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Multi-Objective Optimization of Electrical Discharge Machining Processes Using Artificial Neural Network

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Abstract

The present study provides predictive models for the functional relationship amongst the input and output variables of Electrical Discharge Machine (EDM) environment. The parametric optimization of this process can be regarded as a multi-objective task. No particular parametric combination of input parameters can offer the maximum Material Removal Rate (MRR) and a better surface finish concurrently, due to its conflicting nature. Hence, a Multi-objective optimization approach has been attempted for the best process parametric combinations by modelling EDM process using of Artificial Neural Networks (ANN). It provides an optimized input data set to EDM system and the results show an improvement with a better productivity, a reduced material removal time and product cost at the material removal rate and surface finish. Extensive experiments have been accompanied with a wide range of machining settings, for modelling and, then, for validating the model. The model is quite capable of predicting the MRR and surface roughness. Also, it is found that the quality of the surface decreases as MRR increases. The maximum MRR obtained is 51.58 mm3/min with the surface finish of 0.1466 µm.

Keywords: *Electrical-Discharge Machining, Artificial Neural Network, Material Removal Rate, Surface Roughness*.

1. Introduction

Electrical Discharge Machining (EDM) is a more widely and effectively non-conventional machining process used. It is rather the fourth in the extensively used machining methods, after milling, turning, and grinding process. Therefore, it is regarded as the most conventional Non-conventional machining process. One of the prime advantages of the process is that it can machine any material, regardless of its hardness as long as the material is electrically conductive, by the application of thermal energy. Thus, it is extensively used for manufacturing of aerospace component, forming tools, injection mould, plastic moulds, forging dies, automobile components, and surgical instruments. Generally, these are made from “difficult-to-machine” materials, such as titanium alloys, nickel-based super alloys, and hardened tool steels, etc. Amongst these materials, AISI D2 tool steel has wide varieties of applications in the die material, in tool and die making applications; furthermore, this steel can be hardened and tempered to offer a higher strength and wear resistance as compared to low carbon steels [1 - 4].

Moreover, EDM process has some limitations as well, viz. the high specific energy consumption, inferior machining performance (productivity) and accuracy of the dimensions of EDMed surface are the some major issues in the die sinking EDM process. These shortcomings mostly limit the applications of EDM. Moreover, it is very tough to control the dimensions in EDM, owing to the complexity and non-linearity of the EDM parameters. Hence, investigators are frequently fascinated with the process modelling and optimization of EDM to increase the accuracy of the process. In the past, substantial development has been dispensed to boost the productivity, and also the versatility of EDM process. Many authors [5 - 10] used the various ANN model to determine the process model considering input parameters such as Ip, Ton, V, etc. for the prediction of responses like MRR and Ra and established that they are performing with reasonable accuracy, under varying machining conditions. Recently with the developments in the soft computing techniques the researchers have paid a great deal of attention to the solution of non-linear problems. It has exhibited a great prospective in solving difficult, non-linear, real-life and complex problems in many different fields manufacturing process modelling, multi-objective optimization, pattern recognition, signal processing and control [2, 7, 11 - 14]. Baraskar *et al.* [15] used an empirical model for relating the surface roughness and MRR, RSM has been applied in developing the models. S. Joshi and S. Pande [16] reposted an intelligent approach for process modeling and optimization of 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

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prediction accuracy of the model with less dependence on the experimental data. Yadav and Yadava [17] optimized the process parameters of the slotted electro discharge abrasive grinding process using a combined approach of artificial neural network and non-dominated sorting genetic algorithm II. Das *et al.* [18] used Recurrent Elman Network (REN) for the prediction of the surface roughness in Electrical Discharge Machining (EDM) of SKD 11 tool steel.

In the last two decades, with the developments in the soft computing techniques, researchers have paid a great deal of attention to the solution of non-linear problems. As it has exhibited a great prospective in solving difficult non-linear real- life complex problems in many different fields, manufacturing process modelling, multi-objective optimization, pattern recognition, signal processing and control.

