

## MODELING AND OPTIMIZATION OF WIRE ELECTRICAL DISCHARGE MACHINING IN SINGLE PASS CUTTING OPERATION

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### ABSTRACT

In the present research paper modeling and optimization of wire electrical discharge machining (WEDM) in single pass cutting operation has been carried out. This paper will provide a solution of optimization problem for the selection of the best control setting on a wire cut electrical discharge machine. An advanced artificial neural network is developed to model the machining process. The three most important parameters i.e. cutting speed, surface roughness and dimensional deviation have been considered as measure of process performance. The model is capable to predict the response parameters as function of six different control parameters. Experimental results demonstrate that the proposed ANN model is suitable and the optimization strategy satisfies the real requirement in practice.

**Keywords:** Wire EDM, ANN, Optimization.

### 1. INTRODUCTION

Wire electrical discharge machining (WEDM) has grown tremendously in recent years. This is basically an advanced thermoelectric machining process which is used to cut through complicated contours especially in hard to machine materials. Though several researchers [1-3] have attempted to obtain the optimal solution for this process, but selection of cutting parameters for obtaining higher accuracy and cutting efficiency is not fully solved and in most of the research work only machining speed and surface finish have been considered. Though research work has been done keeping in view of the accuracy aspects [4] but wire offset parameter has so far never been explored in any process modeling and optimization. But the knowledge of wire offset value is very much essential for achieving close dimensional control in practical machining.

In the present set of research study, wire electrical discharge machining of  $\gamma$  titanium aluminide alloy (Ti-44.5 Al-2 Cr-2 Nb-0.3B (at %)) has been considered. They are attracting considerable interest due to their high temperature strength retention, low density ( $3.76 \text{ gm/cm}^3$ ), good creep and oxidation resistance [5]. This alloy is of great interest in aerospace and automobile industries. But it is found that it is extremely difficult to machine by conventional method due to its excellent strength property. No comprehensive research work has been reported so far in the field of wire electrical discharge machining of this alloy. No technology tables or charts are available for wire electrical discharge machining of such important and useful materials in industry. Therefore it is imperative to develop a suitable

machining strategy for optimum and effective machining of  $\gamma$  titanium aluminide alloy.

### 2. EXPERIMENTAL PLANNING

On the basis of literature survey [1-5] and preliminary investigations, the following six parameters i.e. pulse on time ( $T_{ON}$ ), pulse off time ( $T_{OFF}$ ), peak current ( $I_P$ ), servo reference voltage (SV), wire tension (WT) and dielectric flow rate (discharge pressure) (FR) were chosen as input.

Table 1: Factors and their levels

Parameters	Levels		
	Level 1	Level 2	Level 3
$T_{ON}$ ( $\mu\text{ s}$ )	0.8	1.1	1.6
$T_{OFF}$ ( $\mu\text{ s}$ )	14	20	30
$I_P$ (amp)	120	170	220
WT (gm)	900	1140	1380
SV (volt)	2	6	10
FR ( $\text{kg/cm}^2$ )	7	8.5	10

Table 1 shows different levels of these control parameters considered for single pass cutting operation. The range of control factors are kept as wide as possible to obtain large variation in response parameters. Beyond these ranges of control factors the machining process is not feasible due to various reasons i.e. insufficient pulse energy, instability, wire breakage etc. There are other factors, which can be expected to have an effect on the measure of performance. In order to minimize their effects these

other parameters are held constant i.e. product size and shape (rectangular), temperature of the dielectric (28<sup>0</sup>C), conductivity of the dielectric (20 mho), work piece thickness (15mm), pulse Peak voltage setting (75V), wire feed setting (6m/min), servo feed setting, wire type (0.25 mm dia brass) and angle of cut (vertical).

