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REGULAR PAPER

# Investigating Wire Electric-Discharge Machining (WEDM) Parameters for Improved Machining of D2 Steel: A Multi-Objective Optimization Study

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## Abstract

Wire Electric-Discharge Machining (WEDM) represents a non-traditional approach to metal cutting, providing the advantage of precision manufacturing over conventional methods. In recent years, the metal machining industry has witnessed numerous benefits in terms of high speed and accuracy through the utilization of WEDM in both additive and subtractive manufacturing processes. This research focuses on studying the process parameters and their impact on surface roughness, energy consumption, kerf width, and material removal rates in Wire Electric-Discharge Machining of D2 steel. The Taguchi approach to experimental design (L16) was employed to conduct cutting experiments at varying levels of ON Time, OFF Time, Servo Voltage, and Wire Tension. Experimental results were optimized using ANOVA and Grey Relational Analysis to refine the process inputs and achieve performance measures that minimize surface roughness, power consumption, and kerf width while maximizing material removal rate. Statistical analysis revealed that ON Time is the most significant factor (73%) affecting both individual and multiple responses. The optimized model indicates that significant improvements can be simultaneously achieved in all response parameters by selecting the optimal combination of parameters. This not only enhances the part quality but contributes positively towards process sustainability and productivity.


**Keywords** Wire EDM · Multi-objective optimization · D2 steel · Energy consumption · Surface roughness · Material removal rate

## Abbreviations

| | |
|---|---|
| WEDM | Wire Electric-Discharge Machining |
| SEC | Specific Energy Consumption |
| ON | ON Time |
| OFF | OFF Time |
| SV | Servo Voltage |
| WT | Wire Tension |
| SR | Surface Roughness |
| MRR | Material Removal Rates |
| GRA | Grey Relational Analysis |
| GRC | Grey Relational Coefficient |
| RSM | Response Surface Methodology |
| ANOVA | Analysis of Variance |
| CEM$^{TM}$ | Carbon Emission Signature |

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## 1 Introduction

Research in the field of metal machining is driven by the demand for precision and high-quality metal cutting. Among non-conventional methods, Wire Electric-Discharge Machining (WEDM) is notable for its ability to machine electrically conductive metal alloys, allowing the production of intricate shapes with enhanced surface quality and machining characteristics. WEDM is a non-conventional manufacturing process that employs short, high-energy electric sparks between oppositely charged electrodes—the wire and workpiece—to facilitate material removal [1]. A dielectric fluid serves as the medium to regulate energy discharge. Unlike traditional machining processes, WEDM is a non-contact manufacturing method that achieves material removal through the melting induced by the intense heat generated within the sparking zone [2]. In WEDM, the lack of contact between the tool and workpiece eliminates cutting forces, leading to the achievement of tight tolerances and excellent surface finishes by minimizing mechanical deformation. This method also stands out for its ability to minimize material wastage, making it more appealing compared to other machining techniques.

EDM has found extensive applications in precision machining across various industries, including mold and die manufacturing, extrusion, blanking, and metal fabrication. This widespread use is driven by the demand for producing intricate shapes, attaining superior surface quality, and maintaining high dimensional accuracy throughout the manufacturing process [3]. Moreover, the process is well-suited for machining exotic and high-strength alloys, as it generates no cutting forces during operation. Recent applications extend to machining sintered carbide, advanced ceramics, and modern composites, all of which have demonstrated promising results. Particularly in electronics, aerospace and biomedical device manufacturing, where optimal product performance is crucial, there is a pressing need for thorough investigations to improve surface quality and productivity [4].

Recent studies have examined various materials, including aluminum, titanium, steel, copper, and brass, using WEDM techniques summarized in Table 1. The machining process is inherently intricate and often entails adjusting numerous control parameters to attain the desired output and performance. These input parameters encompass ON Time (ON), Off Time (OFF), Servo Voltage (SV), Wire Tension (WT), current intensity, discharge time, and frequency, as highlighted in several studies [5–8]. Consequently, even minor fluctuations in these input values can noticeably influence the outputs, particularly surface roughness, energy consumption, and material removal rates, which are mostly emphasized in the reported studies [1].

The impact of process parameters on key responses such as Surface Roughness (SR) and Material Removal Rate (MRR) has been extensively explored in research on WEDM. For example, studies have found that smaller values of pulse-on time and voltage yield optimal surface roughness when machining AISI O1 tool steel [6]. In another study feed rate and gap width were found critical factors for enhancing MRR in optimal machining of Inconol-718

**Table 1** Summary of WEDM optimization studies

| Sr. No | Research work | Optimization technique | Optimization objectives |
|---|---|---|---|
| 1 | Azam et al. [21] | Contour plots | •SR |
| 2 | Vijaykumar et al. [22] | Desirability analysis | •SR<br>•Erosion rate |
| 3 | Carmita Camposeco-Negrete[23] | Desirability analysis | •Machining time<br>•SR<br>•MRR<br>•Total energy consumption |
| 4 | George et al. [24] | Teaching–learning based algorithm (weighted multi-objective) | •Cylindricity<br>•Roundness<br>•SR |
| 5 | Sana et al. [25] | Non-dominated sorting genetic algorithm (NSGA-II) | •MRR<br>•SR<br>•SEC |
| 6 | Sana et al. [26] | Multi-objective genetic algorithm | •Electrode wear rate<br>•Overcut |
| 7 | Su et al. [27] | Genetic algorithm-based neural network | •SR<br>•Tool wear rate<br>•MRR |
| 8 | Zahoor et al. [28] | Multi-objective genetic algorithm | •SR<br>•Cutting speed<br>•Dimensional deviation |
| 9 | Kumar et al. [29] | Teaching learning-based algorithm | •SR<br>•MRR<br>•Tool wear rate<br>•Overcut<br>•Circularity |

[9]. Similarly, surface roughness was observed to improve with a decrease in pulse duration, open circuit voltage, and wire speed in studies involving WEDM of SAE 4140 steel [5]. Furthermore, investigations on high-strength armor steel identified pulse-on time, pulse-off time, and spark voltage as significant factors affecting MRR and surface roughness [10]. Optimization studies on hot die steel revealed that smaller current and shorter pulse off duration contribute to improved surface quality and overall performance in WEDM [11]. Meanwhile, wire speed was found to be the major factor for achieving optimal surface quality in WEDM of D2 steel, with gap voltage and current being key factors for MRR [7]. Modeling approaches have also been employed to predict performance metrics such as MRR, Surface Finish (SF), and Surface Waviness, allowing for the prediction of these responses across a wide range of inputs [7]. However, limited research has addressed the importance of energy consumption, underscoring the need for a thorough investigation of machining parameters for suitable energy analysis and overall performance enhancement in WEDM machining of D2 steel.

Many studies have investigated various factors influencing process outcomes, but many have overlooked energy consumption, which is crucial for sustainable production as it directly impacts environmental performance. WEDM process is significantly more energy-intensive compared to conventional machining methods due to its minimal material removal during cutting [12]. Specific energy consumption (SEC) and material removal rate were modeled in the WEDM process. Since the process involves controlled localized melting and evaporation by precisely controlled electric sparks, electrical energy consumption plays a significant role in the environmental impact of the process. Thus, the total energy consumption of the machine tool is influenced by factors such as type, construction, and process parameters, which can be categorized as process-dependent and independent units [13]. For example, in WEDM of steel (AISI P20), electricity accounted for 64% of the total impact during one hour of machining [14]. Considering the process-level environmental performance of electro discharge machining of aluminum (3003) and steel (AISI P20), reducing electrical energy consumption was reported to lead to both environmental and economic savings. A similar study reported that two-thirds of the total energy was consumed during non-cutting operations, leading to significant carbon emissions [15]. In summary, WEDM presents several drawbacks, including limitations on electrically conductive materials, slow machining speeds, and environmental concerns due to its reliance solely on electricity.

In recent years, a significant amount of research has also focused on the multi-optimization of process parameters to achieve optimal machining outcomes in both conventional and non-conventional methods. Various techniques, including response surface methods, Taguchi methods, and hybrid approaches, have been employed to achieve multiobjective optimization [16–20]. These models are beneficial for analyzing conflicting objectives like surface roughness, energy consumption, cost, material removal rates, and other performance metrics, enabling informed decision-making and providing valuable information on trade-offs between quality, productivity, and sustainability. For instance, in [21], contour plots between input and output variables were utilized to identify favorable WEDM parameters for improving the surface roughness of HSLA steel. The desirability function approach was utilized to analyze the micro WEDM of Inconel 625 superalloy, focusing on surface roughness and erosion rate identification [22]. Another similar example explored the relationship between four optimization objectives in WEDM of AISI O1 tool steel, and later linked the results to reduced carbon emissions [23]. The teaching–learning based algorithm was used to optimize cylindricity, roundness, and surface quality in a WEDM-turning setup [24]. More recently, [25, 26] explored various perspectives of powder-mixed electric discharge machining through multi-objective optimization schemes like NSGA-II and MOGA, demonstrating the effectiveness of using such methods in analyzing novel WEDM variations. A summary of the significant optimization studies reviewed by the authors is shown in Table 1.

