Volume : 2 | Issue : 3 | Mar 2013 • ISSN No 2277 - 8179

A Review on Prediction of EDM Parameters using Artificial Neural Network

Engineering

KEYWORDS: EDM, ANN, MRR, TWR, GA, MSE

Vishnu D Asal — ME Student, Department of Mechanical engineering, GEC Dahod, GTU Ahmadabad.

Prof.R.I.Patel — Associate Professor, Department of Mechanical engineering, GEC Dahod, GTU Ahmadabad

ABSTRACT

ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. Interest in using Artificial Neural Networks (ANNs) for forecasting has led to a tremendous surge in research activities in the past decade. While ANNs provide a great deal of promise, they also embody much uncertainty. Researchers to date are still not certain about the effect of key factors on forecasting performance of ANNs. This paper presents a Literature survey of ANN applications in forecasting of EDM parameters which controls the MRR, TWR, Surface Roughness, Radial overcut etc.

INTRODUCTION

Artificial Neural Networks (ANNs) are non-linear data driven self adaptive approach as opposed to the traditional model based methods. ANN is one of the branches of Artificial Intelligence (AI). ANNs are powerful tools for modeling, especially when the underlying data relationship is unknown. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. ANNs imitate the learning process of the human brain and can process problems involving non-linear and complex data even if the data are imprecise and noisy. Thus they are ideally suited for the data which are known to be complex and often non-linear.

A very important feature of this network is their adaptive nature, where “learning by experience/examples” replaces “programming” in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available. If there is no experience, there will be no learning. It imitates the human mind.

The NNs exhibit mapping capabilities, that is, they can map input patterns to their associated output patterns.The NNs learn by examples. Thus, NN architectures can be ‘trained’ with known examples of a problem before they are tested for their ‘inference’ capability on unknown instances of the problem. They can, therefore, identify new objects previously untrained.

The NNs possess the capability to generalize. Thus, they can predict new outcomes from past trends.The NNs are robust systems and are fault tolerant. They can, therefore, recall full patterns from incomplete, partial or noisy patterns.The NNs can process information in parallel, at high speed, and in a distributed manner.

2. LITERATURE REVIEW

G Krishna Mohana Rao, G Ranga Janardhana, D. Hanumantha Rao and M. Srinivasa Rao et al.[2] presented work that was 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,

Input Parameters	Hidden layers	Training data sets	Production data Sets	Network Out put
Current Voltage Machining time Type of material	03	36	04	Surface Roughness

Table-1. Details of ANN model.

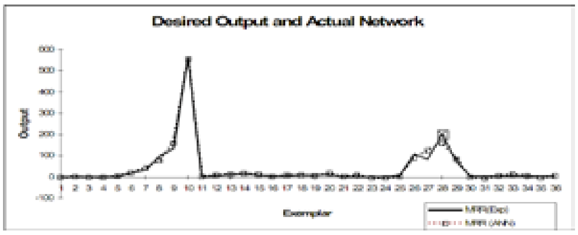


Fig-1. Comparison of experimental and ANN output without GA for MRR

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

Table-2. Results from production data sets Metal removal rate.

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. Table 1 shows the details of ANN model.

Fig.1 shows Comparison of experimental and ANN output without GA for MRR. 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.

Table-2 shows the results from production of ANN model and comparison with experimental response. Table 3 shows conditions for training the ANN with GA Metal removal rate.Table-4 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.

G Krishna Mohana Rao, G Ranga Janardhana, D. Hanumantha Rao and M. Srinivasa Rao et al.[3] optimized the surface roughness 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 surface roughness (SR) 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. It is further observed that the error when the network is optimized by genetic algorithm has come down to less than 2% from more than 5%. Sensitivity analysis is also done to find the relative influence of factors on the performance measures. It is observed that type of material effectively influences the performance measures.

Seung-Han Yang, J. Srinivas, Sekar Mohan, Dong-Mok Lee and Sree Balaji et al. [4] proposed an optimization methodology for the selection of best process parameters in electro discharge machining. Regular cutting experiments are carried out on die-sinking machine under different conditions of process parameters. The system model is created using counter-propagation neural network using experimental data. This system model is employed to simultaneously maximize the material removal rate as well as minimize the surface roughness using simulated annealing scheme. Finally consistency of the method is tested with several initial trail values.

