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Novel EDAS-Taguchi and EDAS-Taguchi-Pareto Methods for Wire EDM Process Parametric Selection of $Ni_{55.8}Ti$ (Nitinol) Shape Memory Alloy

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ABSTRACT

The EDAS (evaluation based on distance from average solution) method is a broadly utilized tool for multi-criteria analysis with the ability to handle several conflicting criteria. The Taguchi method is an optimization tool with economic capability in experimentation. This article presents EDAS Taguchi (EDAS-T) method based on EDAS and the Taguchi method. It also presents EDAS Taguchi-Pareto (EDAS-TP) method framed from EDAS and Taguchi-Pareto methods. Furthermore, data from the literature to test the proposed methods are presented, which the results are compared. This research shows that the EDAS method produces the optimum combination of parameters at a run with a current of 4A, pulse on time of 50 µs, pulse off time of 14ms, and powder concentration of 1 g/L. Also, the EDAS-Taguchi method reveals a current of 4A, pulse on time of 60 µs, pulse off time of 14 µs, and powder concentration of 1 g/L. However, the principal result is that using the EDAS Taguchi-Pareto method, the optimal current is 3A, pulse on time is 60 µs, and powder concentration is 0.75g/L. The EDAS Taguchi-Pareto method eliminated the pulse off time and pulse on time, claiming that it is not significant to the system's optimum performance. The principal novelty of this article is that it introduces a mechanism of concurrently optimizing and selecting the wire EDM process parameters using the EDAS-Taguchi-Pareto method. The optimization is parallelly conducted as selection occurs, providing an initial notification to ascertain timely detection and control of local optimality of parameters to global optimization before final selection. This is unlike most evaluations, where optimization is done differently from the selection. This study is the first to develop and use EDAS methods for the WEDM process of $Ni_{55.8}Ti$ shape memory alloy.

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1. INTRODUCTION

The shape memory alloys involving Nitinol, copper-based alloys, and non-manganese-silicon alloys have exceptional focus by top manufacturers in various sectors, including consumer electronics and home appliances, aerospace and defense, biomedical and automotive (Guo et al., 2013; Kulkarni et al., 2018; Mwangi et al., 2020; Davis et al., 2021). By projection, the world's shape memory alloys market will expand from its present value of USD 11.0 billion to an estimated value of USD 18.8 billion in 2027 (Markets and Markets, 2021). At present, the nitinol kind of shape memory alloys tops the segmental market, according to Markets and Markets (2021) reports. The rapid growth in nitinol use among producers and users of wires, rods, ribbons, and sheets has made the success of nitinol market leadership possible (Markets and Markets, 2021). Besides the biomedical aspect of the industry, aerospace and defense have also promoted Nitinol in various manufacturing industries (Mwangi et al., 2020; Davis et al., 2021; Markets and Markets, 2021). Accordingly, Nitinol has become an important shape memory alloy as the global market has recognized its need in product manufacturing. Therefore, it requires substantial research attention on the distribution of its resources during its forming and welding processes (Guo et al., 2013; Fu et al., 2016;

Kulkarni et al., 2018; Liu et al., 2014, 2018; Majumder and Maity, 2018; Roy and Mandal, 2019; Roy et al., 2020; Naresh et al., 2020; Mwangi et al., 2020; Chaudhari et al., 2021b; Davis et al., 2021).

Thus, during the forming (including machining) and welding processes, the process engineer requires an insight into the best parameter upon which judgments on the allocation of resources to parameters would be given. Resources are significant to the efficiency and development of the machine shop. For example, the process engineer must manage the dielectric medium to cut the conductive material, Nitinol. Suppose the amount of dielectric provided is meager due to poor resource distribution to the dielectric requirement. In that case, the tool wear may be unnecessarily high, leading to avoidable tool changing and maintenance costs.

Consequently, in response to the resource control and distribution issues encountered during the materials' wire electrical discharge machining (EDM), multi-criteria methods have been developed and introduced in the machining arena (Okponyia and Oke, 2020). Multicriteria methods are assessment structures for systematically supporting complicated decisions such as the parametric selection during the wire electrical discharge machining problem. It tackles the machining problem that possesses conflicting criteria in a situation where the objectives are pre-specified. But the wire electrical discharge machining is advantageous, possessing high machining strength and elevated aspect ratios of components (Liu et al., 2018).

Accordingly, researchers have implemented multi-criteria methods in electrical discharge machining systems (Okponinia and Oke, 2020). However, there is sparse research on implementing multi-criteria methods in the wire electrical discharge machining arena. This study suggested that the multi-criteria method exhibits substantial potential to be adopted in the wire electrical discharge machining (WEDM) process to enhance resource distribution along with parametric conceptions. Significantly, implementing multi-criteria methods could afford the process engineer to consider complicated trade-offs among WEDM process parameters. Research by Okponyia and Oke (2020) has revealed that the adoption of multi-criteria methods in the electrical discharge machining industry is still in its infancy. Hence, there is a limited multi-criteria analysis conducted on the nitinol smart material during the electrical discharge machining process of the product. However, the authors (Okponyia and Oke, 2020) recognized the multi-criteria methods as important tools in the machining industry to ascertain the best choice of parameters for resource control motivations. Therefore, the article's objective is to present two novel methods, namely EDAS-Taguchi and EDAS-Taguchi-Pareto methods, for the wire electrical discharge machining of $Ni_{55.8}Ti$ shape memory alloy and establish the best parameters in the machining process. Although a sparse application of multi-criteria methods for the nitinol smart materials exists, adopting the EDAS-Taguchi method and the EDAS-Taguchi-Pareto method will enhance the resource distributions to the parameters during the WEDM process. Consequently, gaining insight into the whole structure of these newly proposed methods for the WEDM process of $Ni_{55.8}Ti$ shape memory alloy can assist in solving the resource deployment problem.

Besides, carefully selecting the best parameters with the objective of concurrent optimization of parameters in the wire electrical discharge machining is often problematic to process engineers and researchers (Das and Chakraborty, 2020). The challenge stems from the wide availability of process control parameters (Das and Chakraborty, 2020). This challenge is complicated as there are conflicting responses that the process engineer needs to contend with (Das and Chakraborty, 2020). Another complexity of this challenge is the multiple optimization techniques available, where choosing a simple one is engaging. There is a need to choose the best parameter for the economic conservation of resources in this problem. There is also the need to attain the utmost potential of this machining process with the establishment of the optimal blend of electrical discharge machining parameters (Das and Chakraborty, 2020). Unfortunately, failing to obtain the best parameter does not always reveal the true resource needs. Occasionally, it yields extremely misleading effects concerning resource distribution based on parametric strengths and needs. Furthermore, the absence of an optimal parametric setting puts the WEDM process performance level at the risk of poor output. However, it is known that a slight change of a parametric setting from the optimum may lead to a chain of problems in quality deficiency, wasteful usage of resources, and unbudgeted loss of manpower.

Das and Chakraborty (2020) criticized the current approach in machining, where the operator's knowledge of handbooks by manufacturers is the reference point. But this approach is limited to specific work material and shape characteristic combinations (Das and Chakraborty, 2020). Unfortunately, the nitinol smart material considered in this article may be subjected to very complicated shapes not pre-meditated by either the equipment manufacturer or the operator. Thus, these two parties are in a dilemma and cannot solve the machining problem accurately. At best, these parties' present solution yields optimal solutions. However, optimal solutions are more beneficial to the EDM process for enhanced income for the machine shop.

Regarding the specific outcomes of this study, the results obtained from the analysis may provide the workshop with information that will help more effectively understand and tackle parametric process requirements concerning the wire EDM machining of Nitinol within the workshop environment. The results of this study could as well benefit the machining of other smart materials, including Ti6Al4V alloy, by increasing understanding of their most preferred parameters, as this is presently ignored in investigations concerning smart memory alloys. This study is motivated by the unprecedented acceptance rate of nitinol shape memory alloy and the projected expanded market, especially in the biomedical area of engineering. Nitinol shape memory alloy has experienced extensive studies on wire electrical discharge machining, and this research information has met the needs of process engineers monitoring the WEDM facilities. Although the distribution of WEDM resources is made according to guidance by intuition and direction by the superior to the operators, the present operational modalities on the distribution of resources for WEDM operations need to be questioned and re-examined for improvements. A multi-criteria approach can ascertain those objective placements of important factors and the allocated needs are achieved. This avoids excessive disbursement of resources to a particular parameter while other parameters lack the needed resources. To the best of the authors' knowledge, extremely little research has considered selecting and optimizing WEDM parameters while machining the nitinol shape memory alloy. The choice of parameters and optimization is still based on intuition and the instruction given to the operator by the superior since equipment manual recommendations cannot work. Therefore, it is urgent to evolve methods to select and optimize the parameters of the WEDM during the machining of the nitinol shape memory alloy.

