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Application of Type-2 Fuzzy AHP-ARAS for Selecting Optimal WEDM Parameters

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Abstract: Machining of the nickel-based alloy is very demanding due to its extreme mechanical properties, for example, higher fatigue strength, better corrosion and creep resistance feature, substantial work hardening capability, and appreciable tensile and shear strength. Owing to these properties, the selection of machining parameters is a major challenge for modern machining industries. Therefore, the present experimental work is carried out to select the best parametric combination of the wire electrical discharge machining (WEDM) machine for reducing machining cost and human effort. The Trapezoidal Interval Type-2 fuzzy number (T2FS) integrated Analytical Hierarchy Process (AHP)-based Additive Ratio Assessment (ARAS) method is used for selecting the best WEDM process parameters of Inconel-800 superalloy. Finally, the results were compared with some existing multi-criteria decision-making methods to confirm the validity of the adopted method. The comparison shows that Type-2 Fuzzy AHP-ARAS synergy can help to formulate the problem and facilitate the assessment and ranking of WEDM process parameters when multiple criteria are jointly considered.

Keywords: Inconel 800; wire electrical discharge machining (WEDM); Type-2 Fuzzy; additive ratio assessment method



Citation: Sen, B.; Hussain, S.A.I.; Gupta, A.D.; Gupta, M.K.; Pimenov, D.Y.; Mikołajczyk, T. Application of Type-2 Fuzzy AHP-ARAS for Selecting Optimal WEDM Parameters. *Metals* **2021**, *11*, 42. <https://doi.org/10.3390/met11010042>

Received: 3 December 2020
Accepted: 24 December 2020
Published: 27 December 2020

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1. Introduction

Owing to their extreme mechanical properties, for instance high strength and creep-corrosion resistance, chromium-nickel-based alloys possess very dull machinability [1,2]. However, these alloys are useful in the aerospace, aviation and nuclear industries, where the elevated temperature is the primary concern [3–5]. Moreover, electric discharge machining (EDM) is a process of repetitive sparking cycles. A series of electrical pulses generated by the pulse generator unit is applied between the workpiece and the traveling wire electrode. In the event of spark discharge, there is a flow of current across the wire electrode–workpiece gap. The energy content of a single spark discharge can be expressed as a product of pulse on time with the peak current. The energy contained in a tiny spark discharge removes a fraction of workpiece material. A large number of such time-spaced tiny discharges between the workpiece and wire electrode causes the electro-erosion of the workpiece material. Primarily, electric discharge machining exists in the form of die-sinking machines and in the 1960s, the wire electrode cut type of machines were developed for the purpose of making tools (dies) from hardened steel. In fact, wire electrical discharge machining is a technological advancement in non-traditional machining processes, where traveling wear removes the materials from the workpiece. This non-conventional machining is very useful to cut electrically conductive materials by

using an electro-thermal mechanism [6–8]. The application of the WEDM process creates new possibilities in the rapid manufacturing of form tools from cemented carbides [9]. This replaces the traditional shaping of these tools by grinding. As the dielectric fluid used during machining is ionized between the gap of wire and workpiece material, a path has been created for each discharge. In fact, several discharges in the wire-workpiece region are responsible for the material cutting operation [10]. With each discharge, a high temperature was generated, and the workpiece is get melted. Finally, particles were removed by the flushing of dielectric fluids [11–14].

The optimal parametric selection of any machining process is a vital issue. The wire-cut machining is poised with various conflicting functions. Therefore, several compromise solutions may be generated, which are mathematically incomparable. Thus, it has become a challenge for researchers to determine the best parametric conditions, as the WEDM deals with various input and response parameters. Multi-criteria decision-making approaches can be a viable option to deduce the optimal set of WEDM parameters. Machining parameter selection is also a decision-making problem and can be influenced by uncertainty. Thus, the implementation of fuzzy theory can be the best tool for dealing with decision-based uncertainty. Moreover, to tackle the uncertainty of the real world, T2F sets have been the most widely used technique in recent studies. Thus, in the present study, ARAS amalgamated T2F logic is applied to select the optimum parametric combination and resolve the uncertainty. The credit of integrating T2FS with AHP belongs to Uçal Sarı et al. (2013) [15], who also applied the integrated approach for selecting a warehouse. Abdullah and Najib (2014) [16] suggested a scale based on Chen and Lee (2010) [17] for its use in AHP-IT2FS. Kahraman et al. (2014) [18] suggested an AHP based IT2FS whose result was compared with that of the Buckley's type-1 and type-2 fuzzy AHP method. Kiliç and Kaya (2015) [19] applied a hybridized mathematical model of T2F-AHP and T2F-TOPSIS to evaluate investment projects in Turkey. Yazici and Kahraman (2015) [20] proposed an IT2FS-based VIKOR technique, which was used by Ghorabae (2015) [21] for robot selection. Ghorabae et al. (2014) [22] developed another IT2FS-based COPRAS model for ranking of the alternatives. Chen (2014) [23] and Chen (2014) [24]'s outranking methods ELECTRE and PROMETHEE were hybridized with IT2FSs. The result obtained from the proposed method in [25] was compared with the result obtained from Hatami-Marbini and Tavana, (2011) [26] and Chen et al. (2006) [27]. Hosseini and Tarokh (2011) [28] extended the DEMATEL method with IT2FS to find the criteria-weight based on a linguistic variable. In recent times, T2FSs has been widely used to deal effectively with uncertainty. The amalgamation of T2FS with the MCDM method is becoming a major flare in decision making. Zhou et al. (2016) [29] applied a novel approach by coupling the T2FS and factor space approach with MCDM. According to Sukhveer Singh and Harish Garg (2016) [30], the decision-makers encounter a problem regarding preferences of objectives. They observed that the concept of Type-2 Intuitionistic Fuzzy Sets (T2IFS) was favorable over the general T2FS. Finally, they developed distance measures based on the T2IFS decision-making method. AbitBalin (2017) [31] integrated T2FS with the VIKOR method for selecting the auxiliary system of a ship's main diesel engine. Abdullah et al. (2017) [32] amalgamated IT2FSs and Simple Additive Weighting (SAW) for allocating a preferable ambulance location. Gong et al. (2016) [33] developed a model based on a Bonferroni mean operator and the possibility degree to solve the MCDM problem. To deal effectively and efficiently with uncertainty, T2FS was used in the method. Runkler et al. (2016) [34] studied the role of IT2FS in uplifting decision making. They also extended Bellman and Zadeh's [35] concept that decision making is based on goals and constraints to IT2FS.

