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Research Paper

Optimization of EDM processparameters: A Review

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Abstract— *The Performance of the Electrical Discharge Machining is generally evaluated on the basis of Material Removal Rate (MRR), Tool Wear Rate (TWR), Relative Wear Ratio (RWR) and Surface Roughness (SR). The discharge current, pulse on time, pulse off time, arc gap, and duty cycle these are the important EDM machining parameters affecting to the performance measures of the process. The researchers has been evaluated the performance of the EDM on the basis of MRR, TWR, RWR, and SR for various engineering materials. The several approaches are identified in the literature to solve the problems related with optimization of these parameters. After the evaluation of these approaches it would help to compare their main features and their relative advantages or limitations to allow choose the most suitable approach for a particular application and also throw light on aspects that needs further attention. In view of above, this paper presents a review of development done in the optimization of EDM related process parameters.*
Keywords*—**EDM, MRR, RWR, SR, Taguchi.***

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I. INTRODUCTION

Electrical Discharge Machining (EDM) is an important manufacturing process for machining hard metals and alloys [2]. This process is widely used for producing dies, molds, and finishing parts for aerospace, automotive, and surgical components [3]. The process is capable of getting required dimensional accuracy and surface finish by controlling the process parameters [4]. EDM performanceis generally evaluated on the basis of Material Removal Rate (MRR), Tool Wear Rate (TWR), Relative Wear Ratio (RWR), and Surface Roughness (SR) [3].

The important EDM parameters affecting to the performance measures of the process are discharge current, pulse on time, pulse off time, arc gap, and duty cycle [9].In EDM, for optimum machining performance measures, it is an important task to select proper combination of machining parameters [13]. Generally, the machining parameters are selected on the basis of operators experience or data provided by the EDM manufactures. When such information is used during Electrical Discharge Machining, the machining performance is not consistent. Data provided by the manufacturers regarding the parameter settings is useful only for most commonly used steels. Such data is not available for special materials like Maraging steels, ceramics, and composites. For these materials, experimental optimization of performance measures is essential. Optimization of EDM process parameters becomes difficult due to more number of machining variables and slight changes in a single parameter significantly affect the process.

Thus, it is essential to understand the influence of various factors on EDM process. Analytical and statistical methods are used to select best combination of process parameters for an optimum machining performance. Different author use different combination of process parameters. They analyze the experimental data by plotting Interaction graphs, Residual plots for accuracy and Response curves. Some other methods used by different author for analysis of Taguchi's DOE data related to Electrical Discharge Machining (EDM) and Wire ElectricalDischarge Machining (WEDM) are Regression analysis,Response Surface Methodology, Central Composite Design (CCD), Feasible-Direction Algorithm, SA algorithm, Pareto, Artificial Bee Colony (ABC), Grey Relational Analysis, Genetic Algorithm, Fuzzy clustering, Artificial Neural Network, Tabu-Search Algorithm, Principle component method etc.

Most of the author used L27 Orthogonal Array. Generally the effect of Pulse ON time, Pulse OFF time, Spark gap set Voltage, Peak current, Flushing Pressure, Work piece height, wire tension and wire feed on the material removal rate, surface roughness, and gap current is investigated.

II. VARIOUS TECHNIQUES FOR OPTIMIZATION OF EDM PROCESS PARAMETERS

The studies use several optimization techniques they may be classical or numerical based and have lead to evolved techniques used in modern technical scenario. After going through the literature the major optimization techniques and tools utilized by the researchers are as follows:

A. RSM Optimization Tools

Central Composite Design, Box-Behnken Design, 3- Level Factorial Design, Hybrid Design , One Factor Design, Pentagonal Design, Hexagonal Design, D-Optimal Design Distance-Based Design, Modified Distance Design, User-Defined Design, Historical Data Design.

B. Other Optimization Technique

Multi-response optimization, artificial neural network, grey entropy, Taguchi Technique, Back Propagation NeuralNetwork, Fuzzy Logic, Linear Regression Technique,Grey-Taguchi Method, simulated annealing, Multi-Objective Genetic Algorithm, Feasible-Direction Algorithm, SA algorithm, Pareto, Artificial Bee Colony (ABC), Tabu-Search Algorithm, Principle component method, Trust region method.