The study highlights regarding contribution to knowledge are as follows:

a) The EDAS-Taguchi-Pareto method highlights a new way of jointly optimizing and selecting wire EDM process parameters by ignoring unimportant parameters and focusing on the parameters that strongly impact the process outcomes.
b) It introduces a mechanism that priorities the wire EDM process parameters according to their importance in attaining the process goals.
c) It highlights process evaluation parameters and attributes previously unclear in wire EDM process machining of Nitinol and increases researchers understanding of the subject.
d) Implementing the combined theories of Taguchi optimization, Pareto principle, and EDAS method to offer new reasoning and enlargement of ideas in evaluating Nitinol during the wire EDM machining.
e) Establishing previously unknown flaws in wire EDM research regarding Nitinol to properly place the research pursuits and advance nitinol research.

Furthermore, in this article, the EDAS method has been fused with the Taguchi and Taguchi-Pareto method to create a new way of optimizing and selecting the wire EDM process parameters during the processing of nitinol material. However, the effective implementation of the method is possible only under certain assumptions. The principal assumption is that the utmost result is obtainable only by reducing the deviation from a target. Moreover, the new method was developed on the assumption that the decision-makers to evaluate the wire EDM process parameters conduct the assessment on clear thought and reasoning. Unfortunately, certain decision-makers may be biased and such inputs into the parametric assessment may bring out wrong results.

Furthermore, the positive distance from the average and the negative distance from the average may not be rationally computed. Besides, the operation of the method is subjected to some limitations. To define the limitations, the following illustration is helpful. The method proposed has its outputs as the optimal parametric settings that consist of values at which each of the factors should be operated to obtain the most beneficial effects for the system. Unfortunately, the results provided by the optimal parametric setting are only comparative and do not particularly state what parameters exhibit the greatest influence on the performance attribute value.

2. LITERATURE REVIEW

In the literature survey that follows, the two broad classifications of general and EDAS research are elaborated upon. The general subsection discusses the work done in electrical discharge machining, wire EDM, nitinol material, and related areas. The EDAS research subsection limits the discussion only to EDAS-based studies.

2.1. General

Nickel-titanium (Nitinol) alloys stand out as unique functional materials capable of exhibiting shape memory and superelasticity properties. The shape memory property of Nitinol is demonstrated by the material's ability to deform at a particular temperature and regain its initial shape while being heated beyond its transformation temperature (commonly called austenite finish temperature). However, the superelastic property of Nitinol refers to its reversible response to stress imposed on it, transforming its phase between the austenitic and martensitic stages of a crystal and back to its initial shape. These two outstanding native properties of shape memory and superelasticity demonstrated by the nitinol alloy quickly impose the name smart alloy on it. Based on the importance of Nitinol in the industrial environment, users of this smart material are wide-ranging in automotive, medical, and aerospace applications (Naresh et al., 2020).

Furthermore, enormous challenges are experienced by the process engineer while attempting to deploy conventional methods of machining Nitinol (Naresh et al., 2020). It is found that nitinol alloy is extremely hard to machine through the traditional approach. The extraordinary properties of Nitinol in ductility are low thermal conductivity, severe work hardening, and temperature sensitivity. These properties put the outcome of conventional machining unsatisfactory as substantial tool wear and extremely poor surface finish are experienced. Nonetheless, the wire electrical discharge machining (EDM) process has been proposed to tackle this problem. However, by deploying the wire EDM process, understandably, the process parameters could be selected and optimized through multi-criteria and optimization methods. Thus, a literature review is conducted to establish the research gap that the current article bridges in this section. Now, a brief literature review is showcased here.

Mwangi et al. (2020) examined the potential of micro-EDM to substantially change Nitinol by expanding the discharge energy to lower the thermal hysteresis and creating a three-peak reverse stage change on heating. Furthermore, the authors assisted in establishing the features of the nitinol micro-EDM process. It was established that arcing is the principal phenomenon behind the three peak change characteristics. It was also noted that the thermal damage stimulated by arcing yields elevated residual strain, lowered elongation to failure, reduced plateau stresses, and loss of machining accuracy.

Naresh et al. (2020) established an association between the four principal WEDM parameters of gap voltage, pulse off time, peak current, and pulse on time as input parameters and surface roughness and metal removal rate as output parameters. The utilized method of analysis is the artificial neuro-fuzzy inference system predictive structure. It was concluded that the coefficient of correlation regarding the metal removal rate and surface roughness was near unity (i.e., 0.9945). In contrast, the coefficient of determination and the average error percentage installed for the surface roughness yielded 0.9891 and 2.04 correspondingly. However, values of 0.9738 and 1.70% were obtained for the coefficient of determination and the average error percentage regarding the material removal rate.

Davis et al. (2021) transformed the medical-type $Ni_{55.6}Ti_{44.4}$ alloy surface using the lowest machining time and dimensional differences by employing zinc powder mixed micro-electrical discharge machining. The authors established a relative study of the micro tool electrodes (namely brass and copper) and zinc tool electrodes while making a relationship with 6g/t PPC that aims to achieve the largely enhanced machinability and transformed stratum on the $Ni_{55.6}Ti_{44.4}$ alloy surface. Substantial enhancements were reported from the outcomes of the morphological, compositional, and dimensional characteristics of the charged $Ni_{55.6}Ti_{44.4}$ alloy surface. Chandhari et al. (2021) improved the performance of nitinol shape memory alloy by blending multi-walled carbon nanotubes while the surface roughness and the material removal rate were also considered. It was established that a significant enhancement of the machining performance existed with the blending of the MWCNTs, which was achieved by enhancing the material removing rate and lowering the surface roughness. By deploying the TLBO algorithm, the optimal solution for the multiple responses was obtained. It was also concluded that the introduction of MWCNTs significantly lowered the recast layer thickness and related surface defects.

Fu et al. (2016) compared the characteristics of the while layer created by laser cutting versus electrical discharge machining. The medium of comparison is the surface topography, examined through the scanning electron microscope. Further comparison was achieved by using electron backscatter diffraction to examine grains' orientation and sizes. Besides, the hardness of the white layer was examined using nano-indentation. The study concludes that the white layer created by the laser cutting approach has a greater uniform spread on surfaces compared with the electrical discharge machining option. Kulkarni et al. (2018) considered optimizing parameters for the wire electrical discharge machining process while targeting the maximum values of material removal rate and the lowest values of the surface roughness, with the work material being nickel-titanium (Nitinol). The identified key parameters are the pulse on time, spark gap set voltage, wire feed, and pulse off time. The following was revealed by deploying a combination of the Taguchi method and ANOVA and analysis of means. The optimal wire feed was 6m/min, the pulse off time was 25 µsecs, pulse on time was 1/5 µsecs, and the spark gap set voltage was 40V. It was concluded that wire feed attained the most significant position in the evaluation, affecting material removal rate and surface roughness.

Guo et al. (2013) established the dynamic mechanical characterization of Nitinol during the cutting process on the electrical discharge machining. It was reported that extremely elevated strength and specific heat are associated with the large flank and quick crater wear. It was added that the stratum of austenitic white during cutting was triggered by deformation. However, the twined stratum of martensitic white was triggered by quenching in the electrical discharge machining.

Roy et al. (2020) produced an experimental study on nitinol-60 to optimize two distinct responses of surface roughness average and machining speed for the wire electrical discharge machining process. Based on the Box-Behnken design of the response surface approach, the peak machining speed was 2.6218 mm/min, while the least roughness average was 1.6563mm. In comparison, the single objective optimization approach was adopted. However, for multiple objectives, the peak machining speed and the least roughness average were 2.1007mm/min and 1.7072mm, respectively. The conclusion is that the proposed methods produce a good resemblance to the predictions.

Lin et al. (2014) conducted a process capability study regarding wire EDM with DI water-oriented dielectric while machining nitinol $Ni_{50.8}Ti_{49.2}$ using a principal cut and then four trim cuts. It was understood through a 6-sigma distribution analysis that the roughness average for the one principal cut and four trim cuts are different. By evaluating using white layers, thick strata of 2 to 8mm associated with micro-cracks in the principal cut were experienced. However, extremely thin white strata ranging between 0 and 2mm were noticed for the four trim cuts. In addition, it was affirmed that the white stratum by the four trim cuts is roughly 150% of the principal cut. Furthermore, Nitinol was obtained as the prevalent element in the evaluated microhardness.

Majumder and Maity (2018) attempted to predict some aspects of the WEDM process, focusing on Nitinol's microhardness and surface roughness. The applied tool is the general regression neural network. At the same time, the following parameters were the focus of the study: flushing pressure, pulse on time, wire tension, discharge current, and wire feed. These are the machining inputs. In addition, the multi-objective optimization based on ratio analysis, MOORA, was applied to make the optimization more robust. It was concluded that the parametric combination is the pulse on time of 12 µs discharge current of 10A. However, the flushing pressure is 8 bar, wire tension of 12N, and wire feed of 150mm/s and gave the accepted results.

