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Investigation and Analysis of MRR in Spark Erosion Machining Through Artificial Neural Network

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ABSTRACT
EDM is an advanced machining process for machining, hard material parts which are difficult to machined 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. In present scenario numbers of researchers have explored a number of ways to improve EDM efficiency. The optimum selection of manufacturing condition is very important in manufacturing processes as they determine surface quality, dimensional accuracy of the obtained parts. EDM process is based on thermoelectric energy between the work piece and an electrode. A pulse discharge occurs in a small gap between the work piece and the electrode and removes the unwanted material from the parent metal through melting and vaporizing. 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. Experimental data was gathered from Die sinking EDM process for copper-electrode and steel-workpiece (D2 tool steel). It is aimed to develop a behavioral model using input-output pattern of raw data from EDM process experiment. The behavioral 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 and TWR between them. A feed forward neural network based on back-propagation is a multilayered architecture made up of one or more hidden layers (layer 1 - 6 neurons & layer 2 – 9 neurons) placed between the input (1 layer–4 neurons) and output (1 layer-2 neuron) layers. The artificial neural network is compared with manufacturing problems such as tool life, dimensional accuracy, etc.

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I. INTRODUCTION

Objectives:

- **Implementation of Taguchi Analysis for design of experiments**

  Purpose: The design data set was formed with the combination of 4 influential parameters namely I_p, T_{on}, V_g, A_e. Thus a sequential design approach was followed for 32 experimentations.

- **Machine setting for achieving an optimum Material Removal Rate and a Carbon Free machined cavity.**

  Purpose: MRR is the higher-the-better performance characteristic. Due to the presence of powders in the dielectric fluid increases the micro- hardness and reduces the micro-cracks on the machined surface due to a reduction of losing alloying elements residing onto the work-piece.
- **Study of modern computational tool-Artificial Neural Network**

  Purpose: Artificial Neural Networks (ANNs) models is to be proposed for the prediction of MRR in Electrical Discharge Machining (EDM). For this purpose a well-known programs, namely Matlab with associated toolboxes was employed.

- **Validation and analysis of the ANN data output with respect to the experimental output.**

  Purpose: The validation can be concluded that there is good agreement between network predicted and experimental results.ANN developed model can predict the amount of material removal rate on the basis of various input parameters influencing the whole process of EDM machining of dies, mould cavities, etc.

II. METHODOLOGY

Procedural Steps

- Referring research paper to know the most influential parameters of EDM.
- Understanding and forming optimal sets and combinations of input parameters.
- Collecting experimental data for developing neural network model.
- Understanding and developing ANN model with the best suitable algorithm.
- Collecting experimental data for validation and prediction purpose for the developed ANN model.

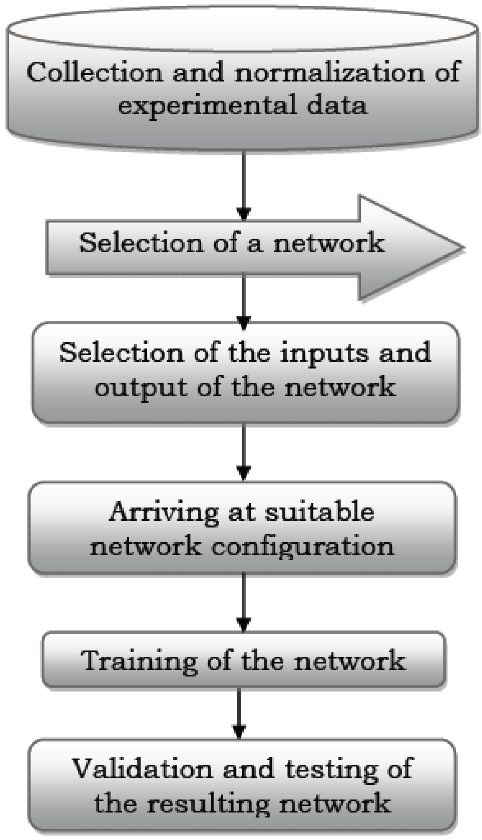


Fig 1 : Procedural Steps

APPLICATION OF ARTIFICIAL NEURAL NETWORK TO PREDICT MRR OF EDM

In the past two decades, neural networks have been shown to be highly flexible modelling tools with capabilities of learning the mathematical mapping between input and output variables for nonlinear systems. The main objective is to model EDM process for optimum operation representing a particular problem in the manufacturing environment where defining the optimization objective function using a smooth, continuous mathematical formula is not possible.

