HYBRID MODELING AND OPTIMIZATION OF HARDNESS OF SURFACE PRODUCED BY ELECTRIC DISCHARGE MACHINING USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHM

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ABSTRACT

The present work is aimed at optimizing the hardness of surface produced in 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 by varying the peak current and voltage and the corresponding values of hardness 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.

Keywords: surface hardness, hybrid model, optimization, electric discharge machining, artificial neural network.

Notations

V	Average 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. INTRODUCTION

The selection of appropriate machining conditions for suitable hardness during the electric discharge machining (EDM) process is based on the analysis relating the various process parameters to hardness. 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 for hardness 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 hardness 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 hardness.

The settings for new materials such as: Titanium alloys, Aluminum 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 hardness. 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, it is not possible to define the optimization objective function using a smooth and continuous mathematical formula. It has been hard to establish models that accurately correlate the process variables and performance of EDM process. Improving the surface hardness is still a challenging problem that constrains the expanding application of the technology. When new and advanced materials appear in the field, it is not possible to use existing models and hence experimental investigations are always required. Undertaking frequent tests or many experimental runs is also not economically justified. Hence, 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 particularly for hardness of the surface generated. 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 the hardness. 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. The developed hybrid model is validated with some of the experimental data, which was not used for developing the model.

2. REVIEW OF LITERATURE

In the past few decades, a few EDM modeling tools correlating the process variables and hardness have been developed. Tsai and Wang (2001) 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 (Tsai and Wang, 2001). Jeswani *et al*. (1978) studied the effects of work piece and electrode materials on surface roughness (SR) and suggested an empirical model, which focused solely on pulse energy, whereas, Zhang *et al*. (1997) 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 metal removal rate (MRR) while the pulse-on time has more influence on the SR and white layer. Lin, C.L. *et al*. (2002) employed gray relational analysis for solving the complicated interrelationships between process parameters and the multiple performance measures of the EDM process. Marafona and Wykes (2000) used the Taguchi method to improve the tool wear rate (TWR) by introducing high carbon content to the electrode prior to the normal sparking process. Lin, J. L. *et al*. (2000) employed it with a set of fuzzy logic to optimize the process parameters taking the various performance measures in to consideration. Tzeng and Chen (2003) optimized the high speed EDM process by making use of dynamic signal to Noise ratio to classify the process variables into input signal, control and noise factors generating a dynamic range of output responses. Kesheng Wang *et al*. (2003) 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*. (2006) used an user friendly fuzzy based system for the selection of electro discharge machining process parameters. Effects of other important parameters like current, voltage and machining time on SR were not considered. Even though efforts were made by some authors to characterize the discharge machining of new materials like Ti6Al4V, 15CDV6 etc, modeling and optimization using hybrid technique was not attempted (Krishna Mohana Rao et. al., 2006a, 2006b, 2006c, 2006d, 2006e, 2007).

The EDM process has a very strong stochastic nature due to the complicated discharge mechanism (Pandit and Mueller, 1987) 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 has been concerned with the improvement made to the performance indices, such as MRR, TWR and SR. Hence, a constant drive towards reducing the SR and appreciating the MRR, TWR and metallurgy of EDMEd surface will continue to grow with the intention of offering a more effective 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 (Stovieck, 1993). An attempt has been made by Yin Fong Tzeng *et al*. (2003) 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 the recently developed materials like Ti6Al4V, HE15, 15CDV6 and M250 have not been explored till now. It is further proved that much work has not been done to create a model for hardness, 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 hardness. 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. EXPERIMENTAL DETAILS

A number of experiments were conducted to study the effects of various machining parameters on hardness of the surface produced in EDM process. These studies have been undertaken to investigate the effects of current, voltage, machining time and type of material on hardness. All the four materials were discharge machined

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with copper tool electrode. Kerosene was used as dielectric medium. The experiments were conducted on ELEKTRA 5535 *PS EZNC Die Sinking Electric Discharge Machine. Work pieces were cut into specimens by power hacksaw and then machined to the size of (44 x 54 x 43mm). In the same way Aluminum block was cut into four specimens of each (39 x 50 x 37mm). The work pieces were cut on the power hacksaw at length of 25mm 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. Hardness is measured with Hardness machine which is shown in Figure-1.

