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OPTIMIZATION OF WIRE ELECTRICAL DISCHARGE MACHINING PROCESS USING TAGUCHI METHOD AND BACK PROPAGATION NEURAL NETWORK

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ABSTRACT*: In this study, it is attempted to model and optimize the wire electrical discharge machining (WEDM) process using Taguchi design of experiment and artificial neural network. A neural network with back propagation algorithm was developed to predict the performance characteristic, namely surface roughness. An approach to determine optimal machining parameters setting was proposed based on the Taguchi design method. In addition, analysis of variance (ANOVA) was performed to identify the significant parameter affecting the surface roughness. Experimental confirmations were carried out to indicate the effectiveness of this proposed optimization method and a good improvement was obtained. The performance of artificial neural network (ANN) was measured with the mean square error and it was observed that the developed ANN model could predict effectively.*

KEYWORDS: *Wire electrical discharge machining process, artificial neural network, Taguchi design method, optimization, modeling.*

GERİ BESLEMELİ YAPAY SİNİR AĞLARI VE TAGUCHİ METODU KULLANILARAK TEL EROZYON İLE KESME SÜRECİ OPTİMİZASYONU

ÖZET: *Bu çalışmada, yapay sinir ağları ve Taguchi deneysel tasarımı kullanılarak tel erezyonu ile kesme sürecinin modellemesi ve optimizasyonu yapılmıştır. Yüzey pürüzlülüğü performans karekteristiğini tahmin etmek için, geri yayılma algoritmalı bir yapay sinir ağı geliştirilmiştir. Optimal kesme parametre kombinasyonunu belirlemek için Taguchi deneysel tasarım algoritması kullanılmıştır. Ayrıca, yüzey pürüzlülüğüne etki eden önemli parametreleri belirlemek için varyans analizi (ANOVA) uygulanmıştır. Önerilen optimizasyon yönteminin etkinliğini göstermek için doğrulama deneyleri yapılmış ve iyileştirmeler elde edilmiştir. Ortalama kare hata ile yapay sinir ağının performansı ölçülmüş ve geliştirilen modelin etkin olduğu görülmüştür.*

ANAHTAR KELİMELER: *Tel erezyonu ile kesme süreci, yapay sinir ağları, Taguchi tasarım metodu, optimizasyon, modelleme.*

