# Anfis Optimization Of Cutting Parameters For Mrr In Turning Processes

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## Abstract:-

The objective of this research is to obtain an optimal setting of CNC turning parameters [cutting speed (165, 200 and 250 m/min), feed rate (0.05, 0.06 and 0.07 mm/rev) and depth of cut (0.5, 0.75 and 1 mm)] which result in an optimal value of material removal rate (MRR). It's necessary to find a suitable optimization process to obtained optimum values of cutting parameters for maximum material removal rate. In machining process was carried out on aluminum ENAC-43400 alloy in a CNC turning machine by using a carbide cutting tool. The model for the material removal rate (MRR), as a function of cutting parameters, is obtained using Adaptive Neuro Fuzzy Inference System (ANFIS) in MATLAB 7.2 Software for optimization of MRR in CNC turning.

The results obtained, material removal rate (MRR) are about (4125-17500 $mm^3$/min), and max. material removal rate obtained (17500 $mm^3$/min) at condition higher cutting speed (250 m/min), higher feed rate (0.07 mm/rev) and higher depth of cut (1 mm). The ANFIS modeling technique can be effectively used for the optimization of material removal rate at the error of training data 2.255%.

**Keywords: CNC turning process, material removal rate, ANFIS**.

## 1. INTRODUCTION

In many industrial applications related to the turning process, control and optimization of surface quality and material removal rate (MRR) are the most important performance measures and considered as the main response [9]. In machining operation, the quality of surface finish and the material removal rate are important requirements of workpieces and parameter in manufacturing engineering. During the turning operation, the cutting tool and the metal bar are subjected to a prescribed deformation as a result of the relative motion between the tool and workpiece both in the cutting speed direction. As a response to the prescribed deformation, the tool is subjected to thermal loads on those faces that have interfacial contact with the workpiece or chip. In the metal-cutting process, during which chips are formed, the workpiece material is compressed and subjected to plastic deformation. Usually the material removal occurs in a highly hostile environment with high temperature and pressure, in the cutting zone. The ultimate objective of the science of metal cutting is to solve practical problems associated with efficient material removal in the metal cutting process. To achieve this, the principle governing the cutting process should be understood. Knowledge of this principle predicts the practical result of the cutting process and thus the select the optimum cutting conditions for each particular case [8]. From past so many years it has been recognized that conditions during machining such as Cutting speed, Feed and Depth of Cut (DOC) should be selected to optimize the economics of machining operations. Manufacturing industries in developing countries suffer from a major drawback of not running the machine at their optimal operating conditions. Machining industries are dependent on the experience and skills of the machine tool operators for optimal selection of cutting conditions. In machining industries the practice of using hand book based conservative cutting conditions are in progress at the process planning level. The disadvantage of this unscientific practice is the decrease in productivity due to sub optimal use of machining capability [3].

The literature survey has revealed that several researchers attempted to calculate the optimal cutting conditions in turning operations.

