FUZZY MODELING FOR ELECTRICAL DISCHARGE MACHINING OF ALUMINUM ALLOY

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ABSTRACT

Electrical discharge machining (EDM) is widely used process in the production of mould / dies, aerospace, automobile and electronics industries where intricate complex shapes need to be machined in very hard materials. The selection of the AISI 64430 was made taking into account its wide range of applications in the industrial field: defense, pharmaceutical, aerospace, shipbuilding industries etc. In this paper an attempt has been made to develop the mathematical model for predicting die-sinking electrical discharge machining of AISI 64430 (HE 30) aluminum alloy characteristics such as the metal removal rate (MRR), the tool wear rate (TWR), the surface roughness (Ra value) and the hardness(HRB) using fuzzy mathematical method. The process parameters taken in to consideration were the current (I), the open-circuit voltage (V), the servo (Sv) and the duty cycle (η). A fuzzy rule base characterizing the relationship between input and output parameters was built through experiments. The design of experiments technique has been used to conduct the experiments, which in turn reduced the number of experiments. The prediction of metal removal rate, the tool wear rate, the surface roughness and the hardness was achieved under the condition of given input parameters by rule-based fuzzy reasoning. The predicted results were analyzed through experimental verification. The model predicted values and measured values were fairly close to each other. To have more precise investigation into the model, a regression analysis of experimental and predicted outputs was performed. It was found that the R^2 (R: coefficient of determination) values are 0.9015, 0.9702, 0.9932 and 0.844 for the metal removal rate, the tool wear rate, the surface roughness and the hardness, respectively.

Keywords: *EDM, Fuzzy rule base, Aluminum alloy, Machining parameters*

1. INTRODUCTION

Electric discharge machining (EDM), sometimes colloquially also referred to as spark machining, spark eroding, burning, die sinking or wire erosion. It is a non-traditional manufacturing process whereby a desired shape is obtained using electrical discharges (sparks). EDM is a complex phenomenon where several disciplines of science and branches of engineering are involved in its theory. It is primarily used for hard metals or those that would be very difficult to machine with traditional techniques. Material is removed from the work piece by the thermal erosion process, i.e., by a series of recurring electrical discharges between a cutting tool acting as an electrode and a conductive work piece, in the presence of a dielectric fluid. This discharge occurs in a voltage gap between the electrode and work piece. Heat from the discharge vaporizes minute particles of work piece material, which are then washed from the gap by the continuously flushing dielectric fluid [1].

The EDM process was invented by two Russian scientists, Dr. B.R. Lazarenko and Dr. N.I. Lazarenko in 1943 in the Technical Institute of Moscow during the Second World War [2]. Chen and Luo [3] studied the main effect of thermal energy in the case of micro-energy EDM to explain hypothetically the non-linear correlation between surface roughness and discharge energy per pulse and very smooth surfaces achieved only by applying very short discharge pulses. The surface roughness parameters (*R*a and *R*q) were modeled in function of the intensity (*I),* pulse time (t_i) and pause time (t_0) factors. Factorial design of experiments combined with techniques of regression was applied for modeling the behavior of functions depending on several variables. As it can be observed, the factor having the most important influence on the surface roughness is the factor of intensity. Furthermore, it has been observed that there is a strong interaction between the I and the t_i factors being advisable to work with high I values and low t_i values [4].

Tarng *et al* [5] studied the use of fuzzy set theory in constructing new pulse discriminator in electrical discharge machining. To obtain optimal classification performance, a machine learning method based on a simulated annealing algorithm is adopted to automatically synthesize the membership functions of the fuzzy pulse discriminator. It has been found that the trapezoid-shaped membership functions are suitable for the developed fuzzy pulse discriminator. In the recent years many researchers had used regression models, analysis of variance [6-8] and Taguchi methods [9] for modeling and analyzing the influence of process variables over some specific response.

Yih-fong Tzeng and Fu-chen Chen [10] designed the ideal function of an EDM system coupled with Taguchi methods for process optimization. A two-step optimization strategy has been applied. The first step is to reduce the functional variability of the EDM system to enhance process robustness. The second step is to increase the machining accuracy by adjusting the slope of the best-fit line between the input signals and the output responses. Mahdavinejad [11-12] studied optimization and control of EDM process using the neural model predictive control method and the method of model predictive control based on artificial neural networks with output parameters of the system to minimize the number of non-successive pulses is used. To determine the value of stability process parameter, a fuzzy analysis method is developed to distinguish the single pulse discharge type. As the optimizing algorithm of model predictive controller, a genetic algorithm on parameters of pulse on and off time, discharge current, gap size and its variations rate, are used and also the method of execution of changes on a convenient electric discharge machine has been explained. From the testing results the electric discharge machining of WC-Co confirms the capability of the system of predictive controller model based on neural network with 32.8% efficiency increasing in stock removal rate. Marcel Sabin Popa [13] presented the importance of all parameters that can influence the quality of the process and in the EDM Process in the industry of machine building. The main parameters that are followed during the process are the precision and the roughness of the surface. The collective tried to emphasis the importance variation of the roughness concerning some machining parameters. Prabhu and Vinayagam [14] developed the Regression model to predict surface roughness of AISI D2 in Electrical Discharge Machining (EDM) process. In the development of predictive models, machining parameters of Pulse current, Pulse on duration, voltage were considered as model variables. Analysis of variance and F-test were used to check the validity of regression model and to determine the significant parameter affecting the surface roughness. Kathiresan and Sornakumar [15] developed Aluminum alloy-silicon carbide composites using vortex method and pressure die casting technique. The EDM studies showed that the MRR and the surface roughness are greatly influenced by the current and percent weight silicon carbide. The MRR increases with an increase in the current and decrease in the percent weight of silicon carbide. The surface finish improves with decrease in the current and increase in the percent weight of silicon carbide. Shabgard and Shotorbani [16] developed mathematical model of machining parameters in electrical discharge machining of FW4 welded steel, for relating the Material Removal Rate (MRR), Tool Wear Ratio (TWR) and surface roughness (Ra) to machining parameters (current, pulse-on time and voltage). The effects of machining parameters in respect of listed technological characteristics were analyzed and the results showed that, the developed mathematical models, can adequately describe the performance within the limits of the factors being studied.

