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Investigation of Milling Parameters Effect on Material Removal Rate Using Taguchi and Artificial Neural Network Techniques

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ABSTRACT

The Artificial Neural Network (ANN) and numerical methods are used widely for modeling and predict the performance of manufacturing technologies. In this paper, the influence of milling parameters (spindle speed (rpm), feed rate (mm/min) and tool diameter (mm)) on material removal rate were studied based on Taguchi design of experiments method using (L_{16}) orthogonal array with 3 factor and 4 levels and Neural Network technique with two hidden layers and neurons. The experimental data were tested with analysis of variance and artificial neural network model has been proposed to predict the responses. Analysis of variance result shows that tool diameters were the most significant factors that effect on material removal rate. The predicted results show a good agreement between experimental and predicted values with mean squared error equal to (0.000001), (0.00003025), (0.002601) and (0.006889) respectively, which produce flexibility to the manufacturing industries to select the best setting based on applications.

1. Introduction

Identification the optimum machining conditions is considers as a continual engineering task whose aims to minimize the costs of production and achieving the required quality of product. In milling process, Material Removal Rate MRR is one of the most significant performance measures. For an efficient milling process the higher (MRR) is required which is considered as the factor that influences directly the hour rate of machining and the cost of production. [1-3]

Due to this, the optimization of cutting parameters becomes very important. Recently, researchers attempt to optimize the conditions of machining utilizing different approaches such as Genetic Algorithm (GA), artificial neural network, simulated annealing, gray relational analysis...etc.

Miloš J. Madić et al. 2011 developed Taguchi optimized ANN model and presented high accuracy of prediction. Experiments and analyses have been shown that Artificial Neural Network (ANN) architectural and training parameters can be optimally calculated in a systematic way, thus to avoid the procedure of error and long trials [4]. Reddy Sreenivasulu 2013 presented the effect of depth of cut (d), feed rate (f) and cutting speed (N) on surface roughness and damage of delamination on (GFRP) composite material through the process of end milling. Taguchi approach is used to examine the characteristics of machining for GFRP. From ANOVA results, the most important factors influencing the responses are the depth of cut and cutting speed. ANN has been utilized to make a comparison between experimental results with predicted results, which demonstrate good agreement between the experimental measurements and the predictive model results [5].

Sener Karabulut 2015 studied the effect of effect of milling parameters on surface roughness and cutting force of AA7039/Al2O3 metal matrix composites. Taguchi was used to conduct the milling tests and the effects of the cutting parameters on the force of cutting and surface roughness were calculated by utilizing ANOVA. Regression analysis and ANN have been applied for predicting of the force of cutting and surface roughness. From the output results, ANN shows predicting for the force of cutting and surface roughness with a Mean Squared Error (MSE) equivalent to (6.66%) and (2.25%) respectively [6].

Amber Batwara and Prateek Verma 2016 established a new process model for predicting the MRR and surface roughness in various practical applications. Model equations for response MRR and surface roughness was predicted accurately by ANN approach and Minitab software which produce good prediction equal to (90) % for responses and can be utilized by any cutting according to machining process manufacture [7].

Nabeel H. Alharthi et al. 2017 used regression analysis and artificial neural network ANN for predicting surface roughness. Five models of neural network were developed and Regression analysis used to build a mathematical model which is represent the surface roughness as a function of the process parameters. The coefficient of determination is 94.93% and 93.63% for the best neural network model and regression analysis respectively [8].

2. Experimental Work

A. Selection of Material

The workpiece material used for present work was alloy of mild steel. Mild steel is considered as one of the extreme flexible and versatile material and its used in many industries because of its good mechanical strength and low cost. Generally, mild steel has low elasticity. However, it is easy to form when machining. The dimension of each work piece is (100 mm, 100 mm, 20 mm) as illustrated in Fig 1. Table 1 illustrate the chemical composition of the used alloy.

Table 1. Chemical Composition of mild steel alloy

Sample	Workpiece material
C%	0.16
Mn%	0.786
P%	0.0107
Si%	0.19
Mo%	0.002
S%	0.0114
Cu%	0.0187
Cr%	0.0346
Al%	0.0351
Ni%	0.0069
Fe%	Bal.

