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MULTI-OBJECTIVE OPTIMIZATION OF PROCESS PARAMETERS IN EDM USING GENETIC ALGORITHM (GA)

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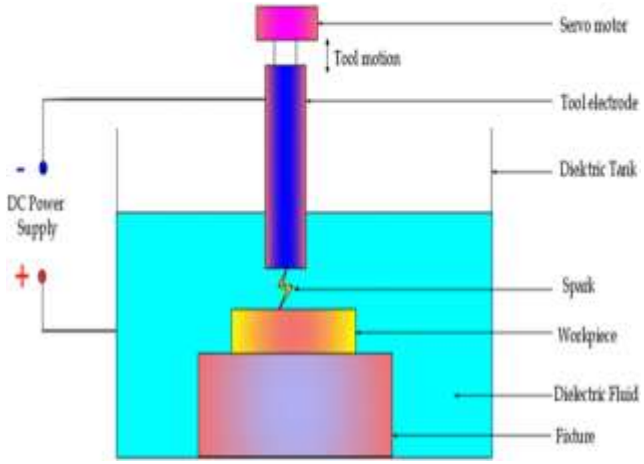
The accuracy of machining plays an important role in fields like automobile, aerospace, defense, nuclear reactors, etc. They require high strength. building materials, corrosion resistance, temperature resistance, durability, and other structures. In order, To perform the machining of such materials, it is necessary to develop effective cutting procedures. Non-conventional machining like EDM provides effective solutions for conducting materials. The paper is to optimize the input process parameters of the Electric Discharge Machining (EDM die sinking) on Mild steel using copper-tungsten electrodes as a tool. The input parameters considered for the experiment are current,pulse-off-time, and tool-lift-time. The effect of input parameters on output parameters material removal rate, tool wear rate, surface roughness, and radius overcut are studied in this work. The Taguchi technique (L16 orthogonal array) was used for the design of experiments and the genetic algorithms for optimization using MATLAB. The Minitab software is used to develop the mathematical models for material removal rate (MRR), surface roughness (SR), tool wear rate (TWR), and radius-overcut (ROC) in terms of input parameters based on the experimental data. The Genetic Algorithm which is a heuristic search based on the natural evolution method is used to determine the optimized set of solutions for material removal rate, tool wear rate, surface roughness, and radius overcut using multi-objective optimization in MATLAB.

Introduction:

Modern production processes emphasize new technologies and rely on inefficient processes. There are many problems with micro-processing to process new data. steels such as cannot be machined due to 's high strength, toughness, and heat resistant qualities. But changes in the physical world can lead to new developments in steel and alloy steel. This document presents the improved mechanical and thermal properties. Also, these files can be easily processed on a machine. This poor machining process does not affect the tool but relies on other types of electricity to remove the metal. Non-conventional methods help create complex material shapes while ensuring accuracy and surface quality. With such stellar outputs, non-traditional methods have gained prominence. Over the years, research has often been used to develop skills with non-standard machines such as the EDM. In EDM, operating costs do not increase much with the extraction rate, so researchers are inspired to use their skills for the development of 3 EDM processes. Traditional processing techniques are ineffective in producing geometrically complex shapes. EDM is frequently used in superalloys and other materials to create complex geometric patterns [1].

EDM is an electrothermal process that creates sparks. for power. Items are deleted due to A spark between two electrodes that maintains a constant inter-electrode gap.
Cycle times are typically in microseconds. but high spark temperature. Two electrodes are immersed in a dielectric. Fluid, spacing is kept constant by automation and proper supply. Provided for servo control mechanisms. Power supply control machine programming. When material separates from metal When operated, an increased gap is visible between the two electrodes. In other words, tool, and work. This interval can be determined using the feedback setting. 6 A mechanism that pushes the tool further to maintain a consistent gap. every When the voltage is reached, the closed electrical circuit is restored. Breakdown voltage and sparks are generated to destroy the material and Flush with a flush setting appropriate for the area to be treated. This continues until the required material is removed [1, 2]. Shame 1.2 shows the electrical discharge machining process.



