Prabha Materials Science Letters
Vol. 3, No. 1, 123-145, 2024
https://doi.org/10.33889/PMSL.2024.3.1.009

Ram Arti Publishers

# An Extensive Review of Various Optimization Techniques for Electric Discharge Machining

**Abhishek Singh**
Department of Industrial and Production Engineering,
Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, India.
*Corresponding author*: abhisheksingh12987@gmail.com

**Rajiv Kumar Garg**
Department of Industrial and Production Engineering,
Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, India.
E-mail: gargrk@nitj.ac.in

**Anish Sachdeva**
Department of Industrial and Production Engineering,
Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, India.
E-mail: asachdeva@nitj.ac.in

(Received on December 25, 2023; Revised on February 19, 2024 & March 20, 2024; Accepted on March 21, 2024)

**Abstract**
In this paper, an investigation of wire and electric discharge machining has been provided. Wider possibilities for the creation of composites and sophisticated materials were made possible by advances in machining science. As research in this area continues, more materials with complicated meteorological structures and strong mechanical resistance capabilities are emerging. Because of the exceptional strength, toughness, and hardness of these materials, advanced machining techniques are replacing traditional machining techniques in this industry. One unique type of advanced machining technique used in this research is electrical discharge machining. It has also been discussed how these machining methods might develop in the future. This paper serves as both a research tool and a step in that direction. The best settings for the processes outlined above will aid in boosting diverse sectors' output. The research on non-conventional machining processes with diverse optimisation strategies is presented in this review. The optimisation techniques taken into account for the current work were Taguchi's, artificial neural networks, particle swarm optimisation, response surface approach, grey connection analysis, and genetic algorithm.

**Keywords-** Metal matrix composites, EDM, Wire electric discharge machining, Artificial neural network, Material removal rate, Surface roughness.

## 1. Introduction

Machining of difficult or advanced materials is required because material development is progressing so quickly. The requirements of modern manufacturing sectors include high precision and accuracy, minimal surface roughness, shorter machining times, and reduced costs when creating products with complicated geometries, micro and macro sizes, and hard materials. These requirements can be met by applying non-traditional machining techniques, particularly EDM (Tonday & Tigga, 2019). Non-conventional machining procedures are the name given to these novel machining techniques. A common non-conventional material removal technique used to make dies, punches, and moulds is electrical discharge machining(EDM) (Garg et al., 2010). In comparison to traditional machining, these new techniques have a number of benefits, including improved surface polish, increased tool life, superior precision and accuracy throughout machining, less waste, and increased productivity (Gautam et al., 2022). EDM is extensively utilised for surgical components. The tool manufacturing, automotive, and aerospace sectors all use this technology. Regardless of the work piece's hardness, the appropriate surface finish can be measured and achieved throughout the wire EDM machining process on any intricately shaped work piece (Subrahmanyam & Nancharaiah, 2020). Electrically conductive objects of any shape, hardness, or toughness can be machined successfully using this technology (Kansal et al., 2007).

### 1.1 History of EDM

Since its invention in the 1950s, the manufacturing sector has employed the EDM technique. The EDM machine and computer systems were connected in the 1980s. Since then, hard materials with intricate shape profiles can be machined using EDM technology. The EDM technique is suitable for machining a variety of materials. It also includes difficult machining of: (1) Al/ZrO2(p)-MMC; (2) Ti6Al4V super alloy; (3) monocrystalline silicon ingot; (4) AISI D2 tool steel; (5) Inconel 718; (6) Si3N4-TiN composite; and (7) thermal-barrier-coated nickel super alloys (Gautam et al., 2022; Prasanna et al., 2017). To overcome the limits of the fundamental EDM process, numerous modifications have been introduced, which include the use of: (1) wire EDM; (2) micro-EDM; (3) cryogenic cooling; (4) die-sinking electric discharge machining; and (5) piezoelectric self-adaptive micro-electric discharge machining. These EDM process variations each have their own unique advantages and restrictions, making them suited for the machining of advanced materials.

### 1.2 EDM Working Principle

EDM is a non-traditional technique of machining various metals that has been invented to be more cost-effective when used on modern alloys and composite materials (Prasanna et al., 2017). This sort of machining process is one of the non-contact ones. The heat energy of the spark is utilised in this thermo-electric process to eliminate material completely from the work piece. The fact is that very little force is generated by the tool while cutting materials. Multiple electrical sparks produced between the tool and the work materials with a constant electric field are used to remove the metal in a dielectric environment (Choudhary et al., 2017). The utilised dielectric fluid serves as a cooler and also removes the debris that has built up on the surface of the machine. Its operating mechanism entails regulated high frequency pulses that generate numerous sparks per second to erode material from the work piece in a dielectric fluid media. The DC pulse generator generates a quick and repeating spark between two electrodes; the narrowest spacing between the two electrodes determines where the spark will occur. The constant bombardment of ions and electrons produces a plasma channel (Tripathy & Tripathy, 2017). The temperature of the very small area under the spark is extremely high, ranging from 8000°C to 12000°C, which causes material from the localised area of the tool and work piece to partially melt and vaporise, Craters are left behind once the material is removed. The work item is then created with a hollow that roughly resembles the tool. The polarity and operation settings should be carefully chosen to reduce tool wear. Additionally, the spark gap can be adjusted to meet the machining conditions, like the MRR (Prasanna et al., 2017). For the EDM and its many variations, there are a number of process parameters that must be set. These include: gap voltage, peak current (Ip), pulse time on (Ton), dielectric pressure, electrode rotational speed, and duty factor. MRR, deviations in dimensions, wear of electrode, surface quality, and overcut are response characteristics that are impacted by these input variables. These response characteristics, which were constrained by the fundamental EDM process, were improved by the different adjustments made to the EDM process.

### 1.3 Main Parameters of EDM

Main parameters of EDM machine are classified into parts
(i) Process parameters
(ii) Performance parameters

### 1.3.1 Process Parameters
The machining process performance metrics are managed by the EDM process parameters. The main process parameters can be classified into four categories (Figure 1), which are as follows:
(i) Electrical parameter
(ii) Non-electrical parameter
(iii) Electrode parameter
(iv) Powder parameter

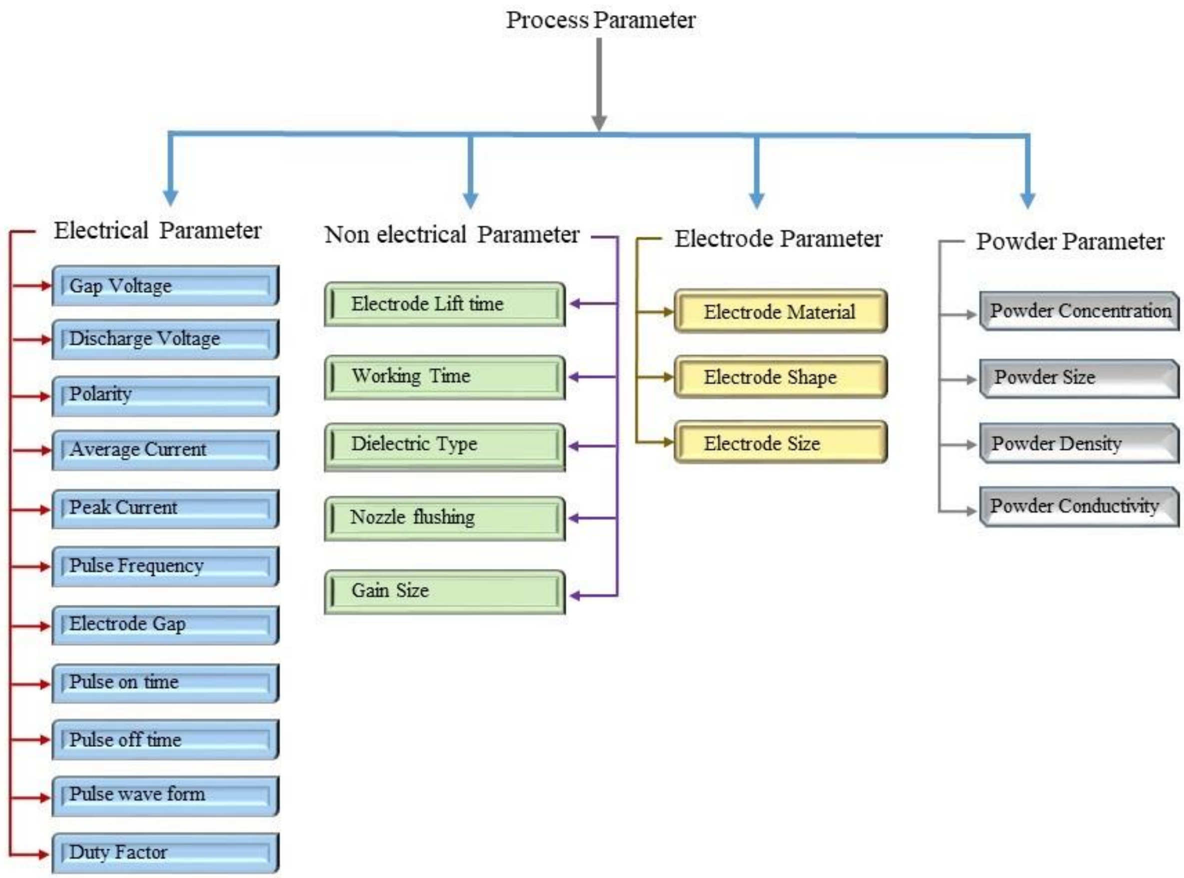


**Figure 1.** EDM process parameter.

### 1.3.2 Performance Parameters
Performance parameters measure the various process performances of the EDM result (as per Figure 2), which are as follows:
(i) *Wear ratio* (*WR*):- The ratio of tool wear rate to material removal rate is known as WR. It is employed as a performance metric to quantify the material combinations of tool work pieces since distinct material combinations result in varying TWR and MRR values. The tool work piece material combination that provides the best TWR and MRR circumstances is indicated by a material combination pair with the lowest WR.
(ii) *Tool wear rate* (*TWR*):- TWR, a performance metric for the erosion rate of the tool electrode, is often considered when assessing the geometrical precision of the machined feature. It is stated as the

volumetric amount of tool electrode material removed per unit of time. TWR, the electrode's weight differential before and after the performance session, is calculated using the material volume removed from the tool per unit of machining time and is expressed as a percentage of MRR (Gangil & Pradhan, 2017).