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I. INTRODUCTION

Among the nonconventional machining processes, electro discharge machining is considered to be one of the most important processes for machining intricate and complex shapes in various electrically conductive materials. The wire electro discharge machining process contributes a predominant role in some manufacturing sectors recently; since this process has the capacity to cut complex and intricate shapes of components in all electrically conductive materials with better precision and accuracy. In this operation the material removal occurs from any electrically conductive material by the initiation of rapid and repetitive spark discharges between the gap of the work and tool electrode connected in an electrical circuit. And the liquid dielectric medium is continuously supplied to deliver the eroded particles and to provide the cooling effect [1]. The technologies of WEDM have been emphasized significantly and have improved rapidly in recent years owing to the requirements in various manufacturing fields [2]. Several researchers have attempted to improve the performance characteristics namely the surface roughness, cutting speed, dimensional accuracy and material removal rate. But the full potential utilization of this process is not completely solved because of its complex and stochastic nature and more number of variables are involved in this operation. Investigations into the influences of machining input parameters on the performance of WEDM have been widely reported. Some researchers [3-5] have focused on the performance characteristics in WEDM process. Ramakrishnan and Karunamoorthy [6] developed a mathematical model using the response surface methodology. Huang et al. [7] determined the effect of WEDM process parameters (pulse-on time, pulse-off time, table feed rate, flushing pressure and workpiece surface and machining history) on the gap width, the surface roughness and the white layer depth of the machined workpiece surface using Taguchi method. Tosun et al. [8] investigated the effect and optimization of machining parameters on the cutting width and material removal rate (MRR) in WEDM based on Taguchi method. Mohammadi et al. [9] applied statistical analysis of WEDM turning on MRR using Taguchi techniques. Lin et al. [10] studied the effects of machining parameters in electrical discharge machining on the machining characteristics of SKH 57 high speed steel. Moreover, they determined the optimal combination levels of machining parameters based on Taguchi method. Tosun and Cogun [11] investigated experimentally the effects of cutting parameters on wire electrode wear in WEDM. Tarng et al. [12] examined 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. Scott et al. [13] used a factorial design method to determine the optimal combination of control parameters in WEDM, the measures of machining performance being the MRR and the surface finish. Spedding and Wang [14] developed the mathematical models using response surface methodology (RSM) and they also used artificial neural networks (ANN) in the WEDM process. Yuan et al. [15] carried out multi-objective optimization based on Gaussian process regression to optimize the high speed WEDM process, considered mean current, on-time and off-time as input parameters and MRR and surface roughness as output responses. Kuang and Chıang [16] developed the mathematical models using RSM to investigate the influences of machining parameters on the performance characteristics of MRR and surface roughness in WEDM process. Tosun et al. [17] investigated the effect of the pulse duration, open circuit voltage, wire speed and dielectric flushing pressure on the workpiece surface roughness in WEDM process. Mahapatra and Patnaik [18] developed a model to optimize WEDM machining parameters such as discharge current, pulse duration, pulse frequency, wire speed, wire tension and dielectric flow rate on the performance characteristics of MRR and surface roughness in WEDM process using Taguchi Method. Puri and Bhattacharyya [19] performed a parametric study on the geometrical inaccuracy of the part caused by the wire lag and attempted to model WEDM process by using Taguchi method. Spedding and Wang [20] examined the modeling techniques using RSM and ANN to predict the process performance such as the cutting speed, the surface roughness and the surface waviness in WEDM. Liao et al.[21] proposed an approach of determining the parameter settings in WEDM based on Taguchi design method and the analysis of variance. Rajurkar and Wang [22] carried out to determine the variation of machining performance outputs, namely MRR and surface finishing with machining parameters by using thermal modeling. Gokler and Ozangozu [23] studied the selection of the most suitable cutting and offset parameter combination to get a desired surface roughness for a constant wire speed and dielectric flushing pressure. Hascalik and Caydas [24] investigated experimentally the effects of puls on time, voltage, dielectric fluid circulation pressure and wire feed rate parameters on micro structure and surface roughness in WEDM. Han et al. [25] carried out to investigate the effect of discharge current on machined surfaces by conducting thermo-analysis on material removal in the finish cut of WEDM using the finite element method. Ho et al. [26] provided a review on the various academic research areas involving the WEDM process. Most of the investigations mentioned above studied the effect of cutting variables such as speed, feed rate and depth of cut on surface roughness by considering one variable at a time. Moreover, there are rarely studies on the control of surface roughness. The present study focuses on both modeling and prediction of surface roughness and optimization of process performance characteristic in WEDM process to obtain the desired surface roughness.

II. EXPERIMENTAL PROCEDURE

In this experimental study, all the experiments were conducted on an Acutex WEDM machine. WEDM machining set up was shown in Fig.1. Pulse duration (400-1000 ns), open circuit voltage (100-270 V), wire speed (0.06-0.2 m/s) and dielectric flushing pressure (0.6-1.6 MPa) were selected as input parameters and surface roughness was selected as output parameter. Surface roughness (*Ra*) measurements were made by using Phynix TR–100 portable surface roughness tester.