It is evident from Table 1 that WEDM optimization is a wide topic, and researchers have approached it with numerous techniques. Due to the complexity of the trade-offs between WEDM performance indicators, a gradual shift was observed in the general optimization approach from simpler, intuition-based methods like the usage of contour plots to more systematic, heuristic techniques that are capable of exploring the design space more efficiently. Moreover, multi-objective optimization has emerged as a suitable approach for such problems, offering a more comprehensive perspective of multi-dimensional WEDM behaviors. The full extent of multi-objective methods, however, has rarely been studied, with most efforts being limited to a limited number of objectives (typically 2–3). In this study, we aim to enrich the current literature by presenting a more holistic approach to multi-objective optimization of WEDM by factoring in three distinct quality measures and power consumption. This approach can contribute to a greater understanding of the complex interactions between various WEDM parameters and quality metrics, providing industrial manufacturers with a better context of their processes and optimization methodologies. D2 steel is chosen for this study owing to its widespread use in WEDM applications including the manufacturing of punches, dies, and precision shearing blades.

## 2 Experimental Setup

Experiments were conducted on the JS EDM 5-Axis Wi-640S submerged type machine with a worktable size of 870 × 680 mm. The experimental procedure is shown in Fig. 1. A 0.25 mm consumable copper electrode was used for all experiments. An 8 mm thick and 20 mm wide rectangular workpiece was used, and all cuts were taken along the 20 mm. This allowed sufficient time for the cutting operation to stabilize after the initial wire entry. Deionized water was used as the dielectric fluid.

The composition of the D2 steel workpiece used was verified by Optical Emission Spectroscopy. The results are shown in Table 2.

**Table 2** Material composition of workpiece

| Material | Composition % |
|---|---|
| C | 1.67 |
| Cr | 12.02 |
| Si | 0.371 |
| Mn | 0.327 |
| Mo | 0.70 |
| Fe | 83.4 |
| V | 1.09 |

## 3 Experimental Design

Preliminary experimentation was conducted to roughly understand the effects of various controllable parameters on the WEDM performance indicators. Three input parameters (**ON Time**, **OFF Time**, **Servo Voltage**) were initially identified as significant. While ON, OFF, and SV have been widely reported in the literature as having significant effects on WEDM processes, WT has not been thoroughly investigated in the literature [30]. Since wire-related issues like wire breakage and electrode consumption were commonly encountered in our workshop, WT has also been added to the inputs to enrich this study and to gauge its effectiveness in evaluating WEDM performance.

Four-factor levels are used for each parameter. The factor levels are based on the machine tool manufacturer's recommendations for minimum and maximum values for the chosen workpiece material of D2 and workpiece thickness of 8 mm. The maximum range was initially employed in factor level selection to fully map the behavior of response parameters across the input space. However, preliminary experimentation was used to narrow the setting for WT as the wire frequently breaks at high WT settings. Table 3 provides an overview of the experimental inputs.

Four response parameters (SR, MRR, power consumption, and kerf width) were chosen for detailed performance analysis of experimental results. The defined research problem of investigating the tradeoffs between part quality (SR,

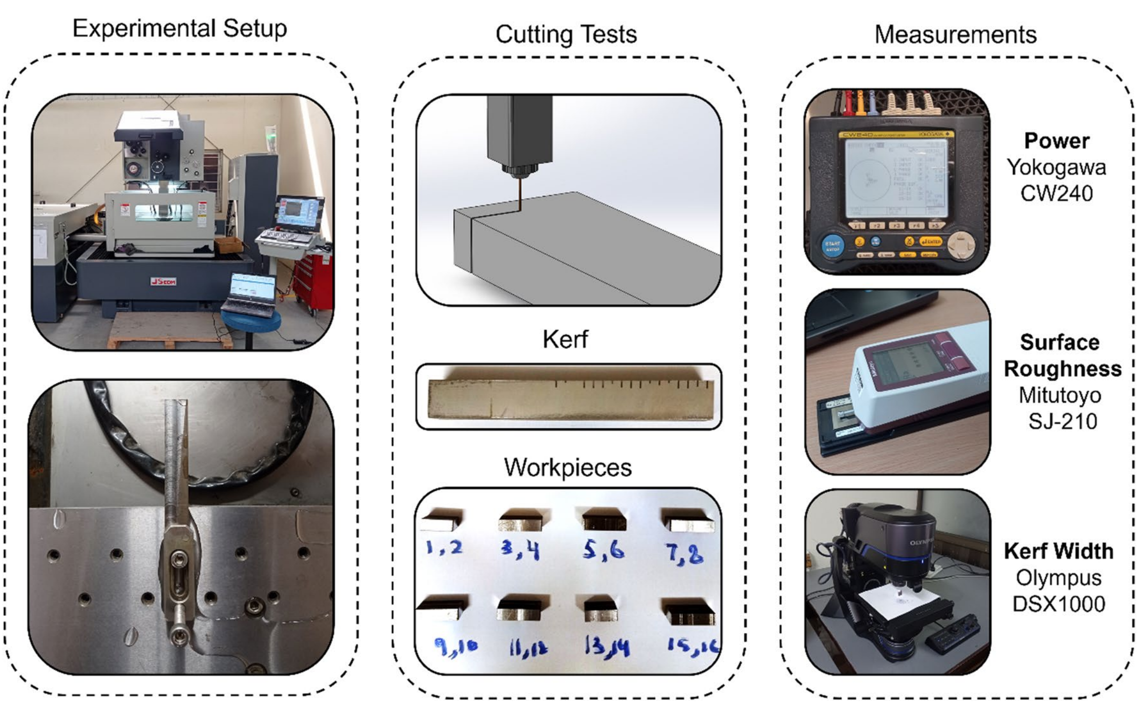



**Fig. 1** Experimental setup

**Table 3** Experimental parameters and levels

| Factor | Levels | Units |
|---|---|---|
| On Time (ON) | 2 6 10 14 | μs |
| Off Time (OFF) | 10 12 14 16 | μs |
| Servo Voltage (SV) | 35 40 45 50 | V |
| Wire Tension (WT) | 9 10 11 12 | N |

**Table 4** L16 Taguchi array

| Trail | Parameters | | | |
|---|---|---|---|---|
| | ON | OFF | SV | WT |
| 1 | 2 | 10 | 35 | 9 |
| 2 | 2 | 12 | 40 | 10 |
| 3 | 2 | 14 | 45 | 11 |
| 4 | 2 | 16 | 50 | 12 |
| 5 | 6 | 10 | 40 | 11 |
| 6 | 6 | 12 | 35 | 12 |
| 7 | 6 | 14 | 50 | 9 |
| 8 | 6 | 16 | 45 | 10 |
| 9 | 10 | 10 | 45 | 12 |
| 10 | 10 | 12 | 50 | 11 |
| 11 | 10 | 14 | 35 | 10 |
| 12 | 10 | 16 | 40 | 9 |
| 13 | 14 | 10 | 50 | 10 |
| 14 | 14 | 12 | 45 | 9 |
| 15 | 14 | 14 | 40 | 12 |
| 16 | 14 | 16 | 35 | 11 |

kerf width), productivity (MRR), and environmental impact (Power consumption) in WEDM dictated the choice of these parameters.

A Taguchi-based Design of Experiments approach was adapted for data collection owing to its capability of mapping the entire design space with minimal experimental effort. The L16 orthogonal array in Table 4 was obtained using the four factors and four levels.

### 3.1 Data Collection

Power consumption was measured using Yokogawa CW240 power meter. Since the power meter was installed on the mains power supply of the machine, it recorded both machine idling power and cutting power. The idling power comprises non-productive energy consumption by auxiliary components like dielectric pumps, wire tensioners, and machine tool control system. It was experimentally pre-verified that the idle power is approximately 2.21 kW during standard idling cycles. Therefore, the cutting power was calculated as the difference between the total power and the idle power. This approach has been adopted from the literature used for machining processes [31–33].