(iii) *Material removal rate* (*MRR*):- The rate of machining is typically determined using MRR, a performance metric for the erosion rate of the work piece. The expression for it is the volumetric amount of work piece material eliminated per unit of time. To compute MRR, the weight difference of the work piece before and after the experiment is employed.

(iv) *Surface roughness* (*SR*):- Surface roughness (SR) is a surface parameter categorization that describes an amplitude characteristic. It is one of the numerous surface parameters that may be used to measure SR. The SR of the work piece can be expressed in a number of ways, including arithmetic average (Ra), average peak to valley height (R), and peak roughness (R).

(v) *Heat affected zone* (*HAZ*):- The HAZ is the region of base material, which could be a metal that hasn't melted but has had heat-intensive cutting operations changed to its microstructure and characteristics (Gangil et al., 2017a).

(vi) *Surface quality* (*SQ*):- A wide performance metric called "surface quality" is used to characterise the state of the machined surface. Recast layer thickness (RLT), microcrack density, SR, and the size of the heat-affected zone (HAZ) are some of its constituent parts. A surface's lay, surface roughness, and waviness come together to create its surface finish, also known as surface topography or surface texture.

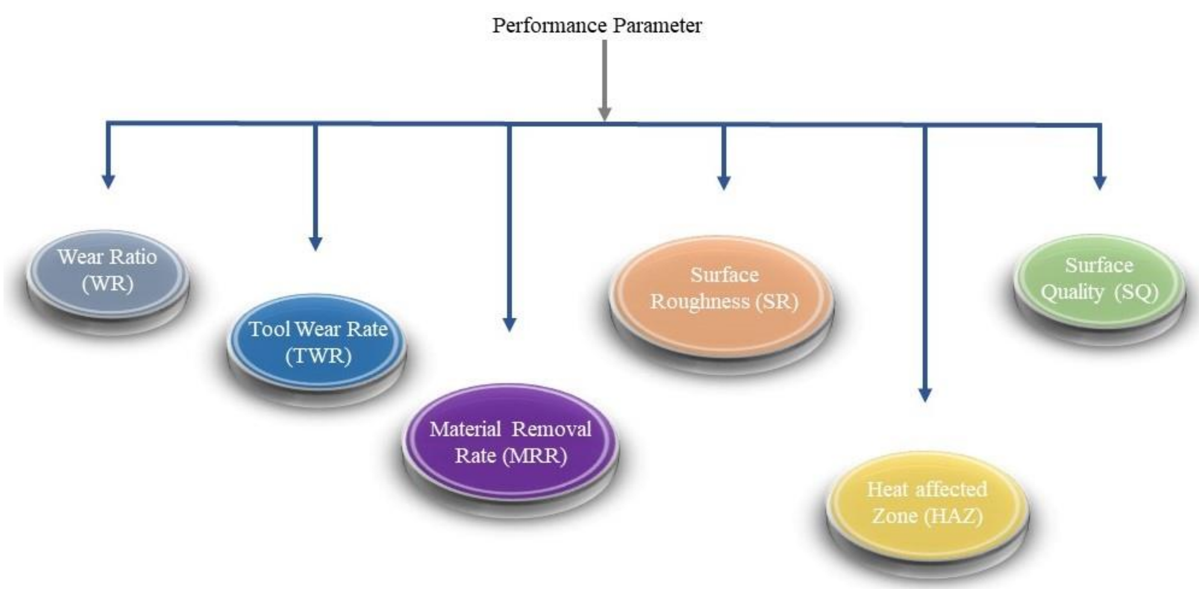


**Figure 2.** EDM performance parameter.

## 1.4 Wire Electric Discharge Machining

One of the more sophisticated machining techniques, Wire Electric Discharge Machining (WEDM), allows for the machining of extremely complex forms (Sureban et al., 2019). Wire of predetermined diameters serves as the electrode in the WED machine. The non-stationary electric discharge that forms between the travelling wire and the work piece is what causes the material to be removed from the work piece (Ukey et al., 2023). The WEDM method involves applying an appropriate voltage across a tool and work piece that are separated by a dielectric fluid. The tool and work piece erode as a result of the ionisation of the dielectric fluid, which accelerates the release of electrons due to the presence of an electric field (Jaiswal et al., 2018). This method is typically used to create punch dies, cutting tools, and other hard-to-machine materials. Although the method has long been recognised as the industry standard for machining in the tools, dies, and moulds sector (Choudhary et al., 2017). The schematic diagram of Wire EDM is shown in Figure 3.

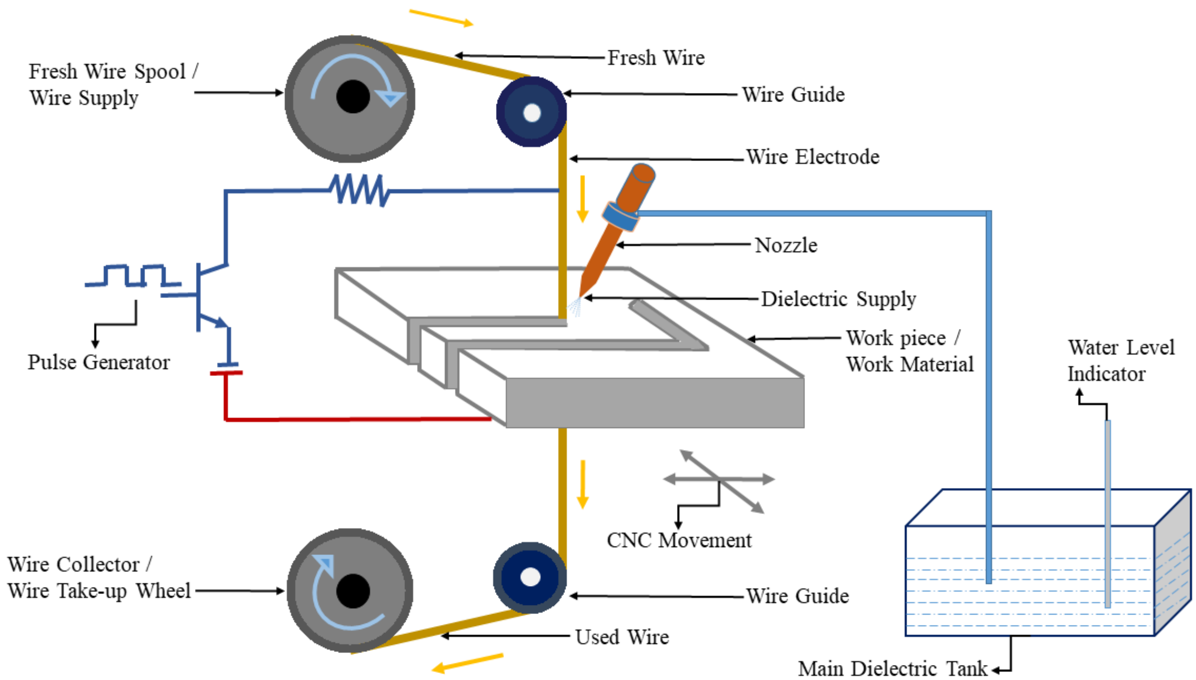


**Figure 3.** Schematic diagram of wire EDM.

The Wire Electric Discharge Machining (WEDM) technique can be used to machine a variety of electrode wire types, which are: (1) copper wire, (2) brass wire, and (3) zinc-coated brass wires. The WEDM process' output response varies depending on the kind of wire utilised in the procedure. Because of this, the ideal input parameters also vary based on the type of wire being used, which are: (1) wire feed (WF), (2) pulse on time, (3) servo voltage (SV), and (4) pulse off time (Sureban et al., 2019). For this process, the input parameters that are examined are: (1) the wire feed, (2) pulse Off Time, (3) servo voltage, and (4) pulse On Time. The output responses that have received the most attention include: (1) the material removal rate, (2) surface roughness, (3) current, (4) Duty factor, (5) flushing pressure, dielectric, and (6) tool type.

### 1.5 Powder Mixed Electro- Discharge Machining

A kind of electrical discharge machining (EDM) called powder mixed electrical discharge machining (PMEDM) makes use of finely abrasive, electrically conductive powder combined with a dielectric fluid. When compared to traditional EDM, this enhances EDM performance and yields a better surface polish (Joshi & Joshi, 2019). Powder Mixed Electro-Discharge Machining (PMEDM) is a relatively recent method that has provided a new avenue for enhancing EDM's process capabilities and producing a surface finish that is nearly mirror-like, with fewer surface cracks and homogenised white layer (Tripathy & Tripathy, 2017). Inter-electrode space is increased when a sufficient fine powder is added to the dielectric fluid, which lowers the fluid's insulating strength and makes it easier to remove debris (Goyal, 2017). With the addition of conductive powder particles, machining rates can be increased and surface quality can be enhanced.

## 2. Review of EDM Machining Processes

Chen et al. ( 2010), Chopde et al. (2014), and Gajjar et al. (2015) observed that the Pulse On Time (Ton) or pulse duration is the most important constraint to improve machining qualities. Goyal (2017) also says that Current and Pulse Off Time (Toff) are important parts of improving Material Removal Rate (MRR). Somashekar et al. (2010) observe that feed rate, gap voltage and capacitance are important parameters for Material removal rate (MRR). Shrivastava & Dubey (2013) and Aggarwal et al. (2015) observed that Pulse On Time (Ton) and Ip are the main input parameters which may affect MRR. Kumar & Kumar (2014) find that Electrode, Current Ton and Gap voltage are the main input parameters which can give high Material removal rate (MRR) and Surface Roughness (SR). Guo et al. (2016) find that TWR rises as the flushing pressure and current rise. The researchers must select the many input parameters and their levels in a way that provides us with the optimal parameter to achieve several goals, including: (1) enhancing the Material Removal Rate (MRR), (2) extending the tool's life, (3) reducing scrap, etc. To accomplish these many objectives, various optimization techniques are employed, including: (1) Taguchi methodology; (2) grey relation analysis; (3) response surface methodology; (4) non-dominating sorting genetic algorithm; and (5) elitist teaching learning-based optimization. In Table 1, grinding processes that have been done recently using Electric discharge machining (EDM) and Wire Electric Discharge Machining (WEDM) are shown. Eswaramoorthy & Shanmugham (2015) analyse that the DoE method is the best to optimise wire-EDM parameters. Goyal et al. (2018), Goyal et al. (2021), Maity & Mishra (2018), and Raj & Kumar (2015) have shown, these optimisation techniques are now used in multi-objective approaches and hybrid methods. Researchers like Bhatt & Goyal (2019), Goyal & Ur Rahman (2021), Maity & Mishra (2018), and Raj & Kumar (2015) used RSM and Taguchi's techniques to optimise input and response parameters. Pandey et al. (2017) tried to use hybrid optimisation techniques to optimise the parameters. Electrical discharge cladding, wire EDM machining, and other new research on these topics have also been done (Pramanik et al., 2021).

