Advances in Materials Research, *Vol. 6, No. 2 (2017) 169-184*
DOI: https://doi.org/10.12989/amr.2017.6.2.169

Modeling of surface roughness in electro-discharge machining using artificial neural networks

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(Received November 21, 2016, Revised July 7, 2017, Accepted July 11, 2017)

Abstract. Electro-Discharge machining (EDM) is a thermal process comprising a complex metal removal mechanism. This method works by forming of a plasma channel between the tool and the workpiece electrodes leading to the melting and evaporation of the material to be removed. EDM is considered especially suitable for machining complex contours with high accuracy, as well as for materials that are not amenable to conventional removal methods. However, several phenomena can arise and adversely affect the surface integrity of EDMed workpieces. These have to be taken into account and studied in order to optimize the process. Recently, artificial neural networks (ANN) have emerged as a novel modeling technique that can provide reliable results and readily, be integrated into several technological areas. In this paper, we use an ANN, namely, the multi-layer perceptron and the back propagation network (BPNN) to predict the mean surface roughness of electro-discharge machined surfaces. The comparison of the derived results with experimental findings demonstrates the promising potential of using back propagation neural networks (BPNNs) for getting a reliable and robust approximation of the Surface Roughness of Electro-discharge Machined Components.

Keywords: artificial neural networks (ANNs); back propagation neural networks (BPNNs); mean surface roughness; electro-discharge machining (EDM); normalization

1. Introduction

Electro-Discharge Machining is the most widely used and successful technique, among the various non-conventional machining methods, for the high precision manufacturing of a plethora of conductive materials regardless of their mechanical properties. It has been to be a very efficient and effective method for producing complex geometries on difficult-to-work materials; however,

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http://www.techno-press.org/?journal=amr&subpage=7 ISSN: 2234-0912 (Print), 2234-179X (Online)

meta-models enhancing the computational efficiency of a numerical analysis process. This major advantage of a trained ANN over conventional numerical analysis procedures like regression analysis, under the condition that the training and validation data cover the entire range of input parameters values, is that the results can be produced with much less computational effort (Hornik *et al.* 1989, Adeli 2991, Plevris and Asteris 2014 and 2015, Giovanis and Papadopoulos 2015, Mansouri and Kisi 2015, Asteris and Plevris 2013, 2016, Asteris *et al.* 2016, Zhang *et al.* 2016, Xu and Gao 2016, Mansouri *et al.* 2016, Asteris and Kolovos 2017, Asteris *et al.* 2017).

2.1 Back-propagation neural networks

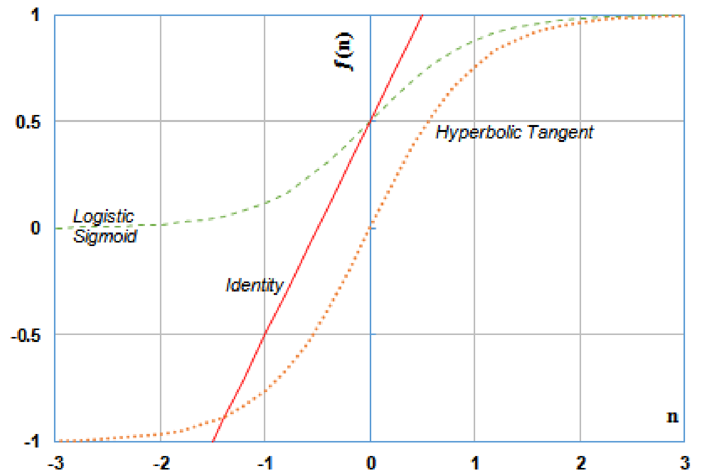
In the present study, we use a Back-Propagation Neural Network (BPNN). This type of NN, works, as follows. During a training phase, the output of the network is compared with the correct answer to compute the error, based on a predefined error function. Then the error is fed back, from the output layer of the network, all the way down to the input layer, through the various intermediate-hidden layers of the network. Based on the error-the discrepancy between the computed and the desired output value, the algorithm adjusts the adaptive weights-the plastic contacts of the connections to the nodes, in each layer of the network. The algorithm, by changing the weights of the connections, seeks to modify the network response, in a direction that reduces the error. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to a state of relatively small output error. At this stage, the network will have reached a certain target function. As the algorithm's name implies, the errors propagate backwards from the output to the input nodes, through the various inner layers nodes. Thus, back-propagation is used to calculate the gradient of the error of the network with respect to the network's modifiable weights. To adjust the weights properly, we use a variant of the back propagation algorithm, based on the Levenberg-Marquard Algorithm (Lourakis 2005) for non-linear optimization. In order to minimize the error, the derivative of the error function with respect to the network weights is calculated, and the weights are then adjusted to reduce the error (thus descending on the surface of the error function). For this reason, back-propagation can only be applied on networks with differentiable activation functions. Back-propagation can give to suitable local networks with quick convergence on satisfactory local error minima.