TRAINING THE EXPERIMENTAL DATA FOR ANN

Experiments were conducted in order to gather data for training or learning to the neural network purposes. The training data set includes a number of cases, each containing values for a range of input and output variables. The first decisions will be needed to make are: which variables to use, and how many (and which) cases to gather. The choice of variables (at least initially) is guided by intuition. A value for the material removal rate constant, has been identified based on the empirical analysis carried out on the experimental data and compared with the simulation result from the model using Matlab software tool.

Collecting experimental data for validation and prediction purpose for the developed ANN model.

Although, the network successfully derived the complexrelationship between the input values and MRR of EDM process. After successful training of the network, it is expected to have mapped the desired relationship between the various input and output parameters. The network should also be able to generalize this relationship for its application for new problems. The validation can be concluded that there is good agreement between network predicted and experimental results. Hence, it can be concluded that this ANN model serves as a good model for predicting MRR.

EXPERIMENTAL SETUP

This chapter deals with the experimental setup of the project. In this chapter light is thrown on various aspects such as the machines used, their specifications, materials used for the experimentation, laboratory used, etc. This chapter gives the importance of the various machines used and their applications. This chapter also enlighten the composition and various properties of the material used in the experimentation. Besides the main experimental set up other machines and tools used in the completion of the experimentation are also enlisted in this chapter.

Laboratory used

Table 1 : List of the laboratory and machines used

Sr. no	Laboratory	Machine
1.	Workshop	Electric Discharge Machine
		Automatic hack saw
		Grinder
2.	Metallurgy lab	Rockwell Hardness tester

Machines used

The various machines used in this project are as follows

Electric discharge machine

This machine is soul of this project. All the experimentation of the project are carried out on this machine. It works on the principle of spark erosion as discussed earlier. Figure 6.1 shows the actual setup of the electric discharge machine (EDM).

Fig 2 : EDM Experimental Setup

The specifications of the electric discharge machine (EDM) are given in the table 6.2 The EDM machine is a non-conventional type of machine which finds its applications in mould making industries.

Table 3. EDM Machine Technical Specification

Size of Machine	Length X Width X Height	1250 X 1800 X 1100 mm
Work Head Technical Data	Travel of the Quill	150 mm
Co-ordinate Table	Mounting Surface(Length x Width)	400 X 250 mm
	Maximum Work piece Height :	200mm
	Maximum Work piece Weight:	200Kg
	Longitudinal Travel (X-Axis)	240mm
	Transverse Travel (Y-Axis)	150mm
	Maximum Table- Z-slide spindle distance universal axis:	325mm
	Minimum Table- Z-slide spindle distance universal axis	150mm
Work tank size	Length X Width X Height	685 X 445 X 290mm
	Motor Specification	0.5HP, 0.37KW, 415V, 3 Ph, 50 Hz

Digital weighing machine

This machine is shown in the figure 6.2. It is a weighing machine with the measured weight indicated in a digital display. It was used for measuring the response of the experimentation i.e. the metal removal rate and the tool wear rate by weighing both work piece and tool before and after the electric discharge machining on various input parameter. This is a very sensitive machine with a least count of 0.001 grams.

Fig 3. Digital Weighing Machine

Material used

Work piece material

D2 steel is an air hardening, high-carbon, high-chromium tool steel. It has high wear and abrasion resistant properties. It is heat treatable and will offer a hardness in the range 55-62 HRC, and is machinable in the annealed condition. D2 steel shows little distortion on correct hardening. D2 steel's high chromium content gives it mild corrosion resisting properties in the hardened condition.

Table 5 : Thermal Properties for Cu.

