9th INTERNATIONAL SYMPOSIUM ON MEASUREMENT AND QUALITY CONTROL (9th ISMQC)
November 21 – 24, 2007, IIT Madras

ESTIMATION OF SURFACE ROUGHNESS AND DIMENSIONAL ACCURACY USING PROCESS PARAMETERS IN WIRE CUT EDM BY ARTIFICIAL NEURAL NETWORK

Manjunatha, B. B. and Ravindra, H. V.
Dept. of Mech. Engg., P.E.S. College of Engg., Mandya – 571 401
E-mail: mailhovera@yahoo.com

Nixon Kuruvila
Dept. of Mech. Engg., Sahrdaya College of Engg. & Tech., Thrissur
E-mail: nixonkuruvilak@yahoo.co.in

Abstract: *Wire cut EDM is a widely accepted non-traditional material removal process to manufacture components with intricate shapes and profiles irrespective of hardness. Due to complicated stochastic process mechanisms in wire-EDM, the relationships between the cutting parameters and cutting performance are hard to model accurately. Experiments were carried out machining the SKD11/D2A2, Tungsten Carbide and Mild steel material using brass wire of diameter 0.25mm as tool. The input process parameters considered during experiments were servo voltage, offset distance, machining speed, pulse-on and pulse-off. Data's were taken for different thickness and for different materials of same thickness and corresponding dimensional accuracy and roughness were measured. Artificial neural network is used for the estimation of the dependent parameters (dimensional accuracy and roughness) of WEDM. Finally, from the comparison it was observed that at 90% data in training, data estimated using Artificial Neural Network correlates well with measured value.*
Key words: *WEDM, artificial neural network, roughness, dimensional accuracy.*

1. INTRODUCTION

The conventional machining processes remove material by chip formation, abrasion, or micro chipping. There are situations where these processes are not satisfactory, economical, and may impossible because of newer and more exotic materials have been developed in the past few decades. Hence Conventional machining operations tend to reach their limitations, as relatively more complicated shaped jobs are required to be manufactured. Technological advances have lead to an increasing use of high strength, high hardness materials in manufacturing industries. In the machining of these materials, traditional manufacturing processes are increasingly being replaced by more advanced techniques. These factors lead to evolution of non-traditional machining process. Comparing to some of the non-traditional machining process the EDM machining has some outstanding feature. In the EDM, to obtain the greater dimensional accuracy and to machine intricate shape, Wire-cut Electric Discharge Machine [WEDM] is used.

Puri and Battacharya (2003) have described wire lag phenomenon in WEDM and the trend of the variation of the geometrical inaccuracy caused due to wire lag with various machine control parameters. Tarng, et. al. (1995) in their paper discussed about the determination of optimal cutting parameters in wire electrical discharge machining. It is found that the neural network can clearly clarify the complicated relationships between the cutting parameters and cutting performance. Lee and Tain (2003) in their paper analyzed the relationship between EDM parameters and surface crack formation. Based up on the experimental results, they established a crack prediction map, which indicate whether or not cracks are likely to form for a given pulse-on and pulse current combination. Shankar Singh et. al. (2004) conducted studies on the electric discharge machining of hardened tool steel using different electrode materials. After analyzing the results of the experiments they found that for the EN-31 work material, Copper and aluminium electrodes offer high MRR. Copper and Copper tungsten electrodes offer comparatively low electrode wear for the tested work material. Taguchi's method which is one of the methods of robust design of experiments is widely used to optimize multi responses of the wire cut electric discharge machining operations. By applying the Taguchi's good improvement is obtained.

This paper presents an intelligent approach for process parameter estimation made by investigation of different approach in a WEDM process and compares the estimated value with measured value of dimensional accuracy and roughness.

2. ARTIFICIAL NEURAL NETWORKS

The structure of the brain is found to be a highly developed mechanism, which is capable of performing immensely impressive tasks. The things that the computer is capable of doing, the brain manages exceptionally well, and the idea behind neural imputing is that by modeling the major features of the brain and its operation, the computers that exhibit many of the useful properties of the brain can be produced. Though the structure of the brain is complex, it can be viewed as a highly interconnected network of relatively simple processing elements, there is a need for the model that can capture important features of real neural systems in order that it will be similar behavior. However, the model must deliberately ignore many small effects, if it is to be simple enough to implement and understand. The aim of a model is to reduce simplified version of a system, which retains the same general behavior, so that stem can be more easily understood.

