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Optimization of the Wire Electric Discharge Machining Process of Nitinol-60 Shape Memory Alloy Using Taguchi-Pareto Design of Experiments, Grey-Wolf Analysis, and Desirability Function Analysis

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A B S T R A C T

The nitinol-60 shape memory alloy has been rated as the most widely utilized material in real-life industrial applications, including biomedical appliances, coupling and sealing elements, and activators, among others. However, less is known about its optimization characteristics while taking advantage to choose the best parameter in a surface integrity analysis using the wire EDM process. In this research, the authors proposed a robust Taguchi-Pareto (TP)-grey wolf optimization (GWO)-desirability function analysis (DFA) scheme that hybridizes the TP method, GWO approach, and DFA method. The point of coupling of the TP method to the GWO is the introduction of the discriminated signal-to-noise ratios contained in the selected 80-20 Pareto rule of the TP method into the objective function of the GWO, which was converted from multiple responses to a single response accommodated by the GWO. The comparative results of five outputs of the wire EDM process before and after optimization reveals the following understanding. For the CR, a gain of 398% was observed whereas for the outputs named Rz, Rt, SCD, and RLT, losses of 0.0996, 0.0875, 0.0821, and 0.0332 were recorded. This discrimination of signal-to-noise ratio based on the 80-20 rule makes the research different from previous studies, restricting the data fed into the GWO scheme to the most essential to accomplishing the TP-GWO-DFA scheme proposed. The use of the TP-GWO-DFA method is efficient given the limited volume of data required to optimize the wire EDM process parameters of nitinol.

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1. INTRODUCTION

In the past several decades, the Taguchi method (TM), and more recently, the Taguchi-Pareto (TP) and Taguchi-ABC (TABC) methods are the fastest and most promising optimization approaches in the history of engineering optimization (Oji and Oke, 2020; Okanminiwei and Oke, 2020). This is due to their simplicity and the values they deliver toward qualitative and quantitative decision-making information (Francis et al., 2022). The low experimental cost implementation adds to their popularity (Sharma et al., 2021; Paulson et al., 2023). This is coupled with the unique deliverables of the TP and TABC methods, capable of concurrent optimization and prioritization of parameters (Oji and Oke, 2020; Okanminiwei and Oke, 2020). In the wire EDM process, the TP and TABC methods had just been introduced where there is a demand for additional optimization procedures to the TM. Researchers are expected to overcome the limitation of not being able to concurrently optimize and prioritize parameters. This makes way for a double optimization method to further improve the quality of the solution for the wire EDM process parameters. However, the double optimization method is further compelling when the potential of employing evolutionary algorithms that contains smart intelligence is considered (Adekola et al., 2022). The GWO method, for instance, uniquely delivers optimization results based on the organized kingdom of the grey wolves, demonstrating the attainment of wire EDM processing goals precisely and timely (Adekola et al., 2022; Ozule et al., 2022).

Furthermore, shape-memory alloys (SMAs) are a material class of great interest in the engineering field, owing to their unique properties that are highly desirable in various engineering applications (Chan et al., 2023). One particular type of shape memory alloy is nitinol (a nickel-titanium shape memory alloy) (Chan et al., 2023). Now a brief review of the important literature is given starting with Chaudhari et al. (2020a) that attributed the popularity of nitinol to its popularity to the distinct capability of the alloy to be restored to its original shape by magnetic, mechanical, or thermal loading after it has undergone deformation (Chan et al., 2023). The application areas of nitinol include, but are not limited to, the automobile, aerospace, and medical fields (Chaudhari et al., 2020a; Mwangi et al., 2020; Davis et al., 2021; Chan et al., 2023), for uses ranging from actuators to microelectromechanical system devices (Chaudhari et al., 2020a). In some cases, other elements are added to nitinol to enhance its properties. Copper can be added to nitinol to form TiNiCu SMAs, which outperform nitinol in the actuation response, ductility, and hysteresis temperature change (Manjaiah et al., 2018). In like manner, copper and zirconium can be added to nitinol to form NiTiCuZr SMA, which has the added benefit of increased functional fatigue properties as well as higher resistance to corrosion and wear (Balasubramaniyan et al., 2022).

Inevitably, with every upside, there is a corresponding downside. SMAs, despite their superior physical properties, when compared with other alloys, is a bit problematic to machines (Mwangi et al., 2020; Davis et al., 2021; Chan et al., 2023). The greatest strengths of SMAs as alloys (their strain hardening, super-elasticity, high specific strength, and high resistance to wear and corrosion) are equally their greatest weaknesses when it comes to cutting the alloy (Chaudhari et al., 2020a). Additionally, in the process of machining this alloy, problems such as failure of the tool, long machining time, and poor quality of machined surfaces, may be encountered (Bisaria and Shandilya, 2020). This has birthed research into the discovery of unconventional methods of machining shape memory alloys such as wire-electric discharge machining (WEDM). Chaudhari et al. (2020a) noted that the issues faced with conventional machining processes have been overcome to a good extent by WEDM, seeing as there is no contact between the WEDM tool (the wire) and the alloy workpiece.

The WEDM process can be optimized by varying the values of the input parameters involved in the process until a suitable combination is found that produces optimal output conditions (Mwangi et al., 2020; Naresh et al., 2020). Various research efforts have been made toward the optimization of the WEDM process by scientists and engineers alike

(Sharma et al., 2021; Vora et al., 2022; Paulson et al., 2023). For instance, Balasubramaniyan et al. (2022) researched to make a comparison between fiber laser machining and WEDM whereas Chaudhari et al. (2020a) and Chaudhari et al. (2020b) studied the effect of WEDM on the surface characteristics of the machined nitinol using energy dispersive X-ray (EDX) analysis and scanning electron microscopy (SEM). Similarly, Manjaiah et al. (2018) determined how the surface and the subsurface of the NiTiCu SMA alloy were modified by the WEDM process and the effect of input parameters on the output parameters relating to the surface quality of the alloy.

Various approaches can be taken in the optimization of the WEDM; the Differential scanning calorimetry (DSC) test is one such method, which Balasubramaniyan et al. (2022) used in conducting research. Another such method is digital microscopy imaging, used by Chaudhari et al. (2020). Similar to the aforementioned method is 3D surface analysis, utilized by Chaudhari et al. (2020b). Chaudhari et al. (2020a) also made use of digital microscopy imaging and Scanning Electron Microscopy (SEM). These methods are useful in optimizing output parameters with quantifiable numerical values such as peak-to-valley height (Balasubramaniyan et al., 2022), material removal rate, surface roughness, and recast layer thickness (Manjaiah et al., 2018), and those with unquantifiable numerical values such as surface roughness (Manjaiah et al., 2018; Balasubramaniyan et al., 2022), microhardness, machined surface phase changes.

From the studies carried out, Balasubramaniyan et al. (2022) observed that the WEDM produced better results than laser machining, producing machined samples with 28.2% lower peak-to-valley height, 11.9% lower microhardness, and an overall smoother surface. Chaudhari et al. (2020a) made a unique discovery, which is that the point on the surface of the machined alloy that was exposed greatly to the dielectric fluid had the highest surface roughness. Likewise, Chaudhari et al. (2020b) found that the surface roughness on the top and bottom works surfaces had higher and lower surface roughness respectively. Chaudhari et al. (2020a) and Chaudhari et al. (2020b), through EDX analysis, saw that the tool electrode did not remain on the machined surface. The results of the experiments and analysis done by Manjaiah et al. (2018) indicated that greater discharge energy was caused by longer pulse-on time, which further led to greater material removal rates, greater surface roughness, and a higher recast layer thickness. In addition, this longer pulse-on time led to an increase in the microhardness of the machined alloy by about 59%. Finally, the shape recovery ability of the SMA may be attributed to the machined surface undergoing a phase change.

