

Process optimization of Titanium alloy machining with Wire Electro Discharge Machining using Taguchi's Grey Relational Analysis

M. RADHADEVI¹, G. VIJAY KUMAR^{*,1}, P. GOPALAKRISHNAIAH¹

*Corresponding author

¹Department of Mechanical Engineering,

Prasad V Potluri Siddhartha Institute of Technology,

Vijayawada, Andhra Pradesh, India,

devi.radham@gmail.com, gvkumar@gmail.com*, gopalakrishna982@gmail.com

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Abstract: Titanium alloys have exceptional mechanical properties together with high strength to weight ratio and have widespread applications in the aerospace sector. Generally, these alloys have drawback with machinability. Wire-Electro Discharge Machining (WEDM) is in use to make complex shapes. Titanium alloy efficient machining includes choosing appropriate process parameters to optimize the performance characteristics. The present experimental investigation deals with process optimization of Wire Electro Discharge Machining (WEDM) process on Titanium grade 5 material using brass wire of 0.25 mm. Servo Voltage, Peak current, Pulse-on-time and Pulse-off-time, are considered as input parameters. Experiments are carried out utilizing Taguchi's L27 orthogonal array. Every process parameter is analyzed at 3 levels by using Grey Relational Analysis (GRA). The finest process parameters that optimize the Wire Wear Ratio (WWR) and Surface Roughness (SR) are identified. ANOVA is accomplished to estimate the significance of all input parameters on output performance characteristics. Confirmation tests are conducted. Experimental results are in acceptable concurrence with the confirmation test values.

Key Words: Process optimization, WEDM, GRA, WWR, SR

1. INTRODUCTION

Titanium has been employed in the field of aerospace for many years. Titanium alloys are largely utilized for the airframe and the engine parts. The Titanium materials are very hard to machine by using conventional machining process. Wire Electro Discharge Machining process can be used to machine hard materials which have intricate profiles which are unable to machine by traditional process. Also, the parts produced by this process are precise and very accurate. So it finds extensive applications in the aerospace, die making industry, and medical industries. In the current scenario, there are so many developed materials that need to benefit from process optimization. Otherwise, good quality products with optimal cost cannot be obtained. Many researchers have worked on different materials to optimize process parameters in the WEDM process, which can benefit potential users in the aerospace industry.

B. Singh et. al [1] found the Pulse on-time parameter which has a great effect on the output response of Wear Ratio. WEDM process was done on Nimonic 263 material using Brass wire

0.25mm. G. Rajyalakshmi et. al [2] studied the parameters optimization on Inconel 825 material using Taguchi's orthogonal array. 36 experiments are conducted and found the optimistic process parameters for improvement in the machining process. Manjaiah M. et al. [3] established the optimistic input process parameters using L_{18} orthogonal array on machining of $Ti_{50}Ni_{40}Cu_{10}$ with brass wire 0.25 mm. In the analysis, the significance of Peak current is found, which reduces the surface roughness at the lower peak current from the SEM graphs.

Raymond Magabe et. al [4] conducted 16 experiments on Shape memory alloys employing Taguchi's orthogonal array L_{16} and sorting algorithm for analyzing productivity (MRR and SR). Brass wire electrode coated with Zinc was employed in the WEDM process. S.Y. Martowibowo et. al [5] studied the effect of WEDM process input process parameters on ASSAB 760 Medium carbon steel, for enhancing MRR and SR. Machining was done in taper and vertical motion modes with 0.2 mm brass wire. Carmita Camposeco-Negrete [6] conducted experiments on AISI O1 tool steel material utilizing S/N ratio and ANOVA to find the influence of every input parameter on output responses in the WEDM process (Machining time and SR). Pulse off time and Servo voltage are the major factors for reducing machining time and Surface roughness.

RV Rao et.al [7] used RSM method to build a mathematical model of constraints in WEDM process. ABC algorithm was applied to achieve desired surface finish at maximum machining speed. Pragya Shandilya et.al [8] mainly focused on cutting width (kerf), found the voltage and wire feed rate as significant factors, which affected the kerf. WEDM process was done on $Sic_p/6061$ Al MMC. Ahmed A. A. Alduroobi et. al [9] performed experiments on AISI 1045 steel for optimization of input process parameters with Taguchi (DOE), ANOVA techniques. ANN model was constructed to determine MRR and SR. Amit Kumar et.al [10] developed the Process parameter optimization using Grey – based RSM technique to determine MRR, Kerf width, and SR. HSS M2 grade material was taken as a work piece and Molybdenum wire is used in the WEDM process.