Farhad Kolahan et al. have been investigate the multi objective optimization of turning process using grey relational analysis and simulated annealing algorithm. It has been found that the developed multi objective model is then optimized by simulated annealing algorithm (SA) in order to determine the best set of parameter values [2]. C. Natarajan et al. have been investigation of cutting parameters of surface roughness for a non-ferrous material using artificial neural network in CNC turning. It has been found that comparison of the experimental data and ANN results show that there is no significant difference and ANN was used confidently. The results obtained, conclude that ANN is reliable and accurate for solving the cutting parameter optimization [1]. Ilhan Asiltürk and Mehmet Çunkas have been found that the effect of cutting speed, feed rate and depth of cut on surface roughness of AISI 1040 steel. It have been implemented full factorial experimental design to increase the confidence limit and reliability of the experimental data, Artificial neural networks (ANN) and multiple regression approaches, it have been compare multiple regression and neural network using statistical methods. It has been found that the proposed models are capable of prediction of the surface roughness. The ANN model estimates the surface roughness with high accuracy compared to the multiple regression model [5]. H. K. Dave et al. have been found that the effect of machining conditions on material removal rate and surface roughness during CNC turning of different materials using TiN coated cutting tools. It have been found that the analysis of optimum cutting conditions to get the lowest surface roughness and maximum material removal rate in CNC turning of different grades of EN materials by Taguchi method [4]. M. Kaladhar et al. have been investing the effects of process parameters on surface finish and material removal rate to obtain the optimal setting of these process parameters. And the Analysis of Variance (ANOVA) is also used to analyze the influence of cutting parameters during machining. In this work, AISI 304 austenitic stainless steel workpieces are turned on computer numerical controlled (CNC) lathe by using Physical Vapor Deposition (PVD) coated cermets insert (TiCN-TiN) of 0.4 and 0.8 mm nose radii. It have been found that the feed and nose radius is the most significant process parameters on workpiece surface roughness. However, the depth of cut and feed are the significant factors on material removal rate. Optimal range and optimal level of parameters are also predicted for responses [6]. Tian Syung Lan have been investigate the effect of cutting speed, feed, cutting depth, tool nose runoff with three levels (low, medium, high) material removal rate in finish turning based on L9 (34) orthogonal array. It have been found that the material removal rates from the fuzzy Taguchi deduction optimization parameters are all significantly advanced comparing to those from the benchmark. Also it has been declare that contributed the satisfactory fuzzy linguistic approach for the MRR in CNC turning with profound insight [12]. Shukry H. Aghdeab et al. studied the optimal parameters of turning process (cutting speed, spindle speed, feed rate and depth of cut) which results in an optimal of surface roughness for machining aluminum alloy ENAC43400 shaft in a CNC turning machine. The results obtained show that the surface roughness (Ra) was about (1.06-1.41μm). The developed objective model is modeled using the regression method then was optimized by the simulated annealing method in order to determine the best set of turning parameter values. The present work concludes that the simulated annealing method can be used for high precision modeling and estimation of turning parameters [11]. Shukry H. Aghdeab et al. investigated optimal values of CNC turning parameters (cutting speed, depth of cut and feed rate) which result in an optimal value of surface roughness by Taguchi method was carried out on machining of aluminum ENAC-43400 material in dry cutting using CNC turning machine. The results obtained of the surface roughness (Ra) are about (1.14-1.91) μm, and the best was at cutting speed 250 m/min, feed rate 0.05 mm/rev and depth of cut 0.5 mm which is refers to the optimum machining parameters [10].

The aims of this work are studying the effect of cutting speed, feed rate, and depth of cut on material removal rate in CNC turning processes, the best experimental value of the material removal rate, and the optimal setup of parameters for max. material removal rate by using Adaptive Neuro Fuzzy Inference System (ANFIS).

## 2. EXPERIMENTAL PART

Main factors [cutting speed (165, 200 and 250 m/min), feed rate (0.05, 0.06 and 0.07 mm/rev), and depth of cut (0.5, 0.75 and 1 mm) effect on the material removal rate (MRR) in CNC turning process. The experiments were conducted on CNC lathe type Star-Chip 450 by using a carbide cutting tool, located at the Machine Tool Laboratory in University of Technology, as shown **in Fig. 1.**


**Fig. 1 CNC lathe use in experimental work.**

Basically the material removal rate (MRR) is related to three machining parameters [cutting speed (S), feed rate (F) and depth of cut (D)]. Material removal rates are determined by the following equation [7]:

$$MRR = S \times F \times D \quad \text{………( 1)}$$

Where:
MRR = material removal rate ($mm^3/min$).
S = cutting speed (mm/min).
F = feed rate (mm/rev).
D = depth of cut (mm).

The work material used for this paper is Aluminum ENAC-43400 alloy. The diameter of the material is 46mm and length is 150 mm.

The chemical composition of the work material is given in **Table. 1**, and mechanical properties of this work material as shown in **Table .2.**

**Table. 1 Chemical composition of Al ENAC-43400 alloy.**

| Element | Si | Fe | Mg | Mn |
|---|---|---|---|---|
| Wt % | 10.40 | 0.72 | 0.34 | 0.21 |

| Cr | Cu | Ti | Zn | Other | Al |
|---|---|---|---|---|---|
| 0.02 | 0.1 | 0.05 | 0.15 | 0.15 | Bal. |

**Table. 2 Mechanical properties of Al ENAC-43400 alloy [12].**

| Mechanical Properties | Al ENAC-43400 Alloy |
|---|---|
| Tensile Strength | 240 MPa |
| 0.2% Proof Strength | 140 MPa |
| Brinal Hardness Number | 70 |

| | |
|---|---|
| Elongation at Fracture | 1% |
| Poisson’s ratio | 0.3 |

The turning experiments were conducted are given in **Table. 3**.

The workpiece was mounted using a pneumatic chuck in CNC lathe center and the clamping pressure was set as 8 bar. The machining parameters like cutting speed, feed rate and depth of cut were selected based on the manufacturer’s recommendations. The tests were performed on a CNC lathe. The workpiece was clamped onto the turret of the CNC machine table. A computer numerical control program was written to perform the turning process. The parameters defined in the turning machine were cutting speed (m/min), feed rate (mm/rev) and depth of cut (mm).