A.Thillaivanan P. Asokan K.N.Srinivasan R.Saravanan et al. [5] in this paper the complexity of electrical discharge machining process which is very difficult to determine optimal cutting parameters for improving cutting performance has been reported. Optimization of operating parameters is an important step in machining, particularly for operating unconventional machining procedure like EDM. An approach to determine parameters setting is proposed. Based on the Taguchi parameter design method and the analysis of variance, the significant factors affecting the machining performance such as total machining time, oversize and taper for a hole machined by EDM process, are determined. Artificial neural networks are highly flexible modeling tools with an ability to learn the mapping between input variables and output feature spaces. The superiority of using artificial neural networks in modeling machining processes make easier to model the EDM process with dimensional input and output spaces. On the basis of the developed neural network model, for a required total machining time, oversize and taper the corresponding process parameters to be set in EDM by using the developed and trained ANN are determined. In addition, in this paper a feedforward-backpropagation neural network is developed for getting the parameters i.e. current and feed for a required total machining time, oversize and taper of a hole to be machined by EDM, which are given as inputs. The collected experimental data are used for training and testing the network.

An EDM machine, developed by SPARKONIX (I) LTD. was used as the experimental machine. The work material, electrode and the other machining conditions were as follows (1) Work piece (anode), Stainless Steel 340C; (2) Electrode (cathode), Tungsten Ø 1.6mm; (3) Dielectric fluid, Kerosene; (4) Workpiece height, 50mm; (5) workpiece length, 100mm. A total of two machining parameters (current and feed) were chosen for the controlling factors and each parameter have levels as shown in Table 5. M K Pradhan, R Das and C K Biswas et al. [6] in this work, two different artificial neural networks (ANNs) models: Back propagation neural network (BPN) and radial basis function neural network (RBFN) are presented for the prediction of surface roughness in die sinking Electrical Discharge Machining (EDM). The pulse current (Ip), the pulse duration (Ton) and duty cycle (t) are chosen as input variable with a constant voltage 50 volt, surface roughness is the output parameters of the model. A widespread series of EDM experiments was conducted on AISI D2 steel to acquire the data for training and testing and it was found that the neural models could predict the process performance with reasonable accuracy, under varying machining conditions. However, RBFN is faster than the BPNs and the BPN is reasonably more accurate. Moreover, they can be considered as valuable tools for EDM, by giving reliable predictions and provide a possible way to avoid time and money consuming experiments. Table-6 shows the Experimental machining parameters.

S.N. Joshi, S.S. Pande et al. [7] this paper reports an intelligent approach for process modeling and optimization of electric discharge machining (EDM). Physics based process modeling using finite element method (FEM) has been integrated with the soft computing techniques like artificial neural networks (ANN) and genetic algorithm (GA) to improve prediction accuracy of the model with less dependency on the experimental data. A two-dimensional axi-symmetric numerical (FEM) model of single spark EDM process has been developed based on more realistic assumptions such as Gaussian distribution of heat flux, time and energy dependent spark radius, etc. to predict the shape of crater, material removal rate (MRR) and tool wear rate (TWR). The model is validated using the reported analytical and experimental results. A comprehensive ANN based process model is proposed to establish relation between input process conditions (current, discharge voltage, duty cycle and discharge duration) and the process responses (crater size, MRR and TWR) .The ANN model was trained, tested and tuned by using the data generated from the numerical (FEM) model. It was found to accurately predict EDM process responses for chosen process conditions. The developed ANN process model was used in conjunction with the evolutionary non-dominated sorting genetic algorithm II (NSGA-II) to select optimal process parameters for roughing and finishing operations of EDM. Experimental studies were carried out to verify the process performance for the optimum machining conditions suggested by our approach. The proposed integrated (FEM–ANN–GA) approach was found efficient and robust as the suggested optimum process parameters were found to give the expected optimum performance of the EDM process.

The following ranges of the input process parameters were chosen for study.

- Discharge current: 5–10–20–30–40 A
- Discharge duration: 25–50–100–300–500–700 μs
- Duty cycle: 50–65–80%
- Break down voltage: 30–40–50 V
- Work material: AISI P20 mold steel
- Tool material: Copper

Fig. 2 shows the proposed approach for the development of intelligent process model for EDM using FEM, ANN and GA. It primarily comprises of three stages:

- Numerical (FEM) modeling of the EDM process considering the thermo-physical characteristics of the process.
- Development of ANN based process model based on the data generated using the simulation of the numerical (FEM) model.
- Optimum selection of process parameters using GA based optimization of ANN process model.