Kozak and Gulbinowicz [17] studied the effect of the tool electrode wear on the accuracy of the Rotating Electrical Discharge Machining. Two mathematical models of Rotating Electrical Discharge Machining has been developed: the first one considers machining with the face of the end tool electrode and the second one considers EDM with the lateral side of the electrode. The software for computer simulation of EDM machining with the side and face of the electrodes has been developed.

In the present work, an attempt has been made to develop the mathematical model for predicting die-sinking electrical discharge machining of AISI 64430 (HE30) aluminum alloy characteristics such as the metal removal rate (MRR), the tool wear rate (TWR), the surface roughness (Ra value) and the hardness (HRB) using fuzzy mathematical method. The process parameters taken in to consideration were the current (I), the open-circuit voltage (V), the servo (SV) and the duty cycle (η). The model predicted values and measured values were fairly close to each other. Their propinquity to each other indicates the developed model can be effectively used to predict the MRR, TWR, Ra and HRB in the machining of AISI 64430 aluminum alloys. To have more precise investigation into the model, a regression analysis of experimental and predicted outputs was performed.

2. MATERIALS AND METHODS

The work piece material chosen for the present investigation was aluminum alloy AISI 64430 (HE30) which is having a wide range of applications in aerospace, structural and general engineering items such as rail & road, transport vehicles, bridges, cranes, roof trusses, rivets etc. The chemical composition of material is given in Table 1.

Table 1. Chemical composition of aluminum alloy 64430.

Composition	Min	Max
copper	-	0.1
Magnesium	0.4	1.2
Silicon	0.6	1.3
Iron	-	0.6
Manganes	0.4	1
Others	-	0.3

2.1. Fuzzy Modeling of Electrical Discharge Machining Process

In 1965, the theory of fuzzy sets proposed by Zadeh [18] provided a decision maker with a mathematical tool useful for modeling uncertain (imprecise) and vague data to be present in many real decision problems. Basically, Fuzzy Logic (FL) is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers [19].

Fuzzy logic is one of the most successful of today's technologies for developing sophisticated control systems. It is also popular on account of its capability for developing rule-based expert systems. Fuzzy controllers and fuzzy reasoning have found particular applications in industrial systems that are very complex and cannot be modeled precisely even under various assumptions and approximations. Fuzzy logic proved to be an effective means for dealing with objectives that are linguistically specified [20]. Linguistic terms such as low, medium and high may be defined by fuzzy sets. Fuzzy set theory has attracted the attention of many researchers in the mathematical and engineering fields. A fuzzy set, as name implies, is a set without a crisp boundary. That is, the transition is gradual and this smooth transition is characterized by membership functions. The fuzzy inference system or fuzzy model is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning.
The basic structure of the fuzzy inference system consists of three conceptual components which are rule base, data base and reasoning mechanism. A rule base, which contains a selection of fuzzy rules and a data base, which defines the member ship functions used in the fuzzy rules. A reasoning mechanism, which performs the fuzzy reasoning based on the rules and given facts to derive a reasonable output or conclusion [21]. The structure of the fuzzy logic controller is shown in Fig 1. Although, there are several fuzzy models available, in this paper Mamdani fuzzy inference method [22] a commonly used fuzzy logic methodology, is utilized as kernel of the fuzzy logic controller for modeling the electric discharge machining process.

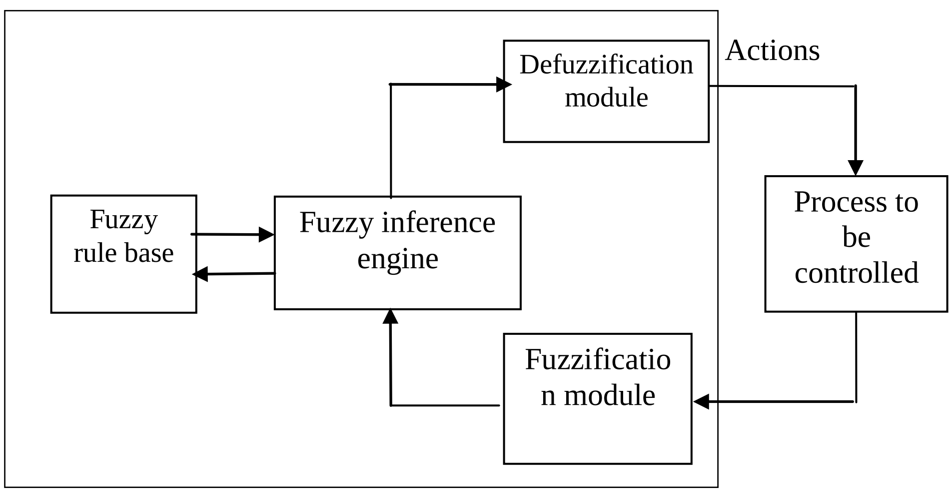

Figure 1. Structure of the Fuzzy logic controller.

2.1.1. Fuzzy Expressions

For the prediction of output parameters such as metal removal rate, tool wear rate, surface roughness and hardness, the EDM process is modeled using four input parameters such as current, open-circuit voltage, servo and duty cycle. The first step in establishing the algorithm for fuzzy model is to choose the shape of the fuzzy membership function or fuzzy sets of the process variables. The fuzzy expressions for different input parameters and output parameters are shown in Fig 2-9.

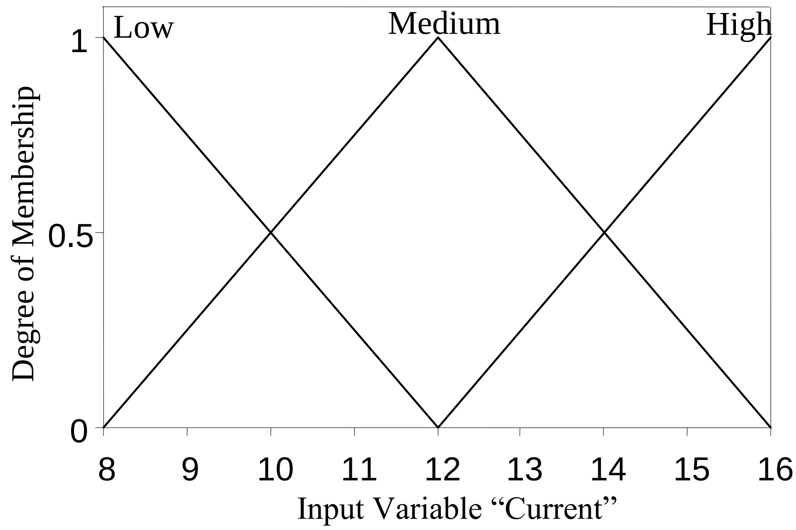

Figure 2. Member ship function of Current.