Furthermore, the ARAS method was introduced by Zavadskas and Turksis (2010) [36], in which it was used for the evaluated microclimate in office rooms. Tupenaite (2010) [37] assessed the renovation projects by ARAS and compared the results with SAW, TOPSIS and COPRAS. Bakshi and Sarkar (2011) [38] used the ARAS method for the selection of optical fiber for the telecommunication sector. Balzentiset. al. (2012) [39] integrated uncertainty with the ARAS method for economic sector evaluation. The result thus obtained was

compared with some entrenched uncertainty based MCDM methods like fuzzy TOPSIS and Fuzzy VIKOR. Chatterjee and Bose (2013) [40] developed a hybrid fuzzy-based ARAS method for ranking the vendors for a wind farm, which was used the following year by Barak et al. (2014) [25] for the selection of hydraulic fracturing treatment. However, from the above literature review, it was manifested that very few manuscripts were published on the hybrid type-2 Fuzzy-ARAS approach in the manufacturing domain. Therefore, the objective of the current study is to develop a Fuzzy coupled MCDM approach for the problem in question. The results of this developed method are equated with some prevailing methods to report the validity of T2F-AHP-ARAS.

The selection of the optimal values of different process parameters of WEDM is very important for enhancing machining performances. Several mathematical approaches, such as gray relational analysis, Pareto optimality, desirability function, simulated annealing, etc., have already been successfully implemented by researchers. However, most of the time, the researchers have found sub-optimal solutions. Thus, an ideal backdrop was created to explore the efficacy of an integrated Fuzzy coupled MCDM model to minimize the ambiguity and uncertainty of the criteria weights. The quality of the developed model will be enhanced when type-2 Fuzzy logic is coupled with a prominent ARAS model. Whereas type-2 Fuzzy logic handled the uncertainties in the values of the membership function, ARAS obtained the best possible solution. Thus, in the present study, a mathematical endeavor was undertaken to select the optimal parametric combination of the WEDM machine.

2. Materials and Methods

Materials and Measuring Equipment

The cutting operation was carried out on a WEDM machine (ELPULS-40 A DLX). Taguchi's L18 orthogonal array was used as the design of the experiments. A 0.25-mm thick brass wire was used for cutting. De-ionized water was used as a di-electric fluid. Commercially available Inconel 800 was used as a workpiece. The variable WEDM parameters were selected after an extensive literature review and are shown in Table 1; the values of fixed machining parameters are shown in Table 2. Furthermore, the surface roughness of the cutting zone was measured by a 3D profilometer. Cutting time was measured by a digital stopwatch. The MRR (gm/min) is calculated by utilizing Equation (1). The width of kerf (mm) was observed with an optical microscope. To find out the power consumption (kWh) during the cutting, Equation (2) is used. Finally, for observing the load power, a 3 Ø wattmeter was coupled to a transformer. Figure 1 shows the spark event on WEDM during the metal cutting operation.

$$MRR = \text{Kerf thickness} \times \text{workpiece thickness} \times \text{cutting speed} \times \text{material density} \quad (1)$$

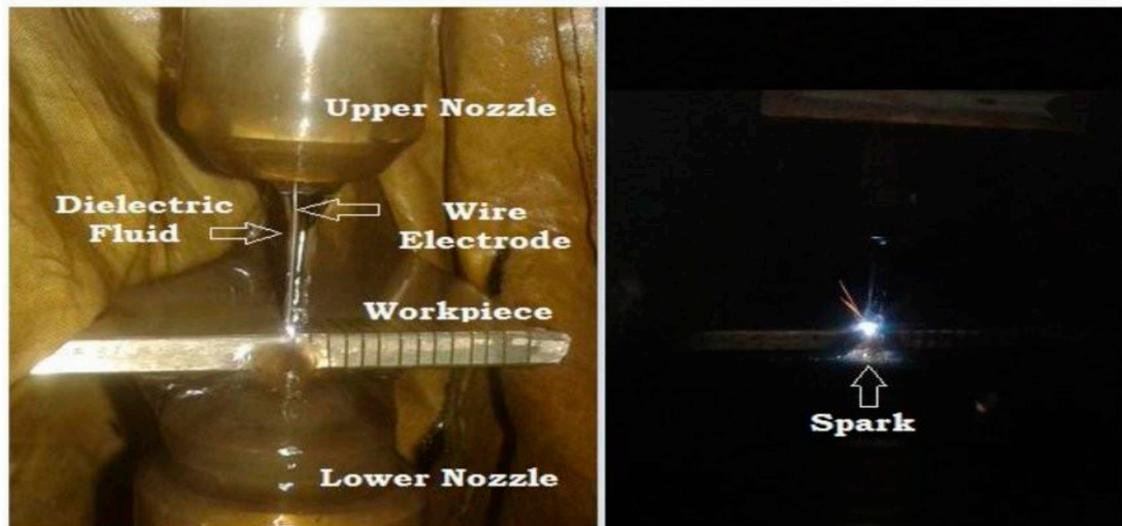
$$\text{Power consumption} = \frac{\text{load power} \times \text{machining time}}{1000 \times 60} \quad (2)$$

Table 1. Range of variable machining inputs.

Parameters	Machine Units	Machine Units for Present Work
Pulse on time (μs)	105–126	105, 108, 111, 114, 117, 120
Pulse off time (μs)	40–63	63, 60, 57
Peak current (A)	70–230	230, 220, 210
Spark gap voltage (V)	10–50	20, 35, 50

Table 2. Range of fixed machining inputs.

Parameters	Machine Units	Machine Units for Present Work
Wire tension (gram)	4–12	6
Wire feed (mm/min)	4–12	8
Water pressure (1 unit, 15 kg/cm ²)	1	1
Peak voltage (2 units, 110 volt DC)	2	2
Servo feed (1050 unit)	1050	1050

**Figure 1.** Material removal due to spark event in WEDM.

3. Preliminaries

This section gives a brief description of the key concepts related to the T2FS and the ARAS method is given.

3.1. Fuzzy Sets

In the universe of discourse U , \tilde{A} is termed as fuzzy sets (FS), if it is typified by membership value ($\mu_{\tilde{A}}$) that maps every element of U to a real-valued number in $[0, 1]$.

$$\tilde{A} = \{x, \mu_{\tilde{A}}(x) | x \in U\} \quad (3)$$

where $\mu_{\tilde{A}}(x)$ denotes the membership value of $x \in U$.

