VOL. 3, NO. 1, FEBRUARY 2008 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

DEVELOPMENT OF HYBRID MODEL AND OPTIMIZATION OF METAL REMOVAL RATE IN ELECTRIC DISCHARGE MACHINING USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHM

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ABSTRACT

The present work is aimed at optimizing the metal removal rate of die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters. The experiments are carried out on Ti6Al4V, HE15, 15CDV6 and M-250. Experiments were conducted by varying the peak current and voltage and the corresponding values of metal removal rate (MRR) were measured. Multiperceptron neural network models were developed using Neuro solutions package. Genetic algorithm concept is used to optimize the weighting factors of the network. It is observed that the developed model is within the limits of the agreeable error when experimental and network model results are compared for all performance measures considered. It is further observed that the maximum error when the network is optimized by genetic algorithm has been reduced considerably. Sensitivity analysis is also done to find the relative influence of factors on the performance measures. It is observed that type of material is having more influence on the performance measures.

Keywords: model, hybrid, EDM, MRR, optimization, artificial neural network, genetic algorithm.

Notation

V	-Voltage
A	-Current
Ip	-Peak Current
I max	-Maximum current
t	-Machining time
Y_k	-Output of the network
Q_k	-Measured performance
E_k	-Simple mean square error
Z_j	-Output at the hidden layer
W	-Weights of the network
R_a	-Surface roughness
R_{min}	-Minimum values of the real variables
R_{max}	-Maximum values of the real variables
N	-Normalized value of the real variable

1.0. INTRODUCTION

The selection of appropriate machining conditions for the optimum MRR during electric discharge machining (EDM) process is based on the analysis relating the various process parameters to metal removal rate (MRR). Traditionally this is carried out by relying heavily on the operator's experience or conservative technological data provided by the EDM equipment manufacturers, which produced inconsistent machining performance. The parameter settings given by the manufacturers are only applicable for the common steel grades. The settings for new materials such as Titanium alloys, Aluminum alloys, special steels, advanced ceramics and metal matrix composites (MMCs) have to be further optimized experimentally. Optimization of the EDM process often proves to be difficult task owing to the many regulating machining variables. A single parameter change will influence the process in a complex way. Thus the various factors affecting the process have to be understood in order to determine the trends of the process variation. The selection of best combination of the process parameters for an optimal MRR involves analytical and statistical methods. In addition, the modeling of the process is also an effective way of solving the tedious problem of relating the process parameters to the metal removal rate.

The settings for new materials such as: Titanium alloys, Aluminium alloys and special steels have to be further optimized experimentally. It is also aimed to select appropriate machining conditions for the EDM process based on the analysis relating the various process parameters to MRR. It is aimed to develop a methodology using an input-output pattern of data from an EDM process to solve both the modeling and optimization problems. The main objective of this research 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. It has been hard to establish models that accurately correlate the process variables and performance of EDM process. When new and advanced materials appear in the field, it has not been possible to use existing models and hence experimental investigations are always required. Undertaking frequent tests or many experimental runs is also not economically justified. In light of this, the present work describes the development and application of a hybrid artificial neural network (ANN) and genetic algorithm (GA) methodology to model and optimize the EDM process.

At first, experiments involving discharge machining of Ti6Al4V, HE15, 15CDV6 and M250 at various levels of input parameters namely current, voltage and machining time are conducted to find their effect on metal removal rate. The second phase involves the establishment of the model using multi-layered feed forward neural network architecture. GA finds the optimum values of the weights that minimize the error between the measured and the evaluated (output from the network) performance parameters, where genetic evolution establishes a strong intercommunication between the neural network pattern identification and the GA optimization tasks. Hybrid models are developed for metal removal rate. The developed hybrid model is validated with some of the experimental data, which was not used for developing the model.