The vital apprehension in EDM is the slower MRR, poor surface quality and precise duplication of the complex tool profile into the die cavity. To improve the MRR, generally a greater discharge current is essential. However, due to this, there is a deterioration of the accuracy of the machined product. The aim of the present analysis is to attain the optimum input parameters for the process by RSM. This may facilitate increasing the productivity (MRR) of the process and precision of the EDMed product. Concurrently, it may lead to the production of complex shapes accurately in shorter lead times. In this trend several efforts have been made for modelling analysing, and optimisation of the EDM process. The intension is to find the suitable parameters that increase the productivity without affecting the surface quality much. EDM process is a very complex process, it is a stochastic process too, and it is affected by many parameters; henceforth it is very difficult to select the parametric combination that could establish the greatest machining performance, i.e., higher MRR along with a decent surface finish. Moreover, these responses MRR and Surface finish are contradictory in nature. Higher MRR is required to achieve high productivity, and a lower surface roughness is required to achieve better surface quality. The aim of the current analysis is to recommend the optimum input process parameters for the process using artificial neural network. This analysis provides an optimized input data set to EDM system and the results show an enhancement and facilitate enhancing the productivity (MRR) and quality accuracy of EDMed components.

2. Experimental Environment

Experiments were conducted as per the following machining condition:

- Processing Machine : Electronica Electraplus PS 50ZNC die-sinking EDM machine Figure 1.
- Work piece material : AISI D2 (DIN 1.2379) tool steel, density 7.7 g/cc, rectangular in shape having a thickness of 4 mm. (with negative polarity).
- Electrode material : electrolytic copper with 30mm diameter with positive polarity
- Flushing : Pressure of 0.3 kg f /cm^2, side flushing technique.
- Dielectric fluid : Commercial grade EDM oil (specific gravity=0.76, freezing point = 94°C).
- Machining Time: 15 min

Figure 1. Experimental setup

Since the influencing parameters of EDM are very diverse and complex, it is therefore chosen on the basis of the literature survey, machining capability, manufactures manual, preliminary experiments and the experience. The four input process parameters, viz. *Ip*, *Ton*, *Tau*, and *V* along with the ranges are illustrated in Table 1. The parametric range of pulse current varies from 5 A to 15 A as per the availability in the machine. Pulse duration varies in the range of 50 µs to 100 µs. The duty cycle varies from 50 to 83 and voltage from 40 to 50. To reduce the significance of the unaccounted factor on the response the experiments were carried out in a random order. The responses were observed for each experiment and the results were displayed.

Table 1. Machining Parameters along with their levels.

Input Parameters	Unit	Levels and Values
Ip	A	5, 6,7,8,9,10,11,12,13,14,15
Ton	µs	50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100
τ		50, 66.5, 75, 80, 83
V	V	40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50

2.1. Measurement of Response

The response MRR is computed as the volume of material loss from the work material divided by the duration of machining. The obtained Weight loss is transferred to volumetric loss (mm^3/min) using the following equation 1. To calculate the MRR the following equation:

$$MRR = \frac{\Delta V_W}{Ta} = \frac{\Delta W_W}{\rho_W T} \quad (1)$$

where ΔV_W is the loss of volume the work material , ΔW_W is the loss of weight of the work piece, T is the machining time of the process, and ρ_W = 7700 kg/m^3 is the density of the work material. Precision balance (Sartorius, Japan) with a resolution of 0.001 gram was used to measure the weight of the work piece before and after the machining process. For an effective assessment of the EDM process, the greater MRR is considered as the best machining performance.

The other response considered for this analysis was surface roughness. It is regarded as the degree of product quality that influences the cost of the product. This response is also influenced by the input parameters.

The surface roughness of the EDMed surfaces were measured by a portable stylus type profilometer, Talysurf (Taylor Hobson, Surtronic 3+) for the quantitative valuation of the influence of EDM process parameters on the response surface finish. Generally, it is described as the arithmetic mean value of the profile calculated from centerline. It is defined as:

$$R_a = \frac{1}{L}\int_0^L |y(x)|\, dx \quad (2)$$

where L is the total measured sampling length, y is the profile curve and x is the direction of the profile.

The instrument is set to a sampling length L = 0.8 mm, filter 2 CR, measuring speed 1 mm/s and 4 mm evaluation length. The contour obtained during the measurement was digitized and latter regulated over the dedicated advanced surface finish analysis software, Talyprofile.

The measurement of the roughness was carried out in four different direction to catch all kind of irregularities and the average of the all measurements were taken as the Ra value for the evaluation. The experimental design matrix is depicted in Table 2 along with the measured MRR and Ra, respectively.

3. Multi-objective Optimization

A multi-objective optimization problem involves more than one objective function that need to be optimized simultaneously. Generally, it is not possible to get a single solution that simultaneously optimizes each objective function. In the present paper, multi-objective optimization problem of the EDM process is solved by minimizing the surface roughness and maximizing the material removal rate.

