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Optimization of Electrical Discharge Machining Process by Metaheuristic Algorithms

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ABSTRACT: Because of its versatility and ability to work with difficult materials, Electrical Discharge Machining (EDM) has become an essential tool in many different industries. It can produce precise shapes and intricate details. EDM has transformed fabrication processes in a variety of industries, including aerospace and electronics, medical implants and surgical instruments, and the shaping of small components. Its capacity to machine undercuts and deep cavities with little material removal makes it ideal for producing complex geometries that would be challenging or impossible to accomplish with conventional machining techniques. Several attempts have been carried out to solve the optimization problem involved in the EDM process. This paper emphasizes optimizing the EDM process using three metaheuristic algorithms: Glowworm Swarm Optimization (GSO), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA). The study's outcome showed that the GWO algorithm outperformed the GSO and WOA algorithms in solving the EDM optimization problem and achieved the minimum surface roughness value of 1.7593µm.

Keywords: Electrical Discharge Machining, Surface Roughness, Optimization, Glowworm swarm optimization, Grey wolf optimizer, Whale optimization.

I. INTRODUCTION

A non-traditional machining technique called electrical discharge machining (EDM) uses sparks or electrical discharges to remove material from a workpiece. In manufacturing, EDM has established itself as one of the fundamental non-traditional machining techniques [1, 2]. The term "non-traditional machining" refers to the removal of surplus material utilizing a variety of methods, including electrical, chemical, thermal, and mechanical energy [3]. Electrically conductive materials with high levels of durability and hardness are often machined using the EDM process [1, 4, 5]. Besides, EDM processes are adaptable since they may continue to operate independently for extended periods [2, 6]. Many industries use EDM, including aerospace, medical, electronics, tool and die manufacturing, and energy. It is a highly effective and adaptable machining process necessary for producing a large variety of goods.

EDM is widely used to machine difficult materials. Electrode machining removes material with an electrical charge between electrodes and the workpiece. As a result, EDM presents significant challenges, especially obtaining the optimal surface roughness (Ra). Ra measures surface quality as part of machining performance measurement. An inadequate Ra can result in poor surface finish, dimension inaccuracies, and reduced process efficiency when using non-traditional machining processes [1]. Achieving the optimal Ra value can be challenging due to factors such as tool wear, material properties, and machine tool limitations. Additionally, the optimal Ra value may vary depending on the specific requirements of the application. This makes it necessary to carefully analyse the trade-off between surface finish and other machining performance outcomes. By understanding the relationship between the machining process parameters and Ra, manufacturers can optimize their processes and achieve the desired results [4, 5]. Soft computing techniques such as fuzzy logic, genetic algorithms, and neural networks were used to overcome this challenge. Soft computing allows manufacturers to tackle complex problems related to non-traditional machining processes and achieve high-quality surfaces [1, 6].

In recent years, several researchers have conducted experiments to improve and comprehend the general performance of the machining process using EDM. As a part of soft computing techniques, metaheuristic algorithms were implemented to optimize the EDM process to obtain good results. A metaheuristic is a significant level structure to create a heuristic optimization algorithm. It may provide an adequate solution to an optimization problem because of its efficient searchability [7]. Metaheuristic algorithms enable finding good solutions with less computational effort. It is also easy to implement as it converges fast. Metaheuristic optimization techniques have been applied to EDM parameters, including Glowworm Swarm Optimization (GSO) [1, 8], Grey Wolf Optimizer (GWO) [9, 10], and Whale Optimization Algorithm (WOA) [11, 12].

The natural Glowworm behavior, in which a Glowworm is lured to other Glowworms that are brighter, served as inspiration for the GSO algorithm's working mechanism. Furthermore, GSO was created for numerical optimization problems, including calculating several optimal multimodal functions. Zainal et al. [8] have proposed a model containing GSO to optimize machining parameters. On the other hand, a study by Baisukhan et al. [9] looked at employing GSO to optimize the tungsten inert gas welding process parameters for austenitic stainless steel. The purpose of the paper was to present the parameters and rank them according to significance within a grey wolf optimization framework. Based on the results, it is determined that using austenitic stainless steel, the GSO technique is a solid choice for forecasting the ideal parameters of the tungsten arc welding process.

In 2014, the Grey Wolf Optimizer (GWO) was developed by Mirjalili, and it was inspired by the behavior of grey wolves (Canis lupus) [13]. The leadership structure and method of hunting used by grey wolves in nature are modeled by the Grey Wolf Optimizer algorithm [14, 10]. Kulkarni et al. [10] have presented a paper on process parameter optimization in WEDM by GWO. It studies the effect of process parameters where GWO was used to optimize the thinning in automotive sealing cover. It is discovered that TON has the greatest influence on MRR, and GWO solved the specified problem where MRR is increased by 10% by the GWO.

Mirjalili and Lewis proposed the Whale Optimization Algorithm (WOA) in 2016 [15]. WOA is an optimization algorithm inspired by nature that mimics the social behavior of humpback whales [16]. An article on the analysis of Kerf in WEDM using RSM and WOA was written by Subham et al. [11]. The experiment indicates that using RSM and WOA, the smallest kerf width was achieved at a high current, low wire feed rate, and low flush pressure. Furthermore, die-sinking EDM utilizing FEM and multi-objective optimization using WOA-CS has been the subject of an experimental and thermal examination by Rama et al. [12]. They propose a computational and experimental study of the effects on a Nimonic C-263 workpiece of a die-sinking EDM and a copper-tungsten (Cu-w) electrode tool. The research output stated that the optimal results in terms of relative error. This category of metaheuristic algorithms is used to enhance the algorithm's convergence rate and avoid being trapped in local optima.

