

EXPERIMENTAL INVESTIGATION AND OPTIMIZATION OF MRR IN μ -ECDM PROCESS BY TAGUCHI, RSM, PSO AND ANN

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Abstract

Electrochemical Discharge Machining process applied for machining of both electrically conducting and non-conducting materials. It became crucial to measure the material removal rate while processing of advanced materials. This paper deals with comparison of optimization of MRR by different techniques like Taguchi method, RSM, PSO and ANN during μ -profile generation on glass material using μ -ECDM process. The experiments were conducted using the combinations of three input parameters such as voltage, electrolyte concentration and pulse frequency based on different experimental design. Increase in voltage and electrolyte concentration results in MRR increase, but with increase in pulse frequency MRR decreases. Optimal value of MRR along with the parametric combinations using all four techniques has been derived and compared.

Keywords: MRR; μ -ECDM, Taguchi L9 array, ANOVA, PSO; ANN; RSM

Introduction

The quality of life of all human beings continues to increase day by day with the invention of new products and components which are developed by different manufacturing methods. Machining is one of the most important manufacturing processes by which different products can be produced with dimensional accuracy in the range of millimeter to nanometer. Conventional machining processes are mainly turning, milling drilling which are performed in machine tools such as lathe, shaper, milling machine and drilling machine etc. These techniques are mainly used for higher material removal rate and large dimension objects. The parts produced by conventional machining are robust.

Machining of sophisticated and advanced materials with complex and intricate shape is almost impossible with existing conventional processes (Grzesik, 2016). Thus, several non-conventional machining such as ultrasonic machining (USM), electrochemical machining (ECM), electric discharge machining (EDM), abrasive jet machining (AJM) etc. have developed over the years (Khandekar and Chakraborty, 2016). The demand of advanced engineering material and precise manufacturing of near net shape product cannot be achieved alone by non-traditional machining, so further extension have been proposed in the form of hybrid machining (Shrivastava and Dubey, 2014).

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Electrochemical discharge machining (ECDM) is one such hybrid machining process that can be used for processing of any material, whether it is electrical conducting or non-conducting. This machining technique combines ECM and EDM (Kulkarni *et al.*, 2002). ECDM can be used to make 3D components of any shape and size even in micro and nano dimensional range by controlling heat affected zone and overcut. μ -holes can be made along with μ -channels through which different types of fluid can flow that can be applied in the medical field for micro surgery (Singh and Dvivedi, 2016). High temperature along with fast chemical etching in ECDM enables it to machine hard to machine materials such as quartz, glass, ceramic etc. This is due to high electrical energy discharged on the electrode tip during electrolysis (Dafade and Waghmare, 2015). An auxiliary electrode is used and connected to one terminal of main power supply. Tool electrode is connected to another terminal. Generally, workpiece is kept near tool and all these are immersed in electrolyte solutions. Whenever the main power is on electrolysis occurs and bubbles begin to form near tool. These bubbles act as barrier to flow current between cathode and anode. If the supply voltage gradually increases, this barrier becomes stronger. But at a certain voltage which is called critical voltage, high electric field is built and discharge takes place near the tool. Since the workpiece is kept there, the material is removed from the work piece (Ghosh, 1997). The quality of this hybrid machining process can be measured in terms of material removal rate (MRR), heat affected zone (HAZ) overcut, roundness and surface quality etc. by various authors and the process parameters influencing the output quality are identified as pulse frequency, voltage, electrolytic concentrations, tool immersion depth etc. (Skrabalak *et al.*, 2004; Sarkar *et al.*, 2006; Paul and Hiremath, 2013; Razfar *et al.*, 2013; Madhavi and Hiremath, 2016).

The most significant factors can be analyzed statistically by analysis of variance (ANOVA) and different optimization techniques can be applied to find out best parametric combination to get best output (Razfar *et al.*, 2013). Taguchi analysis is one of the best optimization techniques that minimize the cost and time of experimentation. This technique increases efficiency and offer robust design and at the same time better quantitative knowledge are obtained by doing less experiments (Paul and Hiremath, 2013). RSM gives better results for continuous factors. The experiment number is higher than Taguchi but better approximation can be achieved (Anderson and Whitcomb, 2017).

