The Machining Parameter Design Using Fuzzy Theory in Electrical Discharge Machining Drill

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Abstract

Electric discharge machining drill (EDM-drill) is a process to machine fine holes. EDM-drill is specially used for drilling of difficult-to-cut materials such as high-strength steel, titanium and cemented carbide processing. The machining parameters of EDM-drill include voltage, PWM (pulse width modulation), machining speed, discharge capability, flushing rate, etc. These machining parameters affect the accuracy of the work-piece, the wear consumption of electrodes, surface roughness and machining time. As there are many machining parameters and machined results of work-pieces, it is difficult to establish the relations between the machining parameters and the results. A fuzzy system is presented to predict the relations. The machining parameters and results are normalized using the principal component analysis (PCA) and expressed as membership function (MF). Fuzzy rules are created by fuzzy rule-base which from MF and fuzzy inference is carried out. By this method, it is possible to obtain reasonably the machining parameters, which is necessary for the required machined results. On other hands, the machined results can also be predicted with the given machining parameters. The proposed fuzzy system is implemented using MATLAB. Actual experiments and Fuzzy inference are carried out in same machining conditions and the results are compared.

1. INTRODUCTION

Electric Discharge Machining is the accurate processing technology that processes electric conductor material with using electronic energy. Electric Discharge Machining is the fundamental processing method in metallic mold industry that occupies approximately 60~70% of the whole processing time of metallic mold manufacture. Using hollow shaft to electrode, Electric Discharge Machining-Drill is easily able to process the hole, which has from about tens of µm to mm, as the kind of Electric Discharge Machining. The best advantage of Electric Discharge Machining-Drill is to process complicated processing surface with the high shape accuracy, regardless of the degree of material and, due to no mechanical touch between tool and processed materials, it is also the advantage that the problem; like vibration, bending, and damage of tool is not happened. On the other hand, because EDM is the way to remove the material in fine discharge it takes long processing time. Moreover, in accordance with the emission of debris accrued in processing the roughness of processed surface and processing accuracy are changed. And, due to the occurrence of the abrasion of electrode while processing shape error revision considering abrasion loss is needed. In case of the blind hole used in processing metallic pattern, the entry depth of electrode and actual processing depth are different. Y.C. Choi *et al*. suggested the real-time electrode wear monitoring method [1]. B. Izquierdo *et al.* suggested the numerical model to predict the wearing of electrode [2]. Thus, the accurate entry depth of electrode and machining parameter are necessary for processing precise deep blind hole, and it is often decided through the experiences of those who process. So, in this paper, the processing result of diverse condition is exploited through principle component analysis and fuzzy inference. Ulaş Çaydaş *et al*. suggested the ANFIS model to predict the surface roughness [3]. Also, M. R. Shabgard *et al.* suggested the fuzzy method to predict the MRR [4]. This way, the rational processing parameter needed to processing is obtainable, and the processing results from diverse processing parameter are predictable before processing.

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2. THEORY

2.1. PRINCIPAL COMPONENTS ANALYSIS (PCA)

Principal components analysis creates several new artificial parameters that preserve as much information as possible, through doing applicably linear transformation to lots of variable vector. Through this artificial parameter, a large number of high-level vectors of variables reduced low-dimensional to summary the entire system. This is geometrical optimization method to search well-invoked plane to the data that exist on diverse plane, and this is comprised of the entire system compared with the relativeness of factors. In other words, through explaining the most of entire dispersion to a minority of principal component, the first appeared one derives as explaining the main part of entire dispersion, and the principal component that is appeared after is in maximum explained to the other dispersion not mentioned before with having separate relationship [5, 6]. However, principal components analysis can be that the variable which has the biggest dispersion is understood to important dispersion due to the difference of unit of measure between variables, so it is important to apply to principal component analysis after standardizing the whole data to standard normal deviation in order to avert such an error. The injected factors stated in this paper are existed to Voltage, Pulse Width Modulation, Machining Speed, Discharge Capability, Flushing Rate, and the resulted factors stated are wearing diameter of work-piece, wearing of tool radius, tool wearing ratio and average roughness. Thus, there are total 11-factors which are dispersed on the 11-dimensional plain. These 11-dimensional data are reduced to 9-dimension, and they help the process of arithmetic operation more quickly. Principal components analysis is progressed as following process [7, 8].