Figure 2 shows the different phases of power consumption during a cutting cycle, taken from one of the experimental runs. In phase 1, the wire has not yet begun to cut, and the machine consumes only idle power. In phase 2, the wire begins the cut, and the power rises sharply. Power

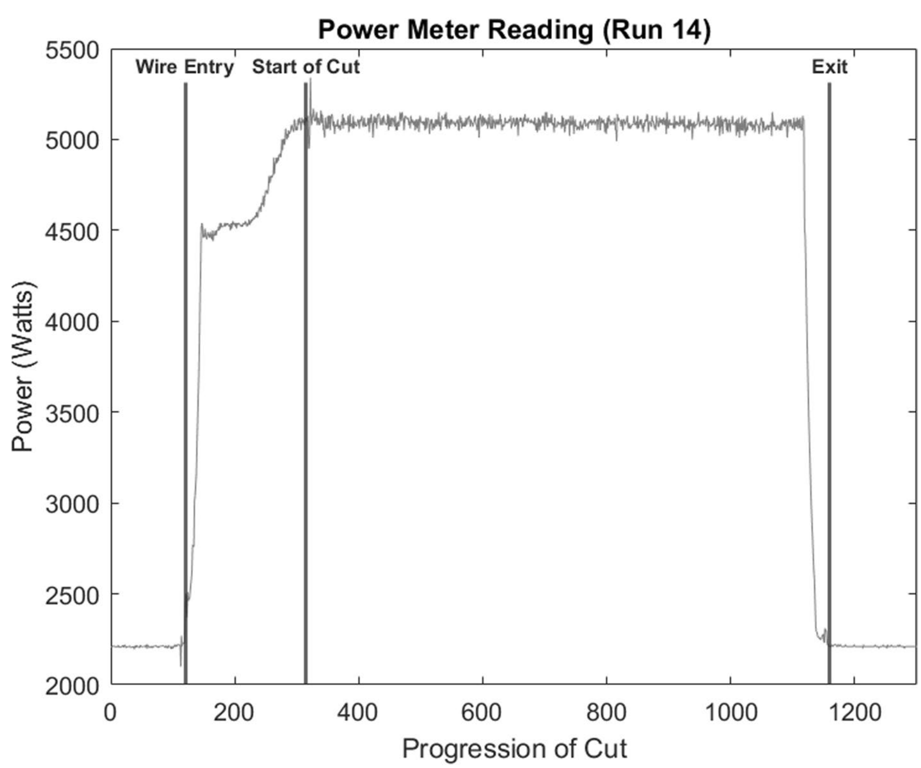



**Fig. 2** Different phases of power variation (Experiment #14)

consumption, however, takes some time to reach a stable value. The gradual increase of power in the latter half of this phase was a common observation. It signifies that the wire is not cutting the entire thickness of the workpiece, which is mainly due to workpiece mounting errors causing it to be slightly inclined. Phase 3 shows the actual power consumption for the cut, where power fluctuates about a specific value. At the end of the cut, power consumption drops abruptly as the wire exits the workpiece and returns to the initial value representative of the machine's idling condition. The cutting power was computed using Eq. 1:

$$\text{Cutting power} = \text{Power cut} - \text{Power air} \tag{1}$$

Surface roughness was measured by the Mitutoyo SJ-210 surface tester. An average of five readings was taken for each workpiece to eliminate random variations in the testing. To measure the kerf width, a small cut was taken for each experimental condition, as shown in Fig. 1. Care was taken to let the cut stabilize. The resultant kerf was measured using an Olympus DSX1000 optical microscope at three distinct points as indicated in Fig. 3. The average of these three readings was taken to reduce measurement errors.

The MRR was computed using Eq. 2. The volume of the material removed during the cut can be simplified as a perfect cuboid as wide as the kerf width. Its length and height are the pre-measured workpiece length (20 mm) and thickness (8 mm), respectively. The time taken for each cut was measured using a stopwatch.

$$Material\ Removal\ Rate = \frac{Kerf\ Width\ x\ Cut\ Length\ x\ Workpiece\ Thickness}{Time\ Taken} \tag{2}$$

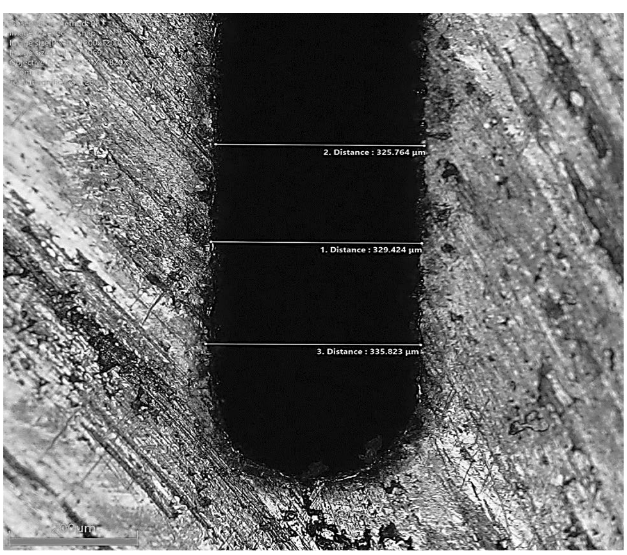



**Fig. 3** Kerf width measurement

It is important to mention here that these experiments were conducted under certain limiting conditions, deviations which may affect the accuracy of results. The ambient temperature was 25 °C on average, the WEDM machine was recently purchased, and approximately 5–10 min breaks were taken between each experiment. Furthermore, the relative accuracy and calibrations of the measurement equipment also has a bearing on the accuracy of the collected data.

## 4 Results and Discussions

The experimental conditions in Table 4 were conducted twice and the average values of the results are shown in Table 5. No significant deviations were observed for any parameter combination.

### 4.1 Analysis of Variance

An Analysis of Variance (ANOVA) study was performed on the experimental results at 95% confidence level for the regression model using the Minitab 21 software. The ANOVA results are tabulated in Table 6. Results suggest that among the selected WEDM parameters, ON time is the most significant factor that affects the GRG with a contribution of 73% followed by the interaction of the ON and OFF times whereas the SV and WT have the least influence on affecting the output responses. Figure 4 shows the relative dependence of WEDM performance on the chosen inputs.

The strong contribution of ON time has been previously reported in several publications for similar conditions [6, 34]. While the factor of 73% seems high, it is to be noted that this figure conveys its relative significance within the pool of selected parameters and performance indicators.

In subsequent sections, to better understand these phenomena, the main effects plots for all response parameters are discussed to better understand the physical relationship between all WEDM parameters and performance indicators.

### 4.2 Analysis of Surface Roughness

Figure 5 shows the response of the process parameters on the surface roughness Ra. The most significant factor affecting surface roughness is ON time, showing the surface to consistently worsen as pulse duration increases. A longer pulse duration leads to high-intensity energy deposition to the cutting zone, removing more particles and creating deeper craters in the workpiece surface [35, 36]. These particles are then flushed away from the cutting zone during the OFF time. When more of these particles are present in the spark gap for a given pulse-OFF duration, flushing efficiency can decrease, deteriorating the surface quality due to phenomena

**Table 5** Responses for cutting experiments

| Exp # | Parameters | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|
| | ON ((µs) | OFF (µs) | SV (V) | WT | Surface Roughness ($R_a$, µm) | Kerf (µm) | Power (W) | MRR ($mm^3/s$) |
| 1 | 2 | 10 | 35 | 9 | 1.575 | 310.504 | 2400 | 0.019256062 |
| 2 | 2 | 12 | 40 | 10 | 1.487 | 313.44267 | 2410 | 0.017783981 |
| 3 | 2 | 14 | 45 | 11 | 1.369 | 317.82567 | 2370 | 0.015047465 |
| 4 | 2 | 16 | 50 | 12 | 1.437 | 313.858 | 2350 | 0.013066339 |
| 5 | 6 | 10 | 40 | 11 | 2.482 | 329.417 | 2730 | 0.137190044 |
| 6 | 6 | 12 | 35 | 12 | 2.587 | 324.53567 | 2710 | 0.126051256 |
| 7 | 6 | 14 | 50 | 9 | 2.435 | 330.337 | 2520 | 0.075794853 |
| 8 | 6 | 16 | 45 | 10 | 2.505 | 321.78933 | 2550 | 0.07469739 |
| 9 | 10 | 10 | 45 | 12 | 2.987 | 336.125 | 3010 | 0.218963029 |
| 10 | 10 | 12 | 50 | 11 | 2.797 | 336.74833 | 2850 | 0.182869705 |
| 11 | 10 | 14 | 35 | 10 | 3.029 | 332.76967 | 2920 | 0.202376156 |
| 12 | 10 | 16 | 40 | 9 | 2.829 | 334.92267 | 2800 | 0.173347041 |
| 13 | 14 | 10 | 50 | 10 | 2.990 | 356 | 2880 | 0.18465875 |
| 14 | 14 | 12 | 45 | 9 | 2.968 | 359.64733 | 2870 | 0.197853986 |
| 15 | 14 | 14 | 40 | 12 | 3.206 | 347.41367 | 2850 | 0.187296193 |
| 16 | 14 | 16 | 35 | 11 | 3.142 | 342.22733 | 2830 | 0.188285073 |

