APPLICATION OF A TAGUCHI-BASED NEURAL NETWORK FOR FORECASTING AND OPTIMIZATION OF THE SURFACE ROUGHNESS IN A WIRE-ELECTRICAL-DISCHARGE MACHINING PROCESS

UPORABA TAGUCHIJEVE NEVRONSKE MREŽE ZA NAPOVEDOVANJE IN OPTIMIRANJE POVRŠINSKE HRAPAVOSTI PRI POSTOPKU ŽIČNE EROZIJE

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Prejem rokopisa – received: 2012-02-16; sprejem za objavo – accepted for publication: 2012-06-01

Wire-electrical-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 materials. WEDM erodes workpiece materials by a series of discrete electrical sparks between the workpiece and an electrode flushed or immersed in a dielectric fluid. The WEDM process is particularly suitable for machining hard materials as well as complex shapes. In this paper, a neural network and the Taguchi design method have been implemented for minimizing the surface roughness in a WEDM process. A back-propagation neural network (BPNN) was developed to predict the surface roughness. In the development of a predictive model, machining parameters of open-circuit voltage, pulse duration, wire speed and dielectric flushing pressure were considered as the input model variables of the AISI 4340 steel. An analysis of variance (ANOVA) was used to determine the significant parameters.

Keywords: WEDM, Taguchi-design method, neural network, surface roughness

Žična erozija (WEDM) je modifikacija potopne erozije (EDM) in se uporablja že dolgo časa za izdelavo rezilnih in drugih orodij ter strojnih delov. WEDM erodira obdelovanec z iskrenjem med obdelovancem in elektrodo, ki se spira, oziroma je potopljena v dielektrično tekočino. WEDM-postopek je še posebej primeren za obdelavo trdih materialov, kot tudi za kompleksne oblike. V tem članku sta bili uporabljeni nevronska mreža in Taguchijeva metoda načrtovanja za zmanjšanje hrapavosti površine. Pri razvoju modela za napovedovanje hrapavosti so bili upoštevani parametri obdelave: električna napetost, trajanje pulza, hitrost žice in tlak dielektrične tekočine za spiranje kot vhodne spremenljivke pri obdelavi jekla AISI 4340. Analiza variance (ANOVA) je bila uporabljena za določanje vplivnih parametrov, ki vplivajo na površinsko hrapavost (R_a). Na koncu je bil uporabljen Taguchijev približek za določitev optimalnih parametrov procesa.

Ključne besede: WEDM, Taguchi oblikovanje, nevronska mreža, površinska hrapavost

1 INTRODUCTION

The technologies of the wire-electrical-discharge machining (WEDM) have been emphasized significantly and have improved rapidly in recent years due to the requirements in various manufacturing fields. WEDM is used to produce complex two- and three-dimensional shapes through electrically conductive workpieces by using a wire electrode¹⁻³. As shown in **Figure 1**, the sparks are generated between the conductive workpiece and a wire electrode flushed with, or immersed in, a dielectric fluid². The degree of accuracy of the workpiece dimensions obtainable and the fine surface finishes make WEDM particularly valuable for the applications involving the manufacture of stamping dies, extrusion dies and prototype parts.²



Figure 1: Working principle of a WEDM process⁴ **Slika 1:** Shematičen prikaz WEDM-postopka⁴

Materiali in tehnologije / Materials and technology 46 (2012) 5, 471-476

Y. KAZANCOGLU et al.: APPLICATION OF A TAGUCHI-BASED NEURAL NETWORK FOR FORECASTING ...

The most important performance measures in WEDM are cutting speed, workpiece surface roughness and cutting width.² Discharge current, discharge capacitance, pulse duration, pulse frequency, wire speed, wire tension, average working voltage and dielectric flushing conditions are the machining parameters that affect the performance measures.^{1–4}

