World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:8, No:4, 2014

General Regression Neural Network and Back Propagation Neural Network Modeling for Predicting Radial Overcut in EDM: A Comparative Study

Raja Das, M. K. Pradhan

Abstract—This paper presents a comparative study between two neural network models namely General Regression Neural Network (GRNN) and Back Propagation Neural Network (BPNN) are used to estimate radial overcut produced during Electrical Discharge Machining (EDM). Four input parameters have been employed: discharge current (Ip), pulse on time (Ton), Duty fraction (Tau) and discharge voltage (V). Recently, artificial intelligence techniques, as it is emerged as an effective tool that could be used to replace time consuming procedures in various scientific or engineering applications, explicitly in prediction and estimation of the complex and nonlinear process. The both networks are trained, and the prediction results are tested with the unseen validation set of the experiment and analysed. It is found that the performance of both the networks are found to be in good agreement with average percentage error less than 11% and the correlation coefficient obtained for the validation data set for GRNN and BPNN is more than 91%. However, it is much faster to train GRNN network than a BPNN and GRNN is often more accurate than BPNN. GRNN requires more memory space to store the model, GRNN features fast learning that does not require an iterative procedure, and highly parallel structure. GRNN networks are slower than multilayer perceptron networks at classifying new cases.

Keywords—Electrical-discharge machining, General Regression Neural Network, Back-propagation Neural Network, Radial Overcut

I. Introduction

ELECTRICAL discharge machining is one of the extensively accepted advanced machining processes used to machine components with intricate shapes and profiles. It is the most popular non-conventional manufacturing process extensively used to machine electrically conductive materials. Its unique feature of using thermal energy to machine components regardless of its hardness and strength has been its matchless advantage for the manufacture of mould, die, and critical components used in automotive, aerospace, and surgical equipment and other industrial applications [1], [2]. Productivity and accuracy of the dimensions of EDMed surface are two of the major issues in the die sinking EDM process [3]. It is very difficult to regulate the dimensions in EDM, due to the complexity and nonlinearity of the EDM parameters in relation to the response Radial Overcut or Gape (G). Radial overcut is the amount the cavity in the workpiece is cut larger than the size of the electrode used in the machining process. The distance between the surface of the work and the surface of the electrode (overcut) is equal to the length of the spark discharged [4].

Dr. Raja Das, is with VIT University, Vellore, Tamil Nadu, INDIA.
Dr. M. K. Pradhan, is with the Maulana Azad National Institute of Technology, Bhopal, 462051, India.
Corresponding Author: Dr. M. K. Pradhan, E-mail: mohanrkl@gmail.com

An EDM cavity produced is always larger than the electrode size and the difference in the size of the electrode, and the size of the cavity (or hole) is termed as the overcut. This overcut greatly influences the dimensional accuracy of the component produced. It becomes more critical when the component tolerance prerequisites are inflexible for manufacturing precision component in modern manufacturing industries like aeronautics, nuclear, mould tools and die making industries etc. Several studies have revealed that the overcut is correlated with many variables, comprising EDM parameters, such as discharge voltage, current, duty fraction, and pulse duration, etc. [5], [6], [7], [8], [9] and [3]. Recently, the soft computing techniques such as artificial neural networks (ANN) have exhibited great potential in resolving difficult non-linear real-life complex problems in many diverse fields manufacturing process modeling, multi-objective optimization, pattern recognition, signal processing and control [2], [10], [6], [11].

Although numerous efforts have been made to map EDM process with soft computing modeling and the influence of the machining parameters on various responses have been studied, but uses of GRNN on modeling of Radial overcut of EDM process are rare. Moreover, use of this model on AISI D2 tool steel which has immigrant range of application in the field of manufacturing, makes it special, is a rare case. The objective of the present work is thus on the developing two soft computing approach namely GRNN and BPNN for process modeling of EDM process between them in terms of accuracy and predicting capability could assist the selection of input parameters of the EDM process required to generate a minimal radial overcut to improve the accuracy. Extensive experiments were conducted, and the proposed models use results of experimental investigation on EDMed AISI D2 tool steel, considering pulse current, pulse duration, duty fraction, and voltage as input parameters, which varied over a wide range, from roughing to near-finishing machining conditions Table I. The performances of the developed models are compared. Such a investigation would help in developing a relevant model for simulation of the EDM process.

