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Prediction of Cutting Forces Obtained through Cryo-Treated and Untreated Cutting Tools Using Optimum ANN Determined by Taguchi Design[1]

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ABSTRACT

This experimental and statistical study addresses the prediction of cutting forces by using the optimum Artificial Neural Network employed by Taguchi design. For this purpose, input and output transfer function and training algorithm were selected as control parameters, while Mean Square Error was chosen as output parameters for evaluating optimum ANN structure with S/N ratios. ANN structure was optimized through Taguchi L9 orthogonal design, which occurred 5 set-up for utilizing all training function. The results of the prediction values that make the cutting forces optimum for each set-up were compared with each other according to the MSE values of the S/N ratios. For each set, the hidden transfer function, output transfer function and training function used in the optimal ANN structure were determined. The optimal ANN structure for cutting forces obtained in turning experiments were logsig transfer function in hidden layer, Tlm training function and pureline transfer function in output layer, while R square was at 0.999945. It was found that ANN based Taguchi orthogonal design was successful in evaluating the experimental results.

Taguchi Dizayn ile Belirlenen Optimum ANN Kullanarak Kriyojenik İşlem Uygulanmış ve Uygulanmamış Kesici Takımlarla Elde Edilen Kesme Kuvvetlerinin Tahmini

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Bu deneysel ve istatiksel çalışma, Taguchi Dizayn dayalı optimum Yapay Sinir Ağları kullanarak kesme kuvvetlerinin tahminini ele almaktadır. Bu amaçla, S/N oranları ile optimum ANN değerlendirmek için çıkış parametreleri olarak Ortalama Kareleri Hatası seçilirken, kontrol parametreleri olarak ise giriş ve çıkış transfer fonksiyonları ve eğitim fonksiyonları seçilmiştir. ANN yapısı, tüm eğitim fonksiyonlarının uygulanması için 5 setten oluşan Taguchi L9 ortogonal dizilim seçilerek optimize edilmiştir. S/N oranların MSE değerlerine göre, kesme kuvveti değerlerini optimum yapan tahminleri elde etmek için her bir set birbirleri ile karşılaştırılmıştır. Her bir set için optimum ANN yapısında kullanılan gizli ve çıkış katmanlarındaki transfer fonksiyonları ve eğitim fonksiyonları belirlenmiştir. Tornalama deneylerinde elde edilen kesme kuvvetlerini optimum yapan ANN yapısı gizli katmanda transfer fonksiyonu logsig, eğitim fonksiyonu Tlm ve çıkış katmanda transfer fonksiyonu pureline olduğunda R kare değeri 0,999945 bulunmuştur. Deney sonuçları değerlendirildiğinde, Taguchi ortogonal dizilime dayalı ANN yapısı başarılı olduğu bulunmuştur.

1. INTRODUCTION

Cutting forces occurring during machining directly affect cutting performance and unit part cost. For these reasons, cutting forces have attracted constant attention of researchers for years, and many studies have been and are still being conducted. Despite the developments in cutting tool materials, high cutting forces occurring during machining cause cutting tool wear. Therefore, cryogenic process, which provides toughness, hardness and wear resistance for cutting tools, is of great importance. Even though cutting tools withstand high cutting forces thanks to the cryogenic process, analyzing and predicting the values of cutting forces occurring during machining has a crucial place in machining. It is of great importance to precisely determine and analyze all effective cutting forces in order that machining can be long-lasting, high quality, safe and economical. Therefore, in recent years, many studies have been carried out in the literature on the analysis and prediction of cutting forces occurring during the turning process using Artificial Neural Network (ANN) techniques and Taguchi method (Patel and Bhatt, 2018; Gürbüz and Gönülaçar, 2021; Hanief et al., 2017; Madić and Radovanović, 2011; Başak and Baday, 2016; Gürbüz et al., 2016; Sugiono et al., 2012; Özkan et al., 2009; Gurbuz et al., 2012; Ulas and Ozkan, 2019; Yalcin et al., 2013; Baday, 2016; Asilturk et al., 2012; Kara et al., 2015; Çelik and Türkan, 2020; Baday and Ersöz 2020; Jeyakumar et al., 2013; Kurt et al., 2010; Kilickap et al., 2017; Karabulut, 2015). A summary of the studies conducted in the literature is given below:

Patel et al. (2018) applied Taguchi design to optimize a set of parameters for an ANN structure, which was trained with feed forward back-propagation. In ANN structure parameters such as two training algorithm, three transfer functions in the hidden layer, three transfer functions in the output layers, three increment factors, three decrement factors, three learning rates, three momentums and three hidden neurons in the first layer were used. Gürbüz and Gönülaçar (2021) evaluated the cutting forces and surface roughness results obtained by turning using Signal to Noise (S/N) ratios and ANNs. The authors stated that R^2 values obtained by ANN and S/N ratios were quite high to predict the values of the experimental results. Additionally, according to S/N ratios, they found that feed rate, cutting speed and MQL flow rate are the most effective control factors on cutting force and surface roughness. Hanief et al. (2017) studied prediction and modeling of cutting force, which were obtained from turning of red brass, by employing regression analysis and ANN. They found that estimation of the cutting force with ANN construction is much better than that of regression model. Madić et al. (2011) developed optimal selection of ANN and architectural parameters by using Taguchi orthogonal design. They used L18 orthogonal array for training ANN structure and architectural parameters. They determined that Taguchi design optimized the employed ANN structure and achieved high estimation accuracy. Çelik and Türkan (2020) demonstrated the effect of cutting parameters on cutting forces using Taguchi design. They found that the most effective parameter on cutting forces was the feed rate. Additionally, the authors suggested a low feed rate to obtain low cutting forces. Başak and Baday (2016) examined surface roughness and cutting force with analysis of variance (ANOVA) and regression analyses. They stated that according to results of ANOVA feed rate was the most significant cutting parameter on surface roughness; and they obtained R^2 = 94.2%, 94.6% values for surface roughness and cutting force, respectively. Gürbüz et al., (2016) estimated the surface roughness results obtained when turning AISI 1050 steel with different cutting parameters and cutting tools using ANN with empirical equations. The authors found the average error value as 0.018% for R^2, which they used to estimate surface roughness results. Therefore, they stated that the estimated values were within acceptable values. Sugiona (2012) investigated the optimal BPNN architecture based on Taguchi orthogonal design according to mean squared error (MSE) indicator. They used S/N, ANOVA and analysis of mean (ANOM) for identifying Taguchi results. They observed that the trained BPNN, optimized by Taguchi, was used to tackle with uncertain hidden layer parameters. Özkan et al. (2009) investigated the estimation of cutting forces obtained from different cutting parameters during turning operation through using ANN model. They indicated that the implemented ANN model was well matched with prediction of cutting forces. Gürbüz et al., (2012) put forward a new approach based on ANNs to determine the effects of different chip breakers on cutting forces in the turning of AISI 1050. They used the fermi transfer function and backpropagation-learning algorithm in ANN structure. According to trained ANN, they found that R^2 values highly rate to predict the results of cutting forces. Ulas et al. (2019) examined estimation of cutting forces attained during turning AISI 2205 (Duplex) stainless steels, AISI 304 (Austenitic) and AISI 420 (Martensitic) by using ANN model. They established that estimation of cutting force with experimental data and ANN model were well matched with each other. Yalcin et al. (2013) investigated the optimization of cutting parameters with ANN based Taguchi design for surface roughness, cutting force and temperatures in face milling. To train ANN model, they used Taguchi L8 design, which corresponds with eight run experiments. As a result, they found that an effective ANN model was trained. Baday

(2016) employed ANN structure for estimation of cutting forces by using ANN in his study. The cutting forces were obtained during turning of AISI 1050 steel, in which he applied to spheroidization heat treatment in dry condition. ANN structure was utilized in training functions, network type and adaption learning function in Trainlm, Bfgs, Scg, Feed-forward back propagation and Learngd, respectively. In addition, one hidden layer rangeing 10 from 15 neurons was selected to achieve the best R^2 result. Asiltürk et al. (2012) carried out the prediction of cutting forces in turning 4140 steel considering cutting parameters such as cutting speed, feed rate and depth of cut by using ANN structure. They found that the implemented ANN structure had good performance for estimation of cutting forces. Kara et al. (2015) used ANN model in their study to estimate the cutting forces, which are attained from machining of AISI 304 steel. They received input parameters such as cutting speed, feed rate and coating type in ANN model. They determined that the estimation of the values of cutting forces obtained from ANN model and experiments were in good agreement with each other. Baday et al. (2020) performed the prediction of cutting forces by using ANN model in turning of AISI 1050 steel considering cutting parameters and cutting tool conditions, which were cryogenically treated and untreated. They identified that the prediction values of cutting forces obtained from ANN structure during training and experimental values coincide perfectly with the regression lines, which make R^2 = 0.99874 in training. Jeyakumar et al. (2013) studied the effect of machining parameters such as nose radius feed rate, spindle speed and depth of cut on the cutting forces. They estimated cutting forces with response to surface methodology considering machining parameters. They indicated that estimated and experimental values of cutting forces were in good agreement with each other according to the results obtained from response surface methodology. Kurt et al. (2010) applied a mathematical model to estimate the cutting forces. Considering the cutting parameters such as feed rate, depth of cut, cutting speed, and rake angle of the chip breaker of cutting insert, they carried out prediction of cutting forces via using regression analysis, a statistical analysis method. Kilickap et al. (2017) used response surface methodology and ANN model in Milling of Ti-6242S to optimize the tool wear, surface roughness and cutting force. The trained ANN network was selected as Levenberg-Marquardt (LM) and the weights of neuron were trained. They stated that cutting force, surface roughness and tool wear values obtained from RSM and ANN were found to be very close to those of experimental studies. Karabulut (2015) studied the optimization of cutting force and surface roughness during milling of AA7039/Al_2O_3 metal matrix composites by using Taguchi method and ANN. The milling tests were carried out by using Taguchi L18 mixed orthogonal array, which is an experimental design method. According to ANOVA, the effect of machining parameters on the cutting force and surface roughness were identified. He indicated that the feed rate was the most effective factor on cutting force.

