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# OPTIMIZATION OF WEDM PARAMETERS USING MACHINE LEARNING: A COMPARATIVE ANALYSIS OF SELECTED REGRESSION MODELS

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***Abstract:*** This paper discusses the influence of selected parameters (ON, OFF and SV) on surface quality and machining time during WEDM. The study used a multivariate ANOVA to test the statistical significance of the factors considered. In addition, machine learning algorithms such as Support Vector Regression (SVR) and polynomial regression were applied to further investigate the influence of the parameters. A comparative analysis of the algorithms showed that models based on the Support Vector Regression algorithm perform the best in predicting the roughness parameter Ra and machining time separately. SVR performs better with nonlinear data, making it more accurate in predicting machining time values than simpler regression models. The study showed that all ON, OFF and SV parameters have a significant effect on surface roughness and machining time. Further analysis of the experimental results showed that the application of machine learning methods to optimise the EDM process, by selecting appropriate operating parameters for the WEDM machine, resulted in better surface quality and reduced machining time. These results have practical significance for the metalworking industry and indicate potential opportunities to improve the performance of the WEDM process.

***Key words:*** WEDM, surface quality, machining time, machine learning algorithms.

## 1. INTRODUCTION

WEDM is a process for cutting electrically conductive materials such as steel, aluminum, brass, titanium or graphite. This cutting process uses a wire made of copper, brass, molybdenum or tungsten, which is guided through the workpiece material. WEDM applies the phenomenon of electrospark erosion, in which electrical discharges occur between the electrode wire and the workpiece [12]. The machining process takes place in the immersion of the dialectic fluid. As the current flows through the wire electrode, it creates a series of repetitive electrical impulses in the workpiece-electrode gap. These series of sparks cause intense, localized heating that raises the temperature in the contact area to 12,000 °C [16]. The workpiece surface exposed to the wire electrode is machined due to the localized melting and vaporization that results from the intense heating. The resulting molten debris during cutting is removed by a circulating dielectric fluid [1]. WEDM makes it possible to cut very difficult-to-machine materials and produce complex shapes with high precision and repeatability. Advantages of this method also include the lack of direct contact between the tool and the workpiece, which minimizes tool wear and allows thin, delicate parts to be cut without risk of damage. The process is used in a wide range of industries, such as the manufacture of tools, injection molds, precision parts for machinery and equipment, and other products requiring high precision and repeatability.
However, WEDM also has its drawbacks. The process is time-consuming, which affects production costs. In addition, the process can result in surface irregularities on the workpiece. The above disadvantages can pose a serious challenge to industrial production. To address this challenge, a comprehensive analysis of the influence of individual WEDM processing parameters on the established outcome factors is necessary. In the existing scientific literature on this topic, researchers have focused on analysing the effects of various electrical and hydro-mechanical parameters on the quality of machined surfaces [3], geometric accuracy and cutting performance [10]. It is worth noting that the most important factors affecting the quality and efficiency of cutting are electrical parameters [2], such as the duration of the electric pulse and the voltage of the electric current. These parameters determine the amount of energy that is delivered to the erosion gap and affect the size and stability of the plasma channel, which in turn affects the geometric dimensions of the workpiece being cut, the structure of the workpiece, and the stability and speed of machining. Studies show that the longer the

duration of the electrical pulse, the faster the removal of material, but the quality of the cut surface is lower. Electrical voltage is considered the most important parameter affecting the quality of the machined surface - the higher the voltage value, the lower the surface quality [2]. The intensity of the electric current affects the machining speed and geometric accuracy of the cut parts - higher intensity speeds up machining but contributes to shape errors.
Other studies show that the speed at which wire is fed into the workspace also affects machining stability - the lower the speed, the greater the likelihood of wire breakage, forcing slower machining and poorer surface quality. On the other hand, a high wire voltage leads to greater wire straightness, which promotes the stabilization of the electrical voltage between the two electrodes and the generation of a greater heat flux. This results in increased material erosion at corners and dimensional errors, especially at corners. The above studies indicate the need to optimize WEDM parameters. The traditional approach to this problem is based on an experimental trial-and-error approach, in which manual adjustments are introduced to individual process parameters to obtain optimal results. However, this process is time-consuming and expensive. Therefore, artificial intelligence methods, such as machine learning algorithms, are increasingly being applied to optimize machining processes. In this paper, we will focus on the study of the influence of electrical parameters on surface roughness and WEDM machining performance. We will also present the results of a comparative analysis of various regression models, such as SVR and Multiple Linear Regression (MLR), to predict optimal machining parameters.