III. ISSUES RELATED TO OPTIMIZATION OF EDM PROCESS PARAMETERS

The optimization process focuses on four vital components these are:

A. Input process parameters

Work Piece Material, Percentage Composition, Electrode Material, Peak Current, Discharge Current, Pulse on time, Pulse off time, Cutting Speed, Dielectric flushing pressure, Arc Gap, Duty Cycle, Taper Angle, Tool Shapes, Tool Area, Voltage, Rotational Speed of Electrode, Feed Rate, Pulse Frequency, Wire Speed, Wire Tension, Dielectric Flow Rate, Spark Gap Voltage, Axial–radial depth of cut, Machining Tolerance.

B. Process performances

Material Removal Rate (MRR), Tool Wear Rate (TWR), Relative Wear Ratio (RWR), and Surface Roughness (SR), kerf (width of cut), Dimensional deviations, Stability factor(S_f).

C. Work piece material

The materials investigated on WEDM generally of HSS and other Tool materials are Hot Die material, Cold Die material, Nickel alloys and Titanium alloys which are hard compare to other material. These materials are AISI M2, AISI D2, AISI D3, AISI D5, AISI H11, AISI 4140, SKD 11, En 16, En 19, En 31, En 32, 1040, 2379, 2738, Inconel,

Ti alloys, Al alloys, 7131 cemented, Tungsten Carbide (WC) , Al 7075-B_4C MMC, Titanium (grade-2), CK45 steel, EN-31 die steel, Inconel-600, High strength low alloy steel (HSLA), D2 tool steel (1.5%C, 12% Cr, 0.6%V, 1% Mo, 0.6% Si, 0.6% Mn and balance Fe), Al-SIC (20%), stainless steel AISI 304, medium carb on steel (EN8), Maraging steel (MDN 300), WPS DIN 1.2379/AISI D2 tool steel, AISI A2 tool steel, Maraging steel (MDN 250), WPS DIN 1.2379 tool steel, γ-TiAl, cryogenic-treated D-3 steel, SKD 61 steel, copper–steel (EN-8), Al2O3/6061Al composite etc.

D. Electrode material

The material used for electrode can be copper, brass, tungsten, graphite, steel, Copper–tungsten, copper–chromium alloy, haste alloy, molybdenum, chromium coated copper alloy, Brass-CuZn37, coated ceramic tool, Al–Cu–Si–TiC P/M composite material, Al-10%SiCp composites etc.

IV. EXISTING RESEARCH EFFORTS

Using Taguchi design, **Chen et al. (2013)** optimized the EDM processing parameters for milling A6061-T6 aluminum alloy using the Taguchi design approach. This study used four EDM parameters to measure Surface Roughness: pulse current, time on, duty cycle and machining length (SR). ANOVA and ANOM approaches are used to find the best machining settings and the relative effect of each parameter on the surface roughness (SR). The size of the SR is mostly governed by the Ip and parameters, according to the findings. Because of the use of suitable processing settings, a CuZn40 is discovered to have lower mean surface quality than A6061-T6.

For the machining of Al/SiCp metal matrix composites, **Guleryuz et al. (2013)** studied the influence of EDM settings on the SR (PM). The process parameters were Ip, electrode type, Ton, particle reinforcement weight ratio, and V. Using the Taguchi orthogonal design, an experimental plan L18 was created to conduct research. Ton (34 percent) and Ip (31.26 percent) were shown to be the most influential factors in the study. In addition, the SR's 6.71 percent particle reinforcement contributes to its overall strength.

EDM of EN31 tool steel was studied by **Das et al. (2012),** who investigated the influence and optimization of machine settings on the rate of material removal (MRR). Using Taguchi's L27 Orthogonal Array, machining parameters are selected (OA). ANOVA was used to assess the impact of machining parameters on MRR, and the analysis Signal-to-Noise (S/N) ratio was used to establish the optimal machining parameter combination. The results demonstrate that Ip has the greatest impact on MRR, followed by Toff and V. Increasing Ip and Toff has been shown to enhance MRR.