If $MRR = f_1(I_P, T_{on}, \tau, V)$ and $R_a = f_2(I_P, T_{on}, \tau, V)$ Multi-objective optimization problem can be represented by

Maximize $f_1(I_P, T_{on}, \tau, V)$

Minimize $f_2(I_P, T_{on}, \tau, V)$

Subject to

$5 \le I_P \le 15$

$50 \le T_{on} \le 100$

$50 \le \tau \le 83$

$40 \le V \le 50$

$I_P, T_{on}, \tau, V \in Z$

Table 2. Experimental value of the responses MRR and Ra.

Run Order	*Ip* A	*Ton* µs	*Tau* %	*V* volt	MRR mm^3 /min	Ra µm
1	10	75	66.5	45	9.04	5.98
2	5	50	50	50	5.18	5.01
3	5	100	83	40	5.25	5.03
4	5	50	83	40	8.87	4.71
5	15	100	50	50	51.09	8.10
6	10	75	66.5	45	8.95	6.12
7	5	100	50	40	4.35	4.89
8	15	100	50	40	51.00	10.93
9	5	100	83	50	6.97	5.70
10	15	100	83	40	33.02	12.49
11	5	50	83	50	14.12	5.19
12	10	75	66.5	45	8.42	6.54
13	15	50	83	40	20.00	12.01
14	10	75	66.5	40	8.94	8.20
15	10	75	83	45	9.36	7.13
16	15	75	66.5	45	33.08	9.68
17	10	50	66.5	45	9.18	5.87
18	5	75	66.5	45	5.36	6.07
19	10	75	66.5	45	10.35	5.55
20	15	50	83	50	29.16	8.43
21	5	50	50	40	4.61	4.59
22	15	50	50	40	29.74	10.49
23	10	75	66.5	45	11.01	6.25
24	10	75	50	45	9.25	5.92
25	15	50	50	50	33.10	7.43
26	5	100	50	50	4.35	5.59
27	15	100	83	50	33.11	9.01
28	10	75	66.5	50	11.01	6.35
29	10	100	66.5	45	10.43	7.27
30	10	75	66.5	45	9.35	6.75

4. Artificial Neural Networks

Artificial Neural Networks (ANNs) are simple electronic devices modelled after the neural structure of the brain. ANNs are powerful tools for many complex applications such as optimization, system identification and pattern reorganization. ANNs are capable to learn from experiments and to perform non-linear mappings. The processing elements of neural networks are called artificial neurons, or nodes. ANN consists of input layers, which are multiplied by weights, and then evaluated by a mathematical mapping which computes the activation of the neuron. Another function determines the output of the artificial neuron. The artificial neurons of ANNs process the information.

Neural networks are categorized by their structure, activation functions and training algorithms. Each type of

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neural networks has its own input-output characteristics; therefore, it could be applied only in some specific processes. In this one, a neural network is employed for modeling the MRR and the Ra in the EDM process. One of artificial neural networks, i.e., Back-Propagation Neural Network (BPNN) is discussed. The BPNN model consists of an input layer, one or two hidden layers, and an output layer in a forward multi-layer neural network. The architecture of a BPNN with n inputs nodes, r outputs nodes and a single hidden layer of m nodes is shown in Figure 2. All the nodes have been multiplying the weights connected with them. Therefore, the output O_k can be expressed as:

$$o_k = \sum_{j=1}^{m} W2_{kj} f\left(\sum_{i=1}^{n} W1W1_{ji} x_i + b1_j\right) + b2_k \qquad (3)$$

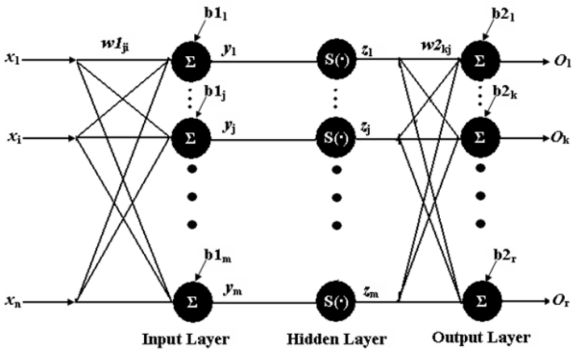

Figure 2. Back-propagation Network

where function f is the transfer function or activation function, $W1_{ji}$ is the weight between the ith input node and jth hidden, $W2_{ji}$ is the weight between the jth hidden node and kth output node, $b1_j$ is the bias at jth hidden node and $b2_k$ is the bias at kth output node.

