J Intell Manuf (2008) 19:283–292
DOI 10.1007/s10845-008-0081-9

Artificial neural network models for the prediction of surface roughness in electrical discharge machining

Angelos P. Markopoulos · Dimitrios E. Manolakos · Nikolaos M. Vaxevanidis

Received: 1 January 2007 / Accepted: 1 July 2007 / Published online: 24 January 2008
© Springer Science+Business Media, LLC 2008

Abstract In the present paper Artificial Neural Networks (ANNs) models are proposed for the prediction of surface roughness in Electrical Discharge Machining (EDM). For this purpose two well-known programs, namely Matlab® with associated toolboxes, as well as Netlab®, were employed. Training of the models was performed with data from an extensive series of EDM experiments on steel grades; the proposed models use the pulse current, the pulse duration, and the processed material as input parameters. The reported results indicate that the proposed ANNs models can satisfactorily predict the surface roughness in EDM. Moreover, they can be considered as valuable tools for the process planning for EDMachining.

Keywords Artificial neural networks · Modeling · Surface roughness · Electrical discharge machining (EDM)

Introduction

Electrical discharge machining (EDM) is one of the most extensively used non-conventional material removal processes. It is considered especially suitable for machining complex contours, for high accuracy and for materials that are not amenable to conventional removal methods (Ho and Newman 2003). To achieve electrical discharge machining by the preferential erosion of the work electrode, a succession of discrete discharge pulses is applied between the tool and the workpiece both immersed in a dielectric fluid. Stability of operating conditions is usually secured by a servo-controlled mechanism, so that the cutting tool impresses its complementary shape on the workpiece with a small "over-cut".

However, EDM is a thermal process with a complex metal removal mechanism, involving the formation of a plasma channel between the tool and workpiece electrodes, melting and evaporation action and shock waves. As a result phase changes, tensile residual stresses, cracking and metallurgical transformation of the machined material may be observed. The above are included in the term "surface integrity" and determine the operational behavior of the machined parts (Mamalis et al. 1987).

It should be noted that although nowadays EDM is an established technology in tools and dies industry and is also integrated within CIM/CAPP environments (De Silva and McGeough 2000), is still one of the expertise-demanding processes in the manufacturing industry. A complete, clear, and scientifically admissible theory of EDM has not yet been established. The best explanation of EDM material removal mechanism is offered by the thermo-electric theory, as established by extensive experimental studies; for an overview see (Mamalis et al. 1987; Ho and Newman 2003). Three stages can be distinguished:

(i) Ionization and arc formation at a localized area between the electrodes, following the application of a voltage exceeding the breakdown voltage.
(ii) The occurrence of the main discharge as an electron avalanche striking the anode; low electrical resistance in the discharge channel, hydraulic restriction of the dielectric and the magnetic pinch effect establish high current densities. The cathode is struck by ions and is heated less rapidly than the anode.

A. P. Markopoulos · D. E. Manolakos (✉)
Mechanical Engineering Department, Manufacturing Technology Division, National Technical University of Athens, Athens, Greece
e-mail: manolako@central.ntua.gr

N. M. Vaxevanidis
Department of Mechanical Engineering Teachers, Institute of Pedagogical and Technological Education, N. Heraklion Attikis, Greece

(iii) Local melting and evaporation follow and material is removed from the site of the discharge by explosion occurring after the cessation of the electrical discharge. The current density decreases with increasing discharge duration, the discharge tending to become an arc. De-ionization of the plasma channel occurs after the completion of the whole cycle and a new cycle can start at the site of the closest electrode distance.

The dominating thermal mechanism briefly described above is also the reason for the 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 (Mamalis et al. 1990; Rebelo et al. 2000; Tsai and Wang 2001a; Petropoulos et al. 2004).

In the past decade, Artificial Neural Networks (ANNs) have emerged as a highly flexible modeling tool applicable in numerous areas of manufacturing discipline (Dimla et al. 1997; Dini 1997; Briceno et al. 2002; Ezugwu et al. 2005; Feng et al. 2006). An artificial neural network is defined as "a data processing system consisting a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain" (Tsoukalas and Uhrig 1997). Actually, ANNs are models intended to imitate some functions of the human brain using its certain basic structures. ANNs have been shown to be effective as computational processors for various associative recall, classification, data compression, combinational problem solving, adaptive control, modeling and forecasting, multisensor data fusion, and noise filtering (Davalo et al. 1991). As far as EDM is concerned, the relative literature includes publications where ANNs are applied, mainly, for the estimation or prediction of the material removal rate, the optimization and the on-line monitoring of the process (Kao and Tarng 1997; Tsai and Wang 2001b; Wang et al. 2003; Panda and Bhoi 2005) whilst prediction of surface finish is presented only by Tsai and Wang (2001c).

In the present paper the application of novel ANN models for the prediction of the center-line average surface roughness, R_a of electrical discharge machined surfaces is discussed. The proposed models use data for the training procedure from an extensive experimental research concerning surface integrity of EDMed steels (Mamalis et al. 1987, 1990; Vaxevanidis 1996). The workpiece material, the pulse current, I_e and the pulse duration, t_p were considered as the input parameters of the models. More specifically, five steel grades, namely a mild steel, a carbon steel, and three alloyed steels, were tested while the pulse current, and the pulse duration varied over a wide range, from roughing to near-finishing conditions.

