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Prediction of surface roughness in Electrical Discharge Machining of SKD 11 TOOL steel using Recurrent Elman Networks

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Abstract:

Elman Networks is a one of the dynamic recurrent neural networks. In this research it is used for the prediction of surface roughness in Electrical Discharge Machining (EDM). Training of the models was performed with data from series of EDM experiments on SKD 11 (AISI D2) Tool steel; in the development of predictive models, machining parameters of discharge current, pulse duration and duty cycle were considered as model variables with a constant voltage 50 volt. For this reason, extensive experiments were carried out in order to collect surface roughness dataset. The developed model is validated with a new set of experimental data, and predictive behavior of models is analyzed. The reported results indicate that the proposed model can satisfactorily predict the surface roughness in EDM. And can be considered as valuable tools for the process planning for EDMachining.

Keywords: Surface Roughness; Electrical Discharge Machining; Recurrent Elman Networks.

1. Introduction

Due to capability of manufacturing components of any hardness and shape on wide range of conductive engineering materials, electro discharge machining (EDM) is one of the well-established manufacturing methods in modern manufacturing field. In this manufacturing technique, material removal is caused by repetitive minute electric discharges within the electrode-workpiece-die electric interface. Each discharge, due to high energy concentration, removes from the workpiece surface a small quantity of material in form of molten metal drops and even vapors, meanwhile the discharge location on the workpiece surface is in part stochastic and in part dependent on surface micro relief. The outcome of such a unit-event is the characteristic crater. The mechanism of the crater formation is a complex phenomenon involving several disciplines of science and branches of engineering. The theories revolving around the formation of plasma channel between the tool and the workpiece, thermodynamics of the repetitive spark causing melting and evaporating the electrodes, micro-structural changes, and metallurgical transformations of material, are still not clearly understood. However, it is widely accepted that the mechanism of material erosion is due to intense local heating of the workpiece causing melting and evaporation of workpiece. Therefore, it is hard to establish a model that can accurately predict the performance by correlating the process parameter.

Surface roughness (Ra) is a significant upshot in the manufacturing process and it materializes a major part in the manufacturing system. Therefore, characterization, prediction, and modeling of quality of EDMed component surface roughness play a vital role. The component, having good surface, improves the fatigue strength, wear resistance and corrosion résistance of the surface. Ra depends on different machining parameters and its prediction and control is a query to the researchers.

Artificial neural networks are simplified models of the central nervous system. They are networks of highly interconnected neural computing elements. In the recent past, neural networks have been shown to be the highly flexible modeling tools surely due to their well-known characteristics of adaptability and non-linear universal mapping approximations. It has the capability to handle problems such as modeling, estimating, prediction, optimization, diagnosis and adaptive control in complex non-linear systems. It is observed that the neural network applications play a very important role in predicting surface roughness in EDM. Recurrent neural networks are useful for storing information about time and particularly suitable for time series prediction [1]. Tsai and Wang [2] applied various neural network architectures for the

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prediction of the Ra and MRR in EDM and agreed to the predictions based upon the models. Indurkhya and Rajurkar [3] attempted to model a 9-9-2 size back propagation neural network for the prediction of Ra and MRR., where the 9 different machining parameters, such as machining depth, tool radius, orbital radius, radial step, vertical step, offset depth, pulse on time, pulse off time and discharge current are selected as input parameters are used to determine the two outputs Ra and MRR. The model predictions are compared with estimates obtained via multiple regression analysis, and found more accurate and also less sensitive to noise induced in the experimental data than that of multiple regressions model. Panda and Bhoi [4] developed an artificial feed forward neural network to predict MRR of SKD 11 grade steel. This model performs well under the stochastic environment of actual machining conditions without understanding the complex physical phenomena exhibited in EDM, and provides faster and more accurate results. They found that the 3-4-3-1 neural architecture has the highest correlation coefficient and used it for the analysis. Wang et al. [5] combined the capabilities of Artificial Neural Network (ANN) and genetic algorithm to find an integrated solution to the existing problem of modeling and optimization of EDM processes. Markopoulos et al. [6] proposed ANN models for the prediction of Ra of EDMed surfaces. The experiments were conducted on five steel grades, namely a mild steel, a carbon steel, and three alloyed steels, were tested while pulse current (Ip) and the pulse duration (Ton) varied over a wide range. Results reveled that proposed ANNs models can satisfactorily predict the response. Pradhan and Biswas [7] presented a neuro-fuzzy model to predict MRR of AISI D2 tool steel with different process parameter such as Ip, Ton and duty cycle (τ), and the model predictions were found to be in good agreement with the experimental results. Pradhan et al. [8] applied the neural network models namely back-propagation and radial basis function for the prediction of Ra. Using Ip, Ton and τ as input parameters, experiments are conducted on D2 steel. It is reported that former shows slightly better performance than the latter, however latter model is faster. Portillo [9;10] used recurrent neural network approach to detect in advance the degradation of the cutting process due to the memorization capability and the dynamic character of the Elman architecture.