Sr. No.	Properties	Values
1	Thermal conductivity	386 (W/m K)
2	Specific Heat	0.383 (J/gm K)
3	Latent heat of Melting	133 (J/gm)
4	Latent heat of Vaporization	5066 (J/gm)
5	Melting Temp.	1063(°C)
6	Boiling Temp.	2562(°C)

Tool electrode material

Copper is most commonly used EDM tool material against En31 as work piece material. Copper is selected as the tool material. A square tool was taken for experiments. Figure 4 shows the actual tool electrode with their cross section and table 4 consists of properties and dimensions of copper electrode respectively.

Fig 4. Square Tool

Fig 5. Square Tool

Table 6. Tool Properties

Materials Selected	Chemical composition(%)	Application
AISI D2	C 1.4-1.6 Si 0.6 Mn 0.6 Cr 11- 13 Mo 0.7- 1.2 V 1.1 Co 1 Ni 0.3	1. Extremely high wear resistant 2. Excellent size stability in heat treatment 3. Used for stamping, cold forming dies. 4. Used in punches, thread rolling dies, trim dies.

Dielectric Fluid

Dielectric fluid serves three important purposes in EDM.

- To insulate Inter Electrode Gap.
- To flush away the debris from the machined area.
- Acts as coolant to assist during heat transfer between the electrodes

Table 7 : Properties of EDM Oil.

Sr. No.	Property	Value
1	Viscosity	$15.4*10^{-6}$ (m^2/s)
2	Thermal Diffusivity	$70.7*10^{-9}$ (m^2/s)
3	Thermal Conductivity	0.110 (W/m K)

Fig 6: Positioning of workpiece and tool using fixtures

Fig 7 : NC Display Unit

III. Results and discussion from Neural Network Analysis

Here the influence of input parameters i.e., ANN architectures, learning/training algorithms and nos. of hidden neuron on performance parameters MSE and R have been investigated with the help of sequential incremental approach. A network was trained with different possible combinations of parameters, shown in Table 7. A trial-and-error approach was used to ascertain the optimal structure. The selected best neural network model is trained (three times), substituting the set of the training data acquired from the experimental results. Testing was performed using experimental data that were not used for training purposes. The validation of the ANN model was performed using production data that comprises input data only. The impact of the process parameters on MRR was investigated.

Table 7. Observation table for Neural Network method

S.No.	No. of hidden layer	Network Architecture	Momentum Factor	No. of training repetitions	Max. Epochs	MSE	R-value
1	2	4-8-5-1	0.4	3	50000	2.668×10^{-1}	0.97485
2	2	4-7-6-1	0.5	2	40000	5.7263×10^{0}	0.98342
3	1	4-10-1	0.4	3	60000	1.4838×10^{2}	0.84892
4	3	4-7-5-4-1	0.4	3	60000	1.8552×10^{-2}	0.98046
5	2	4-6-9-1	0.6	2	30000	1.78×10^{-2}	0.92651
6	2	4-10-5-1	0.5	3	50000	1.12×10^{-2}	0.98134
7	3	4-8-10-4-1	0.7	2	40000	2.382×10^{-2}	0.91142
8	2	4-8-4-1	0.4	3	60000	3.381×10^{-2}	0.94131
9	2	4-8-4-1	0.5	2	50000	1.063×10^{-1}	0.97037
10	1	4-12-1	0.5	3	30000	2.082×10^{2}	0.70464

Results and discussion from Modelling MRR of EDM Process:

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. From Table 7. minimum MSE and maximum R value was found, so weights and bias matrix of this run was consider for modelling MRR. ANN modelling of MRR with the optimal process parameter setting has been shown here.

MATLAB representation of ANN topology that has been utilized for modeling is shown in Figure 8.

Weights and biases used for generating the ANN outputs which will be further used in the fitness function of GA based multi-objective. For producing the ANN output with the help of weight and bias matrix following equation has been used

$$a^2 = f^2(W^2 f^1(W^1 p + b^1) + b^2)$$

where a2 is output vector of second layer, f represents the transfer function, W1 and W2 are the weight matrix of first hidden layer and second hidden layer respectively, p is the input vector, b1 and b2 are the bias vector of first layer and second layer respectively.

