Comparisons of neural network models on surface roughness in electrical discharge machining

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***Abstract* —** In this work, two different artificial neural networks (ANNs) models: Back propagation neural network (BPN) and radial basis function neural network (RBFN) are presented for the prediction of surface roughness in die sinking Electrical Discharge Machining (EDM). The pulse current (Ip), the pulse duration (Ton) and duty cycle (τ) are chosen as input variable with a constant voltage 50 volt, surface roughness is the output parameters of the model. A widespread series of EDM experiments was conducted on AISI D2 steel to acquire the data for training and testing and it was found that the neural models could predict the process performance with reasonable accuracy, under varying machining conditions. However, RBFN is faster than the BPNs and the BPN is reasonably more accurate. Moreover, they can be considered as valuable tools for EDM, by giving reliable predictions and provide a possible way to avoid time and money consuming experiments

Keywords—Back propagation neural network, Electrical discharge machining, Radial basis function neural network, Surface roughness.

1. INTRODUCTION

Electrical Discharge Machining is one of the earliest non-conventional processes most widely and successfully applied for the machining of various electrically conductive materials regardless of its hardness. It has been distinctively and comprehensively used for manufacturing moulds, punch and dies for blanking, shearing and progressive die tooling, automatic stamping dies and used as the components/products used in biomedical, automobile, aircraft, and microelectronic industries [1]. It works on a thermal erosion process by a complex metal removal mechanism, involving the formation of a plasma channel between the tool and the workpiece, in which the repetitive spark cause melting and even evaporating the workpiece. As a result, tensile residual stresses, cracking and metallurgical transformation of the machined material may be observed.

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All such characteristics are termed as “surface integrity” that would help to determine the operational behavior of the machine parts [2]. Several researches are being carried out on the study of surface integrity (including surface topography) induced by EDM. Due to the complexity in nature, there is a lack of analytical models correlating the process variables and surface finish. For the prediction of surface roughness, empirical models as well as multi-regression analysis are usually applied. Tsai and Wang [3] developed a semi-empirical model in which parameters affecting the surface roughness were identified using design of experiments (Taguchi method). Petropoulos [5] presented a multi-parameter analysis of surface finish imparted to Ck60 steel plates by electro-discharge machining. The interrelationship between surface texture parameters and process parameters is emphasized.

In the recent past, ANNs have emerged as a highly flexible modeling tool for manufacturing sectors. ANNs are found to be effective as computational processors for various associative recall, classification, data compression, combinational problem solving, adaptive control, modeling, forecasting, multisensor data fusion, and noise filtering. In the literature, Back-propagation technique and Radial basis function have been employed for modeling the processes. Tsai [4] used RBFN on the neural network for predicting MRR in EDM process using aluminum and iron workpiece. However, Kao [6], Panda [7] and Angelos [9] used Back-propagation technique on neural network for predicting on-line monitoring, MRR and Surface roughness, respectively, in EDM process.

The application of novel ANN models for the prediction of the center-line average surface roughness 'Ra' of electrical discharge machined surfaces is discussed in this paper. The proposed models use data for the training procedure from an extensive experimental research-concerning surface integrity of EDMed AISI D2 steels. The Ip, Ton, and τ were considered as the input parameters of the models and they are varied over a wide range, from roughing to near-finishing conditions. The proposed neural networks trained with the feed forward back propagation algorithm and Radial Basis function were proven to be accurately predicting, providing surface roughness without conducting experiments.

The objective of this work is to establish a better process model based on neural network by comparing prediction from the discussed models under the effect of Ip, Ton, and τ in EDM process.

Table 1 Experimental machining parameter

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

2. EXPERIMENTATION

2.1. EXPERIMENTAL SETUP

A number of experiments were conducted to study the effects of various machining parameters on EDM process. These studies were undertaken to investigate the effects of Ip, Ton, and τ on surface roughness. Where, the duty cycle is the ratio of Ton to sum of Ton and spark off time (Toff) in percentage. The selected workpiece material for the research work is AISI D2 (DIN 1.2379) tool steel. D2 steel was selected due to its emergent range of applications in the field of manufacturing tools in mould industries.

