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Original Article

Surface roughness prediction of machined aluminum alloy with wire electrical discharge machining by different machine learning algorithms

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ABSTRACT

Aluminum alloys are preferred in aviation, aerospace and automotive industries because of their high strength and durability compared to their lightness. Precision production of parts is very important in such industries. Therefore, precision machining of aluminum, which is difficult to manufacture with traditional methods, with non-traditional methods such as wire electrical discharge machining (WEDM), is a very popular approach. Surface roughness has an impact on the important properties of materials such as strength, wear resistance and fatigue strength. Experimental determination of surface roughness of surfaces machined with WEDM is time consuming and costly. These cost and time losses can be eliminated by predicted surface roughness with machine learning algorithms. In this study, Al7075 aluminum alloy was machined with different parameters (voltage, pulse-on-time, dielectric pressure and wire feed) with WEDM. Each parameter is at 3 levels, so 81 experiments were carried out. The surface roughness of the machined surfaces was measured by surface profilometer. The lowest surface roughness was 2.490 μm machined at 8 V voltage, 8 μs pulse on-time, 25 bar dielectric pressure and 2 mm/min wire feed. The experiments for machining of Al7075 via WEDM were modeled by machine learning methods. Four different models of two different methods were used for the prediction of surface roughness values of machined samples with WEDM. These models were ELM, W-ELM, SVR and Q-SVR. All of the models were applied to the data set and the W-ELM model was the best performing model with the value of 0.9720 R^2. Thus, the W-ELM model has excellent potential in manufacturing industry which produced parts with WEDM.

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1. Introduction

In industries such as aerospace and automotive, it is very important to reduce weight and costs in order to reduce fuel costs, exhaust emissions and improve the performance of vehicles [1–3]. Aluminum is one of the most preferred metals in the manufacturing industries due to its recycling potential, lightness, low cost and good corrosion properties. However, the low strength of aluminum limits its usage areas. To overcome this situation, aluminum can be alloyed with different elements to improve its strength. Thus, aluminum alloy parts with high specific strength can find use areas in aviation, aerospace, automotive and defense industries [4–8]. Among the aluminum alloys, Al7075 aluminum alloy which is alloyed with high content Zn, Mg and Cu elements, is widely preferred in these industries due to its corrosion resistance, igh strength and toughness [9,10].

Aluminum is a metal that is difficult to machining and tends to plastering to machine tools. Therefore, they are very difficult to machined precisely with traditional manufacturing methods. Wire electrical discharge machining (WEDM) is one of the most common, popular and widely known non-traditional machining methods processes for machining precise geometries used in the manufacturing industries. The main principle in machining with WEDM is to erode the surface by creating erosion on the material surface with the controlled spark created between the workpiece and the moving wire under a suitable dielectric fluid. Since it is possible to produce high precision and quality parts in this method, the interest in this method is increasing day by day. Also in the manufacturing industry, this method is frequently used in the machining of all kinds of conductive materials, as it can be machine complex, sensitive, and irregular shapes of the surfaces [11–16]. In addition, it is a very important manufacturing method in the production of parts that require high surface quality and degree of dimensional accuracy. The most important process factors defining the machinability of the process in addition to the cost in WEDM machining method are the material removal rate (MRR), dimensional accuracy (DA) and surface roughness (SR). Also, the SR, DA and MRR are changed by changing the parameters such as voltage, dielectric pressure, pulse-on-time, pulse-off-time, wire electrode material, wire tension, wire feed rate and peak current in WEDM machining [17–21]. Among these factors, surface roughness is one of the most important quality features to determine and evaluate the quality of the machined parts. In addition, the surface roughness of the manufactured parts affects properties such as corrosion resistance, friction, fatigue strength, wear resistance, holding lubricant, light reflection, heat transfer and ability of

distributing. Therefore, it is desired that the surface roughness of the produced parts is low [18,22–26]. Surface roughness is associated with surface texture and surface integrity and defines the geometry of the workpiece surface. Due to the complexity of the formation of the surface roughness mechanism depending on the machining process, it is very difficult to determine the surface roughness by analytical equations [27].

Prediction the results of time-consuming and costly experiments that are difficult to determine analytically with the machine learning algorithms, have found application in many areas. Among these areas, energy [28], materials science [29], health [30], mechanical and manufacturing engineering [31], electrical engineering [32], civil engineering [33], biology [34] and physics [35] etc. can be shown. Also extreme learning machine (ELM) and support vector regression (SVR) was used successfully in these areas [36]. In addition to its accuracy, WEDM method is a long time and costly manufacturing method. Also in WEDM method, surface roughness, manufacturing times and cost change with changing production parameters and the size of the part. By predicting the surface roughness that will occur on the surfaces of the materials according to different machining parameters, using machine learning algorithms, the most suitable machining parameters can be determined in advance and thus loss of labor, cost and time can be prevented. Especially when designing a new and complex parts, design engineers can be provided with significant advantages in terms of cost and workforce [37,38]. The previous studies related to the current study are given in the Table 1.

In present study, the Al7075 aluminum alloy was machined with WEDM at different parameters and surface roughness values were determined experimentally. A total of 81 different surface roughness data were obtained. The obtained surface roughness values were predicted with using different machine learning methods which are ELM, W-ELM, SVR and Q-SVR. The 10 k-fold method is used for the performance analyze of the models. In section II, experimentally, how the surface roughness is obtained and the proposed models are explained in detail. In section III, the results of the predictions using the proposed models are presented. The general results obtained from the study are given in the last section.

2. MATERIAL and METHODS

2.1. Data acquisition

In this study, commercially Al7075 T6 aluminum alloy in a diameter of 10 mm was used as workpiece material. The chemical composition of Al7075 is given in Table 2. Sodick SL400Q brand WEDM machine was used in machining process. The workpiece was fixed on WEDM (Fig. 1a) and machined (Fig. 1b) at parameters given in Table 3. In each parameter, a 5 mm piece was cut and the all machined samples are seen in Fig. 2. The surface roughness values of samples were measured at vertical and horizontal direction of machined surfaces with Mitutoyo SJ-201 profilometer. Surface roughness measurements are taken from 0.8 mm length at 6 different distances on vertical and horizontal direction each. The surface roughness values were determined by calculating the average of these measurements. The surface roughness values of experimental samples are shown in Fig. 3–12. The lowest surface roughness value was measured as 2.490 in sample machined at 8 V voltage, 8 μs pulse on-time, 25 bar dielectric pressure and 2 mm/min. wire feed. The highest surface roughness value was measured as 3.177 in sample machined at 4 V voltage, 8 μs pulse on-time, 50 bar dielectric pressure

Table 1 – Literature researches.