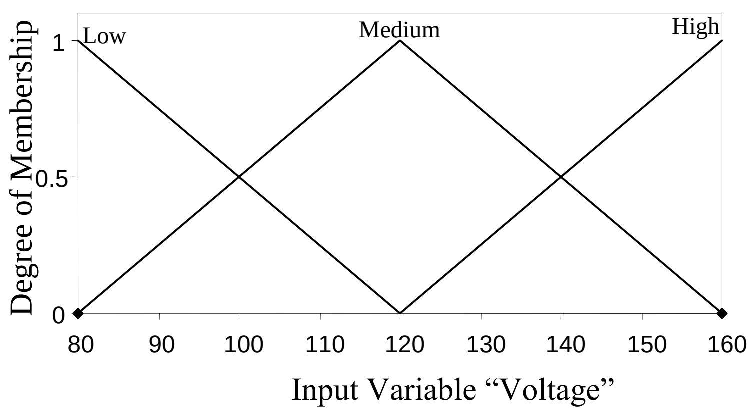

Fig 3. Member ship function of Voltage.

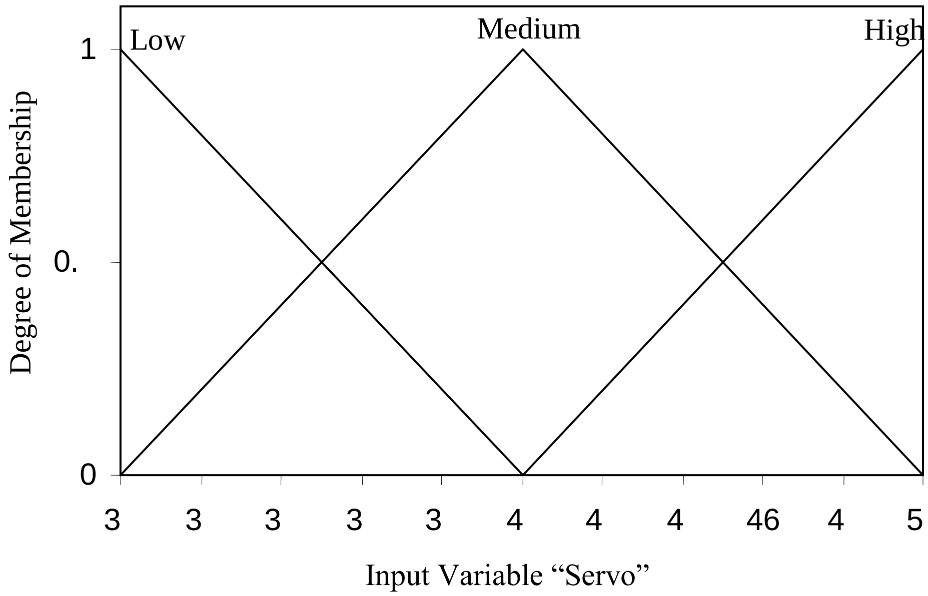

Figure 4. Member ship function of Servo.

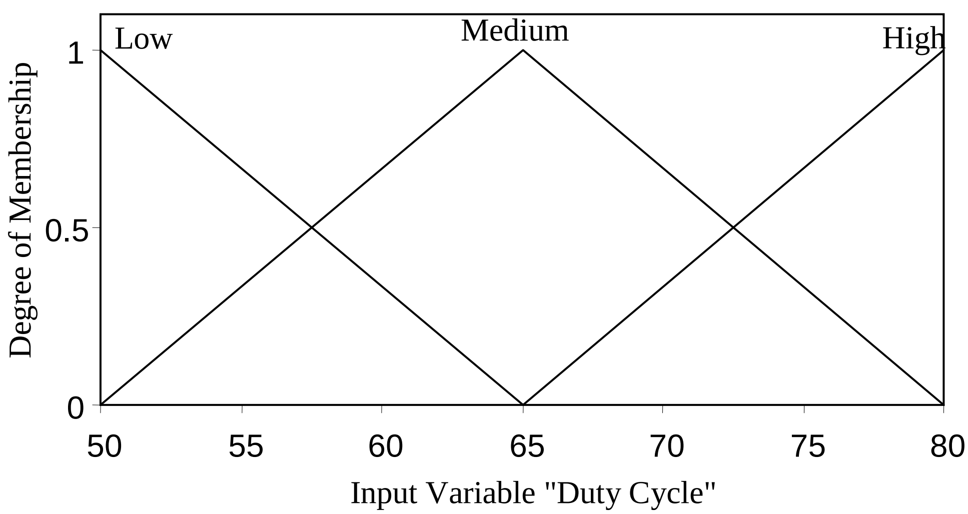

Figure 5. Member ship function of Duty Cycle.

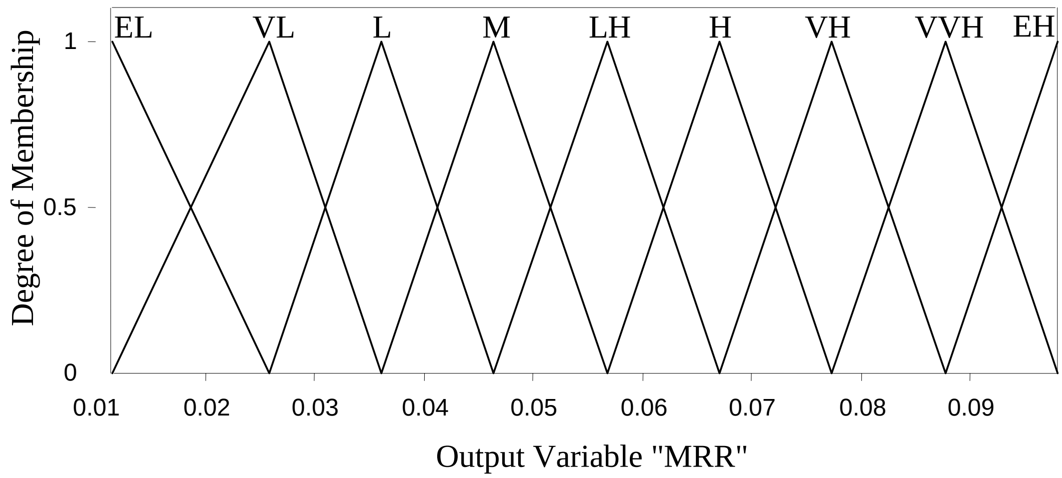

Figure 6. Member ship function of MRR.

