Experimental Study of Surface Roughness in Wedm Process and Ann Modelling

Piyush Pant, Navneet K Pandey, S. Rajesha, Gaurav Jain

Abstract-Surface roughness is an effective parameter in representing the quality of machined surface and is one of the most common performance measurements in machining process. This paper reports the effect and optimization of pulse-on time, gap voltage, wire feed rate on surface roughness in wire electrical discharge machining (WEDM) process for die steel D3 using L27 orthogonal array. Signal-to noise (S/N) ratio and ANOVA are used as statistical analyses to achieve optimum levels and to study the population distribution of the response characteristic respectively. It has been found that pulse on-time is the most significant factor affecting the surface roughness. The experimental data is later used to model the surface roughness using artificial neural network.

Keywords: Surface roughness, Taguchi, Wire cut electrical discharge machining, Die steel Artificial neural networks.

I. INTRODUCTION

Wire EDM has revolutionized the tool and die, mold and metal working industries. It is probably the most exciting and diversified machine tool developed for this industry in the last fifty years, and has numerous advantages to offer. It can machine anything that is electrically conductive regardless of the hardness, from relatively common materials such as tool steel, aluminum, copper, and graphite, to exotic space-age alloys including hastaloy, waspaloy, inconel, titanium, carbide, polycrystalline diamond compacts and conductive ceramics. The wire does not touch the workpiece, so there is no physical pressure imparted on the workpiece compared to grinding wheels and milling cutters. The amount of clamping pressure required to hold small, thin and fragile parts is minimal, preventing damage or distortion to the workpiece. The accuracy, surface finish and time required to complete a job is extremely predictable, making it much easier to quote, WEDM leaves a totally random pattern on the surface as compared to tooling marks left by milling cutters and grinding wheels. The WEDM process leaves no residual burrs on the workpiece, which reduces or eliminates the need for subsequent finishing operations. Die-making industry is very important to down-stream industries and any technological changes in the die-making industry surely affect those down-stream manufacturing. . New materials with high hardness and toughness, such as die and tool steels, are being developed which are difficult to be machined by conventional manufacturing techniques such as milling, drilling and turning. Hence, non-traditional machining processes are employed. WEDM is widely used to machine these. Surface roughness describes the geometry and surface textures of the machined parts (Nalbant et al., 2007).

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There are several ways to describe surface roughness, such as roughness average (Ra), root-mean-square (rms) roughness (Rq) and maximum peak-to-valley roughness (Ry or max), etc.(http://www.prediv.com/smg/parameters.html). Ra is defined as the arithmetic value of the profile from centre line along the sampling length and can be expressed by the following mathematical relationship (Ozc¸ elik et al., 2005):

$$R_a=\frac{1}{L}\int_0^L|Y(x)|dx \qquad (1)$$

Where,
R_a = Arithmetic average deviation from the mean line
L = Sampling length
Y = Ordinate of the profile curve

ANN refers to the computing systems whose fundamental concept is taken from analogy of biological neural networks. Many day to day tasks involving intelligence or pattern recognition are extremely difficult to automate, but appear to be performed very easily by animals. The neural network of an animal is part of its nervous system, containing a network of specialized cells called neurons (nerve cells). Neurons are massively interconnected, where an interconnection is between the axon of one neuron and dendrite of another neuron, referred to as synapse. Signals propagate from the dendrites, through the cell body to the axon; from where the signals are propagate to all connected dendrites. A signal is transmitted to the axon of a neuron only when the cell 'fires'. A neuron can either inhibit or excite a signal according to requirement.

II. LITERATURE SURVEY

Pradhan et. al. optimized micro-EDM process parameters for machining Ti-6Al-4V super alloy. Poros et. al. studied the efficiency of wire EDM for two different difficult to machine materials-titanium alloys and cemented carbides. Qu et. al. demonstrated the feasibility of applying the cylindrical wire EDM process for high MRR machining of free-form cylindrical geometries. Sarkar et. al. performed experimental investigation on trim cutting using WEDM of TiAl alloy. Kanlayasiri et. al. investigated the influence of WEDM machining variables on surface roughness of newly developed DC 53 die steel of width, length and thickness 27, 65 and 13 mm, respectively. Panda et. al. has developed an ANN model (using feed forward neural architecture) using Levenberg-Marquardt learning algorithm and logistic sigmoid transfer function to predict the material removal rate. Pradhan et. al. compared the performance and efficiency of back propagation neural network (BPN) and radial basis function neural network (RBFN) for the prediction of SR in EDM. Thillaivannan et. al. have explored a practical method of optimizing machining parameters for EDM process under the minimum total machining time based on Taguchi method and Artificial neural network. Rao et. al. presented a work aimed on

