Optimization of Electric Discharge Machining Based Processes

Roan Kirwin, Aakash Niraula, Chong Liu, Landon Kovach and Muhammad Jahan

Abstract The results of Electrical Discharge Machining (EDM) are characterized through many parameters. These include, material removal rate, surface finish, geometrical accuracy, tool wear, and kerf width. The three main types of EDM, wire, sinker, and micro EDM all have similar characteristics in relation to input parameters and their effects on the results. The typical EDM system is too complex to accurately model the effect of all the parameters together. Therefore, it is necessary to create an optimization algorithm to predict the results of specific input parameters. Various techniques such as Taguchi robust design, grey relational analysis, desirability, genetic algorithm, and neural network etc. have been used for optimization of EDM based processes. This chapter first briefly introduces all the aforementioned optimization processes and comprehensively discusses their implementation and effect for optimization of EDM based processes.

Keywords EDM · Wire-EDM · Optimization · Design-of-experiment · Surface roughness · Material removal rate · Fuzzy

1 Introduction

Electric Discharge Machining (EDM) is a non-traditional machining technique where the desired shape, size and geometry are obtained by thermoelectric erosion by electric sparks [1]. In general, machining is conducted by melting and vaporizing materials using electrical energy assisted by dielectric fluid. Dielectric fluid acts both as flushing source to carry melted and re-solidified craters, and as controlling agent for spark gap between electrode and workpiece. Workpiece and tool electrode act as cathode and anode, and maintain no contact throughout the machining process. For this reason, EDM is preferred when machining hard but electrically conductive materials as using conventional machining processes can be challenging.

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EDM is categorized into mainly two types: Sinker EDM and wire EDM [2]. Sinker EDM is used to drill holes and cavities using an electrode of desired shape and profile. Sinker EDM uses profiled electrode to machine and is adopted for complex shapes as the electrode can be fabricated for various shapes. Wire EDM uses a wire to cut material, and is used to machine intricate shapes as the accuracy is extremely high. Micro-EDM is the variant of EDM where it is used at micro scale, along with micro level tools, axes resolution, and discharge energy [3]. The micro-EDM applies for both sinker and wire EDM, in addition to other micro-EDM varieties. Machining quality of EDM depends on several pre-built parameters. These parameters control the machining process, and can prominently change the output such as production time, surface roughness, over-cut, and dimensional accuracy in addition to desired material removal rate and electrode wear rate. Some of the common input parameters in EDM are [1–3]:

Gap voltage: Potential difference between anode and cathode for a cycle
Peak current: Maximum current that is used in machining per cycle
Pulse on time: Time duration for which current flows per cycle
Pulse off time: Time duration between two consecutive pulses
Duty cycle: Percentage of pulse on time over sum of pulse on time and pulse off time
Spark gap: Distance between electrode and the workpiece
Flushing pressure: Pressure at which the dielectric is dissipated

Given the impact of parameters and ever changing output demand, it can be difficult to find combination of variables that provides desired output. Numerous methods are used to approximate the favorable parameters. Statistical methods provide inexpensive and reliable means to test the effect of input variables to predict the desired outcome. In addition, some of the statistical methods like response surface method, and Taguchi method greatly aid in designing theoretical studies. This book chapter discusses the common statistical approaches in the beginning, and then transitions to provide overview of research works on optimization of EDM, based on various optimization techniques. In addition to studies on common wire and sinker EDM, descriptive review of research on optimization of smaller scale micro-EDM is also included in this chapter. Upon review of research works, the chapter ends by providing future avenues for subsequent research works on optimization of EDM parameters.

2 General Optimization Techniques

2.1 Single Variable Optimization

2.1.1 Taguchi Method

Taguchi method, sometimes called robust design method, is a statistical method that envisaged by Genichi Taguchi to optimize the quality of industrial goods, and recently was applied in the engineering, biotechnology and many other fields [4]. For the experimental design, Taguchi developed some well-structured guidelines. A set of arrays, named orthogonal arrays, is used in this method. These standard arrays could help the user find the minimum number of experiments that tell the full information of all the factors influencing the optimization results, i.e. performance parameters. Additionally, for each experiment, how the level combination of the input design variables is chosen, decides the crux of the orthogonal arrays method [5].

For the Taguchi method, the following steps need to be followed in order to design a good experiment.

1. Independent variable selection

Before the actual experiment is conducted, the researchers need to identify the key setting parameters that will influence the final performance parameters. For EDM process, different EDM machines need researchers to consider different setting of parameters. For example, when the wire EDM machine is used as the experimental setup, the parameters that researchers need to consider are pulse on time, pulse off time, peak current, gap voltage, servo voltage, servo feed rate, dielectric flow rate, wire speed or wire feed and wire tension. Depending on the potential research field, the researchers need to pick several or all of the setting parameters as the independent variables.

2. Number of level settings selection for each independent variable

Usually, the number of levels decided by getting the relation between the performance parameter and the independent variables. When the performance parameter has a linear relationship with the independent variables, 2 level settings are needed due to the fact that 2 points define a line. Similarly, when there is a quadratic relationship between the performance parameter and the independent variables, 3 level settings are needed. For all the nonlinear relationship, the number of level setting goes higher as the order of the relationship goes higher. For example, cubic relationship corresponds to a level setting of 4, quadratic relationship corresponds to a level setting of 5 and so on.

3. Orthogonal array selection

For orthogonal array, there are many standard arrays available, and each array corresponds to different number of independent design variable and level. For example, in Table 1, a typical L_9 orthogonal array layout is presented. In L_9 orthogonal array, the users aim to investigate the influence of 4 different independent variables with 3 set of (level) values followed. The array assumes that any of two factors are independent from each other. If there is any case, where the two factors have a strong interaction with each other, the orthogonal array would no longer be a suitable method for the experiment design.

In Table 1, there are 4 independent variables. And under each independent variable sections, there are 3 different level values. In order for user to get a better view of the influences of the independent variables, experiments need to be conducted

Table 1 Layout of typical L_9 orthogonal array [6]

$L_9(3^4)$ orthogonal array					
Experiment #	Independent variables				Performance parameter value
	Variable 1	Variable 2	Variable 3	Variable 4	
1	1	1	1	1	P1
2	1	2	2	2	P2
3	1	3	3	3	P3
4	2	1	2	3	P4
5	2	2	3	1	P5
6	2	3	1	2	P6
7	3	1	3	2	P7
S	3	2	1	3	P8
9	3	3	2	1	P9

under each combination. For example, in the first experiment, all the independent variables are set as level 1. After the experiment 1, the performance parameter value is recorded as p1. In the second experiment, the first independent variable is set as level 1, all the other independent variables are set as level 2 and the performance parameter value is recorded as p2. And so on for the rest of the experiments. Under these circumstances, a total of 9 experiments need to be conducted. And after all the experiments are conducted, 9 different performance parameter values are recorded. Once the results are achieved, the user needs to use optimized technique to find out optimum combination.

Depending on the numbers of the independent variables and the level of each independent variable, the orthogonal array has large number of variations. For two level designs, the Taguchi method has L4, L8, L12 and L16 orthogonal arrays; for three level designs, the Taguchi method has L9 and L27 orthogonal arrays; And for mixed level designs, the Taguchi method has L8, L16 and L18 orthogonal arrays. Additionally, for L16 orthogonal arrays, there are four different types of number of the independent variables and the levels combination. Once the orthogonal array type is decided, the overall structure of the whole experiment is outlined.

4. Experiment data and results analyzation

After all the experiments are conducted, the data are analyzed by the Taguchi signal to noise ratio (S/N) method. The signal to noise ratio is the ratio of mean value (signal) to the ratio of standard deviation (noise). The signal-to-noise ratio method is applied to determine the optimized settings based on the results. The S/N ratio has three different functions, larger is better, nominal is the best, and smaller is better. In the EDM machining parameters analysis, the S/N ratio of the smaller-the-better and the larger-the-better are the most useful characteristics and can be expressed as Eqs. (1) and (2) below [7].

$$(S/N)_S = -10\lg \frac{1}{n_k}\sum_{l=1}^{n_k} y_l^2 \tag{1}$$

$$(S/N)_L = -10\lg \frac{1}{n_k}\sum_{l=1}^{n_k} \frac{1}{y_l^2} \tag{2}$$

2.1.2 ANOVA

Analysis of variance (ANOVA) is a process by which a set of independent variables are analyzed for their influence on a single dependent variable. ANOVA is intended to demonstrate how strongly each independent variable is correlated with a change in the dependent variable [8]. At early stages of experimentation, ANOVA is used to narrow down which independent variables have the greatest effect and therefore should be studied. Also, later in the process, ANOVA is used to ensure that the results are statistically significant. A software package, such as R or SPSS [9], is typically used to perform ANOVA analysis because it is an extremely common method of statistical analysis. ANOVA produces both an F value and a percent of contribution for each independent variable. An F value references whether that parameter is significant at a specific confidence level. While a percentage contribution value measures the relative impact that a parameter has with respect to the rest of the parameters [10]. An example ANOVA table is included in Table 2.

2.1.3 Signal to Noise Ratio (S/N)

Signal-to-noise ratio (S/N) is used to optimize parameters once their individual impact on the independent variable is known. This ratio is commonly used in the

Table 2 ANOVA data table for surface roughness (Ra) [10]

Control factors	dof	Sum of squares	Mean squares	F-ratio	Percentage contribution
M	1	0.0012	0.0012	0.233	0.233
V_O	2	0.1267	0.0634	11.810	24.625
P_N	2	0.2683	0.1342	25.004	52.147
P_F	2	0.0172	0.0086	1.6051	3.343
V_S	2	0.0029	0.0015	0.2738	0.563
F_W	2	0.0438	0.0219	4.0786	8.531
T_W	2	0.0115	0.0058	1.074	2.235
P_D	2	0.032	0.0160	2.985	6.219
Error	2	0.0107	0.0054	–	2.122
Total	17	0.5145	–	–	100.00

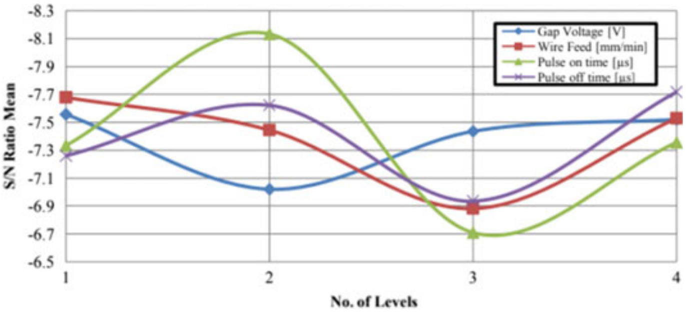

Fig. 1 Mean S/N ratio for effects of process parameters on surface roughness in EDM [11]

Taguchi method after ANOVA. S/N uses so-called control factors and noise factors. Control factors are defined as parameters that have a significant impact on the dependent variable while noise factors are defined as parameters that have no significant impact. S/N is a function of the output characteristic and the number of trials. This is demonstrated in Eq. (3) below.

$$\frac{S}{N_{LB}} = -10\ \log\left(\frac{1}{r}\sum_{i=1}^{r} y_i^2\right) \tag{3}$$

where, r equal to the number of trials and y_i equal to the output characteristic. This specific equation favors lower value output characteristics. This would be used for dependent variables such as surface roughness or kerf width that are typically desired to be minimized. There are separate equations for characteristics that are to be maximized or be normal [11].

