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Investigation and Analysis of MRR in Spark Erosion Machining Through ANN

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ABSTRACT

EDM is an advanced machining process for machining, hard material parts which are difficult to machine by conventional machining process. There are various types of products which can be produced by using Die-sinking EDM, such as dies, mould, parts of aerospace, automobile industry and surgical components can be finished machined by EDM. The objective of the paper is to achieve maximum MRR and a good surface integrity in finish cut by optimizing process variables. This paper presents a method that can be used to automatically determine and optimize the processing parameters in the EDM sinking process with the application of artificial neural networks (ANN).In the industrial tool room survey availability of machining data is prime concern in terms of tuned process parameter for precision machining. Experimental investigations are performed to study the effect of pulse current, pulse on time, area of electrode and gap voltage on response of MRR, in case of ram EDM.

Keywords : Electric Discharge Machining (EDM), AISI D2 steel, Artificial Neural Network (ANN), Material Removal Rate.

I. INTRODUCTION

In this technological era, manufacturing industries are facing challenges from such advanced difficult to machine materials, viz. super alloys, ceramics and composites and stringent design requirements (high surface quality, high precision, high strength, complex shapes, high bending stiffness, good damping capacity, low thermal expansion and better fatigue characteristics) and machining costs. There is a growing trend to use light weight and compact mechanical component in the recent years; there-fore there has been an increased interest in the advance materials in modern day industries.[4]

The electric discharge machining is a non-traditional manufacturing process based on electro thermal phenomenon of material erosion. A series of discrete sparks between tool electrode and workpiece removes the material in the presence of dielectric fluid. As the tool does not come in contact of workpiece hence surface texture is free of any stresses and cutting forces impressions. EDM is well suited for machining of forging dies, injection moulds and automobile parts. [1-3]

ANN can be optimized with a genetic algorithm (GA) and node deleting algorithm so that the number of hidden nodes of ANN will be determined automatically and scientifically. ANN can be trained with GA and BP algorithms, so that the local least solution can be avoided and the training speed enhanced. The experiment has proved that the utilization of mirror processing conditions generated from the above method will consequently lead to both good small-area mirror processing results and desired processing precision and efficiency. [3]

Trias Andromeda, AzliYahya, Nor Hisham, Kamal Khalil, Ade Erawan in his research paper Predicting Material Removal Rate of Electrical Discharge Machining (EDM) using Artificial Neural Network for High I_{gap} currentpresents a prediction of Material Removal Rate (MRR) in Electrical Discharge Machining (EDM) using Artificial Neural Network (ANN). Experimental data were gathered from Die sinking EDM process for copper-electrode and steel-workpiece. It is aimed to develop a behavioural model using input-output pattern of raw data from EDM process experiment. The behavioural model is used to predict MRR and then the predicted MRR is compared to actual MRR value. The results show good agreement of predicting MRR between them. [5]

Angelos P. Markopoulos In this paper Artificial Neural Networks (ANNs) models are proposed for the prediction of surface roughness in Electrical Discharge Machining (EDM). For this purpose two well-known programs, namely Matlab with associated toolboxes, as well as Netlab, were employed. Training of the models was performed with data from an extensive series of EDM experiments on steel grades; the proposed models use the pulse current, the pulse duration, and the processed material as input parameters. The reported results indicate that the proposed ANNs models can satisfactorily predict the surface roughness in EDM. Moreover, they can be considered as valuable tools for the process planning for EDM Machining.[6]

The ability to achieve complex geometries and intricate shapes with high degree of accuracy especially when used along with CNC makes it more accurate and superior from any other machining techniques. Inspite of all these positive characteristics, the EDM machine has some drawbacks. Some of the very common problems among these which causes wastage of time, removal or erosion of electrode material from the electrode.

As we know that EDM process works on the erosion of material or work-piece due to the spark produced between the surface of electrode and the work-piece. Thus the MRR is expressed as the ratio of the difference of weight of the workpiece before and after machining to the machining time and density of the material. Material removal determines both machining rate and tool electrode wear rate. MRR is the higher-the-better performance characteristic.

The objective of this paper is to obtain and analyse the optimized parameters such as pulse on current (Ip), Pulse On Time (Ton)**,**Gap Voltage(Vo) which decide the output parameter Metal Removal Rate (MRR) and hence perform screening using Artificial Neural Networks. The following objectives are listed below:

- To model the material removal rate of EDM machining process for the optimized parameters.
- Study of modern mathematical tool- Artificial Neural Network.
- Machine settings to obtain carbon free surface. Optimization of MRR in correlation with depth of cut.