3.2. Type-2 Fuzzy Sets

In the simplest language, the T2FS can be defined as the blurriness of T1F membership functions [41]. If $\tilde{\tilde{A}}$ is a T2FS on the universal discourse of X then it is defined as follows:

$$\tilde{\tilde{A}} = \{ \langle (x, u); \mu_{\tilde{\tilde{A}}}(x, u) \rangle | \forall x \in X, \forall u \in J_x \subseteq [0, 1] \} \quad (4)$$

where $\mu_{\tilde{\tilde{A}}}(x, u)$ represent the secondary membership grade such that $0 < \mu_{\tilde{\tilde{A}}}(x, u) < 1$. $\tilde{\tilde{A}}$ can be conveyed as

$$\tilde{\tilde{A}} = \int_{x \in X} \int_{u \in J_x} \left[\frac{\mu_{\tilde{\tilde{A}}}(x, u)}{(x, u)} \right] \quad (5)$$

3.3. Interval Type-2 Fuzzy Sets

IT2FS is a special case of T2FS. For the condition $\forall \mu_{\tilde{A}}(x, u) = 1$, then the T2FS \tilde{A} is called IT2FS [42]. The IT2FS can be described as follows:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \left[\frac{1}{(x, u)} \right] \tag{6}$$

3.4. Footprint of Uncertainty

The footprint of uncertainty (FOU) [43] can be defined as the two-dimensional support of the secondary membership grade. It is the union of all primary membership grades. FOU is often described by upper membership function (\tilde{A}^U) and lower membership function (\tilde{A}^L) where \tilde{A}^U and \tilde{A}^L are T1FS.

3.5. Trapezoidal Interval Type-2 Fuzzy Number

An interval type-2 fuzzy number is termed a trapezoidal interval type-2 fuzzy number (TrI2N) (Figure 2), if \tilde{A}^U and \tilde{A}^L are type-1 trapezoidal fuzzy number [21]. If \tilde{A} is a TrI2N, then it can be defined as follows:

$$\tilde{A} = (\langle a^U, b^U, c^U, d^U; h_1(A^U), h_2(A^U) \rangle, \langle a^L, b^L, c^L, d^L; h_1(A^L), h_2(A^L) \rangle) \tag{7}$$

where $a^U < a^L, b^U = b^L, c^U = c^L$ and $d^U > d^L; (a^U, b^U, c^U, d^U, a^L, b^L, c^L, d^L) \in \mathbb{R}$.

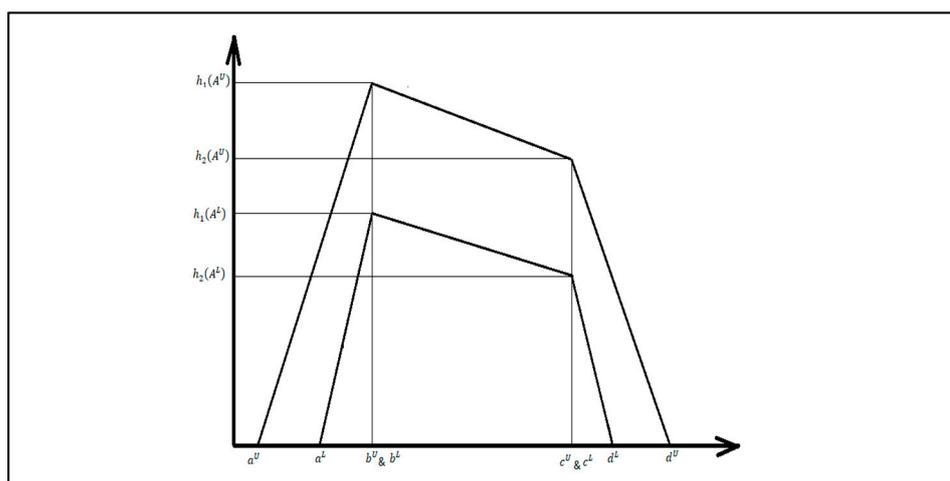


Figure 2. Diagrammatic representation of TrI2N.

3.6. Operations of TrI2N

Considering two TrI2Ns:

$$\tilde{A} = (\langle a_1^U, a_2^U, a_3^U, a_4^U; h_1(A^U), h_2(A^U) \rangle, \langle a_1^L, a_2^L, a_3^L, a_4^L; h_1(A^L), h_2(A^L) \rangle)$$

$$\tilde{B} = (\langle b_1^U, b_2^U, b_3^U, b_4^U; h_1(B^U), h_2(B^U) \rangle, \langle b_1^L, b_2^L, b_3^L, b_4^L; h_1(B^L), h_2(B^L) \rangle)$$

and the arithmetic operations are as follows [27]:

Addition

$$\tilde{A} \oplus \tilde{B} = (\langle a_1^U + b_1^U, a_2^U + b_2^U, a_3^U + b_3^U, a_4^U + b_4^U; \min\{h_1(A^U), h_1(B^U)\}, \min\{h_2(A^U), h_2(B^U)\} \rangle, \langle a_1^L + b_1^L, a_2^L + b_2^L, a_3^L + b_3^L, a_4^L + b_4^L; \min\{h_1(A^L), h_1(B^L)\}, \min\{h_2(A^L), h_2(B^L)\} \rangle) \tag{8}$$

Subtraction

$$\tilde{A} \ominus \tilde{B} = (\langle a_1^U - b_4^U, a_2^U - b_3^U, a_3^U - b_2^U, a_4^U - b_1^U; \min\{h_1(A^U), h_1(B^U)\}, \min\{h_2(A^U), h_2(B^U)\} \rangle, \langle a_1^L - b_4^L, a_2^L - b_3^L, a_3^L - b_2^L, a_4^L - b_1^L; \min\{h_1(A^L), h_1(B^L)\}, \min\{h_2(A^L), h_2(B^L)\} \rangle) \tag{9}$$

Multiplication

$$\tilde{A} \otimes \tilde{B} = (\langle a_1^U \times b_1^U, a_2^U \times b_2^U, a_3^U \times b_3^U, a_4^U \times b_4^U; \min\{h_1(A^U), h_1(B^U)\}, \min\{h_2(A^U), h_2(B^U)\} \rangle, \langle a_1^L \times b_1^L, a_2^L \times b_2^L, a_3^L \times b_3^L, a_4^L \times b_4^L; \min\{h_1(A^L), h_1(B^L)\}, \min\{h_2(A^L), h_2(B^L)\} \rangle) \tag{10}$$

Inverse

$$\tilde{A}^{(-1)} = \frac{1}{\tilde{A}} = \left(\langle \frac{1}{a_4^U}, \frac{1}{a_3^U}, \frac{1}{a_2^U}, \frac{1}{a_1^U}; h_1(A^U), h_2(A^U) \rangle, \langle \frac{1}{a_4^L}, \frac{1}{a_3^L}, \frac{1}{a_2^L}, \frac{1}{a_1^L}; h_1(A^L), h_2(A^L) \rangle \right) \tag{11}$$