Eq. 3 presents a kind of function to convert neuron from weighted input to output and also is a kind of network to make non-linear influence into the BPNN. The present study chooses the most general tan-sigmoid transfer function S(·) and is defined as $f(x)) = 2/(1 + \exp(-2x)) - 1$, where the range of the value is $(-1, 1)$. And if a linear function is chosen for this transfer function, such as $f(x) = x$, the whole ANN architecture will become the linear influence from the input layer to the output layer.

In case of BPNN a typical node in the input-layer receives the input vector, sums them as per their weight and bias vectors, passes it through a transfer function and gives an output. This output is then compared with the actual data, and the error is computed. This error is then propagated backwards and used for updating the weight and bias vectors of the neurons. When this process is finished for all the input vectors, it is called as 1 epoch. Once one epoch is over, the mean squared error between the actual output values and the corresponding target values is determined iteratively. The process is repeated until the mean squared error is reached to a particular tolerance value. Once the mean squared error reaches the desired tolerance level, through the training process, the weights are updated and stored so as to present the desired output, which can be used later to predict outputs for a different set of inputs. The learning is based on conjugate gradient descent algorithm. At this stage, the architecture of a network is defined and treated as the trained ANN.

5. Optimization Approach

The trained ANN model is capable of determining the response parameters as a function of four different control (input) parameters, i.e., *Ton*, τ , *Ip*, *V*. An attempt was made to generate the highest number of input, output parameter combinations to get more number of optimum points. The input parameters (four in numbers) were divided into all possible levels, as given in Table 1. These considerations resulted in 11 × 10 × 5 × 11 = 6050 possible input combinations. The developed ANN model was used to determine the MRR and Ra for all possible levels of the 6050 combinations. Finally, the results of this study proposed best of these combinations

6. Results

In the present BPNN model, the inputs of the model are *Ton*, τ, *Ip*, *V.* The outputs of the model are MRR and Ra. A set of training, validation and testing was performed by 30 data where 22 data were used for training, 6 data were used for validation and 6 for testing. The training data were applied to train the BPNN model, where the testing data were used to verify the adequacy of the trained BPNN model for the prediction of MRR and Ra. The one hidden layered BPNN and two hidden layered BPNN were trained with a different number of neurons. After data training, through different combinations of number of neurons, the comparison results of the actual versus the ANN were obtained. The Mean Absolute Error (MAE) and Mean Percentile Error (MPE), as the difference between actual and ANN, was determined for each MRR and Ra value. Finally, the graphs at hidden neurons were plotted for comparison MRR (actual vs. ANN) and Ra (actual vs. ANN). These graphs are presented in Figures 4 and 5. The most agreeable hidden layers neurons were found 2 and 3 for BPNN model, as shown in Figure 3. The satisfactory MAE and MPE of the trained BPNN for training, validation and testing data sets are given in Tables 3 and 4. Figures 6 and 7 indicate the variation in ANN model values and it can be observed that all the MRR and Ra values through ANN model are coinciding with the actual experimental values. Further, no abnormality in actual Vs ANN data comparison is apparent in the Figures 6 and 7. The Figures show that the performance of ANN model is very close to the actual MRR and Ra, which, in comparison, indicates that the ANN model results are closer to actual outputs. Here, it can be concluded that the ANN model provides better results in the EDM process using D2 steel.

Another parameter, which we have considered to compare the proposed ANN model result with experimental result, is the regression analysis or the R-value. Figure 8 shows the R values based on ANN model and the experimental data for the MRR and Ra. The solid line represents the best possible regression fit between targets and outputs for training, validation, testing and all data sets. The value of R, which is shown on the top of Figure 8, represents the relation-ship between those two. In neural networks, R=1 indicates the perfect match between targets and outputs. Since the net-works cannot be made to learn perfectly, the general value of R lies near to 1. The closer its value to 1, the better the neural network is. On the other hand, the value of R close to 0 indicates the nonlinear relationship between targets and outputs. For the present study, the input parameters were divided into all possible levels within their working range as illustrated in Table 1. The ANN model was developed to predict the MRR and Ra for all combination levels of the input parameters. The neural network was simulated with 6050 the data set. After training, a list of 50 optimized input-output parameter combinations was obtained through ANN and is presented in Table. 5. Table 5 indicates the output parameter, the MRR in decreasing order and corresponding Ra at 50 optimized input parameter combinations. It also helps to select the input parameter combination at the required MRR.

