RESEARCH ARTICLE OPEN ACCESS

A Review of Research on Improvement and Optimization of Performance Measures for Electrical Discharge Machining

C. R. Sanghani[1], Dr. G. D. Acharya[2]
[1]Ph. D. Scholar, R. K. University, Rajkot- 360020, Gujarat, India,
[2]Principal, Atmiya Institute of Technology & Science, Rajkot- 360005, Gujarat, India,

Abstract
Electrical Discharge Machining (EDM) is a non conventional machining method which can be used to machine electrically conductive work pieces irrespective of their shape, hardness and toughness. High cost of non conventional machine tools, compared to conventional machining, has forced us to operate these machines as efficiently as possible in order to reduce production cost and to obtain the required reimbursement. To achieve this task, machining parameters such as pulse on time, pulse off time, discharge current, gap voltage, flushing pressure, electrode material, etc. of this process should be selected such that optimal value of their performance measures like Material Removal Rate (MRR), Surface Roughness (SR), Electrode/Tool Wear Rate (EWR/TWR), dimensional accuracy, etc. can be obtained or improved. In past decades, intensive research work had been carried out by different researchers for improvement and optimization of EDM performance measures using various optimization techniques like Taguchi, Response Surface Methodology (RSM), Artificial Neural Network (ANN), Genetic Algorithm (GA), etc. This paper reviews research on improvement and optimization of various performance measures of spark erosion EDM and finally lists down certain areas that can be taken up for further research in the field of improvement and optimization for EDM process.
Keywords: Electrical discharge machining, Optimization, MRR, Surface roughness, TWR, Dimensional accuracy

I. INTRODUCTION

Electrical discharge machining (EDM) is one of the most promising advanced manufacturing processes used in industry for high-precision machining of all types of electrically conductive materials such as metals, metallic alloys, graphite, or even some conductive ceramic materials, irrespective of the hardness. It is widely used in the manufacture of mould, die, automotive, aerospace and surgical components (Ho and Newman, 2003). But due to its low machining efficiency and poor surface finish it is restricted to further applications and requires lot of research to improve its performance (McGeough, 1988). It is difficult to comprehend, expect and optimize EDM process performance because there are so many dependent and independent variables that have direct or indirect influence on machining efficiency, which makes it complex and difficult to model. To reduce its production cost and to improve product quality, optimization of machining processes are required (Lonardo and Bruzzone, 1999). However, experimental optimization of any machining process is costly and time consuming due to the complex, coupled and non-linear nature of the input–output variables of machining processes (Liao and Chen, 1998). Hence, many researchers have concentrated on improvement and optimization of performance measures of EDM process by using different modifications and optimization methods like Taguchi, response surface methodology, artificial neural network, genetic algorithm, grey relational analysis, fuzzy logic, factorial design etc. with variation of different electrical and non-electrical process parameters.

1.1 Overview of spark erosion EDM process

The EDM process was invented by two Russian scientists, Dr. B.R. Lazarenko and Dr. N.I. Lazarenko in 1943. It is a non-traditional machining process based on removing material from workpiece by means of successive electrical discharges occurring between an electrode and a workpiece (Fonda et al., 2007). This electric sparking process is carried out in a dielectric liquid (Masuzawa and Tanaka, 1983) or in gas (Kunieda and Yoshida, 1997; Kunieda and Furudate, 2001; Kunieda et al., 2003). Dielectric must have low-viscosity, high dielectric strength, quick recovery after breakdown, effective quenching/cooling and flushing ability (Wong et al., 1995; Jilam and Pandey, 1984; Masuzawa and Tanaka, 1983).

Spark is initiated at the peak between the contacting surfaces of electrode and workpiece and exists only momentarily. Metal as well as dielectric will evaporate at this intense localized heat. Sparking occurs in a frequency range from 2,000 to 500,000 sparks per second causing it to appear that many sparks are occurring simultaneously. The spark removes material from both the electrode and workpiece, which increases the distance between the electrode and the workpiece at that point. This causes the next spark to occur at the next-closest points between the electrode and workpiece (Jameson, 2001). The volume of material removed per discharge is typically in the range of 10^{-6}–10^{-4}mm^3 and the material removal rate (MRR) is usually between 2 and 400 mm^3/min (Kalpajian and Schmid, 2003) depending on specific application.

1.2 EDM process parameters

The most common process parameters and performance measures used by various researchers in their research work regarding optimization of EDM process is shown in Figure 1.

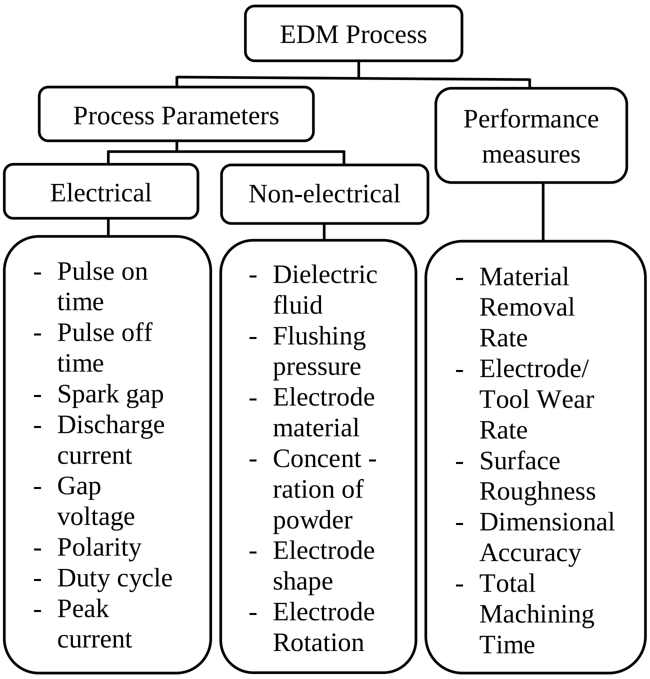

Fig-1: Process parameters and performance measures of EDM

II. OPTIMIZATION TECHNIQUES

Various optimization techniques generally used for improvement and optimization of performance measures of EDM process have been described below:

2.1 Taguchi method

Taguchi method is a scientifically disciplined mechanism for evaluating and implementing improvements in products or processes. These improvements are aimed at improving the desired characteristics by studying the key variables controlling the process and optimizing the procedures to yield the best results. Taguchi recommends orthogonal array (OA) for lying out of experiments. To design an experiment is to select the most suitable OA and to assign the parameters and interactions of interest to the appropriate columns. The use of linear graphs and triangular tables suggested by Taguchi makes the assignment of parameters simple (Roy, 1990). The analysis of variance (ANOVA) is the statistical treatment most commonly applied to the results of the experiments in determining the percent contribution of each parameter against a stated level of confidence. Study of ANOVA table for a given analysis helps to determine which of the parameters need control (Ross, 1988). Taguchi method uses a statistical measure of performance called signal-to-noise ratio. The S/N ratio can be used to measure the deviation of the performance characteristics from the desired values. Generally, there are three categories of performance characteristics in the analysis of the S/N ratio as follows (Roy, 1990; Phadke, 1989):

- Larger-the-better characteristics

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \qquad (1)$$

- Smaller-the-better characteristics

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right) \qquad (2)$$

- Nominal-the-better characteristics

$$\frac{S}{N} = -10\log\left(\frac{\bar{y}}{s_y^2}\right) \qquad (3)$$

Where y_i is the experimentally observed value and n is the repeated number of each experiment, $\bar{y}$ is the average of observed data and s_y^2 is the variance of y. For each type of characteristics, with the above S/N transformation, the higher the *S/N* ratio the better is the result. Optimization of performance measures using parameter design of the Taguchi method is summarized (Mohamad et al., 2012) in the steps as shown in Figure 2. Summary of the researches in improving and optimizing performance measures of EDM using Taguchi technique is shown in Table 1.