Liu et al. (2018) established an association between surface integrity and fatigue life using nitinol samples in the wire-EDMed process. Machining of the nitinol samples for surface integrity at the principal cut was substantially enhanced using subsequent trim cuts. It was reported that nitinol samples at the finish trim cut revealed lower surface roughness and a thinner white layer compared with the principal cut. The outcome of the fatigue testing revealed that the outputs of the finish cut enhanced fatigue life by 485 compared with the outputs of principal cuts. It was added that a thinner white layer, indicating lower tensile residual stress, is advantageous to fatigue performance and will yield extended fatigue life.

Roy and Mandal (2019) explored the quantitative information on the wire-EDM machined surfaces and related it to the average peak-to-valley height, utmost peak-to-valley heights, recast layer thickness, and surface crack density. Two quantitative techniques of Monte Carlo simulation and response surface methodology were applied. It was reported that there is a concurrence of the proposed methods with the experimental results.

Chakala et al. (2019) analyzed the influence of input characteristics on the outputs. The inputs are the peak current, pulse on time, voltage, and pulse off time. However, the outputs are the surface roughness and metal removal rate. The experiments were performed using Nitinol on the wire EDM process. The two examination methods are the analysis of variance and central composite design. It was reported that at lower measurable values, the pulse on time and peak current exhibited higher significant characteristics to enhance the material removal rate and surface finish. The methods agree with the experiments.

2.2. EDAS research

It is thought that some specific information about EDAS research is necessary to provide a clearer picture of the research gap bridged in the present study and the importance of this contribution. Hence, a brief mention of past literature on the EDAS method is given in this section. The EDAS method is an interesting multi-criteria method originally developed by Keshavarz-Ghorabaee in 2015 to solve inventory problems characterized by multiple and conflicting factors. However, based on the success of the method in engineering practice and the common attributes that the production process of Nitinol being processed under the wire EDM process share with inventory, the EDAS method appears appropriate to solve the wire EDM process parametric selection and optimization problem. The EDAS method is based on the theory of averages. Averages, often denoted as mean values, represent the proportion of the sum of values generated from the wire EDM process parameters to the total number of values obtainable for the set of parameters.

Consequently, the theory of averages that the EDAS method evolved from reveals a more or less predictable proportion of the random trials to the occurrences of parametric value generation events. However, of interest to Keshavarz-Ghorabaee is to define two terms that represent deviations from the averages, whose principle was introduced by Jakob Bernoulli. The positive and negative distances from averages are these terms carved out by the developer of the EDAS method. Thus, the EDAS method is widely known to be evaluated based on the distances in the directions of positive and negative navigations; these are evaluated from the average solution independently and in line with the non-beneficial as well as beneficial criteria selected.

In this solution approach to the EDAS method, beneficial and non-beneficial criteria are common terms. From the perspective of wire EDM process parametric determination of nitinol material, beneficial criteria are those whose higher values are required to advance towards the goal of the machining system of attaining improved material removal rate and enhancing surface roughness. However, suppose the reverse happens such that any attempt to increase the value of a criterion reduces the material removal rate, and the surface roughness increase. In that case, the criterion is the non-beneficial type.

Moreover, in a study on milling, the EDAS method was one of the multi-criteria approaches Trung (2021) utilized to evaluate the value of cutting factors while considering improved material removal rate and minimized surface roughness of the B410 steel being milled. The author declared the novelty of using EDAS for the milling situation. Further literature survey on EDAS reveals the continued interest of researchers to integrate the method with other methods since the outstanding performance of the hybrids continues to evolve in the cases. Thus, this provides a strong motivation in the present work to combine the EDAS method with other methods, particularly optimization methods that have been relatively ignored in the literature. A brief account of the evidence of these unions is found in the following.

Siqi et al. (2019) combined the EDAS method with the Picture 2-linguistic environment. Besides, Shaaban and Abd (2020) identified the optimal parameters in diesel engine operation by deploying the combined EDAS method and entropy weights. Furthermore, Krishankumar et al. (2021) applied the combined two-sided hierarchy and EDAS method to the urban mobility problem to prioritize zero-carbon measures. Besides, the EDAS method is still preferred by some authors in hybrid forms, as demonstrated by Rashid et al. (2021) in the choice of industrial robots. The authors integrated the best worst method and the EDAS framework and compared the results with the outcome of the VIKOR approach from applying the method. It was concluded that the method was robust, and the eight to one ratio approach to sensitivity analysis using the problem offered a stable and reliable result. Das and Chakraborty (2020) modified the classical EDAS method to produce a novel approach to processing parts on non-conventional machining systems. The method's validity was ascertained with demonstrated examples using published data from the non-conventional machining domain.

2.3. Summary of the literature study

Based on the literature review conducted in this study, there is strong evidence that Nitinol is one of the most promising and proven smart materials widely used in automobiles, aerospace, and biomedical industries due to its distinct attribute of the ability to remember its shape under deformation as it is slightly heated up. However, a new shape may be obtained as it reaches its transformation temperature. The proper of remembering its structure when slightly heated is an advantage in its usage in numerous aerospace, automobile, and biomedical applications. However, a prominent problem is the inability of the literature to identify the parameters of the wire EDM process according to their importance and strengths. The present literature on Nitinol and wire

EDM process parametric selection lacks adequate information. According to the authors' understanding, extremely few studies about selection and optimization on a sole basis or concurrently and related topics have been undertaken. It was found that the current literature on the subject of concurrent selection and optimization of wire EDM process parameters of Nitinol is inadequate and very weak.

3. METHODS

3.1. Principal factors used during the experiment

In this article, novel parametric optimization and selection methods are elaborated for the advanced technology of nano-graphene mixed dielectric fluid-based wire EDM process where Nitinol is being processed. However, selecting the major factors that dominate the working operation during the experiment is critical and is discussed here. However, the wire EDM process elements contribute to the attainment of nitinol machined component accuracy, the desired surface roughness index, minimized environmental influences, superior output quality, the improved lifespan of components, and a high production rate. Thus, the essential factors considered by Chaudhari et al. (2021a) but adopted in the present study are as follows. First, the pulse on-time factor is considered. This is the time that the machining activity is conducted. Often, machining speed increases when the pulse on time is regulated to an increased value. The consequence is that the removal rate of the nitinol material increases. The mechanism at which this happens is that as the pulse on-time increases, both the energy discharged and the intensity of the spark enlarges, making the volume of materials being removed increase. Next is the pulse off time, which describes the rest period when the dielectric is reionized. During this same period, the molten material solidifies, prepared for washing out from the spark gap.

Two principal terms of interest to describe the pulse-off time activities are stability and instability of sparks generated during machining. Instability of sparks often results from very short pulse off periods, and the system is prone to extensive short-circuiting. Conversely, when the pulse off time is high, higher machining time results and stability of the sparks is guaranteed. Furthermore, powder concentration is a key factor in the wire EDM process that declares the degree of powder mixtures in the process. Next, the current is an important factor within the wire EDM process. Apart from these factors, the two responses of material removal rate (MRR) and surface roughness are associated with the system. The MRR is computed as the product of the feed rate, wire diameter, and thickness of the workpiece. The surface roughness is measured as the roughness average and shows a variance from the expected fitness of the material finishing.

3.2. The developed methods

The methods used in this study are of two parts. The EDAS method, one of the methods proposed to solve the selection problem in the WEDM process of Nitinol, was obtained from the literature in such works as Das and Chakraborty (2020). Although the Taguchi method and the Taguchi-Pareto method are both obtainable in the literature, no study has attempted to integrate the EDAS method and the Taguchi method as EDAS-Taguchi. No study seems to have coupled the EDAS method and Taguchi-Pareto method. However, to have coupled with the EDAS method and the Taguchi method, the Taguchi-Pareto method seems to be completely ignored in machining nitinol for the WEDM process parameters. The EDAS method was coupled with the Taguchi method to introduce the economy of experimentation into the work and, at the same time, optimize the parameters in concurrence with selection. However, the additional advantage that the Pareto feature of the EDAS Taguchi-Pareto method introduces to the system of assessment is that it ignores the parameters that are not important to the goals of optimizing and selection for the process. It retains only the parameters that only promote these goals.

3.3. The EDAS (Evaluation based on distance from average solution) method

The EDAS (Evaluation based on distance from average solution) method was announced to the research world by Keshavrz-Ghorabaee and colleagues. The method works by computing the positive and negative distances between each alternative and the average alternative. It is stated here that the context of the word "alternative" in this computation is a particular number of options that can be produced. The EDAS method is a multi-criteria decision method that effectively solves conflicting methods. Here the decision-maker needs to aggregate the positive distance from the alternative solution and the negative distance from the alternative solution. According to their preferences, the decision-maker adjusts the proportions of these distances (positive and negative from each alternative solution). The method is flexible for the process engineer choosing the WEDM process parameter.