Experiments were conducted on Electronica Electraplus PS 50ZNC die sinking machine. An electrolytic pure copper. with a diameter of 30 mm was used as a tool electrode (positive polarity) and workpiece materials used were steel square plates of dimensions 15 ×15 mm^2 and of thickness 4 mm. Commercial grade EDM oil (specific gravity = 0.763, freezing point= 94°C) was used as dielectric fluid. Lateral flushing with a pressure of 0.3 kgf/cm^2 was used. The test conditions are depicted in Table 1. To obtain more accurate result, every test run was performed with 15 min of machining and three repeatasions.

2.2. SURFACE ROUGHNESS MEASUREMENTS:

Roughness measurement was done using a portable stylus type profilometer, Talysurf (Taylor Hobson, Surtronic 3$^+$). The profilometer was set to a cut-off length of 0.8 mm, filter 2CR, and traverse speed 1 mm/s and 4 mm evaluation length [10]. Roughness measurements, in the transverse direction, on the workpieces were repeated four times and average of four measurements was recorded. The measured profile was digitized and processed through the dedicated advanced surface finish analysis software, Talyprofile for evaluation of the roughness parameters.

2.3. SURFACE ROUGHNESS

Surface roughness is an important parameter in the EDM process. The parameters that affects roughness are Ip, Ton, and τ. It is a measure of the technological quality of a product, which mostly influence the manufacturing cost of the product. It is defined as the arithmetic value of the profile from the centerline along the length.

This can be express as

$$R_a = \frac{1}{L}\int \left|y(x)\right|dx\| \quad (1)$$

Where L is the sampling length, y is the profile curve and x is the profile direction. The average surface roughness Ra is measured within L = 0.8 mm. Ra measurements of electro-discharge machined surfaces were taken to provide quantitative evaluation of the effect of EDM parameters on surface finish.

3. Artificial Neural Networks

One type of network sees the nodes as 'artificial neurons'. These are called artificial neural networks (Fig. 1). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron (Fig. 2). When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal through the axon. This signal might be sent to another synapse, and might activate other neurons.

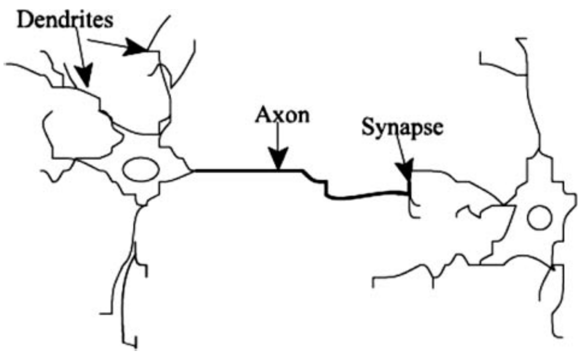

Figure 1 Natural Neurons

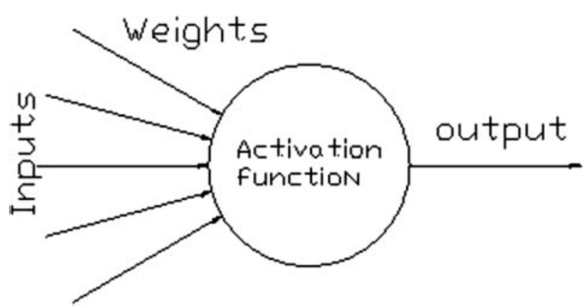

Figure 2 An artificial neurons

The complexity of real neurons is highly abstracted when modeling artificial neurons. These consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependence of a certain threshold). ANNs combine artificial neurons in order to process information.

In past, several studies have been reported on the development of neural networks based on different architectures. Neural networks are characterized by their architecture, activation function and learning algorithms. Each type of neural networks would have its own input-output characteristics; and therefore it could be applied only on some specific process.

In this study, two neural networks are employed for modeling the 'Ra' in the EDM process. Two networks are discussed as follows.

