GRA Coupled with Fuzzy Linguistic Reasoning for Quality Productivity Improvement in Electrical Discharge Machining (EDM)

Thesis submitted in partial fulfillment of the requirements for the Degree of

Bachelor of Technology (B. Tech.)

In

Mechanical Engineering

By

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Certificate of Approval

This is to certify that the thesis entitled **GRA Coupled with Fuzzy Linguistic Reasoning for Quality Productivity Improvement in Electrical Discharge Machining (EDM)** submitted by ***Sri Deepak Kumar Agarwal*** has been carried out under my supervision in partial fulfillment of the requirements for the Degree of ***Bachelor of Technology*** in ***Mechanical Engineering*** at National Institute of Technology, NIT Rourkela, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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DEEPAK KUMAR AGARWAL

Abstract

In the present work, the use of the grey relational analysis and fuzzy logic combined with Taguchi method has been proposed for optimizing Electrical Discharge Machining (EDM) process with multiple responses involved. The study aims at simultaneous optimization of quality and productivity. Quality and productivity are correlated inversely. If product quality is intended to be increased then extent of productivity is to be compromised and vice versa. Therefore, a compatible balance is necessary between productivity and product quality. The study addresses a case study related to EDM in which material removal rate (MRR) and surface roughness (R_a value) of the machined work surface have been optimized.

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1. Introduction and State of Art

That present manufacturing industries are facing challenges from these advanced materials viz. super alloys, ceramics, and composites, that are hard and difficult to machine, requiring high precision, surface quality which increases machining cost. To meet these challenges, non-conventional machining processes are being employed to achieve higher metal removal rate, better surface finish and greater dimensional accuracy, with less tool wear. Electric Discharge Machining (EDM), a non-conventional process, has a wide applications in automotive, defense, aerospace and micro systems industries plays an excellent role in the development of least cost products with more reliable quality assurance **(Pandey and Singh, 2010)**.

Tsai and Wang (2001) studied the comparisons on predictions of surface finish for various EDM machined work materials with the change of electrode polarity based upon different neural-networks models and a neuro-fuzzy network model. **Huang and Liao (2003)** applied grey relational analyses to determine the optimal selection of machining parameters for the Wire Electrical Discharge Machining (Wire-EDM) process. **Rao et al. (2008)** aimed at optimizing the metal removal rate of die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters.

Lajis et al. (2009) reported the cutting of Tungsten Carbide ceramic using electro-discharge machining (EDM) with a graphite electrode by using Taguchi methodology. The Taguchi method was used to formulate the experimental layout, to analyze the effect of each parameter on the machining characteristics, and to predict the optimal choice for each EDM parameter such as peak current, voltage, pulse duration and interval time. It was found that these parameters had a significant influence on machining characteristic such as metal removal rate (MRR), electrode wear rate (EWR) and surface roughness (SR). The analysis of the Taguchi method revealed that, the peak current significantly affected the EWR and SR, while, the pulse duration mainly affected the MRR. Experimental results were provided to verify this approach.

Nee (2010) presented the artificial neural network model to predict the optimal machining parameters for Ti-6Al-4V through electrical discharge machining (EDM) using copper as an electrode and positive polarity of the electrode. The objective of this paper was to investigate how the peak current, servor voltage, pulse on- and off-time in EDM effect on material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR). Radial basis function neural network (RBFN) was used to develop the Artificial Neural Network (ANN) modeling of MRR, TWR and SR.

Muthu Kumar et al. (2010) demonstrated optimization of Wire Electrical Discharge Machining process parameters of Incoloy800 super alloy with multiple performance characteristics such as Material Removal Rate (MRR), surface roughness and Kerf based on the Grey–Taguchi Method.

Parashar et al. (2010) proposed statistical and regression analysis of material removal rate (MRR) using design of experiments for WEDM operations. **Malhotra et al. (2011)** optimized the operating performance measure i.e. surface roughness (SR) of side flushing type of electrical discharge machining process on EN-31 die steel using copper electrode.