Shailesh Kumar Dewanganet.al [11] carried out the experimentations on AISI P20 steel for optimizing the process parameters using PCA based Taguchi's grey relational analysis. Their prime objective was to maximize MRR and minimize overcut. Abhilash P. et.al [12] developed ANN classification model to predict process failure by conducting 81 experiments for Inconel 718. Muhammad Azam et.al [13] studied the WEDM parameters on HSLA steel by means of static analysis (DOE) & SEM (Scanning Electron Microscopy). ANOVA was performed and found T_{on} & Wire speed as significant parameters which affected the recast layer. Priyaranjan Samal et. al [14] deliberated the Micro structure and characteristics of machining for Hypereutectic Al-Si alloys while varying the Silicon material percentage to obtain better MRR & SR values using Central Composite design method. Kapil Kumar and Sanjay Agarwal [15] made an effort to optimize WEDM process parameters to achieve maximum MRR & min SR of high speed steel using Multi objective genetic algorithm. Farshid Alavi et. al [16] examined the optimistic parameters for Micro EDM process of Titanium material by design of experiments and found the most influencing parameters as Voltage & Capacitance. ANOVA & MANOVA were performed.

Vivek Aggarwal et.al [17] focused on improving the cutting rate of Inconel 718 material and found the t_{on} is the most impelling parameter to achieve Max cutting rate & min surface roughness. Anish Kumar et.al [18] conducted experiments on Titanium (Grade 2) using Box-Behnken design method to improve parameters of WEDM to get better machining rate, dimensional deviation, SR and WWR. S.S. Mahapatra et.al [19] studied the WEDM process variables which affect the MRR, SR and kerf. Also mathematical models were developed to optimize three objectives using non-linear regression method. D. V. S. S. V. Prasad et.al

[20] studied WEDM optimistic process parameters with Response Surface Methodology to achieve lower kerf and WWR values.

Hence, the present work mainly deals with Wire EDM process parameters multi optimization using Taguchi's GRA to obtain optimum process parameters which minimize the SR and WWR values of Titanium alloys used in the aerospace industry. The experimentation is conducted on Titanium grade 5 material which is used for Aircraft structural components and aerospace fasteners.

In this work, the numerical models are deduced using Minitab software and ANOVA is performed to evaluate the significance of all process variables contribution on responses. A confirmation test was performed and the experimental results were found to be correlated with each other.

2. WORK MATERIAL DETAILS & EXPERIMENTAL SETUP

Titanium grade 5 material is taken as workpiece for the present research problem. This material exhibits important properties like corrosion resistance and greater strength to density ratio. It finds extensive usage in Aerospace, marine and medical industries. Brass wire with a diameter of 0.25mm is used as an electrode when cutting the Titanium workpiece. The workpiece composition is listed in Table 1.

Table 1. Composition of Titanium grade 5 material

| Element | Nitrogen | Carbon | Iron | Oxygen | Aluminum | Vanadium | Titanium |
|---------|----------|--------|-------|--------|----------|----------|----------|
| Wt. % | <0.05 | <0.10 | <0.30 | 0.20 | 6.00 | 4.00 | 90.00 |

The experimentation is carried out using Wire Electric Discharge Machine Enova 1S (Fig. 1). Brass wire is employed as an electrode for machining of Titanium workpiece.

The parameters, Servo Voltage, Peak current, T_{on} and T_{off} play a significant role in Wire EDM machining process, which affects the output performance characteristics like SR, WWR, MRR, spark gap etc.

In the present research problem, Servo Voltage, Peak current, T_{on} and T_{off} are taken as input process variables. The main objective of the current effort is to enhance the input variables that reduce the WWR of the electrode and the SR of the Titanium workpiece specimen.



Fig. 1 Enova 1S Wire EDM



Fig. 2 Mitutoyo -Taly surf



Fig. 3a Electrode – Brass wire



Fig. 3b Balance – ConTECH



Fig. 4a Titanium work piece - specimen



Fig. 4b Titanium plate

Mitutoyo Taly surf (Fig. 2) has been used to find the workpiece surface roughness. The measurement is taken on the periphery of the workpiece specimen at three locations to calculate the average value d . Three readings are taken to calculate the final surface roughness value. The weight of the wire (electrode) (Fig. 3a) is measured by using a Balance (Fig. 3b), to calculate the wire wear ratio.