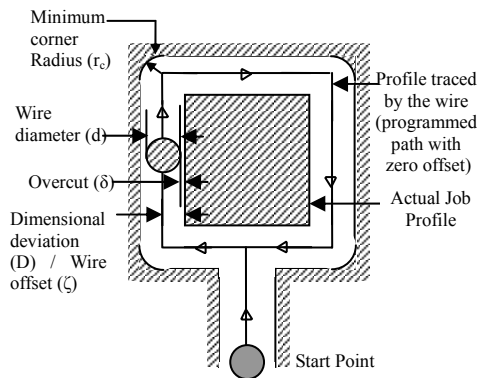


Fig 1. Profile produced by the wire in WEDM.

In the present case the cutting performance of WEDM is measured by three important response parameters i.e. cutting speed (mm/min), surface roughness (Ra micron) and dimensional deviation (D in mm). During WEDM

Table 2: Experimental data used for training

Exp No	Machining Speed (mm/min)	Average R <sub>a</sub> (micron)	Wire Offset (mm)
1	2.67	2.77	0.142
2	2.15	2.78	0.148
3	1.38	2.78	0.150
4	2.24	2.85	0.147
5	2.12	2.81	0.147
6	2.08	2.97	0.151
7	1.84	2.33	0.151
8	1.69	2.48	0.146
9	0.98	2.30	0.141
10	2.1	2.82	0.151
11	1.56	2.64	0.148
12	1.78	2.78	0.146
13	2.58	2.87	0.148
14	2.56	2.92	0.156
15	2.25	3.03	0.150
16	1.69	2.39	0.148
17	1.14	2.30	0.140
18	1.07	2.42	0.140

profile traced by the wire and the job profile are not same. The perpendicular distance between the actual profile and the profile traced by the wire is equal to half of the width of the cut as seen from Fig. 1. Thus the actual job produced by WEDM is either undersized or oversized depending upon whether the job is punch or die. This deviation in dimension is equal to the half the width of

the cut. Thus from Fig. 1 it follows:

$$\text{Dimensional deviation (D)} = 0.5 \times \text{dia of the wire (d)} + \text{overcut } (\delta) \quad (1)$$

The effective method to eliminate dimensional deviation is to shift the wire during cutting by an amount which is equal to dimensional deviation. This amount and direction of shift of the wire can be controlled through part programming. This shift of wire through part programming is commonly termed as wire compensation or wire offset [6]. Hence incase of rough cutting, to eliminate dimensional deviation or dimensional inaccuracy this wire offset ( $\zeta$ ) must be equal to dimensional deviation. The orientation of this wire offset (i.e. left or right with respect to the programmed path) depends upon the direction (CW or CCW) of cutting and type of job (i.e. die or punch).

Table 3: Experimental data used for cross validation

Exp No	Machining Speed (mm/min)	Average R <sub>a</sub> (micron)	Wire Offset (mm)
1	2.24	3.16	0.151
2	1.14	2.55	0.139
3	2.10	2.31	0.145
4	2.90	2.84	0.152
5	2.87	2.72	0.150
6	1.65	2.62	0.150

It may be noted that though the magnitude of dimensional deviation and wire offset are equal but their usage are kept different. The term dimensional deviation has been used as response parameter during rough cutting experiment in WEDM with zero wire offset. But, wire offset is a control setting in WEDM part programming to eliminate or minimize dimensional inaccuracy during actual machining.

The design of experiment consists of 18 experimental runs (L<sub>18</sub>, Table 1). Another 6 experiments were carried out to obtain the validation data set required modeling based on early stopping method of training (Table 2). The experiments were performed on ELECTRA, SUPERCUT 734, series 2000 CNC Wirecut-EDM machine. For each experimental run, the specified input parameter combination was set and the workpiece was machined. The cutting speed was then recorded. Surface roughness was measured by SURFCOM 120A surface texture measuring instrument. The dimensional deviation values were calculated by measuring the job dimension. The job dimensions were measured by digital micrometer having least count 0.001mm.