The topology of neural network refers to its framework as well as its interconnection scheme. The framework is often specified by the number of layers and the number of nodes per layer. The types of layers include Input layer, Hidden layer and Output layer. A connection between nodes in different layers is called an 'interlayer connection'. The term 'connectivity' refers to how nodes are connected. Full connectivity means that every nodes in one layer is connected to every node in its adjacent layer. Mosarni and Muto (2003) in their paper discussed about the Radial based function (RBF) Artificial Neural Network approach for prediction of Material Removal Rate(MRR) and surface roughness. The Input parameters are current, voltage, period of pulse-ON Period of pulse-OFF the output parameters are surface roughness and MRR. The output MRR and surface roughness obtained from RBF Artificial Neural Network is compared with experimental results and error is calculated.

3. EXPERIMENTATION

The experiments were conducted using FANUC ROBOCUT I-09 WEDM. The work materials used are mild steel, tungsten carbide and SKD11/D2A2. Chemical composition of these materials is given in Table 1.

Table 1 Chemical compositions of the work piece material

Material	Composition
SKD11/D2A2	Carbon, Silicon, Manganese, Chromium and Molybdenum
Tungsten Carbide (TC)	Iron and Chromium
Mild Steel (MS)	Iron, Steel

The chemical composition of tool material is given in Table 2. Experimentation was done in two stages. In first stage, thickness of the materials was kept constant and machining was done. In second stage, thickness of SKD11/D2A2 material was varied and machining was done. In both the cases the parameters measured are servo voltage, offset distance, feed rate, pulse-on time and pulse-off time. The roughness of machined surface and dimensional accuracy were measured using HANDYSURF and CMM respectively. Machining was stopped at regular intervals and the surface roughness and dimensional accuracy were measured.

Table 2 Specification of wire (tool)

S. No.	Description	
1	Material	Brass
2	Diameter (mm)	0.1 to 0.3
3	Specific weight	8.5
4	Melting point	900^0 C
5	Coefficient of linear expansion	0.0012

Table 3 shows the input parameters and measured parameters for SKD11/D2A2 material of 30 mm thickness. From the table, it can be observed that the dimensional accuracy increases and surface roughness decreases with increase in number of pass. As a result surface becomes smoother and finally surface becomes super finished and meets the required dimensional accuracy value. Similarly, the above experimental procedure was performed to check the dimensional accuracy and surface roughness for tungsten carbide and mild steel material for the same thickness of 30 mm. From results it is observed that the servo voltage has an influence on surface roughness and dimensional accuracy of the material. As servo voltage increases surface roughness decreases and dimensional accuracy increases. The effect of servo voltage on dimensional accuracy and surface roughness are as shown in Fig.1 and Fig. 2.