## 3. Methodologies

### 3.1 Optimization Techniques of EDM

These optimization techniques help increase productivity, cut down on waste, make tools last longer, and give a better finish on the surface by giving optimized parameters for machining. In order to further improve performance by minimising the drawbacks of one method and using the benefits of another, these optimisation techniques are also used in hybrid and multi-objective methods. There are numerous optimization techniques, some of which are listed below with the help of Figure 4, which are as follows:

(i) Tagauchi method
(ii) Genetic algorithm method
(iii) Simulated annealing method
(iv) Artificial bee colony method
(v) Grey relationship analysis
(vi) Response surface method
(vii) PSO method

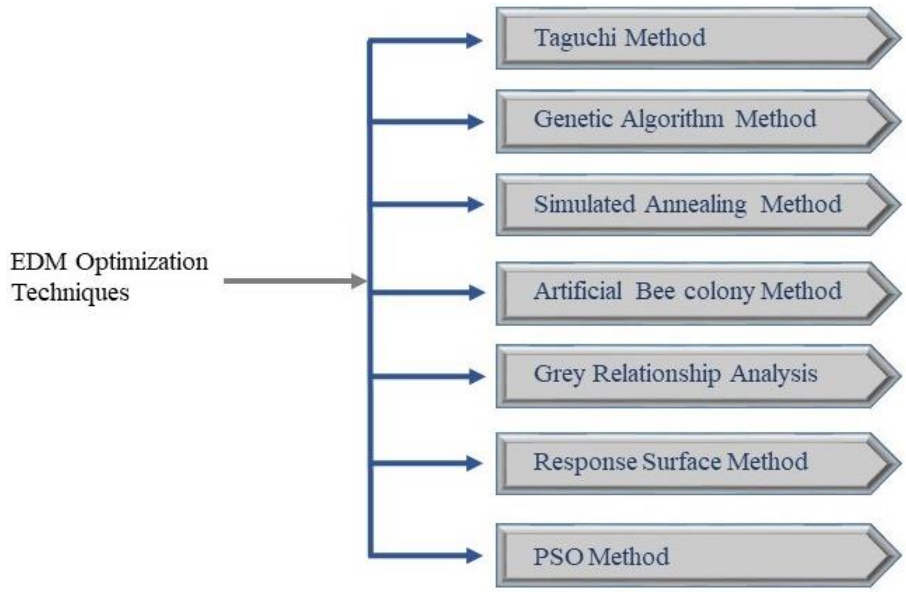


**Figure 4.** EDM optimization techniques.

### 3.1.1 Tagauchi Method
One of the greatest experimental techniques for determining the fewest tests that must be conducted while staying within the parameters and level range that is allowed is the Taguchi method.

### 3.1.2 Genetic Algorithm Method
The global elite is parallelly and randomly searched through crossover, mutation, and reproduction processes, according to the probabilistic basis upon which the GA was built. The survival of the fittest approach is the only one used by these algorithms to search for better solutions while maintaining and managing a population of responses. With a non-dominant sorting genetic set of rules II, lengthy lower backs maximised the outcome of the procedure by using a multi-goal optimisation technique. This provides an EDM parameter optimisation version that mimics a decision using genetic algorithms.

### 3.1.3 Simulated Annealing Method
When evaluating the objective function that yields the global optimum solution, the SA optimisation technique uses random numbers as its basis. The method known as SA mimics how metals naturally cool down over time. SA offers an excellent solution for a wide range of combinatorial problems and is more practical to use than other global optimisation techniques like GA and TS. Both the starting temperature and the decrement (cooling down) factor are parameters of standard SA. Outperforming GA approaches, SA techniques were utilised by the researchers to optimise process parameters for mechanical-type advanced machining. One-point search is used in the simulated annealing process. Annealing molten metal to code it is similar to the simulated annealing procedure (Gangil et al., 2017b).

### 3.1.4 Artificial Bee Colony Method
Inspired by the astute hunting techniques of honey bees, they devised the ABC method, which maximises numerical problems. This exploration technique, like the concepts of ACO and PSO, can lead to high-quality solutions. When the ACO was first used, it was for combinatory issues. At the moment, it is used to address problems pertaining to continuous optimisation.

### 3.1.5 Grey Relationship Analysis

Deng (1989) introduced the grey system theory that can be utilised to resolve the intricate linkages between the many performance parameters. It created new techniques for resolving the intricate relationships between the many performance characteristics (Gangil et al., 2017c). It is an effective method for estimating the behaviour of a discrete data problem and an uncertain system with little information needed. There are three different kinds of systems: black (no information), white (all information), and grey (imperfect information), which means that only a small amount of information is needed to forecast how an uncertain system and discrete data problem will behave. We must apply data preprocessing to the initial experimental data in order to prevent this influence. Data processing has a range of zero to one (0–1). The process of normalisation involves transforming the data into a similar sequence. Normalisation requires three things: Nominal is the best, higher is better, and lower is better (Gangil et al., 2017a).

### 3.1.6 Response Surface Method

The Response Surface Methodology (RSM) is a collection of computational and numerical techniques that are suitable for exploring and illustrating problems when the result is subject to partiality depending on many input parameters (Bagal et al., 2019), which is explained with the help of Figure 5. The ultimate objective of this methodology, which is based on experimental design, is to assess industrial facilities' optimal performance with the least amount of experimental work. In this case, the inputs are referred to as variables or factors, and the outputs are the responses that the factors cause to generate the system. Subsequently, the RSM was demonstrated in the creation of new procedures and goods. It has been effectively implemented in various scientific domains, including biology, medicine, vehicles, aviation, etc. Using a series of planned experiments to find the best response is the fundamental concept of RSM. RSM looks into the relationship that exists between one or more response variables and a number of illustrative factors (Gangil & Pradhan, 2017).

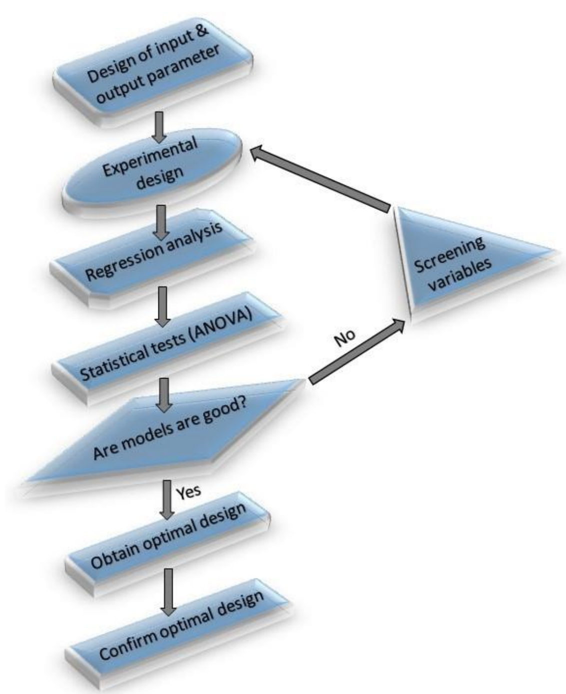


**Figure 5.** Flowchart of RSM process & its procedure.

### 3.1.7 PSO Method

Genetic algorithms necessitate intricate encoding and decoding procedures, which are not necessary for the PSO approach. The actual value is a particle that adjusts its internal velocity to find the optimal answer. Potential solutions in PSO are referred to as particles and mimicking insect or bird swarms. These particles follow the existing optimum particles and fly through the problem space. Managing the restrictions of the non-linear equation and assessing the impractical particles are crucial. This is mostly because the particles produced throughout the process might not adhere to the system's limitations, producing particles that are not possible. The particles that better satisfy the imposed objective function are those that represent the optimal PSO solution (Quarto et al., 2022). The PSO method is explained with the help of Figure 6.

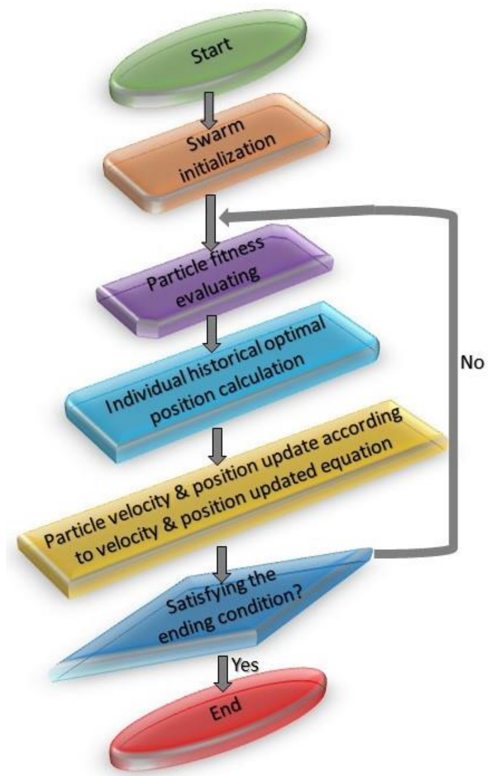


**Figure 6.** PSO algorithm flowchart.

**Table 1.** Work done by EDM machining processes in the last ten years.

| Author & Year | Method | Objectives | Material to Work | Input parameters | Optimization techniques | Finding |
|---|---|---|---|---|---|---|
| Chiang & Chang (2006) | WEDM | 1) Surface Removal Rate<br>2) SR | 1) $Al_2O_3$ | 1) V,<br>2) Ton,<br>3) Toff,<br>4) Arc-on-time,<br>5) Arc-off-time,<br>6) Cutting radius of work piece,<br>7) Wire feed,<br>8) Water flow | 1) GRA | A mathematical model is unable to contain |