The proposed feed-forward neural networks trained with the back propagation algorithm were proven to be successful, resulting in reliable predictions, providing a possible way to avoid time- and money-consuming experiments.

Artificial neural networks overview

Two main and important features of neural networks are their architecture, i.e., the way that the network is structured, and the algorithm used for its training. After the appropriate training, the selected network has the ability to interconnect one value of output to given input. These two features of neural networks along with some techniques used for the improvement of their performance are briefly presented below. Note that the origin, the development and the mathematical details for implementing the ANNs can be found in a number of excellent reference works, see for example (Davalo et al. 1991; Fausset 1994; Haykin 1999); therefore they are not discussed here.

Neural network's architecture

Artificial neural networks are mathematical representations of the human brain function. The "core" element of a neural network is the neuron. Neurons are connected to each other with a set of links, called synapses and each synapse is described by a synaptic weight. Neurons are placed in layers and each layer's neurons operate in parallel. The first layer is the input layer. The activity of input units represents the non-processed information that entered the network; at that layer neurons do not perform any computations. The hidden layers follow the input layer and the activity of each hidden unit is determined from the activity of the input units and the weights at the connections of input and hidden units. A network can have many or none hidden layers and their role is to improve the network's performance. The existence of these layers at the network becomes more necessary as the number of input neurons grows. The last layer is the output layer. The behavior of output units depends upon the activity of the hidden units and the weights between hidden units and output units. The output of the layer is the output of the whole network; output layer neurons, in contrast to input layers, perform calculations.

There are two types of neural networks: the feed-forward and the recurrent ones. Feed-forward neural networks allow the signals to travel in only one direction: from input to output, i.e., the output signal of a neuron is the input of the neurons of the following layer and never the opposite. The inputs of the first layer are considered the input signals of the whole network and the output of the network is the output signals of last layer's neurons. On the contrary, recurrent networks include feedback loops allowing signals to travel forward and/or backward (Fausset 1994). Feed-forward neural networks are characterized by simple structure and easy mathematical description (Haykin 1999); therefore they were selected for the modeling of surface roughness in the present paper.

In general, there is not a standard algorithm for calculating the proper number of hidden layers and neurons. For relatively simple systems, as the present case, a trial-and-error approach is usually applied in order to determine which architecture is optimal for a problem. Networks that have more than one hidden layers have the ability to perform more complicated calculations. However, for most applications, one hidden layer is enough, while for more complicated applications the simulation usually takes place using two hidden layers (Ezugwu et al. 2005; Tsai and Wang 2001c; Feng et al. 2006). The existence of more than necessary hidden layers complicates the network, resulting in a low speed of convergence during training and large error during operation. Therefore, the architecture of a neural network always depends upon the specific situation examined and must not be more complex than needed (Davalo et al. 1991).

Neural network's training

Once the number of layers and the number of units in each layer are selected the network's weights must be set in order to minimize the prediction error of the network; this is the role of the training algorithms. The historical cases that were gathered are used to automatically adjust the weights in order to minimize this error. The error of a particular configuration of the network can be determined by running all the training cases through the network and comparing the actual output generated with the desired or target outputs. The differences are combined together by an error function resulting the network's error. Usually the mean square error (MSE) of the network's response to a vector p, is calculated, according to the equation:

$$E_p = \frac{1}{2}\sum_{i=1}^{l}\left(d_{p,i} - o_{p,i}\right)^2$$

In the preceding equation $o_{p,i}$ are the values of the output vector which occur for the input vector p and $d_{p,i}$ the values of the desirable response corresponding to p. The procedure is repeated until MSE becomes zero. Each time that the program passes through all pairs of training vectors an epoch is completed; training usually ends after reaching a great number of epochs.

One of the frequently used training algorithms is the back-propagation (BP) algorithm. It is usually applied in feed-forward networks with one or more hidden layers (Dini 1997; Tsai and Wang 2001c). The input values vectors and the corresponding desirable output values vectors are used for the training of the network until a function is approached which relates the input vectors with the particular output vectors. When the value of the mean square error is calculated, it is propagated to the back in order to minimize the error with the appropriate modification of the weights.

Another important parameter of the neural network models is their ability to generalize, i.e., the ability of neural networks to provide logic responses for input values that were not included in the training. Correctly trained back-propagation networks are able to perform generalization; this ability provides the opportunity of training the network using a representative set of input-desirable output values pairs.

Improvement techniques

When an algorithm is applied to the network random values are given to the weight factors. The convergence speed and the reliability of the network depend upon the initial values of weights; thus different results may be observed during the application of the same algorithm to the network. There are only a few elements that can guide the user for the selection of the proper values. A wrong choice may result to small convergence speed or even to network's paralysis, where training stops. Furthermore, due to the fact that the algorithm searches for the minimum error, the network may be stabilized at a local minimum instead of the total minimum. As a result, most of the times, incorrect response values of the network are produced. To overcome these problems variations of the most used algorithms have been proposed; for further information on this topic Fausset (1994) and Haykin (1999) may be consulted. Worth mentioning, also, that a very common and simple technique used for overcoming problems of this type is the repetition of the algorithm many times and the use of different initial values of the weight factors.