A. Back-propagation Network
B. Radial basis function network

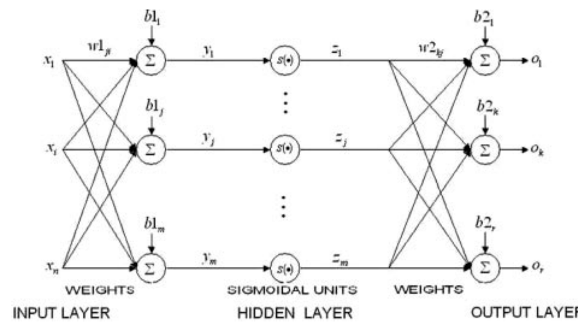

Figure 3 Schematic diagram of back-propagation network

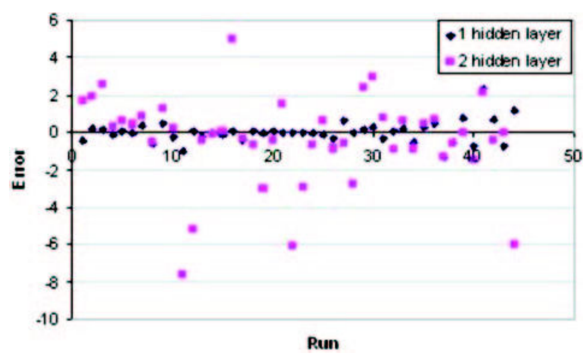

Figure 4 Comparison of Errors for hidden layers

3.1. Back-propagation Network

Back-propagation networks are composed of layers of neurons. The input layer of neurons is connected to the output layer of neurons. The training process of BPN is undertaken by changing the weights such that a desired input-output relationship is realized. A schematic diagram of a BPN with n inputs nodes, r outputs nodes and a single hidden layer of m nodes are shown in Fig. 3. In the figure, the number of the hidden layers is critical for the convergence rate during the training of parameters for a given numbers of nodes at inputs and outputs layers [4]. In addition, numerical experiments did not show any advantage of a double hidden layer over a single layer network as shown in Fig. 4. So, only single hidden layer networks are used in this work and all the connections have been multiplying weights associated with them. The input nodes have a transfer function of unity and the activation function of the hidden and output nodes are sigmoidal $S(\bullet)$ and linear, respectively.

Referring to Fig. 1 the net input to the *j*th hidden neuron is given by

$$y_j(x) = \sum_{i=1}^{n} w1_{ji} x_i + b1_j \tag{2}$$

Where $w1_{ji}$ is the weight between the *i*th input node and *j*th hidden node and $b1_j$ is the bias at *j*th hidden node. The output of the *j*th hidden node is described as:

$$z_j(x) = 1/(1 + \exp(-y_j(x))) \tag{3}$$

Given an input vector *x*, the output, value $o_k(x)$ of the *k*th output node is equal to the sum of the weighted outputs of the hidden nodes and the bias of the *k*th output node, and is expressed as:

$$o_k(x) = \sum w2_{kj} z_j + b2_k \tag{4}$$

Where $w2_{kj}$ is the weight between the *j*th hidden node and *k*th output node, $b2_k$ is biasing term at the *k*th output node.

The Back Propagation learning process works in small iterative steps:

1. First one of the example cases is applied to the network,
2. Second the network produces some output based on the current state of its synaptic weights (initially, the output will be random).

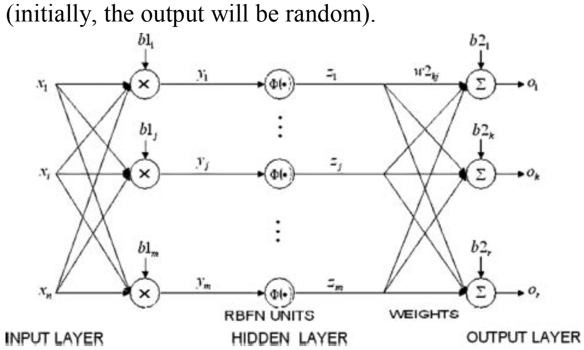

Figure 5 Schematic diagram of radial basis function network

This output is compared to the known-good output, and a mean-squared error (MSE) signal is calculated. The error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The weight changes are calculated to reduce the error signal for the case. The whole process is repeated for each of the example cases, then back to the first case again, and so on. The cycle is repeated until the overall error value drops below some predetermined threshold. At this point, it is said that the network has learnt the problem "good enough" - the network will never exactly learn the ideal function, but rather it will asymptotically approach the ideal function.