Table 1 continued…

| | | | | | | |
|---|---|---|---|---|---|---|
| Yilmaz et al. (2006) | EDM | 1) EW,<br>2) SR,<br>3) Erosion rate | 1) AISI 4340 | 1) Pulse interval,<br>2) Pulse duration,<br>3) Ip,<br>4) Flushing rate<br>5) Gap control, | 1) Fuzzy logic | Triangular membership functions, fuzzy-expert rules, and the centroid area approach are used in fuzzy models' fuzzification and defuzzification processes, respectively. |
| Mandal et al. (2007) | EDM | 1) MRR,<br>2) TWR | 1) C40 Steel | 1) Pulse off time<br>2) Ip,<br>3) Ton, | 1) ANN with BPNN | The on-dominating sorting GA-II technique is a multi-objective optimisation technique. |
| Tzeng & Chen (2007) | EDM | 1) precision Accuracy | 1) SKD11 | 1) Ip,<br>2) Powder size<br>3) Ton,<br>4) Duty cycle,<br>5) Powder concentration, | 1) Fuzzy logic | The effectiveness of each parameter is determined by examining the correlations between the machining precision and accuracy using a fuzzy logic system. |
| Rangajanardhaa (2009) | EDM | 1) SR | 1) Steel alloy M-250.<br>2) Ti6Al4V,<br>3) Al alloy HE15,<br>4) Steel alloy 15CD | 1) Ip,<br>2) V | 1) ANN with GA | ANNs with multiple perceptions were created with the Neuro Solutions software. Utilising the GA approach, the network's weighting and factors are optimised. |
| Yang et al. (2009) | EDM | 1) MRR,<br>2) SR | 1) Steel | 1) Ton,<br>2) Pulse-off-time,<br>3) Ip,<br>4) V | 1) NN<br>2) SA, | A counter-propagation neural network is used to generate the model based on experimental data. |
| Kumar et al. (2010) | Abrasive -mixed EDM | 1) MRR,<br>2) SR | 1) EN-24 tool steel | 1) Concentration of abrasive powder in dielectric fluid | 1) GRA | When compared to other variables, the impact of abrasive particles was highly significant. |
| Chen et al. (2010) | WEDM | 1) SR,<br>2) Cutting velocity,<br>3) MRR | 1) Pure tungsten | 1) Servo V,<br>2) Arc of time,<br>3) Ton,<br>4) Water pressure<br>5) Pulse-off-time,<br>6) Wire feed rate,<br>7) Wire tension, | 1) ANN integrated with SA | It was found that the most important component was the pulse-on time. based on the conformation experiments and the outcome. |
| Somashekhar et al. (2010) | Micro-EDM | 1) MRR | 1) Aluminium | 1) Feed rate,<br>2) Gap V,<br>3) Capacitance, | 1) GA<br>2) ANN, | Compared to other factors, capacitance was found to cause more variance in MRR. |
| Joshi & Pande (2011) | Die-sinking EDM | 1) Crater<br>2) size,<br>3) MRR,<br>4) TWR | 1) AISI P20 Mold steel | 1) Break down V,<br>2) Ip,<br>3) Discharge Duration<br>4) Duty cycle,<br>5) Discharge V, | 1) FEM,<br>2) GA<br>3) ANN, | There were no mathematical models that discussed input-output variables. |

Table 1 continued…

| | | | | | | |
|---|---|---|---|---|---|---|
| Reza et al. (2012) | EDM | 1) MRR,<br>2) EWR,<br>3) SR | 1) SS 304 | 1) V,<br>2) Polarity,<br>3) Ip,<br>4) Dielectric pressure<br>5) Ton<br>6) Depth diameter | 1) GRA | With the EDM control parameters optimized, there is a 0.1639 improvement in the grey relational grade. |
| Atefi et al. (2012) | EDM | 1) SR | 1) Hot work steel DIN1.2344 | 1) Ton<br>2) Pulse-off-time,<br>3) Pulse Ip,<br>4) Pulse V, | 1) ANN | In order to lower error in the optimisation of intricate and non-linear problems, hybrid models are used. |
| Kohli et al. (2012) | EDM | 1) MRR | 1) AISI 1040 | 1) Ton<br>2) Toff<br>3) Ip, | 1) Fuzzy logic | The suggested fuzzy model was found to be in good accord with the outcomes of the experiment. |
| Shrivastava & Dubey (2013) | EDDG | 1) MRR,<br>2) TWR | 1) Cu-iron-Gr MMC | 1) Ton<br>2) Ip, | 1) GRA<br>2) ANN,<br>3) GA, | enhanced both the wheel wear rate and MRR by roughly 31% and 76%, respectively. |
| Baraskar et al. (2013) | Die sinking EDM | 1) MRR,<br>2) SR | 1) EN-8 carbon steel | 1) Pulse-on-duration<br>2) Ip,<br>3) Ton,<br>4) Toff, | 1) NSGA-II<br>2) RSM, | The optimisation toolbox was directly used to produce results. |
| Zhang et al. (2013) | EDM | 1) MRR | 1) Mold steel 8407 | 1) Ip<br>2) Polarity,<br>3) Pulse duration,<br>4) V, | 1) FEM | The characteristics of EDM plasma are being investigated using a novel approach. |
| Dhanabalan et al. (2013) | EDM | 1) MRR,<br>2) EWR | 1) Inconal 718 | 1) Ton,<br>2) Ip<br>3) Toff, | 1) GRA | The modified approach utilised here is effective in both detraining the ideal input parameter setting. |
| Agrawal et al. (2013) | PMEDM | 1) TWR | 1) Al/Sic MMC | 1) Pulse-off-time,<br>2) Ton,<br>3) Ip,<br>4) Powder concentration | 1) ANN | When graphite powder is mixed with dielectric, the TWR during MMC machining is greatly decreased. |
| Sivaprakasam et al. (2014) | Micro-WEDM | 1) MRR,<br>2) SR, | 1) Ti-6Al-4v | 1) Feed rate<br>2) V,<br>3) Capacitance, | 1) GA<br>2) RSM, | The proposed model can be used with a GA and a multi-objective optimisation technique to find the best machining conditions. |
| Das et al. (2014) | EDM | 1) MRR,<br>2) SR | 1) EN 31 | 1) Ip,<br>2) Ton,<br>3) V<br>4) Toff, | 1) ABC Analysis | The analyses are validated by confirmation tests, which show that the results are in good agreement with the experimental data. |
| Kumar & Kumar (2014) | Cryogenic cooled EDM | 1) Electrode<br>2) Wear<br>3) MRR<br>4) SR | 1) Al-10% SiCp MMC | 1) Electrode<br>2) Current<br>3) Ton<br>4) Gap voltage | 1) Gray relation analysis | The optimisation of several parameters has been undertaken in order to attain a favourable a high MRR and SR. |

Table 1 continued…

| | | | | | | |
|---|---|---|---|---|---|---|
| Chopde et al. (2014) | WEDM | 1) SR | 1) AISI D2 tool steel | 1) Ton<br>2) Toff<br>3) Ip<br>4) Gap Voltage | 1) Taguchi technique | Ton identified the crucial element for raising the SR. |
| Tiwary et al. (2015) | μ EDM | 1) MRR<br>2) TWR<br>3) Taper of μ EDM | 1) Ti6Al4V alloy | 1) Ton<br>2) Flushing pressure<br>3) pressure<br>4) Ip<br>5) Spark gap voltage | 1) Using a response surface | The findings of the experiment and those predicted indicate a strong correlation. |
| Dewangan et al. (2015) | EDM | 1) WLT,<br>2) SCD,<br>3) SR | 1) AISI P20 | 1) Tool-work time,<br>2) Tool-lift time<br>3) Pulse-on time,<br>4) Ip, | 1) Fuzzy logic<br>2) GRA, | Hybrid optimization approach with a grey-fuzzy basis for optimum EDM parameter selections that enhance surface integrity. |
| Raj & Kumar (2015) | EDM | 1) MRR | 1) EN45 Steel | 1) Toff<br>2) Ton<br>3) Ip<br>4) Spark gap voltage | 1) Taguchi technique | The parameters Toff and Current are crucial for enhancing the MRR. |
| Aggarwal et al. (2015) | EDM | 1) Cutting rate<br>2) SR | 1) Inconel 718 | 1) Gap voltage<br>2) Wire feed rate<br>3) Ip<br>4) Ton<br>5) Wire tension<br>6) Toff | 1) RSM technique | Ton and Ip discovered the most crucial variable. |
| Singh et al. (2015) | Wire EDM | 1) Dimensional deviation | 1) EN8 Steel | 1) Servo voltage<br>2) Wire feed<br>3) Toff | 1) Taguchi technique | Variation in dimension is most significantly impacted by servo voltage. |
| Gajjar & Desai (2015) | WEDM | 1) MRR<br>2) Kerf width<br>3) SR | 1) EN-31 Steel | 1) Ton<br>2) Servo voltage<br>3) Toff | 1) GRA technique | The Ton has identified the key element. |
| Eswaramoorthy & Shanmugham (2015) | WEDM | 1) MRR<br>2) SR<br>3) Electrode wear | 1) Titanium | 1) Ton<br>2) Gap voltage<br>3) Toff<br>4) Wire feed rate<br>5) Wire tension<br>6) Dielectric pressure | 1) Taguchi's technique | The method used by Taguchi has effectively optimised the numerous replies. |
| Dongre et al. (2015) | WEDM | 1) Kerf width<br>2) Cutting speed<br>3) SR | 1) Mono-Crystalline Silicon Ingot | 1) Work piece width<br>2) Ip<br>3) Wire diameter<br>4) Duty cycle | 1) Response surface technique | It has achieved the enhanced SR. |
| Selvarajan et al. (2016) | EDM | 1) MRR<br>2) TWR<br>3) Circularity<br>4) Cylindricity | 1) Si3N4-TiN Composite | 1) Dielectric Pressure<br>2) Ton<br>3) Current<br>4) Toff | 1) GRA technique | The experimental results show major improvements in the process. |
| Rengasamy et al. (2016) | EDM | 1) MRR<br>2) TWR | 1) Al 4032 Alloy | 1) Ton<br>2) Current<br>3) Composites<br>4) Toff | 1) Taguchi's methodology | The Al 4032 composite alloy's process parameter variation for the results. |
| Guo et al. (2016) | EDM Drilling | 1) Machining time<br>2) TWR<br>3) SR | 1) Coated Ni alloy | 1) Duty factor<br>2) Flushing pressure<br>3) Discharge current<br>4) Pulse duration | 1) Gray relation analysis technique | TWR rises as the flushing pressure and current rise. |

