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Latest Research Trend of optimization Techniques in Electric Discharge Machining (EDM): Review Article

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Abstract

Electrical Discharge Machining (EDM) is a non conventional machining process which can be used to machine electrically conductive work piece. The electric discharge machine provides an effective solution for machining hard conductive materials and reproducing complex shapes. EDM involves the phenomena such as: spark initiation, dielectric breakdown, and thermo-mechanical erosion of metals. High cost of non conventional machine tools, compared to conventional machining, Optimization is one of the techniques used in manufacturing process area to arrive for the best manufacturing conditions, which is an essential need for industries towards manufacturing of quality products at lower cost. In this paper various optimization technique such as Taguchi method, artificial neural network (ANN), Genetic Algorithms (GA), grey relational analysis (GRA), Response Surface Methodology (RSM) used in the field of electric discharge machining process. The main objectives of optimization are to (i) maximize the material removal rate (MRR), (ii) minimize the surface roughness value and (iii) maximize the tool wear ratio.

***Key words:** EDM, MRR, TWR, EWR, SR, SQ, GRA, RSM, ANN, GA etc*

1. Introduction

1.1 Introduction of EDM

Electrical Discharge Machining (EDM) is non traditional, high precision metal removal process using thermal energy by generating a spark to erode the workpiece. The workpiece must be a conductive electricity material which is submerged into the dielectric fluid for better erosion. EDM machine has wide application in production of die cavity with large components, deep small diameter hole and various intricate holes. The EDM process was invented by two Russian scientists, Dr. B.R. Lazarenko and Dr. N.I. Lazarenko in 1943. The first numerically controlled EDM was invented by Makino in Japan. It is also used for finishing parts for aerospace and automotive industry and surgical components. This technique has been developed in the late 1940s where the process is based on removing material from a part by means of a series of repeated electrical discharges between tool called the electrode and the work piece until the gap is small enough so that the impressed voltage is great enough to ionize the dielectric. Short duration discharges are generated in a liquid dielectric gap, which separates tool and work piece. The material is removed with the erosive effect of the electrical discharges from tool and work piece. EDM does not make direct contact between the electrode and the work piece where it can eliminate mechanical stresses chatter and vibration problems during machining. The basic EDM system consists of an electrode and the work piece connected to a DC power supply and placed in a di-electric fluid. EDM process showing in the fig.1

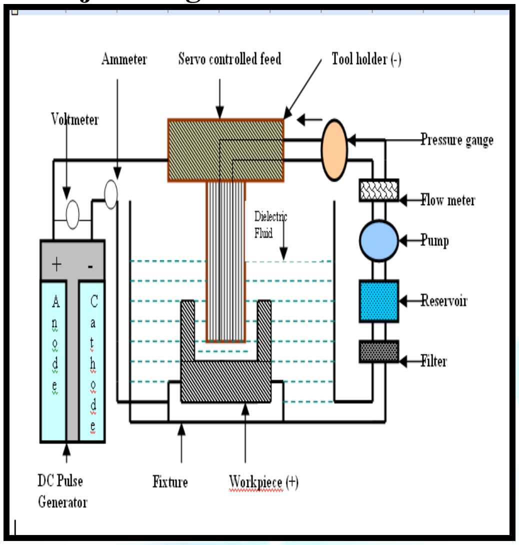

Figure.1 EDM process [Choudhary & Jadoun (2014)]

1.2 Application, Advantages & Limitations of Electric Discharge Machining

TABLE-1

Applications	Advantages	Limitations
1. used for mould & die - making tool but is becoming a common method of making prototype and production parts, especially in the aerospace, automobile and electronics industries 2. Slots, keyways, square & hex drives Gears, splines 3. Small or deep holes, especially in hardened 4. Removal of broken taps and drills 5. Hard tapping 6. Machining of carbide	1. Machining complex & intricate shape. 2. Internal corners down to R .001[.025mm] 3. Small features down to .004" [.10mm] 4. Very high accuracy process 5. Precise control of surface finish 6. No cutting forces 7. High degree of automation 8. Virtually no geometric limitations 9. Machining hard material	1. The need for electrical conductivity 2. Predictability of the gap 3. The slow rate of material removal. 4. The additional time and cost used for creating electrodes for ram/sinker EDM. 5. Taper effect at the edge of machined cavity 6. Specific power consumption is very high. 7. Power consumption is high.

1.3 Principle of Electric Discharge Machining

- In this process the metal is removed from the work piece due to erosion caused by rapidly recurring spark discharge taking place between the electrode (tool) and work piece.
- A thin gap of about *5 micrometer* is maintained between the tool and work piece by a servo system as shown. Both tool and work piece are submerged in a dielectric fluid. Kerosene/EDM oil is *a* very common type of liquid dielectric *used,* although, gaseous dielectrics are also used in certain cases.
- The tool is made cathode and work piece as anode.
- When the voltage across the gap becomes sufficiently high it discharges through the gap in the form of a spark in an interval ranging from 10µs to few hundred µs.
- Positive ions and electrons are accelerated (as shown in fig 1.), producing a discharge channel that becomes conductive. It is just at this point when the spark jumps causing collisions between ions and electrons creating a channel of plasma, a sudden drop

of the electric resistance of the previous channel allows that current density reach a very high value producing an increase of ionization and the creation of a powerful magnetic field.

- The moment spark occurs; sufficient pressure develops between work and tool as a result of which a very high temperature is reached - and at such high pressure and temperature some metal is melted and eroded. Such localized extreme rise in temperature leads to material removal. Material removal occurs due to instant vaporization of the material as well as due to melting.
- The molten metal is not removed completely but only partially. Once the potential difference is withdrawn, the plasma channel no longer sustains. As the plasma channel collapses, it generates a pressure (shock waves), which evacuates the molten material thus forming & at such high pressure and temperature some metal is melted and eroded. Such localized extreme rise in temperature leads to material removal. Material removal occurs due to instant vaporization of the material as well as due to melting.