Propose an ANN model for optimizing and validating the process.

II. EDM EXPERIMENTATION

The equipment used to perform the experiments is a die-sinking EDM machine of type Electronica E-20, which has pulse generator. The pressure used for the dielectric fluid is 3.1kgf/cm2, under jet flushing. The workpiece material used in experimentation is AISI

D2 alloy steel which is used in the inner core and sections of the cold work dies and moulds.

Figure 1 : Experimental die sink EDM

Furthermore, the copper tool is selected in a prismatic form with a transverse area of 15mm × 15mm and 50mm in height. The copper rods with 98% purity and 8.94 g/cc density were machined with good surface finish and exact dimensions as tool electrodes. Copper electrodes and workpieces were ground carefully so as to provide stable machining conditions in EDM process.

A. Design of Experiments

A sequential incremental design approach was followed. The nature of variation of response with respect to a particular factor helps in deciding the levels of the factor. Though there are a large number of parameters involved in the EDM process, but in this work the level of the generator current pulse intensity (Ip), pulse time (Ton), gap voltage (Vg) have been taken into account as design factors. Corresponding levels of parameters are mentioned in Table 1.

Table 1: Machining parameters with levels

Symbol	EDM machining parameters and levels				
		1	2	3	4
Ip	Pulse Current (amps)	3	5	7	10
Ton	Pulse-on Time (sec)	0.11	0.17	0.29	0.38
Vg	Gap Voltage (volt)	130	135	140	145
Ae	Electrode Geometry (mm^2)	L10 x W10	L15 x W15	L17 x W17	L20 x W20

B. Response Variable – MRR

The material MRR is expressed as the ratio of the difference of weight of the workpiece before and after machining to the machining time and density of the material. Material removal determines both machining rate and tool electrode wear rate. MRR is the higher-the-better performance characteristic. It is generally expressed in mm^3/min.

C. Artificial Neural Network (ANN)

An artificial network consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections.A number of ANN models have been trained to model performance parameters of EDM process using software MATLAB. To obtain an improved prediction model, generally ANN architectures, learning/training algorithms and nos. of hidden neurons are varied, but the variations have been made in a random manner. So here for the design of experiment a sequential incremental design has been implemented to achieve the optimal of above for modelling and solution.

The data set is divided into three parts in the ratio of ½: ¼: ¼. With ½ of the data used for training, ¼ for the test and ¼ of the validation of the network selected randomly by nntool of MATLAB.

Md. Ashikur Rahman Khana in this work speaks about Modelling can facilitate the acquisition of a better understanding of such complex process, save the machining time and make the process economic. Thus, the present work emphasizes the development of an artificial neural network (ANN) model.[8]

D. Mean Square Error and Correlation Factor

The error function that has been used here for supervised training is average mean squared error function. The mean square error (MSE) of the network's response to a vector *p*, is calculated, according to the equation:

$$E_p = \frac{1}{2}\sum_{i=1}^{l}\left(d_{p,i} - o_{p,i}\right)^2$$

In the preceding equation $o_{p,I}$ are the values of the output vector which occur for the input vector *p* and $d_{p,I}$ the values of the desirable response corresponding to *p*. The procedure is repeated until MSE becomes zero. Each time that the program passes through all pairs of training vectors an epoch is completed; training usually ends after reaching a great number of epochs. [4]

Correlation coefficient can be used to determine how well the network output fits the desired output. If we have a sample set $\{x_i,y_i\}$ of *n* pairs of data values the correlation between them is given by the ratio of the covariance (the way they vary jointly) to the square root of the variance of each variable. This is effectively a way of standardizing the covariance by the average spread of each variable, to ensure that the correlation coefficient, *r*, falls in the range [-1,1].

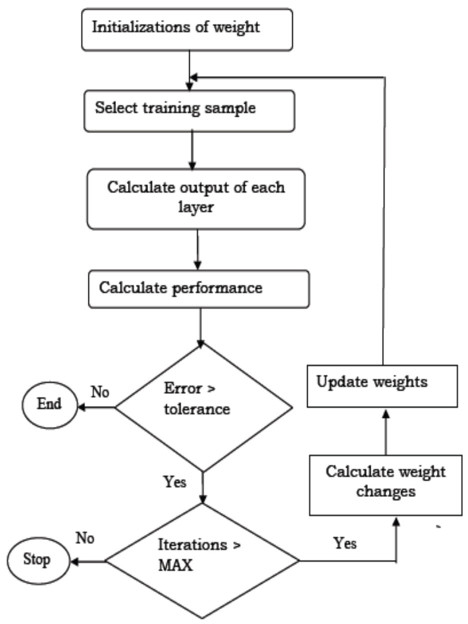


Figure 2 : Flow ofANN Architecture

III. RESULTS AND ANALYSIS

The experimental results for surface roughness in finish cut machining for AISI D2 are shown in Table2. The variables considered in the experiments are current intensity (Ip), pulse on time (Ton) and gap voltage (Vg), where the behavior of each parameter significantly affects the surface roughness. The experimental output is recorded in table 2.

