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Surface Roughness Prediction of Electro-discharge Machined Components Using Artificial Neural Networks

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ABSTRACT

Electro-Discharge machining (EDM) is a thermal process comprising a complex metal removal mechanism, which involves the formation 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 negatively affecting the surface integrity of EDMed workpieces need to be taken into account and studied in order to achieve the optimization of the process. Recently, artificial neural networks (ANN) have emerged as a novel modeling technique capable to provide reliable results and readily integrated into a lot of technological areas. In this paper, ANN models for the prediction of the mean surface roughness of electro-discharge machined surfaces are presented. The comparison of the derived results with experimental findings demonstrates the promising potential of using back propagation neural networks (BPNNs) for the 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)

INTRODUCTION

Electro-Discharge Machining is the most widely and successfully applied technique, among the various non-conventional machining methods, for high precision manufacturing of a plethora of conductive materials regardless of their mechanical properties. It has been proved to be a very efficient method in producing complex geometries on difficult-to-work materials; however, there are several problems pertaining to the resulting surface roughness and texture which in turn affects product quality and limits possible applications. Due to these problems, which are associated with the random nature of surface formation there is lack of analytical models for predicting roughness and empirical models are usually employed based on multi-regression analysis (Petropoulos et al. 2004, Petropoulos et al. 2009, Vaxevanidis et al. 2013,

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Al-Ghamdi and Aspinwall 2014, Al-Ghamdi and Taylan 2015, Das et al. 2014, Kumar et al. 2014, Moghaddam and Kolahan 2015, Pattnaik et al. 2014, Porwal et al. 2014, Pradhan and Das 2015, Pramanick et al. 2014, Rahman Khan et al. 2014, Sarkheyli et al. 2014 and Wang et al. 2014). Detailed and in-depth state-of-the-art reports can be found in Shrivastava and Dubey (2014) and Rao and Kalyankar (2014).

The surface roughness describes the geometry of the surface to be machined and it is interrelated with surface texture and surface integrity. The formation of surface roughness mechanism is very complicated and mainly depends on the machining process (Vaxevanidis et al., 2014) Hence, it is very difficult to determine the surface roughness through analytical equations.

Artificial Neural Networks (ANNs) have emerged as a novel modeling technique applicable to a number of technological areas, especially for problems where the input and output values cannot be directly connected by simple equations. This technique has also found applications to the modeling of manufacturing processes and particularly to EDM (Dini, 1997). So far the relative literature includes mainly publications concerning the application of ANNs for the determination of the removal rate of the process, the optimization of its parameters as well as its on-line monitoring (for a review see Markopoulos et al. 2008). Other artificial intelligence methods such as fuzzy logic and genetic algorithms have also been used for modeling the EDM process (Wang et al., 2003, Rangajanardhaa & Rao, 2009).

In the present paper the application of ANN models for the prediction of the surface roughness of electrical discharge machined surfaces is investigated. These models use data from an extensive experimental research performed concerning surface integrity of EDMed steels and is also a follow-up to a statistical multi-parameter surface roughness analysis already published (Petropoulos et al. 2004, Petropoulos et al. 2006). Three tool steels, namely AISI D2, P20 modified and premium H13 were tested. Based to a design-of-experiments methodology, the pulse current I_e and the pulse-on time, t_p, which are considered to be the main operational parameters, were ranging, from roughing to near finishing, resulting to z different pulse energies.

The ANN models presented in this paper take into consideration the workpiece material, the pulse current and the pulse-on time as input parameters in order to predict the center-line average R_a surface roughness. The suggested neural networks were trained with experimental data from the previous mentioned series of experiments. The proposed neural networks have been proven to be very successful, exhibiting very reliable predictions, and thus providing a possible way to avoid time- and money-consuming experiments.

ARCHITECTURE OF ARTIFICIAL NEURAL NETWORKS

This section summarizes the artificial neural networks (ANNs) mathematical and computational aspects. Special emphasis is given on a heuristic algorithm which is proposed for the development of a reliable and robust ANN that can predict the mean surface roughness of electro-discharge machined surfaces. ANNs are information processing models configured for a specific application through a training process. Trained ANN maps rapidly a given input into the desired output quantities (similar to curve fitting procedures) and thereby can be used as 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, Asteris and Plevris 2013 and 2016, Asteris et al. 2016).

Back-Propagation Neural Networks

In the present study, we use a Back-Propagation Neural Network (BPNN). In this type of NNs, the output values are compared with the correct answer to compute the value of a predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by a small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to a state of small calculation error. At this stage the network has reached a certain target function. As the algorithm's name implies, the errors propagate backwards from the output nodes to the inner ones. 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 weights properly, a general method is applied for non-linear optimization, called gradient descent. 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 $\mathrm{i} - \mathrm{th}$ 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 individual element inputs $p_1, \ldots, p_R$ are multiplied by the weights $w_{1,1}, \ldots, w_{1,R}$ and the weighted values are fed to the summing junction. At that point, the dot product (W.p) of the single row matrix $W = [w_{1,1}, \ldots, w_{1,R}]$ and the column vector $p = [p_1, \ldots, p_R]^T$ 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:

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \ \ldots + \ w_{1,R}p_R + b = Wp + b \tag{2}$$

