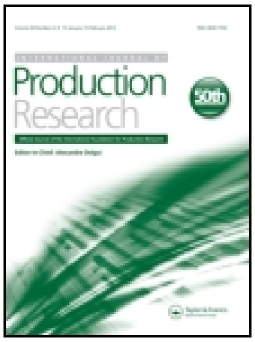

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Umit Yalcin , Aslan Deniz Karaoglan & Ihsan Korkut

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Optimization of Cutting Parameters in Face Milling with Neural Networks and Taguchi based on Cutting Force, Surface Roughness and Temperatures

Umit Yalcin[a], Aslan Deniz Karaoglan[b]* and Ihsan Korkut[c]

[a]*Machinery and Metal Technology Program, Balikesir University, 10145, Balikesir, TURKEY;* [b]*Department of Industrial Engineering, Balikesir University, 10145, Balikesir, TURKEY;* [c]*Department of Manufacturing Engineering, Faculty of Technology, Gazi University, 06100, Ankara, TURKEY*

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Prediction of cutting parameters as a function of cutting force, surface roughness and cutting temperature is very important in face milling operations. In the present study, the effect of cutting parameters on the mentioned responses were investigated by using artificial neural networks (ANN) which were trained by using experimental results obtained from Taguchi's L8 orthogonal design. The experimental results are compared with the results predicted by ANN and the Taguchi method. By training the ANN with the results of experiments which are corresponding with the Taguchi L8 design, with only eight experiments an effective ANN model is trained. By using this network model the other combinations of experiments which did not perform previously, could be predicted with acceptable error.

Keywords: face milling; artificial neural networks; Taguchi; prediction

1. Introduction

The importance of low cost, high quality products and shortened manufacturing time is undisputed in industrial applications. Improved computer numerical control (CNC) technologies are capable of achieving high accuracy and very short processing times. As well as cutting tool and machine tool capabilities, cutting parameters are also effective in achieving these goals. Face milling is a common machining method in most industrial applications and much research has been done to determine the cutting parameters for material/tool duo. Output measurements (responses), namely cutting forces, surface roughness or tool wear, are investigated widely in the literature (Altıntas 2000; Aykut et al. 2007; Bernardos and Vosniakos 2002; Escalona and Maropoulos 2010; Ghosh et al. 2007; Kaya, Oysu, and Ertunc 2011). Neural networks are used for prediction and optimisation of cutting parameters in milling operations to obtain desired responses such as cutting force, surface roughness and tool wear in recent years.

It is clear that the prediction of cutting parameters as a function of cutting force, surface roughness and cutting temperatures is very important. One of the resultant phenomenon of the cutting parameters is cutting force. Influence of the machining conditions on cutting forces for milling was investigated by Aykut et al. (2007) and Kaya, Oysu, and Ertunc (2011). The cutting tests were carried out under dry conditions using uncoated inserts. In the study presented by Aykut et al. (2007), feed-forward back-propagation neural network was used for modelling the effects of machinability on chip removal cutting parameters for face milling of stellite 6 in asymmetric milling processes. Cutting forces with three dimensions were predicted by changing cutting speed (Vc), feed rate (f) and depth of cut (ap) under dry conditions.

Other indicator of the quality of machining is surface roughness. Saglam and Unuvar (2003) used feed-forward back-propagation neural network (NN) for tool condition monitoring in face milling and evaluated against cutting force data. NN was used for feature selection in order to estimate flank wear (Vb) and surface roughness (Ra) during the milling operation. Cutting speed, feed rate, depth of cut and two cutting force components are used as cutting parameters. Bajic, Lela, and Zivkovic (2008) examined the influence of cutting parameters on surface roughness in face milling by using NNs. Cutting speed, feed rate and depth of cut factors are used as the predictor of the surface roughness. El-Sonbaty et al. (2008) used feed-forward back-propagation neural network for the analysis and prediction of the relationship between the cutting conditions and the corresponding fractal parameters of machined surfaces in face milling operation to determine the appropriate cutting conditions, in order to achieve specific surface roughness profile geometry, and hence achieve the desired tribological performance (e.g. friction and wear) between the contacting