An examination and optimization of the EDM settings for machining ZrO2 ceramics has been demonstrated by **Chen and Lee (2010).** In order to reach the required level of electrical conductivity for the EDM process, adhesive copper and aluminum foils were applied to the surface of the electrically non-conductive ceramic. The experimental investigation examined machining features including MRR, TWR, and SR by using the Taguchi experimental design approach and an L27OA. MRR and SR were shown to be highly impacted by Ip and pulse length, with sticky conductive substance being the most closely associated characteristic to TWR. With high efficiency, high accuracy, and outstanding surface integrity, a technology for molding electrically non-conductive ceramics was created.

Ti-6Al-4V alloy spur tooth gears may be manufactured utilizing the Wire Electro Discharge Machining (WEDM) process using MATLAB to determine the interpolation points, according to **Huertas Talon et al. (2010).** Mathematical model equations that allow the wire path to be estimated can be simplified using this program. These electro-erosion characteristics were measured on an ONA PRIMA S-250 using ONA PRIMA S-250. Taguchi OA was used to determine the best cutting parameters for Ti alloy. An alternative to traditional machine tools for working with electrically conductive materials is the WEDM technology demonstrated here (milling, turning or boring). Due to its high-quality finish, the WEDM technique lowers or eliminates the need for further polishing operations.

Marafona and Araujo (2009) used Taguchi approach to build a model that incorporates the impact of alloy steel hardness on the MRR and the SR. Work-piece hardness directly influences MRR and SR, and while SR's strong confirmation was a strong one, MRR's was a weak one because of an interplay of factors. Thus, for SR, the additive model can predict with an average error of 0.4 percent, however for MRR, this type of result does not enable the additive model to accurately forecast. Since work-piece hardness and its interactions were considered, a linear regression model was created for MRR. MRR is predicted by this model with an average inaccuracy of 1.06%. Using this method, it is shown that the hardness of the work piece is also a factor in the EDM process.

Taguchi approach was used by **Lajis et al. (2009)** to investigate the possibility of EDM machining Tungsten Carbide ceramics using a graphite electrode. The Taguchi technique was used to create the experimental design, analyze the effects of various parameters, such as Ip, V, pulse length, and interval time, on the machining characteristics, namely MRR, TWR, and SR, and forecast the best option Taguchi method. These characteristics have been proven to have a substantial impact on the machining quality. The Taguchi method study demonstrates that the TWR and SR are mostly affected by the pulse length, but the Ip has a considerable effect on both.

EDM machining features such as MRR, TWR, and SR were studied by **Lin et al. (2008)** utilizing Electrolytic Copper as a tool and SKD61 steel as the workpiece. The parameters p, Ip, pulse length, high-voltage auxiliary current (IH), no-load voltage, and servo reference voltage were all designed using Taguchi's L18OA (Sv). Magnetic force assisted EDM has the potential to achieve high efficiency, superior machining stability, and high quality surface integrity to satisfy the demands of current industrial applications by analyzing discharge waveforms. For example, a lower REWR (relative electrode wear ratio) and a smaller SR (surface roughness ratio) were found when using magnetic force aided EDM over regular EDM.

The machining properties of AISID2 die steel were studied by **Kansal et al. (2007)** using silicon powder mixed with kerosene as the EDM's dielectric fluid. In addition to Ip, Ton and Toff, the powder concentration, gain and nozzle flushing have been taken into account. Machining rate is a common metric for assessing the efficiency of a given process (MR). According to the results of this study, there is no significant difference between the mean and variance in Mean Residual (MR) for any of the specified parameters except for the flushing of the nozzle. The ANOVA shows that Ip and powder concentration have the highest percentage contribution to MR.

To better understand how EDM machining settings affect a variety of machining properties, **Lin et al. (2006)** conducted research on this topic. Machine parameters for high-speed steel (SKH57) that include MRR, TWR, and SR measurements. The Taguchi technique was used to conduct the trials on the L18 OA. IH, auxiliary current with high voltage (IH), pulse length and no-load current are all key factors that are affected by the machining characteristics of the machine. Servo reference voltage is also important. Both MRR and SR went up with Ip use. The MRR and likewise the SR first rose and subsequently decreased as the pulse length grew. At a given peak current, the TWR decreased as the pulse length grew.