## 2. TEST PROCEDURE

### 2.1 Materials and equipment used in the tests

The tests were carried out on chromium-nickel-molybdenum alloy steel 40CrMnNiMo8-6-4 (Table 1) which selected mechanical properties are listed in Table 2. The material was delivered as 280x150x10mm plates.

Table 1. Chemical composition of the steel used in the study [%], [9]

| C | Si | Mn | Cr | Ni | Mo | S |
|---|---|---|---|---|---|---|
| 0.37 | 0.3 | 1.4 | 2.0 | 1.0 | 0.2 | <0.01 |

Table 2. Selected mechanical properties of the steel used in the study [9]

| Trade name of steel | Density [g/cm$^3$] | Hardness [HB] | Tensile strength; Rm, [MPa] | Yield point; Re, [MPa] |
|---|---|---|---|---|
| IMPAX | 7.8 | 330 | 1020 | 900 |

The cut samples were rectangles measuring 85x5x20 mm (Fig. 1). Each sample contained about 40 sample surfaces (20 surfaces on each side) cut using different parameters.

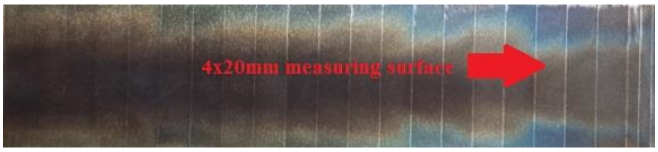

Fig. 1. Cut samples


Fig. 2. Fanuc C600iC machine

Experimental tests were carried out on a Fanuc C600iC WEDM electrical discharge machine (Fig. 2). The working electrode was CuZn37 brass wire of 0.2 mm diameter and 900 MPa strength. The electric medium was distilled and deionized water with a resistance of R = $5\cdot10^4$ Ωcm.

### 2.2 Measurement methods

Surface roughness measurements were made using an SJ210 roughness meter. The machining time of individual samples was measured using the built-in functions in the machine controller.

## 2.3 Selection of the parameters under consideration and experimental procedure

The basis for determining the appropriate input parameters for the experimental tests was to determine their actual values and the adjustable variability ranges for the adopted type of planned experiment. Input factors $X_1$, $X_2$, and $X_3$ are respectively the electric pulse time ON, pause time between pulses OFF and servo voltage SV. Using the recommended values of the machine manufacturer's parameters and the literature analysis [2, 3, 10], tests were carried out to check the maximum, central and minimum levels of the considered parameters for machining stability (here -1, 0 and 1, respectively) (Table 3).

The empirical test was conducted in accordance with Response Surface Methodology (RSM) using a Box-Behnken experiment plan. The choice of this planning technique was dictated by the need to minimize the number of experiments, and at the same time maintain a good estimation of the response surface. Due to the relatively low quality of the prediction of the dependent variables under consideration based on measurements from one experiment, it was decided to retry the BB plan with changed parameter values. Re-trials of sample cutting were terminated on the 6th attempt, due to the sufficient accuracy of the prediction and the lack of its progression. The relationship, between the prediction accuracy of the considered features and the number of samples is shown in the graphs (Fig. 3, 4).

The machining time t and the surface roughness parameter Ra were used as the evaluation of the machining parameters (Table 4).

