Modelling of Effects of Various Chip Breaker Forms on Surface Roughness in Turning Operations by Utilizing Artificial Neural Networks

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ABTRACT

In this study, the effects of different chip breaker forms and cutting parameters on the surface roughness on machined surfaces were investigated experimentally in turning of AISI 1050 steel; and values of surface roughness obtained from experiments were determined with empirical equations using artificial neural networks. The utilizing of ANN was offered to determine the surface roughness depending on chip breaker forms and cutting parameters of AISI 1050 steel. The back propagation learning algorithm and fermi transfer function were used in artificial neural network. Experimental measurements data were employed as training and test data in order to train the neural network created. The best fitting training data set was attained with ten neurons in two hidden layers 6 of which were at first hidden layer and 4 of which were at second hidden layer, making it possible to predict surface roughness with precision at least as good as that of the experimental error over the entire experimental range. After network training, R^2 value was found as 0.978, and average error as 0.018%. When the results of mathematical modelling are examined, the computed surface roughness is observed to be apparently within acceptable values.

Keywords: Chip Breaker Forms, Surface Roughness, Artificial Neural Network (ANN), Turning

Tornalama Operasyonlarında Farklı Talaş Kırıcı Formlarının Yüzey Pürüzlülüğü Üzerinde Etkilerinin Yapay Sinir Ağları Kullanılarak Modellenmesi

ÖZ

Bu çalışmada, AISI 1050 çeliğinin tornalanmasında, farklı talaş kırıcı formlarının ve kesme parametrelerinin işlenmiş yüzeylerdeki yüzey pürüzlülüğü üzerinde etkileri deneysel olarak araştırılmış ve deneylerden elde edilen yüzey pürüzlülük değerleri yapay sinir ağları kullanılarak ampirik eşitlikler ile belirlenmiştir. AISI 1050 çeliğinin talaş kırıcı formlarına ve kesme parametrelerine bağlı olarak yüzey pürüzlülüğünü belirlemek için yapay sinir ağların kullanımı önerilmiştir. Yapay sinir ağında geri yayılım öğrenme algoritması ve fermi transfer fonksiyonu kullanılmıştır. Oluşturulan sinir ağını eğitmek amacıyla eğitim ve test verisi olarak deneysel ölçüm verileri uygulanmıştır. Bütün deneysel aralık üzerinde yüzey pürüzlülüğünü en iyi hassasiyet ile tahmin etmek için, en uygun eğitim veri seti, mümkün oldukça deneysel hatanın en az olduğu, on nöronlu iki gizli katmanlı ilk gizli katmanında 6, ikinci gizli katmanda 4 nöron ile elde edilmiştir. Ağ eğitildikten sonra, R^2 değeri; 0.978 ve ortalama hata değeri; 0.018% olarak bulunmuştur. Matematiksel modellemenin sonuçları incelendiğinde, hesaplanan yüzey pürüzlülüğünün açık bir şekilde kabul edilebilir değerler içerisinde olduğu görülmüştür.

Anahtar kelimeler: Talaş Kırıcı Formları, Yüzey Pürüzlülüğü, Yapay Sinir Ağları (YSA), Tornalama

1. INTRODUCTION (GİRİŞ)

Surface roughness has been one of the most significant criteria in numerous mechanical products in many areas, and had great significance in the assessment of machining accuracy. The surface roughness in a turning operation is directly influenced from cutting parameters (feed rate, cutting speed, depth of cut) and by cutting tool geometry (cutting edge form, nose radius, chip breaker form, etc.). One of the most important parameters constituting cutting tool geometry is chip breaker forms. The most common method for chip breaking is the use of chip breakers on the cutting tools. Chip breakers can be utilized for increasing chip breakability which results in efficient chip control and advanced productivity. Cutting resistance is lowered and the workpiece is given a better surface finish by chip breakers. Of different process parameters, surface finish is the most significant factor determining the quality of a workpiece. Thus the measurement of

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surface roughness is a very crucial stage in metal cutting.

By a number of researchers, Mathematical models have been developed to estimate the surface roughness. Palanikumara at al. [1] analysed surface roughness in turning of FRP tubes by PCD tool, they developed empirical models correlating the surface roughness with cutting parameters such as feed rate and cutting speed. Cakir at al. [2] evaluated a mathematical modelling by examining the effects of cutting parameters and different coating material on predicting surface roughness. Also, they revealed that among the cutting parameters followed by cutting speed, feed rate has the most significant influence. Abouelatte at al. [3] predicted that surface roughness depends on tool vibrations and cutting parameters in turning. They utilized four models in order to foresee the surface roughness together with the tool vibrations and cutting parameters. The attained results are quite accurate and appropriate for predicting surface roughness. Lin at al. [4], comparing a few Mathematical models, modelled cutting force and surface roughness for turning and established the best model among them. Lalwani at al. [5] developed a model by investigating the effect of cutting parameters on cutting forces and surface roughness in finish hard turning. In their surface roughness model, the feed rate ensures primary help and exhibits most significant affect.

The development of neurobiology has permitted scientists to setup Mathematical models of neurons to simulate neural behaviour. Approaches of Artificial Neural Network (ANN) have been renowned types of evaluation calculation methods for the last decades. ANNs are good alternatives to conventional empirical modelling depending on polynomial and linear regressions in the field of process engineering [6]. ANN has already been implemented to different fields by numerous researchers [7-11]. Furthermore, in order to estimate the surface roughness of machined workpieces under different machining and cutting conditions, ANN models were used by a number of researchers. Kim et al. [12] assessed the performance of commercial chip breakers, after he used a neural network that was trained by means of the backpropagation algorithm. Crucial element forms (land, breadth, radius, etc.) directly affecting the chip formations were selected among the commercial chip breakers and were employed as input values of the neural network. Consequently, Kim et al. bettered the performance assessment method and put it into practices it to mercantile cutting tools, resulting in a significant performance. In his study, Karayel [13] submitted an ANN approach for estimation and control of surface roughness. ANN can generate a correct relationship between surface roughness and cutting parameters. Accordingly, ANN can be employed for modelling surface roughness so as to estimate real approximate values before the stage of machining. Ezugwua et al. [14] improved an ANN model for the analysis and estimation of the relationship between cutting and processing parameters during high-speed turning. With the contribution of the neural model, a good performance was obtained with correlation coefficient between model estimation and empirical values. Ranganathan et al. [15] developed an ANN, predicting surface roughness of the machined workpiece. The most significant parameter to decide on surface roughness is the combination of feed rate and cutting speed, however the depth of cut is the least important parameter to estimate surface roughness of the machined surface. They observed a good coherence between the experimental results and predictive models. Venkata Rao at al. [16] employed the ANN to estimate surface roughness, tool wear and amplitude of workpiece vibration. The trained ANN was used to estimate surface roughness, tool wear and workpiece vibration. It was found that there is coherence between experimental data and estimated values. The estimated values were compared with the collected experimental data and percentage error was calculated. Kumar and Chauhan [17] developed ANN model which can be employed to analyse the influences of the chosen process parameters on surface roughness. It is apparent from the analysis that feed rate has important contributions. Natarjan at al. [18] developed an ANN model by means of feed-forward back-propagation network method to estimate surface roughness. The surface roughness could be effectively estimated by employing feed rate, cutting speed and depth of cut as input parameters. Taking the individual parameters, into consideration, they found that feed rate was the most effective parameter, followed by cutting speed and depth of cut. Nalbant et al. [19] modelled the experimental study of the effects of coated and uncoated inserts and cutting parameters on surface roughness through ANN. ANN might be employed as a good alternative in analysing the influences of processing parameters and cutting tool geometry on the average surface roughness. Soleimanimehr at al. [20] employed neural networks to estimate surface roughness and machining force in turning. The test of the trained networks displayed good coherence existing between their estimations and the experimental results. Paulo Davim at al. [21] studied the effect of cutting parameters by ANN models for predicting surface roughness in turning. Among cutting parameters, both cutting speed and feed rate are more important than depth of cut on surface roughness.