2.0. LITERATURE REVIEW

In the past few decades, a few EDM modeling tools correlating the process variables and surface finish have been developed. Tsai and Wang [1] established several surface models based on various neural networks taking the effects of electrode polarity in to account. They subsequently developed a semi-empirical model, which dependent on the thermal, physical and electrical properties of the work piece and electrode together with pertinent process parameters. It was noted that the model produces a more reliable surface finish prediction for a given work under different process conditions [2]. Jeswani *et al.*, [3] studied the effects of work piece and electrode materials on SR and suggested an empirical model, which focused solely on pulse energy, whereas, Zhang *et al.*, [4] proposed an empirical model, built on both peak current and pulse duration, for the machining of ceramics. It was realized that the discharge current has a greater effect on the MRR while the pulse-on time has more influence on the SR and white layer. Lin *et al.*, [5] employed gray relational analysis for solving the complicated interrelationships between process parameters and the multiple performance measures of the EDM process. Marafona and Wykes [6] used the Taguchi method to improve the TWR by introducing high carbon content to the electrode prior to the normal sparking process. Lin *et al.*, [7] employed it with a set of fuzzy logic to optimize the process parameters taking the various performance measures in to consideration. Tzeng and Chen [8] optimized the high speed EDM process by making use of dynamic signal to Noise ratio to classify the process variables in to input signal, control and noise factors generating a dynamic range of output responses. Kesheng Wang *et al.*, [9] discussed the development and application of hybrid artificial neural network and genetic algorithm methodology to modeling and optimization of electric discharge machining. But, they considered only the pulse on time and its effect on MRR. Oguzhan Yilmaz *et al.*, [10] used a user friendly fuzzy based system for the selection of electro discharge machining process parameters. Effect of other important parameters like current, voltage and machining time on TWR, SR, over cut and hardness is not considered. Even though efforts were made by some authors [11-16] to characterize the discharge machining of new materials like Ti6Al4V, 15CDV6 etc, modeling and optimization using hybrid technique was not attempted.

The EDM process has a very strong stochastic nature due to the complicated discharge mechanism [17] making it too difficult to optimize the sparking process. In several cases, S/N ratios together with the analysis of variance (ANOVA) techniques are used to measure the amount of deviation from the desired performance measures and identify the crucial process variables affecting the process responses. A vast majority of the research work have been concerned with the improvement made to the performance indices, such as MRR, TWR and SR. Hence, a constant drive towards appreciating the MRR, TWR and metallurgy of EDMEd surface will continue to grow with the intension of offering a more affective means of improving the performance measures. Furthermore, the traditional EDM will gradually evolve towards micro electro discharge machining (MEDM) by further manipulating the capability of computer numerical control (CNC) but the MRR will remain a prime concern in fulfilling the demand of machining part in a shorter lead-time.EDM has made a significant inroad in the medical, optical, dental and jewelry industries, and in automotive and aerospace R and D areas [18]. An attempt has been made by Yin Fong Tzeng et al. [19] to present a simple approach for optimizing high speed electric discharge machining. These applications demand stringent machining requirements, such as the machining of high strength temperature resistant (HSTR) materials, which generate strong research interests and prompt EDM machine manufacturers to improve the machining characteristics.

With regard to characterization of materials on EDM it is found that recently developed materials like Ti6Al4V, HE15, 15CDV6 and M250 are not explored till now. It is further proved that much work has not been done to create a model, which can predict the behavior of these materials when they are discharge machined. The scattered work done in the area of modeling does not include all-important parameters such as current, voltage and machining time. Hence, in light of the available literature it is aimed to address EDM on recently developed materials like Ti6Al4V, HE15, 15CDV6 and M250 considering different input variables for optimum solution with an aim to optimize MRR. Finding an optimal solution by creating a model of the process using neural network and then selecting the weights with the help of genetic algorithms is the main objective of present study.

3.0. EXPERIMENTAL DETAILS

3.1. Experimental setup

A number of experiments were conducted to study the effects of various machining parameters on EDM process. These studies have been undertaken to investigate the effects of current, voltage, machining time and type of material on metal removal rate. All the four materials were discharge machined with copper tool electrode. Kerosene is used as dielectric medium. The experiments are conducted on ELEKTRA 5535 *PS EZNC DIE SINKING ELECTRIC DISCHARGE MACHINE.

3.2. Experimental procedure

Figure-1 depicts the work piece prepared. They were cut into specimens by power hacksaw and then machined to the size of (44 x 54 x 43) mm. In the same way Aluminium block was cut into four specimens of each (39 x 50 x 37) mm. The work pieces were cut on the power hacksaw at length of 25 mm and then machined on lathe machine to get the mirror surface. The process parameters are being set as per the procedure i.e. varying the voltage at constant current, and varying the current at constant voltage to get the different results for each readings of input. After each experiment the weights of specimen and electrode are measured with digital weighing machine.

3.3. Testing and evaluation of MRR

Metal removal rate is directly calculated from experimental data. The weight of the specimen is taken before and after the machining process using a digital weighing machine. Before weighing the specimen is cleaned and dried to relieve it from debris and dirt. The difference of weight before and after machining gives the weight loss of the work piece during machining process. This weight is divided with machining time to get the metal removal rate in mm^3/min. The accuracy of digital weighing machine is 10 mgs. A stopwatch with an accuracy of 0.01 min is used to measure the machining time.