Nonconventional optimization techniques are trending now a days. Particle Swarm Optimization (PSO) mimics the behaviour of flocks of birds or

swarm of fish for finding the optimal solution (Venter and Sobieszcanski-Sobieski, 2003). Artificial Neural Network (ANN) imitates the teaching learning behaviour of neurons to predict the optimal parametric combination.

In this work, μ -ECDM process has been investigated for maximizing the material removal rate. The process parameters have been chosen based on previous works such as voltage, electrolytic concentration and pulse frequency. Taguchi L_9 array and RSM technique has been used for designing the experiments. ANOVA has been performed for introspecting the effect of parametric inputs over the response material removal rate. The percentage contribution of these process parameters over the response material removal rate has been derived. Taguchi optimization technique along with PSO and ANN algorithms for maximum material removal rate has been performed statistically. The mathematical regression model along with the optimized results for maximum material removal rate has been validated by performing confirmatory tests using suggested parametric combination and material removal rate has been calculated. The theoretical and experimental material removal rate values have been compared and the error percentage has been identified.

Related Works

Over the years many researchers have been investigating on ECDM process. Basak and Ghosh (1996) first time inquired into the causes of spark generation near the tool electrode through the gas bubbles in ECDM process and stated that spark generation was a switching process between the tool and the electrolyte. Yang *et al.* (2010) analyzed the surface roughness of different tool electrode materials in ECDM method. The authors showed that surfaces of tungsten-carbide and machining characteristics is better when compared with tungsten and stainless-steel tool while drilling of μ -holes. Abou Ziki and Wüthrich (2013) studied different force components associated with tool-electrode of spark based chemical engraving process to develop an algorithm based on force feedback signal. Zhang *et al.* (2016) proposed a variant of ECDM method by employing a tube electrode by varying its inner diameter and recommended that tube electrode with double hole gives good machining responses. Paul *et al.* (2016) had done a comparative study between direct current and pulse direct current on material removal rate using ANSYS 13 software in ECDM process and with the help of thermal modeling showed that Pulse DC is better for higher material removal rate and lower

temperature. Guo *et al.* (2016) first time utilized Ion-Beam with Spark based technology successfully and with the help of this technique, fabricated different micro and nano-electrodes in 3D shape of up to 10 μm in diameter. Paul and Jose (2018) attempted to modify the shape of the tool to get better results of produced micro-holes in terms of accuracy and stated that size of holes generated by drill bit was very closed to the desired results compared to the cylindrical tool. Harugade *et al.* (2019) employed a high rotational tool electrode made up of WC materials in ECDM process in order to reduced heat affected zone area and overcut by varying it's feed rate. Saini *et al.* (2020) investigated the material removal rate of ECDM process by varying tool electrode materials and electrolytes. Experimental results revealed that brass electrode provided higher material removal rate compared to the Cu and tungsten tool with KOH type electrolyte while machining a polymer composite material.

Skrabalak *et al.* (2004) applied adaptive fuzzy-logic in ECDM process to control the output parameters and tried to reduce the cracks formation and roughness of the surface produced. Sarkar *et al.* (2006) successfully performed μ -drilling operation on silicon carbide materials using ECDM process and studied different response parameter such as material removal rate, Overcut and HAZ area. Madhavi and Hiremath (2016) studied the effect of various input process variables on different responses like material removal rate, Tool Wear Rate, Radial Overcut while performing of machining operation to make holes and channels on Borosilicate and Soda-lime Glass materials and using S/N ratio showed the optimized parametric condition for getting better results. An attempt had been made to model the ECDM micro-drilling of silicon nitride ceramics using GA-and PSO-trained radial basis function neural network by Shanmukhi *et al.* (2015). Applied voltage, electrolyte concentration and inter-electrode gap are considered as inputs and metal removal rate (MRR), radial overcut (ROC) and heat affected zone (HAZ) are treated as outputs of the model. Prediction of MRR of ECDM process using regression analysis and ANN has been observed in the works of Sathisha *et al.* (2014). The authors have found that the prediction of ANN model for MRR is better as compared to the Regression model. The two models of ECDM process were recommended to predict the MRR for grooving of ECDM for the given range of process parameters by the authors. Antil (2020) investigated RSM and ANN when applied to anticipate different parameters in electrochemical discharge machining of SiC reinforced epoxy composites. In ANN, Feed forward back spread neural system has been utilized to anticipate the data among response and input