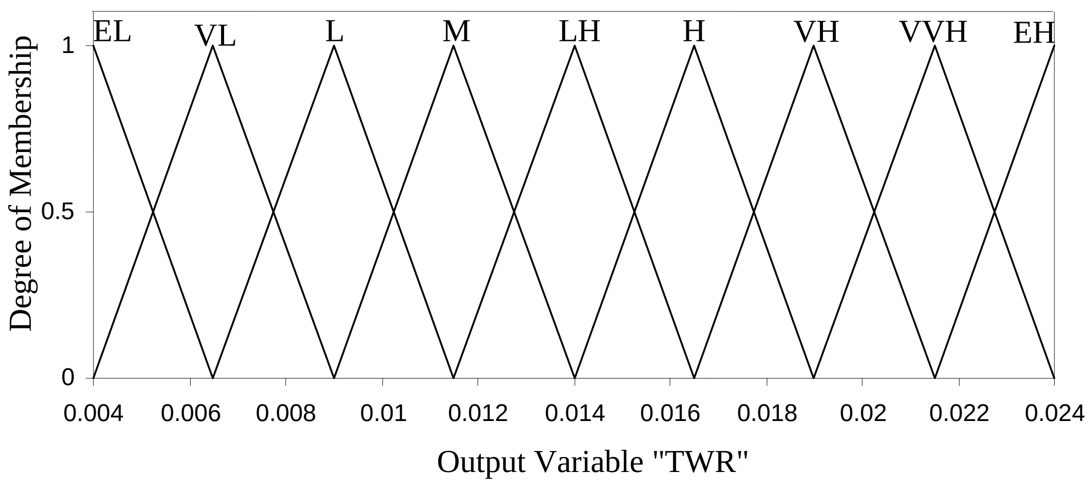

Figure 7. Member ship function of TWR.

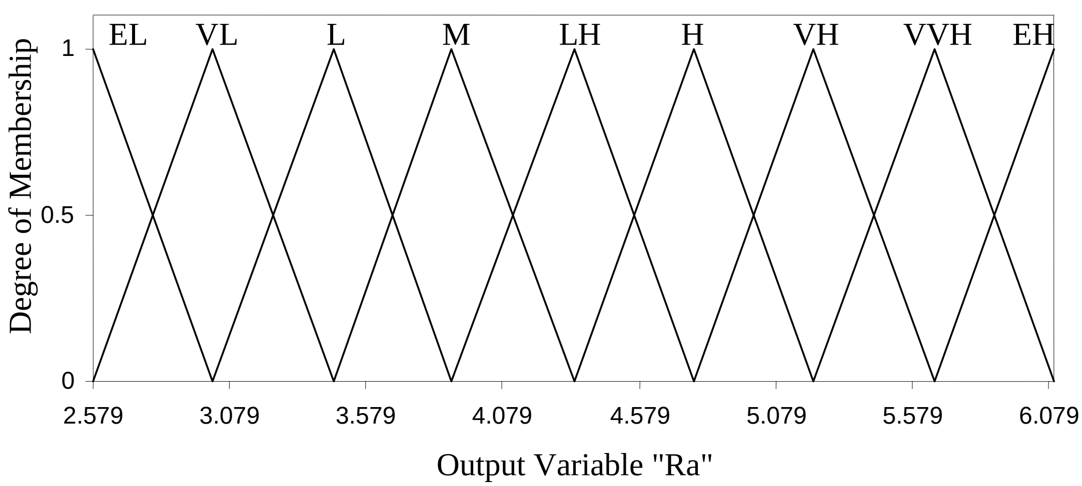

Figure 8. Member ship function of Surface Roughness.

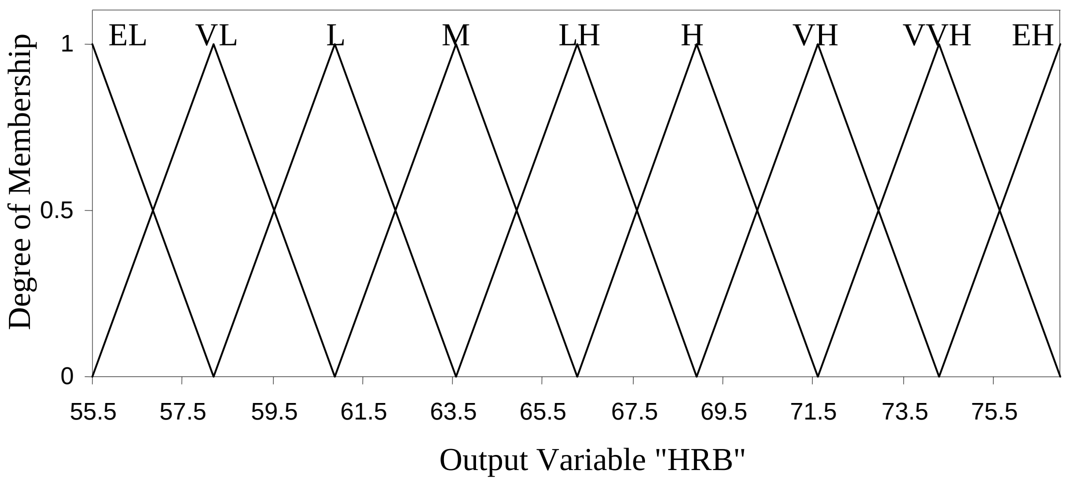

Fig 9. Member ship function of Hardness.