Division

$$\frac{\tilde{A}}{\tilde{B}} = \tilde{A} \otimes \tilde{B}^{(-1)} = (\langle a_1^U \times \frac{1}{b_1^U}, a_2^U \times \frac{1}{b_2^U}, a_3^U \times \frac{1}{b_3^U}, a_4^U \times \frac{1}{b_4^U}; \min\{h_1(A^U), h_1(B^U)\}, \min\{h_2(A^U), h_2(B^U)\} \rangle, \langle a_1^L \times \frac{1}{b_1^L}, a_2^L \times \frac{1}{b_2^L}, a_3^L \times \frac{1}{b_3^L}, a_4^L \times \frac{1}{b_4^L}; \min\{h_1(A^L), h_1(B^L)\}, \min\{h_2(A^L), h_2(B^L)\} \rangle) \tag{12}$$

3.7. Ranking of Tri2N

Previous authors have developed a ranking algorithm for T2FS, which is utilized to develop an extension of the fuzzy TOPSIS method [44]. Further, in [17], the extended fuzzy TOPSIS method was applied in a decision-making approach whereby the alternatives are assessed in the form of linguistic terms on the basis of the criteria. The ranking of a Tri2N

$\tilde{A} = (\tilde{A}^U, \tilde{A}^L) = (\langle a_1^U, a_2^U, a_3^U, a_4^U; h_1(A^U), h_2(A^U) \rangle, \langle a_1^L, a_2^L, a_3^L, a_4^L; h_1(A^L), h_2(A^L) \rangle)$ is the difference of the basic ranking score and the average of the standard deviation of the \tilde{A} . The basic ranking score of \tilde{A} is denoted by $Br(\tilde{A})$ which is calculated as follows:

$$Br(\tilde{A}) = M_1(\tilde{A}^U) + M_1(\tilde{A}^L) + M_2(\tilde{A}^U) + M_2(\tilde{A}^L) + M_3(\tilde{A}^U) + M_3(\tilde{A}^L) + h_1(A^U) + h_2(A^U) + h_1(A^L) + h_2(A^L) \tag{13}$$

where

$$\left. \begin{aligned} M_1(\tilde{A}^K) &= 0.5 * [a_1^K + a_2^K]; K \in \{U, L\} \\ M_2(\tilde{A}^K) &= 0.5 * [a_2^K + a_3^K]; K \in \{U, L\} \\ M_3(\tilde{A}^K) &= 0.5 * [a_3^K + a_4^K]; K \in \{U, L\} \end{aligned} \right\} \tag{14}$$

The average of the standard deviation of \tilde{A} is denoted by $sd(\tilde{A})$ which is calculated as follows:

$$sd(\tilde{A}) = \frac{S_1(\tilde{A}^U) + S_1(\tilde{A}^L) + S_2(\tilde{A}^U) + S_2(\tilde{A}^L) + S_3(\tilde{A}^U) + S_3(\tilde{A}^L) + S_4(\tilde{A}^U) + S_4(\tilde{A}^L)}{4} \tag{15}$$

where

$$\left. \begin{aligned} S_q(\tilde{A}^K) &= \sqrt{0.5 * \left[\sum_{i=q}^{(q+1)} \{a_i^K - 0.5 * \sum_{i=q}^{(q+1)} (a_i^K)\}^2 \right]}; 1 \leq i \leq 3; K \in \{U, L\} \\ S_q(\tilde{A}^K) &= \sqrt{0.5 * \left[\sum_{i=1}^4 \{a_i^K - 0.5 * \sum_{i=1}^4 (a_i^K)\}^2 \right]}; i = 4; K \in \{U, L\} \end{aligned} \right\} \tag{16}$$

The rank of \tilde{A} is calculated as follows:

$$Rank(\tilde{A}) = Br(\tilde{A}) - sd(\tilde{A}) \tag{17}$$

4. Proposed Tri2N Analytical Hierarchy Process (AHP) Integrated ARAS Method

Selecting the best WEDM parameters settings on the basis of the performance measures is a case of multi-criteria decision making (MCDM). The performance parameters based on

which the decision is taken are called criteria. The degree to which a criterion influences the section of the best WEDM parameters is termed the weightage of the criteria [45]. Computation of the criteria weights is done by applying the fuzzy integrated analytical hierarchy process (AHP). The proposed ranking method is the integration of the AHP and ARAS method. Conferring to the ARAS method, the profitability function, which is helpful in selecting the decision alternatives, is proportional to the relative effect of values and criteria weights. The weightage of the criteria is the degree to which the criteria affects the final decision. The steps for the proposed algorithm is as follows:

Step 1. Formation of the decision matrix

The value of the performance measures as obtained from the experimental design forms the decision matrix. The number of designed experiments is the alternatives, and the number of performance measures based on which the decision is to be taken are the criteria. If there are 'm' alternatives and 'n' criteria, then the decision matrix (D) is represented as

$$D = \begin{matrix} & & C_1 & C_2 & C_3 & \cdots & C_n \\ \begin{matrix} A^1 \\ A^2 \\ A^3 \\ \vdots \\ A^m \end{matrix} & \left[\begin{array}{cccccc} d_{11} & d_{12} & d_{13} & \cdots & d_{1n} \\ d_{21} & d_{22} & d_{23} & \cdots & d_{2n} \\ d_{31} & d_{32} & d_{33} & \cdots & d_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & d_{m3} & \cdots & d_{mn} \end{array} \right] \end{matrix}$$

Step 2: Addition of the idle best value in the decision matrix

When the best solution is unknown, for a benefit criterion, the maximum value is always preferred and vice-versa for a non-benefit criterion. The main idea is to create a virtual best alternative with respect to which all other feasible alternatives are compared. The matrix is called the initial decision matrix.

Step 3: Computation of normalized decision matrix

$$I = \begin{matrix} & & C_1 & C_2 & C_3 & \cdots & C_n \\ \begin{matrix} A^1 \\ A^2 \\ A^3 \\ \vdots \\ A^m \end{matrix} & \left[\begin{array}{cccccc} d_{01} & d_{02} & d_{03} & \cdots & d_{0n} \\ d_{11} & d_{12} & d_{13} & \cdots & d_{1n} \\ d_{21} & d_{22} & d_{23} & \cdots & d_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & d_{m3} & \cdots & d_{mn} \end{array} \right] \end{matrix}$$

$$r = \begin{cases} \frac{(d_{mn})}{\sum_{m=1}^i (d_{mn})}, & \text{for benefit criteria} \\ \frac{(\frac{1}{d_{mn}})}{\sum_{m=1}^i (\frac{1}{d_{mn}})}, & \text{for non - benefit criteria} \end{cases} \quad (18)$$

where r is the element of the normalized decision matrix. The normalized decision matrix (R) is represented as

$$R = [r]_{(i \times j)} = \begin{bmatrix} r_{01} & r_{02} & r_{03} & \cdots & r_{0j} \\ r_{11} & r_{12} & r_{13} & \cdots & r_{1j} \\ r_{21} & r_{22} & r_{23} & \cdots & r_{2j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{i1} & r_{i2} & r_{i3} & \cdots & r_{ij} \end{bmatrix}$$