Iqbal and Khan (2011) aimed to optimize the process parameters during EDM milling of stainless steel by using copper electrode. The selected input parameters used for the study were voltage, rotational speed of the electrode and feed rate while the responses were material removal rate (MRR), electrode wear ratio (EWR) and surface roughness

(Ra). Response surface methodology was used in the study. The experimental design was formed by using design expert software. Central Composite design (CCD) was used to identify the optimum operating condition in order to obtain maximum MRR, minimum EWR and minimum Ra as response.

Lin et al. (2002) reported the use of the grey relational analysis based on an orthogonal array and fuzzy-based Taguchi method for optimizing the multi-response process. Both the grey relational analysis method without using the S/N ratio and fuzzy logic analysis were used in an orthogonal array table in carrying out experiments for solving the multiple responses in the electrical discharge machining (EDM) process. Experimental results showed that both approaches could optimize the machining parameters (pulse on time, duty factor, and discharge current) with considerations of the multiple responses (electrode wear ratio, material removal rate, and surface roughness) effectively.

Lin and Lin (2005) reported the use of the grey-fuzzy logic based on orthogonal array for optimizing the electrical discharge machining process with multi-response. An orthogonal array, grey relational generating, grey relational coefficient, grey-fuzzy reasoning grade and analysis of variance were applied to study the performance characteristics of the machining process. The machining parameters (pulse on time, duty factor and discharge current) with considerations of multiple responses (electrode wear ratio, material removal rate and surface roughness) were found effective. The grey-fuzzy logic approach could help to optimize the electrical discharge machining process with multiple process responses.

2. Grey Relation Theory

In grey relational analysis, experimental data i.e. measured features of quality characteristics are first normalized ranging from zero to one. This process is known as grey relational generation. Next, based on normalized experimental data, grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated grey relational grade. This approach converts a multiple- response- process optimization problem into a single response optimization situation, with the objective function is overall grey relational grade. The optimal parametric combination is then evaluated which would result highest grey relational grade. The optimal factor setting for maximizing overall grey relational grade can be performed by Taguchi method **(Datta et al., 2008)**.

In grey relational generation, the normalized roughness average R_a, corresponding to Lower-the-Better (LB) criterion can be expressed as:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \qquad \textbf{(1)}$$

MRR should follow Higher-the-Better criterion (HB), which can be expressed as:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \qquad \textbf{(2)}$$

Here $x_i(k)$ is the value after the grey relational generation, $\min y_i(k)$ is the smallest value of $y_i(k)$ for the kth response, and $\max y_i(k)$ is the largest value of $y_i(k)$ for the kth response. An ideal sequence is $x_0(k)$ $(k = 1, 2, 3......, 9)$ for the responses. The definition of grey relational grade in the course of grey relational analysis is to reveal the degrees of relation between the sequences say $[x_0(k)\ and\ x_i(k),\ i = 1,2,3.......,9]$. The grey relational coefficient $\xi_i(k)$ can be calculated as:

$$\xi_i(k) = \frac{\Delta_{\min} + \psi\Delta_{\max}}{\Delta_{0i}(k) + \psi\Delta_{\max}} \quad \textbf{(3)}$$

Here $\Delta_{0i} = \|x_0(k) - x_i(k)\|$ = difference of the absolute value $x_0(k)$ and $x_i(k)$; ψ is the distinguishing coefficient $0 \le \psi \le 1$; $\Delta_{\min} = \forall j^{\min} \in i \forall k^{\min} \|x_0(k) - xj(k)\| =$ the smallest value of Δ_{0i} ; and $\Delta_{\max} = \forall j^{\max} \in i \forall k^{\max} \|x_0(k) - xj(k)\| =$ largest value of Δ_{0i} . After averaging the grey relational coefficients, the grey relational grade γ_i can be computed as:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \quad \textbf{(4)}$$

Here $n =$ number of process responses. The higher value of grey relational grade corresponds to intense relational degree between the reference sequence $x_0(k)$ and the given sequence $x_i(k)$. The reference sequence $x_0(k)$ represents the best process sequence. Therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal. The mean response for the grey relational grade with its grand mean and the main effect plot of grey relational grade are very important because optimal process condition can be evaluated from this plot.

However, the method has a shortcoming. Difficulty is faced in assigning response weights. Because of the responses are not equally important in practice. Response priority weights may vary depending on decision-makers perception. To avoid this kind of uncertainty the study explores the concept of fuzzy logic.