Moreover, it adopts few data for pre-processing and calculations. The desirability of the alternatives is determined based on their distances from the average solution. In this method, there are important features of interest. The first measure is the positive distance from average (PDA) while the second feature is the negative distance from the average. These two measures are capable of revealing the difference between each solution (option) and the average solution. The alternatives are examined with the higher values of the PDA in mind, while lower values than the negative solution are desired compared to the average solution. In applying the EDAS method, it is assumed that more than one option is available for evaluation. The following are the steps involved in implementing the EDAS method (Keshavarz-Ghorabaee et al., 2015).

Step 1: Select the most important criteria that describe the options.

Step 2: Construct the decision-making matrix (X_{ij}). Here, X_{ij} represents the performance value of the i^{th} option on the j^{th} criterion.

Step 3: Establish the average solution by noting every criterion, where AV is the average solution. The Average Solution is

$$AV_j = \frac{\sum_{i=1}^{n} X_{ij}}{n} \tag{1}$$

Step 4: Calculate the positive distance from the average (*PDA*) and the negative distance from the average (*NDA*) and develop matrices according to the type of criteria (beneficial or non-beneficial).

Calculate the positive distance from the average.

If a j^{th} criterion is beneficial:

$$PDA_{ij} = \frac{\max(0,(X_{ij} - AV_j))}{AV_j} \tag{2}$$

Consider Eq. (2), the average value is first calculated. The positive distance from the average solution is established for a beneficial criterion by subtracting this average value from the criterion value. This is the outcome compared with zero while the upper value of these two options is chosen, restricting the choice to positive values. Furthermore, the final value is obtained by dividing the outcome by the average value.

If a j^{th} criterion is non-beneficial:

$$PDA_{ij} = \frac{\max(0,(AV_j - X_{ij}))}{AV_j} \tag{3}$$

Calculate the negative distance from the average:

If a j^{th} criterion is beneficial:

$$NDA_{ij} = \frac{\max(0,(AV_j - X_{ij}))}{AV_j} \tag{4}$$

By explaining the relation between Eq. (3) and Eq. (4), it is essential to refer to Eq. (2) and Eq. (5), previously explained in this section. Eq. (3) is for the non-beneficial situation and reverses the order of positioning the terms at the numerator of Eq. (2). Here, the criterion being evaluated is subtracted from the average solution, and the results chosen are the maximum between zero and the value obtained. Then this outcome is divided by the average solution. However, notice that Eq. (3) is for the position distance from the averages while considering the non-beneficial criteria. Furthermore, Eq. (4) is similar to Eq. (3), except that the negative distance from the average values is considered, and the beneficial criterion is analyzed.

If a j^{th} criterion is non-beneficial:

$$NDA_{ij} = \frac{\max(0,(X_{ij} - AV_j))}{AV_j} \tag{5}$$

Eq. (5) follows the same procedure, but a small change occurs in the direction of evaluation done with Eq. (2). While Eq. (2) considers the movement in the positive direction, the direction of movement for Eq. (5) is negative. Notwithstanding, Eq. (2) represents the beneficial criterion, while Eq. (5) shows the evaluation for non-beneficial criteria.

Step 5: Establish the weighted sum of *PDA* and *NDA* for all alternatives. The word "all alternatives" refers to a certain number of alternatives that can be created.

A weighted sum of PDA:

$$SP_i = \sum_{j=1}^{m} w_j PDA_j \tag{6}$$

Step 6: Normalize the values of *SP* and *SN* for all alternatives.

Normalize the values of SP_i and SN_i using:

$$NSP_i = \frac{SP_i}{\max_i (SP_i)} \tag{7}$$

$$NSN_i = 1 - \frac{SN_i}{\max_i (SN_i)} \tag{8}$$

Eq. (8) implies that SN_i will be first considered, and this value is divided by the maximum of the SN_i, and then the obtained value will be subtracted from 1.

Step 7: Calculate the appraisal score (*AS*) for all alternatives.

Estimate the Average normalized Values of SP_i and SN_i using:

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \tag{9}$$

Step 8: Rank the alternatives according to decreasing values of appraisal score (*AS*). The alternative with the highest *AS* is the best choice among the candidate alternatives.

3.4. The EDAS-Taguchi method

Step 1: Follow steps 1 to 8 of the EDAS method in section 3.3.

Step 2: Compute the signal to noise ratio according to the smaller the better criterion:

$$SN = -10\log_{10} \frac{1}{n} \sum_{i=1}^{n} y_{ij} \tag{10}$$

Step 3: Compute the response table.

Step 4: Determine the delta values and ranks of parameters.

3.5. The EDAS-Taguchi-Pareto method

Step 1: Follow steps 1 to 8 of the EDAS method in section 3.3 and steps 1 to 2 of the EDAS-Taguchi method.

Step 2: Conduct the analysis of variance on the data.

Step 3: Use the information from step 2 of this section to determine the most important and least important parameters.

Step 4: Eliminate the least important parameters from the analysis.

Step 5: Decide on the relevant parameters.

The EDAS-Taguchi method and the EDAS Taguchi-Pareto method proposed in this article have the following potentials (advantages) to be used in practice. Items 1 to 3 apply to the EDAS-Taguchi method, while all the items apply to the EDAS-Taguchi-Pareto method.

1. It considers the economy of experimentation, thereby stimulating cost reduction.
2. It is objective in the ranking of parameters.
3. It amounts to distance associations and optimal parametric settings, thus evolving a reliable performance measure.
4. Its application allows parametric disintegration and prioritization of complicated process parameters in the context of multiple parameters affecting the process decisions.
5. It simultaneously permits the concurrent prioritization and optimisation of multiple process parameters and projects elaborate quantitative information.
6. It establishes the most critical parameters with a basis.

4. RESULTS AND DISCUSSIONS

4.1. The EDAS method, EDAS-Taguchi method, and EDAS-Taguchi-Pareto method

In this section, the results and explanations for behaviors of the data using the EDAS method, EDAS-Taguchi method, and the EDAS-Taguchi-Pareto method are given. First, information on the EDAS method is presented. The starting point of evaluation for the EDAS method is the computation of the average solution. But four parameters are analyzed: the current, pulse on time, the pulse of time, and powder concentration. These four parameters were established as the most important influencers of the performance of the WEDM process considered in this study. The current, also termed the discharge current, is a central feature of the wire EDM that establishes the machining properties regarding the accuracy of machining or machining speed. In some instances, the varying discharge currents are possible with alternative workpiece thicknesses. The second principal factor considered in this article is the pulse on time, which evaluates the time difference of when sparks that erodes the nitinol smart material takes place. These sparks are activated between the electrode (wire) and the nitinol rod used as the samples in this work.

Furthermore, the pulse off time is another significant factor that indicates the rest time. Here, the term pulse off time is the time to reionize the dielectric. Usually, as the pulse-off time grows, a higher machining time is expected from the WEDM process. The fourth parameter, powder concentration related to the intensity of the powder used in the process. Recently, the powder mixture is an evolving term that describes a scheme in the electro-thermal aspect that contains shape and coat deposits on the nitinol rod. Thus, from the above discussion, the average of the parameters over the sixteen experimental trials is sought (Table 3 of Chaudhari et al., 2021a). For example, consider the column undercurrent with values of 1, 1, …, 4 for experimental trials 1, 2 up to 16, respectively. The average of the sixteen counts is 2.5, taken as the AV_j, where j = 1, 2, …, 16. (Equation (1). Similarly, the averages for the other parameters of pulse on time, pulse off time, and powder concentration is computed and shown in Table 1.