Table 3. Selection of parameter values for testing

| No. | Level | ON [μs] | OFF [μs] | SV [V] |
|---|---|---|---|---|
| 1 | -1 | 5 | 14.6 | 15 |
| | 0 | 9 | 19.7 | 20 |
| | 1 | 7 | 24.8 | 25 |
| 2 | -1 | 5 | 14.6 | 15 |
| | 0 | 8 | 21.9 | 22 |
| | 1 | 11 | 29.2 | 29 |
| 3 | -1 | 7 | 14.6 | 18 |
| | 0 | 12 | 24.8 | 34 |
| | 1 | 17 | 35 | 48 |
| 4 | -1 | 15 | 18 | 10 |
| | 0 | 27 | 32.4 | 18 |
| | 1 | 30 | 46.8 | 26 |
| 5 | -1 | 3 | 10 | 10 |
| | 0 | 6 | 19 | 19 |
| | 1 | 9 | 28 | 28 |
| 6 | -1 | 15 | 40 | 3 |
| | 0 | 22 | 60 | 4 |
| | 1 | 29 | 80 | 5 |

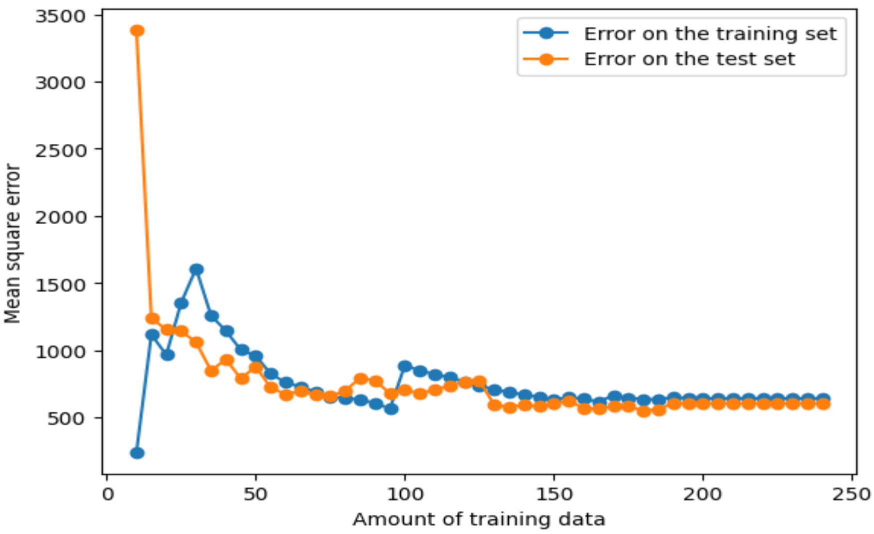

Fig. 3. Effect of the amount of data on the prediction error of processing time in the training and test set

Table 4. Selection of output quantities

| No. | Variable | Measurement | Unit |
|---|---|---|---|
| 1 | $R_a$ | Surface roughness parameter | µm |
| 2 | t | Machining time | seconds |

Table 5. Summary list of test results

| Test No | Controlled factors on a real scale | | | Measurement results | |
|---|---|---|---|---|---|
| No | ON [µs] | OFF [µs] | SV [V] | t[s] | Ra [µm] |
| 0 | 5 | 14.6 | 22 | 132 | 3.05 |
| 1 | 11 | 14.6 | 22 | 132 | 3.33 |
| 2 | 5 | 29.2 | 22 | 180 | 3.09 |
| 3 | 11 | 29.2 | 22 | 150 | 3.72 |
| 4 | 5 | 21.9 | 15 | 132 | 3.19 |
| ... | ... | ... | ... | ... | ... |
| 241 | 22 | 60 | 4 | 210 | 4.11 |
| 242 | 22 | 60 | 4 | 204 | 4.82 |
| 243 | 22 | 60 | 4 | 210 | 4.27 |
| 244 | 22 | 60 | 4 | 204 | 5.16 |
| 245 | 22 | 60 | 4 | 204 | 4.61 |

