# Modeling and Optimization of Electrical Discharge Machining Process Parameters using Artificial Neural Network

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***Abstract*—Electric Discharge machining(EDM) is a thermo-electric, Non-traditional machining process used for machining precise and intricate shapes on hard and difficult to machine materials such as ceramics, haste-alloys, titanium, high strength alloys which are mostly used in medical and aerospace industries. The input and output parameters are optimized using ANN by back propagation algorithm. The experiments are conducted on PH Steel using Copper Tungsten as electrode. The result shows that current, pulse on time and pulse off time have significant effect on MRR and TWR. Experimental values are closely related to ANN values with the variation of 8 to 10 percentage error.**

***Keywords*— *Electrical Discharge Machining, EDM, Artificial neural network, Non-traditional machining***

## I. Introduction

Die Sink EDM, also called cavity type EDM or volume EDM, consists of an electrode and work piece submerged in an insulating liquid such as oil or, other dielectric fluids. The electrode and work piece are connected to a suitable power supply. The power supply generates an electrical potential between the two parts. As the electrode approaches the work piece, dielectric breakdown occurs in the fluid, forming a plasma channel, and a small spark jumps.

These sparks usually strike once at a time since it is very unlikely that different locations in the inter-electrode space have the identical local electrical characteristics which would enable a spark to occur simultaneously in all such locations. These sparks happen in huge numbers at random locations between the electrode and the work piece. As the base metal is eroded, and the spark gap gets increased, the electrode is lowered automatically by the machine so that the process can be continued uninterrupted. Large number of sparks occur per second, with the actual duty cycle carefully controlled by the setup parameters. These controlling cycles are sometimes known as "on time" and "off time".

The on time setting defines the length or duration of the spark. Thus, a longer on time produces a deeper cavity for that spark and all subsequent sparks for that cycle, creating a rougher finish on the work piece and vice versa. Off time is the period of time that one spark is substituted by another. A longer off time allows the flushing of dielectric through a nozzle for cleaning the eroded debris, subsequently avoiding a short circuit. These settings can be maintained within micro seconds. The typical part geometry is a complex 3D shape, mostly with small or odd shaped angles. Vertical, orbital, directional, helical, conical, rotational, spin and indexing machining cycles are often used.

## II. Tool And Work Material

### *A. COPPER TUNGSTEN- tool material*

*1) Composition:*

TABLE I. TABLE STYLES

| *Element* | *%composition* |
|---|---|
| Copper | 20 |
| Tungsten | 80 |

*2) Tool Specifications:*

*a) Diameter:* 12mm

*b) Length:* 20mm

*c) Tap size:* M6

*3) Tool Properties:*

*a) Density:* 15.60 gm/cc

*b) Composition:* 80W:20Cu

*c) Rockwell hardness:* RC22

*d) Electrical conductivity:* 49 % I.A.C.S

*e) Thermal conductivity:* 1.82 W/CM °C

### *B. PH STEEL - work material*

*1) Composition:*

TABLE II. COMPOSITION OF WORK MATERIAL

| ELEMENT | %COMPOSITION |
|---|---|
| Carbon | 0.06 max |
| Manganese | 1.00 max |
| Phosphorus | 0.050 max |
| Sulphur | 0.040 max |
| Silicon | 1.00 max |
| Chromium | 15.00 - 18.50 |
| Nickel | 3.00 - 6.00 |
| Copper | 3.00 - 5.00 |

| | |
|---|---|
| Columbium plus Tantalum | 0.15 - 0.45 |

2) *Specifications:*
   a) *Size:* 10mm×60mm×60mm
   b) *Weight:* 140 g
3) *Properties Of Ph Steel:*
   a) *Rockwell hardness:* C45
   b) *Density:* 7.80 gm/cc
   c) *Electrical resistivity:* 77 micro ohm-cm
   d) *Thermal conductivity:* 17.9 W/mk at 149 C
   e) *UTS (Ultimate tensile strength):* 1448 Mpa
   f) *Specific heat:* 0.46 kJ/Kgk

## III. Artificial Neural Network

### A. Back Propagation Algorithm

The back propagation algorithm (Rumelhart and McClelland) is being used in layered feed-forward ANNs. The neural network is arranged in an order such that the signals that are forwarded are by virtue of their feedback signals. The network receives inputs by means of neurons in the input layer, and the output of the network is given by means of the neurons on an output layer. There are one or more intermediate hidden layers. The BPA uses supervised learning ability, by which we provide the algorithm with examples of the inputs and outputs we want the network to compute, and thus the error (variations between actual and expected results) is calculated. The aim of the BPA is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the aim is to adjust them such that the error will be minimal.

The activation function of the artificial neurons in ANNs implementing the BPA is a weighted sum (the addition of the inputs x multiplied by their respective weights w):

$$A_j(\bar{x}, \bar{w}) = \sum_{i=0}^{n} x_i w_{ji}$$

We can see that the activation depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoidal function:

$$O_j(\bar{x}, \bar{w}) = \frac{1}{1 + e^{A_j(\bar{x}, \bar{w})}}$$

The goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. We can define the error function for the output of each neuron:

$$E_j(\bar{x}, \bar{w}, d) = \left(O_j(\bar{x}, \bar{w}) - d_j\right)^2$$

## IV. Experimental Analysis

We constructed an appropriate ANN model to find out value of MRR and EWR. Initially experiments are conducted on the Work material by varying the input parameters. Full factorial experimental design approach can be used to optimize a process. The various input parameters will be taken under experimental investigation and then model will be prepared. The results obtained will be analysed and the models will be produced using MATLAB 7.01 Software. The input variables if chosen with help of the model will help in improving the life of work piece, material as well as it will enable the effective and efficient working of the EDM machining process. Tool material is of copper tungsten its high wear resistance and dimensional stability.

### A. MRR and TWR Calculations

- Wb: Weight of the work-piece before machining (g)
- Wa: Weight of the work-piece after machining (g)
- Tb: Weight of the tool before machining (g)
- Ta: Weight of the tool after machining (g)
- t: Machining time (min)
- MRR: Metal removal rate
- TWR: Tool wear rate.

MRR = $1000*(W_b - W_a)/t$ mg/min

TWR = $1000*(T_b - T_a)/t$ mg/min

## V. Results And Conclusion

The experiments are conducted by varying the inputs based on the available machine settings and tool and work material properties to study the effect of input parameters on the performance measures like Metal Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (SR).

The following conclusions are made from the work done:

- The value of Metal removal rate is increasing with increase in the value of Current.
- Metal removal rate in EDM Machining will first increase and then decrease with increase in the pulse on time.
- Tool wear rate will increase linearly with increase in the Current.
- The values of Tool wear rate increases with increase in pulse on time and then decreases.
- From the Experimental values the optimal values for MRR and TWR and SR are shown in the table
- Experimental values are closely related to ANN values with Max 15 to 20 % error.

TABLE III. EXPERIMENTAL VALUES FOR THE GIVEN PROCESS PARAMETERS

| | | **Current (Amp)** | **$T_{ON}$ (µs)** | **$T_{OFF}$ (µs)** |
|---|---|---|---|---|
| **Max MRR** | 333.9 mg/min | 18 | 200 | 50 |
| **Min TWR** | 0.333 Mg/min | 3 | 10 | 50 |
| **Min SR** | 1.783 | 3 | 10 | 50 |

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