II. EXPERIMENTATION

Experimental method and procedure: The CNC Electrical Discharge die sinking machine “Electronica Electra plus PS 50ZNC”(Fig. 1), which has the provisions of programming in the Z-vertical axis and manually operated X and Y axes was used to conduct the experiment in order to get the modeling data. The internal detail of the workpiece is presented in Fig. 2 A cylindrical pure copper (99.9% Cu) was used as a tool electrode with a diameter of 30 mm (Fig. 3). Commercial grade EDM oil (specific gravity = 0.763, freezing point= $94°$C) was used as dielectric fluid, the power supply was linked with the tool electrode (Tool: positive polarity, work piece: negative polarity). A lateral flushing system was employed for effective flushing of machining debris from the working gap region with a pressure of 0.4 kgf/cm^2. The work piece material used was AISI D2 steel plates with chemical composition by weight of 1.5 % C, 0.3% Si, 0.3 % Mn, 1.0% Mo, 12.0 %, Cr, 0.3%, Ni 0.8 % V and 1.0 % Co, which is extensively used in the mould industry. The work specimen was AISI D2 tool steel, which is widely used in tool and die industry.

Work piece material was initially a circular bar of diameter 100 mm and was cut into specimens of thickness 10 mm by a power hacksaw. The top and bottom faces of the work piece were ground to make it a flat and good-quality surface finishes prior to experimentation. The bottom of the cylindrical electrode was polished by a very fine grade emery sheet prior to every experimental run. Each treatment of the experiment was run for 15 min, and the time was measured with a stopwatch of accuracy 0.1 s. The work piece as well as the tool were detached from the machine, cleaned, and dried up, to make it free from the dirt, debris, and dielectric.

Fig. 1. Experimental setup

Fig. 2. EDM configuration: (1) Electrode Holder (2) Copper Electrode (3) AISI D2 Specimen(4) Sample Holder

Fig. 3. Copper Electrode and AISI D2 workpiece

A. Radial overcut or Gap (G)

G (μm) is expressed as half the difference of diameter of the hole produced to the tool diameter, that is

$$G = \frac{(d_i - d_t)}{2} \tag{1}$$

Where d_t is the diameter of the tool and d_i is the diameter of the impression or cavity produce by the tool on the work piece.

TABLE I
INPUT VARIABLES USED IN THE EXPERIMENT AND THEIR LEVELS.

Variable	Unit	levels	
		Min.Value	Max. Value
Discharge current (*Ip*)	A	4	16
Pulse on time(*Ton*)	μs	100	500
Duty fraction(*Tau*)		4	8
Voltage (*V*)	volt	40	60

III. ARTIFICIAL NEURAL NETWORK

In order to map any nonlinear function Artificial Neural Networks (ANN) are the universally accepted function approximator. They have become a powerful tool for many complex applications such as optimization, non-linear system identification, and pattern recognition. Built on the concept of human nervous system, they have become a powerful tool for many complex applications. Like a human brain this is an adaptive, nonlinear parallel computer that is capable of organizing neurons to perform certain tasks. ANN consists of inputs, which are multiplied by weights, and then computed by a mathematical function which determines the activation of the neuron. Another function computes the output of the artificial neuron. ANNs combine artificial neurons in order to process information.

The architectural design, activation function and learning algorithms are the basic characteristics of Neural networks. It includes an input layer used to present data to the network, output layer to produce ANN's response, and one or more hidden layers in between. Historically, the initial developments of neural network were based on different architectures and are characterized by their activation function and learning algorithms. In this study, two neural networks are employed for modeling the G in the EDM process. Two networks are discussed as follows:

- Back-Propagation Neural Network
- General Regression Neural Network

A. Back-Propagation Neural Network Model

The BPNN model contains an input layer, one or two hidden layers, and an output layer in a forward multi-layer neural network. A schematic diagram of a BPNN with n inputs nodes, r outputs nodes and a single hidden layer of m nodes are shown in Fig. 4. Therefore, the output o_k can be expressed as:

$$O_k(x) = \sum_{j=1}^{m} w2_{kj}.f\left(\sum_{i=1}^{n} W1_{ji}x_i + b1_j\right) + b2_k, \quad (2)$$

where function f is the transfer function or activation function, x_i is the input value, $W1_{ji}$ and $W2_{kj}$ are weighted values, $b1_j$ and $b2_k$ are thresholds.