A BPNN is a feed-forward, multilayer network of standard structure, i.e., neurons are not connected with each other in the layer they belong to, but they are connected with all the neurons of the previous and subsequent layer. A BPNN has a standard structure that can be written as

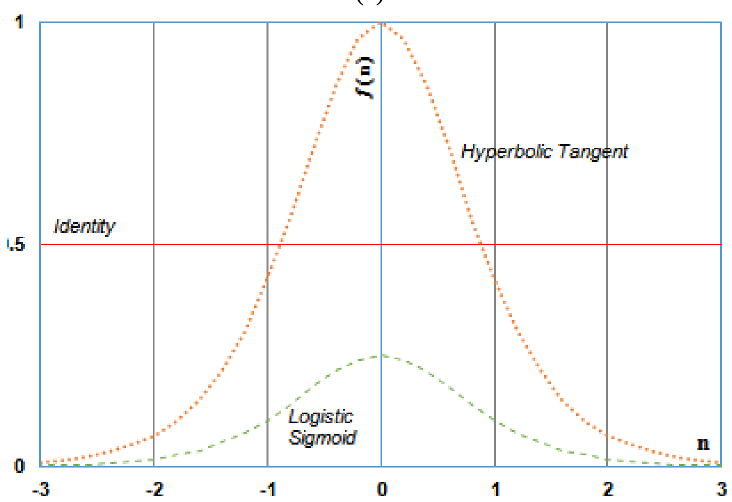
$$\mathrm{N} - \mathrm{H}_1 - \mathrm{H}_2 - \cdots - \mathrm{H}_{\mathrm{NHL}} - \mathrm{M} \tag{1}$$

where N is the number of input neurons (input parameters); $\mathrm{H_i}$ is the number of neurons in the $\mathrm{i-th}$ hidden layer for $\mathrm{i} = 1, \ldots, \mathrm{NHL}$; NHL is the number of hidden layers and M is the number of output neurons (output parameters). Fig. 1 depicts an example of a BPNN composed of an input layer with 5 neurons, two hidden layers with 4 and 3 neurons respectively and an output layer with 2 neurons, i.e., a 5-4-3-2 BPNN.

Another notation for a single node (with the corresponding R-element input vector) of a hidden layer is presented in Fig. 2. For each node, the inputs signals $\mathrm{p}_1, \ \ldots, \ \mathrm{p_R}$ to that node are multiplied by the weights $\mathrm{w}_{1,1}, \ \ldots, \ \mathrm{w}_{1,\mathrm{R}}$ of the connections to that node and the weighted values are fed to the summing junction. At that point, the dot product (W.p) of the single row matrix $\mathrm{W} = [\mathrm{w}_{1,1}, \ldots, \mathrm{w}_{1,\mathrm{R}}]$ and the column vector $\mathrm{p} = [\mathrm{p}_1, \ \ldots, \ \mathrm{p_R}]^{\mathrm{T}}$ is generated. The threshold b (bias) is added to the dot product forming the net input n which is the argument of the transfer function f



(a)



(b)

Fig. 3 Common activation functions (a) and their derivatives (b)

$$f(\mathrm{n}) = \mathrm{n} \tag{3}$$

$$f'(\mathrm{n}) = 1 \tag{4}$$

This function yields output values in the interval (-∞, +∞), while its derivative always yields output values equal to 1. It is worth mentioning that the combination of using nonlinear activation functions among the neurons of hidden units and the identity function for the output layer leads to a robust form of nonlinear regression. The network can predict continuous target values using a linear combination of signals that arise from one or more layers of nonlinear transformations of the input.