This integrated approach of model development (FEM–ANN–GA) has a peculiar merit that it is based on accurate FEM analysis and not on experimental data collection, which could be costly, time consuming and error prone.

RBFN is alternative supervised learning network architecture to the multilayered perceptrons (MLP). The topology of the

RBFN is similar to the MLP but the characteristics of the hidden neurons are quite different (Fig. 3). It consists of an input layer, one hidden layer and an output layer. The input layer is made up of source neurons with a linear function that simply feeds the input signals to the hidden layer. The neurons calculate the Euclidean distance between the center and the network input vector, and then passes the result through a non-linear function (Gaussian function/ multiquadric /thin plate spline, etc.). It produces a localized response to determine the positions of centers of the radial hidden elements in the input space.

Fig. 4 shows the schematic diagram of a BPNN configuration with two hidden layers, one input layer and output layer each. BPNN configuration with SCG algorithm was tried out. Exhaustive numerical experimentation was carried out to choose the optimal BPNN architecture by varying the number of hidden layers (single and two layered) and number of neurons in each hidden layer (from 4 t o 30). The 4-5-28-4 BPNN architecture was found to be more accurate and generalized with very good prediction accuracy (of about 7%) in comparison with the 4-250-4 RBFN configuration. RBFN and BPNN were developed and extensively tested for their prediction performance and generalization capability. Though the RBFN is fast and easy to configure, BPNN network with SCG training algorithm provided more accurate process model and has more potential for modeling of complex manufacturing processes such as EDM. Optimal BPNN based net- work architecture 4-5-28-4 was found to give good prediction accuracy (with mean prediction error of about 7%).

PARAMETERS	LEVELS					
	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
CURRENT (A)	1	2	3	4	5	6
FEED (mm/min)	0.28	0.2825	0.2875	0.29	-	-

Table-5 Process parameters and their levels

Parameter of experiment	Values
Current (Ip) in A	1, 5, 10, 20, 30, 50
Pulse on time in μs	5,10, 20, 30,50,100, 200
Discharge voltage (V)	50
Duty cycle (t)	1 12
Polarity	Positive

Table-6 Experimental machining parameter

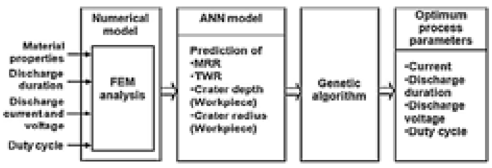
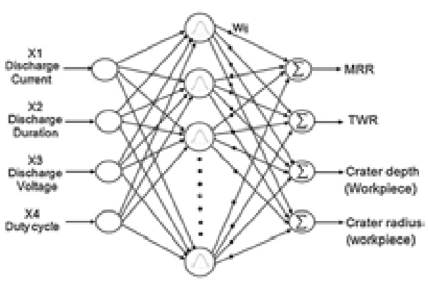


Fig.2 EDM process model development and optimization approach



Reza Atefi, Ali Razmavar, Farhad Teimoori and Farshad Teimoori et al. [8] in this work, the influence of different EDM parameters (pulse current, pulse voltage, pulse on-time, pulse off-time) in finishing stage on the surface quality (Ra) as a result of application copper electrode to a work piece (hot work steel DIN1.2344) has been investigated. Design of the experiment was chosen as full factorial and artificial neural network has been used to estimate surface roughness. Finally a hybrid model has been designed to reduce the artificial neural network errors. The experiment results indicated a good performance of proposed method in optimization of such a complex and non-linear problems.

First, ANN has been designed for the prediction of Ra and then a hybrid model (a combination of statistical analysis and ANN) has been designed to reduce the errors of ANN and to predict the Ra.

For designing and training of ANN model, the programming in Matlab software was used. Training procedures were as follow:

1. Defining the inputs and outputs of the network
2. Defining error function of the network
3. Obtaining the trained output data for input vector data.
4. Comparing real outputs with test outputs.
5. Correcting ANN weights based on error value.
6. Repeating "Correct ANN weights based on error value" to reach minimum error.

The input parameters considered in the experiments include discharge current (I), voltage (V), pulse-on time (T) and pulse-off time (Ton). The output parameter considered in experiments includes surface roughness (Ra).