In this paper, the effects of different chip breaker forms and the variations in the cutting parameters (cutting speed, feed rate and depth of cut) on the surface roughness in turning of AISI 1050 steel was investigated [22, 23]. The purpose of the study proposes a new approach based on artificial neural networks (ANNs) to determine the effects of different chip breaker forms on the surface roughness in machining of AISI 1050 with empirical equation. The empirical equation with high accuracy is obtained by ANN using experimental data obtained from experimental studies.

2. MATERIAL AND METHODS (MATERYAL VE YÖNTEM)

2.1. Experimental Study (Deneysel Çalışma)

In the tests, workpiece material of AISI 1050 (DIN 1.1210) is mostly employed in manufacturing. The chemical composition of AISI 1050 steel obtained by spectral analysis is shown in Table1.

Table 1: The chemical composition of AISI 1050 steel (AISI 1050 Çeliğin kimyasal bileşimi)

% C	%Si	%Mn	%P	%S	%Cr
0,430	0,212	0,730	0,0197	0,0390	0,0776
%Mo	**%Ni**	**%Al**	**%Co**	**%Cu**	**%Fe**
0,00752	0,0972	0,0110	0,00603	0,297	98,06

As specified by ISO 3685, SNMG 120408R inserts and PSBNR 2525M12 tool holder having 75° approaching angle were utilized in the experiments. Five groups of chip breaker forms were also utilized in the experiments. The chip breaker forms are STD, MS, GH, SA and MA of Mitsubishi Co. [24]. These inserts are Mitsubishi UC6010 coated grade corresponding to ISO P15 grade. The geometry of the chip breaker being sold by Mitsubishi is illustrated in Table 2. and Figure 1. Though chip breakability can be expressed by various parameters, the study, chip breakability was assessed by two shape elements such as lengths and angles, which were the most significant elements affected during chip breaking. Technical specifications of cutting tools are presented in Table 3. [24].

Table 4. Levels of input parameters (Girdi parametre seviyeleri)

Cutting speed, V (m/min)	150 – 200 – 250 – 300 - 350
Feed rate, f (mm/rev)	0,15 – 0,25 – 0,35
Depth of cut, a (mm)	1,6 – 2,5

Average surface roughness (Ra) was measured using “Mahr-Perthometer M1” a surface roughness measuring device. The measurements were repeated three times in 5.6 mm sample length and arithmetic averages were taken. 30 tests were fulfilled for each chip breaker form.

Table 2. Chip breakers could be determined shape elements (Talaş kırıcıların geometrik özelliklerinin belirlenmesi)

Chip breaker Type	Shape elements (Lengths (ℓ) and Angels (α)) for determined chip breaker				
	α_1	ℓ_1	α_2	ℓ_2	α_3
STD	0°	0.25	15°	1.05	15°
MS	15°	0.50	25°	0.95	25°
GH	0°	0.32	18°	2.48	25°
SA	10°	0.30	25°	0.57	35°
MA	6°	0.2	22°	0.9	30°

Tablo 3. Technical specifications of cutting tools used for the tests (Deneylerde kullanılan kesici takımların teknik özellikleri)

Grade	Hardness (HRA)	Torsional Strength (Gpa)	Coated Method	Coating Layer	
				Composition	Thickness
UC6010	90,5	2,0	CVD	Three layer TiCN-Al_2O_3-TiN	Thick

Machining tests were performed by using five levels of cutting speeds, three levels of feed rate and two levels of cut depth. The cutting parameters used in the experiments are shown in Table 4. JOHNFORD T35 CNC Lathe was used in the tests.

A total of 150 experiments were fulfilled with dry condition using new (unused) inserts in the tests. The unvarying/stable surface roughness values were determined after whole machining was done, and decided on the surface roughness values for each test.

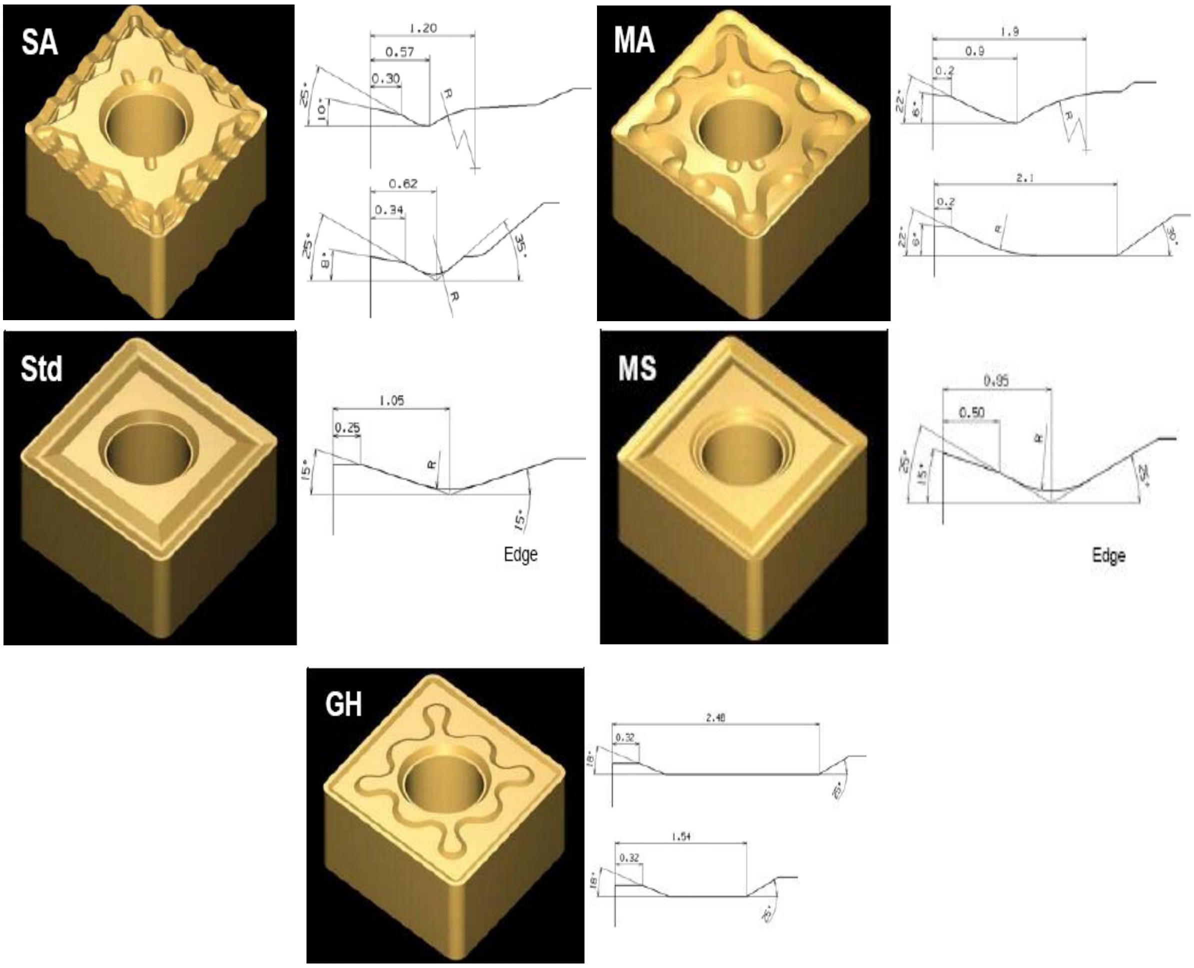


Figure 1. The cutting tools used for the tests and their chip breaker forms [24] (Deneylerde kullanılan kesici takımlar ve talaş kırcı formları)