3.2. Radial Basis Function Network

The schematic diagram of a RBFN with *n* inputs and *r* outputs is shown in Fig. 5. It has a feed forward structure consisting of a single hidden layer of *m* locally tuned units (RBFNs) which are fully interconnected to an output layer of r linear units. The input nodes pass the incoming input vector to the hidden nodes. The connections between the hidden nodes and the input nodes (first layer connections) are not weighted. The connections between hidden nodes and output nodes (second layer connections) are weighted and the output nodes are simple simulations.

The commonly used Gaussian basis function $\Phi(\cdot)$ is used for the hidden units. All hidden units simultaneously receive the n-dimensional real-valued input vector *x*. It should be noticed that the first layer weights are absent, because the outputs of hidden units are not calculated using the sigmoidal activation mechanism. Rather, each hidden unit's output is obtained by calculating the closeness of the input *x* to an *n* dimensional parameter vector μ_j associated with the *j*th hidden units.

Referring to Fig. 5, the net input to the *j*th radial basis neuron is given by

$$y_j(x) = b1_j(\|x - \mu_j\|) \tag{5}$$

Where the bias $b1_j$ is a fixed function of the width of the receptive field σ_j that follows the sensitivity of the *j*th radial basis neuron to be adjusted and is described below,

$$b1_j = \sqrt{(-\log(0.5))}/\sigma_j \tag{6}$$

The output of the *j*th radial basis neuron is described as:

$$z_j(x) = \exp(-(y_j(x))^2) \tag{7}$$

Given an input vector x, the output, value $o_k(x)$ of the kth output node is equal to the sum of the weighted outputs of the hidden nodes and the bias of the kth output node and is described by.

$$o_k(x) = \sum_{j=1}^{m} w_{kj} z_j + b2_k \tag{8}$$

Where w_{kj} is the weight between the jth hidden node and kth output node.