Researcher(s)	Machined material	Input parameters	Output parameters	Number of experiments	Prediction method
Rao et al. [39]	BIS-24345 aluminum alloy	Pulse On time Pulse Off time Peak Current Dielectric pressure Wire Feed rate Wire tension Spark gap Voltage Servo Feed	Material removal rate	18	Artificial neural network
Surya et al. [17]	Al7075-TiB_2 MMC	Pulse On time Pulse Off time Peak Current Bed speed	Surface roughness Material removal rate Dimensional accuracy	27	Artificial neural network
Thankachan et al. [18]	Al-Sn-SiC MMC	Pulse On time Pulse Off time Wire Feed rate Sn wt% SiC wt%	Surface roughness Material removal rate	32	Artificial neural network
Gurupavan et al. [40]	Al-5 wt% Si_3N_4 MMC	Pulse On time Pulse Off time Peak Current Bed Speed	Surface roughness Material removal rate Dimensional accuracy Electrode wear	27	Artificial neural network
Shandilya et al. [41]	Al6061-10 wt% SiC MMC	Pulse On time Pulse Off time Servo Voltage Wire Feed rate	Material removal rate	29	Artificial neural network
Phate and Toney [42]	AlSiCp MMC	Pulse On time Pulse Off time Wire Feed rate Peak Current	Surface roughness Material removal rate	27	Artificial neural network
Yusoff et al. [37]	Inconel 718	Pulse On time Pulse Off time Peak Current Servo Voltage Dielectric pressure	Surface roughness Material removal rate Cutting speed Sparking gap	22	Artificial neural network
Singh et al. [43]	AA 6063	Pulse On time Pulse Off time Peak Current Servo Voltage	Surface roughness	81	Support Vector Machine

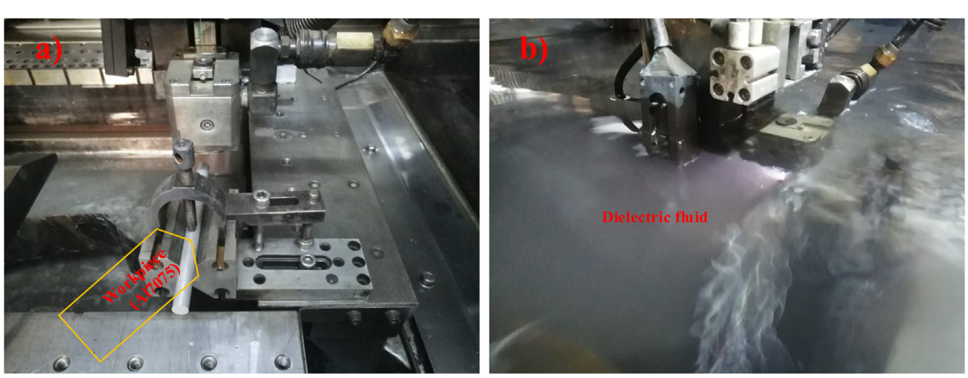

Fig. 1 – a) Experimental set-up and fixed workpiece and b) Machining of workpiece.gr1

Table 2 – Chemical composition of Al7075 aluminum alloy.

Element	Al	Si	Fe	Cu	Mn	Mg	Zn	Cr	Other
Content (wt%)	Bal.	0.4	0.5	1.2–2.0	0.3	2.1–2.9	5.1–6.1	0.18–0.28	0.25