2.2. Mathematical Modelling: Artificial Neural Network (Matematiksel Modelleme: Yapay Sinir Ağları)

Artificial neural networks (ANN) have been used widely in numerous application fields. Researchers have been applying the ANN technique in a successful way to different fields and many others such as economics, engineering, mathematics and medicine. ANNs have been trained to accomplish the limitations of the traditional approaches and to work out complex problems. ANNs have been utilized for a number of purposes for example optimization, data compression, multi-sensor data fusion, classification, forecasting, speech, pattern recognition, vision, etc. Today, ANNs have been trained to figure out complicated problems that are challenging for traditional approaches [25]. ANNs have resolved the limitations the traditional approaches by extracting sought after information utilizing input data. Such as specific equation form is not need by ANN. However, it needs adequate input-output data. Moreover, it can constantly retrain the new data, so that it will suitably be able to adapt to novel data. ANN has been studied to cope with the problems related to incomplete or imprecise information [26].

The advantages of ANNs are rapidity, simplicity and capacity for learning out of examples when compared with classical methods. Therefore, engineering effort can be reduced in these fields. These can be learned from examples and be dealt with non-linear problems. In addition, they display robustness and fault tolerance. The tasks that ANNs cannot process influentially are those necessitating high correctness and precision as in logic and arithmetic [27].

A significant phase of a neural network is the training step, where an input is introduced to the network with the required output and the weights are regulated so that the network attempts can generate the required output. The weights, after training, include meaningful information, while before training, they are haphazard and do not have any meaning. If it reaches an adequate level, training terminates and the network utilizes the weights to take decisions to determine patterns or to define relations in test data [28].

There are various learning algorithms. One of the most significant algorithms is the back-propagation algorithm, having different variants. Standard back-propagation is a gradient descent algorithm. It is very challenging to know which training algorithm will be the quickest one for a submitted problem.

ANN with back-propagation algorithm learns by alternating the weights, and these alterations are saved as knowledge. Some statistical methods, essentially RMS, R^2, cov, maximum error (%), average error (%) values, were utilized for comparison. Error during the learning is called as root-mean-squared (RMS), and specified as follows [27]:

$$RMS = \left((1/p) \sum_j \left| t_j - o_j \right|^2 \right)^{1/2} \qquad (1)$$

Also, absolute fraction of variance (R^2) and coefficient of variation in percent (cov) are stated as follows, respectively:

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \qquad (2)$$

$$cov = \frac{RMS}{o_{mean}} * 100 \qquad (3)$$

where t is target value, o is output value, p is pattern, and o_{mean} is the mean value of all output data. Input and output layer are normalized in the range of (-1, 1) or (0, 1) [27].

3. RESULTS AND DISCUSSION (BULGULAR VE TARTIŞMA)

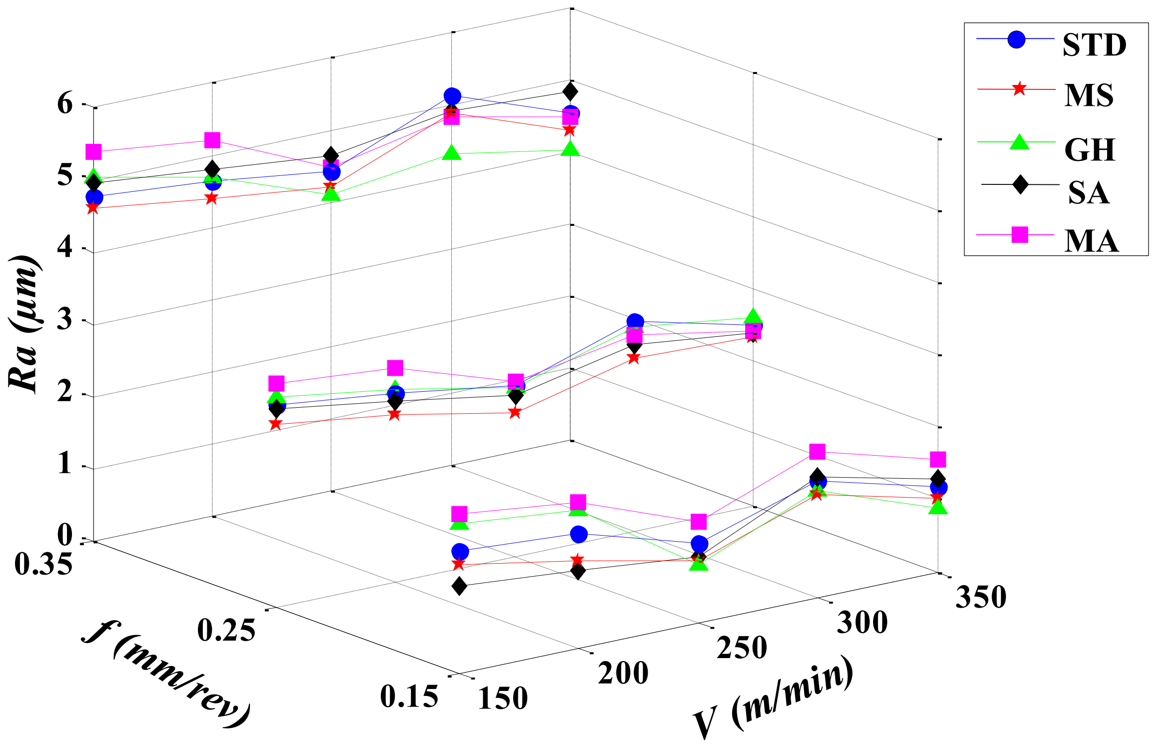
3.1. Experimental Results (Deneysel Sonuçlar)

The surface roughness Ra (µm) values measured by cutting tests according to change in different chip breaker forms and alterations in cutting parameters (cutting speed, feed rate and depth of cut) are shown in Figure 2. Theoretically, surface roughness is a function of feed rate and nose radius. But in practice; cutting speed, cutting depth, cutting tool geometry (cutting edge form, chip breaker form, etc.) and tool wear have influence on surface roughness as well. When the graphs in Figure 2. are studied, it is seen that surface roughness Ra (µm) values decreases with increasing a certain cutting speed (from V=150 m/min to V=250 m/min) for all chip breaker forms. This situation is in agreement with the literature [29-31]. Decreasing surface roughness values by increasing the cutting speed can be explained that it is easy for deformation process to occur because of the increasing temperature at high speeds. It is stated in built up edge theory that a rough surface is attained at lower cutting speed and a smooth surface at higher speed. This phenomenon can be seen on the cutting tool's surface as a result of a low speed machining process. By increasing not only cutting speed but also feed rate, it has been stated by some researchers that this built up edge occurrence could be eliminated [32, 33]. However, when cutting speed was increased (from V=250 m/min to V=350 m/min) for all of the chip breaker forms, the surface roughness values were first observed to be on increase then again on decrease, a declining trend. This situation can be explained by higher cutting speed, above the range recommended by the producer for these cutting tools [24]. When speed limits were exceeded, the cutting tools were expected to wear faster, which has negative impact on surface quality. In the experiment, the best surface quality could achieved with V=150, 200 m/min, f=0,15 mm/rev and a=1,6 mm with cutting tool having SA chip breaker form. SA chip breaker form gave the best results with these parameters, which is suggested for light cutting by manufacturer [24]. Generally, the highest surface roughness values were obtained for the tool having the MA and GH chip breaker type while the lowest surface roughness values were obtained for the tool having the MS chip breaker type. In this situation, it can be explained that excellent surface quality can be obtained with MS chip breaker form which has a sharp cutting edge and because the place where MA chip breaker begins to break chip is smaller than other chip breaker forms (Figure 1.).