**Table 6** ANOVA results

| Source | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | *P*-Value |
|---|---|---|---|---|---|---|---|
| Model | 13 | 0.203268 | 99.43% | 0.203268 | 0.015636 | 26.85 | 0.036 |
| Linear | 4 | 0.149119 | 72.94% | 0.030908 | 0.007727 | 13.27 | 0.071 |
| ON | 1 | 0.148248 | 72.52% | 0.030549 | 0.030549 | 52.45 | 0.019 |
| OFF | 1 | 0.000409 | 0.20% | 0.000109 | 0.000109 | 0.19 | 0.708 |
| SV | 1 | 0.000043 | 0.02% | 0.000293 | 0.000293 | 0.50 | 0.552 |
| WT | 1 | 0.000419 | 0.20% | 0.000058 | 0.000058 | 0.10 | 0.781 |
| Square | 4 | 0.038212 | 18.69% | 0.025114 | 0.006278 | 10.78 | 0.087 |
| ON*ON | 1 | 0.037802 | 18.49% | 0.009032 | 0.009032 | 15.51 | 0.059 |
| OFF*OFF | 1 | 0.000266 | 0.13% | 0.000266 | 0.000266 | 0.46 | 0.569 |
| SV*SV | 1 | 0.000005 | 0.00% | 0.012679 | 0.012679 | 21.77 | 0.043 |
| WT*WT | 1 | 0.000139 | 0.07% | 0.014656 | 0.014656 | 25.17 | 0.038 |
| 2-Way Interaction | 5 | 0.015937 | 7.80% | 0.015937 | 0.003187 | 5.47 | 0.162 |
| ON*OFF | 1 | 0.000154 | 0.08% | 0.000583 | 0.000583 | 1.00 | 0.422 |
| ON*SV | 1 | 0.000457 | 0.22% | 0.000639 | 0.000639 | 1.10 | 0.405 |
| ON*WT | 1 | 0.000289 | 0.14% | 0.000289 | 0.000289 | 0.50 | 0.554 |
| OFF*SV | 1 | 0.001726 | 0.84% | 0.014722 | 0.014722 | 25.28 | 0.037 |
| OFF*WT | 1 | 0.013311 | 6.51% | 0.013311 | 0.013311 | 22.86 | 0.041 |
| Error | 2 | 0.001165 | 0.57% | 0.001165 | 0.000582 | | |
| Total | 15 | 0.204433 | 100.00% | | | | |

| S | R-sq | R-sq(adj) | PRESS | R-sq(pred) |
|---|---|---|---|---|
| 0.0241327 | 99.43% | 95.73% | 0.856875 | 0.00% |

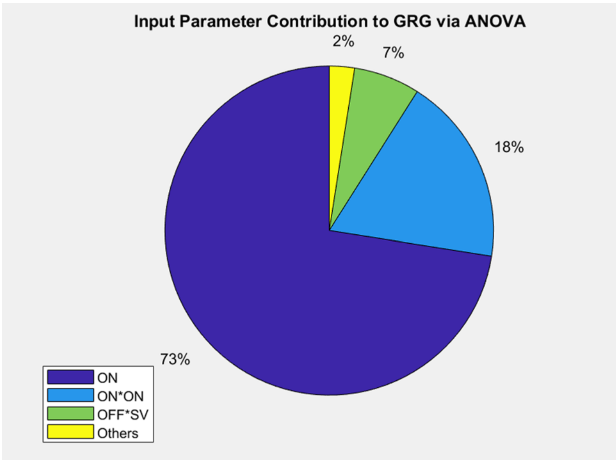



**Fig. 4** Major contributing factors to WEDM performance

like solidification of removed particles and gas entrapment [21].

The mild effect of SV on surface roughness is also worth noting. It is evident that higher SV values cause surface quality to improve, as also observed in [37]. At higher SV values, the machine's controller maintains a larger gap (kerf) between the workpiece and tool, allowing more space to accommodate and flush away the removed particles, thus preserving surface quality. Moreover, the larger gap also decreases the intensity of the sparking action, improving surface quality [36].

OFF time and WT have no clear relationship with surface roughness. Similar observations were previously reported [38]. This can be explained by the fact that neither of these parameters contributes to energy deposition to the cutting zone, which is the main reason for material removal and surface quality. As stated, OFF time merely provides time for flushing away removed particles. We postulate that as long as the OFF time is not short enough to prevent the flushing of all particles from the cutting zone, it should remain an insignificant factor for surface roughness.

### 4.3 Analysis of Material Removal Rates

Figure 6 shows the change in the MRR with the change in process parameters.

It is evident from the results that ON times and WT increase the MRR, with more ON time leading to a higher material removal rate and the OFF time and SV having the opposite effect. This is a direct consequence of these parameters controlling the amount of energy input to the cutting zone. With regards to SV, a weak but noticeable link with MRR is observed. At higher SV settings, the workpiece exhibits a lower MRR, despite a larger kerf. This trend is due to the low concentration of productive, high-energy electric arcs between the two electrodes as a high SV creates a wider gap between them, as also observed and postulated in [39].

Furthermore, MRR exhibits a weak but strictly positive trend with WT [40]. The wire electrode is maintained tauter at higher WT, which leaves more room for removed particles to be flushed away rather than getting stuck inside the cutting zone and acting as an electrical contact between the wire and workpiece. When such contact occurs, a short circuit forms between the wire and workpiece, prompting the machine's controller to retreat the tool slightly to clear debris from the cutting zone. This short delay causes the MRR to decrease.

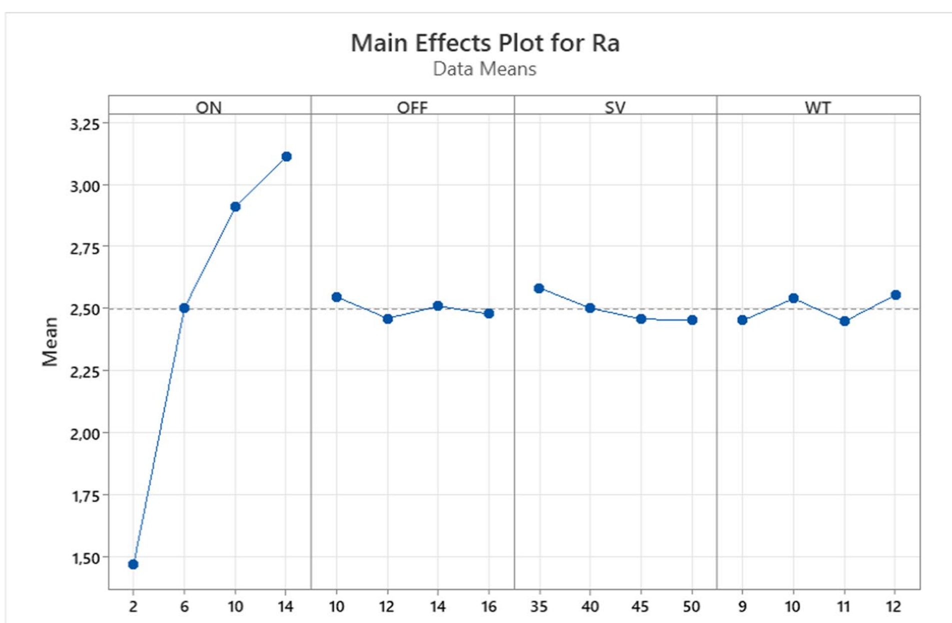



**Fig. 5** Main effects plot for surface roughness

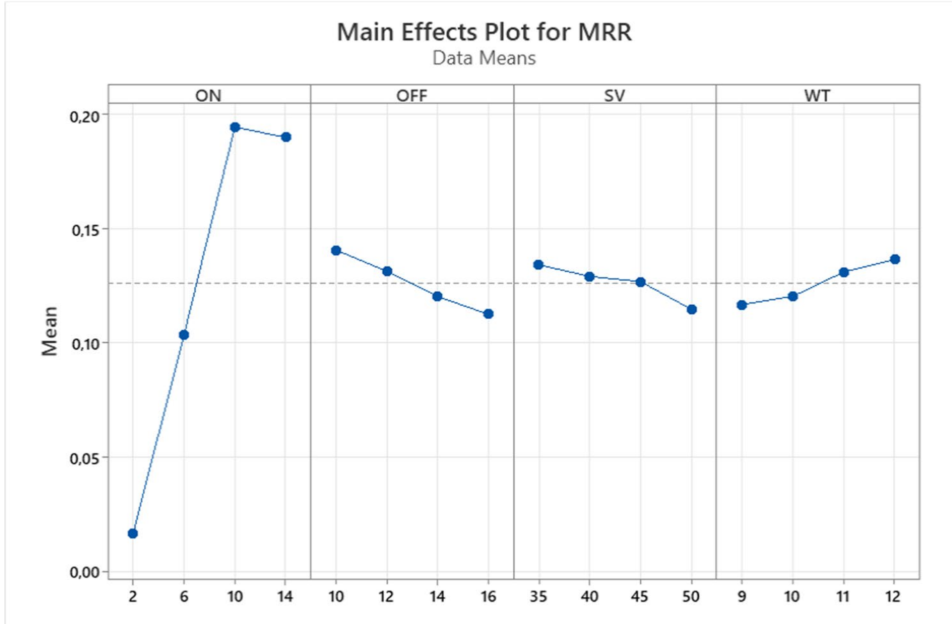



**Fig. 6** Main effects plot for material removal rate

Additionally, it was observed that at lower WT values, the wire itself has a higher probability of coming into contact with the workpiece due to its slackness, particularly at its top and bottom edges.