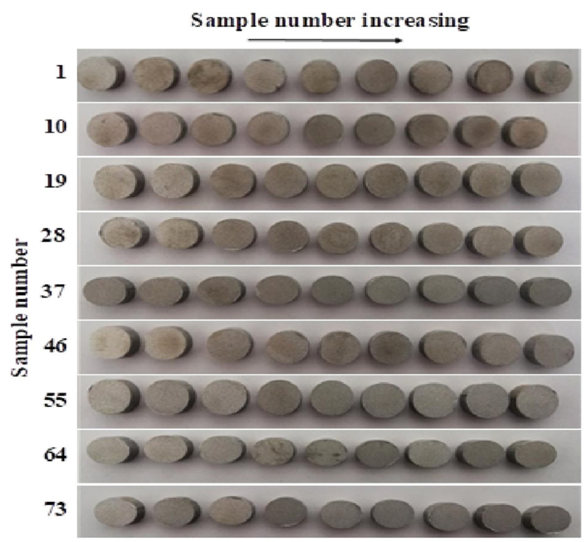

Fig. 2 – Machined Al7075 aluminum alloys with WEDM.gr2

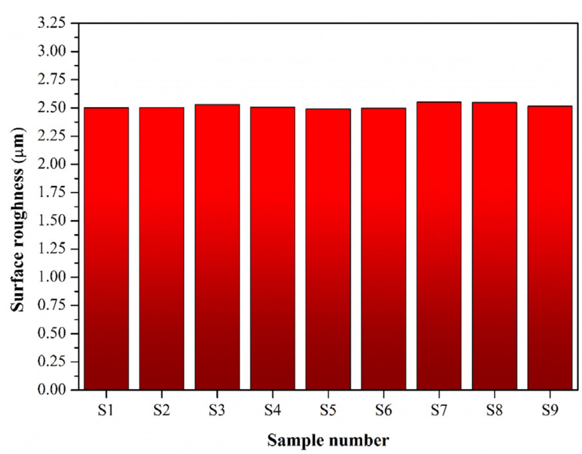

Fig. 3 – Surface roughness values of samples S1-S9.gr3

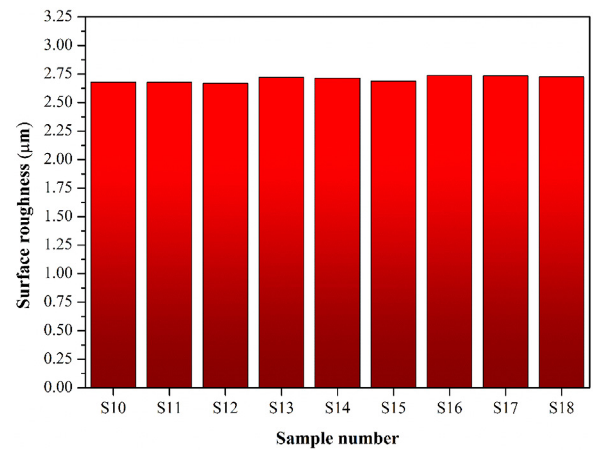

Fig. 4 – Surface roughness values of samples S10-S18.gr4

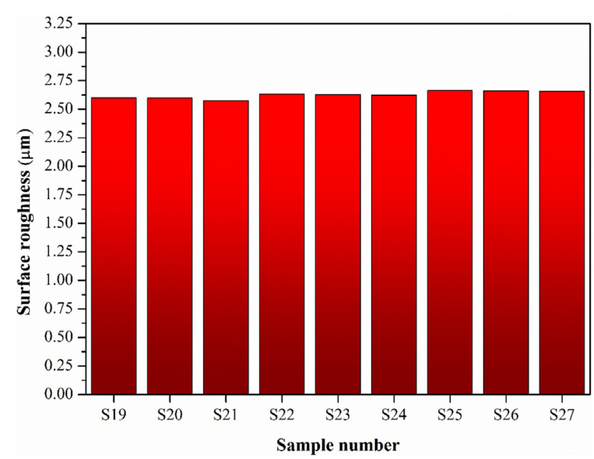

Fig. 5 – Surface roughness values of samples S19-S27.gr5

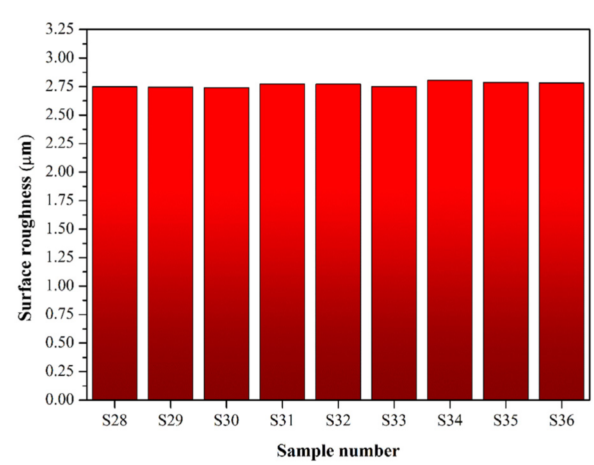

Fig. 6 – Surface roughness values of samples S28-S36.gr6

and 6 mm/min. wire feed. The surface roughness values are lower at low wire feed and dielectric pressure.

2.2. *Proposed models*

2.2.1. *Support vector regression machine*

Support Vector Machine (SVM) is a different supervised learning approach to regression and classification [44,45]. Drucker et al. defined the Support Vector Regression Machines (SVR) for the solution of regression problems in 1997 [46]. The SVR uses the structural risk minimization (SRM) principle [47] and it can be successfully applied in many research fields. The SVR uses different kernels such as Linear, RBF, Gaussian, Polynomial [48]. The problem space and dataset define the kernel types and function parameters [49]. The inputs of a problem and the calculated/observed outputs of

Table 3 – WEDM machining parameters of Al7075 aluminum alloy.

Sample number	Voltage (V)	Pulse-on-time (μs)	Dielectric pressure (Bar)	Wire feed (m/min.)	Fixed parameters
1	4	4	25	2	Peak current: 2215 A Pulse-off-time: 0.15 μs Wire tension: 1600 g MAO: 254 Servo voltage: +20 V Wire electrode material: Brass Wire electrode Diameter: 0.25 mm
2	8	4	25	2	
3	12	4	25	2	
4	4	8	25	2	
5	8	8	25	2	
6	12	8	25	2	
7	4	12	25	2	
8	8	12	25	2	
9	12	12	25	2	
10	4	4	50	2	
11	8	4	50	2	
12	12	4	50	2	
13	4	8	50	2	
14	8	8	50	2	
15	12	8	50	2	
16	4	12	50	2	
17	8	12	50	2	
18	12	12	50	2	
19	4	4	75	2	
20	8	4	75	2	
21	12	4	75	2	
22	4	8	75	2	
23	8	8	75	2	
24	12	8	75	2	
25	4	12	75	2	
26	8	12	75	2	
27	12	12	75	2	
28	4	4	25	4	
29	8	4	25	4	
30	12	4	25	4	
31	4	8	25	4	
32	8	8	25	4	
33	12	8	25	4	
34	4	12	25	4	
35	8	12	25	4	
36	12	12	25	4	
37	4	4	50	4	
38	8	4	50	4	
39	12	4	50	4	
40	4	8	50	4	
41	8	8	50	4	
42	12	8	50	4	
43	4	12	50	4	
44	8	12	50	4	
45	12	12	50	4	
46	4	4	75	4	
47	8	4	75	4	
48	12	4	75	4	
49	4	8	75	4	
50	8	8	75	4	
51	12	8	75	4	
52	4	12	75	4	
53	8	12	75	4	
54	12	12	75	4	
55	4	4	25	6	
56	8	4	25	6	
57	12	4	25	6	
58	4	8	25	6	
59	8	8	25	6	
60	12	8	25	6	
61	4	12	25	6	
62	8	12	25	6	
63	12	12	25	6	

– Table 3 (Continued)

Sample number	Voltage (V)	Pulse-on-time (μs)	Dielectric pressure (Bar)	Wire feed (m/min.)	Fixed parameters
64	4	4	50	6	
65	8	4	50	6	
66	12	4	50	6	
67	4	8	50	6	
68	8	8	50	6	
69	12	8	50	6	
70	4	12	50	6	
71	8	12	50	6	
72	12	12	50	6	
73	4	4	75	6	
74	8	4	75	6	
75	12	4	75	6	
76	4	8	75	6	
77	8	8	75	6	
78	12	8	75	6	
79	4	12	75	6	
80	8	12	75	6	
81	12	12	75	6	