2.2 Response Surface Methodology (RSM)

The Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response (Montgomery, 2005). It is used in the development of an adequate functional relationship between a response of interest, *y*, and a number of associated control (or input) variables denoted by x_1, x_2... x_n. In general, such a relationship is unknown but can be approximated by a low-degree polynomial model of the form

$$y = f\left(x_1, x_2, \dots x_n\right) + \varepsilon \tag{4}$$

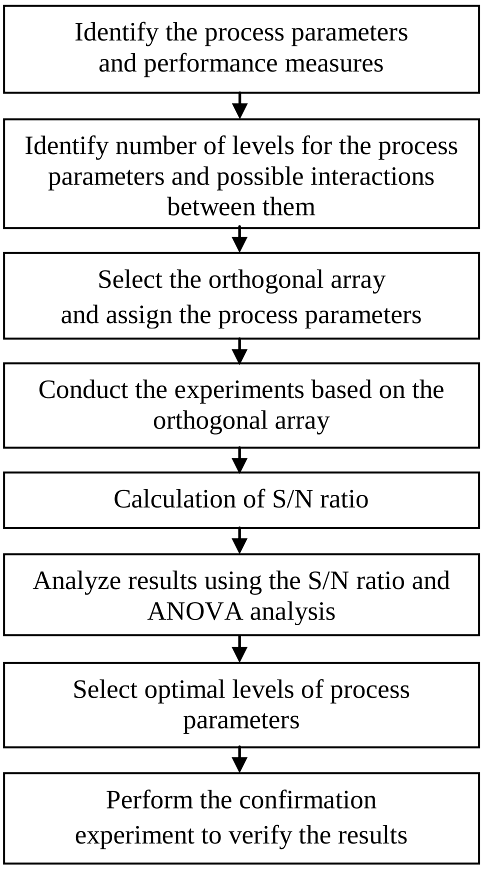

Fig-2: Steps in Taguchi Methodology

where response y is a function of control variables x_1, x_2... x_n denoted as f plus the experimental error ε. The error term ε represents any measurement error or other type of variations not counted in f. It is a statistical error that is assumed to distribute normally with zero mean and variance s^2. If the response is defined by a linear function of independent variables, then the approximating function is a first order model. A first-order model can be expressed as

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \tag{5}$$

If there is a curvature in the response surface, then a higher degree polynomial should be used. The approximating function with two variables is called a second-order model:

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j}\sum \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ij} x_i^2 + \varepsilon \tag{6}$$

where ε is the error observed in the response y. x_i is the linear input variables, x_{ii}^2 and $x_i x_j$ are the squares and interaction terms of input variables respectively. The unknown second order regression coefficients are β_o, β_i, β_{ij} and β_{ii}, which can be estimated by the least square method. The response can be represented graphically, either in the three-dimensional space or as contour plots that helps in visualizing the shape of the response surface. The summarized researches in improving and optimizing performance measures of EDM process using RSM technique is shown in Table 2.

Table 1: Summary of Taguchi method used in improving and optimizing performance measures of EDM

No.	**Author/Year**	**Process parameters**	**Performance measures**	**Remarks**
1	Raghuraman et al. (2013)	Current, pulse on time, pulse off time	MRR, TWR, surface roughness	An investigation for the optimal set of process parameters such as current, pulse on and off time to identify the variations in MRR, TWR and SR is carried out.
2	Khanna and Garg (2013)	Pulse on time, pulse off time, current, voltage	MRR	For the MRR, the influencing factors in descending order are voltage, discharge current, pulse-on and pulse off time.
3	Gopalakannan et al. (2013)	Pulse current, gap voltage, pulse on time, pulse off time	MRR, EWR, surface roughness	The Taguchi based grey relational analysis is adopted to optimize multiple characteristics namely MRR, EWR and SR for EDM process.
4	Syed and Palaniyandi (2012)	Peak current, pulse on-time, concentration of the powder, polarity	MRR, EWR, surface roughness, white layer thickness	An addition of aluminium metal powder in distilled water is resulted in high MRR, good surface finish, and minimum white layer thickness.

5	Dave et al. (2012)	Orbital radius, orbital speed, current, gap voltage, pulse on time, duty factor	MRR	It is found that current along with orbital radius have significant effect on MRR.
6	Kumar et al. (2012)	Polarity, type of electrode, peak current, pulse on time, duty cycle, gap voltage, retract distance, concentration of fine graphite powder	TWR, Wear ratio	It is found that TWR and WR are minimum with the use of cryogenically treated copper electrode.
7	Singh (2012)	Pulse current, pulse on time, duty cycle, gap voltage, tool electrode lift time	MRR, TWR, surface roughness	The order of importance of the process parameters to the multi-performance characteristics is pulse current, aspect ratio, tool electrode lift time, pulse on time, gap voltage and duty cycle.
8	Nipanikar and Ghewade (2011)	Pulse on time, peak current , duty cycle, gap voltage	MRR, EWR, overcut, half taper angle of the through holes	The peak current significantly affects the MRR and radial overcut and pulse on time significantly affects the EWR.
9	Govindan and Joshi (2010)	Discharge current, gap voltage, pulse off-time, gas pressure, electrode speed, radial clearance of shield at bottom	MRR, TWR	At low discharge energies, single-discharge in dry EDM could give larger MRR and crater radius compared to that of the conventional liquid dielectric EDM.
10	Abdulkareem et al. (2010)	Current, pulse on-time, pause off-time, gap voltage	Electrode wear	Cooling of an electrode can reduce the electrode wear by 27%.
11	Thillaivanan et al. (2010)	Current, feed	Total machining time	A practical method of optimizing cutting parameters for EDM under the minimum total machining time based on Taguchi method and ANN is presented.
12	Jung and Kwon (2010)	Input voltage , capacitance, resistance, feed rate, spindle speed	Electrode wear, entrance and exit clearances	It is attempted to find the optimal machining conditions for drilling of a micro-hole of minimum diameter and maximum aspect ratio.
13	Ponappa et al. (2010)	Gap voltage, pulse on-time, pulse off-time, servo speed	Taper angle, surface finish	The process parameters such as pulse-on time, pulse-off time, voltage gap, and servo speed have been optimized to get better surface finish and reduced taper.
14	Kao et al. (2010)	Discharge current, open voltage, pulse duration, duty factor	MRR, EWR, surface roughness	The effects of discharge current, open voltage, pulse duration and duty factor on MRR, EWR and SR are studied.
15	Chattopadhyaya et al. (2009)	Peak current, pulse on time, electrode rotation	MRR, EWR, surface roughness	Taguchi method is used to determine the main influencing factors affecting the selected technological variables such as MRR, EWR and SR.
16	Lin et al. (2009)	Machining polarity, peak current, auxiliary current with high voltage, pulse duration, no load voltage, and servo reference voltage	MRR, EWR, surface roughness	Experimental results showed that EDM is a feasible process to shape conductive ceramics.
17	Khandare and Popat (2009)	Current, pulse time, work material	MRR, surface roughness	It is observed that the most influential factor for MRR and SR is current intensity.