Table 1 continued…

| | | | | | | |
|---|---|---|---|---|---|---|
| Rahang & Patowari (2016) | EDM | 1) TWR<br>2) Material transfer rate<br>3) SR<br>4) Edge deviation | 1) Aluminium | 1) Ton<br>2) Ip<br>3) Compact load | 1) Taguchi's method | The changed surface has got the improved hardness. |
| Garg et al. (2016) | Wire EDM | 1) Spark gap<br>2) MRR | 1) Al/ZrO2(p)-MMC | 1) Machining voltage<br>2) Wire tension<br>3) Wire feed rate<br>4) Pulse width<br>5) Work piece height | 1) Response surface technique | The model that was created displays good arrangement with the findings. |
| Pragadish & Pradeep Kumar (2016) | Dry-EDM | 1) MRR<br>2) SR | 1) AISI D2 Steel | 1) Gap voltage<br>2) Current<br>3) Pressure<br>4) Ton | 1) GRA method | Along with pressure, the current has identified the most crucial variables. |
| Fu et al. (2016) | Piezoelectric Self adaptive Micro-EDM | 1) SR | 1) Steel tool | 1) Spindle speed<br>2) Open voltage<br>3) Feed speed<br>4) Adjustable capacitor | 1) Taguchi's technique | The SR has increased with decreasing open voltage and adjustable capacitor. |
| Raj & Prabhu (2017) | Wire EDM | 1) MRR<br>2) SR | 1) Titanium | 1) Toff<br>2) feed rate<br>3) Ton | 1) RSM method | The crucial elements that affect the SR are found in Ton and Toff. |
| Khullar et al. (2017) | EDM | 1) MRR<br>2) SR | 1) AISI 5160 | 1) Ip<br>2) Ton<br>3) Flushing modes<br>4) Toff | 1) RSM &<br>2) Non dominating sorting GA | As Ip and Ton rise, MRR also rises. |
| Bhosle & Sharma (2017) | µEDM Drilling | 1) MRR<br>2) Taper Angle<br>3) Overcut | 1) Inconel 600 | 1) Ton<br>2) Voltage<br>3) Toff<br>4) feed rate<br>5) Capacitance | 1) Grey relation analysis technique | Voltage and capacitance are the two factors that have the most impact on the responses. |
| Alavi & Jahan (2017) | µEDM | 1) Machining time<br>2) TWR<br>3) Crater size<br>4) Hardness | 1) Ti6Al4V | 1) Servo voltage<br>2) TN coating<br>3) Capacitance<br>4) Electrode rotational speed | 1) Anova &<br>2) Manova technique | Voltage affects the amount of time spent cutting and the size of the crater. |
| Bose & Pain (2018) | EDM | 1) MRR<br>2) Over Cut | 1) Mild Steel | 1) Spark gap<br>2) Gap current<br>3) Duty factor<br>4) Ton | 1) Response surface technique | For overcuts between 87.44 $mm^2$ and 14.44 $mm^2$, the obtained MRR ranges from 0.0065 gm/sec to 0.0017 gm/sec. |
| Maity & Mishra (2018) | µEDM | 1) Recast layer thickness<br>2) Over cut<br>3) MRR | 1) Inconel 718 | 1) Ip<br>2) Ton<br>3) Voltage<br>4) Toff | 1) Teaching learning<br>2) Artificial bee colony algo. | The Pareto-optimal solutions discovered using various techniques. |
| Faisal & Kumar (2018) | EDM | 1) MRR<br>2) Average roughness | 1) Oil Hardened Non-Shrinking Steel | 1) Voltage Gap<br>2) Ton<br>3) Toff<br>4) Pulse current | 1) Heuristic and<br>2) PSO Optimization technique | The proposed algorithm delivers the best values for the created model. |
| Gangil & Pradhan (2018) | EDM | 1) MRR<br>2) EWR | 1) Ti6Al4V | 1) Voltage<br>2) Ton<br>3) Current<br>4) Duty cycle | 1) Response surface technique | Ip has identified the key variable that has the most impact on the answers. |

Table 1 continued…

| | | | | | | |
|---|---|---|---|---|---|---|
| Kandpal et al. (2018) | EDM | 1) MRR | 1) Al based MMC | 1) Pulse current<br>2) Duty factor<br>3) Ton | 1) Taguchi technique | As the Ton and pulse current rise, MRR gets better. |
| Ahuja et al. (2020) | Wire EDM | 1) CS<br>2) SR<br>3) CR | 1) ZM21 Mg alloy | 1) Toff<br>2) Ton<br>3) SV<br>4) WF | 1) RSM and<br>2) Desirability approach method | The improvement in the specimen's surface is visible by SEM and XRD. |
| Jaiswal et al. (2018) | Wire EDM | 1) SR,<br>2) CS | 1) D3 die steel | 1) Servo voltage,<br>2) Pulse On time,<br>3) Wire tension<br>4) Pulse off time, | 1) Taguchi's approach,<br>2) MOORA | They discovered minimal Ra and improved cutting speed. |
| Bagal et al. (2019) | Wire EDM | 1) Surface quality,<br>2) Tool wear rate (TWR),<br>3) KW | 1) Stainless Steel | 1) Current<br>2) Ton,<br>3) Toff, | 1) Genetic Algorithm and Simulated Annealing, Combine RSM-TOPSIS | Ra, kf, and TWR all rise as Ton time tends to increase. |
| Tonday & Tigga (2019) | WEDM | 1) SR | 1) Inconel 718 | 1) Ton,<br>2) Cutting voltage (CV)<br>3) Wire feed rate (WF),<br>4) Toff,<br>5) Flushing pressure (FP), | 1) Taguchi technique,<br>2) RSM,<br>3) analysis of variance | The information is nearly real-time machining time needed to machine a 22 mm diameter circular bar. Inconel 718's surface was characterised. |
| Subrahmanyam & Nancharaiah (2020) | Wire-cut EDM | 1) SR,<br>2) MRR | 1) Inconel 625 | 1) Discharge current,<br>2) Servo voltage (SV)<br>3) Ton,<br>4) Toff, | 1) Taguchi method along with<br>2) ANOVA | Toff plays a significant role in MRR and Ra Tonne. |
| Babu et al. (2019) | WEDM | 1) Ra,<br>2) MRR | 1) Inconel 750 | 1) Current<br>2) Ton,<br>3) Toff,<br>4) Voltage, | 1) Combined ANN and<br>2) PSO method | The artificial neural network that was used to create the association between the process parameters and the output values found that the root mean square error was the same as it was for MRR and SR. |
| Chaudhari (2019) | WEDM | 1) MRR,<br>2) Micro-hardness (MH),<br>3) Surface quality | 1) (Ni55.8Ti) super-elastic SMA | 1) Discharge Current<br>2) Ton,<br>3) Toff, | 1) RSM<br>2) Heat-transfer search (HTS) algorithm and | The outcomes demonstrated that while Toff and current had a considerable impact on MRR, they had the most effects on SR and MH. |
| Das et al. (2019) | WEDM | 1) TWR,<br>2) KW,<br>3) surface quality | 1) SS 304 grade stainless steel w | 1) Wire tension (WT),<br>2) Ton,<br>3) Toff,<br>4) Servo voltage (SV), | 1) Grey-fuzzy approach<br>2) RSM and<br>3) TOPSIS method, | It was discovered that pulse ON time was the most important factor for tool wear rate, kerf width, and surface roughness. |
| Kumar et al. (2020) | WEDM | 1) Spark gap (SG) width,<br>2) MRR | 1) Hybrid Al Composite<br>2) Al-matrix | 1) Pulse peak current (Ip)<br>2) Spark gap-set voltage (SV)<br>3) Ton,<br>4) Toff,<br>5) Wire feed rate (WF),<br>6) Wire tension (WT) | 1) Regression analysis,<br>2) ANOVA (analysis of variance) | An improvement of 33.72% and 27.28% in the ideal parametric configuration for both MRR and SG. |

Table 1 continued…

| | | | | | | |
|---|---|---|---|---|---|---|
| Goyal, et al. (2021) | WEDM | 1) MRR, spark gap, kerf width | 1) Ni49Ti51 shape memory alloy | 1) Current, 2) Wire feed rate 3) Ton, 4) Toff, 5) Wire tension | 1) ANN, 2) Response surface methodology (RSM), 3) BPNN approach | Ton and I.P. are the most important parameters for MRR. |
| Ishfaq et al. (2020) | WEDM | 1) SR, 2) cutting rate, 3) kerf width | 1) Al6061-7.5% SiC squeeze-casted composite | 1) Current, 2) Pulse, 3) Voltage | 1) Multi-objective genetic algorithm, 2) Response Surface Methodology | They discovered the ideal combination of properties for the chosen material. |
| Kumar et al. (2019) | WEDM | 1) Tool wear rate, 2) MRR, 3) SR | 1) Stainless steel AISI 630 | 1) Wire feed rate 2) Discharge Current, 3) Ton, 4) Toff | 1) Fuzzy approach | The fuzzy model system provides an overall accuracy of 90%. |
| Lalwani et al. (n.d.) | Wire EDM | 1) KW, 2) SR, and 3) Material removal rate | 1) Inconel 718 Alloy | 1) Peak Current, 2) Ton, 3) Toff, 4) Servo Voltage, 5) Wire Tension | 1) Response surface methodology , 2) Artificial neural network (ANN)-based models, 3) NSGA- II | The factor that affects Inconel 718 machining the most is TONNE. KW, Ra, and MRR are good fits for RSM models. |
| Sen et al. (2021) | WEDM | 1) Power Consumption, 2) MRR, 3) Kerf Thickness, | 1) Inconel 800 | 1) Peak Current, 2) Peak voltage, 3) Pulse on Time, 4) Pulse off Time, 5) Spark gap Voltage, 6) Wire tension, 7) Wire feed, 8) Water pressure, 9) Servo feed | 1) Type-2 Fuzzy AHP-ARAS | The best and most cautious method of machining Inconel 800 is to use a non-conventional machining strategy. |
| Kulkarni et al. (2020) | Wire EDM | 1) MRR, 2) TWR, 3) SR | 1) Medical Grade NiTiNOL Memory Alloy | 1) Servo voltage (SV), 2) Ton, 3) Toff, 4) Wire feed (WF) | 1) Modified differential evolution, 2) RSM | It is discovered that SV is a more important process element with lower SR and TWR in order to get higher MRR. |
| Ishfaq et al. (2020) | WEDM | 1) Surface quality and 2) MRR | 1) Al6061 | 1) Servo voltage, 2) Wire feed, 3) Open voltage, 4) Wire tension, 5) Ton, 6) Toff, 7) Pressure | 1) Taguchi-based parametric optimization | The primary controlling factor is pulse length, which accounts for 51% and 88% of surface finish and MRR, respectively. |
| Doreswamy et al. (2021) | Wire-EDM | 1) MRR | 1) SiCp reinforced Al6061 composite | 1) Current, 2) Voltage 3) Ton, 4) Toff, 5) Wire speed | 1) Taguchi approach, 2) ANOVA | The voltage, ton, toff, wire speed, and current all had a major impact on the material removal rate. |