One of the problems that occur during the training of neural networks is over-fitting which undermines their generalization ability. The error appears to be very small at the set of the training vectors, however, when new data are imported to the network the error may become extremely large. This phenomenon is attributed to fact that the network memorized the training examples and did not learn to generalize under the new situations. The generalization ability of a network is assured when the number of training data is quite greater than the number of network's parameters. However, when the network is large the relations between input and output become rather complicated. Hence, a network should not be larger than needed to solve the given problem. Note, also, that two improvement techniques were applied during modeling, namely, normalization of the used data and the early stopping technique. Both these techniques and their application to the particular problem are briefly discussed in section "Matlab® models."

Experimental results

EDMachining

EDMachining was performed on an industrial EMT1.10/ AGIE machine of 100 V open voltage, with rectangular pulse generator of 30 A maximum current and adjustable pulse duration 5–1,000 µs and duty factor. Electrolytic copper of a rectangular work area $40 \times 22\ mm^2$ was used for tool electrode of positive polarity. The removal of debris was achieved by lateral flushing with a pressure of 0.3 bar in a hydrocarbon dielectric. The depth of cut was kept constant 0.5 mm for all specimens machined. The test conditions varying for the pulse current, $i_e = 6$, 12, 18 and 26 A and for the pulse duration, $t_p = 50$, 100, 300 and 500 µs.

The test materials cover a wide range of structural and high strength steels and are classified as follows:

- mild steel (St 37)
- alloyed steels (C 45 and 100Cr6)
- high strength low alloyed (HSLA) steels; grades of this type tested were strengthened with different mechanisms, namely:
  - a microalloyed (Mic/al 1) steel (0.06% C, 0.87% Mn, 0.047% Nb, 0,013% Ni, 0.01% Cr, V and Ti) with the strengthening mechanism being characterized by dispersion hardening and grain refinement by microalloying.
  - a dual-phase (DP 1) steel (0.075% C, 0.82% Mn, 0.035% Ni and 0.037% Cr) where the strengthening mechanism involves the introduction of martensite islands in a ferritic matrix by appropriate heat treatment.

Surface roughness values R_a were obtained with a "Talysurf" recorder (Taylor Hobson). The cut-off was set at 0.8 mm and the roughness values were the average of at least 20 measurements per specimen.

The process parameters and the corresponding average surface roughness values are tabulated in Table 1. From these results it can be concluded that when pulse current or pulse duration are increased, surface roughness is also increasing. High pulse energy results in high material removal rates but at the same time to poor surface roughness. This is a common feature of manufacturing processes; especially in EDM, a high metal removal rate not only results in poor surface finish but is also associated with intensification of surface damage such as crack generation, etc. (Mamalis et al. 1990). To overcome this problem, fine cutting conditions may be imposed at the final stage of processing (Vaxevanidis 1996).

ANNs modeling

For the formulation of the ANNs and the modelling of EDM two discrete software programs were used, namely: Matlab® with the neural networks toolbox (Demuth and Beale 2001) and Netlab®.

Matlab® is a well-known program used for modeling purposes. Its neural networks toolbox is user-friendly and the creation of neural networks is performed by using a small amount of commands; the program has a data base with functions, algorithms and commands for this purpose. A lot of the reported ANNs have been designed with this software; see for example (Ezugwu et al. 2005; Tsai and Wang 2001b,c; Wang et al. 2003).

Netlab® consists of a toolbox of Matlab® functions and scripts based on the approach and techniques described in the relevant literature (Bishop 1996). The Netlab® toolbox is designed to provide the central tools necessary for the simulation of theoretically well founded neural network algorithms and related models to be used in research and applications development. The Netlab® library includes software implementations of a wide range of data analysis techniques, many of which are not yet available in standard neural network modeling packages; for the principles behind Netlab® and its modeling abilities see also Nabney (2004).

Neural network models

Matlab® models

In general, a neural network is characterized by its important features such as the architecture, the activation function and the learning algorithms (Fausset 1994). Several models were designed and tested in order to determine the optimal architecture, the most suitable activation functions and the best training algorithm suitable for the prediction of R_a. Each model was tested more than once in order to evaluate whether it truly converges to a low value or not. After this trial-and-error procedure the model selected was a feed-forward neural network with two hidden layers consisting of five and three neurons, respectively. The activation function in both the hidden layers was the hyperbolic tangent sigmoid transfer function and in the output layer was the linear transfer function. The training algorithm used was the back propagation (BP) algorithm. The architecture of the selected (optimized) network is presented in Fig. 1.