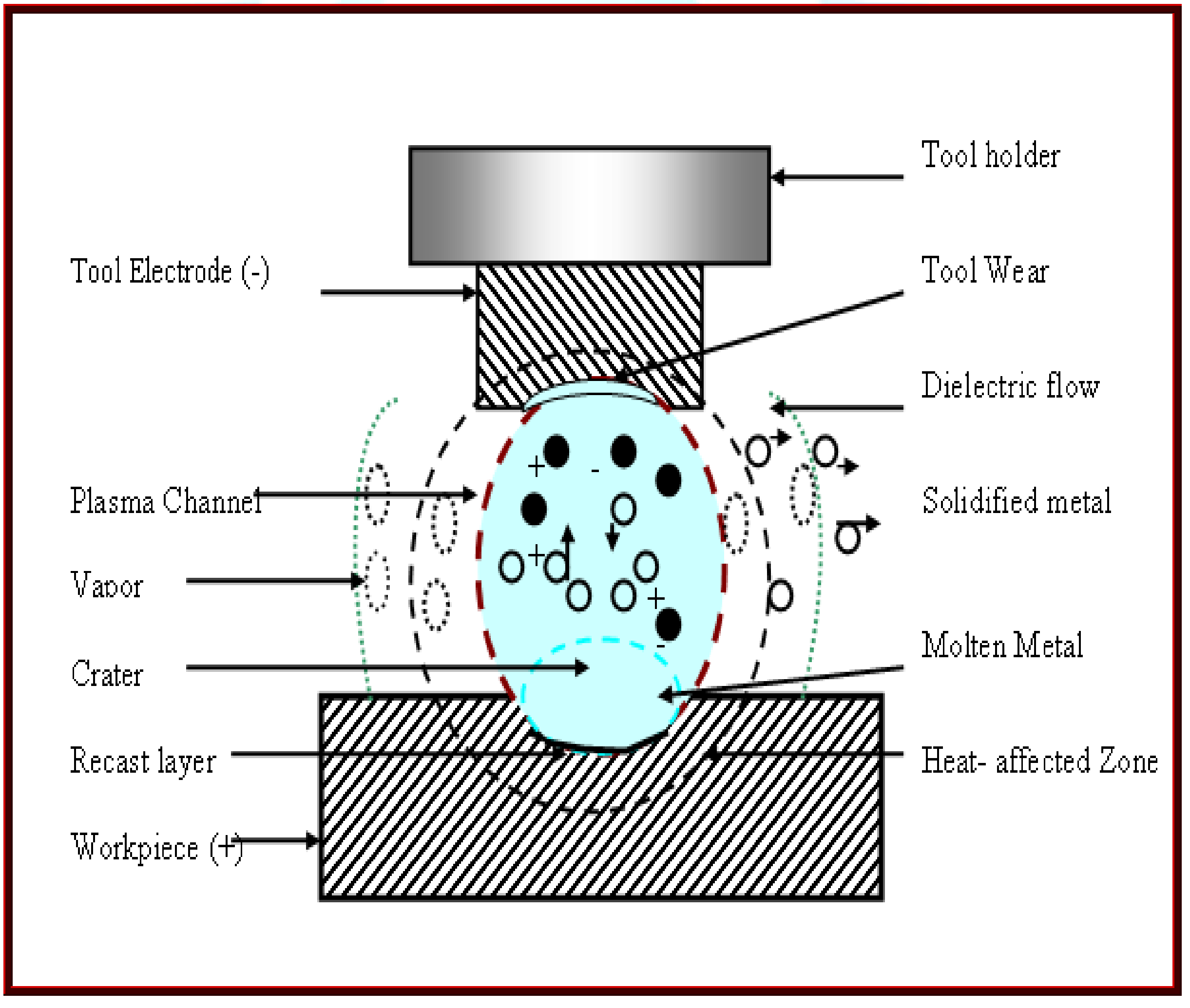

Fig. 2 Principle of Electric Discharge Machining

1.4 Important parameters of EDM

EDM Parameters mainly classified into two Categories

1. *Process parameters:* The process parameters in EDM are used to control the performance measures of the machining process. Process parameters are generally controllable machining input factors that determine the conditions in which machining is carried out. These machining conditions will affect the process performance result, which are gauged using various. Process parameters classified into two categories one is Electrical parameters & other is non Electrical parameters.

2. *Performance measures:* These parameters measure the various process performances of EDM results.