2.1.2. Degree of Membership Functions of Input and Output Variables

The first stage in the application of fuzzy logic to model the EDM process is identifying the variation ranges of input and output variables. Then the range of each process variable is divided into group of fuzzy subsets. Each fuzzy sub set is given a proper name and assigned a member ship function. The membership function is assigned without depending on the results of the experiments. In general membership functions are classified into trapezoidal, triangular and square and their combinations etc. In the present work triangular membership functions are selected for fuzzy input and output parameters. The membership functions for input and output parameters are

Current (I):

The current range of 8 to 16A can be divided into three fuzzy sets as {low, medium, high} and is $\mathbf{I} = \{\mathbf{I_1}, \mathbf{I_2}, \mathbf{I_3}\}$ expressed in vector form. The degree of membership function of current is shown in Fig 2.

The membership function of current in equation form is listed as follows:

$$I_1(x) = \frac{12 - x}{4}, x \in [8,12]$$

$$I_2(x) = \begin{cases} \frac{x - 8}{4}, x \in [8,12] \\ \frac{16 - x}{4}, x \in [12,16] \end{cases}$$

$$I_3(x) = \frac{x - 12}{4}, x \in [12,16]$$

Voltage (V):

The range of voltage is 80 to 160 volts and is divided into three fuzzy sets as {low, medium, high} and is $\mathbf{V} = \{\mathbf{V_1}, \mathbf{V_2}, \mathbf{V_3}\}$ expressed in vector form. The degree of membership function of current is shown in Fig 3.

Servo(SV):

The range of Servo30 to 50% and is divided into three fuzzy sets as {low, medium, high} and is $\mathbf{SV} = \{\mathbf{SV_1}, \mathbf{SV_2}, \mathbf{SV_3}\}$ expressed in vector form. The degree of membership function of current is shown in Fig 4.

Duty Cycle(η):

The range of dutycycle is 500 to 80 and is divided into three fuzzy sets as {low, medium, high} and is $\boldsymbol{\eta} = \{\boldsymbol{\eta_1}, \boldsymbol{\eta_2}, \boldsymbol{\eta_3}\}$ expressed in vector form. The degree of membership function of current is shown in Fig 5.

Output variable -MRR

The more the fuzzy sets of the output variable, the nearer is the prediction value to the real value. As output variable, the metal removal rate range from 0.015 to 0.98 and is divided into nine fuzzy sets as {Extremely Low, Very Low, Low, Medium, Less High, High, Very High, Very Very High, Extremely High}. It is $\mathbf{M = \{M_1, M_2, M_3, M_4, M_5, M_6, M_7, M_8, M_9\}}$ expressed in vector form. The membership function of MRR is shown in Fig 6.

Output variable –TWR

The range of tool wear rate range from 0.004 to 0.024 and is divided into nine fuzzy sets as {Extremely Low, Very Low, Low, Medium, Less High, High, Very High, Very Very High, Extremely High}. It is $\mathbf{T = \{T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8, T_9\}}$ expressed in vector form. The membership function of TWR is shown in Fig 7.

Output variable –Surface Roughness (Ra)

The range of surface roughness range from 2.579 to 6.099 and is divided into nine fuzzy sets as {Extremely Low, Very Low, Low, Medium, Less High, High, Very High, Very Very High, Extremely High}. It is $\mathbf{R = \{R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8, R_9\}}$ expressed in vector form. The membership function of Ra is shown in Fig 8.

Output variable –HRB

The range of hardness range from 55.5 to 77 and is divided into nine fuzzy sets as {Extremely Low, Very Low, Low, Medium, Less High, High, Very High, Very Very High, Extremely High}. It is $\mathbf{H = \{H_1, H_2, H_3, H_4, H_5, H_6, H_7, H_8, H_9\}}$ expressed in vector form. The membership function of HRC is shown in Fig 9.

2.1.3. Establishing the Fuzzy Rule Base of Input and Output Variables

Determining of the relationship between input and output variables

In order to determine the relationship between input and output variables, the EDM experiments were conducted using factorial design in the design of experiment by considering the affecting parameters of current, open-circuit voltage, servo and duty cycle. The values of each parameter used in the experiments were set to the value when parameter membership degree is 1. For example, the fuzzy sets of current are {low, medium, high}, the degree of membership is equal to 1, the corresponding current will be {8A, 12A, 16A}, the current values will be used in experiments. In this way, the Voltage is 80V, 120V, 160V}, the Servo is {30%, 40%, 50%}, the dutycycle is {50, 65, 80} for the experiments.

Each experiment will result in output parameters, which should be determined to belong to which fuzzy sets of the output variable. So the value of the output parameters should be put into the membership function of the output variables to calculate its degree of membership. Then they will be identified to belong to which fuzzy sets using the principle of maximum degree of membership.

2.1.4. Establishment of Rule Base

The relationship between input and the output in fuzzy system is characterized by a set of linguistic statements which are called fuzzy rules. They are defined based on the experimental work, expert and engineering knowledge. One experiment results in one fuzzy rule. If all the fuzzy rules are saved in a data base, a fuzzy rule base will be established. The number of fuzzy rules in fuzzy system is related to the number of fuzzy set for each input variable. In this study 25 fuzzy rules were established. The fuzzy rules can be expressed by:

$F(I_i, V_j, SV_k, \eta_l) \rightarrow M_p, T_q, R_r, H_s$ (i, j, k, l $\in$ [1,3], p, q, r, s $\in$ [1,9]); i, j, k, l, p, q, r, s $\in$ z

Few examples of the fuzzy rules in linguistic form are shown below.

Rule 1: *If current is low and Voltage is low and Servo is low and dutycycle is low then MRR is Low and TWR is Low and Ra is low and HRB is low*

Rule 2: *If current is High and Voltage is low and Servo is low and dutycycle is low then MRR is Extremely High and TWR is Extremely High and Ra is Very High and HRB is High.*

Rule 3: *If current is Low and Voltage is High and Servo is low and dutycycle is low then MRR is Low and TWR is Very low and Ra is low and HRB is High etc.,*

These rules are formed based on the experimental results presented in Table 3.