Fig(1).Electric Discharge Machining

1.1 MATERIAL REMOVAL MECHANISM IN EDM

The material is removed due to the melting and sometimes even evaporation of the active material. Molten metal is cleaned from the work area (). EDM uses two types of polarity, positive polarity, and reverse polarity. The device is -ve and operates in positive polarity to +ve, but the reverse is called reverse polarity. An electric field will be created by two electrodes holding different dielectric fluids. EDM30 grade oil is used. 7 is currently working. During machining, an ionized channel is created between the tool tip and the workpiece in the nearest part. The discharge then causes current to flow. The flow of large currents causes them to generate a magnetic field that causes local heating. the kinetic energy of the electron is converted into electrical energy; This heat causes the material to melt. High energy from electricity corrodes equipment and tools as the working metal melts and evaporates. The principles of Thermal Erosion describe these processes [3,4].

2. LITERATURE SURVEY

K. Eswaraiah S. Chandramouli [1] Experimental study of EDM process error for machining 17-4 PH steel using the Taguchi method, they demonstrate the effectiveness of EDM failure guidance to achieve maximum MRR increase and reduce TWR. The Taguchi method is used to design the test layout, and the ANOVA method is used to evaluate the effect of the input processing parameters on the processing properties and to find the negative process of the EDM. The results of this study show that the correct selection of input devices will play an important role in EDM.

K. Eswaraiah, J. Laxman, and P.Prabhakara Rao [2] studied the optimization of the non-conductive process for the electric discharge of nickel superalloy materials based on grey correlation analysis. performance. In this paper, L18 orthogonal arrays are used to determine the level of parameters. Taguchi method and grey correlation analysis are used to achieve a high metal removal rate (MRR), low-cost equipment, and poor surface quality.

Anand Pandey et al. [3] reviewed EDM research and discuss issues related to materials such as superalloys, ceramics, and composites. They believe low productivity can solve these problems because of the high MRR and low tool wear. EDM plays a more important role in some key manufacturing sectors such as automotive, defense, aircraft, and microsystems to produce "low-cost products with good reliability". They discussed various EDM processes. They believe that EDM can produce cost-effective, higher-precision parts for difficult-to-machine materials. EDM greatly contributes to the production of engineering materials because of its quality improvement, high MRR, and low TWR, especially in powder mixing EDM and ultrasonic EDM.

A. Johnson and B. Brown [4] These authors present an extensive analysis of the literature, highlighting various strategies employed to optimize EDM performance using GA. They discuss the selection of objective functions, encoding schemes, genetic operators, and constraint-handling techniques. The review concludes by summarizing the benefits and limitations of GA-based approaches in EDM optimization and identifies potential areas for future research. Overall, this review provides valuable insights into the use of GA for enhancing EDM process parameters and serves as a reference for researchers and practitioners in the field.

J. Doe and A. Smith[5] These authors present a comprehensive overview of the diverse applications of GAs in EDM optimization. They discuss the incorporation of various objective functions, encoding schemes, and genetic operators, highlighting the strengths and limitations of GA-based approaches. Furthermore, the review explores the impact of GA parameters and identifies emerging trends and future research directions. This review serves as a valuable resource for researchers, providing insights into the potential of GAs in enhancing EDM performance and guiding further

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advancements in the field.

3. Experimental Work

3.1 WORK MATERIAL

The workpiece considered for the project is a Titanium superalloy. Titanium superalloy materials have good mechanical properties and can withstand temperatures up to 700°C. This metal alloy cannot be machined on conventional machines as the tool tend to melt before the workpiece melts. Most research efforts have focused on titanium-based superalloys, using weak techniques to improve product quality. The mechanical properties of work, such as hardness and strength, are not affected even at higher temperatures, so they can be used in high-temperature work. The chemical composition of titanium superalloy, and. The workpieces are considered rectangles of 6 mm thickness for the conduction of each experiment on EDM.