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the effect of various machining parameters on hardness. S. Di et al. analyzed the kerf width in micro-WEDM and developed a model between machining parameters and wire vibration amplitude, explaining the variety of kerf width in the micro-WEDM process. Gokler et. al. conducted series of experiments on selected steels (1040, 2379 and 2738) of various thicknesses to develop charts for selecting the most suitable combinations of cutting and offset parameters in order to get the desired surface roughness in the WEDM process. Ho et. al. reviewed the vast array of research work carried out from the spin-off from the EDM process to the development of the WEDM. Ozdemir et. al. investigated the machinability of standard GGG40 nodular cast iron by A300 Fine Sodick Mark XI WEDM using different parameters. Shunmugam et. al. used a multiple regression model to represent relationship between input and output variables and a multi-objective optimization method based on a non-dominated sorting genetic algorithm (NSGA) is used to optimize wire-EDM process. Chiang et. al. presented an approach for the optimization of the WEDM process of Al_2O_3 particle reinforced material with two performance characteristics, e.g. SR and MRR, based on the grey relational analysis.

III. IDENTIFIED GAPS IN THE LITERATURE

After a comprehensive study of the existing literature, a number of gaps have been observed in machining of WEDM.

a. Most of the researchers have investigated the influence of a limited number of WEDM process parameters on the performance measures of the work piece.
b. Very limited work has been reported on the effect of machining parameters on the machining characteristics in WEDM of AISI D3 Die steel.
c. Attempts to create an ANN model for response characteristic in WEDM process of AISI D3 Die steel are still scarce.

IV. EXPERIMENTAL DETAILS

A. WORK PIECE MATERIAL

The work-piece material used is AISI D3 die steel whose properties are shown in the Table 1 & 2

Table 1: Chemical Composition of the Material

Element	Weight %
C	2.00-2.35
Mn	0.6
Si	0.6
Cr	11.00-13.50
Ni	0.3
W	1
V	1
Cu	0.25
P	0.03
Si	0.03
Fe	Remaining

Table 2: Mechanical Properties (at 25^0C)

Density (*1000kg/m^3)	7.7
Poisson's Ratio	0.27-0.30
Elastic Modulus (GPa)	190-210
Surface hardness	60 RC

V. EXPERIMENTAL RESULTS AND ANALYSIS – TAGUCHI DESIGN METHOD AND ARTIFICIAL NEURAL NETWORK

A. PARAMETER ASSIGNMENT

The levels of the individual process parameters are given in Table 3.

Table 3: Process Parameters and their Levels

Process Parameter	Reading for each variable		
	Level 1	Level 2	Level 3
Pulse ON time (T_{ON}) in µs	30	40	50
Gap voltage (V_G) in volt	10	20	30
Wire feed rate (F) in m/min	15	20	25

B. EXPERIMENTAL RESULTS

Table 4: Experimental Results for Surface Roughness

Expt No.	Ton	Vg	F	Mean R	Signal to noise ratio
1	30	10	15	4.8625	-13.74
2	30	10	20	4.7525	-13.54
3	30	10	25	4.67	-13.39
4	30	20	15	4.8425	-13.7
5	30	20	20	4.7675	-13.57
6	30	20	25	4.61	-13.28
7	30	30	15	4.85	-13.72
8	30	30	20	4.67	-13.39
9	30	30	25	4.57	-13.2
10	40	10	15	4.995	-13.98
11	40	10	20	5.395	-14.65

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12	40	10	25	4.9425	-13.88
13	40	20	15	5.345	-14.56
14	40	20	20	5.0825	-14.12
15	40	20	25	5.215	-14.35
16	40	30	15	5.1425	-14.22
17	40	30	20	5.345	-14.56
18	40	30	25	5.1675	-14.27
19	50	10	15	6.225	-15.88
20	50	10	20	5.755	-15.2
21	50	10	25	5.9075	-15.43
22	50	20	15	5.7825	-15.25
23	50	20	20	6.12	-15.74
24	50	20	25	5.9425	-15.48
25	50	30	15	6.35	-16.06
26	50	30	20	6.0975	-15.71
27	50	30	25	6.2925	-15.98

