Comparative Neural Network Models on Material Removal Rate and surface Roughness in Electrical Discharge Machining

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ABSTRACT

Electro-discharge machining (EDM) is increasingly being used in many industries for producing molds and dies, and machining complex shapes with material such as steel, cemented carbide, and engineering ceramics. The stochastic nature of EDM process has frustrated number of attempts to model it physically. Artificial neural networks (ANNs), as one of the most attractive branches in Artificial Intelligence (AI), has the potentiality to handle problems such as prediction of design and manufacturing cost, material removal rate (MRR), diagnosis, modeling, and adaptive control in a complex design and manufacturing systems. This paper uses Back Propagation Neural Network (BP) and Radial Basis Function (RBF) approach for prediction of material removal rate and surface roughness and presents the results of the experimental investigation. Charmilles Technology (EDM-ROBOFORM200) in he mechanical engineering department is used for machining parts. The networks have four inputs of current (I), voltage (V), Period of pulse on (T_{on}) and period of pulse off (T_{off}) as the input processes variables. Two outputs results of material removal rate (MRR) and surface roughness (Ra) as performance characteristics. In order to train the network, and capabilities of the models in predicting material removal rate and surface roughness, experimental data are employed. Then the output of MRR and Ra obtained from neural net compare with experimental results, and amount of relative error is calculated.

Keywords

EDM, ANN, BP, RBF.

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INTRODUCTION

Electro-discharge machining (EDM) is non-conventional, process, which erodes material from the work piece by a series of discrete sparks between a work-piece and tool electrode immersed in a liquid dielectric medium. These sparks are generated between two closely spaced electrodes and will melt and vaporize tiny amounts of the work-piece, which are then ejected and flushed away by the dielectric [1]. EDM has

been used effectively in machining hard, high-strength, and temperature-resistant metals, and since there is no physical contact between the two electrodes, slender and fragile tasks can be machined conveniently, making the process more versatile. Comprehensive qualitative and quantitative analysis of the material removal mechanism and subsequently the development of model(s) of material removal are not only necessary for a better understanding of the process but also are very useful in parametric optimization, process simulation. Operation and process planning, parametric analysis (i.e. understanding the influence of various process parameters on the process performance measures), verification of the experimental results, and improving the process performance by implementing/incorporating some of the theoretical findings [2]. A systematic study of the phenomenon of the electrical discharge in a liquid dielectric has proven to be very difficult due to its complexity. The erosion by an electric discharge involves phenomena such as heat conduction, melting, evaporation» ionization, formation, and collapse of gas bubbles and energy distribution in the discharge channel. These complicated phenomena coupled with surface irregularities of electrodes, interactions between two successive discharges, and the presence of debris particles make the process too abstruse, so that complete and accurate physical modeling of the process has not been established yet [3,4]. There are a lot of theoretical studies concerned with microscopic metal removal arising from a single spark, the effects being modeled from heat conduction theory [5,6,7and 8]. Recent established models for EDM are mainly based on empirical data or basically data driven models. Ghoreishi and Atkinson [9, 10] employed statistical modeling and process optimization for the case of EDM drilling and milling. Wang and Tsai [11, 12] proposed semi-empirical models of the material removal rate, surface finish and tool wear on the work and the tool for various materials in EDM, employing dimensional equations based on relevant process parameters for the screening experiments and the dimensional analysis. Artificial neural networks (ANNs), as one of the most attractive branches in artificial intelligence, has the potentiality to handle problems such as modeling, estimating, prediction, diagnosis, and adaptive control in complex non-linear systems [13]. The capabilities of ANNs in capturing the mathematical mapping between input variables and output features are of primary significance for modeling machining processes. The use of neural networks in both EDM and wire-EDM (WEDM) processes has also been reported. Kao and Tamg [14]. Liu and Tamg [15] have employed feed forward neural networks with hyperbolic tangent functions and abductive networks for the classification and on-line recognition of pulse-types. Based on their results, discharge pulses have been identified and then used for controlling the EDM machine. Indurkhya and Rajurkar [16] developed a 9-9-2-size back propagation neural network for orbital EDM modeling. Spedding and Wang [17, 18], and Tamg et al. [19] have developed BP neural networks for modeling of WEDM. Experimental results have shown that the cutting performance of WEDM can be greatly enhanced using the neural model. Tsai and Wang [20,21] have been presented seven models for predictions of surface finish and material removal rate of work in EDM process and then compared based upon six neural networks and a neuro-fuzzy network with pertinent machine process parameters given by the DOE method. The networks, namely the LOGMLP, the TANMLP, the RBFN, the Error TANMLP, the Adaptive TANMLP, the Adaptive RBFN and the ANFIS have been trained and compared by the same experimental data together with the change of electrode polarity condition. Neural networks have become a very useful tool in the modeling of complicated systems. This is because neural networks have an excellent ability to learn and to generalize (interpolate) the complicated relationships between input and output variables. Also, the ANN behaves as model free estimators, i.e., they can capture and model complex input-output relations without the help of mathematical model.