*Corresponding author. Email: deniz@balikesir.edu.tr

surfaces. The input parameters of the artificial neural network (ANN) models were the cutting parameters such as rotational speed, feed, depth of cut, pre-tool flank wear and vibration level. The output parameters of the model were the corresponding calculated fractal parameters such as fractal dimension 'D' and vertical scaling parameter 'G'. Lela, Bajic, and Jozic (2009) examined the influence of cutting speed, feed, and depth of cut on surface roughness in face milling process by using support vector machines (SVM), and Bayesian neural network (BNN) and searched the influence of cutting parameters on surface roughness. The prediction of surface roughness at face milling with ANNs has also been investigated by Munoz-Escalona and Maropoulos (2010). They developed different ANN; they selected radial base neural networks (RBNN), feed forward back propagation neural networks (FF-BP NN) and generalised regression neural networks (GRNN) for the prediction of surface roughness (Ra) and the data used for training these networks were derived from experiments conducted using a high-speed milling machine. They applied the Taguchi method which is the well-known design of experiment technique that is used to reduce the time and cost of experiments. They observed that FF-BP NN is achieving the best results. They used five inputs (cutting speed, feed per tooth, axial depth of cut, chip width and chip thickness) and concluded that strong correlation between chip thickness and the surface roughness followed by the cutting speed. Gan, Huang, and Zheng (2010) developed least squares support vector machines (LS-SVM) for the analysis and prediction of the relationship between the cutting conditions and the corresponding fractal parameters of machined surfaces in face milling operations in order to achieve specific surface roughness profile geometry, and hence achieve the desired tribological performance (e.g. friction and wear) between the contacting surfaces. The input parameters of the LS-SVM were the cutting parameters such as rotational speed, feed, and depth of milling. The output parameters of the LS-SVM were the corresponding calculated fractal parameters: fractal dimension 'D' and vertical scaling parameter 'G'. Razfar et al. (2010a) proposed a new approach for determination of the optimal cutting parameters to obtain minimum surface roughness in face milling of X20Cr13 stainless steel by coupling feed forward artificial neural network and the harmony search (HS) algorithm to obtain minimum surface roughness. Razfar et al. (2010b) presented an approach to the determination of the optimal cutting parameters to create minimum surface roughness levels in the face milling of X20Cr13 stainless steel. The proposed approach is to use a particle swarm optimisation (PSO)-based neural network to create a predictive model for the surface roughness level that is based on experimental data collected on X20Cr13. The optimisation problem is then solved by using a PSO-based neural network for optimisation system. In the following year Razfar et al. (2011) presented a new approach to determine the optimal cutting parameters leading to minimum surface roughness in face milling of X20Cr13 stainless steel by coupling FF BP-NN artificial neural network and HS algorithm.

Since cutting forces are directly related to increase of cutting speed, cutting speed is a parameter that directly affects tool life (Altintas 2000). Other types of literature are about the estimation of tool wear using neural networks. Lin and Lin (1996) used NN to identify the tool wear conditions by using the inputs the mean values of cutting forces, feed rate, and work piece geometry. The NN is trained to estimate the average flank wear on cutter inserts. Ghosh et al. (2007) proposed to develop a NN-based sensor fusion model for tool condition monitoring (TCM). Some features extracted from a number of machining zone signals, namely cutting forces, spindle vibration, spindle current, and sound pressure level had been fused to estimate the average flank wear of the main cutting edge. As a conclusion cutting force signals features predict tool wear fairly well.

Cutting temperature is also importance. When the literature is reviewed, it is observed that the cutting forces, surface roughness and especially the temperature are not searched for the cut depth, feed rate, cutting speed, and coolant factors together. This observation has been the motivation for the present work.

The remaining sections are organised as follows. Section 2 describes the materials and methods. The experimental design and FF BP-NN model analysis with an illustrative example are given in Sections 3 and 4, respectively. Discussions on the results and conclusions are pointed out in Sections 5 and 6.

2. Materials and methods

In this study, the effect of cutting parameters (cut depth, feed rate, cutting speed and coolant) on cutting force, surface roughness and cutting temperature were investigated. Johnford VMC 850 CNC Machining Centre was used to perform these experiments. Work piece dimension, tool diameter and geometry selection were made by considering ISO 8688 tool life testing in milling Part 1 standards. Cutting parameters and the properties of tools and work pieces used in these experiments are given in Table 1. Optimum milling parameters were selected according to catalogue values for tool supplier's document.

For the force measurements Kistler 9257B 3-Component Dynamometer and Kistler 5070A Amplifier were used as shown in Figure 1. In this setup, a fixture is designed to support the work pieces to dynamometer using M8 at 8 point.

Table 1. Experimental conditions.

Work piece	SAE 1050 (AISI 1050)							
Chemical composition (%)	C	Si	Mn	Cr	P	S	Mo	N
	0.49	0.19	0.65	0.03	0.01	0.005	0.01	0.08
Dimensions (mm)	75 × 375 × 20							
Tool holder	AFR 75 0125 12 R06 4 0, Dia 125 mm, 6 teeth							
Insert	Bohler SPKN 1203 SBF							
Cutting parameters								
Cut depth (mm)	1.25 – 2							
Feed rate (mm/teeth)	0.05 – 0.1							
Cutting speed (m/min)	100 – 130							
Coolant	Dry – wet							
Coolant	Rocol ultracut 390H, 20.6 °C, Ph 10.10							