### 3. MODELING OF WEDM USINS ANN TOOL

Artificial Neural Network (ANN) is a highly flexible modeling tool with the ability to learn the mapping between input and output. For this case, a two-layer network, with tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer were considered. This is a useful structure for function

approximation (or regression) problems. One of the problems that occur during neural network training is called overfitting. To guard the network from overfitting cascade-forward back-propagation neural network based on early stopping in combination with Bayesian regularization has been implemented. Levenberg-Marquardt algorithm was used for training. The value of training parameters (i.e.  $\mu$  and its step size) was adjusted in order to reduce the speed of convergence. The algorithm works best when the network inputs and

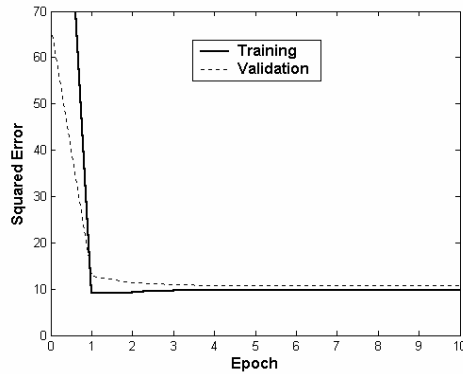


Fig 2. Variation of training and validation mean squared error with progress of training

targets are scaled so that they fall approximately in the range [-1, 1]. Hence inputs and targets were scaled accordingly before training. 4 neurons are used in the hidden layer. As there are 6 inputs and 3 outputs, the number of neurons in the input and output layer has to be set to 6 and 3 respectively. Experimental result shown in Table 2 and 3 has been used as training and validation data set respectively. After carrying out training it was observed that the final trained network uses approximately 18 parameters (i.e. weights and biases) out of 61 initial total weights and biases in 6-30-3 network. A plot of the training and validation errors is shown in Fig. 2. The training stopped after 10 iterations because the validation error increased.

#### 4. POST-TRAINING ANALYSIS

Analysis of the network response was performed. A linear regression between the network output and the

Table 4: Prediction error of the ANN model

Exp No	Prediction error (%)		
	Machining Speed (mm/min)	Average $R_a$ (micron)	Wire offset (mm)
1	8.48	4.43	1.04
2	8.77	5.10	3.60

corresponding targets was carried out. For 3 response parameters 3 regressions were performed. All outputs track the target quite well and correlation coefficients (R-value) are 0.912, 0.907 and 0.902 for cutting speed, surface roughness and dimensional deviation

respectively. All of them are very close to 1, which indicates that the model is quite suitable for this process.

The model is tested further against another two experimental data for which the input parameter setting were chosen arbitrarily. On the basis of verification experimental result prediction error has been evaluated and shown in Table 4. It is observed that ANN model prediction is quite close to the experimental observation. In the table prediction error has been defined as follows.

$$\text{Prediction error\%} = \left| \frac{(\text{Exp result} - \text{Predicted result})}{\text{Exp result}} \right| \times 100 \quad (2)$$

#### 5. PARAMETRIC OPTIMIZATION THROUGH ANN MODEL

The ANN model was used to predict the response parameters i.e. cutting speed, surface finish and dimensional deviation for all possible combinations of

Table 5: Factors and their levels used for optimization

Parameters	Level 1	Level 2	Level 3	Level 4	Level 5
$T_{ON}$ ( $\mu$ s)	0.8	1	1.2	1.4	1.6
$T_{OFF}$ ( $\mu$ s)	14	16	19	24	30
$I_p$ (amp)	120	140	160	180	220
WT (gm)	900	1020	1140	1260	1500
SV (volt)	2	4	6	8	10
FR ( $\text{kg}/\text{cm}^2$ )	7	7.75	8.5	9.25	10

level of the input factors. Then the optimal combinations were searched out from all these combinations. For better optimization all the input parameters have been divided into 5 levels within their working range as illustrated in Table 5. This helps in generating more number of predictions ( $5^6=15,625$ ). The ANN model was used to predict the cutting speed, surface finish and dimensional deviation for all possible combination level of factors i.e. 15,625 combinations. From all these predictions it was observed that within the given parametric range cutting speed is varying between 0.95 mm/min to 2.83 mm/min, surface roughness is varying between 2.37  $\mu$ m to 3.02  $\mu$ m and the dimensional deviation value is varying between 0.137 mm to 0.157 mm.