The Logistic Sigmoid Activation Function

Step 1: Normalization of data: The normalization is carried out in a pre-processing stage. Pre-processing has been proved to be the most crucial step of any type problem in the field of soft computing techniques such as the artificial neural networks techniques.

Step 2: Development and training of several neural networks: The development and training of the NNs occurs with a number of hidden layers ranging from 1 to 2 and with a number of neurons ranging from nip-1 to 15, where nip correspond to input parameters. Each one of the NNs is developed and trained for a number (nf) of activation functions as well as with and without the use of data preprocessing techniques (step 1).

Step 3: Determination of mean square error: For each one of the above trained NNs the mean square error (MSE) is computed for a set of data (validation data) which have not been used during the training process (training data) of the ANNs.

Step 4: Establishment of upper and lower limits: Upper and lower limits are introduced for each one of the output parameters based on experimental or numerical data as well as reasonable estimations by the users.

Step 5: Selection of optimum architecture: The optimum architecture is the one that gives the minimum mean square error while all the computed output parameters for all the validation data are between the upper and lower limits.

It should be emphasized the importance of the limits established at Step 3 based on the user's expertise, since it is needed wide experience not only in relation to the neural networks but also to the specific field applied in order to establish reasonable estimations.

3. Results and discussion

In this section, the reliability, the effectiveness and the robustness of the above proposed algorithm, for finding of the best architecture of a BPNN, is presented through a step-by-step approach. In particular, the proposed algorithm has been applied for the prediction of the mean surface roughness of electro-discharge machined surfaces.

3.1 Experimental

ED Machining was performed on a HOSTEK SH-38GP (ZNC-P type) electro-discharge machine-tool with working voltage of 30V and open circuit voltage of 100V. Fifty four experiments were conducted in typical dielectric oil (BP250) with electrolytic copper being used as the tool electrode (anode). In particular, three different tool steels, namely AISI D2, P20 modified and premium H13 were machined (cathode), with the specimens being in the form of square plates of dimensions 70 mm×70 mm×10 mm. We varied the pulse current Ie and the pulse-on time, tp, which are considered to be the main operational parameters, over a range from roughing to near finishing. More specifically Ie was set at 5, 10, 15, 20, 25, 30 (A) and tp at 100, 300 and 500 (μs).

We performed the surface texture analysis, using a Rank Taylor-Hobson Surtronic 3+ profilometer equipped with the Talyprof® software. The cut-off length was selected at 0.8 mm whilst 20 measurements were conducted on every specimen at random directions, as it is known that EDMachining generates geometrically isotropic texture (Petropoulos *et al.* 2009). It is worth mentioning that the surface roughness parameter considered was the center-line average (mean) surface roughness, Ra. Worth mentioning that Ra is by far the most commonly used parameter in