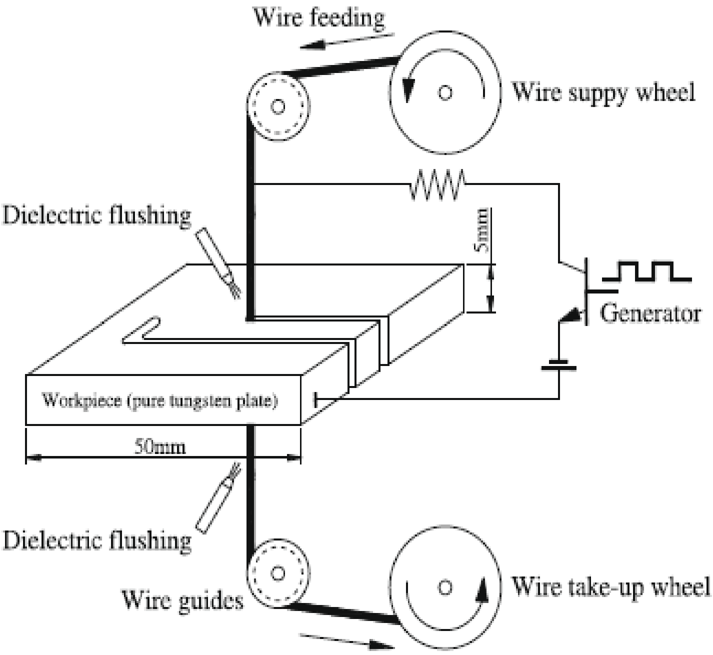

Figure 1. *WEDM machining set up.*

To obtain a reliable database, each experiment was repeated four times and their average was taken as *Ra* value mean values. The work material, electrode and other machining conditions were given in Table 1.

Table 1. *Machining conditions in WEDM process.*

Workpiece	AISI 4340
Electrode	CuZn37
Workpiece dimensions (mm)	150x150x10
Table feed rate (mm/min)	8.2.
Pulse interval time (μs)	18
Wire diameter (mm)	0.25
Wire tensile strength (N/mm^2)	900
Cut-off length (mm)	0.8

According to the Taguchi design concept, a L18 mixed orthogonal array table was chosen for the experiments. The orthogonal array table used in the Taguchi design method was applied to the back propagation netrwork (BPN) as testing data. BPN was developed to predict surface roughness.

III. MODELING AND OPTIMIZATION

The present paper deals with the modeling of of performance characteristic in WEDM process taken simultaneously and the optimization of process parameters corresponding to a desired surface roughness. In any machining process a model has to be developed relating the machining outputs to the machined parameters. Then, the developed model can be used for prediction, process control or optimization. The settings of the process parameters are determined by using Taguchi's experimental design method. At first combination of process parameters are selected by orthogonal array for numerical experimenting by Taguchi method. Then the optimum conditions are predicted via the Taguchi method. The analysis of variance (ANOVA) is employed to find the optimal process parameter levels and to analyze the effect of these parameters surface roughness. After that, an ANN model was trained and the optimum conditions are predicted by means of ANN procedure.

III. 1. Design of Experiment in Taguchi's Method

An efficient method of experimental planning design of experiment is proposed by Taguchi. To minimize production cost and time, Taguchi [8] developed procedures that apply orthogonal arrays of statistically designed experiments to efficiently obtain the best model with the fewest possible experiments. Taguchi method is a simple, efficient and systematic approach to estimate performance characteristics at a reduced cost. The orthogonal arrays are specifically arranged to enable sufficient information to be collected by conducting only the minimum number of experiments. According to the Taguchi's method, the quality characteristics are evaluated by their signal-to-noise (SNR) that are originated from the field of communication to assess the quality of sound or graphics. The optimum machining parameter combination was obtained by using analysis of SNR. There are several SNR available depending on the types of characteristics. Nominal is the best, higher is the better and lower is the better. We would SNR if the system is optimized when the response is as small as possible [1-3]. The SNR for LB (lower is better) characteristic is calculated as Equations (1) and (2).

$$L_j = \frac{1}{n}\sum_{i=1}^{n} y_i^2 \qquad (1)$$

$$\eta_j = -10\log L_j \qquad (2)$$

where *yi* is the response value, *Lj* is the loss function, *nj* is the SNR

The larger SNR, the better the quality characteristic is. In this study, to reduce cost and time, each of the tests is replicated four times in order to obtain its SNR. The final step of the Taguchi's parameter design after selecting the optimal parameter is to predict and verify the improvement of the performance characteristics with the selected optimum machining parameters.