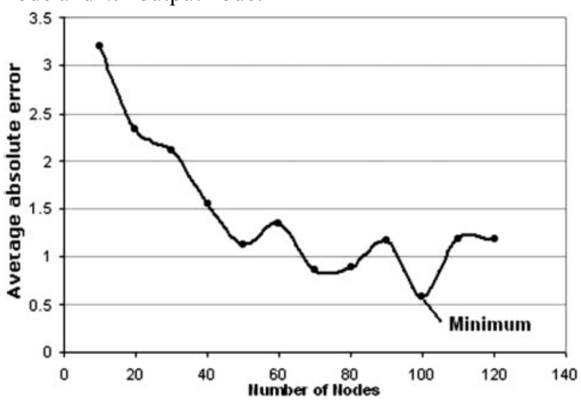

Figure 6 Comparison of average errors for various nodes on BPN

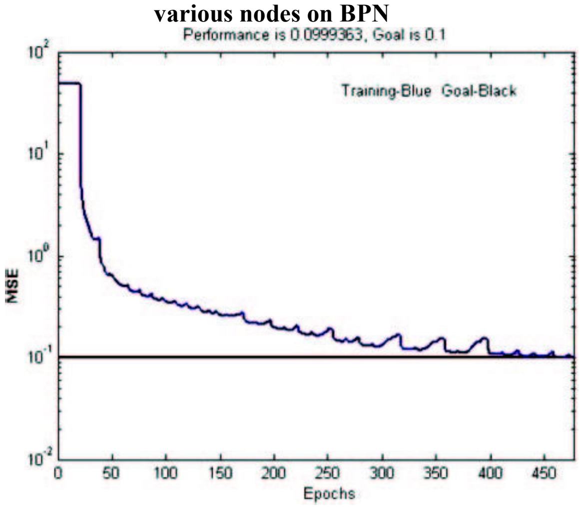

Figure 7 Learning behavior of BPN model for surface roughness

It may be noted that here that the choice of $\Phi(\cdot)$ and μ_j be made carefully so that the RBFNs be able to match closely to the performance of the two-layer back propagation neural networks. The RBFNs employ a hybrid two-stage training scheme which decouples the learning task from both hidden and outputs layers and thus eliminates the need for slow back error propagation. In the training process, the sum of the MSE criterion function is considered as the error function, and it is minimized over the given training data sets by adaptively updating the free parameters of the RBFN. These parameters are the radial basis function centers (μ_j, s) their widths (σ_j, s) and the second layer weights (w_{kj}, s). The RBFN is trained in three steps. Firstly, the hidden node centers are determined, secondly the hidden widths are determined and thirdly the second layer connection weights are determined.

In this section, widths of all Radial basis function units are taken to be equal, which is known as the spread factor (SF) of the RBFN. If SF is too small, overfitting can occur, while underfitting may occur if SF be too large. Therefore, it is of very important to choose a proper value for SF in order to achieve better generalization ability of the RBFN. Finally, once the hidden units are synthesized, the second layer weights are computed by using the supervised least-square rule.

4. Result and Discussion

Initially, the architecture and the topology of the networks i.e. the number of hidden layers and the number of neurons in each layer in the networks are decided. The process parameters Ip, Ton, and τ are taken as the inputs and Surface Roughness (Ra) is taken as output. Thus, there are three input nodes and one output node. The variation of process parameters for different experimental set (Run) is as presented in Table1.

The size of the network becomes very large for large number of training patterns. As such, the data for training are selected judiciously. Out of 44 experimental data 35 training data sets are considered for both the networks to compare the performances. Besides, 9 testing sets outside the training data set are selected for testing the neural networks. Both the ANNs were trained with the above data sets to reach the error goal (0.1). The performance of two neural network models is studied with the special attention to their generalization ability and the training time.

It is always a difficult task to find a optimal configuration of BPN. There is no exact rule for setting 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 BPN, 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 was observed that the network performed well with 100 nodes (Fig 6). The learning behavior of BPN model for surface roughness is shown in Figure 7 and error goal met at 478 epochs.