Step 4: Computation of weighted normalized decision matrix

$$\varphi_{mn} = w_f^j \times r_{mn} \quad (19)$$

$$W = \begin{bmatrix} \varphi_{01} & \varphi_{02} & \varphi_{03} & \cdots & \varphi_{0j} \\ \varphi_{11} & \varphi_{12} & \varphi_{13} & \cdots & \varphi_{1j} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} & \cdots & \varphi_{2j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \varphi_{i1} & \varphi_{i2} & \varphi_{i3} & \cdots & \varphi_{ij} \end{bmatrix}$$

Step 5: Computation of weights of the criteria

AHP is an effective as well as efficient decision support system tool that helps to recognize and define a problem in detail. It breaks down the problem into its constituent parts, which are then structured hierarchically. One of the advantages of using AHP is that it allows the decision makers (DM) to subjectively assess the alternatives on the basis of the criteria. Moreover, due to the existence of uncertainty in human psychology, DMs favors assessing the alternatives subjectively. Meanwhile, it is worth pointing out that in order to reach a precise decision, it is crucial to consider the views of more than one decision maker (DM). Decision-making problems which involve more than one DM are called multi-criteria group decision making (MCGDM). The 1–9 scale defined by Saaty to quantify the subjective assessment [46] fails to aggregate the views in a scenario in which decision is taken by a group of DMs [47,48]. With the development of fuzzy sets (FSs), it is applied to quantify the subjective assessment of the criteria. The major advantage of using fuzzy logic for quantifying the subjective assessment is its ability to aggregate the views of different DMs in a group decision-making environment [41]. However, on the basis of the falsificationism concept of Karl Popper [49], Mendel argued that the application of interval type-2 fuzzy sets for quantifying the subjective assessment is more scientifically correct than the application of general fuzzy logic [50,51]. Hence, in this paper, the subjective assessment of the criteria is quantified using interval type-2 fuzzy sets which are then integrated with AHP for computing the weightage of the criteria. The steps applied for computing the weights of any criteria are described below.

Step 5.1: Formation of aggregated pairwise comparison matrix:

For computing the weights, the views of the three decision-makers are integrated. The aggregation of the pairwise comparison matrices is done to incorporate the knowledge of decision makers of different backgrounds. The aggregation is done according to the interval value aggregating operator as discussed in the literature [41], which is done as follows:

$$\tilde{a}_{ij} = \frac{\sum_{k=1}^l \tilde{a}_{ij}^k}{l} \quad (20)$$

where \tilde{a}_{ij}^k indicates the k th decision maker's preference of i^{th} criterion over j^{th} criterion. Considering that the aggregated pair-wise comparison matrix is represented by A^k , then

$$A^k = \begin{matrix} & \begin{matrix} C_1 & C_2 & C_3 & \cdots & C_n \end{matrix} \\ \begin{matrix} C^1 \\ C^2 \\ C^3 \\ \vdots \\ C^n \end{matrix} & \begin{bmatrix} \tilde{a}_{11}^k & \tilde{a}_{12}^k & \tilde{a}_{13}^k & \cdots & \tilde{a}_{1n}^k \\ \tilde{a}_{21}^k & \tilde{a}_{22}^k & \tilde{a}_{23}^k & \cdots & \tilde{a}_{2n}^k \\ \tilde{a}_{31}^k & \tilde{a}_{32}^k & \tilde{a}_{33}^k & \cdots & \tilde{a}_{3n}^k \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1}^k & \tilde{a}_{n2}^k & \tilde{a}_{n3}^k & \cdots & \tilde{a}_{nn}^k \end{bmatrix} \end{matrix}$$

where $\forall (\tilde{a}_{jj}^k) = 1$ and $\tilde{a}_{ij}^k = \frac{1}{\tilde{a}_{ji}^k}$, $(i, j) \in (1, 2, 3, \dots, n)$

The linguistic ratings used by the decision makers for assessing the criteria and their corresponding TrI2N are revealed in Table 3. The aggregated pair-wise comparison matrix formulated according to Equation (20) is demonstrated in Table 4.

Table 3. Linguistic terms and corresponding Tri2N.

Sl. No.	Definition	Satty Fuzzy Scale	Interval Type-2 Fuzzy Numbers
1	Equally Important (EI)	$\tilde{1}$	$(\langle 1.0, 1.3, 1.6, 1.9; 1, 1 \rangle, \langle 1.1, 1.3, 1.6, 1.8; 0.9, 0.9 \rangle)$
2	Weakly Important (WI)	$\tilde{3}$	$(\langle 2.8, 3.1, 3.4, 3.7; 1, 1 \rangle, \langle 2.9, 3.1, 3.4, 3.6; 0.9, 0.9 \rangle)$
3	Fairly Important (FI)	$\tilde{5}$	$(\langle 4.6, 4.9, 5.2, 5.5; 1, 1 \rangle, \langle 4.7, 4.9, 5.2, 5.4; 0.9, 0.9 \rangle)$
4	Strongly Important (SI)	$\tilde{7}$	$(\langle 6.4, 6.7, 7.0, 7.3; 1, 1 \rangle, \langle 6.5, 6.7, 7.0, 7.2; 0.9, 0.9 \rangle)$
5	Absolutely Important (AI)	$\tilde{9}$	$(\langle 8.2, 8.5, 8.8, 9.0; 1, 1 \rangle, \langle 8.3, 8.5, 8.8, 9.0; 0.9, 0.9 \rangle)$
6		$\tilde{2}$	$(\langle 1.9, 2.2, 2.5, 2.8; 1, 1 \rangle, \langle 2.0, 2.2, 2.5, 2.7; 0.9, 0.9 \rangle)$
7	The intermittent values	$\tilde{4}$	$(\langle 3.7, 4.0, 4.3, 4.6; 1, 1 \rangle, \langle 3.8, 4.0, 4.3, 4.5; 0.9, 0.9 \rangle)$
8	between two adjacent scales	$\tilde{6}$	$(\langle 5.5, 5.8, 6.1, 6.4; 1, 1 \rangle, \langle 5.6, 5.8, 6.1, 6.3; 0.9, 0.9 \rangle)$
9		$\tilde{8}$	$(7.3, 7.6, 7.9, 8.2; 1, 1), \langle 7.4, 7.6, 7.9, 8.1; 0.9, 0.9 \rangle)$

Table 4. Aggregated pairwise comparison matrix.