This is a rate of material removed from either work piece or tool Electrode.

EWR = [1000* Electrode weight difference (gm)]/ [density (gm/cc)*machining Time (min)] (1)

4.0. HYBRID MODEL

First, an initial population of individuals is generated at random. Second, related neural network model is developed using Neurosolutions package. This package can give ANN models with and without the application of GA tool. ANN models are developed for both the cases to find the advantage of using GA for optimizing the weights of ANN. Lastly the three operators of GA: selection, crossover and mutation were applied to produce a new generation. The above operations were repeated until the given limitation number N of generations was reached. Combining the capabilities of ANN and GA, a methodology has been developed using an input-output pattern of data from an EDM process to solve both the modeling and optimization problems. In implementing this hybrid GA and ANN approach, the capability of neural networks to model and predict ill structured data is exploited together with the power of GAs for optimization. The functional optimization problem for this hybrid system can be expressed as follows:

Optimize Y = f(X, W) (2)

Where, Y represents the performance parameters; X is a vector of the input variables to the neural network, and W is the weight matrix that is evaluated in the network training process. F (.) represents the model for the process that is to be built through neural network training. To achieve the goal, a two-phase hybridization has been implemented. These two phases can be categorized as the modeling and optimization phase. The following relations were used to combine the inputs of the network at the nodes of the hidden layer and the output layer, respectively.

$$H_j = \sum_i v_{ij}.X_i, \qquad O_k = \frac{\sqrt{\sum_{k=1}^{z}\sum_{k=1}^{z}(Y_k - Q_k)^2}}{\sqrt{\sum_{k=1}^{z}(Y_k - Q_k)^2}} \tag{3}$$

Both outputs at the hidden ($Z_j = f(H_j)$) and output layer ($Y_k = f(O_k)$) are calculated using sigmoid function, mainly because of its well known use as transfer function for many applications. Combining equation (2) and (3), the relation for the output of the network can be given as equation (4).

$$Y_k = f\,(O_k) = f\,(\sum_j Wjk.Zj\,) = f(\sum_j Wjk\,.(\sum_i v_{ij}.X_i,\,)) \tag{4}$$

Finally the output of the network (Y_k) was compared with the measured performance (Q_k) of the process using a simple mean square error (E_k) as shown in equation (5)

$$E_k = \sqrt{\sum_{k=1}^{z}(Y_k - Q_k)^2} \tag{5}$$

To find the optimum structure and define the correlations, the errors were used as fitness functions with the weights of each link as chromosomes. After modeling in a GA tool, a relative importance concept has been used to establish a measure of significance for each input variable by defining the range of the chromosomes between 0 and 1 so that higher values are associated with more important variables. Further, the sum of the weights over all input variables at a node was constrained to +/- 0.1, so that the RI values could represent the percent contribution of each respective variable to the model performance.

5.0. MODELING OF EDM PROCESS

5.1. Introduction

Comprehensive, qualitative and quantitative analysis of the EDM process and the subsequent development of models of metal removal rate is not only necessary for a better understanding of the process but are also very useful in parametric optimization, process

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simulation, operation and process planning, parametric analysis, verification of the experimental results, and improving the process performance by incorporating some of the theoretical findings of N K Jain and V K Jain [21]. Successful integration of optimization techniques and adaptive control of EDM depends on the development of proper relationships between output parameters and controllable input variables, but the stochastic and complex nature of the process makes it too difficult to establish such relationships. The complicated machining phenomenon coupled with surface irregularities of electrodes, interaction between two successive discharges, and the presence of debris particles make the process too complex, so that complete and accurate physical modeling of the process has not been established yet [22, 23].

The unfulfilled need of physical modeling of EDM has motivated the use of data based empirical methods in which the process is analyzed using statistical techniques. M. Ghoreishi *et al.*, [24] employed statistical and semi-empirical models of the MRR, SR and tool wear. But, the error analysis between predictions and experimental results showed that the models, especially the MRR model, have reasonable accuracy only if MRR is large. This reduces the reliability and versatility of their models for use under various machining conditions for different materials. Having compared the results of neural network model with estimates obtained via multiple regression analysis, Indurkhya and Rajurkar [25] concluded that the neural network model is more accurate and also less sensitive to noise included in the experimental data. But, they did not present any method of determining optimal input conditions to optimize the process for an arbitrary desired surface roughness. Tsai and Wang [26, 1] applied various neural network architectures for prediction of MRR and Ra in EDM. Compared with their previous semi-empirical models reported in [27, 2] the selected networks had considerable lower amounts of error, but no discussion was paid to the determination of operating conditions for different materials.