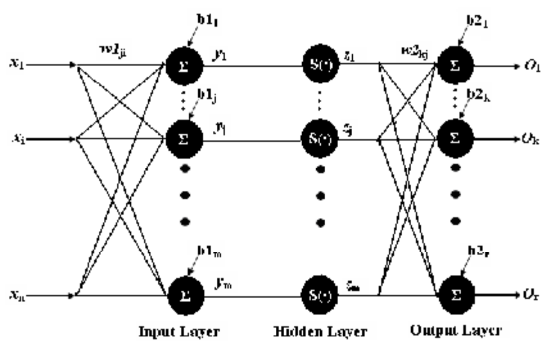

Fig. 4. Schematic Diagram of BPNN

In (2), function is a kind of mapping rule to convert neuron from weighted input to output and also is a kind of design to introduce non-linear influence into the BPNN. This study chooses the most general binary logistic sigmoid function $S(\bullet)$ and is defined as follows:

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

The standard back propagation is a gradient descent algorithm, in which the network weights are moved along the negative of the gradient of the performance function. In this algorithm, the weighted update at iteration t is given by

$$\Delta w(t) = -\eta \frac{\partial E}{\partial w}(t) + \alpha \delta w(t-1) \quad (4)$$

where $E = \frac{1}{2}\sum(T_k - Q_k)^2$: η is the learning rate parameter; and α is the momentum parameter. E represents the sum-of-square error of the model with regard to the observed data. The error function is optimizing during training process by using the mean squared error criterion. The output is compared to the actual output and Mean Squared Error is obtained. The obtained error is then propagated backwards through the network and changes are made to the weights at each node in each layer. The whole process is repeated until the overall error value drops below some predetermined threshold. At this point, the ANN has learnt the problem.

B. General Regression Neural Network Model

The GRNN has been used to be effective at solving difficult function mapping and prediction problems. The GRNN is regression tool that has a dynamic network structure [12], [13]. Its theory is based on the approximate estimation of the probability density function from observed samples using Parzen-window estimation. It approximates any arbitrary function between input and output vectors.

The GRNN model is a probabilistic model between an independent random vector X(input) and a dependent scalar random variable Y(output). Let x and y be the particular measured values of X and Y respectively, $\hat{f}(x,y)$ and is the joint continuous probability density function of X and Y. The estimate of joint probability density in GRNN is given by

$$\hat{f}(x,y) = \frac{1}{(2\pi)^{(d+1)/2}} \times$$
$$\frac{1}{n}\sum\left[exp\left(\frac{(x-x_i)^T(x-x_i)}{2\sigma^2}\right) exp\left(\frac{(y-y_i)^2}{2\sigma^2}\right)\right] \quad (5)$$

where n is the number of sample observations, σ is the spread parameter, x_i is the i^{th} training vector, y_i is the corresponding value. The conditional mean of Y given x (the regression of Y on x) given by;

$$E[Y/x] = \frac{\int_{-\infty}^{\infty} Y.f(x,Y)dY}{\int_{-\infty}^{\infty} f(x,Y)dY} \quad (6)$$

Using (5), and (6) becomes;

$$\hat{y}(x) = E[Y/x] = \frac{\sum_{i=1}^{n}\left[y_i\ exp\left(\frac{-d_i^2}{2\sigma^2}\right)\right]}{\sum_{i=1}^{n} exp\left(\frac{-d_i^2}{2\sigma^2}\right)} \quad (7)$$

where d_i is the distance between the input vector and the ith training vector, and is given by;

$$d_i^2 = (x-x_i)^T(x-x_i) \quad (8)$$

The estimate $\hat{y}(x)$ is thus a weighted average of all the observed y_i values where each weight is exponentially proportional to its Euclidean distance from x. The spread parameter should be smaller than the mean distance between the input vectors.

