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Article

Verification of Fuzzy Inference System for Cutting Speed while WEDM for the Abrasion-Resistant Steel Creusabro by Conventional Statistical Methods

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Abstract: Wire electrical discharge machining is an unconventional machining method for the production of complex-shaped and very precise parts. Because of the high energy consumption of this machining process, it is necessary to maximize the cutting speed for its appropriate implementation. The abrasion-resistant steel Creusabro 4800 was chosen as the test material for this experiment, which is widely used especially for machines working in mines and quarries. In order to maximize the cutting speed, a fuzzy inference system (FIS) has been built, which uses 18 expert propositions to "model" the cutting speed based on five selected input parameters: gap voltage, pulse on time, pulse off time, discharge current, and wire feed. The obtained results were further verified by a design of experiment consisting of 33 tests for five selected input factors. Using the fuzzy inference system, the optimum machine parameters setup was found to maximize the cutting speed, in which the gap voltage = 60 V, pulse on time = 10 μs, pulse off time = 30 μs, wire feed = 10 m·min^{-1} and discharge current = 35 A. The predicted value of the cutting speed using the fuzzy inference system is 6.471 mm·min^{-1}.

Keywords: WEDM (wire electrical discharge machining); electrical discharge machining; fuzzy inference system; FIS; Creusabro; cutting speed; design of experiment

1. Introduction

Wire electrical discharge machining (WEDM) is a widely used technology in the automotive, aerospace, military, and medical industries. It is an unconventional machining technology that uses a thermoelectric principle to cut the material. There are no requirements on the machined material in terms of mechanical properties, only it must be at least electrically conductive [1,2]. WEDM is generally perceived as an energy-intensive machining technology, therefore maximizing the cutting speed is a key parameter in terms of process optimization [3,4]. High abrasion-resistant steels such as Creusabro 4800 are used, thanks to their unique mechanical properties, for a variety of machines or in mines and quarries for scrap metal processing machines [5].

Fuzzy logic originated in response to the shortcomings of classical binary logic. It allows not only to represent uncertainties in any process, but also to make meaningful use of vague concepts from the common speech [6]. Zadeh laid the foundations of this branch of mathematics in 1965 [7].

A design of experiment (DoE) is a set of statistical and mathematical methods used to develop, improve, or optimize any process. The methodology of the design of experiment is extensively used especially in industry, typically in situations where only a few input variables potentially influence the observed measure of process quality (response). These input variables must then be controlled, at least for the duration of the experiment [8].

Çaydaş et al. [9] focused in their study on the development of the adaptive neuro-fuzzy inference system model that could predict the thickness of the white layer and the average roughness of the surface during the WEDM process. They chose open circuit voltage, pulse duration, wire feed rate, and dielectric flushing pressure as the input parameters for that model, which combined the function of fuzzy inference with the learning ability of artificial neural network. Lin [10] focused their research on the use of the grey-fuzzy logic approach based on orthogonal array in order to optimize the WEDM process with multi-response. They came to the conclusion that the machining parameters like duty factor, pulse on time and discharge current are effective while considering the multiple responses. Thus, this approach can be employed for the optimization of the electrical discharge machining process with multi-responses of the process. Salman et al. [11] investigated the roughness value while applying copper electrode-hardened powder metals to a workpiece. Besides, they employed the WEDM method during the application of copper, copper-tungsten, and graphite electrodes to the same material. The parameters for the experiments were designed using the Taguchi method. Tzeng et al. [12] studied the optimization of the precision and accuracy of the high speed WEDM process employing the fuzzy logic analysis and Taguchi methods. It was found out that duty cycle, pulse time, and peak value of discharge current are the most important parameters, while the powder size and powder concentration are the least influential on the high-speed WEDM process design. Yan et al. [13] applied a closed-loop wire tension control system for micro-WEDM process to guarantee a smooth wire transport and a constant tension value in their study. They proposed a genetic algorithm-based fuzzy logic controller for the investigation of the dynamic performance of the closed-loop wire tension control system. It was proved that the proposed controller is able to reach faster transient response and smaller error than a PI controller. Yan et al. [14] tried to develop an adaptive control system in order to monitor the process, identify, and control the micro-WEDM process. As the control parameter for that system, the short circuit ratio was selected. For the servo feed control, a self-organizing fuzzy sliding mode controller was proposed. One more fuzzy logic controller was designed for the control of the short circuit ratio at a pre-determined level. According to the results of the experiments the developed adaptive control system has faster machining and better machining stability compared to a conventional control scheme. Rajyalakshmi et al. [15] studied the process parameters optimization of multi-response characteristics of the WEDM process of Inconel 825 employing the Taguchi method and fuzzy-grey relational analysis. As the results of the experiments, the optimal combination of influential input parameters was defined. Moreover, the suggested approach of Taguchi and fuzzy-grey relational analysis was proved as sufficient for identifying the influential parameters of the WEDM process. Rupajati et al. [16] tried to optimize the thickness of the recast layer and surface roughness in the WEDM process employing Taguchi method and fuzzy logic. L_{18}mixed-orthogonal array table was selected as a work material for the experiments. The WEDM process parameters like open voltage, arc on time, off time, and servo voltage were considered in the experiments. According to the obtained results, the machining performance characteristics of the WEDM process can be efficiently improved using the combination of Taguchi method and fuzzy logic. Soepangkat et al. [17] investigated the optimization of the thickness of recast layer and surface roughness of the WEDM process using AISI D2 steel as an experimental material. They employed Taguchi method, fuzzy logic, and grey relational analysis applying different flushing pressure, open voltage, on time, off time, and servo voltage to study the multiple performance characteristics. The combination of the methods proved to be very efficient for the WEDM process of AISI D2 steel as was shown by the results of the experiments.