It is observed that the neural network is widely used in EDM process for the prediction of responses and effect of the parameters on them. However recurrent neural network is not used yet for the prediction of Ra in EDM. Though this net has been efficient identification tool in many areas as they have dynamic memories. In this study, recurrent neural network approach, named Elman network [11], is used for the prediction of the center-line average surface roughness, Ra 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 D2 steels. Ip, Ton, and τ were considered as the input parameters of the models. The Ip, Ton, and □ varied over a wide range, from roughing to near-finishing conditions. The proposed neural networks trained with the feed forward back propagation algorithm and were proven to be successful, resulting in reliable predictions, providing a possible way to avoid time and money-consuming experiments.

2. Experimental Details

Experiments were conducted on Electronica Electraplus PS 50ZNC die sinking machine. A cylindrical pure copper was used as a tool electrode (of positive polarity) with a diameter of 30 mm and workpiece materials used were AISI D2 tool steel square plates of dimensions 35 ×35 mm^2 and 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 kg f /cm^2 was used. Keeping the voltage constant at 50 V, number of experiments was conducted to investigate the effects of Ip, Ton and τ on Ra, where τ is defined as:

$$\tau = \frac{\text{Ton}}{\text{Ton} + \text{Toff}} \times 100 \quad (1)$$

The experimental conditions and the levels of the input parameters are shown in Table 1. Each treatment of the experiment was run for 15 minutes and the Ra was measured.

Table 1. Experimental conditions

Sparking voltage in V	50
Current (Ip), in A	1 5 10 20 30 50
Pulse on Time (Ton), in µs	5 10 20 30 50 100 150 200 500 750
Duty Cycle (τ) in %	50 85 92
Dielectric used	Commercial grade EDM oil
Dielectric flushing	Side flushing with pressure
Work material	SKD 11 tool steel
Electrode material	Electrolytic pure Copper
Electrode polarity	Positive
Work material polarity	Negative

3. Surface Roughness Measurement

The Ra is used to portray the technical surface quality of an engineering component. It has a very significant influence on the manufacturing outlay of a product. A good quality surface enhances the fatigue strength, corrosion, and wear-resistance of the workpiece. There is a number of ways by which surface roughness of a component is described, such as roughness average (Ra), root-mean-square (rms) roughness (Rq) and maximum peak-to-valley roughness (Ry or Rmax), etc. In this work, Ra is used, which is measured using Talysurf (Taylor Hobson, Surtronic 3^+). The profilometer was set to a cut-off length of 0.8 mm, filter 2CR, traverse speed 1 mm/second and 4 mm evaluation length. Roughness measurements, in the transverse direction, on the workpieces were repeated four times and average of four measurements of surface roughness parameter values was recorded. The measured profile was digitized and processed through the dedicated advanced surface finish analysis software Talyprofile for assessment of the roughness parameters. Ra can be defined as the arithmetic value of the profile from centerline along the sampling length. It can be express as

