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# PREDICTION OF SURFACE ROUGHNESS IN WIRE ELECTRICAL DISCHARGE MACHINING USING DESIGN OF EXPERIMENTS AND NEURAL NETWORKS*

U. ESME**, A. SAGBAS AND F. KAHRAMAN

Dept. of Mechanical Education, Tarsus Technical Education Faculty, Mersin University, 33400, Tarsus-Mersin, Turkey
Email: uguresme@gmail.com

**Abstract–** Wire erosion discharge machining (WEDM) is a modification of electro discharge machining (EDM) and has been widely used for a long time for cutting punches and dies, shaped pockets and other machine parts on conductive work materials. The surface finish of the machined surface mainly depends on the pulse duration, open voltage, wire speed and dielectric flushing pressure. In the present work, two of the techniques, namely factorial design and neural network (NN) were used for modeling and predicting the surface roughness of AISI 4340 steel. Surface roughness was taken as a response variable measured after WEDM and pulse duration, open voltage, wire speed and dielectric flushing pressure were taken as input parameters. Relationships between surface roughness and WEDM cutting parameters have been investigated. The level of importance of the WEDM cutting parameters on the surface roughness was determined by using the analysis of variance method (ANOVA). The mathematical relation between the workpiece surface roughness and WEDM cutting parameters were established by regression analysis method. This mathematical model may be used in estimating the surface roughness without performing any experiments. Finally, predicted values of surface roughness by techniques, NN and regression analysis, were compared with the experimental values and their closeness with the experimental values determined. Results show that, NN is a good alternative to empirical modeling based on full factorial design.

**Keywords–** Surface roughness, factorial design, NN, WEDM

## 1. INTRODUCTION

Electrical discharge wire cutting, more commonly known as WEDM, is a spark erosion process used to produce complex two and three dimensional shapes through electrically conductive workpieces by using a wire electrode. The sparks are generated between the workpiece and a wire electrode flushed with or immersed in a dielectric fluid [1]. The wire, which unwinds from a spool, feeds through the workpiece. A power supply delivers high frequency pulses of electricity to the wire and the workpiece. The gap between the wire and workpiece is flooded with a localized stream of deionized water which acts as the dielectric. Workpiece material is eroded ahead of transporting the wire by spark discharges, which are identical with those in conventional EDM [2].

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 workpiece. A small pool of molten metal is formed on the workpiece 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 workpiece and the wire, leaving small craters. This action is repeated hundreds

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**Corresponding author

of thousands of times each second during WEDM processing. This removes material from the workpiece in shapes opposite to that of wire [2, 3].

The degree of accuracy of the workpiece 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 workpieces requires many hours of manual grinding and polishing [1,4].

The most important performance measures in WEDM are cutting speed, workpiece 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 [1].

Tosun et al. [1] determined the effect of machining parameters on the cutting width and material removal rate based on the Taguchi method. Tosun and Cogun [2] investigated, experimentally, the effect of cutting parameters on wire electrode wear. Tosun et al. [3] investigated the effect of the cutting parameters on the size of erosion craters (diameter and depth) on wire electrode experimentally and theoretically. Cogun and Savsar [5] investigated the random behaviour of the time-lag durations of discharge pulses using a statistical model for different pulse durations, pulse pause durations, and discharge currents in EDM.

Scott et al. [6] have developed formulas for the solution of a multi-objective optimization problem to select the best parameter settings on a WEDM machine. They used a factorial design model to predict the measures of performances as a function of a variety of machining parameters. Wang and Rajurkar [7] have developed a WEDM frequency monitoring system to detect on-line the thermal load on the wire to prevent the wire from rupture. Spur and Schoenbeck [8] have investigated a finite element model and have explained the impact of a discharge on the anode as a heat source on a semi-infinite solid whose size and intensity are time-dependent in WEDM. Tarng et al. [9] developed a neural network system to determine settings of pulse duration, pulse interval, peak current, open circuit voltage, servo reference voltage, electric capacitance and wire speed for the estimation of cutting speed and surface finish. Spedding and Wang [10] presented a parametric combination by using artificial neural networks and they also characterized the roughness and waviness of the workpiece surface and cutting speed. Liao et al. [11] performed an experimental study to determine the variation of the machining parameters on the MRR, gap width and surface roughness. They have determined the level of importance of the machining parameters on the metal removal rate (MRR). Lok and Lee [12] compared the machining performance in terms of MRR and surface finish by the processing of two advanced ceramics under different cutting conditions using WEDM. Ramakrishnan and Karunamoorthy [13] developed an artificial neural network with Taguchi parameter design. Tsai et al. [14] found relationships between the heterogeneous second phase and the machinability evaluation of the ferritic SG cast irons in the WEDM process. Sarkar et al. [15] studied the features of trim cutting operation of wire electrical discharge machining of $\gamma$-titanium aluminide. Caydas et al. [16] developed an adaptive neuro-fuzzy inference system (ANFIS) for modeling the surface roughness in the WEDM process.