18	Tzeng and Chen (2007)	Open circuit voltage, pulsed duration, duty cycle, peak current, powder concentration, electrode lift, time interval for electrode lift	Precision, accuracy	The application of a fuzzy logic analysis coupled with Taguchi experiment is simple and efficient in developing a high speed EDM process.
19	Zarepour et al. (2007)	Pulse on-time, current, voltage, the engaging time between workpiece and electrode	Electrode wear	The effect of machining parameters of EDM process and pre-EDM roughing on electrode wear are experimentally investigated.
20	Kansal et al. (2007)	Peak current, pulse on time, pulse-off time, concentration of powder, gain, nozzle flushing	MRR	Powder mixing into the dielectric fluid of EDM is one of the innovative developments that ensure better machining rates at desired surface quality.
21	Kansal et al. (2006)	Pulse duration, peak current, concentration of powder, duty cycle	MRR, TWR, surface roughness	The concentration of added silicon powder and peak current are the most influential parameters for MRR, TWR and SR.
22	Lin et al. (2006)	Polarity, peak current, auxiliary current with high voltage, pulse duration, servo reference voltage	MRR, EWR, surface roughness	When the EDM process is used to machine SKH 57 HSS, it is observed that the MRR, EWR and SR increase with the peak current.
23	George et al. (2004)	Pulse current, gap voltage, pulse-on-time	MRR, EWR	The process variables affecting electrode wear rate and MRR, according to their relative significance, are voltage gap, peak current and pulse on time, respectively.
24	Wang and Tsai (2001)	Polarity of tool, servo std. voltage, discharge time, quiescent time, peak current, main power voltage, tool material, work material, temp. of dielectric fluid	MRR, TWR	A semi empirical model of the MRR on the work and the tool for various materials is established by employing dimensional analysis.
25	Marafona and Wykes (2000)	Ram speed, current intensity, Pulse duration, duty factor, compression, sensitivity of the servo, relative withdrawal, cycle time	MRR, TWR, surface roughness	A two-stage EDM machining process is developed giving a significantly improved material removal rate.
26	Wang and Yan (2000)	Polarity, peak current, pulse duration, power supply voltage, rotation of electrode, flushing pressure	MRR, TWR, surface roughness	EDM blind-hole drilling with a rotational eccentric through-hole electrode reaches a higher MRR although the EWR is higher.

Table 2: Summary of RSM in improving and optimizing performance measures of EDM

No	Author/Year	Process parameters	Performance measures	Remarks
1	Tzeng and Chen (2013)	Discharge current, gap voltage, pulse on-time, pulse off-time	MRR,EWR, surface roughness	The higher discharge energy with the increase of discharge current and pulse on time leads to a more powerful spark energy, and thus increased MRR.

2	Ayesta et al. (2013)	Current intensity, pulse time, servo voltage	Electrode Wear, machining time	The best parameters for low electrode wear and low erosion time are those that combine low intensity, high pulse time and low servo voltage.
3	Rajendran et al. (2013)	Pulse on time, pulse off time, current	EW, recast layer thickness	The pulse current is directly proportional with resolidified layer thickness and crack density.
4	Assarzadeh and Ghoreishi (2013)	Discharge current, pulse-on time, duty cycle, gap voltage	MRR,TWR, surface roughness	RSM, employing a rotatable central composite design scheme, has been used to plan and analyze the experiments for optimization of MRR, TWR and SR.
5	Wagh et al. (2013)	Discharge current, pulse duration, pulse off time, gap voltage	MRR	A face centred central composite design matrix is used to conduct the experiments on AISI D2 and it is found that discharge current and pulse duration are significant factors for MRR.
6	Jabbaripour et al. (2012)	Pulse current, pulse on time, open circuit voltage	MRR, TWR	Increase of pulse energy by increasing pulse current or pulse on time leads to increase of average thickness and micro hardness of recast layer.
7	Rajesh and Anand (2012)	Working current, working voltage, oil pressure, spark gap pulse-on time, pulse off time	MRR, surface finish	Empirical models for MRR and SR are developed by conducting a designed experiment.
8	Solhjoei et al. (2012)	Current, pulse-on time, voltage	MRR, stability factor	Mathematical models for relating the MRR and Stability factor to input parameters like current, pulse-on time and voltage are developed.
9	Padhee et al. (2012)	Concentration of powder in the dielectric fluid, pulse on time, duty cycle, peak current	MRR, surface finish	Mathematical models for prediction of MRR and SR through the knowledge of four process variables are developed using RSM and statistically validated.
10	Sánchez et al. (2011)	Peak current , pulse-on time, pulse-off time	MRR,EWR, surface roughness	An inversion model, based on the least squares theory, which involves establishing the values of the EDM input parameters to ensure the simultaneous fulfilment of MRR, EWR and SR is developed.
11	Patel et al. (2011)	Discharge current, pulse on time, duty cycle, gap voltage	MRR,EWR, surface roughness	EDMed material unevenness increases with discharge current and pulse-on time and the recast layer thickness increases with the pulse-on time.
12	Iqbal and Khan (2010)	Voltage, rotational speed of electrode, feed rate	MRR,EWR, surface roughness	Voltage and rotary motion of electrode are the most significant machining parameters influencing MRR, EWR and SR.
13	Habib (2009)	Pulse on time, peak current, average gap voltage, % of SiC in the aluminium matrix	MRR,EWR, surface roughness, gap size	The developed models reflect the complex, interactive and higher order effects of the various process parameters on performance measures.
14	Saha and Choudhury (2009)	Gap voltage, discharge current, pulse- on time, duty factor, air pressure, spindle speed	MRR,TWR, surface roughness	Current, duty factor, air pressure and spindle speed are found to have significant effects on MRR and surface roughness.

15	Sohani (2009)	Discharge current, pulse on-time, pulse off-time, tool area, tool shape	MRR, TWR	The best tool shape for higher MRR and lower TWR is circular, followed by triangular, rectangular, and square cross sections.
16	Patel et al. (2009)	Discharge current, pulse on time, duty cycle, gap voltage	Surface roughness	The two-stage effort of obtaining a SR model by RSM and optimization of this model by a trust region method is resulted in the improved surface quality.
17	Chiang (2008)	Discharge current, pulse on time, duty factor, open discharge voltage	MRR,EWR, surface roughness	The main significant factors for MRR are discharge current and duty factor while discharge current and pulse on time are significant for EWR and SR.
18	Kuppan et al. (2008)	Peak current, pulse on-time, duty factor, electrode speed	MRR and depth averaged surface roughness	MRR is more influenced by peak current, duty factor and electrode rotation; whereas depth averaged surface roughness is strongly influenced by peak current and pulse on time.
19	Tao et al. (2008)	Discharge current, pulse duration, pulse interval	MRR, surface roughness	Near dry EDM exhibits the advantage of good machining stability and surface finish under low discharge energy input.
20	Luis and Puertas (2007)	Current intensity, pulse time, duty cycle	MRR,EWR, Surface roughness	A methodology is developed to work out the values of technological tables employed in the programming of EDM for the conductive ceramic materials.
21	Chiang et al. (2007)	Quantity, diameter, and area fraction of spheroidal graphite particle	Resolidified layer thickness and ridge density	The quantity and area fraction of graphite particle are the most influential factors on the resolidified layer thickness and ridge density in the EDM process.
22	Kansal et al. (2005)	Pulse on time, duty cycle, peak current, concentration of silicon powder	MRR, surface roughness	The increasing concentration of the silicon powder in the dielectric fluid increases MRR and improves SR.
23	Puertas et al. (2004)	Current intensity, pulse time, duty cycle	MRR, EW, surface roughness	In order to obtain a good surface finish in the case of tungsten carbide, low values should be used for both current intensity and pulse time.
24	Soni and Chakraverti (1994)	Current, Electrode rotations	MRR, EWR, surface roughness	It is found that rotating the electrode improves the MRR due to improved flushing action and sparking efficiency but results in high SR.

2.3 Artificial Neural Network (ANN)

An artificial neural network is a model which runs like a human brain by using many neurons consecutively and it collects information by a learning process (Haykin, 2009). Complex problems whose analytical or numerical solutions are difficult to be obtained that can be solved by utilizing adaptive learning ability of neural networks (Rafiq et al., 2001). Generally, the design of a neural network is composed by three main steps: configuration −how layers are organized and connected; learning – how information is stored; generalization − how neural network produces reasonable outputs for inputs not found in the training (Haykin, 1999). The multi-layer perceptions neural network is formed from numerous neurons with parallel connection, which are jointed in several layers (Constantin, 2003). The structure of this network contains of network's input data, numbers of hidden middle layers with numerous neurons in each layer and an external layer with neurons connected to output. A multilayer perception with one hidden layers is shown in Figure 3.