## 4.4 Analysis of Kerf Width

The gap created between the electrode and workpiece by material removal is called the kerf. The kerf width is an important parameter for dimensional accuracy. An accurate estimate of the kerf width helps machine tool operators decide how much the wire should be offset from its nominal toolpath to achieve the desired tolerance.

Figure 7 shows that the kerf gets wider with ON time and, in contrast, narrower with OFF time [41]. This is a direct consequence of these two parameters controlling energy deposition to the cutting zone, as postulated in [42].

The kerf width also shows a monotonically increasing trend with WT. This is due to the greater wire bowing effect at low WT settings, where slackness in the wire causes larger vibrations and creates a wider kerf by eroding extra material from the workpiece [43]. This kind of wire deflection was also visibly observed during low WT runs in this

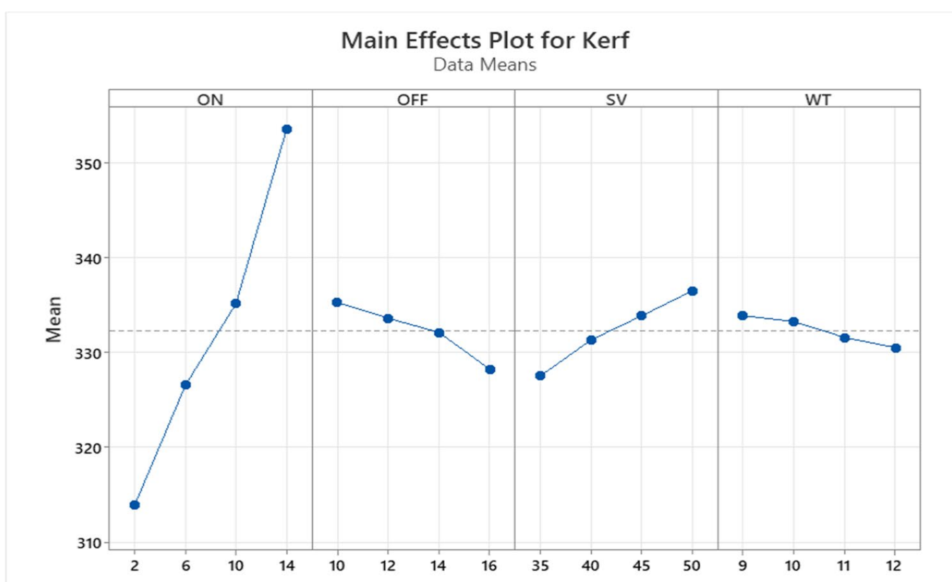



**Fig. 7** Main effects plot for kerf width

experimentation, where the wire appeared to be at an angle to the vertical at its start and end points along the workpiece.

### 4.5 Analysis of Power Consumption

Figure 8 shows that power consumption depends significantly on ON time. This is a commonly observed result in WEDM [6, 44], as ON time is the main parameter to control energy deposition to the cutting zone. It is unexpected to see power consumption drop at the highest level of ON time, however. This anomaly may be explained by the fact that power consumption is an indicator of instantaneous energy utilization, which is influenced by the local condition of the cutting zone. According to [45], excessive debris and low dielectric fluid concentration in the cutting zone decrease pulse energy utilization by causing frequent micro short circuits. These micro short circuits also lead to decreased pulse frequency as the machine tool controller slightly retracts the wire to clear the unflushed particles before initiating a new cut. The authors visibly observed more debris around the cutting area during the high ON time runs, and the machine tool's control panel also indicated frequent short circuits.

Power consumption decreases with increasing OFF time due to its effect on energy deposition. Servo voltage and wire tension show insignificant correlations with power consumption [44].

In summary, the preceding discussions show that ON time plays a pivotal role in affecting all WEDM performance indicators. However, conflicting trends have been identified for other inputs, as also seen in the correlation plot (Fig. 9). It is clear that all performance indicators act in opposition to at least one other. For example, the MRR vs. SR plot shows a strong positive correlation, indicating that both cannot be maximized at the same time. Therefore, there is a need to perform a more in-depth investigation to propose an optimal solution for Wire Electro-Discharge Machining (WEDM) of D2 steel.

Consequently, the subsequent section presents the optimization results achieved through Grey Relational Analysis (GRA), aimed at delivering a more sustainable and refined solution to enhance machining responses.

## 5 Multi-Objective Optimization

GRA was used to improve the decision-making for optimal parameter identification and the optimization of the EDM parameters. GRA based on the Taguchi method converts a multi-response problem into a single unique function. The methodological approach is presented in Fig. 10. The steps involved in performing GRA are given as follows:

1. Data Preprocessing

The first step in the GRA is the conversion of each response to a common scale (0–1) by normalizing all the responses. Normalization of the responses depends on the particular objective. Energy consumption, kerf width, and surface roughness (Ra) are to be minimized whereas MRR is to be maximized for optimized performance. The values for power consumption, kerf width, and SR are estimated as "smaller the better" using Eq. 3 whereas the MRR the "larger the better" approach was used, and the sequence is normalized using Eq. 4.