parameters. The training information comprises of values for voltage, inter-electrode gap, electrolyte concentration and duty factor to predict MRR and taper. The author suggested that ANN models can be proficiently used for the validations of single/multi-objective optimization during ECDM of SiC reinforced epoxy composites. Mediliyegedara *et al.* (2006) conducted a preliminary study of a pulse classification system. By observing the voltage and current waveforms, pulses were classified in to five groups. A feed-forward neural network was trained to classify pulses with various activation functions. Five different activation functions have been employed for comparison. The trained neural networks were simulated. A quantitative analysis was performed to evaluate the performance of pulse classification system. The simulation results showed that an ANN with the SATLINS and SATLIN functions take longer to train, but their classification accuracy is comparable with that of other activation functions. Rajput *et al.* (2019) presented a review of effective process parameters for ECDM process. PSO techniques has been identified by authors as useful for optimizing the process parameters.

Materials and Methods

This section is divided into two sub sections: experimental setup and process parameters.

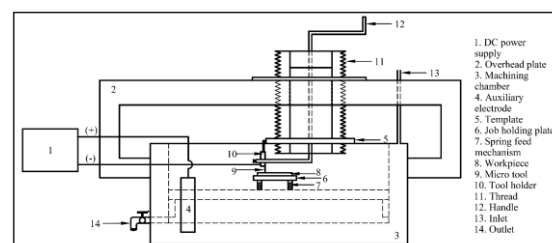


Figure 1. Shows schematic diagram of experimental setup

Experimental Setup

All the experiments were carried out with the help of following experimental setup shown in Figure 1. The set up consist of DC power supply which supply electrical power. Overhead plate is fixed and through which a thread is moving. The handle operates the template which is contacted to tool holder and micro tool. The machining operation mainly takes place in the machining chamber. The workpiece has been held on job holding plate which is controlled by spring feed system in the chamber. The electrolyte has entered through the inlet and used electrolyte has been collected by using outlet

tap. One terminal of Pulsed DC power supply is connected to the tool and another terminal to the auxiliary electrode. Both direct and reverse can be used depending on the desired response factor. Here, direct polarity is used which means that tool is connected to the negative (-ve) terminal and the auxiliary electrode which is made up of graphite, is connected to the positive (+ve) terminal. Job is held in a job holding unit which is supported by four springs so that spring feed is given to the job. The function of inlet is to supply electrolyte to the main machining chamber and through outlet it is drawn out along with chips. The micro tool acts as cathode and held in a tool holder. The work piece is made of glass. A 400 μm diameter stainless steel tool has been used in direct polarity for the experiment. NaOH solution is used as electrolyte in the experiment. A constant 50 mm inter electrode gap is maintained during the experiment.

Process Parameters

Three input process parameters that are, voltage, electrolyte concentration and pulse frequency have been selected to study their effect on material removal rate during micro-machining of glass materials. In this work, four techniques have been applied to establish relationship between input parameters and output. The optimized result has been tabulated and compared after confirmatory

experiment. The complete methodology has been shown in a block diagram in Figure 2. The range of process parameters has been shown in Table 1. Experimental planning was designed based on L_9 array as shown in Table 1. The analysis of Taguchi and RSM approach have been performed in Minitab 18 software. Material Removal Rate is the amount of material is removed from the job per unit time. Here it is expressed as $\mu\text{g/s}$. Another set of experiments have been performed flowing 3 factor 5 level central composite design (CCD) following same process parameters as Table 1, for comparison of RSM optimization approach. MRR has been identified as response parameters and for optimization larger is better approach has been chosen. The Data from Taguchi Design of experiment has been used to train an ANN. This ANN has 3 input neurons, 1 output neuron and 2 hidden layers i.e., 3-2-1 structure. This ANN have been used as regression ANN and all 27 possible combination of input parameters are predicted. The optimized data from the ANN has been observed. Regression equation found from RSM-CCD approach has been fed to PSO algorithm for maximizing the MRR and the global best value for MRR along with parametric combination has been studied. A confirmatory test has been performed to check the optimized combination and the percentage errors have been calculated.