The next step in the evaluation using the EDAS method is the computation the positive distance from the average solution, referred to as the PDA. It is important to

Table 1 Average solution based on Taguchi's DOE data from Chaudhari et al. (2021a)

	Factors			
Description	**Current**	**Pulse on time**	**Pulse off time**	**Powder concentration**
AV_j	2.5	45	16	0.625

Number of observations = 16, AV_j is the average value for experimental trials where j = 1, 2, 3, …, 16

Table 2. Positive Distance from Average (PDA) Solution

Weights	**0.4400**	**0.0900**	**0.1300**	**0.3400**
S/N	**Current**	**Pulse on time**	**Pulse off time**	**Powder concentration**
1	0.0000	0.0000	0.3750	0.0000
2	0.0000	0.0000	0.1250	0.0000
3	0.0000	0.1111	0.0000	0.2000
4	0.0000	0.3333	0.0000	0.6000
5	0.0000	0.0000	0.1250	0.2000
6	0.0000	0.0000	0.3750	0.6000
7	0.0000	0.1111	0.0000	0.0000
8	0.0000	0.3333	0.0000	0.0000
9	0.2000	0.0000	0.0000	0.6000
10	0.2000	0.0000	0.0000	0.2000
11	0.2000	0.1111	0.3750	0.0000
12	0.2000	0.3333	0.1250	0.0000
13	0.6000	0.0000	0.0000	0.0000
14	0.6000	0.0000	0.0000	0.0000
15	0.6000	0.1111	0.1250	0.6000
16	0.6000	0.3333	0.3750	0.2000

Table 3. A weighted sum of PDA

S/N	Current	Pulse on time	Pulse off time	Powder concentration	***SP**_i*
1	0.0000	0.0000	0.0488	0.0000	0.0488
2	0.0000	0.0000	0.0163	0.0000	0.0163
3	0.0000	0.0100	0.0000	0.0680	0.0780
4	0.0000	0.0300	0.0000	0.2040	0.2340
5	0.0000	0.0000	0.0163	0.0680	0.0843
6	0.0000	0.0000	0.0488	0.2040	0.2528
7	0.0000	0.0100	0.0000	0.0000	0.0100
8	0.0000	0.0300	0.0000	0.0000	0.0300
9	0.0880	0.0000	0.0000	0.2040	0.2920
10	0.0880	0.0000	0.0000	0.0680	0.1560
11	0.0880	0.0100	0.0488	0.0000	0.1468
12	0.0880	0.0300	0.0163	0.0000	0.1343
13	0.2640	0.0000	0.0000	0.0000	0.2640
14	0.2640	0.0000	0.0000	0.0000	0.2640
15	0.2640	0.0100	0.0163	0.2040	0.4943
16	0.2640	0.0300	0.0488	0.0680	0.4108

emphasize here that the basis of an evaluation of the EDAS method is to evaluate the parameters (alternatives) while taking note of their positive and negative distances from the average alternative. To emphasize what was previously mentioned in the section on methods, the context of the word "alternative" in this computation is a particular number of options that can be produced. This is made possible by first examining the weights to be used. However, a similar study was conducted elsewhere whose weights are adopted in the present study. The weights of the parameters are derived from the combined methods of the analytic hierarchy process and entropy method, which are subjective and objective, respectively. Accordingly, the weights are 0.44, 0.09, 0.13, and 0.34 for the respective factors of current, pulse on time, pulse off time, and powder concentration. These weights are indicated in Table 2 along the first row of entries.

Next, the entries are computed under all the four factors of current, pulse on time, pulse off time, and powder concentration for all the sixteen experimental trials. Considering the first experimental trial, it is interesting to know how the values of 0, 0, 0.3750, and 0 were obtained for the respective factors of current, pulse on time, the pulse of time, and powder concentration. First, the four factors are classified as beneficial according to the experience of the researchers. Thus, based on the practice experience of both authors of this article, a consensus was reached to classify current, pulse on time, and powder concentration as beneficial criteria. It is envisaged that the process engineer would prefer the maximum values of this category of factors as increasing the values will benefit the WEDM process. Likewise, it was agreed that pulse off time is not a beneficial criterion since lower values of this criterion are often desired. Being guided by Equations (2) and (3), the values of the positive distance from the average solution are computed as follows. By revisiting experimental trial one under the current factor, it is known that current is a beneficial factor, and Equation (2) is used to evaluate the criterion.

First, by considering the numerator of Equation (2), the difference between X_{ij} and AV_j is first obtained. Notice that the X_{ij} is the actual current value for experimental trial 1, 1A. But the average solution, $AV_{j,}$ was evaluated as 2.5A, which gives a difference of -1.5A. But the maximum between 0 and -1.5A is chosen, which is 0. The denominator is 2.5A, and placing 0 over 2.5A yields 0. By following this procedure, all values for the current experimental trials 1 to 16 are obtained and displayed in Table 2.

The procedure is extended to pulse on time and powder concentration to fill part of Table 2 for all experimental trials 1 to 16. However, out of the four factors considered in this article, one stands out as a non-beneficial criterion that requires Equation (3) for computation. In this case, consider experimental trial 1 under pulse off time. Here, the value of the criterion is 10 µs. But the numerator of Equation (3) contains the subtraction of X_{ij} (which is 10 µs) from the average solution, 16 µs. This gives 6 µs. The maximum of 0 and 6 is 6. But the result being 6 µs divided by 16 µs (the value at the denominator) gives 0.375.

Following a similar approach for this non-beneficial criterion, the values for all the other fifteen experimental trials are computed as shown in Table 2. The next step is to obtain the weighted sum of the PDA. In this case, all the values obtained for both the weights (the AHP-entropy values adopted from a previous study) and the computed positive distance from the average solution are used. Table 3 shows the results of this computation. To illustrate how Table 3 is obtained, consider the experimental trial 1. Under the factor current, the value to insert at the intersection of experimental trial 1 and current is obtained as follows. First, the weight is established as 0.44, while the value at the intersection, which is read from Table 2, is 0. Hence the product of these two numbers is 0. This value of 0 is inserted in Table 3 at the intersection of experimental trial 1 and current. Therefore, all the entries in Table 3 are completed by following the procedure. The weighted sum of the PDA is calculated, and the results are shown in Table 3.

Table 4. Negative distance from Average Solution

Weights	0.4400	0.0900	0.1300	0.3400
S/N	**Current**	**Pulse on time**	**Pulse off time**	**Powder concentration**
1	0.6000	0.3333	0.0000	0.6000
2	0.6000	0.1111	0.0000	0.2000
3	0.6000	0.0000	0.1250	0.0000
4	0.6000	0.0000	0.3750	0.0000
5	0.2000	0.3333	0.0000	0.0000
6	0.2000	0.1111	0.0000	0.0000
7	0.2000	0.0000	0.3750	0.6000
8	0.2000	0.0000	0.1250	0.2000
9	0.0000	0.3333	0.1250	0.0000
10	0.0000	0.1111	0.3750	0.0000
11	0.0000	0.0000	0.0000	0.2000
12	0.0000	0.0000	0.0000	0.6000
13	0.0000	0.3333	0.3750	0.2000
14	0.0000	0.1111	0.1250	0.6000
15	0.0000	0.0000	0.0000	0.0000
16	0.0000	0.0000	0.0000	0.0000

Table 5. A weighted sum of NDA

S/N	Current	Pulse on time	Pulse off time	Powder concentration	SN_i
1	0.2640	0.0300	0.0000	0.2040	0.4980
2	0.2640	0.0100	0.0000	0.0680	0.3420
3	0.2640	0.0000	0.0163	0.0000	0.2802
4	0.2640	0.0000	0.0488	0.0000	0.3128
5	0.0880	0.0300	0.0000	0.0000	0.1180
6	0.0880	0.0100	0.0000	0.0000	0.0980
7	0.0880	0.0000	0.0488	0.2040	0.3408
8	0.0880	0.0000	0.0163	0.0680	0.1723
9	0.0000	0.0300	0.0163	0.0000	0.0463
10	0.0000	0.0100	0.0488	0.0000	0.0588
11	0.0000	0.0000	0.0000	0.0680	0.0680
12	0.0000	0.0000	0.0000	0.2040	0.2040
13	0.0000	0.0300	0.0488	0.0680	0.1468
14	0.0000	0.0100	0.0163	0.2040	0.2303
15	0.0000	0.0000	0.0000	0.0000	0.0000
16	0.0000	0.0000	0.0000	0.0000	0.0000

Note: The SP_i and SN_i values are then normalized, and their average estimates

Table 3 is the weighted sum of PDA, where PDA is the positive distance from the average solution. The idea of the weighted sum is to employ a mathematical device to conduct the sum to provide some component elements of the computation with more effects on the results than other elements within the same set. There is an opportunity to weigh and combine the multiple elemental inputs and explore a joint analysis with this. It works by obtaining the product of the focused field values for each elemental input through the defined weights. Then all the inputs are added to produce an output. In Table 3, the outcome is indicated in the last column as SP_i. Next, the negative distance from the average (NDA) solution is evaluated by applying the principles applied earlier for the positive distance from average (PDA). The NDA results are shown in Table 4. The transformation that Table 2 experienced uses the same idea to transform Table 4 into Table 5, with the outcome being SN_i.

Now, having obtained the SP_i and SN_i values, the next stage is the transformation of the values into normalized values while their average is being estimated. The normalization is shown in Table 6, with the averages displayed also. Table 6, from which the ASi is developed, is called the average normalized values. The terms NSP_i and NSN_i are averaged to reveal how the nitinol experimental data performs. But the normalization of each term, NSP_i, and NSN_i imply that the variables that each contains are compared to each other. The reason is that in the previous form (before normalization), the nitinol experimental data contains measures that are not unique. This problem needs to be tackled before applying the EDAS method. At this computation stage, anything pointing to the right is positive and regarded as the positive distance from the average. Also, anything pointing towards the left is negative and taken as the negative distance from the average.