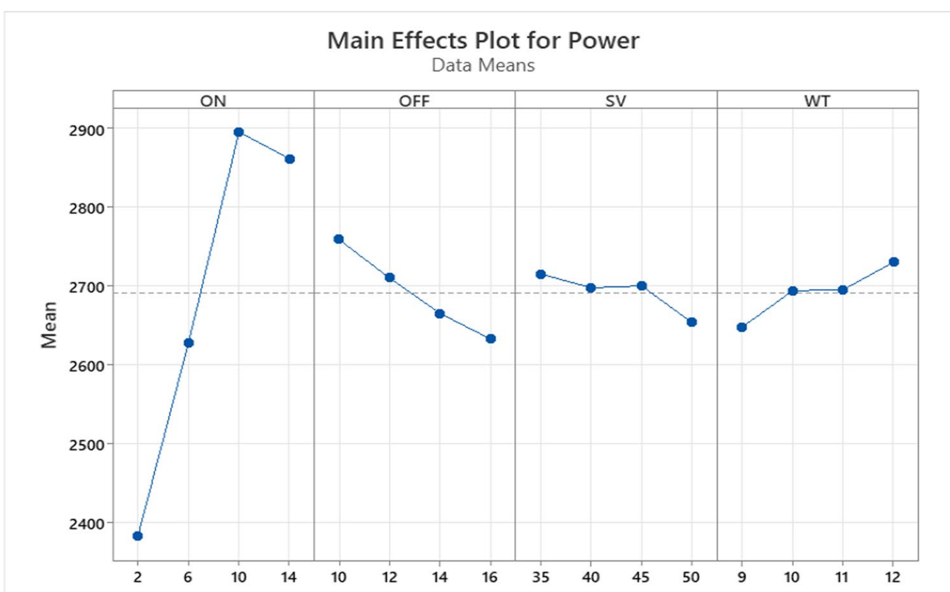



**Fig. 8** Main effects plot for power consumption

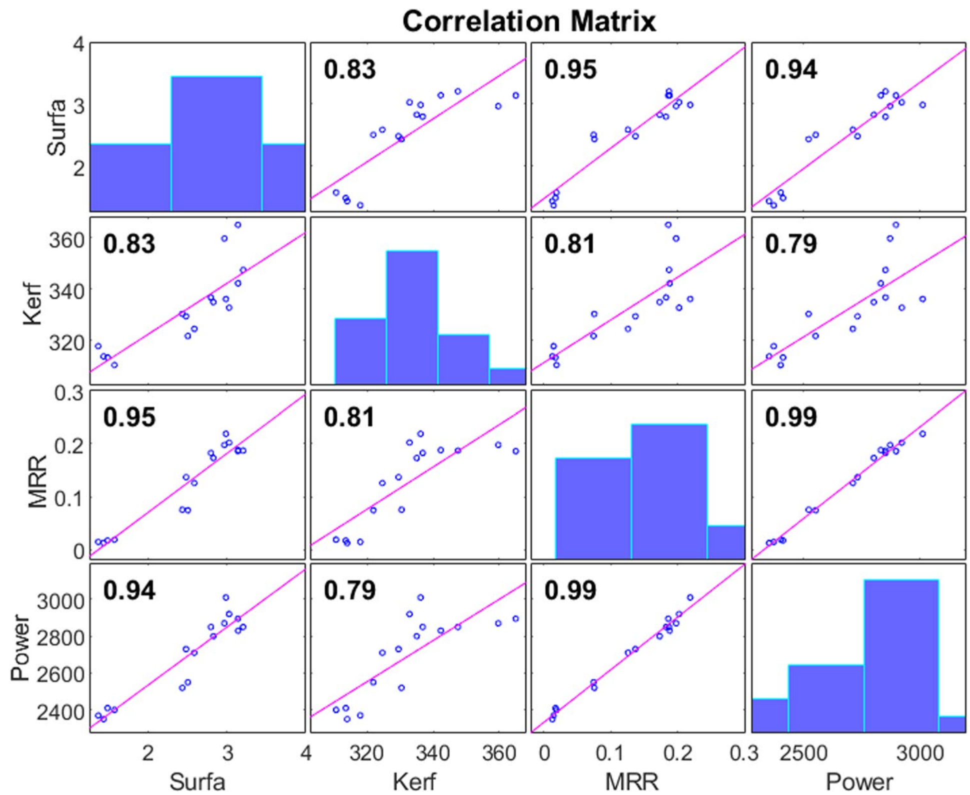



**Fig. 9** Correlation matrix for response parameters

$$Zij = \frac{max\,(yij, i = 1, 2, .....n) - yij}{max\,(yij, i = 1, 2, .....n) - min\,(yij, i = 1, 2, .....n)} \quad (3)$$

$$Zij = \frac{yij - max\,(yij, i = 1, 2, .....n)}{max\,(yij, i = 1, 2, .....n) - min\,(yij, i = 1, 2, .....n)} \quad (4)$$

where *max* $(y_{ij})$ and *min* $(y_{ij})$ represent the maximum and minimum values of the experimental data for each response. $Y_{ij}$ and $Z_{ij}$ represent the true and normalized values respectively.

2. Calculation of Grey Relational Coefficients (GRC)

GRC is calculated from the normalized values using Eq. 5. GRC relates the ideal value of the response to the experimental values.

$$\gamma(Zo, Zij) = \frac{\Delta min + \xi \Delta max}{\Delta oj(k) + \xi \Delta max}\, 0 < \gamma(Zo, Zij) \le 1 \quad (5)$$

$\Delta max$ and $\Delta min$ are the largest and smallest values of the deviation sequence, respectively. The deviation sequence, $\Delta oj(k)$, in the above equation can be estimated by Eq. 6

$$\Delta oj(k) = |(Zo(k) - Zij(k)| \quad (6)$$

where *Zo (k)* and *Zij (k)* represent the reference and comparability sequence, respectively. In this study, the value of ξ (distinguishing coefficient) is taken as 0.5, which can range between 0–1. The values of GRC estimated for the four responses are shown in Table 7.

3. Calculation of Grey relational grade (GRG)

GRG converts the multiple GRC into a combined factor using the weight factor for each response. Weighted GRG was computed using Eq. (7). This research used equal weights methods (Eq. 8) to assign to four responses, which has yielded practical results previously [46].

$$Grade\,(Zo, Zij) = \sum_{k=1}^{n} \omega_K \gamma(Zo, Zij) \quad (7)$$

$$\sum_{k=1}^{n} \omega_K = 1 \quad (8)$$

The best value of GRG obtained out of all the cutting conditions was observed for experiment #4 ranked as 1 (shown bold in Table 7). Optimal parameters were then identified by response surface optimization of the calculated GRG values (Table 7) and a regression equation was obtained.

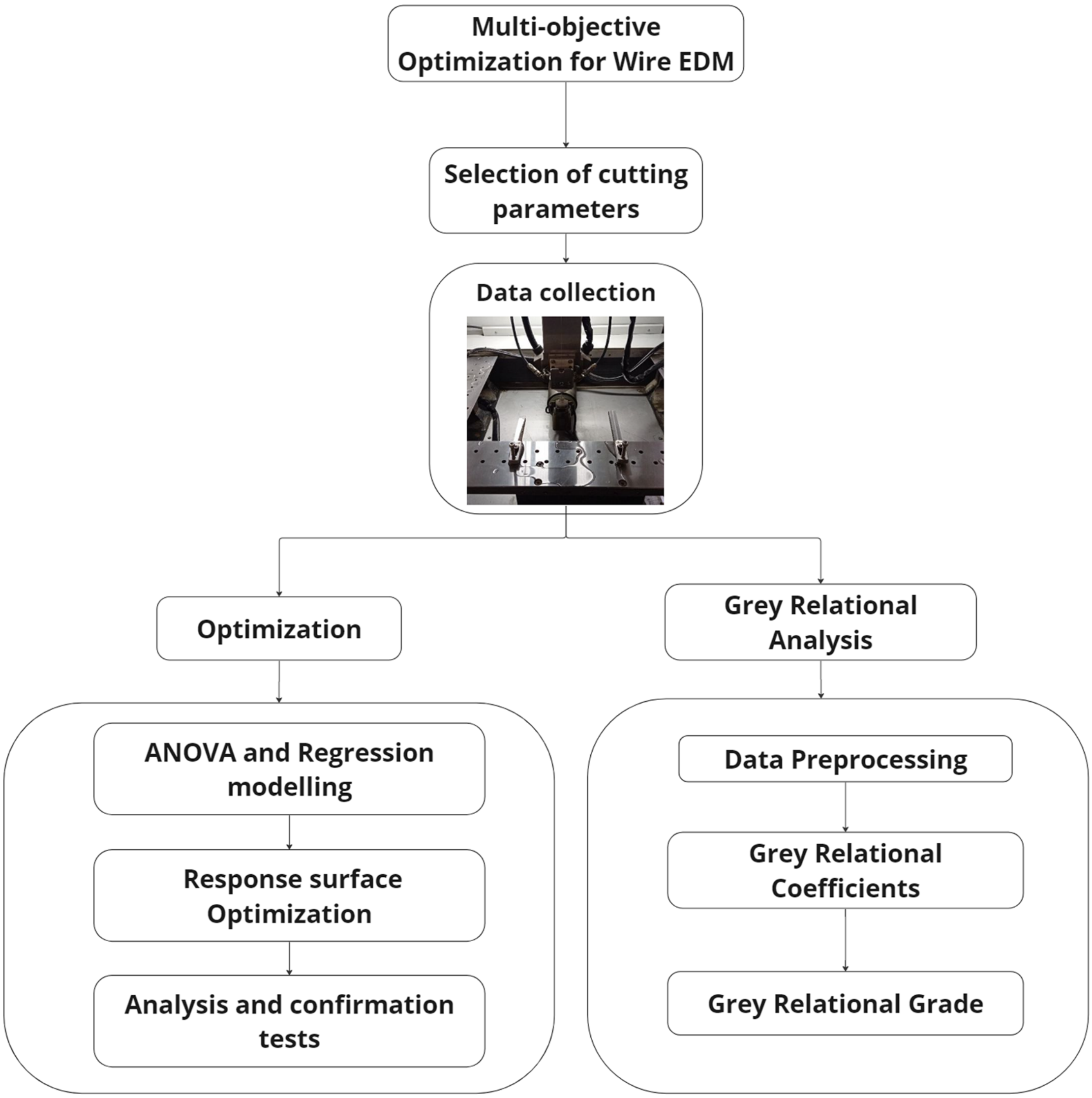



**Fig. 10** Multi-objective optimization process flow

## 6 Regression Model for GRG Function

A multi-objective function for GRG was developed using a second-order RSM model. The model equation is shown in Eq. (9) with insignificant terms eliminated from the equation.

Figure 11 presents a comparison between the GRG values obtained from optimization and regression modeling, where the maximum error is within 2%.