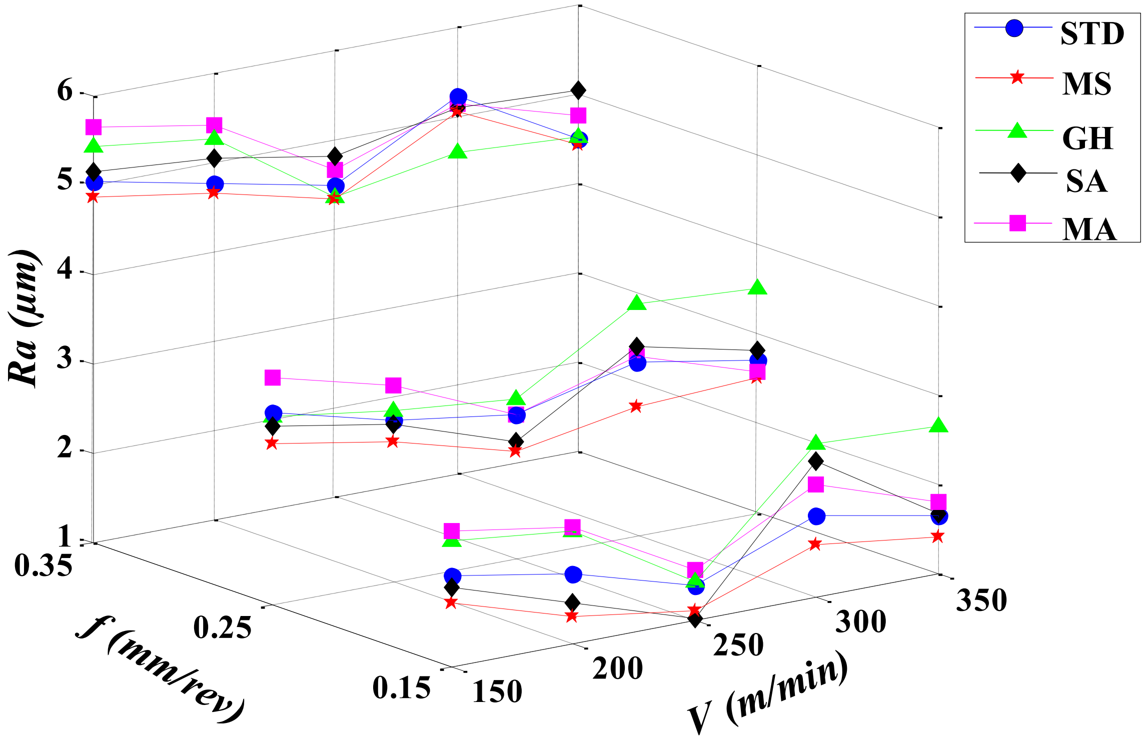
For all chip breaker forms in the experiments, when the surface quality is examined in terms of cutting depth, increasing the cutting depth worsen the surface quality for all cutting tools (Figure 2.). This result is expected due to increasing chip cross-section. When the graphs in Figure 2. are examined, the best effect on surface quality depending on the feed rate can be seen that surface roughness values increase with increasing feed rate for all chip breaker types. In this case, a basic theoretical model for surface roughness is approximated by the following equation:

$$R_{max} = \frac{f^2}{8 x r_\varepsilon} \qquad (4)$$

Where f is the feed rate, r_ε is the tool nose radius and R_{max} is maximum surface roughness. According to this model, increasing surface roughness increases the feed rate [34]. In cutting conditions where cutting speed is 250 m/min, feed rate is 0,15 mm/rev and cutting depth is 1,6 mm; and the best surface quality values in cutting conditions where cutting speed is 300 m/min, feed rate is 0,35 mm/rev and cutting depth is 2,5 mm; and the worst surface quality values are measured for all chip breaker forms.



a) a=1.6 mm



b) a=2.5 mm

Figure 2. Variation of surface roughness (μm) depending on chip breaker forms (Talaş kırıcı formlarına bağlı olarak yüzey pürüzlülük (μm) değişimleri)

3.2. Results of Mathematical Analysis (Matematiksel Analizlerin Sonuçları)

In Figure 3. the ANN structure is shown. Variant of the algorithm utilized in the study is LM. Inputs and outputs are normalized in (0, 1) range. Neurons in input layer do not have any transfer function. Fermi transfer function has been utilized. In the simplest form, products and biases are simply outlined, after that it is transformed through a transfer function to produce a consequence, and ultimately the output value is obtained [35].

Five different chip breaker forms were used in the input layer of the network. The surface roughness was in the output layer. The basic parameters such as cutting speed, feed rate and depth of cut were considered as input for ANN. The neural network was designed with 8 input data and two hidden layers, the first of which had 6 neurons and second had 4 neurons, and the output layer with 1 neuron. This structure is shown in Figure 3.

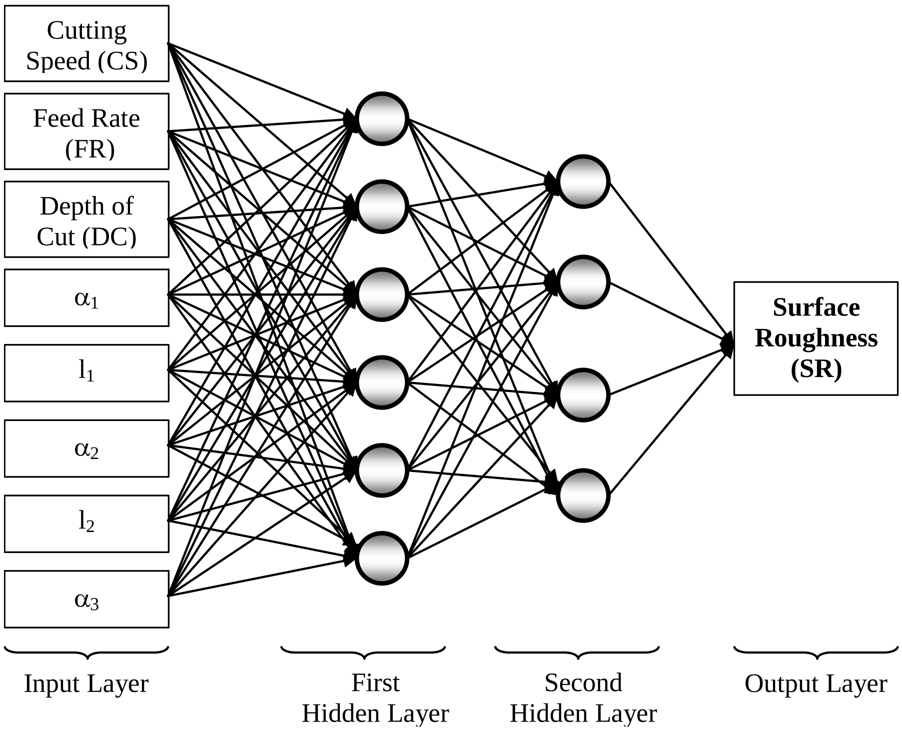


Figure 3. ANN architecture with input and output parameters (Girdi ve çıktı parametreleri ile YSA mimarisi)

The new formulations dependent on main cutting parameters for the outputs are given with Eqs.5-7. The equations can be used for estimation of surface roughness using different main cutting parameters.

$$SR = \frac{1}{1+e^{-4(1,055843F_1+1,132543F_2+1,201490F_3-1,782217F_4-0.5)}} \tag{5}$$

Where; F_i (i=1,2,…,4) can be calculated by Fermi function as given Eq.6.

$$F_i = \frac{1}{1+e^{-4(N_i-0.5)}} \tag{6}$$

Where; N_i (i=1,2,…,4) can be calculated by Eq.7.

$$Ni=M_{1i}*L1+M_{2i}*L2+M_{3i}*L3+M_{4i}*L4+M_{5i}*L5+M_{6i}*L6 \tag{7}$$

The constants (M_{ij}) in Eq.7 are given in Table 5.