3. Fuzzy Inference System (FIS)

Fuzzy logic is a superset of conventional (*boolean*) logic that has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false. A fuzzy inference system (FIS) defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. A fuzzy rule based system consists of four parts **(Gupta et al., 2011)**:

1. ***knowledge base,***
2. ***fuzzifier,***
3. ***inference engine and***
4. ***defuzzifier.***

Fuzzifier: The real world input to the fuzzy system is applied to the fuzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier convert this precise quantity to the form of imprecise quantity like ‘large’, ‘medium’, ‘high’ etc. with a degree of belongingness to it. Typically the value ranges from 0 to 1.

Knowledge base: The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules where as the rule base contains a number of fuzzy IF-THEN rules.

Inference engine: The inference system or the decision making input perform the inference operations on the rules. It handles the way in which the rules are combined.

Defuzzifier: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

The first step in system modeling was the identification of input and output variables called the system variables. In the selection procedure, the inputs and the outputs are taken in the form of linguistic format. A linguistic variable is a variable whose values are words or sentences in natural or man-made languages. Linguistic values are expressed in the form of fuzzy sets. A fuzzy set is usually defined by its membership functions. In general, triangular or trapezoidal membership functions are used to the crisp inputs because of their simplicity and high computational efficiency. In the present study, a fuzzy set $\tilde{A}$ is represented by triangular fuzzy number which is defined by the triplet (a, b, c). Membership function $\mu_{\tilde{A}}(x)$ is defined as:

$\forall - x, - a, - b, - c \in R$

$$\mu_{\tilde{A}}(x) = 0, \text{ if } x < a \text{ else} \left(\frac{x-a}{b-a} \right), \text{ if } a \le x \le b \text{ else} \left(\frac{c-x}{c-b} \right), \text{ if } b \le x \le c \text{ else } 0, \text{ if } x > c$$

Using a defuzzification method, fuzzy values can be obtained into one single crisp output value. The centre of gravity, one of the most popular methods for defuzzifying fuzzy output functions, is employed in the study. The formula to find the centroid of the combined outputs: $\hat{y}_i = \dfrac{\int y_i \mu_{ci}(y_i) dy}{\int \mu_{ci}(y_i) dy}$ **(5)**

4. Experiments

The work material selected for this study was 304L grade stainless steel which is used widely for making the heat exchangers and chemical containers. The chemical composition of this material is: 0.03% C, 2.0% Mn, 0.75% Si, 0.045% P, 0.03% S, 18-

20% Cr, 8-12% Ni and 0.1% N. Hardness of the supplied steel is about 92 HR B. The material is machined directly with pre-hardened condition and no heat treatment is required to be carried out. Cupper tool-electrode (30 mm diameter) has been selected as a machining tool for this EDM process.

The various process or machining parameters of EDM are discharge current, working voltage, pulse on time, pulse of time, duty factor and dielectric flow rate. The multiple responses (related to the process as well as product quality) are overcut, undercut, and various surface roughness parameters of statistical importance.

The process parameters and their ranges considered here based on the idea of literature review and experience of some preliminary experiments shown in **Table 1**. The experimental work has been carried out on Electric Discharge Machine, model ELECTRONICA- ELECTRAPULS PS 50ZNC (die-sinking type). Commercial grade EDM oil (specific gravity= 0.763, freezing point = 94˚C) was used as dielectric fluid. The machining performance has been evaluated by two important process responses namely surface roughness (SR), and material removal rate (MRR). The surface roughness has been measured by the Talysurf (Taylor Hobson, Surtronic 3+). **Table 2** represents selected orthogonal array design and corresponding response data.

5. Proposed Methodology

The methodology used for the optimization is grey relational analysis (GRA) coupled with fuzzy inference system. Grey relational analysis has been utilized to compute grey relation coefficients for individual responses. These have been fed to a Fuzzy Inference System (FIS) as inputs; whose output has been defined as Multi-Performance

Characteristic Index (MPCI). MPCI has been optimized finally by Taguchi method. Taguchi method has been used to find an optimal solution at some discrete points at the experimental domain which can be easily adjusted in EDM machine. It is based on two principle namely quadratic quality loss function and Signal-to-Noise (S/N) ratio. The loss function has been used to measure the process response deviating from the desired value and the value of the loss function has been further transformed into an S/N ratio.