On a signal-to-noise ratio graph, the difference between these factors is very apparent because control factors will have a high degree of slope while noise factors have a small slope. Figure 1 shows an example of signal-to-noise ratio (S/N) chart. The optimal parameters are chosen by the highest mean S/N ratio for each set of parameters [12].

2.2 *Multiple Variable Optimization*

All of the aforementioned single dependent variable optimization methods are able to be adapted for multiple dependent variables. Typically, they are used as initial stepping stones to organize the data and then new set of organized data is analyzed again using other techniques such as multiple linear regression or neural networking. Other times, some normalization is applied so the dependent variables can be combined into one which can be optimized in the preceding ways.

2.2.1 Grey Relational Analysis (GRA)

The most common adaptation applied to the Taguchi method is grey relational analysis. Grey relational method is a data analysis method, which is used to measure the relation between the parameters. For two or more parameters where there is no information available in between, the situation is defined as black. For two or more parameters with perfect information, the situation is defined as white. In reality, neither of these situations happen in the experiment. So, for the situation in between the black and white, the relation is defined as grey. In the grey relational method, the degree of relation is defined as grey relational grade. For the situation of black relation, the grey relational grade is 0. For the situation of white relation, the grey relational grade is 1. And for the situation of grey relation, reality, the grey relational grade is between 0 and 1.

Typically, the grey relational method contains the following processing steps [13]:

- Normalize the experimental results of each response variable.
- Determine the grey relational coefficient for each response variable.
- Calculate the grey relational grade by the mean value of grey relational coefficient.
- Perform the response table and response graph for each level of the process parameters.
- Recognize the obvious and invisible variable factors and select the optimal level of the process parameter.
- Confirm test and verify the optimal levels of process parameter.

Mathematically finding the grey relational grades can be performed through a modification of the S/N formula. All data must be normalized by Eqs. (4) and (5) below before plugging it into the standard smaller the better S/N equation. With y_i = characteristic and k as the population size, the smaller the better equation (Eq. 4) is used, because the optimization direction is performed during the normalization step. The Grey relational coefficients that were fed into the modified S/N become the Gray relational grades. These grades are used as a measure of performance for multi response optimization [14].

$$x_i(k) = \frac{\max(y_i)k - (y_i)k}{\max(y_i)k - \min(y_i)k} \tag{4}$$

$$y_i(k) = \frac{(y_i)k - \min(y_i)k}{\max(y_i)k - \min(y_i)k} \tag{5}$$

2.2.2 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a group of statistical methods that analyze the response of interest in terms of many different variables to optimize the response. RSM is an alternative of the Taguchi method. RSM was developed significantly earlier than the Taguchi method and requires more expertise but can outperform Taguchi in some situations. RSM allows for the analysis of the interaction of two independent variables simultaneously. This is typically realized by creating a second order response surface equation for each of the dependent variables. Occasionally, if the correlation is not strong enough for a simple second order polynomial equation to model, a log transformation could be required [15].

2.2.3 Multiple Regression Technique

The multiple regression technique is typically used to create models. After analysis by ANOVA or GRA or S/N, the parameters that are revealed to be significant can be related to the independent variables by multiple regression. All the independent variables must be normalized because they generally do not have the same units or ranges. This allows them to be directly related to the dependent variable through generally a polynomial relationship. These normalized values are typically called coded variables and vary from -1 to 1. A value of -1 corresponds to the minimum of this specific independent variable, while a value of 1 corresponds to the maximum value. Because insignificant variables are discarded, a simpler equation can be created similar to Eq. (6) below.

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_1 x_2 \tag{6}$$

where ŷ represents the dependent variable, the β values represent the coefficients, and the statistically significant x values are the aforementioned coded variables. This case is for linear relationships that are not necessarily orthogonal. Higher β values indicate a higher influence of that coded variable on the dependent variable. Many papers rely solely on the P value to say that the results are statistically significant, but that is not necessarily true, and a method of residual should be performed to ensure statistically accurate result [16].

2.2.4 Desirability Function

Desirability function optimization is performed by first normalizing the response parameters into a desirability function d_i with the range $0 \geq d_i \geq 1$. When the response parameter is at the desired target then $d_i = 1$ and if it is outside a specified range $d_i = 0$. Each desirability function is then assigned a weight, r_i. The weight of each of the desirability functions changes its polynomic order. All of the desired ability functions are then combined using a weighted geometric mean. This is demonstrated in Eq. (7) below.

$$D = \left(d_1^{i_1} d_2^{i_2}\right)^{1/(i_1+i_2)} \tag{7}$$

The majority of statistical software, such as Minitab®, use a reduced gradient algorithm with multiple starting points to maximize the overall desirability function.

However, this is not necessarily the true optimal solution if the boundary is non-convex. A local maximum may be achieved, so some manual tweaking is necessary in this method. This can be done by changing the weighting of the individual desirability functions [15].

2.2.5 Pareto Optimization

Pareto optimization is based on a concept called non-inferiority. Non-inferiority is defined as being reached when improving one response absolutely requires the decrease in quality of another response variable. As this is a multi-objective optimization, there are more than one "optimal" solution and this manifests itself as an optimal front. Imagine a scatter plot with surface roughness on one axis and 1/MRR on the other. Graphed on this plot are a series of results from parametric testing. The data will be distributed in a cloud. If each data point that were on the bottom left side of the cloud were connected, this would form an optimal front. This process can severely reduce the problem size of an optimization problem. It can be applied to not only individual response variables but also normalized and combined variables allowing many more response dimensions [15].

2.2.6 Genetic Optimization Algorithms

Genetic algorithms (GA) perform optimizations through an evolutionary approach. In general, they work by randomly seeding an initial population of random weights for each response parameter. The best individual is chosen and a new population is generated by randomly applying a certain amount of mutation to the individual. This process is repeated either a set number of times or until the rate of convergence reaches a set threshold [7]. A common application of genetic optimization is called the Non-Dominated Sorting Genetic Algorithm (NSGA). This adapts Pareto Optimization to work with the genetic algorithm to ensure only non-inferior solutions are found. The non-inferior front that is found in Pareto optimization is also called the non-dominated solution set.

The process of a non-dominated genetic sorting algorithm is as follows:

1. A set of chromosomes are generated within the solution space that have all the input variables on each chromosome. This is the initial population.
2. These chromosomes are sorted based on the following rules, if satisfied they are marked dominated else they are non-dominated.
   a. Response A of Chromosome A < Response A of Chromosome B
   b. Response B of Chromosome A < Response B of Chromosome B
3. All non-dominated solutions are ranked 1.
4. The sorting is repeated with already ranked chromosomes removed and new non-dominated chromosomes are ranked 2.

5. This process is repeated until all chromosomes in the population are ranked.
6. A dummy fitness value is assigned to the rank 1 chromosomes.
7. The normalized Euclidean distance is calculated between each rank 1 chromosome and the rest of the rank 1 subpopulation.
8. The Sharing function values are calculated for each of this subpopulation which are then used to calculate the niche count. Sharing functions are based on the largest distance allowed between chromosomes in a niche group. The niche count is used to estimate the clustering close to a specific chromosome.
9. The dummy fitness values are then divided by the niche count to find the shared fitness value of the rank 1 subpopulation.
10. This process is repeated until all ranks are assigned a shared fitness value.
11. The fitness values are used to choose which chromosomes to mate and mutate to form the next generation population.
12. This entire process is repeated on the next population.

Non-dominated Sorting Genetic Algorithm (NSGA) will generate varying results depending on the parameters chosen such as population size and mutation rate. Higher mutation rate will typically lead to a faster convergence but a less accurate one while a larger population size will lead to a higher convergence rate at the expense of computational power [17].

2.2.7 Neural Networking

Neural networking works similarly to genetic algorithm optimization in that it is an iterative process. Neural networking simulates the learning process of neurons, connections that lead to advantageous results are reinforced while connections that are useless or have a negative impact fade in strength. These neurons are made up of levels. The first set of neurons are the input neurons that receive the input parameters which, in the case of WEDM, are things such as pulse on time, wire tension, and open voltage. Each of the input neurons is then linked to the first 'hidden' layer. There can be one or more hidden layers depending on how the input parameters are related to each other and the guessed order of the input output relation. More complex relationships between the input variables and the response variables require more hidden layers to model. The drawback of more hidden layers is a longer convergence time and a less accurate result. Typically, the lowest complexity model that gives an effective result will be the best model. Using overly complex models or overtraining a model can lead to overfitting, which looks like a very effective model for the data already collected but is a very poor predictor of new data. Each of the connections between the two layers is assigned a weight and these weights are adapted using a system similar to the genetic algorithm optimization discussed above [8]. Figure 2 shows the block diagram listing the steps for optimization using back propagation neural networking [18].

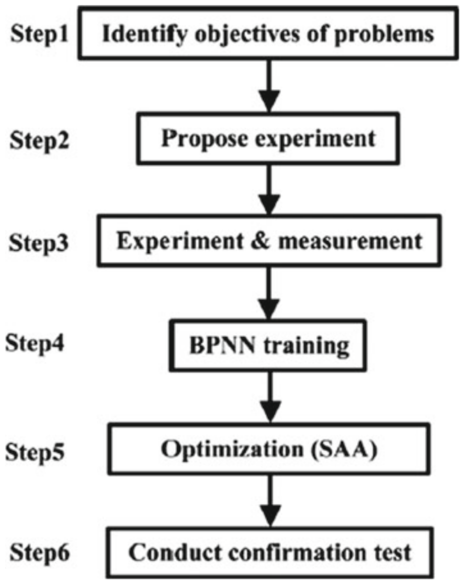

Fig. 2 Flow chart showing the steps of back propagation neural networking (BPNN) for optimization [18]

2.2.8 Simulated Annealing

Simulated annealing is applied to neural networks to ensure a speedy convergence while allowing for a more accurate result than a typical high entropy neural network training scheme. Its namesake, metal annealing, is the slow reduction of heat from a chaotic state to a cooler more rigid state. The slow cooling rate allows crystals to form and the final state to be highly ordered. With a very high cooling rate crystals do not have time to grow and the final metal is amorphic with the metal stuck in a high energy state. Simulated annealing applies these ideas to a neural net. As the system is trained the entropy allowed between generations is decreased so large changes can be made early and the model can be generally optimized. As iterations pass the system entropy is ‘cooled’ which simply means that the size of changes between generations, or the mutation rate, is decreased. This allows the system to make smaller changes, as it approaches what is theoretically the optimal, or the most ordered crystalline, solution [19]. In many cases, the simulated annealing is integrated with the neural network to perform the optimization. Figure 3 shows the flow chart of an integrated neural network and simulated annealing.

