An ANFIS-Based Approach for Predicting the Surface Roughness of Cold Work Tool Steel in WEDM

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Abstract – **Wire electrical discharge machining known as non-traditional machining processes, has a significant role in the manufacturing industry. Conductive materials, which can have intricate and complex forms, can be obtained regardless of hardness. In this study, the surface roughness of Sleipner cold work steel is evaluated under various machining process parameters in the WEDM process. In the experiments the feed rate, current, and pulse on time are used as independent variables. In order to predict the surface roughness, an Adaptive Neuro-Fuzzy Inference system was applied based on experimental data.**

Keywords- **ANFIS, WEDM, cold work tool steel, surface roughness.**

1. Introduction

In the manufacturing industry, wire electrical discharge machining (WEDM) is accepted as a non-traditional manufacturing method. The WEDM operation is based on thermoelectric energy transferring between a wire electrode and the work piece loaded in the anode and cathode [1]. The continuously travelling wire electrode, upon passing the current, shapes the work piece using the electron discharge as spark(s) between the wire and work piece. The work piece and wire electrode are covered by die-electric fluid during operation [2]. Fig.1 shows the basic schematic of the WEDM process. In this study, surface roughness, considering as output parameter, was investigated in WEDM. During machining, the feed rate (fr), current (I), and pulse on time (P_{On}) are used as independent variables. Four different parameters were chosen for all the input variables. The Adaptive Neuro-Fuzzy Inference system (ANFIS) prediction method was implemented under these machining conditions and achieved the predicted results for surface roughness. Two different membership functions were used during modelling the ANFIS for the experimental data and a Sleipner cold work tool steel alloy was chosen as work piece material. Sleipner tool steel is especially used in die making industry. However, it can be adopted for various applications such as base materials.

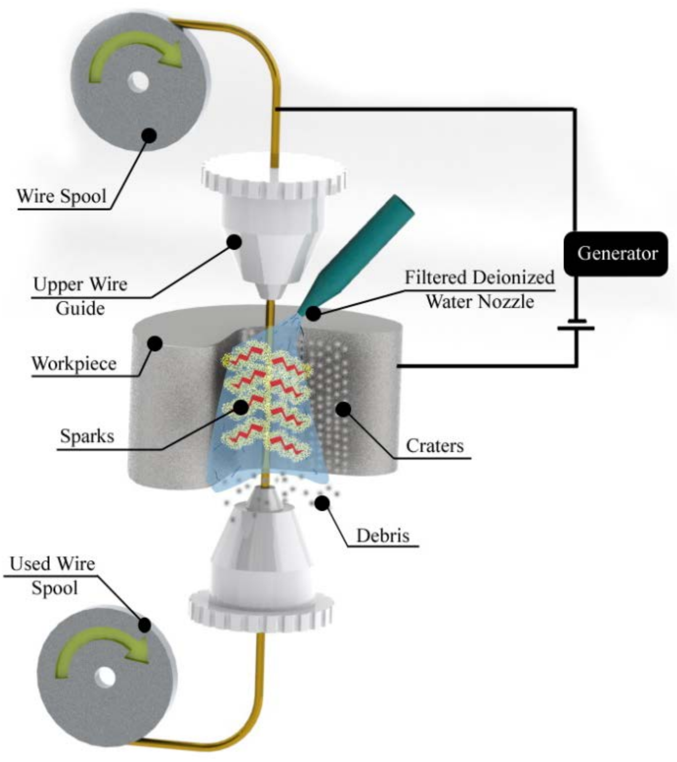


Fig. 1 Schematic of WEDM process.