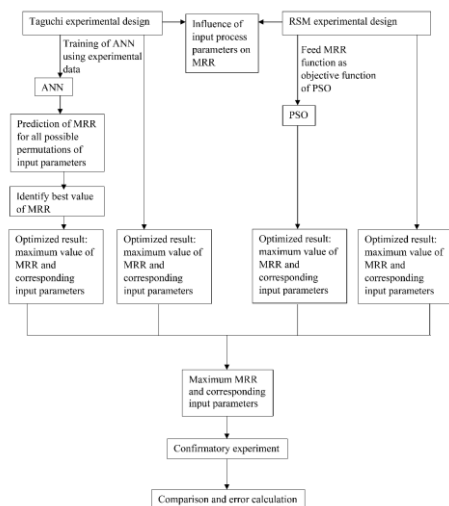


Figure 2. Shows the methodology in block diagram

Table 1. Shows process parameters for the experiment

Input parameters	Level 1	Level 2	Level 3
Voltage (V)	30	40	50
Electrolyte concentration (wt%)	10	15	20
Pulse frequency (Hz)	400	600	800

Results and Discussion

The results from Taguchi, RSM, PSO and ANN have been discussed in this section along with confirmatory experiment. Error calculation with respect to confirmatory experiment has been analyzed to identify most appropriate experiment designing and optimization technique for MRR in electro chemical discharge machining. Figure 3 depicts the micro-tool of stainless-steel materials before machining. SEM image of profile produced on glass materials is shown in Figure 4.

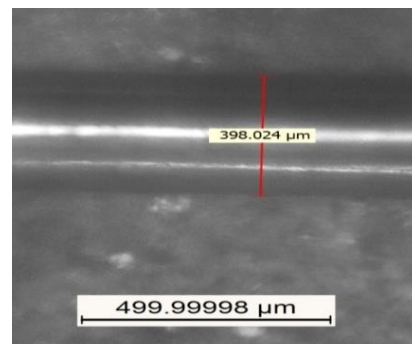


Figure 3. Shows μ -tool made up of stainless-steel

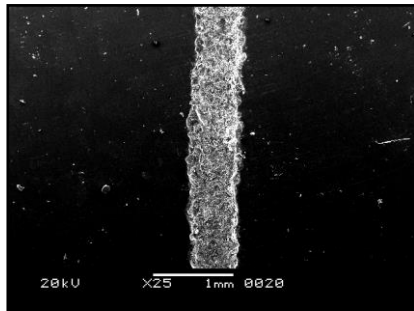


Figure 4. Shows SEM image of μ -profile after machining using μ -tool

Table 2. Shows material removal rate obtained at different parametric combination

Exp No.	Voltage (V)	Electrolyte concentration (wt%)	Pulse frequency (Hz)	MRR ($\mu\text{g/s}$)
1	30	10	400	3.77
2	30	15	600	3.11
3	30	20	800	3.44
4	40	10	600	5.11
5	40	15	800	6.00
6	40	20	400	9.55
7	50	10	800	7.55
8	50	15	400	11.15
9	50	20	600	12.95

Taguchi Method Results

All the input parametric combinations based on orthogonal L_9 array have been set to calculate the response parameter material removal rate. The experiments have been conducted at fixed time. Table 2 shows the material removal rate obtained at different parametric combination. The mean effect plot as shown in Figure 5 has been derived by Taguchi analysis. It is evident from the graphs that material removal rate has increased with the increasing of voltage values and electrolyte concentration values, but it observed to be decrease with the increasing of pulse frequency. The S/N ratio curves with the objective to maximize the material removal rate have been shown in Figure 6, depicts that with increase of voltage and electrolyte concentration, the values of S/N ratio are increased. The pulse frequency observed to show opposite nature i.e., with the increasing pulse frequency S/N ratio has been reduced. The optimal value of material removal rate with desirability 1.00 by Taguchi optimization technique found to be 13.35 $\mu\text{g/s}$ for a parametric combination of Voltage 50 V, electrolyte concentration 20 wt% and Pulse frequency 400 Hz as shown in Figure 7. The linear regression fit model has been employed and the regression equation has been found. The model has R^2 and R^2 (adjusted) values 98.04% and 96.87%

