better), TWR (lower the better) and EWR (lower the better), (2) comparison of traditionally used TOPSIS (i.e. MW-TOPSIS) with SDV-TOPSIS, AHP-TOPSIS, entropy-TOPSIS and fuzzy-TOPSIS.

2. Materials and Methods

2.1. Experimental details

In this research study, Inconel 718 superalloy of square cross-section (100mm×100mm ×4mm) as shown in Fig.1a was used as the work material for machining in a die-sinking EDM (Sparkonix MOS, 35A, ZNC) shown in Fig.1b. The mechanical strength and chemical composition of Inconel 718 superalloy can be retrieved from [8]. A cylindrical pure tungsten electrode (tool of diameter 2 mm and length 4 cm) as shown in Fig.1c and EDM oil (dielectric medium) of density 0.764 were used to perform the procedure. The experimental conditions with process parameter levels, i.e., the input responses for controlled operation are depicted in Table 1 with a duty cycle of 50%.

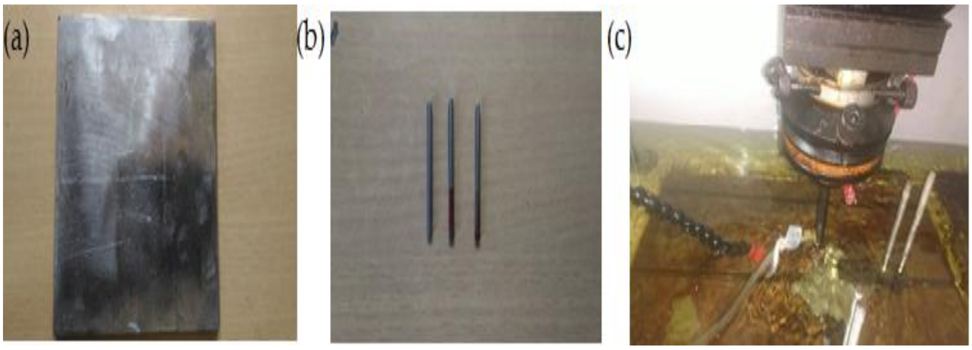

Fig. 1 (a) Inconel 718 workpiece (b) Tungsten tool (c) Machining of Inconel with Tungsten tool in EDM oil

Table 1 Process parameters and their levels

Process parameter	Units	Level 1	Level 2	Level 3
Pulse-on time	μs	50 (A1)	100 (A2)	200 (A3)
Flushing Pressure	Kg/cm^2	0.3 (B1)	0.4 (B2)	0.5 (B3)
Discharge current	A	18 (C1)	20 (C2)	22 (C3)

The experimental design was created using Taguchi L9 mixed orthogonal array with equal weight distribution at each level. The factor selection and their levels were developed based on pilot tests and literature surveys. The set of trials were designed and executed on the 3×3 level settings depicted in Table 2 on Inconel 718 workpiece and tungsten electrode in EDM. The working configuration for tool and job piece was initially positioned at the origin, and the machining duration for each trial was set for 14 minutes and 1.5 mm depth. The performance measurement of each run was carried out by measuring MRR ($mm^3/$

min) as per eq. (1), TWR (g) and EWR (%) as per eq. (2). The weight losses of the tool and material were measured using an electronic weighing balance.

Table 2 Experimental values of MRR, TWR and EWR

Exp. No.	Pulse-on time (μs)	Flushing Pressure ($\mathrm{Kg/cm^2}$)	Discharge Current (A)	Parameter combinational	MRR ($\mathrm{mm^3/min}$)	TWR ($\mathrm{mm^3/min}$)	EWR
1	50	0.3	18	A1B1C1	0.07597	0.01192	0.29487
2	100	0.4	18	A2B2C1	0.1225	0.0121015	0.23195
3	200	0.5	18	A3B3C1	0.11189	0.014906	0.28475
4	50	0.4	20	A1B2C2	0.14257	0.01819	0.29984
5	100	0.5	20	A2B3C2	0.19825	0.02149	0.25458
6	200	0.3	20	A3B1C2	0.1988661	0.023233	0.27438
7	50	0.5	22	A1B3C3	0.125326	0.00986166	0.18481
8	100	0.3	22	A2B1C3	0.200095	0.025867	0.30361
9	200	0.4	22	A3B2C3	0.2088095	0.0150057	0.16595

2.2. Multi-criteria decision-making by TOPSIS

TOPSIS is a robust and widely accepted MCDM technique in operation research and production engineering. In this method, the best alternatives are searched based on the closeness coefficient, i.e. the distances from the ideal best and ideal worst solution. The basic idea behind the method is to evaluate the alternatives on the Euclidian distance scale, so that the least span from the ideal best and farthest from the ideal worst solution is achieved. The alternatives are then ordered based on their rank. The steps for the TOPSIS approach are as follows—

Step 1: Decision matrix design and assumption of the weight matrix.
Let $D = x_{ij}$ be a decision matrix, where$x_{ij} \in \mathbb{R}$.