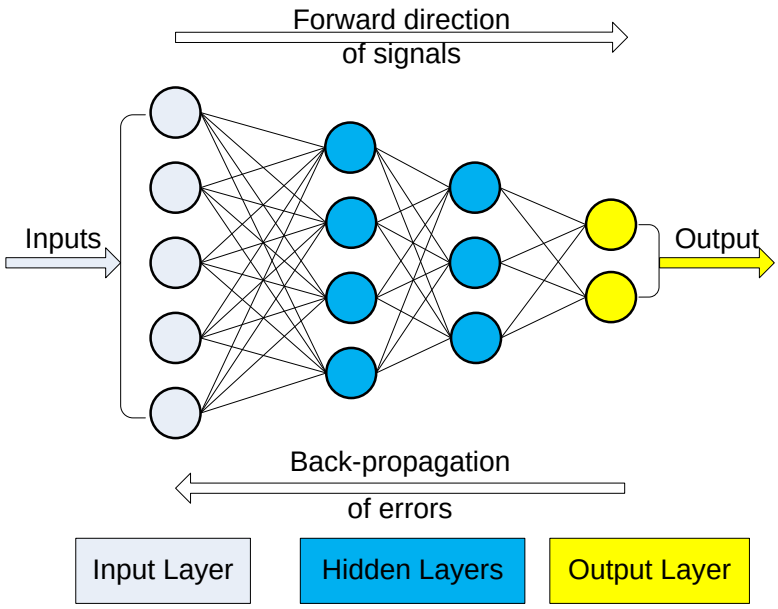


Fig.1 A 5-4-3-2 BPNN.

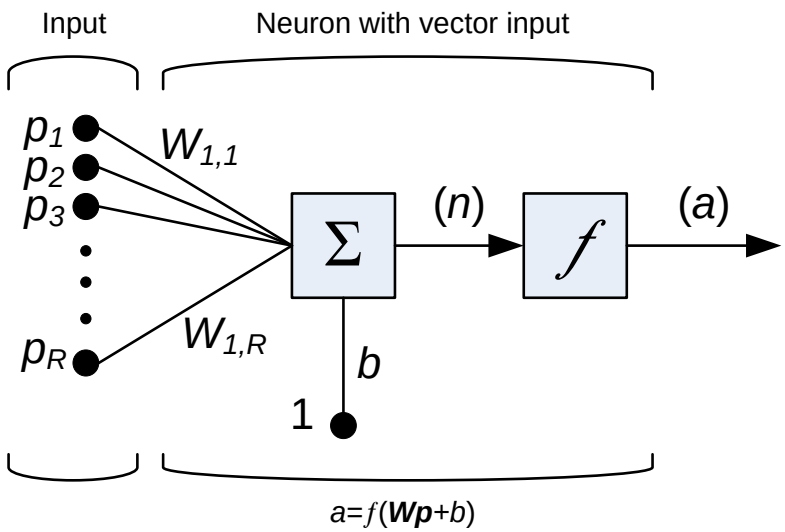


Fig.2 A neuron with a single R-element input vector.

Transfer functions

The choice of the transfer function may strongly influence the complexity and performance of neural networks. Transfer functions are used in ANNs as activation functions connecting the weights w_i of a neuron i to the input. Although sigmoidal transfer functions are the most commonly used, there is no a priori reason why models based on such functions should always provide optimal decision borders. Past studies (Bartlett 1998, Karlik and Olgac 2011) have proposed a large number of alternative transfer functions. In the present study the following functions are used:

The identity ('linear') transfer function

The simplest transfer function commonly used is that of the identity activation function (Fig. 3). The output of the identity function and its derivative are given by

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

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

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

Another function, which is often used as output activation function, is the logistic sigmoid (Fig. 3). The output of this function and its derivative are given by

$$f(\mathrm{n}) = \frac{1}{\mathrm{e}^{-\mathrm{n}}+1} \tag{5}$$

$$f'(\mathrm{n}) = \frac{1+\mathrm{e}^{-\mathrm{n}}+1}{(1+\mathrm{e}^{-\mathrm{n}})^2} \tag{6}$$

This function, yielding output values in the interval [0, +1] is suitable for binary classification problems for which the outputs values are in the interval [0, +1].

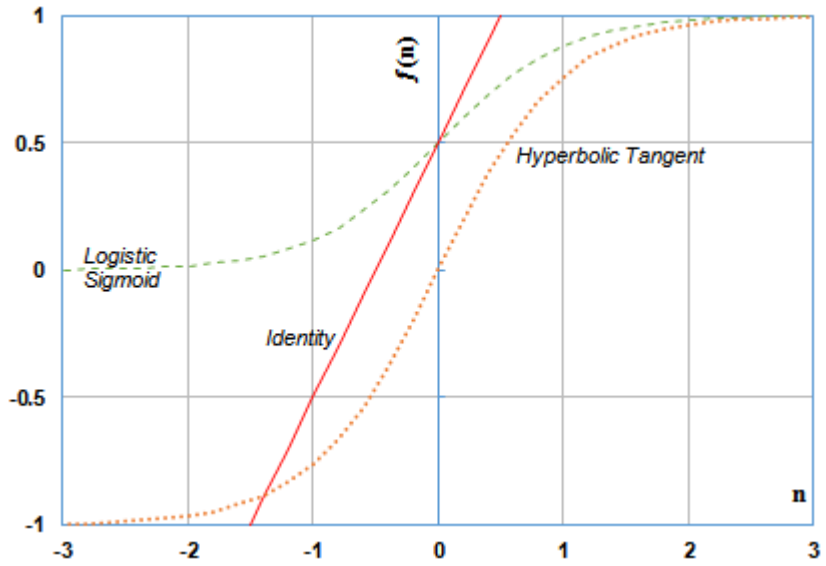
The Hyperbolic Tangent activation function