Research by **Simao et al. (2003)** shown that electron beam melting (EDM) may be used to intentionally alloy the surfaces of diverse work piece materials. Experiments on the surface alloying of AISI H13 hot work tool steel during a die sink operation employing partly sintered WC/Co electrodes working in a hydrocarbon oil dielectric. The impact of important operational parameters on output metrics was studied using a L8fractional factorial Taguchi experiment (TWR, SR, etc.). The percentage contribution ratios (PCR) for Ip, p, and Ton were 24, 20, and 19 percent, respectively, when it came to micro hardness.

According to **Nikalje et al. (2013),** Taguchi approach was used to analyze and optimize MDN 300 steel in EDM. Measures such as MRR, TWR, SR, and the relative wear ratio are critical (RWR). The machining factors, Ip, Ton, and Toff, were taken into account in the experiment. SR and MRR had similar ideal values of the variables; however the optimal levels of TWR and SR factors were different. Analysis of the machined surface's structural characteristics was carried out using SEM in order to better understand the effect of various factors on it.

Tungsten carbide MRR was studied in depth by **Kodlinge and Khire (2013),** who used Kerosene as the dielectric medium for EDM operation. It was decided to test Ip, electrode diameter, and Ton using a 23-factorial design approach. ANOVA shows that Ip has the most significant impact on MRR of the three variables studied.

As a consequence of using a copper electrode on hot work steel DIN1.2344, **Atefi and Amini (2012)** evaluated the effect of several EDM parameters, namely Ip, V, Ton, and Toff, on the TWR. The Design of Experiments (DOE) was decided to be a complete factorial. It has been decided to use an artificial neural network (ANN) to choose the appropriate machining settings and to achieve a specific TWR. The ANN mistakes have been reduced using a hybrid model, which has now been developed. Results showed that the suggested strategy worked well in solving complicated and non-linear optimization problems.

On EN-8 alloy steel with copper and aluminum tool electrode, **Pradhan and Jayswal (2011)** conducted a thorough experimental research using 23 complete factorial designs. Hardened material was machined using two electrodes with varied Ip, Ton and duty factor values. Using the identical dielectric medium, copper outperformed aluminum in terms of surface polish (m). As a result, copper was recommended as a good electrode material.

Copper electrode application to hot work steel DIN 1.2344 was studied by **Amini et al. (2010)** to see how different EDM parameters such as Ip, V, Ton and Toff affected the SR in the finishing stage. "Full factorial selection of DOE was made. Statistical analysis and an artificial neural network (ANN) have been utilized to choose the best machining settings and achieve a specific SR. The ANN mistakes have been reduced using a hybrid model, which has now been developed. When used to optimize nonlinear, difficult problems, the proposed technique performed well.

Conventional WEDM on a copper substrate for micro-fabrication was examined by **Ali and Mohammad (2008).** Predictions of SR and peak-to-valley height (Rt) based on Ip, Ton and gap voltage were made using statistical models. With increasing Ton, the SR fell, while with increasing Ip and gap voltage the SR rose. For example, micro spur gears with a surface roughness less than a centimeter and dimensional accuracy of 12 percent were produced using the improved parameters.

Ip, Ton, air gap voltage, and MRR, TWR, and ROC of EDM with Al4Cu6Si alloy10% SiCP composites were studied by **Dhar et al. (2007).** The PS LEADER ZNC EDM machine and a cylindrical brass electrode with a diameter of 30 mm were used to analyze the outcomes of the experiment. Machine parameters have been linked to each other in an advanced non-linear mathematical model. MRR, TWR, and ROC values rise nonlinearly with increasing current, indicating that the models are significant. This was confirmed by means of ANOVA. MRR and radial ROC rise as pulse duration increases

Lee and Tai (2003) used a complete factorial design based on Ip and Ton parameters using D2 and H13 tool steels as materials to investigate the relationship between EDM parameters and surface fractures. It is found that SR, WLT, and the tension generated by EDM all contribute to the development of surface fractures. There are two ways to raise WLT and caused stress by increasing Ton: MRR increases as Ip are raised, resulting in a large variation in the thickness of the white layer. Thick white layers are more prone to cracking than their thinner counterparts. It will be a valuable tool in improving the EDM process's quality.

