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A fuzzy TOPSIS method for surface integrity criteria ranking using the wire electrical discharge machining process

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Abstract

The objective of this study is to propose a method called the fuzzy technique for order preference by similarity to the ideal solution (F-TOPSIS) to select parameters of the wire electrical discharge machining (WEDM) process. Consequently, the parameters principally influencing the outputs of the WEDM process were identified and examined using the F-TOPSIS framework where the inputs of three decision makers, representing their opinions are incorporated into the analysis. The idea of parametric selection in a WEDM process is multicriteria-based when the production of nitinol-60 smart memory alloy (SMA) is critically considered. Current approaches of TOPSIS and analytic hierarchy process (AHP) evaluations to select the WEDM parameters fail because of the constraints of linguistic evaluations, but the use of F-TOPSIS crosses over the restriction to choose the best parameters in a WEDM process for nitinol-60 SMA. In this work, the experimental results obtained from published research were utilised to validate the proposed method. The validation of the suitability of F-TOPSIS, aided by the published work on the WEDM process, analysed the surface integrity of nitinol-60 SMA. From the five outputs, the closeness coefficients of the best and worst are found to be 0.7567 and 0.2838, respectively. This research aids the process engineer in optimising the outputs in the WEDM process, to select the best output. Hence, the research showcased how the WEDM process could select outputs efficiently, thus aiding process engineers to maintain the process to optimise parametric resource allocations and guarantee utmost productivity.

Keywords: Nitirol-60, Smart memory alloy, Fuzzy TOPSIS, Multicriteria

Introduction

In the world of today, metals and their alloys play an extensive role in the manufacturing of products within the following industries: medical, aerospace aeronautics and manufacturing [13, 26]. Norgate and Jahanshahi [21] discussed the high influence that metals have in achieving the global sustainability requirements in existing and emerging areas as previously mentioned. Nitinol-60 is an example of a metal alloy with outstanding properties including high strength and durability, malleability, ductility, electrical and thermal conductivity, high melting point and high tensile strength [8, 13, 17, 27, 31].

Once obtained from nature, metals unarguably undergo some refining processes and are finally processed further to achieve the desired geometric properties such as shape, length and surface area, usually through machining [13, 31]. Although machining is categorised as conventional and unconventional, the latter type is the best fit to manufacture nitinol in a WEDM process due to its difficult-to-cut nature [13, 14].

However, during the experimental process on the WEDM system to process nitinol-60, the operator and researchers are subjected to some degrees of linguistic quantifications where the exercise of judgement on experimental data concerning parameters is often challenging and words such as high, low and medium often dominate their judgements. Hence, it becomes apparent that crisp numerical expression of data is inefficient considering the WEDM processing of nitinol-60 material. This leads to some confusion about material distribution decisions when confronted with material planning for the machining of nitinol-60 using the WEDM process. Thus, the crisp numerical value evaluation may be unsuitable and lead to wrong decisions. For this reason, the ranking of run orders involving the outputs of the WEDM process while manufacturing nitinol-60 is determined optimally to obtain ranks for the run after evaluating their performance scores. The ranking decision produces the best ranking at which specimens with better output responses emerge [29]. In this article, the particular problem to be solved is the linguistic qualification of the WEDM process. The need arises from the fact that machining systems are relatively expensive and specialised processes, and as such, the best way to make the most use of the process is to linguistically quantify the experimental data and reduce or eliminate wrong decision-making [4, 7, 20]. To the best of the authors' knowledge, previous studies have failed to tackle the uncertainty and imprecision of the experimental data to evaluate the optimal runs, performance scores and ranks of data while considering outputs. Hence, this work seeks to tackle and reduce the linguistic quantification problem, to linguistically quantify the WEDM process for nitinol-60 SMA. The fuzzy multicriteria decision-making (MCDM) was utilised for the design of experiments for the outputs. In the present study, the fuzzy MCDM method simply provides data from more instances, avoiding conducting the process. In this case, the process instituted is the WEDM of nitinol-60 SMA regarding a recorded set of parameters (duty factor, time on and time off).

Furthermore, a brief analysis of the work to date on the parametric selection and experimental analysis of nitinol is required to appreciate the gap bridged in the present study. Here, we trace the research journey in recent times from 2020 to 2023. Therefore, a review showing the graduation of studies to the recent period is given as follows: Bisaria et al. [5] mainly employed the following parameters to analyse the surface integrity of $Ni_{55.95}Ti_{44.05}$ from the experimental perspective: spark gap voltage, pulse-on-time, wire tension, pulse-off time and wire feed rate. However, Okponyia and Oke [22] failed to consider the micro-structural approach for a multicriteria perspective to analyse the parameters of the WEDM to machine $Ni_{55.8}Ti_{44.2}$ (nitinol). Besides, they incorporated current and powder concentration as new parameters that were ignored in Bisaria et al. [5]. They concluded that the current is the most important parameter from the results of the two versions of the methods tested by them. These methods are the combined Taguchi-EDAS and the combined Taguchi-Pareto-EDAS methods. Although focused on surface quality, the method of testing by Balasubramaniyan et al. [3] in the WEDM process of NiTiCuZr alloy is ultrasonic vibration. Recently, Adedeji et al. [1] coupled the Taguchi-Pareto method and the grey wolf optimiser while using the desirability function analysis to translate the multiple outputs into a single response when machining the nitinol-60, using the WEDM process. From these studies, there is a research gap, which is an obstacle to reliable decision-making by the process engineers in the WEDM process. All the studies mentioned above show a complete absence of how to reduce uncertainties and imprecision while choosing the best parameter in the WEDM process. Undeniably, these issues are due to equipment calibration errors and measurement errors by the operator but the literature has been silent on this issue while selecting parameters in the WEDM process.

This paper addresses the problem of linguistic quantification of outputs of the WEDM process while machining the nitinol-60 SMA. Recently, Adeniran et al. [2] provided several sides to this problem. The first is that crisp numerical values used are ineffective when evaluating experimental outcomes of the WEDM process by ignoring the judgements of engineers, operators and system owners. They impact the solution and lead to wrong machining decisions. The second problem is the weight index, which has no certainty of what approach to adopt to evaluate this. Thus, solving these problems improves performance potentially for the WEDM problem. Then, we can establish a realistic and innovative weight assignment fuzzy-based method, denoted by the weight index as input to the performance score for the WEDM problem.