Table 1 continued…

| | | | | | | |
|---|---|---|---|---|---|---|
| Kumar et al. (2022) | WEDM | 1) MRR, 2) SR, 3) SG | 1) Al-Hybrid Composites | 1) Spark gap-set voltage (SV), 2) Wire feed rate (WF), 3) Pulse peak current (Ip), 4) Ton, 5) Toff, 6) Wire tension (WT) | 1) AHP and Genetic Algorithm | ideal circumstances for hybrid composites machining. |
| Natarajan et al. (2022) | WEDM | 1) Surface roughness (SR) 2) Material removal rate (MRR) | 1) Stainless Steel | 1) Voltage (V), 2) Mean current (I), 3) Ton, 4) Toff, 5) Wire feed (WF) | 1) Taguchi, 2) ANOVA, 3) GRA | The most important process variables and the ideal optimisation technique for different steel types. |
| Chaudhari et al. (2022) | Near dry WEDM | 1) material removal rate (MRR), and 2) surface roughness (SR) | 1) Nitinol Shape Memory Alloy | 1) Current, 2) Ton, 3) Toff, | 1) ANOVA, 2) A teaching–learning-based optimization (TLBO) | Determine the best possible setup for the process parameters. |
| Sharma et al. (2023) | WEDM | 1) Maximum surface roughness (Rz) 2) Dimensional accuracy (DA), 3) Average surface roughness (Ra), | 1) Pure Titanium | 1) Servo Voltage, 2) Ton, 3) Toff, 4) Wire Tension | 1) Swarm Optimization (PSO) 2) Evaluation Based on Distance from 3) Average Solution (EDAS) and Particle | notable decrease in surface flaws |
| Balaji and Narendranath (2023) | Wire-EDM | 1) MRR, Ra | 1) Ni–Ti-Hf shape memory alloy | 1) Wire Feed, 2) Ton, 3) Toff, 4) Servo Voltage | 1) CNN-based SEM-image classification 2) PSO | Minimal percentage errors for both input parameter sets |
| Kosaraju et al. (2023) | WEDM | 1) material removal rate (MRR) 2) and surface roughness (Ra) | 1) Inconel 600 | 1) Pulse-on time, 2) Current, 3) Pulse-off time, | 1) Taguchi analysis | Experimental analysis was done to optimise the process parameters for the Inconel 600 alloy using both untreated and cryogenically treated zinc electrodes. |

## 4. Conclusion and Future Scope

This paper is about the different output and input parameters of modern machining methods and how they can be optimised. Wire-EDM and EDM are two current machining methods that were looked at for this work. The literature review looks for modern machining processes, which include: (1) the work piece material; (2) the input parameters; (3) the response parameters; and (4) the optimisation method used. There is a section called "Remarks" that talks about what the authors learned from their works. Here are some of the things that were noticed during the review:-

- In order to achieve the optimal production conditions a crucial requirement for enterprises seeking to produce high-quality goods at reduced costs the EDM optimisation technique is applied in the manufacturing process sector in this review study.
- As new materials keep getting better, experts keep coming up with new ways to work with them. During the time period under study, the EDM process has changed in many ways, such as with Wire-EDM, piezoelectric self-adaptive micro-EDM, cryogenic cooled EDM, Dry-EDM, etc. These versions were used a lot to cut and shape different types of traditional and advanced materials.
- It was discovered that advanced optimisation methods have been used successfully to figure out how process parameters affect the responses. Researchers have come up with optimization methods, such as combined ANN–NSGAII, fuzzy TOPSIS, genetic algorithm through particle swarm optimization, GRA, etc., to find the best way to machine something. Researchers use integrated ANN–NSGAII optimization methods most of the time now.

**Conflict of Interest**
The authors confirm that there is no conflict of interest to declare for this publication.

**Acknowledgments**
I am very much thankful to Dr. Rajiv Kumar Garg, Professor (H.A.G.), Dr. B.R. Ambedkar National Institute of Technology, Jalandhar for supervising during the present research work. I also thankful to my co-supervisor Dr. Anish Sachdeva, Professor (Dean Student Welfare), Dr. B. R. Ambedkar National Institute of Technology, Jalandhar for their valuable guidance and support.

## References

Aggarwal, V., Khangura, S.S., & Garg, R.K. (2015). Parametric modeling and optimization for wire electrical discharge machining of Inconel 718 using response surface methodology. *International Journal of Advanced Manufacturing Technology*, *79*, 31-47. https://doi.org/10.1007/s00170-015-6797-8.

Agrawal, A., Dubey, A.K., & Shrivastava, P.K. (2013). Modeling and optimization of tool wear rate in powder mixed EDM of MMC. In *2nd International Conference on Mechanical and Robotics Engineering*, (pp. 17-18). Pattaya, Thailand.

Ahuja, N., Batra, U., & Kumar, K. (2020). Experimental investigation and optimization of wire electrical discharge machining for surface characteristics and corrosion rate of biodegradable Mg alloy. *Journal of Materials Engineering and Performance*, *29*(6), 4117-4129. https://doi.org/10.1007/s11665-020-04905-8.

Alavi, F., & Jahan, M.P. (2017). Optimization of process parameters in micro-EDM of Ti-6Al-4V based on full factorial design. *International Journal of Advanced Manufacturing Technology*, *92*(1-4), 167-187. https://doi.org/10.1007/s00170-017-0103-x

Atefi, R., Javam, N., Razmavar, A., & Teimoori, F. (2012). The investigation of EDM parameters on electrode wear ratio. *Research Journal of Applied Sciences, Engineering and Technology*, *4*(10), 1295-1299.

Babu, K.N., Karthikeyan, R., & Punitha, A. (2019). An integrated ANN - PSO approach to optimize the material removal rate and surface roughness of wire cut EDM on INCONEL 750. *Materials Today: Proceedings*, *19*, 501-505. https://doi.org/10.1016/j.matpr.2019.07.643.

Bagal, D.K., Barua, A., Jeet, S., Satapathy, P., & Patnaik, D. (2019). MCDM optimization of parameters for wire-EDM Machined stainless steel using hybrid RSM-TOPSIS, genetic algorithm and simulated annealing. *International Journal of Engineering and Advanced Technology*, *9*(1), 366-371. https://doi.org/10.35940/ijeat.a9349.109119.

Balaji, V., & Narendranath, S. (2023). Optimization of wire-EDM process parameters for Ni–Ti-Hf shape memory alloy through particle swarm optimization and CNN-based SEM-image classification. *Results in Engineering*, *18*, 101141. https://doi.org/10.1016/j.rineng.2023.101141.

Baraskar, S.S., Banwait, S.S., & Laroiya, S.C. (2013). Multiobjective optimization of electrical discharge machining process using a hybrid method. *Materials and Manufacturing Processes*, *28*(4), 348-354. https://doi.org/10.1080/10426914.2012.700152.

Bhatt, D., & Goyal, A. (2019). Multi-objective optimization of machining parameters in wire EDM for AISI-304. *Materials Today: Proceedings*, *18*, 4227-4242. https://doi.org/10.1016/j.matpr.2019.07.381.

Bhosle, R.B., & Sharma, S.B. (2017). Multi-performance optimization of micro-EDM drilling process of Inconel 600 alloy. *Materials Today: Proceedings*, *4*(2), 1988-1997. https://doi.org/10.1016/j.matpr.2017.02.045

Bose, G.K., & Pain, P. (2018). Metaheuristic approach of multi-objective optimization during EDM process. *International Journal of Mathematical, Engineering and Management Sciences*, *3*(3), 301-314. https://doi.org/10.33889/ijmems.2018.3.3-022.

Chaudhari, R., Kevalramani, A., Vora, J., Khanna, S., Patel, V.K., Pimenov, D.Y., & Giasin, K. (2022). Parametric optimization and influence of near-dry WEDM variables on nitinol shape memory alloy. *Micromachines*, *13*(7), 1-19. https://doi.org/10.3390/mi13071026.

Chaudhari, R., Vora, J.J., Prabu, S.S.M., Palani, I.A., Patel, V.K., Parikh, D.M., & de Lacalle, L.N.L. (2019). Multi-response optimization of WEDM process parameters for machining of superelastic nitinol shape-memory alloy using a heat-transfer search algorithm. *Materials*, *12*(8), 1277. https://doi.org/10.3390/ma12081277.

Chen, H.C., Lin, J.C., Yang, Y.K., & Tsai, C.H. (2010). Optimization of wire electrical discharge machining for pure tungsten using a neural network integrated simulated annealing approach. *Expert Systems with Applications*, *37*(10), 7147-7153. https://doi.org/10.1016/j.eswa.2010.04.020.

Chiang, K.T., & Chang, F.P. (2006). Optimization of the WEDM process of particle-reinforced material with multiple performance characteristics using grey relational analysis. *Journal of Materials Processing Technology*, *180*(1-3), 96-101. https://doi.org/10.1016/j.jmatprotec.2006.05.008.

Chopde, I.K., Gogte, C., & Milind, D. (2014). Modeling and optimization of WEDM parameters for surface finish using design of experiments. In *International Conference on Industrial Engineering and Operations Management* (pp. 1830-1839). Bali, Indonesia.

Choudhary, R., Garg, H., Prasad, M., & Kumar, D. (2017). Effect of Cryogenic treatment of tool electrode on the machining performance and surface finish during electrical discharge machining of hastelloy C-4. *Materials Today: Proceedings*, *4*(2), 1158-1166. https://doi.org/10.1016/j.matpr.2017.01.132.

Das, M.K., Kumar, K., Barman, T.K., & Sahoo, P. (2014). Application of artificial bee colony algorithm for optimization of MRR and surface roughness in EDM of EN31 tool steel. *Procedia Materials Science*, *6*(Icmpc), 741-751. https://doi.org/10.1016/j.mspro.2014.07.090.