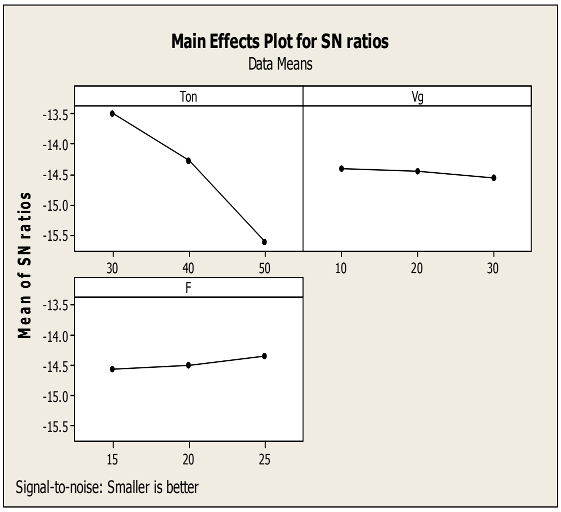

Figure 1: Effects of Process Parameters on Surface Roughness (S/N Data)

Table 5: Response Table for Surface Roughness (S/N Data)

Level	T_{ON}	V	F
1	-13.5	-14.41	-14.57
2	-14.28	-14.45	-14.49
3	-15.63	-14.56	-14.36
Delta	2.13	0.16	0.21

Rank	1	3	2

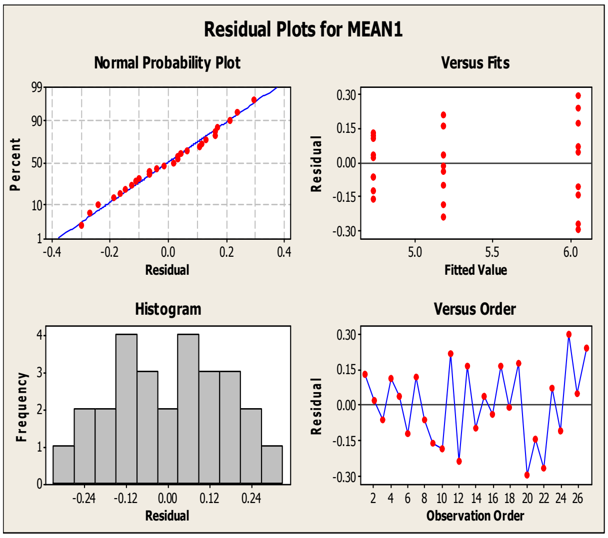

Figure 2: Residual Plots for Surface Roughness (obtained using minitab 16)

C. NORMALISED DATA

To produce similar output for similar input and thus to avoid overfitting, normalization is carried out using the equation suggested by Sanjay and Jyothi :

$$x_i = \frac{x_i - \min_i}{\max_i - \min_i} * 0.8 + (0.1) \qquad (2)$$

for each value x_i of i^{th} attribute, $\min_i$ and $\max_i$ are the minimum and maximum value of that attribute over the training set.

Table 6: Normalised Data

Exp	Ton	V	F	R
1	0.1	0.1	0.1	0.231333
2	0.1	0.1	0.5	0.181943
3	0.1	0.1	0.9	0.1449
4	0.1	0.5	0.1	0.222353
5	0.1	0.5	0.5	0.188678
6	0.1	0.5	0.9	0.11796
7	0.1	0.9	0.1	0.22572
8	0.1	0.9	0.5	0.1449
9	0.1	0.9	0.9	0.1
10	0.5	0.1	0.1	0.290825
11	0.5	0.1	0.5	0.470425
12	0.5	0.1	0.9	0.267253
13	0.5	0.5	0.1	0.447975
14	0.5	0.5	0.5	0.330113
15	0.5	0.5	0.9	0.389605
16	0.5	0.9	0.1	0.357053
17	0.5	0.9	0.5	0.447975
18	0.5	0.9	0.9	0.368278
19	0.9	0.1	0.1	0.843095
20	0.9	0.1	0.5	0.632065
21	0.9	0.1	0.9	0.700538
22	0.9	0.5	0.1	0.644413
23	0.9	0.5	0.5	0.79595
24	0.9	0.5	0.9	0.716253

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25	0.9	0.9	0.1	0.89922
26	0.9	0.9	0.5	0.785848
27	0.9	0.9	0.9	0.873403

D. TRAINING DATA

23 readings are randomnly selected from normalized data in table 6 for ANN training (Table 7).