II. RELATE WORKS

Recent years have seen researchers employ various metaheuristic algorithms to optimize surface roughness in EDM process. In addition, metaheuristic algorithms such as GSO, Genetic Algorithm (GA), etc. have shown promising results in minimizing surface roughness and maximizing other process characteristics, such as Material Removal Rate (MRR) and Tool Wear Rate (TWR). These studies highlight the potential use of metaheuristic algorithms as efficient and reliable tools for the optimization of EDM processes. Bhowmick et al, in 2023 applied response surface methodology (RSM) and Fuzzy Logic to optimize MRR and Ra of titanium mixed EDM for Inconel 718. In this study, Madani-based fuzzy logic was applied to predict responses in optimized conditions. The RSM desirability function approach was used to minimize surface roughness and maximize MRR. ANOVA shows that powder concentration, pulse current, gap voltage, and pulse on time affect MRR and surface roughness significantly. Using fuzzy results, we found that MRR predicted accurately by 89.21 % and surface roughness predicted by 91.23 %. The optimized input parameters are powder concentration = 8 g/l, pulse current = 9.5 A, gap voltage = 60 V, pulse on time = 150 μs and pulse off time = 20 μs and the corresponding optimum values of MRR and surface roughness are 16.623 mm3/min and 3.71 μm respectively. The SEM result indicates that the width of the surface crack is found more in the optimized sample than the sample having the least surface roughness. Based on the EDX analysis, a very small amount of copper and titanium particles were included on the surface [17].

Singh et al., in 2022 presented a study of optimization of EDM parameters using machine learning algorithm. In this paper, a Genetic algorithm (GA) and a Teacher Learning-Based Optimization (TLBO) will be used to optimize different process inputs in electrical discharge machining of Cu-based shape memory alloys. A study was conducted to examine the variation in machining input parameters along with response parameters. The process input factors considered were pulse on time (Ton), pulse off time (Toff), peak current (Ip), and gap voltage (GV), and their effects on dimension deviation (DD) and tool wear rate (TWR). Main runs have been planned using a central composite design matrix. Two-dimensional and three-dimensional graphs illustrate the response parameters and machining inputs with Machine Learning techniques used for machining Cu-based Shape Memory Alloy (SMA) in EDM operations [18].

Sharma and Singh in 2023 used Taguchi approach to optimize EDM input parameters such as peak current, pulse on time, pulse off time, and gap voltage. The material removal rate (MRR), tool wear rate (TWR) and surface roughness of AA6068 are measured and suitable parameters are discussed. Response characteristics are influenced most by peak current. 0.0444 g/min of MRR was found to be optimal at the combination of process parameters I = 8 amps current, Vg = 40 V gap voltage, Ton = 100 microseconds, and Duty cycle Toff = 80%, the optimal electrode wear or tool wear rate is 0.00044 g/min. However, best surface finish (3.617 μm) was found to be optimal I = 4 amps current, Vg = 80 V gap voltage, Ton = 80 microsecond, and Duty cycle Toff = 40% [19].

Moreover, in a study conducted by Agarwal et al., in 2021, hybrid adaptive neuro-fuzzy inference system (ANFIS) and Rao algorithm was implemented in modelling and optimization of surface roughness in EDM. In this study, response surface methodology (RSM) has been applied to experimental design and data generation. An artificial neural network (ANN) model is developed and optimized for Ra using the same data set. ANFIS, an adaptive neurofuzzy inference system (ANFIS), has been developed. Rao algorithm and Jaya algorithm have been applied to optimize the developed ANFIS model. The ANFIS model outperforms the ANN model on a variety of statistical parameters, including mean square error, mean absolute error, root mean square error, mean bias error, and mean absolute percentage error. Machined surfaces are significantly improved by both optimization algorithms. Based on the comparison of the Rao algorithm with the Jaya algorithm, it was found that the Rao algorithm performed better [20].

The modelling and optimization of hot-worked AISI2312 steel alloy was carried out using Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN). A study conducted by Azani Moghadda and Kolahan in 2020 considered surface quality, material removed from the workpiece, and tool erosion ratio as performance characteristics. Optimizing the process aims to minimize Tool Wear Rate, Surface Roughness, and Material Removal Rate simultaneously. A neural network with back propagation algorithm (BPNN) was used to examine the relationship between process input parameters and output characteristics. For the optimization of multi-response processes, the PSO algorithm was used. A set of confirmation tests was conducted to verify the accuracy of the proposed optimization procedure. The proposed modeling method (BPNN) can accurately simulate the authentic EDM process with less than 1% error, and the optimization technique (PSO algorithm) is quite efficient in process optimization (less than 4% error) [21].

This study utilized the full factorial design of the experiment (DOE) to collect the datasets required for the Regression modelling. To simulate the actual process of EDM, a Regression model of Ra was developed and tested. As a final step, the Regression model was embedded in a various optimization algorithm such as GSO, GWO and WOA which specified the optimal process of EDM input parameters.

III. METHODS AND MATERIAL

The EDM process is a thermoelectric process that is perfect for machining hard and brittle materials that are difficult or impossible to machine with conventional methods because it does not require physical contact between the electrode and the workpiece. The methodology of optimizing the EDM process using three metaheuristic algorithms is presented in Figure 1.