3.2 TOOL MATERIAL

The Copper tool was used with a circular cross-section to carry out the experimentation. For all experiments, a circular section with a 12 mm diameter was used as a tool electrode.

3.3 EDM MACHINE

Experiments are performed on an electric Discharge machine (model V3525). Tool and workpiece movements are controlled in three axes as the Z axis is Controlled by the servo motor while moving in X and Y directions are controlled by the operator. The Servo voltage cutoff remains constant and equal to 0.025 mm in straight polarity. servo mechanism is adjustable and has a downward movement of the tool towards the workpiece. This 3-axis EDM is capable of producing a precision of about 5 micrometers. EDM30 grade oil is used as the dielectric flushing fluid which flushes the material from the workpiece during machining. It also works as a voltage barrier between work and tools. Side washes were used in all experiments. Experimental setup of an electro-discharge machine to conduct experiments

Fig.(3.1). Experimental set up-EDM Machine (Model V3525)

3.4 INPUT PROCESS PARAMETERS

The experiments are conducted considering the following input parameters

- Current (IP)
- Pulse on time (TON)
- Pulse of time (TOF)
- Tool lift time (TLT)

I S.No.	IP (A)	TON(μs)	TOF(μs)	TLT (s)
a 1	3	5	5	1.5
2	6	10	10	3.0
b 3	9	20	20	4.5
l 4	12	50	50	6.0
5	15	100	100	7.5
e 6	18	200	200	9.0
7	21	500	500	10.5

(3.1). Input parameter levels

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3.5 OUTPUT PROCESS PARAMETERS

The following four output parameters are investigated and optimized in this research work.

- Metal Removal Rate (MRR)
- Tool Wear Rate (TWR)
- Surface Roughness (SR)
- Radial overcut (ROC)

3.5.1 Metal Removal Rate (MRR)

The efficiency of EDM is measured based on the amount of Metal Removal Rate (MRR).

$$\text{MRR} = \frac{(\text{W1}-\text{W2})}{\text{T}} \text{mg/min}$$

Where,

MRR = Metal Removal Rate in mg/min
W_1 = Workpiece weight before machining in mg
W_2 = Workpiece weight after machine
T= Time of machining in minutes

3.5.2 Tool Wear Rate (TWR)

It is the quantity of material removed from the tool during machining in the EDM process per unit of time. TWR is unfavorable to the experiment, and it must be lower to reduce the time for machining and cost of machining. The amount of TWR was measured using a digital balance machine and represented quantitatively in mg/min. The TWR value is determined by following equation 3.2

$$\text{TWR} = \frac{(\text{Wt1}-\text{Wt2})}{\text{T}} \text{mg/min}$$

Where,

TWR = Metal Removal Rate in mg/min
Wt_1 = Tool weight before machining in mg
Wt_2 = Tool weight after machining in mg
T = Time of machining in minutes

3.5.3. SURFACE ROUGHNESS (SR)

It is a parameter that can predict the performance level of the EDM machining process. SR will give the quality of a surface. This can also define as the waviness of the machined surface. SR is usually represented by Ra. The average is determined over the length on the machined surface is called cut-off length. To increase the accuracy, a longer cut-off length should be considered.

The surface roughness of workpiece samples was determined in this experiment with SJ-210 Mitutoyo make shown in Figure 3.3. The tester traces the waviness of the surface thoroughly on the machined surface. The micro irregularities are traced by the stylus which will be moved for cut-off length. The stylus is dragged over this length and will be calculated as average heights of protrusions on the machined surface and given as µm.