WEDM machining characteristics have been investigated with different parameters on various materials in order to evaluate the optimal machining data. Antar et al. [3] used Cu core coated wires (ZnCu50 and Zn rich brass) for WEDM machining Udimet 720 nickel based super alloy and Ti-6Al-2Sn-4Zr-6Mo titanium alloy. They achieved better results using coated wire up to 70% compared to uncoated wire under the same machining conditions using WEDM. Jangra et al. [4] developed a mathematical model using diagraph and matrix method related to the machinability of a tungsten carbide composite in WEDM. Reddy et al. [2] undertook experimental investigations on the material removal rate (MRR) and surface roughness in WEDM. All the machining processes were applied to EN 19 & AISI 420 materials. Experimental designs carried out using the Taguchi Technique with four input variables and the impact of each input was estimated using ANOVA. In the literature it was reported that in comparison with other experimental materials EN 19 gave better results for MRR; however, AISI 420 material gave a better surface finish in the WEDM process. Krishnan and Samuel [5] investigated the optimization of material removal rate and surface roughness in wire electrical discharge turning using a multi-objective optimization method. The Taguchi design was used in these experiments. The study was trained in neural network and performance tested. Suganthi et al. [6] employed a micro-electrical discharge machining and hybrid process of micro-wire electrical discharge grinding to evaluate inaccuracies during machining. They investigated the metal removal rate, surface roughness and tool wear ratio results. The authors developed an ANFIS model and back propagation (BP) based on artificial neural network (ANN) models. The results from the two different models were compared and showed that the ANFIS model gave better results than the BP- based ANN. Çaydaş et al. [7] developed an ANFIS to model the surface roughness on D5 tool steel in the WEDM process and investigated the metallographic properties. Tosun et al. [8] reported the material removal rate and the effect of machining parameters based on the Taguchi method in WEDM. Guven et al. [9] compared the modelling WEDM machining parameters on surface roughness. In their study, back propagation and general regression neural networks models were used. Kuriakose and Shunmugam [10] presented an interaction between input and output variables in the WEDM process and used multiple regression models. They also implemented a multi objective method based on a non-dominated sorting genetic algorithm. Wang et al. [11] determined the feasibility of removing the recast layer after EDM machining on an Ni-based super alloy using mechanical grinding and etching. The experiments were designed using the Taguchi technique. As can be seen in previous studies, generally it was the machining parameters that were investigated. The data in experiments aimed to optimize and obtain predictions from different mathematical models. The objective of the research reported in this paper was to analyse the relationship between the input parameters in the WEDM process and the ANFIS based surface roughness prediction in comparison with experimental results.

2. Theoretical Foundation

2.1. Surface Roughness

The surface roughness is used as a measurement for the material surface texture. After any operational process, the topography structure over material changes at the micro level. The surface roughness is generally calculated based on arithmetic average of absolute values (Ra) [12]. Regarding Fig. 2, the Ra can be expressed as follows Eq. (1,2) [13]:

$$\mathrm{R_a} = \frac{1}{L}\int_0^L |y|\,dx = \frac{1}{L}\left(\sum S_{ui} + \sum S_{lj}\right) = \frac{S}{L} \tag{1}$$

Therefore,

$$S_u + S_l = \frac{R_a}{R_t} \quad \text{or} \quad R_a = R_t(S_u + S_l) \tag{2}$$

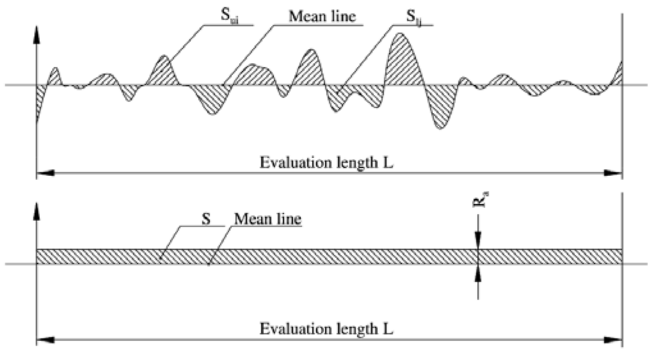


Fig. 2 Scheme of surface roughness Ra [13]:

In industry, the surface roughness measurement is very important for accurate precision and long service life. So surface roughness assists to determine the performance of any mechanical component with strategic importance, since irregularities in the surface may form nucleation sites for cracks or corrosion. However, hyper roughness values are often problematic for materials, achieve to desired values on surface roughness is difficult and costly in manufacturing. Fig. 3 shows the experiment of measurement experimental work pieces.

Fig. 3 Measurement of surface roughness.

2.2. Adaptive Neuro-fuzzy Inference System (ANFIS) Architecture

A fuzzy inference system was applied to two inputs “m”,“n” and one output “f”. For a first-order Sugeno fuzzy model, a typical rule sets with two fuzzy if–then rules can be written as [14]:

Rule 1: if m is A_1 and n is B_1THEN

$$f_1 = p_1 m + q_1 n + r_1 \quad (3)$$

Rule 2:if m is A_2 and m is B_2 THEN

$$f_2 = p_2 m + q_2 n + r_2 \quad (4)$$

where A_1,A_2,B_1, andB_2 are nonlinear parameters and p_1,p_2,q_1,q_2,r_1 and r_2 are linear parameters. The ANFIS architecture (Fig. 4) consists of five layers.

