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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 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 pulsating current flowing through to create a spark between 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 Taguchi Technique, Design of Experiments (DOE), Response Surface Methodology (RSM), 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 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 wire and 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. Taguchi Technique of Optimization

Taguchi technique is an optimization technique based on the fundamentals of reducing variability in a process to make it robust. A robust mechanism is such that is 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 techniques uses the controllable independent parameters, uncontrollable noise parameters and the 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, Signal to Noise Ratio (S/N) is selected and calculated for the data [10].

The S/N ratio help us determine the optimum parameters. Next step is the validation studies, 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.

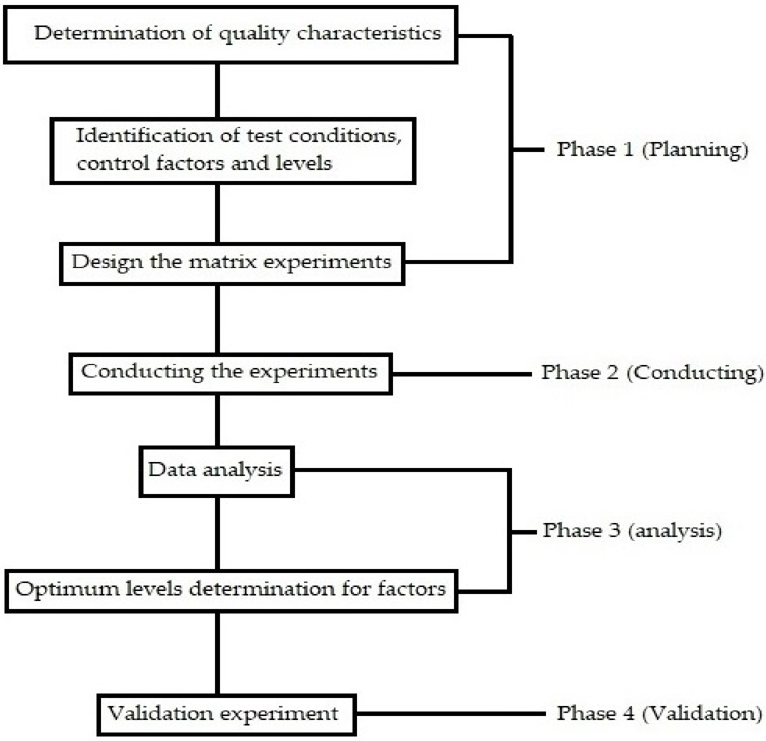

Figure 1. Process flow diagram of Taguchi Technique.

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 from Analysis of Variance (ANOVA) table. Their founding's concluded that Material Removal Rate (MRR) was most influenced by current and gap voltage, whereas wire speed and flushing pressure affected surface roughness the most. Another comprehensive study to optimize material removal rate (MRR), 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 purpose in confirmatory experiment. Puri [15] enquired about the issues concerning with the variability in wire tension. Taguchi Technique was also used by Marafona [16] to devise a new algorithm for optimization using copper-tungsten electrode.

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

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 (4) will give a better estimation of a first order relationship equation [17].

$$Y = \left(Ax_1^{b1}x_2^{b2}x_3^{b3}x_4^{b5} \dots \dots \dots . . x_n^{bn}\right) \tag{4}$$

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

$$Y = \left(A_0x_0 + A_1x_1 + A_2x_2 + \cdots \dots \dots \dots . . + A_nx_n\right) \tag{5}$$

Here Y is plotted on algorithmic scale, A are the constants but now we will use 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 the Figure 2. Process flow diagram for RSM is given below [19]. Researchers have used this technique for the 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 of cutting speed and dimensional deviation for WEDM on HLSA. The key findings concluded with the development of most crucial parameter that is pulse-on time and its two factor interactions. In addition to that, 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 deign and a multi linear regression analysis for validation studies. A total of seven optimal solution were plotted out of 117 points. The final solution was then predicted from the seven solutions. Furthermore, Prasad [17] also carried out research of empirical modelling and optimization using RSM. Saurav Datta [22] used RSM coupled with grey-Taguchi Technique to develop a mathematical model emphasizing on influence of parameters. All the features were assumed to be unrelated with each other.

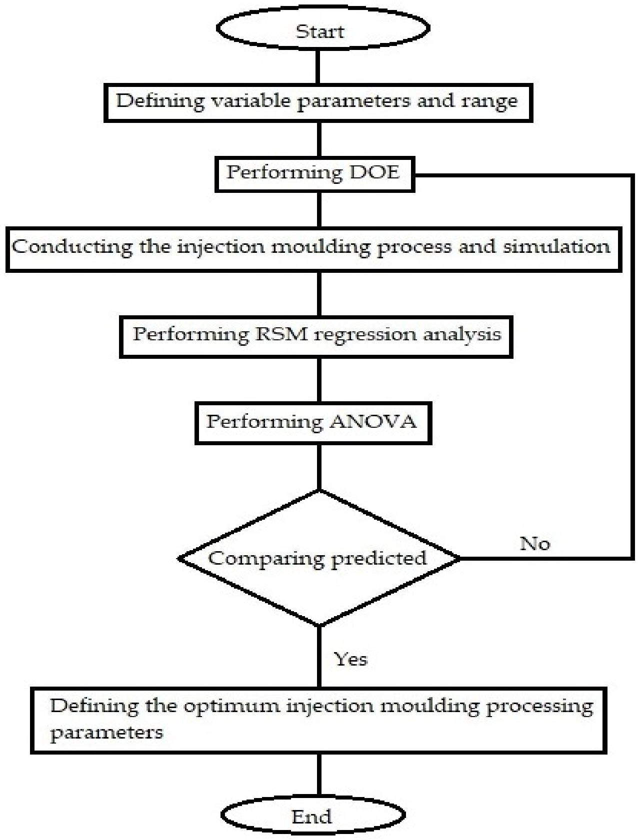

Figure 2. Process flow diagram of RSM [19].