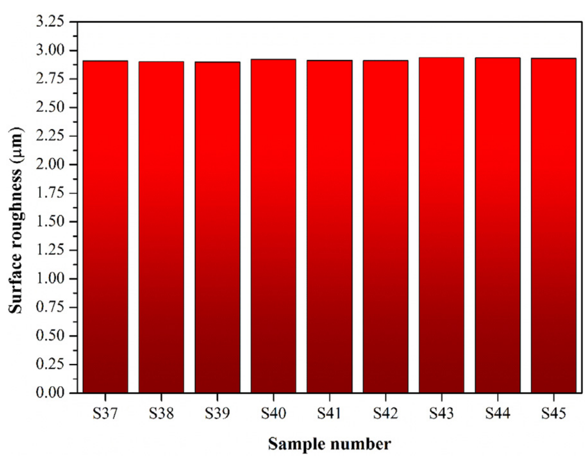

Fig. 7 – Surface roughness values of samples S37-S45.gr7

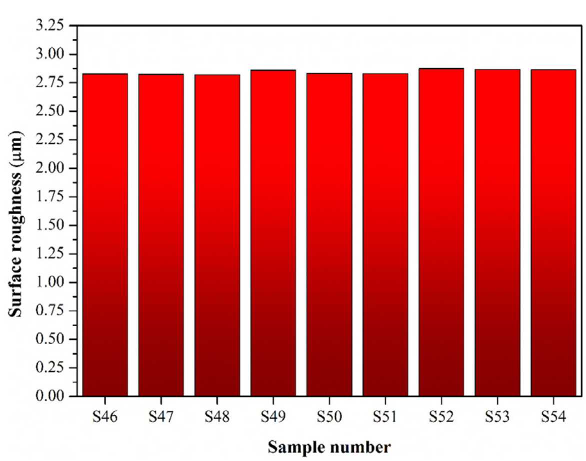

Fig. 8 – Surface roughness values of samples S46-S54.gr8

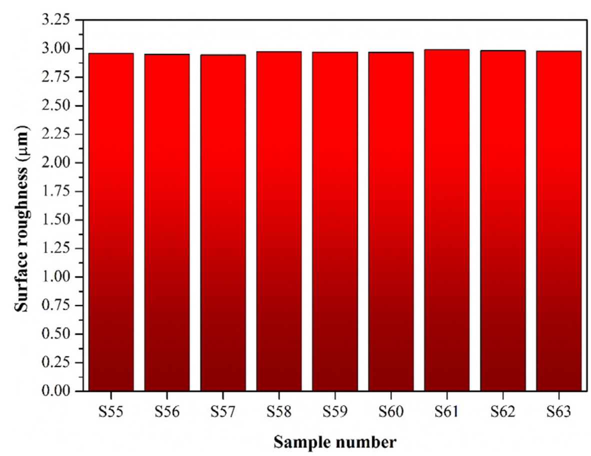

Fig. 9 – Surface roughness values of samples S55-S63.gr9

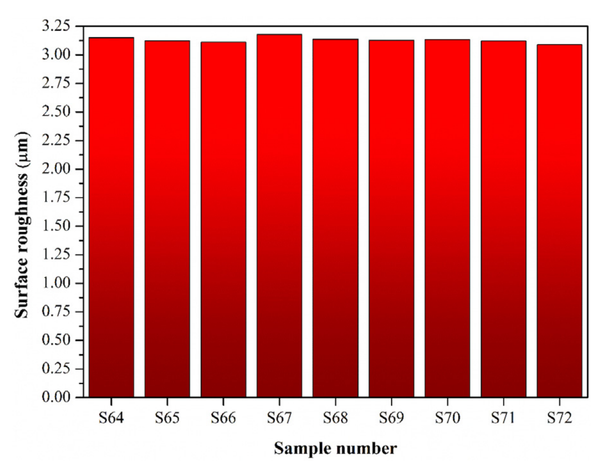

Fig. 10 – Surface roughness values of samples S64-S72.gr10

this problem establish the structure of the dataset [50]. The choice of the type of kernel that is most suitable for use in the designed SVR model depends on the structure of the dataset [29].

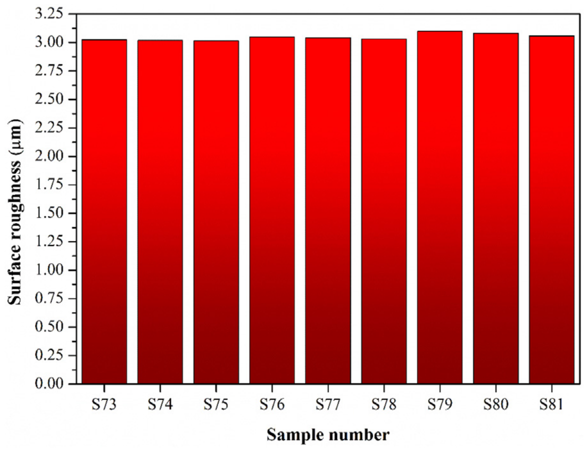

Fig. 11 – Surface roughness values of samples S73-S81.gr11

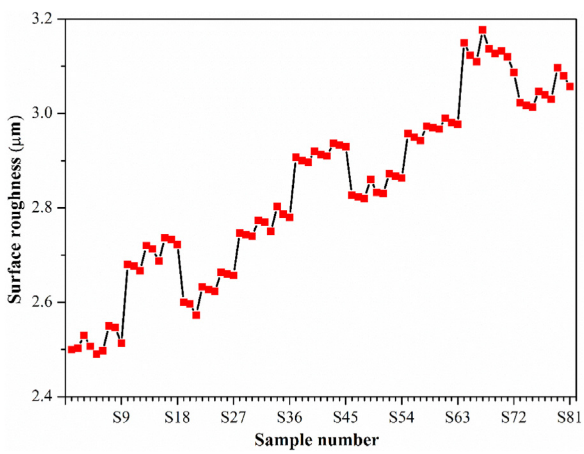

Fig. 12 – Surface roughness values of samples S1-S81.gr12

The input vector is set to the n-dimensional experimental dataset and it uses as the input vector. The output vector has a one-dimensional target vector. $X = \{x_1, x_2, \ldots, x_n\}$ represents the input vector and $T = \{t_1, t_2, \ldots, t_n\}$ represents the output vector [51].

$$f(x) = w^T \varphi(x) + b \tag{1}$$

The $\varphi(x)$ is a nonlinear function, b is the bias value and w^T is the weight vector. The goals of the SVR are to find the w and b values which reducing the x values to those that indicate the lowest regression risk. It is represented with Eq. 1.

To reduce the error Eq. 2. can be used.

$$\underset{w,b}{\text{Minimize}}\ \frac{1}{2} w^T . w + C \sum_{i=1}^{l} \left(\xi_i + \xi_i^*\right) \tag{2}$$

C value determines the complexity of the learning machine. The large C value increases the accuracy while making the machine more complex [49].

The trained SVR model creates estimations using the Eq. 3.

$$f(x) = \sum_{i=1}^{l} \theta_i \varphi(x, x_i) + b \tag{3}$$

The dataset that is used in this study, creates better results with quadratic kernel function s. The quadratic kernel function has given with the Eq. 4. [52].

$$L_{quad}(f(x) - y) = (f(x) - y)^2 \tag{4}$$

2.2.2. *Extreme learning machine*

Artificial neural networks (ANN) is used in many different research fields because of its high compatibility. The reason why ANN is used in many research fields is its ability to train models that produce acceptable results in any problem space [33]. But ANN has a disadvantage with its training method. The training and the error reduction process is carried out with iterations. The iterations cause delays. Extreme Learning Machines (ELM) developed as single-hidden layer feedforward networks (SLFNs) to elimination of the learning process delays [53]. Due to its shortened learning time, ELM is common type of SLFNs. The ELM needs more hidden neurons to determine the input weights and hidden biases [54]. A single-output ELM model can be expressed as in the Eq. 5.