The previous works show that the research works are focused on the effect of machining parameters, discharge energy, theory and experimental verification crater formation on the wire electrode. The present study focused on the modeling and prediction techniques to determine the direct effect of the WEDM parameters on the surface roughness.

## 2. EXPERIMENTAL SET UP AND PROCEDURE

The experimental studies were performed on an Acutex WEDM machine tool. Different settings of pulse duration ($t$), open circuit voltage ($V$), wire speed ($S$) and dielectric flushing pressure ($p$) were used in the experiments. Table feed rate (8.2 mm/dak), pulse interval time (18 $\mu s$ ), and wire tension (1800 g) are kept constant during the experiments.

AISI 4340 steel plate was used as a workpiece material with 150x150x10 mm dimensions. CuZn37 Suncut brass wire with 0.25 mm diameter and 900 N/mm$^2$ tensile strength was used in the experiments. Workpiece average surface roughness ($R_a$) measurements were made by using Phynix TR–100 portable surface roughness tester. Cut-off length ($\lambda$) and traversing length ($l$) were set as 0.3 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 selected as the output parameter. Four measurements were made and their average was taken as $R_a$ value for a machined work surface. Two 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. Two levels of factors are referred to as low (-1) and high (+1).

Table 1. Factors and levels for factorial design

| WEDM parameters | Low level (-1) | Base level (0) | High level (+1) |
|---|---|---|---|
| Pulse duration, *t* (ns) | 200 | 550 | 900 |
| Open circuit voltage, *V* (V) | 60 | 180 | 300 |
| Wire speed, *S* (m/min) | 4 | 8 | 12 |
| Dielectric flushing pressure, *p* (kg/cm$^2$) | 6 | 11 | 16 |

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. A regression equation obtained from a full factorial design was used by the Design-Expert software and NN modeling was developed by using Qwiknet software.

## 3. PREDICTION TECHNIQUES

### *a) Design of experiments*

A scientific approach to planning experiments must be incorporated in order to perform an experiment most effectively. Statistical design of experiments is the process of planning the experiments so that appropriate data can be collected which may be analyzed by statistical methods resulting in valid and objective conclusions [17].

Factorial design is widely used in experiments involving several factors where it is necessary to investigate the joint effects of the factors on a response variable. A very important special case of the factorial design is that where each of the k factors of interest has only two levels. Full factorial design is often used to fit a first order response surface model and to generate the factor effect estimates. Factorial design has been employed to determine the minimum number of experiments to obtain an adequate model for the responses.

If surface roughness is represented by $R_a$, the linear regression equation for these experiments could be written as;

$$\begin{aligned} R_a = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_1x_2 + a_6x_1x_3 + a_7x_1x_4 \\ + a_8x_2x_3 + a_9x_2x_4 + a_{10}x_3x_4 \end{aligned} \tag{1}$$

where $a_0$ is the response variable of surface roughness at the base level; $a_1$, $a_2$, $a_3$, $a_4$ are coefficients associated with each variable, $a_5$, $a_6$, $a_7$, $a_8$, $a_9$, $a_{10}$ are interaction coefficients, $x_1$ : pulse duration, $x_2$ : open circuit voltage, $x_3$ : wire speed, and $x_4$ : dielectric flushing pressure at two levels are used to arrive at a full two level factorial experiment or $2^k$ number of experiments.

***b) Neural network (NN)***

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 [18].

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) [19] 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 perceptron. A multi-layer perceptron 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 has been used. The most popular learning algorithm for multilayer networks is the back-propagation algorithm and its variants [20].The ANN is trained by a learning algorithm that performs the adaptation of weights of the network iteratively until the error between target vectors and the output of the ANN is less than an error goal [20-21]. The algorithm used in this study is shown in Fig. 1.