An optimization of the process parameters is the key step of the Taguchi method in achieving high quality without an increased cost. This is because an optimization of the process parameters can improve the quality, and the optimum process parameters obtained with the Taguchi method are insensitive to the variation of environmental conditions and other noise factors. Basically, the classical process-parameter design is complex and not easy to use.5,6 An advantage of the Taguchi method is that it emphasizes the mean-performance characteristic value close to the target value rather than a value within certain specification limits, thus improving the product quality. Additionally, the Taguchi method for experimental design is straightforward and easy to apply to many engineering situations, making it a powerful yet simple tool. It can be used to quickly narrow the scope of a research project or to identify problems in a manufacturing process from the data already in existence.5-8

A large number of experiments have to be carried out when the number of the process parameters increases. To solve this task, the Taguchi method uses a special design of orthogonal arrays to study the entire process-parameter space with only a small number of experiments. Using an orthogonal array to design the experiment can help the designers to study the influence of multiple controllable factors on the average quality characteristics and variations in a fast and economic way, while using a signal-to-noise ratio (*S/N*) to analyze the experimental data can help the designers of a product, or a manufacturer, to easily find out optimum parametric combinations.⁵⁻⁸

Investigations into the influences of the machining input parameters on the performance of WEDM have been widely reported. Huang et al.¹ determined the effect of the 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 a machined workpiece surface using the Taguchi method. Tosun et al.² investigated the effect and optimization of the machining parameters on the cutting width and the material-removal rate (MRR) in WEDM based on the Taguchi method. The experimental studies were conducted with a varying pulse duration, open-circuit voltage, wire speed and dielectric flushing pressure. Mohammadi et al.³ applied the statistical analysis of WEDM turning on MRR using the Taguchi techniques. They considered the effects of the input parameters (power, time-off, voltage, servo, wire speed, wire tension and rotational speed) on the responses (MRR, surface roughness). Lin et al.⁹ investigated the effects of the machining parameters in electrical discharge machining on the machining characteristics of the SKH 57 highspeed steel. Moreover, they determined the optimum combination levels of the machining parameters based on the Taguchi method. Tosun and Cogun¹⁰ experimentally investigated the effects of the cutting parameters on the wire-electrode wear in WEDM. On the basis of ANOVA and F-Test, they found that the most effective parameters of the wire-wear ratio are the open-circuit voltage and pulse durations.

Tarng et al.¹¹ developed a neural-network system to determine the settings of pulse duration, pulse interval, peak current, open-circuit voltage, servo-reference voltage, electric capacitance and wire speed for an estimation of the cutting speed and the surface finish. Scott et al.¹² used a factorial-design method to determine the optimum combination of control parameters in WEDM, the measures of the machining performance being the MRR and the surface finish. It was found that discharge current, pulse duration and pulse frequency are significant control factors. Spedding and Wang¹³ developed mathematical models using the response-surface methodology (RSM) and an artificial neural network in the WEDM process. They considered the effects of the input parameters (pulse width, time between two pulses, wire mechanical tension and wire-feed speed) on the responses (cutting speed and surface roughness). Yuan et al.¹⁴ carried out a multi-objective optimization based on the Gaussian process regression to optimize the high-speed WEDM process, considering mean current, on-time and off-time as the input parameters and MRR and surface roughness as the output responses. Kung and Chiang¹⁵ developed mathematical models using RSM to investigate the influences of the machining parameters on the performance characteristics of MRR and surface roughness in a WEDM process. Esme et al.¹⁶ constructed both a mathematical model and a neural-network model to predict, reproduce and compare the types of surface roughness under different machining conditions. On the basis of a literature review some insight has been gained

Table 1: Comparison between neural networks and the Taguchi design method $^{\rm 17}$

Tabela	1:	Primerjava	med	nevronskimi	mrežami	1N	Taguchi	metodo
oblikov	anj	a ¹⁷						

Comparison	Neural networks	Taguchi design	
Computational time	Long	Medium	
Model development	Yes*	No	
Optimization	Through a model	Straight	
Understanding	Moderate	Normal	
Software availability	Available	Available	
Optimization sensitivity	High	Normal	
Application rate (usage frequency)	Frequent	Rare	

* No factor-interaction effects

into the use of neural networks and Taguchi design methods for modeling and optimizing different WEDM processes. The main advantage of the neural-network method is that it provides modeling and predictions. The main advantage of the Taguchi design method is that it provides an optimization and analyzes the effect of each process parameter on the responses. **Table 1** shows a comparison between neural networks and the Taguchi modeling and optimization method¹⁷.

