Application of Fuzzy Logic and TOPSIS in the Taguchi Method for Multi-Response Optimization in Electrical Discharge Machining (EDM)

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Certificate of Approval

This is to certify that the thesis entitled **APPLICATION OF FUZZY LOGIC AND TOPSIS IN THE TAGUCHI METHOD FOR MULTI-RESPONSE OPTIMIZATION IN ELECTRICAL DISCHARGE MACHINING (EDM)** submitted by ***Sri Umakanta Behera*** 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, Rourkela, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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UMAKANTA BEHERA

Abstract

Recently optimization of multi-response problems is a most focusing area of research. This study highlights application of fuzzy logic and TOPSIS in the Taguchi method to optimize a multi-response problem on Electrical Discharge Machining (EDM). In many manufacturing/production contexts, it is still necessary to rely on the engineering judgment to optimize the multi-response problem; therefore uncertainty seems to be increased during the decision-making process. Therefore, development of efficient multi-response optimization philosophies is indeed required. In this work, the experiment has been carried out by using 304L grade stainless steel as a work material and a copper as a tool electrode in EDM. Conversely, optimal process parameter setting has been selected successfully based on requirements of quality as well as productivity. A case study has been reported towards optimizing material removal rate (MRR) and roughness average of the EDM machined product in order to make a compromise balance between quality and productivity.

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1. Introduction and State of Art

Electric discharge machining (EDM) is a nonconventional machining process whereby a desired shape is obtained using electrical discharges (sparks). Material is removed from the work piece by a series of rapidly recurring current discharges between two electrodes, separated by a dielectric liquid and subject to an electric voltage. One of the electrodes is called the tool-electrode, while the other is called the work piece-electrode, or 'work piece'.

Tzeng and Chen (2003) presented a simple approach for optimizing high-speed electrical-discharge machining (EDM). The approach began with designing the ideal function of an EDM system coupled with Taguchi methods for process optimization. It was proposed that the ideal function had linear relationship between the input signal (intended dimension) and the output response (product dimension). This model aimed to develop a robust machining process enabling high precision and accuracy of machining a product. In this study, a two-step optimization strategy was applied. The first step was to reduce the functional variability of the EDM system to enhance process robustness. The second step was to increase the machining accuracy by adjusting the slope of the best-fit line between the input signals and the output responses. Experimental results showed that the use of the proposed model was simple, effective, and efficient in the development of robust and high-quality EDM machining processes.

Wu et al. (2005) investigated the effect of surfactant and Al powders added in the dielectric on the surface status of the work piece after EDM. An optimal surface roughness (Ra) value was achieved under the following parameter positive polarity, discharge current, pulse duration time, open circuit potential, gap voltage and surfactant

concentration. The surface roughness status of the work piece was improved up to 60% as compared to that EDM under pure dielectric with high surface roughness.

Ghoreishi and Assarzadeh (2006) used two supervised neural networks, namely back propagation (BP), and radial basis function (RBF) for modeling EDM process. The networks had three inputs of current, voltage and period of pulses as the independent process variables, and two outputs of material removal rate (MRR) and surface roughness (Ra) as performance characteristics. Experimental data, employed for training the networks and capabilities of the models in predicting the machining behaviour were verified. For comparison, quadratic regression model was also applied to estimate the outputs. The outputs obtained from neural and regression models were compared with experimental results, and the amounts of relative errors were calculated. Based on these verification errors, it was shown that the radial basis function of neural network was superior in this particular case, and has the average errors of 8.11% and 5.73% in predicting MRR and Ra, respectively. Further analysis of machining process under different input conditions was investigated and comparison results of modeling with theoretical considerations shows a good agreement, which also proved the feasibility and effectiveness of the adopted approach.

Mahapatra and Patnaik (2006) used Taguchi's parameter design to identify significant machining parameters: discharge current, pulse duration, pulse frequency, wire speed, wire tension, and dielectric flow affecting the performance measures of WEDM. The relationship between control factors and responses like metal removal rate (MRR), surface finish (SF) and cutting width (kerf) were established by means of nonlinear regression analysis, resulting in a valid mathematical model. Finally, genetic algorithm, a

popular evolutionary approach, was employed to optimize the wire electrical discharge machining process with multiple objectives. The study demonstrated that the WEDM process parameters could be adjusted to achieve better metal removal rate, surface finish and cutting width simultaneously.

Kansal et al. (2006) described an investigation towards optimization of EDM process in which silicon powder was suspended into the dielectric fluid. Taguchi's method with multiple performance characteristics has been adopted to obtain an overall utility value that represented the overall performance of powder mixed EDM (PMEDM). The four input process parameters, viz. silicon powder concentration added into dielectric fluid, peak current, pulse duration and duty cycle, were optimized with consideration of multiple performance characteristics including machining rate, surface roughness and tool wear rate.

Routara et al. (2007) studied the influence of machining parameters of EDM for machining of tungsten carbide (WC) using electrolyte copper of negative polarity on machining characteristics. The second order mathematical models in terms of machining parameters were developed for surface roughness prediction using response surface methodology (RSM) on the basis of experimental results.

Reesa et al. (2008) investigated the technological capabilities of a micro machining process for performing Wire Electro Discharge Grinding (WEDG). In this study, the effects of different factors on the achievable surface finish after WEDG were investigated. An experimental study employing the Taguchi parameter design method was conducted to identify the most important main cut machining parameters that affect the surface quality of the machined parts. The obtained results were used to analyze the

effects of the investigated parameters on the achievable surface roughness, and ultimately to select the optimum technological parameters for performing WEDG.

Singh and Garg (2009) investigated the effects of various process parameters of WEDM (like pulse on time, pulse off time, gap voltage, peak current, wire feed and wire tension) to reveal their impact on material removal rate of hot die steel (H-11) using one variable at a time approach. The optimal set of process parameters was also predicted to maximize the material removal rate. It was found that material removal rate (MRR) directly increased with increase in pulse on time and peak current while decreased with increase in pulse off time and servo voltage.

