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Estimating surface roughness for different EDM processing parameters on Inconel 718 using GEP and ANN

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ABSTRACT

Nickel-based alloys have good mechanical properties along with excellent corrosion and oxidation resistances. Inconel 718, which is in the nickel-based alloy group, has excellent fatigue strength, corrosion resistance, high temperature resistance, and also features such as high strength, toughness and deformation hardening. The biggest disadvantage of Ni alloys is their poor processability. Especially in the machining method, expensive tools should be used. In addition, high surface roughness values obtained as a result of machining in such materials negatively affect the fatigue resistance. On the other hand, difficult-to-machine materials can be manufactured cheaply and easily by methods known as non-traditional production. The most widely used of these methods is the Electrical Discharge Machining (EDM) due to its precision and machining capabilities. The Inconel 718 material used in this study was etched by EDM method using different process parameters. The effects of finishing process parameters on surface roughness after scouring were determined. In the study, the probable surface roughness value estimation model was created by using the process parameters and the surface roughness values obtained as a result of these parameters using the artificial intelligence methods ANN and GEP. For this study, it was concluded that the ANN method is more suitable than the GEP method.

Introduction

Nickel-based materials are widely used in the aerospace, medical, nuclear and chemical industries due to their excellent resistance to creep, corrosion and thermal fatigue at high temperatures [1,2]. Inconel 718, one of the nickel-based alloys, is known as the basic superalloy with high temperature resistance, excellent fatigue and corrosion resistances along with creep rupture resistance. Inconel 718 belongs to the “hard to process” material group due to its toughness, tendency to deformation hardening and resistance to shear caused by shear stress. It has an adverse effect on tool life because of its low thermal conductivity and hard abrasive compound. This situation causes poor final surface roughness properties and the need for finishing process as a result of the tool life of the Inconel 718 material and the machining parameters not selected properly. High roughness increases the fatigue resistance of the material and causes early deformation [3,4]. Methods known as non-conventional manufacturing are known to be used in the processing of materials that are difficult to process or in the creation of complex structures. Sometimes, non-conventional processing methods can be used as a continuation of another processing method, that is, as a post process, with the advantage of obtaining good surface roughness [5]. Due to these conditions mentioned above, parts that are difficult to process such as Inconel 718 can be processed using non-conventional manufacturing methods [6]. The most widely used of these methods is the Electrical Discharge Machining (EDM) method [7,8]. EDM method is a non-contact material removal process with periodic sparks between tool and part in dielectric fluid. This method can be applied to all electrically conductive materials regardless of material hardness. Since adjusting the desired geometry for complex parts is quite difficult and expensive in other methods, this is not an issue for EDM. For this reason, it is preferred in many sectors such as automotive, mold making, space and medicine [9].

The processing of Inconel alloys with EDM has been the subject of many studies due to the advantages of these alloys and the superior properties of EDM method mentioned above. When the studies were examined, it was determined that the effect of process parameters such as current density, pulse time, duty cycle

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and polarity for EDM method were discussed, and the success of the process depends on these parameters. Çağdas and Hasçalik [10] researched the effects of parameters such as pulse-on time, pulse-off time and pulse current on electrode wear and white layer thickness in their study. The authors concluded that the pulse current is the most important parameter. Dhanabalan et al. [11] investigated the impact of peak current of pulse-on time and pulse-off time on Inconel 718 and 625 surface roughness. Habib [12] determined the effect of current, opening voltage and pulse-on time on the surface properties of Al/SiCp composite processed using copper electrode in EDM method. Using Taguchi method, he examined the effect of process parameters such as rotation speed of the electrode and pulse-on time. Dewangan and Biswas [13] considered copper electrode and AISI P20 tool steel as work materials in their study and optimized the process parameters with Taguchi multiple response method. Sengottuvel et al. [14] determined the effect of input parameters and tool geometry on material removal rate, tool wear rate and surface roughness by using copper electrode in the EDM method of Inconel 718 material using ANOVA analysis. The authors determined that the best tool geometry is rectangular section. Li and Wei [15] examined the processability characteristic of Inconel 718 using Wire-EDM and Sinking-EDM methods used Cu–SiC electrodes.