	Surface Roughness			Cutting Velocity			Material Removal Rate			Kerf Thickness			Power Consumption		
	D ₁	D ₂	D ₃	D ₁	D ₂	D ₃	D ₁	D ₂	D ₃	D ₁	D ₂	D ₃	D ₁	D ₂	D ₃
Surface roughness	EI	EI	EI	WI	FI	EI	SI	AI	SI	FI	WI	FI	FI	SI	AI
Cutting Velocity	$\frac{1}{WI}$	$\frac{1}{FI}$	$\frac{1}{EI}$	EI	EI	EI	$\frac{1}{SI}$	$\frac{1}{AI}$	$\frac{1}{SI}$	WI	WI	WI	FI	FI	SI
Material Removal Rate	$\frac{1}{SI}$	$\frac{1}{AI}$	$\frac{1}{SI}$	SI	AI	SI	EI	EI	EI	SI	FI	AI	SI	SI	FI
Kerf Thickness	$\frac{1}{FI}$	$\frac{1}{WI}$	$\frac{1}{FI}$	$\frac{1}{WI}$	$\frac{1}{WI}$	$\frac{1}{WI}$	$\frac{1}{SI}$	$\frac{1}{FI}$	$\frac{1}{AI}$	EI	EI	EI	$\frac{1}{WI}$	EI	$\frac{1}{FI}$
Power consumption	$\frac{1}{FI}$	$\frac{1}{SI}$	$\frac{1}{AI}$	$\frac{1}{FI}$	$\frac{1}{FI}$	$\frac{1}{SI}$	$\frac{1}{SI}$	$\frac{1}{SI}$	$\frac{1}{FI}$	WI	EI	FI	EI	EI	EI

Step 5.2: Calculation of column-wise geometric mean (G^m)

The geometric mean of fuzzy comparison values is calculated as

$$\tilde{G}^j = \left[\prod_{j=1}^n \tilde{a}_j \right]^{\left(\frac{1}{n}\right)}, (j = 1, 2, 3, \dots, n) \tag{21}$$

The column-wise geometric mean of the aggregated pairwise comparison matrix is shown in Table 5.

Table 5. \tilde{G}^j of the various criteria.

Criteria	Geometric Mean (\tilde{G}^j)
Machining time	$(\langle 3.28, 3.65, 4.00, 4.35; 1, 1 \rangle, \langle 3.41, 3.65, 4.00, 4.27; 0.9, 0.9 \rangle)$
Cutting Velocity	$(\langle 0.86, 0.96, 1.06, 1.17; 1, 1 \rangle, \langle 0.90, 0.96, 1.06, 1.14; 0.9, 0.9 \rangle)$
Material Removal Rate	$(\langle 2.04, 2.24, 2.41, 2.59; 1, 1 \rangle, \langle 2.11, 2.24, 2.41, 2.53; 0.9, 0.9 \rangle)$
Kerf Thickness	$(\langle 0.28, 0.31, 0.35, 0.38; 1, 1 \rangle, \langle 0.29, 0.31, 0.35, 0.37; 0.9, 0.9 \rangle)$
Power consumption	$(\langle 0.42, 0.46, 0.51, 0.55; 1, 1 \rangle, \langle 0.43, 0.46, 0.51, 0.54; 0.9, 0.9 \rangle)$

Step 5.3: Calculation of fuzzified weights (\tilde{w}_f^j)

The fuzzified weight is the normalized fuzzy values of the geometric mean of fuzzy comparison values of each criterion.

$$\tilde{w}_f^j = \frac{\tilde{G}^j}{\sum_{j=1}^n \tilde{G}^j}, (j = 1, 2, 3, \dots, n) \tag{22}$$

The fuzzified weights as computed by the Equation (22) is shown in Table 6.

Table 6. \tilde{w}_f^j of the criteria of pairwise comparison matrix.

Criteria	Fuzzified Weights (\tilde{w}_f^j)
Machining time	(⟨0.39, 0.47, 0.56, 0.68; 1, 1⟩, ⟨0.42, 0.47, 0.56, 0.64; 0.9, 0.9⟩)
Cutting Velocity	(⟨0.08, 0.10, 0.12, 0.14; 1, 1⟩, ⟨0.09, 0.10, 0.12, 0.13; 0.9, 0.9⟩)
Material Removal Rate	(⟨0.21, 0.24, 0.29, 0.34; 1, 1⟩, ⟨0.22, 0.24, 0.29, 0.32; 0.9, 0.9⟩)
Kerf Thickness	(⟨0.05, 0.06, 0.07, 0.09; 1, 1⟩, ⟨0.05, 0.06, 0.07, 0.08; 0.9, 0.9⟩)
Power consumption	(⟨0.03, 0.04, 0.05, 0.06; 1, 1⟩, ⟨0.04, 0.04, 0.05, 0.06; 0.9, 0.9⟩)

Step 5.4: Computation of the weights of the criteria

The weights of the criteria are computed according to the Equation (23).

$$w_f^j = \frac{\text{Rank}(\tilde{w}_f^j)}{\sum_{j=1}^n \text{Rank}(\tilde{w}_f^j)} \quad (23)$$

The computed weights of the criteria are shown in Table 7.

Table 7. Weights for the criteria.

Criteria	Weights (w_f^j)
Machining time	0.50
Cutting Velocity	0.13
Material Removal Rate	0.27
Kerf Thickness	0.05
Power consumption	0.05

Step 6: Calculation of the optimality function

Optimality function (S^i) is the sum of all the weighted normalized values of an alternative for the different criteria, which is computed according to Equation (24).

$$S^i = \sum_{j=1}^n (\varphi_{ij}), \quad (i = 0, 1, 2, 3 \dots m) \quad (24)$$

Step 7: Ordering and Ranking of Alternatives

The alternative with the maximum value of optimality function is the most effective and is ranked the first, and the other alternatives are ranked on the basis of descending value.

5. Results and Discussions

In this section, the result acquired after employing the proposed Tri2N integrated AHP-ARAS method is discussed.

5.1. Computation of the Best Cutting Parameters

A total of 18 experiments were designed, as shown in Table 8, and the result obtained after conducting the experiments, in the form of a decision matrix, are shown in Table 9.

After the formation of the decision matrix, in the next step, the best solution for each criterion is computed and added as the zeroth experiment in the decision matrix to form the initial decision matrix, which is shown in Table 10.

Table 8. Designed experiment.