1. First, Data from experiments is normalized as Equation 1. The $x_i(j)$ means the value of j^{th}parameters and n^{th} experiment. Because the unit and size of each factor are totally different, the process of normalization is proceeded in order to catch unified result, same as processed result.

$$x`_i(j) = \frac{x_i(j) - \min(x(j))}{Max(x(j)) - \min(x(j))}$$

Equation 1: Normalized

2. Second, new value from normalized data is arranged in correlation coefficient array (R) in Equation 2. $cov(\, x_i'(j), x_i'(l)\,)$ means the covariance of sequence $x_i'(l)$ and $\sigma_{x_i'(j)}, \sigma_{x_i'(l)}$ means the standard deviation of sequence $x_i'(l)$

$$R_{jl} = \frac{cov(\, x_i'(j), x_i'(l)\,)}{\sigma_{x_i'(j)} \times \sigma_{x_i'(l)}} \quad j = 1,2, \dots \dots \dots, m \quad , \quad l = 1,2, \dots \dots \dots, m$$

Equation 2: Correlation coefficient array (R)

R shows the correlation coefficient of each date. For example, $x_{1,n}$ shows the correlation of 1^{st} factor and n^{st} factor.

$$R_{jl} = \begin{bmatrix} x_{1,1} & \cdots & x_{m,1} \\ \vdots & \ddots & \vdots \\ x_{1,m} & \cdots & x_{m,m} \end{bmatrix}$$

3. Third, eigenvalue and eigenvector is calculated from R matrix. Throughout the system, eigenvalue means the weight each argument is called the weight factor. The higher this value is high, which best represent the distribution of the whole system. Eigenvector means the direction of weight factor in N-spaces.

2.2. MEMBERSHIP FUNCTION (MF)

Membership function is applicable information indicates the degree of membership about membership function. The higher the degree of membership is the approximate value that membership function represents is knowable. [9] In this paper, the principal component organized to 9-dimension on verse 2.1 is expressed and it is written to membership function. In general, membership function is composed as triangular shape, trapezoid-shape, bell-shape, and Gaussian. Linear function has high calculation speed, but it's difficult to apply the non-linear shape. Non-linear function has high accuracy than linear shape, but the calculation is complicated. Therefore, in order to get the best result with the minimal number through principal component analysis it is significant to choose the minimal number. Triangular function and trapezoidal function are selected for convenient calculate and efficiency. Figure 1 and Equation 3 shows the triangular function. Figure 2 and Equation 4 shows the trapezoidal function.

$$\mathrm{f(x,a,b,c)} = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases}$$

Equation 3: Triangular function

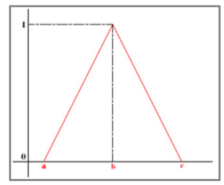

Figure 1. Shape of triangular function.

$$\mathrm{f(x,a,b,c,d)} = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \frac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases}$$

Equation 4: Trapezoidal function

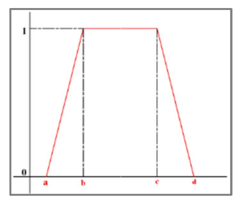

Figure 2. Shape of trapezoidal function.

The x-axis is composed with input machining parameter. Y-axis indicates the grades of membership. Grade of membership is determined by evalulation criteria and by this criteria, membership of each input machining parameter is determined. Input machinig parameters which have the best surface roughness get '1' in Y axis. Reminder input machinig parameters get grade of membership following with their surface roughness.

2.3. FUZZY LOGICS (FL)

Recently equipped intelligence which has the ability to judge the complex system is increased. But these systems have problems that it can process relatively simple problem. Fuzzy logic has been proposed to solve the ambiguity problem as in the human way of thinking. Generally, fuzzy logic inference Engine/process can be divided in three steps. First, set the membership function using input variable and the output variable. Second, set IF-THEN rules to solve the problem and third, fuzzy inference according to the rules of procedure [9].

Fuzzy logic general structure is composed of a structure as shown in the following Figure 3.

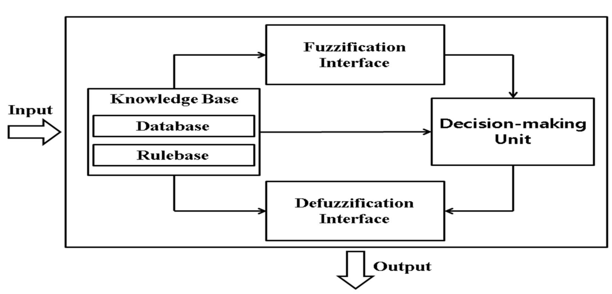

Figure 3. Experiment device & EDM Drilling.

