Research article

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Multi-objective optimization of near-dry electric discharge machining process using genetic algorithm and scalarization

Abstract

Near Dry Electric Discharge Machining (NDEDM) represents a significant advancement in advanced manufacturing by replacing the conventional dielectric pool with a spray-based dielectric delivery system, thereby enhancing both the portability and practicality of the process. This study focuses on optimizing the key process parameters: (i) Current (A), (ii) Pulse-on Time (μs), (iii) Gap Voltage (V), (iv) Liquid Flow Rate (ml/min), and (v) Workpiece Feed Rate (mm/min) for the purpose of achieving a balanced outcome in terms of (i) Material Removal Rate (MRR), (ii) Tool Wear Rate (TWR), and (iii) Surface Roughness (SR). The primary objective was to maximize MRR while minimizing both TWR and SR. A multi-objective Genetic Algorithm was used for optimization, utilizing predictive regression models developed through multiple regression analysis of the data obtained from experiments that were designed using the Taguchi Design of Experiments approach. Scalarization techniques were applied to incorporate weighted preferences for each response, thereby enabling in an exploration of the trade-offs among MRR, TWR, and SR. The study did reveal a valuable insight into the interdependencies of machining parameters, with the multi-objective genetic algorithm demonstrating high predictive accuracy—as was evident from minimal deviation between the predicted outcome and experimental outcome. The optimized results highlight a favorable balance, enhancing productivity while concurrently maintaining quality, and contribute meaningfully to the field of machining optimization.

Keywords: near-dry EDM, optimization, genetic algorithm and scalarization

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Introduction

Electric Discharge Machining (EDM) is a well-established non-traditional machining process that is extensively used for the shaping of hard, brittle, and electrically conductive materials with good dimensional accuracy and surface integrity. The working principle of EDM is based on the thermoelectric energy that is generated by a series of controlled electrical discharges between the tool electrode and the workpiece material, separated by a dielectric medium. This process does enable in the machining of complex geometries and even high-strength materials that are otherwise difficult to machine using conventional techniques. However, conventional EDM requires large volumes of hydrocarbon-based dielectric fluids, which are not only flammable and expensive but also pose serious health and environmental risks due on account of the emission of toxic fumes and waste disposal challenges.[1,2]

In light of increasing global concern for environmental sustainability, there has been a concerted effort within the manufacturing community to develop greener and safer alternatives to traditional EDM. Several studies have explored use of the following: (i) biodegradable dielectrics,[3] (ii) the approach of minimum quantity lubrication,[4] and (iii) alternative dielectric delivery systems[5] as viable steps toward sustainable machining. Among these, Near-Dry EDM has emerged as a promising advancement. It operates with a two-phase dielectric fluid—a mixture of a small amount of liquid dielectric [such as deionized water, kerosene, or other compatible fluids] that is atomized in a high-velocity air stream—and sprays it directly into the inter-electrode gap. This innovative modification drastically reduces the consumption of dielectric fluid while concurrently improving process safety, portability, and operational cleanliness.[6,7]

The use of near-dry conditions in EDM has been reported to produce comparable, and in some cases, superior machining performance in terms of MRR, TWR), and SR, when compared to the conventional setups. Singh et al.,[8] demonstrated the application of mist-type dielectrics in EDM could lead to improved debris flushing and reduced tool wear. Rao and Kumar[9] reported enhanced machining efficiency under near-dry conditions with significantly lower thermal damage to the workpiece. Despite these advantages, achieving an optimal performance under near-dry EDM conditions require precise tuning of the process parameters since the interplay between thermal energy distribution, dielectric delivery, and material removal becomes more complex in the absence of a conventional dielectric pool.

In this study, we investigate and optimize the effect of five critical input parameters in the near-dry electric discharge machining process. These essentially include the following:

(i) Discharge current (A),

(ii) Pulse-on time (μs),

(iii) Gap voltage (V),

(iv) Liquid flow rate (ml/min), and

(v) Workpiece feed rate (mm/min). These parameters are known to significantly influence three key output responses:

(a) MRR in mm^3/min,

(b) TWR in mm^3/min, and

(c) SR in μm.