The purpose of the present work is to present an efficient and integrated approach to cover main drawbacks of previously stated researches in this regard. An attempt is made to relate the input variables to metal removal rate of EDM process for different materials with the help of ANN and optimizing the weights of the network using Genetic algorithm. A software package Neuro solutions has been used for the purpose of forming the ANN and optimizing it with GA. First, a feed forward neural network is developed to establish the process model. Training and testing of the network are done using experimental data. Developed models are tested with a part of experimental data, which is not used for training purpose.

5.2. Development of ANN model for predicting the metal removal rate

Modeling of EDM with feed forward neural network is composed of two stages: training and testing of the network with experimental machining data. The scale of the input and output data is an important matter to consider, especially, when the operating ranges of process parameters are different. The scaling or normalization ensures that the ANN will be trained effectively without any particular variable skewing the results significantly. As a result, all the input parameters are equally important in the training of network. Mapping each term to a value between –1 and 1 using the linear mapping formula did scaling.

$$N = \frac{(R - R_{\min}) x (N_{\max} - N_{\min})}{(R_{\max} - R_{\min})} + N_{\min} \qquad (6)$$

where, N : normalized value of the real variable: $N_{min} = -1$ and $N_{max} = 1$ R: real value of the variable; R_{min} and R_{max} : minimum and maximum values of the real variable, respectively,

5.2.1. Network topology, training and testing

A Generalized feed forward networks is used for developing ANN model. These networks are used for a generalization of the MLP (Multi-layer perceptron) such that connections can jump over one or more layers. The network has three inputs of current (I), voltage (V) and machining time (t) and output of MRR. The size of hidden layers is one of the most important considerations when solving actual problems using multi-layer feed forward network. Three hidden layers were adopted for the present model. Attempts have been made to study the network performance with a different number of hidden neurons. A number of networks are constructed, each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The general network is supposed to be 4-n-1, which implies 4 neurons in the input layer, n neurons in the hidden layer and one neuron in the output layer. Using a neural network package developed in Neuro Solution, different network configurations with different number of hidden neurons were trained, and their performance is checked. The experimental data used for training and production is given in Table-1.

Table-1. Data sets for ANN model.

Material	Current	Voltage	Mach. time	MRR	Remarks
Ti	4	50	100	0.609	Data sets for training the network
Ti	8	50	69	0.687	
Ti	12	50	74	0.705	
Ti	16	50	65	0.722	
Ti	16	70	189	0.287	
Al	4	50	6.15	18.002	
Al	8	50	5	31.428	
Al	12	50	2	96.428	
Al	16	50	0.866	136.09	
Al	20	50	0.766	564.155	
15CDV6	5	50	60	3.547	
15CDV6	10	50	45	4.216	
15CDV6	15	50	20	10.64	
15CDV6	20	50	15	16.41	
MiS	12	50	25	8.5	
MiS	5	50	65	4.31	
MiS	10	50	45	5.63	
MiS	15	50	30	8.46	
MiS	20	50	25	9.75	
MiS	25	50	20	12.25	
Ti	16	30	132	0.684	
Ti	16	40	123	0.899	
Ti	16	50	130	0.712	
Ti	16	60	167	0.595	
MiS	12	55	30	7.12	
Al	16	30	1.75	108.16	
Al	16	40	0.9	83.33	
Al	16	50	0.866	202.078	
Al	16	60	1.6	68.73	
MiS	12	60	35	5.07	
15CDV6	12	40	45	4.44	
15CDV6	12	45	35	5.38	
15CDV6	12	50	30	6.71	
15CDV6	12	55	40	4.58	
15CDV6	12	60	45	5.2	
MiS	12	40	40	5.09	
MiS	12	45	30	7.29	Production data sets
15CDV6	25	50	12	22.41	
Ti	20	50	68	0.896	
Al	16	70	1.25	108.57	

5.3. Development of ANN model for predicting the material removal rate

Data given in Table-1 is utilized to develop the network. Data set 1 to 36 are considered for training the model, data sets 37 to 40 are used for production. Material type is considered as symbol. Tables-2 and 3 give the details of network. The errors obtained after training of the network with 30000 epochs and multiple training (three times) are given in Table-4.

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Table-2. Details of ANN model.

Input Parameters	Hidden layers	Training data sets	Production data Sets	Network Out put
1.Current 2.Voltage 3.Machining time 4.Type of material	03	36	04	Surface roughness

Table-3. ANN training details.