Knowledge base is defined as Database and Rule-Base. Knowledge Base means membership function described on verse 2.2, and Rule-Base means Fuzzy Logic rule. Fuzzification interface makes input machining parameters to membership function. Defuzzification interface converse the membership function to machining parameters. Decision-making Unit has rules which defined by user to decide the optimum outputs from variable input machining parameters. In this paper, Fuzzy IF-THEN rule is referred. Figure 4 shows IF-THEN rule & Min-max inference. IF-THEN rule derives overall conclusion as using the addition between membership function described on Database.

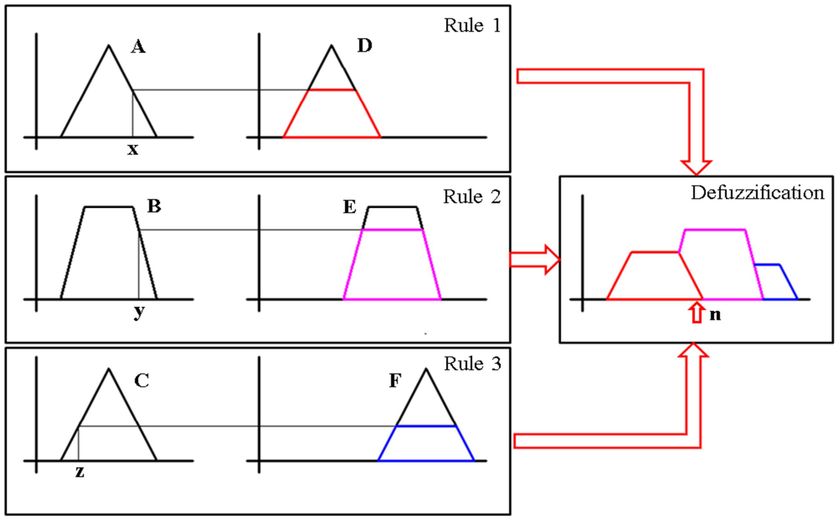

Figure 4. IF-THEN Rule & Min-Max inference.

As Figure 4, each rule is defined by users. Rule 1 is defined as “IF x is A, THEN n is D”. In Figure 4 there are 3 rules. All rules are collected and Defuzzificated. To the part of inference rule, Mamdani’s Minimum arithmetic is used. Membership function is calculated on each input and membership function which has minimum value gives to the consequence. In the part of conclusion, maximum arithmetic is used. Maximum method is used to figure out the result of the defuzzification method that takes the approximate value of the maximum value. This method was used due to this reason: in fuzzy control, each part of the Membership function of the conclusion needs to be considered so the center of gravity method works well and the highest fuzzy number that has the biggest membership function should be selected.

3. EXPERIMENTS

Experiments were carried out in total 115 times with various changing of the input coefficients. These 115 experiments are selected from previous study. The experimental apparatus, We used the electric discharge machine CSCAM. Work-piece is SKD-11 which is Heat treated steel. Work-piece size is $50 \times 20 \times 10$ for easy handling. The direction of electrode entry is Y-axis. The material of electrode is copper and cut out in $\emptyset 1 \times 100$mm for check the wear of electrode. Water is used for Dielectric. Figure 5 shows the EDM-drilling machine and Table 1 shows the material and size of each machining materials.

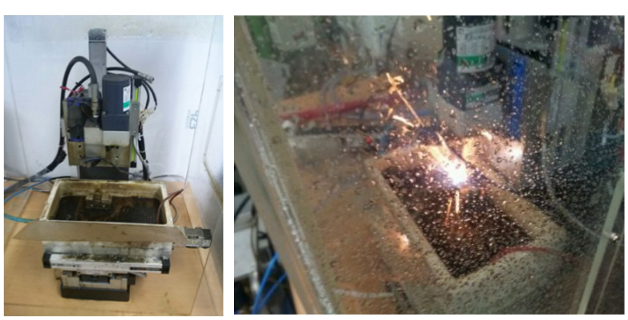

Figure 5. Experiment device & EDM Drilling.

	Material	**Size(mm)**
Work-piece	SKD-11 (Heat treated steel)	50 X 20 X 10
Electrode	Copper	Ø1 X 100
Dielectric	Water	

Table 1. Material and Size of Work-piece and Electrode.