The weight measurement is done three times and the final wire wear ratio value is calculated by averaging the three readings. Fig. 4a shows the titanium workpiece specimen after machining the titanium plate (Fig. 4b).

3. EXPERIMENTAL RESULTS & DISCUSSIONS

Taguchi’s L27 orthogonal design (Table 3) is used to carry out the 27 experiments. To this end, four input process parameters at 3 levels (Table 2) are considered for the experimentation. The wire wear ratio and the surface roughness values have been calculated using the readings which are taken from measuring apparatus.

Table 2. Experimental parameter levels for WEDM process

| S. No. | Factor | Parameter | Units | L1 | L2 | L3 | Range |
|--------|--------|------------------------------|---------------------------|-----|-----|-----|---------|
| 1 | A | Pulse on time (T_{on}) | micro seconds (μs) | 100 | 103 | 106 | 100-106 |
| 2 | B | Pulse off time (T_{off}) | micro seconds (μs) | 55 | 58 | 61 | 55-61 |
| 3 | C | Servo Voltage (SV) | volts(v) | 5 | 6 | 7 | 5-7 |
| 4 | D | Peak Current (IP) | Amperes | 10 | 11 | 12 | 10-12 |

By using these experimental results, Grey analysis is performed to obtain the optimized input process parameters that minimize the wire wear ratio and the surface roughness. ANOVA is implemented to know the percentage role of each variable on the output responses.

Table 3. Experimental results with L27 Orthogonal array

| Experiment number | T _{on} (μs) | T _{off} (μs) | SV (v) | IP (A) | WWR | SR (μm) |
|-------------------|----------------------|-----------------------|--------|--------|---------|---------|
| 1 | 1 | 1 | 1 | 1 | 0.16340 | 1.13556 |
| 2 | 1 | 1 | 1 | 1 | 0.08170 | 1.15917 |
| 3 | 1 | 1 | 1 | 1 | 0.08170 | 1.10556 |
| 4 | 1 | 2 | 2 | 2 | 0.05447 | 1.75417 |
| 5 | 1 | 2 | 2 | 2 | 0.05447 | 1.74167 |
| 6 | 1 | 2 | 2 | 2 | 0.27233 | 1.61000 |
| 7 | 1 | 3 | 3 | 3 | 0.08170 | 1.69111 |
| 8 | 1 | 3 | 3 | 3 | 0.05447 | 1.66389 |
| 9 | 1 | 3 | 3 | 3 | 0.08170 | 1.66222 |
| 10 | 2 | 1 | 2 | 3 | 0.46296 | 1.84278 |
| 11 | 2 | 1 | 2 | 3 | 0.08170 | 1.84444 |
| 12 | 2 | 1 | 2 | 3 | 0.08170 | 1.94806 |
| 13 | 2 | 2 | 3 | 1 | 0.65359 | 1.47222 |
| 14 | 2 | 2 | 3 | 1 | 0.59913 | 1.47000 |
| 15 | 2 | 2 | 3 | 1 | 0.59913 | 1.47167 |
| 16 | 2 | 3 | 1 | 2 | 0.57190 | 1.95250 |
| 17 | 2 | 3 | 1 | 2 | 0.59913 | 1.89917 |
| 18 | 2 | 3 | 1 | 2 | 0.57190 | 1.95083 |
| 19 | 3 | 1 | 3 | 2 | 0.49020 | 2.16333 |
| 20 | 3 | 1 | 3 | 2 | 0.68083 | 2.08917 |
| 21 | 3 | 1 | 3 | 2 | 0.81699 | 2.12333 |
| 22 | 3 | 2 | 1 | 3 | 0.95316 | 2.18583 |
| 23 | 3 | 2 | 1 | 3 | 0.54466 | 2.21333 |
| 24 | 3 | 2 | 1 | 3 | 0.70806 | 2.25000 |
| 25 | 3 | 3 | 2 | 1 | 0.19063 | 2.03167 |
| 26 | 3 | 3 | 2 | 1 | 0.21786 | 2.01333 |
| 27 | 3 | 3 | 2 | 1 | 0.16340 | 2.02583 |

Grey Analysis is performed to assess the optimized input variables. The first step is to translate the experimental values into S/N (Signal-to-Noise) ratios. Taguchi's S/N ratios, which are log functions, serve as an objective function to predict the optimum results. The used Signal to Noise ratios are:

- a) Smaller – the –better, b) Larger – the - better and c) Nominal –the - better.