Thus, understanding and establishing the linguistic quantification of experimental data collected during the WEDM process is challenging because of human (operators) errors in recording, the errors generated by the equipment and the environmental errors imposed on the equipment such as highly varying temperature and pressure. Moreover, the linguistic quantifications should be simple enough to be understood by the operator and stakeholders of the WEDM process. Often, the researchers make decisions by relying on crisp numerical values, which may be misleading and inaccurate based on the possible uncertainty and fuzziness in the data collection process. The operator records the experimental values for all the parametric inputs and the outputs of the WEDM process are equally recorded while machining the nitinol-60 SMA. Also, the various pieces of equipment within the WEDM process generate data under controlled conditions of temperature, humidity and pressure. However, the controls could fail due to malfunctioning, old age, or obsolescence, thereby generating incorrect data for decision-making. Thus, the mode of interpreting the data generated is a very essential aspect of data management for the WEDM process while manufacturing the nitinol-60 SMA. The quantification of the WEDM parametric data should be linguistically evaluated to allow a correct evaluation of the situation and decision-making. In this paper, we proposed a method to express the experimental data of WEDM process parametric observations as linguistic qualifications using the fuzzy TOPSIS (F-TOPSIS) process that depends on normalised and weighted normalised data to evolve performance scores that finally bring out ranks for the run orders by considering the outputs in the WEDM process of nitinol-60 SMA. Introducing the F-TOPSIS method into the processing of nitinol-60 SMA on the wire electrical discharge machining would assist in creating precise swapping between several multicriteria and easily represent the preferences of the operations and decision maker within the WEDM process [12]. Moreover, it exhibits straightforward computational steps [12, 29]. The chief contributions of this paper are as follows:

1. Conceptualization, linguistic quantification and parameterization of the WEDM process while producing nitinol-60 SMA.
2. Establishment of a method that combines normalisation and weighted normalisation and weighted normalisation of experimental data into performance score and then the ranks of the run orders to evaluate optimal runs for the experiment while conducting the WEDM process of nitinol-60 SMA.
3. Preparation of experimental data of the WEDM process as a basis for linguistic quantification of outputs.
4. A reasonable weights index of 0.2 derived from an equal apportioning of weights to the outputs is established.

Literature review

A literature review is often written to offer a background idea on the subject matter of the article. In this case, multicriteria analysis was applied to the WEDM process to identify gaps and emphasise the relevance of the research. Consequently, the studies presented are associated with the multicriteria analysis of the WEDM process while discussing the effect of analyses on the nitinol-60 SMA material.

Surface integrity has been widely studied focusing on diverse aspects including the following. Kumar and Singh [15] utilized the Taguchi's technique and grey relational analysis to optimize the surface characteristics in wire electrical discharge machining focusing on Inconel X-750 alloy. The parameters of interest are the spark gap voltage, wire tension, wire feed rate, pulse-off time, pulse-on time and peak current. The responses to measure surface integrity are the cutting speed and surface roughness. Raj and Prabhu [25] presented in modeling and analysis scheme, leading to the coupling of the principal component analysis method and the grey relational framework for the performance analysis of titanium alloy on the WEDM facility. In between the analysis, the L9 orthogonal matrix of the Taguchi method was deployed as a stepping stone for further analysis. It was found that the wear rate of brass (whose usage was compared with that of molybdenum) wires increased with a growth in the input energy when machining titanium alloy compared with a lower wear rate for molybdenum wire. Besides, Thankachan et al. [30] deployed a multi-objective optimisation method developed from the combined framework of the Taguchi method and grey relational analysis to assess the machining attribute of wire-cut electrical discharge machining. The focus parameters are the different volume fractions of boron nitride, wire feed rate, pulse discharge on time and pulse discharge off time. The responses are the surface roughness and the material removal rate. In addition, Karthik et al. [11] presented experimental results that address the effect of materials as well as the parameters of the WEDM scheme on the performance of the system while machining the Al/AlCoCrFeNiMo0.5 MMC. The target responses are the reduced kerf width, improved surface finish and material removal rate. It was concluded that by applying a multi-objective optimisation scheme through the TOPSIS method, the surface finish and material removal rate increased while the kerf width declined in value. Mouralova et al. [19] analysed the influence of machine set-up parameters on the oxygen presence on the surfaces of metals. The parameters are discharge current, gap voltage, wire feed, pulse off time and pulse on time. Kumar et al. [16] analysed the microstructure together with the optimization of Inconel 825. The analysed parameters are spark gap voltage, pulse-on time, wire feed, pulse-off time, peak current and wire tension. In addition, Sen et al. [28] analysed electrode materials as well as process parameters and their influences on the responses of the WEDM process. The studied responses are recast layer thickness, surface morphology and surface roughness. Balasubramaniyan et al. [3] machined the NiTiCuZr SMA subjected to the WEDM of the ultrasonic vibration type. The outputs of the process are the surface roughness and material removal rate. However, the parameters of interest are the servo voltage, pulse on time, pulse off time and applied current.

Furthermore, the search for multicriteria studies such as TOPSIS, VIKOR, ELECTRE, AHP and DEMATEL was carefully reviewed in the literature concerning the nitinol-60 SMA. Then, the survey focused on available research on the multicriteria-based WEDM process, among others. To date, several studies have been conducted on the optimisation and selection of metals in WEDM as can be seen in Ikedue and Oke [9] using the Al7075/Al_2O_3/SiC composite and in the application of AZ91 magnesium alloy by Ikedue et al. [10]. However, the specific applications of nitinol SMA are expanding with a review by Adeniran and Oke [2] and application studies in Adedeji et al. [1] and Okponyia and Oke [22]. These studies intend to improve the parameters of the machining process in optimisation predictions and their rankings. However, all the studies have ignored the uncertainty introduced by the operator from the equipment and the error caused by the pieces of equipment themselves. Some literature accounts elsewhere that problems, which show similarity in characteristics have been solved through the intervention of the F-TOPSIS method. Though the TOPSIS method which is the foundation for F-TOPSIS was introduced in 1981 by Hwang and Yoon, later extended in 1987 and 1993 by Yoon, Hwang, Lai and Liu, the introduction of linguistic variables to TOPSIS was much later. Nădăban [20] provided an extensive background of the development of F-TOPSIS in a literature review. F-TOPSIS achieves ideal solutions and mechanises processes to overcome uncertainty and ambiguity while selecting machining parameters. The F-TOPSIS is popular for being straightforward in symbolising human preferences, computationally simple and permits trade-offs when multiple criteria are considered. In the past few years, F-TOPSIS has become an interesting subject and tool to research because of the mentioned advantages. Priyadarshini et al. [24] established how the turning parameters could occur using F-TOPSIS. It was asserted that F-TOPSIS aided the optimal parametric performance determination for the turning process while analysing the influence of each system parameter on the specific energy consumption, surface roughness and material removal rate. Pawanr et al. [23] applied F-TOPSIS to the traditional machining system but not the non-conventional WEDM system. They established a multi-objective optimisation method to select the optimal thresholds of cutting parameters while processing an aluminum piece. The key parameters studied are the depth of art, feed rate and speed. These parameters are different from the ones pursued here, which are cutting rate, recast layer thickness, maximum peak-to-valley-height, average peak-to-valley height and cutting rate, respectively. The differences in the types of parameters studied and the machining methods strengthen the need for the present study. It was concluded that F-TOPSIS yielded optimal results validated with the Taguchi method. Bhatia and Diaz-Elsayed [4] developed a multi-criteria-making method to help small and medium enterprises adopt technologies through the evaluation of parameters by F-TOPSIS. The prediction of quality, tool wear and equipment efficiency was declared as the most important elements to the decision-makers in the industry.

