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Techniques Used for Process Optimization of Wire Electrical Discharge Machining: A Review †

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Abstract: With the rapidly progressing world in the field of manufacturing, non-conventional machining still requires numerous advances. The requirement of machining a material with a Brinell hardness greater than 200 BHN with utmost precision and intricate geometric features is catered, to some extent, by Wire Electric Discharge Machining (WEDM). WEDM is a non-conventional electro-thermal contactless machining process in which the cutting operation involves a thin strand of metallic wire with a pulsating current flowing through to create a spark between the workpiece and wire. The complexity of this operation demands countless input parameters to be optimized to produce the best possible results. Various techniques have been used by researchers for this purpose. This paper reviews five such techniques of optimization including the Taguchi technique, Design of Experiments (DOE), Response Surface Methodology (RSM), the Genetic Algorithm (GA) and a combination of different techniques. Furthermore, an analysis is provided for the best three approaches for each technique. This paper also discusses an in-depth knowledge of the applications of these techniques along with the process flow diagram to summarize the process.

Keywords: Design of Experiments; multi-linear regression; Response Surface Methodology; Taguchi technique; wire electrical discharge machining

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1. Introduction

In the intricate landscape of modern machining, Wire Electrical Discharge Machining (WEDM) has etched its significance as a versatile and precise method for shaping conductive materials. At the heart of achieving exceptional results in WEDM lies the optimization of machining parameters [1]. The non-contact subtractive cutting process uses a thin strand of wire with a pulsating current flowing through to erode through the workpiece material. This erosion happens due to the thermal energy of sparks produced by the intense electric field between the wire and the workpiece [2]. A cooling and control function is provided by the dielectric fluid which is constantly being showered [3]. This review paper embarks on a comprehensive exploration of the diverse spectrum of optimization techniques tailored for enhancing WEDM processes [4] by meticulously dissecting the array of methodologies ranging from classical DOE to Taguchi DOE [5].

2. Literature Study

As industries seek to push the boundaries of material machining, the amalgamation of various techniques not only shapes the present but also propels the trajectory of future advancements in the pursuit of manufacturing excellence. All such techniques are studied below for a better overview of their functioning [6].

2.1. The Taguchi Technique of Optimization

The Taguchi technique is an optimization technique based on the fundamentals of reducing variability in a process to make it robust. A robust mechanism damps the unnecessary variation from the input and gives a continuous, steady, and stable output. To find the best settings, the Taguchi technique entails planning a series of experiments in which the input parameters are varied, monitoring the output reaction, and doing statistical analysis [7]. This optimization technique uses the controllable independent parameters, uncontrollable noise parameters and resulting dependent parameters [8]. This approach starts with selecting a suitable customized Orthogonal Array (OA) for the required problem from the pre-defined Oas [9]. Secondly, the Signal-to-Noise ratio (S/N) is selected and calculated for the data [10].

The S/N ratio helps us determine the optimum parameters. The next step is the validation studies, where you can validate or verify the results from a confirmation experiment [11]. The process flow diagram of the Taguchi technique is shown in Figure 1.