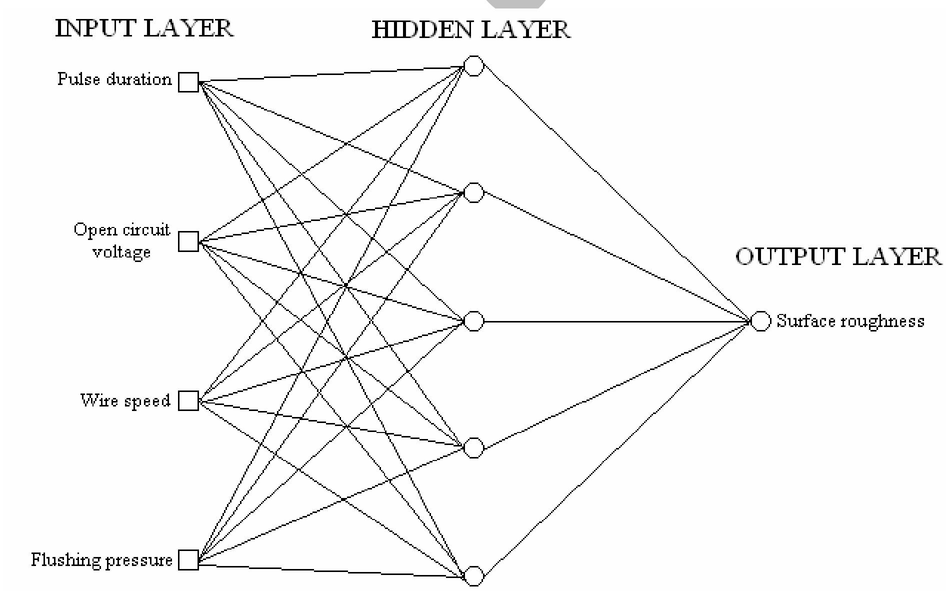



Fig. 1. BPN network used for modeling

There are different learning strategies in a neural network such as supervised learning reinforcement learning and unsupervised learning. The learning set consists of the inputs and the outputs used in training the network. In our case, we have used supervised learning approach.

## 4. RESULTS AND DISCUSSION

The experiments were carried out under different process conditions. Table 2 shows the full factorial design matrix and training set used for NN analysis.

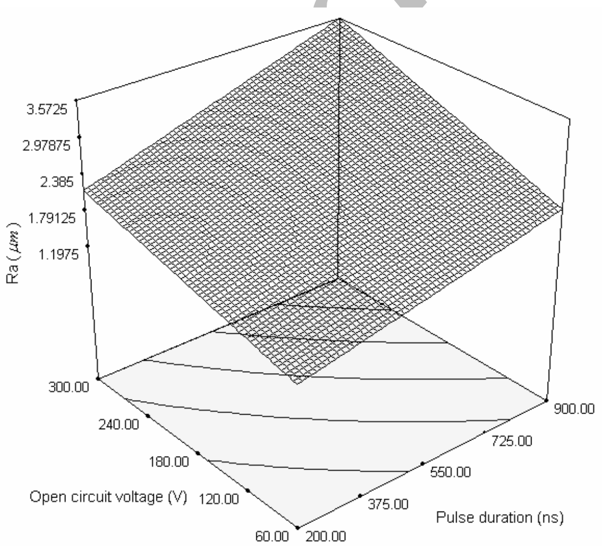
Table 2. Full factorial design matrix and NN training set

| Process parameters | | | | | Response |
|---|---|---|---|---|---|
| Run | t (ns) | V (V) | S (mm/min) | p (kg/cm$^2$) | $R_a$ ($\mu m$) |
| 1 | 200 | 300 | 12 | 16 | 2.12 |
| 2 | 200 | 60 | 4 | 16 | 1.13 |
| 3 | 900 | 60 | 4 | 6 | 2.14 |
| 4 | 200 | 60 | 12 | 16 | 1.24 |
| 5 | 200 | 300 | 12 | 6 | 2.32 |
| 6 | 200 | 300 | 4 | 16 | 1.98 |
| 7 | 900 | 60 | 12 | 16 | 2.15 |
| 8 | 900 | 300 | 12 | 6 | 3.85 |
| 9 | 200 | 300 | 4 | 6 | 2.1 |
| 10 | 900 | 300 | 4 | 16 | 3.24 |
| 11 | 900 | 60 | 12 | 6 | 2.26 |
| 12 | 900 | 300 | 12 | 16 | 3.65 |
| 13 | 900 | 60 | 4 | 16 | 2.01 |
| 14 | 200 | 60 | 4 | 6 | 1.18 |
| 15 | 900 | 300 | 4 | 6 | 3.55 |
| 16 | 200 | 60 | 12 | 6 | 1.24 |