Table 1 offers information on the previous studies that were directed at the WEDM process. Nonetheless, notice that these articles hardly considered uncertainty and imprecision in the solution of the selection and optimisation problem. Previous studies on the selection and optimisation of WEDM process parameters. Overall, these articles provide a substantial understanding of the selection and optimisation process. Moreover, they fell short of exploring the effect of uncertainty and imprecision in analysis and were unable to reduce them. This is the principal weakness of the papers since their efforts were directed to crisp numerical value analysis within the WEDM process. To bridge this gap, the present study aims to investigate the WEDM process, analyse its parameters and introduce an imprecision reduction on the process parametric data.

Methods

Experimental details

Figure 1 shows a simplified process flow of the WEDM process. This is applicable to the case drawn here from Roy and Mandal [27]. As declared in the experiments conducted by Roy and Mandal [27], the experimental setup (Fig. 2) consists of a cylindrical workpiece (rod), which is 8 mm and $L = 100$ mm. Notice that the rectangular workpiece may be replaced by a cylindrical rod.

Table 1 Previous articles on the selection and optimisation of the WEDM process

S/No	Author(s)	Method	Solution approach
1	Raj and Prabhu [25]	Multivariate statistical techniques and multicriteria decision-making	Principal component analysis, grey relational analysis
2	Thankachan et al. [30]	Mathematical modeling	Response surface methodology
3	Majumder and Maity [17]	Artificial intelligence, multicriteria decision-making, fuzzy logic	GRNN, MOORA-fuzzy
4	Roy and Mandal [27]	Mathematical modeling	Response surface methodology
5	Karthik et al. [11]	Mathematical modeling	Taguchi method, ANOVA and TOPSIS
6	Das and Chakraborty [8]	Multicriteria decision making	Grey correlation-based TOPSIS
7	Okponyia and Oke [22]	Multicriteria decision making, mathematical modeling	EDAS-Taguchi, EDAS-Taguchi-Pareto
8	Chaudhari et al. [6]	Metaheuristics	Teaching learning-based optimisation algorithm, multi-objective teaching learning-based optimisation algorithm
9	Vakharia et al. [31]	Artificial intelligence and machine learning	Singular generative adversarial network, dense Net deep learning
10	Adedeji et al. [1]	Mathematical modeling and metaheuristics	Taguchi-Pareto, grey wolf algorithm, desirability function analysis
11	Ikedue et al. [10]	Mathematical modeling, metaheuristics, multicriteria decision making	AHP, Taguchi method and modified Taguchi methods, genetic algorithm
12	Ikedue and Oke [9]	Mathematical modeling	Taguchi, Taguchi Pareto, Taguchi-ABC methods

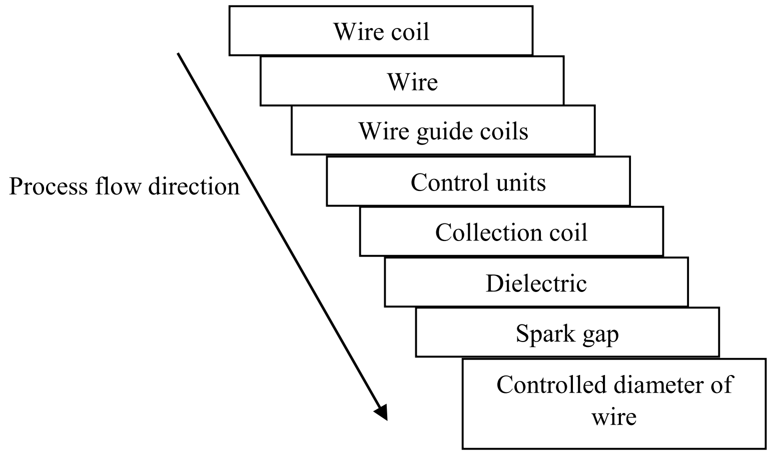

Fig. 1 Simplified process flow in the WEDM process

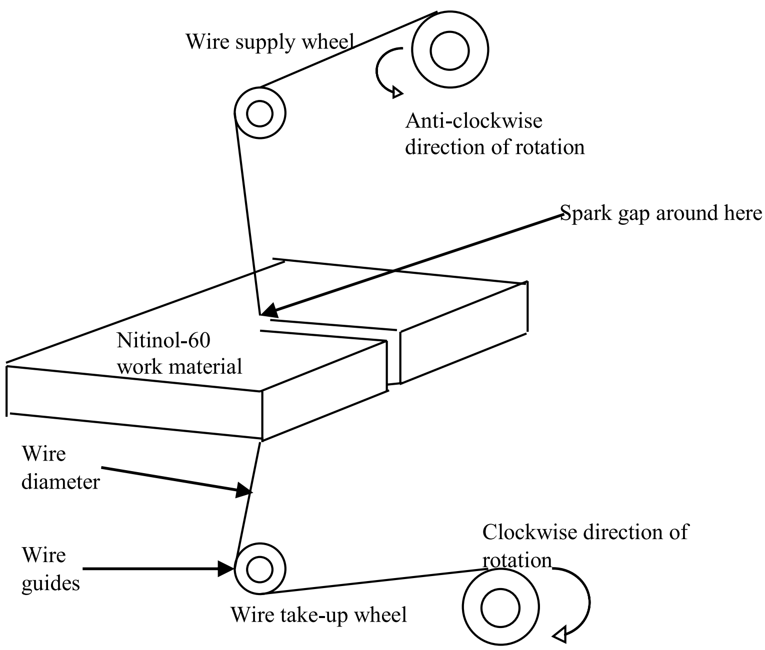

Fig. 2 A typical WEDM setup (see [32])

The standard setup has two simple clamps. The clamps hold the cylindrical initial-60 materials, which will be reduced in size but still maintain the cylindrical shape after the machining process. The work materials (nitinol-60) will have to be in contact with the lower arm of the WEDM machine to clean it up. Notice that nitinol-60 is a suitable material for the machining process, and this serves as the reason for its choice. Incompatible material may not be machined by the WEDM setup. Inserts will be used on the material, and they will be tapped off. It was assured that the workpiece was held properly before the machine started work. Introduce fixtures for the nitinol-60 machining application and connect the wire to it for the functioning of the

WEDM. Notice that inserts are also needed and their working is synchronised with that of the fixture to work properly.