For training the designed models the experimental data tabulated in Table 1 were used. These data were treated in order to become suitable to be used in the program. Initially, the different types of workpiece material were assigned a number, from 0 to 4, in order to become arithmetic; only numeric values are allowed as input data. Then all the data were normalized; i.e., all input and output data were suitably transformed so that their mean value become equal to zero and the standard deviation equal to one. Normalization is a method used in neural networks so that all the data present a

Table 1 Input parameters and experimental results

Input			Output
Workpiece material	Pulse current, I_e (A)	Pulse duration, t_p (μs)	Roughness, R_a(μm)
St 37	6	50	7.05
St 37	6	100	7.35
St 37	12	100	8.80
St 37	26	100	10.80
St 37	12	300	10.90
St 37	18	300	11.60
St 37	12	500	12.45
St 37	26	300	12.30
St 37	18	500	13.70
St 37	26	500	14.50
C 45	12	100	8.00
C 45	18	100	10.30
C 45	18	300	11.60
C 45	12	500	12.20
C 45	18	500	12.50
C 45	26	500	13.40
100Cr6	26	50	8.30
100Cr6	26	100	10.00
100Cr6	26	150	11.70
100Cr6	18	300	11.90
100Cr6	26	500	12.10
100Cr6	26	300	12.30
100Cr6	18	500	13.50
100Cr6	26	500	14.20
Mic/al 1	12	100	6.80
Mic/al 1	18	100	7.80
Mic/a. 1	26	100	8.80
Mic/al 1	12	300	10.30
Mic/al 1	18	300	10.30
Mic/al 1	12	500	10.20
Mic/al 1	26	300	11.65
Mic/al 1	18	500	11.80
Mic/al 1	26	500	13.40
DP 1	12	100	7.30
DP 1	18	100	7.60
DP 1	26	100	7.80
DP 1	12	300	7.40
DP 1	18	300	8.70
DP 1	12	500	8.90
DP 1	26	300	10.30
DP 1	18	500	10.80
DP 1	26	500	12.00

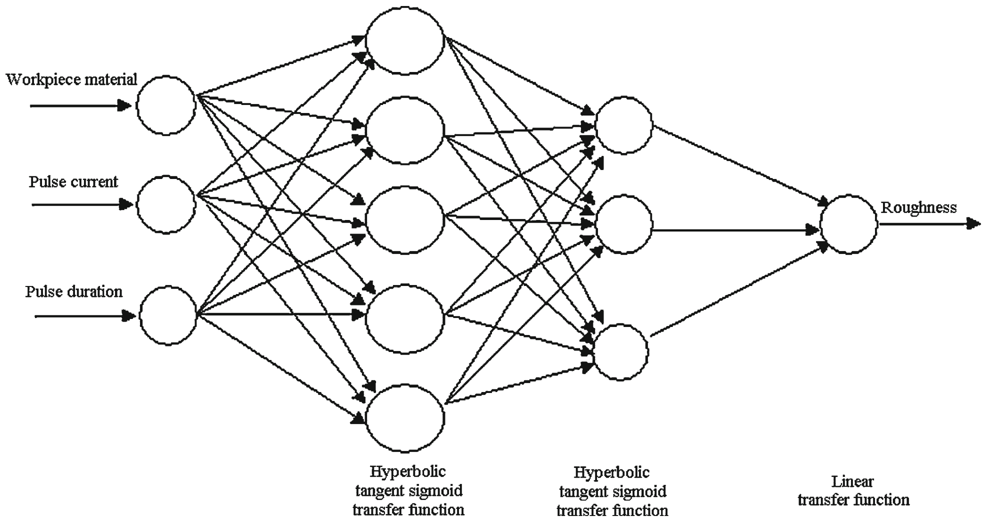

Fig. 1 Final neural network architecture

logical correlation. Otherwise, the neural network could suppose that a value is more significant than the others because its arithmetic value is greater. This could damage the generalization ability of the network and lead to overfitting. After normalization all inputs are equally significant for the training of the network.

For the improvement of generalization of a neural network the early stopping technique was used. By this methodology the existing data are separated in three subsets. The first subset consists of the training vectors, which are used to calculate the gradient and to form the weight factors and the bias. The second subset is the validation group. The error in that group is observed during training and likewise training group normally decreases during the initial phase of training. However, when the network begins to adjust the data more than needed the error in that group raises and when that increase continues for a certain number of repetitions, training stops. Finally, the third subset is the test group and its error is not used during training. It is used to compare the different models and algorithms. In order to use this technique, 1/2 of the data were used for training, 1/4 were used for validation and 1/4 were used for testing. The selection of the data constituting the three groups was performed in stochastic way so that training was not performed partially, e.g. for workpiece material 100Cr6 only, a fact that could had lead to an erroneous generalization; moreover all data are equally represented in each subset.