The authors investigated processing performance (surface roughness, surface topography, surface alloying, and electrode wear) in their studies, and achieved lower wear on Cu–SiC electrodes compared to conventional Cu electrodes. Jerald et al. [16] processed the Inconel 600 material by peircing in micro-EDM method using a Cu electrode. They achieved the best material removal rate (MRR) and the lowest tool wear rate in negative polarity. Aggarwal et al. [17] developed an experimental model to estimate the surface roughness and cut-off rate during the processing of Inconel 718 alloy under different conditions. In their study, Salman and Cengiz Kayacan [18] examined the Ra (mm) roughness values as a result of applying powder metals (cold work tool steel) hardened with a series of copper electrodes to the workpiece using different EDM parameters. At the same time, they proposed a mathematical relationship between the roughness values obtained from the experiments modeled using gene expression programming (GEP) method and the surface roughness and the parameters affecting it with the GEP model. Cakir et al. [19], in a study on the estimation of performance parameters, investigated the capacities of Adaptive Neuro-Fuzzy Inference System (ANFIS), gene expression programming (GEP) and artificial neural networks (ANF) with the experimental data obtained from EDM process and they reported that Adaptive Neuro-Fuzzy Inference System (ANFIS), was slightly better than other models. Suryaa et al. [20] researched the estimation and comparison of the process performances of the Al7075-TiB2 composite during the WEDM process in order to obtain maximum material removal rate (MRR), minimum dimensional error (DE) and better surface roughness. They developed an artificial neural network (ANN) model to predict parameters. It has been reported that the predicted processing characteristics are compatible with the experimental values.

In this study, the surface roughness values of the materials, which were removed by using 160 different EDM process parameters, were measured on Inconel 718 parts with two different diameters. In the roughness measurements, the arithmetic mean of the values obtained by measuring from two different locations was taken. In addition, the surface microstructure was examined by Scanning Electron Microscope (SEM) in order to determine the changes in the microstructure of the process. In the study, artificial intelligence techniques were also used to estimate the surface roughness at various processing parameters. The aim here is to investigate the feasibility of artificial neural networks and gene expression programming and also to compare these techniques. It is possible to perform a large number of experiments using the trial-and-error method to obtain the desired surface roughness. Multiple experiments will result in higher costs due to waste of material and time. Artificial intelligence methods enable the models who trained with data sets obtained as a result of experiments to learn. Trained models will be able to produce results very close to accurate for other untested processing parameters, minimizing experiment costs and time waste. In the study, the gene expression programming model was created with the Automatic Problem Solver 2.0 software, and the artificial neural network model was created with the MATLAB 2017 (R13) software package. The experimental studies required for training and testing of the models were carried out on a wire wear machine.

Prediction with artificial intelligence methods

It is known that artificial intelligence methods are widely used in the solution of problems involving variables that are not linear and have complex relationships with each other. Major artificial intelligence techniques are Expert Systems ANN: artificial neural networks, Fuzzy Logic, Support Vector Machine and Genetic Algorithms. Artificial intelligence methods are very convenient methods for data estimation, classification and clustering. In the study, the surface roughness values of Inconel 718 materials manufactured with different EDM processing parameters were estimated by artificial neural networks (ANN) and gene expression programming (GEP). In the use of the two methods, it was aimed to make a comparison and determine the most appropriate method.

Artificial neural networks (ANN)

Artificial neural network (ANN) is a flexible mathematical structure that can determine the complex (nonlinear) relationships between input and output data sets. ANN models have been found useful and effective, especially in problems where the properties of operations are difficult to describe using physical equations [21]. Artificial neural networks consist of artificial neurons which make similar calculations on their inputs. An artificial neural network consists of a series of processing elements that are highly interconnected, and transforms a set of inputs into desired outputs. The result of the transformation is determined by the properties of the elements and the weights associated with the connections between them. By changing the connections between nodes, the network can adapt to desired outputs [22]. Artificial neural networks can solve a wide variety of problems such as handwriting and face recognitions, and are used extensively in deep learning, one of the most popular subfields of data science [23]. Artificial neural networks are divided into two classes as supervised learning and unsupervised learning according to learning principles. Supervised learning refers to the adaptation of a network's behavior to a specific input-output relationship. The backpropagation algorithm created by Rumelhart and McClelland (1986) is a supervised algorithm [24].

Today, neural networks are used to solve numerous problems related to manufacturing processes. The topic of artificial neural networks (ANN) is of the great interest among various scientists and engineering groups as an alternative method for solving "fuzzy" problems [25]. In the production area, artificial neural networks are applied in vision systems, robot path planning and pattern recognition system of data trends used to analyze production systems. For example, in additive manufacturing methods, as a result of the thermal nature of the processes and the high temperature variation throughout the part, the parts produced undergo thermal deformations leading to dimensional inaccuracies. With an artificial neural network-based