In this article, we have selected nitinol-60 SMA as the focus material for machining based on the following outstanding advantages: high mechanical performance, elevated proportion of power to weight, huge deformation and actuation force, minimal operation voltage, elevated specific strength, wear resistance, damping capacity and frequency response. Other advantages of nitinol-60 are elevated corrosion and chemical resistance as well as compactness and lightness [18]. Besides, notice that the research areas available in WEDM metallic materials are broad, encompassing studies on electrode wire, material surface, machining characteristics, dielectric fluid and discharging systems, among others [26]. However, this study concentrates attention on the material surface. But surface engineering and science may be divided into important parts, such as interfaces of liquid, gas and solid gas. Thus, this study, through the solid surface of the material, which does not touch the wire, but which permits actions in the air (consisting of gases such as oxygen) may be said to operate in the solid–gas interface. Furthermore, this research particularly focuses attention on surface integrity, within the surface engineering framework. The dataset obtained from the wire-EDM experiments, provided by Roy and Mandal [27], was based on the use of a cylindrical workpiece of diameter and length of 8 mm and 100 mm, respectively. The machine used plays a significant role in determining the reliability of the machine products. Thus, the ELECTRA MAXICUT e 734 machine was used. By chemical composition, the nitinol-60 used in this study has two main ingredients, namely nickel and titanium having composite percentages of 60% and 40%, respectively when measured by weight. Also, the wire electrode employed for the nitinol-60 experiment is a zinc-coated brass having a diameter of 25 mm. The results obtained from the experiments, drawn from Roy and Mandal [27], are shown in Table 2.

Table 2 Experimental data [27]

		Beneficial CR	**Non-beneficial Rz**	**Non-beneficial Rt**	**Non-beneficial SCD**	**Non-beneficial RLT**
Run order	1	2.354	9.458	12.354	0.0134	9.102
	2	2.454	10.384	13.1962	0.0205	11.762
	3	2.405	9.803	12.636	0.0154	9.801
	4	2.288	9.566	12.351	0.0137	8.913
	5	1.478	8.295	11.5991	0.0116	8.623
	6	2.395	9.794	12.4635	0.0146	9.381
	7	2.157	9.337	12.261	0.0128	8.872
	8	2.424	10.126	12.9236	0.0179	10.673
	9	2.557	9.859	13.3912	0.0224	12.306
	10	2.416	10.006	12.842	0.0169	10.364
	11	1.584	8.813	11.6321	0.0115	8.304
	12	1.749	8.882	11.703	0.0116	8.366
	13	1.911	9.122	11.8116	0.0121	8.432
	14	2.312	9.565	12.362	0.0136	8.978
	15	2.108	9.227	12.154	0.0126	8.675

Outputs of the WEDM process

To achieve efficient WEDM processing of the nitinol 60 SMA, which is the goal of this work, it is essential to establish the expected outputs from the process. These outputs, which are the principal outputs of the WEDM process, were first observed through a literature review exercise and then selected by Roy and Mandal [27]. Based on the need to establish the outputs of the WEDM process, the following outputs are discussed.

Cutting rate

Process engineers ought to consider the cutting rate in the WEDM process since it has a direct influence on the quality of nitinol-60 SMA produced from the system. The lower the cutting rate, the less time it takes the WEDM machine to produce a high-quality surface finish, thereby reducing the possibility of being rejected, which arises from a customer's dissatisfaction with the quality of a product.

Procedure for the F-TOPSIS implementation

The steps used in carrying out the F-TOPSIS on numerical data are as follows:

Step 1:Obtain and arrange experimental data and determine which parameters are beneficial (to be optimised) and non-beneficial (to be minimised): In this article, the concept of benefits derivable from the institution of outputs for the WEDM process is introduced and the two terms, namely beneficial parameters and non-beneficial parameters are used to indicate which of the outputs will be more desirable to the system and the extent is quantitatively measured by the degree to which the outputs moves towards or deviates from the goal of the WEDM process. Consequently, in the context of the present work, beneficial parameters are the outputs that profit the WEDM's process assessment and its reporting processes. However, non-beneficial parameters are the reverse of the beneficial parameters where they do not profit the process in its evaluation and reporting processes.

Step 2 Normalise the data using Eqs. (1) and (2): Looking closely at the outputs of the WEDM process, they are different in units. For instance, the cutting rate is measured in minimum while the duty factor is assessed in percentage. However, does a 5% growth in the cutting rate equate to a 5% growth in the duty factor? This is difficult to answer since these outputs are not of the same units. Similar problems had existed in the engineering literature and the approach taken in the past to resolve the issue was to normalise these output parameters. This means that the WEDM process output data will be organised and evaluated using some normalising indices to make them appear similar in all fields and records (i.e. data items look similar).

For non-beneficial parameters, the chosen ratio is (Eq. 1)

$$\left(\text{Minimum}X_{ij}\right)/X_{ij} \tag{1}$$

To evaluate the non-beneficial parameters for the WEDM process, the analyst needs to first obtain the minimum value of the X_{ij} among all the options and then multiply it by the actual value of the X_{ij} of interest, Eq. (1).

For beneficial parameters, the following ratio is evaluated (Eq. 2):

$$X_{ij}/\left(\text{Maximum}X_{ij}\right) \tag{2}$$

To calculate beneficial parameters for the WEDM process, the researcher needs to multiply the parameter X_{ij} by the reciprocal of the maximum item of X_{ij} Eq. (2).