As a result of the literature research, analyses and predictions of cutting forces were made by many authors using ANN and Taguchi method (Patel and Bhatt, 2018; Gürbüz and Gönülaçar, 2021; Hanief et al., 2017; Madić and Radovanović, 2011; Başak and Baday, 2016; Gürbüz et al., 2016; Sugiono et al., 2012; Özkan et al., 2009; Gurbuz et al., 2012; Ulas and Ozkan, 2019; Yalcin et al., 2013; Baday, 2016; Asilturk et al., 2012; Kara et al., 2015; Baday and Ersöz 2020; Jeyakumar et al., 2013; Kurt et al., 2010; Kilickap et al., 2017; Karabulut, 2015). Whether the cutting tool used for chip remove is new or worn, it will cause the cutting forces to change. Cutting forces will increase significantly in worn or expired cutting tools. Therefore, the toughness, hardness and wear resistance that the cryogenic process provides for the cutting tool are very important. In this study, unlike the literature, the analysis and prediction of the cutting forces obtained with cryogenically treated cutting tools were carried out using ANN and Taguchi method.

2. DESIGN of EXPERIMENTAL SETUP

2.1. Machining experiment conditions and results

Medium carbon AISI 1050 steel, which is widely used in industry, was used as the workpiece material for the turning experiments. Workpieces are supplied with a diameter of 60 mm. For turning experiments, the outer surfaces and face of the workpieces were turned and then center holes were opened and they were made ready for machining. The cutting parameters used in the turning experiments were determined by taking into account the recommendations of the cutting tool manufacturer and ISO 3685 conditions. Accordingly, cutting parameters in the turning experiments were taken as feed 0.1-0.2 and 0.3 mm/rev, cutting speeds 180, 200 and 220 m/min, and constant depth of cut 2 mm. The cutting parameters used in turning experiments and the values of these parameters are given in Table 1.

Table 1. Cutting parameters

Feed (mm/rev)	0.1 – 0.2 – 0.3
Cutting Speed, V (m/min)	180, 200, 220
Depth of cut, a (mm)	2

The cutting forces and surface roughness results obtained from the turned workpieces depending on the machining conditions and cutting parameters are given in Table 2.

Table 2. Machining parameters, main cutting force and surface roughness values

	Machining parameters			**Experiment Results**	
Exp. No	**Heat Treatment Condition**	**Cutting Speed**	**Feed**	**Main Cutting Force, Fc**	**Surface Roughness, Ra**
1	Cryo-treated	180	0.1	599	0.517
2	Cryo-treated	180	0.2	948	0.967
3	Cryo-treated	180	0.3	1306	1.058
4	Cryo-treated	200	0.1	588	0.563
5	Cryo-treated	200	0.2	933	1.077
6	Cryo-treated	200	0.3	1280	1.123
7	Cryo-treated	220	0.1	577	0.653
8	Cryo-treated	220	0.2	926	1.16
9	Cryo-treated	220	0.3	1255	1.2
10	Untreated	180	0.1	588	0.548

11	Untreated	180	0.2	935	1.057
12	Untreated	180	0.3	1289	1.15
13	Untreated	200	0.1	576	0.62
14	Untreated	200	0.2	925	1.11
15	Untreated	200	0.3	1277	1.257
16	Untreated	220	0.1	566	0.737
17	Untreated	220	0.2	910	1.28
18	Untreated	220	0.3	1247	1.333

The most common ANN structure consists of three layers: input layer, hidden layer and output layer. In this study, input parameters were selected as cutting speed, feed rate and heat treatment condition. Output parameters were selected as main cutting force (Fc). Depending on input parameters, ANN structure was utilized to train the feed forward back propagation. ANN model used in this study is presented in Figure 1. ANN flowchart and data processing method to explain the procedure carried out is given in Figure 2.