Table 5. Constants M_{ij} in Eq.7 (Eşitlik 7'deki M_{ij} sabitleri)

M	N1	N2	N3	N4
1	0,171891	-0,289214	-1,497433	1,073023
2	0,068703	-0,369862	-0,398348	0,306286
3	0,62627	0,571017	0,012783	-6,298365
4	-0,248395	0,482941	0,461106	-3,724602
5	-0,306341	-0,342500	-3,931813	-0,254916
6	0,333525	-0,405640	0,359195	-0,324608

Where; L_i (i=1,2,…,6) can be calculated by Fermi function according to Eq.8.

$$L_i = \frac{1}{1+e^{-4(K_i-0.5)}} \tag{8}$$

Where; K_i (i=1,2,…,6) can be calculated according to Eq.9.

$$K_i = C_{1i} * \alpha_1 + C_{2i} * l_1 + C_{3i} * \alpha_2 + C_{4i} * l_2 + C_{5i} * \alpha_3 + C_{6i} * CS + C_{7i} * FR + C_{8i} * DC \tag{9}$$

The constants (C_{ij}) in Eq.9 are given in Table 6.

To be used in training data, Figure 4. presents the ANN performances of determination of surface roughness. In general perspective, according to the results obtained, deviation of surface roughness between measurement and prediction of ANN is negligible in the range of ±0.1 (Figs. 5-10) for different chip breaker forms.

Table 6. Constants C_{ij} in Eq.9 (Eşitlik. 9'daki C_{ij} sabitleri)

	K_1	K_2	K_3	K_4	K_5	K_6
C_{1i}	-1,288310	0,214114	-0,634474	1,515728	0,262504	-3,407598
C_{2i}	0,00001	0,000002	0,000015	0,0000012	0,0000023	0,000012
C_{3i}	1,403666	3,786108	1,074671	-1,983599	3,710879	1,346782
C_{4i}	-0,460162	0,839807	-0,530084	0,121980	-2,332993	-0,636907
C_{5i}	-0,394440	-6,378991	-1,114890	2,385003	0,952700	-0,661086
C_{6i}	0,637851	1,752643	0,269953	-0,960354	-2,880759	1,415238
C_{7i}	0,264350	-6,149504	-0,652018	-4,494210	-0,449337	0,439126
C_{8i}	-0,876865	-0,278050	1,267351	0,523114	-0,301040	1,364840

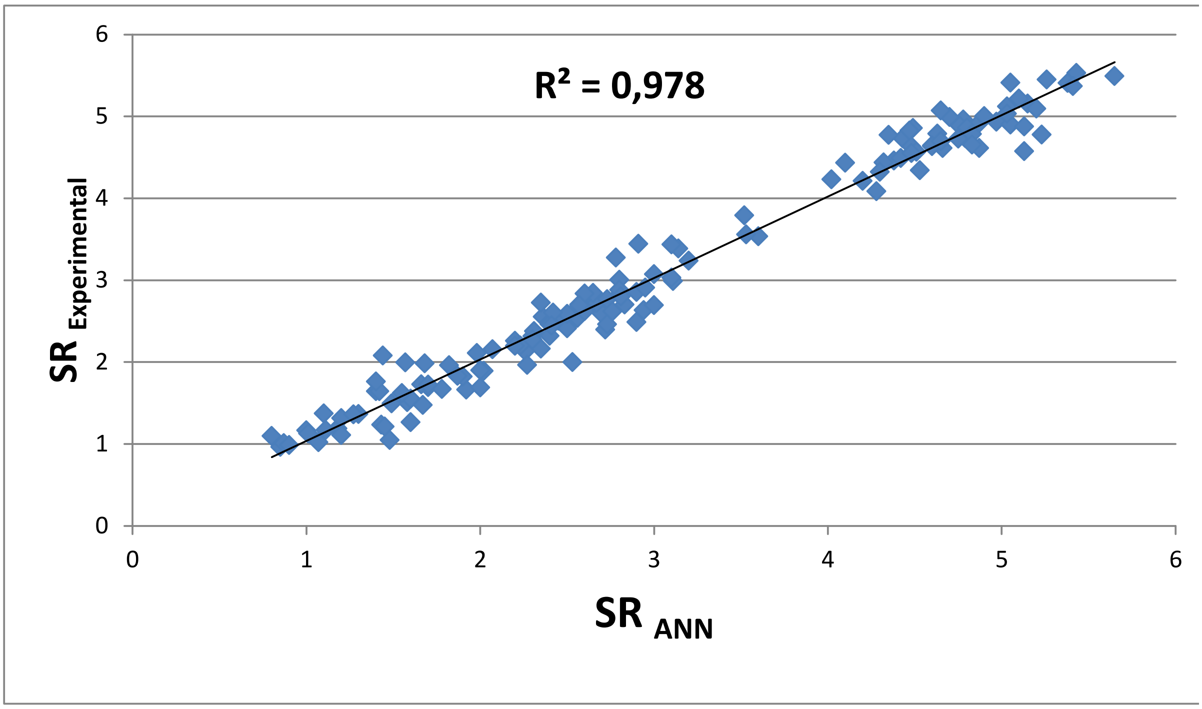


Figure 4. Comparison of the $SR_{Experimental}$ data and SR_{ANN} ($SR_{deneysel}$ veri and SR_{ANN} karşılaştırılması)