Step 3 Determine criteria for assigning linguistic terms to parameters: In discussing the parameters of the WEDM parameters, the lens of linguistic quantification was used. Also, using the F-TOPSIS method while processing the nitinol-60 SMA, applying the idea of decision makers' contributions to the evaluation agrees with the standard procedure and will make the work robust. Thus, the standard practice is to involve three decision-makers to linguistically quantify the parameters. In this context, the decision-makers are those with experience in the working of the WEDM process and have knowledge that leads to the efficient operation of the process. The decision-makers are versed in identifying and establishing the constraints of the WEDM process, including the resources available in the system. In contributing to the evaluation of the linguistic quantities for the WEDM process, the decision-makers who may be engineers and managers with current and past responsibilities assist in making deliberate, thoughtful decisions through the organisation of associated information and establishing options. However, in this particular situation, decision-makers are scarce and alternative means of representing the three decision-makers must be devised to still have some resemblance of the inputs from the three decision-makers. Thus, the standard deviation, mean and range of the outputs were considered to represent the decision makers 1, 2 and 3, respectively.

Furthermore, the standard deviation, mean and range of quantities are defined as descriptive statistics that measure how dispersed the data is when benchmarked against the mean. The present researchers opted to use standard deviation as the representative judgement of decision maker 1 because it will assist in knowing the various outputs of the WEDM process when the data is distributed. For decision maker 2, the researchers decided to adopt the mean of the outputs, which shows the typical value and hence a measure for all observations. The decision maker 3 is represented by a range, which is important to have access to each value in an array. It is often defined as the difference occurring when the lowest value is subtracted from the highest value.

Step 4 Assign linguistic values to the rank values

Step 5 Using the previous table, apply the linguistic values to the parameters. In the table below, decision maker 1 refers to ranking based on standard deviation, decision maker 2 refers to ranking based on the mean of values, and decision maker 3 refers to ranking based on the range of the values.

Step 6 Assign fuzzy numbers to the linguistic values or linguistic terms. The table below was used in this work

Step 7 Apply the fuzzy numbers to the parameters, as shown below, to obtain a fuzzy weightage table.

Step 8 Obtain a fuzzy-weighted decision matrix by multiplying the fuzzy weight with the normalised data.

Step 9 Determine the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS): The following equations are relevant:

$$\overline{x_{ij}} = \left(a_{ij}, b_{ij}, c_{ij}\right) \tag{3}$$

$$a_{ij} = \min_{k}\left[a_{ij}^{k}\right] \tag{4}$$

$$b_{ij} = \frac{1}{k}\sum_{i=1}^{k} b_{ij}^{k} \tag{5}$$

$$c_{ij} = \max_{k}\left[c_{ij}^{k}\right] \tag{6}$$

FPIS and FNIS concepts: A solution may be described as ideal if the criterion value considered and that of the best criterion value are nearly equal. However, a fuzzy idea solution is one in which there is a near equal of the fuzzy number (fuzzy criterion) and the best fuzzy number (best criterion). Moreover, there are two types of fuzzy ideal solutions. The first type is the fuzzy positive ideal solution, FPIS and the second type is the fuzzy negative ideal solution, FNIS. The issue of a positive or negative solution is dependent on whether the criterion being considered is beneficial or non-beneficial. A beneficial criterion is desirable by the process engineer as it is known to add value towards the achievement of the goal of the WEDM process. This goal is to create complicated shapes and geometrics with the least resources of time and others. Moreover, a non-beneficial criterion is one, which produces undesirable effects on the achievement of the goal of the WEDM process, and it is therefore not wanted by the process engineer. From the foregoing, the FPIS may then be described as a fuzzy criterion with a beneficial impact on the WEDM process with a criterion value and that of the best criterion that is almost equal. Then, the FNIS is a fuzzy criterion with a non-beneficial impact on the WEDM process exhibiting a criterion value, which is almost equal to the best criterion.

Step 10 Calculate the difference between FPIS (d_i^+) and FNIS ($d_{i.}^-$) for each parameter using Eqs. (7) and (8)

For each fuzzy entry (a_1, b_1, c_1), with A^+ being (a_2, b_2, c_2), and A^- being (a_3, b_3, c_3),

$$d_i^+ \sqrt{\left(\frac{1}{3(a_1 - a_2)^2} + (b_1 - b_2)^2 + (c_1 - c_2)^2\right)} \tag{7}$$

$$d_i^- \sqrt{\left(\frac{1}{3(a_1 - a_3)^2} + (b_1 - b_3)^2 + (c_1 - c_3)^2\right)} \tag{8}$$

Step 11 Calculate the closeness coefficient CC_i for each run order using Eq. (9)

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{9}$$

Step 12 Rank the values in descending order of magnitude (highest to lowest)

Results and discussion

In Roy and Mandal [27], experiments on nitinol-60 were conducted and the verifiable experimental results were displayed in their work. However, due to the limitation of not having access to the experimental rig by the current authors, the experimental data of Roy and Mandal [27] was employed to validate the method proposed in this work. Moreover, the term "experiments" in the context of the present article has two interpretations. The first interpretation concerns the conduct of experiments and the display of experimental results, which the present authors do not claim to have done. The second interpretation relates to statistical experimentation using the orthogonal arrays, which is an element of the present study. To be clear, the present study uses Roy and Mandal's experimental data and the statistical experiments regarding orthogonal arrays to obtain practical and useful results.

Furthermore, the steps used to conduct the F-TOPSIS (Technique for Order of Performance by Similarity to Ideal Solution) on numerical data are stated here. F-TOPSIS effectively operates where the performance values within the decision matrix fail to possess the attributes of crisp numerical values but exhibit linguistic terms, which are judged by three decision-makers (i.e. decision maker 1, decision maker 2 and decision maker 3) in the present article. The situation considered here is one where the best run order is to be chosen based on the output values. The outputs considered are CR, Rz, Rt, SCD and RLT. Table 2 shows the normalised experimental data where two distinct categories of outputs are given, namely the beneficial criterion and the non-beneficial criterion. The outputs regarded as beneficial criteria are the CR and Rz. However, non-beneficial criteria are Rt, SCR and RLT (Table 3). Interestingly, the values obtained in Table 3 are derived from Table 2 and two examples of how these values are calculated will be demonstrated with the beneficial criterion and the non-beneficial criterion. Now, we start with the beneficial criterion, CR. By observing Table 1 and CR under run order 1, a value of 2.354 is given. But Eq. (2) is used since CR is a beneficial output. The value of interest, X_{11} is 2.354 but the maximum value of $X_{ij,}$ which is read from all the values in the column of CR for all entries in the run order 1 to 15 is 2.557 (i.e. run order 9). By dividing 2.354 by 2.557, a value of 0.921 is obtained. This value is recorded at the intersection of CR and run order 1 in Table 3. However, to calculate for a non-beneficial parameter, Rz (run order 1) Eq. (1) is used where the minimum X_{ij} is identified as 8.295 (run order 5). But X_{ij} is 9.458. Therefore, 8.295 divided by 9.458 gives 0.877, which is inserted at the intersection of Rz and run order 1. Table 3 shows the normalised data after using Eqs. (1) and (2).