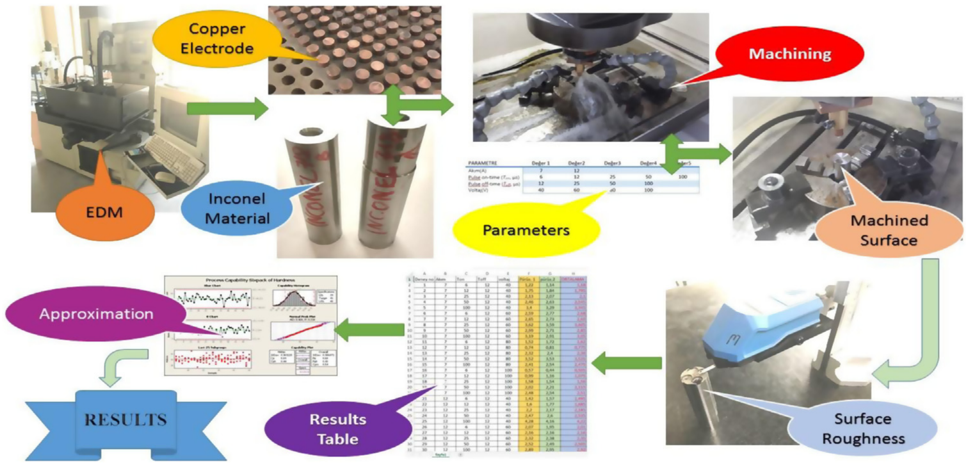

Fig. 1. Work-flow chart of the study.

methodology, the geometric design of the part that will help prevent deformation is provided ([26] September). The design process consists of the construction and testing of alternative designs using simulation methods. Dobrzanski (2005) developed a model using an artificial neural network to minimize the risk in product manufacturing and to search for the most appropriate chemical composition of steel on a specific technical process. The design process consists of the construction and testing of alternative designs using simulation methods.They used artificial neural networks to analyze the outputs obtained from simulation models and to support the design process [27].

Gene expression programming

Gene expression programming, such as genetic algorithms and genetic programming, is a genetic algorithm in which populations of individuals are used, selected for fitness, and genetic variation is introduced using one or more genetic operators [28]. Gene expression programming is presented as a new technique for creating computer programs using a genotype/phenotype genetic algorithm [22]. Gene expression programming uses character linear chromosomes composed of structurally organized genes in a head and tail. Chromosomes function as a genome. The purpose of chromosome selection is to encode expression trees. The creation of these separate entities (genome and expression tree) with different functions allows the algorithm to operate with high efficiency, which greatly exceeds current applicable techniques. Among the problems chosen to demonstrate the power and versatility of gene expression programming, there are symbolic clustering, continuous generation with constant generation, cellular automaton rules for density classification, and binary concept learning [29]. Bagatur and Onen [30] used the gene expression programming model to generate a mathematical function for predicting air entrainment by water jet. In another study, monthly soil temperature was estimated using gene expression programming with the help of air temperature, depth, relative humidity and solar radiation data [31].

Materials and methods

An experimental series of studies have been planned to control and predict the surface roughness after machining by EDM method on the Inconel material. Fig. 1 shows the flow chart of the work plan. In the experimental study, two Ø22 mm diameter and 85 mm bar Inconel 718 material were used. In order to improve the surface roughness on the Inconel material, machining process was realized

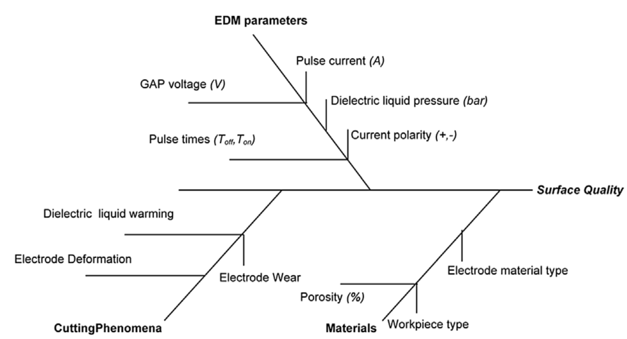

Fig. 2. Fishbone diagram showing the effect of EDM method on surface roughness.

Table 1
EDM cutting parameter group.

Parameter	Value 1	Value 2	Value 3	Value 4	Value 5
Current (A)	7	12	–	–	–
Pulse on-time (T_{on}, µs)	6	12	25	50	100
Pulse off-time (T_{off}, µs)	12	25	50	100	
Voltage (V)	40	60	80	100	

with EDM method. In the study, EDM-CNC-983 model EDM device with CNC feature, produced by AjanCNC company shown in Fig. 1, was used for machining. High conductivity copper electrode was used as the electrode (set) in the study. Copper material is the most widely used electrode type in EDM method thanks to its low cost and high conductivity [32].

