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Research Paper

MODELING OF SURFACE ROUGHNESS IN WIRE ELECTRICAL DISCHARGE MACHINING USING ARTIFICIAL NEURAL NETWORKS

P Vijaya Bhaskara Reddy[1]*, Ch R Vikram Kumar[1] and K Hemachandra Reddy[2]

*Corresponding Author: **P Vijaya Bhaskara Reddy,** ✉ vijaydharma@yahoo.co.in

In this paper the Artificial Neural Network (ANN) model is developed to predict the surface roughness in Wire Electrical Discharge Machining (WEDM) of WP7V steel, which is used in automobile industry. The neural network model is trained with experimental results conducted using L16 orthogonal array by considering the input parameters such as pulse duration, open voltage, wire speed and dielectric flushing pressure at four different levels. The mathematical relation between the work piece surface roughness and WEDM cutting parameters is also established by multiple regression analysis method. Predicted values of surface roughness by NN and regression analysis, are compared with the experimental values and their closeness with the experimental values. The predicted values in neural network with two hidden layers are very close to the experimental results than regression values. The complete experimental and modeling results are presented and analyzed in this paper

Keywords: Wire EDM, Multiple regressions, ANN.wp7v

INTRODUCTION

The Wire Electrical Discharge Machining (WEDM) process has gained momentum for its practical applicability in the current manufacturing scenario. The suitability of the process is greatly exhibited while generating complicated job in contours, making through holes, producing straight tapered jobs and so on. Wire Electrical Discharge Machining is a spark erosion process used to produce complex two and three dimensional shapes through electrically conductive work pieces by using a wire electrode. The sparks are generated between the work piece and a wire electrode flushed with or immersed in a dielectric fluid (Tosun *et al.*, 2004). The wire, which unwinds from a spool, feeds through the work piece. A power supply delivers high

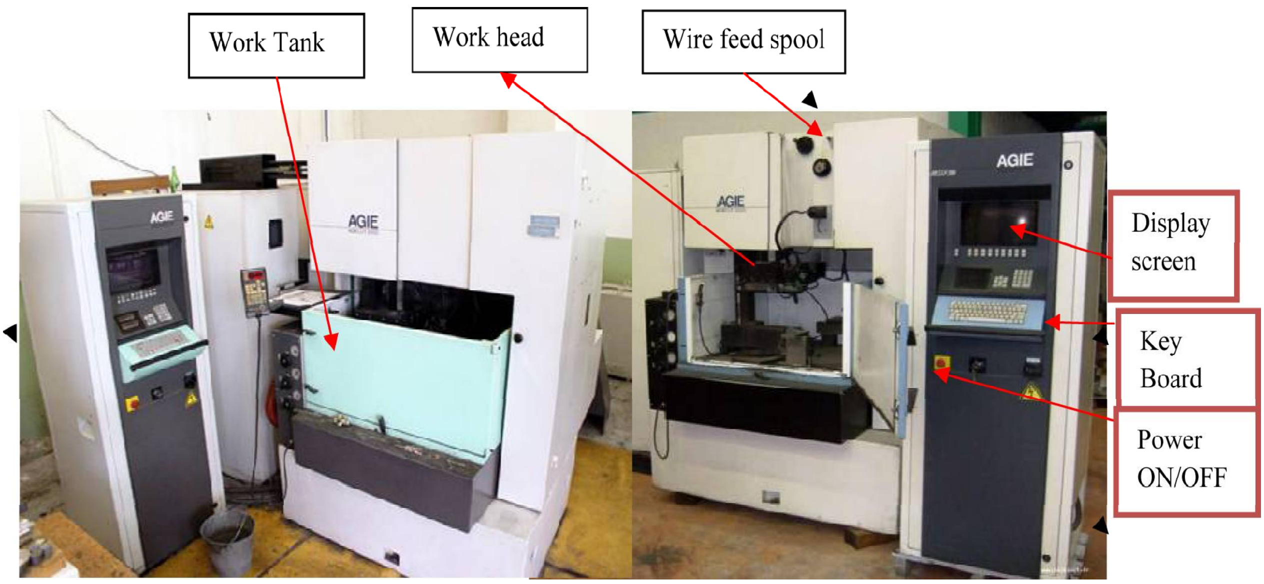
[1] Department of Mechanical Engineering, N.B.K.R, I.S.T, Vidyanagar, Nellore (Dt.), Andhra Pradesh 524413, India.
[2] J N T University College of Engineering, Anantapur, Andhra Pradesh, India.