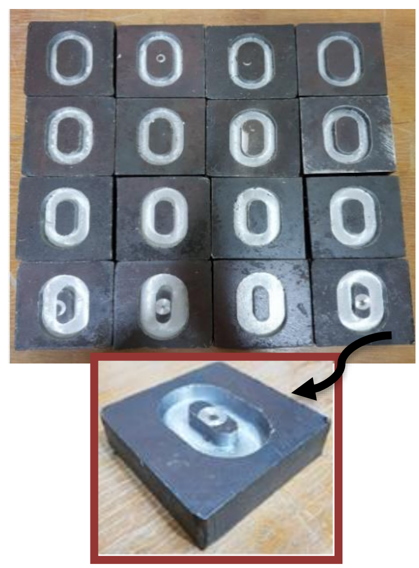

Figure 1. Work piece Samples of Mild Steel Alloy

B. Selection Parameters and Their Levels

The CNC machines play a major role in modern machining industry to increase productivity within lesser time. In this study, the experiments have been carried out on CNC milling machine (CNC ACCUWAY UM-85) as shown in Fig 2. to perform (8mm) cylindrical pocket on mild steel work piece under the cutting conditions by High speed steel, four flutes milling cutter. Control parameters are the parameters that influence the material removal rate of machined surface and include, depth of cut (mm), feed rate (mm/min) and spindle speed (rpm). Three cutting parameters are taken into consideration and each parameter is specified at four levels. Table 2. shows parameters values and the levels used for experiments. [9,10].

Figure 2. (CNC ACCUWAY UM-85) milling machine

Table 2. Process Parameters and Levels

Sr. No.	Process Parameter	Levels			
		1	*2*	*3*	*4*
1	Spindle Speed (rpm)	910	930	960	1000
2	Feed Rate (mm/min)	93	95	98	102
3	Tool Diameter (mm)	8	10	12	14

C. Calculation of Material Removal Rate (MRR)

MRR for the workpiece material can be expressed as the volume of material has been removed per unit time and is expressed in mm^3/sec. MRR is directly proportional to the production rate. Higher the MRR value, higher the productivity and vice versa [1,3,11]. MRR has been calculated using the equation (1) for each run: [12]

$$\mathbf{MRR} = \mathbf{wdf} \qquad \mathrm{mm3/sec} \tag{1}$$

Where:
w: cut width (mm)
d: cut depth (mm)
f: feed rate (mm/min)

3. Experimental Design and Optimization

A. Taguchi Approach and Experimental Design method

Design of Experiments using Taguchi method produces an efficient, simple and systematic approach for determining the optimum conditions of machining in the manufacturing process [13]. In this work, the tool diameter (d), feed-rate (f) and spindle speed (N) were considered for determining the effect of machining parameters on the material removal rate. A unique design was proposed by Taguchi for an orthogonal array (OA) to check all the parameters with a little number of trails for experiments to minimize the experimental process. L_{16} orthogonal array is selected in this study and the experiments generated with help MINITAB 18 statistical package. Signal to Noise (S/N) ratio was used through Taguchi method to measure the characteristic of performance which deviate from the required values. (S/N) ratio has been calculated according to Taguchi's (larger-the-better) approach which aims to maximize the material removal rate by based on the equation (2) [6]. Table 3. shows Taguchi orthogonal L_{16} Array and Experimental Results. Fig.3 shows the main effect plot of signal to noise ratio.

Larger – The - Better:

$$\mathrm{S/N} = -10 \log((\sum 1/yi2)/n) \tag{2}$$

Where:
n: the number of measurements.

yi: the value of the measured characteristics.

Table 3. Taguchi orthogonal L_{16} Array and Experimental Results

S.N.	Spindle speed (rpm)	Feed-rate (mm/min)	Tool Diameter (mm)	MRR (mm^3/sec)	S/N Ratio (η)
1	910	93	8	٩٩,٢	٣٩,٩٣٠٢
2	910	95	10	١٢٦,٧	٤٢,٠٥٥٥
3	910	98	12	١٥٦,٨	٤٣,٩٠٦٩
4	910	102	14	190.4	٤٥,٥٩٣٣
5	930	93	10	١٢٤,٠	٤١,٨٦٨٤
6	930	95	8	١٠١,٣	٤٠,١١٢٢
7	930	96	14	١٨٢,٩	٤٥,٢٤٤٣
8	930	102	12	١٦٣,٢	٤٤,٢٥٤٤
9	960	93	12	١٤٨,٨	٤٣,٤٥٢١
10	960	95	14	١٧٧,٣	٤٤,٩٧٤٢
11	960	98	8	١٠٤,٥	٤٠,٣٨٢٣
12	960	102	10	١٣٦,٠	٤٢,٦٧٠٨
13	1000	93	14	١٧٣,٦	٤٤,٧٩١٠
14	1000	95	12	١٥٢,٠	٤٣,٦٣٦٩
15	1000	98	10	١٣٠,٧	٤٢,٣٢٥٥
16	1000	102	8	١٠٨,٨	٤٠,٧٣٢٦