The MSE of training of the selected ANN was about 0.088 and its training took almost 700 epochs to complete. The MSE of all the three groups when the early stopping technique was applied during the training of the neural network are presented in Fig. 2. From this figure it is evident that validation and testing group MSEs are higher than that of the training group, as expected. Moreover, they have similar

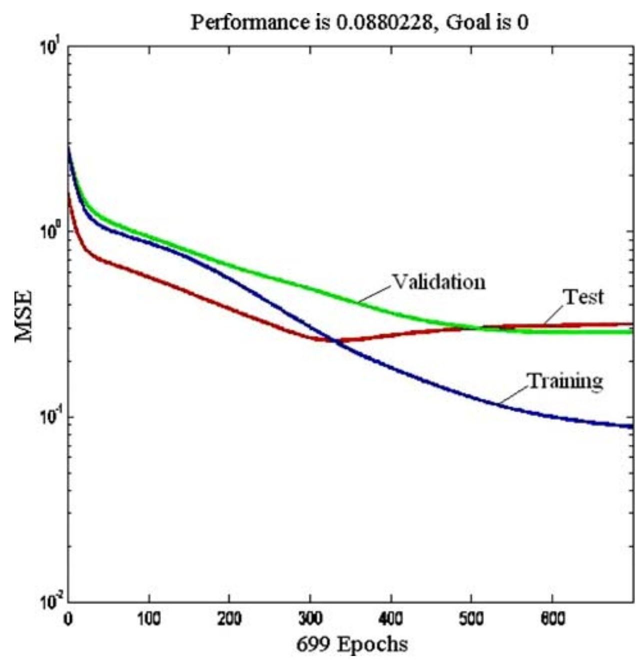

Fig. 2 Results of the neural network training

values which indicate that the proposed neural network possesses good generalization ability, thus being able to model EDM process.

For the evaluation of the generalization ability of the trained neural network a linear fit between the output of the model and the experimental data, for all the measured values presented in Table 1, without discrimination to which group they belong, was performed. The linear fit is presented in Fig. 3; note that T and A represent the experimental results and the outputs of the model, respectively. The best linear

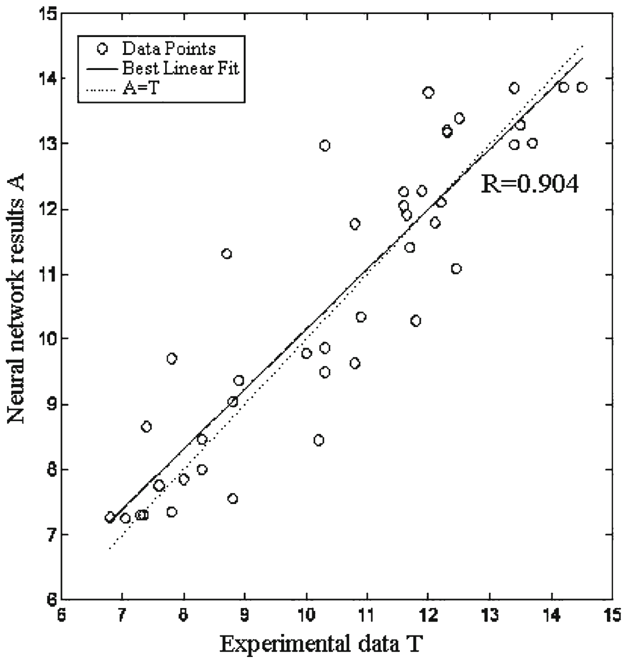

Fig. 3 Correlation between experimental data and neural network output

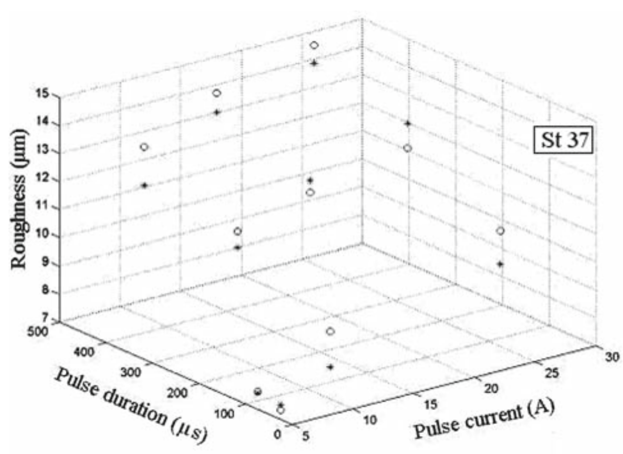

Fig. 4 Experimental data and neural network modeling with Matlab® for St 37 steel

fit function is calculated as: $A = 0.922T + 0.934$, while the correlation coefficient was calculated, $R = 0.904$.

This result indicates that the neural network can very satisfactorily predict the output data required. Furthermore, in Figs. 4–6 the center-line average surface roughness (R_a) versus the pulse current and pulse duration, for all five steel grades, is presented. In the same figures both the experimental data and the neural network outputs are given. It is evident that for all five materials the experimental and the calculated values exhibit small discrepancies, indicating once more the reliability of the neural network constructed with Matlab®.