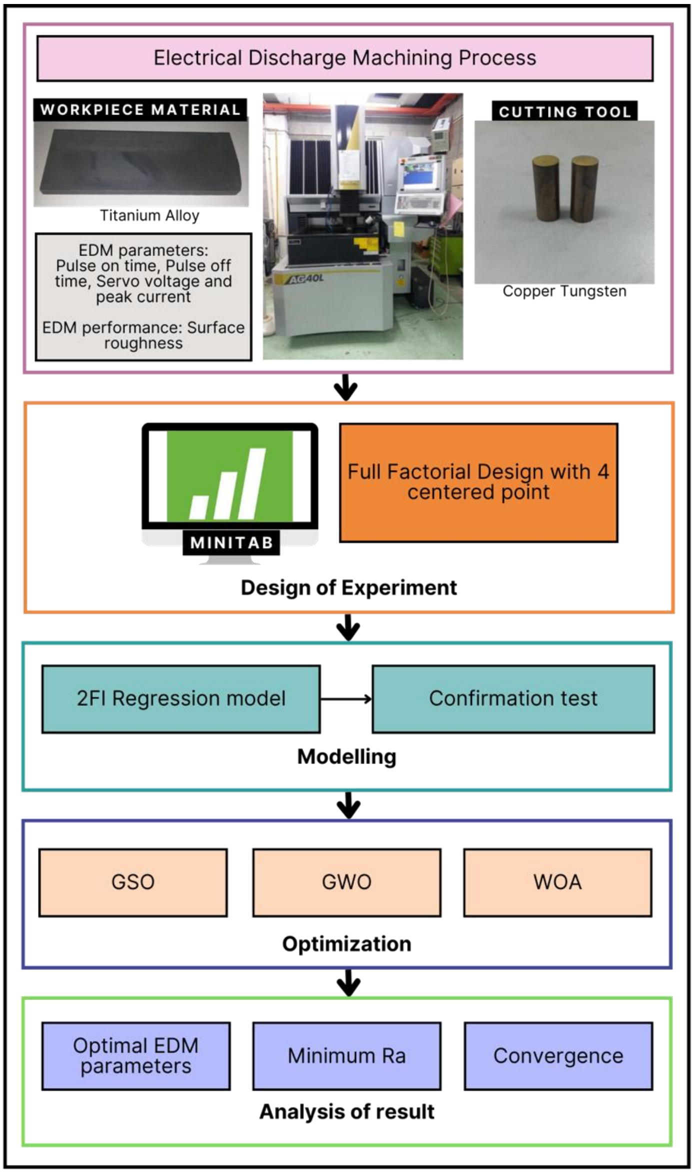

FIGURE 1. The experimental steps.

The machine used is a die-sinking electrical discharge machining process type Sodick AG40-L. The workpiece material considered is titanium alloy, and copper-tungsten is an electrode tool. It produces smooth surface finishes, making it suitable for precision machining applications. It is also known for its high reliability and durability, ensuring consistent performance for extended periods of time. The Sodick AG40-L machine is also known for its ability to remove material efficiently and precisely. Pulse on time, pulse off time, peak current, and servo voltage are selected as EDM parameters, which will affect the quality of surface roughness (Ra). The experiments were run according to the full factorial design of the experiment (DOE) with four centered points, which were designed by using Minitab. Four centered points indicate the central level of four different EDM parameters. The experimental results were then studied to develop the Two Factor Interaction (2FI) Regression model of Ra. The significance of the developed 2FI regression model is validated using a confirmation test. Then, an optimization process using GSO, GWO, and WOA is performed, considering the 2FI regression model of Ra as their objective function. Optimal EDM parameters, minimum Ra values, and convergence rate are observed and compared.

1. EXPERIMENTAL SETUP OF THE EDM

The experiments were conducted using a full factorial design technique involving two levels of machining parameters, with the addition of four center points. This experiment consisted of a total of 20 runs, which included 16 regular runs and four center-point runs. With Design Expert 7.0, the parameter combinations by fractional were acquired. Figure 1 shows the experimental setup of EDM. The arrangement of the experiment's parameters was noted as coded terms: the center point (cp), low level (-), and high level (+).

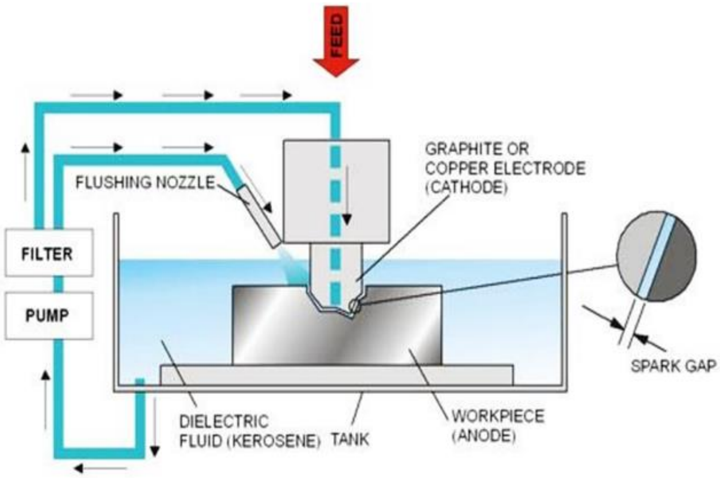

FIGURE 2. Experimental setup of the EDM process [22].

Because copper-tungsten electrodes have a longer lifespan and a better surface polish than graphite electrodes, they are used extensively. The electrode for EDM experiments is made of copper-tungsten alloy render, which has certain thermal properties. The copper-tungsten electrodes are cut into small pieces using a wire electrical discharge machine (WEDM). The cut electrode with the specification of 20 mm length and 8mm diameter is shown in Figure 2. The machining layout of the workpiece, electrodes, and the image of the diameter of the holes are shown in Figure 2 and Figure 3, respectively.