WEDM is a technological operation where the highest cutting speed is required because of the energy intensity of the process. The purpose of this study is to find the setup of machine parameters that maximize the cutting speed of the widely used wear-resistant steel Creusabro. The cutting speed of this steel has not been studied in any study yet, and finding its maximum is crucial for the efficient WEDM machining of these steel types. This study follows previous extensive research [18–22] concerning the WEDM of metallic materials with a possible heat treatment.

2. Experimental Setup and Material

2.1. Experimental Material

The samples for the experiment were made of abrasion-resistant steel Creusabro 4800. To be able to study the microstructure of materials, metallographic specimens were made out of the samples; they were prepared using common techniques—by wet grinding and polishing with diamond pastes using the automatic preparation system TEGRAMIN 30 from Struers (Westlake, Cleveland, OH, USA). The final mechanical-chemical polishing was performed with the OP-Chem suspension from Struers. After chemical etching, the material structure was analyzed using light microscopy (LM) on anAxio Observer Z1m ZEISS (Carl-Zeiss-Straße, Oberkochen, Germany).

Creusabro 4800 is an abrasion-resistant steel with an increased wear resistance because of the presence of hard particles of titanium, molybdenum, and chromium carbides. Its chemical composition according to standard in weight percent is 0.2% C, 1.6% Mn, 0.2% Ni, 1.9% Cr, 0.4% Mo, 0.2% Ti, max 0.005% S, max 0.018% P, Fe-balance. Its high thermal resistance allows it to be used in environments where the temperature reaches up to 400 °C and also has the ability to absorb deformation forces resulting from impact abrasion. This steel has a hardness of 370 HB, a tensile strength of 1200 MPa, a yield strength of 900 MPa, and also has a high deformation hardening capacity of up to 70 HB. Because of its high temperature resistance, it is used in mines and quarries, in the steel and cement industry, foundry and agricultural technology [5,23]. An input 8 mm-thick prism semi product was used for the experiment. The microstructure shown in Figure 1c is fine-grained and completely homogeneous, martensitic-bainitic, containing residual austenite.