3 Optimization Techniques Used in Wire EDM

Most wire electro-discharge machining (WEDM) optimizations seek to increase material removal rate (MRR) or decrease the kerf width while decreasing surface

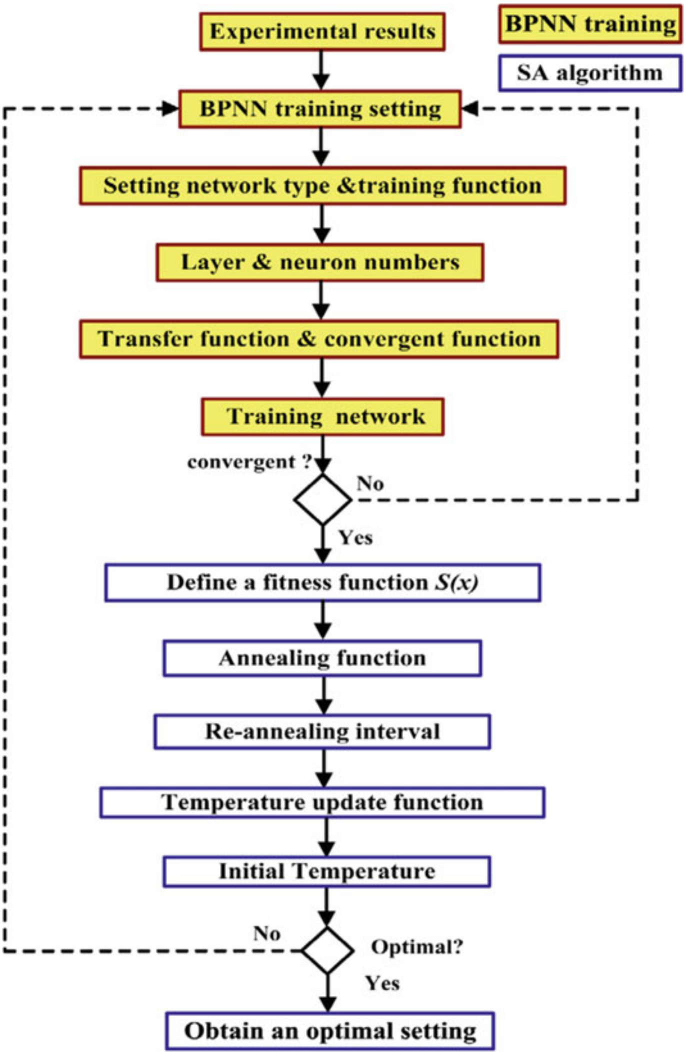

Fig. 3 Integrated neural network and simulated annealing steps for optimization [18]

roughness. The requirement of optimizing two variables simultaneously greatly complicates the process. The Taguchi method was developed in order to optimize a single dependent variable [20]. In order to optimize more than one variable another statistical technique is needed. Common analyses include Grey relational method, neural networking, response surface methodology, the desirability function, and Pareto optimality. While the majority of optimizations in this space are optimizing for at least two characteristics, sometimes it is desired that a single variable be optimized. Such cases are simpler to optimize using a standard Taguchi method or another method such as the finite element method.

3.1 Taguchi Method, ANOVA, S/N Ratio

As the Taguchi method is more oriented towards experimental design, all of the single variable optimization methods used Taguchi to create the initial parametric layout of the experiments. Goswami and Kumar [21] optimized the wire-EDM process for machining of Nimonic alloy using Taguchi approach along with utility concept. Taguchi's robust methodology was used for design of experiments and multi-response optimization method was used to study the effect of pulse on time, pulse off time, and peak current on the material removal rate (MRR), surface roughness (SR) and surface topography. The optimized process conditions were identified for MRR and SR using both single- and multi-response optimization techniques. In addition, the effect of parameters on microstructure and recast layer under the machined surface was studied. It was found that multi-response optimization with utility concept provided optimized parameters that could be used to improve the wire EDM performance.

Ramakrishnan and Karunamoorthy [22] optimized the wire-EDM operation for machining tool steel using multi-response optimization methods with Taguchi's robust design approach. The experiments were planned using Taguchi's L16 orthogonal array to study the effect of wire-EDM operating parameters on MRR, SR, and wire wear ratio. ANOVA was applied to study the level of importance of each machining parameter on the wire EDM performance. It was found based on ANOVA that pulse on time and ignition current intensity had more significant influence on wire EDM performance than other operating parameters. It was reported that the proposed optimization method could successfully predict the wire-EDM performance and could be applied to improve the machining performance.

Manna and Bhattacharyya [12] investigated the effect of operating parameters experimentally and optimized the process using Taguchi's optimization technique during wire-EDM of aluminum-reinforced silicon carbide metal matrix composite (Al/SiC-MMC). A Taguchi L18 orthogonal array was used to design the experiments and identify S/N ratio, and then ANOVA and F-test were used to identify the significant parameters affecting the wire EDM performance. Mathematical models were developed using the Gauss elimination method and compared with the experimental results. The model was found to successfully predict the optimum conditions suggested by the experiments.

Mahapatra and Patnaik [23] optimized the wire-EDM process for machining D2 tool steel using the Taguchi method. The significant parameters influencing the wire-EDM process were identified and their effect on wire EDM performance of D2 tool steel was studied. The relationship between the input machining parameters and output performance parameters were established using model developed by non-linear regression analysis. It was demonstrated that the optimization technique enabled adjustment of machining parameters to obtain higher material removal rate while minimizing the surface roughness during wire-EDM of D2 steel.

Tilekar et al. [24] optimized the process parameters for wire EDM of aluminum and mild steel using Taguchi method for obtaining minimum surface roughness and kerf width. Single objective Taguchi method was used for optimization of process parameters, while ANOVA was used to test statistical significance of each process parameter on influencing the wire EDM performance. The ANOVA results show that spark on time and wire feed rate has significant effect on kerf width, whereas spark on time and input current influences the surface roughness more significantly.

ANOVA was also used in almost all papers as an initial analysis of the impact of specific parameters on response variables. Kanlayasiri and Boonmung [16] used design of experiments, ANOVA, and regression model to investigate the impact of machining parameters on surface roughness of a new die steel, DC53. The ANOVA was used to identify the parameters that influenced the wire EDM process most significantly. It was determined that pulse on time and peak current had the largest impact on the surface roughness. The mathematical model was developed by multiple regression method, and was validated by experimental data with the prediction error less than 7%.

Signal-to-noise ratio (S/N) is the most common way to optimize parameters after performing ANOVA. Manna and Bhattacharyya [12] attempted to optimize MRR, surface roughness, gap current, or spark gap in WEDM of Al/SiC-MMC composite using S/N. As S/N optimization does not create a true model, it can only optimize the tested parameters without any interpolation between values, the returned optimization is in terms of the original experimental values. This specific study was able to optimize for each of the desired response parameters. Figure 4 shows the comparison of experimental results with the predicted results obtained from developed mathematical models [12]. It can be seen that the proposed mathematical model can predict the outcome of the experiments quite successfully during wire EDM of Al/SiC-MMC.

Ikram et al. [10] sought to optimize effect of eight operating parameters on MRR, SR, and kerf width during WEDM of D2 tool steel. This was performed using Taguchi's design of experiment (DOE), ANOVA, and S/N. The S/N returned an optimal setting for each of the eight parameters for MRR or surface roughness. It was deduced that higher MRR required a higher pulse on time and open voltage, while a lower surface roughness required the opposite.

3.2 Grey Relational Analysis

Rajyalakshimi and Venkata Ramaiah [25] strove to optimize MRR, surface roughness, and spark gap in WEDM of Inconel 825. Optimization using Grey relational analysis on nine input parameters and three output parameters were able to improve MRR from 119 to 126 mm^3/min, spark gap from 15 to 13 μm, and surface roughness from 1.68 to 1.44 μm.

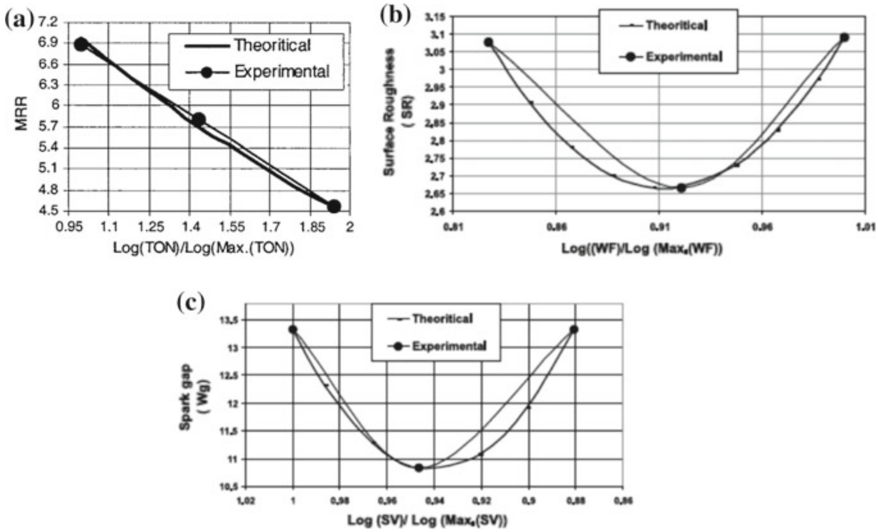

Fig. 4 Comparison of experimental results with developed mathematical models for **a** MRR, **b** surface roughness, and **c** spark gap [12]

Bobbili et al. [14] attempted to optimize WEDM machining of ballistic grade aluminum alloy with four input parameters and three response parameters. Using grey relational analysis, three of the input parameters were found to have a significant impact and were optimized. Significant improvements in MRR, surface roughness, and gap current were observed with a 6% error.

Durairaj et al. [11] applied grey relational theory and Taguchi optimization technique to optimize the cutting parameters during wire EDM of SS304 steel. The goal of the optimization was to identify optimum parameters for minimum kerf width and best surface finish separately and simultaneously. Taguchi's L16 orthogonal array was used for designing experiments. It was found that the Taguchi optimization and grey relational theory provided two different settings of optimized parameters. In Taguchi optimization technique, the parameters combination for minimum surface roughness were 40 V gap voltage, 2 mm/min wire feed, 6 μs pulse on time, 10 μs pulse off time, and for minimum kerf width the combination was 50 V gap voltage, 2 mm/min wire feed, 4 μs pulse on time, 6 μs pulse off time. According to grey relational analysis, the optimized parameters setting to get both the minimum surface roughness and the nominal kerf width were 50 V gap voltage, 2 mm/min wire feed, 4 μs pulse on time and 4 μs pulse off time.