In the present work, two of the techniques, namely, the neural network with a back-propagation network (BPN) and the Taguchi design method have been employed. Qwiknet 2.23 software and Taguchi Soft program were used for the NN modeling and the Taguchi optimization technique, respectively. Open voltage, pulse duration, wire speed and dielectric flushing pressure were selected as the input factors, whereas surface roughness (R_a) was selected as the response. A BPN model was developed for the prediction of the surface roughness. An analysis-of-variance (ANOVA) table was used to determine the significant WEDM parameter affecting the surface roughness. An approach to determine the optimum machining-parameter setting was proposed on the basis of the Taguchi design method.

2 EXPERIMENTAL SET-UP AND THE TEST PROCEDURE

In this experimental study, all experiments were conducted on an Acutex WEDM machine. The WEDM machining set-up is shown in **Figure 2**.

The work material, electrode and other machining conditions are given in **Table 2**.

 Table 2: Constant machining condition set-up

 Tabela 2: Podatki o nastavitvi naprave

Workpiece	AISI 4340
Wire material	CuZn37
Workpiece dimensions (mm)	$150 \times 150 \times 10$
Table feed rate (mm/min)	8.2
Pulse-interval time (µs)	18
Wire diameter (mm)	0.25
Wire tensile strength (N/mm ²)	900
Machining cut-off length (mm)	0.8
Traversing length (mm)	5

Open-circuit voltage (150–250 V), pulse duration (600, 800, 1000) ns, wire speed (6, 8, 10) mm/min and dielectric flushing pressure (10, 12, 14) kg/cm² were selected as the input parameters and surface roughness was selected as the output parameter. Surface-roughness (R_a) measurements were made by using a Phynix TR-100 portable surface-roughness tester with $\lambda = 0.03$ mm for the cut-off length. Three measurements were taken and their average was calculated as R_a value. According to the Taguchi orthogonal-design concept an L_{18} mixed orthogonal-array table was chosen for the experiments.



Figure 2: WEDM machining set-up Slika 2: WEDM-naprava

The orthogonal-array table used in the Taguchi design method was applied to BPN as testing data. BPN was developed to predict the surface roughness. The optimum machining-parameter combination was obtained by using an analysis of the signal-to-noise (S/N) ratio. The signal-to-noise (S/N) ratio is a measure of the magnitude of the data set relative to the standard deviation. If the S/N is large, the magnitude of the signal is large relative to the noise, as measured with the standard deviation.^{8,18,19} There are several *S/N* ratios available depending on the types of characteristics. The nominal ratio is the best, higher is better and lower is better. We would select the S/N if the system is optimized when the response is as small as possible.^{1–5} The S/N ratio for the LB (lower is better) characteristic is calculated by using Equations (1) and $(2)^5$:

$$L_{j} = \frac{1}{n} \sum_{k=1}^{n} y_{i}^{2}$$
(1)

$$\eta_i = -10 \lg L_i \tag{2}$$

where y_i is the response value, L_j is the loss function, n_j is the *S*/*N* ratio.

3 EXPERIMENTAL RESULTS AND DATA ANALYSIS

A 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). **Table 3** shows a Taguchi L_{18} orthogonal-array plan of the experiment and a training set for the neural-network application.