S. No.	Description
1.	Number of epochs: 30,000
2.	Weights: online update
3.	Training: Multiple

Table-4. Error analysis for the network of Metal removal rate.

(a)

All Runs	Training Minimum	Training Standard Deviation
Average of minimum MSEs	0.001271529	0.000681472
Average of final MSEs	0.001271529	0.000681472

(b)

Best Network	Training
Run #	3
Epoch #	30000
Minimum MSE	0.000805938
Final MSE	0.000805938

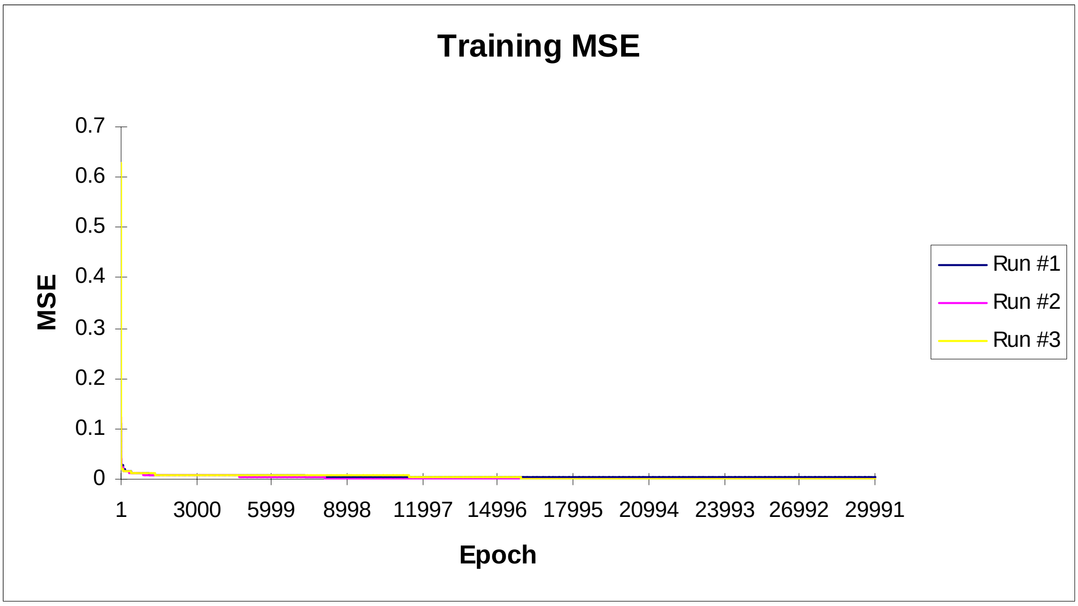

Figure-1. Learning behavior of ANN model for MRR.

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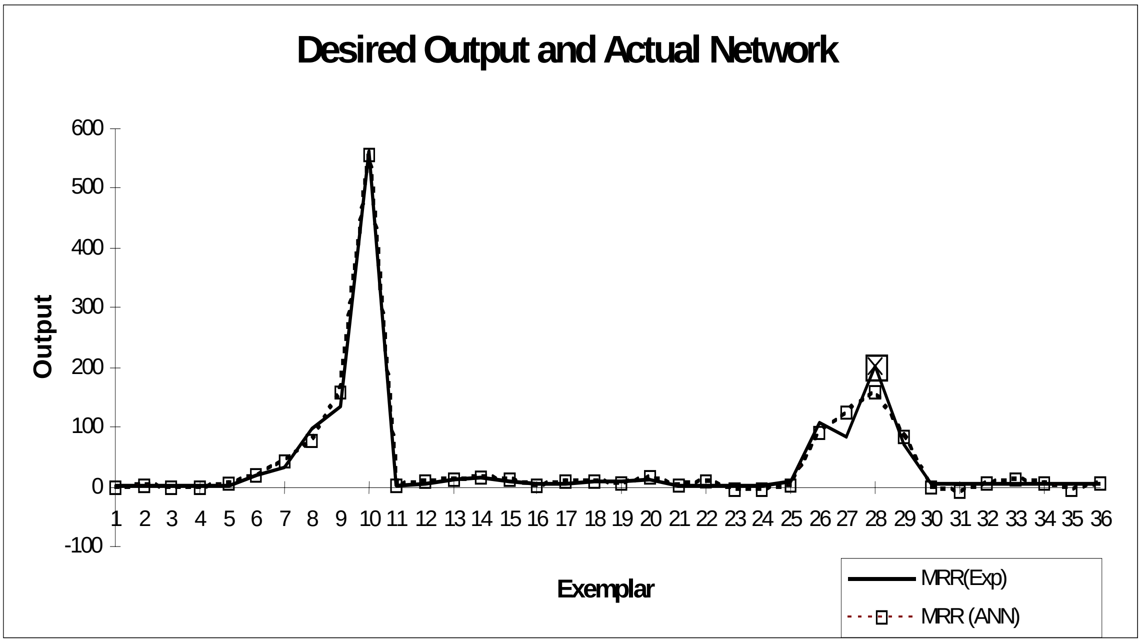

Figure-2. Comparison of experimental and ANN output without GA for MRR.