The first four conditions exhibit relatively higher GRG values, indicating exceptionally good performance in comparison to the other cutting conditions. This further

$$
\begin{aligned}
GRG = {} & 9.94 + 0.1948ON - 0.319OFF + 0.843SV - 4.831WT - 0.01462ON * ON \\
& + 0.00102OFF * OFF - 0.00563SV * SV + 0.1420WT * WT - 0.00156ON * OFF \\
& - 0.000573ON * SV + 0.00132ON * WT - 0.02780OFF * SV + 0.1413OFF * WT
\end{aligned} \tag{9}
$$

**Table 7** GRC and GRG calculated from responses

| Trail | Parameters | | | | Grey Relational Coefficients | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ON | OFF | SV | WT | GRC (Ra) | GRC(kerf) | GRC(Power) | GRC(MRR) | GRG | Rank |
| 1 | 2 | 10 | 35 | 9 | 0.8171 | 1.0000 | 0.8684 | 0.3402 | 0.7564 | 3 |
| 2 | 2 | 12 | 40 | 10 | 0.8861 | 0.8932 | 0.8462 | 0.3385 | 0.7410 | 4 |
| 3 | 2 | 14 | 45 | 11 | 1.0000 | 0.7704 | 0.9429 | 0.3355 | 0.7622 | 2 |
| **4** | **2** | **16** | **50** | **12** | **0.9318** | **0.8799** | **1.0000** | **0.3333** | **0.7863** | **1** |
| 5 | 6 | 10 | 40 | 11 | 0.4521 | 0.5651 | 0.4648 | 0.5573 | 0.5098 | 10 |
| 6 | 6 | 12 | 35 | 12 | 0.4299 | 0.6365 | 0.4783 | 0.5256 | 0.5176 | 9 |
| 7 | 6 | 14 | 50 | 9 | 0.4629 | 0.5534 | 0.6600 | 0.4183 | 0.5236 | 8 |
| 8 | 6 | 16 | 45 | 10 | 0.4471 | 0.6853 | 0.6226 | 0.4164 | 0.5429 | 6 |
| 9 | 10 | 10 | 45 | 12 | 0.3621 | 0.4895 | 0.3333 | 1.0000 | 0.5462 | 5 |
| 10 | 10 | 12 | 50 | 11 | 0.3914 | 0.4835 | 0.3976 | 0.7404 | 0.5032 | 11 |
| 11 | 10 | 14 | 35 | 10 | 0.3563 | 0.5246 | 0.3667 | 0.8612 | 0.5272 | 7 |
| 12 | 10 | 16 | 40 | 9 | 0.3861 | 0.5016 | 0.4231 | 0.6930 | 0.5009 | 12 |
| 13 | 14 | 10 | 50 | 10 | 0.3617 | 0.3507 | 0.3837 | 0.7501 | 0.4615 | 16 |
| 14 | 14 | 12 | 45 | 9 | 0.3649 | 0.3333 | 0.3882 | 0.8298 | 0.4791 | 14 |
| 15 | 14 | 14 | 40 | 12 | 0.3333 | 0.3997 | 0.3976 | 0.7648 | 0.4738 | 15 |
| 16 | 14 | 16 | 35 | 11 | 0.3413 | 0.4365 | 0.4074 | 0.7704 | 0.4889 | 13 |

The values shown bold are the best values for GRG and is the ranked 1st

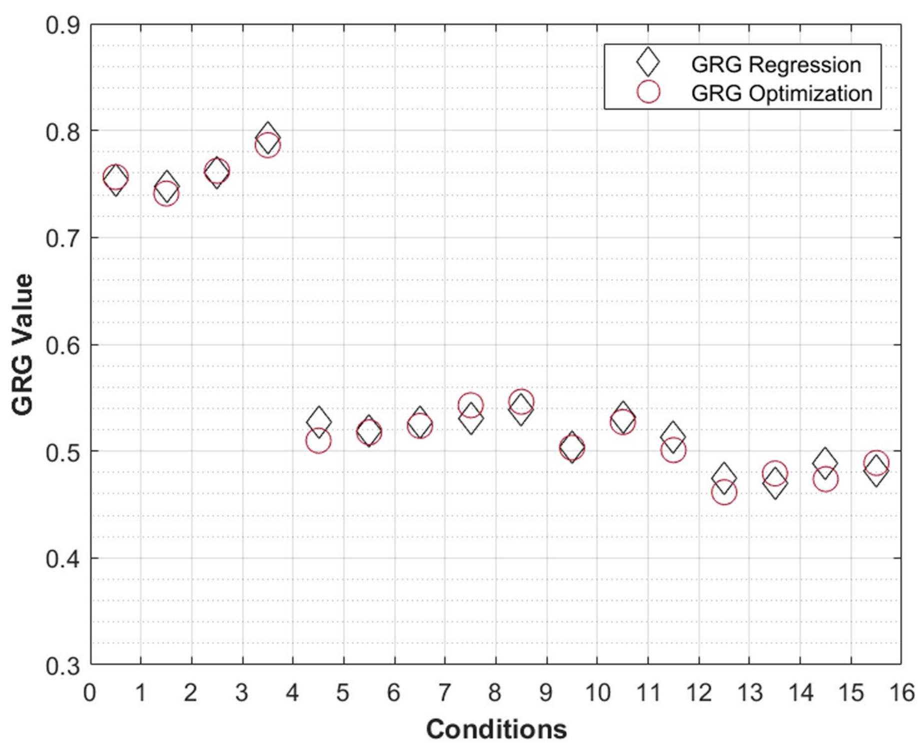



**Fig. 11** Comparison of GRG obtained from regression and response surface

corroborates previous observations that ON time is the most important parameter for WEDM quality since these four runs had the lowest ON time value (2 µs). The surface plot in Fig. 12 exhibits similar trends.

It is to be noted that the applicability of the developed model is only limited to the cutting conditions investigated in the current study.

The aggregate effect of input parameters on WEDM performance can be gauged from their relationship with the GRG. From Figs. 13 and 14 setting a low ON time is undoubtedly the most effective way to maximize performance. However, there is also a stable region in the middle two levels (6 and 10 µs), allowing users room for enhancing factors like MRR without compromising much

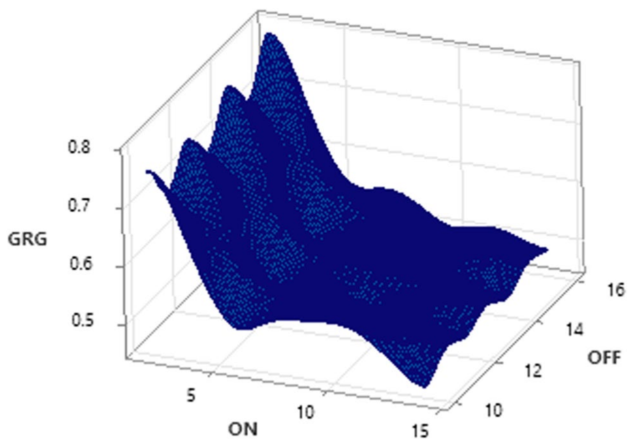



**Fig. 12** Response surface plot for GRG against ON and OFF time

on other measures of quality. OFF time, SV, and WT each have minimal effects on performance in contrast to ON time. However, the individual trends observed in this study can be useful in making critical shop floor decisions for fine-tuning the process according to quality requirements.

### 6.1 Regression model optimization

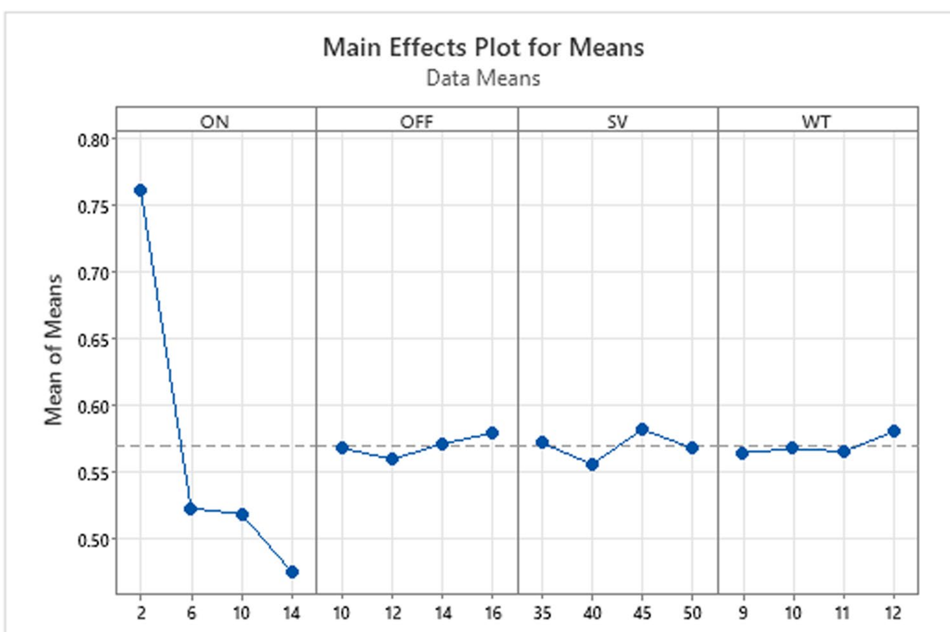
Optimal WEDM parameters were identified by using response surface optimization. The best combination that will result in optimal performance is shown in Fig. 15. These conditions were experimentally validated to confirm the accuracy of the model. For comparison purposes, the results of this optimized run were compared with the best run from the previously conducted experimentation. Based on the GRG-based ranking in Table 7, exp #4 was the best with a rank of 1. The results are shared in Table 8. A significant improvement of 24% was recorded for surface roughness and appreciable improvements in power consumption, MRR, and Kerf were also achieved. This validates the utility of multi-objective optimization in WEDM parameter selection applications.