ARTIFICIAL NURAL NETWORK MODELS OF EDM PROCESS

In the current work, three supervised neural networks for modeling the EDM process are compared. The first one is a Logistic Sigmoid Multi-layer Perceptron (LOGMLP); the Second is a Hyperbolic Tangent sigmoid Multi-layer Perceptron (TANMLP) and third is a Radial Basis Network (RBN) with Gaussian activation functions. The LOGMLP and TANMLP are two different BP neural networks. The LOGMLP is a Back propagation neural network with log-sigmoid transfer function in hidden layer and output layer, but the TANMLP is a Back propagation neural network with tangent-sigmoid transfer function in hidden layer and output layer. The BP Neural Network is very popular, especially in the area of manufacturing modeling, as its design and operation are relatively simple. The radial basis network has some additional advantages such as rapid convergence and less error. In particular, most commonly used RBNs involve fixed basis functions with linearly appearing unknown parameters in the output layer. Radial Basis networks may require more neuron than standard feed-forward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available. In contrast, multi-layer BP ANNs involve adjustable basis functions. That result in nonlinearly appearing unknown parameters. It is commonly known that linearity in parameters in RBN allow the use of least squares error based updating schemes that have faster convergence than the gradient-descent methods used to update the nonlinear parameters of multi-layer BP ANN. On the other hand, it is also known that the use of fixed basis functions in RBN results in exponential complexity in terms of the number of parameters, while adjustable basis functions of BP ANN can lead to much less complexity in terms of the number of parameters or network size [22]. However, in practice, the number of parameters in RBN starts

becoming unmanageably large only when the number of input features increases beyond about 10 or 20, which is not the case in our study. Hence, the use of RBN was practically possible for our problem. The general network topology for BPNN is shown in fig.1. A typical RBF network is shown in fig.2. MATLAB ☐ Neural Network Tool Box was used as a platform to create the networks.
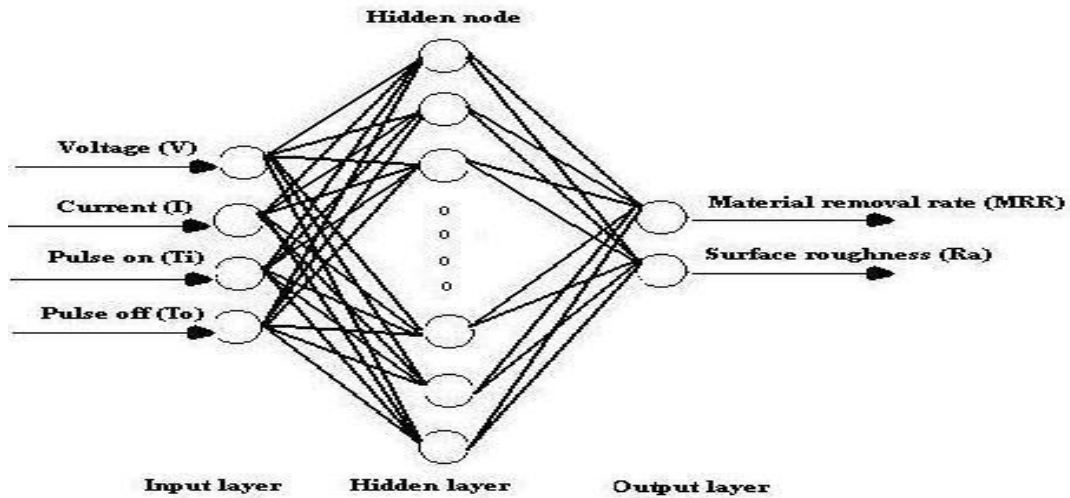