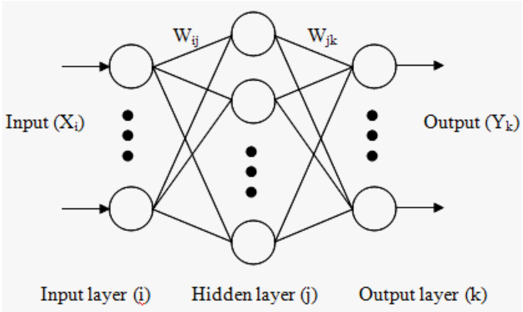

Fig-3: Three-layered feed forward neural network

ANNs are broadly classified into feed forward and back propagation networks. Feed forward networks are those in which computation flows from the input nodes to the output nodes in a sequence. In a back propagation network, signals may propagate from the output of any neuron to the input of any neuron. The artificial neuron evaluates the inputs and determines the strength of each by its weighting factor. The result of the summation function for all the weighted inputs can be treated as an input to an activation function from which the output of the neuron is evaluated. Then the output of the neuron is transmitted to subsequent neurons along the outgoing connections to serve as an input to them. When an input is presented and propagated forward through the neural network to compute an output for each neuron, the Mean Square (MS) error between the desired output and actual output is computed. To reduce the MS error as rapidly as possible, an iterative error reduction of the gradient-descent method with adding a momentum term (Rumelhart and McCelland, 1989) is performed. After the learning process is finished, the neural network memorizes all the adjusted weights and is ready to predict the machining performances based on the knowledge obtained from the learning process (Su et al., 2004). Table 3 summarized the researches in improving and optimizing performance measures of EDM using ANN technique.

2.4 Genetic Algorithm (GA)

The GA was developed on the probabilistic basis that the global optimum is searched in a random and parallel manner through operations of reproduction, crossover and mutation (Goldberg, 1989). These algorithms maintain and control a population of solutions and implement their search for better solutions based on 'survival of the fittest' strategy. GA can solve linear and non-linear problems by exploring all regions of the state space and exploiting promising areas with a set of potential solutions or chromosomes (usually in the form of bit strings) that are randomly generated or selected. The entire set of these chromosomes comprises a population. Figure 4 shows a flow chart for a simple GA (Su et al., 2004).

According to Figure 4, a GA starts with randomly initializing the parent chromosomes represented in a bit string, and the fitness of these chromosomes is then calculated based on the objective function. The goal of reproduction process is to allow the genetic information, stored in the artificial strings having good fitness, survive the next generation. Crossover involves splitting up two chromosomes and then combining one half of each chromosome with the other pair. Mutation involves flipping a single bit of a chromosome. The chromosomes are then evaluated by using a certain fitness criteria and the best ones are kept while the others are removed. The process is repeated until the solution with best fitness to meet the objective function criteria is received. Table 4 summarized the researches in optimizing process parameters of EDM using GA technique.

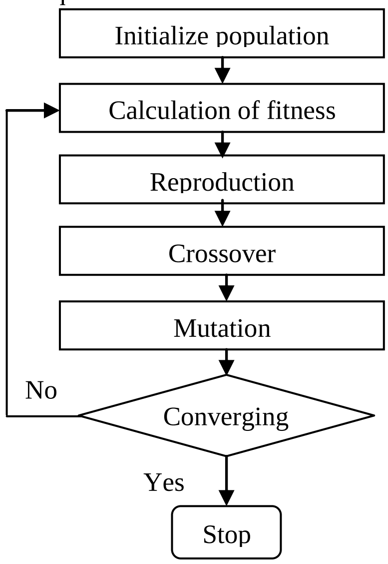

Fig-4: Flow chart of a simple GA

2.5 Grey Relational Analysis (GRA)

Grey Relational Analysis theory developed for the new methods for solving the complicated interrelationship among the multiple performing characteristics. The grey system theory is an efficient technique, which requires limited information to estimate the behavior of an uncertainty system & discrete data problem. Figure 5 shows simple steps in GRA (Mohan et al., 2004).

Normalizing involves transforming the original sequence to comparable sequence. This is known as grey relational generating. There are three conditions of normalization:

- Lower is better

$$X_i^*(k) = \frac{\max X_i(k) - X_i(k)}{\max X_i(k) - \min X_i(k)} \tag{7}$$

- Higher is better

$$X_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)} \tag{8}$$

- Nominal the best

$$X_i^*(k) = \frac{1 - \left| X_i(k) - X_o b(k) \right|}{\max X_i(k) - X_o b(k)} \tag{9}$$

Table 3: Summary of ANN in improving and optimizing performance measures of EDM

No	Author/Year	Process parameters	Performance measures	Remarks
1	Tzeng and Chen (2013)	Discharge current, gap voltage, pulse on-time, pulse off-time	MRR, EWR, surface roughness	The back propagation neural network/GA gives better prediction results in the experimental runs than regression models based on the RSM method.
2	Atefi et al. (2012)	Pulse current, pulse voltage, pulse on-time, pulse off-time	Surface roughness	A hybrid model, combination of statistical analysis and ANN, is designed to reduce the error in optimization of complex and non-linear problems.
3	Bharti et al. (2012)	Shape factor, pulse-on-time, discharge current, duty cycle, gap voltage, flushing pressure, tool electrode lift time	MRR, surface finish	The average percentage difference between experimental and ANN's predicted value is 4 and 4.67 for MRR and SR respectively.
4	Andromeda et al. (2011)	Gap current, pulse on time, pulse off time, sparking frequency	MRR	The capability of ANN to follow the dynamical behaviour of the EDM process is not precisely accurate.
5	Mahdavinejad (2011)	Discharge current, pulse on time, pulse off time	MRR, surface Finish	ANN with back propagation algorithm is used to model the process. MRR and SR are optimized as objectives by using NSGA II.
6	Joshi and Pande (2011)	Discharge current, discharge duration, duty cycle, break down voltage	Crater size, MRR, TWR	ANN process model is used in conjunction with the NSGA-II to select optimal process parameters for roughing and finishing operations of EDM.
7	Thillaivanan et al. (2010)	Current, feed	Total machining time	A feedforward-backpropagation neural network is developed to get the parameters for required total machining time, oversize and taper of a hole to be machined by EDM.
8	Rao et al. (2008)	Peak current, voltage	MRR	Multiperceptron neural network models are developed using neuro solutions package and GA concept is used to optimize the weighting factors of the network.
9	Markopoulos et al. (2006)	Pulse current, pulse-on time	Centre-line average and the maximum height of the profile surface roughness	A feed forward ANN trained with the Levenberg- Marquardt algorithm is employed for the prediction of the surface roughness.
10	Fenggou and Dayong (2004)	Peak current, pulse width	Processing depth	The automatic determination and optimization of EDM sinking processing parameters by ANN are efficient and applicable. It can also realize automatic determination of processing conditions.

11	Su et al. (2004)	Pulse-on time, pulse-off time, high-voltage discharge current, low-voltage discharge current, gap size, servo-feed, jumping time, working time	MRR, TWR, surface roughness	The developed neural network with the aid of a GA has sufficient prediction and reasoning capability to generate optimal process parameters from rough cutting stage to finish cutting stage.
12	Tsai and Wang (2001)	Discharge time, peak current	Surface roughness	The comparison on predictions of surface finish for various work materials based upon six different neural-networks models and a neuro-fuzzy network model is illustrated.