Table 3. Error for MRR

Error	Training data	Validation data	Testing data
MAE	0.580003721	2.421624627	0.827826794
MPE	7.626796553	16.92452563	9.800317507

Table 4. Error for Ra

Error	Training data	Validation data	Testing data
MAE	0.864459133	0.849570064	0.815860784
MPE	12.1634995	14.11580632	10.8702371

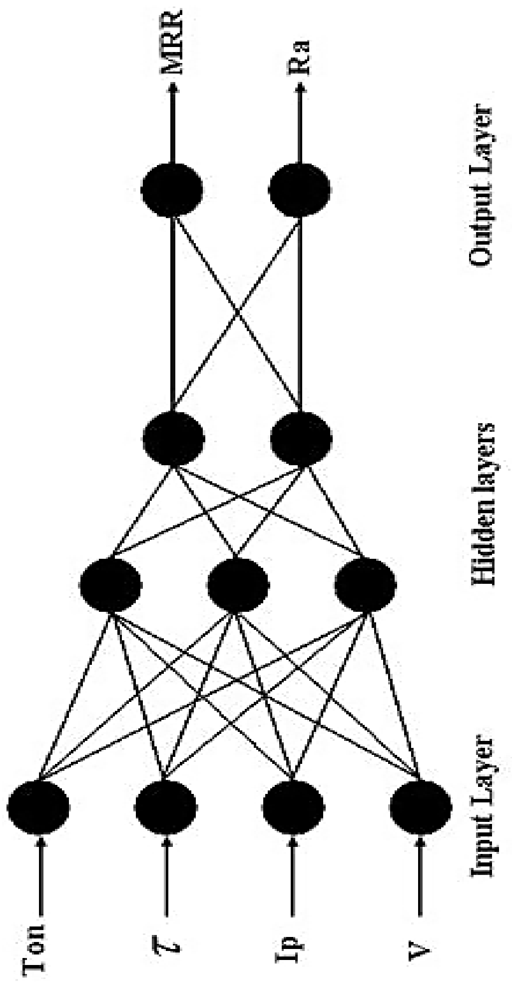

Figure 3. BPNN for prediction of MRR and Ra

Table 5. Sorted out list of optimum input-output parameter combinations

Sl. No.	*Ip* A	*Ton* μs	*Tau*	*V*	MRR *mm*^{3}*/min*	Ra μm
1	15	100	50	40	51.59	10.47
2	15	100	50	41	51.51	10.43
3	15	100	50	42	51.43	10.40
4	15	100	50	43	51.34	10.36
5	15	100	50	44	51.25	10.32
6	15	100	50	45	51.15	10.27
7	15	100	50	46	51.04	10.23
8	15	95	50	40	50.94	10.51
9	15	100	50	47	50.92	10.18
10	15	95	50	41	50.87	10.48
11	15	100	50	48	50.80	10.13
12	15	95	50	42	50.80	10.44
13	15	95	50	43	50.72	10.41
14	15	100	50	49	50.67	10.07
15	15	95	50	44	50.64	10.37
16	15	95	50	45	50.55	10.33
17	15	100	50	50	50.54	10.01
18	15	95	50	46	50.45	10.28
19	15	95	50	47	50.35	10.24
20	15	95	50	48	50.24	10.19
21	15	95	50	49	50.13	10.13
22	15	90	50	40	50.07	10.55
23	15	90	50	41	50.01	10.52
24	15	95	50	50	50.01	10.08
25	15	90	50	42	49.95	10.48
26	15	90	50	43	49.88	10.45
27	15	90	50	44	49.81	10.41
28	15	90	50	45	49.73	10.38
29	15	90	50	46	49.65	10.34
30	15	90	50	47	49.56	10.29
31	15	90	50	48	49.47	10.24
32	15	90	50	49	49.36	10.19
33	15	90	50	50	49.26	10.14
34	15	85	50	40	48.93	10.58
35	15	85	50	41	48.89	10.56
36	15	85	50	42	48.84	10.53
37	15	85	50	43	48.78	10.49
38	15	85	50	44	48.72	10.46
39	15	85	50	45	48.66	10.43
40	14	100	50	40	48.63	10.08
41	15	85	50	46	48.59	10.39
42	15	85	50	47	48.51	10.35
43	14	100	50	41	48.50	10.02
44	15	85	50	48	48.43	10.30
45	14	100	50	42	48.36	9.96
46	15	85	50	49	48.34	10.25
47	15	85	50	50	48.25	10.20
48	14	100	50	43	48.21	9.89
49	14	100	50	44	48.05	9.82
50	14	100	50	45	47.89	9.75