The primary objective was to achieve a balanced optimization—**maximizing MRR**, which reflects productivity, while **minimizing the TWR and SR**, which are critical for tool life and surface quality.

The multi-objective nature of this problem is inherently challenging due on account of the conflicting trends in the behaviour of the performance metrics. For example, an increase in discharge current may enhance MRR but could also lead to higher TWR and poor SR. To address this complexity, we used a **Multi-Objective Genetic Algorithm** -a well-established metaheuristic technique for solving optimization problems involving multiple conflicting objectives. It is capable of generating a set of Pareto-optimal solutions, thereby allowing decision-makers to select the most suitable trade-off based on need of a specific application.[10,11]

To support the optimization process, a structured experimental design was formulated using the Taguchi Design of Experiments method. The Taguchi's orthogonal array approach ensures a systematic and statistically efficient exploration of the input space while minimizing the number of experiments required.[12] The resulting experimental data were analysed using multiple regression techniques in Minitab Statistical Software so as to generate predictive mathematical models for the MRR, TWR, and SR. These models were subsequently used as fitness functions in the genetic algorithm optimization.

Through the combined approach of experimental design, statistical modelling, and evolutionary computation, this study does provide a comprehensive insight into the parametric influence and optimization of the near-dry EDM process. The results not only validate near dry EDM as a viable and sustainable alternative to conventional EDM but also offers practical guidelines for improving machining efficiency while minimizing environmental impact. This research contributes to the evolving field of green manufacturing and expands the prevailing knowledge base for the purpose of optimization of the non-traditional machining process.

Methodology

This section outlines the experimental procedure, parameter selection, data analysis, and optimization techniques used in the present study. The goal was to evaluate and optimize the performance of Near-Dry EDM by considering key input parameters and their influence on the three critical output responses:

(i) MRR,

(ii) TWR, and

(iii) SR.

Experimental setup

The experimental trials were conducted using a modified EDM setup capable of near-dry operation. A two-phase dielectric system was utilized, comprising a fine mist of dielectric fluid (a blend of deionized water and air) that was atomized using a high-pressure air-assisted spray nozzle. This arrangement did ensure in a consistent delivery of the dielectric into the inter-electrode gap. The machining tests were performed on a EDM machine, and the workpiece material selected was high speed steel (HSS) due to its high hardness and industrial relevance. A copper tubular electrode was used, and constant flushing conditions were maintained throughout the experiments.

Selection of input parameters and output responses

Based on prior studies and preliminary investigations, five key input parameters were selected:

(a) Discharge Current (A)

(b) Pulse-on Time (μs)

(c) Gap Voltage (V)

(d) Liquid Flow Rate (ml/min)

(e) Workpiece Feed Rate (mm/min)

The levels of each parameter were carefully chosen based on both machine capabilities and recommendations in the published literature. These parameters were studied to understand their impact on the following output responses:

(a) MRR in mm^3/min

(b) TWR in mm^3/min

(c) SR in μm

The design of experiments

A Taguchi-based Design of Experiments (DOE) approach was used to both plan and execute the machining trials efficiently. An L_{27} orthogonal array was selected based on the number of parameters and levels considered, minimizing experimental runs while concurrently maintaining statistical robustness.

The Taguchi method did facilitate in a systematic study of the multiple factors with minimal resource expenditure while also enabling in an identification of parameter significance through signal-to-noise (S/N) ratio analysis.

Data collection and response measurement

Each experimental run was replicated to ensure repeatability while ensuring a reduction in the random error. Material removal was calculated based on a difference in weight of the workpiece before machining and after machining, using a high-precision digital balance. Tool wear was similarly measured by tracking weight loss of the tool electrode. Surface roughness was measured using a contact-type surface profilometer, averaging three readings from different locations on the machined surface so as to ensure accuracy.

Regression analysis

The experimental results were analysed using Minitab Statistical Software. A multiple linear regression analysis was conducted for each output response to develop predictive models that relate the input parameters to MRR, TWR, and SR. The adequacy of each regression model was assessed using the coefficient of determination (R2R^2R2) and analysis of variance (ANOVA) to verify significance of the individual terms.

The regression equations served as objective functions for subsequent optimization using a genetic algorithm.