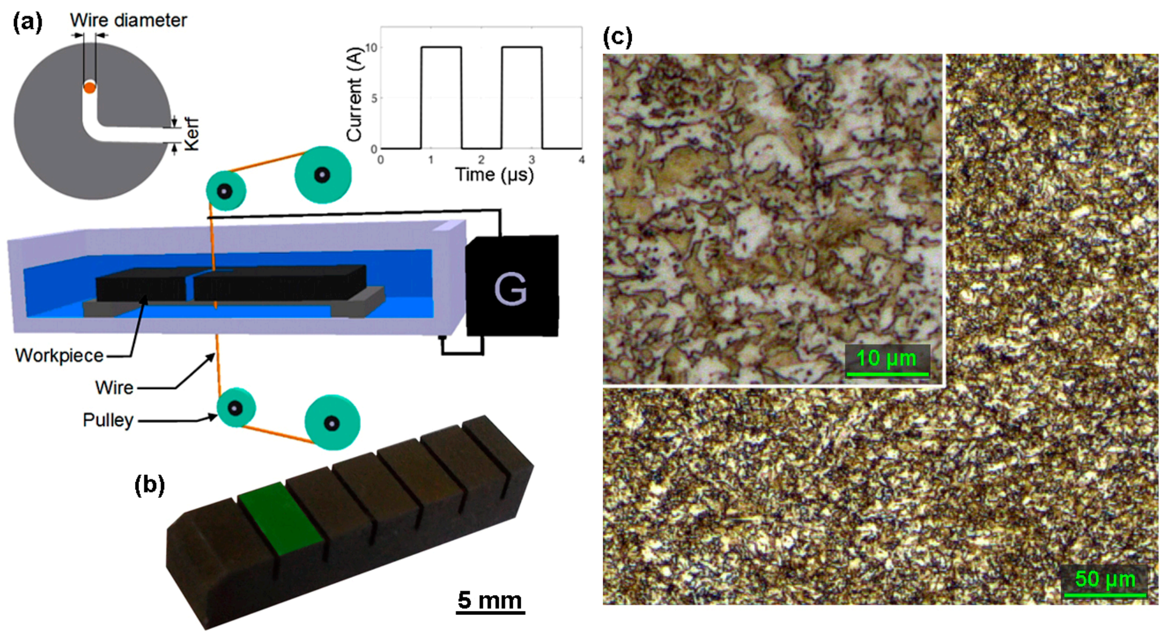

Figure 1. (**a**) Scheme of WEDM (wire electrical discharge machining); (**b**) produced samples-one sample labeled green; (**c**) microstructure of Creusabro 4800.

2.2. WEDM Machine Setup

High precision five axis WEDM machine used in this study was computer numeric control (CNC) machine EU64 from company MAKINO (Meguro, Tokyo, Japan). As electrode, brass wire ø0.25 mm PENTA CUT E (60 Cu/40 Zn) was used. During the entire machining process, the samples were completely immersed in a dielectric liquid, which was deionized water. Unconventional WEDM technology also differs from common conventional technologies in machining speed or cutting control. WEDM does not allow a direct adjustment of the cutting speed when programming the machine but the speed is based on the setting of individual machine parameters. The WEDM cutter used a direct speed measurement during the machining process. Cutting speed is constant throughout the machining process.

The design of experiment was based on monitoring the influence of five independent machine setup parameters, which were gap voltage (U), pulse on time (T_{on}), pulse off time (T_{off}), discharge current (I), wire feed (v), and their limiting values, which are given in Table 1. The limiting values of individual parameter setup were determined on the basis of very extensive previous tests [24]. The actual cutting speed on the WEDM machine was read during the machining process.

Table 1. limiting values of machine parameters setup.

Parameter	Gap Voltage (V)	Pulse on Time (μs)	Pulse off Time (μs)	Wire Feed ($m \cdot min^{-1}$)	Discharge Current (A)
Minimum	50	6	30	10	25
Maximum	70	10	50	14	35

2.3. Mamdani Fuzzy Inference System

The Mamdani fuzzy inference system (FIS) always fuzzifies the crisp values of the input variables to several discrete levels using the membership functions. The rules (if-then) are then applied to these fuzzy sets. The aggregation of the results of these rules is the fuzzy response set described again by only a few discrete levels represented by the membership functions. After defuzzyfication of this value, the "expected" response value is obtained, with the principle of FIS functioning shown in Figure 2.

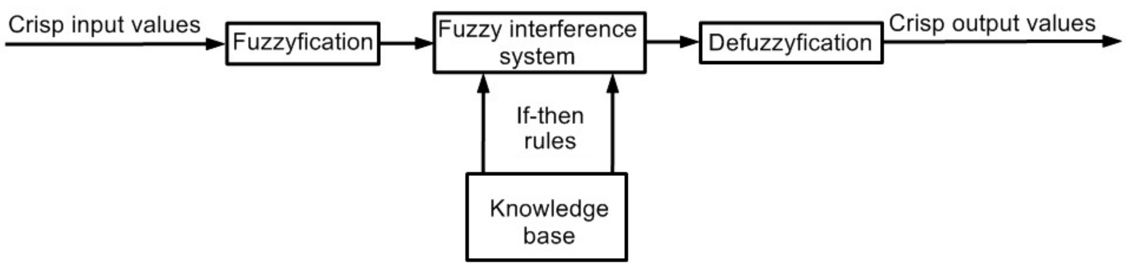

Figure 2. The scheme of fuzzy inference system (FIS) (fuzzy inference system) functioning.