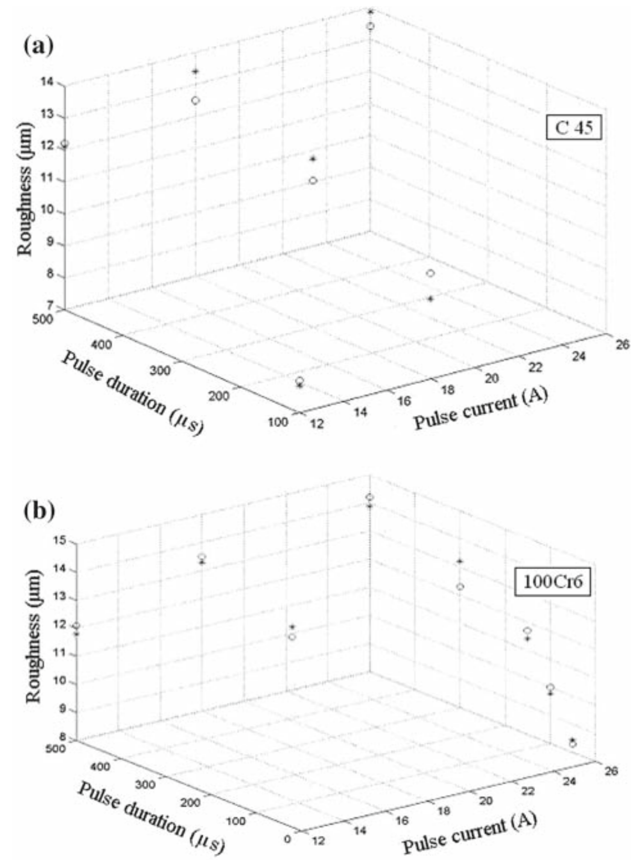

Fig. 5 Experimental data and neural network modeling with Matlab® for alloyed steels; (**a**) C 45 steel grade and (**b**) 100Cr6 steel grade

The proposed model can be saved and used for the prediction of surface roughness, given that the pulse current and duration are within the limits of the model and the workpiece material is one of the five steel grades tested.

Netlab® models

Netlab® software was also used for the design of neural network models in order to predict surface roughness. When designing with Netlab® five different networks were developed, each one corresponding to a specific steel grade. Once more the data from Table 1 were used for the training of the ANNs. Since the results of each model refer to a specific material, the number of input neurons was decreased to two, inputs being only the pulse current and the pulse duration. The output layer consisted of one neuron as before, corresponding to the surface roughness. This modeling required simpler neural network architecture than the previous one due to reduced number of the inputs; after a trial-and-error procedure a feed-forward ANN with one hidden layer containing five neurons was selected.

The input and output of the program were plotted in three dimensional graphs along with the function that results from

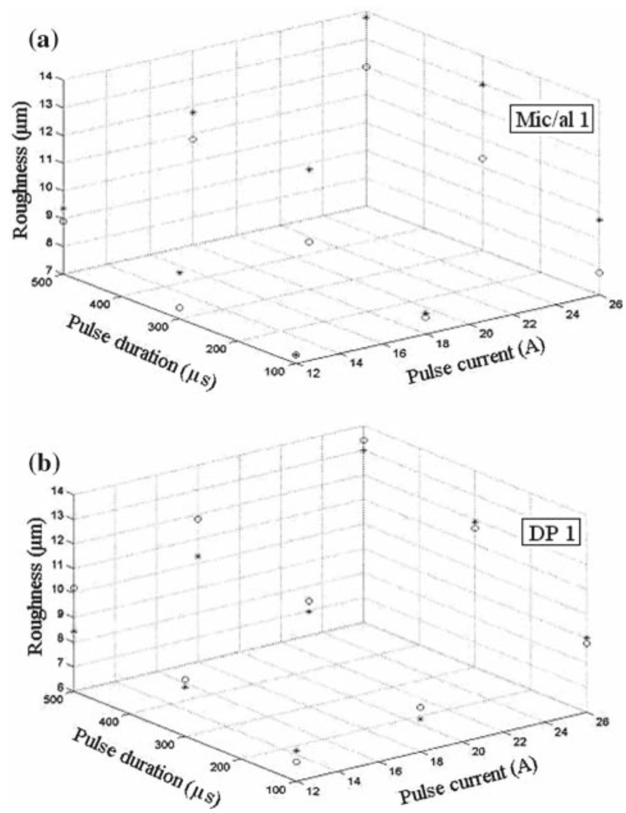

Fig. 6 Experimental data and neural network modeling with Matlab® for HSLA steels; (**a**) Mic/al 1 microalloyed steel grade and (**b**) DP 1 dual phase steel grade

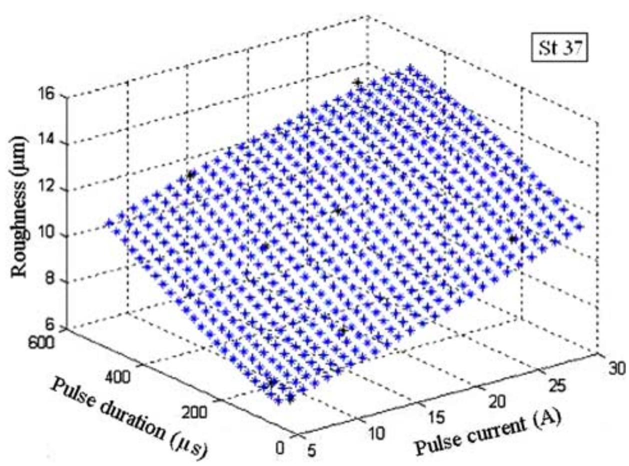

Fig. 7 Neural network modeling with Netlab® for St 37 steel

the trained neural network, see Figs. 7–9. With these plots the surface roughness of the specific workpiece material can be predicted for given values of pulse current and pulse duration. Note also that these figures can be used as guidelines for EDM process planning for the tested materials: When the pulse current and the pulse duration are known the surface roughness can be predicted and vice versa; when a specific surface roughness must be achieved the process parameters can be suitably selected. These plots are user-friendly; people who are not familiar with computers and/or specialized software can easily handle them. Therefore, they can be printed and incorporated into EDM machine tools manuals as work instructions.