Multi-objective optimization using genetic algorithm

A Multi-Objective Genetic Algorithm was used to optimize the near-dry EDM process for simultaneous improvement of MRR, TWR, and SR. The regression models developed were integrated into the fitness evaluation within the genetic algorithm framework.

Given the conflicting nature of the objectives [e.g., high MRR often leads to high TWR or poor SR], a Pareto-based approach was used to identify non-dominated solutions representing optimal trade-offs.

The key Genetic Algorithms parameters are the following:

(a) Population size

(b) Number of generations

(c) Crossover rate

(d) Mutation rate

The scalarization technique was used to assign a weight to each response based entirely on process priorities. Different weight combinations were explored to analyse their influence on optimization of the outcomes.

Validation of optimized results

To verify the reliability of the predicted optimal solutions, confirmatory experiments were conducted using the best parameter combination(s) derived from the genetic algorithm. The predicted value and experimental value were compared to evaluate both model accuracy and overall effectiveness of the optimization approach.

In this research study, the Taguchi design of experiment technique was used to systematically determine the combination of input parameters for the experimental trials. Machining experiments were conducted using a copper electrode on a workpiece material made of high-speed steel (HSS), with each trial lasting five minutes. The experimental data obtained from these trials is presented in Table 1.

Table 1 Data obtained from experimentation

S No.	Current (A)	Pulse on time (μs)	Gap voltage (V)	Liquid flow rate (ml/min)	Workpiece feed rate (mm/min)	Avg. MRR (mm^3/min)	Avg. TWR (mm^3/min)	Avg. SR (μm)
1	4.5	120	40	2	2	0.34	0.003	0.73
2	4.5	120	50	6	5	0.63	0.004	0.92
3	4.5	120	60	10	10	0.81	0.0043	1.02
4	4.5	150	40	6	5	0.52	0.0057	0.95
5	4.5	150	50	10	10	0.82	0.0081	1.05
6	4.5	150	60	2	2	0.38	0.0066	0.78
7	4.5	200	40	10	10	1.5	0.0087	1.15
8	4.5	200	50	2	2	0.79	0.0125	0.87
9	4.5	200	60	6	5	1.2	0.008	0.99
10	6	120	40	6	10	0.73	0.0052	1.1
11	6	120	50	10	2	0.78	0.0045	0.92
12	6	120	60	2	5	0.69	0.0037	0.96
13	6	150	40	10	2	0.97	0.0049	0.93
14	6	150	50	2	5	0.71	0.0066	1.03
15	6	150	60	6	10	1.54	0.0052	1.14
16	6	200	40	2	5	1.34	0.0101	0.91
17	6	200	50	6	10	2.53	0.0085	1.23
18	6	200	60	10	2	1.96	0.0105	1.09
19	9	120	40	10	5	2.37	0.0101	1.07
20	9	120	50	2	10	1.81	0.0091	1.14
21	9	120	60	6	2	1.74	0.0157	0.92
22	9	150	40	2	10	1.59	0.0143	1.23
23	9	150	50	6	2	2.11	0.019	0.79
24	9	150	60	10	5	3.22	0.0121	1.05
25	9	200	40	6	2	2.91	0.0324	0.96
26	9	200	50	10	5	3.87	0.021	1.08
27	9	200	60	2	10	3	0.0194	1.33

Regression analysis and modelling

A regression analysis was performed on the data obtained from the experiments mentioned. The regression analysis was done using the Minitab Statistical Software and the regression equations were obtained for MRR, TWR, and SR respectively and then analyzed to establish the relation between the different input parameters and the resultant response. An analysis of the effects of each parameter on response was done in Minitab itself. The results obtained are as follows:

Regression equations given by Minitab

Avg. MRR (mm^3/min) = -4.347 + 0.3910 Current (A) + 0.01312 Pulse on time (μs) + 0.01261 Gap voltage (V) + 0.0785 Liquid flow rate (ml/min) + 0.0288 Workpiece feed rate (mm/min).