Figure-1 depicts the convergence of MSE with epochs. The comparison between ANN model out put and experimental out put for training data sets are shown in Figure-2. The ANN predicted results are in good agreement with experimental results and the network can be used for production. Hence the production data sets are applied, and Table-5 shows the results from production of ANN model and comparison with experimental response.

Table-5. Results from production data sets Metal removal rate.

S. No.	Experimental	ANN predicted	% Error
1	7.29	8.2	12.48
2	22.41	24.52	9.41
3	0.896	1.22	36.16
4.	108.57	118.96	9.56

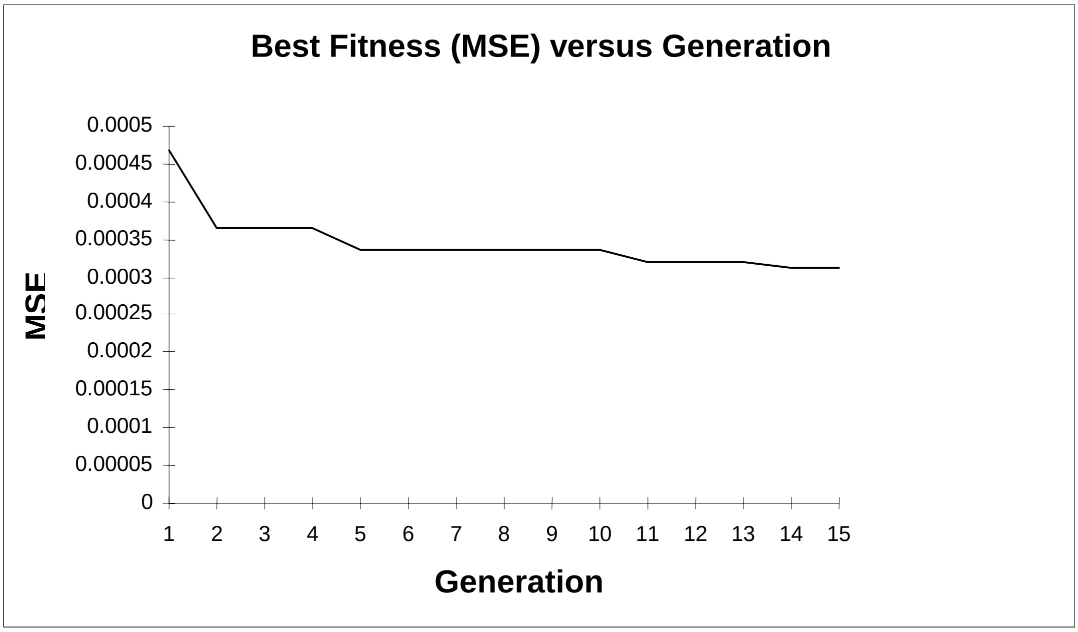

Figure-3. Variation of best fitness with generation for MRR.