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \tag{5}$$

Where $\beta = [\beta_1 \ldots\ldots \beta_i]$ is the output weights vector and $h(x)$ is the output vector. The L represent the l-dimensional hidden-layer. The purpose of ELM is to reduce the training error and the number of hidden neurons between layers [55]. Eq. 6. represent the minimization.

$$\text{Minimize} : H^{\dagger}T^2 \tag{6}$$

$x_i = [x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}]^T$, $y_i = [y_{i1}, y_{i2}, y_{i3}, \ldots, y_{im}]^T \in R^m$ are the input matrix and parameters of the output matrix respectively. The Moore-Penrose generalized inverse matrix used to calculate the ELM output matrix without iterations [55].

The Y matrix represent the output vector in Eq. 7. Hidden layer output matrix;

$$\beta = \begin{bmatrix} \beta_1^T \\ \ldots \\ \beta_M^T \end{bmatrix}_{M \times 1} \quad \text{ve} Y = \begin{bmatrix} y_1^T \\ \ldots \\ y_N^T \end{bmatrix}_{N \times 1} \tag{7}$$

$$\beta = H^{\dagger} Y \tag{8}$$

where H^{+} is the Moore–Penrose generalized inverse of matrix H. The weight matrix β can calculated analytically with Eq. 8.

2.2.3. *Weighted extreme learning machine*

When ELM and Weight - ELM (WELM) are compared, it has been observed that the WELM increases the accuracy rate. In addition, during this increase, there is no loss in short term

Table 4 – Equations of the performance metrics.

Performance Metrics	Equations	
Determination Coefficient (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(E_i - P_i)^2}{\sum_{i=1}^{n}(E_i - \bar{E})^2}$	(10)
Mean Absolute Error (MAE)	$MAE = \frac{\sum_{i=1}^{n}\lvert E_i - P_i\rvert}{n}$	(11)
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(E_i - P_i)^2}{n}}$	(12)

trainingẅhich is the advantage of ELM [56]. The WELM method usually gives better result than ELM.

1 ELM calculate the least squares solutions with minimal norm. So it is hard to control.
2 ELM is based on the empirical risk reduction rule. This method could cause over fitted models.

2.2.4. *Evaluation parameters*

There are evaluation metrics methods for analyzing the performance of the results of the machine learning techniques used in solving regression problems. Three of these metrics were used to evaluate the performance of the designed models. These; used in the study as determination coefficient (R^2), mean absolute error (MAE) and root mean square error (RMSE). Each of these statistical performance metrics provides information about the performance of the proposed model from a different perspective [49] The statistical indices are defined in Table 4. E_i represents the experimental data and P_i are the predicted values of the models. The average of all experimental data represents within $\bar{E}$ in Eq. 9– [49].

$$\bar{E} = \frac{1}{n}\sum_{i=1}^{n} E_i \tag{9}$$

3. RESULTS and DISCUSSION

In this study, the surface roughness values of aluminum alloys machined with WEDM obtained from experiments were tried to be reached with acceptable performance with machine learning methods. With machine learning methods, the system was modeled with high accuracy without having to perform complex experiments and mathematical operations. The prediction of new datasets will be calculated very easily, quickly, and with the low error by the proposed model. In this study, more than one model was proposed and comparative performance analysis was made between these models. Basically, two different methods were used. One of them was ELM, the other was SVR. The main difference between the two methods is training times. The non-iterative training method of ELM, which is different from the ANN algorithm, has significantly reduced training times. The SVR provides iterative training with a risk minimization method.

There are two different methods to analyze the performance of the models. One of them is k-fold, the other is separating data as percentages. in this study, the test part of the dataset was attempted one by one as each piece which was divided into 10 separate pieces with the 10-k-fold method.

Table 5 – Equations of the performance metrics.

Model Name	Kernel	R^2	RMSE	MAE
ELM	Sigmoidal	0.9411	0.0463	0.0357
W-ELM	Sigmoidal	**0.9720**	**0.0364**	**0.0320**
SVR	Linear	0.8824	0.0654	0.0531
Q-SVR	Quadratic	**0.9613**	0.0375	0.0330

This method gives more accurate results than separating the data for the training and testing part.

The training success of the methods generally depends on the dataset. Nothing can be claimed that a method will always work with high accuracy in every dataset. Therefore, in this study, more than one different algorithm and more than one model has been tried. In this study, ELM, W-ELM, SVR and Q-SVR were used to predicted the surface roughness. The 81 data measured from the experiment set were applied to these 4 different models. In these models, voltage (V), pulse-on-time (μs), dielectric pressure (bar) and wire feed (m/min.) were used as input parameters and surface roughness (μm) was used as output. When each of the models is analyzed with performance parameters, it can easily be seen that the W-ELM model achieves better results than all other models. W-ELM predicted the R-squared value at 0.9720 with 1.07% better results than Q-SVR, which has the nearest R-squared value. Also, if a comparison is made over the RMSE values of the W-ELM found by the ratio of the total of the squares of the errors to the total number of samples, it performed better results than the ELM, SVR and Q-SVR models, 21.38%, 44.34% and 2.93%, respectively. It is shown in Table 5.

The Fig. 13–16 shows the prediction made by the designed models and the measured values from the experimental results. The Fig. 13 gives the comparison of the ELM model results and the experimental results. In the Fig. 14 W-ELM model, it can be seen that it fits almost all experimental results. When Fig. 15 is examined, it is seen that the performance values of the SVR model show a graphic incompatible with the experimental results. This graphic provides information about SVR errors. The Q-SVR model results has been compared with the experimental results in the Fig. 16. The Fig. 17, a regression graph that is compatible with the prediction of all models is presented.

The results show that the designed models can be used applications successfully in manufacturing industries which produced parts with WEDM. By using these models especially in industries such as aviation, aerospace, automotive and defense industries, they can provide designers advantages in terms of time, cost and labor loss in the design of parts with good surface properties. The proposed models may find use by design engineers as decision support systems. The Fig. 18. shows the experimental results and all models result in the same graph. It gives more information about the best fitted results.