The input variables were divided into three levels (low, mid, high) and then fuzzified using Gaussian functions. The output variable of the cutting speed v_c was divided into five levels (very low, low, mid, high, very high) and fuzzified in a similar way as shown in Figure 3.

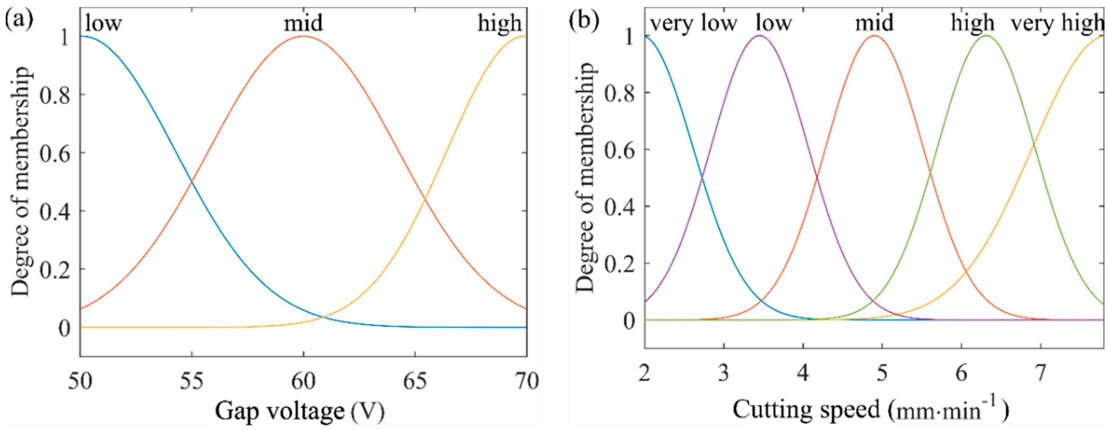

Figure 3. Membership functions of the gap voltage (**a**) and cutting speed (**b**).

For this FIS model, 18 if then rules were used (provided by a WEDM expert along with the technology for machining individual materials provided by the WEDM machine manufacturer) that were applied to the fuzzy sets according to the input value membership functions. Used rules are:

Rule 1: If pulse off time is low and discharge current is low, then cutting speed is very low.
Rule 2: If pulse off time is mid and discharge current is mid, then cutting speed is mid.
Rule 3: If pulse off time is high and discharge current is high, then cutting speed is very high.
Rule 4: If gap voltage is low, then cutting speed is mid.
Rule 5: If gap voltage is mid, then cutting speed is very high.
Rule 6: If gap voltage is high, then cutting speed is low.
Rule 7: If pulse on time is low, then cutting speed is low.
Rule 8: If pulse on time is mid, then cutting speed is mid.
Rule 9: If pulse on time is high, then cutting speed is very high.
Rule 10: If pulse off time is low, then cutting speed is high.
Rule 11: If pulse off time is mid, then cutting speed is mid.
Rule 12: If pulse off time is high, then cutting speed is low.
Rule 13: If discharge current is low, then cutting speed is low.
Rule 14: If discharge current is mid, then cutting speed is mid.
Rule 15: If discharge current is high, then cutting speed is high.
Rule 16: If wire feed is low, then cutting speed is high.
Rule 17: If wire feed is mid, then cutting speed is mid.
Rule 18: If wire feed is high, then cutting speed is low.

The logical operator AND was represented by the minimum of the fuzzy sets, OR was represented by the maximum of the fuzzy sets and the IMPLICATION by "trimming" the membership function to the level obtained with AND/OR. A simple maximum of results (fuzzy sets) of all statements was used for aggregation. The center of gravity of the aggregated fuzzy set was used for defuzzyfication of the result. This process is in great detail described in [7] and similar approach is taken in [25].