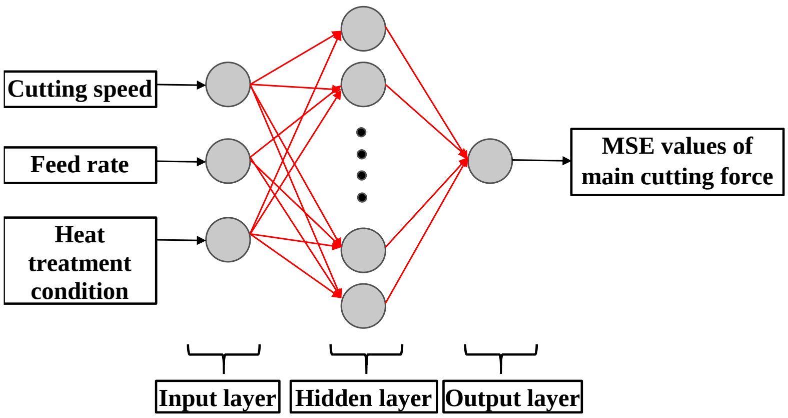

Figure 1. ANN model for experimental values

The main ANN structure in this study consists of three neurons in input layer that represent three control factors (heat treatment condition, cutting speed and feed rate), and one neuron in the output layer that refers to Fc value.

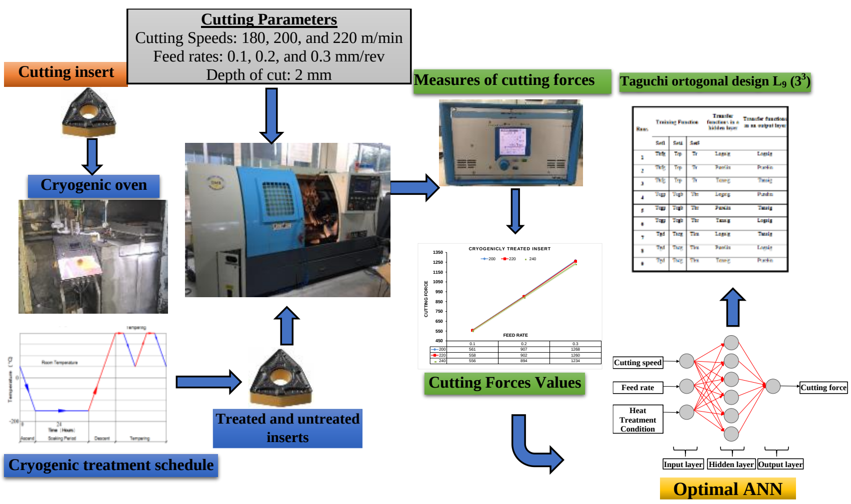

Figure 2. Schematic representation of ANN and experimental setup

In this study, optimal ANN architecture was optimized by Taguchi for robust prediction of Fc. Taguchi design, which is one of experimental design techniques, is used for reducing numbers of experiments. Therefore, it gives manufacturers and designers opportunity to save time. For this purpose, orthogonal and mixed design series were used. Therefore, the researchers chose a lot of variations for this method. Taguchi L9 orthogonal design consists of three control parameters such as input and output transfer functions, which are logsig, tansig and purelin, and training functions, which are train Tbfg, Tcgp, Tgda, Tgdm, Tcgf, Toss, Tgdx, Tlm, Trp, Tcgb, Tscg, Tr, Tbr and Tlm. L9 shows that level numbers of each control parameter are three. Because the number of training functions surpasses three, the training function is divide for 5 set-up for occurring Taguchi orthogonal design. The parameters in each set-up were selected randomly as given in Table 1. Training functions were selected randomly to use in ANN structure. Number of training functions were 14, which were used in Matlab program for training ANN structures, and divided in 5 sets. According to MSE, the assessment of Fc could be reduced when workpieces were machined. Therefore, the bigger was the best choice. The selected training and transfer functions are given in Table 3. The transfer functions in the hidden and output layers were obtained through logsig, purelin and tansig.