There are 7 machining parameters which we can change. Table 2 shows the meanings of machining parameters and Figure 6 shows the machining parameter controller.

No.	Parameters	Meaning
1	Ton(1~63)	"Pulse on" time
2	Toff(1~63)	"Pulse off" time
3	Ip(1~30)	Peak electric current
4	Vs(1~4)	Gap distance
5	R/S(0~1)	Control the Tool federate
6	C(0~31)	Control the Capacity of Discharge
7	V(1~2)	Standard Voltage

Table 2. Meanings of machining parameters.

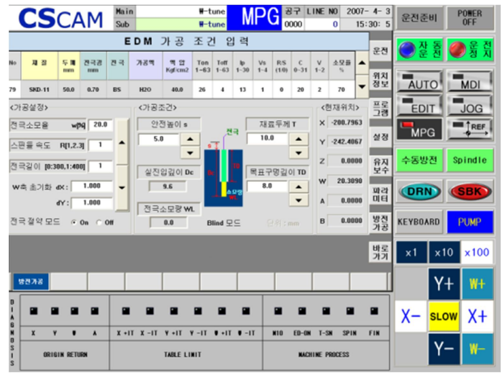

Figure 6. Machining parameter controller.

Also there are 5 parameters which affected by machining parameters. Table 3 and Figure 7 shows the meaning of affected parameters.

No.	Parameters	Meaning
1	W_{di}	Wearing diameter of Work-piece
2	T_{ra}	Wearing of Tool Radius
3	T_{wr}	Tool Wearing ratio
4	Ra	Average Roughness

Table 3. Meaning of affected parameters.

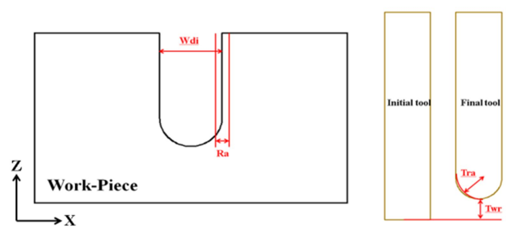

Figure 7. Meaning of parameters.

This paper presents a variety of controllable input variables that was conducted with varying discharge machining. The experiment was conducted 10 times per condition. The experiment was repeatedly done, because micro errors occur under even the same conditions. The average data of the repeated experiments are obtained. The picture below shows some results from the experiments. Roughness is measured by COMPOCAL. Figure 8 shows the results of Electric discharge machining drilling and Figure 9 shows the Roughness measurement by COMPOCAL.

Figure 8. Experiment results in various conditions.

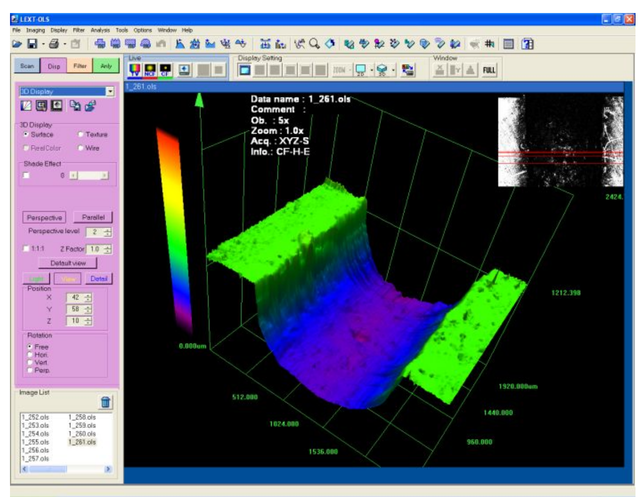

Figure 9. Roughness measurement by COMPOCAL.

The data from experiments above are summarized according to the normalized procedures in section 2.1, and got the result of the correlation coefficient array. The results are show in the Table 4.