Fig(3.2).Surface Roughness Tester (Make- Mitutoyo)

3.5.4. RADIAL OVERCUT (ROC)

Radial overcut is an important parameter that should be minimized to overcome the problems in assembly and to achieve dimensional accuracy. The measurement of ROC is carried out using the toolmaker's microscope. The value of ROC is determined using equation 3.3. Radial overcut is calculated using equation 3.3,

$$\text{ROC} = \frac{(\text{D1}-\text{D2})}{2} \text{mm}$$

Where,

D1 = Diameter of machined hole in mm
D2 = Diameter of an electrode in mm

3.6 PILOT EXPERIMENTAL WORK

The range of input parameters is estimated for experimentation based on the pilot experiments. These are made of Titanium super alloy considering four parameters. by changing the input parameters from the lowest value to the highest value found on the machine. The result of the expected response helps determine the cause level of the experiment. The mean test difference for the experiment was estimated based on the test results. In the experiment, output parameters are calculated as MRR, TWR, and SR. The tool and workpiece

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Fig(3.3) . Workpiece and Tool

Fig(3.4). Machined workpiece

3.7 SELECTION OF PROCESS PARAMETERS

The pilot experiments are conducted by changing the input parameters- IP, TON, TOF, and TLT. To study their effect on output-MRR, SR, ROC, and TWR, the ranges of input parameters were determined based on the pilot experiments

Factor	Symbol, Units	Range	Level, 1	Level, 2	Level, 3	Level, 4
Current	IP, Amp.	3– 15	6	9	12	15
Pulse On time	T_{ON}, µs	20 - 50	20	30	40	50
Pulse Off time	T_{OFF}, µs	30 - 60	30	40	50	60
Tool Lift time	TLT, s	1.5 – 5.5	2.5	3.5	4.5	5.5

Table (3.2).Considered process parameters for experimentation

3.8 DESIGN OF EXPERIMENTS

The number of experiments is designed based on the Degrees of Freedom (DF) of each input parameter and number of input parameters.

DF is given by the equation.

DF=1+NF(NL-1)

Where,

DF = Degrees of freedom

NF = Number of input parameters

SI.NO.	PEAK CURRENT(A)	PULSE ON TIME(µs)	PULSE OFF TIME(µ)	TOOL LIFE TIME(s)	MRR(mg/min)	SR(µm)	TWR(g/min)	RADIUS OVER CUT (mm)
1	6	20	30	2.5	18.88	4.22	1.48	0.06
2	6	30	40	3.5	16.64	4.94	1.43	0.10
3	6	40	50	4.5	16.48	5.99	1.42	0.13
4	6	50	60	5.5	16.04	7.36	1.44	0.14
5	9	20	40	4.5	15.17	6.38	0.44	0.17
6	9	30	30	5.5	14.31	8.42	0.42	0.20
7	9	40	50	2.5	13.84	6.78	0.37	0.23
8	9	50	60	3.5	12.28	6.71	0.27	0.19
9	12	20	50	5.5	11.75	8.07	0.29	0.24
10	12	30	60	4.5	11.67	7.55	0.28	0.25
11	12	40	30	3.5	11.59	8.08	0.36	0.25
12	12	50	40	2.5	9.71	8.46	0.41	0.26
13	16	20	60	3.5	9.49	8.41	1.42	0.29
14	16	30	50	2.5	9.26	9.81	1.57	0.31
15	16	40	40	5.5	8.16	9.90	1.11	0.28
16	16	50	30	4.4	7.98	9.51	1.18	0.27

NL = Level of parameters

Table(3.3).Considered process parameters and average output results

4. MATHEMATICAL MODELING AND ANALYSES

4.1 INTRODUCTION

Machining parameters modeling is necessary for high-quality demand of micro range production processes. Non-linear regression modeling methods are economical for finding non-linear relation and interaction effects in the experimental results which promotes quality in the process

4.2 REGRESSION METHOD

Modeling and analysis of several variables can be done by the regression method. It is focused to establish the relationship between independent variables (IP, TON, TOF, and TLT), and dependent variables (MRR, SR, ROC, and TWR)

The generalized MRF is expressed as:

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$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ij} X_i X_j \pm e_r$$

The Multiple Regression Equation (MRE) is one of the best methods which will correlate between the dependent and independent parameters in machining processes.