**Table. 3 Data obtained for material removal rate in experimental work.**

| No. of experiment | Cutting speed (mm/min)×$10^3$ | Feed rate (mm/rev) | Depth of cut (mm) | MRR experimental ($mm^3$/min) |
|---|---|---|---|---|
| 1 | 165 | 0.05 | 0.5 | 4125 |
| 2 | 165 | 0.05 | 0.75 | 6187.5 |
| 3 | 165 | 0.05 | 1 | 8250 |
| 4 | 165 | 0.06 | 0.5 | 4950 |
| 5 | 165 | 0.06 | 0.75 | 7425 |
| 6 | 165 | 0.06 | 1 | 9900 |
| 7 | 165 | 0.07 | 0.5 | 5775 |
| 8 | 165 | 0.07 | 0.75 | 8662.5 |
| 9 | 165 | 0.07 | 1 | 11550 |
| 10 | 200 | 0.05 | 0.5 | 5000 |
| 11 | 200 | 0.05 | 0.75 | 7500 |
| 12 | 200 | 0.05 | 1 | 10000 |
| 13 | 200 | 0.06 | 0.5 | 6000 |
| 14 | 200 | 0.06 | 0.75 | 9000 |
| 15 | 200 | 0.06 | 1 | 12000 |
| 16 | 200 | 0.07 | 0.5 | 7000 |
| 17 | 200 | 0.07 | 0.75 | 10500 |
| 18 | 200 | 0.07 | 1 | 14000 |
| 19 | 250 | 0.05 | 0.5 | 6250 |
| 20 | 250 | 0.05 | 0.75 | 9375 |
| 21 | 250 | 0.05 | 1 | 12500 |
| 22 | 250 | 0.06 | 0.5 | 7500 |
| 23 | 250 | 0.06 | 0.75 | 11250 |
| 24 | 250 | 0.06 | 1 | 15000 |
| 25 | 250 | 0.07 | 0.5 | 8750 |
| 26 | 250 | 0.07 | 0.75 | 13125 |
| 27 | 250 | 0.07 | 1 | 17500 |

## 3. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

In the present work, develop the intelligent model for optimization MRR using Adaptive Neuro Fuzzy Inference System (ANFIS).

The main problem with fuzzy logic is that there is no systematic procedure to define the membership function parameters. ANFIS eliminates the basic problem in fuzzy system design, defining the membership function parameters and design of fuzzy if-then rules, by effectively using the learning capability of neural network for automatic fuzzy rule generation and parameter optimization [13]. Using a given three input (cutting speed, feed rate and depth of cut) on one output (material removal rate) data set, the Adaptive Neuro Fuzzy Inference System constructs a Fuzzy Inference System whose membership function parameters are tuned using either a back propagation algorithm alone, or in combination with a least squares type of method.

## 4. RESULTS AND DISCUSSION

Using a given input/output dataset, the ANFIS model constructs a fuzzy inference system, as shown in Fig. 2 the Adaptive Neuro Fuzzy Inference System model structure with four layers, three input [cutting speed (S), feed rate (F) and depth of cut (D)], nine hidden and one output material removal rate (MRR) of the network.

The training and testing dataset are obtained from experiments data. The input/output dataset was divided randomly into two stages: training dataset, consisting 21 of the input/output data and testing dataset, consisting 6 of the data.

ANFIS information's:

Number of nodes: 78

Number of linear parameters: 108

Number of nonlinear parameters: 18

Total number of parameters: 126

Number of training data pairs: 21

Number of checking data pairs: 6

Number of fuzzy rules: 27

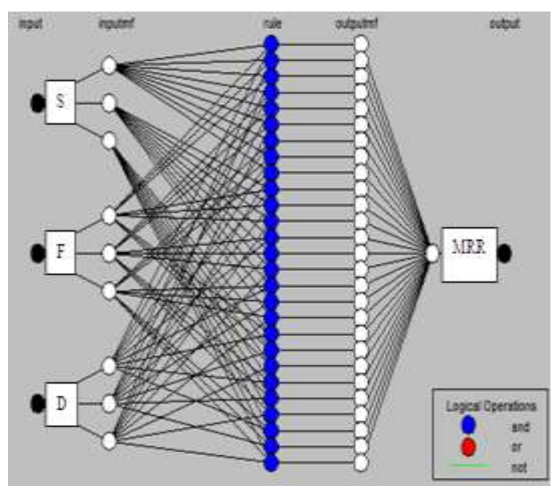


**Fig. 2 Adaptive Neuro Fuzzy Inference System architecture.**

In order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used. The number and type of membership functions, method optimization hybrid or back propagation, and number epoch were changed. Then the best adaptive network architecture was determined. The training epoch for each network is 100, hybrid method optimization, the best results given 3 membership function Gaussian type. When the network training was successfully finished, the ANFIS was tested with validation data.