Moreover, three decision makers are arbitrarily selected, based on the standard deviation (S/D), mean and range of the data. These values were calculated for the data and are

Table 3 Normalised experimental data

		Non-beneficial = (minimum X_{ij})/ X_{ij}; beneficial = X_{ij}/ (maximum X_{ij})				
		Output parameter				
		Beneficial	**Non-beneficial**	**Non-beneficial**	**Non-beneficial**	**Non-beneficial**
		CR	**Rz**	**Rt**	**SCD**	**RLT**
Run order	1	0.921	0.877	0.939	0.858	0.912
	2	0.960	0.799	0.879	0.561	0.706
	3	0.941	0.846	0.918	0.747	0.847
	4	0.895	0.867	0.939	0.839	0.932
	5	0.578	1.000	1.000	0.991	0.963
	6	0.937	0.847	0.931	0.788	0.885
	7	0.844	0.888	0.946	0.898	0.936
	8	0.948	0.819	0.898	0.642	0.778
	9	1.000	0.841	0.866	0.513	0.675
	10	0.945	0.829	0.903	0.680	0.801
	11	0.619	0.941	0.997	1.000	1.000
	12	0.684	0.934	0.991	0.991	0.993
	13	0.747	0.909	0.982	0.950	0.985
	14	0.904	0.867	0.938	0.846	0.925
	15	0.824	0.899	0.954	0.913	0.957

Table 4 Standard deviation, mean and range

Parameters	S/D	Rank	Mean	Rank	Range	Rank
CR	0.13	2	0.866	4	3.872	4
Rz	0.05	4	1.036	2	3.949	3
Rt	0.04	5	1.154	1	4.960	1
SCD	0.15	1	0.797	5	4.849	2
RLT	0.10	3	0.985	3	2.900	5

Table 5 Linguistic terms for rank values

Abbreviation	Rank value	Linguistic value
VL	5	Very low
L	4	Low
M	3	Medium
H	2	High
VH	1	Very high

presented in Table 4. These values are used to rank the parameters in descending order of magnitude (i.e. being assigned to the highest numerical value, and 5 being assigned to the lowest numerical value). Furthermore, Table 4 shows the arbitrarily selected decision makers, which are three and the basis of selection is the standard deviation (S/D), mean and range of the data. These values are used to rank the parameters in descending order of magnitude (i.e. being assigned to the highest numerical value and 5 being assigned to the lowest numerical value).

Table 6 Decision matrix

	Decision maker 1	Decision maker 2	Decision maker 3
CR	H	L	H
Rz	L	M	VL
Rt	VL	VH	L
SCD	VH	VL	VH
RLT	M	H	M

Table 7 Fuzzy numbers

Term	Fuzzy number
VL	1,1,3
L	1,3,5
M	3,5,7
H	5,7,9
VH	7,9,9

After assigning the linguistic values to the rank values, Table 5 is obtained.

It is observed that in Table 5, there is no crisp value assigned to outputs. However, five linguistic terms are used, namely very high, high, medium, low and very low. This classification is consistent with the literature as shown in Chisale and Lee [7], where five grades were used, namely very poor, poor, fair, good and very good. Here are the expected rates for the output of interest in the WEDM process on a five-point scale mentioned above. Based on the five-point scale, Table 6 evolved as a decision matrix showing the minds of each decision maker. Thus, decision maker 1 assigns a high term to CR, decision maker 2 assigns a low term to CR, and decision maker 3 assigns a high term to the CR output (Table 6). It should be noted that if there are no numerical values given, it is extremely difficult to calculate the ranks of the run orders. Therefore, as opposed to directly mapping the linguistic terms for the WEDM process to the weight used in the calculation, the process engineer who decides on the system can evaluate the fuzzy number for the weight of each criterion in the WEDM process using the fuzzy HHP method, which is not discussed in this article.

Furthermore, using Table 5, the linguistic values were applied to the parameters. In Table 6, decision maker 1 refers to ranking based on standard deviation, decision maker 2 refers to ranking based on the mean of values and decision maker 3 refers to ranking based on the range of the values.

Moreover, fuzzy numbers are assigned to the linguistic values or linguistic terms as shown in Table 7.

In Table 7, the five-point scale earlier declared in Table 6 was fuzzified using triangular membership functions as shown in Table 7. Notice also that the triangular membership concept used in the present study is consistent with the one used in Chisale and Lee [7]. For each decision maker, the evaluation is done as presented in Table 8. In this case, where three decision-makers are used, their evaluations need

Table 8 Fuzzy weightage table

	Decision maker 1	Decision maker 2	Decision maker 3
CR	5,7,9	1,3,5	5,7,9
Rz	1,3,5	3,5,7	1,1,3
Rt	1,1,3	7,9,9	1,3,5
SCD	7,9,9	1,1,3	7,9,9
RLT	3,5,7	5,7,9	3,5,7