The GRNN model consists of 4 layers; the input layer, the hidden (pattern) layer, summation layer and the output layer. A schematic diagram of a GRNN with n inputs nodes, one output nodes, a single hidden layer of m nodes and summation layer of two nodes are shown in Fig. 5. All input training data are copied as the weights into the patter units. The summation layer has two units: the first unit sums all the outputs of the pattern layer and assesses the numerator of (6), while the second unit assesses the denominator of (6). The output layer computes the quotient of the two outputs of the summation layer and gives the estimate of the expected value of $\hat{y}(x)$.The only adjustable parameter of the network is σ, the smoothing factor for the kernel function. Since there is no a prior method of selecting this parameter, we tried different values in the range 0.01-0.1.

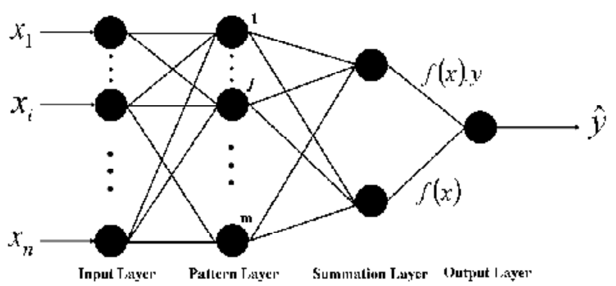

Fig. 5. Schematic Diagram of GRNN

IV. RESULT AND DISCUSSION

In this study, the accuracy of the GRNN model in predicting radial overcut was investigated and results were compared with the BPNN model. 150 set of data under EDM process was used for training and testing of the BPNN and GRNN. Out of 150 experimental data, 135 training data sets are considered for both the models to compare the performance as shown in Table II. Besides, 15 testing data sets outside the training data set are selected for testing the neural networks as shown in Table III. Both the ANNs were trained with the above data sets. The performance of two ANN models is studied with the special attention to their generalization ability and the CPU time. In BPNN model, there is no particular rule for finding the proper number of neurons in the hidden layer to avoid over-fitting or under-fitting to make the learning phase convergent. For the best performance of the BPNN model, the proper number of nodes in the hidden layer is selected through a trial and error method based on the number of epochs needed to train the network. The learning behavior of BPNN model for radial overcut is shown in Fig. 6 and error goal met at 192 epochs. The main advantage of GRNN is fast learning as it is a one-pass training algorithm. It does not require an iterative training process. The training time is just the loading time of the training matrix. Also, it can work both linear and non-linear data. As the sample size increases, the estimate surface converges to the optimal regression surface. Thus, it requires many training samples to span the variation in the data and all these to be stored for the future use. However, there is only one disadvantage that there is no intuitive method for choosing the optimal smoothing factor.

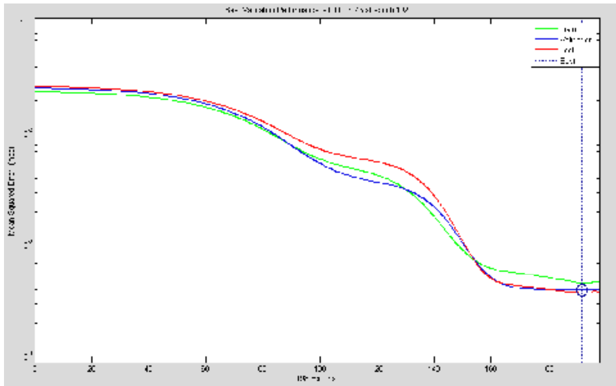

Fig. 6. Training Performance of the model

The comparisons have been depicted in terms of percentage error in figure Table II for validation set of experiments. From Table II it is evident that for current set of data the BPNN result predicts the radial overcut nearer to the experimental values than the GRNN results. But, GRNN is much faster than BPNN with the CPU times of 0.0520 seconds and 6.9230 seconds respectively. In the prediction of radial overcut values the average errors for BPNN and GRNN are calculated as 0.013813 and 0.013733 respectively. Performance of BPNN and GRNN were tested by studying the percentile error G using (9) of each input-target pair of testing data-set as shown in Table III. Predicted ability of the ANN models in output is calculated as follows:

$$Prediction \quad error\ (\%) = \frac{|Expt.\ Value - Pred.Value|}{Expt.\ Value} \times 100 \qquad (9)$$

where Expt. Value = experimental value and Pred. Value = predicted value by the model. The value of the multiple coefficient of R^2 is obtained as 0.8382 for BPNN and 0.9149 for GRNN which means that the fitted line is very close to the experimental results. The Fig. 7 and Fig. 8 are presented showing the coefficient of correlation (R-Value) for GRNN and BPNN models. The correlation coefficient obtained for the validation data set for GRNN and BPNN is 95.65% and 91.55%, respectively, which exhibit the good agreement is obtained for both models. The error for ANN, calculated as the difference between the experimental findings and predicted values for validation data as are shown in Fig. 10. Fig. 11 represents the comparison of predicted (both BPNN and GRNN) and actual results. Both BPNN and GRNN results showed that the predicted values have been very close to experimental values. The above analysis indicates that the GRNN model is superior to the BPNN model.

TABLE II
EXPERIMENTAL RESULTS OF THE EDM EXPERIMENT DONE BY COPPER ELECTRODES FOR FOUR VARIABLES

Run Order	*Ip* A	Ton μs	*Tau*	*V* volt	G μm	Run Order	*Ip* A	Ton μs	*Tau*	*V* volt	G μm
11	10	500	6	60	0.220	68	10	500	6	40	0.240
2	7	200	8	60	0.100	69	4	500	6	60	0.120
3	7	100	6	40	0.110	70	10	100	4	60	0.150
4	10	200	4	60	0.160	71	13	100	8	40	0.200
5	16	400	6	40	0.290	72	7	300	4	40	0.150
⋮											
⋮											
50	16	400	8	60	0.340	117	16	300	4	40	0.280
51	16	500	8	40	0.310	118	7	300	6	40	0.130
52	13	100	4	40	0.190	119	13	500	8	40	0.270
53	4	500	4	60	0.100	120	4	200	4	40	0.070
⋮											
⋮											
63	13	400	6	40	0.250	130	10	300	4	60	0.170
64	10	100	4	40	0.160	131	10	300	6	40	0.170
65	16	100	4	40	0.230	132	7	200	8	40	0.110
66	4	200	8	60	0.039	133	16	100	6	60	0.219
67	13	500	4	40	0.280	134	4	500	6	40	0.120
68	10	500	6	40	0.240	135	7	100	8	40	0.060

TABLE III
TESTING THE CAPABILITY OF MODEL IN THE PREDICTIONS OF G

Run	EDM Parameters				Radial overcut	Back Propagation		General Regression		Percentile	
	Ip	Ton	*Tau*	*V*	G (μm)	Neural Network		Neural Network		Error (%)	
Order	A	μs		volt	Expt.	Pred.	Abs. Err	Pred.	Abs. Err	(BPNN)	(GRNN)
1	16	100	8	40	0.23	0.256	0.027	0.224	0.006	11.70	2.34
2	16	100	4	60	0.22	0.246	0.026	0.219	0.001	12.00	0.41
3	13	300	6	40	0.21	0.248	0.039	0.245	0.035	18.38	14.08
4	13	500	4	60	0.236	0.274	0.038	0.250	0.014	16.14	5.11
5	16	400	4	40	0.3	0.295	0.004	0.290	0.010	1.40	3.38
6	7	200	6	40	0.142	0.105	0.037	0.125	0.017	25.85	16.14
7	4	300	6	40	0.079	0.076	0.003	0.078	0.002	3.16	1.96
8	13	300	6	60	0.21	0.239	0.029	0.220	0.010	13.86	4.18
9	13	100	4	60	0.19	0.190	0.000	0.180	0.010	0.00	5.26
10	7	400	6	40	0.16	0.1556	0.004	0.150	0.010	2.75	6.43
11	7	300	8	40	0.12	0.1305	0.011	0.130	0.010	8.75	7.66
12	16	400	6	60	0.26	0.2917	0.032	0.312	0.052	12.19	17.66
13	13	400	8	40	0.26	0.267	0.007	0.250	0.010	2.77	3.74
14	13	300	8	60	0.3	0.240	0.060	0.280	0.020	20.00	8.33
15	13	200	6	40	0.23	0.227	0.003	0.230	0.000	1.22	0.00
						Average		Average		Average % Err	
						Abs. Err:	0.0138	Abs. Err:	0.0137	10.01	6.45