Data analysis has been carried out by the procedural hierarchy as shown below.

1. Experimental data have been normalized first **(Table 3)** which is known as grey relational generation.
2. Computation of grey relational coefficients for individual responses in all experimental run **(Table 4)**. For calculating grey relational coefficients of MRR, a Higher-the-Better (HB) criterion and for R_a, a Lower-the-Better (LB) criterion has been selected.
3. These grey relational coefficients corresponding to individual responses have been fed as inputs to a Fuzzy Inference System (FIS) **(Fig. 1)**. For each of the input parameters seven triangular type membership functions (MFs) have been chosen as: Very Low (VL), Low (L), Fairly Low (FL), Medium (M), Fairly High (FH), High (H) and Very High (VH) **(Fig. 2-3)**. Based on fuzzy association rule mapping **(Table 5)** FIS combined multiple inputs into a single output termed as Multi-Performance Characteristic Index (MPCI). The linguistic valuation of MPCI has been represented by seven triangular type membership functions (MFs) have been chosen as: Very Low (VL), Low (L), Fairly Low (FL), Medium (M), Fairly High (FH), High (H) and

Very High (VH) **(Fig. 4)**. These linguistic values haven transformed into crisp values by defuzzification method.

4. The crisp values of MPCI **(Table 6)** have been optimized by using Taguchi' philosophy. The predicted optimal setting has been evaluated from *Mean (S/N ratio) Response Plot* of MPCIs **(Fig. 5)** and it became A3 B3 C2 D1.
5. Optimal setting has been verified by confirmatory test.

6. Conclusions

The foregoing study aimed to develop a robust flexible optimization philosophy based on Taguchi method in combination with Grey Relational Analysis and Fuzzy Inference System to search an appropriate combination of process parameter settings based on quality-productivity characteristics of the product and related process.

The study demonstrates application feasibility of the proposed approach with satisfactory result of confirmatory test. The proposed procedure is simple, effective in developing a robust, versatile and flexible mass production process.

Manufacturing process often involves effective and efficient optimization of machining parameters in order to improve cost and production time of machining and also to improve the quality of products as well as to increase productivity. In this context, this present study highlights a multi-response optimization problem for selection of optimal cutting parameters for machining 304l SS as a case study, by using fuzzed logic linguistic reasoning combined with Taguchi's robust design technique. This approach can be recommended for continuous quality improvement and off-line quality control of a process/product in any manufacturing/ production environment.

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Table 1. Domain of experiments

Factors	Symbol and unit	Code	Levels of Factors		
			1	**2**	**3**
Discharge Current	I_P (A)	A	02	06	10
Pulse on Time	T_{ON} (µs)	B	100	550	1000
Duty Factor	τ	C	8	10	12
Discharge Voltage	V (Volt)	D	40	45	50

Constant Parameters:
F_p= 0.25 kgf/cm^2, SEN= 6, ASEN=7, T_w= 0.6 s, T_{up}= 0.7 s, Polarity = (tool – ve and w/p = + ve)

Table 2. Design of experiment and collected response data

Sl. No.	Factorial settings (Coded)				Experimental data	
	A	**B**	**C**	**D**	**MRR (mm^3/min)**	**R_a (µm)**
1	1	1	1	1	0.86191	4.60
2	1	2	2	2	0.47368	2.13
3	1	3	3	3	0.22585	2.67
4	2	1	2	3	2.85429	8.40
5	2	2	3	1	4.87143	8.20
6	2	3	1	2	3.52000	8.07
7	3	1	3	2	4.38095	9.53
8	3	2	1	3	7.40476	13.73
9	3	3	2	1	8.35714	14.00

Table 3. Normalized response data

Sl. No.	Normalized MRR data	Normalized R_a data
1	0.07822	0.79191
2	0.03047	1.00000
3	0.00000	0.95450
4	0.32325	0.47177
5	0.57132	0.48862
6	0.40512	0.49957
7	0.51100	0.37657
8	0.88287	0.02274
9	1.00000	0.00000