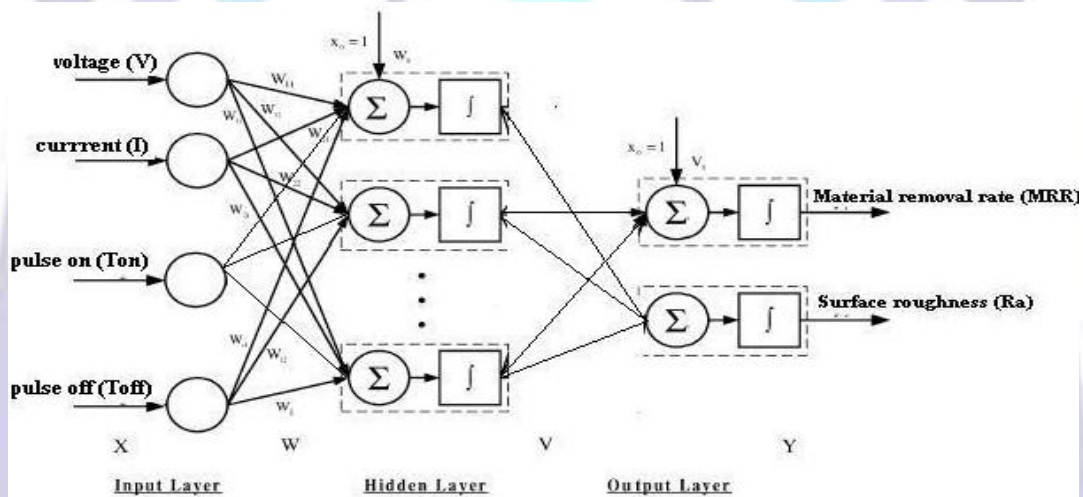**Fig1:Back-Propagation neural network with one hidden layer**

Figure2:Architecture of the RBFN.

EXPERIMENTAL DETAILS

In order to obtain different machining process parameters and output features for training and testing of neural networks, a series of experiments was performed on a ROBOFORM 200 machine. At first, some preliminary tests were carried out to determine the stable domain of the machine parameters and also the different ranges of process variables. Based on preliminary tests results and working characteristics of the EDM machine, discharge current (I), period pulse on (Ti), Period of pulses off (To) and source voltage (V) were chosen as independent input parameters. During these experiments, by altering the values of the input parameters in different levels, stable states of the machining conditions have also been specified. Accordingly, the experiments were conducted with three levels of discharge current, three levels of period of pulses on, three levels of period of pulses off and three levels of source voltage. Table 1 shows the input process variables and their levels in the experiments. Throughout the experiments, SPK steel and commercial copper were used as work-piece and tool electrode materials. Also, the dielectric fluid used was elf oil. Particular attention was paid to ensuring that operating conditions permitted. Effective flushing of machining debris from the working region. Thus, the experiments were done in the planning process mode in which the bottom surface of the electrode is flat and parallel to the work-piece surface. Also, the diameter of cylindrical electrode was equal to the diameter of the round bar work-piece and was chosen to be 12 mm. The total data obtained from machining experiments (3*3*3*3) is 81 and these forms the neural networks' training and testing sets. To achieve validity and accuracy, each test was repeated three times. Material removal rate (MRR) and surface roughness (Ra) were assigned as performance characteristics or process outputs, since the performance of any machining process is evaluated in