frequency pulses of electricity to the wire and the work piece. The gap between the wire and work piece is flooded with a localized stream of deionized water which acts as the dielectric. Work piece material is eroded ahead of transporting the wire by spark discharges, which are identical with those in conventional EDM (Tosun and Cogun, 2003). When each pulse of electricity is delivered from the power supply, the insulating properties of the dielectric fluid are momentarily broken down. This allows a small spark to jump the shortest distance between the wire and work piece. A small pool of molten metal is formed on the work piece and the wire at the point of the spark. A gas bubble forms around the spark and the molten pools. As the pulse of electricity ceases and the spark disappears, the gas bubble collapses. The on-rush of cool dielectric causes the molten metal to be ejected from the work piece and the wire, leaving small craters. This action is repeated hundreds of thousands of times each second during WEDM processing. This removes material from the work piece in shapes opposite to that of wire (Tosun and Cogun, 2003; and Tosun *et al.*, 2003a). The degree of accuracy of the work piece dimensions are obtainable and the fine surface finishes make WEDM particularly valuable for applications involving the manufacture of stamping dies, extrusion dies and prototype parts. Without WEDM the fabrication of precision work pieces requires many hours of manual grinding and polishing (Tosun *et al.*, 2003b and 2004). The most important performance measures in WEDM are cutting speed, work piece surface roughness and cutting width. Discharge current, discharge capacitance, pulse duration, pulse frequency, wire speed, wire tension, average working voltage and dielectric flushing conditions are the machining parameters which affect the performance measures (Tosun *et al.*, 2004). Spedding and Wang (1997) presented a parametric combination by using artificial neural networks and they also characterized the roughness and waviness of the work piece surface and cutting speed. Lok and Lee (1997) compared the machining performance in terms of MRR and surface finish by the processing of two advanced ceramics under different cutting conditions using WEDM. Ramakrishna and Karunamoorthy (2008) developed an artificial neural network with Taguchi parameter design. Caydas *et al.* (2009) developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) for modeling the surface roughness in the WEDM process. Based on the literature the neural network is more effective tool to predict the machining performance parameters for the given input parameters. The objective of the present work is to develop the neural network model to predict the surface roughness for the given set of conditions. In this work an attempt is also made to develop mathematical relation between for the selected parameters and surface roughness using regression analysis. The complete experimental and modeling results are presented and analyzed in this work.

EXPERIMENTAL RESULTS

The experimental studies were performed on an AGIECUT 220 WEDM machine tool as shown in Figure 1. Different settings of pulse duration (t), open circuit voltage (V), wire speed A_w and flushing pressure (p) were used in the experimentation. The work piece used is wp7v steel(0.5%C,7.8%Cr,1.5%V,1.5,%Mo)

Figure 1: Pictorial View of AGIECUT 220



material plate with 220 × 40 × 10 mm dimensions. Zinc coated brass wire with 0.25 mm diameter and tensile strength of 900 N/mm^2 was used in the experiments. Average surface roughness (Ra) measurements were made by using Phynix TR-100 portable surface roughness tester with cut-off length (IC) and traversing length (l) of 20 and 5 mm, respectively. Pulse duration, open circuit voltage, wire speed and dielectric flushing pressure were selected as the input parameters and surface roughness was

Table 1: Factors and Their Levels

Parameters	Levels			
	Level 1	Level 2	Level 3	Level 4
Pulse duration t(μs)	5	10	12	15
Wire speed (Aw) (mm/sec)	100	80	70	60
V (volt)	20	25	35	45
P (bar)	2	2	12	12

Table 2: Surface Roughness Obtained from the Experiments

Exp. No.	Input Parameters				Output Parameters
	V(volts)	t(pd) (μ sec)	Aw (mm/s)	P (bar)	Surface Roughness (μm)
1.	1	1	1	1	2.6
2.	2	2	2	1	2.7
3.	3	3	3	2	3.6
4.	4	4	4	2	3.6

Table 2 (Cont.)