Table 1 Continued

Sample	Material	Input: Material Encoding with 3 parameters			Input: Material Encoding with 1 parameter	Input: Pulse current I_e (A)	Input: Pulse duration t_p (μs)	Output: Mean Surface Roughness, R_a (μm)	Comments *
28	AISI P20	0	1	0	2	20	300	13.06	T
29	AISI P20	0	1	0	2	25	300	13.44	V
30	AISI P20	0	1	0	2	30	300	13.34	T
31	AISI P20	0	1	0	2	5	500	7.39	T
32	AISI P20	0	1	0	2	10	500	10.95	V
33	AISI P20	0	1	0	2	15	500	12.12	Test
34	AISI P20	0	1	0	2	20	500	13.39	T
35	AISI P20	0	1	0	2	25	500	14.18	V
36	AISI P20	0	1	0	2	30	500	14.65	T
37	AISI H13	0	0	1	3	5	100	5.32	T
38	AISI H13	0	0	1	3	10	100	6.01	V
39	AISI H13	0	0	1	3	15	100	6.83	Test
40	AISI H13	0	0	1	3	20	100	7.45	T
41	AISI H13	0	0	1	3	25	100	7.76	V
42	AISI H13	0	0	1	3	30	100	7.96	T
43	AISI H13	0	0	1	3	5	300	6.69	T
44	AISI H13	0	0	1	3	10	300	8.14	V
45	AISI H13	0	0	1	3	15	300	10.11	Test
46	AISI H13	0	0	1	3	20	300	11.59	T
47	AISI H13	0	0	1	3	25	300	12.20	V
48	AISI H13	0	0	1	3	30	300	12.62	T
49	AISI H13	0	0	1	3	5	500	7.68	T
50	AISI H13	0	0	1	3	10	500	8.86	V
51	AISI H13	0	0	1	3	15	500	11.37	Test
52	AISI H13	0	0	1	3	20	500	13.34	T
53	AISI H13	0	0	1	3	25	500	14.15	V
54	AISI H13	0	0	1	3	30	500	14.91	T

Note: T: Training Data; V: Validation Data; Test: Test Data

3.2 Normalization of data

As stated above, the normalization of the parameters considered in the database has a significant impact on the ANN procedure. In theory, it's not necessary to normalize numeric data. However, practice has shown that when numeric data values are normalized, neural network training is often more efficient leading to more accurate predictions. Basically, if numeric data is not normalized, and the magnitudes of two predictors are far apart, then a change in the value of a neural network weight has far more relative influence on the value with larger magnitudes.

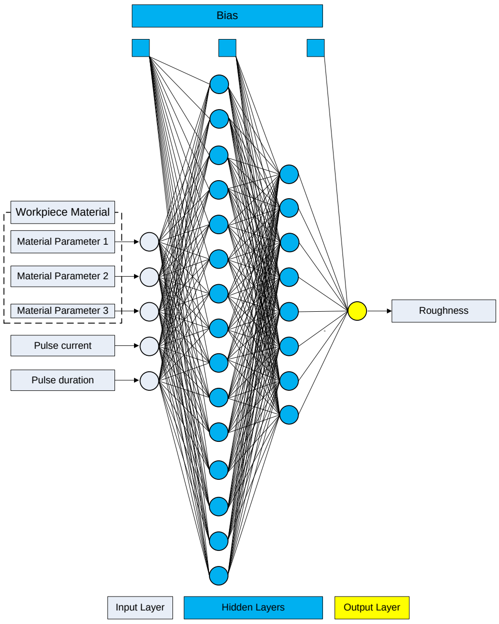


Fig. 4 The Best 5-15-8-1 BPNN based on Pearson's correlation coefficient R

correlation coefficient R and the architecture of the top twenty models are presented in Table 3. Based on these results, the optimum BPNN model is that of 5-15-8-1 (Fig. 4) with Pearson's correlation coefficient R equal to 0.99507 (see first row of Table 3 as well as Fig. 5). This network corresponds to the case of (a) architecture with two hidden layers, (b) the material has been encoded with three input parameters and (c) with ZScore normalization technique. It should be noted that the second one is that of 5-9-8-1 with Pearson's correlation coefficient R equal to 0.99505 (see second row of Table 3) which also corresponds to a NN with two hidden layers and has been derived using the MinMax normalization technique for the case of upper and lower limit value between (-1, 1).

Fig. 6 presents the experimental values in comparison to the predicted values by the optimum BPNN model of 5-15-8-1. It is clear that the mean surface roughness of electro-discharge machined surfaces predicted from the multilayer feed-forward neural network, are very close to the experimental results.

It is also worth mentioning that

• The majority of the top twenty models (19 from 20) corresponds to models with two hidden layers,

• The way of encoding the material is a crucial parameter; in 17 from the top twenty models the material has been modelled using three inputs parameters,

• The majority of the top twenty models (17 from 20), including the optimum one, corresponds to models where the data have been normalized,

• The total of the top twenty models presented in Table 3 have been trained under a number of epochs range between 39 and 168, which means that the developed multilayer feed-forward neural network models can predict the mean surface roughness of electro-discharge machined surfaces with smaller error rates and less computational effort compared with those available in the literature models.