Table 4. Grey relational co-efficient $[\xi_i(k)]$ of individual responses

Sl. No.	$\xi_i(k)$ of MRR	$\xi_i(k)$ of Ra
1	0.35167	0.70612
2	0.34024	1.00000
3	0.33333	0.91659
4	0.42490	0.48627
5	0.53839	0.49437
6	0.45667	0.49978
7	0.50556	0.44506
8	0.81020	0.33846
9	1.00000	0.33333

[The value of distinguishing coefficient (ψ) taken 0.5]

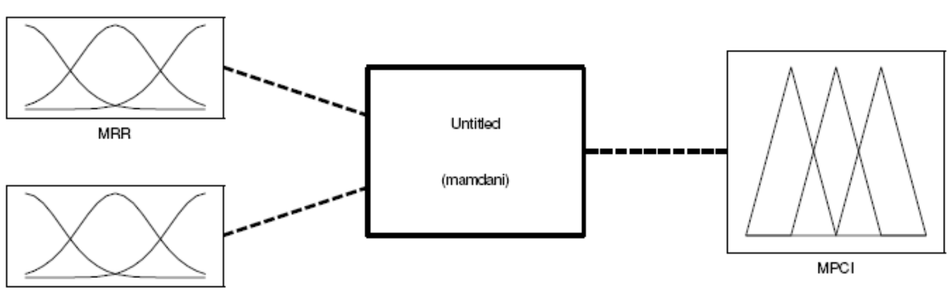


Figure 1. Proposed FIS model

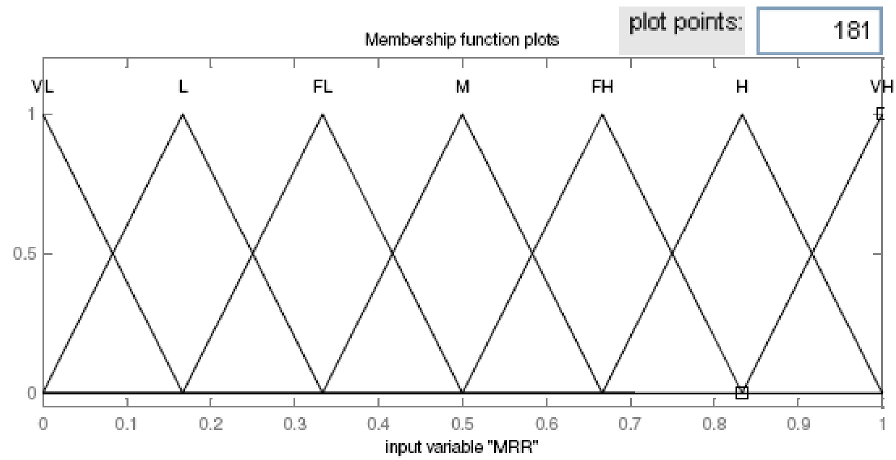


Figure 2. MFs for MRR

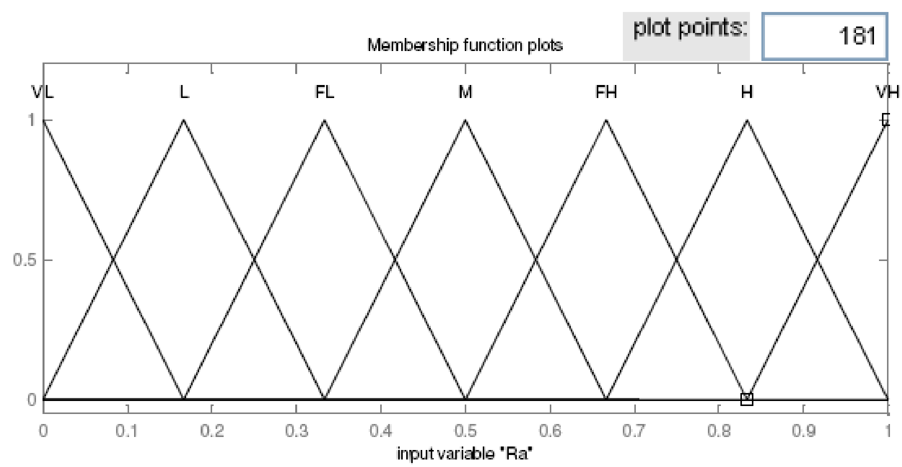


Figure 3. MFs for R_a

Table 5. Fuzzy rule matrix

MPCI		**Normalized S/N Ratio of MRR**						
		VL	**L**	**FL**	**M**	**FH**	**H**	**VH**
Normalized S/N Ratio of R_a	VL	VL	VL	L	L	FL	FL	M
	L	VL	VL	L	FL	FL	M	M
	FL	L	L	FL	FL	M	M	FH
	M	L	L	FL	M	M	FH	H
	FH	L	FL	FL	M	FH	H	H
	H	L	FL	M	FH	FH	H	VH
	VH	FL	FL	M	FH	H	H	VH