Avg. TWR (mm^3/min) = -0.01709 + 0.002448 Current (A) + 0.000100 Pulse on time (μs) – 0.000049 Gap voltage (V) - 0.000015 Liquid flow rate (ml/min) – 0.000325 Workpiece feed rate (mm/min)

Avg. SR (μm) = 0.376 + 0.02487 Current (A) + 0.001185 Pulse on time (μs) + 0.00139 Gap voltage (V) + 0.00528 Liquid flow rate (ml/min) + 0.03317 Workpiece feed rate (mm/min)

Relation between the input parameters and the response (Figures 1–3)

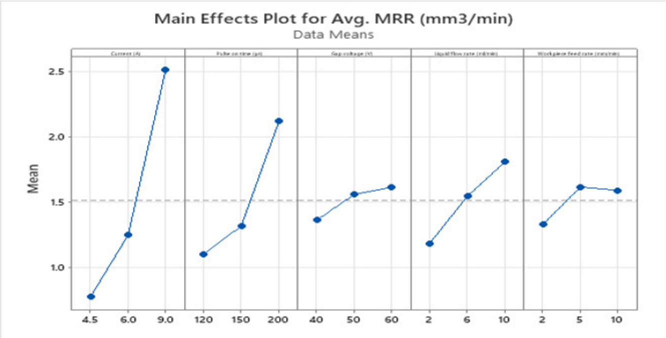

Figure 1 Relation for MRR and the input parameters.

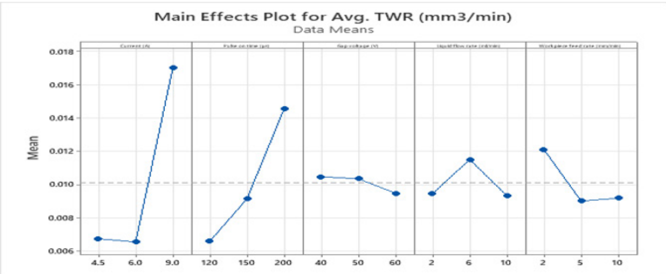

Figure 2 Relation for TWR and the input parameters.

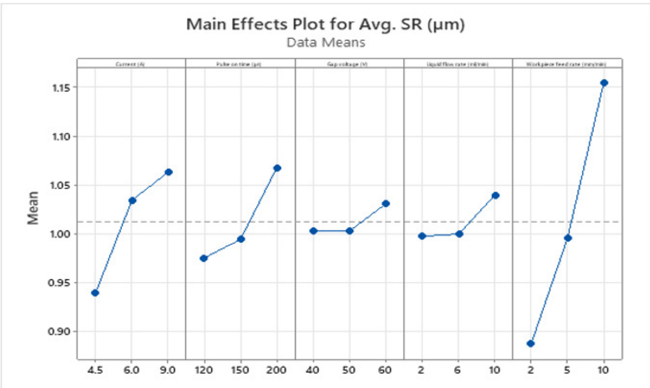

Figure 3 Relation for SR and the input parameters.

Then, we developed a code for prediction of the response in MATLAB where the user has to give the five parameters in software and the predicted output will be shown or displayed in the command window.

Optimization

In the optimization process, the MOGA in MATLAB was used, utilizing the predefined 'gamultiobj' function available in MATLAB. The objective was to maximize the MRR while simultaneously minimizing both the TWR and SR, as evident from the provided code.[14–17]

The code works on the basic principle of genetic algorithm, which uses two set of values as parents and then performs a crossover which gives a new set of parameters that can be put in the pareto front and checked for fitness, which is then treated as parents and once again crossover is performed and the mutations are done to refine the results till such time a best set of solutions is obtained.

After obtaining feasible solutions through the genetic algorithm, which by nature does not guarantee a single optimal outcome—a scalarization approach was introduced to identify the optimal solutions. This method transforms the multi-objective optimization problem into a single-objective problem by combining the multiple criteria into a unified scalar value. Specifically, the scalarization function in the code integrates the objectives of (i) MRR), (ii) TWR, and (iii) SR. It does this by applying user-defined weights to each objective, reflecting their relative importance based on specific requirements. The function then computes a weighted sum for each solution, effectively ranking them in accordance with their aggregated scores. This ranking allows for a selection of top-performing solutions that best balance the trade-offs among the objectives. As a result, the scalarization technique does enable in a tailored optimization process that aligns well with the desired priorities of the user (Figure 4).