Table 2 : Experimental Output

S. No.	Ip amp	Ton sec	Vg volt	Ae mm^2	MRR mm^3/min
1	3	0.11	130	L10x W10	5.1948
2	3	0.17	135	L15x W15	7.4458
3	3	0.29	140	L17x W17	4.2424
4	3	0.38	145	L20x W20	6.0317
5	5	0.11	135	L17x W17	6.9062
6	5	0.17	130	L20x W20	4.2343
7	5	0.29	145	L10x W10	8.8311
8	5	0.38	140	L15x W15	10.505
9	7	0.11	140	L20x W20	3.3697
10	7	0.17	145	L17x W17	2.7705

11	7	0.29	130	L15x W15	1.6161
12	7	0.38	135	L10x W10	10.851
13	10	0.11	145	L15x W15	13.823
14	10	0.17	140	L10x W10	13.391
15	10	0.29	135	L20x W20	2.7417
16	10	0.38	130	L17x W17	6.5800

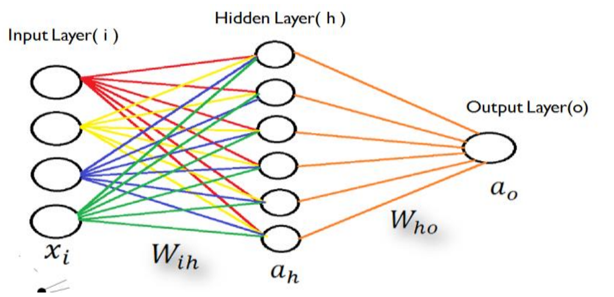
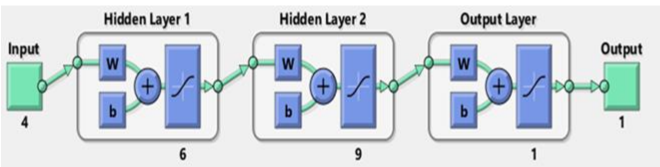


Figure 3 : ANN Architecture and Framework

A. Training Neural Network Using Matlab

The best process parameter setting for ANN modelling was selected with the help of sequential incremental method. The chosen optimal process parameters are Gradient Descent with momentum and adaptive learning rate (GDX) training algorithm, 6 nos. of hidden neurons in first hidden layer, 9 neurons in second hidden layer and MLP neural architecture. Minimum MSE and maximum R value was found, so weights and bias matrix of this run was consider for modelling MRR.Therefore the architecture 4-6-9-1 was selected and trained using nntool in Matlab.



B. The Analysis of MRR

The ANN output data values are recorded in the table 3 for the validating and comparison purpose. The correlation factor for all the data was found to be R=0.96753. Variation of MSE of training, validation and testing data set w.r.t. the epoch has been shown in Figure 5. Validation data set is used to stop the training process in early stopping criteria for providing better generalization. Figure 7.6 shows that the validation error is minimum at epoch 453.

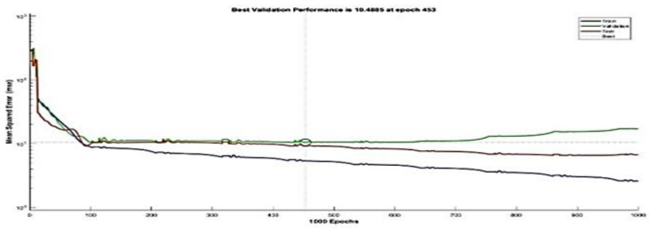


Figure 5 : Variation of MSE w.r.t. epoch

Table 3: Experimental Output

S. No .	Ip amp	Ton sec	Vg volt	Ae mm^2	MRR mm^3/mi n
1	3	0.11	130	L10 x W10	5.16388 7
2	3	0.17	135	L15 x W15	7.42318 3
3	3	0.29	140	L17 x W17	6.97982 5
4	3	0.38	145	L20 X W20	5.03532
5	5	0.11	135	L17 X W17	7.88635 6
6	5	0.17	130	L20 x W20	5.61709 5
7	5	0.29	145	L10 x W10	8.70742 3
8	5	0.38	140	L15 x W15	9.67214 8
9	7	0.11	140	L20 x W20	2.74172 9
10	7	0.17	145	L17 x W17	2.74172 9
11	7	0.29	130	L15 x W15	3.52270 3
12	7	0.38	135	L10 x	12.9675