Operating parameters of the agent EDM machine are Current (I, A), Pulse on-time (Ton, µs), Pulse off-time (Toff, µs), Gap voltage (V), Electrode polarity, fluid pressure ratio (%), application time (s) and withdrawal amount (mm). In the fishbone diagram given in Fig. 2, the parameters affecting the material surface roughness of EDM method are seen [33]. When the literature is examined, the most common parameters used in studies, which have direct effect on surface roughness, are Current (A), Pulse on-time (Ton, µs), Pulse off-time (Toff, µs), Voltage (V) and Liquid pressure (BAR) [18,34–36].

For the selection of the cutting parameters used in this study, it was decided to use Current (A), Pulse on-time (Ton, µs), Pulse off-time (Toff, µs) and Voltage (V) parameters, which were proven to have an effect on the surface roughness. In order not to increase the

Table 2
The six parameters with the best results.

Experiment no	Current (*I*)	T_{on} (μs)	T_{off} (μs)	Voltage (*V*)	R_{a1}–R_{a2} (μm)
16	7	6	12	60	0,57–0,44
43	7	25	25	40	0,48–0,39
45	7	100	25	40	0,44–0,56
46	7	6	25	60	0,27–0,24
78	12	25	25	100	0,46–0,43
81	7	6	50	40	0,38–0,4
86	7	6	50	60	0,38–0,36

number of experiments, fluid pressure was not included in the parameters. Since it is known that the current value has a direct effect on the roughness, the parameter distribution shown in Table 1 has been created by selecting the low current values of 7–12A group, which are accepted as finishing parameters. For other parameters, a fixed value was chosen in accordance with the process.

As seen in Table 1, two different current values are used in the finishing process. Other parameters were selected by making an equal distribution between the lowest and highest values. 160 different cutting parameter sets used in the experimental study were prepared by using the mixed combination made with the values of the parameters.

With 160 different experimental cutting parameters, machining process was carried out as shown in Fig. 1 until it reaches 0.15 mm Z depth in each parameter. After each machining process, the surface was cleaned with compressed air, and the roughness of the surface was measured. The measurement process was carried out from two different points on the surface with the Hommel Verke Tester T500 device. Sampling length (Lc) was taken as 0.25 mm, measurement length (Lm) as 1.25 mm (5.Lc) and traverse length (Lt) as 1.5 mm (Fig. 1). After the experiments, the surface roughness values were measured as R_a and tabulated.

Two different points chosen on the turned surface were measured before the experiments; thus the surface rougness values were found as 0.47–0.54 μm. After each experiment, surface roughness was measured again from two different points chosen on the processed surface. Arithmetic mean of the results was shown in a result table.

Six parameters with the best results after 160 experiments are given in Table 2. The surface roughness value was prepared for the SEM image by cutting a 2 mm thick Ø22 mm wire with the erosion method in order to examine the cross-sectional image of the surface. Selected surfaces were formed via two parameters with the best results and the crater structure on the surface.

For the parameter that gives the best result after EDM, the roughness measurements of the two surfaces have been repeatedly verified. In the study, SEM examinations were also carried out to determine the changes in the microstructure after EDM. Samples with the two best surface roughness values were used for SEM examinations. The FEI QUANTA FEG 250 brand SEM device was used for the examinations, and images were taken from both the cross-sections and the surface of the samples.

Creating GEP and ANN model

The data set obtained from the experimental results was used for gene expression programming and generation of artificial neural network models. In the experiments, 320 results were obtained via 2 measurements for 160 different parameter combinations, and the average of both measurements was determined by using the data sets. There are 4 input parameters and 1 output parameter in the experiments. The data set is also in line with this situation.

GEP

In the gene expression programming model, while the current, pulse time and voltage values consisting of independent variables are used in the Input data set obtained from the experimental results, arithmetic operators (*, /, −, +) and mathematical functions (^, √, E, 1/x, sin, cos, tan) are used. In chromosomes, the number of genes is determined as 5 and the head length is 8. The mutation rate remained 0.044. Product (*) is selected as the connection function type. The training of the model was adjusted for maximum fit, and mean square error (MSE) was determined as the performance criterion.

ANN

MATLAB r2018b program was used to create the ANN model in the study. The data obtained from the experiments were transferred to the Matlab program. The model was developed in Matlab ANN tool. In the artificial neural network, 70% of the data set was used for training, 15% for verification, and 15% for testing. The data to be used in the specified ratios are randomly selected from the input and output data on the ANN background. The training function is Levenberg–Marquardt (trainlm), and the performance function is mean square error. Many attempts have been made with different combinations to create the ANN model. In these trials, almost all of the network type is feed forward and one is the cascade forward propagation type. The number of neurons, the number of hidden layers and the activation function were changed by trial and error to find the highest R ratio and the lowest MSE ratio. As a result of the experiments, the best model was determined according to high R and low error rate. The parameters used for the trials mentioned were given in Table 3.

The structures of the ANN network type used in model creation are shown in Fig. 3.