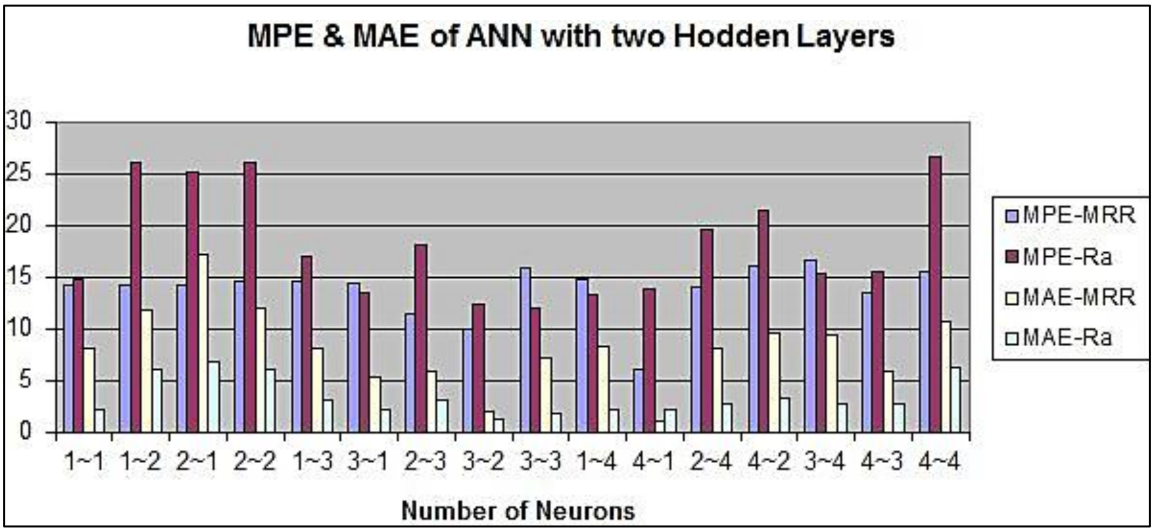

Figure 4. MPE & MAE of ANN with Single Hidden Layer

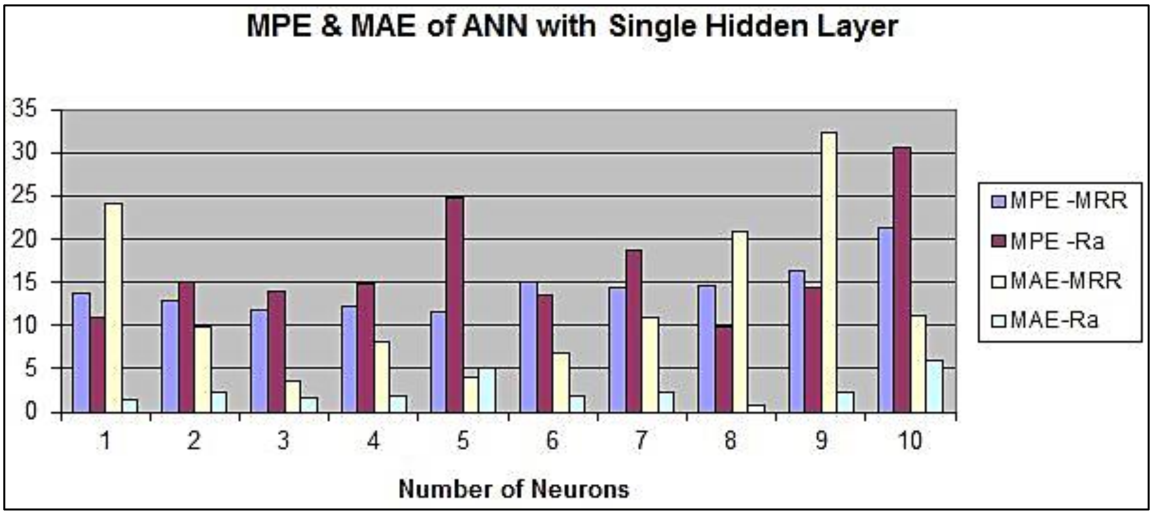

Figure 5. MPE & MAE of ANN with Two Hidden Layer

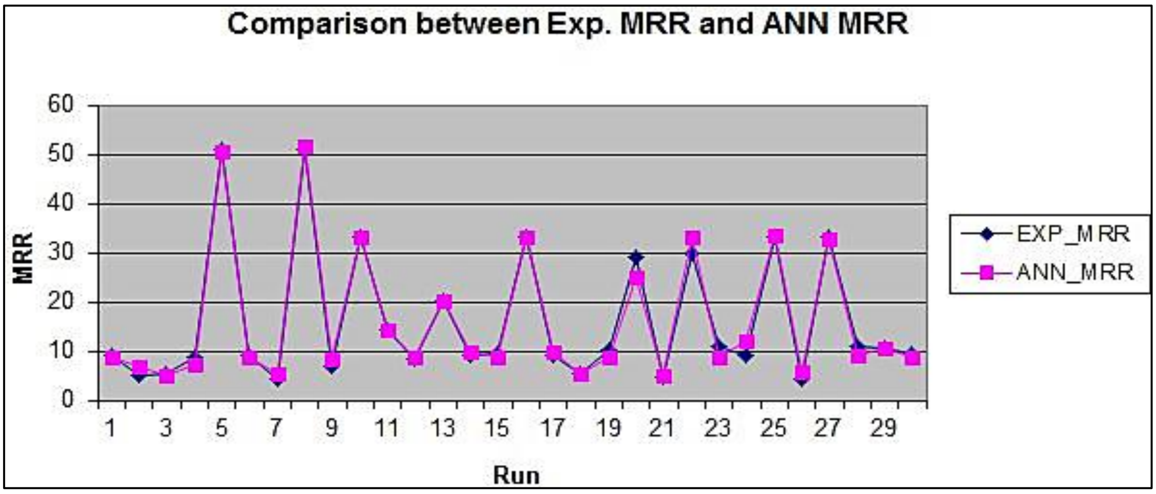

Figure 6. Comparison between Exp. MRR and ANN MRR

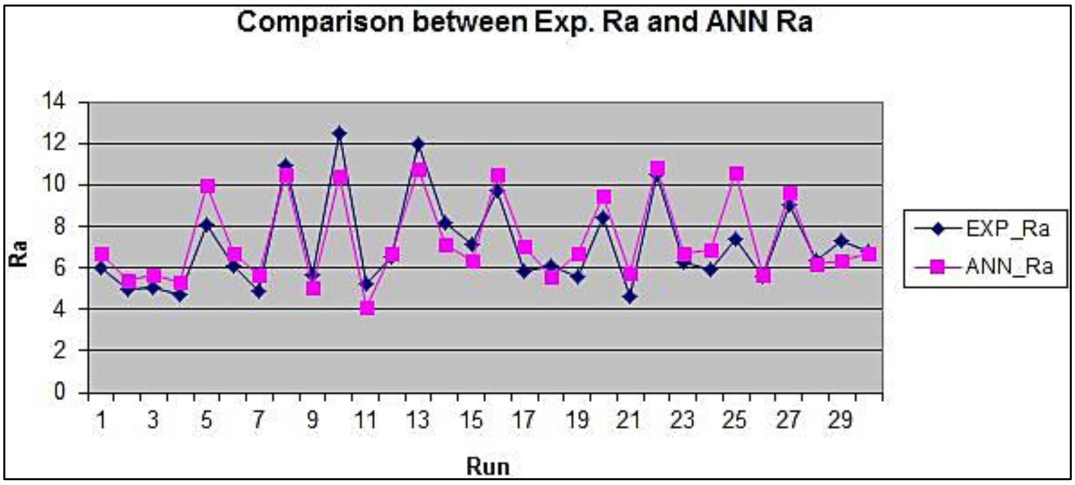

Figure 7. Comparison between Exp. Ra and ANN Ra

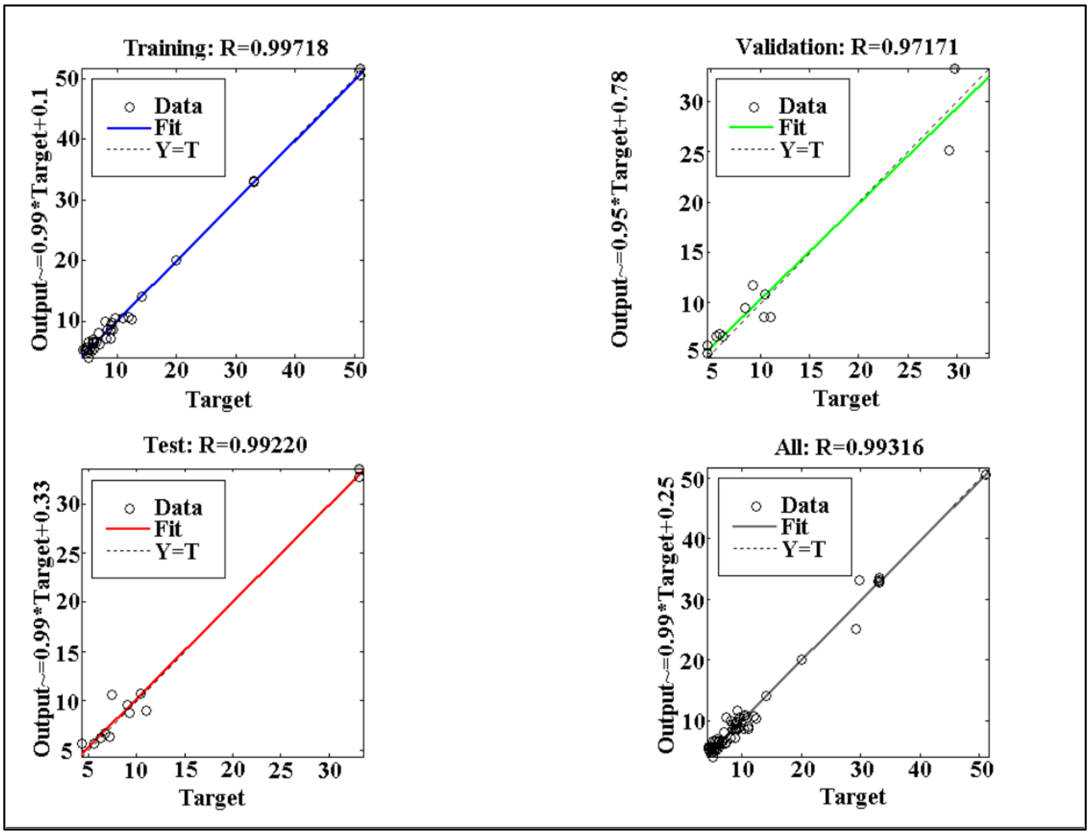

Figure 8. Compression between Target and Output of ANN

7. Discussions

The present work proposes a methodology to determine the optimal combination of control parameters in the EDM process using D2 steel. The ANN model was applied to predict the process performance. It is always a difficult task to find an optimal configuration of BPNN. There is no exact rule for setting the proper number of neurons in a hidden layer to avoid over-fitting or under-fitting to make the learning phase convergent. For the best performance of the BPNN, 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. It is compared with the results obtained from the