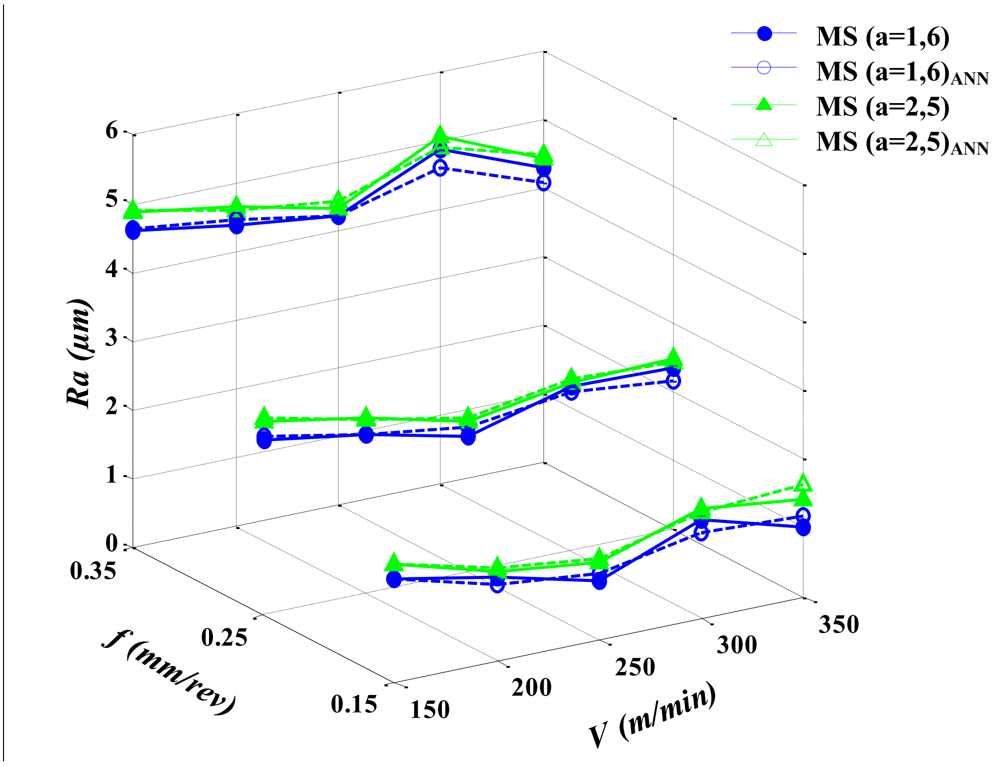


Figure 5. Performance of ANN for chip breaker forms MS (MS Talaş kırıcı formu için ANN performansı)

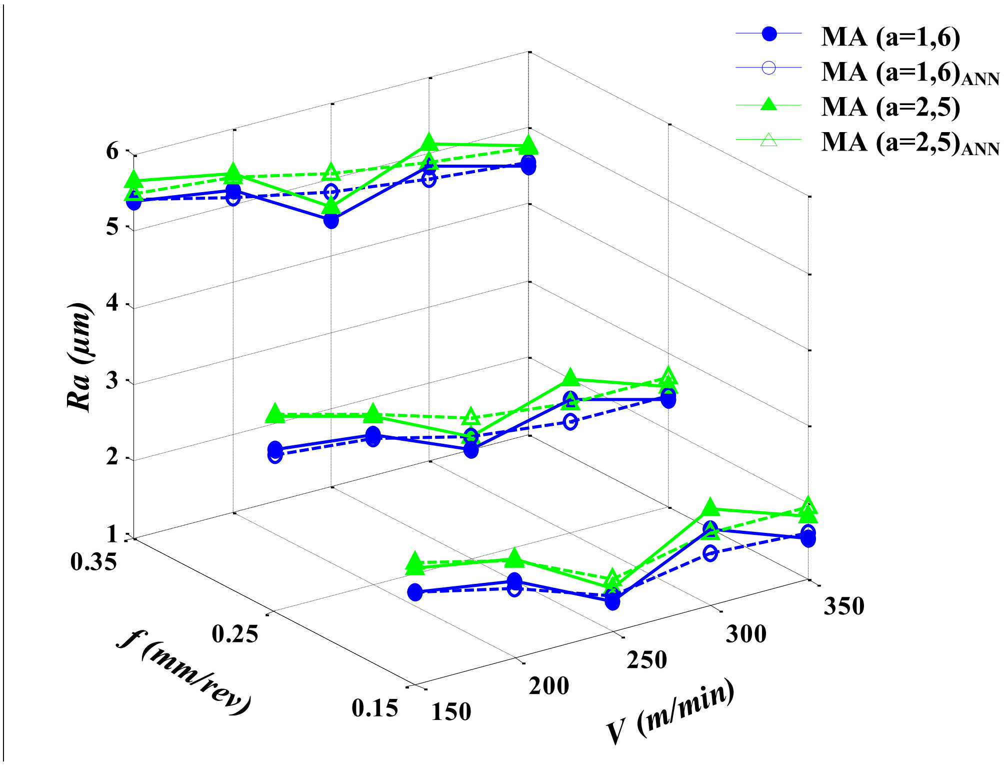


Figure 6. Performance of ANN for chip breaker forms MA (MA Talaş kırıcı formu için ANN performansı)

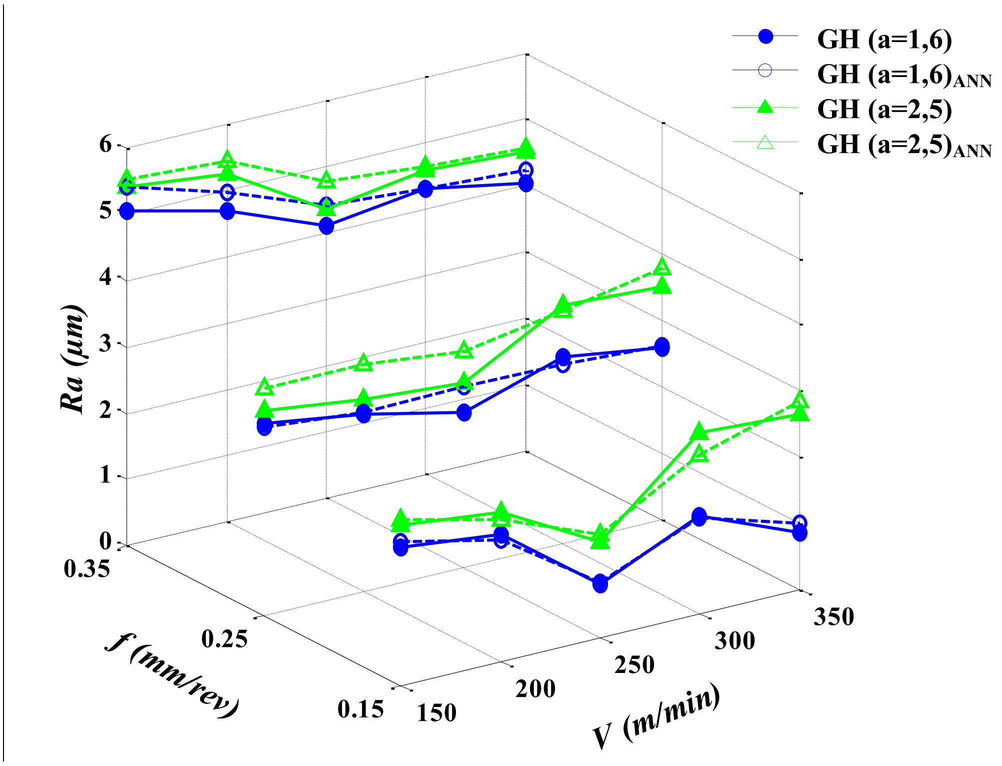


Figure 7. Performance of ANN for chip breaker forms GH (GH Talaş kırıcı formu için ANN performansı)