Using a stir casting process, **Gopalakannan et al. (2012)** tested a newly developed Metal Matrix Composite (MMC) comprising aluminum 7075 reinforced with 10 weight percent Al2O3 particles. The copper electrode was machined using EDM. Response Surface Methodology (RSM) has been used to develop a mathematical model for estimating machining parameters such as MRR, TWR, and SR. Process variables Ip, Ton, V, and Toff were studied in relation to MRR, TWR, and SR using an ANOVA analysis of variance (ANOVA). The goal was to determine which process variables had a major impact on the final product's qualities.

Modeling, optimization and the development of a mathematical model for Ti-5Al-2.5Sn MRR using RSM has been described by **Rahman and colleagues (2010).** This material was EDM'd using a copper electrode with a positive polarity. MRR was correlated with Ip, Ton, V, and Toff as input parameters. ANOVA has been used to assess the validity of the suggested models' fit and appropriateness. The constructed model was found to be within acceptable error bounds, and Ip had a significant impact on performance metrics.

Several EDM characteristics, including MRR, TWR, Gap Size, and SR, were correlated using mathematical models created by **Habib (2009).** (Ip, Ton and SiC percent). Results show that the MRR grows as Ip, Ton, and gap voltage increase while SiC percent increases the MRR decreases. Increasing Ip and Ton increases TWR whereas increasing SiC percent and gap voltage decreases TWR. Several EDM characteristics, including MRR, TWR, Gap Size, and SR, were correlated using mathematical models created by Habib (2009). (Ip, Ton and SiC percent). Results show that the MRR grows as Ip, Ton, and gap voltage increase while SiC percent increases the MRR decreases. Increasing Ip and Ton increases TWR whereas increasing SiC percent and gap voltage decreases TWR. Gap size reduces with increasing % of SiC in the device while increasing voltage and current increase it. Finally, when Ip, Ton, SiC %, and gap voltage increase, the SR increases.

Soveja et al. (2008) used Taguchi methodology and RSM to investigate the effects of operational parameters on the surface laser texturing of TA6V alloy. They'd found a link between SR and MRR, two performance metrics, and several aspects of the process. The laser pulse intensity and frequency were found to be the most critical parameters in the operation of the laser. The SR is inversely proportional to the linear effects of pulse energy and frequency on MRR. When it comes to optimizing MRR, the best combination of parameters is 12.5 kHz pulse frequency and 5mJ pulse energy, both of which maintain a modest SR (Sao5 mm).

Kung and Chiang (2008) developed mathematical models of the MRR and SR in the WEDM process of aluminium oxide-based ceramic material (Al_2O_3+TiC) to correlate the key machining parameters, such as Ip, Ton, duty factor, and wire speed.

An experiment was carried out by **Prajapati et al. (2013)** to investigate the influence of WEDM process parameters on MRR, SR, Kerf, and Gap current. The output parameters of the WEDM of AISI A2 were accurately predicted using an ANN. Experiments using AISI A2 workpiece material are used to acquire the data for the training, testing, and validation phases. Error was found to be very low, with a maximum of 0.14, when comparing the experimental results to the ANN Predicted results. The output parameter ton is more important.

Using the ANN method, **Ndaliman and colleagues (2012)** created behavioral models for predicting the electrical conductivity, thermal conductivity, and density of Cu-TaC compacted electrodes manufactured using the PM process for use in EDM. The MATLAB 2009b Neural Network Toolbox allowed for the creation of 20 hidden layers for feed-forward back-propagation hierarchical neural networks. Copper and tantalum carbide powder electrode compacts for EDM have been created at two different composition and compacting pressure degrees of composition. EDM can't utilize sintered electrodes since they've lost their ability to conduct electricity. They were also discovered to be appropriate for EDM with the pre-sintered electrodes (green compacts). An ANN model was shown to be able to accurately predict the electrode characteristics, compared to the experimental data.

Jia et al. proposed progressive mapping methods and modes for three mappings, including fuzzy identification, LVQ neural network classification, and a judgement mode (2011).A scalar in a range reflecting the sampled point's state was derived through the first mapping using fuzzy rules that combined the complimentary signals with V and Ip. In order to transform this scalar into the appropriate state vector, a LQQ ANN was used Using the judgment mode of the third mapping, vector ratios reveal the discharge pulses. It was shown that this discharging pulses discriminator for MEDM can swiftly and reliably categorize discharging pulses for MEDM based on the results.