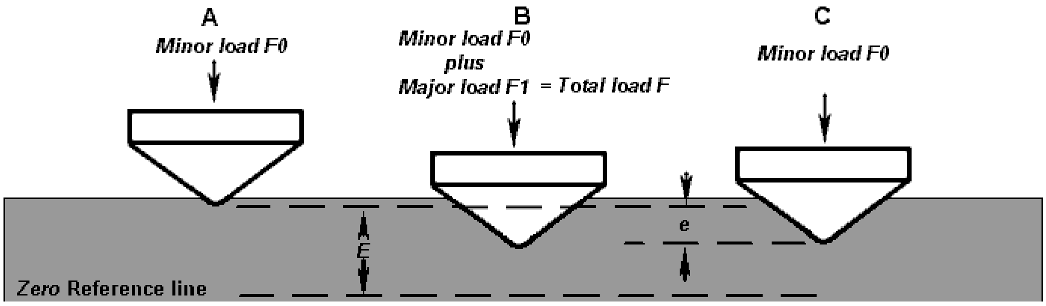

Figure-1. Hardness tester.

4. HYBRID MODEL

The present work describes the development and application of a hybrid ANN and GA methodology to model and optimize the hardness of the surface produced by EDM process. Use of ANN models for prediction of wide range of data is a difficult task. Large differential amplitudes of the solutions targeted at each and every output causes the error surface to be discontinuous and flat in certain regions. GA is a global search method that does not require the gradient data and locates globally optimum solution. The use of GA based learning methods is justified for learning tasks that require ANNs with hidden neurons for a non-linear data, which is the case in the present study. The task of neural network training in ANN is a complicated process, in which a pattern set made up of pairs of inputs plus expected outputs is known beforehand, and used to compute the set of weights that makes the ANN to learn it. The architecture of the network and the weights are evolved by using error back propagation. The optimization of these weights improves the efficiency of the ANN model. In ANN-GA Hybrid model the concepts of GA are used for optimization of weights resulting to the minimization of error between Actual output and ANN predicted output. First, an initial population of individuals is generated at random. Second, related neural network model is developed using Neuro Solutions 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 is given in equation (1).

$$\text{Optimize } Y = f(X, W) \tag{1}$$

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 phases. The following relations were used to combine the inputs of the network at the nodes of the hidden layer and the output layer, respectively.

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

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 optimum utility as transfer function for many applications. Combining equation (1) and (2), the relation for the output of the network can be given as equation (3).

$$Y_k = f(O_k) = f\left(\sum_j Wjk.Zj\right) = f\left(\sum_j Wjk \,.\left(\sum_i v_{ij}.X_i,\right)\right) \tag{3}$$

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 (4).

$$E_k = \sqrt{\sum_{k=1}^{z}(Y_k - Q_k)^2} \quad (4)$$

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 relative importance values could represent the percent contribution of each respective variable to the model performance.

5. MODELING OF EDM PROCESS FOR HARDNESS

Comprehensive, qualitative and quantitative analysis of the EDM process and the subsequent development of models of various performance measures are not only necessary for a better understanding of the process but are also very useful in parametric optimization, process 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 Jain N K and Jain V K (2001). 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 (Pandit and Rajurkar, 1983; McGough, 1998).

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. Ghoreishi, M. *et al*. (2001) 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 (1992) 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. Tsai and Wang (2001) applied various neural network architectures for prediction of MRR and Ra in EDM. Compared to their previous semi-empirical models reported in (Wang and Tsai, 2001) the selected networks had considerable lower amounts of error, but no discussion was paid to the determination of operating conditions for different materials. Krishna Mohana Rao G *et al*. (2009) presented a hybrid network model for predicting the surface roughness of electric discharge machined surface.

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 hardness 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. The following sections depict them in detail.

5.1 Development of ANN model for predicting hardness

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.

$$N = \frac{(R - R_{\min}) x (N_{\max} - N_{\min})}{(R_{\max} - R_{\min})} + N_{\min} \quad (5)$$

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.

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 average current (I), average voltage (V) and machining time (t) and output of hardness. 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.