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{4}$$

Weight vector may be expressed as $W = [w_1 \quad \cdots \quad w_n]$, where $\sum_{j=1}^{n}(w_1 \quad \cdots \quad w_n) = 1$.

The strategies regarding the determination of the weight vector are discussed in the subsequent section.

Step 2: Construction of normalized decision matrix n_{ij} of each criterion using Eq. (5),

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{5}$$

Step 3: Determination of weighted normalized matrix using eq.(6),

$$N_{ij} = w_j * n_{ij} \text{for} i \in [1, m] \text{ and } j \in [1, n] \tag{6}$$

Step 4: Estimation of the ideal positive (best) and ideal negative (worst) solutions using Eqs.(7) and (8), respectively.

$$A_j^{+} = \begin{cases} \max. N_{ij} \mid j \in B \\ \min. N_{ij} \mid j \in C \end{cases} \tag{7}$$

$$A_j^{+} = \begin{cases} \min. N_{ij} \mid j \in B \\ \max. N_{ij} \mid j \in C \end{cases} \tag{8}$$

where B is a vector of benefit function and C is the vector of the cost function, for $i \in [1, m]$ and $j \in [1, n]$.

Step 5: Determination of the separation measurement and relative closeness coefficient. In the TOPSIS, the difference of each response from ideal positive (best) solution is given by Eq. (9).

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} (N_{ij} - A_j^{+})^2} \tag{9}$$

for $i \in [1, m]$ and $j \in [1, n]$.

Similarly, the difference between each response from the ideal negative (worst) solution is given by Eq. (10).

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} (N_{ij} - A_j^{-})^2} \tag{10}$$

for $i \in [1, m]$ and $j \in [1, n]$

Corresponding closeness coefficient (CC_i) of the ith alternative is calculated using:

$$CC_i = \frac{S_i^{-}}{S_i^{+} + S_i^{-}} \tag{11}$$

where $0 \leq CC_i \leq 1$, $i \in [1, m]$

Step 6: The final step is to rank the alternatives in decreasing order of closeness coefficient value.

2.3. Weight allocation without considering uncertainty

2.3.1. Mean weight method

This method is based on the principle of equal weight distribution to all output responses. Equal weights are assigned in this approach to give equal importance to each parameter while evaluating the influence of each parameter on selecting an optimal set for machining. For the current three criteria (MRR, TWR and EWR) EDM optimal process parameter selection problem, the weight vector is expressed as $W = [0.3333 \quad 0.3333 \quad 0.3333]$. Henceforth, in this study, for ease of reference, the solutions from these weights applied to TOPSIS are called as MW-TOPSIS.

2.3.2. Standard Deviation (SDV) method

Standard deviation constructs an unbiased and unprejudiced assignment of weights. It significantly improves the MCDM approach and lessens the personal assigned weight stress as felt in general-TOPSIS. The SDV weights are calculated through the following equations. First, in order to change various scales of the process parameters and normalize them, Eq. (12) is used.

$$B_{ij} = \frac{x_{ij} - \min(x)_{ij}}{\max(x)_{ij} - \min(x)_{ij}} \tag{12}$$

$$SDV_J = \sqrt{\frac{\sum_{i=1}^{m}(B_{ij} - B_j)^2}{m}} \tag{13}$$

where B_j is the average of the values for the ith measure, where $j = 1, 2, 3$.

The weight vector is given by eq. (14) as,

$$W_j = \frac{SDV_j}{\sum_{j=1}^{n} SDV_j} \tag{14}$$

For the current problem, the SDV weight vector is $W = [0.3425 \quad 0.3097 \quad 0.3477]$ and henceforth, the solutions from these weights applied to TOPSIS are called SDV-TOPSIS.

2.3.3. Entropy method

Entropy-TOPSIS is a practical and quick approach to predict the best alternative from all responses. TOPSIS combined with entropy weights remove the subjective bias and uses objective decision to derive suitable weight vectors in order to compute the rank of feasible alternatives. The entropy weight function is assumed to be based on the discrete probability distribution.

$$e_j = \frac{-1}{\ln(m)} \sum_{i=1}^{m} n_{ij} \ln(n_{ij}) \tag{15}$$

Degree of diversity (d) possessed by each criterion is evaluated as,

$$d_j = 1 - e_j, j = 1, 2, 3 \tag{16}$$

And the weight objective for each criterion is given by

$$W_j = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{17}$$

For the current problem, the entropy weight vector is $W = [0.4121 \quad 0.4219 \quad 0.1661]$ and henceforth, in this article, the solutions from these weights applied to TOPSIS are called entropy-TOPSIS.