This is a special optimization problem which deals with simultaneous optimization of multiple objective functions. Here the prime objective is to maximize both  $V_c$  and minimize  $R_a$ . These type of multiple objective optimization problem can be solved by two approaches i.e. either by formulating the problem as constrained optimization algorithm or by searching the Pareto-optimal solutions. In the present research study only constrained optimization approach has been considered. Because of complexity involved in multi-objective optimization algorithm, it is easier to consider only one objective and formulate the other objectives as constraints. For the production purpose, the best combination of parameter level should produce the maximum cutting speed, while maintaining the required surface roughness within the desired limit. Here the cutting speed has been considered as objective function

and surface roughness has been considered as constraints. This requirement may be modeled as constrained optimization problem as follows:

$$\text{Maximize cutting speed} \\ V_c = f(\text{Ton}, \text{Toff}, I_p, \text{WT}, \text{SV}, \text{FR}) \quad (3)$$

$$\text{Subject to } Ra \leq \alpha \\ 0.8 \leq \text{Ton} \leq 1.6 (\mu\text{s}) \quad 14 \leq \text{Toff} \leq 30 (\mu\text{s}) \\ 120 \leq I_p \leq 220(\text{amp}) \quad 2 \leq \text{SV} \leq 10(\text{Volt}) \\ 900 \leq \text{WT} \leq 1500 (\text{gm}) \quad 7 \leq \text{FR} \leq 10 (\text{Kg}/\text{cm}^2)$$

Where  $\alpha$  is the maximum allowable Ra value. The value of  $\alpha$  should be within the range of predicted Ra values i.e. within 2.37  $\mu\text{m}$  to 3.02  $\mu\text{m}$ .

A program has been developed to solve the optimization problem. For example if the required surface roughness of the work piece is less than or equal to 2.7  $\mu\text{m}$ , the best parametric combination would be as follows:

$$\text{Ton} = 1\mu\text{s} \quad \text{Toff} = 30\mu\text{s} \quad I_p = 220 \text{ amp} \\ \text{WT} = 1260\text{gm} \quad \text{SV} = 4\text{Volt} \quad \text{FR} = 10 \text{ kg}/\text{cm}^2.$$

This will yield the highest possible cutting speed  $V_c = 2.36 \text{ mm}/\text{min}$ , maintaining the specified surface finish requirement. The dimensional deviation value for this parameter setting will be 0.148mm. To achieve geometrical precision, the value of wire offset has to be set at 0.148mm in the part programming. It may be noted that any other parameter setting other than this optimum parameter setting either results in lower cutting speed or fails to achieve the stipulated surface finish requirement and geometrical accuracy.

It is sometime desirable to achieve certain minimum corner radius along with the surface finish requirement. This minimum corner radius is equal to wire offset or dimensional deviation value as seen from Fig.1. Under such circumstances, an optimum parametric combination should produce the maximum cutting speed, while maintaining the internal corner radius and also the surface finish within requirements. This may be considered as multi-constrained optimization problem. The model is same as the earlier one except an additional constraint for corner radius, i.e.

$$\text{Maximize cutting speed} \\ V_c = f(\text{Ton}, \text{Toff}, I_p, \text{WT}, \text{SV}, \text{FR}) \quad (4)$$

$$\text{Subject to } Ra \leq \alpha \\ r_c \leq \beta \\ 0.8 \leq \text{Ton} \leq 1.6 (\mu\text{s}) \quad 14 \leq \text{Toff} \leq 30 (\mu\text{s}) \\ 120 \leq I_p \leq 220(\text{amp}) \quad 2 \leq \text{SV} \leq 10(\text{Volt}) \\ 900 \leq \text{WT} \leq 1500 (\text{gm}) \quad 7 \leq \text{FR} \leq 10 (\text{Kg}/\text{cm}^2)$$