III.2. Analysis of Variance (ANOVA)

The purpose of analysis of variance is to elucidate the parameters that govern the WEDM process that markedly influence the surface roughness (*Ra*) to yield information about the impact of each control factor on the results predicted by the ANN model. The total variation in the response is decomposed into component variations related to control factors and their interactions [27]. An ANOVA table includes sums of squares, degrees of freedom, the F-ratios that correspond to the ratios of two mean squares, and the proportions of contribution. These proportions are used to evaluate the importance of each factor to the *Ra* value of interest. Analysis of variance is accomplished by separating the total variability of the surface roughness, which is measured by the sum of the squared deviations from the total mean of the surface roughness, into contributions by each of the machining parameters and the error.

III.3. Artificial Neural Network

Artificial neural network computing is originally inspired by the operations of biological brains. This technique is especially valuable in processes where a complete understanding of the physical mechanisms is very difficult, or even impossible to acquire. The ANN model can be trained by iterating the learning cycles, such that the output response is close enough to the target response. The ANN computing technique, which offers more accurate outcomes than conventional mathematical or statistical techniques, is proposed to be a valuable method for intelligent learning and mathematical modeling. One of the advantages of using the neural network approach is that a model can be constructed very easily based on the given input and output and trained to accurately predict process dynamics. The system functions obtained by ANNs are simulated using the input, weights and output responses [28-29]. Among the several proposed types of artificial neural network models, the back propagation network is the most extensively used learning algorithm [27]. The error at each neuron or node is calculated and the weight for each neuron is modified until the desired error between the actual and the required output is achieved. As WEDM process is stochastic and random in nature, it is very difficult to predict the output characteristics accurately by mathematical equation. And the theories on the process are not sufficient enough to adequately model the complicated surface quality characteristics. So an ANN with back propagation algorithm has been adopted here to model the WEDM process. Moreover, it is proposed a powerful method that combines the ANN technique and the Taguchi’s procedures to improve engineering designs. This proposed approach not only yields a sufficient understanding of the effects of process parameters, but also produces an optimized process to ensure which exhibits the best performance characteristics. The sigmoid activation function of neurons was used to provide a reasonable nonlinear input/output mapping in the hidden layer, and the output layer with a linear equation that can be described as the weighted sum of the outputs of the hidden neurons. It is adopted the supervised learning, using both training and testing samples. Back propagation learning algorithm uses a gradient search technique to minimize the mean square error of the output of the network [28-29]. The number of neurons in the input and output layers is based on the geometry of the problem. However, there is no general rule for selection of the number of neurons in a hidden layer and the number of hidden layers. Hence, the numbers of hidden layers and neurons in the hidden layer have been determined by trial and are based upon the least effective error and the optimal neural network architecture has been designed using the Matlab Neural Network Toolbox. Fig. 2 shows the flow chart used for neural network in this research to reach the minimum mean square error (MSE) for trained and predicted values of surface roughness.