Huang and Liao [5] carried out optimization of wire EDM process for machining SKD 11 tool steel using a combination of Taguchi method, Grey relational analysis and S/N ratio. First the experiments were design using Taguchi's L18 orthogonal arrays, then the parameters were optimized using Grey relational analysis and S/N ratio for obtaining the maximum material removal rate and minimum surface rough-

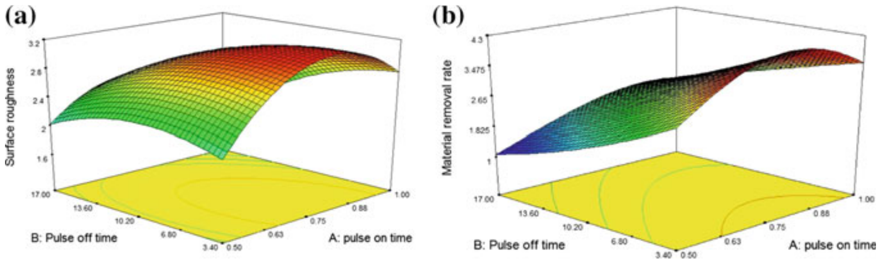

Fig. 5 Surface plots showing interactions of pulse on time and pulse off time with **a** surface roughness, and **b** material removal rate [26]

ness in wire EDM of SKD 11. The statistical analysis, including S/N ratio, ANOVA, and F-test, was carried out to find out the significant parameters for wire EDM.

3.3 Desirability Function and Pareto Optimization

Raj and Senthilvelan [26] optimized the wire EDM machining conditions using desirability function with a goal to improve the surface finish and material removal rate. They used Box-Benkhen approach to design the experiments, and desirability function to empirically model and optimize the process parameters for wire EDM of Ti-6Al-4V alloy. It was found that pulse duration and pulse interval were two important parameters influencing the surface roughness most, whereas pulse interval had the most influence on material removal rate. Higher pulse interval decreased the material removal rate significantly. Figure 5 shows the surface plot representing the influence of pulse on time and pulse off time on the surface roughness and material removal rate during wire EDM of Ti-6Al-4V, as obtained by desirability function optimization [26].

Sarkar et al. [27] sought to model and optimize WEDM of γ-titanium aluminide alloy during trim cutting. Trim cutting was used to increase the surface finish after a roughing operation so the desired response parameters would be below a chosen surface roughness while at the highest machining speed possible. First, the desirability function was used in Minitab and then a Pareto optimization was performed. Both of the techniques were effective at modeling the relationships but the desirability approach required a lot more manual fiddling and tuning than the Pareto optimization approach. Figure 6a shows that multiple optimal points were identified in the Pareto optimization, and when plotted (Fig. 6b), they showed a trend of increasing the surface roughness with the increase of cutting speed [28].

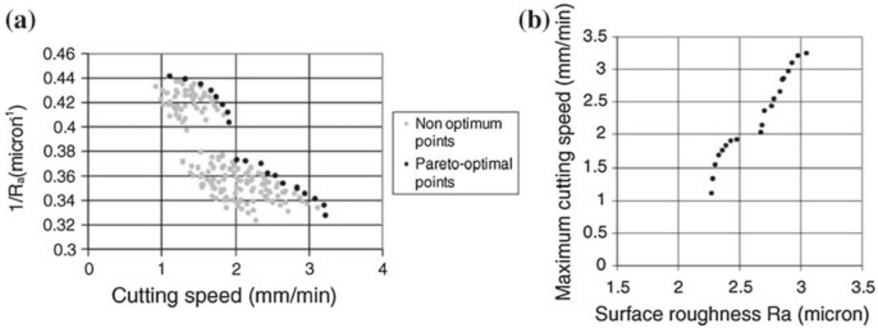

Fig. 6 **a** Multiple optimal solutions for surface roughness based on cutting speed, as suggested by the Pareto-optimal solution, **b** Plot of optimal points in the form of maximum cutting speed versus surface roughness [28]

3.4 Genetic Optimization Algorithms

Mahapatra and Patnaik [29] used the Taguchi method along with ANOVA and S/N as an initial optimization and for data gathering. They then used this data to train a genetic algorithm to predict MRR and surface finish. A model of MRR and surface finish was created with multi regression and were then combined and ran through a genetic algorithm to optimize the input variable to achieve the desired response parameters. The optimal settings for MRR and surface finish agreed well with the confirmation experiments with 4 and 1.5% errors respectively.

Kumar and Agarwal [30] used a multi-objective genetic algorithm to find optimal solutions for MRR and surface finish. The experiments were designed based on the Taguchi's design of experiments to study the effect of operating parameters on wire EDM performance of high speed steel (SKH9). The mathematical model has been developed by non-linear regression analysis. They were able to use the Pareto optimization technique along with non-dominated sorting genetic algorithm (NSGA) to further increase the efficiency of the solutions. Figure 7 shows the proposed multi-objective optimization methodology used in the study [30]. They were able to develop a table with 50 different optimal solutions that would then allow the operator to choose the set that best matches their requirements. Out of 50 optimal solutions, the best parametric combination providing highest MRR while maintaining the minimum surface finish requirement is pulse peak current of 30 A, pulse duration of 37 μs, pulse off time of 50 μs, wire feed of 7 m/min, wire tension of 1260 g, flushing pressure of 2.1 kg/cm^2.

Kuriakose and Shunmugam [17] optimized the wire-EDM process for machining titanium alloy using Non-Dominated Sorting Genetic Algorithm (NSGA) method. A multiple regression method was used to study the effect of operating parameters on the wire EDM performance, while NSGA method was used for optimizing the process. It was found that a number of optimized set of solution could be obtained using the

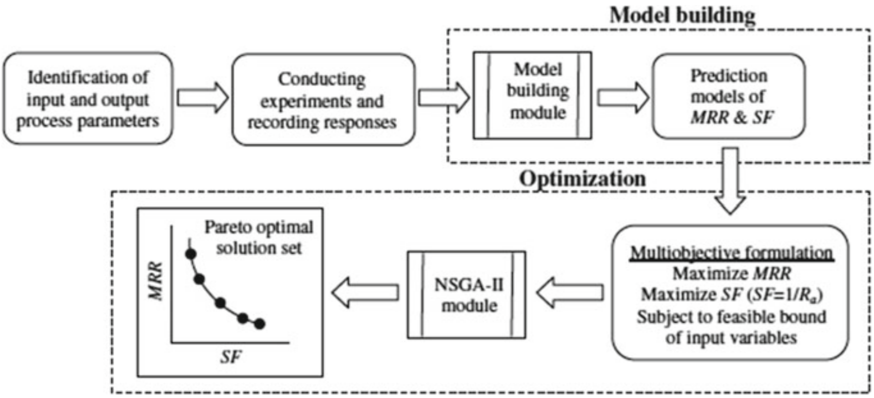

Fig. 7 Proposed multi-objective optimization methodology used in the wire EDM of high speed steel SKH9 [30]

Pareto optimization method. They proposed a table with 36 optimal combination of parameters.

Rao et al. [31] carried out experimental investigation and parametric optimization of wire EDM process for machining Al2014T6 aluminum alloy. The Taguchi method was used to design the experiments and a hybrid genetic algorithm with linear regression model was used for optimization of machining parameters for improved surface finish and material removal rate. It was found that the developed model could successfully predict the machining performance. It was also found from the genetic optimization that the cutting efficiency was important for generation of good quality surface finish. It was also reported that the recast layer in aluminum alloy was comparatively higher than those reported in wire EDM of heavier materials and other lighter material like titanium alloy.

3.5 Response Surface Methodology, Neural Networking and Simulated Annealing

Response surface methodology (RSM) is a comparatively old method of optimization, so it is often used to compare to neural networking optimizations. Speeding and Wang [32] used both RSM and a back-propagation neural network to optimize MRR, surface roughness, and surface waviness. Both models were found to achieve an acceptable level of accuracy with neural networking achieving a slightly higher accuracy. The prediction errors of the neural network model are generally lower than the RSM model.

Yang et al. [33] investigated both RSM and neural networking optimization, but with a more advanced simulated annealing neural networking system for optimizing the wire EDM process. Taguchi L18 orthogonal array was used for designing the

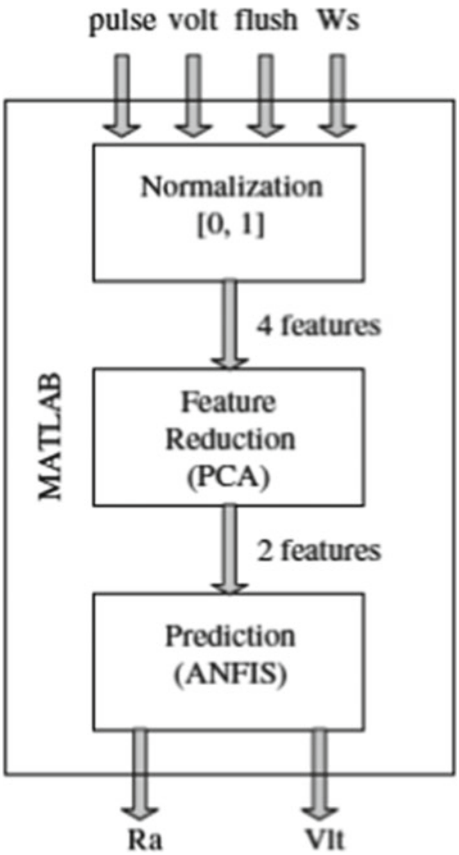

Fig. 8 Block diagram showing different stages of the proposed adaptive neuro-fuzzy interface system (ANFIS) model [34]

experiments before optimizing with RSM and BPNN. The neural network provided a more accurate predictive model than RSM did, but the neural network took more experience and training to implement.

Çaydas et al. [34] developed an adaptive neuro-fuzzy interface system (ANFIS) model to predict the white layer thickness and surface roughness as a function of machining parameters during wire EDM of AISI D5 tool steel. The dual approaches allowed the solution to converge faster and to improve the accuracy of the model. The model and verification experiments were closely correlated within a small margin of error. Figure 8 shows the steps of ANFIS optimization model used in this study. The comparison of the predicted results of surface roughness and white layer thickness with those obtained from experimentation is shown in Fig. 9. It can be seen from the graphs that the proposed model was able to predict the surface roughness and white layer thickness with minimal error.