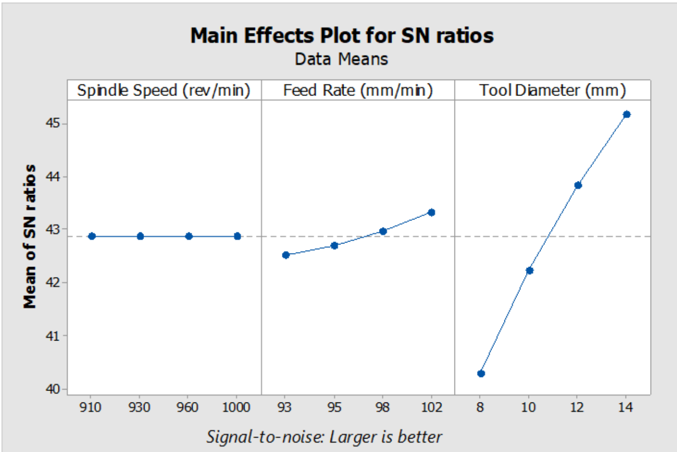

Figure3. Main Effect Plot of Signal to Noise Ratio

B. Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) was used to perform the statistical significance of the milling parameters to study the interactions and contribution of the factors. Table 4. present the (ANOVA) results for (MRR).

Generally, (ANOVA) table include the degree of freedom (DOF) corresponding to the factors, mean square (MS), sum of square (SS), F-ratio and percentage contribution [10,14]. In the present work, the most important cutting parameter is predicted to be the tool diameter with a confidence level equivalent to (95)% and with (97.0114)% contribution. The feed rate and spindle speed contributes 2.8705 % and 0.07903 % to the material removal rate during the milling process.

Table4. ANOVA Results of MRR

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% Contribution
Spindle Speed (rev/min)	3	10.9	3.63	3.97	0.071	0.07903
Feed Rate (mm/min)	3	395.9	131.97	144.36	0.000	2.8705
Tool Diameter (mm)	3	13380.0	4459.99	4878.75	0.000	97.0114
Error	6	5.5	0.91			0.0398
Total	15	13792.2				100

C. Development of ANN Modelling

The Artificial Neural Network has a significant effect to predict linear and nonlinear problems in various areas of engineering. In this paper, Neural network (NN) model consist of three input neurons and one output corresponding to (tool diameter (d), feed–rate (f), spindle speed (N)) and material removal rate MRR respectively. The number of the hidden layer and the number of neurons equal to (2) and (2)respectively. Hebbian learning rule was used to perform the training. Fig 4. shows the graphical representation of the proposed network. Table 5 illustrates the typical observation of the output response.

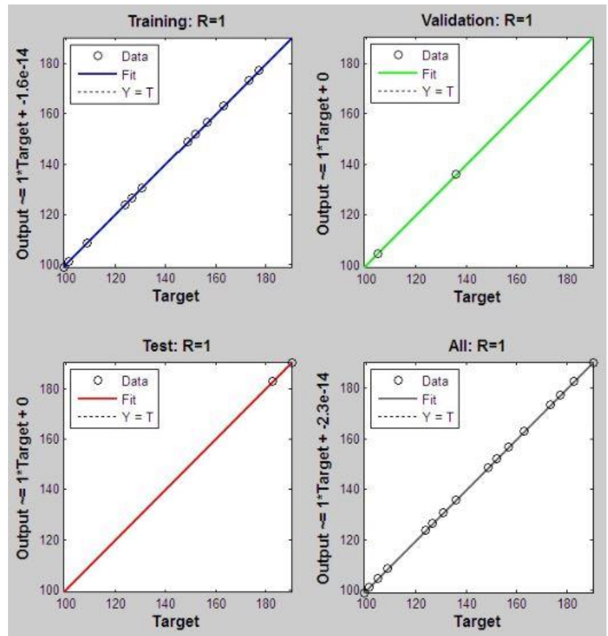

Figure4. Graphical Representation of the Proposd Network

Table5. Observation the Response of the Output

Configuration of Network	3 – 2 – 1
Type of transfer function	Logsig (purelin)
Epoches number	1000
Factor of learning rate (α)	0.1
Hidden neuron size	2
Hidden layer size	2
Number of trails for training	14
Number of trails for testing	2

4. Results and Discussion

The training data has been used to test the Artificial Neural Network (ANN) model. The predicted results indicate that Artificial Neural Network (ANN) model has been applied successfully for the machining parameters of milling mild steel alloy. Table 6 shows the validation for the material removal rate values using ANN.