Table 3 The preference weight distribution based on Saaty nine-point scale

Scale for x_{ij}	Influence	Account for
1	Equal influence	Equally significant
3	Weak influence	Moderately better than other
5	Strong influence	One has a strong influence over other
7	Very Strong influence	One has a very strong influence over other
9	Absolute influence	One has absolute influence over other

2.3.4. AHP method

Analytic hierarchy process (AHP) is known for its outstanding analytical style of solving and predicting convoluted decision-making at different levels of hierarchy or neural system. An improved-AHP can set as many levels of neural/hierarchy and use both objective and subjective influence on the neural decision. In this method for predicting weight vector, a pairwise comparison matrix is developed *via* a scale of the relative importance of attributes and the judgments based on the Saaty AHP& RI index given in Table 3. The preference weights based on Saaty nine-point scale are distributed according to their influence. The AHP weight estimation is based on the following,

$$Y_{ij} = \begin{bmatrix} 1 & \cdots & y_{1n} \\ \vdots & 1 & \vdots \\ y_{n1} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 7 \\ 1 & 1 & 5 \\ 1/7 & 1/5 & 1 \end{bmatrix} \tag{18}$$

where $y_{ij} \in Y_{nn}$ and $\begin{cases} y_{ij} = \frac{1}{y_{ji}}, \text{when } i \neq j \\ y_{ij} = y_{ji}, \text{when } i = j \end{cases}$

Normalized weight W is calculated by normalizing the geometric mean of the comparison matrix as,

$$W_i = \frac{(\prod_{j=1}^{n} y_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} y_{ij})^{\frac{1}{n}}} \tag{19}$$

where $i, j \in [1, n]$.

The AHP weights for the current problem are computed as

$$W = [0.4869 \quad 0.4353 \quad 0.0778].$$

The next step is to estimate consistency index (CI), consistency ratio (CR), and Eigen-value. A vector M is constructed through the product of pairwise comparison matrix and normalized weighted vector for the significance of alternatives.

$$M = [M_i] = y_{ij} \times W_i \text{ , where} i, j \in [1, n] \tag{20}$$

For maximum Eigen-value (Λ) of M,

$$\Lambda = \frac{\sum_{i=1}^{n} b_i}{n} \tag{21}$$

where $b_i = \frac{M_i}{W_i}$ and $i, j \in [1, n]$

$$CI = \frac{\Lambda - n}{n-1} \text{ and } CR = \frac{CI}{RI} \tag{22}$$

where $\Lambda > n$ and$CR < 10\%$. RI is determined for different size matrixes, and its value is 0.58 for a 3×3 matrix.

2.4. Weight allocation under uncertainty by Fuzzification

In the classical set theory, if a classical set of objects (say A), contains some generic elements (say x), then the belongingness of x to A is expressed in terms of membership function $\mu_A(x)$.

$$\mu_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases} \tag{23}$$

Thus, in the classical set, an element has only two options— either to belong or not to belong to the set. However, not necessarily all real-life situations can be classified in such a bivalent manner. Almost all group decision-making tasks are affected by uncertainty; thereby expressing them in terms of classical sets is not always possible.

Zadeh introduced the fuzzy set theory, where partial membership in sets is possible. The fuzzy set theory uses membership functions to permit the gradual assessment of element membership in a set. Thus, a fuzzy set A in X may be represented as [17],

$$A = \{x, \mu_A(x)\}, x \in X \tag{24}$$

where $\mu_A(x): X \to [0,1]$ is the membership function of A and $\mu_A(x)$ is the degree of membership of x in A. $\mu_A(x)$ can take any value between [0,1], capturing partial membership of x in fuzzy set A.

According to Madi et al. [17] "A fuzzy number M is a convex normal fuzzy set M of the real line R such that [18]: There exists exactly one $x_0 \in R$ with $\mu_M(x_0) = 1$ (x_0 is called mean value of M) and $\mu_M(x)$ is piecewise continuous."

Among various fuzzy numbers like triangular fuzzy number (TFN), trapezoidal fuzzy number, bell-shaped fuzzy number, etc., TFN is the most commonly used due to its computational simplicity and intuitiveness. TFN is a triplet of three real numbers (l, m, u) (see Fig. 2a).