Esme et al. (2009) used two techniques, namely factorial design and neural network (NN) for modeling and predicting the surface roughness of AISI 4340 steel. Surface roughness was taken as a response variable measured after WEDM and pulse duration, open voltage, wire speed and dielectric flushing pressure were taken as input parameters. Relationships between surface roughness and WEDM cutting parameters were investigated. The level of importance of the WEDM cutting parameters on the surface roughness was determined by using the analysis of variance method (ANOVA). The mathematical relation between the work piece surface roughness and WEDM cutting parameters were established by regression analysis method. Finally, predicted values of surface roughness by techniques, NN and regression analysis, were compared with the experimental values and their closeness with the experimental values determined. Results show that, NN seemed to be a good alternative to empirical modeling based on full factorial design.

Rao and Rao (2010) aimed at optimizing the hardness of surface produced in die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters. The experiments were carried out on Ti6Al4V, HE15, 15CDV6 and M-250 by varying the peak current and voltage and the corresponding values of hardness were measured. Multiperceptron neural network models were developed using Neuro solutions package. Genetic algorithm concept was used to optimize the weighing factors of the network. Sensitivity analysis was also carried out to find the relative influence of factors on the performance measures. It was observed that type of material effectively influences the performance measures.

Balc et al. (2010) presented research and case studies undertaken in order to improve the EDM-wire cutting. Both, the draft cutting and the finishing cutting were discussed, in order to increase the dimensional accuracy of the part and to keep a high material removal rate.

Khan et al. (2011) proposed artificial neural network (ANN) models for the prediction of surface roughness on first commenced Ti-15-3 alloy in electrical discharge machining (EDM) process. The proposed models used peak current, pulse on time, pulse off time and servo voltage as input parameters. Multilayer perceptron (MLP) with three hidden layer feed forward networks were applied. An assessment was carried out with the models of distinct hidden layer. Training of the models was performed with data from an extensive series of experiments utilizing copper electrode as positive polarity. The predictions based on the above developed models were verified with another set of experiments and were found to be in good agreement with the experimental results.

Rao et al. (2011) considered wire-cut electric discharge machining of aluminum-24345 with experimentation done by using Taguchi's orthogonal array under different conditions of parameters. The response of surface roughness was considered for improving the machining efficiency. Optimal combinations of parameters were obtained by this method.

Rahman et al. (2011) presented the influence of EDM parameters in terms of peak ampere, pulse on time and pulse off time on surface roughness of titanium alloy (Ti-6Al-4V). A mathematical model for surface finish was developed using response surface method (RSM) and optimum machining setting in favor of surface finish were evaluated. Design of experiments (DOE) techniques was implemented. Analysis of variance (ANOVA) was performed to verify the fit and adequacy of the developed mathematical models. The acquired results yield that the increasing pulse on time caused fine surface till a certain value and then deteriorated the surface finish.

Sivapirakasam et al. (2011) aimed to develop a combination of Taguchi and fuzzy TOPSIS methods to solve multi-response parameter optimization problems in green manufacturing. Electrical Discharge Machining (EDM), a commonly used non-traditional manufacturing process was considered in this study. A decision making model for the selection of process parameters in order to achieve green EDM was developed. An experimental investigation was carried out based on Taguchi L_9 orthogonal array to analyze the sensitivity of green manufacturing attributes to the variations in process parameters such as peak current, pulse duration, dielectric level and flushing pressure. Weighing factors for the output responses were determined using triangular fuzzy numbers and the most desirable factor level combinations were selected based on

TOPSIS technique. The model developed in this study could be used as a systematic framework for parameter optimization in environmentally conscious manufacturing processes.

2. Experimentation

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 process parameters and their ranges considered 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.

3. Fuzzy Inference System (FIS)

Fuzzy inference is a computer paradigm unit based on fuzzy set theory, fuzzy IF-THEN-rules and fuzzy reasoning through which multiple input objectives can be successfully converted in to equivalent single output. A fuzzy inference structure comprises with a fuzzifier, an inference engine, a knowledge base, and defuzzifier. Fuzzifier converts the crisp input to a linguistic variable using the membership functions stored in the fuzzy knowledge base. Inference engine converts fuzzy input to the fuzzy output using IF-THEN type fuzzy rules. Then, defuzzifier converts the fuzzy output of the inference engine to crisp using membership functions analogous to the ones used by the fuzzifier. Generally defuzzification of output values is done in centre of area (COA) method.

4. TOPSIS Method

TOPSIS (*technique for order preference by similarity to ideal solution*) method was firstly proposed by **(Hwang and Yoon, 1981)**. The basic concept of this method is that the chosen alternative (appropriate alternative) should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution. Positive ideal solution is a solution that maximizes the benefit criteria and minimizes adverse criteria, whereas the negative ideal solution minimizes the benefit criteria and maximizes the adverse criteria. The steps involved in TOPSIS method are as follows:

Step 1: This step involves the development of matrix format. The row of this matrix is allocated to one alternative and each column to one attribute. The decision making matrix can be expressed as:

$$\mathbf{D} = \begin{array}{c} A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \quad \textbf{(1)}$$

Here, A_i $((i = 1, 2, ..., m)$ represents the possible alternatives; x_j $(j = 1, 2, ..., n)$ represents the attributes related to alternative performance, $j = 1, 2, ..., n$ and x_{ij} is the performance of A_i with respect to attribute $X_{j.}$

Step 2: Obtain the normalized decision matrix r_{ij} .This can be represented as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \textbf{(2)}$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute $X_{j.}$

Step 3: obtain the weighted normalized decision matrix, $\mathbf{V} = \lfloor v_{ij} \rfloor$ can be found as:

$$V = w_j r_{ij} \quad \textbf{(3)}$$

Here, $\sum_{j=1}^{n} w_j = 1$

Step 4: Determine the ideal (best) and negative ideal (worst) solutions in this step. The ideal and negative ideal solution can be expressed as:

a) The ideal solution:

$$A^+ = \left\{ \left(\max_i v_{ij} \,\middle|\, j \in J \right), \left(\min_i v_{ij} \,\middle|\, j \in J' \,\middle|\, i = 1, 2, ..., m \right) \right\} \quad \textbf{(4)}$$

$$= \left\{ v_1^+, v_2^+, ..., v_j^+, ...v_n^+ \right\}$$

b) The negative ideal solution:

$$A^{-} = \left\{ \left(\min_{i} v_{ij} \middle| j \in J \right), \left(\max_{i} v_{ij} \middle| j \in J' \middle| i = 1, 2, ..., m \right) \right\} \quad \textbf{(5)}$$

$$= \left\{ v_1^{-}, v_2^{-}, ..., v_j^{-}, ...v_n^{-} \right\}$$

Here,

$J = \left\{ j = 1,2,....., n \middle| j \right\}$: Associated with the beneficial attributes

$J' = \left\{ j = 1,2,....., n \middle| j \right\}$: Associated with non beneficial adverse attributes

Step 5: Determine the distance measures. The separation of each alternative from the ideal solution is given by n-dimensional Euclidean distance from the following equations:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{+} \right)}, \; i = 1, 2, ..., m \quad \textbf{(6)}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{-} \right)}, \; i = 1, 2, ..., m \quad \textbf{(7)}$$

Step 6: Calculate the relative closeness to the ideal solution:

$$C_i^{+} = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}, \; i = 1, 2, ..., m; 0 \le C_i^{+} \le 1 \quad \textbf{(8)}$$

Step 7: Rank the preference order. The alternative with the largest relative closeness is the best choice.