E.V	**Ton**	**Toff**	**Ip**	**Vs**	**R/S**	**C**	**V**	$\boldsymbol{T_{ra}}$	$\mathbf{W_{di}}$	$\boldsymbol{T_{wr}}$	**Ra**
Ton	1.000	0.413	-0.077	0.089	0.100	-0.194	-0.100	0.028	0.046	-0.019	0.180
Toff	0.413	1.000	0.119	-0.065	-0.005	0.154	0.005	-0.203	-0.271	-0.029	0.354
Ip	-0.077	0.119	1.000	-0.289	0.012	-0.309	-0.012	0.160	0.185	-0.611	0.137
Vs	0.089	-0.065	-0.289	1.000	-0.073	0.074	0.073	0.164	0.054	0.094	-0.231
R/S	0.100	-0.005	0.012	-0.073	1.000	-0.123	-0.493	0.015	0.136	-0.026	-0.077
C	-0.194	0.154	-0.309	0.074	-0.123	1.000	0.123	0.006	-0.071	0.251	-0.009
V	-0.100	0.005	-0.012	0.073	-0.493	0.123	1.000	0.012	-0.171	-0.113	0.069
T_{ra}	0.028	-0.203	0.160	0.164	0.015	0.006	0.012	1.000	0.484	-0.112	-0.091
W_{di}	0.046	-0.271	0.185	0.054	0.136	-0.071	-0.171	0.484	1.000	-0.159	-0.274
T_{wr}	-0.019	-0.029	-0.611	0.094	-0.026	0.251	-0.113	-0.112	-0.159	1.000	0.034
Ra	0.180	0.354	0.137	-0.231	-0.077	-0.009	0.069	-0.091	-0.274	0.034	1.000

* E.V = Eigen Value

Table 4. Correlation coefficient array (R) of machining & affected parameters.

In the Table 4, when those factors are selected, the cumulative proportion equals to the full system.

No.	**Parameter**	**Eigenvalue**	**Disparity**	**Proportion**	**Accumulation rate(%)**
1	Ton	2.09427	0.17206	0.2015221	20.15221
2	Toff	1.92221	0.32243	0.1849655	38.64876
3	Ip	1.59978	0.30427	0.1539396	54.04272
4	Vs	1.29551	0.28838	0.12466	66.50888
5	R/S	1.00713	0.35172	0.0969115	76.19998
8	W_{di}	0.65541	0.11941	0.0630671	82.50669
9	T_{ra}	0.536	0.10547	0.0515768	87.66437
11	Ra	0.43053	0.05028	0.0414279	91.80717
10	T_{wr}	0.38025	0.13621	0.0365897	95.46614
6	C	0.24404	0.01961	0.0234829	97.81443
7	Vs	0.22713	0	0.0218557	100

Table 5. Eigenvalue& Accumulation rate.

Table 5 shows the proportion and accumulation rate of all input machining parameters and output variables. In this paper, 9 parameters are used to predict the whole system in 95.46614%. It's important to select the using parameters because the number of using parameters influences the accuracy and calculating time. Selected parameters used to compose the membership function and Fuzzy logic.

After select parameters, each parameter has changed to membership function. Output variables have their own evaluation criteria. Such as lower roughness can be evaluated as good machining than other parameters which has higher roughness. Input machining parameters have their evaluation criteria from Output variables. The best point of input machining parameters can be changed by output parameters. In this study, Ton parameter has 3 different membership functions. When evaluation criteria is T_{ra} and T_{wr}, the best machining point is 25. Also, evaluation criteria are $W_{di}$and Ra, each best machining points are 35 and 40. Figure 10 is a diagram of the membership function.

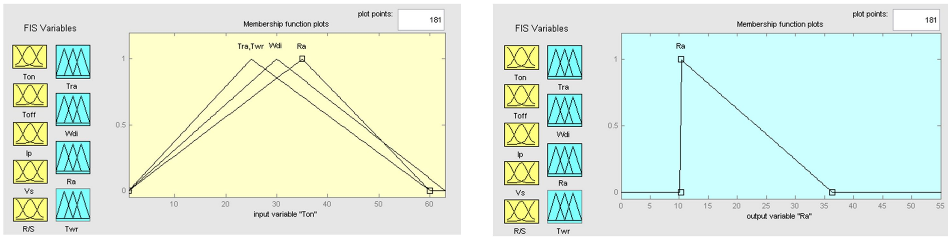

Figure 10. Triangular Membership function for Input machining parameters & output variables.

After create the membership function of the selected parameter, Fuzzy system is composed as Figure 11. Left side of the whole system is membership function of input machining parameters in selected parameters. As figure.11 Ton, Toff, Ip, Vs, R/S, C are used in input machining parameters. The right side of whole system is out variables in selected parameters. W_{di},T_{ra},T_{wr}, and Ra are used in output variables. The center of the system is decision making unit. Mamdani's logic is used and IF-THEN rule is composed in Decision making unit.