terms of these two measures. Then, the mean values of the three response measurements (MRR and Ra) were used as output at each set of parameters. The machining time considered for each test was dependent on the discharge current and much time was allocated to the tests with lower current. The material removal rate (MRR) was estimated by weighing the work-piece on a digital single pan balance before and after the experiments and was reported in gr/hr unit. The surface roughness (Ra) was measured by means of a Mahr with Ra value in microns at a cut-off length of 0.8 mm.

Table 1. Pertinent process parameters and their levels for machining experiments

Process parameters	Operating conditions
Source voltage V (v)	80,160,200
Discharge current I (A)	6,16,48
Period of pulses on Ti (μ sec)	6.4,100,800
Period of pulses off To (μ sec)	12.8,50,400

For normalization of input and output variable, the following linear mapping formula is used:

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

Modeling of EDM process with BP neural networks and RBF network are composed of two stages: training and testing of the networks with experimental machining data. The training data consisted of values for current (I), period of pulses on (Ti), period of pulses off (To), and source voltage (V), and the corresponding material removal rate (MRR) and surface roughness (Ra). In all, 81 such data sets were used, of which 66 data sets were selected at random and used for training purposes while the remaining 15 data sets were presented to the trained networks as new application data for verification (testing) purposes. Thus, the networks were evaluated using data that had not been used for training. The size of hidden layer(s) is one of the most important considerations when solving actual problems using multi-layer feed forward network. In RBF neural network, two parameters need to be defined. Spread factor and goal factor. The spread factor S, has to be specified depending on the particular case in hand. It has to be smaller than the highest limit of the input data and larger than the lowest limit [20-22]. Based on this, and assuming that all the training data is mapped between -1 and 1. The goal factor value is set to zero, since error is a decisive factor in this study. However, it has been shown that BP neural network with one hidden layer can uniformly approximate any continuous function to any desired degree of accuracy given an adequate number of neurons in the hidden layer and the correct interconnection weights Therefore; one hidden layer was adopted for the BP model. For determining the number of neurons in the hidden layer, a procedure of try and error approach needs to be done. That is, attempts have been made to study the network performance with a different number of hidden neurons. Hence, a number of candidate 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. It should be noted that if the number of hidden neurons is too large, the ANN might be over-trained giving spurious values in the testing phase. If too few neurons are selected, the function mapping may not be accomplished due to under-training. Back-Propagation neural network model with one hidden layer is developed. The model is demonstrated in figure 1. Table 2 shows the 15 experimental data sets, which are used for verifying or testing network capabilities in modeling the process. Therefore, the general network structure is supposed to be 4-n-2, which implies 4 neurons in the input layer, n neurons in the hidden layer, and 2 neurons in the output layer. Then, by varying the number of hidden neurons and spread factor, different network configurations are trained, and their performances are checked. The results are shown in table 3.1, 3.2 and 3.3.

TRAINING RESULTS

Each experimental set (except the validation set) is used to train each network. This training is repeated for each topology. The performance is measured by the linear regression (R) of each output (fig.3–8). With this analysis it is possible to determine the response of the network with respect to the targets. A value of 1 indicates that the network is perfectly simulating the training set while 0 means the opposite. For all the cases in this study, the value of R (for all output sets) is shown in Table 5. The case of RBN showed a good fitting pattern for all the cases) as expected since the goal error factor is set to zero.