As the desired output responses (WWR & SR) are to be reduced, Smaller – the – better S/N ratio formula is used as shown in equation (1). The calculated values are tabulated in the Table 4. The Second step is to transform the S/N ratios (η) to Normalized S/N ratios (η_n) utilizing equation (2).(Courtesy Noorul Haq M Muthu J Paul 2008).

$$\frac{S}{N}(\eta) = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n y_{ij}^2 \right) \quad (1)$$

$$\frac{S}{N} ratio = \eta_n = \frac{\max(\eta_i) - \eta_i}{\max(\eta_i) - \min(\eta_i)} \tag{2}$$

$$\Delta = \max(\eta_{n_i}) - \eta_{n_i} \tag{3}$$

$$GRC = \frac{\min(\Delta_i) + \xi \times \max(\Delta_i)}{\Delta_i + \xi \times \max(\Delta_i)} \tag{4}$$

$$GRC = -\frac{1}{m} \sum_{k=1}^m GRC_{ik} \tag{5}$$

where m = the number of output responses.

Table 4. S/N Ratio and Normalized S/N Ratio

| Experiment number | S/N Ratio | | Normalized S/N Ratio | |
|-------------------|-----------|---------|----------------------|--------|
| | WWR | SR(μm) | WWR | SR(μm) |
| 1 | 15.7350 | -1.1042 | 0.3838 | 0.0377 |
| 2 | 21.7556 | -1.2829 | 0.1417 | 0.0666 |
| 3 | 21.7556 | -0.8716 | 0.1417 | 0.0000 |
| 4 | 25.2775 | -4.8814 | 0.0000 | 0.6497 |
| 5 | 25.2775 | -4.8193 | 0.0000 | 0.6396 |
| 6 | 11.2981 | -4.1365 | 0.5623 | 0.5290 |
| 7 | 21.7556 | -4.5634 | 0.1417 | 0.5982 |
| 8 | 25.2775 | -4.4225 | 0.0000 | 0.5753 |
| 9 | 21.7556 | -4.4138 | 0.1417 | 0.5739 |
| 10 | 6.6891 | -5.3095 | 0.7477 | 0.7190 |
| 11 | 21.7556 | -5.3173 | 0.1417 | 0.7203 |
| 12 | 21.7556 | -5.7920 | 0.1417 | 0.7972 |
| 13 | 3.6938 | -3.3595 | 0.8682 | 0.4031 |
| 14 | 4.4496 | -3.3463 | 0.8378 | 0.4010 |
| 15 | 4.4496 | -3.3562 | 0.8378 | 0.4026 |
| 16 | 4.8537 | -5.8118 | 0.8215 | 0.8004 |
| 17 | 4.4496 | -5.5713 | 0.8378 | 0.7614 |
| 18 | 4.8537 | -5.8044 | 0.8215 | 0.7992 |
| 19 | 6.1926 | -6.7025 | 0.7677 | 0.9447 |
| 20 | 3.3393 | -6.3995 | 0.8824 | 0.8956 |
| 21 | 1.7556 | -6.5404 | 0.9461 | 0.9185 |
| 22 | 0.4167 | -6.7923 | 1.0000 | 0.9593 |
| 23 | 5.2775 | -6.9009 | 0.8045 | 0.9769 |
| 24 | 2.9986 | -7.0437 | 0.8961 | 1.0000 |
| 25 | 14.3961 | -6.1570 | 0.4377 | 0.8564 |
| 26 | 13.2363 | -6.0783 | 0.4843 | 0.8436 |
| 27 | 15.7350 | -6.1321 | 0.3838 | 0.8523 |

The next step is to calculate the quality loss function (Δ) values from the normalized S/N ratio values from equation (3). Then Grey relation Co-efficient (GRC) is calculated, using equation (4), where, ξ is the distinguishing co-efficient, whose value will be in the range $0 < \xi < 1$. For both output performance characteristics, the Grey co-efficient is computed using the above four equations. The Grey Relational Grade (GRG) is computed using equation (5). The GRC and GRG values are listed in Table 5.