2.1.5. Prediction of output parameters

The defuzzification method of centroid method is adopted to predict the output parameters as shown in equation in equation. This was carried out with the help of fuzzy logic controller in the MATLAB Tool Box [22].

$$U_f = \frac{\sum_{j=1}^{p} A(\alpha_j) \times f_j}{\sum_{j=1}^{p} A(\alpha_j)}$$

Where U_f is the output of the controller (MRR, TWR, Ra, and HRB)
$A(\alpha_j)$ is the firing area of the j^{th} rule
p is the total number of fired rules
f_j represents the centroid of the area

3. EXPERIMENTAL DETAILS

The experiments were conducted according to factorial design with 9 centre points. The machining parameters chosen for the present investigation are Intensity (I), open-circuit voltage (V), Servo (Sv) and duty cycle (pulse-on time (t_d) is the duration of time (in μ s) the current is allowed to flow per cycle. Pulse-off time (t_o) is the duration of time (in μ s) between two consecutive sparks. On the other hand, duty cycle (η) is the ratio of the pulse-on time to the total pulse time expressed in percentage. Hence it can be expressed mathematically as Duty cycle (η) $= {t_d}/{t_d + t_o} \times 100$). The machining parameters and their levels are presented in Table 2.

Table 2. The machining parameters and their levels.

	Levels		
Controllable factors	Low(-1)	medium (0)	High (+1)
Current	8	12	16
Opencircuit-voltage	80	120	160
Servo	30	50	80
Dutycycle	50	65	80

All the experiments were conducted on ROBOFORM 54 die sinking machine. It is energized by 128A pulse generator. As well a jet flushing system in order to ensure the adequate flushing of the EDM process debris form the gap zone is employed. Pressure of the dielectric fluid is adjusted manually at the beginning of experiment. All the faces of copper tool have been machined by surface grinding to have low surface roughness values and for good holding in the tool holder.

The work pieces and electrodes after machining have thoroughly cleaned with acetone to remove the carbon deposition and the weight measurements were taken on electronic weighing machine, which ha a resolution of 0.0001 grams. Each experiment was repeated twice and the averaged for MRR (grams/min) and TWR (grams/min).
The average surface roughness (microns) was measured three times and averaged. The average surface roughness is the integral absolute value of the height of the roughness profile over the evaluation length and was represented by the following equation.

$$R_a = \frac{1}{L}\int_0^L \left| Y(x)dx \right|$$

Where L= the length taken for observation
Y= the ordinate of the profile curve
The surface roughness was measured by using Talysurf instrument manufactured by Taylor Hobson.
To carryout the hardness experiments on the work piece's, the surface of the EDMed area was machined by surface grinding, and the hardness measurements were carried out on digital macro hardness tester TIME TH 300. The measurements were made three times and averaged. The experimental results with design matrix [22] are presented in Table 3.

Table 3. Experimental conditions and Results.

Exp. No	I	V	SV	η	MRR	TWR	Ra	HRB
1	8	80	30	50	0.0325	0.009	3.384	55.5
2	16	80	30	50	0.0925	0.024	5.249	68.5
3	8	160	30	50	0.0345	0.005	3.165	67.5
4	16	160	30	50	0.098	0.015	5.116	71
5	8	80	30	80	0.022	0.008	2.973	64
6	16	80	30	80	0.0605	0.004	5.249	69.5
7	8	160	30	80	0.0215	0.009	3.916	70.5
8	16	160	30	80	0.061	0.01	5.7	71.5
9	8	80	50	50	0.024	0.009	2.6	70
10	16	80	50	50	0.0268	0.013	5.366	69.5
11	8	160	50	50	0.026	0.007	2.579	77
12	16	160	50	50	0.0745	0.011	3.961	64
13	8	80	50	80	0.0155	0.005	4.599	71
14	16	80	50	80	0.0365	0.008	3.256	75.5
15	8	160	50	80	0.0215	0.011	4.916	65
16	16	160	50	80	0.045	0.008	4.033	65
17	8	120	40	65	0.036	0.009	3.125	64
18	16	120	40	65	0.085	0.005	6.099	66.5
19	12	80	40	65	0.056	0.009	4.788	77
20	12	160	40	65	0.07	0.008	5.6	59
21	12	120	40	50	0.062	0.015	4.409	68
22	12	120	40	80	0.0445	0.009	4.241	66
23	12	120	30	65	0.0805	0.007	5.433	66
24	12	120	50	65	0.0615	0.013	4.826	70
25	12	120	40	65	0.078	0.013	5.283	64

4. RESULTS AND DISCUSSION

The fuzzy model has been developed for predicting the MRR, TWR, Ra and HRB, in terms of Intensity, Open-cirucit Voltage, Servo and duty cycle. The comparison of predicted values of MRR, TWR, Ra and HRB using Fuzzy logic controller with the experimental values for different set of input values are shown in Fig10-13.

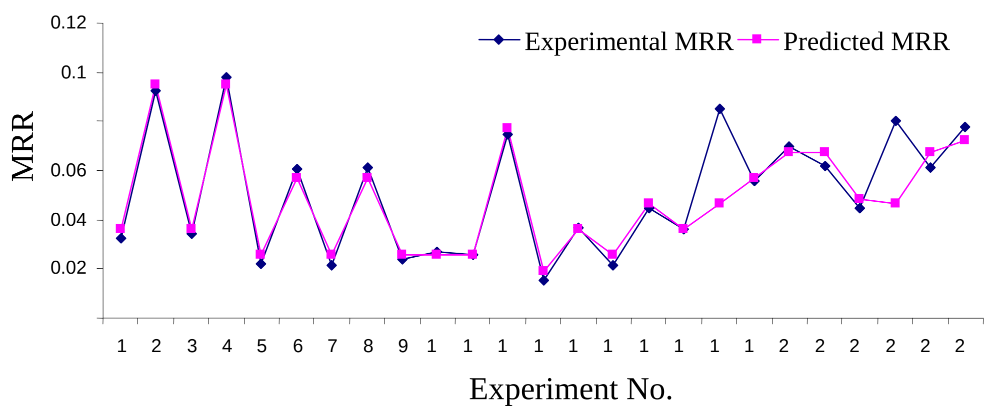

Figure 10. Comparison of results between Experimental and Predicted MRR.