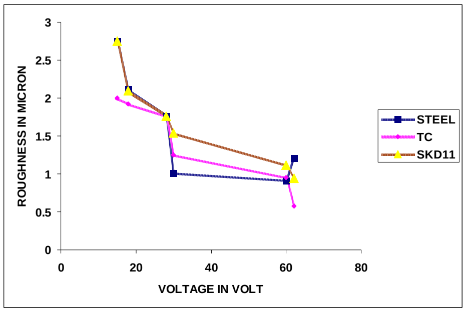

Fig. 1 Voltage v/s Roughness

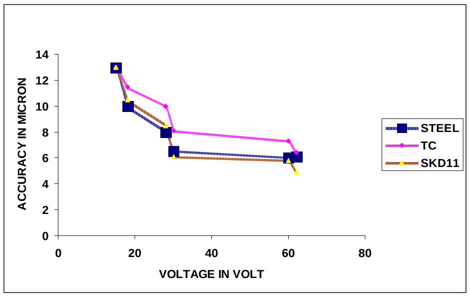

Fig. 2 Voltage v/s Accuracy

Table 3 Readings for the material SKD11/D2A2 of thickness 30 mm

Material	No of Pass	PM	P_{ON} in micro sec	P_{OFF} in micro sec	Servo Voltage in volts	Wire Tension gms	Wire feed rate m/min	Speed (mm/min)	Offset (mm)	Dimensional Accuracy (microns)	Roughness (microns)
SKD11/ D2A2	1	1	10	13	30	1700	10	3.40	0.1500	13	2.75
	1	1	11	18	18	1700	10	4.90	0.183	10.5	2.1
	2	1	2	10	62	1700	12	8.80	0.1300	8.5	1.76
	1	1	12	15	28	1700	10	3.90	0.2040	6.1	1.54
	2	1	3	15	60	1700	12	6.70	0.1440	5.8	1.12
	3	4	2	15	28	1700	12	5.40	0.1340	4.9	0.94
	1	1	12	15	28	1700	10	3.70	0.2070	4.5	0.80
	2	1	3	15	60	1700	12	6.70	0.1470	4.2	0.72
	3	4	2	15	28	1700	12	5.40	0.1370	4.3	0.62
	4	2	60	15	15	1700	12	11.20	0.1320	3.9	0.47

4. ANALYSIS

From the parameters measured during machining, it is not possible to estimate the roughness and dimensional accuracy for a given machining parameter. Thus there is a requirement for more sophisticated method to estimate the theoretical value of roughness and dimensional accuracy. Artificial Neural Network was the tool that works on pattern recognition technique. In the present work ANN was used for estimation. All the machining parameters viz., servo voltage, pulse-on, pulse-off, feed rate and off set distance were taken in to account. ANN was trained and the roughness and dimensional accuracy were estimated. The amount of data in the training set was gradually increased in step of 10% varying from 50% to 90%. Table 4 shows comparison of experimental and estimated values for surface roughness and dimensional accuracy in the successive training set for the material SKD11/D2A2 with thickness 30mm.

Fig. 3 to Fig. 6 represents the comparison between measured and estimated roughness and dimensional accuracy at 80% and 90% data in training set.

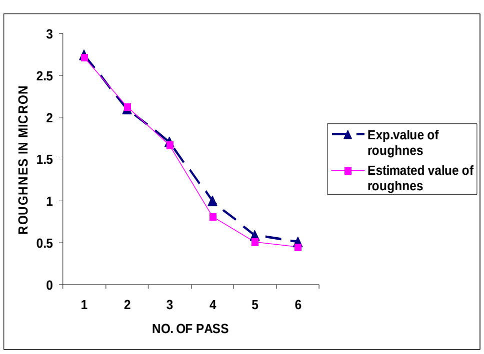

Fig. 3 Comparison of experimental and estimated roughness for SKD11/D2A2 at 80%

From Fig. 3 and Fig. 5, it is clear that roughness curves of both estimated and measured values correlates well. Among these, a better correlation is obtained for 80 % data in the training set. From Fig. 4 and Fig. 6 it is clear that estimated dimensional accuracy correlates well with measured value for SKD11/D2A2 at 30mm thickness of material. Here also, a better correlation is obtained for 80 % data in the training set. This is because neural network at higher percentage of training remembers the training data well and by comparing the test data with more number of training data gives nearest or closed estimated value.