Error function network used mean square error (MSE) procedure as shown in the following equation

$$MSE = \frac{1}{2mN}\sum_{i=1}^{N}\sum_{j=1}^{m}(T_j - O_j)^2 \quad (1)$$

Tj is the target output of the jth neuron, Oj the predicted value of the jth neuron, N the total number of training pattern (definition of epoch in Matlab programming), and m is the number of output nodes. 0.0001is used as the value of MSE. The number of data is 81 and as a result 72 out of 81 were selected for training of network and 9 for testing the network. The number of neurons was selected in hidden layers, transportation function of each neuron, error training method based on minimum error. The choose of the number of neurons in hidden layers, transportation function of each neuron, learning method and training method was based on trial and error to obtain minimum error. The designed ANN had 4 inputs, 15 neurons in first hidden layer, 15 neurons in second hidden layer and 1 neuron in output layer. The training of network used Levenberg-Marquadt (backpropagation) method.

K. P. Somashekhar, N. Ramachandran, and Jose Mathew et al. [9] the present work reports on the development of modeling and optimization for micro-electric discharge machining (μ-EDM) process. Artificial neural network (ANN) is used for analyzing the material removal of μ-EDM to establish the parameter optimization model. A feed forward neural network with back propagation algorithm is trained to optimize the number of neurons and number of hidden layers to predict a better material removal rate. A neural network model is developed using MATLAB programming, and the trained neural network is simulated. When experimental and network model results are compared for the performance considered, it is observed that the developed model is within the limits of the agreeable error. Then, genetic algorithms (GAs) have been employed to determine optimum process parameters for any desired output value of machining characteristics. This well-trained neural network model is shown to be effective in estimating the MRR and is improved using optimized machining parameters.

Kuo-Ming Tsai, Pei-Jen Wang et al. [10] In this study, the comparisons on predictions of surface finish for various work materials with the change of electrode polarity based upon six different neural-networks models and a neuro-fuzzy network model have been illustrated. The neural-network models are the Logistic Sigmoid Multi-layered Perceptron (LOGMLP), the Hyperbolic

Tangent Sigmoid Multi-layered Perceptron (TANMLP), the Fast Error Back-propagation Hyperbolic Tangent Multi-layered Perceptron (Error TANMLP), the Radial Basis Function Networks (RBFN), the Adaptive Hyperbolic Tangent Sigmoid Multi-layered Perceptron, and the Adaptive Radial Basis Function Networks. The neuro-fuzzy network is the Adaptive Neuro-Fuzzy Inference System (ANFIS). Being trained by experimental data initially screened by the Design of Experiment (DOE) method, the parameters of the above models have been optimally determined for predictions. Based upon the conclusive results from the comparisons on checking errors among these prediction models, the TANMLP, RBFN, Adaptive RBFN, and ANFIS model have shown consistent results. Also, it is concluded that the further experimental results have agreed to the predictions based upon the above four models.

Promod Kumar Patowari, Partha Saha, P. K. Mishra et al., [11] in the present work, attempts have been made to model the surface modification phenomenon by EDM with artificial neural networks. Two output measures, material transfer rate and average layer thickness, have been correlated with different process parameters and presented in the form of plots. The ANN has been successfully applied for surface modification with W – Cu P/M sintered electrodes in EDM. The optimized architecture of the neural network has been selected, trained, tested, and used for simulation. The trends of predicted and target values from training and testing are very much close to each other. The simulated results from the networks have been presented and discussed. They are in good agreement with experimental data. Thus, this study has presented an elaborate effect of different process parameters on MTR and LT. This study has added more insight in the surface modification phenomenon by EDM which is still in the state of exploratory research. The predicted results are matching well with the experimental results.

Azli Yahya, Trias Andromeda, Ameruddin Baharom, Arif Abd Rahim and Nazriah Mahmud et al., [12] this literature presents Artificial Neural Network (ANN) architecture to model the Electrical Discharge Machining (EDM) process. It is aimed to develop the ANN model using an input-output pattern of raw data collected from an experimental of EDM process, whereas several research objectives have been outlined such as experimenting machining material for selected gap current, identifying machining parameters for ANN variables and selecting appropriate size of data selection. The experimental data (input variables) of copper-electrode and steel-workpiece is based on a selected gap current where pulse on time, pulse off time and sparking frequency have been chosen at optimum value of Material Removal Rate (MRR). In this paper, the result has significantly demonstrated that the ANN model is capable of predicting the MRR with low percentage prediction error when compared with the experimental result.