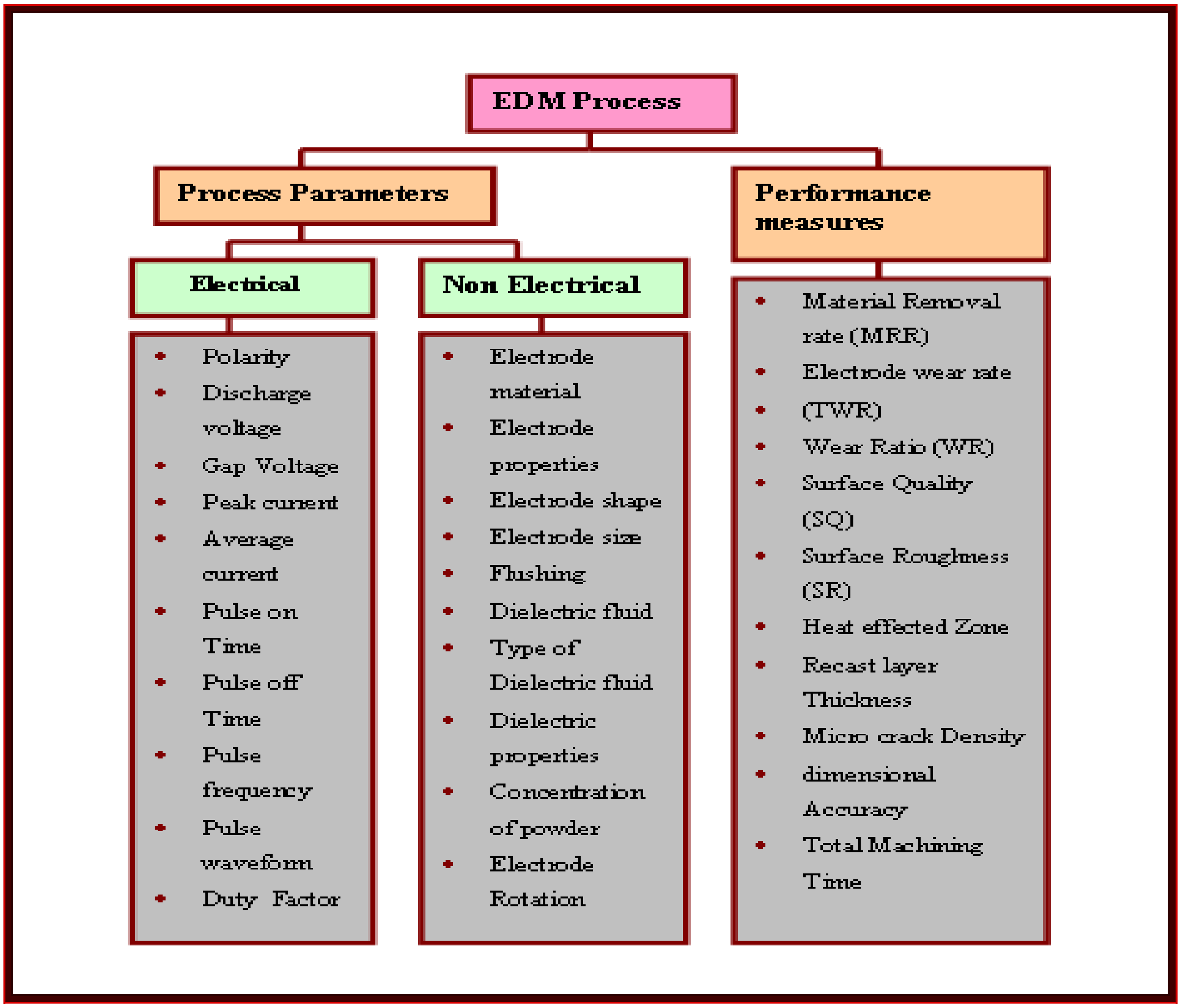

Figure-3 Parameters Classification

1.5 Some important Definition process & performance parameters

TABLE- 2

S.N.	Process parameter	Effect on machining condition

1.	Pulse on time	The pulse on time (*ton*) represents the duration of discharge and is the time during which the electrode material is heated by the high temperature plasma channel. A longer pulse on time will increase the discharge energy.
2.	Pulse off time	The pulse off time (*toff*) represents the duration when no discharge exists and the dielectric is allowed to deionise and recover its insulating properties. A longer pulse off time improves machining stability as arcing is eliminated.
3.	Voltage	The input voltage applied across the tool electrode and workpiece is called the open circuit voltage (*VOC*). The amount of *VOC* influences the spark gap distance. During discharge, *VOC* drops to the discharge voltage (*Vd*) which is influenced by the strength of the dielectric. A larger *Vd* will increase the discharge energy. As *Vd* varies during *ton*, its magnitude may be expressed as an average discharge voltage (*Vav*).
4.	Current	The discharge current (*Id*) is a measure of the amount of electrical charges flowing between the tool and workpiece electrode. As the flow of electrical charges is the primary heating mechanism in electro-thermal erosion, a higher *Id* will increase the discharge energy. As *Id* from an RC-type pulse generator is not constant during *ton*, the magnitude of *Id* may be expressed as a peak current (*Ipk*) or average discharge current (*Iav*).
5.	Discharge energy	This is the electrical energy that is available for material removal. It may be expressed as input discharge energy (*Ein*) or measured discharge energy (*Em*). In an RC-type pulse generator, *Ein* depends on the applied capacitance and *VOC*. The magnitude of *Em* is calculated from measured pulse on time, discharge voltage and discharge current values.
6.	Electrode polarity	Electrode polarity is chosen based on the requirement of electrode wear dominance at a given pulse on time. In micro-EDM, the tool electrode has negative polarity so that wear of the workpiece dominates.
7.	Discharge gap distance	This is the maximum distance separating the anode and cathode at which sustainable discharge is possible. It is influenced by the open circuit voltage and strength of dielectric.
8.	Dielectric	The dielectric serves as a medium in which controlled electrical discharges may be generated. It restricts plasma channel growth and influences the force of plasma channel implosion and expulsion of molten material. The dielectric cools expelled molten material into debris while its flow through the discharge gap aids in debris flushing and cools the electrode by drawing heat away from the discharge location.
9.	Flushing method	Flushing refers to the process of clearing machining debris from and supplying fresh dielectric to the discharge gap. Inadequate flushing causes accumulation of debris within the discharge gap that will lead to unstable machining. The method of flushing used largely depends on the tool electrode and machined feature dimensions.
S. N.	Performance	Process performance results

	parameters	
1.	Material removal rate (MRR)	MRR is a performance measure for the erosion rate of the workpiece and is typically used to quantify the speed at which machining is carried out. It is expressed as the volumetric amount of workpiece material removed per unit time
2.	Tool wear rate (TWR)	TWR is a performance measure for the erosion rate of the tool electrode and is a factor commonly taken into account when considering the geometrical accuracy of the machined feature. It is expressed as the volumetric amount of tool electrode material removed per unit time.
3.	Wear ratio (WR)	WR is the ratio of TWR/MRR and is used as a performance measure for quantifying tool-workpiece material combination pairs since different material combinations gives rise to different TWR and MRR values. A material combination pair with the lowest WR indicates that the tool-workpiece material combination gives the optimal TWR and MRR condition.
4.	Surface quality (SQ)	Surface quality is a broad performance measure used to describe the condition of the machined surface. It comprises components such as surface roughness (SR), extent of heat affected zone (HAZ), recast layer thickness and micro-crack density.

2. Optimization technique

Various optimization Technique generally used for improvement & optimization of performance measure of EDM process have been described below.

2.1. Taguchi Method

Taguchi Method is a new engineering design optimization methodology that improves the quality of existing products and processes and simultaneously reduces their costs very rapidly, with minimum engineering resources and development man-hours. The Taguchi Method achieves this by making the product or process performance "insensitive" to variations in factors such as materials, manufacturing equipment, workmanship and operating conditions. Taguchi‟s philosophy is founded on the following three very simple and fundamental concepts (Ross, 1988; Roy, 1990):

- Quality should be designed into the product and not inspected into it.
- Quality is best achieved by minimizing the deviations from the target. The product or process should be so designed that it is immune to uncontrollable environmental variables.
- The cost of quality should be measured as a function of deviation from the standard and the losses should be measured system-wide.

Taguchi proposes an “off-line” strategy for quality improvement as an alternative to an attempt to inspect quality into a product on the production line. He observes that poor quality cannot be improved by the process of inspection, screening and salvaging. No amount of inspection can put quality back into the product. Taguchi recommends a three-stage process: system design, parameter design and tolerance design (Ross, 1988, Roy, 1990).
Taguchi method is significantly disciplined mechanism for evaluating and implementing improvement in products or processes. These improvement are aim at improving the desired characteristics by studying the key variables controlling the process and optimizing the procedure 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 appropriate columns. the use of linear graph & triangular tables suggested by Taguchi makes the assignment of parameters simple (Roy,

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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 help to determine which of the parameters need control (Ross, 1988). Taguchi method use a statistical measure of performance called signal to noise ratio. The S/N ratio can be use to measure the deviation of the performance characteristics from the desire 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

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

- Smaller the Better Characteristics

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

- Nominal-the better characteristics

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

Where y_i is the experimentally observed value and n is repeated number of each experiment y^{-} is the average of observed data and Sy^2 is the variance of y_i for each type of characteristics, with the above S/N transformation, The higher the S/N ratio the better is the result.