Table 3. Taguchi orthogonal design L_9 (3^3)

Runs	Training Function					Transfer functions in a hidden layer	Transfer functions in an output layer
	Set1	Set2	Set3	Set4	Set5		
1	Tbfg	Tgda	Toss	Trp	Tr	Logsig	Logsig
2	Tbfg	Tgda	Toss	Trp	Tr	Purelin	Purelin
3	Tbfg	Tgda	Toss	Trp	Tr	Tansig	Tansig
4	Tcgp	Tgdm	Tgdx	Tcgb	Tbr	Logsig	Purelin
5	Tcgp	Tgdm	Tgdx	Tcgb	Tbr	Purelin	Tansig
6	Tcgp	Tgdm	Tgdx	Tcgb	Tbr	Tansig	Logsig
7	Tgd	Tcgf	Tlm	Tscg	Tlm	Logsig	Tansig
8	Tgd	Tcgf	Tlm	Tscg	Tlm	Purelin	Logsig
9	Tgd	Tcgf	Tlm	Tscg	Tlm	Tansig	Purelin

2.2. The parameters of ANN structure

ANN performance can be explainable to depend on network structure and network training parameters. Both parameters are defined by the trial and error method. This method can be time consuming during the optimal ANN architecture structure. Therefore, the suitable parameter values must be defined experimentally; or, statistical method can be utilized to find the appropriate parameter values. In existing literature, the structure parameters, which affect ANN architecture, are defined and classified into two group as follow. First, ANN learning parameters consist of momentum, increment and decrement factors, and learning rate. Second, ANN architecture parameters contain training functions in hidden and output layers, training functions and number of neurons in all layers, which are input, hidden and output. For determining optimal ANN structure, transfer functions in hidden and output layers and training functions were used; and corresponding levels are given in Table 3.

Learning parameters were taken constantly for better understanding ANN structure. Furthermore, training algorithm, number of neurons were also taken constantly. Input layer consists of cutting conditions whose neurons are for each input parameters (heat treatment condition, cutting speed and feed rate). Output layer corresponds with cutting force having one neuron. Hidden layer have 10 neurons. Transfer functions in hidden and output layers were selected by Taguchi orthogonal design. Furthermore, training function was chosen randomly for forming Taguchi L9 (3^3) orthogonal array. Date set was divided into two parts. One of parts is training and other part is validation. The percentage of training and validation are 70% and %30, respectively.

2.3. Taguchi orthogonal array

Taguchi method is one of the statistical design techniques utilized to identify the relationship between dependent and independent parameters. Taguchi L9 orthogonal design was used to determine optimal ANN architecture. ANN back propagation feed forward network includes three transfer functions, which are tansig, logsig and purelin. Training functions in ANN structure consist of 14, which are employed with Matlab in ANN tools given in Table 3. Taguchi L9 orthogonal array represents three factors corresponding with three levels for each one. Because number of training functions surpassed three levels, training function was divided into five sets for selecting optimal training functions. Therefore, employing orthogonal design is given in Table 4 - Table 6.

Table 4. R^2 values and S/N ratios of the experimental results for Set 1 and Set 2

Runs	Control Factors				Set1		Set2	
	Training function (Set1)	Training function (Set2)	Transfer functions in a hidden layer	Transfer functions in an output layer	R^2	S/N ratio for Fc (dB)	R^2	S/N ratio for Fc (dB)
1	Tbfg	Tgda	Logsig	Logsig	0.993164	-0.059584	0.993956	-0.052657
2	Tbfg	Tgda	Purelin	Purelin	0.994179	-0.050710	0.994405	-0.048738
3	Tbfg	Tgda	Tansig	Tansig	0.984697	-0.133948	0.988268	-0.102501
4	Tcgp	Tgdm	Logsig	Purelin	0.984487	-0.135799	0.977422	-0.198355
5	Tcgp	Tgdm	Purelin	Tansig	0.993844	-0.053633	0.978420	-0.189493
6	Tcgp	Tgdm	Tansig	Logsig	0.997234	-0.024055	0.997161	-0.024690
7	Tgd	Tcgf	Logsig	Tansig	0.982163	-0.156330	0.971279	-0.253116
8	Tgd	Tcgf	Purelin	Logsig	0.997198	-0.024375	0.999944	-0.000485
9	Tgd	Tcgf	Tansig	Purelin	0.984360	-0.136923	0.992351	-0.066693

Taguchi orthogonal design S/N ratio is used to define the quality property of the selected parameters. The properties in the orthogonal design correspond to the lower is the better, the nominal is the better and the higher is the better. For evaluating ANN structure performance, R square value is used. R square value is desired to be nearest to 1. Thus, the higher is the better is chosen for obtaining optimal structure and its equation as follow:

$$S/N = -10log\frac{1}{n}\left(\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \quad (1)$$

In Equation 1, y_i; the measured values for Fc, n; the number of experiments, $\overline{y}$; the mean of the test results and s; standard deviation of the experimental results (Gürbüz and Baday, 2022). MSE value was desired to be close to 1 so that in this study, S/N ratio was selected the bigger is the best for choosing optimal ANN structure. The applications of ANN have been become widespread and utilized in a great number of fields such as image processing, pattern recognitions, automation and control. These applications use back propagate feed forward ANN architecture structure. The back propagate feed forward neural network, which includes multilayer properties, is the most commonly employed one in estimation.