experiments and the average absolute error obtained for the network. For the input data, the BPNN has almost an identical generalization ability. A BPNN was developed to model the process parameters. Optimal process parameter combinations, corresponding to different MRR and Ra, were determined out of 6050 possible combinations. The presented list of 50 optimum parameter combinations can act as guidelines for effective and efficient machining of D2 steel using EDM process. Through an optimized input data set, the improved output results will enhance the productivity with a better machining surface quality.

Furthermore, the production cost and machining time will be saved through the optimum machining speed in every run. This work in the area of machining D2 steel, through EDM process and ANN application, will solve various challenging problems faced by the engineers and technocrats in the field of modern manufacturing systems. Present manufacturing industries can achieve the ultimate goals of higher productivity (higher MRR), better quality (required surface finish) and lower production cost (reduced material removal time), which would help manufacturers to compete in the world market.

8. Conclusion

The present research paper provides an effective and a novel approach for modelling and the optimisation of the machining conditions of EDM process for attaining the maximum material removal rate and the minimum surface roughness. The extensive experiments were carried out initially and were simulated to generate a huge data. The different parametric combination was used to generate the experimental data. After training, a list of optimized input-output parameter combinations was obtained through ANN and presented. This attempt provides an optimized input data set to EDM system and the results show an improvement, with a better productivity, a reduced material removal time and a product cost at the desired surface finish. The optimised value of the present research is found to be 51.588 mm^3/min with a level of surface finish of 0.0955 µm.

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