Table 5. Grey Relational Coefficients and Grey Relational Grade

| Expt. No. | T _{on} | T _{off} | SV | IP | WWR - GRC | SR- GRC | GRG |
|-----------|-----------------|------------------|----|----|-----------|---------|-------|
| 1 | 1 | 1 | 1 | 1 | 0.448 | 0.342 | 0.395 |
| 2 | 1 | 1 | 1 | 1 | 0.368 | 0.349 | 0.358 |
| 3 | 1 | 1 | 1 | 1 | 0.368 | 0.333 | 0.351 |
| 4 | 1 | 2 | 2 | 2 | 0.333 | 0.588 | 0.461 |
| 5 | 1 | 2 | 2 | 2 | 0.333 | 0.581 | 0.457 |
| 6 | 1 | 2 | 2 | 2 | 0.533 | 0.515 | 0.524 |
| 7 | 1 | 3 | 3 | 3 | 0.368 | 0.554 | 0.461 |
| 8 | 1 | 3 | 3 | 3 | 0.333 | 0.541 | 0.437 |
| 9 | 1 | 3 | 3 | 3 | 0.368 | 0.540 | 0.454 |
| 10 | 2 | 1 | 2 | 3 | 0.665 | 0.640 | 0.652 |
| 11 | 2 | 1 | 2 | 3 | 0.368 | 0.641 | 0.505 |
| 12 | 2 | 1 | 2 | 3 | 0.368 | 0.711 | 0.540 |
| 13 | 2 | 2 | 3 | 1 | 0.791 | 0.456 | 0.624 |
| 14 | 2 | 2 | 3 | 1 | 0.755 | 0.455 | 0.605 |
| 15 | 2 | 2 | 3 | 1 | 0.755 | 0.456 | 0.605 |
| 16 | 2 | 3 | 1 | 2 | 0.737 | 0.715 | 0.726 |
| 17 | 2 | 3 | 1 | 2 | 0.755 | 0.677 | 0.716 |
| 18 | 2 | 3 | 1 | 2 | 0.737 | 0.713 | 0.725 |
| 19 | 3 | 1 | 3 | 2 | 0.683 | 0.900 | 0.792 |
| 20 | 3 | 1 | 3 | 2 | 0.810 | 0.827 | 0.818 |
| 21 | 3 | 1 | 3 | 2 | 0.903 | 0.860 | 0.881 |
| 22 | 3 | 2 | 1 | 3 | 1.000 | 0.925 | 0.962 |
| 23 | 3 | 2 | 1 | 3 | 0.719 | 0.956 | 0.837 |
| 24 | 3 | 2 | 1 | 3 | 0.828 | 1.000 | 0.914 |
| 25 | 3 | 3 | 2 | 1 | 0.471 | 0.777 | 0.624 |
| 26 | 3 | 3 | 2 | 1 | 0.492 | 0.762 | 0.627 |
| 27 | 3 | 3 | 2 | 1 | 0.448 | 0.772 | 0.610 |

The Highest GRG value determines the optimum level of the input parameters, which gives a good quality product. The optimum level of each controllable factor can be calculated by considering the mean of GRG values at each level. The mean values are itemized in Table 6. The level means graph is shown in Fig. 5. By considering the maximization of GRG values, it is found that the optimized set of constraints are A-3, B-2, C-1 D-2 in sequence and assessed the process parameter values as T_{on} 106µs, T_{off} 58 µs, SV 5V and IP 11A.

Table 6. Responsible table for GRG

| Factor | L1 | L2 | L3 | Min- Max | Rank | Optimum |
|--------|--------------|--------------|--------------|----------|------|---------|
| Ton | 0.433 | 0.633 | 0.785 | 0.35 | 1 | L3 |
| Toff | 0.588 | 0.666 | 0.598 | 0.08 | 4 | L2 |
| SV | 0.665 | 0.556 | 0.631 | 0.11 | 3 | L1 |
| IP | 0.533 | 0.678 | 0.640 | 0.14 | 2 | L2 |

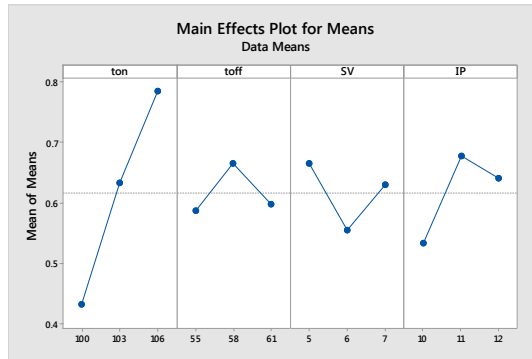


Fig. 5 Level means graph

The experimental results are taken into consideration to conduct the ANOVA using Minitab 17 software package. ANOVA is performed to examine the effect of each input process variable towards the output (WWR, SR) performance characteristics. The analysis results reveal (Table 7) that the pulse – on – time has the major contribution -74.38%, the Peak current has 13.45%, the servo voltage has 7.49 %, and the pulse – off – time has 4.25%. Each input process parameter contribution is shown in Fig. 6.