$$Ra = \frac{1}{L}\int \left| y(x) \right| dx \| \qquad (2)$$

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

4. Predictive Models for Surface Roughness

Recurrent networks are a special type of the dynamic neural nets. The Elman neural network is a simple recurrent neural network. This network is similar to an architecture proposed by Jordan [12]. Eleman network reveals a rich structure that permits them to be highly context-dependent, and also states generalizations across classes of items. Yet, to have a real-time (online) learning ability, standard back propagation (BP) training for Eleman network, known as Elman BP [13]. This architecture is standard feedforward architecture with layers of inputs, hidden units, and output units. It is a single hidden layer feedforward neural network. All neurons in one layer are connected with all neurons in the next layer. The outputs of the hidden layer are allowed to feed back to the context layer, and to augment additional units at the input level. Therefore, the input layer is constituted by the input nodes plus these context nodes. The context unit is fully connected with all the hidden units in a forward manner. The neurons in the context layer hold a copy of the output of the hidden neurons. The output of each hidden neuron is copied into a specific neuron in the context layer. The value of the context neuron is used as an extra input for all the neurons in the hidden layer one-time step later. Therefore, the Elman network has an explicit memory of one time lag.

In Elman network, both the input units and context units activate the hidden units. Since the context units are in the initial state, only the input units contribute to the activation of the hidden units at $t-1$. The hidden units are then fed forward to activate the output units and, at the same time, fed back to activate the context units on the second step at the time t. Now, the context units contain the exact values of those of the hidden units. The information in the context units and input units receive the new input vector to activate the hidden units at time $t+1$. The hidden units then activate the output units, as well as the context units at time $t+2$. The above process is repeated at the next time step. Thus, these context units provide the network with information that is recurrent in time.

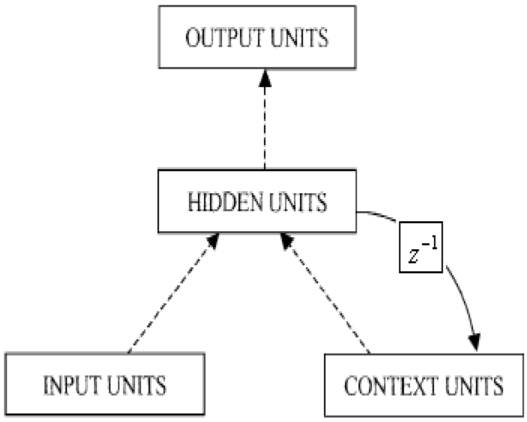

Figure 1. Architecture of the Elman Network.

The structure of an Elman recurrent neural network is illustrated in Fig. 1. Here, I , H , O and z^{-1} are input layer vector, hidden layer vector, context layer vector, output layer vector and unit delay element, respectively. The weight matrix between input layer and hidden layer is $W1$, the weight matrix between context layer and hidden layer is $W2$ and the weight matrix between hidden layer and output layer is $W3$.

At *t*th iteration,

$$x_i(t) \in I, \qquad i = 1, \cdots, n$$
$$z_k(t) \in O, \qquad k = 1, \cdots, l$$
$$y_j(t) \in H, c_j(t) \in C \qquad j = 1, \cdots, m$$

where *i* and *k* are the number of nodes of input layer and output layer respectively and *j* is the number of nodes of hidden layer and context layer. Considering the activation function $f(\bullet)$ for *j*th hidden node, the outputs of the neurons in the hidden layer and output layer for time *t* are can be given by

$$y_j(t) = f\left(\sum_{i=1}^{n} w1_{ij} x_i(t) + \sum_{j=1}^{m} w2_{ij} y_j(t-1)\right)$$

,

$$c_j(t) = y_j(t-1)$$

and

$$z_k(t) = f\left(\sum_{j=1}^{m} w3_{jk} y_j(t)\right)$$

where $w1_{ij} \in W1, w2_{ij} \in W2$ and $w3_{jk} \in W3$

For initial step, $y_i(0) = 0$. The context layer input at $t = 1$ leads to $c_i(1) = 0$. The weights are updated according to

$$w(t+1) = w(t) + \eta \Delta w(t)$$

where η is the learning rate.

That minimizes the approximation error E in the output layer is given by

$$E(w)=\frac{1}{p}\sum_{t=1}^{p}\frac{1}{2}\left(\sum_{k=1}^{l}\left[T_k(t)-z_k(t)\right]^2\right)$$

where $T_k(t)$ is the target value at *t* th iteration and p is the length of the training sequence.