Note: Abs. Err : Absolute Error, Expt.: Experimental, Pred.: Predicted

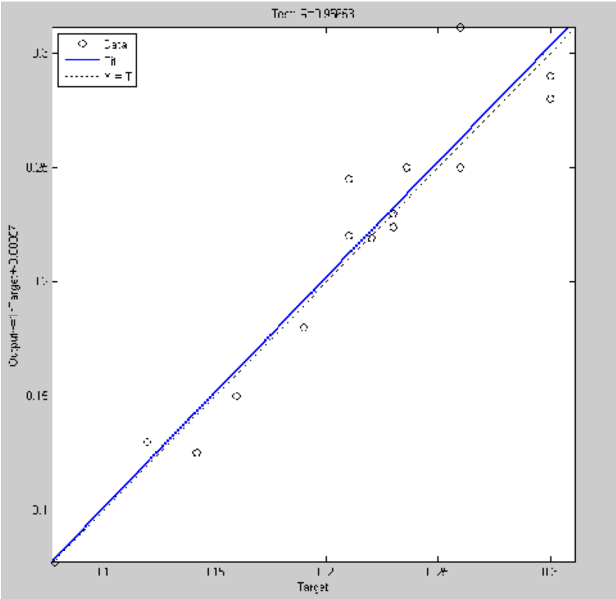

Fig. 7. Correlation between GRNN model prediction and experimental value

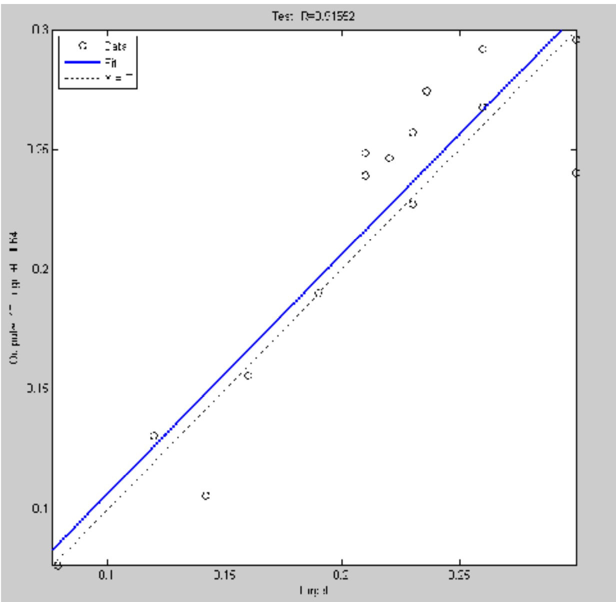

Fig. 8. Correlation between BPNN model prediction and experimental value

V. Influence of Machining Parameters on Radial Overcut

Radial overcut is the difference in the dimension of the electrode, and the dimension of the cavity produced during EDM. It is inherent to the EDM process which is unavoidable although suitable compensations are imparted during the tool design. To achieve the accuracy, minimization of overcut is necessary. Hence, it is required to distinguish the effect of the factors on overcut. Consequently, by controlling them a perfect groove can be created during machining. In this section, the effects of the various parameters are discussed.