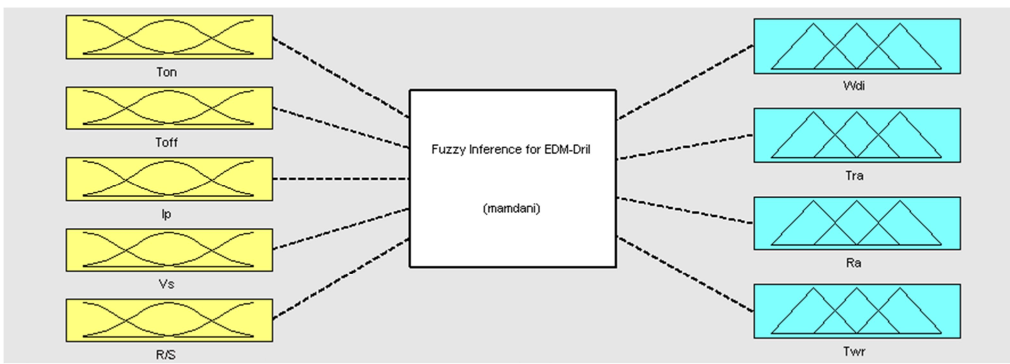

Figure 11. Fuzzy logic system.

Figure 12 shows the results of fuzzy inference of the completed structure. Entering the dimensions which the user wants to input parameters is input to the Fuzzy inference tool through the Decision making unit the value of the input is derived to the value of the result. Thus, the results of the input machining parameters and output variables that are not experiments within the entire system, it is possible to obtain with the same accuracy as the cumulative percentage .

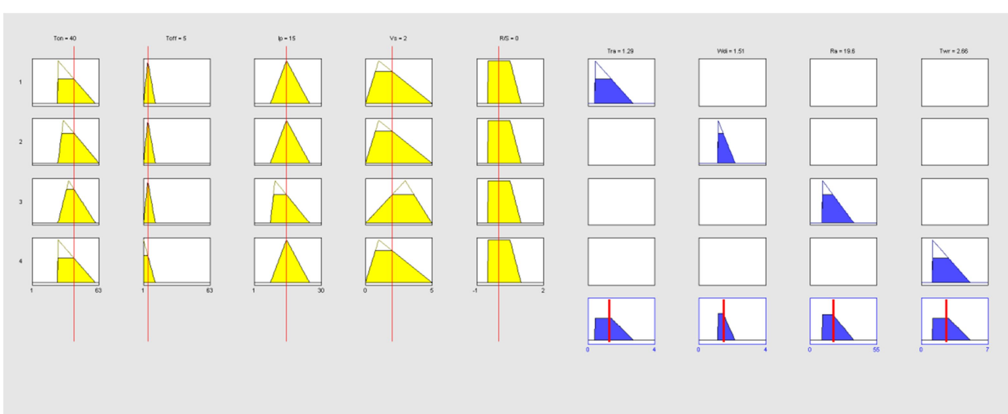

Figure 12. Rule view.

4. CONCLUSION

To verify the Fuzzy system, Electric discharge machining drill drilling a hole with another input machining parameter which not include in entire fuzzy system. The hole shows in Figure 13. The output variables of real drilling hole and predicted output parameters are compared in Table 6.

Figure 13. Experiment results in various conditions.

	Real Experiment(mm)			Inference by fuzzy logic(mm)			Disparity rate (%)		
W_{di}	1.617	1.431	1.437	1.51	1.52	1.51	6.62	6.22	5.08
T_{ra}	1.39	1.175	1.297	1.29	1.28	1.19	7.19	8.94	8.25
T_{wr}	2.602	2.687	2.763	2.66	2.78	2.66	2.22	3.46	2.66
Ra	18.063	21.2	21.821	19.6	23.2	21.2	8.51	13.86	2.85

Table 6. Comparison of Experiment & Fuzzy logic.

As shown in Table.6, the disparity rate is maximum disparity rate in 2.22% and the minimum disparity rate in 13.86%. The average disparity rate is 6.32%. So following the results, the fuzzy inference system gives the affordable data that can use. The results of this paper, Fuzzy inference system is configured with the input machining parameters and output variables which is followed by input machining parameters when Electric discharge machining drill . This is expected to be able to contribute the improvement of productivity through reduction of processing time and improve the accuracy of the work-piece by selecting the suitable parameters for processing. In the future work, we intend to increase accuracy using a variety of methods (linear regression, Artificial Neural Network (ANN), and CART).

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