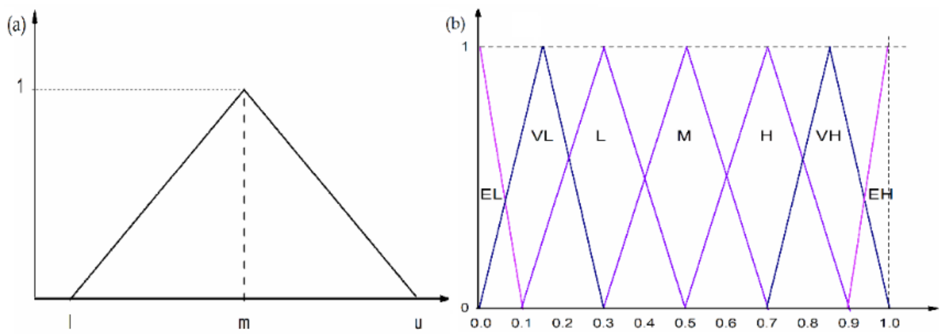

Fig. 2 (a) A typical triangular fuzzy number (b) Linguistic scale selected for the current work

Table 4 Linguistic variables for the importance weight of each output (TFN)

Importance	Symbol	Fuzzy Weight
Extremely low	EL	(0, 0, 0.1)
Very low	VL	(0, 0.1, 0.3)
Low	L	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.7)
High	H	(0.5, 0.7, 0.9)
Very high	VH	(0.7, 0.9, 1)
Extremely high	EH	(0.9, 1, 1)

As seen in Fig. 2, l and u represent the smallest and the largest values; m is the mode or core of the TFN. The range expressed by the TFN i.e. $(u - l)$ is called support. The membership function of the triangular fuzzy number can be expressed as,

$$\mu_A(x) = \begin{cases} 0 & x < l \\ \frac{(x-l)}{(m-l)} & l \le x \le m \\ \frac{(u-x)}{(u-m)} & l \le x \le u \\ 0 & x > u \end{cases} \tag{25}$$

If say, $\tilde{A} = (a_l, a_m, a_u)$ and $\tilde{B} = (b_l, b_m, b_u)$ are two triangular fuzzy numbers, then the distance between two fuzzy numbers is calculated using the vertex method [19].

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}[(a_l - b_l)^2 + (a_m - b_m)^2 + (a_u - b_u)^2]} \tag{26}$$

Linguistic variables are adjectives attributed to the parameters or alternatives. The prime advantage of linguistic variables is that they are expressed in natural language. This makes it easier to incorporate the inherent uncertainties associated with decision-making processes. In any linguistic scale, linguistic variables are represented by a set of corresponding fuzzy numbers. The linguistic scale selected for the current work is shown in Fig. 2b. The fuzzy linguistic terms and their corresponding TFNs, as well as TFN supports, are presented in Table 4. In this work, uneven supports are used so that more significance is given to moderate attitudes. Many researchers argue that such uneven supports stimulate decision-makers to evaluate their decisions more carefully [20].

For any MCDM problem involving n criteria and K experts (decision-makers), the fuzzy significance coefficients or weights ($\widetilde{w_j} = w_{j1}, w_{j2}, w_{j3}$) are calculated as

$$\begin{aligned} w_{j1} &= \min_k \{ {w_{j1}}^k \} \\ w_{j2} &= \frac{\sum_{k=1}^{K} {w_{j2}}^k}{K} \\ w_{j3} &= \max_k \{ {w_{j3}}^k \} \end{aligned} \tag{27}$$

where j = 1, …, n are criteria and k=1, …, k are decision-makers.

Table 5 Ratings given to the three criteria by decision-makers

Response	DM1	DM2	DM3	DM4	DM5	DM6	DM7
MRR	VH	H	EH	EH	M	H	H
TWR	H	H	VH	M	VH	H	VH
EWR	M	M	H	H	M	M	L

Table 6 Aggregated fuzzy weights of the output responses

Output response	Aggregated fuzzy weight
MRR	(0.6143, 0.7857, 0.9143)
TWR	(0.5571, 0.7571, 0.9143)
EWR	(0.3286, 0.5286, 0.7286)

The various steps to be followed during the fuzzy-TOPSIS are as follows,

Step 1: Collect the subjective evaluations of the decision-maker on the importance of weights. The subjective evaluations of the decision-makers for the current work are presented in Table 5.

Step 2: Calculate the fuzzy significance coefficients or weights based on the decision-maker's subjective evaluations by using Table 6 and Eq. (27).