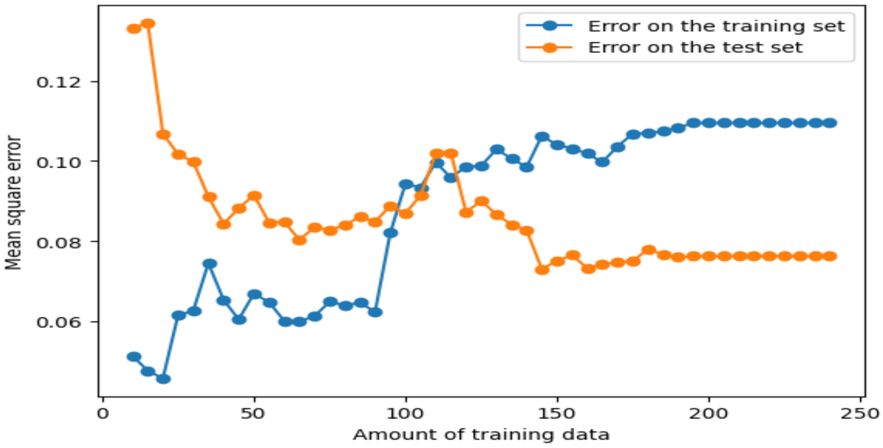


Fig. 4. Effect of the amount of data on the prediction error of the $R_a$ parameter in the training and test set

## 3. RESULTS

After technological, metrological and statistical tests, the obtained results are presented in Table 5.

### 3.1. Statistical model analysis

The study was conducted at an assumed significance level of $\alpha$ = 0.05. Based on the collected results, a correlation matrix containing Pearson's linear correlation coefficients between the experimental variables was developed (Table 6). An ANOVA analysis of variance of all variables was also conducted and shown in Table 7-8 and three-dimensional graphs (Fig. 5, 6) were developed to show the effect of the normalised values of the independent variables on the dependent variable. The values of the dependent variable in the 3D plot were generated based on the prediction of the machine learning model and the values of the input factors were developed using 'griddata' interpolation from the Python library scipy.interpolate.

Table 6. Correlation matrix of explanatory and explained variables

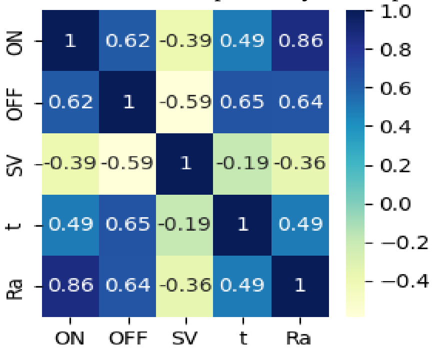


Table 7. Evaluation of the effect of each explanatory variable and the interaction between them on the roughness parameter $R_a$

| | sum_sq | df | F | PR(>F) |
|---|---|---|---|---|
| **ON** | 35.197 | 1 | 318.58 | 1.72E-45 |
| **OFF** | 2.011 | 1 | 18.21 | 2.88E-05 |
| **ON: OFF** | 0.184 | 1 | 1.67 | 1.98E-01 |
| **SV** | 0.127 | 1 | 1.15 | 2.85E-01 |
| **ON: SV** | 0.008 | 1 | 0.08 | 7.84E-01 |
| **OFF: SV** | 0.012 | 1 | 0.10 | 7.46E-01 |
| **ON: OFF: SV** | 0.621 | 1 | 5.62 | 1.86E-02 |

Table 8. Evaluation of the effect of each explanatory variable and the interaction between them on processing time

| | sum_sq | df | F | PR(>F) |
|---|---|---|---|---|
| **ON** | 1254.4 | 1 | 1.46 | 0.228079 |
| **OFF** | 121131.9 | 1 | 141.02 | 9.56228E-26 |
| **ON: OFF** | 1730.59 | 1 | 2.01 | 0.157106 |
| **SV** | 21044.84 | 1 | 24.50 | 1.42468E-06 |
| **ON: SV** | 1040.95 | 1 | 1.21 | 0.2720890 |
| **OFF: SV** | 27419.19 | 1 | 31.92 | 4.66007E-08 |
| **ON: OFF: SV** | 588.68 | 1 | 0.68 | 0.4085926 |