3. Results and Discussion

Unlike Çaydaş et al. [9], Lin [10], Salman et al. [11], Tzeng et al. [12], Yan et al. [14], and Rajyalakshmi et al. [15] studies, this article focuses only on cutting speed optimization. Although this fact significantly simplifies the task, its advantage is the clarity of presented results and much more straightforward mathematical apparatus used. Using the fuzzy inference system, the optimal setup of machine input parameters was found to maximize the cutting speed. This setup is gap voltage = 60 V, pulse on time = 10 µs, pulse off time = 30 µs, wire feed = 10 m·min^{-1}, and discharge current = 35 A, with the predicted cutting speed along with this machine parameters setup is 6.471 mm·min^{-1}. This result is illustrated by the FIS response surface shown in Figure 4. Because of the number of parameters used, it was necessary to fix the three input variables, i.e., pulse on time to 10 µs, discharge current to 35 A, and wire feed to 10 m·min^{-1}. This figure also shows the optimum cutting speed in the selected parameter area.

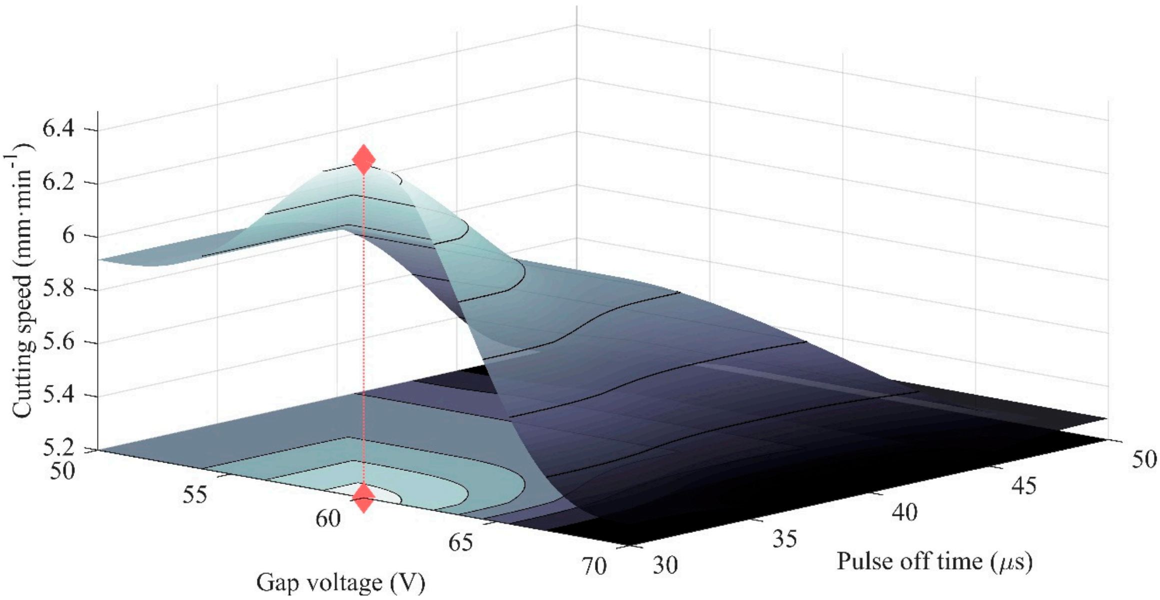

Figure 4. The prediction of cutting speed by FIS depending on the gap voltage and pulse off time with the defined optimum control surface.

The "half response surface central composite design" containing 33 rounds was chosen for the validation experiment. To reduce the possibility of systematic errors, the individual rounds are randomized and divided into two blocks (Table 2). The experiment was supplemented with seven central points in order to capture the variability of the random component acting in the process. This data collection plan is described in detail in Montgomery [26]. The observed cutting speed values are also shown in Table 2.

Table 2. Machining parameters used in the experiment and observed cutting speed.