Das, P.P., Diyaley, S., Chakraborty, S., & Ghadai, R.K. (2019). Multi-objective optimization of wire electro discharge machining (WEDM) process parameters using grey-fuzzy approach. *Periodica Polytechnica Mechanical Engineering*, *63*(1), 16-25. https://doi.org/10.3311/PPme.12167.

Deng, J.L. (1989). Properties of multivariable grey model GM (1, N). *The Journal of Grey System*, *1*(1), 25-41.

Dewangan, S., Gangopadhyay, S., & Biswas, C.K. (2015). Multi-response optimization of surface integrity characteristics of EDM process using grey-fuzzy logic-based hybrid approach. *Engineering Science and Technology, an International Journal*, *18*(3), 361-368. https://doi.org/10.1016/j.jestch.2015.01.009.

Dhanabalan, S., Sivakumar, K., & Narayanan, C.S. (2013). Optimization of machining parameters of EDM while machining inconel 718 for form tolerance and orientation tolerance. *Indian Journal of Engineering and Materials Sciences*, *20*(5), 391-397.

Dongre, G., Zaware, S., Dabade, U., & Joshi, S.S. (2015). Multi-objective optimization for silicon wafer slicing using wire-EDM process. *Materials Science in Semiconductor Processing*, *39*, 793-806. https://doi.org/10.1016/j.mssp.2015.06.050.

Doreswamy, D., Bongale, A.M., Piekarski, M., Bongale, A., Kumar, S., Pimenov, D.Y., Giasin, K., & Nadolny, K. (2021). Optimization and modeling of material removal rate in wire-edm of silicon particle reinforced al6061 composite. *Materials*, *14*(21), 1-18. https://doi.org/10.3390/ma14216420.

Eswaramoorthy, S.B., & Shanmugham E.P. (2015). Optimal control parameters of machining in CNC Wire-Cut EDM for Titanium. *International Journal of Applied Sciences and Engineering Research*, *4*(1), 102-121.

Faisal, N., & Kumar, K. (2018). Optimization of machine process parameters in EDM for EN 31 using evolutionary optimization techniques. *Technologies*, *6*(2), 54. https://doi.org/10.3390/technologies6020054

Fu, X., Gao, L., Zhang, Q., & Liu, Q. (2016). Surface roughness research of piezoelectric self-adaptive micro-EDM. *Procedia CIRP*, *42*(Isem Xviii), 563-568. https://doi.org/10.1016/j.procir.2016.02.252.

Gajjar, D., & Desai, J. (2015). Optimization of MRR, surface roughness and KERF width in wire EDM Using molybdenum wire. *International Journal for Research in Education*, *4*(2), 9-17.

Gangil, M., & Pradhan, M.K. (2017). Modeling and optimization of electrical discharge machining process using RSM: A review. *Materials Today: Proceedings*, *4*(2), 1752-1761. https://doi.org/10.1016/j.matpr.2017.02.017.

Gangil, M., & Pradhan, M.K. (2018). Optimization the machining parameters by using VIKOR Method during EDM process of Titanium alloy. *Materials Today: Proceedings*, *5*(2), 7486-7495. https://doi.org/10.1016/j.matpr.2017.11.420.

Gangil, M., Pradhan, M.K., & Purohit, R. (2017a). Review on modelling and optimization of electrical discharge machining process using modern Techniques. *Materials Today: Proceedings*, *4*(2), 2048-2057. https://doi.org/10.1016/j.matpr.2017.02.050.

Gangil, M., Pradhan, M.K., & Purohit, R. (2017b). Review on modelling and optimization of electrical discharge machining process using modern Techniques. *Materials Today: Proceedings*, *4*(2), 2048-2057. https://doi.org/10.1016/j.matpr.2017.02.050.

Gangil, M., Pradhan, M.K., & Purohit, R. (2017c). Review on modelling and optimization of electrical discharge machining process using modern Techniques. *Materials Today: Proceedings*, *4*(2), 2048-2057. https://doi.org/10.1016/j.matpr.2017.02.050.

Garg, R.K., Singh, K.K., Sachdeva, A., Sharma, V.S., Ojha, K., & Singh, S. (2010). Review of research work in sinking EDM and WEDM on metal matrix composite materials. *International Journal of Advanced Manufacturing Technology*, *50*(5-8), 611-624. https://doi.org/10.1007/s00170-010-2534-5.

Garg, S.K., Manna, A., & Jain, A. (2016). Experimental investigation of spark gap and material removal rate of Al/ZrO2(P)-MMC machined with wire EDM. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *38*(2), 481-491. https://doi.org/10.1007/s40430-015-0394-5.

Gautam, N., Goyal, A., Sharma, S.S., Oza, A.D., & Kumar, R. (2022). Study of various optimization techniques for electric discharge machining and electrochemical machining processes. *Materials Today: Proceedings*, *57*, 615-621. https://doi.org/10.1016/j.matpr.2022.02.005.

Goyal, A. (2017). Investigation of material removal rate and surface roughness during wire electrical discharge machining (WEDM) of Inconel 625 super alloy by cryogenic treated tool electrode. *Journal of King Saud University - Science*, *29*(4), 528-535. https://doi.org/10.1016/j.jksus.2017.06.005.

Goyal, A., Gautam, N., & Pathak, V.K. (2021). An adaptive neuro-fuzzy and NSGA-II-based hybrid approach for modelling and multi-objective optimization of WEDM quality characteristics during machining titanium alloy. *Neural Computing and Applications*, *33*(23), 16659-16674. https://doi.org/10.1007/s00521-021-06261-7.

Goyal, A., Pandey, A., & Sharma, P. (2018). Investigation of surface roughness for Inconel 625 using wire electric discharge machining. In *International Conference on Mechanical, Materials and Renewable Energy* (Vol. 377, No. 1, p. 012109). IOP Publishing. Sikkim, India. https://doi.org/10.1088/1757-899X/377/1/012109.

Goyal, A., & Ur Rahman, H. (2021). Experimental studies on Wire EDM for surface roughness and kerf width for shape memory alloy. *Sadhana - Academy Proceedings in Engineering Sciences*, *46*(3). 160. https://doi.org/10.1007/s12046-021-01684-3.

Goyal, A., UR Rahman, H., & Ghani, S.A.C. (2021). Experimental investigation & optimisation of wire electrical discharge machining process parameters for Ni49Ti51 shape memory alloy. *Journal of King Saud University - Engineering Sciences*, *33*(2), 129-135. https://doi.org/10.1016/j.jksues.2020.01.003.

Guo, Y., Zhang, G., Wang, L., & Hu, Y. (2016). Optimization of parameters for EDM drilling of thermal-barrier-coated nickel superalloys using gray relational analysis method. *International Journal of Advanced Manufacturing Technology*, *83*(9-12), 1595-1605. https://doi.org/10.1007/s00170-015-7685-y.

Ishfaq, K., Anwar, S., Ali, M.A., Raza, M.H., Farooq, M.U., Ahmad, S., Pruncu, C.I., Saleh, M., & Salah, B. (2020). Optimization of WEDM for precise machining of novel developed Al6061-7.5% SiC squeeze-casted composite. *International Journal of Advanced Manufacturing Technology*, *111*(7-8), 2031-2049. https://doi.org/10.1007/s00170-020-06218-5.

Ishfaq, K., Zahoor, S., Khan, S.A., Rehman, M., Alfaify, A., & Anwar, S. (2021). Minimizing the corner errors (top and bottom) at optimized cutting rate and surface finish during WEDM of Al6061. *Engineering Science and Technology, an International Journal*, *24*(4), 1027-1041. https://doi.org/10.1016/j.jestch.2021.01.008.

Jaiswal, A., Peshwani, B., Shivakoti, I., & Bhattacharya, A. (2018). Multi response optimization of wire EDM process parameters. In In *International Conference on Mechanical, Materials and Renewable Energy* (Vol. 377, No. 1, p. 012221). IOP Publishing. Sikkim, India. https://doi.org/10.1088/1757-899X/377/1/012221.

Joshi, A.Y., & Joshi, A.Y. (2019). A systematic review on powder mixed electrical discharge machining. *Heliyon*, *5*(12), e02963. https://doi.org/10.1016/j.heliyon.2019.e02963.

Joshi, S.N., & Pande, S.S. (2011). Intelligent process modeling and optimization of die-sinking electric discharge machining. *Applied Soft Computing Journal*, *11*(2), 2743-2755. https://doi.org/10.1016/j.asoc.2010.11.005.

Kandpal, B.C., Kumar, J., & Singh, H. (2018). Optimisation of process parameters of electrical discharge machining of fabricated AA 6061/ 10% Al2 O3 aluminium based metal matrix composite. *Materials Today: Proceedings*, *5*(2), 4413-4420. https://doi.org/10.1016/j.matpr.2017.12.009.

Kansal, H.K., Singh, S., & Kumar, P. (2007). Technology and research developments in powder mixed electric discharge machining (PMEDM). *Journal of Materials Processing Technology*, *184*(1-3), 32-41. https://doi.org/10.1016/j.jmatprotec.2006.10.046.

Khullar, V.R., Sharma, N., Kishore, S., & Sharma, R. (2017). RSM- and NSGA-II-based multiple performance characteristics optimization of EDM parameters for AISI 5160. *Arabian Journal for Science and Engineering*, *42*(5), 1917-1928. https://doi.org/10.1007/s13369-016-2399-5.

Kohli, A., Wadhwa, A., Virmani, T., & Jain, U. (2012). Optimization of material removal rate in electrical discharge machining using fuzzy logic. *World Academy of Science, Engineering and Technology*, *72*(12), 1674-1679.

Kosaraju, S., Bobba, P.B., & Salkuti, S.R. (2023). Optimization and microstructural studies on the machining of Inconel 600 in WEDM using untreated and cryogenically treated zinc electrodes. *Materials*, *16*(8), 3181. https://doi.org/10.3390/ma16083181.

Kulkarni, V.N., Gaitonde, V.N., Karnik, S.R., Manjaiah, M., & Davim, J.P. (2020). Machinability analysis and optimization in wire EDM of medical grade NiTiNOL memory alloy. *Materials*, *13*(9), 1-17. https://doi.org/10.3390/ma13092184.

Kumar. S.V., & Kumar. M.P. (2014). Optimization of cryogenic cooled EDM process parameters using grey relational analysis. *Journal of Mechanical Science and Technology*, *28*(9), 3777-3784.