For training the network, weights are updated online and the activation function of hidden and output neurons was selected as hyperbolic tangent, maximum training epochs considered was 30000 with multiple training. Training data is given in Table-2. The best network structure of FF neural network model is picked to have 4 neurons in the hidden layer. Table-3 shows the experimental and predicted values for hardness as well as percentage relative errors in verification cases. Good agreement between the neural predictions and experimental verifications has been demonstrated in those machining conditions. Figure-2 depicts the convergence of the output error (MSE) with the number of iterations (epochs) during training of the chosen network.

Table-1. Data sets for ANN model.

Material	Current	Voltage	Machining time	MRR	Hardness	Surface rough	Remarks
Ti	4	50	100	0.609	25	3.4	Data sets for training the network
Ti	8	50	69	0.687	25	4.4	
Ti	12	50	74	0.705	26	4.8	
Ti	16	50	65	0.722	23	5.2	
Ti	16	70	189	0.287	27	6.6	
Al	4	50	6.15	18.002	80	4.6	
Al	8	50	5	31.428	82	4.6	
Al	12	50	2	96.428	76	5.4	
Al	16	50	0.866	136.09	80	5.8	
Al	20	50	0.766	564.155	80	10	
15CDV6	5	50	60	3.547	31	4.82	
15CDV6	10	50	45	4.216	30	4.9	
15CDV6	15	50	20	10.64	29	5.06	
15CDV6	20	50	15	16.41	28	12.5	
MiS	12	50	25	8.5	22	5.92	
MiS	5	50	65	4.31	33	6.5	
MiS	10	50	45	5.63	30	5.78	
MiS	15	50	30	8.46	26	5.6	
MiS	20	50	25	9.75	25	12.5	
MiS	25	50	20	12.25	24	18	
Ti	16	30	132	0.684	24	7	
Ti	16	40	123	0.899	25	5	
Ti	16	50	130	0.712	23	5.2	
Ti	16	60	167	0.595	31	6.2	
MiS	12	55	30	7.12	25	5.4	
Al	16	30	1.75	108.16	79	7.6	
Al	16	40	0.9	83.33	81	4.4	
Al	16	50	0.866	202.078	71	6.8	
Al	16	60	1.6	68.73	80	2.6	
MiS	12	60	35	5.07	28	7.2	

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15CDV6	12	40	45	4.44	28	3.78	
15CDV6	12	45	35	5.38	27	4.06	
15CDV6	12	50	30	6.71	26	4.44	
15CDV6	12	55	40	4.58	27	7.8	
15CDV6	12	60	45	5.2	28	8	
MiS	12	40	40	5.09	25	5.24	
MiS	12	45	30	7.29	23	5.28	Production data sets
15CDV6	25	50	12	22.41	28	18	
Ti	20	50	68	0.896	29	5.4	
Al	16	70	1.25	108.57	80	4.8	

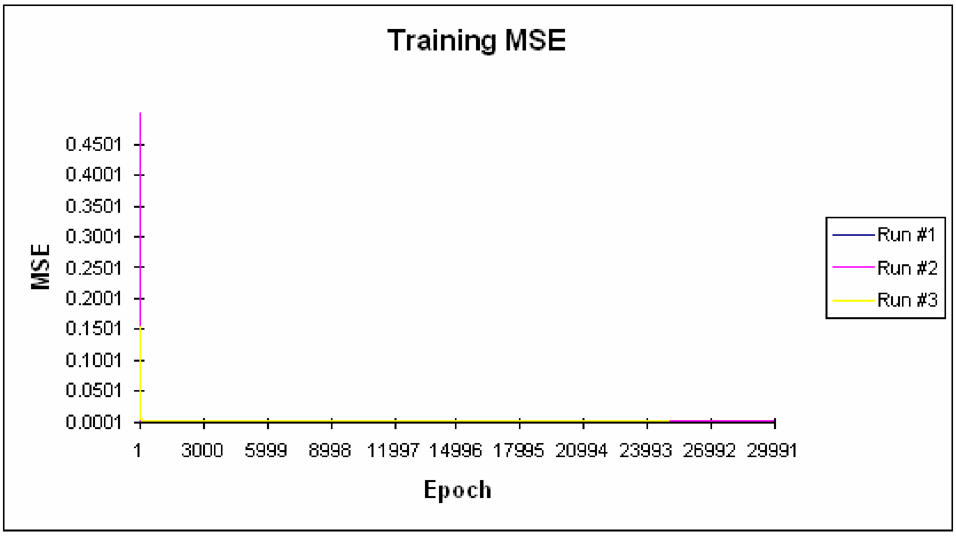

Figure-2. Learning behavior of ANN model for hardness.