4. Conclusions

The lowest surface roughness value was measured as 2.490 and the highest surface roughness value was measured as 3.177. The surface roughness of samples was

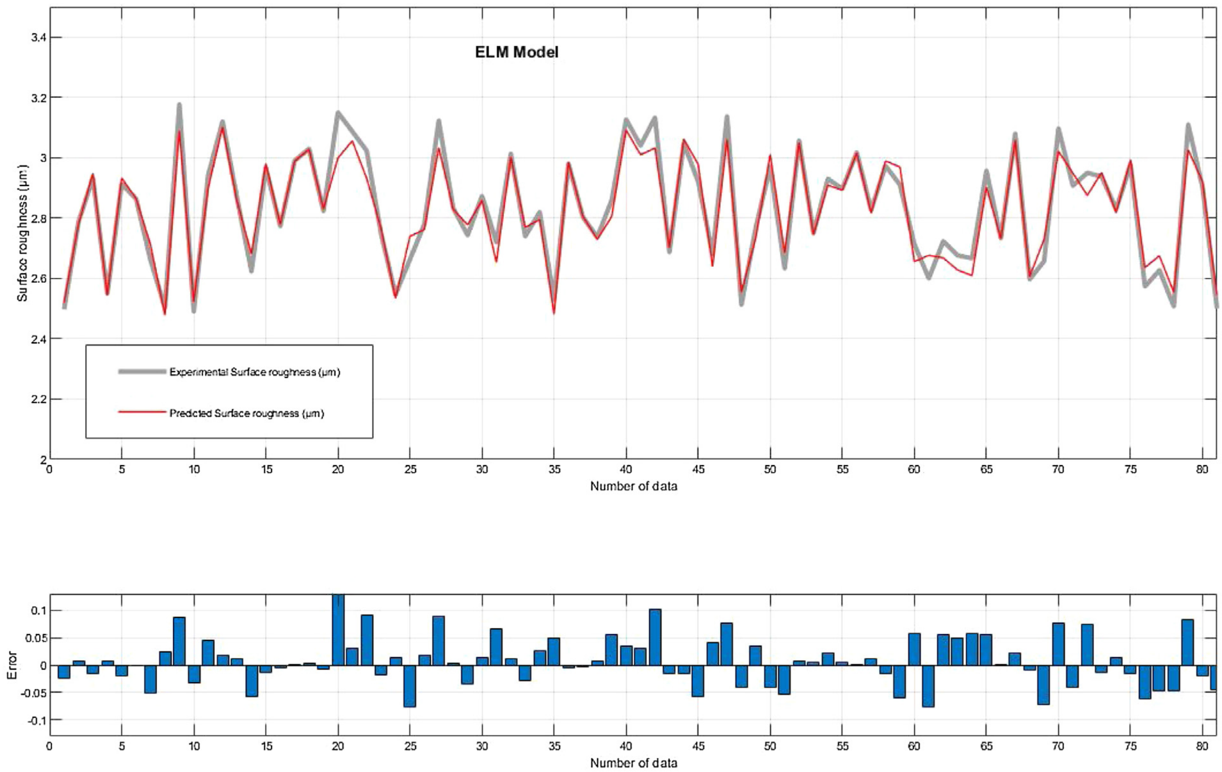

Fig. 13 – Comparison of the experimental results with ELM Model results and errors.gr13

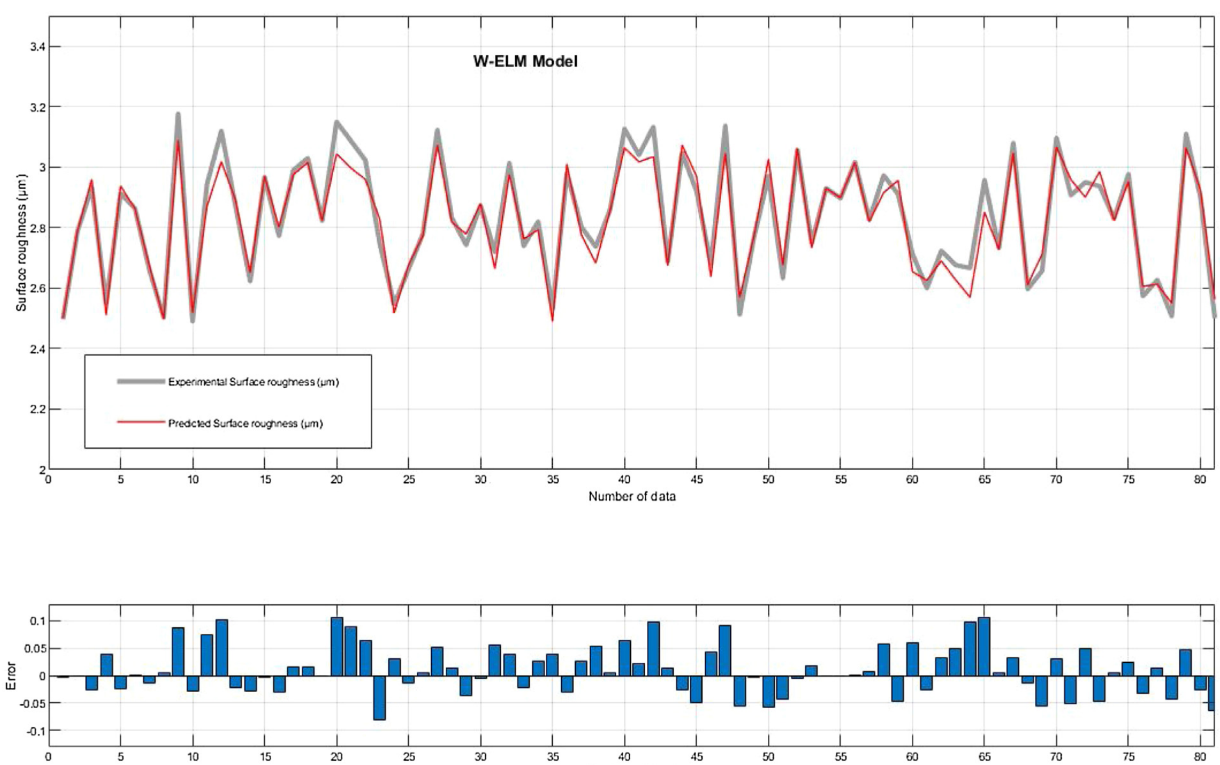

Fig. 14 – Comparison of the experimental results with W-ELM Model results and errors.gr14