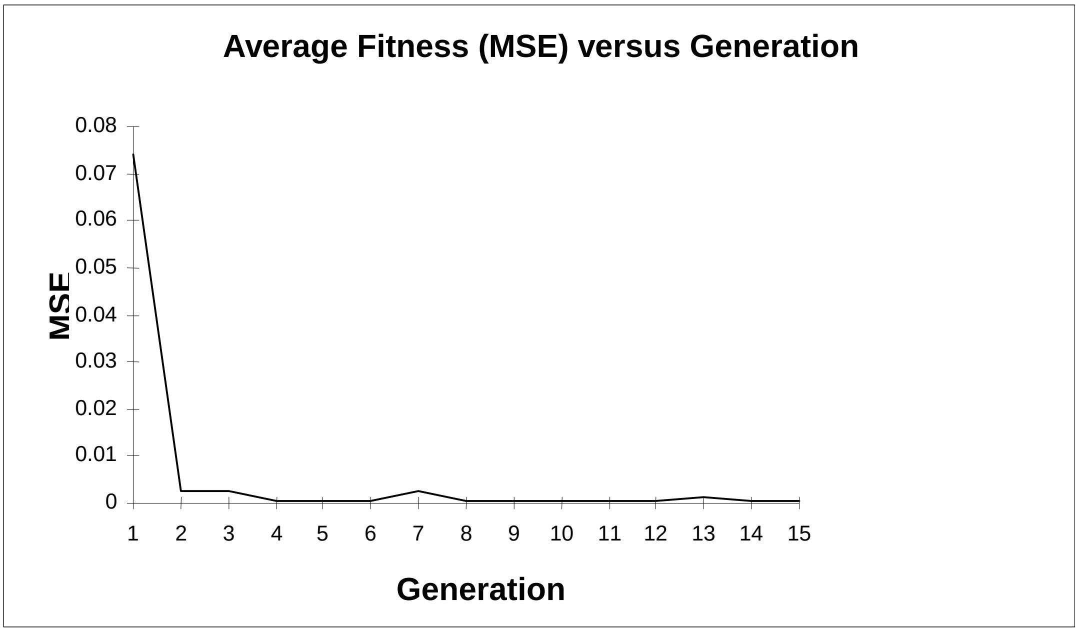

Figure-4. Variation of average fitness with generation for MRR.

The network is trained with the conditions given in Table-6.The results from training the network is depicted in Figures-3 and 4. It is clear that the best fitness is obtained after 14 generations. Similarly the lowest MSE for average fitness is obtained at 9 generation. The corresponding values are given in Table-7.

Table-6. Conditions for training the ANN with GA Metal removal rate.

Number of Input P.E's	04
Number of Hidden P.E.'s	2 With GA
Number of output P.E.s	01
Maximum Epochs	30000
Population size	8
Maximum Generations	15

Table-7. Fitness values Metal removal rate.

Optimization summary	Best Fitness	Average Fitness
Generation #	14	9
Minimum MSE	0.000312556	0.000340645
Final MSE	0.000312556	0.000343021

Table-8. Comparison of best fitness with and without GA Metal removal rate.

S. No.	MSE of ANN without GA	MSE of ANN with GA
1	0.000805938	0.000312556

Table-9. Results from production data sets Metal removal rate.

S. No.	Experimental	ANN predicted	% Error
1	7.29	7.68	5.34979
2	22.41	22.92	2.27577
3	0.896	1.05	17.1875
4.	108.57	113.03	4.10795

Table-10. Sensitivity analysis values for MRR.

Sensitivity	Output MRR
Material (MiS)	89.25300656
Material (15CDV6)	49.34662003
Material (Al)	0
Material (Ti)	41.07240513
CURRENT	1.624554483
VOLTAGE	1.219876705
TIME	0.296884413

Table-8 shows the comparison of MSE for ANN with GA and without GA. It is observed that there is a considerable reduction in MSE for the developed network of ANN with GA.

VOL. 3, NO. 1, FEBRUARY 2008 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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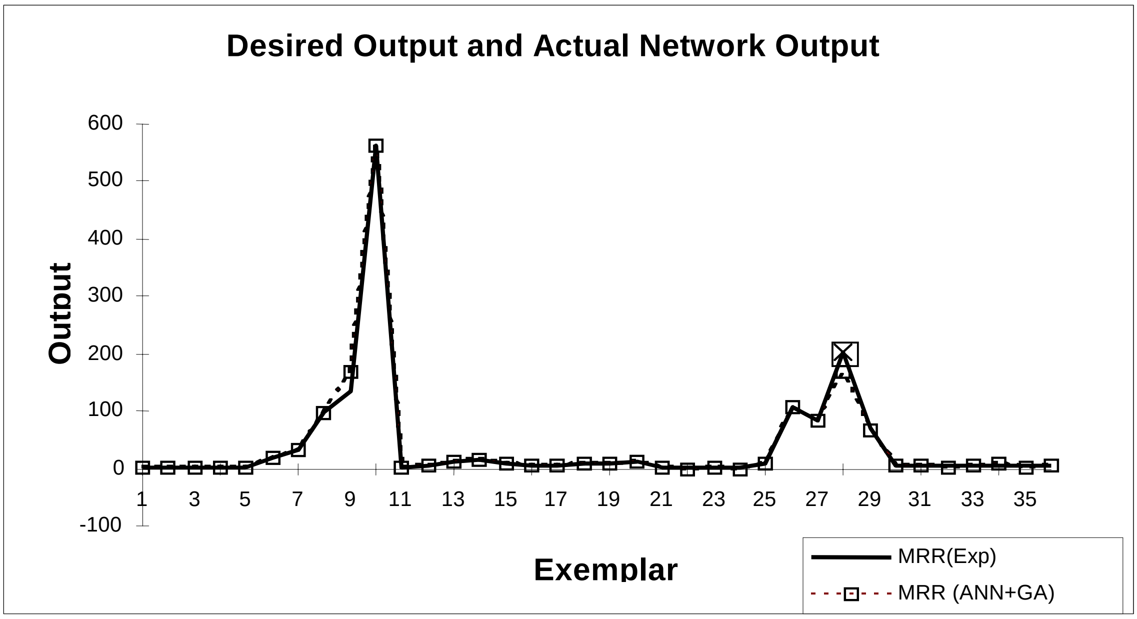