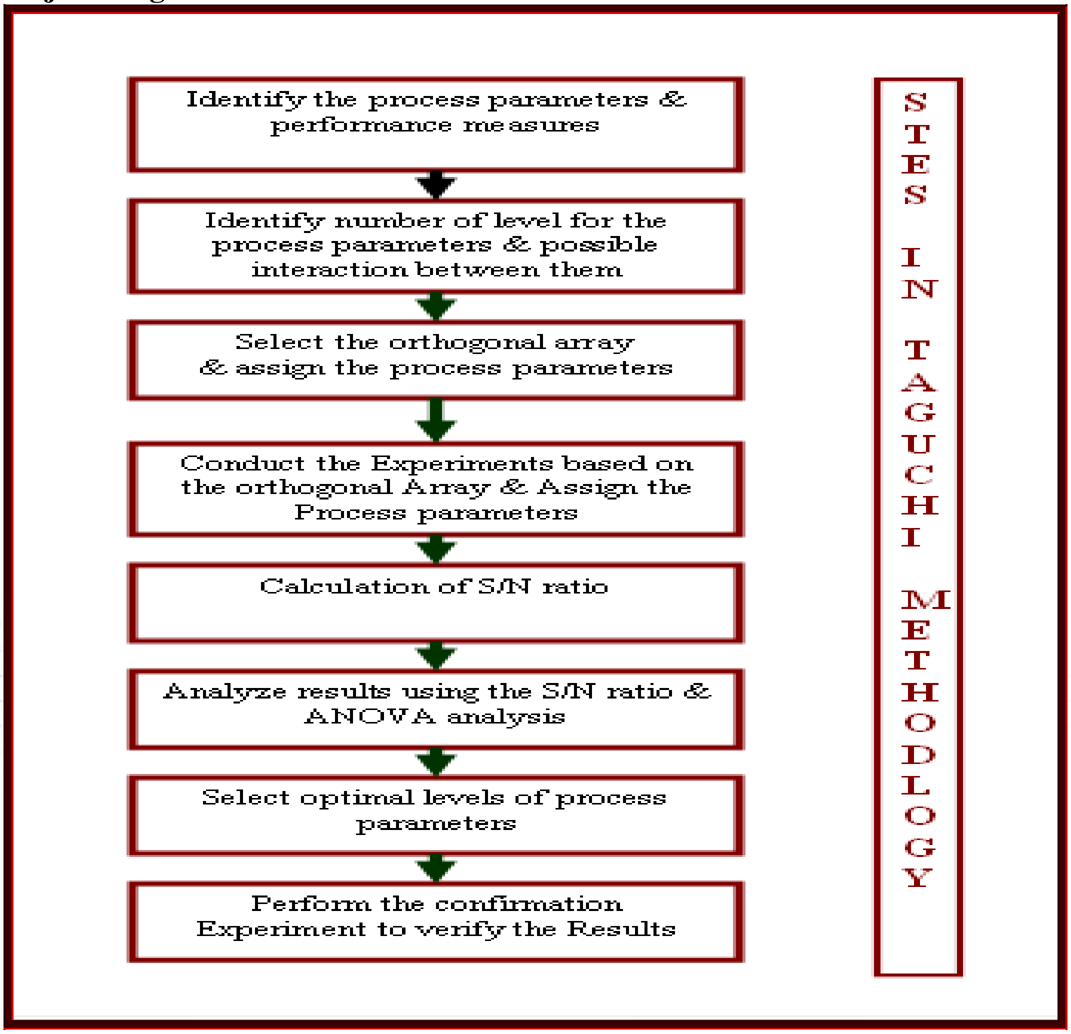

Fig. 4 Steps of Taguchi Methodology

2.1.1 Summary of Taguchi optimization Technique used in improving & optimization performance measure of EDM

TABLE-3

S. No.	Author/ year	Process & Performance parameters	Remark
1.	Wang & Tsai (2001)	Polarity, Servo Std. voltage, Discharge time, Quiescent time, Peak Current, main power Voltage, temp. Of Dielectric fluid, tool material, work material, MRR, & TWR	A Semi empirical model of the material removal rate on the work & tool for various material is established by employing dimensional Analysis
2.	George et al.(2004)	Pulse on-time. Pulse current , gap voltage, MRR &TWR	The EDM process variable affecting MRR &TWR according to their relative significance, are Gap voltage, peak current, pulse on-time respectively.

3.	Lin et al.(2006)	Polarity, peak current, auxiliary current with high voltage, Pulse duration, servo reference, MRR, EWR & Surface roughness	EDM Process is used to machine SKH 57HSS, IT IS Observed that the material removal rate, tool wear rate & surface roughness increased with the peak current.
4.	Kansal et al. (2006)	Peak current, Pulse duration, Duty Cycle, Powder concentration MRR, TWR,& SR	Concentration of added silicon powder in dielectric fluid & peak current are the most influential parameters for TWR,MRR, & surface roughness
5.	Kansal et al. (2007)	Peak current, pulse on time, Pulse off time, Gain , nozzle flushing, powder concentrations & MRR	Powder mixing into the dielectric fluid in EDM achieved the better MRR at desired surface quality
6.	Tzeng &Chen (2007)	Open circuit voltage, Pulse duration, peak current, Powder concentration, Electrode Lift, time interval for electrode lift, Precision Accuracy	Simple & efficient in developing a high speed Electric discharge machining process capability.
7.	Khandare & Popat (2009)	Current, pulse time, work material, MRR, Surface Roughness	It observed that most important factor for MRR & SR is current density
8.	Chattoopad hyaa et al. (2009)	Peak current, pulse on time, electrode rotation, MRR, EWR, Surface Roughness,	In this method used to determine the main influence factor affecting the Selected performance measure variables such as MRR, EWR & SR
9.	Govindan & Joshi (2010)	Discharge current, Gap Voltage, pulse off Time, Gas pressure, Electrode Speed, Radial Clearance shield at bottom, MRR, TWR	At low discharge energies, single-discharge in dry Electric discharge Machining could give larger MRR & crater radius compared to dielectric EDM.
10.	Nipanikar & 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 & radial overcut , pulse on time significantly affects the EWR.
11.	Kumar et al.(2012)	Peak current, pulse on time, polarity, Duty cycle, gap voltage, Retract distance concentration of fine graphite powder, TWR, Wear ratio	TWR &WR are minimum with the use of cryogenically treated Cu electrode
12.	Syed & Palaniyandi (2012)	Peak current, pulse on time, polarity, concentration Al. of the powder, MRR, EWR, SR, White layer thickness	Addition of Al powder in distill water is result in high MRR , good surface finish,& minimum .white layer thickness
13.	Nipanikar (2012)	Peak current, gap voltage, duty cycle, pulse on time, MRR, EWR Radial overcut, ROC	The analysis using Taguchi method reveals that, in general the peak current significantly affects the MRR, EWR and ROC
14.	Kumar A. et	Electrode polarity, electrode type,	By optimizing the machining parameters