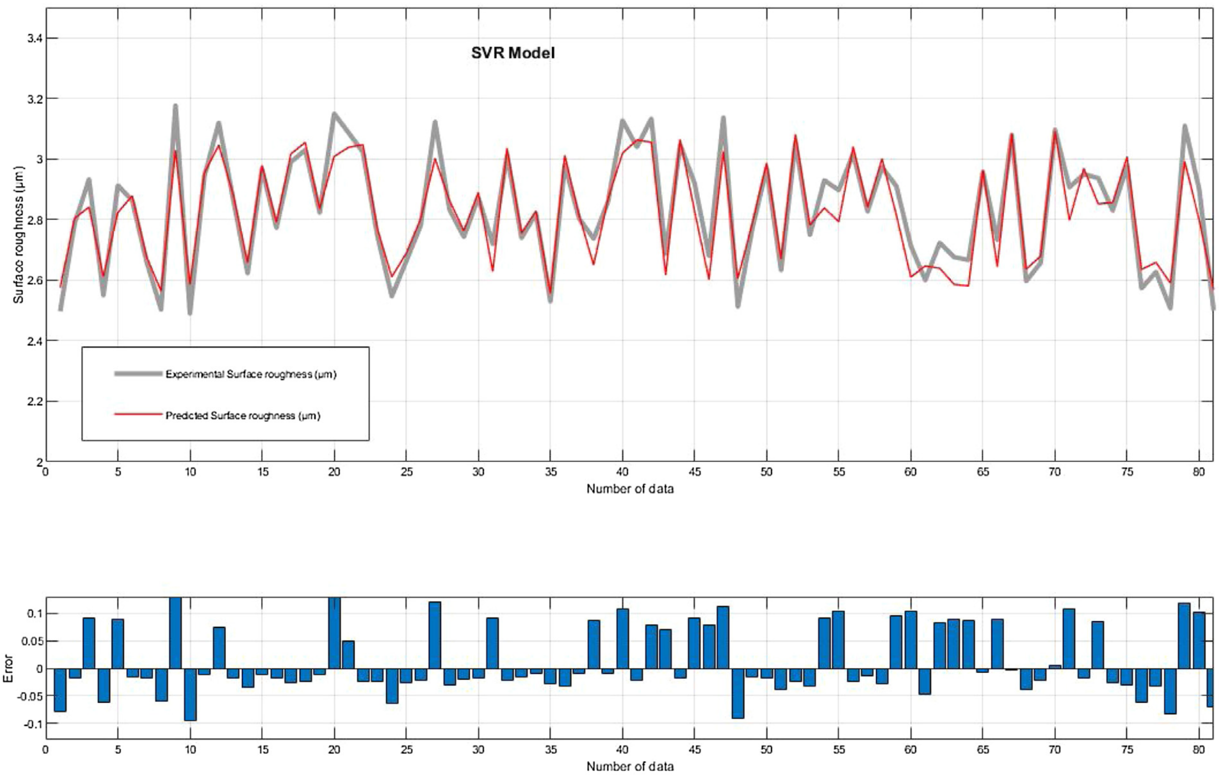

Fig. 15 – Comparison of the experimental results with the SVR Model results and errors.gr15

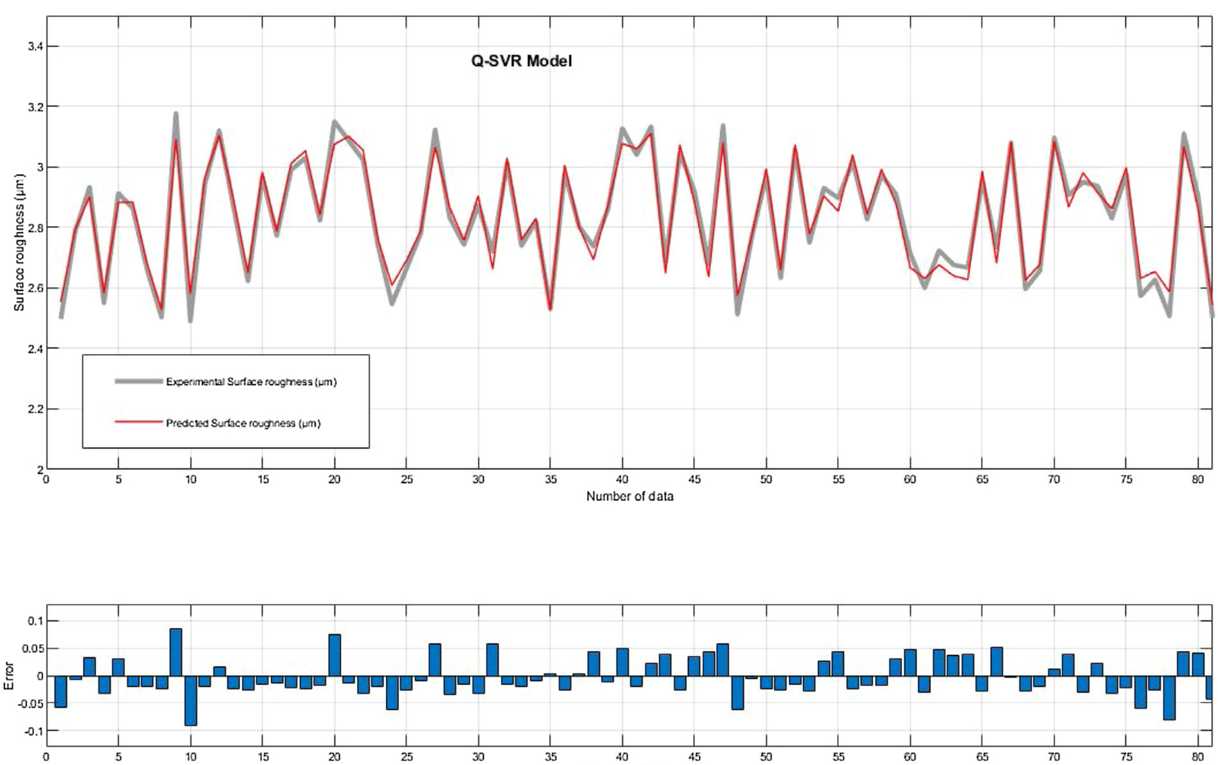

Fig. 16 – Comparison of the experimental results with Q-SVR Model results and errors.gr16