Table 6. Average Normalized Values

S/N	SP_i	SN_i	NSP_i	NSN_i	AS_i	Rank
1	0.0488	0.4980	0.0986	0.0000	0.0493	16
2	0.0163	0.3420	0.0329	0.3133	0.1731	14
3	0.0780	0.2803	0.1578	0.4372	0.2975	13
4	0.2340	0.3128	0.4734	0.3720	0.4227	11
5	0.0843	0.1180	0.1705	0.7631	0.4668	9
6	0.2528	0.0980	0.5114	0.8032	0.6573	4
7	0.0100	0.3408	0.0202	0.3158	0.1680	15
8	0.0300	0.1723	0.0607	0.6541	0.3574	12
9	0.2920	0.0463	0.5908	0.9071	0.7490	3
10	0.1560	0.0588	0.3156	0.8820	0.5988	6
11	0.1468	0.0680	0.2969	0.8635	0.5802	7
12	0.1343	0.2040	0.2716	0.5904	0.4310	10
13	0.2640	0.1468	0.5341	0.7053	0.6197	5
14	0.2640	0.2303	0.5341	0.5377	0.5359	8
15	0.4943	0.0000	1.0000	1.0000	1.0000	1
16	0.4108	0.0000	0.8311	1.0000	0.91553	2

Table 7. S/N ratio values of EDAS-T method

S/N	Current	Pulse on time	Pulse off time	Powder concentration	AS_i	SNRA1
1	1	30	10	0.25	0.04932	26.1395
2	1	40	40	0.50	0.17307	15.2356
3	1	50	18	0.75	0.29753	10.5294
4	1	60	22	1.00	0.42272	7.4789
5	2	30	40	0.75	0.46676	6.6181
6	2	40	10	1.00	0.65730	3.6447
7	2	50	22	0.25	0.16800	15.4938
8	2	60	18	0.50	0.35741	8.9367
9	3	30	18	1.00	0.74896	2.5108
10	3	40	22	0.75	0.59883	4.4539
11	3	50	10	0.50	0.58018	4.7287
12	3	60	40	0.25	0.43099	7.3107
13	4	30	22	0.50	0.61973	4.1559
14	4	40	18	0.25	0.53590	5.4183
15	4	50	40	1.00	1.00000	0.0000
16	4	60	10	0.75	0.91553	0.7665

In Table 6, the AS_i values are of substantial interest to the investigators as they serve as the basis for the ranking. Here the highest value is obtained as 1, linked to experimental trial 15. The other experimental trials are ranked next as experimental trials 16 and 9 hold the second and third positions, respectively. However, the last position in the ranking was experimental trial 1, with an AS_i value of 0.04932. However, from the results of the 1st rank, which is the experimental trial 15, the initial table containing the experimental values is read with the experimental trial attributed to the highest performance. The corresponding values of the parameters are interpreted as a current of 4A, pulse on time of 50 µs, pulse off-time of 14 µs, and a powder concentration of 1g/L is found to be the optimum combination. This is the result obtained by the EDAS method. However, the next phase of the work introduces a new method that combines the EDAS method with the Taguchi method as EDAS-(T)aguchi method or EDAS-T method.

To obtain the results of the EDAS-T method, the point of coupling is the union of the sixteen experimental trials outcome of AS_i, and the orthogonal array transformed values (i.e., 30 for level 1 under pulse on time) and the signal-to-noise criterion of smaller the better, Equation (4). Hence, the number of factors is four, and the number of levels is 4. Thus, an L_{16} orthogonal array proposed by the authors of the referenced article is adopted in this work. Table 7 shows the results of applying Equation (4).

To illustrate the details of Table 7, consider row 2 with the values of 1A, 30 µs, 10 µs 0.25g/L as the current, pulse on time, pulse off time, powder concentration, respectively. The corresponding signal-to-noise ratio is computed by taking the y_i (i = 1, 2, 3, 4) as y_1 = 1A, y_2 = 30 µs, y_3 = 10 µs, and y_4 = 0.25g/L.

Then y_i^2 is obtained for each factor and then summed up. Afterward, the number log is obtained, and the results are multiplied by -10 to yield 26.1395. The procedure is repeated for all the sixteen experimental trials to obtain all

Table 8. Response table for EDAS-Taguchi

Level	Current	Pulse on time	Pulse off time	Powder concentration
1	14.84	9.86	8.82	13.59
2	8.67	7.19	6.85*	8.26
3	4.75	7.69	7.90	5.59
4	2.59*	6.12*	7.29	3.41*
Delta	12.26	3.73	1.97	10.18
Rank	1	3	4	2

values for SNRA1, which is the signal-to-noise ratio. The least and highest values of the SNRA1 are 0 and 26.1395, respectively. Based on the SN ratio values combined EDAS and Taguchi method, the response table is obtained by taking the averages of the SN values. To understand how these averages of SN ratios are computed, a framework of four columns of factors and an additional column of levels is created, as shown in Table 8. Table 8 is the response table that allows the researcher to visualize how the signal-to-noise ratios come out for each of the generated experimental trials in the group of sixteen experimental trials. Although a single criterion of the signal-to-noise ratio, which is smaller the better, is deployed as the representative criterion for the signal-to-noise ratios, in other situations, it may be a combination of the criteria of smaller the better, larger the better, and nominal the best. However, the main purpose of the response table is to evaluate the influence of the signal-to-noise ratios on the outcome by establishing the difference obtained between the highest of the averages of the signal-to-noise ratios based on the orthogonal array features displayed for each experimental trial and the lowest of the averages. This is denoted by the delta values from which ranks are determined. The ranks are shown in a response table to assist the researcher in establishing which parameters out of the principal ones are considered to exhibit the largest influence. The parameters of interest are current, pulse on time, pulse off time, and powder concentration.

In this Table 8, the intersection of the level 1 and current yields 14.846. But how was this value obtained? Revisit Table 7 to identify all level 1 under current and their associated signal to noise ratios. These added all the 26.1395, 15.2356, 10.5294, and 7.4789 and obtained an average of 14.846. Still, on the parameter, current, level 2 is repeated four times, and the associated values are 6.6181, 3.6447, 15.4938, and 8.9367, and the average is obtained as 8.673. The procedure is followed, and all the entries under levels 1 to 4 for all the factors are calculated. But the smaller the better option is preferred. Thus, for each factor, the smallest value is identified and marked, 2.585, 6.123, 6.849, and 3.409, respectively, for current, pulse on time, pulse off time, and powder concentration, respectively. These points are the optimal values of each parameter to define the optimum parametric setting as $C_4POT_4POFT_2PC_4$, which symbolizes current, POT is for a pulse on time, POFT represents pulse off time, and PC symbolizes powder concentration.

The resulting stage is to rank these factors by examining the difference between the highest and the lowest for each factor, obtained as 12.261 for current. Therefore, the ranks are awarded as current, powder concentration, pulse on time, and pulse off time as 1st, 2nd, 3^{rd,} and 4th positions, respectively. Furthermore, from the optimal parametric setting, the EDAS-T yielded values, which were interpreted from the marked values as a current of 4A, pulse on time of 60 µs, pulse off time of 14 µs, and powder concentration 1g/L. The following observation is made to compare the results of the EDAS method with the EDAS-T method. The current in both methods is the same. The pulse on time for the EDAS method is lower than the EDAS-T method by 10 µs. It means that the Taguchi optimization method has revealed the true value of the pulse on the time parameter. However, the pulse off time and the powder concentration remain the same.

From this point, the results of the EDAS (T)aguchi (P)areto method are discussed. This is the principal method proposed in the present article as it has features not previously discussed in the literature. The special feature of the EDAS-TP method is its ability to recognize the most important parameters and eliminate non-contributory factors to the goals of the process. The variance analysis obtained from the analysis of variance method provided the guide by indicating the variance of the factors from the mean, where those factors with huge variance are the main focus of attention. Furthermore, from the results of the response table obtained from the EDAS-Taguchi method, variance computations are analyzed to eliminate irrelevant factors in the presented table. The Taguchi-Pareto follows the 80-20 rule, which states that 80% of the final results are obtained from 20% of the reasons. Tables 9(a) and (b) show the results of the variance analysis of the wire EDM process parameters in the utilization of Nitinol using the EDAS-Taguchi-Pareto method.