Simulated annealing, a modification of standard neural networking, is commonly used to allow a fast convergence while still getting an accurate model. Chen et al. [18] developed a model of WEDM of pure tungsten using the simulated annealing assisted

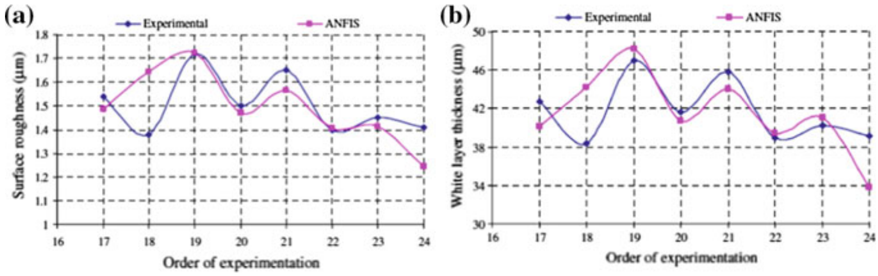

Fig. 9 Comparison of predicted results from ANFIS model with experimental results, **a** surface roughness, and **b** white layer thickness [34]

neural networking approach. In their study, a back-propagation neural network with simulated annealing method was proposed to optimize the parameters for improved surface finish and cutting velocity. This model was extraordinarily accurate for both the average roughness and maximum roughness, but the cutting velocity model was almost six orders of magnitude less accurate. Figure 10 shows the configuration of the proposed back propagation neural network model for wire EDM optimization [18].

Tarng et al. [35], quite a while ago in 1995, developed a simpler neural network to model the WEDM of SUS-304 stainless steel. This paper was written when neural networking was new. As a result, it was more of a proof of concept, but they proved that simulated annealing could indeed be used to increase the efficiency of Wire EDM.

Spedding and Wang [36] modeled the surface generated in wire EDM process using artificial neural network and time series techniques. The experiments were designed using central composite design (CCD). The feed-forward BPNN was used to develop the model and optimize the process. The optimal combination of process parameters for improved surface finish was identified and the wire EDM surface profile were evaluated by predicting the periodic component of the surface.

4 Optimization Techniques Used in Die Sinker EDM

4.1 Response Surface Method

Response surface method is a statistical process to estimate response variables using input parameters. It is useful in quantifying the connection between input and output parameters and is cost effective. Using response surface method, Balasubramanian et al. [37] conducted a study to assess the effects of peak current, pulse on time, dielectric pressure and tool diameter on material removal rate (MRR), surface roughness (SR), and tool wear rate (TWR). Cast and sintered copper electrodes were used to

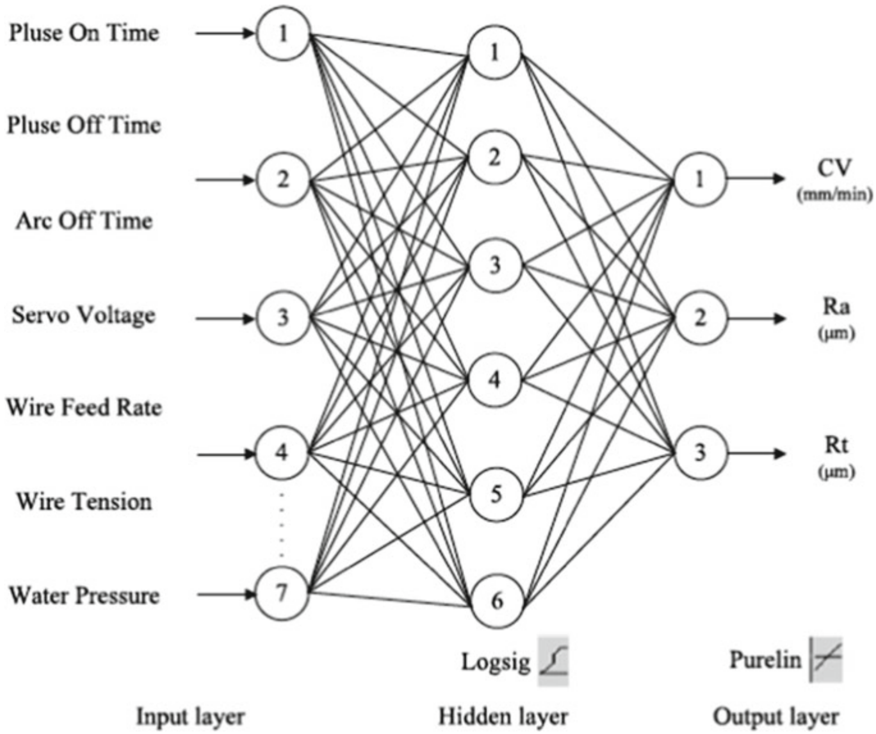

Fig. 10 The configuration of the proposed back propagation neural network (BPNN) model used for optimizing the wire EDM process [18]

machine EN8 and D3 steels. It was found that increasing the pulse on time increased surface roughness with cast copper electrode and increasing peak current increased MRR and TWR on EN-8 and D3. Tool diameter had a directly proportional relationship with MRR, TWR and SR. Both EN-8 and D3 showed higher MRR and lower TWR with cast electrode in comparison to sintered copper electrode. Surface roughness mean values were found to be lower with sintered electrode. High peak current and pulse on time with larger electrode diameter provided high MRR and SR, but low TWR was obtained with sintered copper electrode on EN8. The cast copper electrode provided better MRR, TWR and SR on D3 with low pulse on time and dielectric pressure.

Mishra et al. [38] focused on investigating the effect of hardness on MRR and TWR during die-sinking EDM of EN31 steel using copper electrode. During the experiment, four parameters, pulse on time, pulse off time, peak current and gap voltage, were varied under response surface method to identify changes in response variables. It was found that more than 70% out of 30 experiments had increased machining time for hardened workpiece including increase in tool wear rate as displayed in Fig. 11.

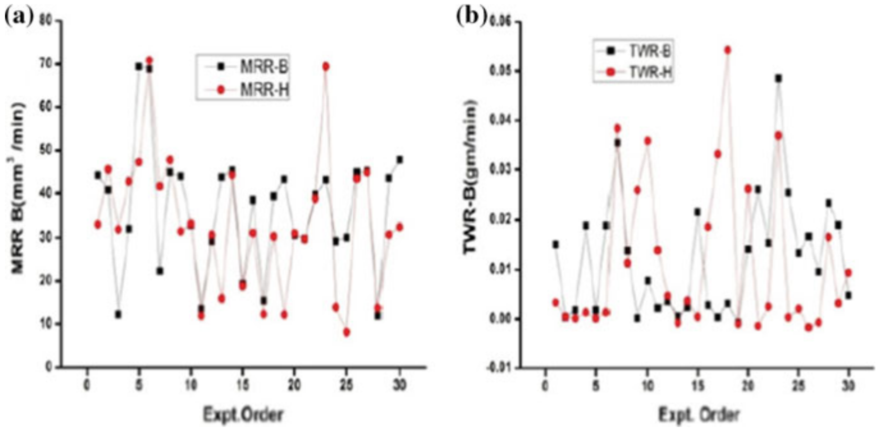

Fig. 11 Comparison of **a** MRR and **b** TWR of base alloy and hardened alloy after die sinking EDM using copper electrode [38]

Payaghan et al. [39] utilized response surface method using current, voltage, pulse on time and duty factor as input parameters during EDM of copper tungsten matrix composite. Copper electrode with Rush lick-30 dielectric fluid was used during the die-sinking operation. It was observed that increasing discharge current and pulse on time increased surface roughness. Overheating and molten metal in addition to discharge column expansion were suggested as the reasons for increase in surface roughness. The optimal machining condition resulted in surface roughness of 3.62 µm. All the results presented had over 95% confidence interval.

Leao et al. [40] explored the effect of different electrodes and dielectric fluids on the electrode life during fast hole EDM drilling of nickel based workpiece. Deionized water and a mixture of water, alcohol and salts were two di-electric fluids, and copper and brass were two electrodes used in this study. With the help of Pareto chart, it was found that drilling time was mostly affected by duty cycle and peak current, along with the interaction of dielectric with duty cycle and peak current. Electrode wear was greatly influenced by the dielectric and duty cycle. Heat generation due to high peak current resulted in low drilling time but high electrode wear. Brass electrode and water mixture dielectric produced the best results with only 47% of electrode wear. Deionized water had higher breakthrough time due to electrode tapering. Overall, the impact of dielectric fluid in optimization of fast hole drilling was justified in the study.

4.2 Taguchi Method

One of the frequent challenges during EDM machining is the tool wear. To provide accurate machining and smoother surface, it is important to gain minimal tool wear by optimizing the process parameters. Urade and Deshpande [41] investigated TWR during die-sinking EDM of EN 31 alloy steel using copper electrode. Parameters such as pulse current, pulse duration, and gap voltage were varied and studied for L16 orthogonal array. It was found that 3 A discharge current with 110 μs pulse duration and 130 V provided optimal quality in regards to TWR. Pulse current was noted to be the most significant factor affecting the response variable.

Lee et al. [42] studied the effect on machining parameters on SR and TWR using Taguchi method while also incorporating utility concept. It was found that current and duty cycle had notable effect on both SR and TWR, during die-sinking EDM of EN31 steel using copper electrode. Interactions between voltage and pulse on time and duty cycle were significant in addition to spark gap and pulse on time. The optimal parameters for die-sinking EDM of EN31 steel using copper electrode were found to be current of 6 A, duty cycle of 9 and pulse on time of 200 μs. Further experiments were conducted to analyze the response variable results with the optimal parameters. Utility value was found to be 8.289, and average surface roughness and average tool wear rate at the optimal setting were found to be 5.102 μm and 0.0092 g/min respectively.

One important characteristics of sinker EDM is flushing method, as it is critical to clean eroded particles from the machining zone. Malhotra et al. [43] utilized slide flushing to study the effect of flushing along with other machining parameters on the surface roughness of EN-31 die steel using die-sinker EDM. Copper electrode was used during the study. L27 orthogonal array was used using input parameters such as current, voltage, pulse on time, duty cycle, spark gap and flushing pressure to study the effects on surface roughness. It was found that current in addition to pulse on time had greater influence on the surface roughness. Interaction between pulse on time and spark gap was also significant. The optimal parameters to produce minimum surface roughness were found to be a combination of 6 A current, 100 μs pulse on time, 0.5 mm spark gap, 0.6 kg_f/cm^2 flushing pressure, and 35 V voltage.

Rath [44] conducted L27 orthogonal array based experiments on EN19 alloy steel using copper electrode on die-sinker EDM. The parameters used were pulse on time, current, and pulse duty factor, and the performance parameters were MRR, TWR, SR, and overcut (OC). It was found that pulse on time was the most dominant parameter that changed MRR and TWR results. MRR was seen to increase with increase in pulse on time to a certain extent, and reduced as the energy transfer was difficult with formation of plasma. OC was seen to increase with increase in pulse on time and open circuit current due to extreme melting and evaporation. Grey Relational Analysis was also utilized to obtain optimal parameters, and they were found to be open circuit current of 30 A, pulse on-time of 3000 μs, and pulse duty factor of 12.