Moreover, based on the insights into previous research outcomes on the wire electrical discharge machining process, it was concluded that studies on the optimization of smart memory alloys in machining are still in demand (Sharma et al., 2021; Vora et al., 2022; Paulson et al., 2023). Also, the exact evidence of two optimization methods with the capability of exploiting the qualitative, quantitative of the Taguchi method and the evolution of any algorithm advantage of GWO and with particular reference to nitinol is still absent in the wire electrical discharge machining literature. Hence, optimization schemes involving the TP, GWO, and the conversion scheme of desirability function analysis where two or more outcomes could be converted into an outcome as illustrated in the present study could be useful to fill the research gap in the optimization of the machining process for nitinol.

Given the reluctance of the literature to tackle the issue of speed of convergence and the accuracy achievable while processing nitinol during the wire EDM process, there is little hope that such goals will be achievable soon except an aggressive effort is launched to change the trend of events. Researchers need a rethink and the development of robust frameworks to incorporate and integrate the two optimization methods of TP and GWO approach, exploiting the quantitative and qualitative deliverable of the Taguchi method, the simultaneous decision data of optimization and prioritization produced by Taguchi-Pareto method (Oji and Oke, 2020) and the speed and accuracy deliverable of the GWO approach. To the best of the present authors' knowledge, previously documented studies within the wire electrical discharge arena have fallen short of understanding how to optimize using two optimization methods concurrently and then aggregating two or more responses to one to finally determine the optimized parameters of the wire electrical discharge machining process. Furthermore, it is not yet clear what behavior in experimental results nitinol exhibits during this machining process when the focus is to optimize the process parameters. Moreover, how to tackle the issue of working with only the most important experimental trials within the performed experiment such that non-important trials to the goals are eliminated has not been resolved so far in the wire electrical discharge machining while processing nitinol. While processing the nitinol using the wire electrical discharge machining, the elimination of non-essential experimental trials to the optimization goals as demonstrated in the Taguchi-Pareto method is a key concern for obtaining the efficient distribution of wire electrical discharge machining resources (Oji and Oke, 2020). Discriminating the experimental trials assures that the limited process resources are distributed in the appropriate quantities to the operators thus eliminating conflicts among them. The neglect of experimental trial discrimination has thus made it a fertile ground for applying the Taguchi-Pareto method, which may be one of the best tools for the combined optimization and prioritization of wire EDM process parameters while machining nitinol material.

Therefore, to overcome the limitations observed in previous research regarding the present research direction, which is the inability to discriminate among experimental trials and consequently parameters, a robust TP-GWO-DFA (Taguchi-Pareto-grey wolf optimization-desirability function analysis) method has been proposed. Pareto has been introduced within the Taguchi method's framework to discriminate among experimental trials. The proposed model serves as a foundation for obtaining efficient process parameters while machining nitinol using the wire EDM process. Once the original experimental trials have been defined, the signal-to-noise ratios that asses based on smaller-the-better, larger-the-better, and nominal best criteria are introduced, and the cumulative signal-to-noise ratios obtained from the cut-off are determined. Then the multiple responses from the experimental data on wire electrical discharged machining are converted through the desirability function analysis to a single response. This is then introduced into the GWO algorithm and the final optimized parameters are delivered for decision-making in mine electrical discharge machining.

As per the literature review, it was found that although the Taguchi method is widely used and it promises minimization of experiments and costs. However, the experimental trials produced by the Taguchi method at present are not the best achievable in the process since the surface integrity of the wire EDM process material may further be improved merely by eliminating the experimental trials that are not the most important to the process goals. Therefore, the deployment of Pareto analysis in the Taguchi-Pareto framework could attain further minimization of experimental counts and the cost of experiments for the surface integrity optimization for nitinol during the machining on wire EDM process can significantly be reduced. Besides, this assurance of enhanced optimization that the Taguchi-Pareto method could deliver according to literature results, it is still worrisome that despite the resource investment and the criticality of resource prudence, no information concerning the speed of convergence and accuracy could be provided. A further investigation of the use of the Taguchi-Pareto method reveals that it could at best treat one response at a time. This means that in a situation such as the machining of nitinol using the wire EDM process, where multiple responses are involved, computations associating parameters to a response are done one-by-one, in turn, until the parametric-response analysis for the process is exploited. This is cumbersome, and energy demanding and the time to achieve these activities in an economically viable option cannot be easily estimated. This, therefore, parts the machining engineer in a dilemma regarding the appropriate tool to use. However, upon further literature search, the huge success of the GWO in achieving a reasonable computational speed of convergence and accuracy when deployed on engineering problems is enviable.

Therefore, it was decided that to overcome the deficiencies of the computational speed of convergence of the solution and accuracy, the GWO method should be deployed in addition to the Taguchi-Pareto method. But while combining the Taguchi-Pareto method and the GWO method, the problems of the speed of convergence of solution and accuracy of the solution may be resolved and the issue of one response per parametric value at a time remains. Furthermore, while searching through the literature, the overwhelming success of the desirability function analysis in resolving the issue of one-response per parametric values for engineering problems is convincing. Therefore, it was thought that using the desirability function analysis as a coupling tool for both the Taguchi-Pareto method and the GWO method will be a worthwhile adventure. It will take each response which was first optimized by the Taguchi-Pareto method and again optimized by the GWO together with other responses to form a multiple response framework. Therefore, in totality, an integrated method of TP-GWO-DFA is developed in the present study.

In this article, a novel integrated TP-GWO-DFA scheme is introduced and deployed to optimize the wire EDM process parameters during the machining of nitinol. The contribution of the article is the introduction of the TP-GWO-DFA method to optimize the process parameters during the machining of nitinol in the wire EDM process.

2. METHODS

Apart from the procedure for the implementation of the TP-GWO-DFA method, there are two issues central to the development of the method proposed in the present study. The first of these issues is the specification of the objective function for each response of the wire EDM process while the second is the establishment of the factor-level structure, which was borrowed data from Roy and Mandal (2019). However, the discussion of the first issue follows.

2.1 Objective function

The GWO method works on the objective function, which is a mathematical representation of the surface integrity optimization problem that establishes how superior a solution, is regarding the goals of the wire EDM process. In the context of surface integrity optimization, there are several objective functions formulated, some of which attempt to optimize a criterion while others attempt to minimize another criterion according to how favorable these criteria are in achieving the surface integrity optimization of the process. In the present article, based on the experimental data of Roy and Mandal (2019), the following objectives are specified for the various outputs identified:

1. Cutting rate: The acronym of this output is CR and the unit of measurement is mm/min. however, in a wire EDM process endeavor, metal cutting is understood as the procedure engaged in whereby unwanted materials are removed through the action of an electrode on the metal, finally obtaining the desired size and shape for the component. But the two qualities of speed and the distance moved over the raw material being cut in the wire EDM process are related to the rate of cutting. Therefore, different operators may use different speeds of cutting using the electrode and move over the same distance. This rate must be maximized. Therefore, the objective function of the cutting rate is maximization.
2. Average peak to valley height: The acronym or representative symbol for when the average is replaced with the maximum. This output is Rz while the unit of measurement is mm. Notwithstanding, in the wire EDM process studies, surface irregularities are recognized on metals during surface roughness evaluations. While considering the length of the metal bar, the largest value of the depth is considered and the average of such is taken over several measurements. Given these discussions, the objective function for the average peak-to-valley heights is minimization.
3. Maximum peak to valley height: the representative symbol is Rz. The explanation given on the average peak-to-valley height is similar to the present

output but diverges when the average is replaced with the maximum. Here, the objective function for the maximum peak-to-valley height is minimization.

4. Surface crack density: The acronym for this output is SCD while the unit of measurement is mm/mm^2. Furthermore, in surface analysis, surface cracking describes a phenomenon occurring in metals such that the surface liquids on a metal being worked on evaporate at a faster rate than could be restored by the rising liquid from within the metal, triggering the shrinkage of the metal. In this respect, the number of cracks per unit volume of the metal is regarded as the surface crack density and it is desired to be a minimization function.
5. Recast layer thickness: The short form for this output is RLT while the unit of measurement is mm. It is desired to be minimized during the wire EDM process of nitinol-60.