In the present study C_i^{+} for each product has been termed as Multi-Performance Characteristic Index (MPCI) which has been optimized by Taguchi method.

5. Data Analysis: Application of FIS

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

1. Computation of (Signal-to-Noise Ratio) S/N ratio of experimental data **(Table 3)**. For calculating S/N ratio of MRR, a Higher-the-Better (HB) criterion and for R_a, a Lower-the-Better (LB) criterion has been selected.
2. S/N ratios have been normalized based on Higher-the-Better (HB) criterion **(Table 4)**.
3. Normalized S/N ratios corresponding to individual responses have been fed as inputs to a Fuzzy Inference System (FIS). For each of the input parameters seven *Gaussian* 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). 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 *Gaussian* 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). These linguistic values have been transformed into crisp values by defuzzification method.
4. The crisp values of MPCI **(Table 2)** have been optimized by using Taguchi' philosophy. The predicted optimal setting has been evaluated from *Mean Response Plot* of MPCIs and it became A3 B2 C1 D1.
5. Optimal setting has been verified by confirmatory test.

6. Data Analysis: Application of TOPSIS

In TOPSIS based Taguchi approach, experimental data have been normalized first using **Eq. (3)**. The normalized data have been furnished in **Table 8**. Elements of normalized decision-making matrix have been multiplied with corresponding response weights to obtain weighted normalized decision-making matrix shown in **Table 9**. Computed *Ideal* and *Negative-Ideal* solutions have been furnished in **Table 10**. Computed distance measures: S^+ and S^- have been tabulated in **Table 11**. Closeness Coefficient (CC) against each experimental run has been calculated using **Eq. (8)** and shown in **Table 12-13**. CC has been optimized (maximized) finally using Taguchi method. **Fig. 8** reveals S/N ratio plot of closeness coefficient values. Optimal parameter combination becomes: which has been verified by confirmatory test. Ranking of factors according to their influence on CC has been shown in **Table 14** (mean response table for S/N ratio of CCs).

7. Conclusions

Taguchi method is an efficient method used in off-line quality control in that the experimental design is combined with the quality loss. This method including three stages of systems design, parameter design, and tolerance design. It is obvious that most industrial applications solved by Taguchi method refer to single-response problems. However, in the real world more than one quality characteristic should be considered simultaneously for most industrial products, i.e. most problems customers concern about optimization of multiple responses. To this end the present study highlights application feasibility of fuzzy logic in Taguchi's optimization philosophy to optimize multiple

requirements of product quality characteristics in Electro Discharge Machining (EDM). Apart from quality; productivity aspects have also been studied. Rough machining with EDM results poor surface finish and generates micro cracks and pores. Finished machining gives better surface finish but with poor material removal rate (MRR). Hence achieving desired quality and high productivity has been considered as a multi-objective optimization problem and attempted to be solved in the present context.

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 data

Factorial settings (Coded)				Experimental data		MPCI Crisp Values
A	B	C	D	MRR (mm^3/min)	R_a (µm)	
1	1	1	1	0.86191	4.60	0.377
1	2	2	2	0.47368	2.13	0.370
1	3	3	3	0.22585	2.67	0.214
2	1	2	3	2.85429	8.40	0.441
2	2	3	1	4.87143	8.20	0.518
2	3	1	2	3.52000	8.07	0.458
3	1	3	2	4.38095	9.53	0.489
3	2	1	3	7.40476	13.73	0.465
3	3	2	1	8.35714	14.00	0.485

Table 3: Computation of S/N ratios

Sl. No.	S/N ratio for MRR (db)	S/N ratio for R_a (dB)
1	-1.2908	-13.2552
2	-6.4902	-6.5676
3	-12.9236	-8.5302
4	9.1099	-18.4856
5	13.7531	-18.2763
6	10.9309	-18.1375
7	12.8314	-19.5819
8	17.3902	-22.7534
9	18.4412	-22.9226

Table 4: Normalized of S/N ratios

Sl. No.	Normalized S/N ratio of MRR	Normalized S/N ratio of R_a
1	0.370887	0.591098
2	0.205115	1
3	0	0.88
4	0.702491	0.271293
5	0.85053	0.28409
6	0.76055	0.292577
7	0.821143	0.204262
8	0.966491	0.010345
9	1	0