Figure-3 also shows the comparison of experimental results and modeling in verifying the network generalization capabilities. Initially, the output from the network is far from the target value. The output slowly and smoothly converges to the target value with more epochs and the network learns the input/output relation of the training samples.

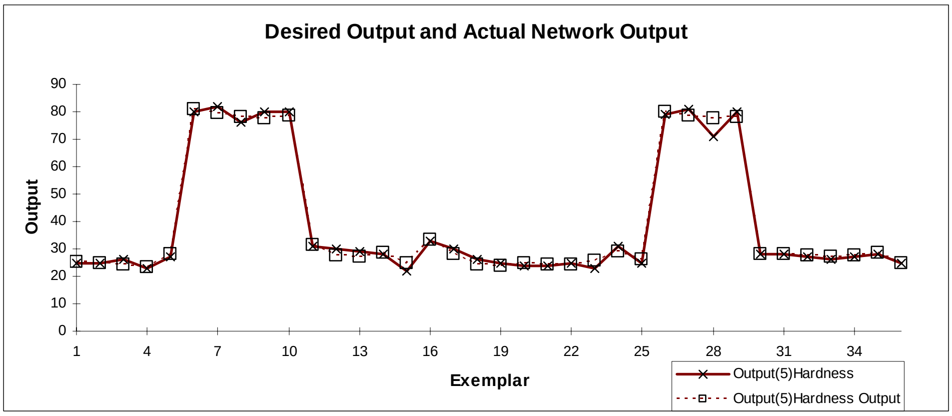

Figure-3. Comparison between experimental and verification data for hardness.

Material type is considered as symbol. Table-2 gives the errors obtained after training of the network with 30000 epochs and multiple training (three times). After training the developed ANN model, it was initially tested

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with trained data. The ANN predicted results are in concurrence with experimental results and the network can be used for production. Hence the production data sets are applied.

It is observed from Table-3 that, the output of the network in terms of mean squared error during training of the network and the error between the desired Hardness and ANN predicted is also in the range of 1.53% too 5.42%. The developed ANN is predicting close to the desired levels, but the % errors are on higher side. In order to reduce the MSE at training and error for production data sets, it is proposed to train the developed network using Genetic Algorithms (GA). The advantage of ANN model with GA is that it optimizes the network weights to minimize the MSE during training of the network.

Table-2. Error analysis for the network of hardness model.

(a)

(a) **All runs**	**Training minimum**	**Training standard deviation**
Average of minimum MSEs	0.001592458	0.000123121
Average of final MSEs	0.001592458	0.000123121

(b)

Best network	**Training**
Run #	3
Epoch #	30000
Minimum MSE	0.001481588
Final MSE	0.001481588

Table-3. Error for predicted values of hardness model without GA.