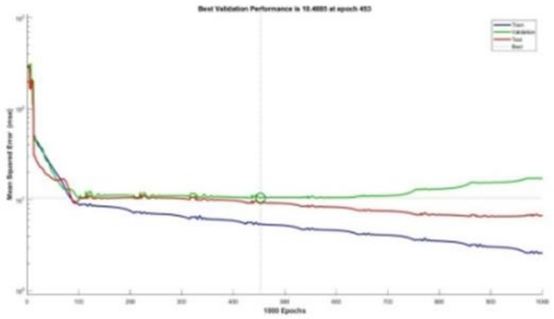


Fig 8 : Variation of MSE w.r.t. epochs

Discussion : Figure 8 shows that the validation error is minimum at epoch 453. So the training was stopped at this point and the weights and biases were used to model MRR.

The dataset divided and trained as mentioned in section 7.1 shows the results of training out and validation of data and summation of all the data were plotted using Matlab 17.

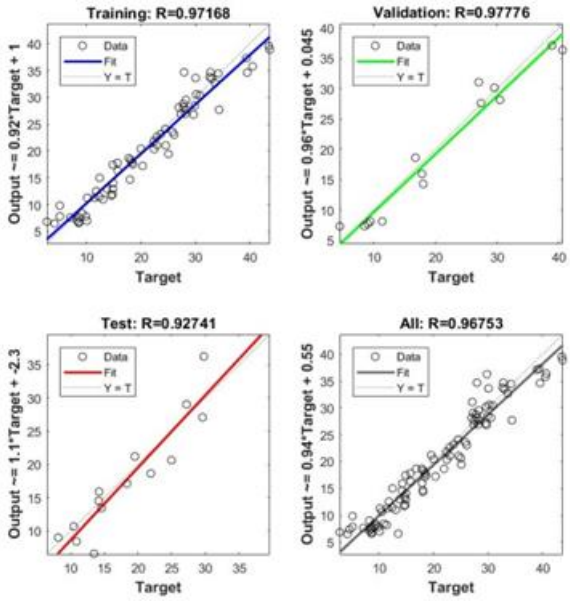


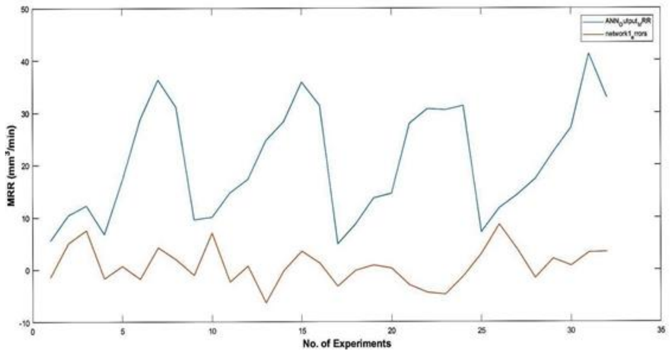
Fig 9 Correlation coefficient

The correlation factor for all the data was found to be R=0.96753.

Table 8 : Output MRR from ANN

Test Run	I_p	T_{on}	V_g	geometry	Experimental output	ANN Output
1	3	0.11	130	L10 x W10	5.1948	5.163887
2	3	0.19	135	L15 x W15	7.44588	7.423183
3	3	0.3	140	L17 x W17	4.242424	6.979825
4	3	0.38	145	L20 X W20	6.03174	5.03532
5	4	0.11	135	L17 X W17	6.9062	7.886356
6	4	0.19	130	L20 x W20	4.23436	5.617095
7	4	0.3	145	L10 x W10	8.83116	8.707423
8	4	0.38	140	L15 x W15	10.50504	9.672148
9	5	0.11	140	L20 x W20	3.369732	2.741729
10	5	0.19	145	L17 x W17	2.77056	2.741729
11	5	0.3	130	L15 x W15	1.61616	3.522703
12	5	0.38	135	L10 x W10	10.85136	12.96754

13	6	0.11	145	L15 x W15	13.82394	18.98275
14	6	0.19	140	L10 x W10	13.39104	16.26992
15	6	0.3	135	L20 x W20	2.741716	4.171575
16	6	0.38	130	L17 x W17	6.58008	8.599452