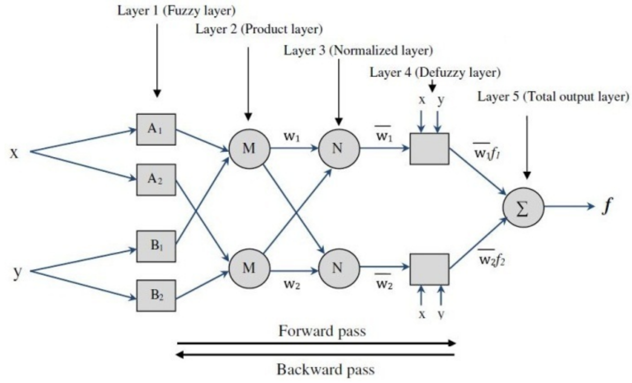


Fig. 4 The ANFIS architecture diagram [15]

The first layer is the fuzzy layer, every node is a square node with a node function in this layer. The relation between the input and output functions can be expressed as:

$$O_{1,i}=\mu_{Ai}(m),\ i=1,2 \quad (5)$$

$$O_{1,j}= \mu_{Bj}(n),\ j=1,2 \quad (6)$$

The second layer, called the product layer, products the firing strength of a rule regarding input signal values. This layer is labelled M. The output node function of this layer can be written as:

$$O_2,\mathrm{i}=w_i= \mu_{Ai}(m)\ \mu_{Bj}(\mathrm{n}),i=1,2 \quad (7)$$

The Third layer, the normalized layer, performs the normalization process of the weight of function. The output function is given as follows:

$$\mathrm{O}_3, i = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad \text{for i=1,2} \quad (8)$$

The fourth layer called the defuzzy layer concerns the last part of the fuzzy rule. The layer output can be expressed as:

$$\mathrm{O}_{4,i} = \overline{w_i}\, f_i(p_i m + q_i n + r_i) \quad \text{i=1,2} \quad (9)$$

The fifth layer, the total output layer, is labelled ∑. This layer output gives the result of the surface roughness in relation to the total input signals. The function can be written as :

$$\mathrm{O}_{5,i} = \sum_i \overline{w_i}\, fi = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad \text{i=1,2} \quad (10)$$

3. Experimental Set Up and Procedure

In experiments, Sleipner cold work tool steel alloy was used as the work piece. The work pieces are prepared in the dimensions of 60x240x24 mm. As shown in Fig. 5 the holes of Ø16 mm diameter were machined in WEDM. The percentages of chemical composition properties of work piece material are given in Table 1.

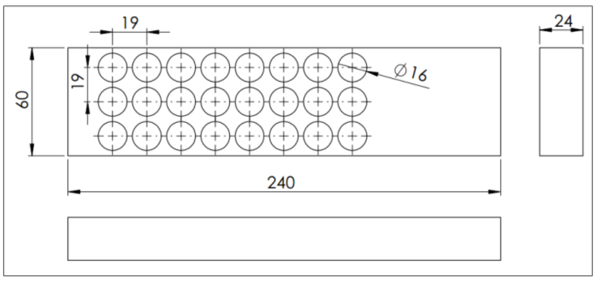


Fig. 5 The specimen dimensions.

Table 1 Chemical composition properties of Sleipner cold work tool steel alloy.

Chemical composition (%)	C	Mn	Mo	Cr	V
	0.9	0.5	2.5	7.8	0.5

In our study, the effect of the cutting parameters on surface roughness is investigated in the WEDM process. The experimental studies were performed on a *Makino U32* WEDM machine. The Pulse On Time (POn , μs), current (I, *A*) and table feed rate (fr, *mm/min*) in the experiments were used as independent parameters and the surface roughness (Ra, μm) was selected as output parameter. The levels of the independent parameters are shown in Table 2.

Table 2 Factors and levels for experiment.