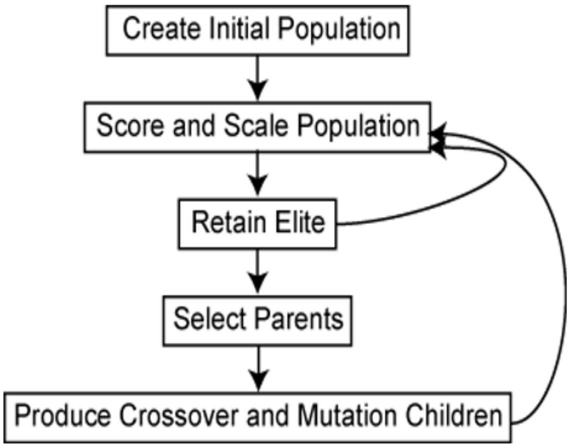

Figure 4 Genetic algorithm flow.

Different weights were assigned, and the results were predicted as shown in Table 2. Weights of 0.1, 0.1, 10 were given, optimizing each parameter to an average level. This parameter set proves valuable when all responses need to be at their optimal level. Emphasis was then placed on TWR and SR by assigning weights of 10, 1, 1 and 10, 1, 0.5, respectively. Lastly, weights of -1, -1, 10 were assigned, prioritizing MRR while keeping TWR and SR at nominal importance levels. The obtained outcomes were as follows.

Experimental observations

The scalarization approach was applied using different weight combinations to evaluate its effectiveness in balancing the trade-offs among MRR, tool TWR, and SR. The outcomes of each experimental setting are summarized below:

Experiment 1 (Weights: MRR = 0.1, TWR = 0.1, SR = 10): A high priority was assigned to minimizing SR, while MRR and TWR were given minimal importance. The resulting SR and TWR were minimized effectively. The MRR reached a relatively high value of 2.31 mm^3/min, primarily attributed to an elevated discharge current.

This configuration is suitable when high surface finish quality is critical, without severely compromising the MRR.

Experiment 2 (Weights: MRR = 10, TWR = 1, SR = 1): Emphasis was placed on minimizing TWR, with moderate importance given to SR and high importance to MRR. The optimization resulted in a significant reduction in both TWR and SR, while also maintaining an optimal MRR. This setup achieved balanced performance across all

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objectives, making it ideal for applications requiring both efficiency and tool longevity.

Experiment 3 (Weights: MRR = 10, TWR = 1, SR = 0.5): Higher priority was given to minimizing TWR and SR, while MRR was treated as a secondary objective. The configuration successfully reduced both the TWR and SR to low levels, while retaining a moderately high MRR retained. This setting is particularly applicable where quality of SR is critical and a reasonable MRR is acceptable.

Experiment 4 (Weights: MRR = -1, TWR = -1, SR = 10): The highest priority was assigned to maximizing MRR, with TWR and SR considered less significant. The MRR was maximized effectively, with only minimal compromises in the TWR and SR. This experimental setup is suitable for high-throughput machining processes where MRR is the primary objective and surface quality is of lesser concern.

Results and discussion

The parameters shown above (Table 2) are been optimized using genetic algorithm. The experiments were conducted using these optimized parameters and the actual responses are summarized in Table 3.

Table 2 Optimized parameters and predicted outputs

Current (A)	Pulse on time (μs)	Gap voltage (V)	Liquid flow rate (ml/min)	Workpiece feed rate (mm/min)	Predicted MRR	Predicted TWR	Predicted SR	Weight (TWR, SR, MRR)
9	133.128	49.2401	5.554	5.767	2.1338	0.0139	1.0443	0.1, 0.1, 10
7.8	120	40	2.81	2.81	1.0819	0.0111	0.876	10, 1, 1
7	120	40	2.2	4	0.75	0.008	0.89	10, 1, 0.5
9	177	43	7.47	8.51	2.86	0.01	1.19	-1, -1, 10