Fig. 9 shows the main effect plot (response graph) for G, where the horizontal line indicates the value of the total mean of the G (viz. 0.177919). It is witnessed that the Ip and Ton are significant factors varying linearly with the response. Since, overcut increases with the pulse energy [14], [15], and as Ip and Ton increases the pulse energy increases, which is responsible for production of spark at the tool work piece interface. The other two factors Tau and voltage have a very little effect on G as compared to Ip. Although, they are significant and with the increase of Tau from 6 to 8, the mean value of G increases 0.1735 to 0.18183, however, with the increase of V from 40 to 60, G decreases by 0.013, which is quite less.

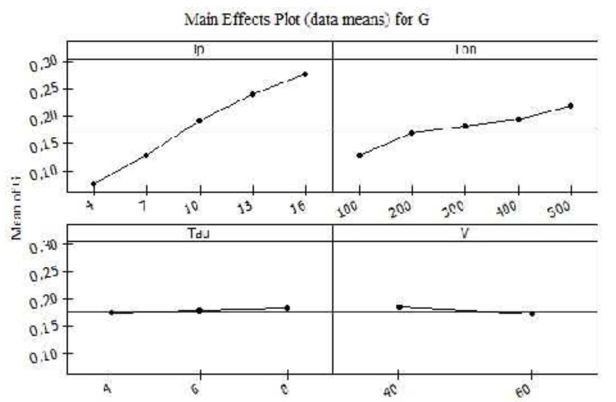

Fig. 9. Main effect plot of the factors on G

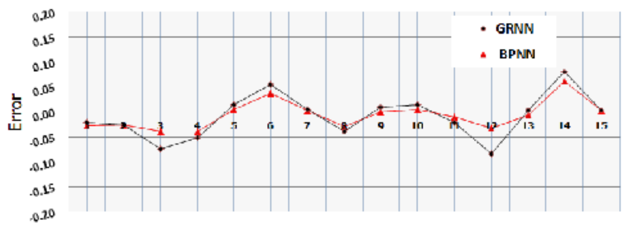

Fig. 10. Error of the Models

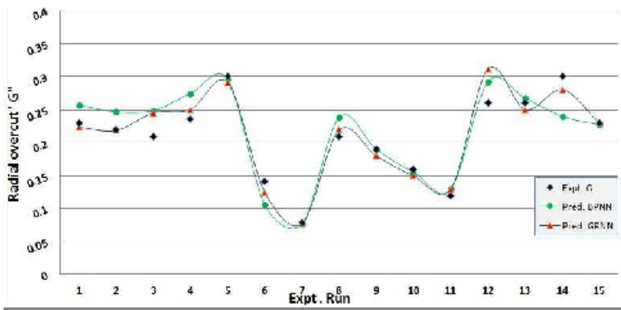

Fig. 11. Comparison between Experimental and Predicted models

VI. Conclusion

This study establishes the significance of the artificial neural network and demonstrates a comparative analysis of two ANN models (GRNN and BPNN) for the prediction of overcut of AISI D2 tool steel using electrical discharge machining. A mixed-level full-factorial design of experiments was being used to generate the input-output database needed for the development of the models. The ANN models are produced using 90% of the experimental data, and the performances of the models are revealed on rest 10% of the data based on prediction accuracy. The performances of both the models are intended with the special attention to their generalization capability and the CPU time. The performance of both the networks is found to be in decent agreement with an average percentage error less than 11%. Moreover, the GRNN model is advantageous as it is a one-pass training algorithm that does not necessitate an iterative training process also it is equally good for linear and non-linear data, but has one disadvantage too i.e. there is no intuitive method for choosing the optimal smoothing factor. Nevertheless, BPNN is more accurate as compared to GRNN with the average prediction errors of 0.013813 and that of GRNN is 0.013733, respectively. However, GRNN is much faster than BPNN with the CPU times of 0.0520 seconds and 6.9230 seconds respectively. The methodology used in this work may be helpful in the future for the estimation of other responses of the EDM process, and this method may also be extended to other input parameters of the process.

ACKNOWLEDGMENT

The authors would like to thank those anonymous reviewers for their helpful comments.

REFERENCES

[1] N. Mohd Abbas, D. G. Solomon, and M. Fuad Bahari, "A review on current research trends in electrical discharge machining (EDM)," *International Journal of Machine Tools and Manufacture*, vol. 47, pp. 1214–1228, Jun 2007.