2.2 Experimental data

This is the table that relates the factors to the diverse levels of experimentation, obtained from Roy and Mandal (2019) and shown in Table 1 in this work. Roy and Mandal (2019) provided the following additional experimental data, in Table 2.

Table 1. Factor and levels for the wire EDM problem (Roy and Mandal, 2019)

Input parameter	Level 1	Level 2	Level 3
DF	0.575	0.701	0.892
GV	40	50	60
FR	2	4	6

Table 2. Experimental data on Box-Behnken Design of Experiment (Roy and Mandal, 2019)

Run order	DF (%)	GV (Volts)	FR (lpm)	CR (mm/min)	Rz (µm)	Rt (µm)	SCD (µm/µm^2)	RLT (µm)
1	0.701	50	4	2.354	9.458	12.354	0.0134	9.102
2	0.892	50	6	2.454	10.384	13.196	0.0205	11.762
3	0.701	30	6	2.405	9.803	12.636	0.0154	9.801
4	0.701	50	4	2.288	9.566	12.351	0.0137	8.913
5	0.575	70	4	1.478	8.295	11.599	0.0116	8.623
6	0.701	30	2	2.395	9.794	12.464	0.0146	9.381
7	0.701	70	6	2.157	9.337	12.261	0.0128	8.872
8	0.892	50	2	2.424	10.126	12.924	0.0179	10.673
9	0.892	30	4	2.557	9.859	13.391	0.0224	12.306
10	0.892	70	4	2.416	10.006	12.84	0.0169	10.364
11	0.575	50	2	1.584	8.813	11.632	0.0115	8.304
12	0.575	50	6	1.749	8.882	11.703	0.0116	8.366
13	0.575	30	4	1.911	9.122	11.812	0.0121	8.432
14	0.701	50	4	2.312	9.565	12.362	0.0136	8.978
15	0.701	70	2	2.108	9.227	12.154	0.0126	8.675

2.3 Signal-to-noise ratio evaluation

For parameters to be minimized, a smaller-the-better signal-to-noise ratio was calculated using Equation (1)

$$\left(\frac{S}{N}\right) = -10\log_{10}\left(\frac{1}{n}\right)\sum Y^2 \tag{1}$$

For parameters to be maximized, a larger-the-better signal-to-noise ratio was calculated using Equation (2):

$$\left(\frac{S}{N}\right) = -10\log_{10}\left(\frac{1}{n}\right)\sum\left(\frac{1}{Y^2}\right) \tag{2}$$

Furthermore, the S/N ratios obtained were then normalized using Equation (3):

$$N\eta_p = \frac{\left(\frac{S}{N}\right)_p - \left(\frac{S}{N}\right)_{\min}}{\left(\frac{S}{N}\right)_{\max} - \left(\frac{S}{N}\right)_{\min}} \tag{3}$$

where

$(S/N)_p$ represents the value of S/N ratio
$(S/N)_{min}$ shows the minimum S/N ratio
$(S/N)_{max}$ reveals the maximum S/N ratio
Y is the value of the parameter being evaluated

2.4 Definitions and explanations of terms

In the article, the wire electric discharge machining is conducted on the nitinol material with the optimization of the process parameters in mind whereas double optimization due to the combined effects of the Taguchi-parents method and the GWO approach is adopted. However, to understand the work, this section explains the import and terms utilized in the work. These are provided as follows.

Duty factors: This is the evaluated proportion of the working period to the total cycle time. It shows the time expiration between when the sparks of an electrode become action.

Gap voltage: Described as the voltage in the gap occurring between the electrode and the workpiece. The electrical discharge machining process is directly proportional to the total energy provided by the sparks. As the settings of the voltage are set high, there is bound to be an increase in the size of the gap. Interestingly, this is desired if the flushing is to be efficient, the stability of the machining and to stimulate the growth of the material removal rate. Notwithstanding there is the tendency of obtaining a more rough wire EDM process, the engineer engages the flushing system to eliminate the particles thereby preparing the process for the next activity, which could be the process of a metallic object different in form, conductivity, and toughness from the previously processed metal. The advantage of flushing is the linkage of the remnant particles to the new workpiece thereby preventing short-circuiting and could potentially damage the electrode finished (surface roughness growth when the higher voltage is used.

Dielectric fluid: This describes the flow velocity of the dielectric engaged in the flushing process. It senses the useful purpose of isolating the electrode from the workpiece. The intention is to create a high current density in the plasma channel. An additional function of the dielectric fluid is to cool down the surface of the electrode. Furthermore, the dielectric fluid imposes a counter pressure on the growing plasma channel. When the wire EDM process engineer notice some particles remaining after surface

Cutting speed: This is described as the comparative velocity between the workpiece surface and the cutting tool. The cutting tool in the present situation is the electrode. Some authorities define it as how fast the nitinol material moves past the cutting edge of the electrode. During the wire EDM process, the specification of the cutting speed is a fast step to determining other parameters such as the temperature of cutting. It is implied that at high cutting speeds high temperatures are involved and vice-versa. The cutting speed also influences the power consumption of the process. It as well influences the electrode's tool life.

Peak to valley height: This evaluates the utmost depth of the surface irregularities on the machined workpiece. This is measured considering a sample length. Hence, the maximum depth that one has on the surface of the machine tool.

Surface crack density: Defined as the number of microcracks found on the surface of the machined workpiece. The formation of microcracks is encouraged by thermal stresses while the wire EDM process has an on-time designation. As the spark intensity grows, there is a corresponding growth in the size and the number of microcracks formed. Thus, the spark intensity may be taken to be responsible for the surface circle density.

Recast layer: This is the stratum formed from molten materials as the wire EDM process progressed. Notice that in the wire EDM process, some materials are melted and cooled, and hardened on the surface. This Layer has a brittle characteristic and is prone to failure. Additionally, it could negatively contribute to the variation in the dimensional attribute and the shape of the workpiece. The recast layer may also contribute to forming a stress point and microcracks can develop on the workpiece as a result of this.

Signal-to-noise ratios: A quotient relating the signals to noise when attempting to qualify the relative proportion of the useful information to less useful information during the wire EDM process. The signals are desired quality of the product (nitinol in machining while the noise is the unwanted element during the wire EDM process. In most evaluations, three variants of criteria are deployed either individually or collectively. A smaller-the-better criterion is one of the implemented criteria in the process. It means that small quantities of signal-to-noise are desirable and applicable in situations where minimization of the property of interest is desired. A larger-the-better criterion is the opposite of the smaller-the-better criterion as the signal-to-noise is desired in high quantities. In this case, the maximization of the response is needed.

Pareto analysis: Used to make wire EDM decisions where the number of input factors is separated into those that exhibit the largest influences on the results as well as those that do not. The principal argument in Pareto analysis is that 80% of the advantages of the wire EDM process are attainable through the 20% of the bulk members (parameters) in the system. Some scholars say that 80% of the problems are stimulated by 20% of the causes. It applies to establishing which experimental trials for the parameters would produce the largest skewed output values having the heart impact on the parameters.

Empirical models (objective functions): They are built up from the data from experiments. Its utility is to minimize or maximize some set criteria in equation form subjected to some constraints that are candidates for minimization or maximization.

Mean absolute deviation: This is the average of the absolute deviation from a given point. It measures the average distance between each data point and the mean.

Mean square error: Evaluates the averages of the squares of errors for the experimental dataset. This is the average square difference between the estimated values and the actual values. Its usefulness is to ascertain that the model assigns larger weights to errors due to the squaring of the function. It is acceptable because the model will not have any utlierso or predictions with huge errors.

2.5 Desirability function analysis

The steps in applying the desirability function analysis to numerical data are listed below:

Step 1: Obtain and arrange experimental data by run order, specifying which parameters are to be optimized and which are to be minimized.