				W10	4
13	10	0.11	145	L15 x W15	18.98275
14	10	0.17	140	L10 x W10	16.26992
15	10	0.29	135	L20 x W20	4.171575
16	10	0.38	130	L17 x W17	8.599452

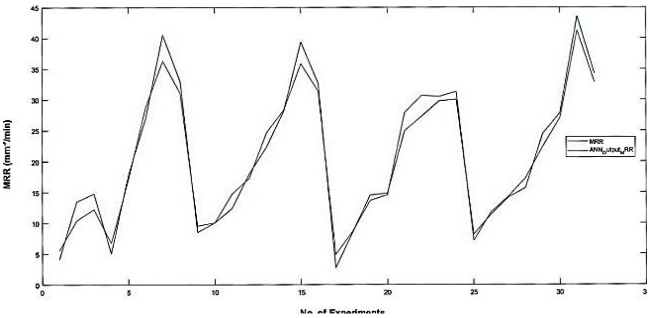


Figure 6 : Comparison of Experimental output to ANN output

C. Optimization and Comparison of MRR Responses

Cubic fit for MRR, A_e and I_p

The surface plot (figure 6) for two variables at same time can be analyzed against MRR within the interval of finish cut to rough cut machining. In the plot of MRR, A_e and I_p the levels from L10 x W10 to L20 x W20 and I_p for 3A to 4.5A (4-5) describes the fine cut machining region. The region enclosed for 5A till 7.5A (7-8) shows the transition from the fine machine cut to the rough cut machining. In the response surface plot of MRR, A_e and I_p the cubic fitting polynomial has been used.. The rough zone of the machining can be seen with increase in current above 8A. Thus, a higher MRR can be obtained in the machine prone region compromising surface finish of the work part.

Cubic fit for MRR, I_p and T_{on}

The surface plot (figure 7) for two variables at same time can be analyzed against MRR within the interval of finish cut to rough cut machining. In the plot of MRR, I_p and T_{on} the levels from 3A to 4.5A (4-5) describes the fine cut machining region. The region enclosed for 5A till 7.5A (7-8) shows the transition from the fine machine cut to the rough cut machining. In the response surface plot of MRR, $I_p$and T_{on} the cubic fitting polynomial has been used. The variation of T_{on} as that compared to current is negligible. Thus, I_p is a dominant affecting MRR. The rough zone of the machining can be seen in the bright yellow zone with increase in T_{on} above 290 µs and higher current values. Thus, a higher MRR can be achieved with increase in T_{on} and increasing current, in the machine prone region compromising surface finish of the work part.

Cubic fit for MRR, V_g and T_{on}

The surface plot (figure 8) for two variables at same time can be analyzed against MRR within the interval of finish cut to rough cut machining. In the plot of MRR, V_g and T_{on} an inverse relationship between V_g and T_{on} can be seen. Thus, the distinct observation for MRR keeping T_{on} as 110 µs can observe that with increase in V_g the steady transition from fine cut machining to rough machining zone. In contrast for a higher value of T_{on} 380 µs (here) transition from rough machining to a finish cut can be seen over a range of V_g. The fine cut zone of the machining can be seen in the dark blue region.