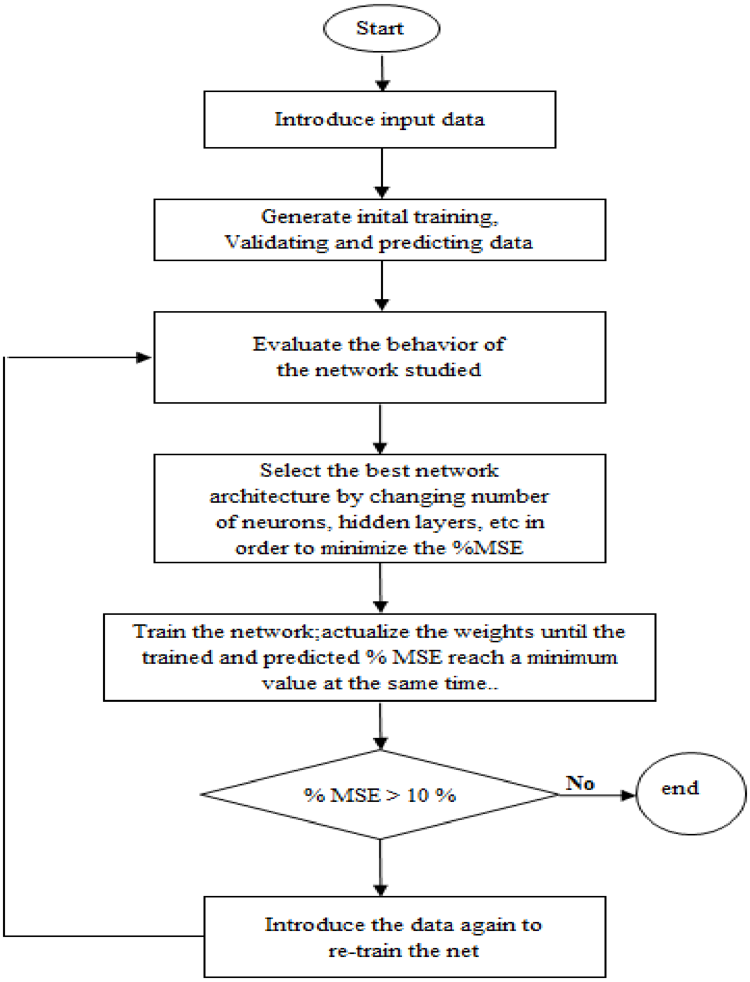

Figure 2. *Flow chart used for neural network.*

IV. EXPERIMENTAL RESULTS AND DISCUSSION

IV.1. Process Modeling by Back Propagation Neural Network

A feed forward neural network based on back propagation is a multilayered architecture made up of one or more hidden layers placed between the input and output layers. The components of the input pattern consisted of the control variables of the machining operation (open circuit voltage, pulse duration, wire speed and dielectric flushing pressure) whereas the output pattern components represented the measured factor (surface roughness). BPN model was developed to predict surface roughness. In this study, we use a three-layered BPN that includes an input layer, a hidden layer and an output layer shown in Fig. 3.

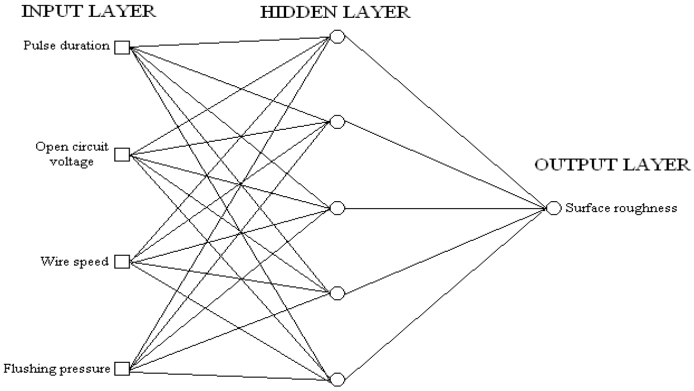

Figure 3. *BPN algorithm used for modeling.*

A total of 54 experimental data are included in a training sample with 42 data, and a testing sample with 12 data. The learning process of BPN is iterative, in that the entire training set is presented to the neural network repeatedly until the root mean square error (RMSE) reaches an acceptable value. However, the training sample is used to update the weights of the neural network model until the RMS error is minimized or is as desired. Training the neural network was performed with an allowable error of 0.01. The iteration is complete when the error is reduced to an acceptable value. The training of the algorithm was stopped at 60000 iterations. Mean prediction error has been calculated by taking the average of all the individual errors, for all the testing patterns. The learning behavior of this particular network is shown in Fig. 4. It can be seen that in most cases, the neural network prediction is very close to the actual value. Different network structures were experimented to obtain the best performance. The simple network of 4-5-1 has exhibited better performance by way of closer prediction indicating that this configuration is good enough in capturing the implied functional relationship between the inputs and outputs.