The ANOVA method has been established in the engineering literature as a discriminatory tool. It could reveal variances of factors to separate the most sensitive to the least sensitive factor to changes in the expected behaviors of the factors. These behaviors are reflected in Table 9a, which reveals the variance analysis. This variance analysis, which is contained in the last column of Table 9a, is used to establish the causes of variation at both the level domain (i.e., 8.3812, 0.7479, 2.4141, and 4.9286 for levels 1 to 4, respectively, and also for the factors. These are given as 28.9570, 2.4656, 0.7278, and 19.2925 for factors current, pulse on time, pulse off time, and powder concentration, respectively of interest are the variations of the parameters from the experimental values. The variance values aid in gaining insight into why

Table 9a. Variance analysis (ANOVA) using the EDAS-Taguchi Pareto method

Summary	Count	Sum	Average	Variance
Level 1	4	47.1130	11.7783	8.3812
Level 2	4	30.9740	7.7435	0.7479
Level 3	4	25.9270	6.4818	2.4141
Level 4	4	19.4080	4.8520	4.9286
Current	4	30.8550	7.7138	28.9570
Pulse on time	4	30.8550	7.7138	2.4656
Pulse off time	4	30.8560	7.7140	0.7278
Powder concentration	4	30.8560	7.7140	19.2925

Table 9b. Source of variation (ANOVA) using EDAS-Taguchi Pareto method

Source of Variation	*SS*	*df*	*MS*	*F*	*p-value*	*F crit*
Levels	104.914	3	34.9713	6.36935	0.01321	3.86255
Factors	2.5E-07	3	8.3E-08	1.5E-08	1	3.86255
Error	49.415	9	5.49056			
Total	154.329	15				

Table 10. Revised response table indicating EDAS-Taguchi-Pareto results

Level	Current	Powder concentration
1	14.846*	13.591*
2	8.673	8.264
3	4.751	5.592
4	2.585	3.409
Delta	12.261	10.182
Rank	1	2

*Optimal parametric setting

instability occurs and what could be initiated to lessen the undesirable variance. Thus, an improved resource planning activity according to the parametric allocations will be achieved.

Consequently, in this article, variance is used to observe how individual parameters of the wire EDM process associate with each other for the provided experiment using the EDAS-Taguchi Pareto method. This article leverages the benefit of the variance mechanism by treating all deviations from the means as being equal by ignoring their directions. However, Table 9b reveals the source of variations, which may broadly be classified as misclassification, random error, measurement error, or systematic error.

In this Table 9a, the values in the last column represent the variance of the factors, notably 28.957, 2.4656, 0.72784, and 19.2925 for the parameters current, pulse on time, pulse off time, and powder concentration are of interest in identifying the importance of the factors. As these numbers need to be converted into percentages, values of 56, 5, 1, and 38 for the current, pulse on time, pulse on time, and powder concentration, respectively. By rearranging these values in order of decreasing importance, current with 56% holds the 1st position, followed by the powder concentration that holds the second position (38%), then the pulse on time (5%) and pulse off time that holds the third and fourth positions, respectively. Applying the Pareto principle with the cut-off at 80% makes it unrealistic to hold only a parameter in the revised response table obtained from the signal-to-noise ratio. Thus, including a second parameter with a substantial value of 38% brings the two parameters captured to 94%. This value of 94% is closer to 80% than 56% and therefore held for the analysis involving the EDAS-Taguchi-Pareto. To proceed with the calculation, the original table of the EDAS-T method containing the S/N ratios is visited (Table 7). From Table 7, the revised response table is termed the "Revised response table indicating EDAS-Taguchi-Pareto results". With this revision, the parameters pulse on time and pulse off time are omitted from the revised table (Table 10). However, note that Table 10 results from implementing the steps in section 3.3. This is meant to accomplish the EDAS-Taguchi-Pareto methodical application in solving the problem. To advance, the value at the intersection of level 1 and current (Table 10) needs to be evaluated from Table 7. The value is obtained by adding 26.1395, 15.2356, 10.5294, and 7.4789 to obtain 14.8459. Other values are obtained as 8.673325, 4.751025, and 2.585175 for levels 2, 3, and 4 of the current parameter. Table 9b shows the source of variations.

Table 7 shows the signal-to-noise ratio values of the EDAS-T method, which evaluates the anticipated and the undesired signals from the data and establishes a ratio between them. It was introduced into industrial engineering and statistical computations by Taguchi on the understanding that similar to data transmission behaviors in analog and digital communications, measurements outside this domain, including imaging processes, are exposed to the fundamental principle of containing both desired and undesired signals. At the same time, noise is acceptable in measurements. A

Table 11. Rearranged S/N ratio values of EDAS-T method according to descending order

S/N	Current	Pulse on time	Pulse off time	Powder concentration	AS_i	SNRA1	Cumulative % SNRA1
1	1	30	10	0.25	0.04932	26.1395	21.18
7	2	50	22	0.25	0.16800	15.4938	33.73
2	1	40	40	0.50	0.17307	15.2356	46.08
3	1	50	18	0.75	0.29753	10.5294	54.61
8	2	60	18	0.50	0.35741	8.9367	61.85
4	1	60	22	1.00	0.42272	7.4789	67.91
12	3	60	40	0.25	0.43099	7.3107	73.83
5	2	30	40	0.75	0.46676	6.6181	79.19*
14	4	40	18	0.25	0.53590	5.4183	83.58
11	3	50	10	0.50	0.58018	4.7287	87.42
10	3	40	22	0.75	0.59883	4.4539	91.02
13	4	30	22	0.50	0.61973	4.1559	94.39
6	2	40	10	1.00	0.65730	3.6447	97.34
9	3	30	18	1.00	0.74896	2.5108	99.38
16	4	60	10	0.75	0.91553	0.7665	100.00
15	4	50	40	1.00	1.00000	0.0000	100.00

*Cut off point due to Pareto analysis of 80-20 rule where 79.19% is approximated as 80%

Table 12. Pareto-centred rearranged S/N ratio values of EDAS-TP method according to descending order

S/N	Current	Pulse on time	Pulse off time	Powder concentration	AS_i	SNRA1	Cumulative % SNRA1
1	1	1	1	1	0.04932	26.1395	21.18
7	1	2	2	2	0.16800	15.4938	33.73
2	1	3	3	3	0.17307	15.2356	46.08
3	1	4	4	4	0.29753	10.5294	54.61
8	2	1	2	3	0.35741	8.9367	61.85
4	2	2	1	4	0.42272	7.4789	67.91
12	2	3	4	1	0.43099	7.3107	73.83
5	2	4	3	2	0.46676	6.6181	79.19*

threshold of 20 to 28db has been set as a good range of the signal to noise in some aspects of communication engineering. Although most works in machining ignore this fact, possibly these values or some other values may be standards to compare the performance of any system. From Table 10, the parametric setting of the process could be established as $C_1PC_{1,}$ which is interpreted as the current of 1A and powder concentration of 0.25g/L. This is the result for the first method of EDAS-Taguchi-Pareto with variance considered. The second method entails rearranging the signal-to-noise ratios in descending order of magnitude. Thus Table 7 is rearranged as Table 11 to produce the cut-off mark of 80%, matching the Pareto rule.

By implementing the Pareto 80-20 rule, only 50% of the total number of experimental trials fits the revised response table. These experimental numbers arranged in order of importance are 1,7, 2, 3, 8,4,12, and 5. But to construct the revised response table based on this method, there is a need to extract the original orthogonal array from the Minitab 18 software, which was used to interpret only the eight experimental trials 1,7, 2, 3,8, 4, 12, and 5. (Table 12). The purpose of using the orthogonal array is to be able to connect each parameter to the signal-to-noise ratio through the levels generated by the Minitab 18 software. Thus a new table (Table 13) is created with four parameters and four levels to allow obtaining the averages of the signal to noise ratio to put into the response table. In Table 13, the first cell is the intersection of the current column with level 1. To obtain the value to be placed here, Table 12 is revisited to know the average signal-to-noise ratio of all the entries on level 1 and for the current parameter. This is read from the second column tagged "current" and is attached to experimental trials 1,7, 2, and 3 since the level for all these trials is 1. The corresponding SN ratios are 21.18, 33.73, 46.08, and 54.61, respectively, while the average is 38.90. For level 2 under current, experimental trials 8, 4,12, and 5 are associated with it, and the corresponding SN ratios to be averaged are 61.85, 67.91, 73.83, and 79.19. The average of these SN ratios is 70.70.

This is to be placed at the intersection of level 2 and current. However, there are no values representing levels 3 and 4, while dashes are used to represent them. The next phase is to compute for level 1 under pulse on time. Here, only two experimental trials are involved, namely, trials 1 and 8. Their average based on the signal-to-noise ratio is 41.52. For level 2 under pulse on time, the average signal-to-noise ratio is 50.82. For levels 3 and 4 under pulse on time, the averages of the SN ratios are 59.96 and 66.90, respectively. For pulse off time, the averages for the SN ratios for levels 1, 2, 3, and 4 are 44.55, 47.79, 62.64, and 64.22, respectively. For powder concentration, the averages of the SN ratios for levels 1, 2, 3, and 4 are 47.51,

Table 13. Response table for EDAS-TP method using Pareto-centred rearranged S/N ratio values in a descending order

Level	Current	Pulse on time	Pulse off time	Powder concentration
1	38.90	41.52	44.55	47.51
2	70.70*	50.82	47.79	56.46
3	-	59.96	62.64	53.97
4	-	66.90*	64.22*	61.26*
Delta	31.8	25.38	19.67	13.75
Rank	1	2	3	4

*Optimal parametric setting

Table 14. Response table for Taguchi method based on Chaudhari et al. (2021a)

Level	Current	Pulse on time	Pulse off time	Powder concentration
1	-31.5369*	-33.7474*	-33.2712*	-33.8370
2	-33.2916	-33.8388	-33.6840	-34.0766*
3	-34.8279	-34.0815	-34.1711	-33.9984
4	-36.1730	-34.1617	-34.7031	-33.9175

*Optimal parametric setting

56.46, 53.97, and 61.26, respectively. From Table 13, the optimal parametric setting is $C_2POT_4POFT_4PC_4$, a current of 2A, pulse on time of 50ms, pulse off time of 18ms, and powder concentration of 1g/L.