### 3.2. Analysis of test results

**Analysis of the influence of independent variables on surface roughness.**

The correlation matrix showed that the dependent variable $R_a$ is strongly positively correlated with the independent variable ON and to a lesser extent with the variable OFF. Both variables have a statistically significant effect on Ra. This influence is depicted in the graph (Fig. 4), which explicitly shows that the higher the value of ON, the higher the value of the roughness parameter Ra. The above findings fully agree with the studies of other authors [9, 11, 13]. The important influence of the ON and OFF parameters on surface roughness is due to the fact that these factors determine the duration and spacing of the electrical pulses and therefore control the amount of heat generated by the electrical discharge [15].When the electrical pulse is on, current flows through the electrode wire and the workpiece, causing the material to melt. The longer the pulse duration, the more heat is generated and the greater melting of the material. If the pulse duration is too short or the intervals between pulses are too long, there is not enough heat to melt the material, resulting in increased surface roughness of the workpiece. On the other hand, a pulse duration that is too long or pulse intervals that are too short can lead to excessive melting of the material, which can cause deformations and defects on the machined surface [6–8]. The SV variable is not significant in this case, that is probably due to the dominant role of ON in this range of parameter values. In contrast, the analysis of variance showed a statistically significant interaction between all the factors studied. SV may contribute to roughness in a specific range of ON and OFF parameter values, as too low a voltage may cause the wire to slow down, which may lead to an increase in surface roughness. Conversely, too high a voltage can cause the processing to be too fast, which can also lead to an increase in Ra. In addition to influencing the speed of wire movement, servo voltage can also affect the intensity and duration of electrical pulses, which also affects material removal and surface quality.

**Analysis of the influence of independent variables on machining time.**

For machining time, none of the input parameters has a clearly dominant influence. The most strongly influential parameter is OFF time, followed by SV. The ON variable was found to be statistically insignificant in this case, although visualisations based on machine learning (Fig. 5) of the effect of this variable on machining time indicate that in cases of extremely low ON values, machining time increases dramatically, as confirmed by studies [5, 14].The main reason for the increase in machining time when OFF is too high is that the material has more time to cool down between successive pulses of current. This means that some of the heat generated during the EDM process will be absorbed by the workpiece and dispersed around it, resulting in a reduction in material removal efficiency [17, 18]. A statistically significant effect of the SV parameter was also observed, the significance of which was explained for the effect on roughness. Analysis of variance also showed an interaction between the OFF and SV parameters.

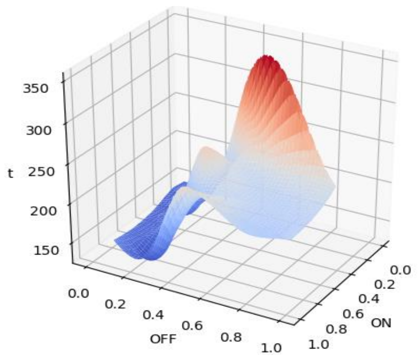


Fig. 5. Prediction of the effect of ON and OFF parameters on processing time

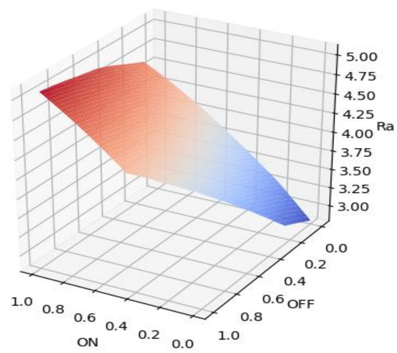


Fig. 6. Prediction of the effect of ON and OFF parameters Ra roughness parameter

**3.3. Selection of machine learning algorithm and hyperparameters**

In order to develop a WEDM model, it was decided to compare statistical methods (linear regression) and the Support Vector Machine learning algorithm, among others. This comparison was carried out using a developed algorithm in Python language, using cross-validation, as well as automatic searching of the parameter space using the GridSearch method from the Scikit-learn programming library.

The scheme of the cross-validation performed is shown in diagram (Fig. 7). The learning set accounted for 80% of the randomly selected data points and the test set accounted for the remaining 20%. During cross-validation, the training set was divided into 4 training subsets and one validation set. Optimization was performed due to the minimum negative mean absolute error (NMAE). The optimization of algorithms and hyperparameters plays a crucial role in the efficient and effective machine learning model development process. In this regard, Table 9 presents the algorithms and hyperparameters that were chosen for the current study. The selection of these algorithms was influenced by the need to minimize computation time, given the relatively low computational complexity of the problem at hand. Furthermore, the relatively small amount of data available in the dataset suggested the use of the Support Vector Machine (SVM) method.