Table 9 Fuzzy weighted decision matrix

	CR	Rz	Rt	SCD	RLT
1	6.444, 2.762, 6.444	2.631, 4.385, 1.462	1.565, 7.824, 2.817	7.152, 1.430, 7.152	4.562, 6.386, 4.562
2	6.718, 2.879, 6.718	2.396, 3.994, 1.331	1.465, 7.325, 2.637	4.675, 0.935, 4.675	3.530, 4.942, 3.530
3	6.584, 2.822, 6.584	2.539, 4.231, 1.410	1.530, 7.649, 2.754	6.223, 1.245, 6.223	4.236, 5.931, 4.236
4	6.264, 2.684, 6.264	2.601, 4.336, 1.445	1.565, 7.826, 2.817	6.995, 1.399, 6.995	4.658, 6.522, 4.658
5	4.046, 1.734, 4.046	3, 5, 1.667	1.667, 8.333, 3	8.261, 1.652, 8.261	4.815, 6.741, 4.815
6	6.557, 2.810, 6.556	2.54, 4.235, 1.412	1.551, 7.755, 2.792	6.564, 1.313, 6.564	4.426, 6.196, 4.426
7	5.905, 2.531, 5.90	2.665, 4.442, 1.481	1.577, 7.883, 2.838	7.487, 1.497, 7.487	4.680, 6.552, 4.680
8	6.636, 2.844, 6.636	2.458, 4.096, 1.365	1.496, 7.479, 2.693	5.354, 1.071, 5.354	3.890, 5.446, 3.890
9	7, 3, 7	2.524, 4.207, 1.402	1.444, 7.218, 2.599	4.278, 0.856, 4.278	3.374, 4.724, 3.374
10	6.614, 2.835, 6.614	2.487, 4.145. 1.382	1.505, 7.527, 2.710	5.671, 1.134, 5.671	4.006, 5.609, 4.006
11	4.336, 1.858, 4.336	2.824, 4.706, 1.569	1.662, 8.310, 2.991	8.333, 1.667, 8.333	5, 7, 5
12	4.788, 2.052, 4.788	2.802, 4.670, 1.557	1.652, 8.259, 2.973	8.261, 1.652, 8.261	4.963, 6.948, 4.963
13	5.232, 2.242, 5.232	2.728, 4.547, 1.516	1.637, 8.183, 2.946	7.920, 1.584, 7.920	4.924, 6.894, 4.924
14	6.329, 2.713, 6.329	2.602, 4.336, 1.445	1.564, 7.819, 2.815	7.047, 1.409, 7.047	4.625, 6.474, 4.625
15	5.771, 2.473, 5.771	2.697, 4.495, 1.498	1.591, 7.953, 2.863	7.606, 1.521, 7.606	4.786, 6.701, 4.786
A+	7, 3, 7	3, 5, 1.667	1.667, 8.333, 3	8.333, 1.667, 8.333	5, 7, 5
A-	4.046, 1.734, 4.046	2.396, 3.994, 1.331	1.444, 7.218, 2.599	4.278, 0.856, 4.278	3.374, 4.724, 3.374

to be merged as fuzzy numbers. This is explained as follows. Here, the idea of group decision-making is introduced to merge the thoughts of the three decision makers. For this case, we assign equal importance to the declarations of each decision maker, i.e. decision makers 1, 2 and 3. The next action is to replace the linguistic term obtained earlier with the fuzzy numbers using the five-point conversion scale in Table 7. By replacing the values of Table 7 in linguistic terms with fuzzy numbers, Table 8 emerges. To calculate the next step, it is desired to have a single matrix referred to as the combined decision matrix. This means that the individual entries are added. Furthermore, the fuzzy numbers are applied to the parameters to obtain a fuzzy weightage table (Table 8).

Next, a fuzzy-weighted decision matrix has been obtained by multiplying the fuzzy weight with the normalised data (Table 9). Also, the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS) have been determined, where FPIS $= A^{+}$ = maximum value and FNIS $= A^{-}$ = minimum value. These results are shown in Table 9. Now, a discussion of how to obtain the value in the combined decision matrix is given as follows: consider the intersection order 1 and CR in Table 9, which gives a fuzzy member of 6.444, 2.762 and 6.444. An interesting question is to explain how this is obtained. To proceed, we call this cell $\overline{x_{ii}}$. This cell depends on three cells in Table 8, which are the intersection of CR with decision maker 1, which is 5,7,9. It also includes the intersection of CR with decision maker 2 (i.e. 1,3,5) as well as the intersection of CR with decision maker 3, which is (5,7,9). The value of k in Eqs. (4), (5) and (6) vary from 1 to 3. This is because there are three decision makers. The *i*th term represents the number of rows, which is the order member that ranges from 1 to 15. These are the criteria or alternatives to be chosen among. The *i*th value represents the member of the columns. It will be seen from Table 8 that for decision maker 1, the intersection with CR, which is 5,7,9 can be written as $a_{11}^1, b_{11}^1, c_{11}^1$. The intersection of CR with decision maker 2, which is 1,3,5 can be written as $a_{11}^2, b_{11}^2, c_{11}^2$. Also, the intersection of CR with decision maker 3, which is 5,7,9 can be written as $a_{11}^3, b_{11}^3, c_{11.}^3$ By looking at the first value of the fuzzy number (6.44, 2.762, 6.444), which is 6.444, also called a_{11} is computed from Eq. (4) as the minimum of (5,1,5), which is 1. By using Eq. (4), it is mathematically expressed as $a_{11} = \min(5,1,5) = 1$. Notice that from Eq. (4), *k* varies from 1 to 3, which is the reason for having three components of the fuzzy numbers. For the second component, which is the b_{11} components, the values to work upon from decisions 1, 2 and 3 are 7, 3 and 7. But the operation in Eq. (5) is to be carried on this. Therefore, $b_{11} = {}^1/_3\ (7+3+7)$, which is 5.667. For the third component, c_{11} the items it contains are 9, 5 and 9. Then, Eq. (6), which is the maximum of 9, 5 and 9, giving 9, is used. Mathematically $C_{11} = \max(9,5,9) = 9$. Similarly, we may compute the fuzzy numbers in each cell by evaluating the minimum value from the a_{ij} components, choosing the mean of the b_{ij} component and the maximum value of the c_{ij} component for the decision matrix at the intersection of CR with decision makers 1, 2 and 3 in Table 9.

Next, the results of the difference between FPIS (d_i^+) and FNIS (d_i^-) for each parameter using Eqs. (7) and (8) are shown in Table 10, where for each fuzzy entry (a_1, b_1, c_1), with A^+ being (a_2, b_2, c_2), and A^- being (a_3, b_3, c_3), Also, the closeness coefficient CC_i is calculated for each run order using Eq. (9). Furthermore, we have ranked the values in descending order of magnitude (highest to lowest) as shown in Table 10.