Table 4: Summary of GA in improving and optimizing performance measures of EDM

No	Author/Year	Process parameters	Performance measures	Remarks
1	Tzeng and Chen (2013)	Discharge current, gap voltage, pulse on-time, pulse off-time	MRR, EWR, surface roughness	The proposed algorithm of GA approach has better prediction and confirmation results than the RSM method.
2	Bharti et al. (2012)	Shape factor, pulse-on-time, discharge current, duty cycle, gap voltage, flushing pressure, tool electrode lift time	MRR, surface roughness	A controlled elitist NSGA controls elitism and forcibly allows the solutions from each non-dominating front to co-exist in the population which leads to true optimal solutions.
3	Rajesh and Anand (2012)	Working current, working voltage, oil pressure, spark gap, pulse on time, pulse off time	MRR, surface Finish	Genetic Algorithm based multi-objective optimization for maximization of MRR and minimization of SR is done by using the developed empirical models.
4	Padhee et al. (2012)	Concentration of powder in dielectric fluid, pulse on time, duty cycle, peak current	MRR, surface Finish	In order to simultaneously optimize both MRR and SR, NSGA II is adopted to obtain the Pareto optimal solution.
5	Mahdavinejad (2011)	Discharge current, pulse on time , pulse off time	MRR, surface Finish	A multi-objective optimization method, NSGA-II is applied and finally pareto-optimal sets of MRR and SR are obtained.
6	Joshi and Pande (2011)	Discharge current, discharge duration, duty cycle, break down voltage	Crater size, MRR, TWR	The proposed integrated (FEM–ANN–GA) approach is found efficient and robust as the optimum process parameters suggested are found to give the expected optimum performance.
7	Rao et al. (2008)	Peak current, voltage	MRR	There is considerable reduction in mean square error when the network is optimized with GA and type of material is having more influence on the performance measures.
8	Su et al. (2004)	Pulse-on time, pulse-off time, high-voltage discharge current, low-voltage discharge current, gap size, servo-feed, jumping time, working time	MRR, TWR, surface roughness	The GA developed based on neural network is good at automatically selecting an optimal process parameter set in accordance with the desired machining performances.

9	Mohan et al. (2004)	Peak current, polarity, volume fraction of SiC reinforced particles, pulse duration, hole diameter of the tube electrode, and speed of electrode rotation	MRR, EWR, surface roughness	In EDM drilling, the rotating tube electrode has produced higher material removal rate than the rotating solid electrode.

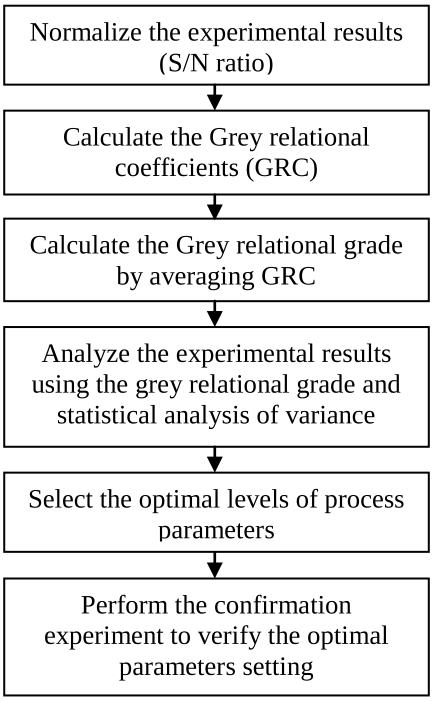

Fig-5: Simple steps in GRA

Where $i = 1, 2,\ldots n$; $k = 1, 2,\ldots m$; $X_i^*(k)$ is the normalized value of the kth element in the i^{th} sequence, $X_0b\ (k)$ is desired value of the k^{th} quality characteristic, max $X_i^*(k)$ is the largest value of $X_i\ (k)$, and min $X_i^*(k)$ is the smallest value of $X_i\ (k)$, n is the number of experiments and m is the number of quality characteristics. The grey relational coefficient can be expressed as

$$\delta_{ij} = \frac{\min_i \min_j \left|x_i^o - x_{ij}\right| + \xi \min_i \min_j \left|x_i^o - x_{ij}\right|}{\left|x_i^o - x_{ij}\right| + \xi \min_i \min_j \left|x_i^o - x_{ij}\right|} \quad (10)$$

Where x_i^0 is the ideal normalized results for the i^{th} performance characteristics and ξ is the distinguishing coefficient which is defined in the range $0 \leq \xi \leq 1$.

The grey relational grade is a weighting-sum of the grey relational coefficients. The overall evaluation of multiple performance characteristics is based on the grey relational grade and it is defined as follows,

$$\alpha_j = \frac{1}{m}\sum_{i=1}^{m}\delta_{ij} \quad (11)$$

Where α_j is the Grey relational grade for the j^{th} experiment and m is the number of performance characteristics. The higher Grey relational grade represents that the experimental result is closer to the ideally normalized value and it implies the better quality. Table 5 summarized the researches in improving and optimizing performance measures of EDM using GRA technique.

Table 5: Summary of GRA in improving and optimizing performance measures of EDM

No	**Author/Year**	**Process parameters**	**Performance measures**	**Remarks**
1	Raghuraman et al. (2013)	Peak current, pulse on time, pulse off time	MRR, TWR, surface roughness	Taguchi Grey relational Analysis is being effective technique for optimization of multi response like MRR, TWR and SR.
2	Gopalakannan et al. (2013)	Pulse current, gap voltage, pulse on time, pulse off time	MRR, EWR, surface roughness	It is found that the utilization of the optimal EDM process parameters combination enhances the grey relation of single EDM quality by 27.71%.
3	Singh (2012)	Pulse current, pulse on time, duty cycle, gap voltage, tool electrode lift time	MRR, TWR, surface roughness	GRA approach could be applied successfully to other operations in which performance measures are determined by many process parameters at multiple quality requests.

4	Rajesh and Anand (2012)	Working current, working voltage, oil pressure, spark gap, pulse on & off time	MRR surface finish	The most influencing factor obtained by the response table is the working current for the EDM process.
5	Dhanabalan et al. (2012)	Peak current, pulse on time, pulse off time	MRR, TWR, surface roughness	GRA greatly simplifies the optimization of complicated multiple performance characteristics by converting them into single GRG.
6	Moghaddam et al. (2012)	Peak current, voltage pulse on time, pulse off time, duty factor	MRR, TWR, surface roughness	The combination of Taguchi technique, GRA and simulated annealing algorithm is quite efficient in determining optimal EDM process parameters.
7	Jung and Kwon (2010)	Input voltage , capacitance, resistance, feed rate, spindle speed	Electrode wear, entrance and exit clearances	GRA is used to determine the optimal machining parameters, among which the input voltage and the capacitance are found to be the most significant.
8	Reza et al. (2010)	Polarity, pulse on duration, discharge current, discharge voltage, machining depth, machining diameter and dielectric liquid pressure	MRR, EWR, surface roughness	The improvement in grey relational grade after optimization of EDM control parameters is 0.1639.
9	Kao et al. (2010)	Discharge current, open voltage, pulse duration, duty factor	MRR, EWR, surface roughness	It is showed that EWR, MRR and SR improved 15%, 12% and 19% respectively when the Taguchi method and GRA are used.

The above discussed optimization techniques were mostly used by researchers in past decades for optimization of performance measures for electrical discharge machining. But now-a-days some other optimization techniques like Simulated Annealing (SA), fuzzy logic, Particle Swarm Optimization (PSO), Principle Component Analysis (PCA), Desirability function, Utility function are being used combined with Taguchi, RSM, ANN, GA, GRA for more accurate prediction of optimum parameters.

Moghaddam et al. (2012) showed that the combination of Taguchi technique, grey relational analysis and simulated annealing algorithm is quite efficient in determining optimal EDM process. A fuzzy logic system is used to investigate relationships between the machining precision and accuracy for determining the efficiency of each parameter design of the Taguchi dynamic experiments by Tzeng and Chen (2007). Fuzzy logic is used by Biswas and Dewangan (2012) to convert multiple responses into a single characteristic index known as Multi Performance Characteristic Index (MPCI) and MPCIs are optimized by using robust Taguchi design. Kohli et al. (2012) concluded that the fuzzy logic system is found to be more simple to evaluate and responsive than experimental models. It is observed by Lin et al. (2002) that the grey relational analysis is more straightforward than the fuzzy-based Taguchi method for optimising the EDM process with multiple process responses. A fuzzy model is employed by Majumder (2013) to provide a fitness function to PSO by unifying the multiple responses and PSO is used to predict the optimal process parametric settings for the multi-performance optimization of the EDM operation. Sivasankar and Jeyapaul (2013) used Desirability Functional Analysis (DFA) to combine multiple quality characteristics into a single performance statistics and particle swarm optimization (PSO) to assign unequal weights to each response for optimization of EDM of ZrB2-SiC composite. Pradhan (2011) revealed that GRA coupled with PCA can effectively acquire the optimal combination of cutting parameters. Assarzadeh and Ghoreishi (2013) applied desirability function (DF) concept to the response regression equations to simultaneously find a set of optimal input parameters yielding the highest accessible MRR along with the lowest possible TWR and surface roughness within the process inputs domain. Taguchi's method with multiple performance characteristics is adopted by Kansal et al. (2006) to obtain an overall utility value that represents the overall performance of powder mixed EDM.