FIGURE 3. (a) The electrode of the EDM experiment and (b) The machined workpiece of the EDM experiment.

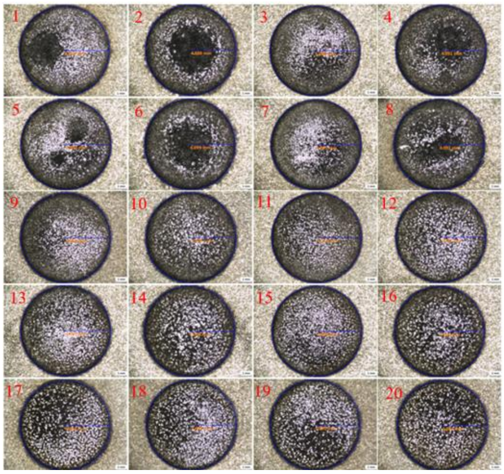

FIGURE 4. Diameter of twenty holes machined workpiece.

For machining parameters to substantially impact the performance of the EDM, they must be chosen properly. The machining parameters that are considered in the EDM experimental are peak current in ampere (IP), servo voltage in volt (SV), pulse on time in s (TON), and pulse off time in s (TOFF). Table 1 shows the list of parameters used for the experiment.

Table 1. Machining parameters of EDM.

Symbol	Machining Parameter	Units	Level		
			Low (-)	Center point (cp)	High (+)
T_{ON}	Pulse on time	μs	150	190	230
T_{OFF}	Pulse off time	μs	60	75	90
I_P	Peak current	ampere	10	11	12
S_V	Servo voltage	Volt	30	45	60

2. THE MODELLING OF THE EDM PROCESS

Regression analysis examines the input and output control parameters in a functionally related process [23]. This approach may be very useful for defining, estimating parameters, and managing data related to the manufacturing process. The regression method was implemented for mathematical modeling. For the modeling process, the input variable will be the experimental data, while the output data will be the regression models.

Among Regression models, 2FI is a statistical method that uses several independent variables, each with two or more levels. Adding interaction terms to a regression model will significantly extend the understanding of the relationships among the variables within the model and allows more hypotheses to be tested. Therefore, the two-factor interaction model is measured. The regression equation is estimated as follows:

$$\bar{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4 \quad (1)$$

where $\bar{y}$ is the surface roughness in μm, x_n are the independent variables (pulse on time, pulse off time, peak current and servo voltage), and β_n are regression or coefficients parameters.

3. THE EDM OPTIMIZATION PARAMETERS

The process of determining the ideal machining parameters is known as optimization. This program was implemented using MATLAB R2022a. EDM performances differ based on parameters such as polarity, no-load voltage, discharge current, plus duration, and electrode materials [24]. Polarity is determined based on the arrangement of the electrode or the work materials so that it can obtain the required MRR with the lowest TWR [25, 26]. No load voltage, sometimes called an open circuit voltage, exists before the current starts to flow. As for voltage, it is chosen by manufacturers [24]. The MRR is directly impacted by discharge current since it permits higher erosion rates at lower amperages [24, 25]. Pulse duration is the length of time that current goes through a single pulse or discharge. Lastly, electrode materials are the elementary thing in the EDM process. When choosing an electrode, one must consider the task's precision, the demands of the manufacturing process, and the workpiece's cost and material. Copper and Graphite are the two most often utilized types of electrode material [26, 24, 27].

The quality of a machined work item is often indicated by surface roughness (Ra). Vibration attached to the workpiece in EDM makes surface roughness (SR) to be improved significantly [28, 29]. Besides, the machined surface has micro-cracks and pores, which results in the Surface Roughness of that workpiece [30, 31]. Ra is measured by calculating the arithmetic mean value as the best estimate of the true value of a set of experimental measurements. Ra is also called a center 69-line average or arithmetic average, which is obtained by averaging the surface height above and below the center line.

4. METAHEURISTICS ALGORITHMS

This section describes the metaheuristics algorithm implemented in optimization of Ra which are GSO, GWO, and WOA algorithms. Glowworm swarm optimization (GSO) algorithm is inspired by the social behavior of fireflies or Glowworms in nature. This algorithm has three main phases: initialization, optimization, and evaluation. In the initialization phase, a set of Glowworms is generated randomly, each Glowworm representing a candidate solution [1]. In the optimization phase, the Glowworms move according to the attraction-repulsion rules, imitating the behavior of fireflies searching for food. Finally, in the evaluation phase, the performance of the optimized solution is evaluated using a specific criterion, and the procedure is iterated until a satisfactory solution is found [8, 9]. One advantage of using the GSO algorithm over other metaheuristic algorithms is that it requires fewer computational resources and less time to find a satisfactory solution [8]. Additionally, the GSO algorithm has demonstrated good performance in finding optimal solutions for complex optimization problems, even in high-dimensional spaces. Furthermore, the GSO algorithm is simple and easy to understand, making it a popular choice for researchers and engineers [1, 8].

The Grey Wolf Optimizer (GWO) algorithm is inspired by the hunting behavior of grey wolves in nature. It has three main phases: initialization, optimization, and evaluation. In the initialization phase, a population of grey wolves is generated randomly, where each grey wolf represents a candidate solution. In the optimization phase, the grey wolves move according to the exploration-exploitation rules, imitating the behavior of grey wolves searching for prey. Finally, in the evaluation phase, the performance of the optimized solution is evaluated using a specific criterion, and the procedure is iterated until a satisfactory solution is found. One advantage of using the GWO algorithm for solving complex optimization problems is that it requires fewer computational resources and less time to find a satisfactory solution [10, 13]. Additionally, the GWO algorithm has demonstrated good performance in finding optimal solutions for complex optimization problems, even in high-dimensional spaces [10]. Furthermore, the GWO algorithm is simple and easy to understand, making it a popular choice for researchers and engineers.