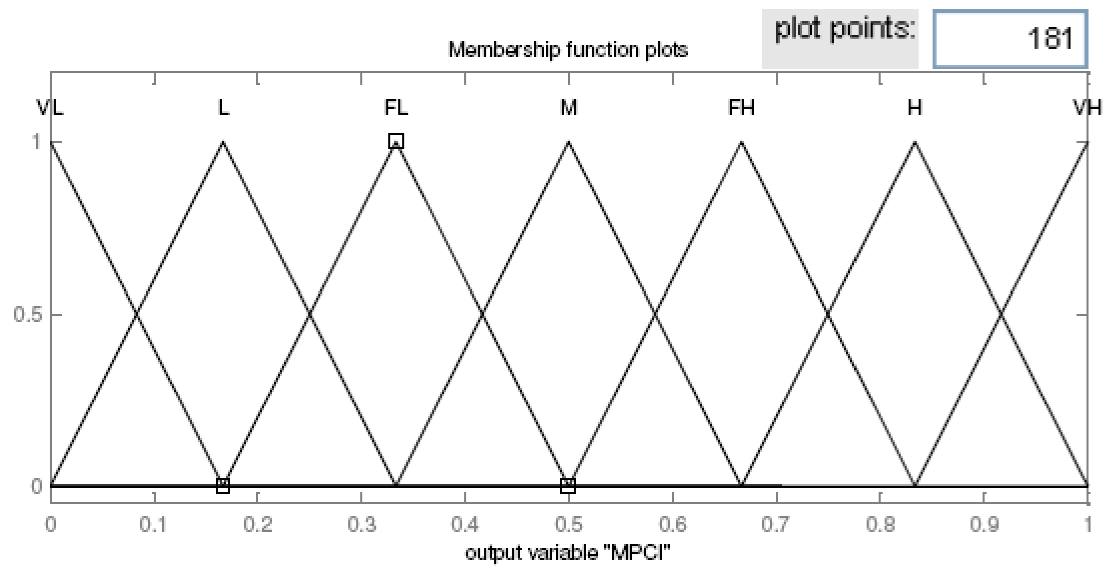


Figure 4. MFs for MPCI

Table 6. MPCI values

Sl. No.	MPCI
1	0.410
2	0.510
3	0.500
4	0.423
5	0.492
6	0.450
7	0.440
8	0.508
9	0.667