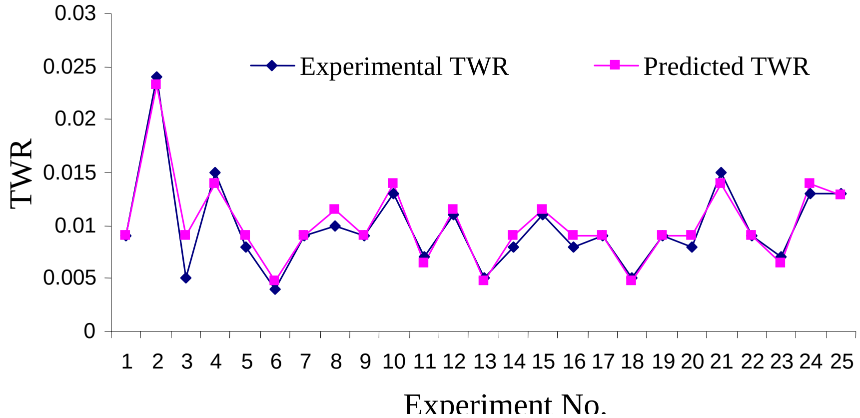

Figure 11. Comparison of results between Experimental and Predicted TWR.

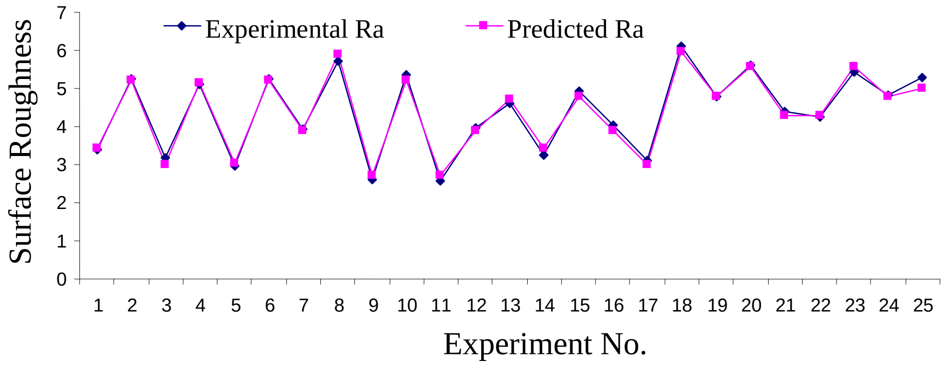

Figure 12. Comparison of results between Experimental and Predicted Ra.

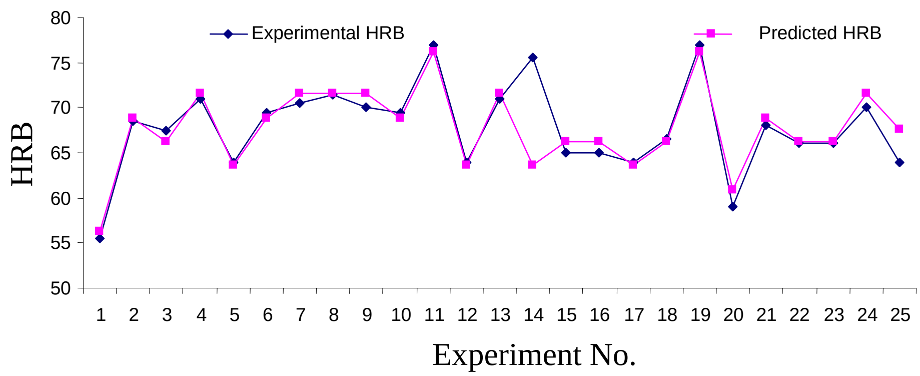

Figure 13. Comparison of results between Experimental and Predicted HRB.

The Fig10-13, showing that, the predicted values using fuzzy model are very good correlation and representation with the experimental results. With fuzzy logic method, we can predict the MRR, TWR, Ra and HRC at any value of the input parameters. The accuracy of prediction depends on the number of fuzzy sets of the input and output variables and the number of experiments conducted.

4.1. Regression Analysis

To have a more precise investigation into the model, a regression analysis of predicted and measured values was preformed as shown in Fig14-17. The adequacy of the developed model can be verified by using R^2. The quantity R^2 called as coefficient of determination is used to judge the adequacy of regression model developed. $0 \le R^2 \le 1$. The R^2 value is the variability in the data accounted for by the model in percentage [22].

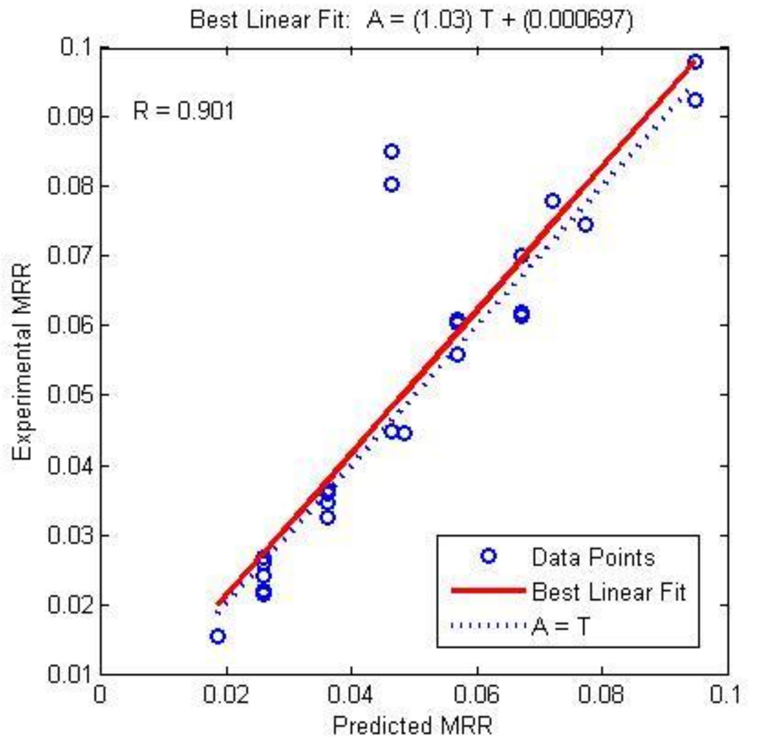

Figure 14. Regression analysis between predicted and Measured MRR.