Exp. no.	Open voltage (V)	Pulse duration (ns)	Wire speed (m/min)	Flushing pressure (kg/cm ²)	Surface roughness (um)
1	150	600	6	10	2.08
2	150	600	8	12	2.20
3	150	600	10	14	2.21
4	150	800	6	10	2.48
5	150	800	8	12	2.51
6	150	800	10	14	2.52
7	150	1000	6	12	2.79
8	150	1000	8	14	2.82
9	150	1000	10	10	2.86
10	250	600	6	14	2.62
11	250	600	8	10	2.69
12	250	600	10	12	2.72
13	250	800	6	12	3.10
14	250	800	8	14	3.06
15	250	800	10	10	3.09
16	250	1000	6	14	3.36
17	250	1000	8	10	3.40
18	250	1000	10	12	3.45

Table 3: L_{18} orthogonal array and a neural-network training set **Tabela 3:** L_{18} ortogonalna matrika za usposabljanje nevronske mreže

The orthogonal-array table used in the Taguchi design method was applied to BPN as testing data. The network structure was selected to be of the 4:5:1 type. The used BPN model is shown in **Figure 3**.

The testing validity of the regression analysis and the neural-network results was achieved by using the input parameters according to the design matrix given in **Table 4**.

The performance of each BPN was calculated with the absolute error (%) of the tested subset. The average absolute error was calculated as 1.08 %. The surface roughness for various machining conditions can be predicted in a quick and accurate manner; the BPN results showed that the predicted values were very close to the experimental values. The value of the multiple coefficient R^2 is 0.99, which means that the explanatory



Figure 3: 4:5:1 (4 inputs, 1 hidden layer with 5 neurons and 1 output) type of the BPN algorithm used for modeling

Slika 3: 4 : 5 : 1 (4 vhodni podatki, 1 skrit nivo s 5 nevroni in 1 izhodni podatek) vrsta BPN algoritma, uporabljenega pri modeliranju

 Table 4: Test set for the validity of the constructed neural network

 Tabela 4: Zbirka podatkov za preizkušanje postavljene nevronske mreže

Exp. no.	Open voltage (V)	Pulse duration (ns)	Wire speed (m/min)	Flushing pressure (kg/cm ²)	Surface r (µ Experi- mental	oughness m) Predicted
1	150	600	8	10	2.20	2.20
2	250	600	6	12	2.62	2.58
3	150	800	8	10	2.53	2.52
4	250	800	6	14	2.95	2.97
5	150	1000	8	10	2.85	2.90
6	150	1000	6	14	2.72	2.68
7	250	1000	10	10	3.56	3.46
8	250	800	10	12	3.13	3.15

Average maximum error: 1.08 %

variables explain 99 % of the variability in the response variable. The predicted values of the surface roughness were compared with the experimental values as shown in **Figure 4**.

The effect and optimization of machining settings for the minimum surface roughness was investigated experimentally. The optimum machining-parameter combination was obtained by analyzing the *S/N* ratio. ANOVA was used to consider the effects of the input factors on the response and was performed on experimental data.



Figure 4: Comparison of experimental and predicted values Slika 4: Primerjava eksperimentalnih in napovedanih vrednosti

Table 5: Results of ANOVA for the surface roughness Tabela 5: Rezultati analize variance (ANOVA) za hrapavost površine

Parame- ter code	Factors	DF	SS	F	MS	Contribution percentage (%)
А	Open-circuit voltage	1	1.404	1378.58	1.401	49.36
В	Pulse duration	2	1.440	711.42	0.720	50.03
С	Wire speed	2	0.015	7.32	0.007	0.52
D	Flushing pressure	2	0.003	1.68	0.001	0.10
Error		10	0.020	_	0.003	_
Total		17	2.844	_		100

Materiali in tehnologije / Materials and technology 46 (2012) 5, 471-476



Figure 5: The effect of machining parameters on the surface roughness

Slika 5: Učinek parametrov obdelave na hrapavost površine

The confidence level was selected as 95 %. The results of ANOVA for the surface roughness are shown in **Table 5**.

After analyzing **Table 4**, it is observed that the open-circuit voltage and the pulse duration have a great influence on the obtained surface roughness. The wire speed and dielectric flushing pressure do not affect significantly the obtained surface roughness. The plot of the mean-factor effects is shown in **Figure 5**.