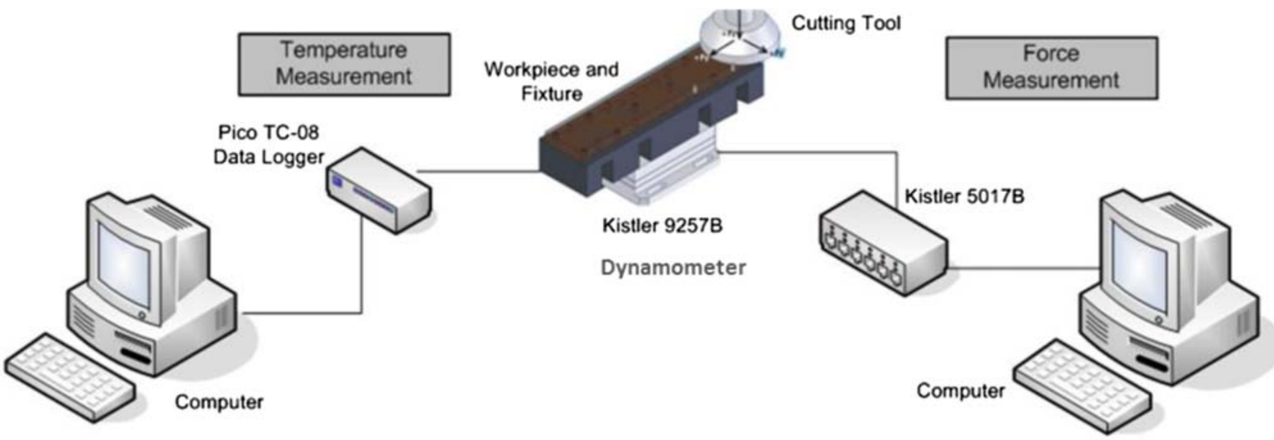

Figure 1. Experimental setup used for force and temperature measurements.

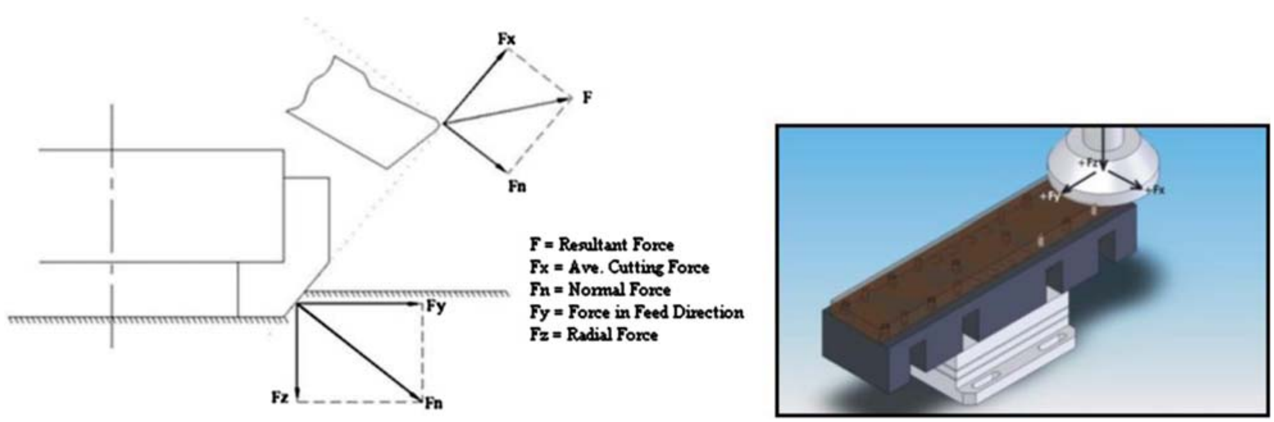

Figure 2. Schematic representations of the force directions.

The directions of cutting forces are shown in Figure 2. Based on these configuration, the resultant force and normal force will be given as $F = \sqrt{F_n^2 + F_x^2}$ and $F_n = \sqrt{F_y^2 + F_z^2}$, respectively. Temperatures are recorded with 1 ms period using Pico TC-08 and Picolog Recorder Software. The values of temperatures are calculated by taking the average value of eight thermocouples for each experimental runs. Mahr Perthometer type M1is used for surface roughness measure-