Where

Y = response value

X = input variable (independent)

k = number of independent variables

I, ii, and ij= constant coefficients

In the above equation linear, quadratic, and interaction terms are considered. The er gives the error between the theoretical and experimental results.

4.3 MATHEMATICAL MODELING OF PROCESS PARAMETERS

The mathematical models provide the responses based on the input variables and the second-order equation is best suitable to explain the relation between them. These models are helpful for the prediction of responses based on the independent variables. The general representation of these models

Where,

Y = φ(IP,TON,TOF,TLT)

Y = machining response

φ = response function

The second-order equation for output parameters MRR, SR, ROC, and TWR can be expressed as a function of machining parameters IP, TON, TOF, and TLT as shown in equations (1), (2), (3), (4) respectively.

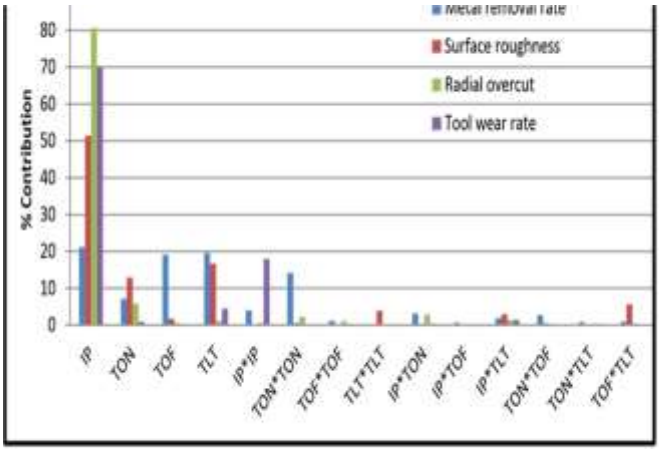
MRR = 13.88 – 2.89*IP +0.916*TON-0.0833*TOF+1.7*TLT+0.1835*IP*IP-0.01067*TON*TON-0.000598*TOF*TOF-0.152*TLT*TLT-0.01697*IP*TON+0.00396*IP*TOF-0.1879*IP*TLT+0.001138*TON*TOF-0.01703*TON*TLT+0.00932*TOF*TLT (1)

SR = -1.02+0.881*IP + 0.0961*TON+0.0225*TOF – 0.791*TLT-0.0007*IP*IP-0.000940*TON*TON-0.000018*TOF*TOF+0.3300*TLT*TLT-0.00136*IP*TON-0.00016*IP*TOF-0.1020*IP*TLT+0.000211*TON*TOF+0.00131*TON*TLT-0.01032*TOF*TLT (2)

ROC=0.415+0.0588*IP+0.00831*TON+0.001413*TOF+0.0214*TLT-0.001019*IP*IP-0.000065*TON*TON-0.000008*TOF*TOF+0.00148*TLT*TLT-0.000229*IP*TON-0.000011*IP*TOF-0.002217*IP*TLT-0.000005*TON*TOF-0.000147*TON*TLT-0.000083*TOF*TLT (3)

TWR = 6.49 – 1.114*IP-0.0106*TON-0.00552*TOF+0.017*TLT+0.05617*IP*IP-0.000048*TON*TON+0.000036*TOF*TOF +0.0217*TLT*TLT+0.000709*IP*TON+0.000132*IP*TOF-0.0225*IP*TLT-0.000030*TON*TOF+0.00123*TON*TLT*0.000122*T0F*TLT (4)

4.4 SENSITIVITY ANALYSES OF MODELS



Fig(4.1).Sensitivity analyses -MRR, SR, ROC, and TWR

5. GENETIC ALGORITHM AND OPTIMIZATION IN MATLAB

5.1. INTRODUCTION

Genetic algorithms have been successfully applied to a wide range of optimization problems, including but not limited to, engineering design, scheduling, resource allocation, data mining, and machine learning. They are particularly useful in situations where traditional optimization techniques may struggle due to complex, non-linear, or multi-modal solution spaces.