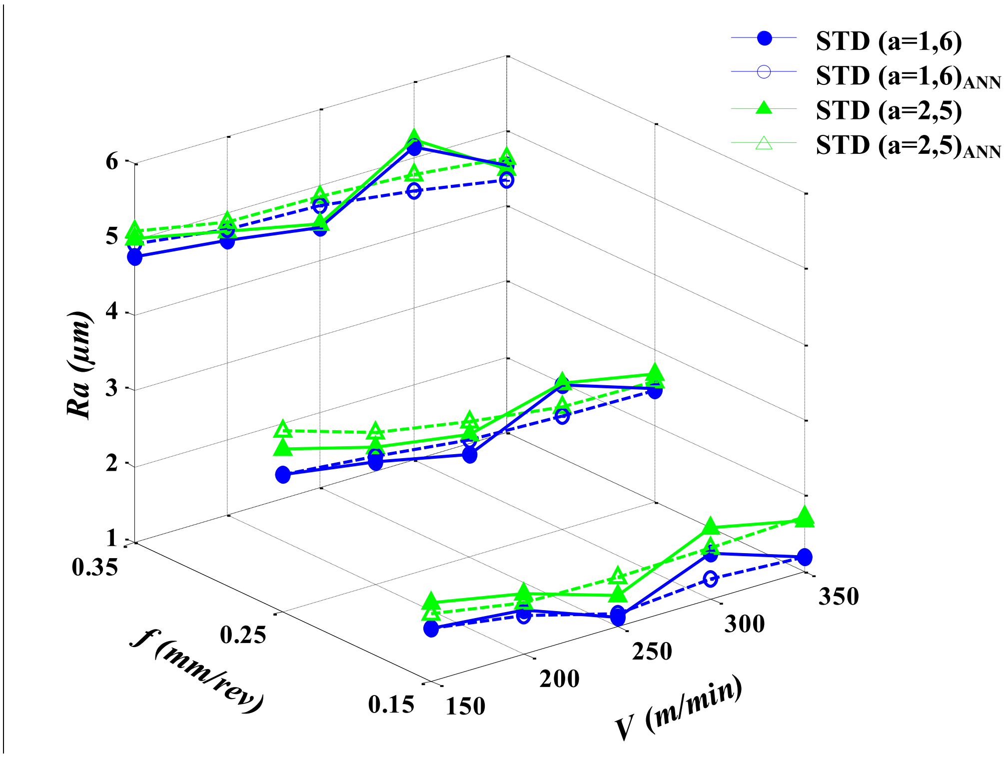


Figure 8. Performance of ANN for chip breaker forms STD (STD Talaş kırıcı formu için ANN performansı)

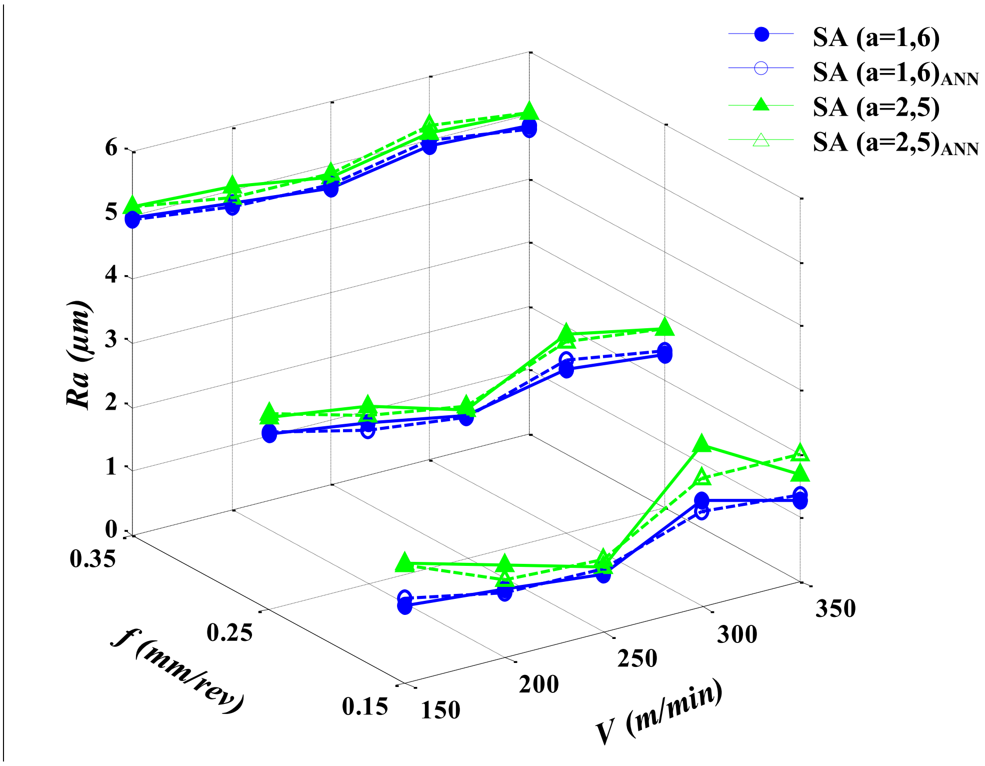


Figure 9. Performance of ANN for chip breaker forms SA (SA Talaş kırıcı formu için ANN performansı)

As the SR values attained by ANN are approximate to the actual values, they cannot be graphically shown together. Accordingly, the following Eq.(8) has been computed as deviation in values, and they have been shown graphically.

$$dSR = \frac{SR_{Measured} - SR_{ANN}}{SR_{Measured}} \qquad (8)$$

In general perspective, according to the results obtained, dSR is in the range of ±10% for all experiments as shown with Figure 10.

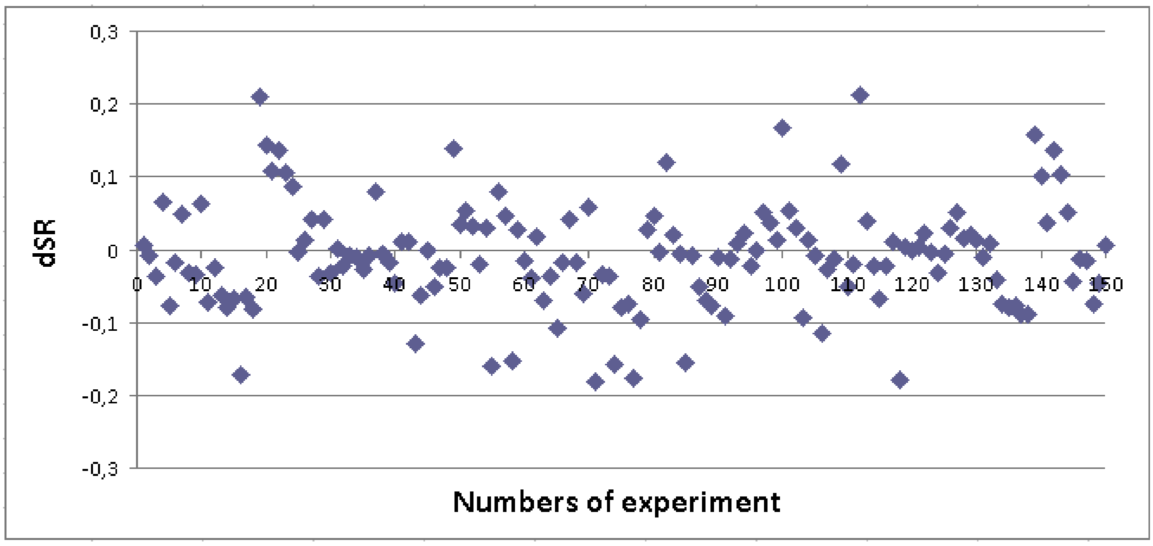


Figure 10. The deviations of surface roughness (Yüzey pürüzlülük sapmaları)

4. CONCLUSIONS (SONUÇLAR)

The results of machining on the AISI 1050 workpiece using different chip breaker forms and the results of artificial neural network (ANN) model of the surface roughness are as follows:

- The surface roughness Ra (µm) values increased with increasing depth of cut and feed rate for all the chip breaker types.
- While improved surface quality was observed by increased cutting speed up to 250 m/min, the surface quality was gotten worsen after 250 m/min.
- Generally, the highest surface roughness values on the chip breaker forms MA, the lowest surface roughness values on the chip breaker forms MS and SA were seen.
- In cutting conditions where cutting speed was 300 m/min, feed rate was 0,35 mm/rev and cutting depth was 2,5 mm, the highest surface roughness values and in cutting conditions where cutting speed was 250 m/min, feed rate was 0,15 mm/rev and cutting depth was 1,6 mm, and the lowest surface roughness values were measured for all chip breaker forms.
- The results of validation and comparative study indicate that the Artificial Neural Networks is based on estimation technique for the surface roughness values.
- A developed chip breaker forms tester with ANN was applied to a commercial cutting tool with different chip breaker forms and various cutting conditions to predict the surface roughness.