The SVM algorithm is widely known for its efficiency in handling small to medium-sized datasets, particularly in cases where the data is linearly or nonlinearly separable. This approach involves finding the optimal hyperplane that maximally separates the data points, thereby providing an optimal classification boundary. The effectiveness of SVM algorithms is attributed to their ability to transform data points by mapping them to a higher-dimensional feature space. In such a space, the data is more likely to be linearly separable. This process is achieved through the use of a kernel function that transforms the input data to a higher-dimensional space where the data points become linearly separable.

Table 9. Selection of parameters for testing

| Algorithm | Hyperparameters |
|---|---|
| SVM | Kernel, C, Gamma, Epsilon |
| Linear regression | |
| Polynomial regression | Degree |
| Spline regression | Degree |

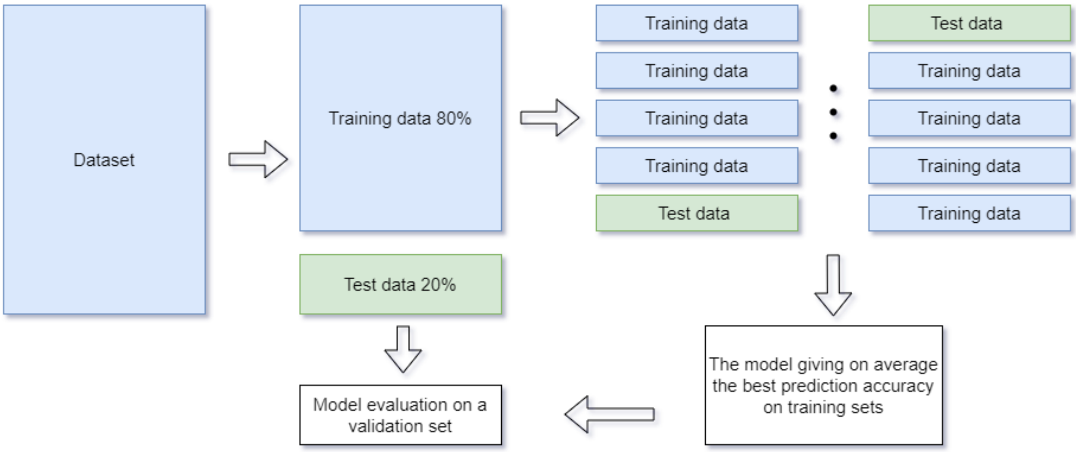


Fig. 7. Diagram of the cross-validation performed

### 3.4. Model performance evaluation

After 873 iterations, during which all possible combinations of parameters and algorithms defined in the search space were tested, MAE (Mean Absolute Error) were calculated from the test set, as well as the coefficient of determination $R^2$. The results are presented in Tables 10-12.

Table 10. Results of model evaluation due to accuracy of machining time prediction

| | MAE | $R^2$ |
|---|---|---|
| SVR(C=100, epsilon=1, gamma=1) | 8.9 | 0.75 |
| Linear regression | 28.3 | 0.31 |
| Polynomial regression (degree = 2) | 18.3 | 0.46 |
| Spline regression (degree = 4) | 20.8 | 0.4 |

Table 11. Results of model evaluation due to accuracy of the roughness parameter Ra

| | MAE | $R^2$ |
|---|---|---|
| SVR(C=1000, epsilon=0.001, gamma=0.01) | 0.24 | 0.8 |
| Linear regression | 0.23 | 0.7 |
| Polynomial regression (degree = 2) | 0.3 | 0.71 |
| Spline regression (degree = 4) | 0.24 | 0.74 |

Table 12. Results of the evaluation of models due to the accuracy of prediction of roughness parameter Ra and machining time simultaneously

| | MAE | $R^2$ |
|---|---|---|
| Linear regression | 0.23 | 0.60 |
| Polynomial regression (degree = 2) | 0.30 | 0.66 |
| Spline regression (degree = 4) | 0.24 | 0.70 |