Step 3: Form the decision matrix as listed in Eq. (4) and normalized decision matrix listed in Eq. (5).

Step 4: Form a fuzzy weighted decision matrix by multiplying the normalized decision matrix listed in Eq. (5) with corresponding fuzzy weights as per Eq. (27).

$$\tilde{D} = \begin{bmatrix} \tilde{N}_{11} & \tilde{N}_{12} & \cdots & \tilde{N}_{1n} \\ \tilde{N}_{21} & \tilde{N}_{22} & \cdots & \tilde{N}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{N}_{m1} & \tilde{N}_{m2} & \cdots & \tilde{N}_{mn} \end{bmatrix} \tag{28}$$

where, $\tilde{N}_{ij} = (w_{j1}N_{ij}, w_{j2}N_{ij}, w_{j3}N_{ij})$ where $i = 1, \dots, m$ and $j = 1, \dots, n$

Step 5: The coordinates for fuzzy positive ideal solution A_j^+ are calculated as

$$\tilde{A}_j^+ = \begin{cases} \text{Max}\, \tilde{N}_{ij} | j \in B \\ \text{Min}\, \tilde{N}_{ij} | j \in C \end{cases} where i = 1, \dots, m \tag{29}$$

The coordinates for fuzzy negative ideal solution A_j^- are calculated as

$$\tilde{A}_j^- = \begin{cases} \text{Min}\, \tilde{N}_{ij} | j \in B \\ \text{Max}\, \tilde{N}_{ij} | j \in C \end{cases} where i = 1, \dots, m \tag{30}$$

where B and C are the index set of beneficial and cost (non-beneficial) criteria, respectively.

Step 6: The Euclidean distance of each alternative from fuzzy positive and negative ideal value is calculated as

$$S_i^+ = \sum_{j=1}^{n} d(\tilde{N}_{ij}, \tilde{A}_j^+)\ i = 1, \dots, m; j = 1, \dots, n \tag{31}$$

$$S_i^- = \sum_{j=1}^{n} d(\tilde{N}_{ij}, \tilde{A}_j^-)\ i = 1, \dots, m; j = 1, \dots, n \tag{32}$$

where $d(.,.)$ represents the distance between two fuzzy numbers calculated by using Eq. (26) and depicted in Table 7.

Step 7: Closeness coefficient CC_i of the alternatives are calculated using Eq. (11) and ranked as per descending order in Table 8.

Table 7 Fuzzy positive and negative ideal value

Output	A+	A-
MRR	(0.2664, 0.3407, 0.3965)	(0.097, 0.124, 0.1443)
TWR	(0.1036, 0.1408, 0.17)	(0.271, 0.3683, 0.4447)
EWR	(0.0701, 0.1127, 0.1554)	(0.1282, 0.2062, 0.2842)

3. Results and Discussion

3.1. Effect of process parameters on MRR

The main effect plot of MRR for various process parameters is shown in Fig. 3a. It is seen that the process variables have a significant effect on MRR. The MRR monotonically increases when the current is increased from 18A to 20A, but slightly decreases when the peak current reaches 22A. For pulse-on time, MRR shows a similar trend as seen in the case of the current. It rises when the pulse-on time is increased and then gets saturated depicting no further pulse-on time effect on MRR. In contrast, the flushing pressure is seen as having less influence on MRR compared to discharge current and pulse-on time. The MRR curve remains unaltered when the flushing pressure changes from $0.3\text{kg/cm}^2$to 0.4kg/cm^2, but MRR drastically drops when the flushing pressure is increased to 0.5kg/cm^2.

3.2. Effect of process parameters on TWR

The main effect plot of TWR for various process parameters is shown in Fig. 3b. The lower, the better is preferred for TWR. It is seen that the process variables have again a non-linear effect on TWR as in MRR. The TWR increases when the current is increased from 18 to 20A but drastically drops when the peak current reaches about 22A, signifying less tool wear at high current. Regarding pulse-on time, TWR shows a similar trend as in MRR; it increases rapidly up to $100\mu s$ but drastically drops at $200\mu s$. The flushing pressure, in this case, seems to have a significant influence in comparison to MRR. At 0.3kg/cm^2pressure, TWR is maximum but it drastically reduces at 0.4kg/cm^2 whereas, at the 0.5kg/cm2, it shows a slight increment in TWR.