Exp No.	Pulse On	Pulse Off	Peak Current	Spark Gap Voltage
1	105	63	230	20
2	105	60	220	35
3	105	57	210	50
4	108	63	230	35
5	108	60	220	50
6	108	57	210	20
7	111	63	220	20
8	111	60	210	35
9	111	57	230	50
10	114	63	210	50
11	114	60	230	20
12	114	57	220	35
13	117	63	220	50
14	117	60	210	20
15	117	57	230	35
16	120	63	210	35
17	120	60	230	50
18	120	57	220	20

Table 9. Decision matrix.

Exp No.	Surface Roughness (μm)	Cutting Velocity (mm/min)	Material Removal Rate (gm/min)	Kerf Thickness (mm)	Power Consumption (kWh)
1	2.21	1.37552	1.4832	339.51	0.65672
2	1.5	1.36799	1.47456	339.39	0.65181
3	1.48	1.18343	1.2872	342.47	0.76895
4	2.1	1.5625	1.67484	337.5	0.58987
5	2.11	1.54321	1.60202	326.86	0.5886
6	2.31	2.38663	2.51291	331.52	0.36872
7	2.61	2.8169	2.98607	333.77	0.30885
8	2.08	2.40964	2.55825	334.28	0.37212
9	2.05	2.29885	2.41967	331.41	0.40745
10	2.35	2.28833	2.35962	324.67	0.39621
11	2.93	4.03226	4.1215	321.83	0.22568
12	2.89	3.87597	3.9503	320.9	0.22876
13	2.84	2.92398	2.86471	308.48	0.31236
14	3.29	4.40529	4.30901	307.98	0.2009
15	3.47	4.25532	4.18502	309.66	0.21503
16	2.92	4.16667	4.10233	310	0.2132
17	3.05	3.90625	3.89358	313.84	0.23808
18	3.16	4.87805	4.89058	315.67	0.18279

After that, the normalized decision matrix is calculated according to Equation (18). The computed weights of the machining performances are shown in Table 7. Then, the weights are multiplied with the normalized decision elements to form the weighted normalized decision matrix, which is presented in Table 11.

In the next step, the value of the optimality function for every alternative is calculated, conferring to Equation (24). Then, the weightage of the optimality function for each alternative with regard to the zeroth alternative is computed according to Equation (25).

$$\text{Weightage} = \frac{S^i}{S^0} \times 100\% \quad (25)$$

Table 10. Initial decision matrix.

Exp No.	Surface Roughness (μm)	Cutting Velocity (mm/min)	Material Removal Rate (gm/min)	Kerf Thickness (mm)	Power Consumption (kWh)
0	1.48	4.87805	4.89058	342.47	0.76895
1	2.21	1.37552	1.4832	339.51	0.656723
2	1.5	1.36799	1.47456	339.39	0.651808
3	1.48	1.18343	1.2872	342.47	0.76895
4	2.1	1.5625	1.67484	337.5	0.589867
5	2.11	1.54321	1.60202	326.86	0.5886
6	2.31	2.38663	2.51291	331.52	0.36872
7	2.61	2.8169	2.98607	333.77	0.30885
8	2.08	2.40964	2.55825	334.28	0.372117
9	2.05	2.29885	2.41967	331.41	0.40745
10	2.35	2.28833	2.35962	324.67	0.396213
11	2.93	4.03226	4.1215	321.83	0.22568
12	2.89	3.87597	3.9503	320.9	0.22876
13	2.84	2.92398	2.86471	308.48	0.31236
14	3.29	4.40529	4.30901	307.98	0.200895
15	3.47	4.25532	4.18502	309.66	0.215025
16	2.92	4.16667	4.10233	310	0.2132
17	3.05	3.90625	3.89358	313.84	0.23808
18	3.16	4.87805	4.89058	315.67	0.182792

Table 11. Weighted normalized decision matrix.

Exp No.	Surface Roughness (μm)	Cutting Velocity (mm/min)	Material Removal Rate (gm/min)	Kerf Thickness (mm)	Power Consumption (kWh)
0	0.0412	0.011	0.023	0.0026	0.0047
1	0.0276	0.0031	0.007	0.0026	0.0013
2	0.0407	0.0031	0.007	0.0026	0.0013
3	0.0412	0.0027	0.0061	0.0026	0.0012
4	0.0291	0.0036	0.0079	0.0026	0.0015
5	0.0289	0.0035	0.0076	0.0025	0.0015
6	0.0264	0.0054	0.0119	0.0026	0.0023
7	0.0234	0.0064	0.0141	0.0026	0.0028
8	0.0293	0.0055	0.0121	0.0026	0.0023
9	0.0298	0.0052	0.0114	0.0026	0.0021
10	0.026	0.0052	0.0111	0.0025	0.0022
11	0.0208	0.0091	0.0194	0.0025	0.0038
12	0.0211	0.0088	0.0186	0.0025	0.0038
13	0.0215	0.0066	0.0135	0.0024	0.0028
14	0.0186	0.01	0.0203	0.0024	0.0043
15	0.0176	0.0096	0.0197	0.0024	0.004
16	0.0209	0.0094	0.0193	0.0024	0.004
17	0.02	0.0088	0.0183	0.0024	0.0036
18	0.0193	0.011	0.023	0.0024	0.0047

The reason for the comparison between the optimality function for each alternative with the zeroth alternative is that it is considered to be the idle solution. Lastly, alternatives are ranked in descending order of the weightage of the alternatives, except for the zeroth experiment. Table 12 shows the ranking of the alternatives.

5.2. Comparison of Results

This subsection implements a comparative assessment with other standards to validate the effectiveness and applicability of the projected methods and observe the efficiency of

the proposed scale. Although this paper presents the first integrated Tri2N based AHP-ARAS method, there are many entrenched Tri2N-based MCDM approaches. To verify the effectiveness and efficiency of the projected technique as well as scale, the result is compared with the results obtained from [18–22].

It can be observed in Table 13 and Figure 3 that the optimal WEDM parameters for all the entrenched integrated methods and the proposed model are the same, i.e., experiment no. 18. However, the ranks of the remaining experiments by the different methods are different. Hence, we can say that the proposed model, including the scale, is both effective and efficient for finding the optimal parameters.

Table 12. Ranking of the alternatives.

Exp No.	Optimality Function	Weightage	Rank
0	0.0824	100	—
1	0.0415	53.90	18
2	0.0545	69.50	2
3	0.0536	69.61	1
4	0.0444	56.65	15
5	0.0438	55.91	16
6	0.0484	58.55	12
7	0.049	58.26	13
8	0.0516	62.43	8
9	0.0509	62.13	9
10	0.0468	57.04	14
11	0.0554	64.10	5
12	0.0545	63.08	7
13	0.0466	55.39	17
14	0.0552	63.10	6
15	0.0531	60.97	11
16	0.0559	64.23	4
17	0.053	61.52	10
18	0.0603	68.51	3

Table 13. Comparative analysis of the obtained results.