[2] K. H. Ho and S. T. Newman, "State of the art electrical discharge machinings (EDM)," *International Journal of Machine Tools and Manufacture*, vol. 43, pp. 1287–1300, Oct 2003.

[3] M. K. Pradhan, "Multi-objective optimization of MRR, TWR and radial overcut of EDMed AISI D2 tool steel using response surface methodology, grey relational analysis and entropy measurement," *J. Manuf. Science and Production*, vol. 12, no. 1, pp. 51–63, 2012.

[4] E. Jameson, *Electrical Discharge Machining*. Society of Manufacturing Engineers, 2001.

[5] S. Dhar, R. Purohit, N. Saini, A. Sharma, and G. H. Kumar, "Mathematical modeling of electric - discharge machining of cast Al-4Cu-6Si alloy-10 wt.% SiCP composites," *Journal of Materials Processing Technology*, vol. 194, pp. 24–29, Nov 2007.

[6] M. K. Pradhan and C. K. Biswas, "Neuro-fuzzy and neural network-based prediction of various responses in electrical discharge machining of AISI D2 steel," *International Journal of Advance Manufacturing Technology*, vol. 50, pp. 591–610, 2010.

[7] H. Chiang and J. Wang, "An analysis of overcut variation and coupling effects of dimensional variable in EDM process," *International Journal of Advanced Manufacturing Technology*, vol. 55, pp. 935–943, 2011.

[8] J. Anitha, R. Das, and M. K. Pradhan, "Optimization of surface roughness in EDM for D2 steel by RSM-GA approach," *Universal Journal of Mechanical Engineering*, vol. 2, no. 6, pp. 205–210, 2014.

[9] O. Belgassim and A. Abusaada, "Investigation of the influence of EDM parameters on the overcut for AISI D3 tool steel," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 226, no. 2, pp. 365–370, 2012.

[10] A. P. Markopoulos, D. E. Manolakos, and N. M. Vaxevanidis, "Artificial neural network models for the prediction of surface roughness in electrical discharge machinings," *Journal of Intelligent Manufacturing*, vol. 19, no. 3, pp. 283–292, 2008.

[11] M. K. Pradhan, R. Das, and C. K. Biswas, "Comparisons of neural network models on surface roughness in electrical discharge machining," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 223, no. 7, pp. 801–808, July 2009.

[12] D. Specht, "A general regression neural network," *Neural Networks, IEEE Transactions*, vol. 2, no. 6, pp. 568–576, 1991.

[13] S. Chartier, M. Boukadoum, and M. Amiri, "BAM learning of nonlinearly separable tasks by using an asymmetrical output function and reinforcement learning," *IEEE Transaction, Neural Networks*, vol. 20, no. 8, pp. 1281–1292, 2009.

[14] M. Jeswani, "Electrical discharge machinings in distilled water," *Wear*, vol. 72, no. 1, pp. 81–88, 1981.

[15] M. K. Pradhan, "Experimental investigation and modelling of surface integrity, accuracy and productivity aspect in EDM of AISI D2 steel," Ph.D. dissertation, National Institute of Technology, Rourkela, 2010.

Dr. Raja Das is an Assistant Professor in the School of Advanced Sciences, VIT University, Vellore, Tamil Nadu, India. He received his M.Sc in Applied Mathematics from National Institute of Technology, Rourkela, India and PhD from Sambalpur University, Odisha, His area of research interest includes modelling, optimisation and soft computing. He has published more than 10 research papers in the international journal and presented more than 10 articles at different international/national conferences.

Dr. M K Pradhan is an Assistant Professor and Head of Production Engineering Laboratory in the Department of Mechanical Engineering, Maulana Azad National Institute of Technology, Bhopal, India. He received his M Tech and Ph.D. from National Institute of Technology, Rourkela, India. His area of research interest includes modelling, analysis and optimisation of manufacturing processes. He has published more than 30 research papers in the international journal and presented more than 35 articles at different International / National conferences. He is a life member of ISTE, IACSIT, IAENG and IE(I).