WEDM parameters	Level1	Level2	Level3	Level4
Feed rate, *f r* (mm/min)	12.39	13.77	15.3	17
Current, *I* (A)	28.43	31.59	35.1	39
Pulse On time, *POn* (µs)	4	4.45	4.95	5.5

During the experiments, the other parameters;40 V Voltage, 5 kg/cm^{2}dielectric flushing pressure, 12 m/min wire speed , 9 kg wire tension and0,3mm wire diameter were kept constant. Each experiment was repeated three times and the average of the three measurements were defined as the base results on completion of the experiments. During the experiments, 30 holes were machined. The surface roughness of the holes is measured using a *Mahr Perthometer M1* surface roughness measurement device. The results are shown in Table 3.

Table 3 Experimental parameters and results [16].

No.	*fr (mm/min)*	*C (A)*	*POn (µs)*	*Ra (µm)*
1	4.95	35.10	15.30	2.840
2	4.45	35.10	15.30	2.800
3	5.50	35.10	15.30	3.012
4	4.95	31.59	15.30	2.646
5	4.95	39.00	15.30	2.947
6	4.95	35.10	13.77	2.626
7	4.95	35.10	17.00	2.855
8	4.95	28.43	15.30	2.572
9	4.00	35.10	15.30	2.725
10	4.95	35.10	12.39	2.577

The ANFIS method was used to predict the surface roughness results. The parameters that were used are shown in Table 4. According to the modelling architecture are shown in Table 4.

Table 4 ANFIS architecture and training parameters.

Membership functions	Gaussian, Bell Shape
Number of output	1
Output	Surface Roughness
Number of membership function	4 4 4
Learning rules	Least square estimation
Number of epoch	200
Learning type	Hybrid
Rules number	64

4. Results and Discussion

Experimental studies in WEDM were used for ANFIS modelling. Two types of prediction were obtained by different membership functions in Sugeno. Although there are many methods for designing architecture, two types of memberships, Gaussian and Bell Shape membership functions, were chosen and applied to model .These prediction and error results are shown in Table 5 and Fig. 6.

Table 5 ANFIS surface roughness prediction results.

No.	*Experimental Results R_a (µm)*	*Gaussian membership function*		*Bell Shape Membership Function*	
		Predicted	Error (%)	Predicted	Error (%)
7	2.855	3.055	-7.01	2.157	24.45
8	2.572	2.416	6.07	2.435	5.33
9	2.725	2.777	-1.91	2.806	-2.97
10	2.577	2.761	-7.14	2.057	20.18
Average error (%)			*5.53*		*13.23*

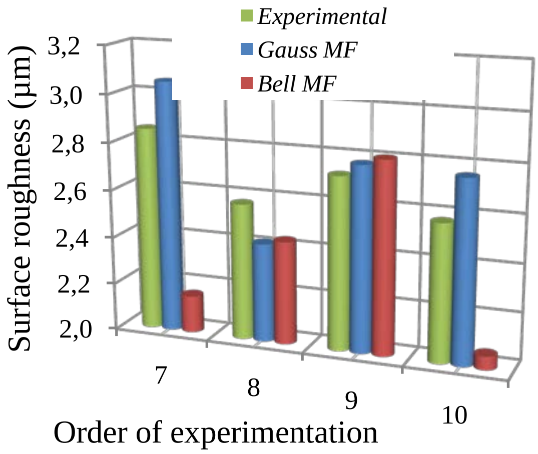
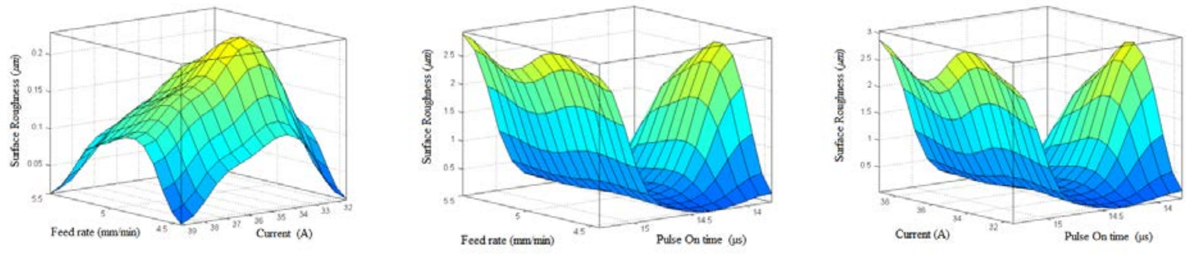