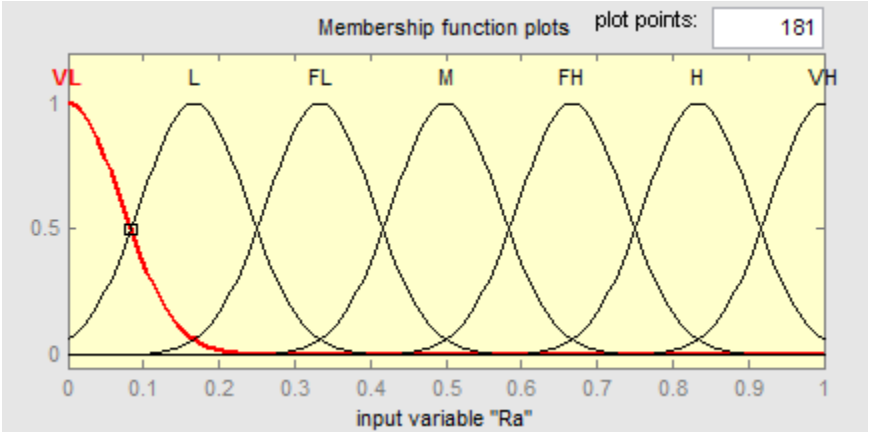

Figure 1: MFs for R_a

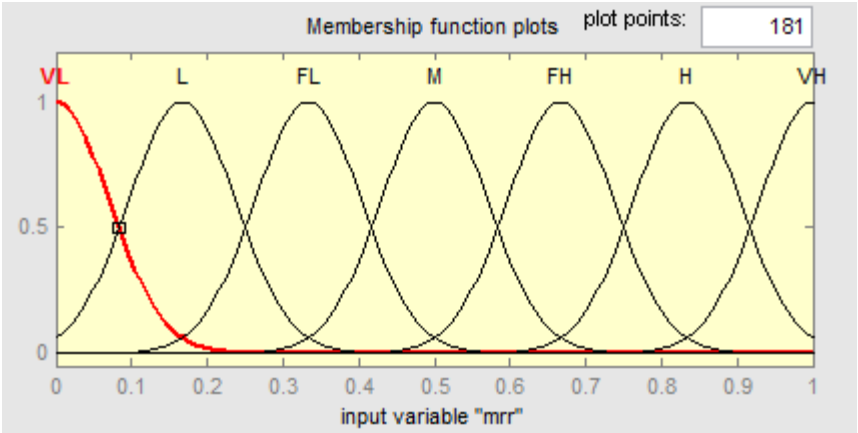

Figure 2: MFs for MRR

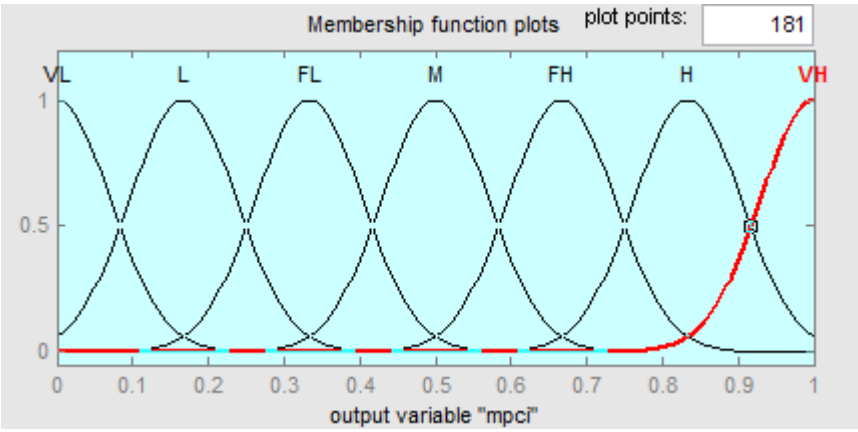

Figure 3: MFs for MPCI

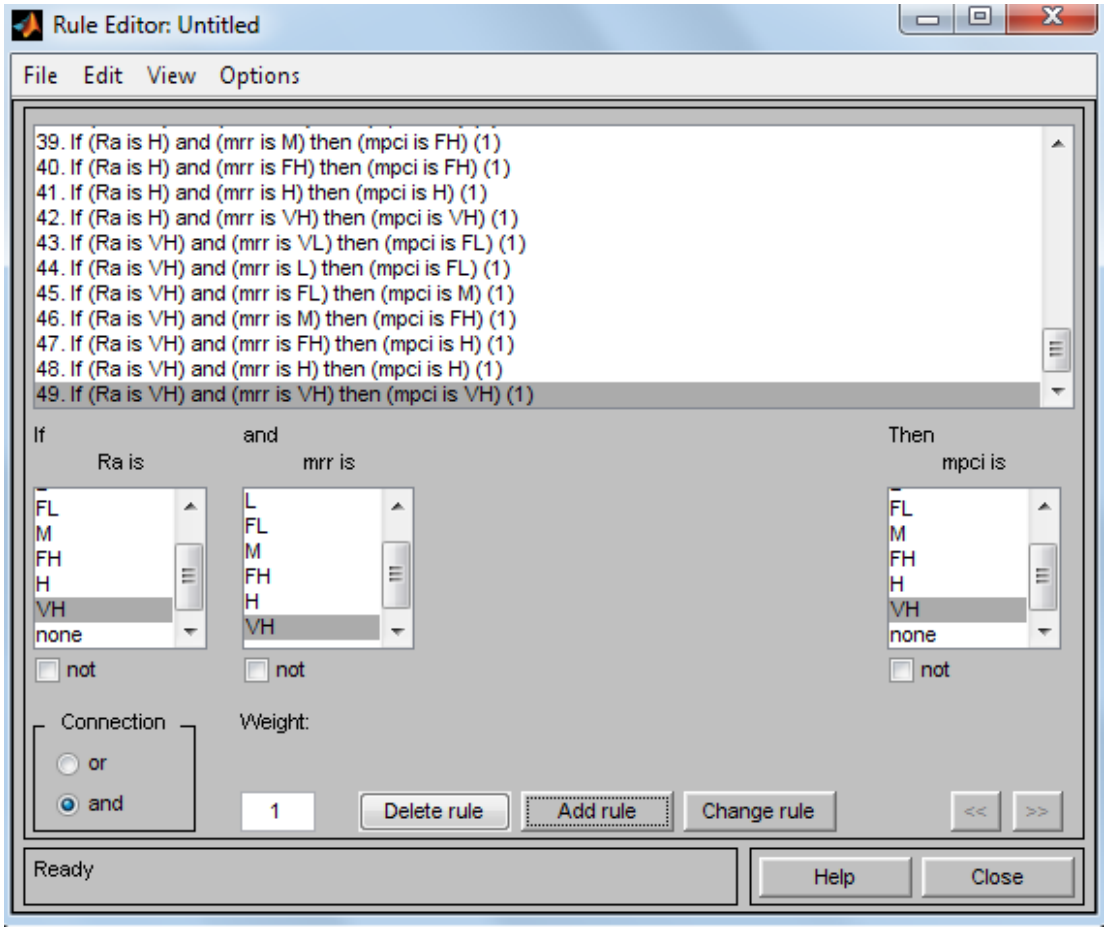

Figure 4: Fuzzy rule viewer

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

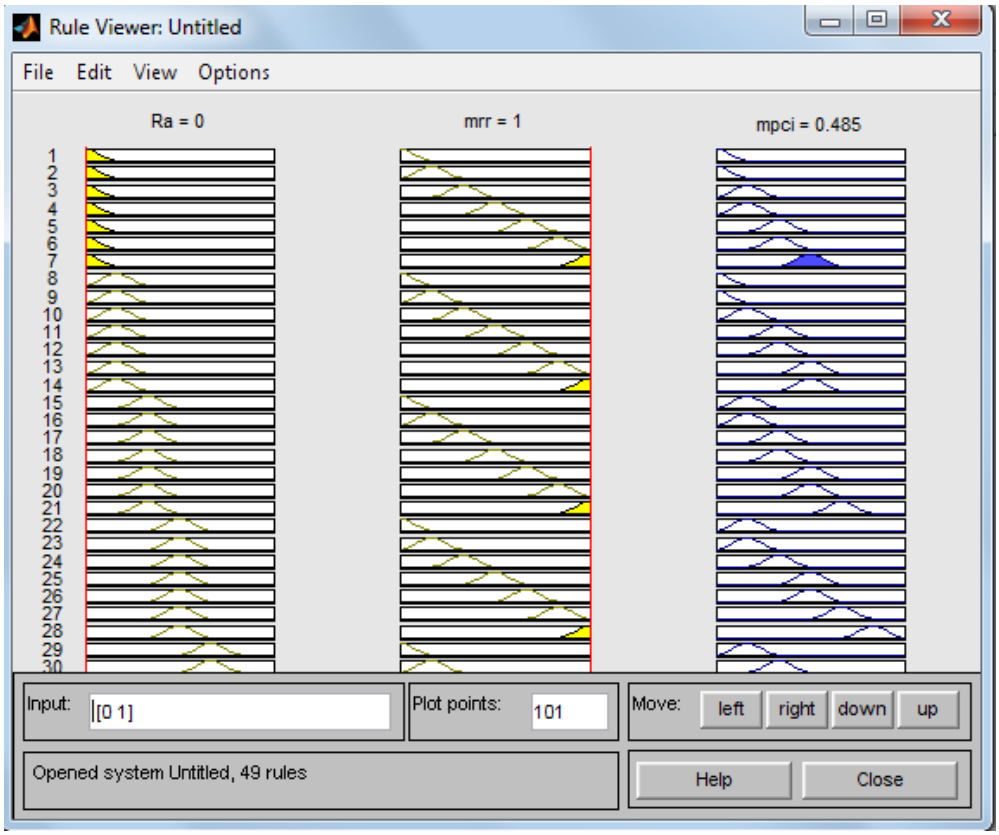

Figure 5: Computation of MPCI

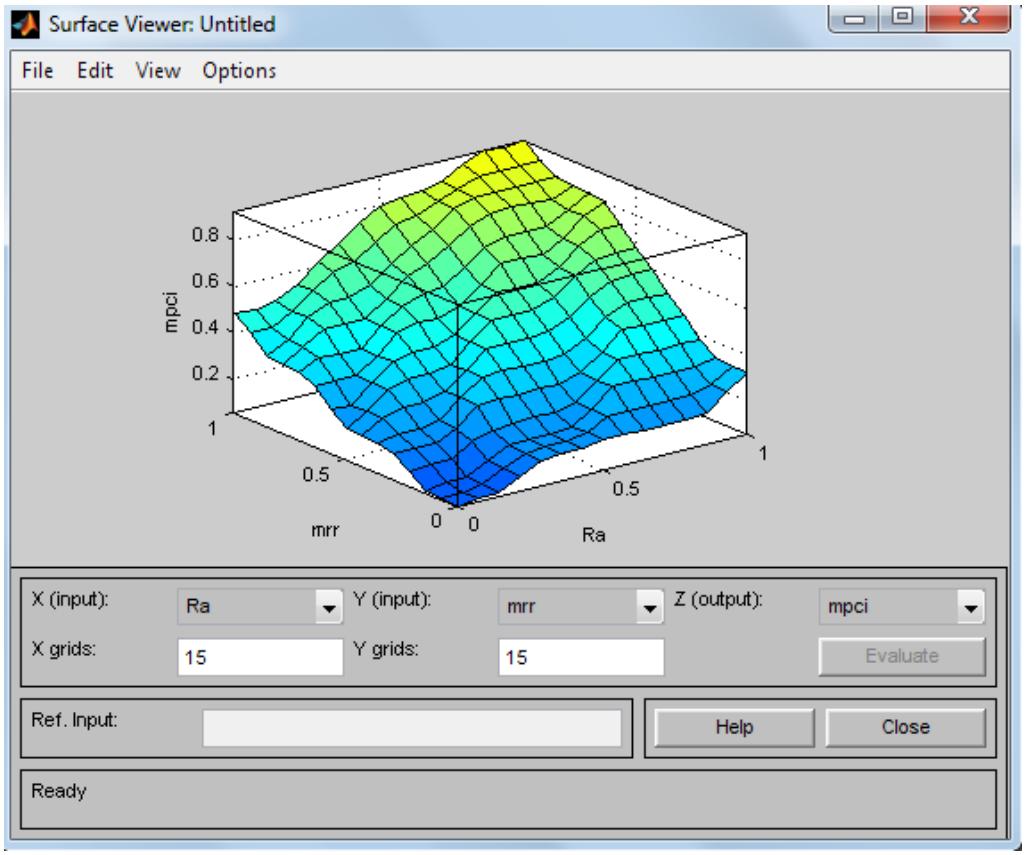

Figure 6: Fuzzy inference surface plot

Table 6: Computed MPCI values and corresponding S/N ratios

Sl. No.	Factorial Settings				MPCI	S/N Ratio of MPCI (dB)	
	A	B	C	D		Experiments	Predicted at Optimal setting
1	1	1	1	1	0.377	-8.4732	-4.42356
2	1	2	2	2	0.370	-8.6360	
3	1	3	3	3	0.214	-13.3917	
4	2	1	2	3	0.441	-7.1112	
5	2	2	3	1	0.518	-5.7134	
6	2	3	1	2	0.458	-6.7827	
7	3	1	3	2	0.489	-6.2138	
8	3	2	1	3	0.465	-6.6509	
9	3	3	2	1	0.485	-6.2852	