Table 5. R^2 values and S/N ratios of the experimental results for Set 3 and Set 4

Runs	Control Factors				Set3		Set4	
	Training function (Set3)	**Training function (Set4)**	**Transfer functions in a hidden layer**	**Transfer functions in an output layer**	**R^2**	**S/N ratio for Fc (dB)**	**R^2**	**S/N ratio for Fc (dB)**
1	Toss	Trp	Logsig	Logsig	0.994325	-0.049437	0.996671	-0.028967
2	Toss	Trp	Purelin	Purelin	0.994290	-0.049736	0.994138	-0.051070
3	Toss	Trp	Tansig	Tansig	0.994605	-0.046985	0.984185	-0.138468
4	Tgdx	Tcgb	Logsig	Purelin	0.977896	-0.194149	0.984286	-0.137574
5	Tgdx	Tcgb	Purelin	Tansig	0.974126	-0.227696	0.993684	-0.055038
6	Tgdx	Tcgb	Tansig	Logsig	0.996550	-0.030018	0.997690	-0.020083
7	Tlm	Tscg	Logsig	Tansig	0.996798	-0.027857	0.991737	-0.072070
8	Tlm	Tscg	Purelin	Logsig	0.993448	-0.057096	0.996576	-0.029796
9	Tlm	Tscg	Tansig	Purelin	0.981512	-0.162085	0.982549	-0.152915

Table 6. R^2 values and S/N ratios of the experimental results for Set 5

Runs	Control Factor			Set5	
	Training function (Set5)	**Transfer functions in a hidden layer**	**Transfer functions in an output layer**	**R^2**	**S/N ratio for Fc (dB)**
1	Tr	Logsig	Logsig	0.994634	-0.046734
2	Tr	Purelin	Purelin	0.994194	-0.050580
3	Tr	Tansig	Tansig	0.991156	-0.077163
4	Tbr	Logsig	Purelin	0.995904	-0.035650
5	Tbr	Purelin	Tansig	0.995265	-0.041224
6	Tbr	Tansig	Logsig	0.999415	-0.005086
7	Tlm	Logsig	Tansig	0.987178	-0.112090
8	Tlm	Purelin	Logsig	0.999945	-0.000475
9	Tlm	Tansig	Purelin	0.991886	-0.070764

3. RESULTS and DISCUSSION

The results of employed ANN based Taguchi orthogonal design are given in Table 4 – Table 6. When R^2 values in Table 4 - Table 6 are examined, R^2 values are found to estimate the cutting forces to be close to 1. Therefore, these R^2 results show that they are statistically significant. The fact that R square is close to 1 shows that it is successful in predicting cutting forces. Graphs of S/N ratios calculated according to R^2 values for Set 1 – Set 5 are given in Figure 3 - Figure 7. The optimal ANN structure for giving the best prediction of cutting force was calculated according to MSE. S/N ratio graph obtained for Set 1 R square values is given in Figure 3. When Figure 3 was examined, it was seen that optimal ANN structure has "Purelin" hidden transfer function, "Logsig" output transfer function and "Tcgp" training function for Set1.

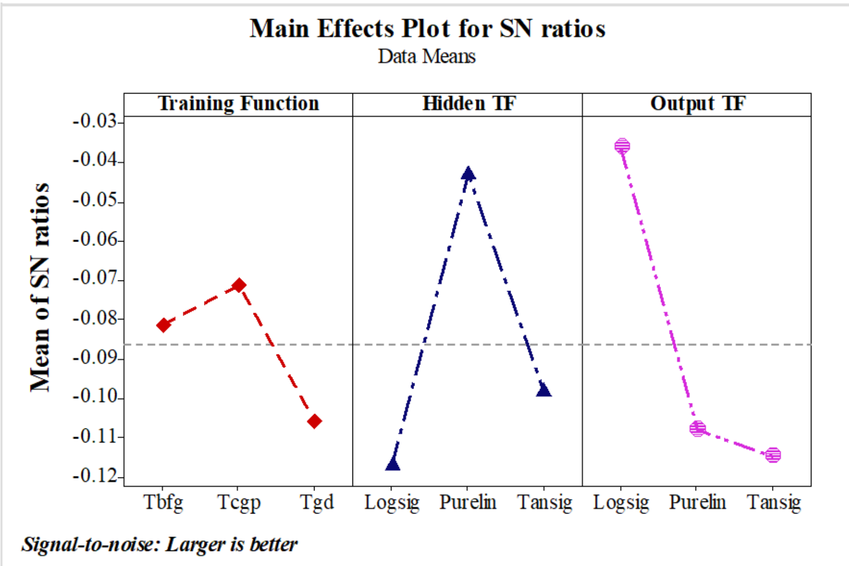

Figure 3. S/N ratios of the experimental results for Set 1.