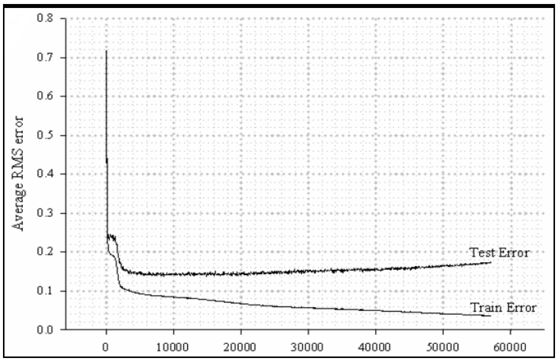

***Figure 4**. Learning behavior of the constructed neural network.*

It can be seen that in most cases, the neural network prediction is very close to the actual value. So the desired surface roughness is obtained between acceptable limits. Different network structures were experimented to obtain the best performance. The simple network of 4-5-1 has exhibited better performance by way of closer prediction indicating that this configuration is good enough in capturing the implied functional relationship between the inputs and outputs. The performance of the neural networks is estimated using the testing samples. To measure the effectiveness of the developed ANN model, the predicted values were compared with the experimental data and shown in Fig. 5.

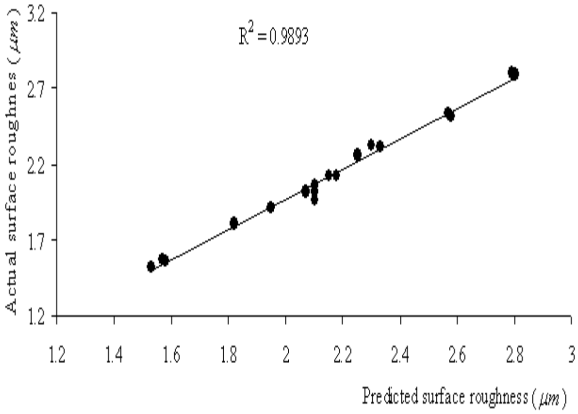

***Figure 5.** Comprasion of experimental values and predicted values.*

The coefficient of determination, R^2, is the goodness-of-fit index, which measures the strength of the linear relationship between the output responses of BPN and the actual value. Furthermore, the R^2 value is 0.989, showing that about 98% of all of the variance in the experimental results can be accounted for by the outputs predicted by BPN. BPN results showed that the predicted values have been very close to experimental values. It is also found that the BPN model for the predicted values generates an average best-fit percentage error of 4.61% from the actual data. Hence, the experimental results confirm that the BPN predicts effectively and the optimal process parameter significantly improves the WEDM process. We believe that the optimal combination of control factors can be directly applied to the WEDM process and conclude that the BPN model proposed here in has resolved the complex of WEDM process that results in satisfactory surface quality characteristics.

IV.2. Optimization of Process Parameters Using Taguchi Design Method

The numbers of factors and levels in this study an Taguchi L18 plan of the experiment using orthogonal arrays were implemented in Table 2.

Table 2. *Experimental design using L18 orthogonal array.*

Exp.no	Open voltage (V)	Pulse duration (ns)	Wire speed (m/s)	Flushing pressure (MPa)	Surface roughness (μm)
1	100	400	0.06	0.6	1.52
2	100	400	0.13	1.0	1.56
3	100	400	0.20	1.6	1.57
4	100	700	0.06	0.6	1.86
5	100	700	0.13	1.0	1.91
6	100	700	0.20	1.6	1.92
7	100	1000	0.06	1.0	2.06
8	100	1000	0.13	1.6	2.12
9	100	1000	0.20	0.6	2.31
10	270	400	0.06	1.6	1.80
11	270	400	0.13	0.6	2.01
12	270	400	0.20	1.0	2.01
13	270	700	0.06	1.0	2.26
14	270	700	0.13	1.6	2.32
15	270	700	0.20	0.6	2.53
16	270	1000	0.06	1.6	2.51
17	270	1000	0.13	0.6	2.79
18	270	1000	0.20	1.0	2.80

The level of importance of the WEDM cutting parameters on the surface roughness was determined by using the analysis of variance method. The mathematical relation between the workpiece surface roughness and WEDM cutting parameters was used in estimating the surface roughness without performing any experiment. ANOVA used to consider effects of input factors on response was performed on experimental data. Confidence level was chosen to be 95 %. Results of ANOVA for surface roughness are shown in Table 3. After analysing Table 3, it is observed that the open circuit voltage and pulse duration have great influence on the surface roughness. It was identified that the open circuit voltage is the most significant parameter; since and percentage contribution of 55.62 %, that is by increasing open circuit voltage, surface roughness is increased, the pulse duration is also considered as significant factor, that is by increasing pulse duration, surface roughness is increased.