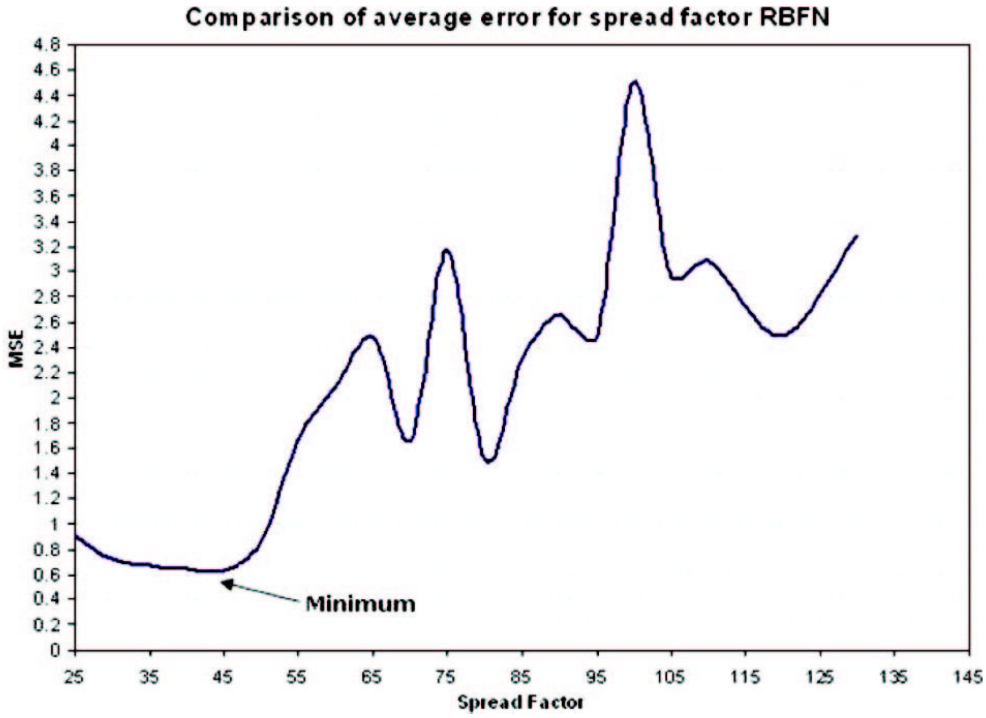

Figure 8 Comparison of average error for various spread factors

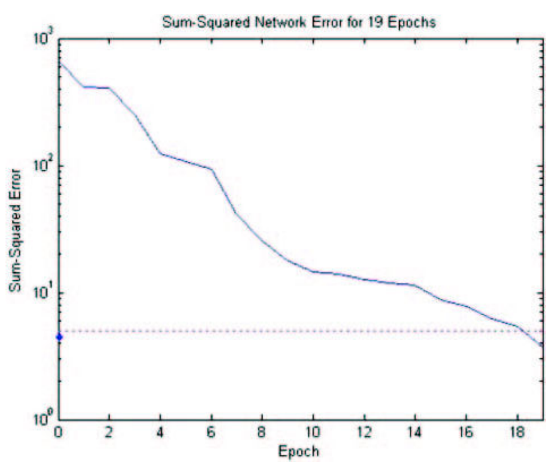

Figure 9 Learning behavior of RBFNN model for surface roughness

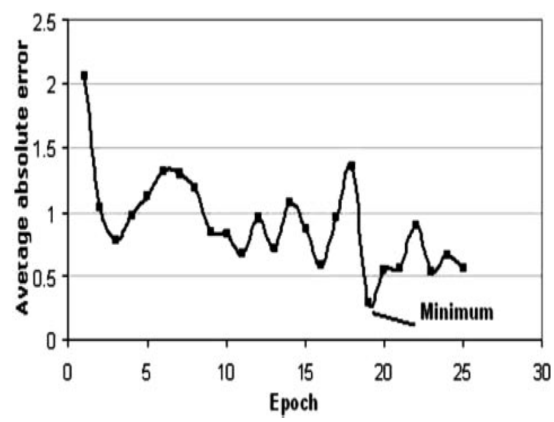

Figure 10 Comparison of average errors for various epochs on RBFN

The RBFN is auto configuring in the sense that it has only one hidden layer with a growing number of neurons during learning to achieve an optimal configuration. The only parameter to be varied to obtain the best generation ability is the spread factor. Computations are carried out for different values of spread factor. It is observed that the best generalization ability of the network is achieved with a SF 45 for the training data as shown in Fig 8. The training performances of the same training data sets are shown in Fig. 9