Number of Sample	Gap Voltage (V)	Pulse on Time (µs)	Pulse off Time (µs)	Wire Feed (m·min^{-1})	Discharge Current (A)	Cutting Speed (mm·min^{-1})	Number of Sample	Gap Voltage (V)	Pulse on Time (µs)	Pulse off Time (µs)	Wire Feed (m·min^{-1})	Discharge Current (A)	Cutting Speed (mm·min^{-1})
1	70	8	40	12	30	5.4	18	60	8	40	12	30	5.4
2	60	8	30	12	30	5.6	19	60	8	40	12	30	5.4
3	60	8	40	12	25	4.9	20	70	6	50	14	25	3.9
4	60	10	40	12	30	6.1	21	50	6	30	14	25	4.9
5	50	8	40	12	30	5.3	22	60	8	40	12	30	5.4
6	60	8	50	12	30	5.1	23	70	10	30	14	25	4.9
7	60	6	40	12	30	4.8	24	50	6	50	10	25	3.9
8	60	8	40	12	35	5.8	25	60	8	40	12	30	5.3
9	60	8	40	10	30	5.4	26	50	10	50	14	25	4.7
10	60	8	40	14	30	5.4	27	50	10	30	10	25	5.5
11	60	8	40	12	30	5.4	28	50	6	50	14	35	4.8
12	50	6	30	10	35	5.3	29	50	10	50	10	35	5.8
13	70	10	50	10	25	4.8	30	70	6	30	14	35	4.9
14	70	10	30	10	35	6.2	31	50	10	30	14	35	5.9
15	60	8	40	12	30	5.4	32	60	8	40	12	30	5.4
16	70	6	50	10	35	4.9	33	70	6	30	10	25	4.6
17	70	10	50	14	35	5.9	-	-	-	-	-	-	-

Because of the use of the "half response surface central composite design," it was redundant to implement the principal component analysis (PCA) as in Çaydaş study [9] because the explanatory variables are already orthogonal to each other because of this DoE and therefore any reduction of dimensionality by PCA is not possible.

Using the known regression analysis tools, a linear regression model has been constructed, which is shown in Table 3 containing only statistically significant members.

Table 3. P-values of statistically significant parameters.

Parameter	*P*-Value
Linear	
pulse on time	0.000
pulse off time	0.000
discharge current	0.000
2–Way Interaction	-
pulse off time and discharge current	0.023
Quadratic	-
gap voltage	0.000

The values of the explanatory variables were standardized to −1, 0, and 1 prior to the calculation, so that the peak of the regression quadrate composed of the quadrates of all predictors was at the central point of the area of interest. The resulting model is not hierarchical, therefore, after transformation into the original values of the explanatory variables, the linear member gap voltage was added, but this only shifts the peak of the used quadric back to the original values of the explanatory variables. The "stepwise" method was used for the selection of the used regressors with a significance level of 5% for both input and exclusion. The mathematical notation of the linear regression model of cutting speed is written in Equation (1):

$$v_c = -6.0963 + 0.2166 \cdot T_{on} - 0.0859 \cdot T_{off} - 0.0027 \cdot I + 0.3573 \cdot U + 0.0021 \cdot T_{off} \cdot I - \\ -0.0029 \cdot U^2. \tag{1}$$

The response area obtained using the least squares method (with the fixed machine setup parameters pulse on time = 10 µs and discharge current = 35 A) is shown in Figure 5.