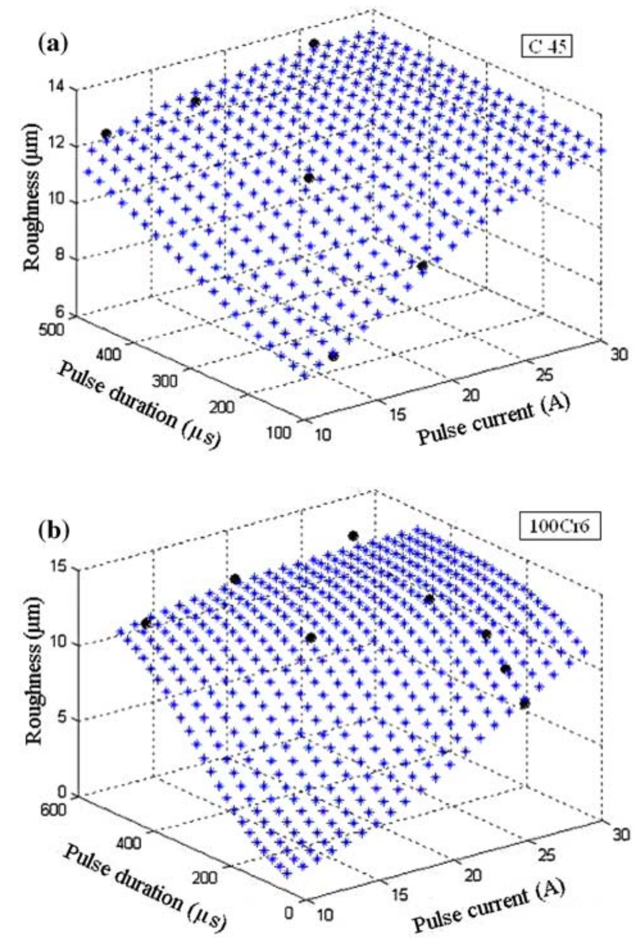

Fig. 8 Neural network modeling with Netlab® for alloyed steels; (**a**) C 45 steel grade and (**b**) 100Cr6 steel grade

Conclusions

In the present paper artificial neural network models for the prediction of surface roughness in Electrical Discharge Machining of various steel grades were proposed and validated with experimental results. For the formulation of the ANNs and the modeling of EDM two discrete programs were used, namely: Matlab® and Netlab®.

For Matlab® model the workpiece material, the pulse duration and the pulse current were used as input parameters for the feed-forward neural network trained with the BP algorithm. This neural network was trained with experimental

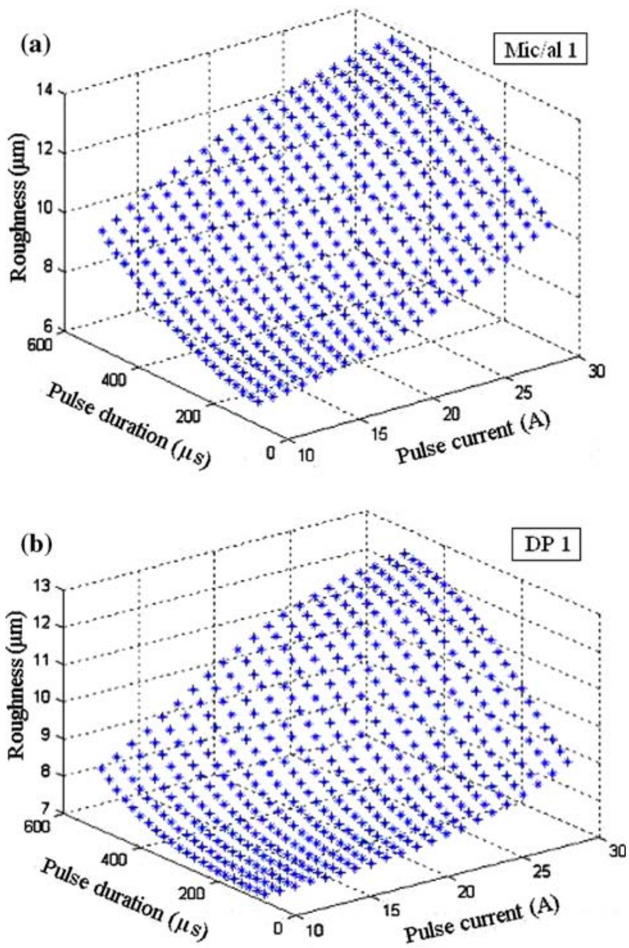

Fig. 9 Neural network modeling with Netlab® for HSLA steels; (**a**) Mic/al 1 microalloyed steel grade and (**b**) DP 1 dual phase steel grade

data acquired from actual EDM experiments. The results obtained indicated that the proposed ANN can successfully predict the surface roughness, within the limits of the input values by which it was trained.