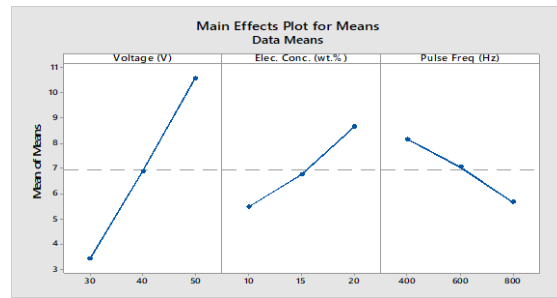


Figure 5. Shows main effect plots for material removal rate

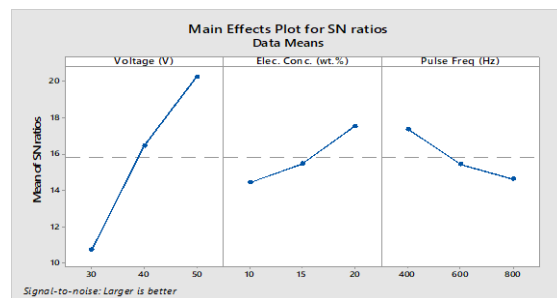


Figure 6. Shows main effect plot of SN ratios

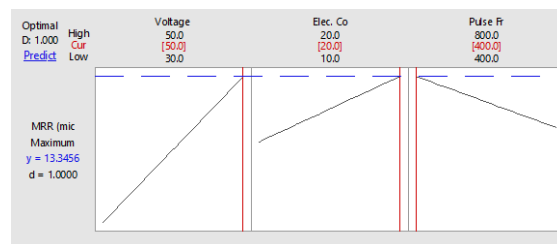


Figure 7. Shows optimization plots by Taguchi method

respectively. The equation for material removal rate has been given as,

$$\text{MRR} = -8.28 + 0.3555x + 0.3170y - 0.00623z \quad (1)$$

where

x = Voltage in V;

y = Electrolyte concentration in wt%;

z = Pulse frequency in Hz

The ANOVA table has been shown in Table 3. It is evident from the table that the error value is not significant and process parameters such as voltage, electrolyte concentration and pulse frequency become significant parameters with P -value ≤ 0.05 . The percentage contribution of every process parameter has been analyzed. The voltage has maximum influence over material removal rate with

74.18% as indicated from the Table 3. The Electrolyte contribution has influence of 14.74% over the material removal rate. Lowest influence has been observed in case of pulse frequency 9.12%. The influence of process parameters has been described graphically in Figure 8.

RSM Approach Results

Response surface approach results are tabulated in Table 4. According to RSM CCD design for 3 factor 3 levels 20 sets of experiments have been performed. The experimental MRR along with experiments are shown in table. The main effect plot found from RSM has been shown in Figure 9. It is evident from the figure that with increasing voltage and electrolyte concentration the MRR increases and with increasing pulse frequency MRR decreases. This is similar to mean effect plots found from Taguchi approach. The optimal value of material removal rate with desirability 1.00 by RSM technique found to be 15.27 $\mu\text{g/s}$ for a parametric combination of Voltage 56.82 V, electrolyte concentration 23.4 wt% and Pulse frequency 263.64 Hz as shown in Figure 10. The regression fit model

has been employed and the regression equation has been found. The model has R^2 and R^2 (adjusted) values 99.3% and 98.67% respectively.

The equation for material removal rate has been given as,

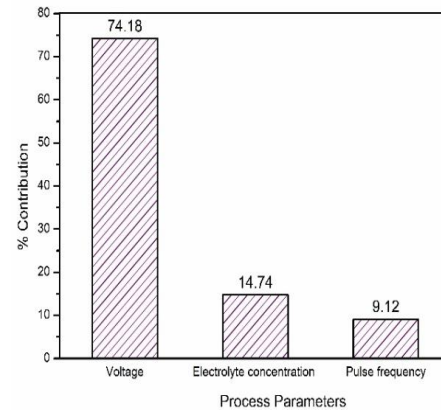


Figure 8. Shows influence of different process parameters over material removal rate in μ -ECDM

Table 3. Shows ANOVA for material removal rate by Taguchi method

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% Contribution = [(Adj SS/Total) x 100%]	Significance
Regression	3	100.227	33.4089	83.57	0.000	98.04	Yes
Voltage (V)	1	75.828	75.8281	189.67	0.000	74.18	Yes
Electrolyte concentration (wt%)	1	15.073	15.0733	37.70	0.002	14.74	Yes
Pulse frequency (Hz)	1	9.325	9.3251	23.33	0.005	9.12	Yes
Error	5	1.999	0.3998				No
Total	8	102.225					