Exp. No.	Input Parameters				Output Parameters
	V(volts)	t(pd) (μ sec)	Aw (mm/s)	P (bar)	Surface Roughness (μm)
5.	1	2	3	2	3.2
6.	2	1	4	2	4.0
7.	3	4	1	1	4.8
8.	4	3	2	1	3.8
9.	1	3	4	1	3.4
10.	2	4	3	1	2.8
11.	3	1	2	2	4.8
12.	4	2	1	2	4.6
13.	1	4	2	2	4.0
14.	2	3	1	2	5.8
15.	3	2	4	1	4.2
16.	4	1	3	1	4.2

selected as the output parameter. Four measurements were made and their average was taken as Ra value for a machined work surface. The input parameters are selected at four different levels as show in Table 1. In the present work L16 orthogonal array is selected for the experimentation and the results obtained for the L16 experiments is shown in Table 2.

Four level factorial design and NN techniques were carried out to predict surface roughness. The level of the factorial design used in the present study is shown in Table 1.

METHODOLOGY

Multiple Regression Analysis

After the surface roughness is obtained for all experiments, a table needs to be filled in order to obtain several values for the analysis. In order to obtain regression coefficient estimates β_0, β_1, β_2 and β_3, it is necessary to solve the given simultaneous system of linear equations.

$$n\beta_0 + \beta_1\sum x_{1i} + \beta_2\sum x_{2i} + \beta_3\sum x_{3i} + \beta_4\sum x_{4i}\sum Yi \quad ...(1)$$

$$\beta_0\sum x_{1i} + \beta_1\sum x_{1i}^2 + \beta_2\sum x_{1i}x_{2i} + \beta_3\sum x_{1i}x_{3i} + \beta_4\sum x_{1i}x_{4i} = \sum x_{1i}\,Yi \quad ...(2)$$

$$\beta_0\sum x_{2i} + \beta_1\sum x_{1i}x_{2i} + \beta_2\sum x_{2i}^2 + \beta_3\sum x_{2i}x_{3i} + \beta_4\sum x_{2i}x_{4i} = \sum x_{2i}\,Yi \quad ...(3)$$

$$\beta_0\sum x_{3i} + \beta_1\sum x_{1i}x_{3i} + \beta_2\sum x_{2i}x_{3i} + \beta_3\sum x_{3i}^2 + \beta_4\sum x_{3i}x_{4i} = \sum x_{3i}\,Yi \quad ...(4)$$

$$\beta_0\sum x_{4i} + \beta_1\sum x_{1i}x_{4i} + \beta_2\sum x_{2i}x_{4i} + \beta_3\sum x_{3i}x_{4i} + \beta_4\sum x_{4i}^2 = \sum x_{4i}\,Yi \quad ...(5)$$

After the simultaneous system of linear equations above is solved the regression coefficient estimates will be substitute to the following regression model for surface roughness

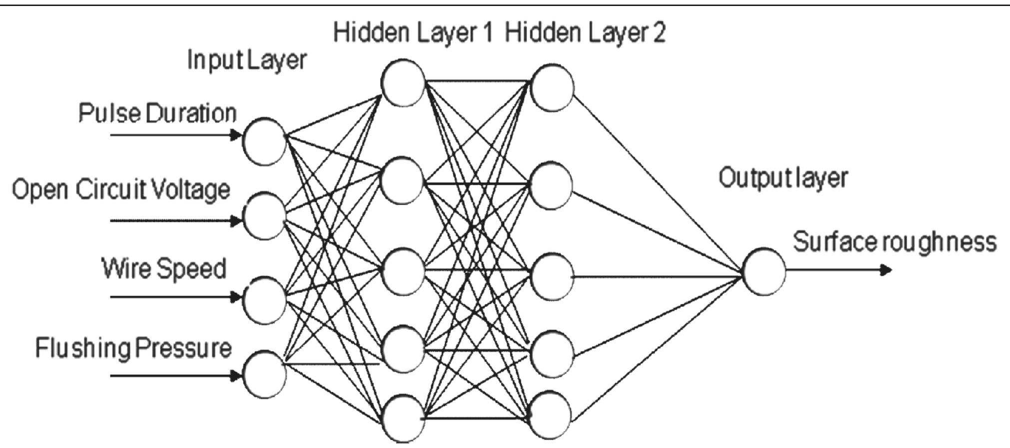
$$Yi = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} \quad ...(6)$$

where; Yi = Surface Roughness (μm), x_{1i} = Gap voltage (v), x_{2i} = Pulse duration (μs), x_{3i} = Wire speed (mm/s), x_{4i} = Flushing pressure (bar)