Ramezan Ali MahdaviNejad et al., [13] the present work is aimed to optimize the surface roughness and material removal rate of electro discharge machining of SiC parameters simultaneously. As the output parameters are conflicting in nature, so there is no single combination of machining parameters, which provides the best machining performance. Artificial neural network (ANN) with back propagation algorithm is used to model the process. A multi-objective optimization method, non-dominating sorting genetic algorithm-II is used to optimize the process. Affects of three important input parameters of process viz., discharge current, pulse on time (Ton), pulse off time (Toff) on electric discharge machining of SiC are considered. Experiments have been conducted over a wide range of considered input parameters for training and verification of the model. Testing results demonstrate that the model is suitable for predicting the response parameters. A pareto-optimal set has been predicted in this work.

S. Assarzadeh & M. Ghoreishi et al., [14] in this research, a new integrated neural- network- based approach is presented for the prediction and optimal selection of process parameters in die sinking electro-discharge machining (EDM) with a flat electrode (planing mode). A 3–6–4–2-size back-propagation neural network is developed to establish the process model. The current (I), period of pulses (T), and source voltage (V) are selected as network in puts. The material removal rate (MRR) and surface roughness (R a) are the output parameters of the model. Experiment al data were used for training and testing the network. The results indicate that the neural model can predict process performance with reasonable accuracy, under varying machining conditions. The effects of variations of the input machining parameters on process performance are then investigated and analyzed through the network model. Having established the process model, a second network, which parallelizes the augmented Lagrange multiplier (ALM) algorithm, determines the corresponding optimum machining conditions by maximizing the MRR subject to appropriate operating and prescribed Ra constraints. The optimization procedure is carried out in each level of the machining regimes, such as finishing (Ra =2 μ m), semi-finishing (R a =4.5 μ m), and roughing (Ra =7 μ m), from which, the optimal machining parameter settings are obtained. The optimization results have also been discussed, verified experimentally, and the amounts of relative errors calculated. The errors are all in acceptable ranges, which, again, confirm the feasibility and effectiveness of the adopted approach.

Qing GAO, Qin-he ZHANG, Shu-peng SU, Jian-hua ZHANG et al., [15] Electrical discharge machining (EDM) process, at present is still an experience process, wherein selected parameters are often far from the optimum, and at the same time selecting optimization parameters is costly and time consuming. In this paper, artificial neural network (ANN) and genetic algorithm (GA) are used together to establish the parameter optimization model. An ANN model which adapts Levenberg-Marquardt algorithm has been set up to represent the relationship between material removal rate (MRR) and input parameters, and GA is used to optimize parameters, so that optimization results are obtained. The model is shown to be effective, and MRR is improved using optimized machining parameters. In this paper, one method to optimize EDM process parameters is introduced, which uses Levenberg-Marquardt algorithm and GA together. An ANN model was set up to represent the relationship between MRR and input parameters, which adapted Levenberg-Marquardt algorithm and its network architecture was 3-26-1. It shows that the net has better generalization performance, and convergence speed is faster. GA is used to optimize parameters. MRR is improved by using optimized parameters; it is close to experiment result. With the increase of current, MRR can be improved. MRR can also be improved when we set proper pulse on time and pulse off time with the same current.

M.M. Rahman et al.,[16] This paper presents the artificial intelligence model to predict the optimal machining parameters for Ti- 6Al-4V through electrical discharge machining (EDM) using copper as an electrode and positive polarity of the electrode. The objective of this paper is to investigate the peak current, servo voltage, pulse on- and pulse off-time in EDM effects on material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR). Radial basis function neural network (RBFNN) is used to develop the artificial neural network (ANN) modeling of MRR, TWR and SR. Design of experiments (DOE) method by using response surface methodology (RSM) techniques are implemented. The validity test of the fit and adequacy of the proposed models has been carried out through analysis of variance (ANOVA). The optimum machining conditions are estimated and verified with proposed ANN model. It is observed that the developed model is within the limits of the agreeable error with experimental results. Sensitivity analysis is carried out to investigate the relative influence of factors on the performance measures. It is observed that peak current effectively influences the performance measures. The reported results indicate that the proposed ANN models can satisfactorily evaluate the MRR, TWR as well as SR in EDM. Therefore, the proposed model can be considered as valuable tools for the process planning for EDM and leads to economical industrial machining by optimizing the input parameters.

