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# Neural network modeling and analysis for surface characteristics in electrical discharge machining

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**Abstract**The problem appeared owing to selection of parameters increases the deficiency of electrical discharge machining (EDM) process. Modelling can facilitate the acquisition of a better understanding of such complex process, save the machining time and make the process economic. Thus, the present work emphasizes the development of an artificial neural network (ANN) model for predicting the surface roughness ($R_a$). Trainingandtestingaredonewithdatathatarefoundsucceedingtheexperimentasdesignofexperiments. The surface topography of the machined part was analysed by scanning electronic microscopy. The result shows thatthe ANN model can predict the surface roughness effectively. Low discharge energy level results in smaller craters and micro-cracks producing a suitable structure of the surface. This approach helps in economic EDM machining.


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*Keywords:* Graphite; modelling; neural network; surface roughness; Ti-5-2.5.

## 1. Introduction

Titanium is used in many industries and commercial applications;however, titanium is a difficult-to-cut material for conventional machining process[1, 2]. A non-conventional technique, EDM can machine this hard material effectively [3].Electrical discharge machining process is highly complex and stochastic. The complicated mechanisms to the process result a lag of established formula correlating the input and output parameters. Modelling can solve the problem araised as of

**Nomenclature**

| | |
|---|---|
| $b$ | bias |
| $h_j$ | value of the output for hidden nodes |
| $I_p$ | peak current |
| $R_a$ | surface roughness |
| $S_v$ | servo-voltage |
| $T_{on}$ | pulse-on time |
| $T_{off}$ | pulse-off time |
| $w_i$ | synaptic weight |
| $x_i$ | input value |

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| | |
|---|---|
| $y_o$ | output for output nodes |

parameter selection and make the process economic [4]. In recent years, the artificial neural network has been transformed into a very useful tool for modelling complex systems [5]. The first research to distinguish the EDM pulse type using artificialintelligence was carried out byKao and Tarng[6]. A feed-forward neural network (NN) was adopted to associate the relationships between tool-workpiece gap signals and various pulse types. Based on this model, EDM pulses under varying machining conditions could be classified quickly and accurately by measuring the voltage and current across the gap between the tool and the workpiece and feeding these data into the developed network. Mahdavinejad showed that there are four completely distinct pulses in EDM, and this system becomes unstable when the number of non-successive pulses, such as arcing, short circuit, and open circuit, is increased against normal discharges during the machining process [7]. Thus, the method of model predictive control based on ANN with output parameters of the system was used to minimize the number of non-successive pulses. Twodifferentartificialneuralnetworkmodels:backpropagationneuralnetwork(BPN)andradialbasisfunctionNNwerepresentedfor thepredictionofsurfaceroughness[8]. An investigation was carried out to study the effect of current and tool dimension on surface roughness for EDM machining [9]. The response variables were predicted using ANN techniques. Influences of EDM parameters on surface quality were analysed conducting the machining on cemented carbide[10].

It is seen that several studies have been conducted by using ANN for distinct materials such as SKD11 workpiece, 94WC–6Co, mild steel (St 37), alloyed steels (C 45 and 100Cr6), high strength low alloyed (HSLA) steels; mild steel, WC-Co, HE15, 15CDV6, and M250, AISID2steel [6,10, 11, 9, 7, 5, 12, 13, 8]. However, the development of the model for predicting surface roughness of Ti-5-2.5 work material in EDM process is still lagging. In this perspective, it is aimed to develop an ANN model that accurately correlates the EDM process variables as peak current, pulse-on time, pulse-off time, servo-voltage and performance, namely surface roughness ($R_a$) of Ti-5-2.5. The experimental work is carried out by using a numerically controlleddie-sinking EDM. The effect of the process parameters on $R_a$ is studied as well. The surface topography of the machined surface has been analysed through scanning electronic microscope.

## 2. Research Methodology

### *2.1. Experimental procedure*

In this research, the surface roughness ($R_a$) is considered as response parameter, and parameters such as peak current($I_p$), pulse-on time($T_{on}$), pulse-off time ($T_{off}$) and servo-voltage ($S_v$) are selected as EDM variables. The ranges of the process parameters were fixed carrying out the preliminary experiment. The cylindrical graphite electrodes with positive polarity were chosen as tool material. The process parameter ranges and machining condition for SEM viewing are presented in Table 1.The experimental work was conducted based on axial point central composite design (CCD) of response surface methodology. Machining was performed, varying $I_p$, $T_{on}$, $T_{off}$, and$S_v$according to the design matrix obtained through CCD. The value of surface roughness was assessed using the Perthometer. Five observations were carried out on different positions of the machined surface for each sample, and the average of these five was taken as the value of $R_a$. Surface texture analysis was carried out by scanning electronic microscopy (SEM) to observe the surface topography of selected specimens. The specimens were machined in EDM as per settings shown in Table 1(b), and were prepared for SEM viewing following EDM.

Table 1. (a) The process parameters and their ranges.

| Process parameters | Range |
|---|---|
| Peak current ($I_p$) | 1–29 A |
| Pulse-on time ($T_{on}$) | 10–350 µs |
| Pulse-off time ($T_{off}$) | 60–300 µs |
| Servo-voltage ($S_v$) | 75–115 V |

(b) Machining setting for SEM viewing.

| Parameters | Setting-1 | Setting-2 | Setting-3 |
|---|---|---|---|
| Peak current ($I_p$) | 2 | 15 | 29 |
| Pulse-on time ($T_{on}$) | 95 | 180 | 320 |
| Pulse-off time ($T_{off}$) | 120 | 120 | 120 |
| Servo-voltage ($S_v$) | 85 | 85 | 85 |

### *2.2.Modelling*

In the present work, feed forwardmultilayer perceptron neural network is applied and developed for predicting the surface roughness. A multiple input neuron model which consists of a single neuron with $x_i$ inputs. In this case, the net input to the transfer function ($f$) and the output for the neuron can be is defined as follow

$$net\_input = \sum_{i=1}^{n} w_i x_i + b \, ; \qquad output = f(\text{net\_input}) \tag{1}$$

Here, $w_i$ is the synaptic weight, and b is the bias. The MLP neural network is formed from numerous neurons with parallel connections, which are joined in several layers [5]. In this research effort a number of networks are constructed, altering numbers of hidden layers, the number of hidden neurons, maximum epochs, training repetition, and momentum factor, and