III. DISCUSSIONS AND CONCLUSIONS

After a detailed analysis of the literature, the following conclusions can be drawn.

- Various approaches like powder additives, different dielectric fluid, tool-workpiece rotation, vibration, cryogenic cooling of electrode, different tool material, etc. have been used by different researchers for improvement in EDM process performance.
- It is found that Taguchi optimization technique is widely used in optimizing machining process parameters of EDM followed by RSM, ANN, GA, and GRA as depicted in Figure 6.

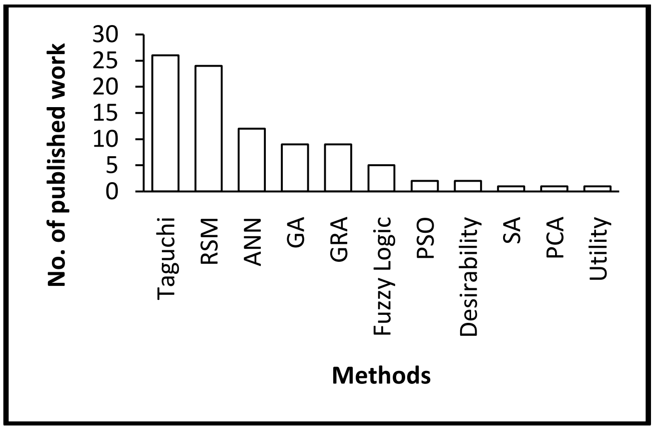

Fig-6: Distribution of collected EDM research publications

- The researches in optimization of performance measures using latest optimization techniques such as SA, fuzzy logic, PSO, PCA, desirability, utility are mostly focused on multi response optimization. The application of latest optimization techniques in optimizing performance measures of EDM process positively gives good results compared to conventional techniques as proven from the literature.
- It is also found that most of the research work has been carried out on improvement and optimization of same performance measures like MRR, EWR, Surface roughness for different materials, but some performance measures like power consumption, dimensional deviation, hardness, etc. are either not much focused or not focused yet. So, this area is yet to be explored more.
- Most of the researchers have concentrated on optimization of single quality characteristic while in present industries, high productivity and product quality with low production cost are important. To achieve that simultaneously, multi response optimization of machining process is required. This area can be taken up for further research as they required more attention.

REFERENCES

[1] Abdulkareem, S.; Khan, A.A.; Konneh, M. (2010) Cooling Effect on Electrode and Process Parameters in EDM. Materials and Manufacturing Processes, 25(6): 462–466.

[2] Andromeda, T.; Yahya, A.; Hisham, N.; Khalil, K.; Erawan, A. (2011) Predicting Material Removal Rate of Electrical Discharge Machining (EDM) using Artificial Neural Network for High Igap current. International Conference on Electrical, Control and Computer Engineering, IEEE, 21-22 June, Pahang, Malaysia.

[3] Assarzadeh, S.; Ghoreishi, M. (2013) Statistical modeling and optimization of process parameters in electro-discharge machining of cobalt-bonded tungsten carbide composite (WC/6%Co). The Seventeenth CIRP Conference on Electro Physical and Chemical Machining, Procedia CIRP, 6: 464–469.

[4] Atefi, R.; Razmavar, A.; Teimoori, F.; Teimoori, F. (2012) The Investigation of EDM Parameters in Finishing Stage on Surface Quality Using Hybrid Model. Journal of Basic and Applied Scientific Research, 2(3): 3061-3065.

[5] Ayesta, I.; Izquierdo, B.; Sánchez, J.A. (2013) Influence of EDM parameters on slot machining in C1023 aeronautical alloy. The Seventeenth CIRP Conference on Electro Physical and Chemical Machining, Procedia CIRP, 6: 129-134.

[6] Bharti, P.S.; Maheshwari, S.; Sharma, C. (2012) Multi-objective optimization of electric-discharge machining process using controlled elitist NSGA-II. Journal of Mechanical Science and Technology, 26(6): 1875–1883.

[7] Biswas, C.K.; Dewangan, S. (2012) Optimisation of EDM Process with Fuzzy Logic Technique. International Conference on Metallurgical, Manufacturing and Mechanical Engineering, 26-27 December, Dubai, UAE, pp.346-349.

[8] Chattopadhyay, K.D. (2009) Development of empirical model for different process parameters during rotary electrical discharge machining of copper–steel (EN-8) system. Journal of Materials Processing Technology, 209(3): 1454–1465.

[9] Chiang, K.T. (2008) Modeling and analysis of the effects of machining parameters on

the performance characteristics in the EDM process of Al2O3+TiC mixed ceramic. The International Journal of Advanced Manufacturing Technology, 37(5-6): 523–533.

[10] Chiang, K.T.; Chang, F.P.; Tsai, D.C. (2007) Modeling and analysis of the rapidly resolidified layer of SG cast iron in the EDM process through the response surface methodology. Journal of Materials Processing Technology, 182(1-3), 525-533.

[11] Constantin, N. (2003) Adaptive Neural Predictive Techniques for Nonlinear Control, Studies in Informatics and Control. 12: 285-291.

[12] Dave, H.K.; Desai, K.P.; Raval, H.K. (2012) Modeling and Analysis of material removal rate during electro discharge machining of Inconel 718 under orbital tool movement. Journal of Manufacturing Systems, 2(1): 12-20.

[13] Dhanabalan, S.; Sivakumar, K.; Narayanan, C.S. (2012) Optimization of EDM Process Parameters with Multiple Performance Characteristics for Titanium Grades. European Journal of Scientific Research, 68(3): 297-305.

[14] Fenggou, C.; Dayong, Y. (2004) The study of high efficiency and intelligent optimization system in EDM sinking process. Journal of Materials Processing Technology, 149(1-3): 83–87.

[15] Fonda, P.; Wang, Z.; Yamazaki, K.; Akutsu, Y. (2007) A fundamental study on Ti–6Al–4V's thermal and electrical properties and their relation to EDM productivity. Journal of Materials Processing Technology, 202(1-3): 583-589.

[16] George, P.M., Raghunath, B.K.; Manocha, L.M.; Warrier, A.M. (2004) EDM machining of carbon–carbon composite—a Taguchi approach. Journal of Materials Processing Technology, 145(1): 66–71.

[17] Goldberg, D.E. (1989) Genetic algorithm in search, optimization, and machine learning. Addison-Wesley, Reading.

[18] Gopalakannan, S.; Senthilvelan, T.; Ranganathan, S. (2013) Statistical optimization of EDM parameters on machining of aluminum Hybrid Metal Matrix composite by applying Taguchi based Grey analysis. Journal of Scientific & Industrial Research, 72(6): 358-365.

[19] Govindan, P.; Joshi, S.S. (2010) Experimental characterization of material removal in dry electrical discharge drilling. International Journal of Machine Tools and Manufacture, 50(5): 431–443.

[20] Habib, S.S. (2009) Study of the parameters in electrical discharge machining through response surface methodology approach. Applied Mathematical Modelling, 33(12): 4397–4407.

[21] Haykin, S. (1999) Neural networks: a comprehensive foundation, 2nd edition, Prentice Hall: New Jersey, USA.

[22] Haykin, S. (2009) Neural Networks and Learning Machines. 3rd edition, Prentice Hall: New Jersey, USA.

[23] Ho, K.H.; Newman, S.T. (2003) State of the art electrical discharge machining (EDM). International Journal of Machine Tools and Manufacture, 43(13): 1287–1300.