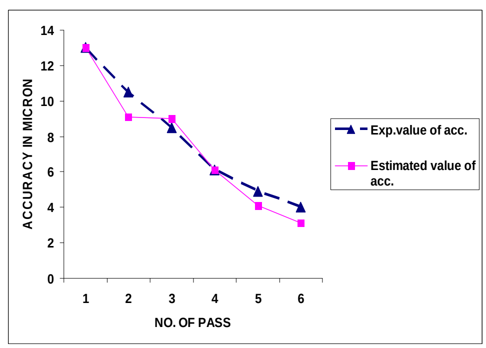

Fig. 4 Comparison of experimental and estimated Accuracy for SKD11/D2A2 at 80%

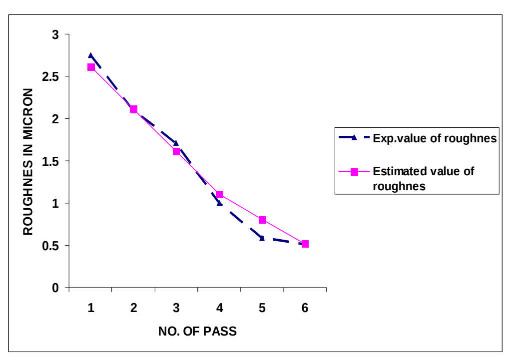

Fig. 5 Comparison of experimental and estimated roughness for SKD11/D2A2 at 90%

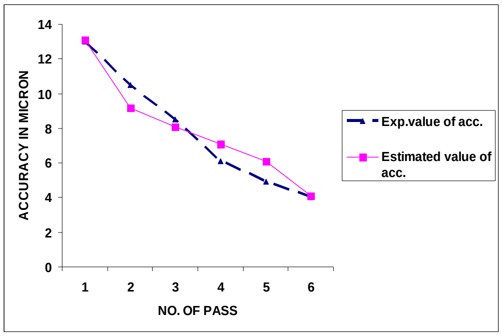

Fig. 6 Comparison of experimental and estimated Accuracy for SKD11/D2A2 at 90%

By observing the results for different material, it shows that the neural network gives better estimation for 80% and least estimation for 50% data in training set. Also it shows that the estimated values at 80% data's in training set correlates well with measured values. By observing the figures it clears that at 90% data in training set the predicted roughness and accuracy are not exactly correlating with the measured values. The general observation from the above results was that the percentage of estimation increases with increase in the amount of data in the training set.

Table 4 Estimated values of dimensional accuracy and surface roughness for 30mm thickness for SKD11/D2A2

%	Roughness (μm)		Accuracy (μm)	
Training	Expected	Estimated	Expected	Estimated
70	2.75	2.7511	13	13.1213
	2.10	2.2113	10.5	9.1212
	1.71	1.7121	8.5	8.9912
	1.0	0.9999	6.1	6.1219
	0.59	0.6121	4.9	4.1212
	0.51	0.5242	4	3.1049
80	2.75	2.7121	13	13.001
	2.10	2.1301	10.5	9.1212
	1.71	1.6712	8.5	8.9912
	1.0	0.8112	6.1	6.1219
	0.59	0.5121	4.9	4.1212
	0.51	0.4513	4	3.1049
90	2.75	2.6112	13	13.1000
	2.10	2.1121	10.5	9.1721
	1.71	1.6121	8.5	8.1023
	1.0	1.1021	6.1	7.1121
	0.59	0.8121	4.9	6.1221
	0.51	0.5148	4	4.1353

5. CONCLUSIONS

Artificial neural network has been attempted for accuracy and surface roughness estimation. It was observed that the performance of neural network gives better results at 80% of data in the training set and predicted value correlates well with measured value. Hence neural network will reduce the number of experimental trials, thus it saves 4M's, i. e. Man, Machine, Materials and Money.

Based on experimental observation, the following conclusions were drawn.

- From the experimental data it was observed that roughness decreases with increase in the number of pass
- The accuracy increases with increase in the number of pass. Since it removes material at each pass to achieve good surface finish.
- The roughness decreases with increasing servo voltage.
- Similarly accuracy increases with increasing the servo voltage.

Based on artificial neural network, following conclusions were drawn. Depending upon number of data in training set, different models were obtained for 50%, 60%, 70%, 80% and 90% data's in training set among which 80% models gave better results.

6. REFERENCES

Lee H. T & Tai. T. Y. (2003). The relation between EDM parameter and surface crack formation, *Journal of Material Processing Tech.*, Vol. 142, pp. 676-683.

Mosarni Kuneleda & Hidauli Muto. (2003). Development of multi-spark EDM, *Annals of CIRP*, Vol. 49, pp. 119-129.

Puri A. B & Bhattacharyya B. (2003). Modeling and analysis of the tool vibration in Wire-cut EDM, *Material Processing Tech.*, Vol. 141, pp. 295-301.

Shanker Singh; Maheswari S. & Pandey P. C. (2004). Some investigation in to electric discharge machining of hardened tool steel using different electrode material, *Journals of Material Processing Technology*, Vol. 149, pp. 272-277.

Tarng, Y. S.; Ma, S. C & Chung, L. K. (1995). The determination of optimal cutting parameters in wire electrical discharge machining, *Int. Journal of Machine Tools & Manuf.*, Vol. 35, No.12, pp. 1693 – 1701.