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5. REFERENCES (KAYNAKLAR)

1. Palanikumara K., Mata F., Paulo Davim J., “Analysis of surface roughness parameters in turning of FRP tubes by PCD tool”, ***Journal of Materials Processing Technology***, 204: 469-474, (2008)
2. Cakir M.C., Ensarioglu C., Demirayak I., “Mathematical modeling of surface roughness for evaluating the effects of cutting parameters and coating material”, ***Journal of Materials Processing Technology***, 209: 102-109, (2009)
3. Abouelatte O.B., Madl J., “Surface roughness prediction based on cutting parameters and tool vibrations in turning operations”, ***Journal of Materials Processing Technology***, 118: 269-277, (2001)
4. Lin W.S., Lee B.Y., Wu C.L., “Modeling the surface roughness and cutting force for turning”, ***Journal of Materials Processing Technology***, 108: 286-293, (2001)
5. Lalwani D.I., Mehta N.K., Jain P.K., “Experimental investigations of cutting parameters influence on cutting forces and surface roughness in finish hard turning of MDN250 steel”, ***Journal of Materials Processing Technology***, 206: 167-179, (2008)
6. Karataş C., Sozen A., Dulek, E., “Modelling of residual stresses in the shot peened material C-1020 by artificial neural network”, ***Expert Systems with Applications***, 36: 3514-3521, (2009)
7. Zuperl U., Cus F., Mursec B., and Ploj T., “A hybrid analytical-neural network approach to the determination of optimal cutting conditions”, ***Journal of Materials Processing Technology***, 157(158): 82-90, (2004)
8. Özek C., Çelik Y.H., “Calculating molding parameters in plastic injection molds with ANN and developing software”, ***Materials and Manufacturing Processes***, 27(2): 160-168, (2012)
9. Kurt A., “Modelling of the cutting tool stresses in machining of Inconel 718 using artificial neural networks”, ***Expert Systems with Applications***, 36: 9645-9657, (2009)
10. Adam A.C., Hiram A.F., Matthew T.B., Steven Y.L., “Workpiece dynamic analysis and prediction during chatter of turning process”, ***Mechanical Systems and Signal Processing***, 22: 1481-1494, (2008)
11. Jamali A., Nariman-zadeh N., Darvizeh A., Masoumi A., Hamrang S., “Multi-objective evolutionary optimization of polynomial neural networks for modelling and prediction of explosive cutting process”, ***Engineering Applications of Artificial Intelligence***, 22: 676-687, (2009)
12. Kim H.G., Sim J.H., Kweon H.J., “Performance evaluation of chip breaker utilizing neural network”, ***Journal of Materials Processing Technology***, 209: 647-656, (2009)
13. Karayel D., “Prediction and control of surface roughness in CNC lathe using artificial neural network”, ***Journal of Materials Processing Technology***, 209: 3125-3137, (2009)
14. Ezugwua E.O., Fadarea D.A., Bonney J., Da Silva R.B., Sales W.F., “Modelling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network”, ***International Journal of Machine Tools & Manufacture,*** 45: 1375-1385, (2005)
15. Ranganathan S., Senthilvelan T., Sriram G., “Evaluation of machining parameters of hot turning of stainless steel (Type 316) by applying ANN and RSM”, ***Materials and Manufacturing Processes***, 25(10): 1131-1141, (2010)
16. Venkata Rao K., Murthy B.S.N., Mohan Rao N., “Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network”, ***Measurement***, 51: 63–70, (2014)
17. Kumar R., Chauhan S., “Study on surface roughness measurement for turning of Al 7075/10/SiCp and Al 7075 hybrid composites by using response surface methodology (RSM) and artificial neural networking (ANN)”, ***Measurement***, 65: 166–180, (2015)
18. Natarajan C., Muthu S., Karuppuswamy P., “Prediction and analysis of surface roughness characteristics of a non-ferrous material using ANN in CNC turning”, ***Int J Adv Manuf Technol***, 57:1043–1051, (2011)

19. Nalbant M., Gökkaya H., Toktaş İ., Sur G., "The experimental investigation of the effects of uncoated, PVD-and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural Networks", ***Robotics and Computer-Integrated Manufacturing***, 25: 211-223, (2009)
20. Soleimanimehr H., Nategh M.J., Amini S., "Prediction of machining force and surface roughness in ultrasonic vibration-assisted turning using neural networks", ***Advanced Materials Research***, 83(86): 326-334, (2010)
21. Paulo Davim J., Gaitondeb V.N., Karnik S.R., "Investigations into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models", ***Journal of Materials Processing Technology***, 205: 16-23, (2008)
22. Gürbüz H., Şeker U., "The effects of chip breaker forms on the surface quality in turning operations", ***I. National Manufacturing Symposium***, October 2-3, Yıldız Technical University, Istanbul, Turkey, 198-206, (2009)
23. Gürbüz, H., "The Effect on The Cutting Tool Stresses of The Different Chip Breaker Form in Turning", ***MSc. Thesis*** (in Turkish), Gazi University, Institute of Science and Technology, Ankara, Turkey, (2006**)**
24. Mitsubishi Carbide, "Turning tools, Rotating tools, Tooling solutions", ***General Catalogue***, A002-A005, (2005)
25. Mohandes M., Rehman S., Halawani T.O., "Estimation of global solar radiation using artificial neural networks", ***Renewable Energy***, 14(1-4): 179-84, (1998)
26. Jang J.S.R., Sun C.T., Mizutani E., "Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence", ***Prentice-Hall International***, (1997)
27. Sözen A., Özalp M., Arcaklioğlu E., "Investigation of thermodynamic properties of refrigerant/absorbent couples using artificial neural networks", ***Chemical Engineering and Processing***, 43: 1253–1264, (2004)
28. Uluer O., Kırmacı V., Atas Ş., "Using the artificial neural network model for modeling the performance of the counter flow vortex tube", ***Expert Systems with Applications***, 36: 12256–12263, (2009)
29. Boothroyd G., "Fundamentals of metal machining and machine tools", Second edition, ***McGraw-Hill,*** New York, 166-172, (1989)
30. Shaw M.C., "Metal cutting principles", ***Oxford University Press***, London, ISBN 0-19-859002-4, 594, (1984)
31. Çiftçi İ., "The influence of cutting tool coating and cutting Speed on cutting forces and surface roughness in machining of austenitic stainless steels", ***Gazi University Faculty of Engineering and Architecture Journal***, 20(2): 205-209, (2005)
32. Munoz–Escalona P., Cassier Z., "Influence of the critical cutting speed on the surface finish of turned steel", ***Wear***, 218: 103-109, (1998)
33. Thamizhmanii S., Kamarudin K., Rahim E.A., Saparudin A., Hassan S., "Tool wear and surface roughness in turning AISI 8620 using coated ceramic tool". ***Proceedings of the World Congress on Engineering*** (July 2-4), Vol II WCE, London, U.K. (2007)
34. Javidi A., Rieger U., Eichlseder W., "The effect of machining on the surface integrity and fatigue life", ***International Journal of Fatigue***, 30: 2050-2055, (2008)
35. Sozen A., "Future projection of the energy dependency of Turkey using artificial neural network". ***Energy Policy***, 37(11): 4827-4833 (2009)