	al.(2013)	peak current, pulse on time, duty cycle, gap voltage, flushing pressure & abrasive concentration in dielectric fluid, effect on dimensional accuracy in terms of overcut.	the overcut is minimized which enhances the quality of machining process.
15.	Vhatkar et al. (2013)	Peak current, Pulse on time, Pulse off time, gap voltage, and concentration of fine silicon powder added, MRR & SR	With the addition of the powders in the dielectric, MRR has been increased to a great extent and the SR has been reduced. Silicon gives better results in terms of MRR & SR.
16.	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 time, & pulse off time to identify the variations in MRR. Tool wear ratio, surface roughness is carried out.
17.	Amit et al. (2013)	peak current, Pulse on Time, Jet pressure & MRR	EDM Drilling and Taguchi technique is used for the optimization of response variables.
18.	Khanna & Garg (2013)	Pulse on time, pulse off time, current, voltage & MRR	For MRR, The Influencing factor in Descending order are arc voltage, discharge current, pulse on time & pulse off time etc.
19.	Modi, M. et al. (2013)	Current, pulse-duration, wheel-speed, duty-cycle and powder-concentration, MRR & SR.	It is observed through ANOVA analysis in the WPC approach that the percentage contribution of various process parameters is powder concentration (19%), pulse on-time (1.5%), wheel speed (1.5%), duty cycle (7%) and current (61%) for the responses under the multi output optimization (maximization of MRR & Minimization of *Ra*) in the PMEDDSG of Ti-6Al- 4V.
20.	Bergaley et al. (2013)	voltage ,current pulse on time , pulse off time , dielectric fluid material , flushing pressure, tool rotation, MRR,& EWR	Electrical and non electrical factors which influence MRR and EWR such as voltage, current pulse on time, pulse off time, dielectric fluid material, flushing pressure, tool rotation etc. Both factors has been focused which governs MRR, EWR and there optimization.
21.	Goyal et al. (2014)	Current, Voltage, Pulse on time, Duty factor constant and by varying two parameters i.e. Grain size of Al. powder & Concentration of Al. powder, MRR & Surface Roughness	Grain size of powder and concentration of powder have a great influence on the SR & MRR) in powder mixed EDM.
22.	Singh, S.S.(2014)	Pulse on time, pulse on time, current	The optimal setting of process parameters for optimum roughness is pulse on time (24µs) pulse off time (9µs) & current (5amp)

2.2 Genetic Algorithm Technique

Genetic algorithms are inspired by Darwin's theory about evolution. Solution to a problem solved by genetic algorithms is evolved. Algorithm is started with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce. Genetic algorithm possesses advantages that do not require any inherent parallelism and gradient information in searching the design space. Now it is a robust adaptive optimization technique. Some researchers investigated GA application in EDM. Long back used a multi objective optimization method, non-dominating sorting genetic algorithm-II to maximize the result of the process. This provides an optimization model based on genetic algorithms for EDM parameters to imitate a decision. Genetic algorithms find application in bioinformatics, phylogenetic, economics, computational science, engineering, chemistry, manufacturing, pharmacometrics, mathematics, physics and other fields.
Outline of the Basic Genetic Algorithm

1. *Start*-Generate random population of *n* chromosomes (suitable solutions for the problem)
2. *Fitness*-Evaluate the fitness $f(x)$ of each chromosome x in the population
3. *New population*-Create a new population by repeating following steps until the new population is complete

    i. *Selection*-Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
    ii. *Crossover*-With a crossover probability cross over the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.
    iii. *Mutation*-With a mutation probability mutate new offspring at each locus (position in chromosome).
    iv. *Accepting*-Place new offspring in a new population

4. *Replace*- Use new generated population for a further run of algorithm
5. *Test*-If the end condition is satisfied, stop, and return the best solution in current population
6. *Loop*-Go to step 2

The steps to apply GA in optimization of machining are as follows (Wang & Jawahir, 2004).
(i) The process parameters are encoded as genes by binary encoding.
(ii) A set of genes is combined together to form a chromosome, which is used to perform those basic mechanisms in the GA, such as crossover and mutation.
(iii) Crossover is the operation to exchange some part of two chromosomes to generate new offspring, which is important when exploring the whole search space rapidly.
(iv) Mutation is applied after crossover to provide a small randomness to the new chromosome.
(v) To evaluate each individual or chromosome, the encoded process parameters are decoded from the chromosome and are used to predict machining performance measures.
(vi) The fitness or objective function is a function needed in the optimization process and the selection of the next generation in the GA.
(vii) After a number of iterations of the GA, optimal results of process parameters are obtained by comparison values of objective functions among all individuals.