The Whale Optimization Algorithm (WOA) is inspired by the feeding behavior of whales. It has three main phases: initialization, optimization, and evaluation. In the initialization phase, a population of whales is generated randomly, where each whale represents a candidate solution. In the optimization phase, the whales move according to the exploration-exploitation rules, imitating the behavior of whales searching for food. Finally, in the evaluation phase, the performance of the optimized solution is evaluated using a specific criterion, and the procedure is iterated until a satisfactory solution is found [12]. One advantage of using the WOA algorithm for solving complex optimization problems is that it requires fewer computational resources and less time to find a satisfactory solution [11, 12]. Additionally, the WOA algorithm has demonstrated good performance in finding optimal solutions for complex optimization problems, even in high-dimensional spaces. Furthermore, the WOA algorithm is simple and easy to understand, making it a popular choice for researchers and engineers. In the optimization phase, the exploration-exploitation rules followed by the whales determine the level of risk they take in searching for food [11, 15, 16].

IV. RESULT AND DISCUSSION

This section analyzes the results obtained based on the experiment on optimizing the EDM process using the metaheuristic algorithm. A comparison of different algorithms was measured based on their effectiveness in optimizing the EDM process. The following sections show the results of the modeling and optimization of the GSO, GWO, and WOA algorithms.

1. EXPERIMENTAL RESULTS

Table 2 shows the experimental results for machining performances. According to Table 2, Ra is found to be at its lowest at the 11th run (2.2949μm) at the combinations of 150μs of TON, 90μs of TOFF, 10A of IP, and 60V of SV. The worst surface roughness was found at 2nd run (3.7860 μm) at the combination of 230μs of TON, 60μs of TOFF, 10A of IP, and 30V of SV.

Table 2. Experimental design and results for machining performances.

Standard order	Machining Parameter				
	TON (μs)	TOFF (μs)	IP (A)	SV (V)	Ra (μm)
1	150	60	10	30	2.6106
2	230	60	10	30	3.7860
3	150	90	10	30	2.6137
4	230	90	10	30	3.5734
5	150	60	12	30	3.4860
6	230	60	12	30	3.4398
7	150	90	12	30	2.5694
8	230	90	12	30	2.9312
9	150	60	10	60	2.4475
10	230	60	10	60	2.3038
11	150	90	10	60	2.2949
12	230	90	10	60	2.4646
13	150	60	12	60	2.5322
14	230	60	12	60	2.5121
15	150	90	12	60	2.5067
16	230	90	12	60	2.5430
17	190	75	11	45	2.3455
18	190	75	11	45	2.6518
19	190	75	11	45	2.5493
20	190	75	11	45	2.4989

2. THE CONFIRMATION TEST

The confirmation test determines if the optimum machining parameters predicted are within an acceptable range of machining parameters. For a variety of combinations of machining parameters, five sets of experiments are carried out. To assess the accuracy of the developed model, percentage error and average percentage error are included. Therefore, Equation (2) is used to calculate the prediction error. The results of the confirmation test of the 2FI model are presented in Table 3.

$$PE(\%) = |Predicted\ value - Experimental\ value| / (Experimental\ value)\ x\ 100 \quad (2)$$

Where PE is the prediction error in %, predicted value is the value obtained from mathematical model developed and experimental value is the value obtained from experiment.

Table 3. Percentage error for Ra in the 2FI model.

Machining Parameters				Experimental value (µm)	Predicted value (µm)	% Error
TON (µs)	TOFF (µs)	IP (A)	SV (V)			
150	60	10	30	2.6106	2.6712	2.32
150	90	10	30	2.6137	2.3754	9.12
230	60	12	30	3.4398	3.1538	8.31
230	90	12	60	2.5430	1.7956	29.39
Average percentage error (%)						10.91

According to Table 3, The prediction errors of the 2FI model are 2.32%, 9.12%, 8.31%, 29.39%, and 5.40%. Thus, the average prediction error for 2FI is 10.91%. Therefore, the confirmation run shows that the 2FI model for every EDM performance gave an average percentage error below 15%, which is a small number suitable for prediction.

3. PERFROMANCE RESULT

This section discusses the optimization process for surface roughness (Ra). The optimization of the EDM process consists of GSO, GWO, and WOA. The optimization using GSO, GWO, and WOA algorithms is carried out in MATLAB 2022a.

1.1 Result of the GSO Algorithm.

The problem for surface roughness (Ra) optimization is described by minimizing Ra as the objective function. The objective functions used for the optimization process of Ra are stated in Equation (2).

$$\begin{aligned}\min imize Ra(T_{ON}, T_{OFF}, I_P, S_V) &= -5.1249 + 0.0422T_{ON} + 0.0174T_{OFF} + 0.8116I_P \\ &- 0.0431S_V + 0.000059T_{ON}T_{OFF} - 0.0029T_{ON}I_P - 0.0003T_{ON}S_V - 0.0051T_{OFF}I_P \\ &+ 0.0005T_{OFF}S_V + 0.0031I_PS_V\end{aligned} \quad (2)$$

Where Ra is surface roughness in µm, T_{ON} is the pulse on time in µs, T_{OFF} is the pulse of time in µs, I_P is peak current in ampere, and S_V is servo voltage in volt. The optimal optimization solutions for 2FI are shown in Table 4.