Step 2: Normalize the data using the formulas below

For non-beneficial parameters, Equation (4)

$$X_{normalised} = \text{Min } (X_{ij}) / X_{ij} \quad (4)$$

For beneficial parameters, Equation (5)

$$X_{normalised} = X_{ij} / \text{Max } (X_{ij}) \quad (5)$$

Step 3: Calculate the desirability index for the output parameters

For parameters to be minimized, Equation (6) was used:

$$d_i = \left(\frac{y_{\min} - (y_j - y_{\max})}{y_{\min} - y_{\max}} \right)^r \quad (6)$$

The conditions to be satisfied by the constituent parameters of d_i are

$d_i = 1$, if $y_j \le y_{\min}$

$d_i = 0$, if $y_j \ge y_{\min}$

Notice that $y_{\min} \le y_j \le y_{\max}$

For parameters to be maximized, Equation (7) was used:

$$d_i = \left(\frac{y_{\max} - (y_j - y_{\min})}{y_{\max} - y_{\min}} \right)^r \quad (7)$$

The conditions to be satisfied by the constituent parameters of d_i are

$d_i = 0$, if $y_j \le y_{\min}$

$d_i = 1$, if $y_j \ge y_{\min}$

Notice that $y_{\min} \le y_j \le y_{\max}$

where

d_i represents the desirability index

y_j is the current value of the output

y_{min} means the minimum value of output

y_{max} is the maximum value of the output

r represents the shape constant

However, a shape constant value of 2 was assumed for this work.

Step 4: The composite desirability is calculated using Equation (8):

$$d_G = \sqrt[w]{d_1 \times d_2 \times d_3} \quad (8)$$

where

d_G is the composite desirability

w is the number of output parameters

d_i is the individual desirability

Step 5: Rank the entries by descending order of magnitude of composite desirability (highest to lowest)

2.6 The TP-GWO-DFA method

The full name for the TP-GWO-DFA method is the combined Taguchi-Pareto-grey wolf optimization algorithm-desirability function Analysis method, which was first applied in a work on thermal friction drilling in 2022 by Nwankiti and Oke (2022). Surprisingly, the TP-GWO-DFA method has never been applied to study endeavors dedicated to machining responses in complicated non-traditional machining environments and this is absent in answering research questions on the wire EDM process and specifically on queries associated with nitinol-60 machining. However, because of its success in effectively delivering a robust result, and its potential for an enhanced system when applied to the tasks of a system, the present authors decided to deploy the method to the wire EDM process, specifically tackling the surface integrity analysis in an optimized manner while dealing, with nitinol-60. In this article, the TP-GWO-DFA method is used to investigate the responses of nitinol-60 that is machined through the wire EDM process. The responses are the cutting rate, average peak-to-valley height, maximum peak-to-valley height, surface crack density, and recast layer thickness. The input that produces these responses are FR, gap voltage, and duty factor. The TP-GWO-DEA method is a combination of three characteristics methods of different origins: The traditional optimization system of the Taguchi method that has the Pareto scheme coupled with it as in the Taguchi-Pareto method, the evolutionary algorithm, represented by the GWO and the multiple response performance index represented by the desirability function analysis. The TP-GWO-DFA method combines the advantages of these three independent methods to achieve a better wire EDM process for the machining of nitinol-60 shape alloy memory. The important advantages of the TP-GWO-DFA method include the following:

1. The TP-GWO-DFA method highlights a mean performance attribute threshold of the wire EDM process data, this value is near the target value thereby enhancing the surface integrity of nitinol-60.
2. It maintains the optimization of the surface integrity of nitinol-60 while at the same time choosing the best parameter that drives the wire EDM process towards its goal attainment.
3. The TP-GWO-DFA method assumes that the solution provided by the Taguchi-Pareto method is not the most attainable in the framework given the capability of the wire EDM process. Consequently, it further optimizes the wire EDM process parameters to produce new superior solutions.
4. The TP-GWO-DFA method has a mechanism that spotlights principally on the optimization of the mean for the multiple responses, converting the predicted responses to a scale-independence value termed desirability for the wire EDM process parameters during the machining of nitinol-60. (Amdoun et al., 2018).

2.7 Procedure to implement the TP-GWO-DFA method

To implement the TP-GWO-DFA method in the wire EDM process and for the machining of nitinol-60, the following steps are part of the three distinct phases that the implementation route follows.

Step 1: Start and establish processing activities: Here, the researchers define the various activities that the wire EDM process should be limited to.

Step 2: Obtain signal-to-noise ratios from experimental trials, factors, and levels: The data used in this study are those of the experiments conducted by Roy and Mandal (2019). In that study, experimental data were collected, which relates the inputs to outputs. Similar to the orthogonal arrays used by Roy and Mandal (2019), this article uses the same experimental trials.

Step 3: Streamline the experimental trials to the most important ones: This is achieved by first deciding which of the signal-to-noise criteria of larger-the-better, smaller-the-better, or nominal the best should be adopted. Irrespective of which is adopted, the signal-to-noise ratios are computed and added up cumulatively to finally arrive at 100%. However, to apply the 80-20 Pareto rule, a percentage chosen to 80% may not be found to be associated with any experimental trial. In this case, the closer of any two cumulative to 80% is chosen. All the experimental trials above this are discarded and taken as not important to the optimization goal for the problem.

Step 4: Determine the empirical models from the screened signal-to-noise ratios: Here, the Minitab 18 software is used where a spreadsheet of parametric values is determined in association with each output. Then a linear equation is developed which puts the response as the dependent variables and the parameters as the independent variables. At one time, only one response is associated with all the parameters to develop an empirical model. Therefore, the number of empirical models developed equates to the number of responses worked on.

Step 5: Introducing the empirical model into GWO for each output. In this instance, a computer program has been developed in C++ language where the aspect including the GWO has the mechanism to absorb an empirical model, which links one output to all the inputs at a time.

Step 6: Use desirability function analysis on the outcome of the GWO. After obtaining the results of the GWO, multiple results are obtained. However, these results need to be combined into a single index, which is achieved through the use of the desirability function analysis.

Step 7: Obtain a joint performance index

2.8 Assumptions

In the development of the TP-GWO-DFA method, there are two basic assumptions, which should be fulfilled to make the method workable. These are stated as follows;

1. When a different analysis models the same wire EDM process during the machining of the nitinol material, the is the possibility of the person concluding on an expanded set of parameters to representative responses are assumed to be the best representative of the system and one that reflects the goals of the system.
2. In the measurement endeavor for the factors representing the wire EDM process, it is assumed that each factor has the goal part (i.e. signal), which is desired, and the bad part (i.e. noise), which is undesirable. The signal-to-noise ratio approach is valuable in evaluating the wire EDM process factors it will reflect the quality content of each factor. It matters because it will reveal the high and low signal-to-noise ratios. It is known that the higher the signal-to-noise ratio value the better the output of the wire EDM process (i.e. responses due to processing nitinol-60 on the wire EDM process). A high signal-to-noise ratio indicates the presence of more useful information regarding signals than the undesired data regarding noise.

3. RESULTS AND DISCUSSION

The principal focus of this article is the development of an integrated method that accounts for Taguchi-Pareto, grey wolf analysis as an optimization method, and desirability function analysis as a coupling method capable of transforming multiple objectives into a single objective. To achieve this aim, results are obtained from the analysis of experimental data provided by Roy and Mandal (2019). The first set of information essential to note in the analysis of results regards the inputs/process parameters. In the surface integrity analysis of processed materials, input parameters allow the machining engineer to offer machining data to an element for further application. In the wire electrical discharge machining regarding nitinol-60 shape memory alloy, the associated parameters are the duty factors, gap voltage, and dielectric flow rate. To achieve the goal of this article it is beneficial to analyze the data from a parametric perspective for several reasons. Firstly, the machining engineer could analyze the data exploring analysis from a dynamic input perspective where each input attains a different value at each time thereby permitting the machining engineer to provide a comprehensive test of the wire EDM process with little room for misunderstanding or misinterpretation of the system's attributes.