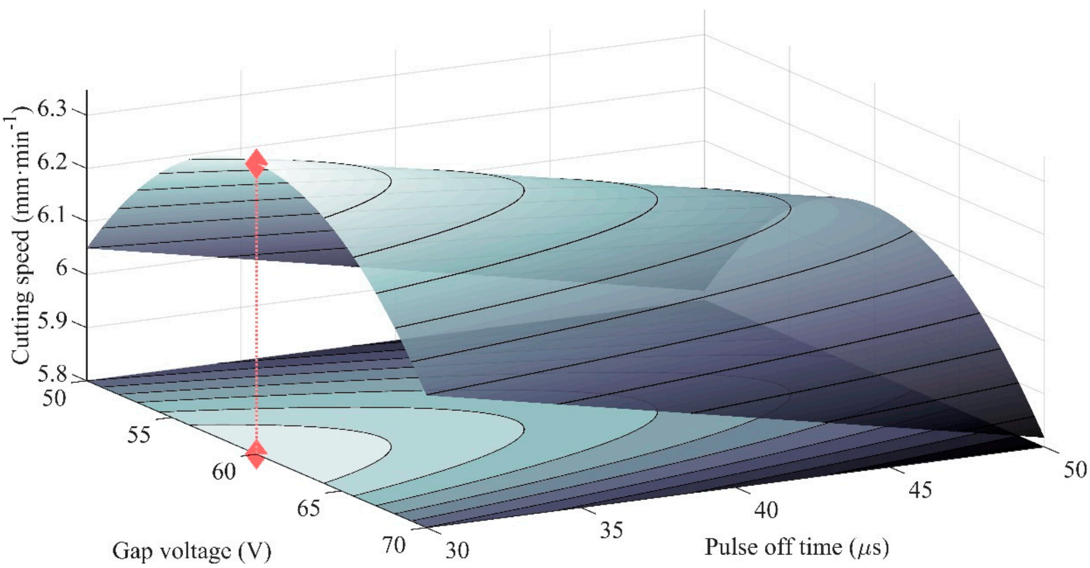

Figure 5. The response area of the cutting speed depending on the gap voltage and pulse off time with the defined optimum.

Main effects plot (Figure 6) shows that "direction" of effects found in the validation experiment is consistent with the rules used for FIS and DoE. Pulse on time and discharge current have a positive effect on the cutting speed, while pulse off time has a negative effect. Gap voltage has a significant quadratic curvature and wire feed is not shown because its action is statistically insignificant according to the DoE outputs.

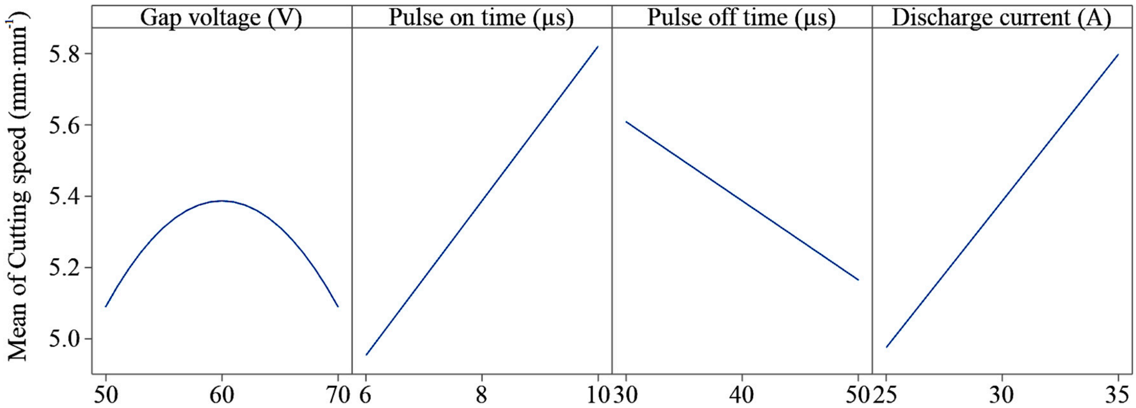

Figure 6. Main effects plot for the mean of cutting speed.

Interaction plot (Figure 7) shows the change of the slope of one effect with regards to the other. Even though the slope changes significantly the interaction is not "strong" enough to reverse the direction of the effect. This means that cutting speed will increase with increasing pulse on time and discharge current, it will decrease with increasing pulse off time and that it has maximum for gap voltage = 60 V. Other interactions are not shown because they are statistically insignificant according to the DoE outputs.