An alternative to the logistic sigmoid is the hyperbolic tangent, or tanh function (Fig. 3).The output of the hyperbolic tangent function and its derivative are given by

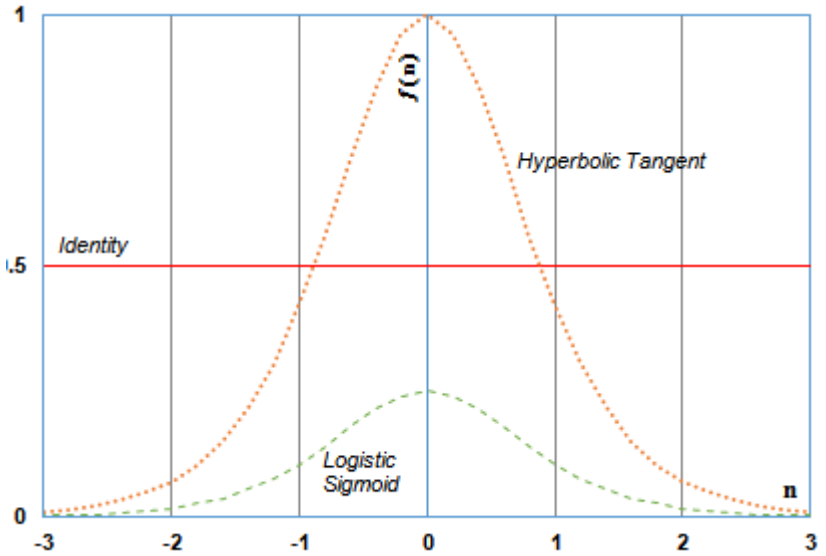
$$f(\mathrm{n}) = \frac{\mathrm{e}^{2\mathrm{n}}-1}{\mathrm{e}^{2\mathrm{n}}+1} \tag{7}$$

$$f'(\mathrm{n}) = 4\frac{\mathrm{e}^{2\mathrm{n}}}{(\mathrm{e}^{2\mathrm{n}}+1)^2} \tag{8}$$

The tanh function is also sigmoidal ("s"-shaped). This function yields output values in the interval [-1, 1], while its derivative yields output values in the interval [0, 1]. Thus strongly negative inputs to the tanh will map to negative outputs. Additionally, only zero-valued inputs are mapped to near-zero outputs. These properties make the network less likely to get "stuck" during training.



(a)



(b)

Fig.3 (a) Common Activation functions, (b) Their derivatives.

Finding the best architecture of a ANN or how to avoid the over-fitting problem

The best architecture of an ANN can be identified, given the known number of parameters for input and output, for the present application), by estimating the optimum number of hidden layers and neurons.

The estimation of the best architecture avoids the over-fitting problem. Over-fitting generally occurs when a model is excessively complex, such as having too many parameters relative to the number of observations as well as when the training data do not cover the entire range of the input parameters values of the problem. As an extreme example, when the number of

parameters is equal or exceeds the observations, a simple model can predict the training data by memorizing them but fails to predict new ones by not learning to generalize. In order to prevent over-fitting several techniques/algorithms and criteria have been proposed (Papadopoulos et al. 2012, Lamanna et al. 2012, Chen 2013, Giovanis and Papadopoulos 2015, Asteris et al. 2016) for determining the correct number of neurons with their hidden layer based mainly on the number of inputs and output parameters (Blum 1992, Boger and Guterman 1997, Berry and Linoff 1997). In the present work, a simple heuristic algorithm is proposed achieving a reliable and robust ANN suitable for predicting the parameter/function that contains a continuous mapping from one finite space to another. The steps of the proposed algorithm which can reliably predict the Surface Roughness of Electro-discharge Machined Components are the following:

Step 1. Normalization of data: The normalization is a pre-processing stage, which 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.

RESULTS AND DISCUSSION

In this section, the reliability, the effectiveness and the robustness of the above proposed algorithm, for the 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.

Experimental

EDMachining 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 x 70 mm x 10 mm. The pulse current, I_e, and the

pulse-on time, tp, which were considered to be the main operational parameters varied over a range from roughing to near finishing. More specifically I_e was set at 5, 10, 15, 20, 25, 30 [A] and t_p at 100, 300 and 500 [μs].

The surface texture analysis was performed 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). The surface roughness parameter considered was the center-line average (mean) surface roughness, R_a. Worth mentioning that Ra is by far the most commonly used parameter in surface finish measurement and for general quality control. Despite its inherent limitations, it is easy to measure and offers a good overall description of the height characteristics of a surface profile (Petropoulos et al. 2004).