Next, the mentioned input parameters are linked to an outcome of the system. For example, the dielectric flow rate may be associated in scope with the (surface roughness). These input factors are often with their units, for example, the dirty factors, with acronyms as DF, are expressed in percentage, gap voltage, GV, expressed in volts, and dielectric flow rate, FR, is expressed in lpm. Besides, since a systems perspective is adopted in the present article whereby any definition of inputs to the wire electrical discharge machining system should be an acronym listed by outputs, it is reasonable to define the outputs at this point and determine whether each of these outputs should be increased or decreased. In this article, there are fire outputs with only one being a candidate for maximization, i.e. cutting rate (CR), expressed in mm/min, and four that are to be minimized. These are the average peak-to-valley height, Rz, in μm, maximum peak-to-valley height (Rt), in μm, surface crack density, in μm/μm^2, and recast layer thickness, RLT, in μm. Table 1 shows the values of the diverse input parameters and the corresponding levels that they appear, which were obtained by Roy and

Mandal (2019), which displayed experimental results proposed by the authors and utilized as the essential information for the proposed method in this article. In Table 1, there are three parameters and values obtained for each level. Table 2 was also obtained from Roy and Mandal (2019) where a design of experiments was coordinated by the authors to those obtain additional value from those obtained from the experiments. However, the authors used the Box Behnken Design of experiments as opposed to the Taguchi-Pareto method, which is a component of the method proposed in this work.

In Table 3, the normalized values for the outputs are specialized. To obtain these values, Equation (3) was adopted. This equation (3) is for the normalization of the signal-to-noise ratios. Notice that based on the factor-level data provided in Table 1, the orthogonal array was introduced and afterward, the signal-to-noise (S/N) ratios were found for all the output parameters according to Equations (1) to (3) in section 2. Then the table showing normalized values is presented as Table 3.

Table 3. Normalized values of outputs

Run Order	DF (%)	GV (Volts)	FR (lpm)	CR	Rz	Rt	SCD	RLT
1	0.701	50	4	0.514	0.407	0.410	0.397	0.405
2	0.892	50	6	1.000	0.397	0.400	0.392	0.387
3	0.701	30	6	0.534	0.980	0.976	0.980	0.973
4	0.701	50	4	0.509	0.406	0.410	0.397	0.406
5	0.575	70	4	0.038	0.005	0.005	0.002	0.004
6	0.701	30	2	0.432	0.999	0.998	1.000	0.997
7	0.701	70	6	0.515	0.000	0.000	0.000	0.001
8	0.892	50	2	0.844	0.406	0.410	0.400	0.401
9	0.892	30	4	0.984	0.991	0.976	0.992	0.952
10	0.892	70	4	0.971	0.0008	0.0006	0.002	0.000
11	0.575	50	2	0.000	0.412	0.417	0.400	0.411
12	0.575	50	6	0.090	0.404	0.409	0.392	0.403
13	0.575	30	4	0.095	1.000	1.000	0.992	1.000
14	0.701	50	4	0.511	0.406	0.410	0.397	0.406
15	0.701	70	2	0.410	0.004	0.004	0.004	0.005

In this section, the comparison is made while the authors mentioned the previous values of the wire EDM process problem before and after optimization. To obtain these values, the original data provided by Roy and Mandal (2019) is referred to (Table 2). However, Table 2 is not sufficient to interprete the data and distinguishes the best from the worst results. Thus, to achieve this, the normalized data (table 3) is used. From Table 3, it should be borne in mind that since CR is desired to be maximum white other parameters (Rz, Rt, SCD) and RLT are desired to be minimum, all the experimental trials 1 to 15 are screened for the best, and worst results so that the optimal results from the GWO will be compared with them. By judging from the normalized data (Table 3), experimental trial 7 gives the best results since out of the fire outputs three already have the least possible value of zero (i.e. Rz, Rt, and SCD). On the other hand, the worst result is experimental trial 13, which has a normalized value of 1 for three out of the five outputs (i.e. Rz, Rt, and RLT). Therefore, the best-normalized values are interpreted from Table 2 as (from experimental trial 7) 0.701% of DF, 70volts of GV, 61pm of FR, 2.157mm/min of Cr, 9.337mm of Rz, 12.261mm of Rt; 0.0128mm/mm^2 of SCD, and 8.872mm of RLT.

Interestingly, on comparing the results of the grey wolf optimization regarding the outputs, CR was obtained as 2.564 which, compared to the normalized value of the experimental data of 0.5145 exhibited roughly 398.5% improvement in the value of CR. Furthermore, there are declines in the performance of Rz, Rt, SCD and RLT by 0.0996, 0.0875, 0.0821 and 2997.4% respectively. However, the main attraction and benefit of using grey optimization is the increased CR performance obtained in its application.

Furthermore, Tables 4 to 8 are the present authors' contributions of the Taguchi-Pareto method to the problem of determining the optimal parameters for a robust output generation in the processing of the nitinol-60 shape memory alloy. The salient aspect shown is the Pareto mechanism, which is also referred to as the 80-20 rule. A Pareto analysis of the parameters obtained was executed. Here, Pareto analysis aims to separate entries with the greatest effect on the performance of the output values to be normalized. These are the cutting rate, average peak-to-valley height, maximum peak-to-valley height, surface crack density, and recast layer thickness. To achieve the goal of Taguchi-Pareto analysis, the normalization of the values for each of the input parameters was first affected. Then the cumulative values of the signal-to-noise ratios were determined. After careful observation, values that were above 80% were taken as less relevant since the signal-to-noise (cumulative) exceeds the limits set by the authors, for practical purposes, they are discarded in the course of the analysis. Tables 4 to 8 show the Pareto analysis conducted on the five outputs. Table 4 is for the cutting rate, Table 5 is for the average peak-to-valley height, Table 6 is for the maximum peak-to-valley height, Table 7 is for the surface crack density while Table 8 is for the recast layer thickness.

Table 4. Pareto table for cutting ratio (CR)

Sr. No.	DF (%)	GV (Volts)	FR (LPM)	CR (mm/min)	$1/DF^2$	$1/GV^2$	$1/FR^2$	$1/CR^2$	S/N	CR Normalized values	Cumulative	% Cumulative
1	0.89	50.00	6.00	2.45	1.26	0.00	0.03	0.17	4.40	1.00	1.00	0.13
2	0.89	30.00	4.00	2.56	1.26	0.00	0.06	0.15	4.34	0.98	1.98	0.27
3	0.89	70.00	4.00	2.42	1.26	0.00	0.06	0.17	4.29	0.97	2.95	0.40
4	0.89	50.00	2.00	2.42	1.26	0.00	0.25	0.17	3.77	0.84	3.80	0.51
5	0.70	30.00	6.00	2.41	2.03	0.00	0.03	0.17	2.52	0.53	4.33	0.58
6	0.70	70.00	6.00	2.16	2.03	0.00	0.03	0.21	2.45	0.51	4.85	0.65
7	0.70	50.00	4.00	2.35	2.03	0.00	0.06	0.18	2.44	0.51	5.36	0.72
8	0.70	50.00	4.00	2.31	2.03	0.00	0.06	0.19	2.43	0.51	5.87	0.79
9	0.70	50.00	4.00	2.29	2.03	0.00	0.06	0.19	2.42	0.51	6.38	0.86
10	0.70	30.00	2.00	2.40	2.03	0.00	0.25	0.17	2.11	0.43	6.81	0.91
11	0.70	70.00	2.00	2.11	2.03	0.00	0.25	0.23	2.02	0.41	7.22	0.97
12	0.58	30.00	4.00	1.91	3.02	0.00	0.06	0.27	0.75	0.10	7.32	0.98
13	0.58	50.00	6.00	1.75	3.02	0.00	0.03	0.33	0.73	0.09	7.41	0.99
14	0.58	70.00	4.00	1.48	3.02	0.00	0.06	0.46	0.52	0.04	7.45	1.00
15	0.58	50.00	2.00	1.58	3.02	0.00	0.25	0.40	0.37	0.00	7.45	1.00

Table 5. Pareto table for the average peak-to-valley height (R_z)