VALIDATION RESULTS OF THE LOGMLP, TANMLP & RBF MODELS

As a result, from table 3.1, the best network structure of BP model is picked to have 10 neurons in the hidden layer with the average verification errors of 20.31% and 5.13% in predicting MRR and Ra, respectively, for TANMLP. Thus, it has a total average error of 12.72% over the 15 experimental verification data sets. And from table 3.2, the best network structure of BP model is picked to have 11 neurons in the hidden layer with the average verification errors of 32.02% and 12.91% in predicting MRR and Ra, respectively, for LOGMLP. Thus, it has a total average error of 22.47% over the 15 experimental verification data sets. As a result, from table 3.3, the best network of RBF model is picked to have 66 neurons in hidden layer, while spread factor is 0.07.The average verification errors of 17.54% and 7.84% in predicting MRR and Ra, respectively. Thus it has a total error of 12.69% over the 15 experimental verification data test. Table 4.1,4.2 and 4.3 shows the comparison of experimental and predicted values for MRR and Ra in verification cases by three neural network models.

CONCLUSION

In this paper, three types of supervised neural networks LOGMLP, TANMLP and RBF have been used to successfully model EDM process. An effort was made to include as many different machining conditions as possible that influence the process. Based on the results of testing each network with some data set which was different from those used in the training phase, it was shown that RBF neural model has superior performance than TANMLP and LOGMLP network model. In summary, the following items can also be mentioned as the general findings of the present research:

Conclusion 1

The TANMLP, LOGMLP and RBF neural networks are capable of constructing models using only experimental data describing proper machining behavior. This is the main attraction of neural networks, which make them suitable for the problem at hand.

Conclusion 2

Modeling accuracy with RBF neural networks is better than TANMLP and LOGMLP. As a result, from table 5, the difference between correlation coefficients (R) for TANMLP and RBF is negligible, because of small difference between their average errors.

Conclusion 3

Discharge current is the dominant factor among the other input parameters, so that, increasing current in a constant level of pulse period and gap voltage, increases MRR and Ra steadily. A high discharge energy associated with high current is capable of removing a chunk of material leading to the formation of a deep and wide crater, and hence, worsening the machined surface quality.

Conclusion 4

 For the effect of pulse period, initially, it is observed that for all values of gap voltage and a constant current, material removal rate and surface roughness increase with increasing pulse period, but these trends continue until about 400 μ sec of pulse period in which MRR gains its maximum value. Although, it is generally understood that increasing pulse period, and hence, pulse-on time, results in greater discharge energy, but with too long pulse durations, the results become reverse. This is mainly because of undesirable heat

Conclusion 5

 In normal EDM, the discharge voltage (V), influenced primarily by the electrode and workpiece materials, is somehow constant so that an increase in source voltage will have little effect on the discharge energy for a given pair of electrode-workpiece   materials. Hence, increasing source voltage alone, does not necessarily confirms the availability of high discharge voltage, which directly affects MRR and Ra.

Conclusion 6

 5.6. High material removal rate and low surface roughness are conflicting goals, which cannot be achieved simultaneously with a particular combination of control setting. To achieve the optimum machining conditions, the goals have to be taken separately in different phases of work with dissipation phenomena of the thermal energy liberated during discharge, which in turn lessens the erosive effects of sparks.

Table 2. Machining conditions for verification experiments.

Test No.	V (v)	I (A)	Ti (μ sec)	To(μ sec)	MRR (gr/hr)	Ra(μ m)
1	80	6	6.4	400	0.2	2.62
2	80	6	800	12.8	0.3	2.87
3	80	16	6.4	400	0.3	3.05
4	80	16	800	12.8	10.0	7.63
5	80	48	100	12.8	63.0	9.75
6	160	6	800	12.8	0.2	2.68
7	160	16	100	12.8	20.4	8.32
8	160	16	800	50	12.8	7.85
9	160	48	100	12.8	55.1	9.31
10	160	48	800	400	44.0	10.61
11	200	6	6.4	400	0.3	2.05
12	200	6	800	50	0.3	2.69
13	200	16	100	12.8	21.6	8.32
14	200	48	6.4	12.8	7.6	4.27
15	200	48	800	50	54	10.43

Table3.1.The effects of different number of hidden neurons on the TANMLP.