When using Netlab® five different networks were developed, each one corresponding to a specific steel grade. This modeling required simpler neural network architecture whilst the agreement between experimental and calculated values was again very good. Moreover, the inputs and outputs of the models were plotted in three dimensional graphs, i.e., R_a values versus pulse duration and pulse current. These user-friendly graphs may be used for the prediction of the outcome of the process as well as for process planning and optimization when the surface roughness is prescribed.

In general, both Matlab® and Netlab® models were proven to perform well for EDM, giving reliable predictions and providing thus a possible way to avoid time- and money-consuming experiments.

References

Bishop, C. M. (1996). *Neural networks for pattern recognition*. Oxford: Oxford University Press.

Briceno, J. F., El-Mounayri, H., & Mukhopadhyay, S. (2002). Selecting an artificial neural network for efficient modeling and accurate simulation of the milling process. *International Journal of Machine Tools and Manufacture, 42*(6), 663–674.

Davalo, E., Naim, P., & Rawsthorne, A. (1991). *Neural networks*. London: Macmillan Education, Limited.

De Silva, A. K. M., & McGeough, J. A. (2000). Computer applications in unconventional machining. *Journal of Materials Processing Technology, 107*, 276–282.

Demuth, H., & Beale, M. (2001). Neural networks toolbox for use with Matlab, User's guide.

Dimla, D. E., Jr., Lister, P. M., & Leighton, N. J. (1997). Neural network solutions to the tool condition monitoring problem in metal cutting - A critical review of methods. *International Journal of Machine Tools and Manufacture, 37*(9), 1219–1241.

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

Ezugwu, E. O., Fadare, D. A., Bonney, J., Da Silva, R. B., & Sales, W. F. (2005). Modelling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network. *International Journal of Machine Tools and Manufacture, 45*(12–13), 1375–1385.

Fausset, L. V. (1994). *Fundamentals of neural networks: Architectures, algorithms and applications*. New Jersey: Prentice Hall.

Feng, C.-X. J., Yu, Z.-G., & Kusiak, A. (2006). Selection and validation of predictive regression and neural network models based on designed experiments. *IIE Transactions, 38*, 13–23.

Haykin, S. (1999). *Neural networks, a comprehensive foundation*. New Jersey: Prentice Hall.

Ho, K. H., & Newman, S. T. (2003). State of the art electrical discharge machining (EDM). *International Journal of Machine Tools & Manufacture, 43*, 1287–1300.

Kao, J. Y., & Tarng, Y. S. (1997). A neural network approach for the on-line monitoring of the electrical discharge machining process. *Journal of Materials Processing Technology, 69*, 112–119.

Mamalis, A. G., Vaxevanidis, N. M., & Karafillis, A. P. (1990). *Surface integrity and formability of steel sheet*. Dusseldorf: VDI Verlag.

Mamalis, A. G, Vosniakos, G. C., Vaxevanidis, N. M, & Prohaszka, J. (1987). Macroscopic and microscopic phenomena of electro-discharge machined steel surfaces: an experimental investigation. *Journal of Mechanical Working Technology, 15*, 335–356.

Nabney, I. T. (2004). *NETLAB: Algorithms for pattern recognition*. London: Springer.

Panda, D. K., & Bhoi, R. K. (2005). Artificial neural network prediction of material removal rate in electro discharge machining. *Materials and Manufacturing Processes, 20*(4), 645–672.

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, 155–156*, 1247–1251.

Rebelo, J. C., Dias, A. M., Mesquita, R., Vassalo, P., & Santos, M. (2000). An experimental study on electro-discharge machining and polishing of high strength copper–beryllium alloys. *Journal of Materials Processing Technology, 103*, 389–397.

Tsai, K.-M., & Wang, P. J. (2001a). Semi-empirical models of surface finish on electrical discharge machining. *International Journal of Machine Tools and Manufacture, 41*(10), 1455–1477.

Tsai, K.-M., & Wang, P. J. (2001b). Comparisons of neural network models on material removal rate in electrical discharge machining. *Journal of Materials Processing Technology, 117*, 111–124.

Tsai, K.-M., & Wang, P. J. (2001c). Predictions on surface finish in electrical discharge machining based upon neural network models. *International Journal of Machine Tools and Manufacture, 41*, 1385–1403.

Tsoukalas, L. H., & Uhrig, R. E. (1997). *Fuzzy and neural approaches in engineering*. New York: Wiley Interscience.

Vaxevanidis, N. M. (1996). *Surface integrity of thermally and mechanically worked metal components, Ph.D. thesis*. Faculty of Mechanical Engineering, National Technical University of Athens, Greece.

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 and Manufacture, 43*, 995–999.