Results

Experimentally, some of the surface roughness values measured by the EDM method as a result of 160 processes with different combinations of 4 input parameters, such as discharge current applied with the copper electrode, pulse on-time, pulse off-time and gap voltage, are shown in Table 4.

Artificial neural network model results

ANN models with different structures determined in the study were trained by running in ***MATLAB*** program. Performance values obtained as a result of the training are also given in Table 5.

Table 3
Different models applied in the study.

Model no	Network type	Educational function	Activation function	Hidden layer number	Number of neurons in hidden layer
1 (4-5-1)	Feed-forward back propogation	Levenberg–Marquardt (trainlm)	Logsig–Tansig	1	5
2	Feed-forward back propogation	Levenberg–Marquardt (trainlm)	Tansig–Tansig	1	5
3	Feed-forward back propogation	Levenberg–Marquardt (trainlm)	Logsig–Logsig–Tansig	2	5–5
4	Feed-forward back propogation	Levenberg–Marquardt (trainlm)	Logsig–Tansig–Tansig	2	5–5
5	Feed-forward back propogation	Levenberg–Marquardt (trainlm)	Logsig–Logsig–Tansig	2	10–5
6	Feed-forward back propogation	Levenberg–Marquardt (trainlm)	Logsig–Logsig–Tansig	2	10–10
7	Cascade-forward backpropogation	Levenberg–Marquardt (trainlm)	Logsig–Logsig–Tansig	2	10–10

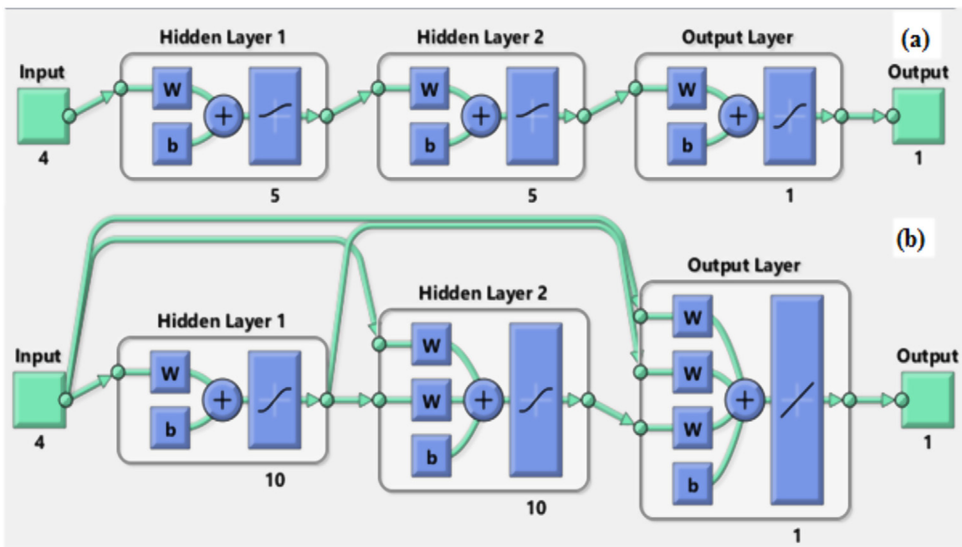

Fig. 3. ANN type of network structures used in model creation, (a) feed forward back propagation, (b) cascade-forward backpropogation neural network.

Table 4
Some of the surface roughness values measured after 320 processes Katman Sayısı.

Experiment no	Current (I)	T_{on} (μs)	T_{off} (μs)	Voltage (V)	R_{a1}–R_{a2} (μm)
1	7	6	12	40	1,22
2	7	12	12	40	1,75
3	7	25	12	40	2,13
4	7	50	12	40	2,46
5	7	100	12	40	3,4
6	12	12	12	60	2,16
7	12	25	12	60	2,32
8	12	50	12	60	2,52
9	12	100	12	60	2,89
10	12	12	12	80	1,26

Table 5
Performance values obtained as a result of training.

Model no	Training R value	Test R value	Verification R value	Total R	Avarage quadratic error
1 (4-5-1)	0,92	0,92	0,92	0,92	0,154
2	0,90	0,86	0,90	0,89	0,194
3	0,85	0,84	0,85	0,85	0,24
4	0,89	0,90	0,92	0,89	0,20
5	0,89	0,93	0,94	0,90	0,19
6	0,964	0,961	0,959	0,962	0,048
7	0,976	0,979	0,985	0,978	0,026