(No. Of hidden neuron	Epoch	Average error in MRR (%)	Average error in Ra (%)	Total average error (%)
8	1529	43.59	6.47	25.03
9	1042	28.44	7.22	17.83
10	1137	20.31	5.13	12.72
11	2076	35.47	8.44	21.96

Table3.2.The effects of different number of hidden neurons on the LOGMLP.

No. Of hidden neuron	Epoch	Average Error in MRR (%)	Average Error in Ra (%)	Total Average Error (%)
6	7437	36.42	10.45	23.44
7	1244	42.28	9.23	25.76
8	334	48.72	10.60	29.66
9	572	37.61	14.48	26.05
10	311	75.14	12.18	43.66
11	848	32.83	12.91	22.87
15	542	67.54	9.31	38.43

Table 3.3. The effects of different spread factor on the RBF model (Radial Basis Network)

Spread factor	Average Error in MRR (%)	Average Error in Ra (%)	Total AverageError (%)
0.01	21.00	7.41	14.21
0.03	20.81	7.17	13.99
0.05	20.54	7.23	13.89
0.06	19.48	7.41	13.45
0.07	17.54	7.84	12.69
0.08	20.87	9.02	14.95
0.09	24.98	10.28	17.63
0.1	28.17	11.51	19.84
0.12	35.85	13.66	24.76
0.15	46.04	16.01	31.03

Table4.1. Comparison of MRR and Ra measured and predicted by the TANMLP neural network.

Test No.	MRR (gr/hr)		Ra (μ m)		Error (%)	
	Experimental	TANMLP model	Experimental	TANMLP model	Error in MRR	Error in Ra
1	0.2	0.15	2.62	2.38	25.00	9.16
2	0.3	0.31	2.87	2.85	3.33	0.7
3	0.3	0.19	3.05	2.88	36.67	5.57
4	10.0	8.96	7.63	7.79	10.4	2.1
5	63.0	63.69	9.75	9.24	1.11	5.23
6	0.2	0.4	2.68	2.80	100.00	4.48
7	20.4	20.79	8.32	8.12	1.91	2.40
8	12.8	12.45	7.85	7.72	2.73	1.66
9	55.1	62.61	9.31	8.85	13.63	4.94
10	44.0	43.00	10.61	10.54	2.27	0.66
11	0.3	0.18	2.05	2.38	40.00	16.10
12	0.3	0.41	2.69	2.80	36.67	4.09
13	21.6	16.40	8.32	8.37	20.07	0.60
14	7.6	7.85	4.27	3.45	3.29	19.20
15	54	55.90	10.43	10.44	3.52	0.10

Table4.2. Comparison of MRR and Ra measured and predicted by the LOGMLP neural network.

No. of Experiments	MRR (gr/hr)		Ra (μ m)		Error (%)	
	Experimental	LOG MLP model	Experimental	LOG MLP model	Error in MRR	Error in Ra
1	0.2	0.14	2.62	2.41	30.00	8.02
2	0.3	0.20	2.87	2.89	33.33	0.70
3	0.3	0.17	3.05	3.05	43.33	0.00
4	10.0	11.98	7.63	7.62	19.80	0.13
5	63.0	54.27	9.75	9.36	13.86	0.40
6	0.2	0.18	2.68	3.48	10.00	29.85
7	20.4	0.12	8.32	8.13	99.41	2.28
8	12.8	12.86	7.85	7.70	0.47	1.91
9	55.1	55.70	9.31	8.23	1.09	11.60
10	44.0	45.86	10.61	10.96	4.23	3.30
11	0.3	0.21	2.05	2.10	36.67	2.44
12	0.3	0.17	2.69	2.76	43.33	7.00
13	21.6	0.12	8.32	6.98	99.44	16.11
14	7.6	11.56	4.27	4.01	52.11	6.09
15	54	56.89	10.43	10.80	5.35	3.55

Table4.3. Comparison of MRR and Ra measured and predicted by the RBF neural network model.