Figure-5. Comparison of experimental and ANN with GA outputs for MRR.

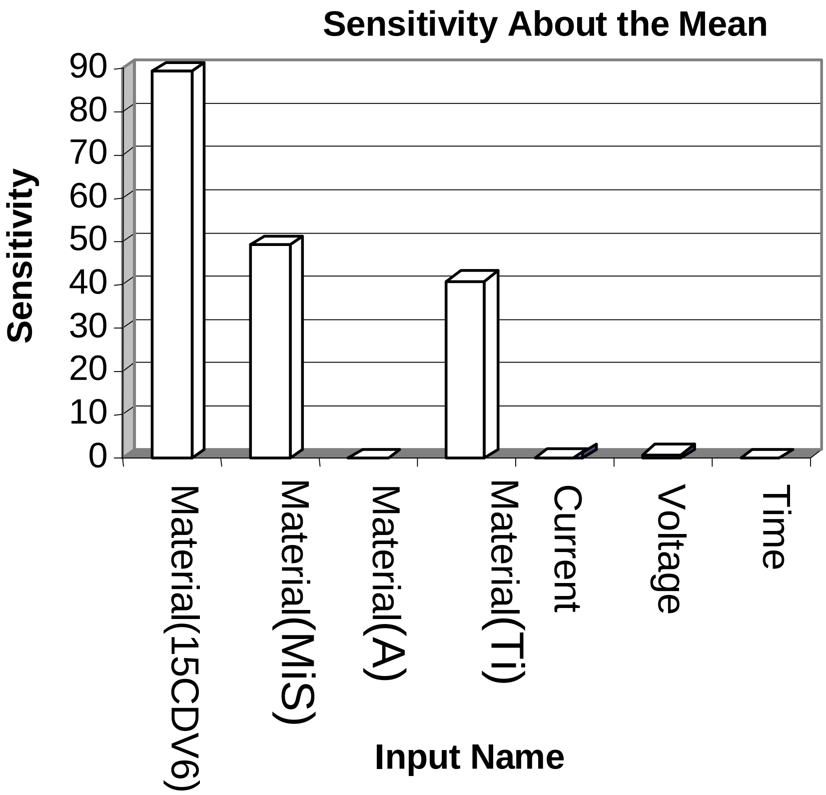

Figure-6. Sensitivity analysis for MRR.

The ANN with GA is tested with trained data sets and the comparison is shown in Figure-5. Comparison is made for all the 36 data sets used for training. Error analysis is made and the results are presented in Table-9. Error varied from in between 2.27% and 17.18%. The % error values are reduced considerably compared to the ANN without GA. The data is further analyzed for sensitivity to identify the influence of the varied input process parameters on output response metal removal rate. The results obtained are shown in figure6 and Table-10. Type of material is having more influence on metal removal rate.

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CONCLUSIONS

From the experiments that were conducted on the Die sinking EDM and the ANN models developed, the following interesting conclusions are drawn:

- When current increases at constant voltage, MRR increases.
- Maximum MRR takes place at a voltage of 40V and 16A.
- In case of titanium, better MRR, reduced over cut and less TWR, are obtained at 15 Amp current and 40V voltage.
- In case of Aluminium alloy also, the MRR value increases with amperage.
- Aluminium material follows the same parabolic curve as that of titanium. But it has maximum MRR at 50V and 16 Amp.
- The MRR increases due to increase of current at constant voltage.
- The MRR increases gradually and then decreases gradually due to the concept of critical resistance of the R-C circuit.
- Hybrid models are developed for MRR considering all the four material together which can predict the behavior of these materials when machined on EDM.
- The developed models are within the limits of agreeable error when experimental and model values are compared for all performance measures considered.
- There is considerable reduction in mean square error when the network is optimized with GA.
- From the sensitivity analysis it is concluded that type of material is having highest influence on all performance measures.

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