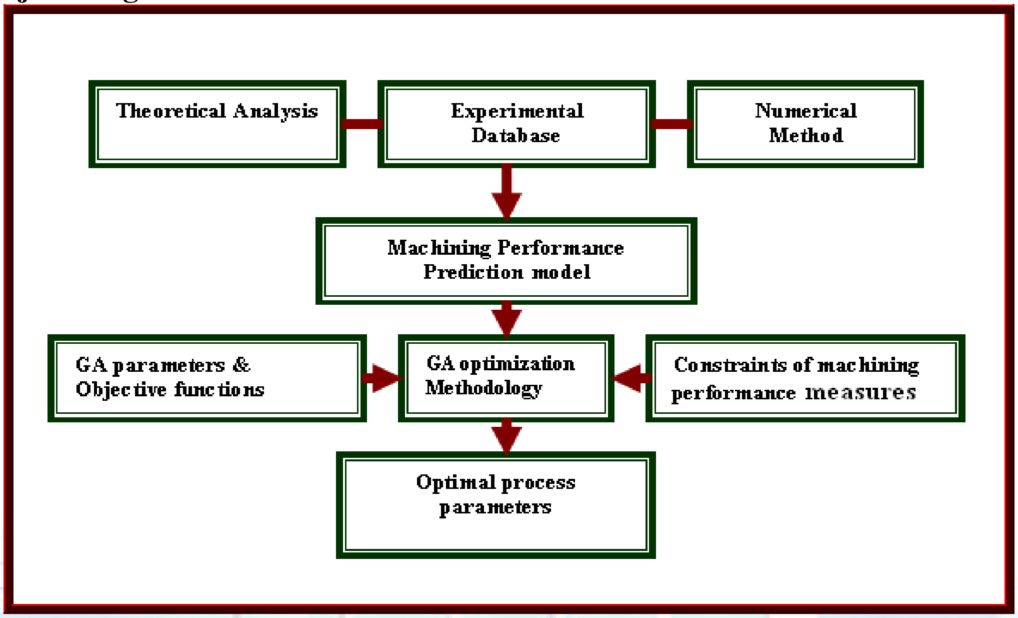

Fig.5 Flow chart diagram for Genetic algorithm

2.2.1 Summary of GA optimization Technique used in improving & optimization performance measure of EDM

TABLE-4

S. No	Author/ year	Process & performance parameters	Remark
1.	Su et al. (2004)	Pulse-on time, pulse off time, high-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 suitable for automatically selecting in optimal process parameters set according with the desire machining performances.
2.	Mahapatra & Patnaik (2007)	Discharge current, pulse duration, pulse frequency, wire speed, wire tension, dielectric flow, MRR, surface roughness and Cutting width (kerf).	The process parameters of WEDM can be adjusted to achieve improved machining performances simultaneously
3.	Gao et al. (2008)	Current, pulse on time and pulse off time & MRR	MRR is improved by using optimized parameters.
4.	Kolahan et al. (2008)	Discharge current Pulse on time, Grain size of Aluminum powder, concentration of powder, MRR & EWR.	Optimize the desire output value. such as MRR increase & reduced the electrode wear
5.	Maji & Pratihar(2010)	Peak current, pulse-on-time, pulse-duty factor, Surface roughness & MRR	The optimal results found to be satisfactory and Pareto-optimal front of solutions had been obtained

6.	Pasam et al. (2010)	Ignition pulse current, short pulse duration, time between two pulses, servo speed, servo reference voltage, injection pressure, wire speed, wire tension , Surface roughness	The optimal values of machining process parameters at level for the selected range and workpiece material are obtained
7.	Mahdavinajad (2011)	Discharge current, pulse on time, pulse off time, MRR & Surface finish	A multi optimization method NSGA-II is applied & finally pareto-optimal sets of MRR & SR are obtained.
8.	Karuvila & Ravindra (2011)	Pulse-on duration, current, pulse-off duration, bed-speed , flushing rate, Dimensional error, surface roughness, & volumetric MRR	The results confirm the efficiency of the approach employed for optimization of process parameters in this study
9.	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 & forcibly allows the solution from each non-dominating front to co-exist in the population which leads to true optimal solutions.
10.	Padhee et al. ((2012)	Peak current, Pulse on time, Duty cycle, Concentration of powder in dielectric fluid, MRR& Surface finish.	In order to simultaneously optimize Both MRR & SR, NSGA II is adopted to obtain the Pareto optimal solution.
11.	Rajesh & Anand (2012)	Working current , working voltage, oil pressure, & spark Gap, pulse on- time, pulse off time, MRR & Surface finish	GA Based multiobjective optimization for maximization of MRR & minimization of SR is done by using the developed empirical models.
12.	Tzeng & Chen (2013)	Discharge current, gap voltage, pulse on-time, pulse off time, MRR, EWR& Surface Roughness	GA approach has better prediction & conformation result then the RSM method.

2.3. Response surface method

In statistics, Response surface methodology (RSM) investigates the interaction between several illustrative variables and one or more response variables. Box and Draper [1987] were introducing RSM in 1951.The most important proposal of RSM is to use a series of designed experiments to attain an optimal response. A second-degree polynomial model is use in RSM. These models are only an approximation, but use it because such a model is easy to estimate and apply, even when little is known about the process. The response surface methodology (RSM) is a collection of mathematical and statistical technique useful for the modeling and Analysis of problems in which a response of interest is influenced by a several variables and the objective is to optimize the response (Montgomery, 2005). It used in the development of an adequate functional relationship between responses of interest.

This model is known as quadratic model, which is as follows:-

If the response surface, defined by a linear function of independent variables. Then the approximate function is first order model:

First order model can be expressed as

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \qquad \ldots (4)$$

If there is a curvature in the response surface, then a higher degree polynomial should be used.

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i,j=1,\ i\neq j}^{k} \beta_{ij} X_i X_j + \varepsilon \qquad \ldots. (5)$$

Where ε is the noise or error observed in the response Y. Xi is the linear input variables, X^2ii and XiXj are the squares and interaction terms, respectively, of these input variables. The unknown second order regression coefficients are βo, βi, βij and βii, which should be determined in the second-order model, are obtained by the least square method. The process of RSM includes designing of a series of experiments for sufficient and reliable measurement of the response and developing a mathematical model of the second order response surface with the best fittings. Obtaining the optimal set of experimental parameters, thus produce a maximum or minimum value of the response. The Minitab Software was used to analyze the data.

2.3.1 RSM Optimization Technique Summary Performance parameters in EDM
TABLE-5

S. No.	Authors /year	Process & Performance parameters	Remark
1.	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.	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.
3.	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.
4.	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.
5.	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.
6.	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.
7.	Kuppan et al. (2008)	Peak current, pulse on time, duty factor, electrode speed, MRR and	MRR is more influenced by peak current, duty factor and electrode rotation; where as strongly

		depth averaged surface roughness	influenced by peak current and pulse on time.
8.	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.
9.	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.
10.	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.
11.	Saha & 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.
12.	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.
13.	Pradhan, M.K. et al (2009)	Discharge current, pulse duration, pulse off time, surface Roughness (SR)	It is found that discharge current, pulse duration, and pulse off time and few of their interactions have significant effect on the SR.
14.	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.
15.	Patel et al. (2011)	Discharge current, pulse on time, duty cycle, gap voltage, MRR, EWR, surface roughness	EDM material unevenness increases with discharge current and pulse on time and the recast layer thickness increases with the pulse on time.
16.	Sanchez et al. (2011)	Peak current, pulse in 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 insure the simultaneous fulfillment of MRR, EWR and SR is developed.
17.	Ojha et al. (2011)	Peak current, pulse on time, diameter of electrode & concentration of chromium powder, MRR & TWR.	These parameters affecting selected performance measures have been identified and optimum process conditions have been found.
18.	Padhee et al. (2012)	Concentration of powder in the dielectric fluid, pulse in 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.
19.	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 & voltage are developed.
20.	Rajesh and Anand (2012)	Working current, working voltage, oil pressure, spark gap pulse on	Empirical models for MRR and SR are developed by conduction a designed

		time, pulse off time, MRR, surface finish	experiment.
21.	Jabbaripour et al. (2012)	Pulse current, pulse on time, open circuit voltage, MRR, TWR	Increase of pulse energy by increasing pulse current of pulse on time leads to increase of average thickness and micro hardness of recast layer.
22.	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.
23.	Assarzadeh and Ghoreishi (2013)	Discharge current, pulse in 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.
24.	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.
25.	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.
26.	Tzeng and Chen (2013)	Discharge current, gap voltage, pulse in 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.
26	Khalid Hussain Syed (2013)	Pulse peak current, pulse on-time and concentration of Al powder, White layer Thickness,	Optical microscopy results show that low thickness of white-layer 17.14 μm is obtained at high concentration of powder of 4 g/l and low peak current of 6 A.
27	Sahoo, M. et al. (2013)	Discharge current(Ip), pulse duration(Ton), duty cycle(τ), MRR electrode wear rate(EWR)	The process parameters with significant influence on MRR & EWR were determined by using RSM.