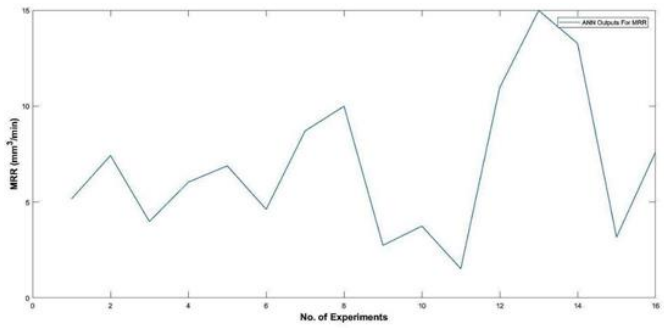


Fig 11: MRR output of prediction data w.r.t. exemplar

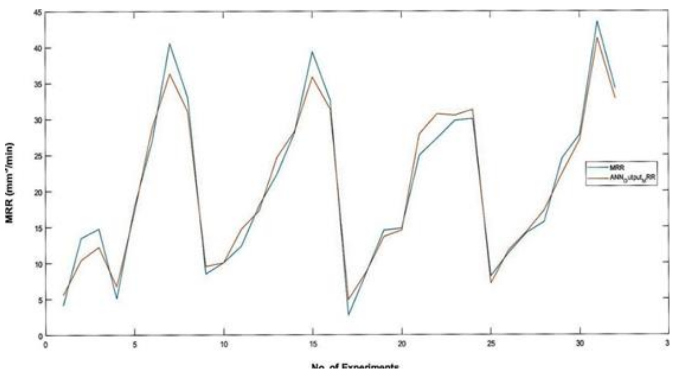


Fig 10. Variation of MRR and MRR output of testing data w.r.t. exemplar

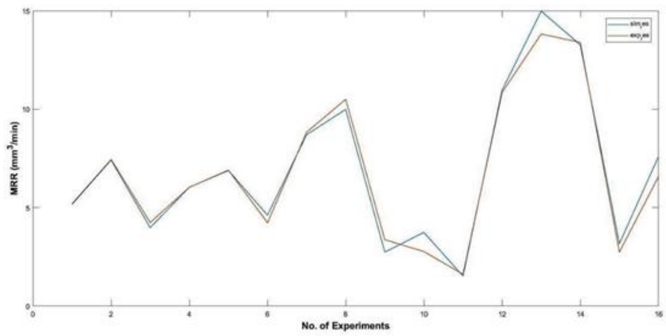


Fig 12 : Variation of MRR and MRR output of validation data w.r.t. exemplar

Discussion: Correlation coefficient between target (Experimental value) and output (ANN output) of training, validation and testing is shown in Figure 10. Figure 11 and 12 shows the variation of MRR (desired output/target) and MRR output (ANN output) of training and testing data set w.r.t. exemplar is shown in Figure 7.10, Along with the predicted MRR outputs Figure 7.10 and quadratic fitting shown in Figure 7.12.

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Discussion: As the degree of the polynomial increases the fit of the curve gets more uniform or in other words increasing the degree of polynomial encompasses more data point thus giving us more close results. Therefore, a quadratic fit between experimental MRR and ANN output MRR was found. Giving us the square of correlation factor as R2=0.94.

MSE: The generalization error can be decomposed into the sum of the bias squared plus the variance. A model which is too simple, or too inflexible, will have a large bias or under fitting, while one which has too much flexibility in relation to the particular dataset will have large variance or over-fitting. The best generalization is obtained when we have the best compromise between the conflicting requirements of small bias and small variance. The purpose of building a behavioral model using artificial neural networks is to make a good prediction for new inputs, not to learn an exact representation of the training data itself.

IV. CONCLUSION

From the main effect plots it can be concluded that for training MSE and R, a 4-10-5-1 neural architecture found to give better result but in case of testing MSE and R, ANN architecture with 4-6-9-1 was found to be the best. As training data set is used to fit the model and testing data set is used to evaluate the model, here main effect plot of testing data set was considered for evaluation of best ANN model. As the neural architecture was found insignificant for test MSE and test R, the conventional MLP neural architecture was selected for modeling. From the main effect plot of test MSE and test R, Gradient Descent with momentum and adaptive learning rate training algorithm with 6 hidden neurons in first hidden layer and 9 neurons in second hidden layer are found to be efficient for optimal values of responses and hence selected for efficient ANN modeling and results were demonstrated.

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