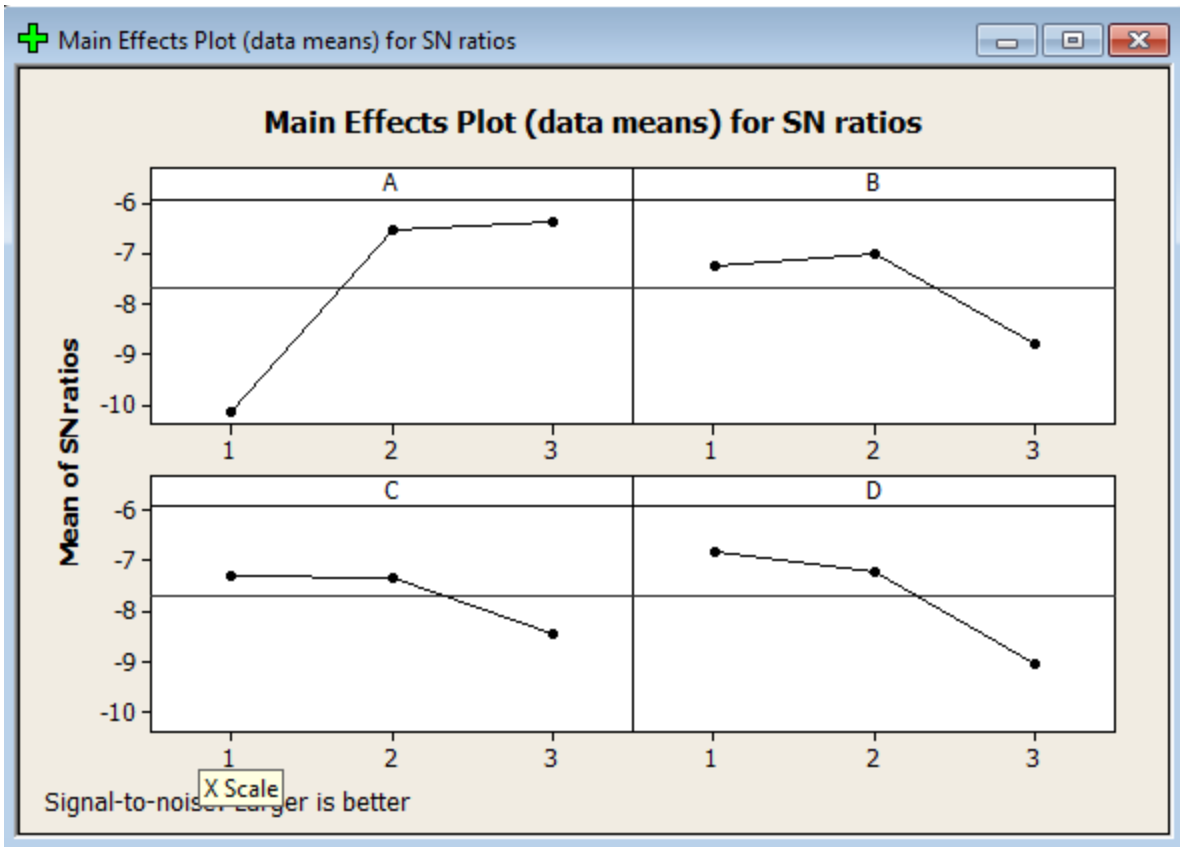

Figure 7: S/N ratio plot for MPCI (Evaluation of optimal setting) **A3 B2 C1 D1**

Table 7: Response table for S/N ratios of MPCI

Level	A	B	C	D
1	-10.167	-7.266	-7.302	-6.824
2	-6.536	-7.000	-7.344	-7.211
3	-6.383	-8.820	-8.440	-9.051
Delta	3.784	1.820	1.137	2.227
rank	1	3	4	2

Table 8: Normalized decision-making matrix

Sl. No.	R_a	MRR
1	0.172503	0.062669
2	0.079876	0.034442
3	0.100127	0.016422
4	0.315006	0.207536
5	0.307506	0.354202
6	0.302631	0.25594
7	0.357382	0.31854
8	0.514885	0.538401
9	0.52501	0.607649

Table 9: Weighted normalized decision-making matrix

Sl. No.	R_a	MRR
1	0.086252	0.031335
2	0.039938	0.017221
3	0.050063	0.008211
4	0.157503	0.103768
5	0.153753	0.177101
6	0.151315	0.12797
7	0.178691	0.15927
8	0.257442	0.269201
9	0.262505	0.303825

Table 10: Ideal and negative-ideal solutions

Sl. No.	Ideal	Negative-Ideal
1	0.039938	0.262505
2	0.303825	0.008211

Table 11: Computed distance measures

Sl. No.	S^+	S^-
1	0.276398	0.177763
2	0.286604	0.222749
3	0.295787	0.212442
4	0.232044	0.141974
5	0.170332	0.200875
6	0.208158	0.163418
7	0.200371	0.172753
8	0.220243	0.261039
9	0.222567	0.295614

Table 12: Closeness coefficient

Sl. No.	C^+
1	0.60859
2	0.562682
3	0.581996
4	0.620409
5	0.45886
6	0.560203
7	0.537009
8	0.457617
9	0.429516

Table 13: Computed S/N ratios of closeness coefficients

Sl. No.	Factorial Settings				C^+	S/N Ratio	S/N Ratio at predicted optimal setting
	A	B	C	D			
1	1	1	1	1	0.608590	-4.31350	-3.31612
2	1	2	2	2	0.562682	-4.99473	
3	1	3	3	3	0.581996	-4.70161	
4	2	1	2	3	0.620409	-4.14644	
5	2	2	3	1	0.458860	-6.76640	
6	2	3	1	2	0.560203	-5.03309	
7	3	1	3	2	0.537009	-5.40037	
8	3	2	1	3	0.457617	-6.78995	
9	3	3	2	1	0.429516	-7.34041	