Table 4. Shows RSM results table

Voltage (V)	Electrolyte concentration (wt%)	Pulse frequency (Hz)	MRR ($\mu\text{g/s}$)
40	15	600	6.78
30	20	400	6.33
40	6.591	600	5.11
23.1821	15	600	1.908
40	15	936.359	5.309
40	23.409	600	8.67
40	15	263.641	8.569
56.8179	15	600	11.841
50	10	400	10.27
40	15	600	6.78
30	10	400	3.77
50	20	800	10.94
40	15	600	6.78
40	15	600	6.78
30	20	800	3.44
40	15	600	6.78
50	10	800	7.55
50	20	400	12.295
30	10	800	0.66
40	15	600	6.78

$$\begin{aligned} \text{MRR} = & -0.08 + 0.2175x + 0.073y - 0.01516z + \\ & 0.000331x^2 + 0.00154y^2 + 0.000001z^2 + \\ & 0.00019xy + 0.000120xz + 0.000198yz \end{aligned} \quad (2)$$

where
 x = Voltage in V;
 y = Electrolyte concentration in wt%;
 z = Pulse frequency in Hz;

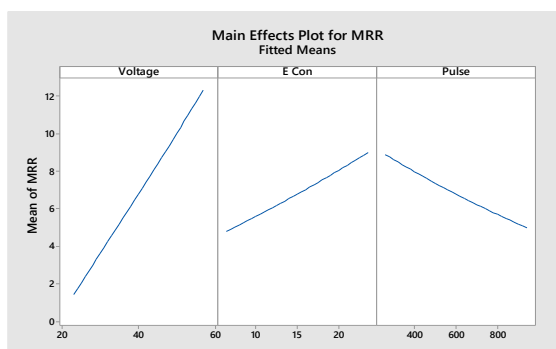


Figure 9. Shows main effect plot from RSM

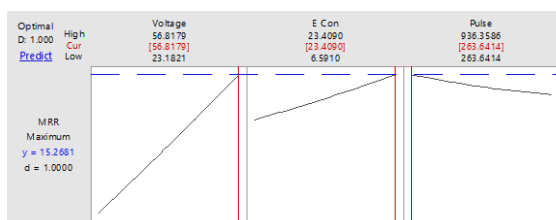


Figure 10. Shows optimization plots by RSM method

The ANOVA table has been shown in Table 5, it is evident from the table that the error value is not significant and process parameters i.e., voltage, electrolyte concentration and pulse frequency become significant parameters with P-value ≤ 0.05 . The ANOVA table suggests that for calculation of MRR in this process the Square and interaction terms are not significant.

ANN Results

The Artificial Neural Network with 3-2-1 configuration has been implemented in this work. The odd numbers of experiment from experimental

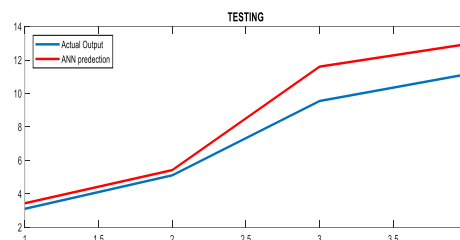


Figure 11. Shows actual MRR and ANN predicted MRR with respect to nos. of iteration

Table 5. Shows ANOVA table from RSM

Source	Adj SS	Adj MS	F-Value	P-Value	Significance
Model	178.036	19.782	157.73	0.000	Yes
Linear	177.188	59.063	470.93	0.000	Yes
Voltage (V)	138.941	138.941	1107.84	0.000	Yes
Electrolyte concentration (wt.%)	20.525	20.525	163.65	0.000	Yes
Pulse frequency (Hz)	17.723	17.723	141.31	0.000	Yes
Square	0.070	0.023	0.19	0.904	No
Voltage*Voltage	0.016	0.016	0.13	0.730	No
E Con*E Con	0.021	0.021	0.17	0.688	No
Pulse*Pulse	0.045	0.045	0.36	0.563	No
2-Way Interaction	0.778	0.259	2.07	0.168	No
Voltage*E Con	0.001	0.001	0.01	0.942	No
Voltage*Pulse	0.463	0.463	3.69	0.084	No
E Con*Pulse	0.314	0.314	2.50	0.145	No
Error	1.254	0.125			No
Lack-of-Fit	1.254	0.251			No
Total	179.29				