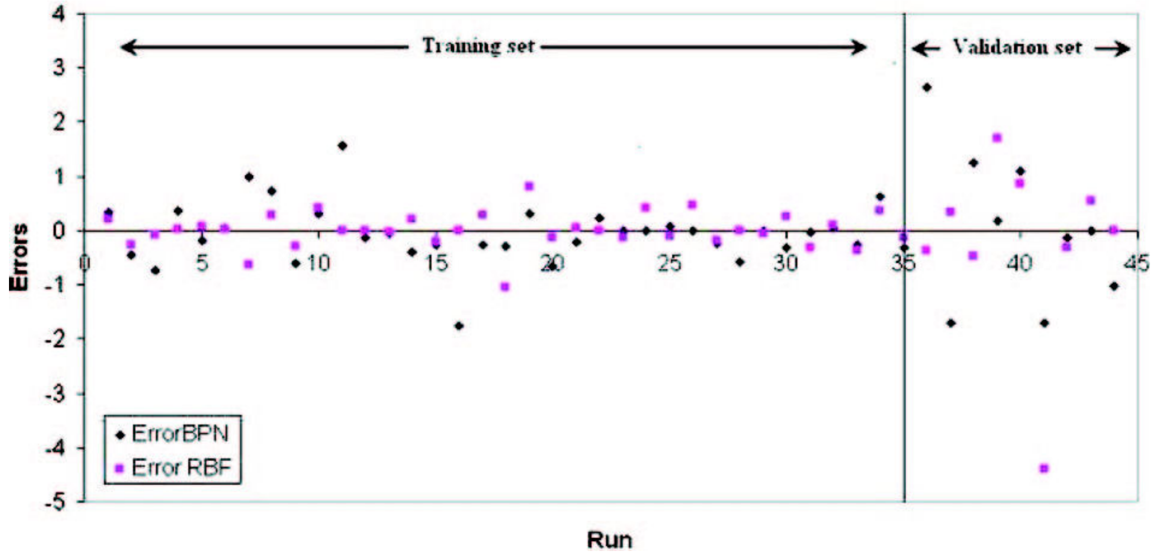

Figure 11 Residuals calculated as the difference between experimental and predicted values for the data set.

ANN's are compared separately with results obtained by experiments and the average absolute error obtained for both the networks. RBFN and BPN models are poorer in predicting Ra at one each of input data but for the rest of the inputs both the models have almost identical generalization ability. The test result accuracy measured in terms of mean absolute error (MAE) for 9 test data are found to be 0.297188 for the BPN and 0.574888 for RBFN. In the case of RBFN, the number of epochs is equal to the number of neurons in the single hidden layer of the network. The error goal is reached in only 19 epochs in RBFN (Fig.10), while 478 epochs are required by the BPN (Fig. 7).

Fig. 11 shows the error for each model, calculated as the difference between the experimental findings and predicted values. It is found that except at two places both the models predict the roughness with reasonable accuracy.

The experimental results and predicted results of 'Ra' by the BPN and RBFN were plotted on the same scale, as shown in Fig. 12. It clearly shows that BPN model is more accurate than RBFN model.

CONCLUSION

In this paper, two artificial intelligence techniques: Back propagation neural network and radial basis function neural network are projected for the prediction of surface roughness of the Electrical discharge machined surface. The results obtained from widespread experiments conducted on AISI D2 steel workpiece materials with diverse machining parameters using copper electrode are compared and validated with the predictions.

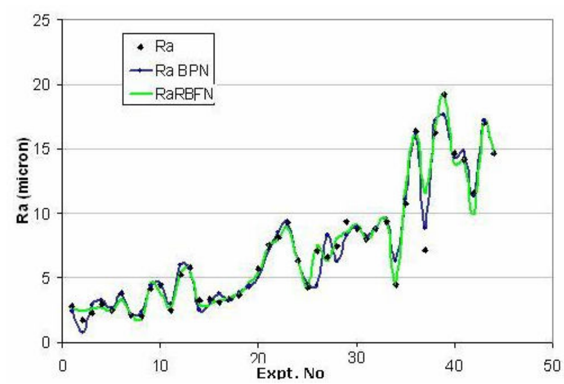

Figure 12 Comparison of surface roughness among the measured data and predictions based on various models: BPN and RBFN

It was found to be close correlation with the experimental results. It was also observed that the RBFN model is quite analogous with BPN for surface roughness prediction and both models offered an agreeable prediction. The BPN demonstrated a slightly better performance compared to the RBFN model i.e. the MAE for test data are 0.297188 for the BPN and 0.574888 for RBFN. However, the RBFN model predicted quite faster. The error goal reached in only 19 epochs while BPN requires 500 epochs. It is important to note that, for BPNs the required number of nodes in the hidden layer found by trial and error method whereas the RBFNs have only one hidden layer with a growing number of neurons. Conclusively speaking, the surface finish of EDMed surface can be predicted by the above models with reasonable accuracy.

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