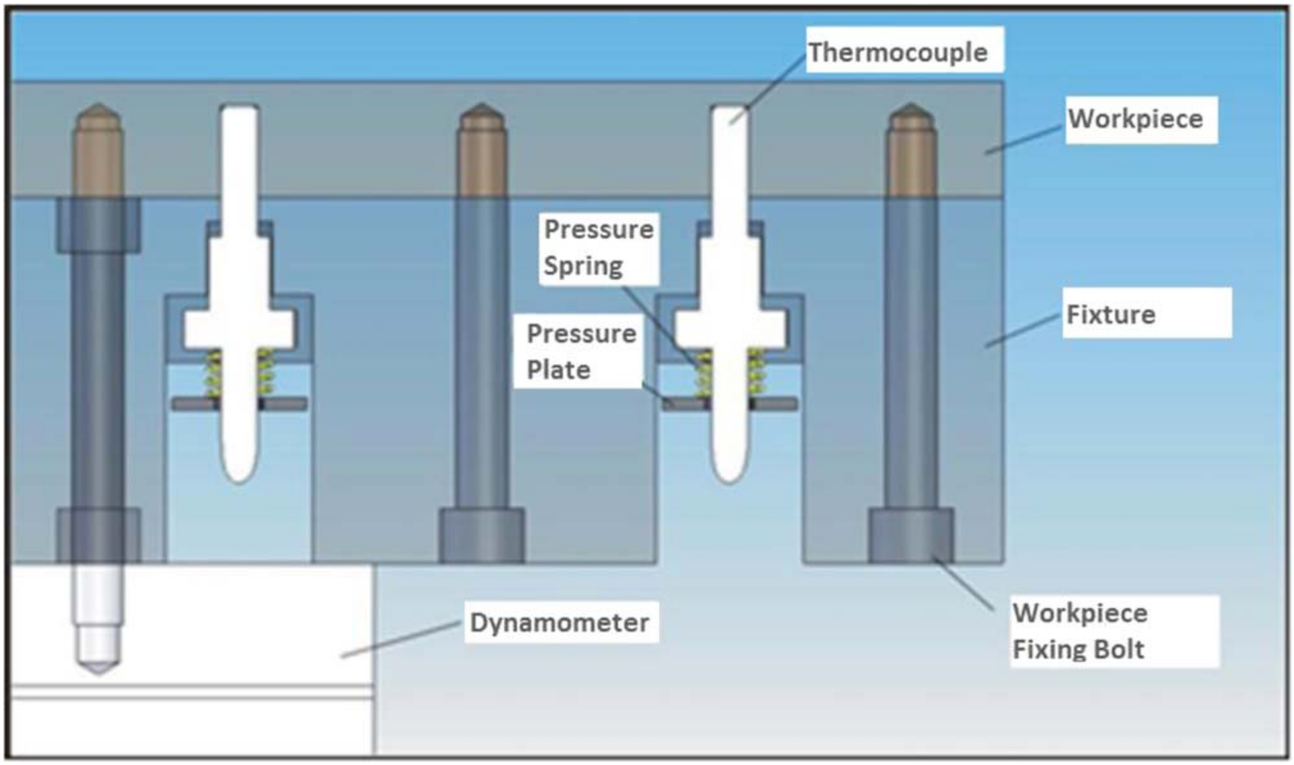

Figure 3. Connection of thermocouples.

ment (measures R_a in μm, stylus travel 0.8 mm, traversing speed 0.5 mm/s). Cutting forces are also recorded to another computer using 8 channel 5017B Amplifier and 9257B Dynometer via DynaWare software (Figure 1).

The experiments were carried out for eight samples in total that correspond to different cutting parameters. It has been well known that relative positions of tool and work piece have an important effect on the output of the face milling operations. Since the tool wear is more crucial than the tool chipping and breakage for tool life the relative positions of tools and work pieces are applied symmetrically in our experiment. Figure 3 shows the assembly method of thermocouples to the work pieces. The depth of holes for thermocouples should be the same in all eight to take the precise measurements. The pressure plate and spring is used to continuously press the thermocouples to the work piece.

3. Experimental design

In this study, four factors (i) cut depth, (ii) feed rate, (iii) cutting speed and (iv) coolant, and two control levels for each control factor were considered, as shown in Table 2. The experiments performed in the present study are not only a time consuming experiment but also cost minimisation in another aspect. As is well known in the literature, the Taguchi method requires less experiment when compared with response surface methodology (RSM) or another design of experiment (DOE) techniques. Another reason for using the Taguchi method is having string factors in the system such as coolant (factor levels: dry or wet). RSM depends on matrix multiplications and can produce optimum solutions with decimals. So RSM is not an appropriate method for the given problem presented in this study. Additionally RSM required a minimum of 30 experiments (for central composite design for four factors) for our problem. Factorial design may be used instead of RSM, but the type of systems shown in the present study may reveal quadratic relations between the factors and factorial design which is not appropriate for this type of problem. Briefly, the Taguchi analysis requires less experiments (this is required for cost and time consuming) for our problem and this method seems more appropriate when it is compared with other commonly used design of experiment techniques (Castillo 2007; Giesbrecht and Gumpertz 2004; Mason, Gunst, and Hess 2003; Montgomery 2001; Roy 2001). Required degrees of freedom to determine the appropriate orthogonal array for Taguchi Design are displayed in Table 3.

The Taguchi method (and other orthogonal arrays) may be used to train small ANN very quickly in a variety of tasks and they could be successfully used to train single layer networks with no difficulty. However, interactions

Table 2. List of actual and corresponding coded values of control factors and their levels.

Factors	Level	
	−1	1
Cut depth (mm)	1.25	2.00
Feed rate (mm/teeth)	0.05	0.10
Cutting Speed (m/min)	100	130
Coolant	Wet	Dry

Table 3. Required degrees of freedom.

Factors	Degrees of freedom
Cut depth	1
Feed rate	1
Cutting speed	1
Coolant	1
Total	4

Table 4. Taguchi L8 (2^4) orthogonal array.

Experiment number	Factors			
	Cut depth	Feed rate	Cutting speed	Coolant
1	−1	−1	−1	−1
2	−1	−1	−1	1
3	−1	1	1	−1
4	−1	1	1	1
5	1	−1	1	−1
6	1	−1	1	1
7	1	1	−1	−1
8	1	1	−1	1

between factors precluded the successful reliable training of multi-layered networks (Viswanathan et al. 2005). The present study is aimed at training ANN with a minimum number of experimental inputs (for time and cost saving) and comparing the results of ANN with the results obtained from Taguchi for the same experimental design for performance comparison. If the possible first order interactions between the main factors are not considered, degrees of freedom are calculated according to Table 3. The calculated degree of freedom is four. But for four factor, two level design, Taguchi analysis required a minimum of eight experiments. So the closer design to the calculated degrees of freedom with minimum number of experiments is L8 which requires only eight experiments. To reduce the number of tests, an L8 (2^4) orthogonal array that only needs eight experimental runs was adopted. The minimum total degrees of freedom required are four and they are listed in Table 3. As a result, an L8 (2^4) orthogonal array, which has four degrees of freedom with two levels is the most suitable one. The orthogonal array can be seen in Table 4, the physical experimental layout is shown in Table 5.