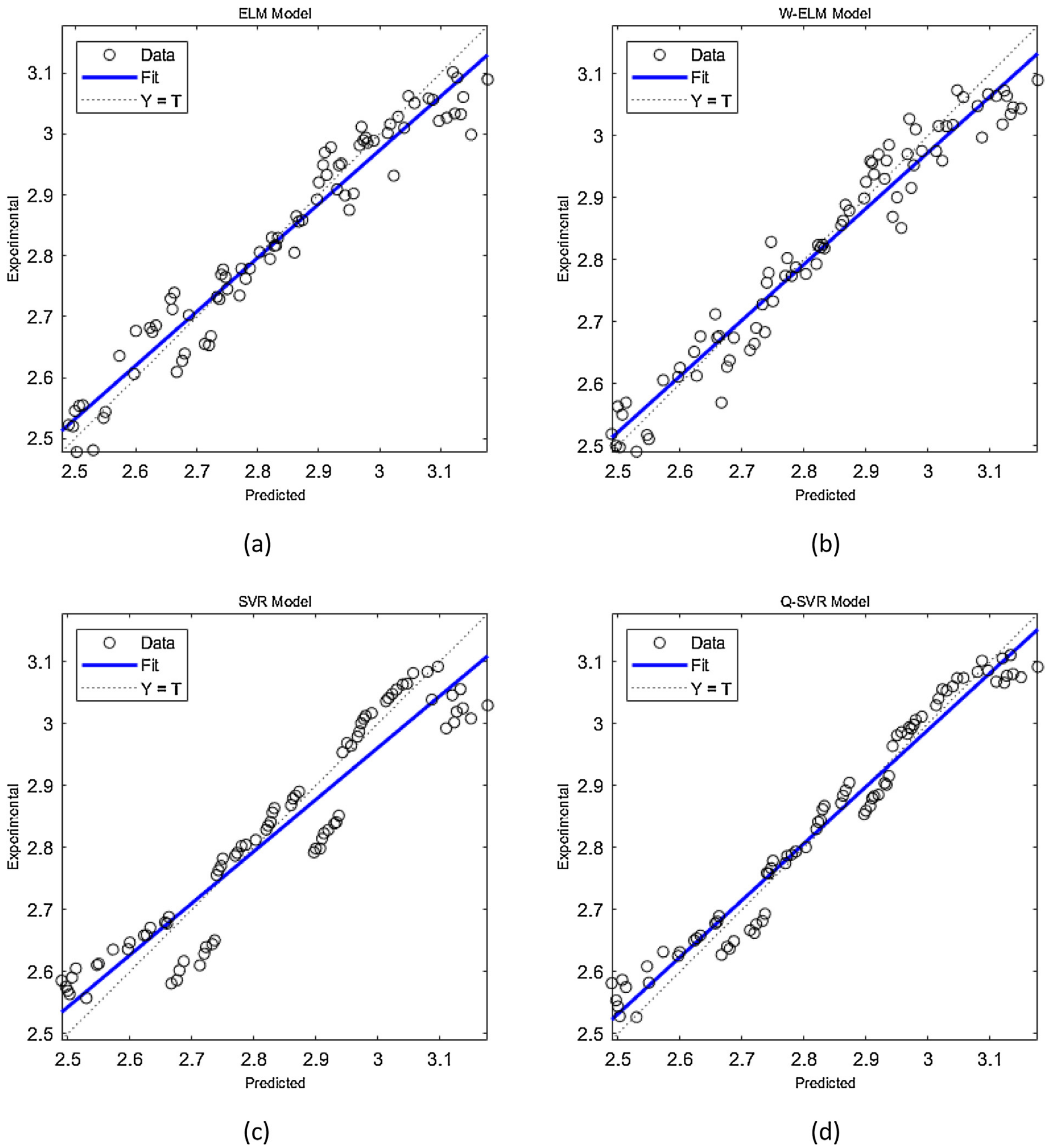

Fig. 17 – Regression results of the models a) ELM Model regression b) W-ELM Model regression c) SVR Model regression d) Q-SVR Model regression.gr17

affected by changing parameters and at low wire feed and dielectric pressure surface roughness values were lower. Preferred in aviation, space and automotive industries, aluminum alloys have high strength and durability compared to their lightweight. Precision machining of aluminum by non-traditional methods such as wire electrical discharge machining (WEDM) is a popular approach. Experimental determination of the surface roughness of surfaces machined with WEDM is time-consuming and costly. In this study, the minimization of these costs, which is very important was achieved with the following performance ratio with machine learning algorithms. Surface roughness values of machined aluminum alloys with WEDM have been successfully predicted by models designed using ELM, W-ELM, SVR and Q-SVR machine learning methods. The R^2 values were 0.9411, 0.9720, 0.8824 and 0.9613 for the ELM, W-ELM, SVR and Q-SVR machine learning methods, respectively. W-ELM has the highest performance and predicted the surface roughness with a value of 0.9720 R^2. The RMSE value of the W-ELM model was calculated as 0.0364. As a result of this study, it was seen that the use of machine learning methods for predicting the surface roughness of machined aluminum alloys via WEDM is possible with a low error rate of

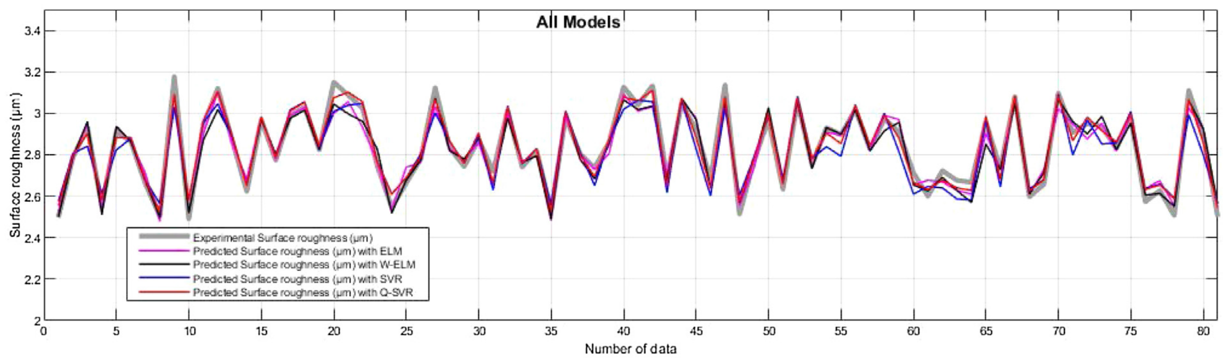

Fig. 18 – The comparison of the results of all models with experimental results.gr18

2.8%. The developed machine learning algorithm model will be used by anyone working in the field without the need for complex mathematical operations or long and costly experiments with high accuracy. By using the W-ELM method to predict surface roughness in the manufacturing industry, it can be reducing experimental time and cost in the manufacture of parts with good surface properties and high dimensional accuracy. By using the proposed models when designing a new part, design engineers will be able to provide design advantages and time will be shortened when making a new design.

Conflicts of interest

The authors declare no conflicts of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to technical limitations.

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