Table 6. Shows training data for ANN

Voltage (V)	Electrolyte concentration (wt%)	Pulse frequency (Hz)	EXP	ANN	Error (%)
30	10	400	3.77	3.77	2.92E-12
30	20	800	3.44	3.53	2.69709
40	15	800	6	6	0
50	10	800	7.55	7.55	0
50	20	600	12.9	12.9	0

values of Table 2 has been used to train the model while the rest are used to validate and test the models. The training and testing data along with errors has been shown in Tables 6 and 7. The actual and predicted curve for testing the ANN model has been shown in Figure 11. It is evident from the plot that ANN prediction is somewhat similar to the experimental MRR. The model training, validation and testing curves are shown in Figure 12 depicting that model is validated with experimental results. The validation suggests the model to be used for prediction as there are low errors so all possible 27 combinations of process parameters have been predicted and tabulated in Table 8. Introspecting Table 8 it has been observed that for parametric combination of 50 V voltage, 20% electrolyte concentration and 400 Hz pulse frequency maximum MRR of 13.44 $\mu\text{g/s}$ can be obtained.

PSO Results

The quadratic regression equation found from RSM approach has been fed into PSO algorithm to find the optimal parametric combination for maximum MRR. MATLAB R2018a has been used to execute the particle swarm optimization. The global best solution for maximum MRR has been observed to be 11.97 $\mu\text{g/s}$. The optimal parametric combination has been found to be voltage 50 V, electrolytic concentration of 20% and pulse frequency of 400 Hz.

Confirmatory Experiment Results

Confirmatory test results in material removal rate of 12.68 $\mu\text{g/s}$ for a parametric combination of Voltage 50 V, electrolyte concentration 20 wt% and pulse frequency 400 Hz. Comparison and errors have been shown in Table 9.

Table 7. Shows testing data for ANN

Voltage (V)	Electrolyte concentration (wt%)	Pulse frequency (Hz)	EXP	ANN	Error (%)
30	15	600	3.11	3.44	10.61
40	10	600	5.11	5.42	6.08
40	20	400	9.55	11.6	21.51
50	15	400	11.15	12.95	16.14

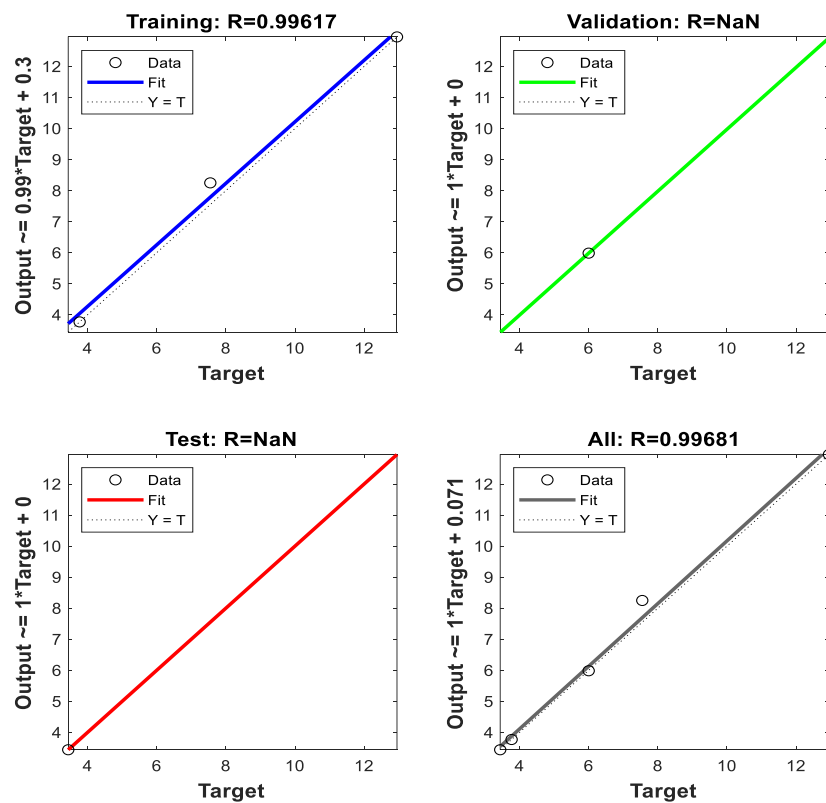


Figure 12. Shows ANN training, testing, validation curves

Table 8. Shows prediction of all possible parametric combination by ANN

Voltage (V)	Electrolyte concentration (wt%)	Pulse frequency (Hz)	MRR ($\mu\text{g/s}$)
50	20	600	12.95
40	15	600	6.78
40	20	600	8.67
50	15	800	9.05
30	20	800	3.44
30	20	400	6.33
30	10	600	2.06
30	15	600	3.11
30	15	800	1.94
50	10	400	10.27
40	20	400	9.55
50	15	600	10.44
50	15	400	11.15
40	10	800	4.11
50	20	800	10.94
50	10	800	7.55
50	20	400	13.44
30	10	400	3.77
30	15	400	4.43
30	20	600	5.22
50	10	600	9.17
40	10	600	5.11
40	20	800	7.27
40	15	400	7.88
40	15	800	6
30	10	800	0.66