4. FF BP-ANN model analysis

At the base of the Taguchi analysis, a feed forward back propagation artificial neural network (FF BP-ANN) was employed for the training, simulating and predicting by using MATLAB (see Ham and Kostanic, 2001 for details of FF BP-ANN topology). Input matrix is calculated by dividing each column of results that are given in Table 5 to maximum value of its each column, and by this way all the results became smaller than 1 and normalised. Preliminary investigations are conducted to choose a suitable network topology and training algorithm for MLP. According to the experimental design performed for investigating the appropriate network topology of MLP network, the design parameters for number of hidden layers (from 1 to 3 increasing one by one), number of neurons at each layer (from 2 to 12 increasing

Table 5. Physical layout for the experiments and experimental results.

	Factors				Results		
Experiment number	Cut depth	Feed rate	Cutting speed	Coolant	Cutting force (Newton)	Surface roughness (R_a in μm)	Cutting temperature (°C)
1	1.25	0.05	100	Wet	814	0.486	220
2	1.25	0.05	100	Dry	890	0.549	270
3	1.25	0.1	130	Wet	1186	1.618	299
4	1.25	0.1	130	Dry	1159	1.734	339
5	2	0.05	130	Wet	1146	0.983	294
6	2	0.05	130	Dry	1418	2.096	299
7	2	0.1	100	Wet	2170	1.142	303
8	2	0.1	100	Dry	1850	1.8	305

two by two), type of activation function (purelin, tansig, logsig), learning rates (from 0.001 to 0.01 increasing with step size 0.0009) and momentum constants (from 0.2 to 0.9 increasing with step size 0.1) are used. The performance measurement is determined as mean square error (mse) and 0.001 is the target mse value. If this performance goal is not met then maximum 250,000 iterations will be performed and mse will be plotted for every 500 iterations. The training was stopped whenever either the error goal has been achieved or the maximum allowable number of training epochs has been met. The mse result of each parameter combination (in total 3780 combinations) is recorded to a matrix that is defined in MATLAB. Experimental runs are carried out to determine the mse for each combination of parameters serially. The parameter combination that gives the minimum mse is selected from the records as optimum training parameters. Minimum mse is reached for network with two hidden layers each have eight neurons with tansig activation function and momentum constant: 0.8, learning rate 0.0028 are found as the optimum training parameters. The network is trained by using the programme codes of Matlab that are given below.

```
P0=[−1 −1 −1 −1; −1 −1 −1 1; −1 1 1 −1; −1 1 1 1; 1 −1 1 −1; 1 −1 1 1; 1 1 −1 −1; 1 1 −1 1]; %Outputs
T=P0’;
Tpre = [0.375115207 0.231870229 0.648967552; 0.410138249 0.261927481 0.796460177; 0.546543779 0.771946565 0.8820059; 0.534101382 0.827290076 1; 0.528110599 0.46898855 0.867256637; 0.653456221 1 0.8820059; 1 0.544847328 0.89380531; 0.852534562 0.858778626 0.899705015]; %Inputs
P = Tpre’;
[Pn,minP,maxP,tn,minT,maxT] = premnmx(P,T);
[S0,Q] = sise(P);
S1 = 8; S2 = 8; S3 = 4;
Net = newff(minmax(P),[S1,S2,S3],{‘tansig’,‘tansig’,‘tansig’},‘traingd’);
net.trainParam.epochs = 250,000;
net.trainParam.goal = 0.001;
net.trainParam.mc = 0.80;
net.trainParam.show = 500;
net.trainParam.lr = 0.0028;
[net,tr] = train(net,P,T);
save TrainedMLP net
```

The training performance of the given network is presented in Figure 4. It is clearly observed from Figure 4 that the goal of 0.1% error is reached at 210,436 epochs.

Results of the ANN predictions with training data set are listed in Table 6 and their rounded and rearranged forms are given in parenthesis with bold.

It is clearly observed from Table 6 that the memorisation capability of the net is good enough for the training data set. The trained network model was then tested using three experimental data points (check data) which were not used in the training process. After performing these three experiments, for the results of experiments, input factors are predicted from the ANN model. The results predicted from the ANN model are compared with those obtained by experiments in Table 7 and Table 8 for three sets of check data.