Table 10 Rank according to TOPSIS

	d_i^+	d_i^-	CC_i	Rank
1	4.091	9.558	0.700	7
2	9.497	4.153	0.304	14
3	5.956	7.693	0.564	11
4	4.375	9.275	0.679	9
5	4.058	9.591	0.703	6
6	5.128	8.521	0.624	10
7	4.022	9.628	0.705	5
8	7.870	5.779	0.423	13
9	9.775	3.874	0.284	15
10	7.210	6.439	0.472	12
11	3.632	10.02	0.734	3
12	3.322	10.330	0.757	1
13	3.463	10.190	0.746	2
14	4.302	9.348	0.685	8
15	3.722	9.928	0.727	4

Research articles previously published in the area of the WEDM process, particularly those reviewed in the present study, offered important insights into both mathematical modeling and experimental analysis aspects of the WEDM process. Nonetheless, these works have up till now paid extremely little attention to uncertainty and precision results. The common deficiency in most of these articles is the relatively little attention to the substantial impact of uncertainty and precision on the results. Fuzzy, which is a solution approach, is related to the analysis of a parameter using multiple probable truth values that may be processed using the same parameter. The concentration of research reports was mainly directed towards the evaluation of crisp numerical values that depended on experimental data in many cases. But to the best of the authors' knowledge, this paper lays claim to be among those inaugural reports on nitinol and where WEDM is used for processing. It is among the papers to consider the decisive influences of fuzziness on the results of analysis. Notably, this paper innovatively expressed the crisp numeric numbers in linguistic terms, passes through the process of normalisation, apply the TOPSIS framework, defuzzify the numbers and state the crips values. Apart from Majumder and Maity [17], by contrasting the present article with the majority of articles in the nitinol literature, this article diverges from the literature by adopting the fuzzy concept for the evaluation of the WEDM process parameters. The findings in the present work reveal the strong influence of uncertainty and imprecision and the extent to which they could be reduced, contributing to improving decision-making on the WEDM process. The derived results establish run order 12 as the best run order ranking 1 and having the CC_i value of 0.757. This CC_i value strongly highlights the importance of reducing uncertainty and imprecision in decision-making since incorrect decisions are reduced.

This shows that it is crucial to reduce imprecision and uncertainty in an optimisation and selection drive. The effect is the savings in resources, time and materials used for the WEDM process. Our findings remain consistent with the previous study by Shamsuzzoha et al. [29] and Kannan et al. [12]. These studies have considered fuzzy decision-making and the selection of the best parameters in complex project selection and the selection of suppliers, respectively. They addressed the analysis and prioritisation of parameters, reducing uncertainty and imprecision under the target item selection scheme using multicriteria decision-making methods. However, these studies are outside the WEDM scheme. So more of the studies appear to have quantitatively described the reduction of uncertainty and imprecision in the WEDM process. Furthermore, our results seem to share a resemblance with those reported by Majumder and Maity [17]. The outcome of their study confirms that the reduction of uncertainty and imprecision in the WEDM process contributes to the inflation of results by using the MOORA-fuzzy method.

The principal motivation to apply F-TOPSIS in the selection and optimisation process of WEDM, using nitinol-60 is that the process of capturing uncertainty and imprecision for the WEDM scheme is simplified to a combination framework. The fuzzy term interpretation with the selection of option for the shortest Euclidean distance from the ideal solution as well as the largest distance from the negative ideal solution are the unique constituents of the F-TOPSIS method. Besides, the F-TOPSIS method has the following advantages over other multicriteria decision-making methods: (1) It is straightforward to calculate [12, 29]. (2) Human preferences are easily represented. The F-TOPSIS method permits explicit trade-offs among the multiple criteria elements of the process [7, 12, 29]. The F-TOPSIS method, when applied to the WEDM process, turns the inputs into outputs in a process which identifies the important parameters of the process and reduces uncertainty and imprecision and the interpretation of the results for improved decision making.

Conclusions

The main motivation for this work is to achieve surface integrity control within the framework of machining the nitinol-60 SMA using the WEDM process. However, more challenging is the ability of the process engineer to choose the best parameter in the process while reducing uncertainty and imprecision in the results obtained for decision-making. This has impacted decision-making in the past where wrong decisions were made with implications for extra spending of time and money as well as morale shrinkage. This challenge was overcome by developing a method called the F-TOPSIS, which was applied to the experimental data of Roy and Mandal [27] on the WEDM process. The following conclusions were obtained from the results of the work:

(1) From the five outputs, the closeness coefficients of the best and worst are found to be 0.7567 and 0.2838, respectively.
(2) The application of the F-TOPSIS method led to the reduction of uncertainty and imprecision, bringing outputs to the following values: CR is 1.749 mm/min as opposed to 2.6177 mm/min obtained by Roy and Mandal [27] for the single parameter optimisation. This indicates a reduction of 33.19%. The Rz, Rt, SCD and RLT were changed by increases of 8%, 2%, 2.65% and 0.39%, respectively.
(3) These increases are desired for non-beneficial parameters, which are these parameters affected in this manner.
(4) This method of F-TOPSIS is potentially useful for the WEDM process.

In future work, we will extend the proposed approach to establish fuzziness incorporated with AHP as fuzzy AHP to select the best run order to yield optimum results while conducting the WEDM process using the nitinol-60 SMA.

Abbreviations

Fuzzy TOPSIS (F-TOPSIS)	Fuzzy technique for order preference by similarity to the ideal solution to select parameters
TOPSIS	Technique for order preference by similarity to the ideal solution to select parameters
MOORA	Multi-objective optimisation on the basis of ratio analysis
fuzzy AHP	Fuzzy analytic hierarchy process
AHP	Analytic hierarchy process
DEMATEL	DEcision MAking Trial and Evaluation Laboratory
VIKOR	Vise Kriterijumaska Optimizacija I Kompromisno REsenje
ELECTRE	Eliminiation Et Choix Traduisant la REalite (Elimination and Choice Translating Reality)
GRNN	General regression neural network
ANOVA	Analysis of variance
MCDM	Multi-criteria decision-making
EDAS	Evaluation on distance from average solution
S/D	Standard deviation
SMA	Smart memory alloy
WEDM	Wire electrical discharge machining process
EDM	Electrical discharge machining process
FPIS	Fuzzy-positive ideal solution
FNIS	Fuzzy-negative ideal solution
CC_i	Closeness coefficient for the *i*th item

(a_{ij}, b_{ij}, c_{ij})	Fuzzy entries for the *i*th item and the *j*th parameter
VL	Very low
L	Low
M	Medium
H	High
VH	Very high
X_{ij}	Response value of the parameter i for the run order j
CR	Cutting rate, mm/min
Rz	Average peak to valley height, µm
Rt	Maximum peak to valley height, µm
SCD	Surface crack density, µm/µm^2
RLT	Recast layer thickness, µm
k	Identify for the decision-maker

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Authors' contributions
BAS contributed to the writing of the manuscript; EF contributed to the writing of the manuscript; WOA contributed to the writing of the manuscript; MKA conceived, analysed and interpreted the data; SAO conceived and interpreted the data and also supervised the computational experimentation, and contributed to writing the manuscript. JR contributed to the writing of the manuscript. All authors have read and approved the manuscript.

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Data for the analysis was extracted from Roy and Mandal [27], and they are in the open-access domain.

Declarations

Competing interests
The authors declare that they have no competing interests.

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