Table 7. ANOVA of Grey Relation Grade

| Source | DoF | Adj SS | Adj MS | F Value | P Value | Percentage Contribution |
|------------------|-----|---------|----------|---------|---------|-------------------------|
| T _{on} | 2 | 0.5608 | 0.280399 | 175.2 | 0 | 74.38 |
| T _{off} | 2 | 0.03205 | 0.016025 | 10.01 | 0.001 | 4.25 |
| SV | 2 | 0.05648 | 0.028239 | 17.64 | 0 | 7.49 |
| IP | 2 | 0.1014 | 0.050698 | 31.68 | 0 | 13.45 |
| Error | 18 | 0.02881 | 0.0016 | | | 0.42 |
| Total | 26 | 0.77953 | | | | |

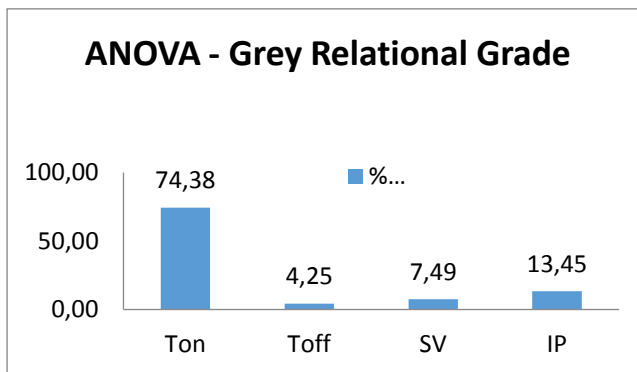


Fig. 6 Percentage of contribution on output responses

The regression analysis is executed using experimental values and mathematical models are developed.

This mathematical model establishes the relationship between the input variables and the output responses. Using these models, an estimation of the output responses can be calculated without conducting more number of experiments. From the analysis, the following regression equations are developed for calculating the wire wear ratio (WWR), the surface roughness (SR) and the grey relational grade (GRG) values.

$$\text{WWR} = -6.63 + 0.0711T_{\text{on}} - 0.0076T_{\text{off}} - 0.0121\text{SV} + 0.0166\text{IP}$$

$$\text{SR} = -12.50 + 0.10319T_{\text{on}} + 0.02739T_{\text{off}} - 0.0025\text{SV} + 0.1898\text{IP}$$

$$\text{GRG} = -6.005 + 0.05866T_{\text{on}} + 0.00162T_{\text{off}} - 0.0171\text{SV} + 0.0536\text{IP}$$

A confirmation test is performed using the optimized input process parameter values from the Grey Relational Analysis. It assessed the performance quality characteristics wire wear ratio and surface roughness values and found good enhancement in the process.

$$\gamma = \mu + (A_i - \mu) + (B_i - \mu) + (C_i - \mu) + (D_i - \mu)$$

μ – Mean of GRC values

Using the above relation, the estimate has found good agreement at the optimized process parameters.

4. CONCLUSIONS

In this work, WEDM process is carried out on Titanium material and an effort has been made to enhance the input parameters to get better performance. The following deductions are drawn.

1. The optimized process parameters assessed from GRA are T_{on} 61 μs , T_{off} 58 μs , SV 5V and IP 11A.
2. The ANOVA analysis shows that the pulse-on-time has the major contribution of 74.38%, the Peak current has 13.45%, the servo voltage has 7.49 %, and the pulse-off-time has 4.25%.
3. Multi regression analysis is performed and mathematical models are developed to evaluate the output responses and enhancement is found in the process.
4. A confirmation test is conducted and good coherence is found between the estimated and experimental investigation values.

The present work can be attributed to machining of the Titanium material used in aerospace sector. As the Titanium is a very costly material, optimistic parameters are needed to get good quality products at minimum cost. In the machining process, if the wire wear is significantly high, there is a chance that the wear particles of the wire electrode will deposit on the machined surface, which may influence the quality of the surface, that is, the dimensional accuracy.

Similarly, to achieve a good surface finish, the Surface Roughness (SR) value has to be minimized. Hence, it requires the recognition of the optimal process parameters that minimize the WWR and the SR values. The conclusions drawn from the above experimentation will be helpful, during Wire Electro Discharge Machining of Titanium material used in aerospace components.

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