2.4. Grey relational analysis (GRA)

GRA theory developed for the new methods for solving the complicated the inter relationship among the multiple performing characteristics. In grey system theory includes three types of systems first black which shows no information in this system, second white which shows all information in this system & third grey system which shows imperfect information. The grey system theory is a efficient technique, which requires a limited information to estimate the behavior of an uncertainty system & discrete data problem. If the sequences range is large, in GRA, the factors are effaceable. Although, if the measured factors are discrete, then wrong results may be produce by GRA. So, for evade this influence, must perform data preprocessing of original experimental data. The range of data processing is zero to one (0-1). Normalizing involves transforming the original sequence to comparable sequence. This is known as grey relational generating. In this study, normalization of the experimental results attained for MRR, TWR & SR.
There are three conditions of normalization-
1) - lower is better

$$\boxed{X_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)}} \quad \dots (6)$$

2) - higher is better

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

3) Nominal the best

$$X_i^*(k) = \frac{1 - \left| X_i(k) - X_0 b(k) \right|}{\max X_i(k) - X_0 b(k)} . \quad \text{.... (8)}$$

But in this study only two conditions are required, lower is better & higher is better.
The normalization is taken by the following equations
where I = 1, 2n, k = 1, 2, y, p; X^*_i (k) is the normalized value of the k_{th} 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 p is the number of quality characteristics.
After the normalization, calculated grey relational coefficient, which shows the interaction between optimal & actual normalized experimental results GRC, can be presented

$$\gamma_i(k) = \gamma(x_0(k)) = \frac{\Delta \min + \zeta \Delta \max}{\Delta_{0,i}(k) + \zeta \Delta \max} \quad \text{...... (9)}$$

I=1; . . . ; n; k= 1; . . . ; p
Where $\Delta_{0,i}(k) = |x_0(k) - x_i(k)|$ is the difference of the absolute value called deviation sequence of the reference sequence $x_0(k)$ and comparability $x_i(k)$. The ξ is the distinguishing coefficient or identification coefficient $0 \leq \zeta \leq 1$. In general, it is set to 0.5. The GRG is a weighting-sum of the grey relational coefficients and it is defined as-

$$\gamma(x_{0,} x_i) = \sum_{n}^{k=1} \beta_k (x_{0,} x_i) .$$

Where β_k represents the weighting value of the k_{th} performance characteris .... (10)
.

$$\sum_{n}^{k=1} \beta_k = 1 . \quad \text{..... (11)}$$

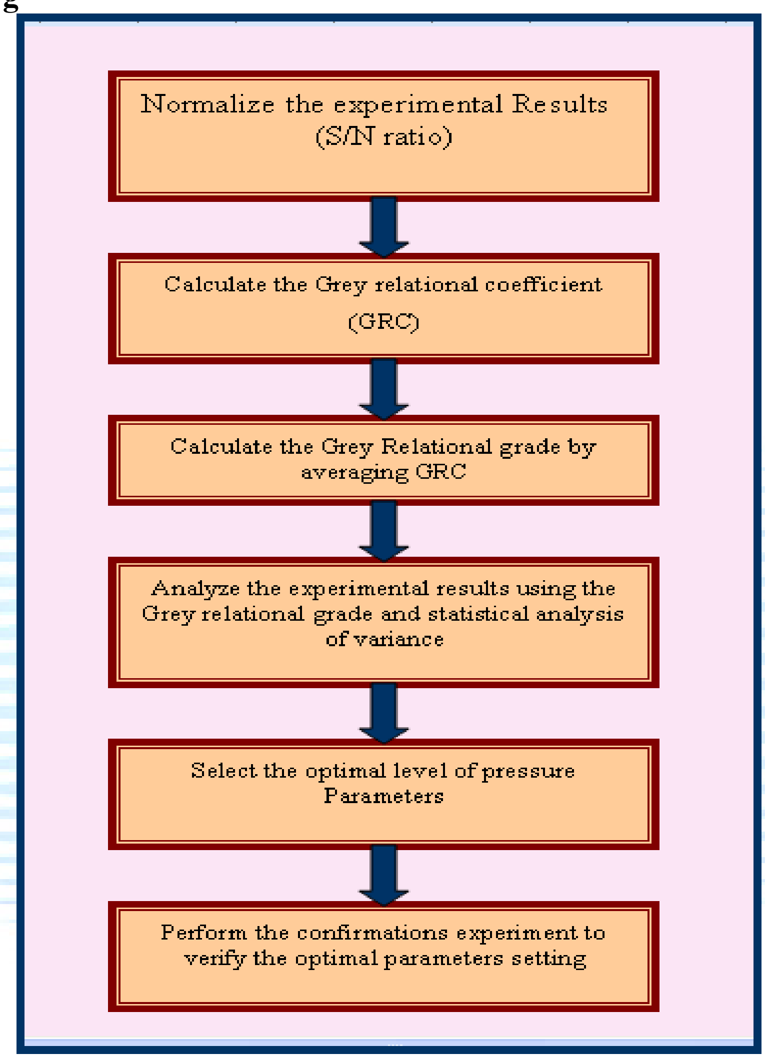

Fig. 6 simple steps in GRA

2.4.1 Summary of GRA in improving and optimizing performance measures of EDM

TABLE-6

S. No.	Authors /year	Process & Performance parameters	Remark
1.	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.
2.	Reza et al. (2010)	Polarity, pulse on duration, discharge current, discharge voltage, machining depth, machining diameter, dielectric	The improvement in grey relational grade after optimization of EDM control parameters is 0.1639.