Table 4. Optimal solutions for GSO.

Method	Optimal Machining Parameters				Minimum Ra (µs)
	TON (µs)	TOFF (µs)	IP (A)	SV (V)	
Actual	150	90	10	60	2.2949
GSO	188	86	10	59	2.0287

According to the result of the GSO optimization, the minimum surface roughness (2.0287µm) using the 2FI model is given at the optimal combination of machining parameters, TON = 188.6636µs, TOFF = 86.6291µs, IP = 110.0605A and SV = 59.3569V. Furthermore, Figure 4 shows the convergence rate of GSO optimization of Ra in the EDM process. The GSO algorithm reached the optimal solution in more than 20 iterations.

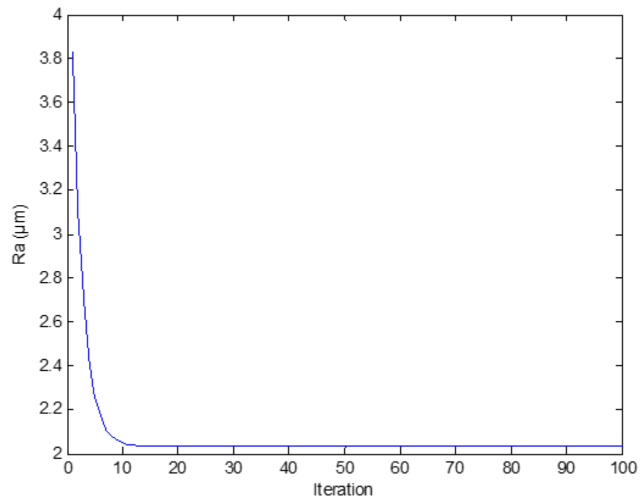

FIGURE 5. Convergence of GSO for Ra.

1.2 Result of the GWO Algorithm.

The depreciation of Ra is subjected to the boundaries of the cutting parameters in Table 5. Table 5 shows the GWO optimization results for the depreciation of Ra with their combination of optimum cutting parameters.

Table 5. Optimal solutions for GWO.

Method	Optimal Machining Parameters				Minimum
	TON (µs)	TOFF (µs)	IP (A)	SV (V)	Ra (µs)
Actual	150	90	10	60	2.2949
GWO	230	60	10	60	1.7593

Table 5 shows that the minimum Ra value (1.7593 µs) for the developed Ra model is given by the combination of cutting parameters ON = 230µs, OFF = 60µs, IP = 10A, and SV = 60V. GWO optimization successfully obtained optimal Ra compared to the experimental result. Figure 5 shows the convergence rate of GWO optimization of Ra in the EDM process. Ra model reached the optimal solution in less than ten iterations.

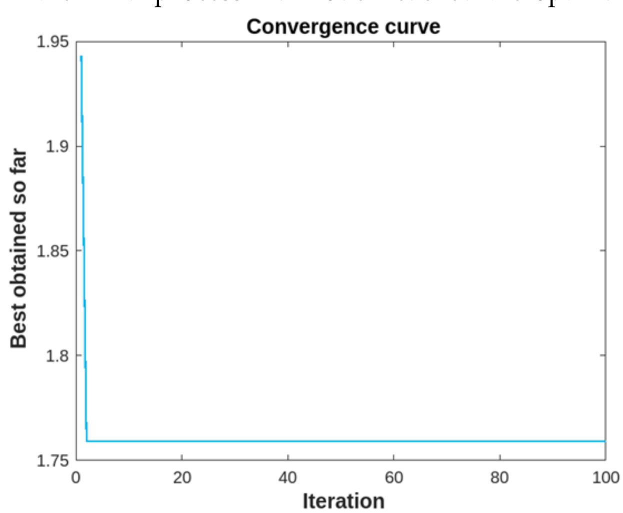

FIGURE 6. Convergence of GWO for Ra.

1.3 *Result of the WOA Algorithm.*

Table 6 displays the experiment and WOA optimization result. The WOA optimization result for the depreciation of Ra with their combination of optimum cutting parameters is presented in Table 6.

Table 6. Optimal solutions for WOA.

Method	Optimal Machining Parameters				Minimum
	TON (μs)	TOFF (μs)	IP (A)	SV (V)	Ra (μs)
Actual	150	90	10	60	2.2949
WOA	230	90	12	60	1.8016

Table 6 shows that the minimum Ra value is 1.8016 μs. The best solution obtained by WOA by combining cutting parameters is ON = 230μs, OFF = 90μs, IP = 12A, and SV = 60V. WOA optimization successfully obtained optimal Ra compared to the experimental result. Figure 6 shows the convergence rate of WOA optimization of Ra in the EDM process, where it reached the optimal solution in less than ten iterations.

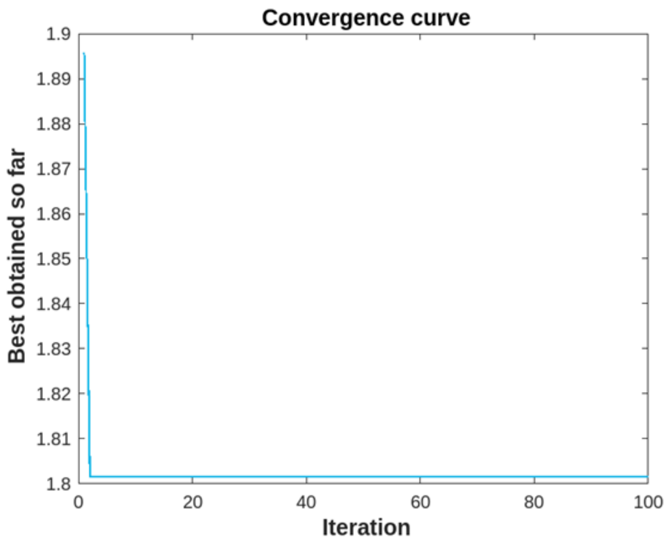

FIGURE 7. Convergence of WOA for Ra.