Table 3 Actual responses obtained for experiments

S. No.	Current (A)	Pulse on time (μs)	Gap voltage (V)	Liquid flow rate (ml/min)	Workpiece feed rate (mm/min)	Actual MRR (mm^3/min)	Actual TWR (mm^3/min)	Actual SR (μm)
1	9	133.128	49.24	5.554	5.767	2.31	0.019	1.038
2	7.8	120	40	2.81	2.81	0.98	0.012	0.91
3	7	120	40	2.2	4	0.82	0.01	0.96
4	9	177	43	7.47	8.51	2.9	0.017	1.2

The experimental results demonstrate ae successful optimization of output parameters—MRR, TWR, and SR—based on user-defined weight combinations applied using the scalarization technique. All four experimental configurations yielded desirable outcomes tailored to specific operational priorities, indicating an overall flexibility and robustness of the proposed hybrid approach combining Genetic Algorithm and scalarization.

The primary objective of this study was to optimize machining performance by establishing a predictive mathematical model that correlates the input parameters with output responses. The multi-objective nature of the problem—maximizing the MRR while minimizing both TWR and SR — necessitated an integration of the genetic algorithm for exploring a feasible solution space coupled with scalarization for the purpose of identifying optimal trade-offs among the conflicting objectives.

The scalarization method effectively transformed the multi-objective optimization problem into a single-objective framework by assigning weights to each output parameter according to the desired level of importance. This allowed for a consolidation of the multiple performance criteria into a single scalar value, thereby enabling in a systematic prioritization and balancing through the optimization process.

The experimental results highlight how different weightings of machining objectives influence overall performance. In the first experiment, prioritizing SR while assigning lower weights to MRR and TWR led to a high MRR with minimal compromise on other metrics, making it ideal for balancing productivity and surface quality. The second experiment aimed to reduce tool wear and surface roughness, with moderate attention to MRR. This approach effectively improved both TWR and SR while still delivering an acceptable MRR, making it suitable for tasks that value tool longevity and fine finishes. In the third experiment, minimizing tool wear was the main priority. Although this caused a slight drop in MRR, the significant reduction in TWR supports its use in high-precision operations where tool preservation is critical. The last experiment focused heavily on maximizing MRR. While this resulted in a minor increase in tool wear and a slight decrease in surface finish, the performance stayed within practical limits, making it appropriate for applications that prioritize throughput over precision.

The accuracy of the genetic algorithm-based prediction model is validated through a comparison with the actual experimental data, as is shown in Table 2 and Table 3. The differences between the predicted value and observed value were negligible, affirming the overall reliability of the model. Notably, MRR of 2.31 mm^3/min was achieved along with a SR of 1.038 μm, thus representing a favorable balance between efficiency of material removal and surface quality. Furthermore, the research also achieved a minimum SR of 0.91 μm, with corresponding MRR and TWR values of 0.98 mm^3/min and 0.012 mm^3/min, respectively. Thus, capability of the proposed approach to generate high-quality surfaces demonstrated efficient material removal and minimal tool wear.

Overall, the results confirm that an integration of the genetic algorithm with scalarization offers a powerful framework for solving a multi-objective optimization problem in advanced manufacturing processes, with strong predictive capability and an adaptability to varying performance requirements. This work adds to the existing body of knowledge in advanced manufacturing systems by providing a robust optimization framework. The findings provide a basis for future research and industrial applications seeking to improve machining efficiency, tool life, and surface integrity through intelligent, data-driven strategies.

Conclusion

This study successfully explored the optimization of machining parameters in the near dry EDM process using a hybrid approach combining multi-objective Genetic Algorithms and scalarization techniques. An integration of Genetic Algorithms with scalarization enabled in simultaneous optimization of conflicting objectives-maximizing MRR while minimizing TWR and SR. The approach demonstrated strong performance in balancing the trade-offs that is crucial for industrial applications. The scalarization techniques helped in obtaining practical relevance by assigning user-defined weights to each output parameter, the methodology allowed for customization based on specific operational goals. The resulting configurations did provide practical solutions for diverse machining scenarios, ranging from high material removal to precision surface finish. The study reinforces the potential of near dry EDM as a viable, energy-efficient alternative to conventional EDM, supporting the advancement of green and sustainable manufacturing practices. The experimental and optimization results do contribute a valuable insight into the process behavior and its suitability for use in modern production environments.

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Conflict of interest

The author declares that there are no conflicts of interest.

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