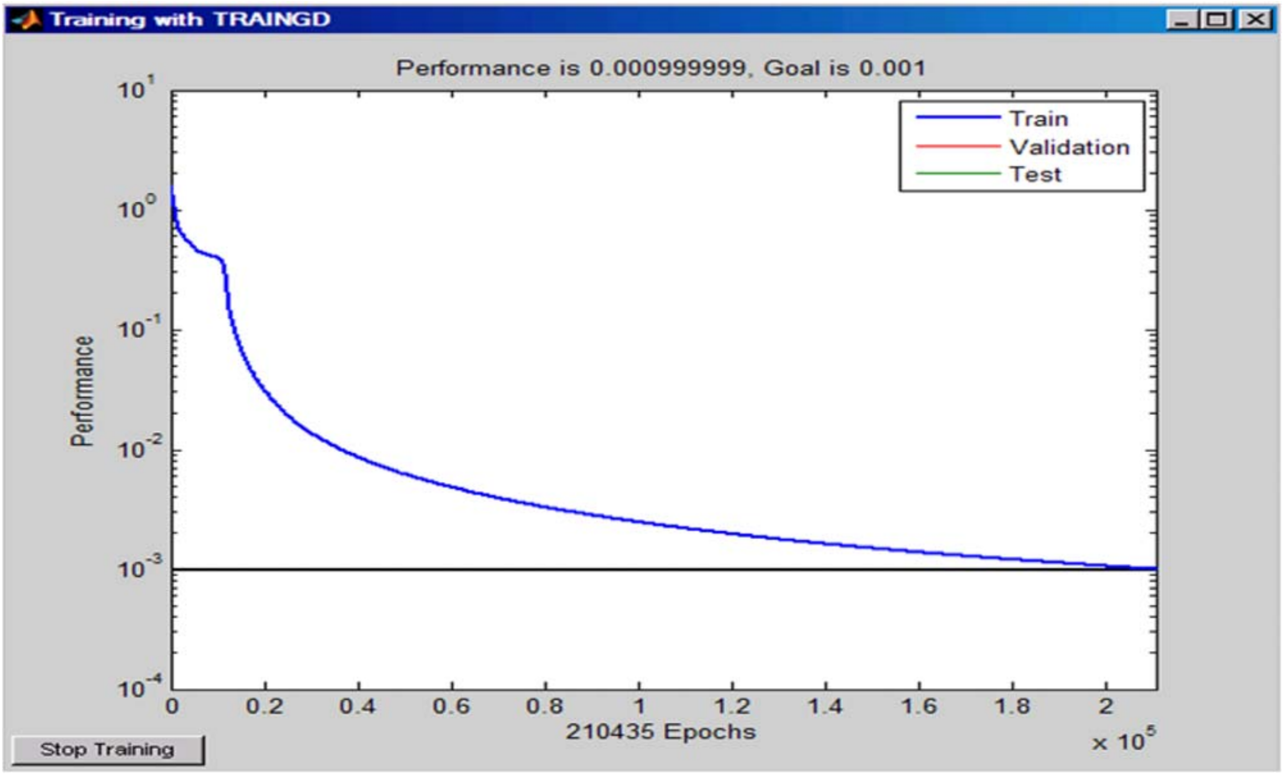

Figure 4. Training performance of the neural network.

Table 6. List of ANN predictions with training data set.

	Results			ANN prediction for input factor levels			
Experiment number	Cutting force	Surface roughness	Cutting temperature	Cut depth	Feed rate	Cutting speed	Coolant
1	0.375115207	0.231870229	0.648967552	−0.9902 **(−1)**	−0.9730 **(−1)**	−0.9786 **(−1)**	−0.9817 **(−1)**
2	0.410138249	0.261927481	0.796460177	−0.9714 **(−1)**	−0.9951 **(−1)**	−0.9746 **(−1)**	0.9700 **(1)**
3	0.546543779	0.771946565	0.8820059	−0.9687 **(−1)**	0.9847 **(1)**	0.9749 **(1)**	−0.9682 **(−1)**
4	0.534101382	0.827290076	1	−0.9535 **(−1)**	0.9481 **(1)**	0.9762 **(1)**	0.9442 **(1)**
5	0.528110599	0.46898855	0.867256637	0.9545 **(1)**	−0.9462 **(−1)**	0.9704 **(1)**	−0.9494 **(−1)**
6	0.653456221	1	0.8820059	0.9608 **(1)**	−0.9633 **(−1)**	0.9715 **(1)**	0.9963 **(1)**
7	1	0.544847328	0.89380531	0.9939 **(1)**	0.9722 **(1)**	−0.9813 **(−1)**	−1.0000 **(−1)**
8	0.852534562	0.858778626	0.899705015	0.9718 **(1)**	0.9768 **(1)**	−0.9572 **(−1)**	0.9873 **(1)**

Table 7. Check data set.

	Factors				Experimental results		
Experiment number	Cut depth	Feed rate	Cutting speed	Coolant	Cutting force	Surface roughness	Cutting temperature
9	1	−1	−1	1	1396	1.002	278
10	−1	−1	1	−1	828	0.932	251
11	1	−1	−1	−1	1861	0.485	267

It is seen from Table 8 that the ANN prediction is in good agreement with the experimental results. To obtain minimum response values of cutting forces, surface roughness, and temperature; the expected outputs of the system [cutting forces, surface roughness, temperature] = [0, 0, 0] is entered as input for the ANN model and the cutting parameters are predicted from the ANN model. The aim is to obtain the optimum cutting parameters. ANN model is predicted the

Table 8. List of ANN predictions with check data set.