Artificial Neural Network

Modeling surface roughness with neural networks is composed of two phases: training and testing of the neural networks with experimental data. Pulse duration, open circuit voltage, wire speed and dielectric flushing pressure have been used as the input layer, while surface roughness was used as the output layer. Neural Networks (NN) are biologically inspired, that is, they are composed of elements that perform in a manner that is analogous to the most elementary functions of the biological neurons. A neural network has a parallel-distributed architecture with a large number of neurons and connections. Each connection points from one node to another and is associated with a weight (Choudhury and Bartarya, 2003). There are several applications of neural networks such as a Back-Propagation Network (BPN) and a General Regression Neural Network (GRNN). In general, BPN seems to be the most utilized neural network. The development of the Back-Propagation Network (BPN) (Purushothaman and Srinivasa, 1994) represents a landmark in the history of neural networks in the way that it provides a computationally efficient method for the training of the multi-layer perception. A multi-layer perception trained with the back propagation algorithm may be viewed as a practical way of performing a non-linear input-output mapping of a general nature. In the current application, the objective was to use the network to learn mapping between input and output patterns. The components of the input pattern consisted of the control variables of the machining operation (pulse duration, open circuit voltage, wire speed and dielectric flushing pressure), whereas the output pattern components represented the measured factors (surface roughness). The nodes in the hidden layer were necessary to implement the nonlinear mapping between the input and output patterns. In the present work, a 4-input, 5-hidden layer, 1 output layer back propagation neural network as shown Figure 2 has been used.

Figure 2: BPN Network Used for Modeling



RESULTS AND DISCUSSION

The experiments were carried out under different process conditions. Table 2 shows the full factorial design matrix. When the mathematical model is obtained, the value of predicted surface roughness for each experiment can be calculated. The regression coefficients calculated from above Equations (1-5) are;

$\beta_0 = -0.4332, \beta_1 = 0.0073, \beta_2 = 0.1182, \beta_3 = 0.0287$ and $\beta_4 = 0.0781$

If surface roughness is represented by Yi, the regression equation obtained from regression analysis based on experiments of the training set can be expressed in Equation (7). After calculating each of the coefficients of Equation (6) and substituting the coded values of the variables for any experimental condition the linear regression equation for surface roughness can be obtained in actual factors as given in Equation (7).

$$Yi = -0.4332 + 0.0073x_{1i} + 0.1182x_{2i} + 0.0287x_{3i} + 0.0781x_{4i} \quad \text{...(7)}$$

This equation indicates that pulse duration has the most significant effect on surface roughness. The coefficients of the pulse duration, open circuit voltage, wire speed and dielectric flushing pressure are positive. Surface roughness increases with increasing pulse duration, open circuit voltage, wire speed and dielectric flushing pressure.

These comparisons have been depicted in terms of percentage error for validation of the set of experiments. From Table 3 it is evident that for our set of data the neural network predicts a surface roughness that is nearer to the experimental values than the regression analysis. In the prediction of surface roughness values the average errors for regression and NN are found to be 13.97% and 6.07% respectively.