		liquid pressure, MRR, EWR & SR	
3.	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.
4.	S.Balasubramanian (2011)	Pulse on time, pulse off time, Applied current, Gap voltage, Wire tension and wire feed rate. MRR & SR	Results show that the optimal condition based on the method can offer better overall quality.
5.	Moghaddam et al. (2012)	Peak current, voltage pulse on time, pulse off time, duty factor, MRR, TWR & SR	The combination of Taguchi technique, GRA and simulated annealing algorithm is quite efficient in determining optimal EDM process parameters.
6.	Dhanabalan et al. (2012)	Peak current, pulse on time, pulse off time, MRR, TWR & SR	GRA greatly simplifies the optimization of complicated multiple performance characteristics by converting them into single GRG.
7.	Rajesh & Anand (2012)	Working current, working voltage, oil pressure, spark gap, pulse-on-time pulse-off -time, MRR & surface finish	The most influencing factor obtained by the response table is the working current for the EDM process.
8.	Singh (2012)	Pulse current, pulse on time, duty cycle, gap voltage, tool electrode lift time, MRR, TWR & SR	GRA approach could be applied successfully to other operations in which performance measures are determined by many process parameters at multiple quality requests.
9.	Raghuraman et al. (2013)	Peak current, pulse on time, pulse off time, MRR, TWR & SR	GRA technique effective for optimization of multi response like MRR, TWR and SR.
10.	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%.
11.	V.S.Ganachari et al (2013)	Concentration of powder (Aluminum + Silicon carbide) in the dielectric fluid, pulse on time, duty cycle, gap voltage, peak	Taguchi method with GRA optimization is adopted to study the effect of independent variables on responses and develop predictive

		current, surface roughness	models. Aim of this experimentation is to find the range (level) of parameters to get the good surface finish

2.5 Artificial Neural Network (ANN)

An artificial neural network is an information-processing system that has certain performance characteristics in common with biological neural networks. Artificial neural networks have been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions that:

1. Information processing occurs at many simple elements called neurons.
2. Signals are passed between neurons over connection links.
3. Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted.
4. Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal.

Elements of Artificial Neural Networks: Processing Units, Topology, Learning Algorithm

Applications of ANN: - Pattern Classification, Clustering/Categorization, Function approximation, Prediction/Forecasting, Optimization, Content-addressable Memory, Control

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 7.

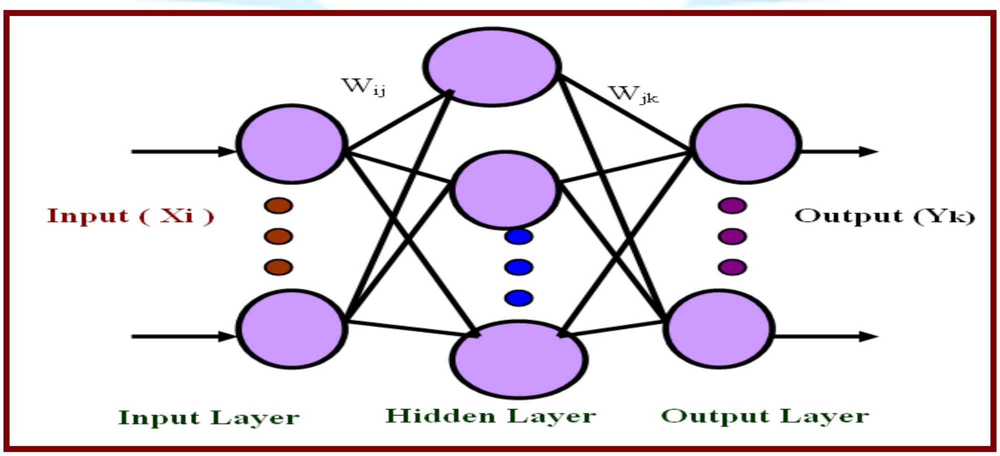

Fig-7 Three-layered feed forward neural network

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.

2.5.1 ANN Optimization Summary improvement in EDM performance

TABLE-7

S. No.	Authors /year	Process & Performance parameters	Remark
1.	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.
2.	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.
3.	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.
4.	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.
5.	Rao et al. (2008)	Peak current, voltage, & MRR	Multi perception neural network models are developed using neuro solutions package and GA concept is used to optimize the weighing factors of the network.
6.	Thillaivanan et al. (2010)	Current, feed. Total machining time.	A feed forward-back propagation neural network is developed to get the parameters for required total machining time. Over size and taper of a hole to be machined by EDM.
7.	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 operation.

8.	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.
9.	Yahya et al. (2011)	Gap current, pulse on time, pulse off time, sparking frequency & MRR	The result has significantly demonstrated that the ANN model is capable of predicting the MRR with low percentage prediction error when compared with the Experimental result.
10.	Andromeda et al. (2011)	Gap current, pulse-on time, pulse off time, sparking frequency & MRR	The capability of ANN to follow the dynamical behavior of the EDM process Is not precisely accurate.
11.	Bharti et al. (2012)	Shape factor, pulse-on-time, discharge current, duty cycle, gap voltage, flushing pressure, tool electrode life time, MRR, & surface finish	The average percentage difference b/w experimental and ANN's predicted value is 4 and 4.67 for MRR and SR respectively.
12.	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.
13.	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 result in the experimental runs than regression models based on the RSM method.
15.	Agrawal A. et al.(2013)	Peak current ,Pulse on time, Pulse of time, Powder concentration, & TWR	Mixing graphite powder in dielectric significantly reduces the TWR during machining of MMC. The peak current has been identified as most significant control factor affecting TWR, followed by powder concentration. The developed ANN model is reliable and adequate to predict the TWR with negligible prediction error.

3-Discussions &Conclusions

- Through the latest optimization technique used in the electric discharge machining (EDM) processes Maximize the material removal rate (MRR), reduced the tool wear rate (TWR) or Electrode wear rate (EWR), improve the surface roughness (SR) & Surface quality (SQ).

- In this paper various approaches like powder additives, different dielectric fluid, tool-workpiece rotation, vibration, cryogenic cooling of electrode, different tool (Electrode) material & work piece, etc. have been used by different researchers for improvement in Electric discharge machining process performance parameters like as: MRR, TWR, SR & SQ etc.

- Most of the researchers have concentrated on optimization of single quality characteristic while in present industries, high productivity & product quality with low production cost are important.

- In this review paper collection of EDM research publications in the field of optimization technique which used in the manufacturing process area to arrive for the best manufacturing conditions, which is an essential need for industries towards manufacturing of quality products at lower cost. Mostly used techniques are Taguchi & RSM.

Table-8 No. of publication work

S.No.	Optimization Method	No. of published work
1.	Taguchi	22
3.	Genetic Algorithms (GA),	12
2.	Response Surface Methodology (RSM)	27
4.	Grey relational analysis (GRA),	11
5.	Artificial Neural Network (ANN)	15

- The researches in optimization of performance measures using latest optimization techniques such as Taguchi, GA, ANN, GRA, RSM, SA, fuzzy logic, desirability, and 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.

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