It is clear that the error between the experimental MRR values and predicted MRR values is found that maximum of (0.17) and minimum of (-0.17) as shown in Fig5. This percentage result of error is acceptable and indicates that the model of (ANN) has been satisfactory predicted for material removal rate.

Table 6. Validation Results Obtained for Material Removal Rate Using ANN

No.	MRR in Experimental Value (mm³/sec)	MRR in Predicted Value (mm³/sec)	Error	MeanSquare Error
1	99.2	99.218	-0.018	0.000001
2	126.7	126.678	0.022	
3	156.8	156.815	-0.015	
4	190.4	190.391	0.009	
5	124	124.019	-0.019	0.00003025
6	101.3	101.280	0.020	
7	182.9	182.908	-0.008	
8	163.2	163.204	-0.004	
9	148.8	148.781	0.019	0.002601
10	177.3	177.308	-0.008	
11	104.5	104.670	-0.17	
12	136	135.943	0.057	
13	173.6	173.430	0.17	0.006889
14	152	152.002	-0.002	
15	130.7	130.699	0.001	
16	108.8	108.803	-0.003	

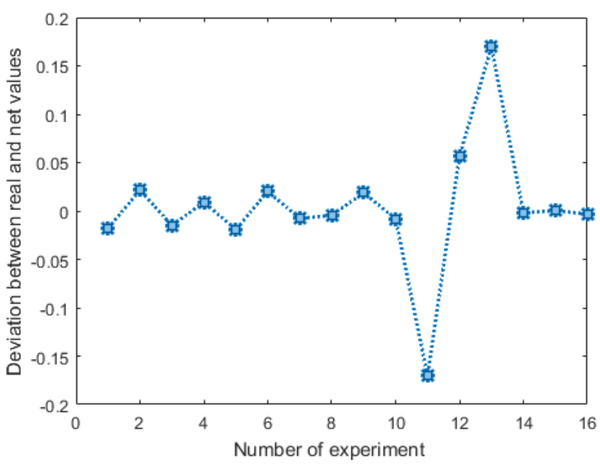

Figure5. Relationship between error and number of experiment

5. Conclusion

In this Experimental study the milling experiments were implemented on CNC milling machine using high speed steel cutting insert under different cutting conditions for several groups of tool diameter (mm), feed rate (mm/min) and spindle speed (rpm). The milling test were performed based on Taguchi (L_{16}) orthogonal array. Both signal to noise ration and ANOVA analysis were used to determine the optimal cutting parameters for material removal rate. The ANOVA results shows that the most effective factor for material removal rate was tool diameter with percentage contribution of (97.0114%), then the feed rate effected by (2.8705%) and the spindle speed has not effected on material removal rate. The experimental data has been learned using ANN. Neural Network has been trained by using (14) patterns. The neural network model shows closed results matching between the actual calculated material removal rate and the predicted output model as shown in figure (6). Where, it can be notice form the results that the total difference between experimental and predicted value less than 0.2% (0.0002), these experimental results showed that ANN can be used successfully for prediction of MRR in the milling of low carbon steel alloy, because it giving higher accuracy and consumes less time.

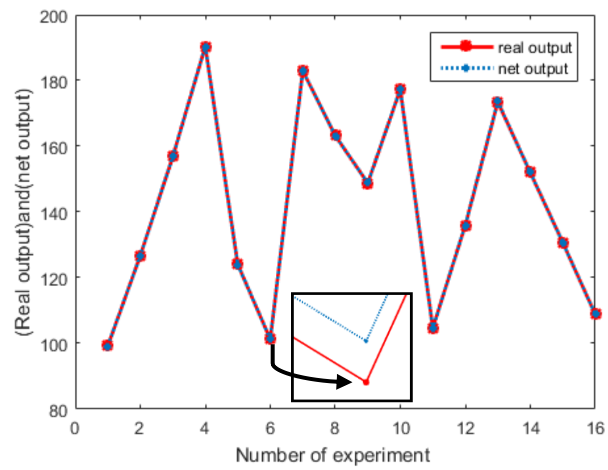

Figure6. The real output and net output

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