The process parameters and the mean surface roughness values measured are tabulated in Table 1. Note that for the present research experiments with operational parameters reported in (Markopoulos et al. 2008 and Vaxevanidis et al. 2013) where repeated and additional experiments were performed in order to follow best practice concerning the design of experiments (Phadke, 1989).

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 a better predictor. 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. In the present study, during the pre-processing stage, the Min-Max Normalization (Delen et al. 2006) has been used. In particular, the two input parameters Pulse current (I_e) and Pulse duration (t_p) as well as the output parameter Roughness (R_a) have been normalized using the Min-Max Normalization which is a simple technique. In particular, to avoid problems associated with low learning rates of the ANN (Iruansi et al. 2010) it is better to normalize the values of the parameters between an appropriate upper and lower limit value of the subject parameter. The above mentioned three parameters have been normalized between [0, 1].

Material Encoding

During the procedure of the BPNN model development were given special emphasis in the materials encoding (modeling) and this due to the fact that the experimental data reported in three different materials (AISI D2, AISI P20 and AISI H13). Specifically, for the simulation of the quality (characteristics) of the materials, two cases have been investigated. In the first case the representation of the material has been achieved through a single input parameter with values 1, 2 and 3 for the materials AISI D2, AISI P20 and AISI H13, respectively. In the second case the representation of the material has been achieved through three input parameters with values 1, 0, 0 for the material AISI D2, 0, 1, 0 for the material AISI P20 and 0, 0, 1 for the material AISI H13.

Table 1: Experimental data/results and input and output parameters of BPNNs

Sample	**Material**	**Input**						**Output**	**Comments ***
		Material Encoding with				Pulse current I_e (A)	Pulse duration t_p (µs)	Mean Surface Roughness, R_a (µm)	
		3 parameters			1 parameter				
`1	AISI D2	1	0	0	1	5	100	3.95	T
2	AISI D2	1	0	0	1	10	100	4.24	V
3	AISI D2	1	0	0	1	15	100	6.42	Test
4	AISI D2	1	0	0	1	20	100	7.95	T
5	AISI D2	1	0	0	1	25	100	7.98	V
6	AISI D2	1	0	0	1	30	100	8.12	T
7	AISI D2	1	0	0	1	5	300	5.26	T
8	AISI D2	1	0	0	1	10	300	8.27	V
9	AISI D2	1	0	0	1	15	300	9.85	Test
10	AISI D2	1	0	0	1	20	300	11.29	T
11	AISI D2	1	0	0	1	25	300	11.97	V
12	AISI D2	1	0	0	1	30	300	12.50	T
13	AISI D2	1	0	0	1	5	500	7.97	T
14	AISI D2	1	0	0	1	10	500	8.48	V
15	AISI D2	1	0	0	1	15	500	11.46	Test
16	AISI D2	1	0	0	1	20	500	13.72	T
17	AISI D2	1	0	0	1	25	500	14.15	V
18	AISI D2	1	0	0	1	30	500	14.71	T
19	AISI P20	0	1	0	2	5	100	4.39	T
20	AISI P20	0	1	0	2	10	100	4.50	V
21	AISI P20	0	1	0	2	15	100	5.61	Test
22	AISI P20	0	1	0	2	20	100	6.94	T
23	AISI P20	0	1	0	2	25	100	8.23	V
24	AISI P20	0	1	0	2	30	100	9.92	T
25	AISI P20	0	1	0	2	5	300	4.92	T
26	AISI P20	0	1	0	2	10	300	8.90	V
27	AISI P20	0	1	0	2	15	300	11.48	Test

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

(Continued)

Table 1: (Continued)

Experimental data/results and input and output parameters of BPNNs

Sample	Material	Input						Output	Comments *
		Material Encoding with				Pulse current I_e (A)	Pulse duration t_p (µs)	Mean Surface Roughness, R_a (µm)	
		3 parameters			1 parameter				
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

BPNN model development

Based on the above described algorithm, 1440 BPNN models have been developed and investigated. Each one of these models was trained by means of 27 datasets (out of the total of 54, that is a 50% percentage) and the reliability of the results was validated by means of 18 datasets (33.33%) and was tested against the remaining 9 data sets (16.67% of total), by calculating the Pearson's correlation coefficient R. The parameters used for the training of NN models are summarized in Table 2. The above data sets have been selected by dividing the total data set (54 experiments) using specified indices as it is shown in the last column ("Comments") of the Table 1.

Table 2: Training Parameters of BBNN models

Parameter	Value
Training Goal	0
Epochs	1000
Learning Rate	0.10
Momentum	0.10
Cost Function	MSE; SSE
Transfer Functions	Tansig (T); Logsig (L)
Initial Weights of Hidden Layers	1.00
Initial Weights of Bias	1.00

Note:
MSE: Mean Square Error; SSE: Sum Square Error
Tansig (T): Hyperbolic Tangent Sigmoid transfer function
Logsig (L): Log-sigmoid transfer function

The total of the 1440 developed NN models, which have been ranked based on Pearson's 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 5-14-10-1 (Figure 4) with Pearson's correlation coefficient R equal to 0.99450 (see first row of Table 3 as well as Figure 6)). 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) without the use of any normalization technique. It should be noted that the second one is that of 5-14-1 (Figure 5) with Pearson's correlation coefficient R equal to 0.99438 (see second row of Table 3 as well as Figure 7) which corresponds to a NN with only one hidden layer. It is also worth mentioning that

- the majority of the top twenty models (18 from 20) corresponds to models with two hidden layers,
- the way of encoding the material is a crucial parameter; in 16 from the top twenty models the material has been modelled using three inputs parameters,
- the total of the top twenty models presented in Table 3 have been trained under a number of epochs range between 43 and 282, 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.