The regression equation obtained from regression analysis based on experiments of the training set can be expressed in Eq. (2). After calculating each of the coefficients of Eq. (1) 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 Eq. (2).

$$R_a = 0.73775 + 0.00116t + 0.003242V - 0.0058S + 0.001089p + 0.00000298tV + 0.0000196tS - 0.000014tp + 0.0000833VS - 0.000056Vp + 0.000313Sp \quad (2)$$

This equation indicates that wire speed has the most significant effect on surface roughness. The coefficients of the pulse duration, open circuit voltage, and dielectric flushing pressure are positive, while wire speed is negative. Surface roughness increases with increasing pulse duration, open circuit voltage, and dielectric flushing pressure and decreases with increasing wire speed. Figures 2-4 show the response surface plots of the WEDM parameters which affect the surface roughness.



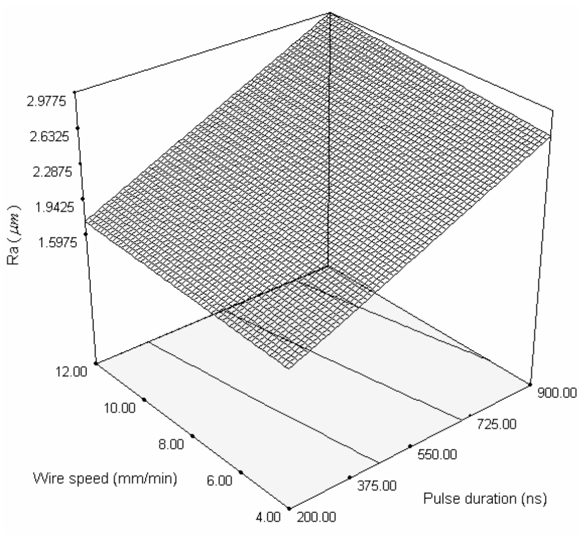
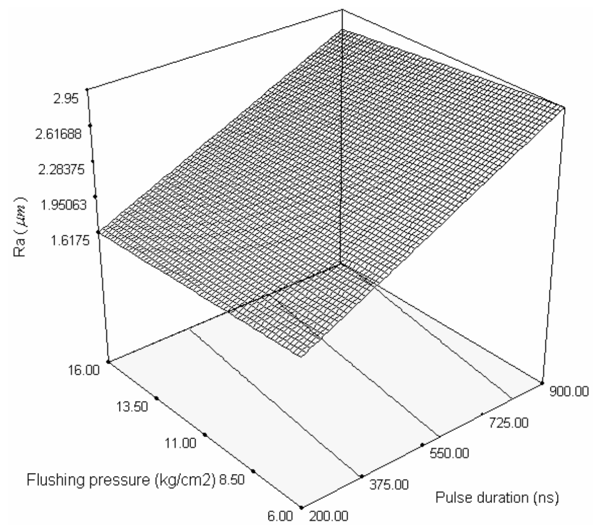
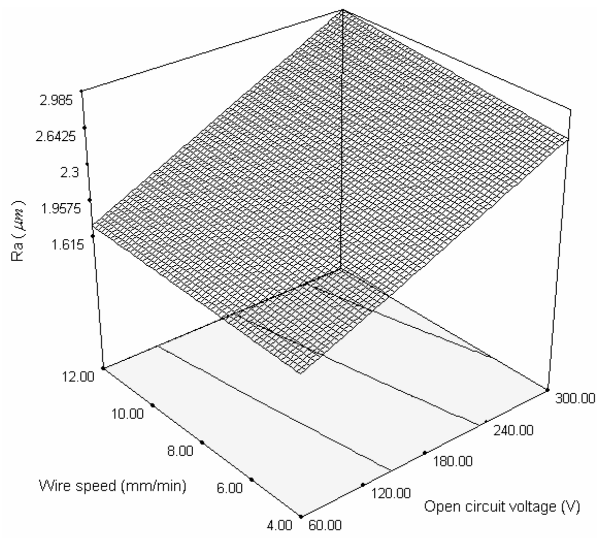




Fig. 2. a) The effect of open circuit voltage and pulse duration on surface roughness,
b) The effect of wire speed and pulse duration on surface roughness