Sr. No.	DF (%)	GV (Volts)	FR (LPM)	Rz (µm)	DF^2	GV^2	FR^2	R_a^2	S/N	Normalized Values	Cumulative	% Cumulative
1	0.58	30.00	4.00	9.12	0.33	900.00	16.00	83.21	-23.98	1.00	1.00	0.15
2	0.70	30.00	2.00	9.79	0.49	900.00	4.00	95.92	-23.98	1.00	2.00	0.29
3	0.89	30.00	4.00	9.86	0.80	900.00	16.00	97.20	-24.04	0.99	2.99	0.44
4	0.70	30.00	6.00	9.80	0.49	900.00	36.00	96.10	-24.12	0.98	3.97	0.58
5	0.58	50.00	2.00	8.81	0.33	2500.00	4.00	77.67	-28.10	0.41	4.38	0.64
6	0.70	50.00	4.00	9.46	0.49	2500.00	16.00	89.45	-28.14	0.41	4.79	0.70
7	0.89	50.00	2.00	10.13	0.80	2500.00	4.00	102.54	-28.14	0.41	5.20	0.76

8	0.70	50.00	4.00	9.57	0.49	2500.00	16.00	91.49	-28.14	0.41	5.60	0.82
9	0.70	50.00	4.00	9.57	0.49	2500.00	16.00	91.51	-28.14	0.41	6.01	0.88
10	0.58	50.00	6.00	8.88	0.33	2500.00	36.00	78.89	-28.15	0.40	6.41	0.94
11	0.89	50.00	6.00	10.38	0.80	2500.00	36.00	107.83	-28.20	0.40	6.81	1.00
12	0.58	70.00	4.00	8.30	0.33	4900.00	16.00	68.81	-30.96	0.00	6.81	1.00
13	0.70	70.00	2.00	9.23	0.49	4900.00	4.00	85.14	-30.96	0.00	6.82	1.00
14	0.89	70.00	4.00	10.01	0.80	4900.00	16.00	100.12	-30.98	0.00	6.82	1.00
15	0.70	70.00	6.00	9.34	0.49	4900.00	36.00	87.18	-30.99	0.00	6.82	1.00

Table 6. Pareto table for the maximum peak-to-valley height (R_t)

Sr. No.	**DF (%)**	**GV (Volts)**	**FR (LPM)**	**Rt (µm)**	**DF^2**	**GV^2**	**FR^2**	**R_t^2**	**S/N**	**Normalized Values**	**Cumulative**	**% Cumulative**
1	0.58	30.00	4.00	11.81	0.33	900.00	16.00	139.51	-24.22	1.00	1.00	0.15
2	0.70	30.00	2.00	12.46	0.49	900.00	4.00	155.34	-24.23	1.00	2.00	0.29
3	0.89	30.00	4.00	13.39	0.80	900.00	16.00	179.32	-24.38	0.98	2.97	0.44
4	0.70	30.00	6.00	12.64	0.49	900.00	36.00	159.67	-24.38	0.98	3.95	0.58
5	0.58	50.00	2.00	11.63	0.33	2500.00	4.00	135.31	-28.19	0.42	4.37	0.64
6	0.70	50.00	4.00	12.35	0.49	2500.00	16.00	152.55	-28.24	0.41	4.78	0.70
7	0.70	50.00	4.00	12.35	0.49	2500.00	16.00	152.62	-28.24	0.41	5.19	0.76
8	0.70	50.00	4.00	12.36	0.49	2500.00	16.00	152.82	-28.24	0.41	5.60	0.82
9	0.89	50.00	2.00	12.92	0.80	2500.00	4.00	167.02	-28.25	0.41	6.01	0.88
10	0.58	50.00	6.00	11.70	0.33	2500.00	36.00	136.96	-28.25	0.41	6.42	0.94
11	0.89	50.00	6.00	13.20	0.80	2500.00	36.00	174.14	-28.31	0.40	6.82	1.00
12	0.58	70.00	4.00	11.60	0.33	4900.00	16.00	134.54	-31.01	0.00	6.82	1.00
13	0.70	70.00	2.00	12.15	0.49	4900.00	4.00	147.72	-31.01	0.00	6.83	1.00
14	0.89	70.00	4.00	12.84	0.80	4900.00	16.00	164.92	-31.04	0.00	6.83	1.00
15	0.70	70.00	6.00	12.26	0.49	4900.00	36.00	150.33	-31.04	0.00	6.83	1.00

Table 7. Pareto table for surface crack density (SCD)

Sr. No.	**DF (%)**	**GV (Volts)**	**FR (LPM)**	**SCD (μm/μm2)**	**DF^2**	**GV^2**	**FR^2**	**SCD^2**	**S/N**	**Normalized Values**	**Cumulative**	**% Cumulative**
1	0.70	30.00	2.00	0.01	0.49	900.00	4.00	0.00	-23.54	1.00	1.00	0.15
2	0.58	30.00	4.00	0.01	0.33	900.00	16.00	0.00	-23.60	0.99	1.99	0.30
3	0.89	30.00	4.00	0.02	0.80	900.00	16.00	0.00	-23.60	0.99	2.98	0.44
4	0.70	30.00	6.00	0.02	0.49	900.00	36.00	0.00	-23.69	0.98	3.96	0.59
5	0.58	50.00	2.00	0.01	0.33	2500.00	4.00	0.00	-27.97	0.40	4.36	0.65
6	0.89	50.00	2.00	0.02	0.80	2500.00	4.00	0.00	-27.97	0.40	5.16	0.76
7	0.70	50.00	4.00	0.01	0.49	2500.00	16.00	0.00	-27.99	0.40	5.16	0.76
8	0.70	50.00	4.00	0.01	0.49	2500.00	16.00	0.00	-27.99	0.40	5.56	0.82
9	0.70	50.00	4.00	0.01	0.49	2500.00	16.00	0.00	-27.99	0.40	5.95	0.88
10	0.58	50.00	6.00	0.01	0.33	2500.00	36.00	0.00	-28.02	0.39	6.35	0.94
11	0.89	50.00	6.00	0.02	0.80	2500.00	36.00	0.00	-28.02	0.39	6.74	1.00
12	0.70	70.00	2.00	0.01	0.49	4900.00	4.00	0.00	-30.89	0.00	6.74	1.00
13	0.58	70.00	4.00	0.01	0.33	4900.00	16.00	0.00	-30.90	0.00	6.75	1.00
14	0.89	70.00	4.00	0.02	0.80	4900.00	16.00	0.00	-30.90	0.00	6.75	1.00
15	0.70	70.00	6.00	0.01	0.49	4900.00	36.00	0.00	-30.91	0.00	6.75	1.00

Table 8. Pareto table for recast layer thickness (RLT)

Sr. No.	DF (%)	GV (Volts)	FR (LPM)	RLT (μm)	DF^2	GV^2	FR^2	RLT^2	S/N	Normalized Values	Cumulative	% Cumulative
1	0.58	30.00	4.00	8.43	0.33	900.00	16.00	71.10	-23.92	1.00	1.00	0.15
2	0.70	30.00	2.00	9.38	0.49	900.00	4.00	88.00	-23.95	1.00	2.00	0.30
3	0.70	30.00	6.00	9.80	0.49	900.00	36.00	96.06	-24.12	0.97	2.97	0.44
4	0.89	30.00	4.00	12.31	0.80	900.00	16.00	151.44	-24.27	0.95	3.92	0.58
5	0.58	50.00	2.00	8.30	0.33	2500.00	4.00	68.96	-28.08	0.41	4.33	0.64
6	0.70	50.00	4.00	8.91	0.49	2500.00	16.00	79.44	-28.12	0.41	4.74	0.70
7	0.70	50.00	4.00	8.98	0.49	2500.00	16.00	80.60	-28.12	0.41	5.14	0.76
8	0.70	50.00	4.00	9.10	0.49	2500.00	16.00	82.85	-28.13	0.41	5.55	0.82
9	0.58	50.00	6.00	8.37	0.33	2500.00	36.00	69.99	-28.14	0.40	4.95	0.73
10	0.89	50.00	2.00	10.67	0.80	2500.00	4.00	113.91	-28.16	0.40	6.35	0.94
11	0.89	50.00	6.00	11.76	0.80	2500.00	36.00	138.34	-28.25	0.39	6.74	1.00
12	0.70	70.00	2.00	8.68	0.49	4900.00	4.00	75.26	-30.95	0.01	6.75	1.00
13	0.58	70.00	4.00	8.62	0.33	4900.00	16.00	74.36	-30.96	0.00	6.75	1.00
14	0.70	70.00	6.00	8.87	0.49	4900.00	36.00	78.71	-30.98	0.00	6.75	1.00
15	0.89	70.00	4.00	10.36	0.80	4900.00	16.00	107.41	-30.99	0.00	6.75	1.00

From the implementation of the Pareto scheme to the various outputs in Tables 4 to 8, the next stage is to develop empirical models for use in the grey wolf optimization algorithm. Therefore, the next subsection presents the results of the empirical model.