Experiment number	Results: Cutting force	Results: Surface roughness	Results: Cutting temperature	Normalised expected results for ANN Prediction: Cutting force	Normalised expected results for ANN Prediction: Surface roughness	Normalised expected results for ANN Prediction: Cutting temperature	ANN Prediction For Input Factor Levels: Cut depth	ANN Prediction For Input Factor Levels: Feed rate	ANN Prediction For Input Factor Levels: Cutting speed	ANN Prediction For Input Factor Levels: Coolant
9	1396	1.002	278	0.6433	0.4781	0.8201	0.9997 **(1)**	−0.9191 **(−1)**	−0.9748 **(−1)**	0.8759 **(1)**
10	828	0.932	251	0.3816	0.4447	0.7404	−0.9980 **(−1)**	−0.9968 **(−1)**	0.9129 **(1)**	−0.9056 **(−1)**
11	1861	0.485	267	0.8576	0.2314	0.7876	0.9539 **(1)**	−0.9758 **(−1)**	−0.9998 **(−1)**	−0.9973 **(−1)**

cutting parameters as −0.9967 (−1), −0.9588 (−1), −0.8691(−1), −0.9988 (−1) for cut depth, feed rate, cutting speed, and coolant; respectively. In other words, for 1.25 cut depth, 0.05 feed rate, 100 cutting speed, and wet cutting; minimum cutting force, surface roughness, and temperature values are obtained.

For the experimental results of physical layout that is given in Table 5, Taguchi analysis is performed with 'smaller is better' criteria by using Minitab Statistical Package Program. Signal-to-Noise ratios (S/N) are displayed in Table 9 for each experiment. For minimising cutting force, surface roughness and temperature together; S/N ratios for each experimental runs are calculated from Minitab. Minitab uses the formula given below in Equation (1) to calculate S/N ratios for 'smaller is better' criteria:

$$S/N = -10\left(\log\left(\sum Y^2/n\right)\right) \tag{1}$$

For example for the first experiment in Table 5 (cut depth: 1.25, feed rate: 0.05, cutting speed: 100, and coolant: wet) S/N ratio is calculated as

Table 9. S/N ratios for L8 design.

Experiment number	1	2	3	4	5	6	7	8
S/N Ratios	−53.7475	−54.5990	−56.9781	−56.8670	−56.6893	−58.4512	−62.0418	−60.6887

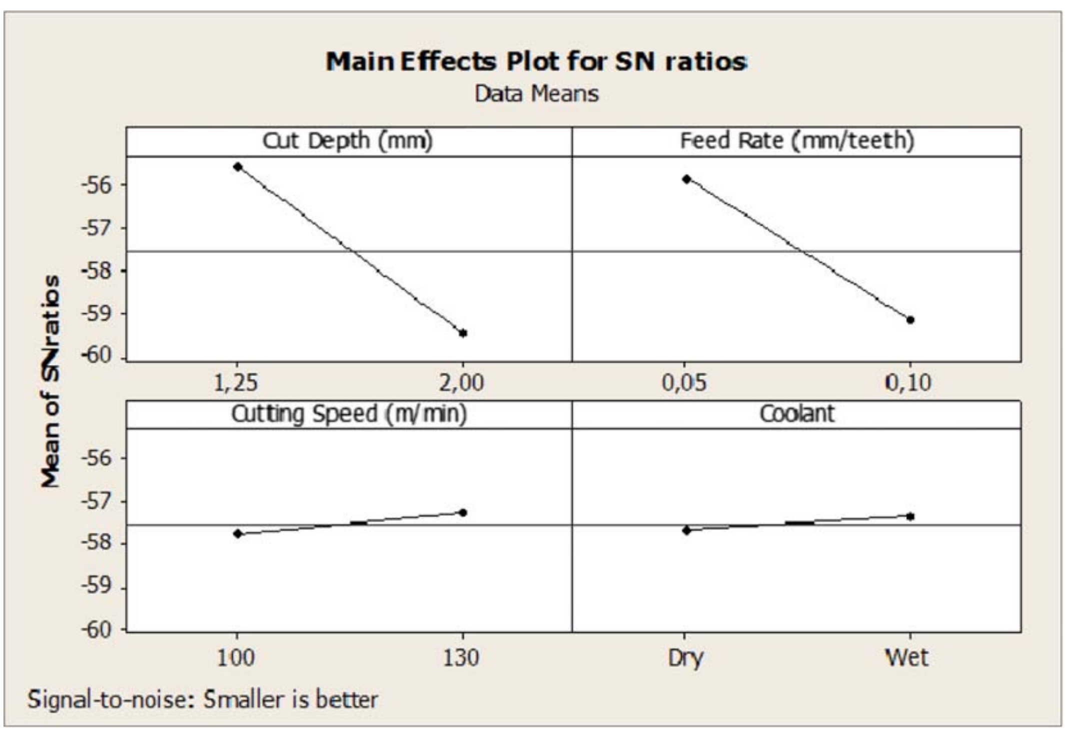

Figure 5. Main effect plot for S/N ratios of experimental results.