S. No.	**Experimental**	**ANN predicted**	**% Error**
1	23	24.32	5.42
2	28	29.33	4.53
3	29	28.35	2.29
4.	80	81.25	1.53

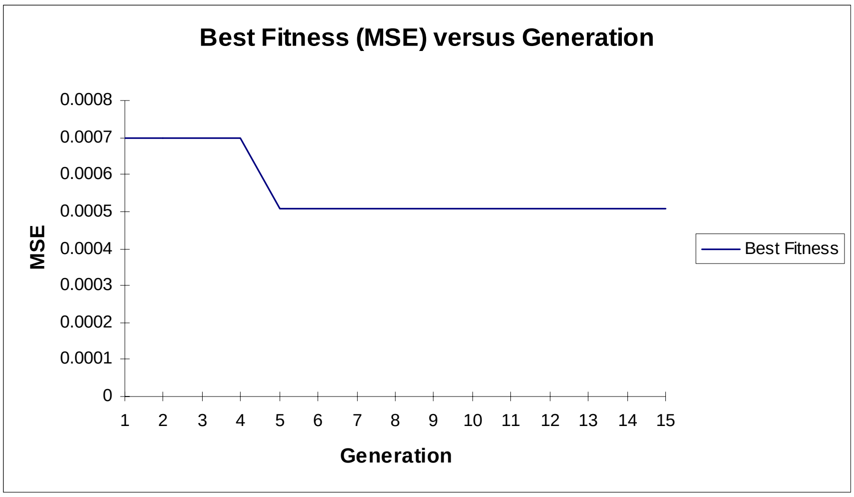

Figure-4. Variation of best fitness with generation for hardness.

The genetic control component implements a genetic algorithm to optimize one or more parameters within the neural network. The most common parameters to optimize are the input columns, the number of hidden processing elements (PE), number of memory taps, and the learning rates. Many other network parameters are available for optimization. In Neuro Solutions the criteria used to evaluate the fitness of each potential solution is the lowest cost achieved during the training run. For developing the ANN with GA for optimization of hidden PE's and network weights, the data sets considered are same as earlier network. The conditions considered for training the ANN with GA are given in Table-4. Table-5 gives the fitness values of the model.

Table-4. Conditions for training the ANN with GA for hardness model.

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-5. Fitness values of hardness model.

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Optimization summary	Best fitness	Average fitness
Generation #	5	12
Minimum MSE	0.000507204	0.000507348
Final MSE	0.000507204	0.000514134

A comparison of best fitness values is made between models with and with out the use of genetic algorithm and is given in Table-6.

Table-6. Comparison of best fitness with and without GA for hardness model.

S. No.	MSE of ANN without GA	MSE of ANN with GA
1	0.001481588	0.000507024

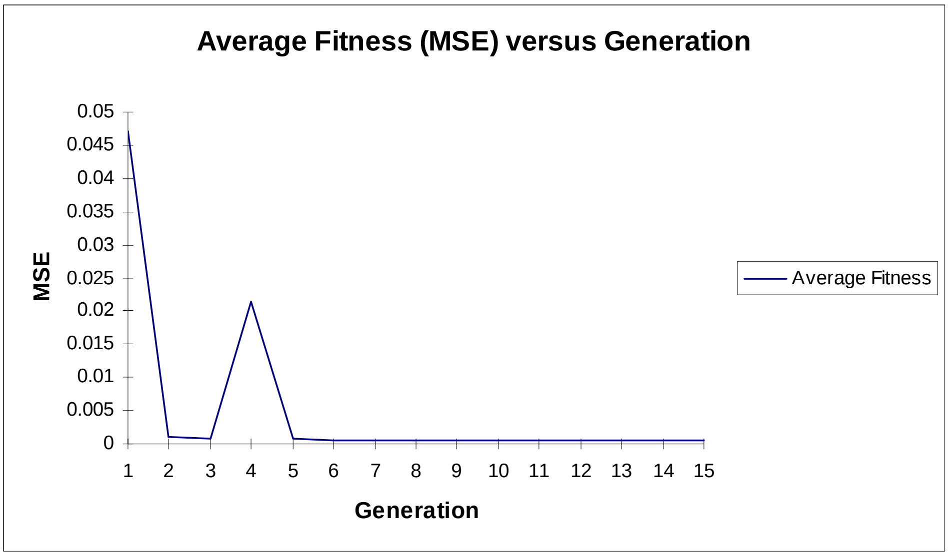

Figure-5. Variation of average fitness with generation for hardness.

The fitness results from training the network are depicted in Figures 4 and 5. It can be seen that after 8 generations the mean square error (MSE) value has become constant. These values are also given in Table-4. Table-5 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. The ANN with GA is tested with trained data sets and the comparison is shown in Figure-6.

As shown in Table-7 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 surface roughness. The results obtained are shown in Figure-7 and Table-8. The type of material has more influence on the performance measures. After type of material, current is the most influencing factor for surface roughness.