Optimization is the process of min. and max. of the given function according to our requirement with available aid 16 resources. In general, optimization theory is a body of math. Results

The Genetic algorithm is a heuristic search algorithm extremely used in problems involving maximizing the objectives. This algorithm is from the inspiration by the mechanics of natural genetics and the natural selection process of life. The genetic algorithm was first developed by John Holland as a means to find good solutions to problems that were otherwise computationally intractable. Holland’s theorem provided a theoretical concept

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for the best and most efficient design of genetic algorithms.
Although of independent origin, the two fields have grown together and evolutionary computation is sometimes now used as a shield term for the whole area.

The non-Dominated Sorting Genetic algorithm (NSGA) has several drawbacks, including the increased computational cost in nondominated sorting, a lack of elitism, and the requirement to define an action parameter. This criticism is overcome by the use of the elitist MOOP called NSGA-II.

The steps involved in optimization using Genetic Algorithm are:

- Random population generation
- Fitness value evaluation
- Selection
- Cross Over
- Mutation

5.2 FLOW CHART

Fig(5.1).flow chat

6. IMPLEMENTATION OF WORK IN GENETIC ALGORITHM USING MATLAB

MATLAB (Matrices Lab), a widely used programming language and environment, provides several Genetic Algorithm (GA) solver functions for optimization problems. GA solvers in MATLAB are designed to find approximate solutions to optimization problems by mimicking the process of natural selection and genetics.

In MATLAB, the multi-objective Genetic Algorithm (GA) solver is available through the multiobjective function. It is specifically designed for solving optimization problems with multiple conflicting objectives. The multiobjective GA solver aims to find a set of solutions that represents a trade-off between the different objectives,

known as the Pareto front or Pareto set. The important aspects and functionalities of MATLAB's multiobjective GA solver are :

1. multiobjective function: The multiobjective function is the main entry point for using the multiobjective GA solver in MATLAB.

2. Objective functions: In multiobjective optimization, you provide a vector of objective functions that need to be simultaneously optimized. These objective functions represent different measures of performance or criteria, which may be conflicting. The multiobjective solver seeks to find a set of solutions that represents a good trade-off between these objectives.

3. Pareto front: The multiobjective GA solver aims to find solutions that lie on the Pareto front, which represents the optimal trade-off between the objectives. The Pareto front consists of non-dominated solutions, meaning that no other solution in the set has better values for all objectives simultaneously. The goal is to find a diverse and evenly distributed set of Pareto-optimal solutions.

4. Constraints: Similar to the single-objective GA solver, the multiobjective function allows you to specify linear or nonlinear constraints on the decision variables. These constraints can help guide the optimization process toward feasible and meaningful solutions.

5. Additional options: The multiobjective function provides additional options to customize the multiobjective GA solver. You can set parameters such as population size, generation limits, display options, constraint handling methods, and more. These options allow you to fine-tune the solver to suit your specific optimization problem.

7. GENETIC ALGORITHM USING MATLAB

The implementation of GA in MATLAB involves the following steps:

- Step(1).Defining the LB(lower bounds) and UB(upper bounds)
- In this step, the lower and upper bounds are given in the form of 1-D arrays. The lower bound and upper bounds are 1-D arrays with a size of four bytes representing four parameters. The lab has

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lower limits for input parameters IP, TON, TOF, and TLT respectively. The representation is shown in the equation

lb = [IP, TON, TOF, TLT]