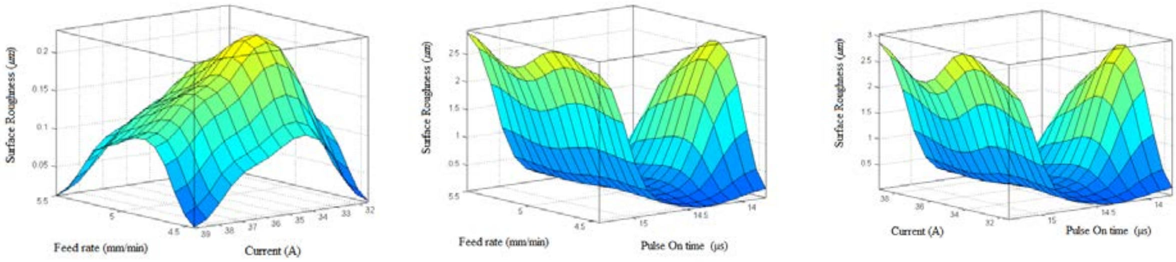
Fig. 6 Comparison of different MF types predicted results with experimental data for surface roughness.

As can be seen in the Table 5, the error rate of the Gaussian membership function gives a better result than the Bell Shape membership function. According to these different membership functions, the interactions between the input variables with surface roughness output are shown Fig. 7 and Fig. 8.The feed rate has worse efficiency with surface roughness around 5mm/min levels against a current rate in (a) and (d) plots in Fig. 7 and Fig. 8. The current surface roughness substantially increases by the feed rate intersection around 34 amps. In (b), (c), (e) and (f) plots, pulse on time at 14.5μs shows the effect of reduction on surface roughness. This positive effect was not observed at the other levels of pulse on time input. The feed rate influence on a pulse on time input at 4.5 mm/min showed a reducing trend. A similar situation is observed in the current and pulse on time around the 33 A value.



(a) (b) (c)

Fig. 7 Comparison input and output in ANFIS with Gaussian membership function.



(d) (e) (f)

Fig. 8 Comparison input and output in ANFIS with Bell Shape membership function.

Figs. 9, 10 and 11 show the initial and final positions of the Bell Shape membership function. There are no noticeable changes on the current variable input plot. However, the pulses on time and feed rate variable plots show a small deviation between the initial and final plots. Similar changes are observed in Figs. 12, 13 and 14. The deviations in the final plots describe optimal premise parameters, after training with hybrid learning algorithms in ANFIS [17].

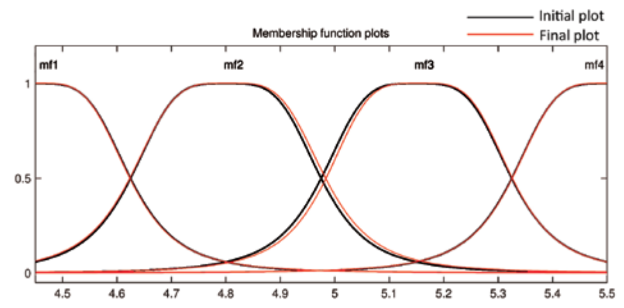


Fig. 9 Initial and final Bell Shape membership function of feed rate input.

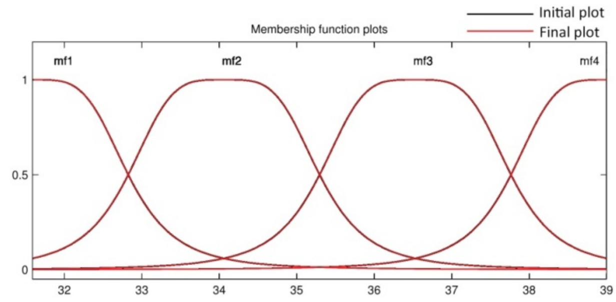


Fig. 10 Initial and final Bell Shape membership function of current input.