Table 3. *Results of the ANOVA for surface roughness.*

Code	Factors	DF	SS	F-ratio	MS	P (%)
A	Open circuit voltage	1	0.990	310.01	0.990	55.62
B	Pulse duration	2	1.430	223.21	0.710	40.04
C	Wire speed	2	0.110	16.79	0.054	3.01
D	Flushing pressure	2	0.046	7.250	0.023	1.30
Error		10	0.032	-	0.003	0.03
Total		17	2.580	-		100

DF: degrees of freedom, SS: sum of square, MS: mean square, P: percentage contribution

The wire speed and dielectric flushing pressure do not present significative percentages of contribution on the obtained surface roughness. It should be noticed that the error associated to the ANOVA table for the Ra was 0.03 %. The effect and optimization of machining settings for minimum surface roughness was investigated experimentally using Taguchi method. In the Taguchi method, the experimental results were transformed into a SNR. The optimum machining parameter combination was obtained by using analysis of SNR. This graph for surface roughness is shown in Fig. 6. The graph shows the change of the SNR when the setting of the control factor was changed from one level to the another. The best surface roughness value was at the higher SNR values in graph. The graphical representation of the effect of the four control factors on surface roughness is shown in Fig. 7.

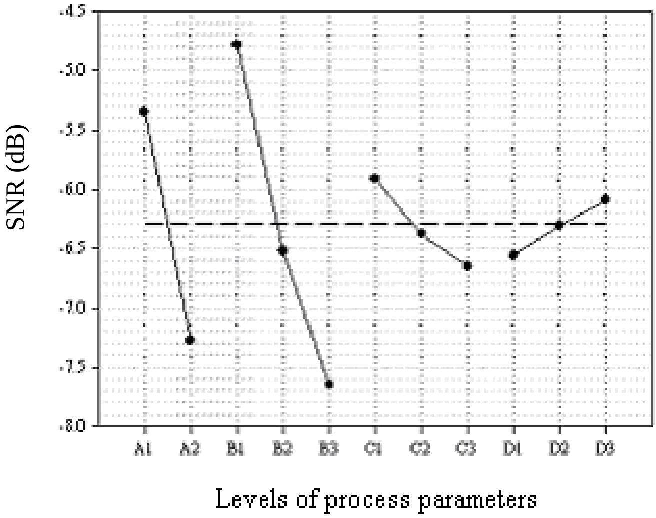

Figure 6. *SNR graph for surface roughness.*

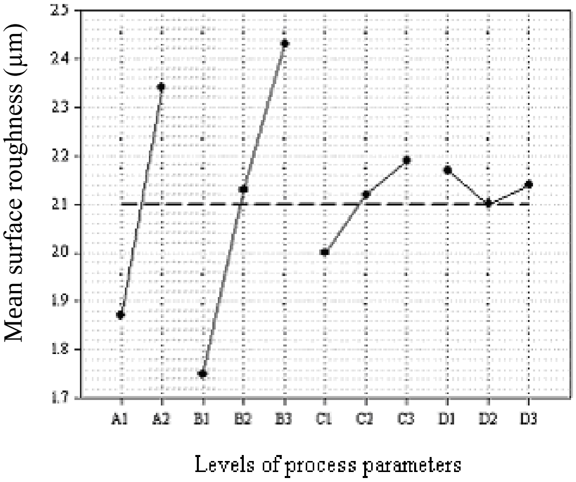

Figure 7. *The effect of process parameters on surface roughness.*

The SNR results were tabulated in Table 4. Similarly, Table 4 indicates that the factors A and B can be treated as significant factors whereas C and D are less significant factors for minimization of surface roughness.