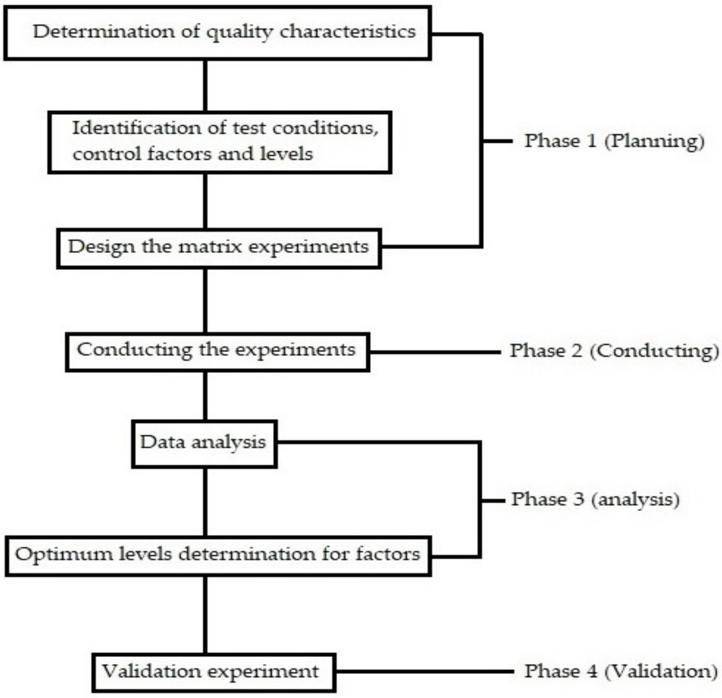

Figure 1. Process flow diagram of the Taguchi technique.

Mohammad Fakkir [12] optimized different parameters of WEDM using this approach. The objective of the research was to optimize three parameters using the L9 OA with a molybdenum wire of 0.2 mm diameter. They found the factors which gave the maximum surface finish. Ajay Kumar et al. [13] also used the same technique on the parametric optimization of D2 Steel. This experiment was a detailed experiment featuring four independent variables and l16 OA. This research was validated from the results in the Analysis of Variance (ANOVA) table. Their findings concluded that the material removal rate (MRR) was most influenced by the current and the gap voltage, whereas wire speed and flushing pressure affected surface roughness the most. Another comprehensive study to optimize the material removal rate (MRR), the Kerf width and surface roughness was carried out by Adeel Akram et al. [14]. It was performed on D2 Steel with L18 OA. ANOVA and S/N ratio calculations were used for data analysis. Furthermore, they also performed a multi-linear regression analysis to generate the regression equation to use it for prediction purposes in a confirmatory experiment. Puri [15] enquired about the issues concerning the variability in wire tension. The Taguchi technique was also used by Marafona [16] to devise a new algorithm for optimization using a copper–tungsten electrode.

The Taguchi technique tops the list with countless advantages. Not only is it easy to grasp but it also reduces the experimental cost, providing precise results due to the fractional factorial Taguchi Orthogonal Array design.

2.2. Response Surface Methodology

Response Surface Methodology (RSM) is an empirical resulting overlap between statistical and mathematical approaches for efficiently developing a solution for a problem with numerous controllable independent parameters. RSM is a pragmatic and easy method. The first step in this approach is finding the relationship equations between the controllable independent variables, uncontrollable noise variables, and uncontrollable dependent variables. Equation (1) will give a better estimation of a first-order relationship equation [17].

$$Y = \left(A x_1^{b1} x_2^{b2} x_3^{b3} x_4^{b5} \ldots\ldots\ldots\ldots x_n^{bn} \right) \quad (1)$$

Y represents the uncontrollable dependent variables, x is the controllable independent variable and A and b are constants that can also be called noise accommodation factors. This equation can be further simplified for a better understanding. This equation transforms to Equation (2) for the first-order model [17].

$$Y = (A_0 x_0 + A_1 x_1 + A_2 x_2 + \ldots\ldots\ldots\ldots + A_n x_n) \quad (2)$$

Here, Y is plotted on an algorithmic scale, A are the constants but now we will use the least square method to estimate them. As the degree of freedom increases, the equations transform into their complex forms [18].

RSM follows a step-by-step approach detailed in Figure 2. A process flow diagram for RSM is given below [19]. Researchers have used this technique for optimization in countless fields including non-traditional machining. One such research was carried out by Neeraj Sharma et al. [20]. The study was caried out on high-speed low-alloy steel (HLSA) with the aim of finding the relationship between cutting speed and dimensional deviation for WEDM on HLSA. The key findings concluded with the development of the most crucial parameter that is the pulse-on time and its two factor interactions. In addition, another study by Ashish Chaudary et al. [21] proposed the optimization of heat-treated ASSAB 88 tool steel. It was a comprehensive study featuring RSM with a full factorial design and a multi-linear regression analysis for validation studies. A total of seven optimal solutions were plotted out of 117 points. The final solution was then predicted from the seven solutions. Furthermore, Prasad [17] also carried out research on empirical modelling and optimization using RSM. Saurav Datta [22] used RSM coupled with the grey-Taguchi technique to develop a mathematical model emphasizing the influence of parameters. All the features were assumed to be unrelated to each other.