Cutting parameters for EDM can be optimised using a Taguchi method and an artificial neural network. **Thillaivanan et al. (2010)** presented a method for doing so. Using a feed-forward-back-propagation neural network, it has been demonstrated that Ip has a significant impact on overall machining time and on the oversize and taper of the hole to be machined by EDM.. A CAPP expert system for EDM automation might be built using this technology, which can be used to a variety of machining settings, including various work material, electrodes, and also more.

For the single-spark EDM process, **Joshi and Pande (2009)** developed a two-dimensional axisymmetric thermal FEM model using assumptions such as Gaussian heat flow distribution and time and energy dependent spark radius. An ANN-based system model was created for different work materials that connected input conditions (discharge power, spark on time, and duty factor) to output responses (crater form, MRR, and TWR). Analytical neural network models were developed, evaluated, and fine-tuned using numerical simulations (FEMs). Accurate predictions of EDM process responses were made using the ANN model.

Factorial design and a neural network (NN) were utilized by **Esme et al. (2009)** to model and forecast the SR of AISI 4340 steel by taking pulse length, open voltage, wire speed, and dielectric flushing pressure into account. Regression analysis has been used to look at the connections between SR and WEDM cutting parameter relationships. The effect of WEDM cutting parameters on the SR was studied using ANOVA. According to the findings, NN is a viable alternative to complete factorial empirical modeling.

It was found that **Gao et al. (2008)** used an ANN in EDM to increase generalization. Machining process models have been developed using several ANN training techniques, such as those developed by the Levenberg-Marquardt, robust and Scaled Conjugate Gradient (SCG) algorithms, as well as the Quasi-Newton algorithm (BFGS). In order to compare the generalization performance of the various models, we used the identical experimental data to train them all.

For EDM surface hardness optimization, **Krishna Mohana Rao and Hanumantha (2010)** used Neuro solutions package to create multi-perception neural network models. It was done by taking into account the effect of different input factors like Ip and V on the hardness of Ti6Al4V, HE15, 15CDV6, and M-250 at the same time. When experimental and network model results were compared, the constructed model was determined to be within acceptable error ranges. Analysis of variables' relative impact on performance metrics was also conducted using sensitivity analysis.

Adaptive Neuro-Fuzzy Inference System (ANFIS) was created by **Suganthi et al. (2013)** to predict different quality responses such as MRR, TWR, and SR by using back propagation and the Adaptive Neuro-Fuzzy Inference System (ANFIS). The feed rate, capacitance, gap voltage, and threshold settings were among the input parameters. We found that the ANFIS-based model was better at modeling and prediction than the ANN model.

ANFIS model, created by **Caydas et al. (2009),** was used to predict WEDM reactions such as SR and WLT. As control parameters, the pulse-on-time, open circuit voltage, dielectric cleaning pressure, and wire feed rate are all considered. The model incorporated fuzzy inference's modeling function with the ANN's capacity to learn. Model predictions were compared with experimental findings to make sure the strategy worked.

ANFIS was utilized by **Gostimirovic et al. (2012)** to calculate the MRR in an EDM sample. Discharge Ip and Ton have been set as the control parameters. MRR can be accurately predicted using the ANFIS model, as per a study. In this case, it is Ip that has the most impact on MRR, following by Ton.

To account for polarity shifts, **Tsai and Wang (2001)** evaluated six different neural networks with a neuro-fuzzy network to arrive at an MRR estimate for various materials. There are a slew of neuro networks that have been trained and evaluated using DOE, including logistic sigmoid and hyperbolic tangent multi-layered perception, as well as the adaptive basis function and the ANFIS. The ANFIS with the Bell-shape membership function was determined to be the most effective.

V. CONCLUSION

The analysis in this area over the past two decades reveals that EDM performance is generally evaluated on the basis of TWR, RWR and SR. The performance is affected by discharge current, pulse on time, pulse off time,arc gap, duty cycle, wire feed, wire tension, servo voltage, rotational speed and flushing pressure. The review paper evaluates the areas and subareas where optimizationtechniques have been deployed. It works on identifyingparameters for optimization and also suitable techniques forEDM mechanism.

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