Table 3: Ranking of the top twenty best architectures of BPNNs based on Pearson's correlation coefficient R

Ranking	Material Encoding	Cost Function	Preprocess	Architecture (Code)	Training Functions	Pearson's R	Number of Epochs
1	3	MSE	No	5-14-10-1	T-L-T	0.99450	67
2	3	MSE	MinMax	5-14-1	T-T	0.99438	66
3	3	SSE	MinMax	5-16-6-1	T-T-T	0.99435	51
4	3	MSE	No	5-13-11-1	T-T-T	0.99363	79
5	3	SSE	No	5-9-9-1	T-T-T	0.99353	117
6	3	MSE	MinMax	5-15-6-1	T-T-T	0.99326	76
7	3	MSE	MinMax	5-9-5-1	T-T-T	0.99293	78
8	3	MSE	MinMax	5-15-9-1	T-T-T	0.99293	114
9	3	MSE	MinMax	5-10-10-1	T-L-T	0.99290	76
10	1	SSE	No	3-15-11-1	T-L-T	0.99287	84
11	3	SSE	No	5-15-8-1	T-T-T	0.99277	63
12	3	SSE	No	5-15-14-1	T-L-T	0.99277	282
13	3	MSE	No	5-12-1	L-T	0.99273	62
14	1	MSE	No	3-11-10-1	T-T-T	0.99257	129
15	3	SSE	MinMax	5-15-6-1	T-L-T	0.99255	64
16	1	MSE	minmax	3-11-8-1	T-T-T	0.99252	43
17	3	SSE	MinMax	5-15-14-1	T-L-T	0.99252	78
18	1	SSE	No	3-10-6-1	T-T-T	0.99251	54
19	3	SSE	No	5-15-11-1	T-L-T	0.99233	79
20	3	MSE	MinMax	5-14-10-1	T-L-T	0.99227	52

Note:
Material Encoding: 3 means that 3 inputs parameters have been used for the encoding of the material encoding while Material Encoding: 1 means that only1 input parameter has been used for the encoding of the material.

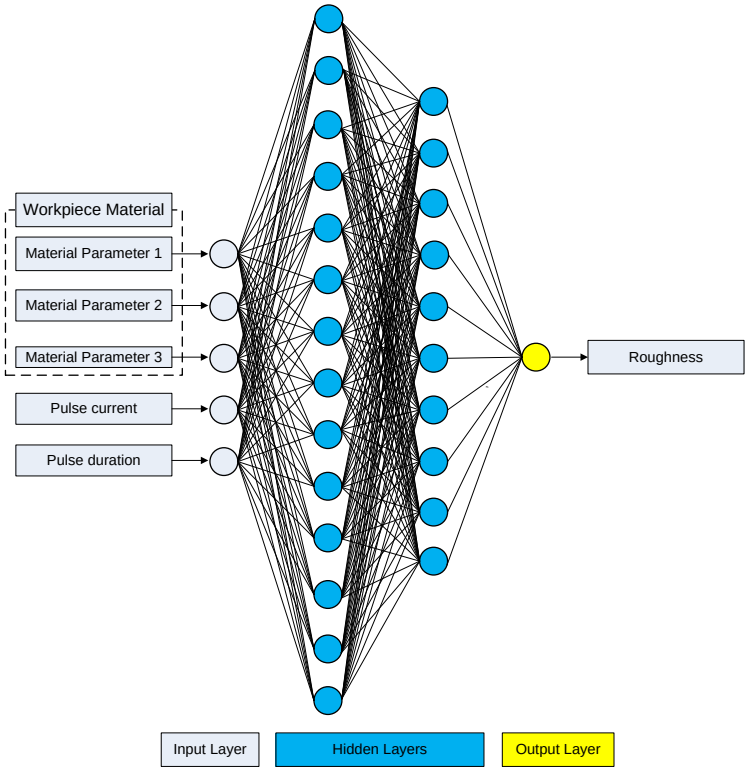


Fig.4 The Best with two hidden layers (5-14-10-1) BPNN based on Pearson's correlation coefficient R.