1.4 *Analysis and Discussion.*

This paper focuses on optimizing the EDM process with three metaheuristic algorithms: WOA, GWO, and GSO. In order to create the 2FI regression model of Ra, the experimental results were analyzed further. A confirmation test is used to verify the developed 2FI regression model's significance. Subsequently, an optimization process with the help of GSO, GWO, and WOA is carried out, with the 2FI regression model of Ra serving as the goal function. We observe and compare the minimum Ra values, the convergence rate of the EDM parameters, and their optimal values. The performance of GSO, GWO, and WOA algorithms was measured based on their effectiveness in optimizing the EDM process. The experimental results show that the GSO algorithm estimates a substantially lower value for the minimal surface roughness (Ra), which has improved the machining process. Based on the comparative analysis made, it is found that the GWO algorithm performed well by achieving a minimum Ra value of 1.7593 when the TON (μs) is 230, TOFF (μs) is 60, IP (A) is 10 and SV (V) is 60. The results show that there is the slightest difference in the Ra values between all three algorithms. Figure 6 shows the variation in the performance of the optimization algorithms.

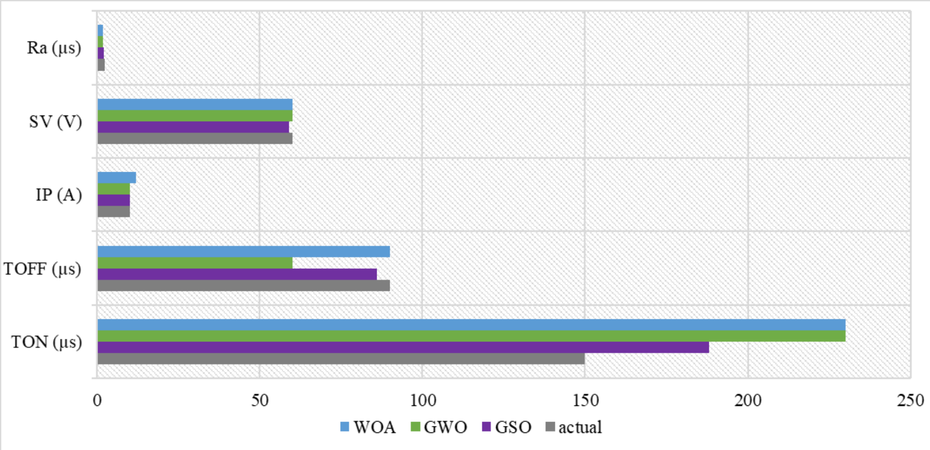

FIGURE 8. The variation in the performance of the optimization algorithms.

V. CONCLUSION

This paper proposes optimization techniques for Electrical Discharge Machining (EDM) using metaheuristic algorithms. A metaheuristic algorithm is a search method created to locate a definitive solution to a complicated and challenging optimization issue. Therefore, metaheuristic algorithms GSO, GWO, and WOA optimize the EDM process. Moreover, this experiment was carried out to solve optimization problems and compare the effectiveness of metaheuristic algorithms. The experimental results showed that these algorithms performed well in their respective ways to optimize the EDM process. The GWO outperformed the WOA and the GSO in solving the EDM optimization problems. It gave a higher optimum value than other algorithms, which is 1.7593µs. Future work should consider the opportunity to improve the performance of the algorithms through a hybrid model that contains GSO and GWO.

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REFERENCES

1. Zainal, N., Zain, A. M., Sharif, S., Hamed, H. N. A., & Yusuf, S. M. (2017). An integrated study of surface roughness in EDM process using regression analysis and GSO algorithm. In *Journal of Physics: Conference Series* (Vol. 892, No. 1, p. 012002). IOP Publishing.
2. Karmiris-Obratański, P., Papazoglou, E. L., Leszczyńska-Madej, B., Zagórski, K., & Markopoulos, A. P. (2021). A comprehensive study on processing ti–6al–4v eli with high power edm. *Materials*, *14*(2), 303.
3. Ming, W., Guo, X., Xu, Y., Zhang, G., Jiang, Z., Li, Y., & Li, X. (2023). Progress in non-traditional machining of amorphous alloys. *Ceramics International*, *49*(2), 1585-1604.
4. Singh, N. K., Agrawal, S., Johari, D., & Singh, Y. (2019). Predictive analysis of surface roughness in argon-assisted EDM using semiempirical and ANN techniques. *SN Applied Sciences*, *1*, 1-8.
5. Zainal, N., Zain, A. M., & Sharif, S. (2016). A study of electrode wear ratio on EDM of Ti-6AL-4V with copper-tungsten electrode. In *MATEC Web of Conferences* (Vol. 78, p. 01013). EDP Sciences.
6. Thakur, A., Rao, P. S., & Khan, M. Y. (2021). Study and optimization of surface roughness parameter during electrical discharge machining of titanium alloy (Ti-6246). *Materials Today: Proceedings*, *44*, 838-847.
7. Sahu, A. K., Thomas, J., & Mahapatra, S. S. (2021). An intelligent approach to optimize the electrical discharge machining of titanium alloy by simple optimization algorithm. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, *235*(2), 371-383.
8. Zainal, N., Zain, A. M., Radzi, N. H. M., & Othman, M. R. (2016). Glowworm swarm optimization (GSO) for optimization of machining parameters. *Journal of Intelligent Manufacturing*, *27*, 797-804.