Table 9. Shows comparison between theoretical and experimental value

Response	Experimental Value	Taguchi		RSM		ANN		PSO	
		Value	Error (%)	Value	Error (%)	Value	Error (%)	Value	Error (%)
MRR	12.78	13.35	4.46	15.78	23.47	13.44	5.16	11.97	6.34

Analysis

The material removal rate has observed to be increasing with increase of voltage and electrolyte concentration which is evident from the mean effect plot. The pulse frequency show opposite nature that is with increasing pulse frequency the material removal rate found to be decreasing. The influence percentage of voltage, electrolyte concentration and pulse frequency over the material removal rate are found to be 74.18%, 14.74%, and 9.12% respectively. Taguchi optimization method to maximize the material removal rate suggests the maximum material removal rate of 13.35 $\mu\text{g/s}$ for a parametric combination of Voltage 50 V, electrolyte concentration 20 wt% and pulse frequency 400 Hz with composite desirability of 1.00. RSM gives the optimized parameters as voltage 56.81 V, 23.4% electrolyte concentration, 263.64 Hz pulse frequency with maximum MRR of 15.27 $\mu\text{g/s}$. ANN gives optimized results for

parametric combination of 50 V voltage, 20% electrolyte concentration and 400 Hz pulse frequency maximum MRR of 13.44 $\mu\text{g/s}$ can be obtained. PSO obtain similar results with Taguchi, the global best solution for maximum MRR has been observed to be 11.97 $\mu\text{g/s}$. The optimal parametric combination has been found to be voltage 50 V, electrolytic concentration of 20% and pulse frequency of 400 Hz. The confirmatory test has been performed with these parametric combinations and material removal rate has been compared with the theoretical material removal rate. The percentage error found to be 4.26% which is within the satisfactory range.

Conclusions

In this research work, Taguchi method is used in μ -ECDM process to introspect the effect of parametric

inputs on material removal rate during profile generation on glass materials. ANOVA table is carried out to review the relative significance of these parameters and linear regression equation is developed. The result shows that material removal rate of μ -ECDM process is increased by increasing both supply voltage and electrolyte concentration but it is decreased while increasing pulse frequency. The optimization techniques have been compared with RSM-CCD, ANN and PSO. It can be concluded that:

- The material removal rate has observed to be increasing with increase of voltage and electrolyte concentration which is evident from the mean effect plot.
- The pulse frequency show opposite nature that is with increasing pulse frequency the material removal rate found to be decreasing.
- The influence percentage of voltage, electrolyte concentration and pulse frequency over the material removal rate are found to be 74.18%, 14.74%, and 9.12% respectively.
- Taguchi optimization method to maximize the material removal rate suggests the maximum material removal rate of 13.35 $\mu\text{g/s}$ for a parametric combination of Voltage 50 V, electrolyte concentration 20 wt% and pulse frequency 400 Hz with composite desirability of 1.00.
- RSM gives the optimized parameters as voltage 56.81 V, 23.4% electrolyte concentration, 263.64 Hz pulse frequency with maximum MRR of 15.27 $\mu\text{g/s}$.
- ANN gives optimized results for parametric combination of 50 V voltage, 20% electrolyte concentration and 400 Hz pulse frequency maximum MRR of 13.44 $\mu\text{g/s}$ can be obtained.
- PSO obtain similar results with Taguchi. The global best solution for maximum MRR has been observed to be 11.97 $\mu\text{g/s}$. The optimal parametric combination has been found to be voltage 50 V, electrolytic concentration of 20% and pulse frequency of 400 Hz.

The confirmatory test has been performed with these parametric combinations and material removal rate has been compared with the theoretical material removal rate. The percentage error found to be 4.26% which is within the satisfactory range.

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