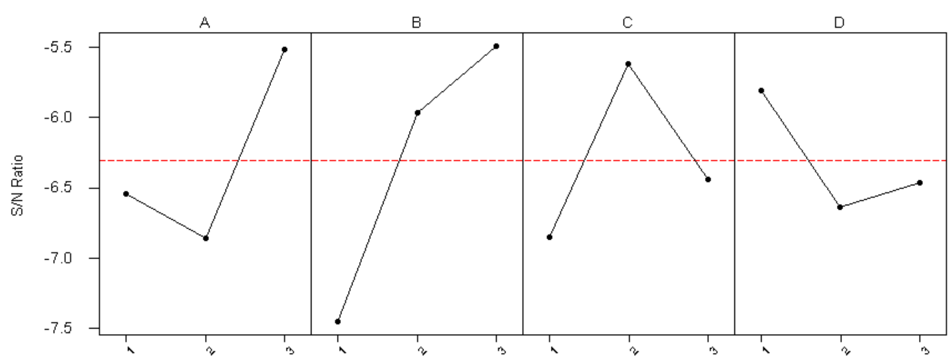
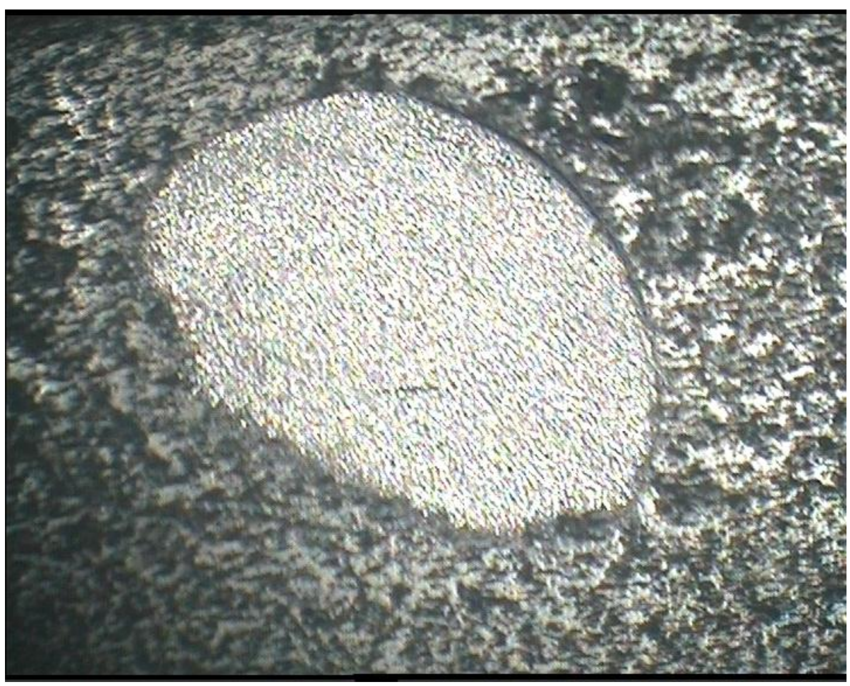


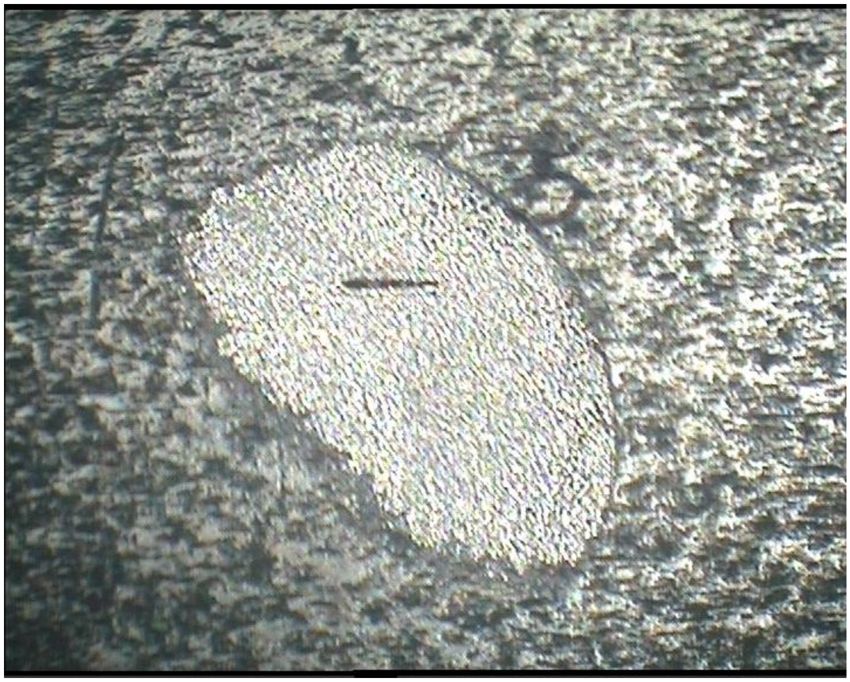
Figure 5. S/N ratio plot for MPCIs (Evaluation of optimal setting)