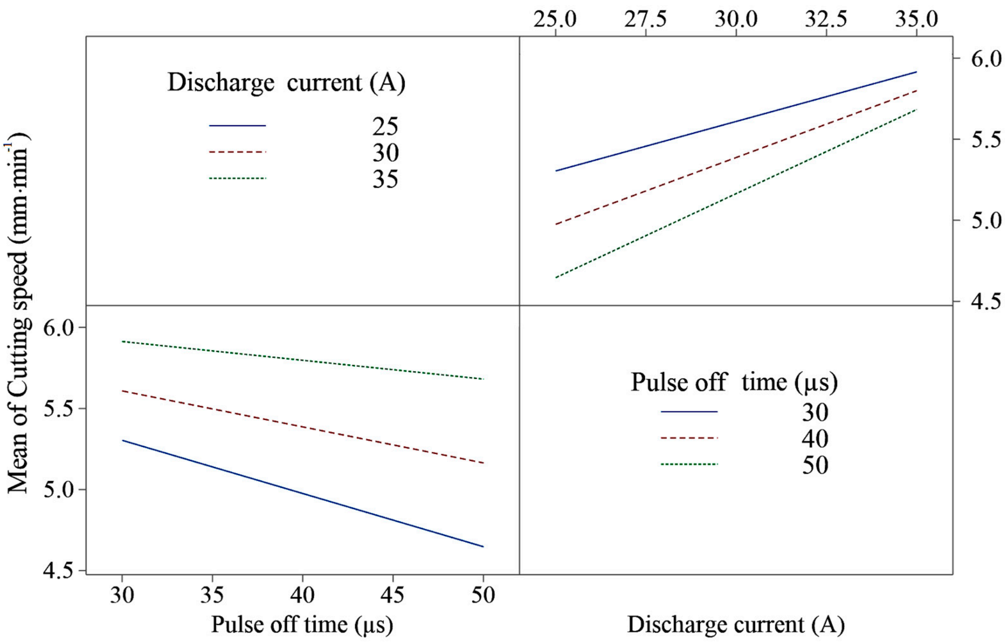

Figure 7. Interaction plot for discharge current and pulse off time.

The optimal setup of the parameters for Creusabro steel machining according to the validation experiment is gap voltage = 60 V, pulse on time = 10 μs, pulse off time = 30 μs, discharge current = 35 A, and the wire feed parameter arbitrarily (according to validation experiment it has no significant statistical influence on the response). The predicted maximum cutting speed by linear regression will be 6.3471 mm·min^{-1} and the optimum position (except for the insignificant wire feed) is consistent with the result obtained from the fuzzy inference system. The results of the regression analysis "confirm the correctness" of the selected explanatory variables for cutting speed and were the same as in the study by Singh [27], which dealt with aluminum alloy machining. In this study the authors did not perform a similar statistical analysis and the effect of these variables on the response was taken as given.

The R-squared coefficient of determination was used to assess the quality of the models in the whole monitored area. The use of this criterion will reveal significant shortcomings in the FIS model, which, using 18 propositional formulas, explains only 20.51% of the response variability. In contrast, a regression model using the same criterion using five regressors describes 90.69% of the observed cutting speed variability. It should be emphasized that "worse" results of the "global" FIS prediction response (as compared to Çaydaş [9] and Singh [27] studies) were achieved using 18 a priori propositions, instead of defining neural network on experimentally determined data. It is undisputed that FIS-based methods have many uses in WEDM for modelling other responses that were studied in Çaydaş [9], Soepangkat [17], Rupajati [16], Yan [13] articles, or multi-criteria optimization of multiple output variables at the same time [12,15].

4. Conclusions

Based on the expert's knowledge, 18 propositional formulas were constructed, which were the basis of the fuzzy inference system of the cutting speed model for WEDM of the abrasion-resistant steel Creusabro 4800, and the following conclusions were reached.

Using the fuzzy inference system, optimum machine parameters setup was found to maximize the cutting speed: gap voltage = 60 V, pulse on time = 10 µs, pulse off time = 30 µs, wire feed = 10 m·min^{-1}, and discharge current = 35 A for a maximum cutting speed of 6.471 mm·min^{-1}.

The result obtained with the fuzzy inference system was subsequently experimentally verified using a design of experiment consisting of 33 rounds, with a real measured cutting speed on a WEDM machine of max. 6.2 mm·min^{-1} for Sample 13.

The response area equation was compiled from the experimental data by regression analysis, and the optimum setup of the machine parameters was also found: gap voltage = 60 V, pulse on time = 10 µs, pulse off time = 30 µs, discharge current = 35 A, and the wire feed parameter was arbitrary (does not have a statistically significant effect on the response) that maximizes the cutting speed up to 6.3471 mm·min^{-1}.

The predicted maximum cutting speed using both models was higher in both cases than in actual sample cutting during the design of experiment.

Based on the above mentioned conclusions, it can be unambiguously stated that the use of a fuzzy inference system may be a suitable tool for locating the optimum machine parameters setup to maximize the cutting speed for the WEDM of Creusabro steel, for a key reason to reduce process energy consumption while reducing the machine time. However, when it is necessary to model cutting speed at some n-dimensional interval, using conventional DoE methods achieves much better results.

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