2.3. The Genetic Algorithm

The Genetic Algorithm (GA) was first found by John Holland in 1970s. This technique works on the basic biologic evolutionary principle of survival of the fittest. The steps in the optimization process will include the selection of all the parameters followed by the crossover stage, which will produce a new set of points. Now, to categorize the data, we use mutation and calculate the crossover and mutation probabilities [23].

GA is used by default to solve maximization problems. However, GA can be implemented on numerous optimization problems in different supporting software including MATLAB and MINITAB at the top. The complete process flow diagram of GA is shown in Figure 3. Shajan Kuriakose [24] used a very specialized approach called the Non-Dominated Sorting Genetic Algorithm for the multi-parameter optimization of wire EDM. NSGA is used to derive a non-dominated solution set. The importance of the study was the prediction of all the optimal combinations for different objective function values. Mehmet Altug [25] investigated the optimization of differently heat-treated portions of a titanium–aluminum alloy (Ti6Al4V). To study the microstructures and layers, scanning electron microscopy and X-ray diffraction were used. After data collection by various methods, optimization was carried out by the Genetic Algorithm. A fitness function was formed for the respective output to predict the values, which were authenticated by the validation study. Selvam [26] concluded that the voltage and the pulse-off time are the main contributors influencing machining time along with the current, the pulse-on time and the pulse-off time for the surface roughness of Hastelloy C-276. Kuruvila [27] studied dimensional error by the Genetic Algorithm and the Taguchi technique. The mathematical model was developed by a regression equation. A high spark intensity was preferred.

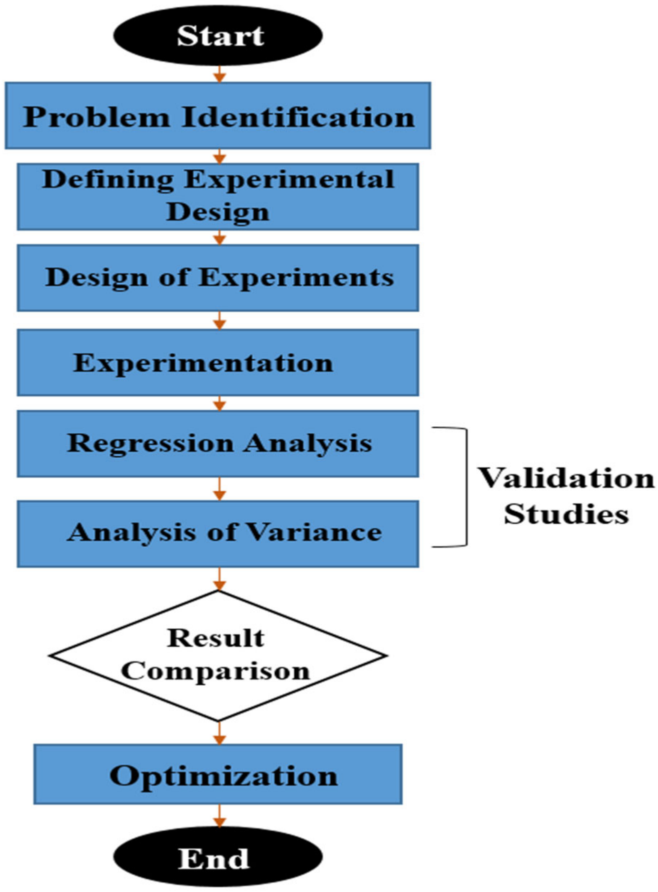

Figure 2. Process flow diagram of RSM.