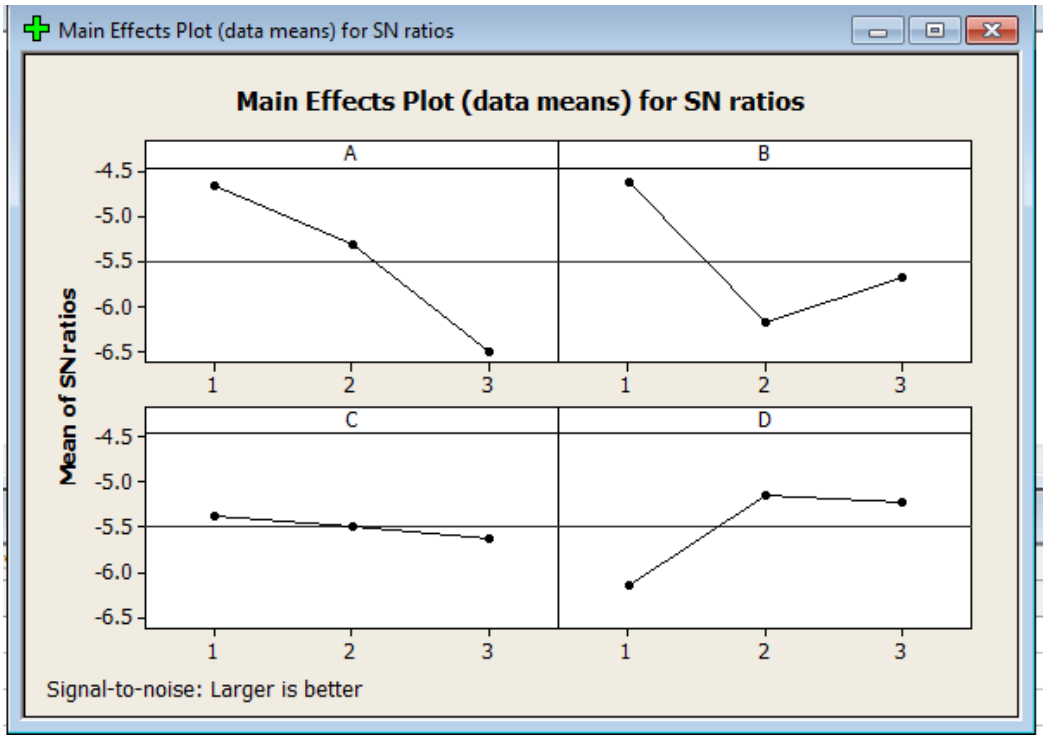

Figure 8: Prediction of optimal setting **A1 B1 C1 D2**
(S/N ratio plot for closeness coefficient)

Table 14: Response table for S/N ratios of MPCI

Level	A	B	C	D
1	-4.670	-4.620	-5.379	-6.140
2	-5.315	-6.184	-5.494	-5.143
3	-6.510	-5.692	-5.623	-5.213
Delta	1.840	1.564	0.244	0.997
rank	1	2	4	3

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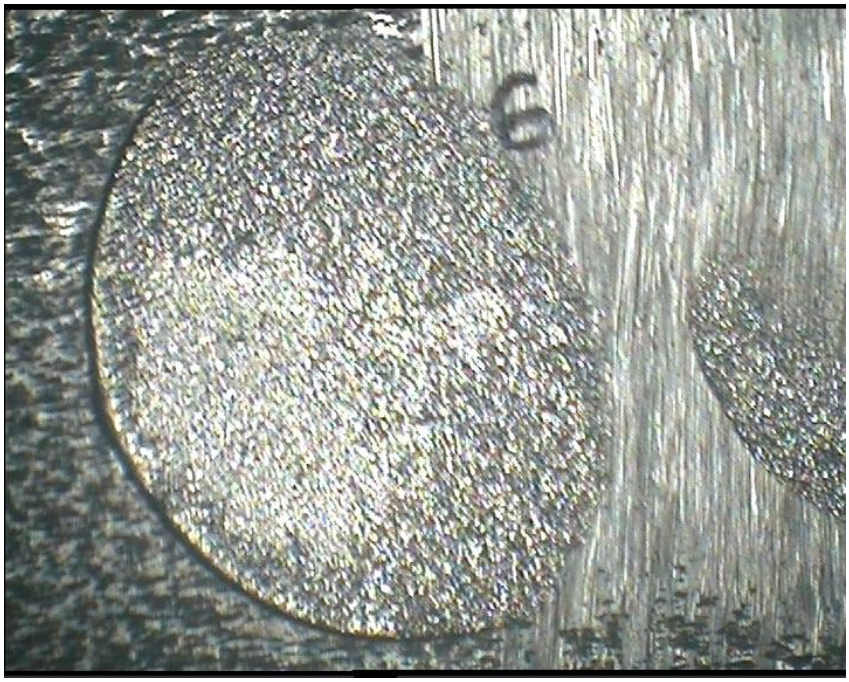
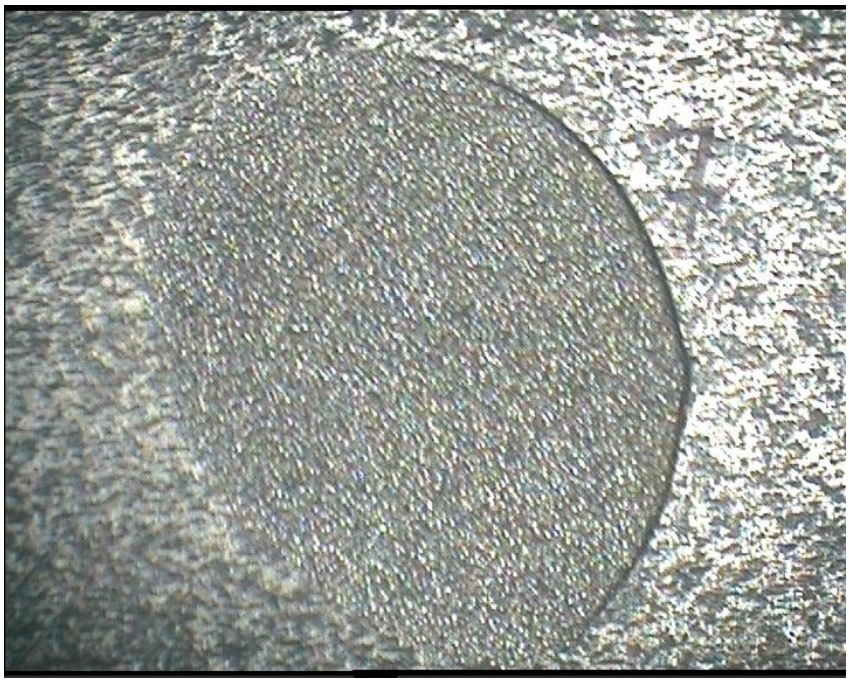
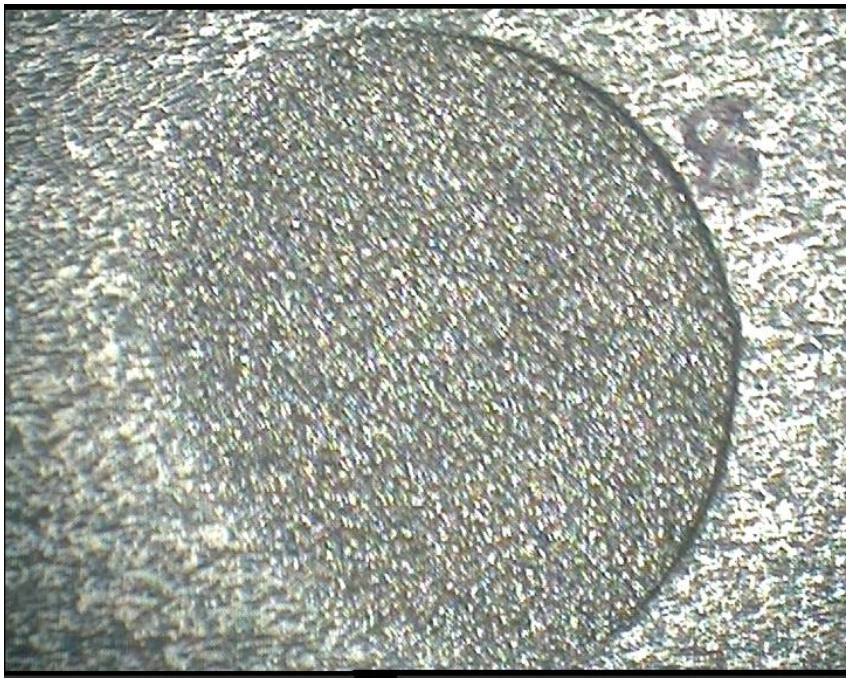
Appendix