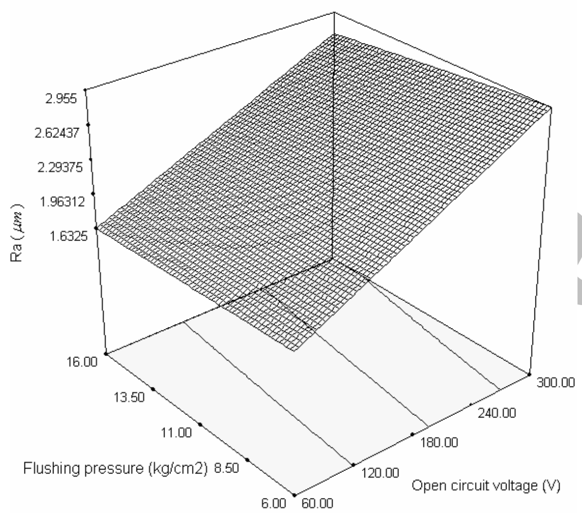



(a)

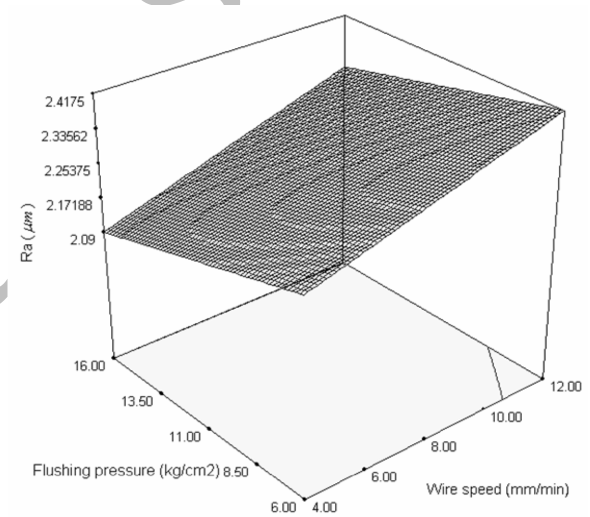



(b)

Fig. 3. a) The effect of flushing pressure and pulse duration on surface roughness,
b) The effect of wire speed and open circuit voltage on surface roughness




(a)




(b)

Fig. 4. a) The effect of flushing pressure and open circuit voltage on surface roughness,
b) The effect of flushing pressure and wire speed on surface roughness

It is clear from the response surface of Figs. 3, 4 and 5 that, increasing the pulse duration increased the surface roughness due to the larger energy of spark, increasing the open circuit voltage increased the surface roughness due to the higher spark energy discharge, increasing wire speed increased the surface roughness due to the increasing material removal rate, increasing the flushing pressure decreased surface roughness due to the cooling effect of the flushing pressure. Testing validity of the regression analysis and NN results was made using the input parameters according to the design matrix given in Table 3.

These comparisons have been depicted in terms of percentage error in Fig. 5 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 7.17 % and 4.90 % respectively.

Table 3. Validation set used for regression and NN analysis

| Exp. no | Pulse duration (ns) | Open circuit voltage (V) | Wire speed (mm/min) | Flushing pressure ($kg/cm^2$) | Surface roughness ($\mu m$) | *Regression* | | *NN* | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Predicted | Error % | Predicted | Error % |
| 1 | 300 | 80 | 4 | 6 | 1.30 | 1.41 | -8.46 | 1.26 | 3.07 |
| 2 | 400 | 90 | 5 | 8 | 1.50 | 1.58 | -5.33 | 1.36 | 9.33 |
| 3 | 500 | 150 | 6 | 10 | 2.08 | 2.00 | 3.84 | 2.02 | 2.40 |
| 4 | 700 | 250 | 10 | 14 | 3.18 | 2.90 | 8.80 | 3.48 | -9.43 |
| 5 | 350 | 60 | 12 | 16 | 1.29 | 1.42 | -9.15 | 1.24 | 3.87 |
| 6 | 450 | 70 | 5 | 16 | 1.58 | 1.50 | 5.06 | 1.53 | 3.16 |
| 7 | 550 | 100 | 8 | 11 | 2.08 | 1.86 | 10.57 | 2.02 | 2.88 |
| 8 | 750 | 180 | 4 | 6 | 2.92 | 2.58 | 11.60 | 3.11 | -6.50 |
| 9 | 850 | 200 | 10 | 8 | 3.27 | 3.00 | 8.25 | 3.47 | -6.11 |
| 10 | 200 | 300 | 12 | 8 | 2.23 | 2.28 | -2.24 | 2.37 | -6.27 |
| 11 | 250 | 300 | 4 | 10 | 1.96 | 2.14 | -9.18 | 2.00 | -2.04 |
| 12 | 300 | 250 | 6 | 20 | 1.89 | 1.94 | -2.64 | 1.81 | 4.23 |
| | | | | | | *Average error: 7.17%* | | *Average error: 4.94%* | |