[24] Iqbal, A.A.; Khan, A.A. (2010) Modelling and analysis of MRR, EWR and surface roughness in EDM Milling through response surface methodology. Journal of Engineering and Applied Science, 5(2): 154-162.

[25] Jabbaripour, B. (2012) Investigating the Effects of EDM Parameters on Surface Integrity, MRR and TWR in Machining of Ti–6Al–4V. Machining Science and Technology: An International Journal, 16(3): 419–444.

[26] Jameson, E.C. (2001) Electrical Discharge Machining. Society of Manufacturing Engineers.

[27] Jilam, S.T.; Pandey, P.C. (1984) Experimental Investigations into the Performance of Water as Dielectric in EDM. International Journal of Machine Tool Design and Research, 24(l): 31-43.

[28] Joshi, S.N.; Pande, S.S. (2011) Intelligent process modeling and optimization of die-sinking electric discharge machining. Applied Soft Computing, 11(2): 2743–2755.

[29] Jung, J.H.; Kwon, W.T. (2010) Optimization of EDM process for multiple performance characteristics using [30] Taguchi method and Grey relational analysis. Journal of Mechanical Science and Technology, 24(5): 1083–1090.

[31] Kalpajian, S.; Schmid, S.R. (2003) Material removal processes: abrasive, chemical, Electrical and high-energy beam. 5th Edition, In: Manufacturing Processes for Engineering Materials, Prentice Hall, New Jersey, pp. 504-558.

[32] Kansal, H.K.; Singh, S.; Kumar, P. (2005) Parametric optimization of powder mixed electrical discharge machining by response

surface methodology. Journal of Materials Processing Technology, 169(3): 427–436.

[33] Kansal, H.K.; Singh, S.; Kumar, P. (2006) Performance parameter optimization (multi characteristics) of powder mixed electrical discharge machining (PMEDM) through Taguchi's method and utility concept. Indian Journal of Engineering & Materials Sciences, 13(3): 209-216.

[34] Kansal, H.K.; Singh, S.; Kumar, P. (2007) Effect of Silicon Powder Mixed EDM on Machining Rate of AISI D2 Die Steel. Journal of Manufacturing Processes, 9(1): 13-22.

[35] Kao, J.Y.; Tsao, C.C.; Wang, S.S.; Hsu, C.Y. (2010) Optimization of the EDM parameters on machining Ti–6Al–4V with multiple quality characteristics. The International Journal of Advanced Manufacturing Technology, 47(1-4): 395–402.

[36] Khandare, S.S.; Popat, M.A. (2009) Experimental Investigations of EDM to optimize Material Removal Rate & Surface Roughness through Taguchi's Technique of Design of Experiments. Second International Conference on Emerging Trends in Engineering and Technology, IEEE, 16-18 Dec, Nagpur, pp. 476-482.

[37] Khanna, R.; Garg, S. (2013) Experimental investigation of machining parameters of electric discharge machine on tungsten carbide (K-10). International Journal of Production technology and management, 4(1): 39-45.

[38] 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: 1674- 1679.

[39] Kumar, A.; Maheshwari, S.; Sharma, C.; Beri, N. (2012) Machining Efficiency Evaluation of Cryogenically Treated Copper Electrode in Additive Mixed EDM. Materials and Manufacturing Processes, 27(10): 1051–1058.

[40] Kunieda, M.; Miyoshi, Y.; Takaya, T.; Nakajima, N.; Yu, Z.; Yoshida, M. (2003) High Speed 3D Milling by Dry EDM. CIRP Annals – Manufacturing Technology, 52(1): 147-150.

[41] Kunieda, M.; Furudate, C. (2001) High Precision Finish Cutting by Dry WEDM. CIRP Annals – Manufacturing Technology, 50(1): 121-124.

[42] Kunieda, M.; Yoshida, M. (1997) Electrical Discharge Machining in Gas. CIRP Annals - Manufacturing Technology, 46(1): 143-146.

[43] Kuppan, P.; Rajadurai, A.; Narayanan, S. (2008) Influence of EDM process parameters in deep hole drilling of Inconel 718. The International Journal of Advanced Manufacturing Technology, 38(1-2): 74–84.

[44] Liao, T.W.; Chen, L.J. (1998) Manufacturing process modeling and optimization based on multi-layer perceptron network. Journal of Manufacturing Science and Engineering, Transactions of the ASME, 120(1): 109–111.

[45] Lin, C.L.; Lin, J.L.; Ko, T.C. (2002) Optimisation of the EDM Process Based on the Orthogonal Array with Fuzzy Logic and Grey Relational Analysis Method. The International Journal of Advanced Manufacturing Technology, 19(4): 271-277.

[46] Lin, Y.C.; Cheng, C.H.; Su, B.L.; Hwang, L.R. (2006) Machining Characteristics and Optimization of Machining Parameters of SKH 57 High-Speed Steel Using Electrical-Discharge Machining Based on Taguchi Method. Materials and Manufacturing Processes, 21(8): 922–929.

[47] Lin, Y.C.; Wang, A.; Wang, D.; Chen, C. (2009) Machining Performance and Optimizing Machining Parameters of Al_2O_3–TiC Ceramics Using EDM Based on the Taguchi Method. Materials and Manufacturing Processes, 24(6): 667–674.

[48] Lonardo, P.M.; Bruzzone, A.A. (1999) Effect on flushing and Electrode Materials on Die Sinking EDM. CIRP Annals – Manufacturing Technology, 48(1): 123–126.

[49] Luis, C.J.; Puertas, I. (2007) Methodology for developing technological tables used in EDM processes of conductive ceramics. Journal of Materials Processing Technology, 189(1-3): 301–309.

[50] MahdaviNejad, R.A. (2011) Modeling and Optimization of Electrical Discharge Machining of SiC Parameters, using Neural Network and Non-dominating Sorting Genetic Algorithm (NSGA II). Materials Sciences and Applications, 2(6): 669-675.

[51] Majumder, A. (2013) Process parameter optimization during EDM of AISI 316 LN stainless steel by using fuzzy based multi-objective PSO. Journal of Mechanical Science and Technology, 27(7): 2143-2151.

[52] Marafona, J.; Wykes, C. (2000) A new method of optimising material removal rate using EDM with copper–tungsten electrodes. International Journal of Machine Tools and Manufacture, 40(2): 153–164.

[53] Markopoulos, A.; Vaxevanidis, N.M.; Petropoulos, G.; Manolakos, D.E. (2008) Artificial neural networks modeling of surface finish in electro-discharge machining of tool steels. 8th Biennial ASME Conference on Engineering Systems Design and Analysis, 4-7 July, Torino, Italy.

[54] Masuzawa, T.; Tanaka, K. (1983) Water-based Dielectric Solution for EDM. CIRP Annals- Manufacturing Technology, 32(1): 119-122.

[55] McGeough, J.A., 1988. Advanced Methods of machining. Chapman and Hall: New York.

[56] Moghaddam, M.A.; Kolahan, F.; Andalib, M. (2012) Application of Grey Relational Analysis and Simulated Annealing Algorithm for Modeling and Optimization of EDM Parameters on 40CrMnMoS86 Hot Worked Steel. 20th Annual International Conference on Mechanical Engineering, 16-18 May, Shiraz, Iran.

[57] Mohamad, A.B.; Siddiquee, A.N.; Khan, Z.A.; Saini, V.K. (2012) Optimization of EDM process Parameters using Taguchi method, International Conference on Applications and Design in Mechanical Engineering, 27-28 February, Penang, Malaysia.

[58] Mohan, B.; Rajadurai, A.; Satyanarayana, K.G. (2004) Electric discharge machining of Al–SiC metal matrix composites using rotary tube electrode. Journal of Materials Processing Technology, 153–154(10): 978–985.

[59] Montgomery, D.C. (2005) Design and Analysis of Experiments: Response surface method and designs. John Wiley and Sons: New Jersey.

[60] Nipanikar, S.R.; Ghewade, D.V. (2011) Electro Discharge Machining of Inconel Material. International Journal of Engineering Research and Technology, 4(2): 157-169.