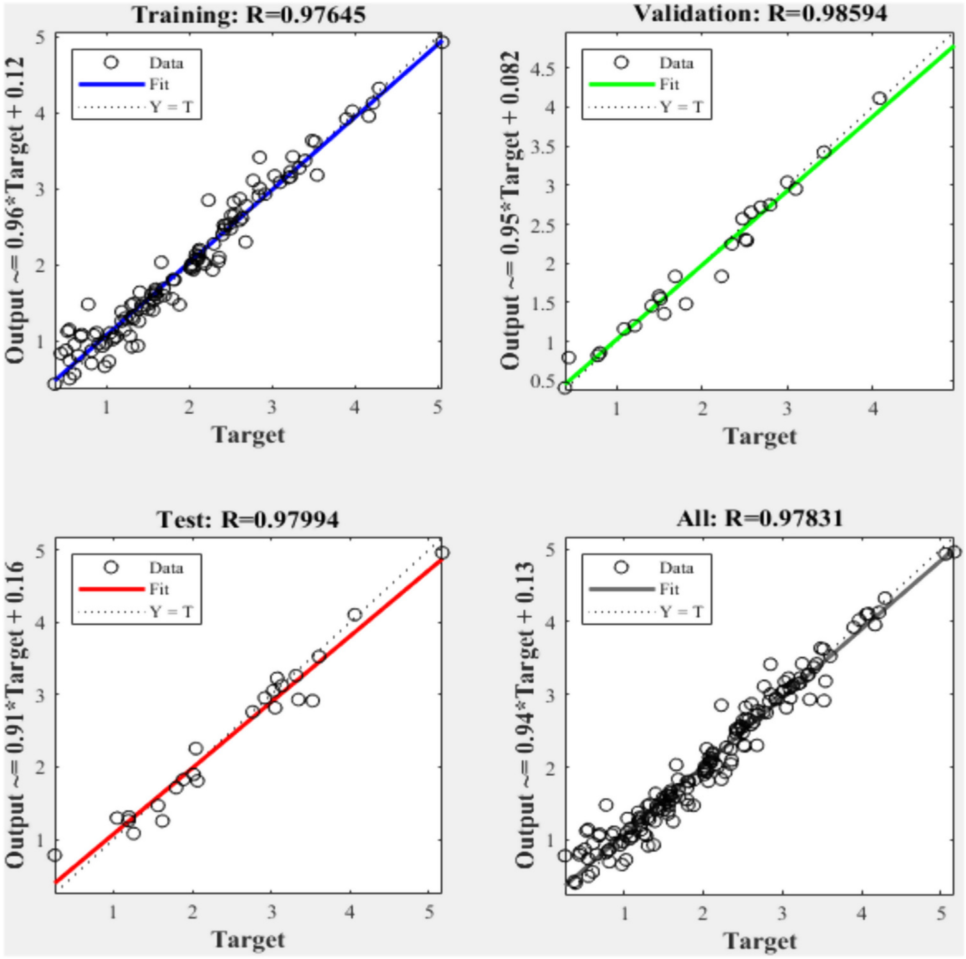

Fig. 4. Best R values obtained as a result of experiments with artificial neural network.

As a result of the experiments, the best R value was obtained in the multi-layer feed-forward back propagation neural network model (model no: 7) (Fig. 4).

Gene expression programming results

The GEP model was run for the best fit (max. 12,800). R-squared values were obtained as 72.9% for training data and 66.2% for test data (Fig. 5). The surface roughness estimation program code (Table 6) and the mathematical equation (Eq. (1)) were derived for the best results using the GEP model.

Table 6
Surface roughness estimation program code for best results using the GEP model.

```
Function APSfunction(ByRef d() As Double) As Double
  Dim dblTemp As Double
  dblTemp = 0
  dblTemp = dblTemp × (Log((d(1) – ((Log((d(0) ^ d(1))))/(((d(2) – d(3)) – d
  (0))))))/Log(10))
  dblTemp = dblTemp × (10 ^ (1/((Sqr((Log(d(2))/Log(10))) ^ ((d(0) + d(3)) – Sqr
  (d(1)))))))
  dblTemp = dblTemp × Exp(((1/(((d(1) + d(3)) × d(0))))/(((Sin(d(0)))/(d(2))))))
  dblTemp = dblTemp × Sqr((10 ^ (((1/((Sin(d(2)) × d(3))))/(Cos((d(0) × d
  (0))))))))
  dblTemp = dblTemp × (Log((d(2) – Tan((((d(2) – d(0)) + d(3)) × Tan(d(3))))))/
  Log(10))
  APSfunction = dblTemp
End Function
```

According to the model created in the study, the Visual Basic Code that the gene expression programming tool has produced.

The variables in the program code are d () = surface roughness (m), d (0) = discharge current (I), d (1) = pulse on-time (s), d (2) = pulse off-time, d (3) = span voltage (V).