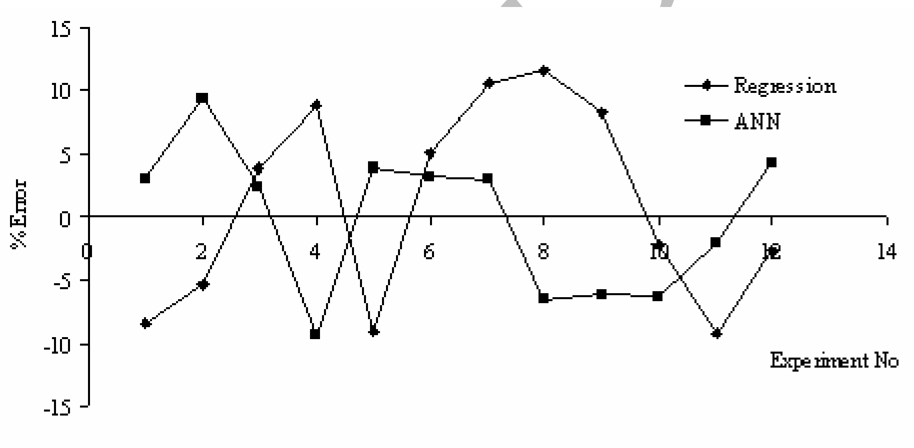



Fig. 5. Comparison of errors in prediction of the surface roughness

The results of analysis of variance analysis (ANOVA) for the WEDM process are presented in Table 4. Statistically, *F*-test provides a decision at some confidence level as to whether these estimates are significantly different or not. Larger *F*-value indicates that the variation of the process parameter makes a big change on the performance characteristics of the surface roughness. According to Table 4, pulse duration and open circuit voltage were found to be the major factor affecting the surface roughness (contribution of 48.5% and 47.66% respectively), whereas wire speed and dielectric flushing pressure were found to be the second ranking factor (contribution of 0.66% and 0.46% respectively).

The analysis results for surface roughness are as follows: The value of the multiple coefficient of $R^2$ is obtained as 0.99, which means that the explanatory variables explain 99% of the variability in the response variable. With the adjusted R-square (Adj $R^2$), a value closer to 1 indicates a better fit. It is generally the best indicator of the fit quality and it was obtained as 0.99. Predicted $R^2$ value was also obtained as 0.99. The statistical analysis showed that the regression model fits well to the observations.

Figure 6 represents the comparison of predicted (both NN and regression) and actual results. Both regression and NN results showed that the predicted values were very close to the experimental values. Because the fitted line is very close to the experimental results with the $R^2$ values of 0.98 and 0.93 for NN and regression analysis respectively.

Table 4. ANOVA analysis of WEDM parameters

| Parameter | Process parameters | Degree of freedom | Sum of square | Variance | F | Contribution percentage (%) |
|---|---|---|---|---|---|---|
| A | Pulse duration | 1 | 5.69 | 5.69 | 660.11 | 48.50 |
| B | Open circuit voltage | 1 | 5.59 | 5.59 | 3177.78 | 47.66 |
| C | Wire speed | 1 | 0.078 | 0.078 | 3124.71 | 0.66 |
| D | Flushing pressure | 1 | 0.054 | 0.054 | 78.56 | 0.46 |
| AB | Interaction | 1 | 0.250 | 0.250 | 43.80 | 2.11 |
| AC | Interaction | 1 | 0.012 | 0.012 | 139.66 | 0.10 |
| AD | Interaction | 1 | 0.009 | 0.009 | 6.76 | 0.08 |
| BC | Interaction | 1 | 0.026 | 0.026 | 5.04 | 0.22 |
| BD | Interaction | 1 | 0.018 | 0.018 | 14.30 | 0.15 |
| CD | Interaction | 1 | 0.0006 | 0.0006 | 10.18 | 0.01 |
| Error | | 5 | 0.0017 | 0.00034 | - | 0.01 |
| Total | | 15 | 11.829 | - | - | 100 |