2.4. Design of Experiments

Design of Experiments (DOE) is a very broad field of study for controlling the variability of a process. However, we will discuss the traditional DOE in this portion. Traditional DOE (TDOE) is a qualitative tool to find, eliminate and stabilize the variation in a process or parameters [28].

The whole process is pictorially represented in the flowchart in Figure 4 [29]. The comprehensiveness and accuracy of the results have made this statistical optimization technique an integral component for precise result-oriented problems. Lingadurai et al. [30] performed a research study to select the optimized WEDM parameters for AISI grade-304 stainless steel using the full factorial DOE technique.

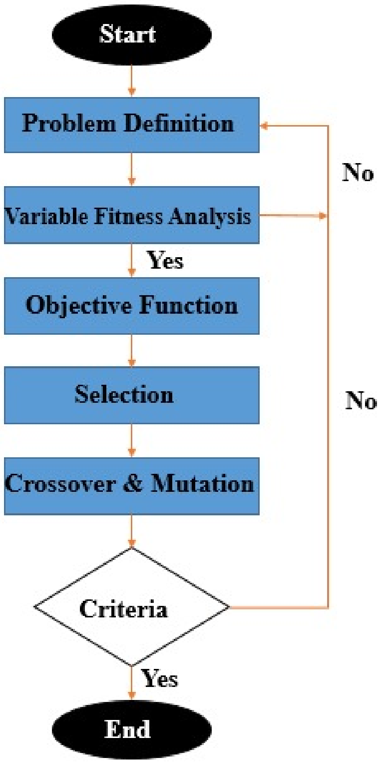

Figure 3. GA flowchart.

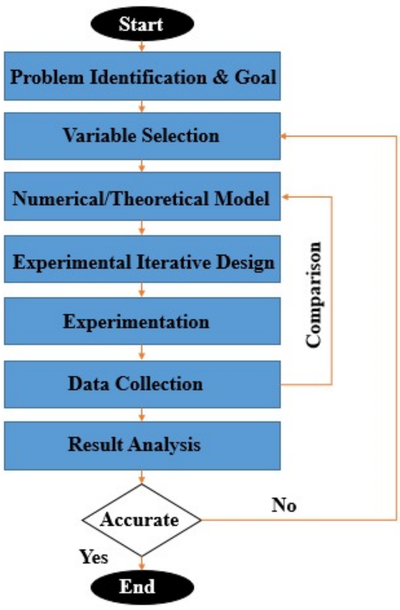

Figure 4. Flowchart of Design of Experiments (DOE).

A range of parameters were optimized including the servo voltage, the pulse-on and -off times and the wire feed rate. The main area of focus for the resulting parameters included the material removal rate (MRR), surface roughness (Ra) and the Kerf width. They accurately predicted that the servo voltage has a major influence on the MRR, the wire feed rate influences Ra and the Kerf width was mainly influenced by the pulse-on time. Esme {U Esme} also carried out research to predict the surface roughness of WEDM using DOE and compared the results with the outputs from neural networks. The impact of a factor from most to least in terms of ranks was calculated by the Analysis of Variance (ANOVA).

2.5. A Combination of Techniques

The dynamics of some of the problems require multiple techniques to be used for various parts. The most common examples for the research using multiple techniques are using the Analysis of Variance (ANOVA) for determining the ranks of the factors from most influential to least influential. In addition, the Taguchi technique, DOE, the Genetic Algorithm and RSM are used for post-process optimization. Finally, regression analysis is utilized for verification of the experiment. Table 1 shows the summary of all the techniques discussed in this paper.

Table 1. Summary of Techniques Used.