Based on above summaries, one can notice that while predicting the roughness parameter Ra and machining time separately, models based on the SVR algorithm perform the best. For the prediction of the machining time value t, the SVR model has a significantly higher accuracy than other models based on linear and polynomial regression. This is due to the fact that SVR is better able than simpler regression models to deal with non-linear data [4] - which is the case for machining time, as indicated by Figure 5. Furthermore, SVR is relatively robust to outliers, thanks to the use of margins and constraints. For Ra prediction, the SVR model is slightly better than the other models. The slight differences are due to the relatively simple relationship between the variables considered and the roughness. The relationship is largely linear.
The difference between the SVR models for Ra and t, lies in the different choice of hyperparameters. The matrices below (Tables 13 and 14) show the effect of the selected model hyperparameters on the prediction error. They show, among others, that for Ra, a relatively high value of the parameter C is the best option. This parameter controls the balance between the model's fit to the training data and its ability to generalise new data. In the case of data with a near linear distribution, the training data will not deviate significantly from the test data, allowing a high C to ensure a good fit of the model to the training data. The opposite is true for the prediction of the machining time, where this parameter must be used reduced. The prediction accuracy of the model's Ra and t values on the test set are shown in Figure 8 and 9, respectively. Table 12 presents an evaluation of the models in terms of the accuracy of predicting processing time and Ra simultaneously. However, it was not possible to apply the SVR model due to the limitation of predicting two features simultaneously [4]. In this case, the comparative analysis showed that the best model would be the model based on 4th degree spline functions.

Table 13. Prediction error of roughness parameter Ra in dependence of SVR - C and Gamma parameters

| C \ Gamma | 0.0001 | 0.001 | 0.01 | 0.1 | 1.0 |
|---|---|---|---|---|---|
| 0.1 | -0.601 | -0.597 | -0.574 | -0.526 | -0.450 |
| 1.0 | -0.597 | -0.574 | -0.537 | -0.480 | -0.440 |
| 10.0 | -0.574 | -0.538 | -0.508 | -0.445 | -0.447 |
| 100.0 | -0.538 | -0.513 | -0.494 | -0.437 | -0.463 |
| 1000.0 | -0.513 | -0.508 | -0.473 | -0.436 | -0.472 |

Table 14. Prediction error of processing time depending on SVR - C and Gamma parameters

| C \ Gamma | 0.0001 | 0.001 | 0.01 | 0.1 | 1.0 |
|---|---|---|---|---|---|
| 0.1 | -31.674 | -31.670 | -31.632 | -31.379 | -28.784 |
| 1.0 | -31.670 | -31.628 | -31.256 | -29.087 | -24.608 |
| 10.0 | -31.628 | -31.224 | -29.001 | -25.059 | -19.457 |
| 100.0 | -31.220 | -29.041 | -26.804 | -22.313 | -17.793 |
| 1000.0 | -29.045 | -26.989 | -24.695 | -19.393 | -17.702 |