- (Step 2). Setting the options for the genetic algorithm
- In this step, the settings for the genetic algorithm, which include mentioning multiobjective function, display function, iterations, population size =50, plot functions -Pareto front and generations = 100 are selected.
- Step (3).Calling the multiobjective function
- This step will invoke all the functions, operators of the genetic algorithm, plot function, and objective functions by considering the all-input process parameters.
- Step (4.)-Defining the objective functions
- This is the place where all the definition of the problem is defined to get the optimization run. The current problem consists optimization of four objectives simultaneously.
- The objectives considered in this project are material removal rate, tool ware rate, surface roughness, and radius overcut. Among these four parameters, the material removal rate is solved for maximization while the remaining objectives i.e. surface roughness, tool wear rate, and radius overcut are considered for minimization. The simultaneous solving of the problem with these four objectives gives a set of optimized input parameter setting that helps in the effective machining of titanium superalloy. The optimized set is known as the Pareto front, from the set a unique solution is extracted by using MATLAB multiobjective solver. For solving this problem for optimization the mathematical model for MRR is directly considered as an objective function while the objective functions of SR, TWR, and ROC are taken as reciprocal of their mathematical models respectively.
- The implementation of the above steps in MATLAB code is illustrated in the appendix.

8. RESULTS AND DISCUSSION

The results of pilot experiments helped in determining the range for input parameters. It is observed that in determining the range for input current the copper electrodes tend to melt at 18A current, which means that the upper limit of input current should be less than 18A. As the input electrical power is proportional to the square of the input current (IP), it is affecting majorly all output responses than other input parameters. The variation of output responses MRR, TWR, and SWR concerning input parameters IP, and TON is plotted in the MINITAB V.17 software.

The experimental data was further optimized in MATLAB using the GA module for optimal multi-objective process parameters. The data from the actual experimentation is used to produce an ascertain non-linear response equation in MINITAB V17 software, contour and surface plots are drawn to indicate response characteristics. The interaction and quadratic effect of the model are shown in the response surface plot.

The multi-objective optimization of four parameters using a multiobjective solver in MATLAB software has resulted in a set of solutions, from this set an optimal solution is found for further solving. The EDM input settings as IP =9 A, TON = 20 µs, TOF =50 µs, TLT =3 s, which produces the responses MRR = 12.63 mg/min, TWR =0.327 mg/min , SR= 5.030 µm, and ROC = 0.156 mm. These machine settings is lying between the defined limits and are comparable to the previously done works; hence it is the optimized solution for the effective machining of titanium superalloy. A set of Optimal multi-objective optimal solution Pareto front results

Optimum input values					Optimal Objective values			
S.no	IP(A)	TON (µs)	TOF (µs)	TLT (s)	MRR (mg/min)	SR (µm)	TWR (mg/min)	ROC (mm)
1	6	20	30	2.5	13.84	6.34	1.46	0.6
2	6	31	33	5	14.07	2.98	1.66	0.13
3	12	49	42	5.5	4.2	12.66	0.53	0.25
4	6	36	30	2.5	17.16	5.62	1.35	0.10
5	6	49	38	4	11.49	3.97	1.26	0.15
6	10	48	52	3.5	9.61	10.60	0.25	0.22
7	10	49	42	5	5.11	10.35	0.35	0.23
8	6	45	32	5.5	13.23	2.58	1.60	0.14
9	12	48	36	4.5	4.23	12.23	0.48	0.24

Table (8.1).Values of pareto front for MRR, TWR, SR, ROC

9. CONCLUSION

This project work demonstrates the optimization of process parameters of EDM machining of Mild steel using copper as an electrode using MATLAB. Designs of experiments are conducted to investigate and optimize the input and output process parameters in the EDM process. The following conclusions are made.

- The experimentation of EDM helped in finding the range of input parameters for performing actual experimentation.

- The DOE by Taguchi method is used to set the estimated regression models to provide effective guideline for setting input variables to achieve the required results of outputs-MRR, SR, ROC, and TWR.

- Linear terms have a higher percentage of the contribution to the output response. Analysis of mathematical models for the MRR, SR, ROC, and TWR are evaluated using MINITAB software.

- It is concluded that the increase in MRR tends to increase the other responses SR, TWR, and ROC when trying to decrease the responses SR, TWR, and ROC MRR also tends to decrease. But using multiobjective optimization using a Genetic algorithm in MATLAB helps in achieving optimum results.

- Multi-objective optimization of output process parameters is obtained in MATLAB using a Genetic algorithm to obtain Optimal output values and results are found to be satisfactory.

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