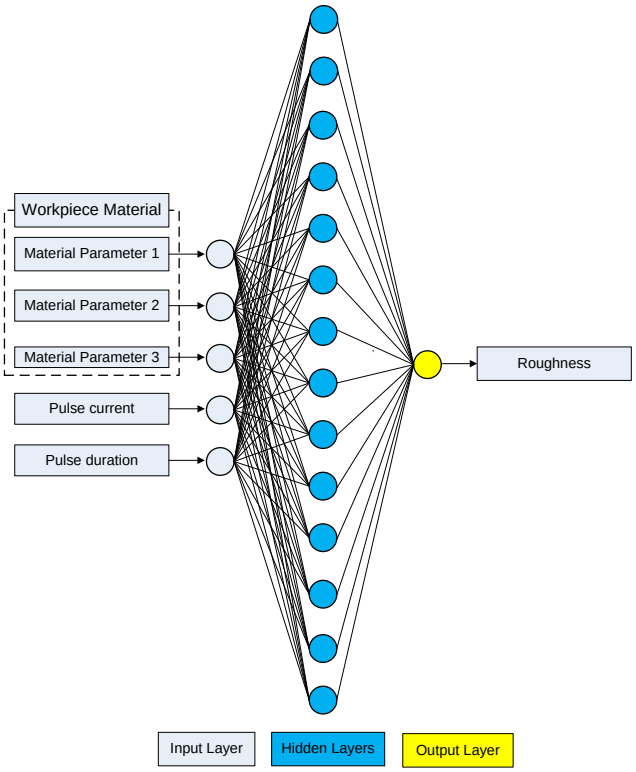


Fig5 The Best with one hidden layer (5-14-1) BPNN based on Pearson's correlation coefficient R.

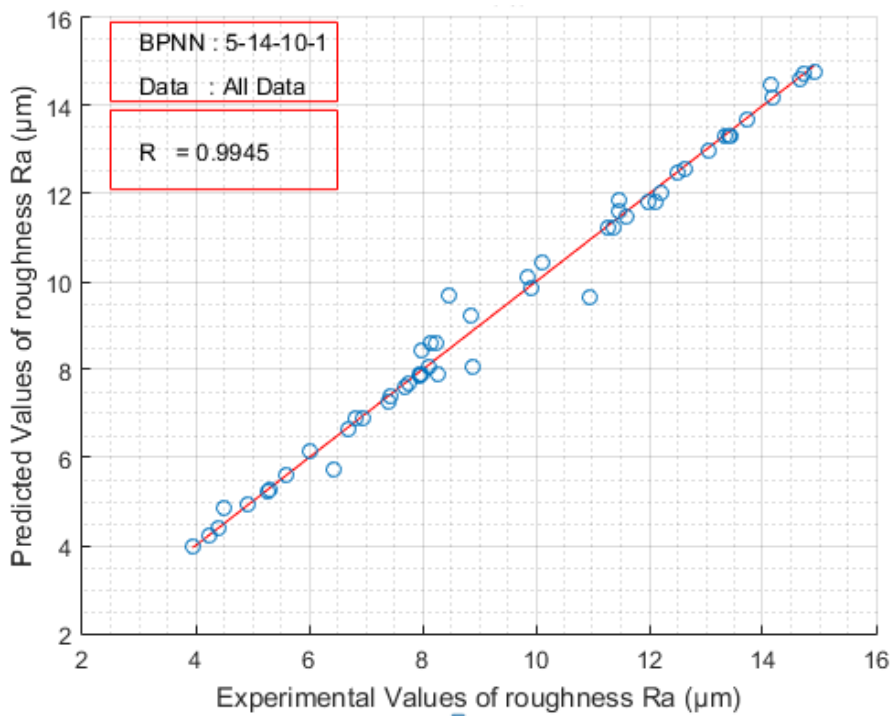


Fig.6 Pearson's correlation coefficient R of the experimental and predicted Roughness, Ra for the best with two hidden layers BPNN (5-14-10-1).

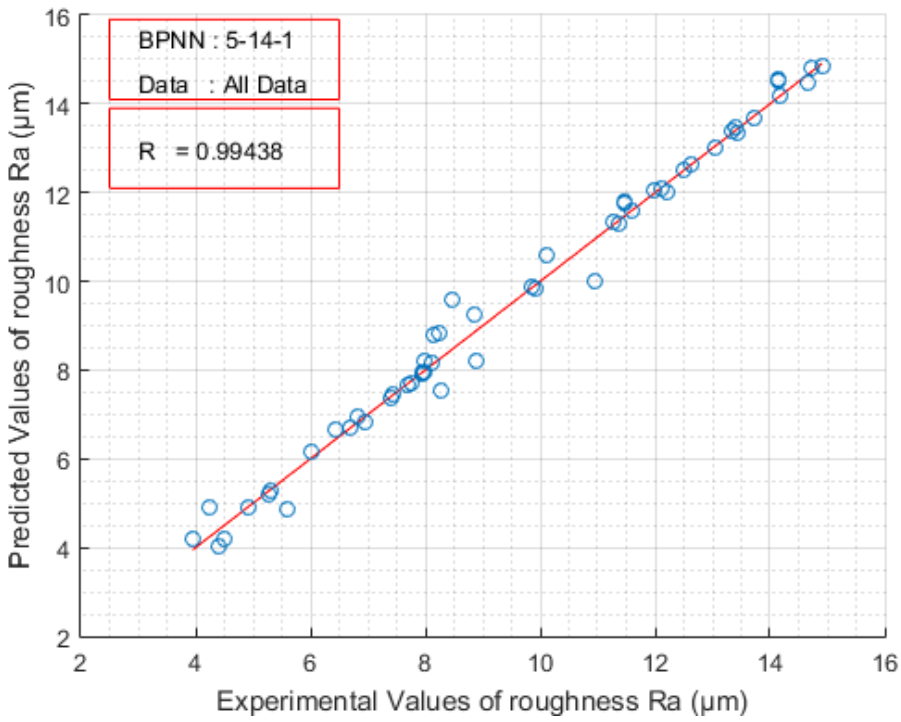


Fig.7 Pearson's correlation coefficient R of the experimental and predicted Roughness, Ra for the best with one hidden layer BPNN (5-14-1).