3.1 Empirical modeling

The authors proceeded in obtaining empirical models (Equations (4) to (8)), which serve as objective functions.

$$\text{Maximize} \quad CR = -1.574 + 2.773\,DF - 0.001\,GV + 0.028\,FR \tag{4}$$

$$\text{Minimize} \quad Rz = 1.719 - 0.023\,DF - 0.025\,GV - 0.003\,FR \tag{5}$$

Minimize Rt = 1.725 - 0.038 DF - 0.025 GV - 0.003 FR (6)
Minimize SCD = 1.699 - 0.004 DF - 0.025 GV - 0.003 FR (7)
Minimize RLT = 1.733 - 0.068 DF - 0.024 GV - 0.003 FR (8)

To achieve this goal, computation using software makes the analysis straightforward forward and the Minitab 18 software was achieved for this purpose. To proceed, using the values obtained from Pareto analysis, the values that were inclusive in the less than 80% cumulative cut-off were used for analysis in the Minitab software, to develop the empirical models. From here, the authors verified the empirical models to find out how chose the values obtained are compared with the experimental values. From the empirical model developed, the various objective functions in optimization are represented by either the sign of minimization (Equations (5) to (8)) or maximization (Equation (4)). Although in the formation of the objective function, constraints are used in solving the objective function, they are not added since the grey wolf algorithm codes are made simple to understand without these constraints and usually only the empirical model is used without constraints in previous applications of the grey wolf algorithm. However, it is recognized as a limitation of the work that could be improved upon in future studies.

By using the values obtained from Tables 4 to 8 in their respective empirical models, the authors obtained the predicted values. This entails substituting the values into the formula. This yielded Table 9, which are the values using the empirical models compared with the values from the experiments.

Table 9. Experimental and empirical model comparison for validation purposes

	Cutting rate (CR)		**Average peak to valley height (R_z)**		**Maximum Peak to Valley Height (R_t)**		**Surface crack density (SCD)**		**Recast layer thickness (RLT)**	
Sr. No.	**Exp.**	**Empirical model**	**Exp.**	**Empirical model**	**Exp.**	**Empirical model**	**Exp.**	**Empirical model**	**Exp.**	**Empirical model**
1	1.00	1.0292	1.00	0.9529	1.00	0.9527	1.00	0.9496	1.00	0.9480
2	0.98	0.9864	1.00	0.9552	1.00	0.9537	0.99	0.9451	1.00	0.9460
3	0.97	0.9587	0.99	0.9458	0.98	0.9411	0.99	0.9438	0.97	0.9336
4	0.84	0.9159	0.98	0.9451	0.98	0.9429	0.98	0.9396	0.95	0.9269
5	0.53	0.5162	0.41	0.4629	0.42	0.4657	0.40	0.4557	0.41	0.4654
6	0.51	0.4885	0.41	0.4551	0.41	0.4557	0.40	0.4544	0.41	0.4510
7	0.51	0.4457	0.41	0.4558	0.41	0.4557	0.40	0.4502	0.41	0.4510
8	0.51	0.4457	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Note: n/a means not applicable

Moving on, the authors calculated the mean square errors between those two values i.e. the values from the experiments and those from the empirical models. This is tabulated in Table 10. The values for the mean absolute deviation and those of the mean square error are obtained and displayed in their respective tables. Finally, there is Table 18 where the mean absolute deviation and the mean square error for each parameter are put side-by-side to facilitate comparison, it was observed that the empirical model may be adopted because the mean square error and the mean absolute deviation are within a reasonable range (Table 10). The values obtained are only marginally different from experimental values when evaluated with the empirical model, this means that the empirical model has a low degree of inaccuracy.

Table 10. A comparison between the MAD and the MSE for the output parameters

Sr. No.	**Output parameters**	**MAD**	**MSE**
1	Cutting Rate (CR)	0.0359	0.0020
2	Average peak to valley height (Rz)	0.0393	0.0018
3	Maximum peak to valley height (Rt)	0.0383	0.0017
4	Surface Crack Density (SCD)	0.0428	0.0021
5	Recast Layer Thickness (RLT)	0.0379	0.0017

Key: Mean absolute deviation (MAD); Mean square error (MSE)

Now that the empirical models have been generated and tested for accuracy, they are now substituted into the grey wolf optimization structure as discussed in the next section:

3.3 Grey wolf optimization

Recall from section 3.1 that an empirical model was developed for each of the outputs, namely the CR, R_z, R_t, SCD, and RLT. Now, the grey wolf optimization is conducted by adapting a C++ code developed by Ugochukwu Nwankiti (with permission) to solve the problem. First, the cutting rate, CR is discussed. For the cutting rate, the first wolf out of ten wolves is considered by generating random numbers for it, shown as 0.201819, 0.0607624, 0.817896. By noting that the objective is to maximize CR, then randomly initialized grey wolf population is developed for wolves as follows:

0.638977	41.2152	5.27158	2.13667
0.844151	48.7082	3.49834	2.52868
0.81238	53.8188	2.99857	2.49544
0.631914	55.7604	4.47725	1.97352
0.607428	47.6461	5.50499	1.91148
0.679532	57.0446	2.27528	2.11038
0.659825	40.4669	4.02423	2.23326
0.856979	49.9973	2.48231	2.49593
0.638851	54.6977	3.96686	2.00938
0.763437	46.6463	5.93567	2.46007
0.844151	48.7082	3.49834	2.52868
0.856979	49.9973	2.48231	2.49593
0.81238	53.8188	2.99857	2.49544

From this generated population, iteration 1 is commenced where r1 and r1 for c1 are taken as 0.202124 and 0.0520951, respectively. The therefore for wolf 1, X1, X2, X3 up to XN yield the following outcomes:

X1:	1.5007	91.7695	9.34515
X2:	0.878619	55.9024	8.64809
X3:	0.915636	60.8674	3.16063
XN:	1.09832	69.5131	7.05129

Then greedy selection is carried out where the present value is 2.13667, Xnew gives 2.36716 the wolf 1 is updated as:

0.892	60	6	2.36716
0.844151	48.7082	3.49834	2.52868
0.81238	53.8188	2.99857	2.49544
0.631914	55.7604	4.47725	1.97352
0.607428	47.6461	5.50499	1.91148
0.679532	57.0446	2.27528	2.11038
0.659825	40.4669	4.02423	2.23326
0.856979	49.9973	2.48231	2.49593
0.638851	54.6977	3.96686	2.00938
0.763437	46.6463	5.93567	2.46007

Then wolf 2 has the following data

X1:	1.74516	100.697	7.23232
X2:	1.20892	69.5454	5.41937

X3:	0.877378	59.4702	3.16715
XN:	1.27715	76.571	5.27295

Likewise, the greedy selection is conducted where the present value is 2.52868 and Xnew is 2.40427. Then we have the following results:

0.892	60	6	2.36716
0.844151	48.7082	3.49834	2.52868
0.81238	53.8188	2.99857	2.49544
0.631914	55.7604	4.47725	1.97352
0.607428	47.6461	5.50499	1.91148
0.679532	57.0446	2.27528	2.11038
0.659825	40.4669	4.02423	2.23326
0.856979	49.9973	2.48231	2.49593
0.638851	54.6977	3.96686	2.00938
0.763437	46.6463	5.93567	2.46007

The routine is conducted for all ten wolves with the results for the tenth wolf as follows: wolf 10:

X1:	1.64899	98.2406	10.1364
X2:	1.06196	65.7912	9.85725
X3:	0.892428	59.8547	3.28446
XN:	1.20113	74.6289	7.75937

Also, the greedy selection is conducted where the present value is 2.46007 and Xnew is 2.36716. Then we have the following results:

0.892	60	6	2.36716
0.844151	48.7082	3.49834	2.52868
0.81238	53.8188	2.99857	2.49544
0.892	60	6	2.36716
0.892	60	6	2.36716
0.892	60	4.12089	2.43556
0.892	60	5.76831	2.38044
0.856979	49.9973	2.48231	2.49593
0.892	60	5.71427	2.38334
0.763437	46.6463	5.93567	2.46007

Now, the new values for alpha, beta and gamma are as follows:

0.844151	48.7082	3.49834	2.52868
0.856979	49.9973	2.48231	2.49593
0.81238	53.8188	2.99857	2.49544

Then the best values for the GWO iteration values for cutting rate (CR) are as follows: for iteration 1, the value obtained in iteration 1, the value obtained is 2.52868 and this is maintained in iteration 2. However, the value changed to 2.56319 in iteration 3 which is again maintained in iterations 4 to 91. In iteration 92, the value obtained changed to 2.56325, which is repeated in iterations 93 through 181. The variations continue until a constant value of 2.56426 is obtained in iterations up to iteration 250, which is the termination point. From the iterations, it is concluded that the best CR value is 2.56426.

Next is to consider the best value for the average peak-to-valley height (Rz). By following a similar procedure for the cutting rate (CR) in the determination of the best value for Rz, the iteration for the program run in C++ showed convergence iteration 500 with a terminating value of Rz as 0.0874532. Then, in the case of surface crack density SCD), 50 iterations were also run to obtain convergence at the best value of 0.0820917. In the next case, the determination of the best value for the recast layer thickness (RLT) when the C++ program code is run for the GWO was done to follow similar procedures for the determination of CR and R_Z earlier. In this situation, the convergence point is 500 iterations and the value is 0.0341648. Furthermore, Table 11 shows the comparative results of five outputs of the wire EDM process before and after optimization. For the CR, a gain of 398% was observed whereas for the outputs named Rz, Rt, SCD and RLT, losses of 0.0996, 0.0875, 0.0821 and 0.0332 were recorded.

Table 11. Optimal values (normalized) for the output parameters after grey-wolf optimization

S/N	Output parameter	Normalized values of outputs before optimization (Table 3)	Optimal normalized values
1	Cutting rate (CR)	0.515	2.5647
2	Average peak-to-valley height (R_z)	0.000	0.0996
3	Maximum peak-to-valley height (R_t)	0.000	0.0875
4	Surface crack density (SCD)	0.000	0.0821
5	Recast layer thickness (RLT)	0.001	0.0342

From the above analysis, we have succeeded in developing optimal points for outputs of the wire EDM process parameters while processing nitinol-60 smart memory alloy. However, it may be interesting to find the corresponding inputs for the process. This will be achieved through the use of the desirability function analysis discussed in the next section.

3.4 Desirability function analysis (DFA)

By following the steps for the DFA, of methods, the experimental values are first referred to as given in Table 2. Table 2 is then used to obtain Table 12.

Table 12. Normalized experimental data

	Maximize	Minimize	Minimize	Minimize	Minimize
	CR	**Rz**	**Rt**	**SCD**	**RLT**
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	1	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	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	1
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

Then the d_i is obtained as the desirability index, Equations (9) and (10). By applying Equations (9), Table 13 is generated.

Table 13. Desirability indices of the various runs

	Desirability index				
No.	**CR**	**Rz**	**Rt**	**SCD**	**RLT**
1	0.381	0.298	0.181	0.044	0.049
2	0.473	0.799	0.708	0.418	0.551
3	0.427	0.467	0.326	0.139	0.149
4	0.326	0.348	0.179	0.056	0.030
5	0	0	0	0.0002	0.009
6	0.417	0.462	0.233	0.098	0.084
7	0.229	0.246	0.141	0.022	0.026
8	0.444	0.645	0.508	0.277	0.314
9	0.578	0.497	0.866	0.513	0.675
10	0.437	0.577	0.453	0.221	0.252
11	0.006	0.068	0.0004	0	0
12	0.036	0.086	0.004	0.0002	0.0004
13	0.093	0.162	0.016	0.005	0.001
14	0.345	0.348	0.184	0.052	0.036
15	0.197	0.201	0.101	0.017	0.012

Then Equation (11) is used to obtain the composite desirability indication. The final step is the ranking of the runs which is produced in Table 14. From Table 14, run order 9 gives the first rank with a value of 0.6646. By obtaining this result, the original experimental data provided by Roy and Mandal (2019) is referred to and attention is paid to run order 9, which gives a DF of 0.892%, GV of 30 volts and FR of 4 lpm.

The results of the TP-GWO-DFA method calculation are different when compared with the results of the literature. The main reason is that this new method evaluates the empirical method to be used from a discriminated Taguchi- signal-to-noise ratio, where the irrelevant 20% are discarded from the cumulative evaluation. While applying only the Taguchi method no discrimination of experimental trials is made therefore, the more important trials leading to the parameters are not identified. Besides, the double optimization, closed by the GWO method is driven by the speed of convergence and precision, which is not considered in the Taguchi method alone.

Therefore, the GWO method further reduces the cost of experimentation that the Taguchi method is known to achieve.

Table 14. Composite desirability and rank

Run order	Composite desirability	Rank
1	0.188	7
2	0.629	2
3	0.332	5
4	0.180	9
5	0	14
6	0.268	6
7	0.129	10
8	0.483	3
9	**0.665**	**1**
10	0.431	4
11	0	14
12	0.009	13
13	0.035	12
14	0.189	8
15	0.096	11

4. CONCLUSIONS

In this paper, the optimization of the wire EDM process parameter was evaluated by a double method while the multiple responses were converted to a single response using the desirability functional analysis (DFA). The combined model used for evaluation is the term TP-GWO-DFA method, which can accurately represent the evaluation of nitinol materials in a wire EDM process. The idea of DFA is borrowed to solve the problem of evaluation of the weight of members. The elevated frequency rates of utilization of the DFA method, the GWO, the Taguchi method and the Pareto method prove their practicability coupled with the simplicity of the coupled method, which makes it suitable for the wire EDM process and specifically when processing the nitinol material. This article contributes to the wire EDM literature by offering a robust scheme for optimization through the integrated TP-GWO-DFA method. Interestingly, the unique feature of the method is the ability to discriminate among experimental trials, leading to the signal-to-noise ratios that account mostly for the method's influences on the model parameters. This discrimination, and ability to streamline the whole experimental trials in the computation of the signal-to-noise ratios to a few essential ones is a feature that differentiates the paper from previous works. The results show that the TP-GWO-DFA scheme proposed in this article sufficiently represents the optimal scores for the parameters of the wire EDM process. Future studies may focus on the sensitivity analysis of the parameters at each stage.

In the previous account by Nwankiti and Oke (2022), the TP-GWO-DFA method proved its efficiency in the analysis of thermal friction parameters in which their characteristics need to be optimized. However, in this article, the authors have shown that the TP-GWO-DFA method is very efficient for establishing the optimization values of parameters when considering diverse responses for the wire EDM process within the machining industry, These results reveal the way of analyzing the wire EDM process parametric optimization problem and open up emerging opportunities for alternative uses in machining and advanced welding problems in the wider aspect of manufacturing engineering.

List of abbreviations

DF	Duty factor, (%)
GV	Gap voltage, Volts
FR	Dielectric flow rate, lpm
CR	Cutting rate, mm/min
R_z	Average peak to valley height, µm
R_t	Maximum peak to valley height, µm
SCD	Surface crack density, $\mu m/\mu m^2$
RLT	Recast layer thickness, µm
$(S/N)_p$	value of S/N ratio
$(S/N)_{min}$	minimum S/N ratio
$(S/N)_{max}$	maximum S/N ratio

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