The S/N ratio graph obtained for Set 2 R square values is given in Figure 4. When Figure 4 was analyzed, it was seen that optimal ANN parameters for Set 2 were "Tgda" training function, "Tansig" transfer function in hidden layer and "Logsig" transfer function in output layer.

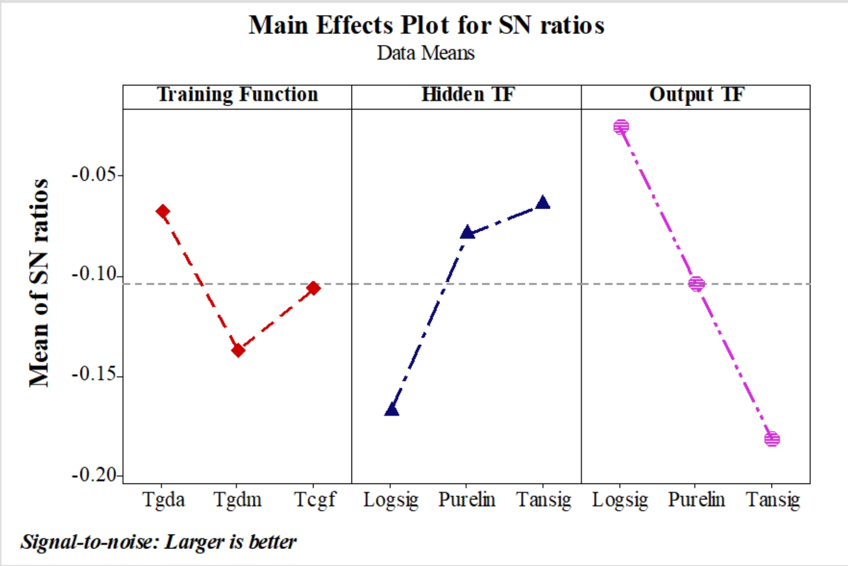

Figure 4. S/N ratios of the experimental results for Set 2

The S/N ratio graph obtained for Set 3 R square values is shown in Figure 5. When Figure 3 was examined, it was seen that optimal ANN parameters for Set 3 were “Toss” training function, “Tansig” transfer function in hidden layer, and “Logsig” transfer function in output layer.

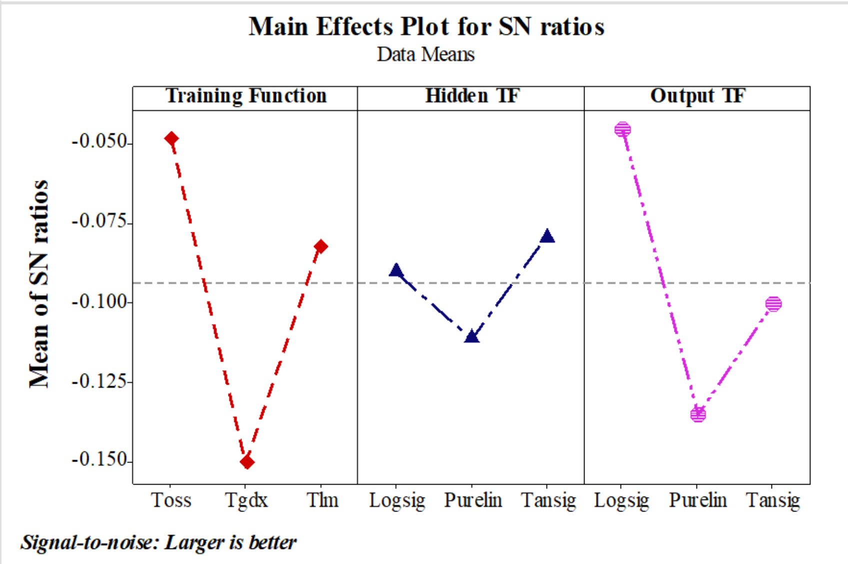

Figure 5. S/N ratios of the experimental results for Set 3

The S/N ratio graph obtained for Set 4 R square values is given in Figure 6. When Figure 6 was examined, it was seen that optimal ANN structure has “Tcgb” training function, “Purelin” transfer function in hidden layer, and “Logsig” transfer function in output layer.