The mathematical expression given by gene expression programming is (1):

$$Ra = \left(\log\left(b - \left(\log\left(\frac{a^b}{c-d-a}\right)\right)\right)\right) * \left(10\left(\frac{1}{\sqrt{logc}^{(a+d-\sqrt{b})}}\right)\right) * \left(e\left(\frac{1}{\frac{(b+c)*\alpha}{\left(\frac{\sin\alpha}{c}\right)}}\right)\right) * \left(\sqrt{10\left(\frac{1}{\frac{((\sin c)+d)}{\cos\alpha*\alpha}}\right)*(\log(c-\tan(((c-a)+d)*\tan d)))}\right) \quad (1)$$

Here Ra = surface roughness, a = discharge current, b = pulse on-time, c = pulse off-time, d = gap voltage.

GEP and ANN prediction model performance metrics

Root mean square error (RMSE), mean absolute error (MAE) and R-squared metrics are commonly used in the evaluation of the model in regression studies. Three performance metrics specified in the evaluation of the success of the models obtained in the study were applied. Below are the formulas for performance metrics (Eqs. (2)–(5)).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \quad (2)$$

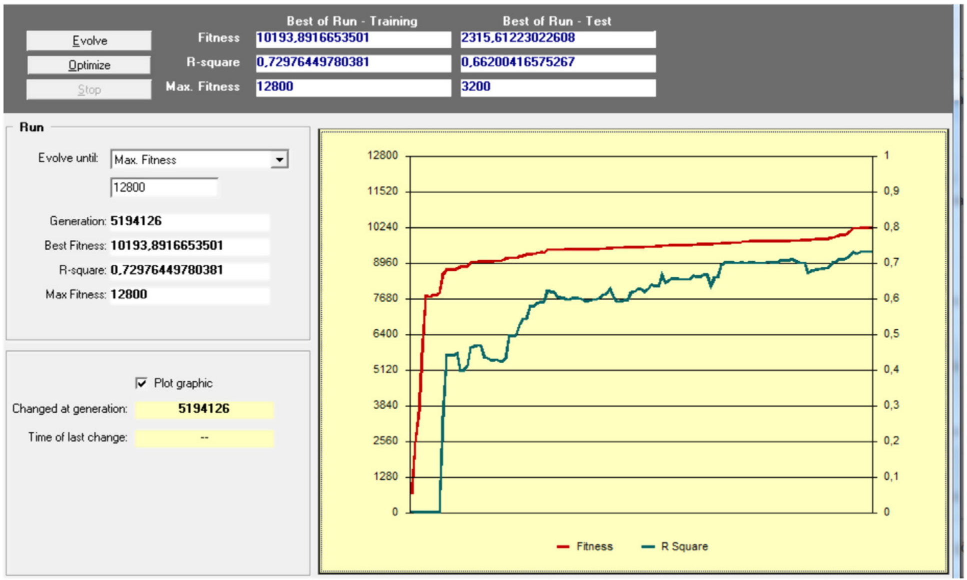

Fig. 5. Best R-squared values obrained by programming.

Table 7
Performance metrics based on predicted values obtained from GEP and ANN models.

Performance matrics	Models	
	GEP (test/train)	ANN (All)
RMSE	0.574/0.512	0.272
MAE	0.437/0.401	0.203
R-square	0.66/0.72	0.93

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y})^2 \tag{3}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y})^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum (y_i - \widehat{y})^2}{\sum (y_i - \overline{y})^2} \tag{5}$$

In the formulas, $\hat{y}$ is the predictive value of y, and $\overline{y}$ is the average value of y. N value refers to the number of data. Performance metrics according to the predicted values obtained from GEP and ANN models were given in Table 7.

When the performance measurement is evaluated, it is seen that the ANN model performs better than the IOP model with 0.203 GEP value, 0.272 RMSE value and 0.93 R-square value.

Surface integrity of EDM work surface

In the study, SEM examinations were carried out for the two samples with the best results from the samples processed with EDM method. In SEM examinations, it is aimed to determine the crack and white base that occur on the part surface after the process. In Fig. 6, the internal structure SEM images of the samples with the best results were given.