NO. of experiment	MRR (gr/hr)		Ra (μ m)		Error (%)	
	Experimental	RBF model	Experimental	RBF model	Error in MRR	Error in Ra
1	0.2	0.3	2.62	2.74	50.00	4.58
2	0.3	0.1	2.87	2.59	66.67	9.76
3	0.3	0.3	3.05	2.74	0.00	10.16
4	10.0	9.3	7.63	7.56	7.00	0.92
5	63.0	54.41	9.75	9.14	13.63	6.26
6	0.2	0.2	2.68	2.99	0.00	11.57
7	20.4	14.58	8.32	7.90	28.53	5.05
8	12.8	13.2	7.85	7.18	3.13	8.54
9	55.1	54.71	9.31	8.63	0.71	7.30
10	44.0	52.0	10.61	10.21	18.18	3.77
11	0.3	0.3	2.05	2.86	0.00	39.51
12	0.3	0.4	2.69	2.66	33.33	1.12
13	21.6	14.21	8.32	7.65	34.26	8.05
14	7.6	7.3	4.27	4.29	3.95	0.47
15	54.0	56.0	10.43	10.37	3.70	0.58

Table 5. Different value of Correlation Coefficient (R)

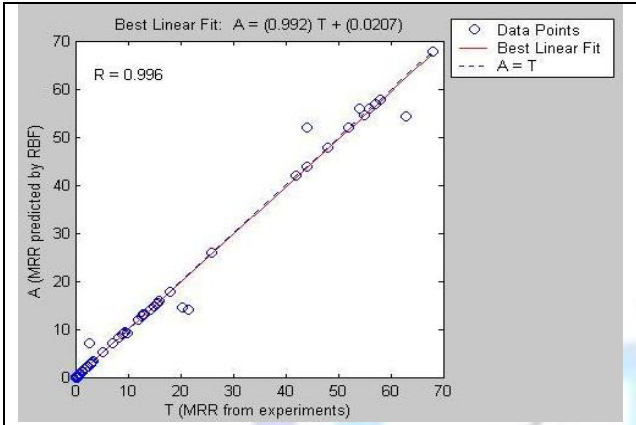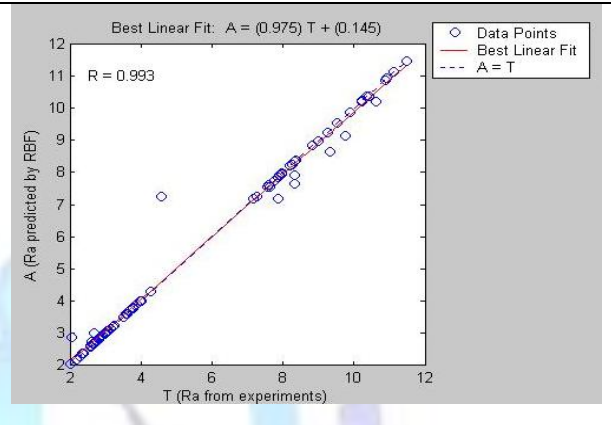| (R) Coefficient	RBF model	TANMLP model	LOGMLP model
R coefficient for MRR	0.996	0.993	0.963
R coefficient for Ra	0.993	0.996	0.988