Table 8 Separation measures, closeness coefficients and ranking order of alternatives

	Triangular membership function			
Exp. No.	di-	di+	Ci	Rank
1	0.2052	0.3355	0.3795	8
2	0.3225	0.2182	0.5965	3
3	0.2280	0.3127	0.4217	6
4	0.2202	0.3205	0.4073	7
5	0.2958	0.2449	0.5470	4
6	0.2585	0.2822	0.4781	5
7	0.3919	0.1488	0.7248	2
8	0.2013	0.3394	0.3723	9
9	0.4682	0.0725	0.8659	1

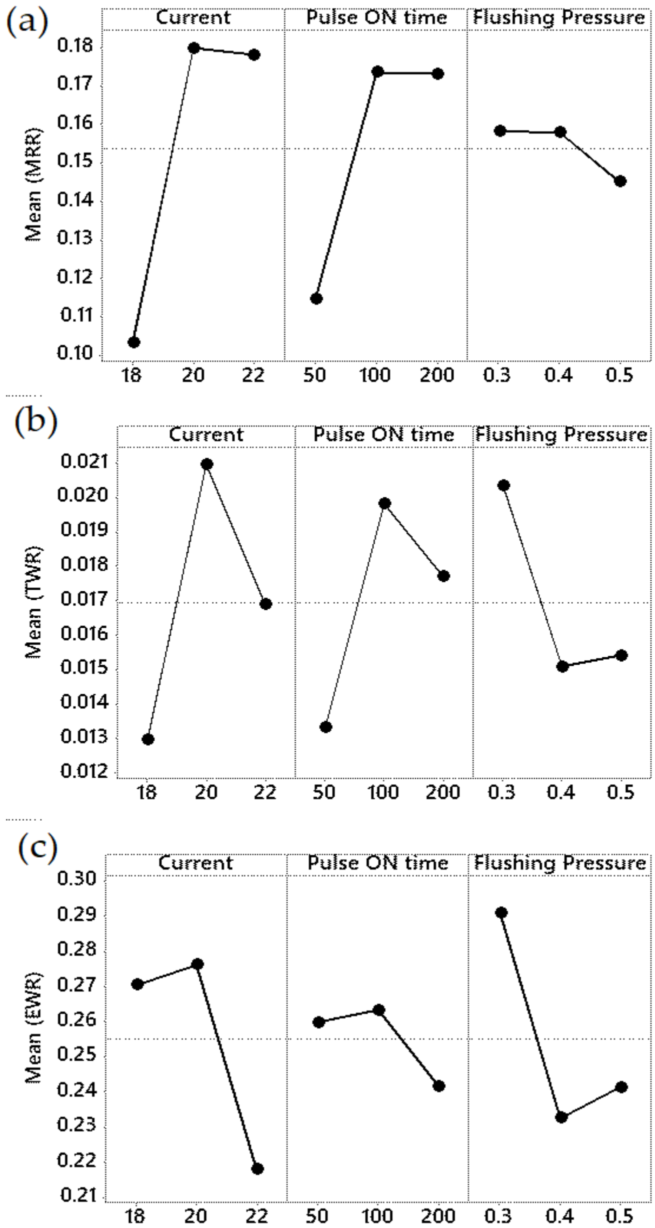

Fig. 3 Effect of the process parameters on (a) MRR, (b) TWR, (c) EWR

3.3. Effect of process parameters on EWR

The main effect plot of EWR for various process parameters is shown in Fig. 3c. the lower, the better is also preferred for EWR. It is seen that the process variables have again a non-linear effect on EWR as in MRR and Writhe EWR increases slightly when the current is increased from 18 to 20A but it sharply drops when the peak current reaches 22A. With pulse-on time, EWR shows the trend opposite to that in the case of MRR and TWR. It slightly rises up till 100μs but it drastically drops down till 200μs. The flushing pressure, in this case, seems to have significant influence and is similar to TWR.