When the images in Fig. 6 are examined, parts in the form of voids, cracks and spheres are observed on the surface. Crack formation in the material is caused by the large thermal strains that occur during the process exceeding the breaking strength of the material surface. During the EDM process, the dielectric liquid is used to remove the molten material from the process surface. The thickness of the white layer can be expressed as an indicator

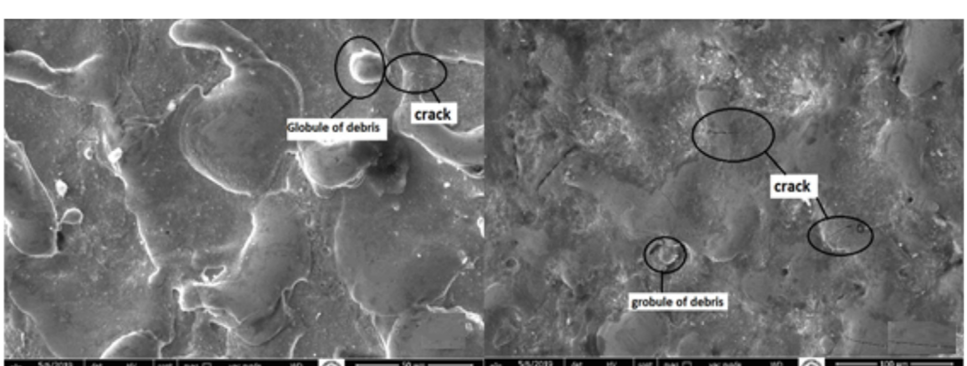

Fig. 6. Mikro structure images of the samples with the best results.

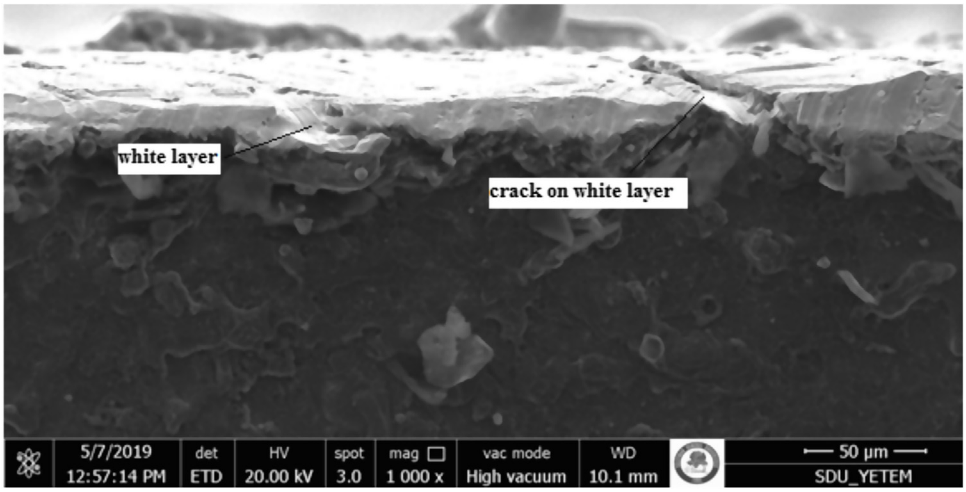

Fig. 7. Formation of a white layer on the sample.

that the chosen process parameters are correct. During removal, the molten material breaks into small pieces and forms a new layer. However, all particles formed during EDM process cannot move away from the process surface, and remain as a layer on the material surface. During the evaporation of the dielectric liquid, this layer remaining on the top of the processed surface is called the unmelted layer or white layer [37]. If there is no equality between energy and transfer during the EDM process, cracks occur on the material surface. These cracks that occur affect the white layer thickness. The white layer occurring on the samples selected in the study is shown in Fig. 7.

Conclusions

It is inevitable that the surface roughness values are obtained poorly in parts where machinability is difficult with machining. This situation also negatively affects the fatigue life of the part. For this reason, materials with difficult machining can be worn by using methods such as EDM.In this study, Inconel 718 bar material was removed by finish turning process and the surface roughness values obtained after the process were measured 0.47–0.54 μm, and these values were reduced to 0.27–0.24 μm by EDM method. It has been proven once again that the best surface roughness values are obtained by using low current value (7A) as Hasçalık and Çaydaş [34], Hasçalık and Çaydaş [35], Li et al. [36], Salman and Cengiz Kayacan [18] stated in their studies. Not only the current value, but also the low voltage value has contributed to the formation of a smooth current in the EDM process.

In the study, although micro cracks were observed in the piece, it was observed that these micro cracks did not progress and remained in small areas. Micro cracks, which are small in size and quantity, will not significantly affect the fatigue life of the part.

In the study, experimental study was set up in computer environment using GEP and ANN methods and models were created. In the created model, the formula that estimates the best surface roughness value for Inconel 718 material has been developed. Some parameters such as adhesion of chips to the surface as a result of chip jams during EDM, abrasion of the electrode used or not in homogeneous structure, calibration deviations in the surface roughness device significantly affect the results obtained from the GEP and ANN methods. For this reason, the parameters that give the best results were tested twice and their accuracy was checked. GEP and ANN methods were compared according to the results obtained. At the end of the study, the prediction accuracy (r2) in ANN was 0.93, and the prediction accuracy (r2) in the GEP model was 0.66. It was determined that the ANN method gave more accurate results for this study.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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