2.3. Genetic Algorithm

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] did an investigating study on the optimization of differently heat-treated portions of titanium-aluminium alloy (Ti6Al4V). To study the microstructures and layers, scanning electron microscope and X-ray diffraction techniques were used. After the data collection by various methods, optimization was carried out by 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 voltage and pulse-off time are the main contributors in influencing machining time along with Current, pulse-on time and pulse-off time for surface roughness of Hastelloy C-276. Kuruvila [27] enquired about dimensional error by Genetic Algorithm and Taguchi Technique. The mathematical model was developed by regression equation. High spark intensity was preferred.

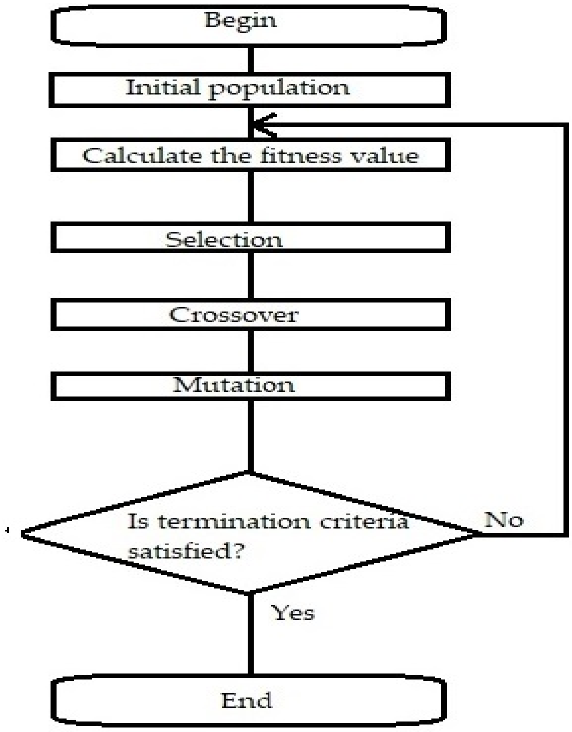

Figure 3. GA flowchart [23].

2.4. Design of Experiment

Design of experiment (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 flow chart 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.

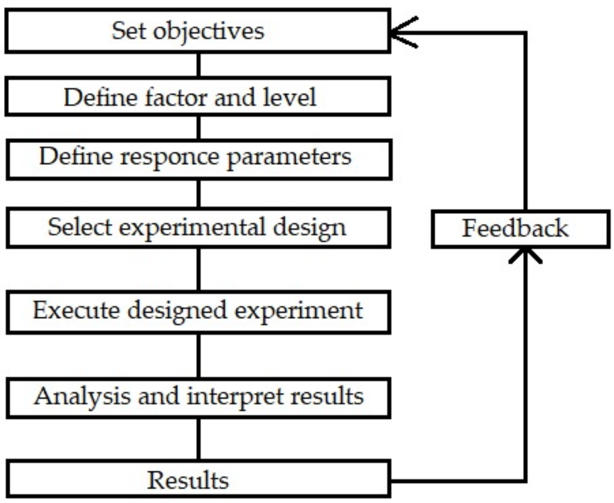

Figure 4. Flowchart of Design of Experiments (DOE) [29].

A range of parameters were optimized including servo voltage, pulse On and OFF time and wire feed rate. The main area of focus for the resulting parameters included material removal rate (MRR), surface roughness (Ra) and kerf width. They accurately predicted that servo voltage has major influence on MRR, wire feed rate influences Ra and Kerf width was mainly influenced by 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 were calculated by analysis of variation (ANOVA).

2.5. 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 to that Taguchi Technique, DOE, 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 the 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 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 MRR	Factors most affecting Ra, kerf and 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 affects 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 relation 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 untreated sample MRR decreases and in annealed sample MRR and Ra increases
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 having unique microstructures
9.	Optimization: Design of Experiment Full Factorial design [28]	Optimization of process parameters for beryllium copper alloys	The final results lie 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 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	Neural network can be a very accurate alternative for the empirical modeling based on full factorial design

3. Conclusions

The crux of this study includes that carrying an optimization study for WEDM parameters require not only the knowledge of non-conventional machining but also the 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 develop techniques for these challenges. Table 2 represents some of the advantages and disadvantages of each technique.

Table 2. Technique Comparison.

S. No	Optimization Technique	Advantages	Disadvantages	Comparability
1.	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 out of all because of easiness to understand, fractional design and economical.
2.	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 Taguchi Technique, but it requires some expertise to understand the modeling.
3.	Genetic Algorithm (GA)	Capable to solve complex and non-linear optimization problems giving diverse solutions.	Complex and lengthy process making it computationally intensive and optimized result is not guaranteed as well.	It is not recommended as the solution convergence is not guaranteed along with the extensive methodology.
4.	Design Of Experiments (DOE)	Efficiency in solving complex problems, robustness, and exploration of factor interactions.	Full factorial design requires extensive experimentation making it expensive. Assumption of linearity is also taken.	It is recommended for the very complex problems with no room for error as it involves the full factorial design to carry experiments on each possible combination.

Furthermore, the most widely used technique among them is the Taguchi technique of optimization and experimental design also upon close examination of all the techniques, we found the best technique to be Taguchi in terms of less time, computational power, and budget requirements along with user friendliness and ease of explanation to a non-technical colleague. In addition to that, Response Surface Methodology RSM also lies close to Taguchi in this regard. It is also a point to ponder that; DOE includes Taguchi technique as well in the section of fractional factorial design. 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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