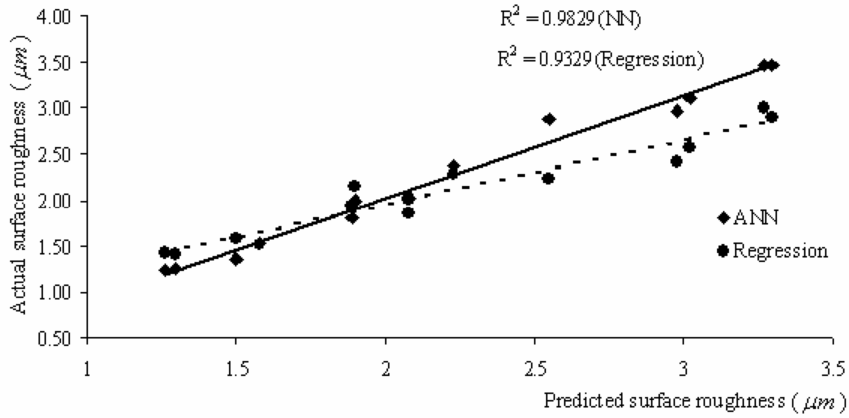



Fig. 6. Graphical representation of comparison of predicted and actual results

After determining the regression equation the response variable, and also training the neural network program, the predictions by both the techniques were found. The learning behavior of this particular network is shown in Fig. 7. Training the neural network was performed with an allowable error of 0.01 (sum of squared error over the output neurons).

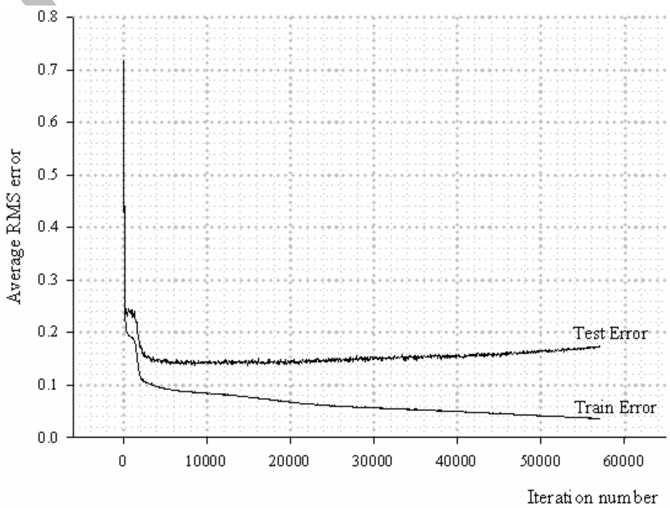



Fig. 7. Learning behavior of the constructed neural network

Once the network was trained such that the maximum error for any of the training data was less than the allowable error, the weights and the threshold values were automatically saved by the program. As the input values from the validation experiments were given to the NN program, the program predicted the required output.

During the training process, initially all patterns in the training set were presented to the network and the corresponding error parameter was found for each of them. Then the pattern with the maximum error was found and used for changing the synaptic weights. Once the weights were changed, all the training patterns were again fed to the network and the pattern with the maximum error was then found. This process was continued until the maximum error in the training set became less than the allowable error specified by the user.

The predicted values for regression equations were obtained by substituting the experimental conditions given in Table 3 in Eq. (2). The predicted values of the response, by both of the prediction methods (i.e. regression analysis and neural network), were compared with the experimental values for the validation set of experiments as indicated in Table 3.

## 5. CONCLUSION

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

- Predictions of the response variables were made using the factorial design and the neural network techniques and the values obtained by both of the methods were compared with the experimental values of the response variables to decide about the nearness of the predictions with the experimental values.
- Increasing pulse duration, open circuit voltage and wire speed increased the surface roughness, whereas increasing the flushing pressure decreased the surface roughness.
- Within the range of input variables for the present case (pulse duration t= 200 to 900 ns, open circuit voltage V= 60 to 300 V, wire speed S= 4 to 12 mm/min and flushing pressure p= 6 to 16 kg/cm$^2$), the results 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 4.78% for NN as compared to 7.17% in the case of regression predictions).