Table 4. *SNR response table for surface roughness.*

Code	Factors	SNR (dB)		
		Level 1	Level 2	Level 3
A	Open circuit voltage	-5.35	-7.28	-
B	Pulse duration	-4.78	-6.52	-7.65
C	Wire speed	-5.91	-6.38	-6.65
D	Flushing pressure	-6.56	-6.31	-6.09

A confirmation experiment was conducted to verify the optimal machining parameters obtained from the parameter design. Table 5 shows results of the confirmation test for surface roughness.

Table 5. *Results of the confirmation test for surface roughness.*

	Initial parameters	Optimal parameters
Level	A1B3C3D1	A1B1C1D3
Surface roughness (μm)	2.35	1.35
SNR (*dB*)	-7.27	-3.18

Based on the SNR, the optimal machining parameters for surface roughness are open circuit voltage at level 1, pulse duration at level 1, wire speed at level 1 and dielectric flushing pressure at level 3. The improvement in SNR from the initial machining parameters to the optimal machining parameters is 4.09 dB. Based on the result of the confirmation test, the surface roughness is decreased 1.74 times. There are a number of publised works that solely study the effects of the machining parameters on the WEDMed surface. We apply the SNR according to Table 5, to analyze the response of means from the experimental results. The experimental results confirmed the validity of the used Taguchi method for enhancing the machining performance and optimizing the machining parameters in WEDM operations. According to the confirmation test, it is possible to decrease surface roughness significantly by using the proposed statistical technique. The results obtained from this study were compared with the previous papers and presented as follows: In the present work, it was observed that the open circuit voltage and the pulse duration have great influence on the obtained surface roughness. The wire speed and dielectric flushing pressure do not present significative percentages of contribution on the obtained surface roughness. Research by Huang [7] found that the most important factor that influences surface roughness is pulse-on time and distance between the wire periphery and the workpiece surface. Tosun [11] found that, the open circuit voltage and the pulse duration have great influence on the obtained surface roughness. The wire speed and dielectric flushing pressure have insignificance influence on the obtained surface roughness. Scott et al. [13] presented that the discharge current, pulse duration and pulse frequency are the significant control factors affecting the MRR and SF, while the wire speed, wire tension and dielectric flow rate have the less effect. Spedding and Wang [14] observed that pulsewidth and time between two pulses are significant factors on the surface roughness. Wire mechanical tension and wire feed speeds are less significant factors. Liao [21] indicated that the MRR and SF are easily influenced by the table feed rate and on time, which can also be used to control the discharging frequency for the prevention of wire breakage. Rajurkar and Wang [22] demonstrated pulse duration, open circuit voltage, wire speed and dielectric fluid pressure are the significant factors on the surface roughness. Esme et al.[30] found that the most important factor that influences surface roughness is open circuit voltage and the pulse duration between the process parameters using ANN. The ANN results of the present study are much similar to concluded by Esme et al.[30].

V. CONCLUSION

This paper presents the prediction and optimization of surface roughness of AISI 4340 steel in WEDM process based on neural network and Taguchi design method. A feed forward back propogation network (BPN) model was developed for the prediction of surface roughness. Open voltage, pulse duration, wire speed and dielectric flushing pressure were chosen as input factors and surface roughness was chosen as response. Predicted values were found very close to experimental values. The main parameters were found as open circuit voltage and pulse duration among four controllable factors that influence the surface roughness using ANOVA. An optimum parameter combination for the minimum surface roughness was obtained by using the analysis of SNR with Taguchi method. The optimal machining parameters for surface roughness are open circuit voltage at 100 V, pulse duration at 400 ns, wire speed at 0.06 m/s and dielectric flushing pressure at 1.6 MPa. This research proposes an effective process parameter optimization approach that integrates Taguchi's parameter design method, back-propagation neural network. The proposed approach can effectively assists engineers in determining the optimal process parameter settings for WEDM process.

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