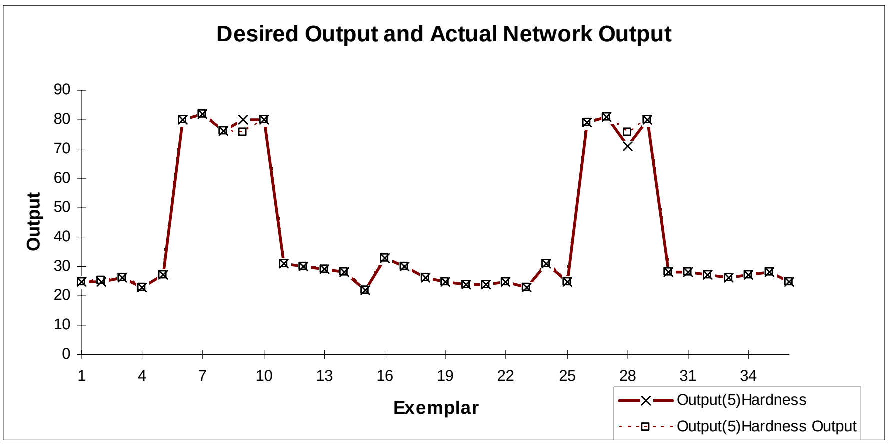

Figure-6. Comparison of experimental and network output with GA for hardness.

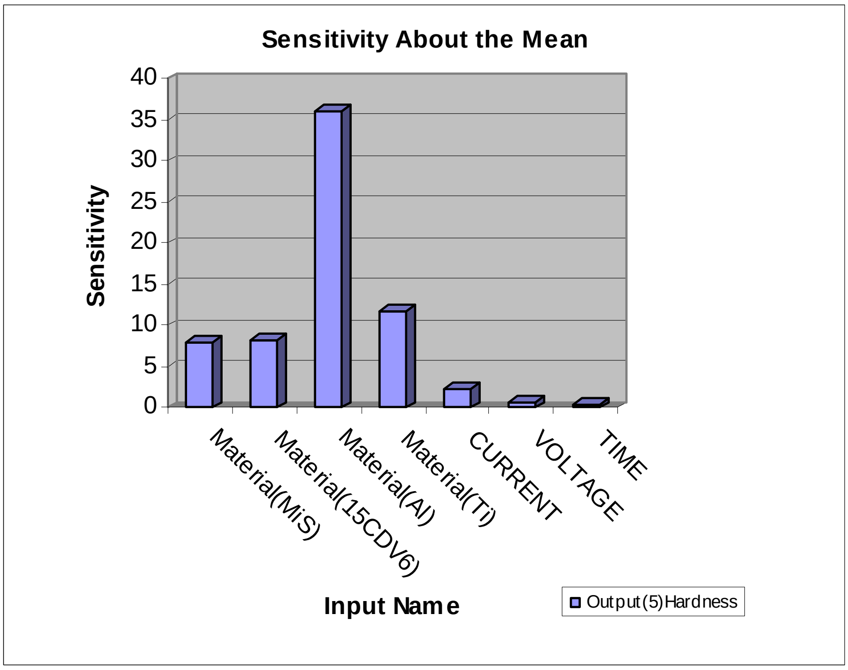

Figure-7. Sensitivity analysis for surface roughness.

Table-7. Results from production data sets for hardness model with GA.

S. No.	Experimental	ANN predicted	% Error
1	23	22.56	1.91
2	28	27.68	1.14
3	29	29.71	2.44
4.	80	79.22	0.97

Table-8. Sensitivity analysis values for hardness model.

Sensitivity	Hardness
Material (MiS)	8.10220461
Material (15CDV6)	8.147062098
Material (Al)	36.10314816
Material (Ti)	11.77153695
Current	2.286740847
Voltage	0.641743116
Time	0.487330683

6. CONCLUSIONS

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

a) Hybrid model is developed for hardness of the surface produced by EDM considering all the four material together which can predict the behavior of these materials when machined on EDM;
b) The developed models are within the limits of agreeable error when experimental and model values are compared for all performance measures considered;
c) There is considerable reduction in mean square error when the network is optimized with GA; and
d) From the sensitivity analysis it is concluded that type of material is having highest influence on all performance measures.

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