The *S/N* graph for the surface roughness is shown in **Figure 6**. It is evident that open-circuit voltage (49.36 %) and pulse duration (50.03 %) have the most significant effect on the surface roughness, which means that by increasing these two parameters we also increase the surface roughness. Wire speed (0.52 %) has little effect on the surface roughness. The effect of dielectric flushing pressure (0.10 %) is negligible.

Optimum factor levels and *S/N* ratios obtained at the end of the Taguchi design technique are summarized in **Table 6**.



Figure 6: *S/N* graph for the surface roughness **Slika 6:** *S/N*-diagram za hrapavost površine

Materiali in tehnologije / Materials and technology 46 (2012) 5, 471-476

 Table 6: Optimum factor levels and their S/N ratios

 Tabela 6: Nivoji optimalnih faktorjev in njihova S/N-razmerja

	Factors	S/N ratio (dB)						
Code		Level 1	Level 2	Level 3	Max- min	Rank		
А	Open-circuit voltage	-7.89	-9.66	_	1.77	2		
В	Pulse duration	-7.63	-8.88	-9.83	2.20	1		
C	Wire speed	-8.65	-8.80	-8.88	0.23	3		
D	Flushing pressure	-8.73	-8.84	-8.75	0.11	4		

Average S/N = -8.80

Based on the *S/N* ratio plot in **Figure 6**, the optimum machining parameters for the 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 1 ($A_1B_1C_1D_1$).

4 CONFIRMATION TESTS

A confirmation experiment is the final step in the first iteration of designing an experiment process.^{5,8} The purpose of the confirmation experiment is to validate the conclusions drawn during the analysis phase. The confirmation experiment is performed by conducting a test with a specific combination of the factors and levels previously evaluated.^{8,20} In this study, after determining the optimum conditions and predicting the response under these conditions, a new experiment was designed and conducted with the optimum levels of the welding parameters. The final step is to predict and verify the improvement of the performance characteristic. The predicted S/N ratio $\hat{\eta}$ using the optimum levels of the welding parameters can be calculated as:^{5,8,20}

$$\hat{\eta} = \eta_m + \sum_{i=1}^n (\overline{\eta}_i - \eta_m)$$
(3)

where η_m is the total mean of the *S/N* ratio, $\overline{\eta}_i$ is the mean of the *S/N* ratio at the optimum level, and *n* is the number of the main welding parameters that significantly affect the performance.^{8,18–20} The result of the experimental confirmation using the optimum surface roughness is shown in **Table 7**.

Table 7: Results of the confirmation experiments for the surface roughness

Tabela 7: Rezultati potrditvenih eksperimentov za hrapavost površine

	Initial parameters	Optimum parameters	
Parameter level	$A_1B_3C_3D_1$	$A_I B_I C_I D_I$	
Surface roughness (µm)	2.86	2.10	
S/N ratio (dB)	-9.13	-6.57	

The improvement in the *S/N* ratio from the initial machining parameters to the optimum machining parameters is 2.56 dB. Based on the result of the

Y. KAZANCOGLU et al.: APPLICATION OF A TAGUCHI-BASED NEURAL NETWORK FOR FORECASTING ...

confirmation test, the surface roughness is decreased 1.36 times.

5 CONCLUSIONS

This study presents a prediction, optimization and modeling of the surface roughness of the AISI 4340 steel in a wire-electrical-discharge machining (WEDM) process based on the Taguchi-based neural network with the back-propagation algorithm method. The following conclusions can be drawn from this study:

- The main WEDM parameters that affect the surface roughness of the machined parts were determined as pulse duration and open-circuit voltage among four controllable factors influencing the surface roughness using ANOVA,
- A neural network based on the back-propagation network (BPN) algorithm was constructed for predicting the surface roughness. The predicted values were found to be very close to the experimental values,
- The optimum parameter combination for the minimum surface roughness was obtained by using the Taguchi design method with an analysis of the S/N ratio,
- The confirmation test supports the finding that the surface roughness is greatly decreased by using the optimum design parameters,
- The obtained results indicate that the BPN model agreed well with the Taguchi analysis.

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