Kumar, A., Grover, N., Manna, A., Chohan, J.S., Kumar, R., Singh, S., Prakash, C., & Pruncu, C.I. (2020). Investigating the influence of wedm process parameters in machining of hybrid aluminum composites. *Advanced Composites Letters*, *29*, 1-14. https://doi.org/10.1177/2633366x20963137.

Kumar, A., Grover, N., Manna, A., Kumar, R., Chohan, J.S., Singh, S., Singh, S., & Pruncu, C.I. (2022). Multi-objective optimization of WEDM of aluminum hybrid composites using AHP and genetic algorithm. *Arabian Journal for Science and Engineering*, *47*(7), 8031-8043. https://doi.org/10.1007/s13369-021-05865-4.

Kumar, A., Maheshwari, S., Sharma, C., & Beri, N. (2010). A study of multiobjective parametric optimization of silicon abrasive mixed electrical discharge machining of tool steel. *Materials and Manufacturing Processes*, *25*(10), 1041-1047. https://doi.org/10.1080/10426910903447303.

Kumar, J., Soota, T., & Rajput, S.K. (2019). Experimental evaluation and modelling of wire-EDM process parameter for stainless steel AISI 630. *Materials Today: Proceedings*, *26*, 1151-1158. https://doi.org/10.1016/j.matpr.2020.02.231.

Lalwani, V., Sharma, P., & Pruncu, C.I. (n.d.). *Response surface methodology and artificial neural network-based models for predicting performance of wire electrical discharge machining of inconel 718 alloy*.

Maity, K., & Mishra, H. (2018). ANN modelling and Elitist teaching learning approach for multi-objective optimization of µ -EDM. *Journal of Intelligent Manufacturing*, *29*(7), 1599-1616. https://doi.org/10.1007/s10845-016-1193-2.

Mandal, D., Pal, S.K., & Saha, P. (2007). Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II. *Journal of Materials Processing Technology*, *186*(1-3), 154-162. https://doi.org/10.1016/j.jmatprotec.2006.12.030.

Natarajan, K., Ramakrishnan, H., Gacem, A., Vijayan, V., Karthiga, K., Ali, H.E., Prakash, B., & Mekonnen, A. (2022). Study on optimization of WEDM process parameters on stainless steel. *Journal of Nanomaterials*, *2022*. Article ID 6765721. https://doi.org/10.1155/2022/6765721.

Pandey, A., Goyal, A., & Meghvanshi, R. (2017). Experimental investigation and optimization of machining parameters of aerospace material using Taguchi's DOE approach. *Materials Today: Proceedings*, *4*(8), 7246-7251. https://doi.org/10.1016/j.matpr.2017.07.053.

Pragadish, N., & Kumar, M.P. (2016). Optimization of dry EDM process parameters using grey relational analysis. *Arabian Journal for Science and Engineering*, *41*(11), 4383-4390. https://doi.org/10.1007/s13369-016-2130-6.

Pramanik, A., Basak, A.K., Prakash, C., Shankar, S., Sharma, S., & Narendranath, S. (2021). Recast layer formation during wire electrical discharge machining of titanium (Ti-Al6-V4) alloy. *Journal of Materials Engineering and Performance*, *30*(12), 8926-8935. https://doi.org/10.1007/s11665-021-06116-1.

Prasanna, P., Sashank, T.V., Manikanta, B., & Aluri, P. (2017). Optimizing the process parameters of electrical discharge machining on AA7075-SiC alloys. *Materials Today: Proceedings*, *4*(8), 8517-8527. https://doi.org/10.1016/j.matpr.2017.07.198.

Quarto, M., D'Urso, G., & Giardini, C. (2022). Micro-EDM optimization through particle swarm algorithm and artificial neural network. *Precision Engineering*, *73*, 63-70. https://doi.org/10.1016/j.precisioneng.2021.08.018.

Rahang, M., & Patowari, P.K. (2016). Parametric optimization for selective surface modification in EDM using taguchi analysis. *Materials and Manufacturing Processes*, *31*(4), 422-431. https://doi.org/10.1080/10426914.2015.1037921.

Raj, S., & Kumar, K. (2015). Optimization and prediction of material removing rate in die sinking electro discharge machining of EN45 steel tool. *Materials Today: Proceedings*, *2*(4-5), 2346-2352. https://doi.org/10.1016/j.matpr.2015.07.296.

Rangajanardhaa, G. (2009). Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm. *Journal of Materials Processing Technology*, *209*(3), 1512-1520. https://doi.org/10.1016/j.jmatprotec.2008.04.003.

Raj, S.O.N., & Prabhu, S. (2017). Modeling and analysis of titanium alloy in wire-cut EDM using Grey relation coupled with principle component analysis. *Australian Journal of Mechanical Engineering*, *15*(3), 198-209. https://doi.org/10.1080/14484846.2016.1251077.

Rengasamy, N.V., Rajkumar, M., & Kumaran, S.S. (2016). An analysis of mechanical properties and optimization of EDM process parameters of Al 4032 alloy reinforced with Zrb2 and Tib2 in-situ composites. *Journal of Alloys and Compounds*, *662*, 325-338. https://doi.org/10.1016/j.jallcom.2015.12.023.

Reza, M.S., Yusoff, A.R., & Shaharun, M.A. (2012). Optimization of control parameters for SR in EDM injection flushing type on stainless steel 304 workpiece. *IOP Conference Series: Materials Science and Engineering*, *36*(1), 1387-1389. https://doi.org/10.1088/1757-899X/36/1/012044.

Selvarajan, L., Narayanan, C.S., Jeyapaul, R., & Manohar, M. (2016). Optimization of EDM process parameters in machining Si3N4-TiN conductive ceramic composites to improve form and orientation tolerances. *Measurement: Journal of the International Measurement Confederation*, *92*, 114-129. https://doi.org/10.1016/j.measurement.2016.05.018.

Sen, B., Hussain, S.A.I., Gupta, A.D., Gupta, M.K., Pimenov, D.Y., & Mikołajczyk, T. (2021). Application of type-2 fuzzy AHP-ARAS for selecting optimal WEDM parameters. *Metals*, *11*(1), 1-16. https://doi.org/10.3390/met11010042.

Sharma, V.S., Sharma, N., Singh, G., Gupta, M.K., & Singh, G. (2023). Optimization of WEDM Parameters while machining biomedical materials using EDAS-PSO. *Materials*, *16*(1), 114. https://doi.org/10.3390/ma16010114.

Shrivastava, P.K., & Dubey, A.K. (2013). Intelligent modeling and multiobjective optimization of electric discharge diamond grinding. *Materials and Manufacturing Processes*, *28*(9), 1036-1041. https://doi.org/10.1080/10426914.2012.700153.

Singh, P., Chaudhary, A.K., Singh, T., & Rana, A.K. (2015). Experimental investigation of wire EDM to optimize dimensional deviation of EN8 steel through Taguchi's technique. *International Research Journal of Engineering and Technology*, *2*(3), 1753-1757.

Sivaprakasam, P., Hariharan, P., & Gowri, S. (2014). Modeling and analysis of micro-WEDM process of titanium alloy (Ti–6Al–4V) using response surface approach. *Engineering Science and Technology, an International Journal*, *17*(4), 227-235. https://doi.org/10.1016/j.jestch.2014.06.004.

Somashekhar, K.P., Ramachandran, N., & Mathew, J. (2010). Optimization of material removal rate in micro-EDM using artificial neural network and genetic algorithms. *Materials and Manufacturing Processes*, *25*(6), 467-475. https://doi.org/10.1080/10426910903365760.

Subrahmanyam, M., & Nancharaiah, T. (2020). Optimization of process parameters in wire-cut EDM of Inconel 625 using Taguchi's approach. *Materials Today: Proceedings*, *23*, 642-646. https://doi.org/10.1016/j.matpr.2019.05.449.

Sureban, R., Kulkarni, V.N., & Gaitonde, V.N. (2019). Modern optimization techniques for advanced machining processes - A review. *Materials Today: Proceedings*, *18*, 3034-3042. https://doi.org/10.1016/j.matpr.2019.07.175.

Tiwary, A.P., Pradhan, B.B., & Bhattacharyya, B. (2015). Study on the influence of micro-EDM process parameters during machining of Ti–6Al–4V superalloy. *International Journal of Advanced Manufacturing Technology*, *76*(1-4), 151-160. https://doi.org/10.1007/s00170-013-5557-x.

Tonday, H.R., & Tigga, A.M. (2019). An empirical evaluation and optimization of performance parameters of wire electrical discharge machining in cutting of Inconel 718. *Measurement: Journal of the International Measurement Confederation*, *140*, 185-196. https://doi.org/10.1016/j.measurement.2019.04.003.

Tripathy, S., & Tripathy, D.K. (2017). Surface characterization and multi-response optimization of EDM process parameters using powder mixed dielectric. *Materials Today: Proceedings*, *4*(2), 2058-2067. https://doi.org/10.1016/j.matpr.2017.02.051.

Tzeng, Y.F., & Chen, F.C. (2007). Multi-objective optimisation of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach. *Materials & Design*, *28*(4), 1159-1168. https://doi.org/10.1016/j.matdes.2006.01.028.

Ukey, K., Sahu, A.R., Gajghate, S.S., Behera, A.K., Limbadri, C., & Majumder, H. (2023). Materials today : Proceedings wire electrical discharge machining ( WEDM ) review on current optimization research trends. *Materials Today: Proceedings*. https://doi.org/10.1016/j.matpr.2023.06.113.

Yang, S.H., Srinivas, J., Mohan, S., Lee, D.M., & Balaji, S. (2009). Optimization of electric discharge machining using simulated annealing. *Journal of Materials Processing Technology*, *209*(9), 4471-4475. https://doi.org/10.1016/j.jmatprotec.2008.10.053.

Yilmaz, O., Eyercioglu, O., & Gindy, N.N.Z. (2006). A user-friendly fuzzy-based system for the selection of electro discharge machining process parameters. *Journal of Materials Processing Technology*, *172*(3), 363-371. https://doi.org/10.1016/j.jmatprotec.2005.09.023.

Zhang, Y., Liu, Y., Shen, Y., Li, Z., Ji, R., & Wang, F. (2013). A new method of investigation the characteristic of the heat flux of EDM plasma. *Procedia CIRP*, *6*, 450-455. https://doi.org/10.1016/j.procir.2013.03.086.