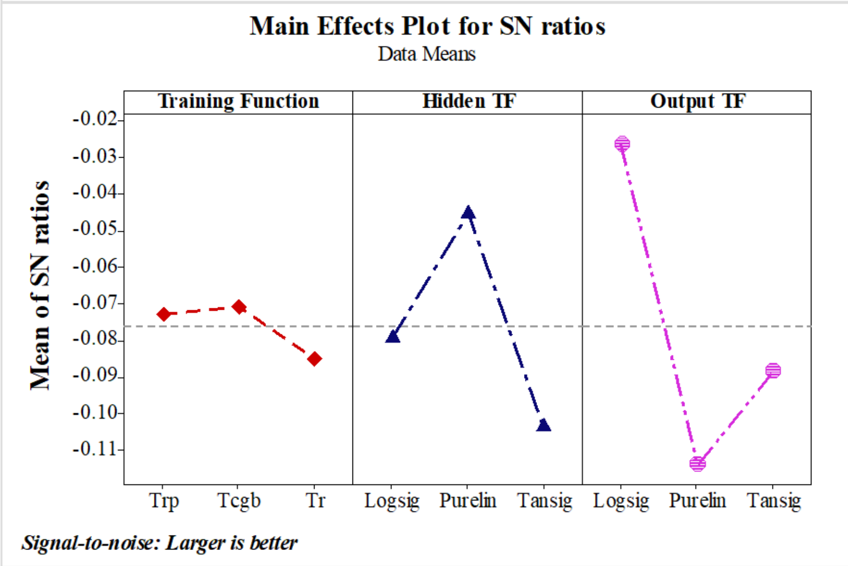

Figure 6. S/N ratios of the experimental results for Set 4

The S/N ratio graph obtained for Set 5 R square values is given in Figure 7. When Figure 7 was analyzed, it was seen that optimal ANN parameters for Set 5 were "Tbr" training function, "Purelin" transfer function in hidden layer, and "Logsig" transfer function in output layer.

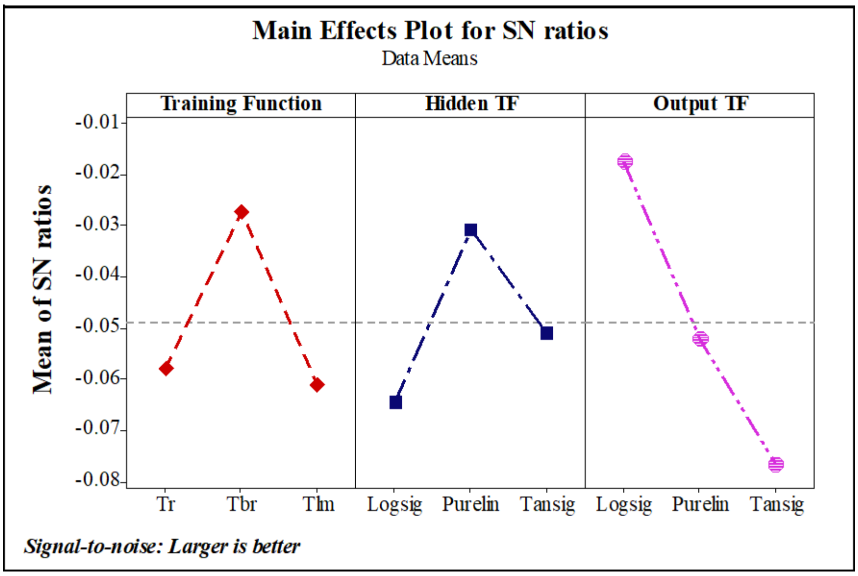

Figure 7. S/N ratios of the experimental results for Set 5

4. CONCLUSION

This present study addresses the selection of optimal ANN structure based Taguchi orthogonal design for predicting cutting forces. Taguchi L9 orthogonal array method was utilized for better comprehensive Fc value. ANN structure was optimized with 5 sets to select best training function and transfer function in hidden and output layers. The obtained results are given as follow:

- For cutting force results, S/N ratios were determined using Taguchi orthogonal design L9.
- For each set, the hidden transfer function, output transfer function and training function used in the optimal ANN structure were determined.

- R square value used to estimate the cutting force values resulting from turning experiments was close to 1. The fact that R square is close to 1 indicates that ANN is successful in predicting cutting forces.
- According to Taguchi S/N ratios that give the optimal ANN value, it was determined that the ANN parameters that give the highest R square value for the training function, input layer and output layer are Tlm, Purelin and Logsig, respectively.
- It was found that ANN based Taguchi orthogonal array was successful in evaluating the experimental results obtained because of machining experiments.

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