CONCLUSIONS

In this paper, the artificial neural networks method was assessed by investigating its accuracy in predicting the mean surface roughness of electro-discharge machined surfaces. In particular, a novel heuristic algorithm was proposed to find the optimum structure of a set of multi layered feed-forward back-propagation neural networks. Based on this algorithm a ranking list of the best architectures of neural network models based on the Pearson's correlation coefficient R was selected. The mean surface roughness of electro-discharge machined surfaces predicted from the multilayer feed-forward neural network, are very close to the experimental results as confirmed by correlation coefficient R. In conclusion, mean surface roughness of electro-discharge machined surfaces can be predicted by multilayer feed-forward neural network model with smaller error rates and less computational effort.

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REFERENCES

Adeli, H. (2001). Neural networks in civil engineering: 1989-2000, Computer-Aided Civil and Infrastructure Engineering, Volume 16, Issue 2, Pages 126-142.

Al-Ghamdi, K.A., Aspinwall, E. (2014). Modelling an EDM process using multilayer perceptron network, RSM, and high-order polynomial, Advances in Mechanical Engineering, 2014, 791242.

Al-Ghamdi, K., Taylan, O. (2015). A comparative study on modelling material removal rate by ANFIS and polynomial methods in electrical discharge machining process, Computers and Industrial Engineering, 79, pp. 27-41.

Asteris, P.G., Plevris, V. (2013). Neural network approximation of the masonry failure under biaxial compressive stress, ECCOMAS Special Interest Conference - SEECCM 2013: 3rd South-East European Conference on Computational Mechanics, Proceedings - An IACM Special Interest Conference, pp. 584-598.

Asteris, P.G., Tsaris, A.K., Cavaleri, L., Repapis, C.C., Papalou, A., Di Trapani, F., Karypidis, D.F. (2016). Prediction of the fundamental period of infilled rc frame structures using artificial neural networks, Computational Intelligence and Neuroscience, 2016, 5104907.

Asteris, P.G., Plevris, V. (2016). Anisotropic Masonry Failure Criterion Using Artificial Neural Networks, Neural Computing and Applications (NCAA), DOI: 10.1007/s00521-016-2181-3.

Bartlett, P.L. (1998). The sample complexity of pattern classification with neural networks: The size of the weights is more important than the size of the network, IEEE Transactions on Information Theory, Volume 44, Issue 2, Pages 525-536.

Berry, M.J.A., Linoff, G. (1997). Data Mining Techniques, NY: John Wiley & Sons.

Blum, A. (1992). Neural Networks in C++, NY: Wiley.

Boger, Z., Guterman, H. (1997). Knowledge extraction from artificial neural network models, IEEE Systems, Man, and Cybernetics Conference, Orlando, FL, USA.

Chen, Z. (2013). An overview of bayesian methods for neural spike train analysis, Computational Intelligence and Neuroscience, Volume 2013, 2013, Article number 251905.

Das, M.K., Kumar, K., Barman, T.K., Sahoo, P. (2014). Prediction of surface roughness in edm using response surface methodology and artificial neural network, Journal of Manufacturing Technology Research, 6 (3-4), pp. 93-112.

Delen, D., Sharda, R., Bessonov, M. (2006). Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks, Accident Analysis and Prevention, 38 (3), pp. 434-444.

Dini, G. (1997). Literature database on applications of artificial intelligence methods in manufacturing engineering, *Annals of the CIRP*, *46*(2), 681-690.

Giovanis, D.G., Papadopoulos, V. (2015). Spectral representation-based neural network assisted stochastic structural mechanics, Engineering Structures, Volume 84, Pages 382-394.

Hornik, K., Stinchcombe, M., White, H. (1989). Multilayer feedforward networks are universal approximators, Neural Networks, Volume 2, Issue 5, Pages 359-366.

Iruansi, O., Guadagnini, M., Pilakoutas, K., Neocleous, K. (2010). Predicting the Shear Strength of RC Beams without Stirrups Using Bayesian Neural Network, in 4th International Workshop on Reliable Engineering Computing (REC 2010).

Karlik, B., Olgac, A.V. (2011). Performance Analysis of Various Activation Functions in Generalized MLP Architectures of Neural Networks, International Journal of Artificial Intelligence And Expert Systems (IJAE), 1(4), 111-122.

Kumar, S., Batish, A., Singh, R., Singh, T.P. (2014). A hybrid Taguchi-artificial neural network approach to predict surface roughness during electric discharge machining of titanium alloys, Journal of Mechanical Science and Technology, 28 (7), pp. 2831-2844.

Lamanna, J., Malgaroli, A., Cerutti, S., Signorini, M.G. (2012). Detection of fractal behavior in temporal series of synaptic quantal release events: A feasibility study, Computational Intelligence and Neuroscience, Volume 2012, 2012, Article number 704673.