According to the study by Prasad et al. [45] on AISI P20 tool steel using die-sinker EDM with copper electrode, MRR increased with increase in pulse current. The analysis of the input parameters, i.e. current, voltage, pulse on time, and pulse off time, were performed using L9 orthogonal array of Taguchi method. Higher pulse on time was attributed to increased MRR due to thermal power improvement, and higher current led to excessive material erosion. It was noted that increase in both voltage and current increased MRR, while TWR was decreased with voltage and increased with current.

Belgassim et al. [46] evaluated the influence of pulse current, pulse on time, pulse off time, and gap voltage on EDM of AISI D3 steel using L9 orthogonal array of Taguchi method. Primary variables of output interests were surface roughness and over-cut. Die-sinker EDM with brass electrode and kerosene dielectric were utilized during machining. Using S/N ratio, pulse current was found to influence the surface roughness the highest. Optimal parameters for best surface finish were determined to be 26 A current, 50 μs pulse on time, 200 μs pulse off time, and 45 V voltage. For over-cut pulse on time was the most influential factor as well.

Shrivastava et al. [47] investigated SR, MRR, and TWR on one of the widely used AISI 202 stainless steel using die-sinker EDM with copper electrode. Taguchi's L9 orthogonal array of four factors and three levels input variables such as pulse on time, pulse off time, peak current and servo voltage were applied. It was seen that pulse on time and servo voltage were the essential factors that affected surface roughness.

Panda et al. [48] used die sinking EDM with a copper electrode on 6061 aluminum alloy. Three input parameters, i.e. duty cycle, pulse on time, and current, were used in Taguchi method to study their effect on MRR. It was found that increase in pulse on time and duty cycle increased MRR. Optimal process parameters were found to be 100 μs pulse on time, 10 duty cycle and 30 A current. Overall, current had the largest impact on MRR.

Instead of using common method of submerged dielectric for machining in die-sinking EDM, Shahril et al. [49] tested the alternative by spraying dielectric fluid during machining. Taguchi method was used to study effect of discharge current, pulse on time and pulse off time on the MRR. Graphite electrode was used to machine tool steel workpiece in the presence of kerosene dielectric fluid. It was found that spray method provided lower machining time but higher surface roughness in comparison to submerged method. The MRR was observed to be higher as pulse on time increased, and found to be lower with increase in pulse off time.

Sangeetha et al. [50] explored die-sinking EDM on different aluminum base metal matrix composites under change in parameters such as current, pulse on time, pulse off time, and tool lifting time. L27 orthogonal array was utilized for designing the experiments with a copper electrode. It was found that reinforcement material for composite, current, and tool lifting time were highly influential in increasing MRR, and reducing SR, cost, and TWR.

Dubey et al. [51] investigated a different composite made of Al and Al_2O_3 to find the optimal parameters for machining using die sinker EDM with copper electrode. The input variables that were analyzed using desirability function and Taguchi method included pulse duration, discharge current, and duty cycle. The effect of operating parameters on the MRR, SR and TWR were also studied. The study confirmed the effectiveness of using desirability function with Taguchi method in a production system to maintain quality control.

Gaikwad et al. [52] studied the effect of input variables, i.e. gap current, pulse on time, pulse off time, workpiece electrical conductivity, and electrode conductivity during EDM of NiTi alloy using copper electrode. The experiments were conducted

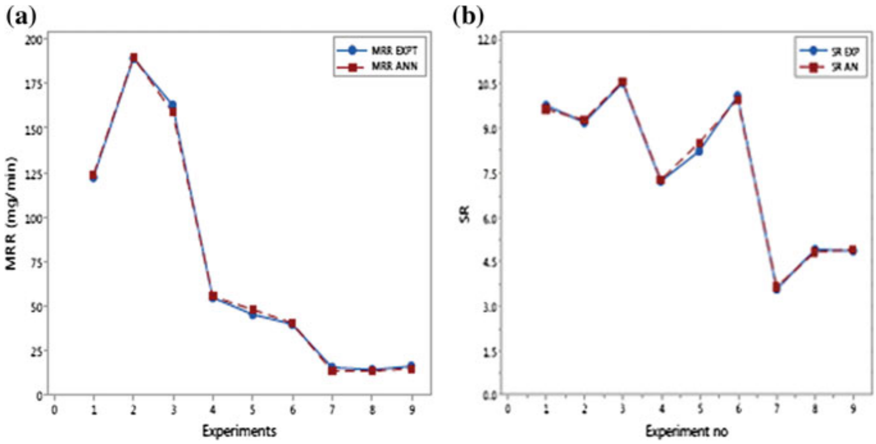

Fig. 12 Comparison of predicted ANN model with experimental results for **a** MRR (tested) and **b** SR (tested) [54]

based on Taguchi's L36 orthogonal array. It was found that gap current, work electrical conductivity and pulse on time had significant effect on MRR. Optimal parameters for obtaining MRR of 7.0806 mm^3/min were found to be 4219 S/m electrical conductivity, 16 A gap current, and 38 μs pulse on time.

Daud [53] carried out experiments with changes in current rates to see the effect on surface of SKD 11 using die-sinker EDM with hollow copper electrode. In the study, pits were machined, and the results of variable current rates were analyzed using Taguchi method. It was found that there was notable relationship between current rate and radius of workpiece. Higher current magnitude led to anomalies in the machined radius due to increase in recast later.

4.3 Artificial Neural Network (ANN)

Chandramouli and Eswaraiah [54] studied the influence of artificial neural network (ANN) on determining machining standard for die sinking EDM. The effect of parameters such as peak current, pulse on time, pulse off time and tool lift time were investigated during the EDM of precipitation hardening stainless steel with copper tungsten as tool electrode. Neural Network Toolbox in MATLAB was used to develop and assess the neural network model. The neural network model had two response variables which included MRR and SR. It was found that the difference between experimental data and predicted data was very low for both MRR and SR with average error as 3.32 and 2.25%. Figure 12 displays comparison of results for testing stage for MRR and SR respectively. The study corroborates the reliance on neural network model for estimating effect of parameters on die-sinker EDM process.

5 Optimization Techniques Used in Micro-EDM

Micro-EDM, developed from EDM, is used to machine parts in micro level. Micro-EDM has the same mechanism as the EDM process, with the differences in size of the tool electrode, axes movement and resolution, and level of discharge energy applied during machining. Similar to EDM process, micro-EDM also contains a series of variations, such as, micro-EDM drilling, micro die-sinking EDM, micro-EDM milling, micro wire-EDM (micro-WEDM) and micro WEDG (wire electro-discharge grinding). There were several optimization methods reported in the past years for optimization of the process parameters for improved micro-EDM performance. Depending on the method type, they could be categorized into three main methods: Taguchi Method, Grey Relational Method and Response Surface Method.

5.1 *Taguchi Method*

Maity et al. [55] applied Taguchi method to identify optimal process parameters of micro-EDM machine while fabricating micro-holes in copper using 300 µm diameter tungsten electrode. L9 orthogonal array design of experiment was applied. It was found that different combinations of optimum parameters could be obtained with different goals. When the goal of the machining was to reduce the machining time, the optimized settings for capacitance, feed rate, rpm and voltage were 0.1 µF, 0.003 µm/s, 1500 RPM and 90 V, respectively. When the goal of the machining was to minimize the recast layer thickness, the optimized settings for capacitance, feed rate, rpm and voltage were 0.0001 µF, 0.0003 µm/s, 1000 RPM and 110 V, respectively. When the goal of the machining was to find the optimized performance for all conditions, the optimized settings were suggested as 0.0001 µF, 0.001 µm/s, 1500 RPM and 120 V, respectively. In all the cases, the capacitance was found out to be the most influential factor in micro-EDM.

Azad et al. [56] used the Taguchi method in the micro-EDM drilling of titanium alloy using tungsten carbide electrode to optimize multiple performance characteristics of titanium alloy. The process parameters varied were pulse on time, frequency, voltage and supply current. And the performance characteristics studied were MRR, TWR and overcut (OC). The Taguchi orthogonal array L18 was found out to be the most suitable experimental design for this study. A confirmation test was also conducted. The Taguchi method was found to be an efficient experimental design method. The optimized process settings for micro-EDM drilling of titanium alloy were finally decided as 80 V voltage, 150 kHz pulse frequency, 1 A current and 50 µs pulse on time.

Kadirvel et al. [57] applied the Taguchi method to find optimized settings for obtaining a higher MRR, a lower TWR and the minimum SR in the micro die-sinking EDM process. During the study, the electrode was 300 µm silver tungsten (AgW) and the workpiece was EN-24 die steel. The Taguchi L16 orthogonal array method was applied under different conditions of gap voltage, capacitance, feed rate, and threshold voltage. After all the experiment, the ANOVA method was applied. The capacitance and the gap voltage were found to be the most significant independent variables influencing the performance characteristics during die-sinking micro-EDM process.

Chiou et al. [58] identified the optimized process parameters for the micro-EDM milling of high-speed steel alloy (SKH59) using tungsten carbide (WC) electrode. Taguchi method L9 orthogonal array was applied. The independent variables, i.e. process parameters, were decided as discharge current, pulse duration, pulse off time and jump distance. The performance characteristics were decided as TWR, MRR and overcut. Each independent variable contained three levels, from high to low. After the orthogonal array was set up, four columns and nine rows were contained in the array chart. The discharge energy was found to have the dominating effect on the three performance characteristics.

Lin et al. [7] applied the Taguchi method to optimize micro-EDM milling process parameters for machining of Inconel 718 alloy using 200 μm tungsten carbide electrodes. After all the Taguchi experiments were conducted, the signal-to-noise ratio (S/N) method was applied to determine the optimized settings based on the results. The S/N ratio has three different functions, larger is better, nominal is the best, and smaller is better. The goal of the study was to find the minimum electrode wear, the maximum material removal rate and the minimum working gap. By applying the Taguchi method, the experimental results showed the electrode wear was decreased by 7%, the MRR increased 357.5%, and the working gap decreased 6.3% in the optimum setting. For micro-EDM milling of Inconel 718 alloy, the optimized settings were found to be 0.5 A peak current, 3 μs pulse on time, 3 μs pulse off time and 60 V gap voltage. The peak current and gap voltage were the two factors that had the most influence on the performance characteristics.