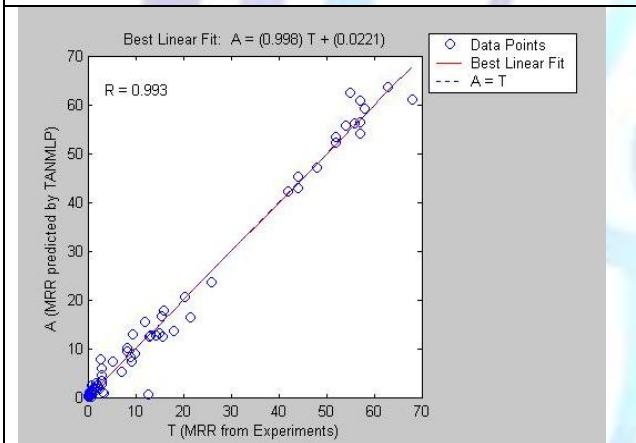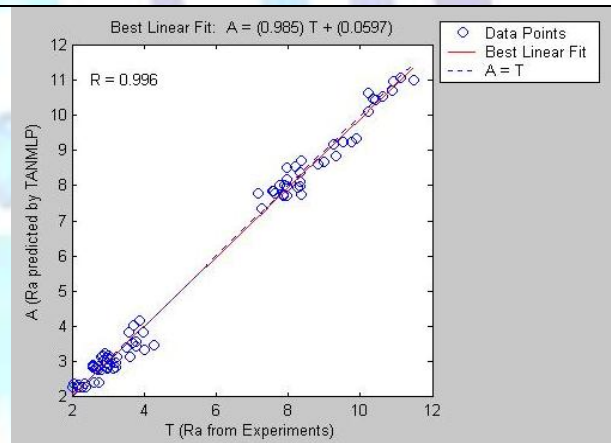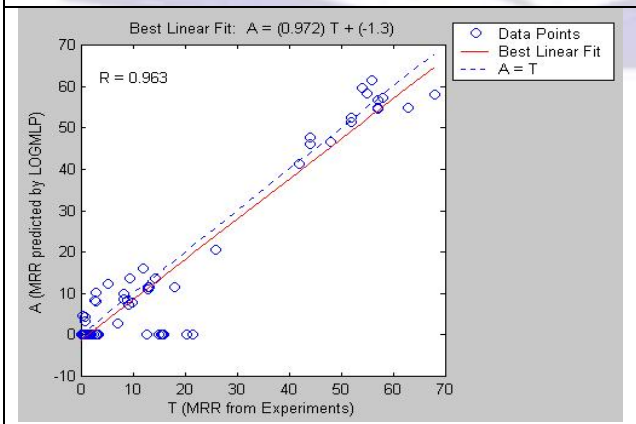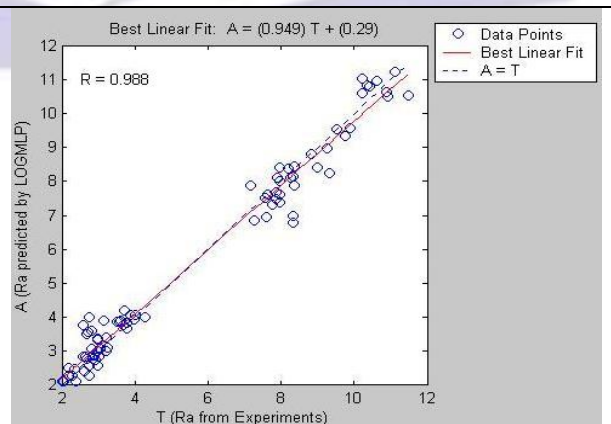|	
Fig3:.Linear regression analysis between RBF network outputs and experimental values for MRR.	Fig4:.Linear regression analysis between RBF network outputs and experimental values for Ra.
Fig.5:.Linear regression analysis between TANMLP network outputs and experimental values for MRR.	Fig6: Linear regression analysis between TANMLP network outputs and experimental values for Ra.
Fig7: Linear regression analysis between LOGMLP network outputs and experimental values MRR	Fig8:Linear regression analysis between LOGMLP network outputs and experimental values for Ra.

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