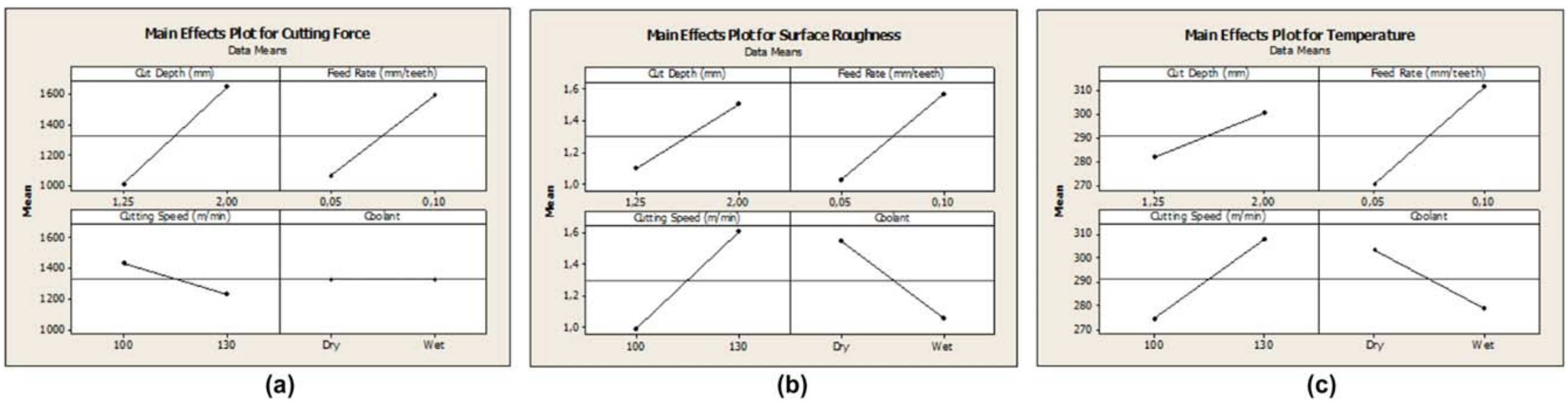

Figure 6. Effect of each control factor to the individual response parameters.

$$S/N = -10\left(\log\left(\frac{814^2 + 0.486^2 + 220^2}{3}\right)\right) = -10(\log 236998.7454) = -10(5.37475) = -53.7475 \quad (2)$$

Other S/N ratios are calculated in the similar way and given in Table 9.

According to the main effect plot for S/N ratios that is given in Figure 5; 1.25 (mm) cut depth, 0.05 (mm/teeth) feed rate, 130 (m/min) cutting speed, and wet cutting is obtained as the best parameter combination that minimise the cutting force, surface roughness and temperature values together. It is assumed that each response factors have equal weighting. Main effect plot for S/N ratios of experimental results for three responses and effect of each control factor to the individual response parameters are given in Figures 5 and 6 respectively.

According to the results of Taguchi analysis that are observed from Figure 5, it is clearly observed that the most important factors that affect the results are cut depth and feed rate. Cutting speed and coolant are less important when they are compared with the first two factors. But when these results are compared with the results obtained from the ANN model, it is observed that the results differ for the level of cutting speed parameter. The ANN model find out that the level of cutting speed must be 100. According to Figure 6, effect of cutting speed to the individual responses was different. Increased cutting speed causes high cutting temperatures, so cutting speed should be low to minimise cutting temperatures (Abukhshim, Mativenga, and Sheikh 2006; Gurbuz, Kafkas, and Seker 2011; Ming et al. 2003; Ulas, Demir, and Ciftci 2012). This outcome shows that the ANN model gives more accurate results when it is compared with the results of Taguchi analysis for the given experimental results.

5. Results and discussions

The highlights of this paper can be summarised as follows:

- When the literature is reviewed, it is observed that the cutting forces, surface roughness and especially the temperature is not searched for the cut depth, feed rate, cutting speed, and coolant factors together. The results demonstrated in the present paper are new in this area.
- The ANN model given in Section 4 provides researchers with the ability to predict optimum combination of milling parameters for the presented cutting forces, surface roughness and the temperature values to the ANN that would be expected from the results of experiment, even for the numerous combinations of these experimental results.
- In the present paper, it is observed that the given ANN model produces more acceptable results when compared with the Taguchi analysis (such as determining the factor level of cutting speed in the case presented in this study).
- By using Taguchi L8 design, with only eight experiments an effective ANN model is trained and by using this model the other combinations of experiments which did not perform, can be predicted. Time and cost minimisation can be carried out by this method.

6. Conclusions

The objective of this paper was to use the neural networks for determining the optimal milling parameter combinations for the desired outputs of experiment for cutting forces, surface roughness and especially the temperature. These three responses for the given cutting parameter set were not investigated together previously. The results demonstrated that ANN is an effective tool for this purpose. By only using the results of eight experiments that correspond with L8 orthogonal array, an effective ANN model was trained and by using this model other combinations of experiments which did not perform before were able to be predicted.

The minimum factor levels of experimental design (cut depth: 1.25, feed rate: 0.05, cutting speed: 100, coolant: wet) are found as the optimum factor levels by ANN. In future research, the obtained optimum factor levels in the present study will be investigated under a representative set of the entire solution space, including as many minima as possible. Based on the training performed with these data, the performance and generalisation capability of ANN to predict the global minimum will be investigated.

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