Weight coefficient matrix $W1$ and $W3$ can be updated using any of the back-propagation algorithms as done in feedforward neural network. But weight coefficient matrix $W2$ can be adjusted using derivative chain rule [14].

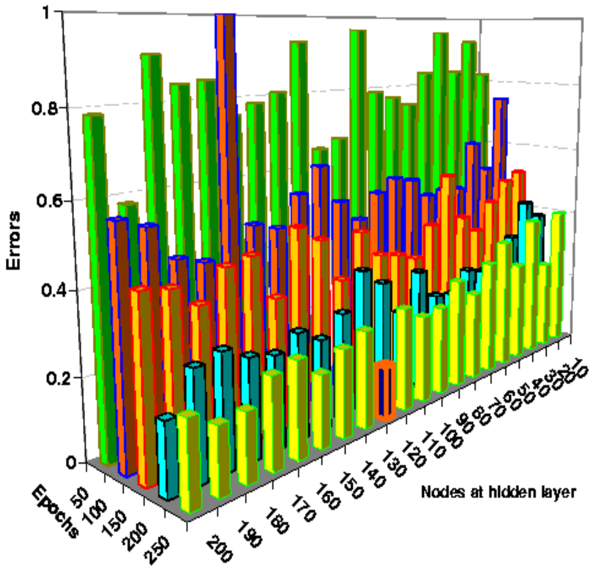

Figure 2 .Errors_ Epochs_ Nodes at hidden layer**.**

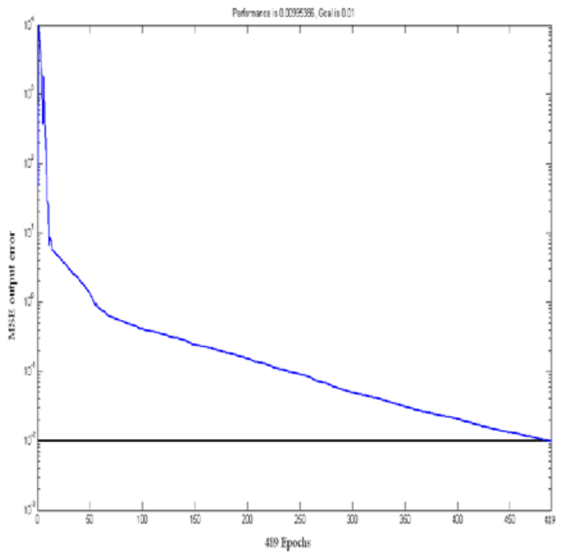

Figure 3: 489 iteration in the Elman's learning process

RNN is observed separately with results obtained by experiments and the average error obtained for the networks. The test result accuracy measured in terms of mean absolute error (MAE) for 9 test data are found to be 0.31355. The experimental results and predicted results of 'Ra' by the RNN were plotted, as shown in Fig 4.

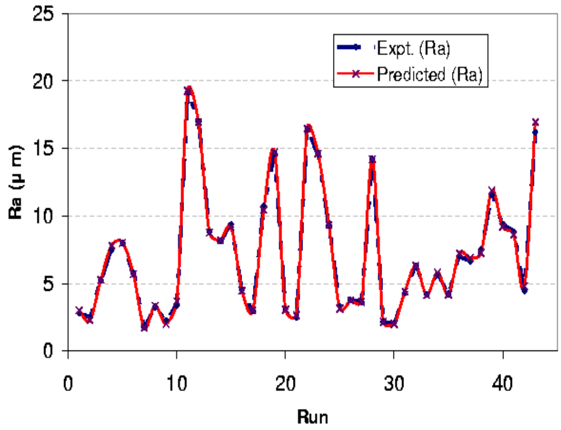

Figure 4. Comparison between experimental and predicted data for Ra.