5.2 Grey Relational Method (GRA)

Grey relational method is a data analysis method, which allows to find the grey relational grade of the parameters used in micro-EDM and identifies their effect on machining performance. Once all the experimental data are collected and the grey relational grades are calculated, the relationship between the process parameters and the performance parameters will be obvious. Bhosle et al. [13] used grey relational method to explore the optimized micro-EDM drilling conditions for machining micro-holes in Inconel 600 alloy using 500 μm diameter tungsten carbide electrodes. The performance characteristic considered were MRR, overcut, taper angle and diametric variance at entry and exit of micro-holes. Table 3 shows the Taguchi design of experiments used in this study and Table 4 presents the grey relation methods resulted from the analysis. The optimized micro-EDM drilling settings were suggested as 175 V voltage, 1000 pF capacitance, 20 μm/s EDM feed rate, 15 μs pulse duration and 50 μs pulse interval. It was found that the capacitance had the high-

Table 3 The design of experiments [13]

Exp. No.	A	B	C	D	E	MRR ($10^{-5}mm^3/s$)	Taper angle (°)	Overcut (μm)	DVEE
1	1	1	1	1	1	2.0401	6.2365	46.28	54.64
2	1	2	2	2	2	2.59	0.4079	50.24	3.56
3	1	3	3	3	3	14.34	0.8112	68.08	7.08
4	2	1	1	2	2	4.3412	3.3479	44.08	29.28
5	2	2	2	3	3	8.597	0.7562	54.88	6.6
6	2	3	3	1	1	33.912	0.7654	79.2	6.7
7	3	1	2	1	3	5.3179	1.6084	42.8	14
8	3	2	3	2	1	12.709	1.416	52.3	12.3
9	3	3	1	3	2	52.462	7.3798	87.2	64.8
10	1	1	3	3	2	1.1112	8.5442	35.44	75.12
11	1	2	1	1	3	4.1387	1.077	49.52	9.4
12	1	3	2	2	1	15.9932	5.2291	77.76	45.76
13	2	1	2	3	1	2.8099	2.5925	40.56	22.64
14	2	2	3	1	2	9.0418	0.3964	51.4	3.72
15	2	3	1	2	3	23.6342	1.2511	79.96	10.92
16	3	1	3	2	3	3.1063	1.0128	39.12	8.84
17	3	2	1	3	1	19.765	0.4629	53.2	4.04
18	3	3	2	1	2	46.2656	0.4766	78.48	1

est influence on performance characteristics followed by the voltage. The feed rate turned out to be the least influential. However, feed rate played important role in controlling the taper angle.

5.3 Response Surface Method

Different from GRA method, the response surface method (RSM) helps the researchers to build a mathematical model between the process parameters and performance parameters in micro-EDM process. Once the mathematical model is set up, the relationship between the parameters can be obtained. Tiwary et al. [59] used the RSM to explore the influence of the micro-EDM process parameters while machining of Ti-6Al-4V. During the study, the electrode was 300 μm brass and the workpiece was Ti-6Al-4V alloy. The process parameters were decided as pulse on time, peak current, gap voltage, and flushing pressure, and the performance characteristics were MRR, TWR, overcut (OC), and taper. With the help of the RSM, a mathematical model was built for these process parameters and performance parameters. In order to test all the possible combinations, a total of 31 experiments were conducted based

Table 4 The example Grey relation method results [13]

Exp. No.	Normalized experimental results				Grey relational coefficient				Grey relational grade
	MRR	Taper	Overcut	DVEE	MRR	Taper	Overcut	DVEE	
1	0.018	0.2832	0.7905	0.2861	0.3373	0.4109	0.7047	0.4118	0.4661
2	0.0287	0.9985	0.714	1	0.3398	0.997	0.6361	1	0.7432
3	0.2576	0.949	0.3693	0.9508	0.4024	0.9074	0.4422	0.9104	0.6656
4	0.0629	0.6377	0.833	0.6405	0.3479	0.5798	0.7496	0.5817	0.5647
5	0.1457	0.9558	0.6244	9575	0.3691	0.9)87	0.571	0.92)6	0.6951
6	0.6387	0.9547	0.1545	0.9561	0.5805	0.9)69	0.3716	0.9192	0.6970
7	0.0819	0.8512	0.8578	0.8541	0.3525	0.7706	0.7785	0.7741	0.6689
8	0.2258	0.8748	0.6742	0.8778	0.3924	0.7997	0.6054	0.8036	0.6502
9	1	0.1429	0	0.1442	1	3684	3333	0.3687	0.5176
10	0	0	1	0	0.3333	0.3333	1	0.3333	0.4999
11	0.0589	0.9164	0.7279	0.9183	3469	0.8567	0.6475	0.8595	0.6776
12	0.2898	0.4068	0.1823	0.4102	0.4131	0.4573	0.3794	0.4587	0.4271
13	0.033	0.7304	0.901	0.7333	0.3408	0.6496	0.8347	0.6521	0.6193
14	0.1544	1	0.6916	0.9977	0.3715	1	0.6185	0.9954	0.7463
15	0.4386	0.8951	0.1398	0.8971	0.471	0.8265	0.3675	0.8293	0.6235
16	0.0388	0.9243	0.9289	0.9262	3421	0.8685	0.8755	0.8713	0.7393
17	0.3632	0.9918	0.6568	0.9932	0.4398	0.9838	0.5929	0.9865	0.7507
18	0.8793	0.9901	0.1684	0.99)6	0.8055	0.9805	0.3754	0.9834	0.7862

on uniform rotatable central method. At the end of each experiment, all 4 of the performance characteristics were also recorded in the database. After all the experiments were conducted, the data were analyzed using “Minitab version 15” software. Based on the built mathematical model, all the coefficients were calculated by “Minitab version 15” for each performance characteristics. The average percentage of prediction errors for MRR, TWR, OC and taper were 2.61, 3.74, 3.21 and 3.7% respectively. The researchers also suggested that in order to achieve the optimized performance characteristics while machining Ti-6Al-4V alloy, i.e. the maximum MRR and the minimum TWR, OC and taper, the pulse on time should be set as 1 μs, the peak current should be set as 2.5 A, the gap voltage should be set as 50 V and the flushing pressure should be set as 0.2 kg/cm^2. Under those settings, the maximum MRR was 0.0777 mg/min, and the minimum values of TWR, OC, and taper were 0.0088 mg/min, 0.0765 mm, and 0.0013, respectively.

6 Conclusion and Future Research

Electrical discharge machining (EDM) usage has been drastically increasing in industrial applications. Therefore, optimization of machining parameters is essential to produce cost effective finished products. This chapter provides a concise overview of the various optimization techniques used in EDM, and entails comprehensive literature work conducted on optimization of EDM based processes using numerous statistical techniques. Die-sinking, fast hole drilling, wire, and micro EDM were used as machining processes with varieties of dielectric fluids and electrodes. Critical information on the findings of optimization in EDM has been covered in this chapter. Below are some of the key results from the chapter:

Wire EDM optimization:

- There have been more studies on optimizing the process parameters for wire EDM compared to die-sinking EDM and micro-EDM, which demonstrates more stochastic nature of the wire EDM process and importance of optimization process parameters in wire EDM.
- Taguchi method was found to be effective in designing the experiments. However, Taguchi based design of experiments are supported by other optimization techniques. ANOVA was used more commonly to identify the significance of each operating parameters on the machining performance.
- In many cases, combination of multiple optimization methods and comparing the outcome of different methods with each other may be an effective approach to identify the optimal process parameters and machining conditions in EDM.
- Among various methods, neural network and simulated annealing were found to be very accurate in predicting the optimum conditions, when compared with experimental results.

- The response surface method was found to be useful in developing empirical models and identifying the influence of individual parameter or combination of parameters on the performance characteristics of EDM.
- The peak current and pulse duration were found to be the two most significant parameters in wire EDM.

Sinker EDM optimization:

- Response surface method and Taguchi method were both found to be effective and recommended in determining optimal parameters and improving quality for sinker EDM optimization.
- Pulse on time, pulse current, and duty cycle were the most significant input parameters affecting material removal rate, surface roughness, tool wear rate, and over-cut during sinker EDM.
- Tool wear rate, material removal rate and over-cut generally increased with current and pulse on time. The electrical conductivity and thermal conductivity of workpiece and electrode material were also found to be significant in affecting output variables in sinker EDM.

Micro EDM optimization:

- The capacitance and the gap voltage were found to be the most significant independent variables influencing the performance characteristics for die-sinking micro-EDM.
- The peak current and spark gap were the two factors that had the most influence on the performance characteristics for micro-EDM milling.
- In micro-EDM drilling, the capacitance had the most influence on both side gap and taper ratio, followed by gap voltage. The feed rate turned out to be the least influential. However, feed rate plays important role in controlling the taper angle.
- The optimized settings depend on the goal of the experiment. Different optimized performance characteristics require different optimized process setting combinations.

New materials with intricate shapes and versatile properties are created frequently to maximize performance and production. Thus, constant effort should be made in the research field to comprehend the impact of machining parameters on the materials and productivity, and to find optimal parameters which can be used in industries. Following are some of the ideas and challenges that can be tackled in the future research:

- Limited research was conducted using various shapes or dimensions of electrodes in die-sinking EDM. Future work should comprise of electrodes with common shapes used in industries. Analysis of dielectric fluid in optimization was insufficient, and needs further exploration.
- Due to growing demand of composites, the optimization techniques in EDM of popular metal matrix composites (MMCs) should be studied.

- Responses such as residual stress, surface morphology, and mechanical properties after EDM must be analyzed moving forward.
- Cost analysis and mass production efficiency should also be studied in addition to optimization to provide pragmatic outcome of changes in parameters.
- After the initial experiments are finished, a repeated set of experiments or machining a final product with optimized settings could be conducted in order to guarantee the optimized results could be used in the future operations in industries.
- Depending on fields of study, the process parameters and the performance parameters could vary and new research should consider optimization in real industrial applications.