CONCLUSION

- The important findings are summarized as follows:
- The unique characteristics of ANNs adaptability, nonlinearity and arbitrary function mapping ability make them quite

suitable and useful for forecasting tasks.
- The findings are inconclusive as to whether and when ANNs are better than classical methods.
- It is observed that there is a considerable reduction in MSE for the developed network of ANN with GA.
- It was found that the neural models could predict the process performance with reasonable accuracy, under varying machining conditions. RBFN is faster than the BPNs and the BPN is reasonably more accurate.
- It is observed that the developed model is within the limits of the agreeable error with experimental results.
- After training, ANNs can be used to predict the outcome of new independent input data.
- Comparisons on checking errors among prediction models, the TANMLP, RBFN, Adaptive RBFN, and ANFIS model have shown consistent results.

REFERENCE

1] Carlos Gershenson, Artificial Neural Networks for Beginners. [2] G Krishna Mohana Rao, G Ranga Janardhana, D. Hanumantha Rao and M. Srinivasa Rao. "Development of hybrid model and optimization of metal removal rate in electric discharge machining using artificial neural networks and genetic algorithm". ARPN journal of engineering and applied sciences, Vol. 3, no. 1, ISSN 1819-6608, February 2008. [3] G Krishna Mohana Rao, G Ranga Janardhana, D. Hanumantha Rao and M. Srinivasa Rao. "Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm". Journal of materials processing technology 209 (2009) 1512–1520. [4] Seung-Han Yang, J. Srinivas, Sekar Mohan, Dong-Mok Lee and Sree Balaji. "Optimization of electric discharge machining using simulated annealing". Journal of Materials Processing Technology (2009). [5] A.Thillaivanan P. Asokan K.N.Srinivasan R.Saravanan,"Optimization of operating parameters for EDM process based on the taguchi method and artificial neural network". International Journal of Engineering Science and Technology Vol. 2(12), 2010, 6880-6888. [6] M K Pradhan, R Das and C K Biswas, "Comparisons of neural network models on surface roughness in electrical discharge machining. "Proc. IMechE Vol. 223 Part B: J. Engineering Manufacture. [7] S.N. Joshi, S.S. Pande, "Intelligent process modeling and optimization of die-sinking electric discharge machining "Applied Soft Computing 11 (2011) 2743–2755. [8] Reza Atefi, Ali Razmavar, Farhad Teimoori, Farshad Teimoori, "The Investigation of EDM Parameters in Finishing Stage on Surface Quality Using Hybrid Model "ISSN 2090-4304 Journal of Basic and Applied Scientific Research, 2(3)3061-3065, 2012. [9] K. P. Somashekhar, N. Ramachandran, and Jose Mathew, "Optimization of Material Removal Rate in Micro-EDM Using Artificial Neural Network and Genetic Algorithms" Materials and Manufacturing Processes, 25: 467–475, 2010. [10] Kuo-Ming Tsai, Pei-Jen Wang, "Predictions on surface finish in electrical discharge machining based upon neural network models" International Journal of Machine Tools & Manufacture 41 (2001) 1385–1403. [11] Promod Kumar Patowari, Partha Saha, P. K. Mishra, "Artificial neural network model in surface modification by EDM using tungsten-copper powder metallurgy sintered electrodes" International Journal of Advance Manufacturing Technology, (2010) 51:627-638. [12] Azli Yahya, Trias Andromeda, Ameruddin Baharom, Arif Abd Rahim and Nazriah Mahmud, "Material Removal Rate Prediction of Electrical Discharge Machining Process Using Artificial Neural Network" Journal of Mechanics Engineering and Automation 1 (2011) 298-302. [13] Ramezan Ali MahdaviNejad, "Modeling and Optimization of Electrical Discharge Machining of SiC Parameters, Using Neural Network and Non-dominating Sorting Genetic Algorithm (NSGA II)" Materials Sciences and Applications, 2011, 2, 669-675. [14] S. Assarzadeh & M. Ghoreishi, "Neural-network-based modeling and optimization of the electro-discharge machining process" International Journal of Advance Manufacturing Technology (2008) 39:488 – 500. [15] Qing GAO, Qin-he ZHANG, Shu-peng SU, Jian-hua ZHANG, "Parameter optimization model in electrical discharge machining process", Journal of Zhejiang University SCIENCE A ISSN 1673-565X (Print); ISSN 1862-1775. [16] M.M. Rahman, "Modeling of machining parameters of Ti-6Al-4V for electric discharge machining: A neural network approach" Scientific Research and Essays Vol. 7(8), pp. 881-890, 29 February,