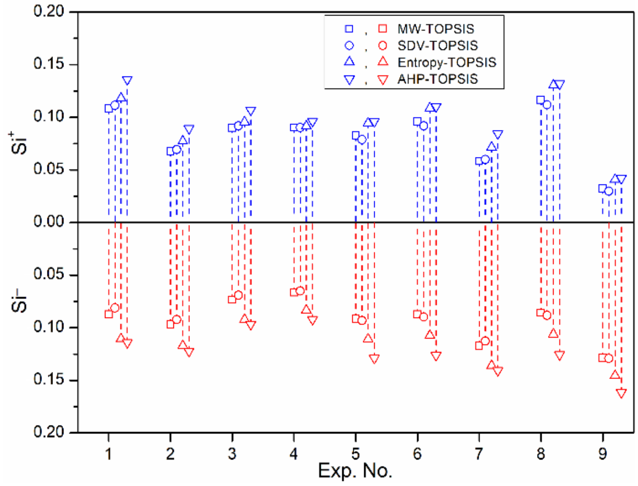

Fig. 4 Euclidean distances of each alternative from PIS and NIS

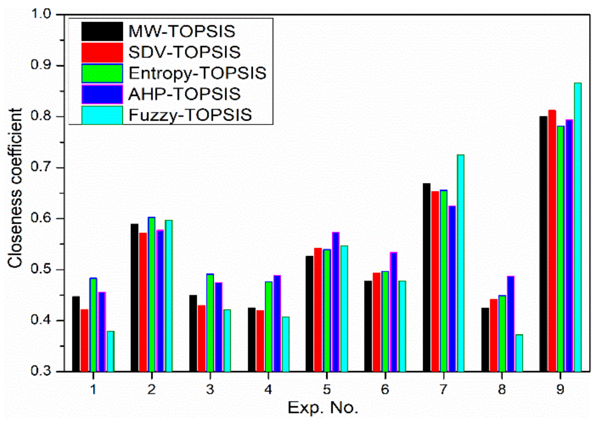

Fig. 5 Closeness coefficients of the alternatives based on different TOPSIS methods

3.4. Optimal process parameter selection

In this section, no uncertainty in the weights assigned to the criteria is considered. Using the criterion weights derived using the four criteria weight allocation methods (namely MW, SDV, Entropy and AHP), their respective weighted normalized matrix is constructed. The weighted-normalized matrix is presented in Table 9. Using this information, the Euclidean distances of each alternative from PIS and NIS are calculated and presented in Fig. 4. It should be noted that for the solution to be effective the Euclidean distance of the alternative from the PIS should be as low as possible, i.e. in Fig. 4 the S_i^+ should be as near the zero line as possible. Similarly, the S_i^- should be as away from the zero line as possible for the solution to be effective. This indicates that the Euclidean distance of the alternative from the NIS should be as high as possible. The variation of the closeness coefficient for each alterative using different TOPSIS methods is shown in. Fig. 5. It is seen that, among all the alternatives, alternative no. 9, i.e. A3B2C3 is the most promising set of process parameters that can be effectively used to simultaneously maximize MRR and minimize TWR and EWR.

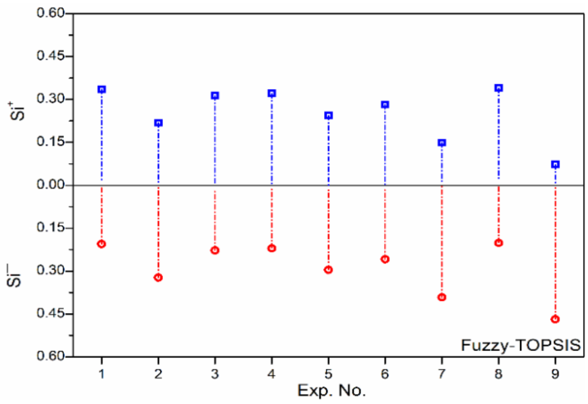

Fig. 6 Euclidean distances of each alternative from FPIS and FNIS of fuzzy-TOPSIS

Table 9 Weighted normalized decision matrix

MW-TOPSIS			SDV-TOPSIS		
MRR	TWR	EWR	MRR	TWR	EWR
0.0526	0.0746	0.1263	0.0540	0.0693	0.1318
0.0848	0.0758	0.0993	0.0872	0.0704	0.1036
0.0775	0.0933	0.1220	0.0796	0.0867	0.1272
0.0987	0.1139	0.1284	0.1014	0.1058	0.1340
0.1373	0.1345	0.1090	0.1410	0.1250	0.1138
0.1377	0.1455	0.1175	0.1415	0.1351	0.1226
0.0868	0.0617	0.0792	0.0892	0.0574	0.0826
0.1385	0.1619	0.1300	0.1424	0.1505	0.1357
0.1446	0.0939	0.0711	0.1486	0.0873	0.0742
Entropy-TOPSIS			AHP-TOPSIS		
MRR	TWR	EWR	MRR	TWR	EWR
0.0650	0.0945	0.0629	0.0768	0.0975	0.0295
0.1048	0.0959	0.0495	0.1239	0.0989	0.0232
0.0958	0.1181	0.0608	0.1132	0.1219	0.0285
0.1220	0.1441	0.0640	0.1442	0.1487	0.0300
0.1697	0.1703	0.0543	0.2005	0.1757	0.0254
0.1702	0.1841	0.0585	0.2011	0.1899	0.0274
0.1073	0.0781	0.0394	0.1267	0.0806	0.0185
0.1712	0.2050	0.0648	0.2023	0.2115	0.0304
0.1787	0.1189	0.0354	0.2112	0.1227	0.0166