References

1. Gupta K, Gupta MK (2019) Developments in non-conventional machining for sustainable production-a state of art review. Proc IMechE Part C J Mech Eng Sci. https://doi.org/10.1177/0954406218811982
2. Jahan MP (2015) Electrical discharge machining (EDM) types, technologies and applications. Nova Science Publishers, Inc., New York
3. Jahan MP, Asad ABMA, Rahman M, Wong YS, Masaki T (2011) Micro-electro discharge machining (MEDM). In: Koç M, Ozel T (eds) Micro-manufacturing: design and manufacturing of micro-products. Willey, pp 301–346
4. Harris LN (1989) Taguchi techniques for quality engineering, Philip J. Ross, McGraw-Hill Book Company, 1988. Qual Reliab Eng Int 5(3):249–249
5. Huang JT, Liao YS (2003) Optimization of machining parameters of wire-EDM based on grey relational and statistical analyses. Int J Prod Res 41(8):1707–1720
6. Sankar, Chapter 2: Introduction to the Taguchi method. University of Massachusetts
7. Lin MY, Tsao CC, Hsu CY, Chiou AH, Huang PC, Lin YC (2013) Optimization of micro milling electrical discharge machining of Inconel 718 by Grey-Taguchi method. Trans Nonferrous Met Soc China (English Ed) 23(3):661–666
8. Ugrasen G, Ravindra HV, Prakash GVN, Keshavamurthy R (2014) Process optimization and estimation of machining performances using artificial neural network in wire EDM. Proc Mater Sci 6(Icmpc):1752–1760
9. Singh PN, Raghukandan K, Pai BC (2004) Optimization by Grey relational analysis of EDM parameters on machining Al-10%SiCP composites. J Mater Process Technol 155–156(1–3):1658–1661
10. Ikram A, Mufti NA, Saleem MQ, Khan AR (2013) parametric optimization for surface roughness, kerf and MRR in wire electrical discharge machining (WEDM) using Taguchi design of experiment. J Mech Sci Technol 27(7):2133–2141
11. Durairaj M, Sudharsun D, Swamynathan N (2013) Analysis of process parameters in wire EDM with stainless steel using single objective Taguchi method and multi objective Grey relational grade. Proc Eng, 868–877
12. Manna A, Bhattacharyya B (2006) Taguchi and Gauss elimination method: a dual response approach for parametric optimization of CNC wire cut EDM of PRAlSiCMMC. Int J Adv Manuf Technol 28(1–2):67–75
13. Bhosle RB, Sharma SB (2017) Multi-performance optimization of micro-EDM drilling process of Inconel 600 alloy. Mater Today Proc 4(2):1988–1997
14. Bobbili R, Madhu V, Gogia AK (2015) Multi response optimization of wire-EDM process parameters of ballistic grade aluminium alloy. Eng Sci Technol Int J 18(4):720–726

15. Kumar K, Ravikumar R (2014) Modeling and optimization of wire EDM process. Int J Mech Mechatron Eng IJMME-IJENS 14:454–457
16. Kanlayasiri K, Boonmung S (2007) Effects of wire-EDM machining variables on surface roughness of newly developed DC 53 die steel: design of experiments and regression model. J Mater Process Technol 192–193:459–464
17. Kuriakose S, Shunmugam MS (2005) Multi-objective optimization of wire-electro discharge machining process by non-dominated sorting genetic algorithm. J Mater Process Technol 170(1–2):133–141
18. Chen HC, Lin JC, Yang YK, Tsai CH (2010) Optimization of wire electrical discharge machining for pure tungsten using a neural network integrated simulated annealing approach. Expert Syst Appl 37(10):7147–7153
19. Yang S-HH, Srinivas J, Mohan S, Lee D-MM, Balaji S (2009) Optimization of electric discharge machining using simulated annealing. J Mater Process Technol 209(9):4471–4475
20. Jung JH, Kwon WT (2010) Optimization of EDM process for multiple performance characteristics using Taguchi method and Grey relational analysis. j Mech Sci Technol 24(5):1083–1090
21. Goswami A, Kumar J (2014) Optimization in wire-cut EDM of Nimonic-80A using Taguchi's approach and utility concept. Eng Sci Technol Int J 17(4):236–246
22. Ramakrishnan R, Karunamoorthy L (2006) Multi response optimization of wire EDM operations using robust design of experiments. Int J Adv Manuf Technol 29(1–2):105–112
23. Mahapatra SS, Patnaik A (2007) Optimization of wire electrical discharge machining (WEDM) process parameters using Taguchi method. Int J Adv Manuf Technol 34(9–10):911–925
24. Tilekar S, Das SS, Patowari PPK (2014) Process parameter optimization of wire EDM on aluminum and mild steel by using Taguchi method. Proc Mater Sci 5:2577–2584
25. Rajyalakshmi G, Venkata Ramaiah P (2013) Multiple process parameter optimization of wire electrical discharge machining on Inconel 825 using Taguchi Grey relational analysis. Int J Adv Manuf Technol 69(5–8):1249–1262
26. Raj DA, Senthilvelan T (2015) Empirical modelling and optimization of process parameters of machining titanium alloy by wire-EDM using RSM. Mater Today Proc 2(4–5):1682–1690
27. Sarkar S, Sekh M, Mitra S, Bhattacharyya B (2008) Modeling and optimization of wire electrical discharge machining of γ-TiAl in trim cutting operation. J Mater Process Technol 205(1–3):376–387
28. Sarkar S, Mitra S, Bhattacharyya B (2005) Parametric analysis and optimization of wire electrical discharge machining of γ-titanium aluminide alloy. J Mater Process Technol 159(3):286–294
29. Mahapatra SS, Patnaik A (2006) Parametric optimization of wire electrical discharge machining (WEDM) process using Taguchi method. J Braz Soc Mech Sci Eng 28(4):422–429
30. Kumar K, Agarwal S (2012) Multi-objective parametric optimization on machining with wire electric discharge machining. Int J Adv Manuf Technol 62(5–8):617–633
31. Rao PS, Ramji K, Satyanarayana B (2014) Experimental investigation and optimization of wire EDM parameters for surface roughness, MRR and white layer in machining of aluminium alloy. Proc Mater Sci 5:2197–2206
32. Spedding T, Wang Z (1997) Study on modeling of wire EDM process. J Mater Process Technol 69(1–3):18–28
33. Yang RT, Tzeng CJ, Yang YK, Hsieh MH (2012) Optimization of wire electrical discharge machining process parameters for cutting tungsten. Int J Adv Manuf Technol 60(1–4):135–147
34. Çaydaş U, Hasçalik A, Ekici S (2009) An adaptive neuro-fuzzy inference system (ANFIS) model for wire-EDM. Expert Syst Appl 36(3 PART 2):6135–6139
35. Tarng YS, Ma S, Chung LK (1995) Determination of optimal cutting parameters in wire electrical discharge machining. Int J Fatigue 35(12):1693–1701

36. Spedding TA, Wang ZQ (1997) Parametric optimization and surface characterization of wire electrical discharge machining process. Precis Eng 20(1):5–15
37. Balasubramanian P, Senthilvelan T (2014) Optimization of machining parameters in EDM process using cast and sintered copper electrodes. Proc Mater Sci 6(Icmpc):1292–1302
38. Mishra BP, Routara BC (2017) Comparative analysis of the performance effectiveness of sinking electrical discharge machining (EDM) process with enhancement in hardness of the parent EN-31 alloy steel. Mater Today Proc 4(9):10235–10239
39. Payaghan NS, Ubale SB, Kadam MS (2014) Analysis & optimization of machining parameters for Ra in EDM process of Cu-W metal matrix composite(MMC). Int J Mech Eng Inf Technol 2(6):477–485
40. Leao FN, Pashby IR, Cuttell M, Lord P (2005) Optimisation of EDM fast hole-drilling through evaluation of dielectric and electrode material. In: 18th international congress of mechanical engineering
41. Urade AD, Deshpande VS (2016) Experimental investigations of EDM process parameters for tool wear rate based on orthogonal array. Int J Sci Res Sci Eng Technol 5(5):415–419
42. Lee DH, Malhotra N, Jung DW (2017) Multi characteristic optimization in die sinking EDM of En31 tool steel using utility concept. In: 2017 8th international conference on mechanical and aerospace engineering, ICMAE 2017, pp 166–170
43. Malhotra N (2013) Optimization of multiple quality characteristics of EDM process for MRR and TWR using utility concept. Adv Prod Eng Manag 8(4):219–230
44. Rath U (2017) Parametric optimization of EDM on EN19 using Grey-Taguchi analysis. Indian J Sci Technol 10(23):1–7
45. Prasad L, Gupta A (2017) An experimental investigation of machining parameters for EDM using copper electrode of Aisi P20 tool steel. Asian J Sci Technol 08(01):4106–4111
46. Belgassim O, Abusada A (2012) Optimization of the EDM parameters on the surface roughness of AISI D3 tool steel. In: Proceedings of the 2012 international conference on industrial engineering and operations management, Istanbul, Turkey, July 3–6, pp 2306–2313
47. Shrivastava SM, Sarathe AK (2014) Experimental investigation of surface roughness of SS-202 in die sinking EDM. Retrieved from https://www.academia.edu/10482710/Experimental_Investigation_of_Surface_Roughness_of_SS-202_in_Die_Sinking_EDM (last accessed on Jan 19, 2019)
48. Panda MR, Sagar S, Panigrahi AK, Swain MK (2016) Experimental analysis and optimization of EDM on AA6061 using. Int J Eng Sci Res Technol 5(4):265–271
49. Shahril M, Yusop M, Azhar MA, Ramli AS, Hamimi I, Razak A (2017) Effect of spray and complete submerged method on material removal rate for EDM die sinking. Int J Appl Eng Res 12(24):973–4562
50. Sangeetha M, Reddy AS, Kumar GV (2017) Optimization of die-sinking EDM process parameters in machining of AMMC-desirability approach. Mech Mater Sci Eng J, 7
51. Dubey S, Agrawal P, Jha A, Tech Student M (2017) A comprehensive study of electro discharge machining of Al/Al_2O_3 composite and it's optimization. Int J Eng Sci Comput, 13963–13966
52. Gaikwad V, Jatti VS (2016) Optimization of material removal rate during electrical discharge machining of cryo-treated NiTi alloys using Taguchi's method. J King Saud Univ Eng Sci, 0–6
53. Daud MR, Samion S, Yahya A, Mahmud N, Liyana N, Hashim S, Nugroho K (2013) The effect of current rates on surface SKD 11 for electrical discharge machine die sinker. In: International conference on mechanical engineering research, Bukit Gambang Resort City, pp 1–3
54. Chandramouli S, Eswaraiah K (2017) Optimization of EDM process parameters in machining of 17-4 PH steel using Taguchi method. Mater Today Proc 4(2):2040–2047
55. Maity KP, Singh RK (2012) An optimisation of micro-EDM operation for fabrication of micro-hole. Int J Adv Manuf Technol 61(9–12):1221–1229
56. Azad MS, Puri AB (2012) Simultaneous optimisation of multiple performance characteristics in micro-EDM drilling of titanium alloy. Int J Adv Manuf Technol 61(9–12):1231–1239
57. Kadirvel A, Hariharan P (2014) Optimization of the die-sinking micro-EDM process for multiple performance characteristics using the Taguchi-based Grey relational analysis. Mater Tehnol 48(1):27–32

58. Chiou AH, Tsao CC, Hsu CY (2015) A study of the machining characteristics of micro EDM milling and its improvement by electrode coating. Int J Adv Manuf Technol 78(9–12):1857–1864
59. Tiwary AP, Pradhan BB, Bhattacharyya B (2014) Study on the influence of micro-EDM process parameters during machining of Ti–6Al–4V superalloy. Int J Adv Manuf Technol 76(1–4):151–160