Markopoulos, A.P., Manolakos, D.E., Vaxevanidis, N.M. (2008). Artificial neural network models for the prediction of surface roughness in electrical discharge machining, Journal of Intelligent Manufacturing, 19 (3), pp. 283-292.

Moghaddam, M.A., Kolahan, F. (2015). An optimised back propagation neural network approach and simulated annealing algorithm towards optimisation of EDM process parameters, International Journal of Manufacturing Research, 10 (3), pp. 215-236.

Papadopoulos, V., Giovanis, D.G., Lagaros, N.D., Papadrakakis, M. (2012). Accelerated subset simulation with neural networks for reliability analysis, Computer Methods in Applied Mechanics and Engineering, Volume 223-224, Pages 70-80.

Pattnaik, S., Karunakar, D.B., Jha, P.K. (2014). A prediction model for the lost wax process through fuzzy-based artificial neural network, Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, 228 (7), pp. 1259-1271.

Petropoulos, G., Vaxevanidis, N.M., Pandazaras, C. (2004). Modeling of surface finish in electro-discharge machining based upon statistical multi-parameter analysis, Journal of Materials Processing Technology, *155*, 1247-1251.

Petropoulos, G., Vaxevanidis, N., Iakovou, A., David, K. (2006). Multi-parameter modeling of surface texture in EDMachining using the design of experiments methodology. InMaterials science forum, 526, 157-162.

Petropoulos, G.P., Vaxevanidis, N.M., Radovanovic, M., Zoler, C. (2009). Morphological: Functional Aspects of Electro-Discharge Machined Surface Textures, Strojniški vestnik, 55(2), 95-103.

Phadke, M.S. (1989). Quality engineering using design of experiments. In Quality Control, Robust Design, and the Taguchi Method, 31-50, Springer US.

Plevris, V., Asteris, P.G. (2014). Modeling of masonry compressive failure using Neural Networks, OPT-i 2014 - 1st International Conference on Engineering and Applied Sciences Optimization, Proceedings, pp. 2843-2861.

Plevris, V., Asteris, P.G. (2014). Modeling of masonry failure surface under biaxial compressive stress using Neural Networks, Construction and Building Materials, 55, pp. 447-461.

Plevris, V., Asteris, P. (2015). Anisotropic failure criterion for brittle materials using Artificial Neural Networks, COMPDYN 2015 - 5th ECCOMAS Thematic Conference on Computational Methods in Structural Dynamics and Earthquake Engineering, pp. 2259-2272.

Porwal, R.K., Yadava, V., Ramkumar, J. (2014). Neural network based modelling and GRA coupled PCA optimization of hole sinking electro discharge micromachining, International Journal of Manufacturing, Materials, and Mechanical Engineering, 4 (1), pp. 1-21.

Pradhan, M.K., Das, R. (2015). Application of a general regression neural network for predicting radial overcut in electrical discharge machining of AISI D2 tool steel, International Journal of Machining and Machinability of Materials, 17 (3-4), pp. 355-369.

Pramanick, A., Saha, N., Dey, P.P., Das, P.K. (2014). Wire EDM process modeling with artificial neural network and optimization by grey entropy-based taguchi technique for machining pure zirconium diboride, Journal of Manufacturing Technology Research, 5 (3-4), pp. 99-116.

Rahman Khan, Md.A., Rahman, M.M., Kadirgama, K. (2014). Neural network modeling and analysis for surface characteristics in electrical discharge machining, Source of the DocumentProcedia Engineering, 90, pp. 631-636.

Rangajanardhaa, G., Rao, S. (2009). Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm. Journal of materials processing technology, 209(3), 1512-1520.

Rao, R.V., Kalyankar, V.D. (2014). Optimization of modern machining processes using advanced optimization techniques: A review, International Journal of Advanced Manufacturing Technology, 73 (5-8), pp. 1159-1188.

Sarkheyli, A., Zain, A.M., Sharif, S. (2015). A multi-performance prediction model based on ANFIS and new modified-GA for machining processes, Journal of Intelligent Manufacturing, 26 (4), pp. 703-716.

Shrivastava, P.K., Dubey, A.K. (2014). Electrical discharge machining-based hybrid machining processes: A review, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 228 (6), pp. 799-825.

Vaxevanidis, N.M., Kechagias, J.D., Fountas, N.A., Manolakos, D.E. (2014). Evaluation of machinability in turning of engineering alloys by applying artificial neural networks, Open Construction and Building Technology Journal, 8 (1), pp. 389-399.

Vaxevanidis, N.M., Fountas, N., Tsakiris, E., Kalogeropoulos G,. Sideris, J. (2013). Multi Parameter Analysis and Modeling of Surface Finish in Electro-Discharge Machining of Tool Steels, Nonconventional Technologies Review, 27(3), 87-90.

Wang, K., Gelgele, H.L., Wang, Y., Yuan, Q., Fang, M. (2003). A hybrid intelligent method for modelling the EDM process, International Journal of Machine Tools & Manufacture, **43**, 995-999.

Wang, G., Zhou, H., Wang, Y., Yuan, X. (2014). Modeling surface roughness based on artificial neural network in mould polishing process, 2014 IEEE International Conference on Mechatronics and Automation, IEEE ICMA 2014, 6885799, pp. 799-804.