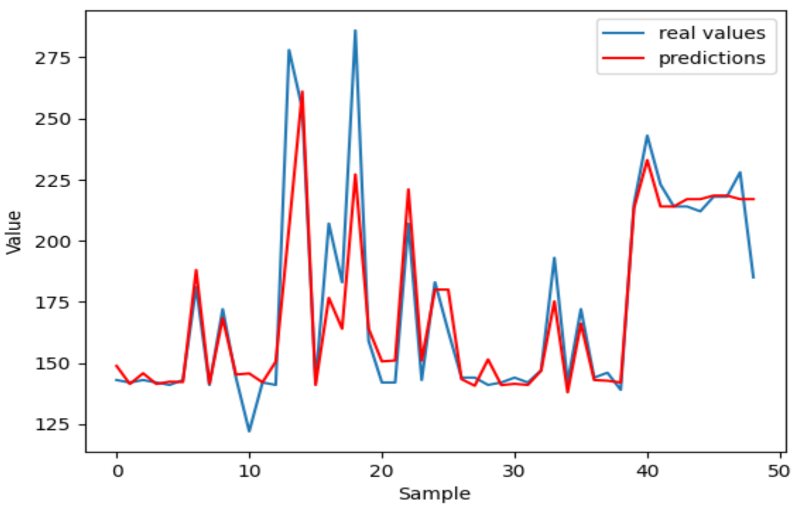

Fig. 8. Line graph for measured values of processing time and predicted values

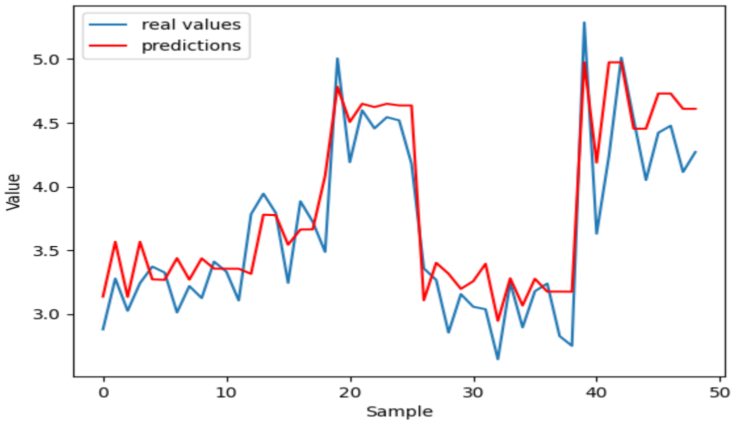

Fig. 9. Line graph for measured values of $R_a$ parameter and predicted values

## 4. OPTIMIZATION

The parameter values were optimized by generating a sequence of values within a predefined range and step size. The step size was set to 5 for the ON and OFF parameters, as well as for the SV parameter. This resulted in a total of 756 unique combinations of parameter values, which were used as input for a previously developed machine learning (ML) model based on spline functions. The ML model predicted the values of Ra and machining time for each parameter combination. In order to find the optimal combination of parameter values with respect to the minimum values of Ra and t, an algorithm was developed and implemented. The algorithm iterated through each of the 756 parameter combinations and selected the combination that yielded the minimum values of Ra and t. The algorithm is presented below in pseudocode:

1. Set the initial values for minimum Ra (min_ra) and minimum machining time (min_t) to infinity.
2. Set the initial values for optimal ON (opt_on), OFF (opt_off), and SV (opt_sv) parameters to 0.
3. For each unique parameter combination in the list of 756 combinations, do the following:
    a. Use the ML model to predict the Ra and machining time values for the current parameter combination.
    b. If the predicted Ra value is less than the current minimum Ra value, then:
        i. Set the minimum Ra value to the predicted Ra value.
        ii. Set the optimal ON, OFF, and SV parameter values to the current combination.
    c. If the predicted machining time value is less than the current minimum machining time value, then:
        i. Set the minimum machining time value to the predicted machining time value.
        ii. Set the optimal ON, OFF, and SV parameter values to the current combination.
4. Return the optimal ON, OFF, and SV parameter values that yielded the minimum Ra and machining time values.

Following the above procedure, the optimum values of Ra = 2.38 µm and t = 125.25 s were found with corresponding parameter values of On = 3, OFF = 55 and SV = 8.

## 6. CONCLUSIONS

Based on the analysis of the results obtained from the conducted tests, the following conclusions were formulated:

1. The ON and OFF parameters have a significant effect on the surface roughness parameter Ra, while the SV parameter is not significant in this range of parameter values.
2. The OFF time has the strongest effect on machining time, followed by SV. The ON parameter was found to be statistically insignificant in this case. The influence of this parameter was only observed for extremely low values, increasing the machining time.
3. Models based on the Support Vector Regression (SVR) algorithm perform the best in predicting the roughness parameter Ra and machining time separately.
4. When predicting Ra and t simultaneously, the most effective model is one based on fourth-order spline functions.
5. The optimal values for the surface roughness parameter Ra and machining time parameter t were found to be 2.38 µm and 125.25s, respectively, with corresponding parameter values of ON = 3, OFF = 55, and SV = 8.

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