Table 7: Training Data

Ton	V	F	R
0.1	0.1	0.1	0.231333
0.1	0.1	0.5	0.181943
0.1	0.1	0.9	0.1449
0.1	0.5	0.1	0.222353
0.1	0.5	0.5	0.188678
0.1	0.9	0.1	0.22572
0.1	0.9	0.5	0.1449
0.1	0.9	0.9	0.1
0.5	0.1	0.1	0.290825
0.5	0.1	0.5	0.470425
0.5	0.5	0.1	0.447975
0.5	0.5	0.5	0.330113
0.5	0.5	0.9	0.389605
0.5	0.9	0.1	0.357053
0.5	0.9	0.5	0.447975
0.5	0.9	0.9	0.368278
0.9	0.1	0.5	0.632065
0.9	0.1	0.9	0.700538
0.9	0.5	0.1	0.644413
0.9	0.5	0.5	0.79595
0.9	0.5	0.9	0.716253
0.9	0.9	0.1	0.89922
0.9	0.9	0.9	0.873403

E. GENERATING AND TRAINING THE ANN MODEL

ANN model was generated for 1 hidden layer, 4 neurons, tansig transfer function. The training data (Table 7) is used for training the ANN using Levenberg–Marquardt training algorithm(Fig 3).

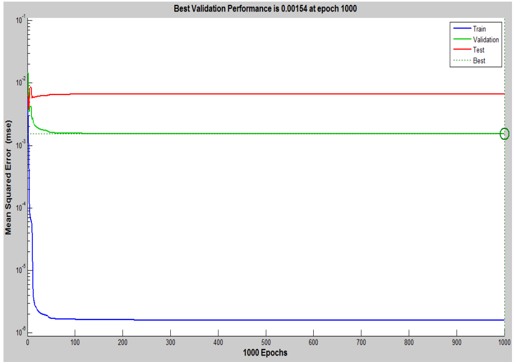

Fig 3: Training the ANN Model

VI. DISCUSSION OF RESULTS

- It is seen from the Figure 1 that the surface roughness increases with an increase in pulse on time and gap voltage but with increase in wire feed rate. With increase in the pulse on time and gap voltage, the discharge energy increases and produces a wider crater whereas, with increase in wire feed rate, less time is available for spark concentration and thus, resulting in the formation of small crater.
- The response table shows the average of the surface roughness for each level of each factor and includes ranks based on delta statistics, which compare the relative magnitude of effects. The delta statistic is the highest minus the lowest average for each factor. Minitab assigns ranks based on delta values; rank 1 to the highest delta value, rank 2 to the second highest, and so on. The ranks indicate the relative importance of each factor to the response. The ranks and the delta values from table 5 show that pulse on time have the greatest effect on surface roughness and is followed by wire feed rate and spark gap set voltage.
- It can be seen from Figure 2 that the residuals follow an approximately straight line in normal probability plot and approximate symmetric nature of histogram indicates that the residuals are normally distributed.
- It can be seen from Figure 1 that the first level of pulse on time, first level of spark gap set voltage, and third level of wire feed rate gives the minimum value of surface roughness.
- The training of the ANN model shows decrease in the mean square error (Fig 3).

VII. SUGGESTIONS FOR FUTURE WORK

Considering the WEDM machining of AISI D3 Die steel work material performed in this experimental work, still there is a scope for further investigation. The following suggestions may prove useful for future work:

1) More than one output parameters should be taken and multi objective optimization should be performed.
2) The effect of the process parameters such as flushing pressure, conductivity of dielectric, wire

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diameter, wire of different materials, work piece height etc. may also be investigated.

3) The effects of machining parameters on recast layer thickness and overcut should be investigated.
4) Efforts should be made to investigate the effects of WEDM process parameters on the performance measures in a cryogenic cutting environment.

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