## REFERENCES

1. Tosun, N., Cogun, C. & Tosun, G. (2004). A study on kerf and material removal rate in wire electrical discharge machining based on Taguchi method. *Journal of Materials Processing Technology*, Vol. 152, pp. 316-322.
2. Tosun, N. & Cogun, C. (2003). An investigation on wire wear in WEDM. *Journal of Materials Processing Technology*, Vol. 134, pp. 273-278.
3. Tosun, N., Cogun, C. & Pihtili, H. (2003). The effect of cutting parameters on wire crater sizes in wire EDM. *Int. J. Adv. Manuf. Technol*., Vol. 21, pp. 857–865.
4. Tosun, N., Cogun, C. & Inan, A. (2003). The effect of cutting parameters on workpiece surface roughness in wire EDM. *Machining Science and Technology*, Vol. 7, pp. 209–219.
5. Cogun, C. & Savsar, M. (1990). Statistical modeling of properties of discharge pulses in electrical discharge machining. *International Journal of Machine Tools and Manufacture*, Vol. 3, pp. 467–474.
6. Scott, D., Boyina, S. & Rajurkar, K. P. (1991). Analysis and optimisation of parameter combination in wire electrical discharge machining. *Int. J. Prod. Res*., Vol. 11, pp. 2189–2207.

7. Wang, W. M. & Rajurkar, K. P. (1992). Monitoring sparking frequency and predicting wire breakage in WEDM. *Sensors and Signal Processing for Manufacturing*, American Society of Mechanical Engineers, Production Engineering Division (PED), New York, NY, Vol. 55, pp. 49-64.
8. Spur, G. & Schoenbeck, J. (1993). Anode erosion in wire-EDM-A theoretical model. *CIRP Ann*., Vol. 1, pp. 253-256.
9. Tarng, Y. S., Ma, S. C. & Chung, L. K. (1995). Determination of optimal cutting parameters in wire electrical discharge machining. *International Journal of Machine Tools Manufacture*. Vol. 35, pp. 1693–1701.
10. Spedding, T. A. & Wang, Z. Q. (1997). Parametric optimization and surface characterization of wire electrical discharge machining process. *Precis. Eng*. Vol. 20, pp. 5–15.
11. Liao, Y. S., Huang, J. T. & Su, H. C. (1997). A study on the machining-parameters optimization of wire electrical discharge machining. *Journal of Materials Processing Technology*, Vol. 71, pp. 487–493.
12. Lok, Y. K. & Lee, T. C. (1997). Processing of advanced ceramics using the wire-cut EDM process. *Journal of Materials Processing Technology*, Vol. 63, pp. 839–843.
13. Ramakrishnana, R. & Karunamoorthyb, L. (2008). Modeling and multi-response optimization of inconel 718 on machining of CNC WEDM process. *Journal of Materials Processing Technology*, Vol. 207, pp. 343–349.
14. Tsai, T. C., Horng, J. T., Liu, N. M., Chou, C. C. & Chiang, K. T. (2008). The effect of heterogeneous second phase on the machinability evaluation of spheroidal graphite cast irons in the WEDM process. *Materials and Design*, Vol. 29, pp. 1762–1767.
15. Sarkar, S., Mitra, S. & Bhattacharyya, B. (2008). Modeling and optimization of wire electrical discharge machining of $\gamma$-TiAl in trim cutting operation. *Journal of Materials Processing Technology*, Vol. 205, pp. 376–387.
16. Caydas, U., Hascalik, A. & Ekici, S. (2008). An adaptive neuro-fuzzy inference system (ANFIS) model for wire-EDM. doi:10.1016/j.eswa.2008.07.019.
17. Gunaraj, V. & Murugan, N. (2000). Prediction and optimization of weld bead volume for the submerged arc process-part 1. *Welding Research Development Supplement*, Vol. 9, pp. 286-294.
18. Choudhury, S. K. & Bartarya, G. (2003). Role of temperature and surface finish in predicting tool wear using neural network and design of experiments. *International Journal of Machine Tools & Manufacture*, Vol. 43, pp. 747–753.
19. Purushothaman, S. & Srinivasa, Y. G. (1994). A back propogation algorithm applied to tool wear monitoring. *International Journal of Machine Tools Manufacture*, Vol. 34, pp. 625–631.
20. Ebrahimi, M., Rezaei, E., Vaseghi, B. & Danesh, M. (2006). Rotor resistance identification using neural networks for induction motor drives in the case of insensitivity to load variations. *Iranian Journal of Science & Technology, Transaction B, Engineering*, Vol. 30, No. B2, pp. 223-236.
21. Joghataie, A. & Amiri, B. (2005). Modeling structure-actuator systems by neural networks. *Iranian Journal of Science & Technology, Transaction B, Engineering*, Vol. 29, No. B3, pp. 323-332.