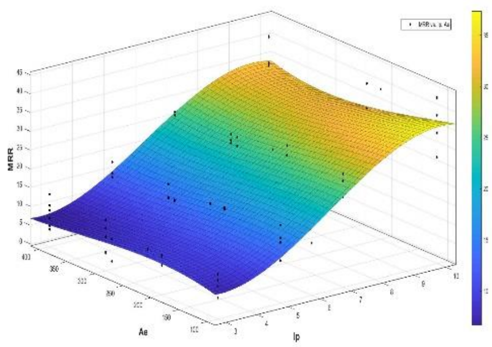


Figure 6 : Cubic fit for MRR, I_p and T_{on}

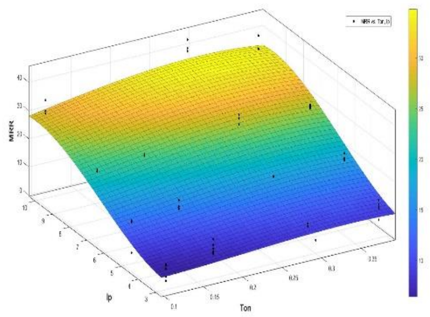


Figure 7 : Cubic fit for MRR, I_p and T_{on}

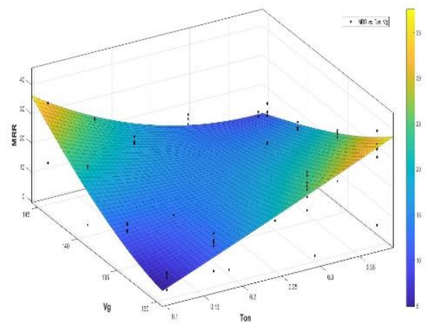


Figure 8 : Cubic fit for MRR, V_g and T_{on}

IV. CONCLUSION

In the EDM sinking process, the polarity of EDM power supply, the pulse width, the pulse interval, the peak current, the electrode's discharging area, the processing depth, the electrode zoom value (the difference between the dimension of the finished workpiece and the electrode dimension), gap voltage etc. are important parameters, having close relations with processing results such as processing speed, processing accuracy and electrode wear rate.

- The peak current is the peak value of an impulsive discharge current, as an important parameter; in combination with discharge pulse width, gap voltage and electrode area determines discharge processing performance in terms of processing speed. Both current peak value and pulse width determine the magnitude of discharge energy.
- The greater the discharge energy is, the faster the processing speed will be, but the worse the surface roughness. In addition, when the pulse energy is kept constant, the proper combination of current peak value and pulse width can realize the maximum corroding removal amount of the workpiece with less electrode wear.
- For a specific EDM power supply, the combination of current peak value and pulse width corresponding to the maximum removal amount is certain, and so is the relevant electrode wear and discharge gap. Therefore, peak current value can be coincident with the value of optimum discharge energy on a one-by-one basis. In general, when the factories design EDM power supply, they will offer sets of combination parameters (polarity, pulse width, pulse interval, gap voltage and current peak value) as usual standard processing conditions to be chosen by users.
- It is mainly the discharge area and the processing depth on the workpiece that determine the amount of removal from the workpiece. The discharge energy (current peak value) of rough machining is determined as per the removed quantity of the workpiece, and of course, the restrictions due to electrode zoom value and temperature deformation layer shall also be taken into account.
- Therefore, the discharge area, the processing depth and the electrode zoom value limit the maximum value of the peak current.

Among so many technology parameters of EDM sinking process, the peak current value for rough machining is the important parameter that has great bearing on the processing efficiency and processing accuracy.

V. REFERENCES

[1]. A. Yahya, C. D. Manning, "Determination of material removal rate of an electro-discharge machine using dimensional analysis", Journal of Physics D: Applied Physics, 37(10), 2004, 1467-1471.

[2]. I.Puertas, C. J. Luis, L. Alvarez , "Analysis of the influence of EDM parameters on surface quality, MRR and EW of WC-Co", Journal of Materials Processing Technology, 153-154, 2004,1026-1032.

[3]. Cao Fenggou, Yang Dayong: "The study of high efficiency and intelligent optimization",25 October 2003

[4]. H. Weule, S. Timmermann, W. Eversheim, "Automation of the Surface Finishing in the Manufacturing of Dies and Molds", CIRP Annals - Manufacturing Technology, 39(1), 1990, 299-303.

[5]. Trias Andromeda, AzliYahya, Nor Hisham, Kamal Khalil, AdeErawan: Predicting Material Removal Rate of Electrical Discharge Machining (EDM) using Artificial Neural Network for High Igap current, June 21-22, 2011

[6]. Angelos P. Markopoulos • Dimitrios E. Manolakos • Nikolaos M.Vaxevanidis: Artificial neural network models for the prediction of surface roughness in electrical discharge machining', 24 January 2008

[7]. J.S. Soni, G. Chakraverti, "Effect of electrode material properties on surface roughness and dimensional accuracy in electro-discharge machining of high carbon high chromium die steel", Journal of Industrial Engineering, 76 , 1995, 46-51.

[8]. Md. Ashikur Rahman Khana, M. M. Rahmanb, K. Kadirgamab: Neural network modelling and analysis for surface characteristics in electrical discharge machining, 2013.

[9]. Lee, S.H. and Li, X.P., 2001.Study of the effect of machining parameters on the machining characteristics in electrical discharge machining of tungsten carbide. Journal of Materials Processing Technology,115(3),344-358.

[10]. Martin T. Hagan, Oklahoma State University Stillwater, Oklahoma .Neural Network Design, 2nd Edition, eBook.

[11]. Chen, Y., and Mahdavian, S., M., Parametric study into erosion wear in a computer numerical controlled electro-discharge machining process, Wear, Vol. 236, pp. 350-354, 1999.