9. Baisukhan, A., Nakkiew, W., & Wisittipanit, N. (2022). Optimization of Tungsten Inert Gas Welding Process Parameters for AISI 304 Stainless Steel. In *Defect and Diffusion Forum* (Vol. 417, pp. 23-28). Trans Tech Publications Ltd.
10. Kulkarni, O., & Kulkarni, S. (2018). Process parameter optimization in WEDM by grey wolf optimizer. *Materials Today: Proceedings*, *5*(2), 4402-4412.
11. Jain, S., Soni, A., Parashar, V., & Reddy, P. (2021). Analysis of Kerf in Wire cut Electric Discharge Machining using RSM and Whale Optimization Algorithm. In *2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE)* (pp. 1-7). IEEE.
12. Chekuri, R. B. R., Eshwar, D., Kotteda, T. K., & Varma, R. S. (2022). Experimental and thermal investigation on die-sinking EDM using FEM and multi-objective optimization using WOA-CS. *Sustainable Energy Technologies and Assessments*, *50*, 101860.
13. Faris, H., Aljarah, I., Al-Betar, M. A., & Mirjalili, S. (2018). Grey wolf optimizer: a review of recent variants and applications. *Neural computing and applications*, *30*, 413-435.
14. Zainal, N, & Zain, A. M. (2023). Parametric Optimization Of Surface Roughness In Die Sinking Electrical Discharge Machining Using Regression And Grey Wolf Optimizer." Computational Intelligence Applications Series 4, 1-11.
15. Gharehchopogh, F. S., & Gholizadeh, H. (2019). A comprehensive survey: Whale Optimization Algorithm and its applications. *Swarm and Evolutionary Computation*, *48*, 1-24.
16. Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. *Advances in engineering software*, *95*, 51-67.
17. Bhowmick, S., Mondal, R., Sarkar, S., Biswas, N., De, J., & Majumdar, G. (2023). Parametric optimization and prediction of MRR and surface roughness of titanium mixed EDM for Inconel 718 using RSM and fuzzy logic. *CIRP Journal of Manufacturing Science and Technology*, *40*, 10-28.
18. Singh, R., Singh, R. P., & Trehan, R. (2022). Machine learning algorithms based advanced optimization of EDM parameters: An experimental investigation into shape memory alloys. *Sensors International*, *3*, 100179.
19. Sharma, H., & Singh, B. (2023). Experimental design based optimization of process parameters for EDM of AA6068. *Materials Today: Proceedings*.
20. Agarwal, N., Shrivastava, N., & Pradhan, M. K. (2021). Hybrid ANFIS-Rao algorithm for surface roughness modelling and optimization in electrical discharge machining. *Advances in Production Engineering & Management*, *16*(2), 145-160.
21. Azadi Moghaddam, M., & Kolahan, F. (2020). Modeling and optimization of the electrical discharge machining process based on a combined artificial neural network and particle swarm optimization algorithm. *Scientia Iranica*, *27*(3), 1206-1217.
22. Singh, R., Singh, R. P., & Trehan, R. (2021). State of the art in processing of shape memory alloys with electrical discharge machining: a review. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *235*(3), 333-366.
23. Soundhar, A., Zubar, H. A., Sultan, M. T. B. H. H., & Kandasamy, J. (2019). Dataset on optimization of EDM machining parameters by using central composite design. *Data in brief*, *23*, 103671.
24. Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). *Introduction to linear regression analysis*. John Wiley & Sons.
25. Tanwar, H., Singh, T., Khichi, B., Singh, R. C., & Singari, R. M. (2021). Study and Design Conceptualization of Compliant Mechanisms and Designing a Compliant Accelerator Pedal. In *Advances in Manufacturing and Industrial Engineering: Select Proceedings of ICAPIE 2019* (pp. 285-295). Springer Singapore.
26. Ganesh, N., Ghadai, R. K., Bhoi, A. K., Kalita, K., & Gao, X. Z. (2020). An intelligent predictive model-based multi-response optimization of EDM process. *Computer Modeling in Engineering & Sciences*, *124*(2), 459-476.
27. Patel Gowdru Chandrashekarappa, M., Kumar, S., Pimenov, D. Y., & Giasin, K. (2021). Experimental analysis and optimization of EDM parameters on HcHcr steel in context with different electrodes and dielectric fluids using hybrid taguchi-based PCA-utility and CRITIC-utility approaches. *Metals*, *11*(3), 419.
28. Tharian, B. K., Jacob, E., Johnson, J., & Hari, V. (2019). Multi-objective parametric optimization in EDM using grey relational analysis. *Materials Today: Proceedings*, *16*, 1013-1019.
29. Nguyen, H. P., Ngo, N. V., & Nguyen, Q. T. (2021). Optimizing process parameters in edm using low frequency vibration for material removal rate and surface roughness. *Journal of King Saud University-Engineering Sciences*, *33*(4), 284-291.
30. Goyal, A., & Ur Rahman, H. U. Z. E. F. (2021). Experimental studies on Wire EDM for surface roughness and kerf width for shape memory alloy. *Sādhanā*, *46*(3), 160.
31. Phate, M., Toney, S., & Phate, V. (2022). Modelling and investigating the impact of EDM parameters on surface roughness in EDM of Al/Cu/Ni Alloy. *Australian Journal of Mechanical Engineering*, *20*(5), 1226-1239.