S. No	Technique Used	Aim	Results
1	Taguchi Technique of Optimization [12]	Process parameter optimization	Optimum process parameters for minimum Ra predicted
2.	Rank of Impact: ANOVA Optimization Analysis: Taguchi Technique [13]	Process parameter optimization for D2 Steel	Optimum parameters for the material removal rate and Ra were determined
3.	Rank of Impact: ANOVA/SN Ratio Optimization Analysis: Taguchi Technique [14]	Process parameters for Ra, Kerf and the MRR	Factors most affecting Ra, Kerf width and the MRR were accurately predicted
4.	Quantitative Relations: Response Surface Methodology Optimization Technique: Harmony Search Algorithm [17]	Optimization of Kerf and Wire Wear Ratio (WWR)	Pulse-on, pulse-off and wire feed mainly affect the Kerf width and WWR
5.	Experimentation: Central Composite Rotatable Design Optimization: Response Surface Methodology [20]	Modeling and multipurpose optimization of WEDM for HLSA	Dimensional deviation and cutting speed were accurately predicted and relations between process parameters were also determined
6.	Experimentation: Central Composite Full Factorial Design Optimization: Response Surface Methodology [21]	Process parameter optimization for heat-treated ASSAB 88 steel	In the untreated sample, the MRR decreases; and in the annealed sample, the MRR and Ra increase
7.	Optimization: Non-Dominating Sorting Genetic Algorithm Verification: Multi-Linear Regression Model [24]	WEDM multi-objective optimization	All the optimum data points were compiled in the Pareto chart
8.	Data Gathering: Scanning Electron Microscopy, X-Ray Diffraction Experimentation: Taguchi Test Design Optimization: Genetic Algorithm [25]	Kerf width variance of heat-treated Ti6Al4V	Different results were formulated for different heat-treated process with unique microstructures
9.	Optimization: Design of Experiment Full Factorial design [28]	Optimization of process parameters for beryllium copper alloys	The final results are close to the predicted model values, hence controlling the variance
10.	Optimization: Design of Experiments [30]	Best selection for AISI-304 Stainless Steel process parameters	DOE analysis concluded that the pulse-on time significantly affects the Kerf width and the wire feed rate affects SR, while the input voltage mainly affects the MRR
11.	Optimization: Design of Experiments Comparison: Neural Networks [31]	Prediction model for Ra in WEDM	A neural network can be a very accurate alternative for empirical modeling based on a full factorial design

3. Conclusions

The crux of this study concludes that carrying out an optimization study for WEDM parameters requires not only knowledge of non-conventional machining but also a mathematical and statistical grasp of the techniques included. Most of the major techniques used in this field were covered, but the rapid progression of manufacturing technology always introduces new challenges and develops techniques for these challenges. Table 2 represents some of the advantages and disadvantages of each technique.

Table 2. Technique Comparison.

Optimization Technique	Advantages	Disadvantages	Comparability
Taguchi Technique	Simple and efficient for small- and medium-scale experiments. Robust solution to noise factors and variability. Fractional factorial design makes it economical.	Complex multi-level factor interactions are not possible. Requires multiple iterations for ultra-fine results.	It is the best approach because it is easy to understand, has a fractional design and is economical.
Response Surface Methodology (RSM)	Models non-linearity and multiple factor interaction smoothly.	Assumes specific functions for modeling and requires a lot of sequential data.	It matches closely to the Taguchi technique, but it requires some expertise to understand the modeling.
Genetic Algorithm (GA)	Capable of solving complex and non-linear optimization problems to give diverse solutions.	Complex and lengthy process, making it computationally intensive and an optimized result is not guaranteed as well.	It is not recommended as solution convergence is not guaranteed along with extensive methodology.
Design of Experiments (DOE)	Efficiency in solving complex problems, robust, and explores factor interactions.	Full factorial design requires extensive experimentation, making it expensive. Linearity is also assumed.	It is recommended for very complex problems with no room for error as it involves a full factorial design to perform experiments on each possible combination.

Furthermore, the most widely used technique among them is the Taguchi technique of optimization and experimental design. Further, upon close examination of all the techniques, we found that this technique is also the best in terms of time efficiency, computational power, and budget requirements along with user friendliness and ease of explanation to a non-technical colleague. Response Surface Methodology is similar in this regard. It must also be considered that DOE includes the Taguchi technique in fractional factorial design as DOE is a broad umbrella covering many optimization and analysis techniques involving fractional and full factorial experimental designs governed by the specific requirements of every research.

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