The variations of prediction error (calculated as the difference between the experimental findings and predicted values) plotted against run for training and validation sets for Eleman's model is shown also in the figure 5. Except for an outlier, the validation set exhibits very accurate prediction. The error for the model, calculated as the difference between the experimental findings and predicted values and the pattern of the residual plot, is scattered, which does not shows any pattern/trend that indicates that the model is certainly adequate. A good model fitting this plot should show a random scatter and have no pattern [12]. However, the absolute percentage prediction error is tabulated in Table.2.

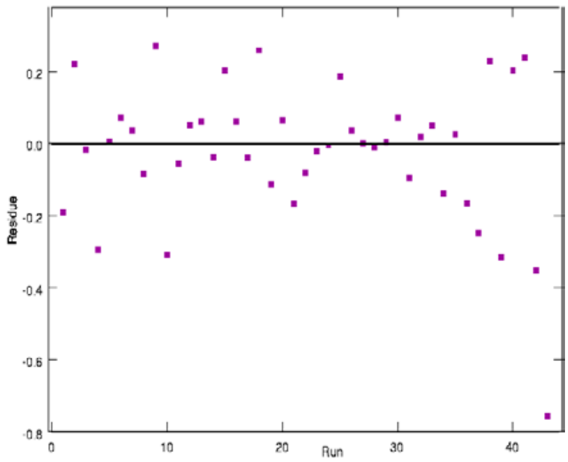

Figure 5.Residual plot vs. Run.

Figure 5 shows the scatter plot of predicted Ra using Elman's network and Experimental Ra, respectively. The correlation coefficients (r) between Experimental and predicted value of Ra is 0.999, from a statistical judgment, the closer this number is to 1, the more powerful the network in correlating the input space to the output space. The plot of Experimental and predicted output is presented in Fig. 6. Since all the points on plot come close to form a straight line, it implies that the data are normal. Therefore, the Elman's network can be used to attain a function that maps input parameters to the desired process outputs in EDM. The predicted values are quite close for most of the data points.

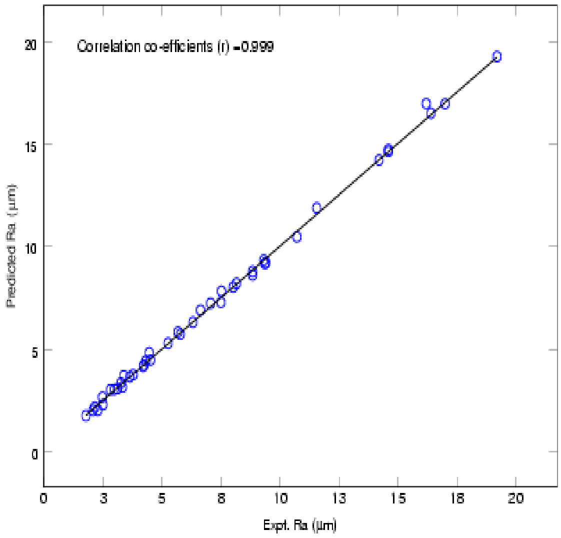

Figure 6. Correlation between experimental data and neural network output.

Table 2. Results from production data sets for surface roughness model

.S. no	Experimental Ra	Eleman's predicted Ra	% error
1	7.06	7.22	2.35
2	6.64	6.88	3.76
3	7.5	7.26	3.07
4	11.56	11.87	2.72
5	9.4	9.19	2.15
6	8.84	8.60	2.67
7	4.46	4.81	7.95
8	16.2	16.95	4.66

5. Conclusion

Elman neural network is discussed in details by predicting Ra. The present study has demonstrated a new application of the Elman recurrent neural network to the prediction of *Ra*. The Elman network has performed satisfactorily in the prediction of Ra. Instead of conducting actual experiments in EDM for different values of machining parameters, a suitable intelligent system can be used to predict Ra. When a desired Ra is obtained, a confirmation test can then be conducted experimentally to verify the predicted Ra. By using this approach, lengthy and time-consuming experimentation in EDM can be reduced. From our work, the potential of using an intelligent learning system for prediction is evident. Therefore, we believe that ANNs can be used as a powerful tool in manufacturing system, as well as other areas in modern manufacturing industry, so that the development tasks can be performed rapidly and efficiently with an increase of productivity, consistency and quality.

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