Here,  $r_c$  is the minimum corner radius (or dimensional deviation value) and  $\beta$  is the maximum allowable corner radius value. The value of  $\beta$  should be within the range of predicted dimensional deviation (D) values (i.e. within 0.137 mm to 0.157 mm) and the symbol of  $\alpha$  and its range remaining same as mentioned before. The program based on multi-constrained optimization was used. For example, if the required surface roughness value and the corner radius is less than or equal to 2.5  $\mu\text{m}$  and 0.145

mm respectively, the best parametric combination which will yield the maximum cutting speed would be as follows:

$$\text{Ton} = 0.8\mu\text{s} \quad \text{Toff} = 14\mu\text{s} \quad I_p = 120 \text{ amp} \\ \text{WT} = 1020\text{gm} \quad \text{SV} = 2\text{Volt} \quad \text{FR} = 7\text{kg}/\text{cm}^2.$$

This control setting will yield the maximum possible cutting speed i.e. 1.99 mm/min while maintaining the corner radius and surface finish within the required limit.

## 6. CONCLUSIONS

In the present research study, single pass wire electrical discharge machining of  $\gamma$  titanium aluminide alloy has been carried out and an advanced ANN model has been proposed to determine the optimal combination of control parameters. A cascade-forward back-propagation neural network based on early stopping in combination with Bayesian regularization has been implemented to construct the WEDM process model. For better dimensional control, dimensional deviation along with surface finish and cutting speed has been considered as the measures of process performance. The ANN model was used to predict the process performance for all possible combinations (15,625). The process was modeled as a constraint optimization problem. A program was developed that will enable one in selecting the optimum parametric combination which will result in maximum productivity (cutting speed) while maintaining the required surface finish criterion within limit. Beside this, the program is also capable of optimizing the machining process (under multi-constraint conditions) while maintaining the surface roughness as well as internal corner radius within specified limit. Research finding and the developed optimization strategy will be very useful in modern manufacturing industries

## 7. ACKNOWLEDGEMENT

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## 8. REFERENCES

1. Scott, D., Boyina, S. and Rajurkar, K.P., 1991, "Analysis and optimization of parameter combinations in wire electrical discharge machining", *Int. J. Prod. Res.*, 29: 2189-2207.
2. Tarng, Y.S., Ma, S.C. and Chung, L.K., 1995, "Determination of optimal cutting parameters in wire electrical discharge machining", *Int. J. Mach. Tools Manufact.*, 35, 1693-1701.
3. Spedding, T.A. and Wang, Z.Q., 1997, "Study on modeling of wire EDM process", *J. of Mater. Proc. Tech.*, 69: 18-28.
4. Puri, A.B. and Bhattacharyya, B., 2003, "An analysis and optimization of the geometrical inaccuracy due to wire lag phenomenon in WEDM", *Int. J. of Mach. Tools and Manufact.*, 43/2: 151-159.
5. Sharman, A.R.C., Aspinwall, D.K. Dewes, R.C., Clifton, D. and Bowen, P., 2001, "The effects of machined workpiece surface integrity on the fatigue life of  $\gamma$ -titanium aluminide", *Int. J. of Mach. Tools and Manufact.*, 41: 1681-1685.
6. Sarkar S., Mitra S. and Bhattacharyya B. (2005)

“Wire electrical discharge machining of gamma titanium aluminide for optimum process criteria yield”, Int. J. of Adv. Manufact. Tech., 7: 207-223.

## 9. NOMENCLATURE

Symbol	Meaning	Unit
$T_{ON}$	Pulse on time	( $\mu$ sec)
$T_{OFF}$	Pulse off time	( $\mu$ sec)
$I_p$	Peak current	(amp)
WT	Wire tension	(gm)
SV	Servo reference voltage	(volt)
FR	Flow rate	(kg/cm <sup>2</sup> )
D	Dimensional deviation/Wire offset	(mm)
$d$	Diameter of the wire	(mm)
$\delta$	Overcut ( $\delta$ )	(mm)
$V_c$	Machining Speed/Cutting speed	(mm/min)
$R_a$	Surface roughness (CLA value)	(micron)
$\alpha$	Maximum allowable $R_a$ value	(micron)
$\beta$	Maximum allowable corner radius	(mm)
$r_c$	Minimum corner radius	(mm)