Now, it is essential to discuss the novelty of this research. Interestingly, recent studies revealed that the subjects that dominate the research area are largely at variance with the selection and optimization of process parameters of wire EDM process while using Nitinol. An important aspect of contributions in this area seems to have researchers focusing on powder mixtures for the electrodes where carbon nanotube particles are mixed with other fluids to improve the EDM process's performance. The surface integrity of nitinol materials is another essential aspect of research. This aspect has two phases. The first phase emphasizes enhancing the surface integrity of Nitinol by introducing Nitinol at the finish trim cut to reduce the surface roughness and produce a thinner white layer than the main cut (Liu et al., 2018). The second phase of the research project details the machined surfaces by exploring parameters such as the recast layer thickness, maximum peak-to-valley height, surface crack density, and the average peak-to-valley height (Roy and Mandal, 2019).

But given a set of process parameters to machine nitinol using the wire EDM technology, there is no guideline to identify the differences in the strengths and importance of the process parameters considered. There is also no mechanism to reject certain parameters as unimportant to the goals of the wire EDM process to focus on those that drive the system's performance. Also, the attribute of concurrent optimization of these parameters and selection for prudent distribution of resources has not been innovatively studied. Consider Liu et al. (2018) reported a key finding that the finish trim cut nitinol specimens showed substantially enhanced fatigue life that exceeds the main cut nitinol specimens by 48% fatigue life quantification. While the result is useful, there is no clear information on the eleven parameters' contributions to the system, as stated in Table 2 of the article. Some of these parameters are the intensity of power, open-circuit voltage, wire traveling speed, and liquid quantity. Which of these parameters contribute topmost to enhancing the surface integrity of the nitinol samples in fatigue life estimations? Then, are these parameters in their optimized states before selection? These questions may not be answered with the present knowledge of the nitinol and wire EDM process literature. As a second example to reveal the weakness of the existing literature, consider Roy and Mandal (2019). The study's principal findings are that all the process parameters, such as the gap voltage, duty factor, and flow rate, are important for all the responses.

Furthermore, an increase in the cutting rate was reported with the duty factor to reach 0.85 but afterward reduced with the duty factor. From these outcomes, an interesting question is how do we concurrently optimize and select these parameters? This question may not be answered since there is an absence of a mechanism to respond to it in the literature.

Thus, the issues of establishing the strengths and importance of parameters, eliminating unimportant parameters, and simultaneously optimizing and selecting parameters during the wire EDM process of Nitinol are fundamentally different from those proposed by earlier researchers and are treated in this study. These issues are innovative, and the proposed solution concerning using the EDAS-Taguchi-Pareto as a principal method in this article is fundamentally different from what researchers and practitioners already know.

Thus, from the above discussion, the concentration of efforts of researchers is outside the selection and optimization domains for the wire EDM process while using Nitinol in recent studies, therefore, justifies the need for this study. Therefore, this study has a new direction for selecting and optimizing wire EDM process parameters, which can overcome the gaps created by other studies already published in the literature. Furthermore, researchers need to explain details about multi-criteria methods such as the EDAS method for selection purposes. Also, details of the Taguchi method and the Taguchi Pareto method, which is a variant of the Taguchi method, need to explain in the literature. There is a need to establish new knowledge based on relevant and new multi-criteria methods on the subject of the selection of parameters for the wire EDM process. To the authors' knowledge, the selection and optimization of wire EDM process parameters are significant subjects that have been downplayed. Hence, there is a need to introduce the EDAS method, a relatively new multi-criteria approach. Also, there is a need to use the Taguchi method and a new variant, the Taguchi-Pareto method, as optimization methods. Thus, this study attempts to amalgamate the EDAS method and Taguchi method/Taguchi-Pareto method to close the existing literature gap.

4.2. Comparison of current methods with the Taguchi method

As far as the authors are aware, few studies have explored the wire EDM parametric selection problem in the context of nitinol material analysis. However, despite the paucity of reports in this arena, the authors decided to illustrate the superiority of the coupled EDAS-Taguchi-Pareto method over the Taguchi method obtained using the same case study. In particular, the optimal parametric settings of the EDAS-TP method and the Taguchi method have been compared to validate the essential task of process optimality determination. Then the differences in the dimensions of each factor were established and commented upon to verify the superiority of introducing the EDAS component of the method.

From the analysis, the optimal parametric setting based on the Taguchi method (Table 14), which was not calculated in Chaudhari et al. (2021a), is the optimal current of 1A, pulse on time of 30 µs, pulse off time of 10 µs and powder concentration is 0.50g/L. However, when the EDAS-Taguchi method was used, the method improved the solution as follows. The effective current improved by 3A, pulse on-time increased by 30 µs, pulse off time also increased by 0.5g/L. Besides, on the application of the EDAS-Taguchi-Pareto method, the effective current improved by 2A over the Taguchi method, pulse on time increased by 30 µs. At the same time, no account was given for pulse off time, indicating that it retains the value of 10 µs while 0.25g/L enhances the powder concentration. The EDAS-Taguchi method seems to exceed the other performance methods from these results.

4.3. Advantages of the proposed methods

The EDAS-Taguchi method and EDAS-Taguchi-Pareto method seem to enhance the selection and optimization objectives substantially; this is an attainment that establishes the need and effectiveness of introducing both EDAS and Pareto analysis into the original Taguchi scheme. Moreover, compared with the Taguchi method, the EDAS component of the EDAS-Taguchi method introduces high efficiency into the computation but triggers comparatively fewer computational procedures compared with other multi-criteria methods such as the PROMETHEE method and the data envelopment analysis (DEA) method (He et al., 2019). An additional advantage of introducing the EDAS method in the EDAS-Taguchi method is that the superior option is evaluated from the viewpoint of the distances from the averages, which does not constrain the decision-maker to establish the ideal solution (Keshavarz-Ghorabaee et al., 2015).

From the foregoing, bearing in mind that one of the methods introduced is the EDAS-Taguchi-Pareto method, apart from the enumerated benefit introduced by the EDAS method into the EDAS-Taguchi-Pareto method, the advantages of the Pareto scheme is also introduced into the framework. Thus, the Pareto analysis assists in establishing and ascertaining the biggest influential factors while eliminating the less influential factors, permitting the concentration of process parametric resources on parameters that matter most in the attainment of the process objectives. Thus, compared with the Taguchi method alone, the EDAS-Taguchi-Pareto method attains further enhancements of the Taguchi method in computational efficiency and streamlines parameters to the most important ones.

5. CONCLUSION

Shape memory alloys obtain their name, smart alloys, because of the unique capability that it demonstrates to retrace their path to the original form. It is believed that only smart materials could achieve such a goal. However, multi-criteria and Taguchi optimization methods were developed to select and optimize some wire-electrical discharge parameters such as current, pulse on time, pulse off time, and powder concentration. These are the EDAS method, combined EDAS method, Taguchi method, joint EDAS method, and Taguchi-Pareto method. Furthermore, choosing the best parameter for the wire electrical discharge machining process is often challenging for the process engineer regarding the machining of nitinol smart material. To tackle this problem, an EDAS, joint EDAS-Taguchi, and combined EDAS-Taguchi-Pareto methods were introduced to establish the best and optimal settings for the various levels of process parameters for the WEDM process with nitinol smart material as the working material for the machining process. Arising from a deep study, it could be ascertained that the proposed method showed competence in establishing superior settings for the input parameters for the WEDM process.

Consequently, it could be concluded that the EDAS, EDAS-Taguchi, and EDAS-Taguchi-Pareto methods, which are straightforward, could be effectively used to establish the best parameter and optimal combination of parameters for the WEDM process. With this framework introduced to the process engineer, it is possible to establish a superior blend of parametric values for the WEDM process while ignoring dependence on the manufacturer's handbook or operator experience in machining. Since our claims stem from the parametric analyses deployed in other researchers' works, there are opportunities to implement the essential validation experiments. Looking into future research, it may be exciting to merge the EDAS method with other performance-enhancing methods such as the quality control charts and even other optimization methods such as genetic algorithm and particle swarm optimization.

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