Sl. No.	Ranking by				
	AHP-IT2FS [18]	TOPSIS-IT2FS [19]	VIKOR-IT2FS [20,21]	COPRAS-IT2FS [22]	Proposed Algorithm
1	18	15	11	18	18
2	3	9	18	9	3
3	2	6	13	8	2
4	15	17	15	16	15
5	17	18	17	17	16
6	13	14	10	14	12
7	12	11	9	10	13
8	9	10	14	11	8
9	11	12	16	12	10
10	14	16	12	15	14
11	5	2	4	4	5
12	7	4	7	6	7
13	16	13	8	13	17
14	6	5	3	2	6
15	10	8	2	5	11
16	4	3	6	3	4
17	8	7	5	7	9
18	1	1	1	1	1

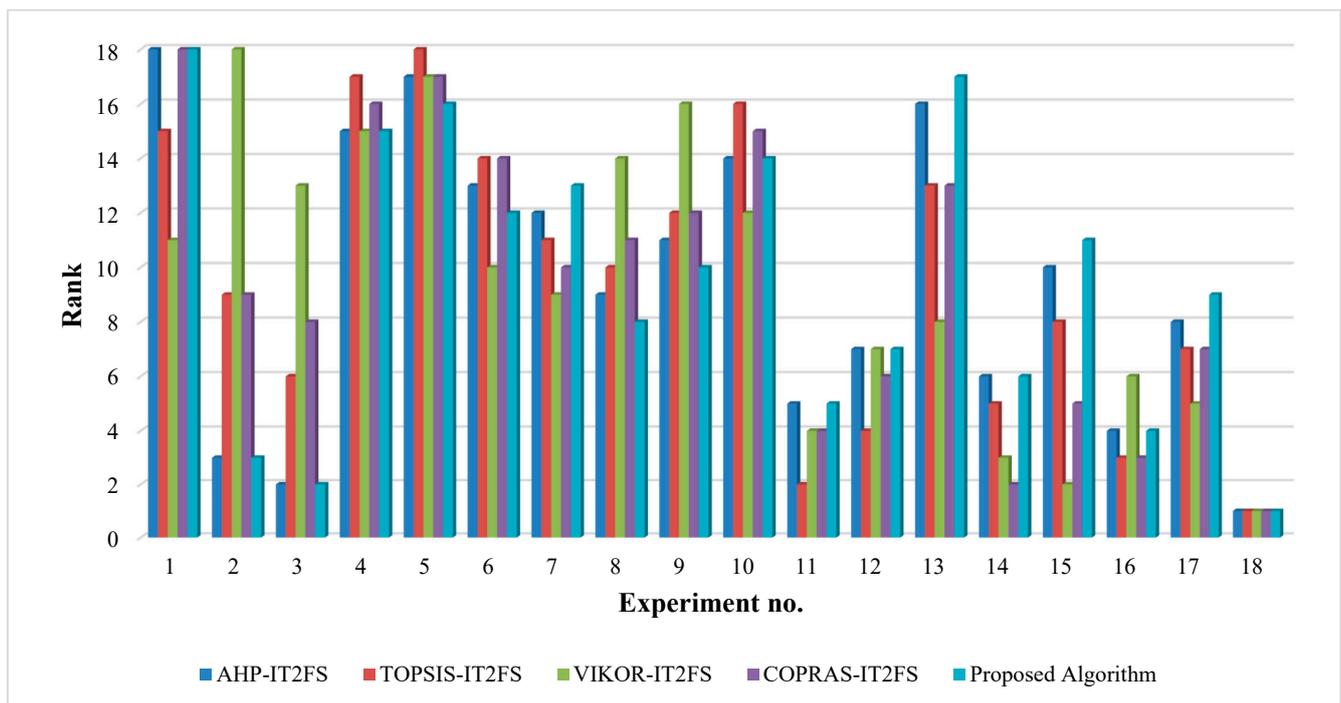


Figure 3. Comparison of the adopted MCDM model with the existing models.

6. Conclusions

Advancement in the nuclear, aerospace, oil and gas, automotive and marine industries has created a need for material with high material strength and less corrosion. The quest for such a material ended with nickel-based alloys named Inconel-800. Although Inconel-800 has excellent mechanical and chemical properties, its machinability is poor. Hence, the non-traditional machining method is the best and most economical way for machining the Inconel-800 superalloy. Out of all the NTM processes, WEDM is the most widely used machining technique for difficult-to-machine materials because of its capacity to produce jobs with minute accuracy and precision. The contributions and findings drawn from the analysis are as follows:

- To improve the machining endeavor and to reduce machining expenses, optimum machining parameters selection is a crucial concern in the manufacturing domain.
- In this paper, an interval type-2 fuzzy-integrated AHP-ARAS method is proposed. In the method, the best WEDM parameter settings are selected by applying the ARAS ranking method and the weightage of the criteria are computed using the AHP method.
- Based on the concept of falsificationism, application of interval type-2 fuzzy sets for quantifying the subjective assessment is more scientifically correct than the application of general fuzzy logic. Hence, interval type-2 fuzzy numbers are applied for handling the uncertainties associated with the subjective assessment of the criteria.
- The proposed model computed the best WEDM parameter settings for machining Inconel-800 superalloy is pulse-on time = 105 μ s, pulse-off time = 57 μ s, peak current = 210 A and spark gap voltage = 50 v.
- For validation purposes, the results of the adopted method were extensively compared with some existing methods proposed by the previous researchers from literature [18–22]. The comparison shows that the results of the Tri2N AHP-ARAS approach are reasonably consistent with the other approaches, which shows the applicability of the proposed approach.

Author Contributions: Conceptualization, B.S., S.A.I.H., A.D.G.; Methodology, B.S., S.A.I.H., A.D.G.; Software, B.S., S.A.I.H., A.D.G.; Validation, B.S., S.A.I.H., A.D.G.; Analysis, B.S., S.A.I.H., A.D.G.; Investigation, B.S., S.A.I.H., A.D.G.; Resources, B.S., S.A.I.H., A.D.G.; Data Curation, B.S., S.A.I.H., A.D.G.; Writing—Original Draft Preparation B.S., S.A.I.H., A.D.G., M.K.G., D.Y.P., T.M.; Writing—Review and Editing, B.S., S.A.I.H., A.D.G., M.K.G., D.Y.P., T.M.; Visualization, B.S., S.A.I.H., A.D.G.; Supervision, B.S., M.K.G., D.Y.P., T.M.; Project Administration, B.S., M.K.G., D.Y.P.; Funding Acquisition, M.K.G., D.Y.P., T.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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