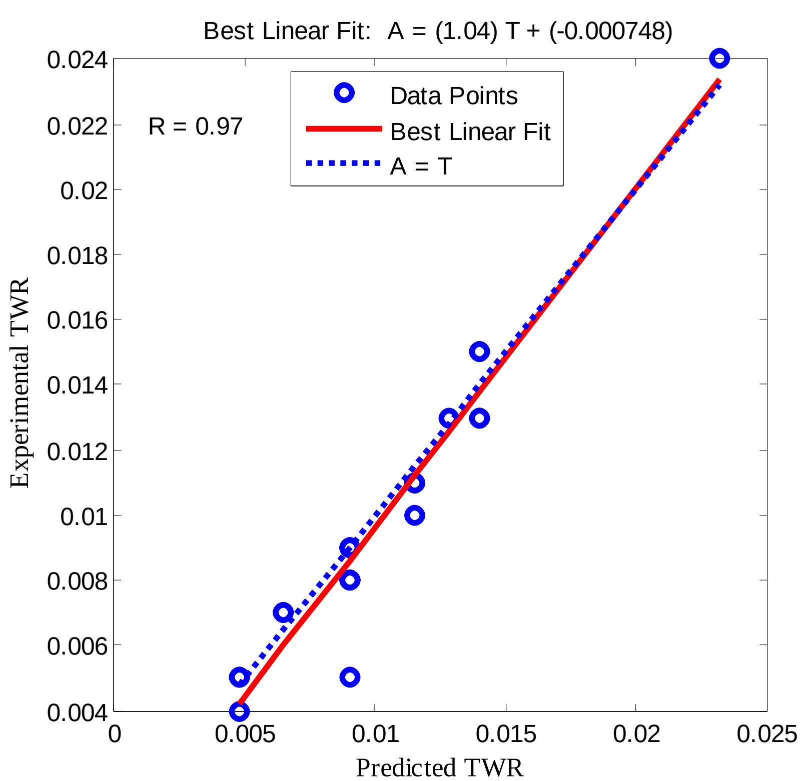

Figure 15. Regression analysis between predicted and Measured TWR.

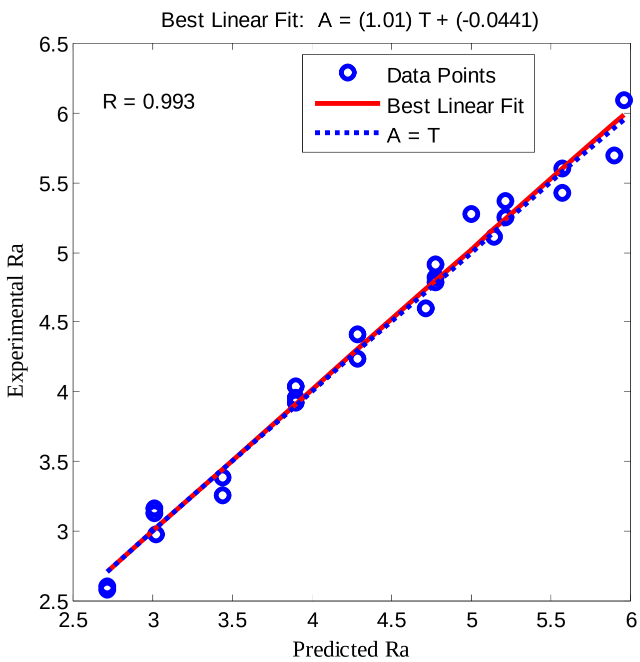

Figure 16. Regression analysis between predicted and Measured Ra.

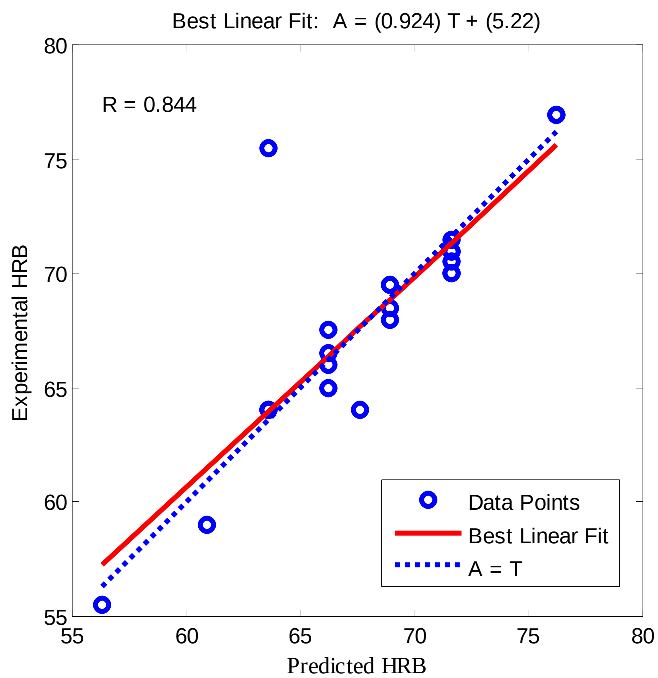

Figure 17. Regression analysis between predicted and Measured HRB.

The regression coefficient is calculated to estimate the correlation between the predicted values by the fuzzy model and the measured values resulted from experimental tests. The regression coefficient is calculated as

$$R^2 = 1 - \left[\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right]$$

Where t_j= targets or experimental values or measured values

o_j= outputs or predicted values

There is high correlation between the predicted values by the fuzzy model and the measured values resulted from experimental tests. The correlation coefficients for MRR, TWR, Ra an HRB were 0.9015, 0.9702, 0.9932 and 0.844 which shows there is strong correlation in modeling MRR, TWR, Ra and HRB as depicted in Fig 14-17 and provided the best accuracy. It is derived from Fig 14-17, that one can definitely predict MRR, TWR, Ra, HRB using the designed fuzzy logic controller. The variation in predicted values can be further reduced by considering more fuzzy member ship functions for the selected range of parameters.

5. CONCLUSIONS

Based on the above discussion, the following conclusions are drawn.

1. Experiments were conducted on ROBOFORM 54 die sinking machine on aluminum alloy 64430 with copper tool material. The data for MRR, TWR, Ra and HRB was collected under different input conditions of intensity, open-circuit voltage, servo and dutycycle.
2. The fuzzy model has been developed with the experimental results for predicting the MRR, TWR, Ra and HRB. The author examined the developed fuzzy model in EDM process. Through experimental verification, the fuzzy system proved capable of prediction of MRR, TWR, Ra and HRB with about 0.9015, 0.9702, 0.9932 and 0.844 accuracy respectively.
3. The results of the study are highly encourages and suggests that fuzzy logic approach is reasonable for modeling the EDM process.
4. The accuracy of the developed model can be improved by increasing the more fuzzy sets of the output variables.

6. REFERENCES

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