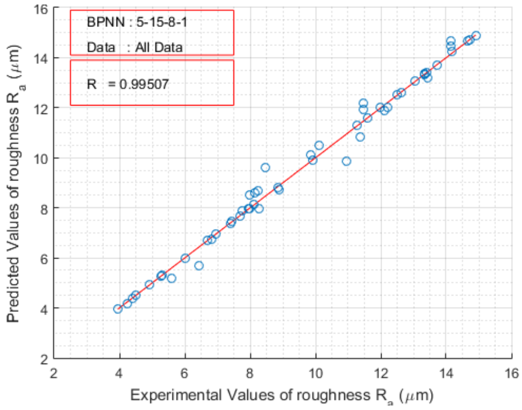


Fig. 5 Pearson's correlation coefficient R of the experimental and predicted Roughness, Ra for the best with two hidden layers BPNN (5-15-8-1)

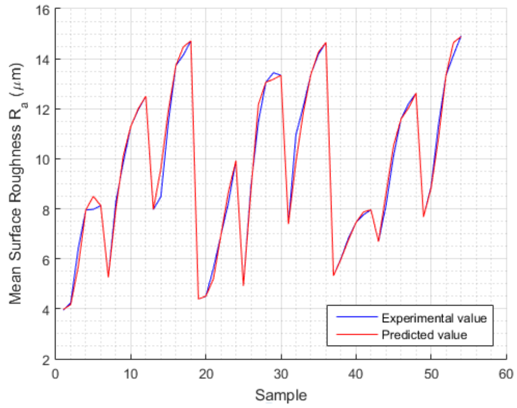
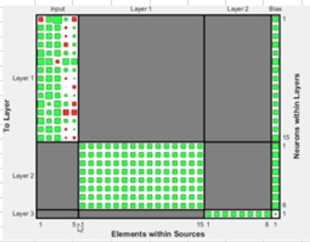


Fig. 6 Experimental vs Predicted values of Surface Roughness

iw{1.1}

-0.737	1.205	2.480	0.526	-0.642
1.104	1.030	0.969	-0.145	0.168
1.126	1.037	0.938	-0.128	0.233
0.863	1.066	0.994	-0.432	0.322
1.384	0.732	1.163	0.423	0.164
1.765	1.369	-0.286	1.095	0.868
0.859	1.115	1.096	0.312	0.215
0.932	1.256	1.012	-0.151	0.024
1.165	1.016	1.036	-0.092	-0.336
0.841	1.566	0.796	0.178	0.154
1.426	0.385	1.439	0.603	-0.483
0.954	0.818	1.363	-0.628	-0.589
1.361	0.727	1.181	0.395	0.176
0.931	1.274	0.985	-0.145	0.071
1.122	0.769	1.010	-0.099	-0.151



b{1.1}
1.052
0.897
0.899
1.077
0.720
1.152
0.929
0.800
0.783
0.797
0.750
0.865
0.732
0.810
1.100

iw{{2.1}}

0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791
0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791
0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791
0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791
0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791
0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791
0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791
0.911	0.789	0.790	0.797	0.794	0.858	0.790	0.790	0.796	0.790	0.785	0.797	0.794	0.790	0.791

b{{2.1}
1.201
1.201
1.201
1.201
1.201
1.201
1.201
1.201

iw{3.2}

0.584	0.584	0.584	0.584	0.584	0.584	0.584	0.584

b{3.1}
0.119

iw{1.1}= Weights values for Input Layers
iw{2.1}= Weights values for first hidden Layers
iw{3.2}= Weights values for second hidden Layers
b{1.1}= Bias values for first hidden layer
b{2.1}= Bias values for second hidden layer
b{3.1}= Bias values for output layer

Fig. 7 Final Weights and Bias Values of the optimum BPNN model 5-15-8-1

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