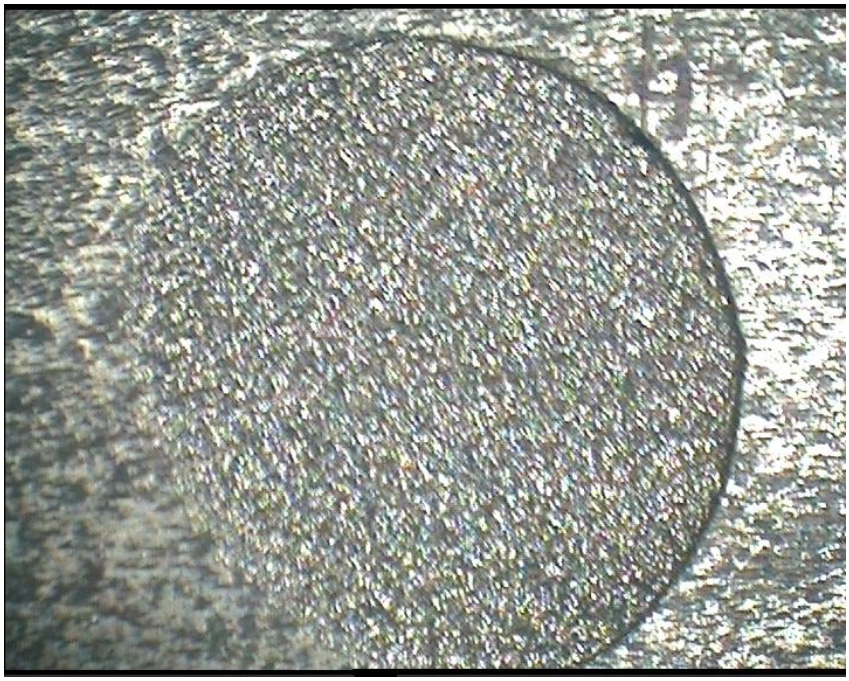
EDM machined surface (Sample No. 6)



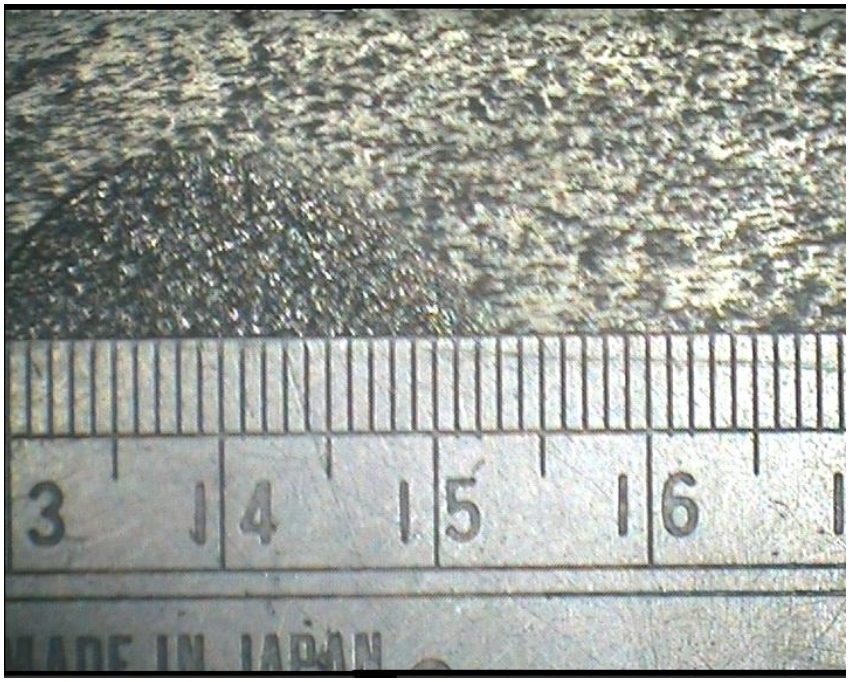
EDM machined surface (Sample No. 7)



EDM machined surface (Sample No. 8)



EDM machined surface (Sample No. 9)



SACALE: 4” ~720 Pixels

Communication

Umakanta Behera, Chitrasen Samantra, Saurav Datta, Siba Sankar Mahapatra, “*Application of Fuzzy Logic in the Taguchi Method for multi-response optimization in EDM*”, International Conference on Modeling, Optimization and Computing (ICMOC 2012), Noorul Islam University, Noorul Islam Centre for Higher Education, Kumaracoil, Thuckalay, Kanyakumari District, Tamilnadu State, India- 629 180, April 10-11 2012. (**Accepted**)