Appendix

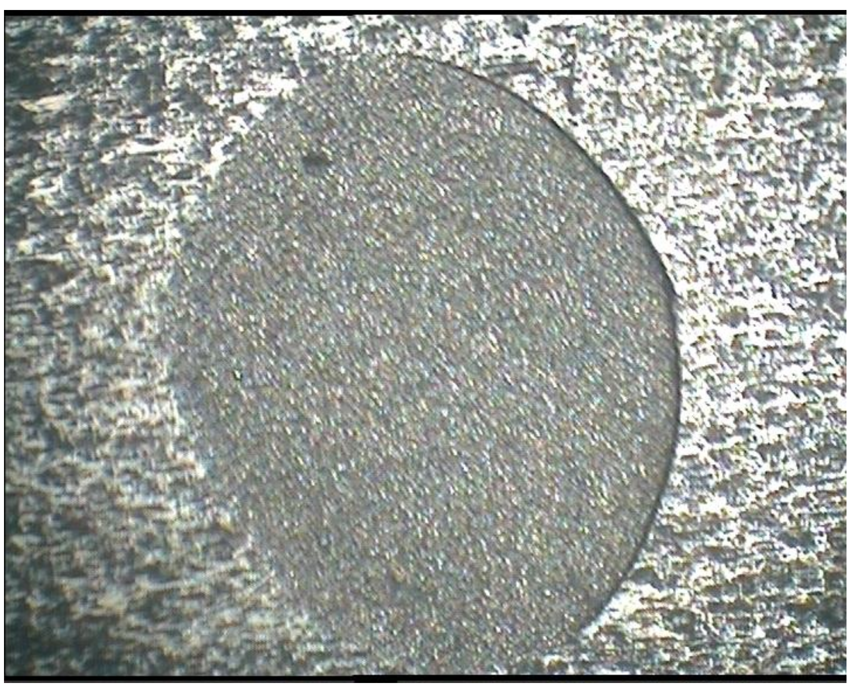
EDM machined surface (Sample No. 1)



EDM machined surface (Sample No. 2)

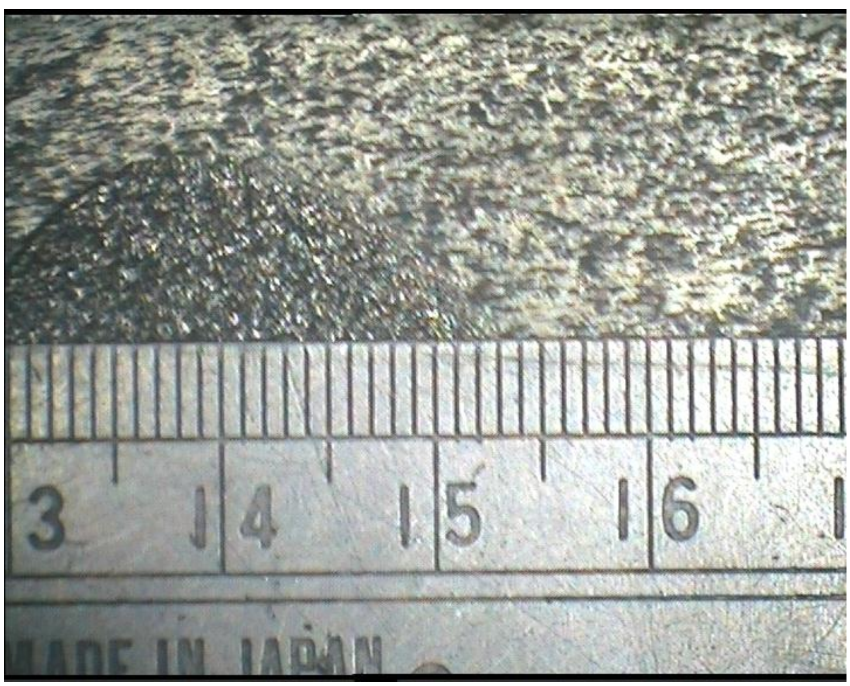


EDM machined surface (Sample No. 3)



EDM machined surface (Sample No. 4)

EDM machined surface (Sample No. 5)



SACALE: 4” ~720 Pixels

Communication

Deepak Kumar Agarwal, Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, SK Patel, "*GRA coupled with fuzzy linguistic reasoning for quality productivity improvement in Electrical Discharge Machining EDM*", The 9th International Conference on Enterprise Systems, Accounting and Logistics 2012 (9th ICESAL 2012) will take place in **Chania**, **Crete Island**, **Greece,** on **June 3-5, 2012**. (**Under Review**)