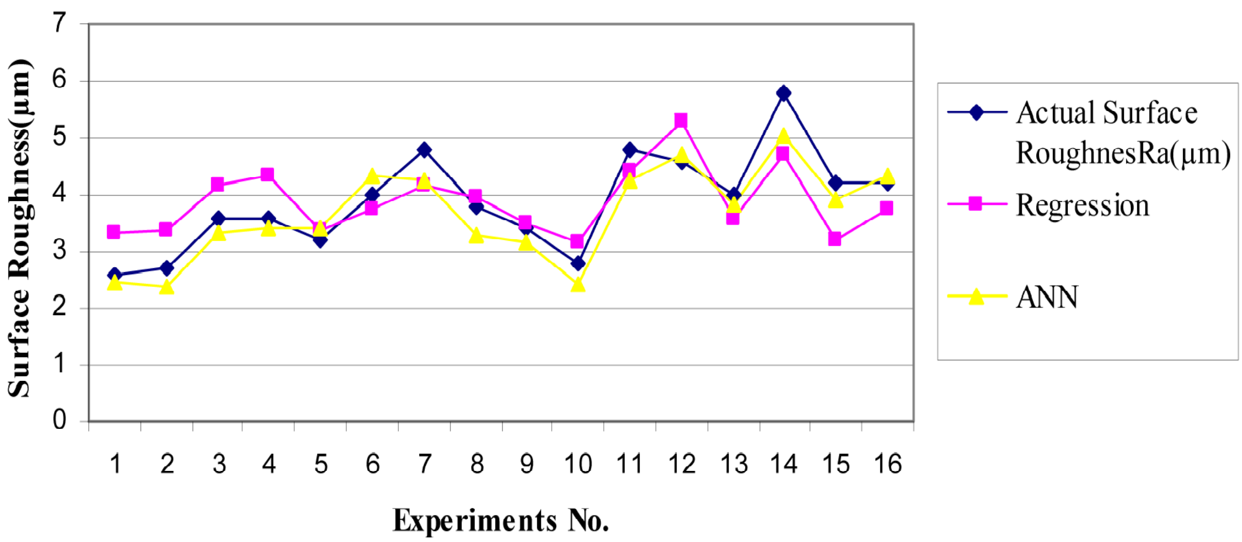
Table 3: Comparison Between Actual and Predicted Surface Roughness

Ex. No.	Actual Surface Roughness (μm)	Regression		ANN	
		Predicted	Error %	Predicted	Error %
1.	2.6	3.33	–28.17	2.4421	6.07
2.	2.7	3.3835	–25.31	2.3681	12.29
3.	3.6	4.1869	–16.30	3.3245	7.65
4.	3.6	4.3275	–20.20	3.4256	4.84
5.	3.2	3.3595	-4.94	3.4317	–7.24
6.	4.0	3.7365	6.58	4.3214	–8.04
7.	4.8	4.1574	13.38	4.2553	11.34
8.	3.8	3.9745	–4.59	3.2751	13.81
9.	3.4	3.5125	–3.31	3.1539	7.24
10.	2.8	3.1695	–13.19	2.3973	14.38
11.	4.8	4.4009	8.31	4.2568	11.31
12.	4.6	5.2930	–15.10	4.7200	–2.61

Table 3 (Cont.)

Ex. No.	Actual Surface Roughness (μm)	Regression		ANN	
		Predicted	Error %	Predicted	Error %
13	4.0	3.5735	10.66	3.8251	4.37
14	5.8	4.7020	18.93	5.0245	13.37
15	4.2	3.1919	24.10	3.8959	7.24
16	4.2	3.7605	10.46	4.3215	–2.98
		Average Error:	13.97%	Average Error:	6.07%

Figure 3: Comparison Between Predicted and Experimental Values of Surface Roughness



CONCLUSION

The prediction of optimal machining conditions for the required surface finish and dimensional accuracy plays a very important role in wire EDM process. The following results can be drawn from this study:

- Predictions of the Surface Roughness was made using the multiple regression and the neural network techniques and the values obtained by both of the methods were compared with the experimental values of the Surface Roughness to decide about the nearness of the predictions with the experimental values.
- Increasing pulse duration, open circuit voltage, flushing pressure and wire speed increased the surface roughness.
- Within the range of input variables for the present case (pulse duration t = 5 to 15 μs, open circuit voltage V = 20 to 45 V, wire speed S = 60 to 100 mm/sec and flushing pressure p = 2 to 12 bar), the results in Figure 3 showed that the neural network comes ahead of regression analysis in nearness of the predictions to the experimental values of surface roughness as the average errors in the surface roughness in the case of the neural network

are less than those obtained using regression analysis (average error is 6.07% for NN as compared to13.97% in the case of regression predictions).

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