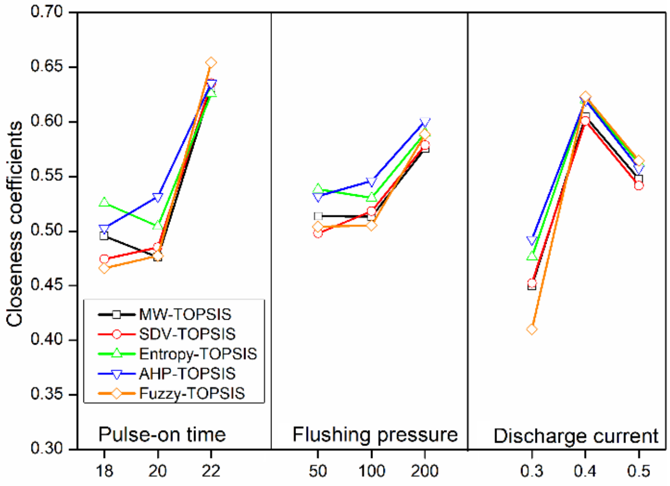

Fig. 7 Process performance of EDM parameters

Table 10 Ranking of alternatives by various TOPSIS methods

Alternative	MW-TOPSIS	SDV-TOPSIS	Entropy-TOPSIS	AHP-TOPSIS	Fuzzy-TOPSIS
1	7	8	7	9	8
2	3	3	3	3	3
3	6	7	6	8	6
4	8	9	8	6	7
5	4	4	4	4	4
6	5	5	5	5	5
7	2	2	2	2	2
8	9	6	9	7	9
9	1	1	1	1	1

3.5. Optimal process parameter selection considering uncertainty in decision

To account for the uncertainty in the decision-making process, the current problem is also evaluated by using a fuzzy-TOPSIS approach. The decision regarding the relative importance of MRR, TWR and EWR is obtained from 7 decision-makers. The 7-point fuzzy scale-based ratings given by the decision-makers are collected in Table 5. Next, these are aggregated and the mean fuzzy weights are created, which are reported in Table 6. The fuzzy positive ideal value (FPIS) and fuzzy negative ideal value (FNIS) are reported in Table 7. Based on these the Euclidean distances of each alternative from FPIS and FNIS are calculated as reported in Table 8 and Fig. 6. Similarly, the closeness coefficients are calculated and reported in Fig. 5. It is seen that, in the fuzzy-TOPSIS, the alternative no. 9 is also found to the best compromise solution among all the alternatives. Fig. 7 shows the average process performance of the EDM process parameters as calculated by different methods. A similar trend is seen for all the methods. The overall optimal set of EDM process parameters was found to be A3B3C2. The ranking of the alternatives by various TOPSIS methods is shown in Table 10.

4. CONCLUSION

In the present article, five different weight allocation strategies are used in conjunction with TOPSIS to predict the optimal process parameter combination in EDM machining of Inconel superalloy. While the methods like mean weight method, standard deviation method, entropy method, and AHP method do not take into account the uncertainty in decision-making process, the fuzzy weight allocation scheme is used to select optimum EDM parameters by the collective decision-making process. Based on the experimental data and the extensive numerical MCDM analysis it can be concluded that—

- All the methods namely, MW-TOPSIS, SDV-TOPSIS, Entropy-TOPSIS, AHP-TOPSIS and Fuzzy-TOPSIS can be effectively used to estimate and optimize the EDM process parameters,
- The 9th alternative, i.e. A3B2C3, is found to be the optimal setting for achieving high MRR, low TWR and low EWR,
- From performance characteristics, it is found that both Entropy & AHP yielded similar results, and
- The optimal set for machining is obtained through proposed MCDM is 22A discharge current, 200µs pulse-on time, and 0.4kg/cm^2 flushing pressure.

It is evident from the experiments that the pure tungsten electrode can be used as a tool in EDM for machining Inconel 718 at a high discharge current (18A-22A) and high pulse-on time (50-200µs) without any rapture. Also, pulse-on time and current have a higher influence on MRR and TWR as compared to dielectric pressure in EDM machining. One limitation of the current study is the use of L9 orthogonal array, which can be effectively used to study the main effects of the process parameters but is unreliable when machine learning based response surface function over the entire domain of the parametric combination is desired. Thus, this study can be further improved by using quasi-random low-discrepancy sampling approaches like Hammersley, Sobol, etc. to design the experiments. Further, for multi-response optimization advanced metaheuristic approaches like cuckoo search, grey wolf optimizer, etc. may be used to generate Pareto solutions.

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