## 7 Environmental Impact of WEDM

It is well-established that WEDM is an energy-intensive process with high environmental impact [47]. Previous studies have also verified that a significant portion of the consumed energy by WEDM is non-productive. For example, [15] calculated the non-working energy to be 62%. In our experiments, roughly only 54.8% of the power was drawn by the pulse for cutting action, with the remaining spent on auxiliary processes.

Pertaining to this situation, it is necessary to take the environmental impact of WEDM into account when optimizing process parameters. In this regard, analyzing the equivalent carbon emissions for a WEDM process is a viable method to evaluate its environmental impact and use it as a factor in parameter selection. The Carbon Emission Signature (CES™) method introduced in [48] is a simple, straightforward way to quantify carbon emissions. Its consideration of the energy mix of local electricity grids also adds geographical context to carbon signature calculations, allowing fruitful comparisons between different manufacturing sites across various locations.

**Fig. 13** Main effects plot for means



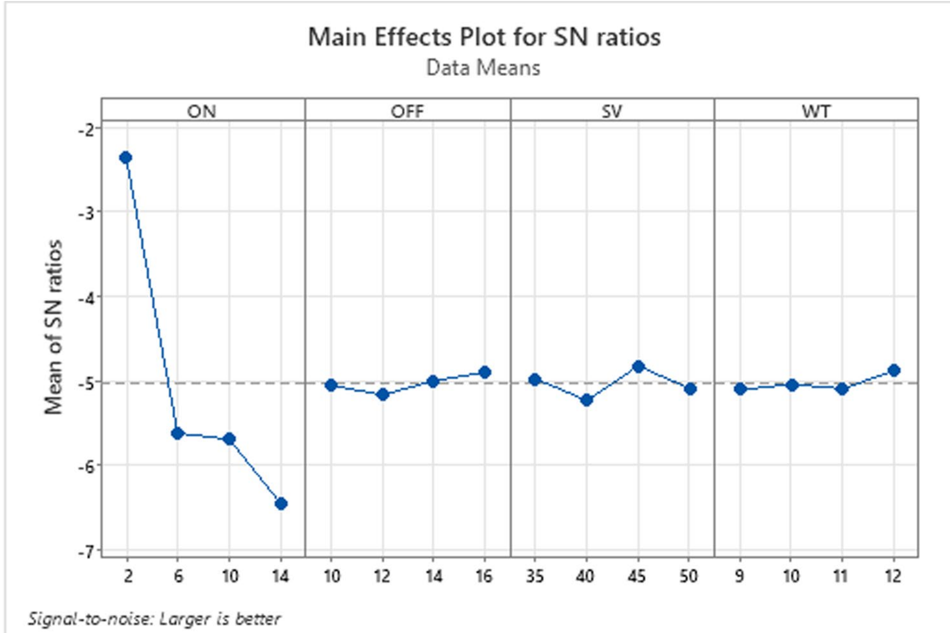



**Fig. 14** Main effects plot for S/N ratio

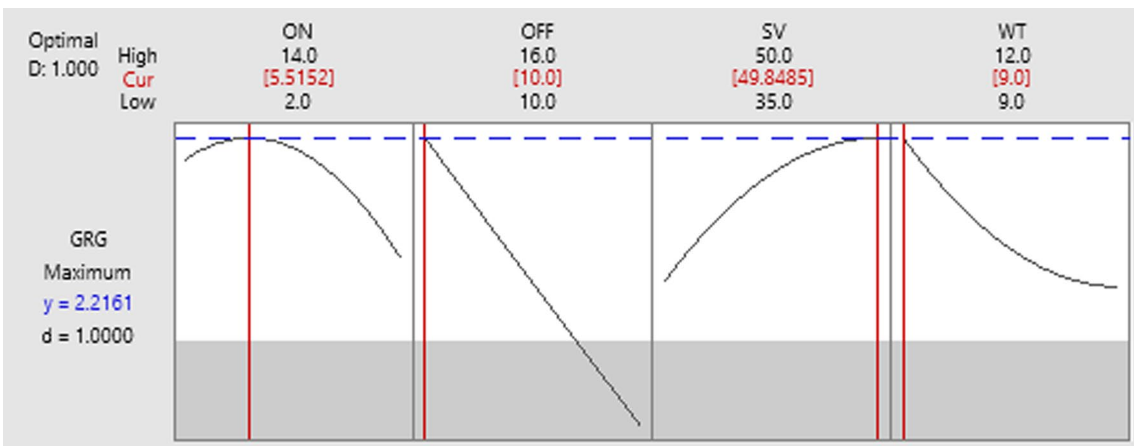



**Fig. 15** Response surface optimization

**Table 8** Comparison of optimized run with best experimental run

| | Conditions | | | | Responses | | | |
|---|---|---|---|---|---|---|---|---|
| | ON | OFF | SV | WT | SR | Kerf | Power Consumption | MRR |
| Best run (Exp #4) | 2 | 16 | 50 | 12 | 1.437 | 313.86 | 2350 | 0.0130663 |
| Optimized run | 5.5 | 10 | 50 | 9 | 1.126 | 296 | 2289 | 0.0125 |
| % improvement | | | | | 24% | 6% | 3% | 4% |

Table 9 shows the fossil fuel energy mix of the three countries the collaborators of this research work in [48]. The carbon emissions have been calculated for the first experimental run, which consumed 4.61 kW of power for 21.5 min. The results show that:

- The environmental impact of WEDM is significant and cannot be ignored during parameter selection and optimization.
- The location of the manufacturing site directly impacts process sustainability. In this case, the United Kingdom

**Table 9** Carbon emissions for different locations

| | Pakistan | Türkiye | United Kingdom |
|---|---|---|---|
| Coal (%) | 18.7 | 34.7 | 2.2 |
| Oil (%) | 11.7 | 0.1 | 0.65 |
| Gas (%) | 35.2 | 22.9 | 38.7 |
| CES™ | 135.0 | 147.5 | 64.28 |
| Carbon Emissions | | | |
| kg $CO_2$ | 0.84 | 0.91 | 0.4 |

would be the best location for manufacturing due to its high reliance on renewable energy sources.

In summary, while achieving high-performance indicators from the manufacturing point of view is crucial for the quality of production, it may not always be in line with sustainability goals and regulations. The outcome of this work directly applies to the real production process on WEDM machines, specifically in selecting quality-enhancing machining parameters and parameter tuning to tackle manufacturability issues. Our future work will investigate this tradeoff between manufacturing and sustainability goals and suggest viable strategies for manufacturers to improve their carbon footprint while maintaining profitability.

## 8 Conclusions

This research investigated the effects of four process parameters (ON, OFF, SV, and WT) on four performance indicators (SR, MRR, kerf width, and power consumption) in WEDM of AISI D2 steel. Statistical analysis was performed to determine the most significant contributing inputs and process physics was discussed in light of the obtained results. An optimization scheme was also adopted to identify the most optimal parameters for simultaneously improving all performance indicators. The following conclusions can be drawn from the analysis of this experimental work:

- The ANOVA-based analysis revealed that ON time is statistically the most significant WEDM parameter (73%) considering all performance metrics. From a physics point of view, it is justified as ON time is the main controlling parameter for energy deposition to the cutting zone.
- OFF time, SV, and WT are not as significant as ON time but, in most cases, showed clear trends against the chosen performance metrics. Understanding such trends can prove helpful in fine-tuning process parameters in shop floor environments.
- A multi-objective GRA optimization was performed to investigate the complex interdependencies identified between performance metrics. The optimized parameter settings achieved improvements in all four objectives (SR: 24%, Kerf: 6%, Power: 3%, MRR: 4%). This confirms that multi-objective optimization schemes are undeniably beneficial for WEDM processes and should be investigated in further detail.
- The environmental impact of WEDM was gauged by mapping the process against its equivalent carbon emissions, and a comparison was also made for conducting the same production in different locations with different energy grids. Combined with the fact that only 54.8% of the consumed power was for cutting, it is concluded that the environmental cost of WEDM cannot be ignored in favor of other performance metrics. Future studies will investigate the sustainability aspects of this work.



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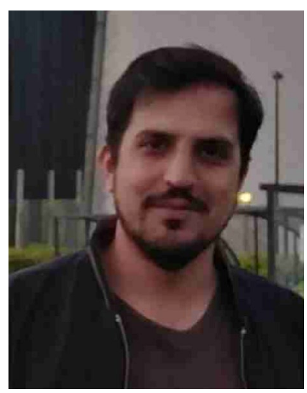

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