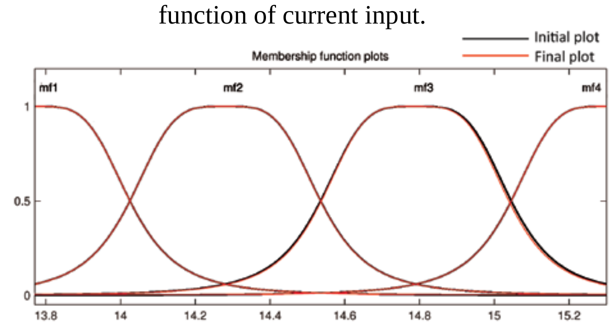


Fig. 11 Initial and final Bell Shape membership function of pulse on time input.

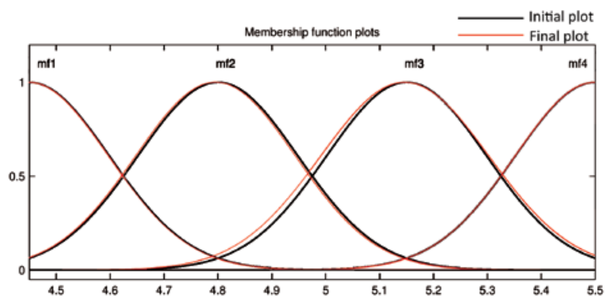


Fig. 12 Initial and final Gaussian membership function of feed rate input.

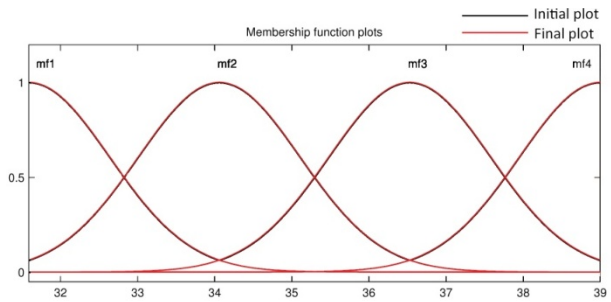


Fig. 13 Initial and final Gaussian membership function of current input.

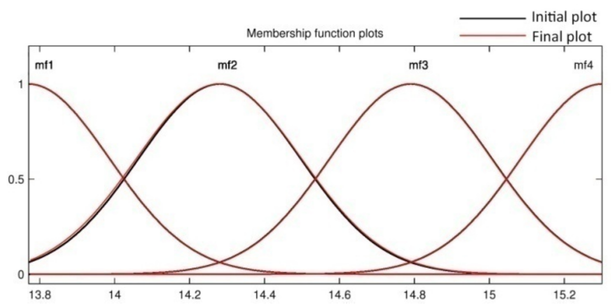


Fig. 14 Initial and final Gaussian membership function of pulse on time input.

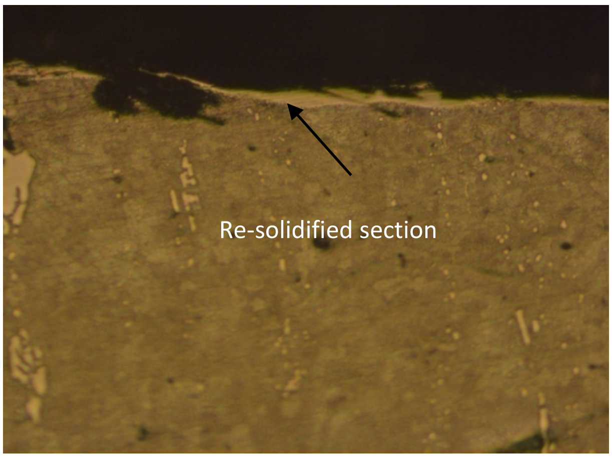


Fig. 15 Cross section view of Sleipner cold work tool steel alloy.

The cross-section of the specimen micrograph is shown in Fig 8. Due to the electro-thermal treatment, a re-solidified section can be seen on the side of the sample material. The electrical discharge affects a specific region at micro level during pulse on time. Where the small particles were removed from the affected area there are craters on material surface as shown in Fig. 15.

5. Conclusions

This paper proposes a method using an Adaptive neuro-fuzzy inference system (ANFIS) in order to predict surface roughness using cutting parameters in relation to different variables. Pulse on time, current and feed rate variables were used as the independent variable parameters. The ANFIS model prediction made with two different methods; the Gaussian membership type at5.53 % is better than the Bell-Shaped membership function at13.23 % given the average error rate. The actual values obtained from the interaction of plots between the variable parameters are shown under experimental conditions.

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