[61] Padhee, S.; Nayak, N.; Panda, S.K.; Dhal, P.R.; Mahapatra, S.S. (2012) Multi-objective parametric optimization of powder mixed electro-discharge machining using response surface methodology and non-dominated sorting genetic algorithm. Sadhana-Academy Proceedings in Engineering Sciences. 37(2): 223–240.

[62] Patel, K.M.; Pandey, P.M.; Rao, P.V. (2009) Determination of an Optimum Parametric Combination using a Surface Roughness Prediction Model for EDM of Al_2O_3/SiCw/TiC Ceramic Composite. Materials and Manufacturing Processes, 24(6): 675–682.

[63] Patel, K.M.; Pandey, P.M.; Rao, P.V. (2011) Study on Machinability of Al2O3 Ceramic Composite in EDM Using Response Surface Methodology. Journal of Engineering Materials and Technology, Transactions of the ASME, 133(2): 1-10.

[64] Phadke, M.S. (1989) Quality engineering using robust design. Prentice-Hall: New Jersey, USA.

[65] Ponappa, K., Aravindan, S.; Rao, P.V.; Ramkumar, J.; Gupta, M. (2010) The effect of process parameters on machining of magnesium nano alumina composites through EDM. The International Journal of Advanced Manufacturing Technology, 46(9-12): 1035–1042.

[66] Pradhan, M.K. (2011) Modelling and Optimisation of Electrical Discharge Machining variables using RSM coupled with GRA and PCA. AICTE Sponsored National Conference on Emerging Trend & its Application in Engineering, 26-28 Dec, Orissa, pp. 109-114.

[67] Puertas, I.; Luis, C.J.; Alvarez, L. (2004) Analysis of the influence of EDM parameters on surface quality, MRR and EW of WC–Co. Journal of Materials Processing Technology, 153–154: 1026–1032.

[68] Rafiq, M.Y.; Bugmann, G.; Easterbrook, D.J. (2001) Neural network design for engineering Applications. Computers and Structures. 79(17): 1541–1552.

[69] Raghuraman, S. (2013) Optimization of EDM parameters using Taguchi method and Grey relational analysis for Mild steel IS 2026. International Journal of Innovative Research in Science, Engineering and Technology, 2(7): 3095-3104.

[70] Rajendran, S.; Marimuthu, K.; Sakthivel, M. (2013) Study of Crack Formation and Resolidified Layer in EDM Process on T90Mn2W50Cr45 Tool Steel. Materials and Manufacturing Processes, 28(6): 664-669.

[71] Rajesh, R.; Anand, M.D. (2012) The Optimization of the Electro-Discharge Machining Process Using Response Surface Methodology and Genetic Algorithms. International Conference on Modelling,

Optimization and Computing, Procedia Engineering, 38: 3941–3950.
[72] Rao, G.K.; Janardhana, G.R.; Rao, D.H.; Rao, M.S. (2008) Development of hybrid model and optimization of metal removal rate in electric discharge machining using artificial neural networks and genetic algorithm. ARPN Journal of Engineering and Applied Sciences, 3(1): 19-30.
[73] Reza, M.S.; Hamdi, M.; Azmir, M.A. (2010) Optimization of EDM injection flushing type control parameters using grey relational analysis on AISI 304 stainless steel work piece. National Conference in Mechanical Engineering Research and Postgraduate Students, 26-27 May, Pahang, Malaysia, pp. 564-571.
[74] Ross, P.J. (1988) Taguchi techniques for quality engineering. McGraw-Hill Book Company: New York.
[75] Roy, R.K. (1990) A primer on Taguchi method. Van Nostrand Reinhold: New York.
[76] Rumelhart, D.; McCelland, J. (1989) Parallel distributed processing. Vol 1, MIT Press: Cambridge.
[77] Saha, S.K.; Choudhury, S.K. (2009) Experimental investigation and empirical modeling of the dry electric discharge machining process. International Journal of Machine Tools and Manufacture, 49(3-4): 297–308.
[78] Sanchez, H.T.; Estrems, M.; Faura, F. (2011) Development of an inversion model for establishing EDM input parameters to satisfy material removal rate, electrode wear ratio and surface roughness. The International Journal of Advanced Manufacturing Technology, 57(1-4): 189–201.
[79] Singh, S. (2012) Optimization of machining characteristics in electric discharge machining of 6061Al/Al_2O_3p/20P composites by grey relational analysis. The International Journal of Advanced Manufacturing Technology, 63(9-12): 1191–1202.
[80] Sivasankar. S.; Jeyapaul, R. (2013) Performance study of tool Materials and optimization of process parameters during EDM on ZrB2-SiC composite through particle swarm optimization Algorithm. International Journal of Engineering, Science and Technology, 5(1): 133-159.
[81] Sohani, M.S.; Gaitonde, V.N.; Siddeswarappa, B.; Deshpande, A.S. (2009) Investigations into the effect of tool shapes with size factor consideration in sink electrical discharge machining (EDM) process. The International Journal of Advanced Manufacturing Technology, 45(11-12): 1131–1145.
[82] Solhjoei, N.; Vafaei, A.; Khalilzadeh, F.; Vafaei, K. (2012) Investigation on Electro Discharge Machining of H13. Research Journal of Applied Sciences, Engineering and Technology, 4(17): 3005-3014.
[83] Soni, J.S.; Chakraverti, G. (1994) Machining characteristics of titanium with rotary electro-discharge Machining. Wear. 171(1-2): 51-58.
[84] Su, J.C.; Kao, J.Y.; Tarng, Y.S. (2004) Optimisation of the electrical discharge machining process using a GA-based neural network, The International Journal of Advanced Manufacturing Technology, 24(1-2): 81–90.
[85] Syed, K.H.; Palaniyandi, K. (2012) Performance of electrical discharge machining using aluminium powder suspended distilled water. Turkish Journal of Engineering and Environmental Sciences, 36(3): 195-207.
[86] Tao, J.; Shih, A.J.; Ni, J. (2008) Experimental Study of the Dry and Near-Dry Electrical Discharge Milling Processes. Journal of Manufacturing Science and Engineering, Transactions of the ASME, 130(1): 1–9.
[87] Thillaivanan, A.; Asokan, P.; Srinivasan, K.N.; Saravanan, R. (2010) Optimization of operating parameters for EDM process based on the Taguchi method and Artificial neural network. International Journal of Engineering, Science and Technology, 2(12): 6880–6888.
[88] Tsai, K.M.; Wang, P.J. (2001) Predictions on surface finish in electrical discharge machining based upon neural network models. International Journal of Machine Tools and Manufacture, 41(10): 1385–1403.
[89] Tzeng, C.J.; Chen, R.Y. (2013) Optimization of Electric Discharge Machining Process Using the Response Surface Methodology and Genetic Algorithm Approach. International Journal of Precision Engineering and Manufacturing, 14(5): 709-717.
[90] 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.

[91] Wagh, P.B.; Deshmukh, R.R.; Deshmukh, S.D. (2013) Process parameters optimization for surface roughness in EDM for AISI D2 steel by response surface methodology. International Journal of Mechanical Engineering & Technology, 4(1): 203-208.

[92] Wang, C.C.; Yan, B.H. (2000) Blind-hole drilling of Al_2O_3/6061Al composite using rotary electro-discharge machining. Journal of Materials Processing Technology, 102(1-3): 90-102.

[93] Wang, P.J.; Tsai, K.M. (2001) Semi empirical model on work removal and tool wear in electrical discharge machining. Journal of Materials Processing Technology, 114(1): 1-17.

[94] Wong, Y.S.; Lim, L.C.; Lee, L.C. (1995) Effects of Flushing on Electro-Discharge Machined Surfaces. Journal of Materials Processing Technology, 48(1-4): 299-305.

[95] Zarepour, H.; Tehrani, A.F.; Karimi, D.; Amini, S. (2007) Statistical analysis on electrode wear in EDM of tool steel DIN 1.2714 used in forging dies. Journal of Materials Processing Technology, 187–188: 711–714.