**Figs. 3, 4 and 5** show the 3D surface profile obtained during neuro fuzzy modeling and the effect of the machining parameters [cutting speed (S): (165, 200 and 250 m/min), feed rate (F): (0.05, 0.06 and 0.07 mm/rev) and depth of cut (D): (0.5, 0.75 and 1 mm)] on the material removal rate (MRR are about (4125-17500 $mm^3$/min). This plots clearly predicts that material removal rate value increases up to certain level and increases with increases in cutting speed, feed rate and depth of cut

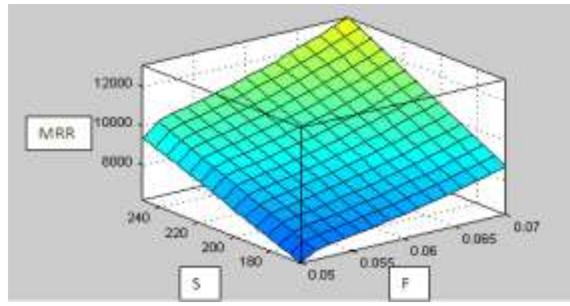


**Fig. 3 3D plot, influence of cutting speed (S) and feed rate (F) on the material removal rate (MRR).**

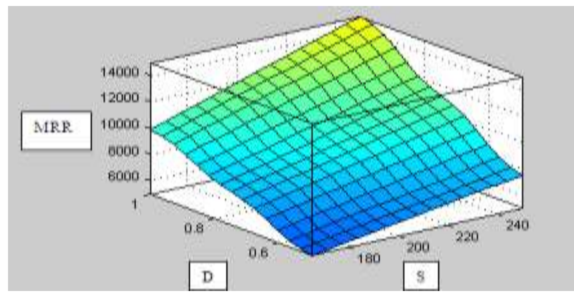


**Fig. 4 3D plot, influence of depth of cut (D) and cutting speed (S) on the material removal rate (MRR).**

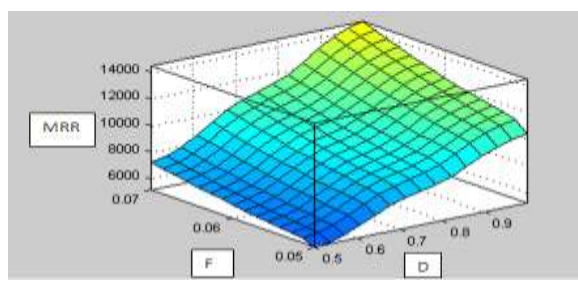


**Fig. 5 3D plot, influence of feed rate (F) and depth of cut (D) on the material removal rate (MRR).**

There are three levels of each factor of cutting parameters used in the experimental: cutting speed (165, 200, 250m/min), feed rate (0.05, 0.06, 0.07 mm/rev) and depth of cut (0.5, 0.75, 1 mm). Thus, there were totally 27 number of experiments in this paper. The input layers of ANFIS consist of three parameters (S, F and D) and the output layer corresponds to MRR.

Fig. 6 describes the comparison of experimental work and ANFIS model for the MRR, respectively on number of experiments (27 samples). It proved that the method used in this work is feasible and could be used to optimize the material removal rate in an acceptable error rate for CNC. The compared lines seem to be close to each other indicating with good agreement at accuracy 97.745 % for training data sets.

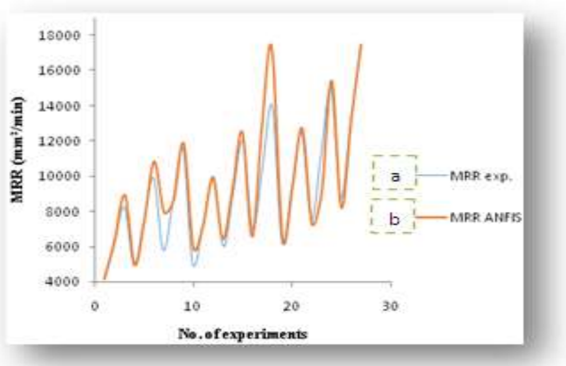


**Fig. 6 Correlation of MRR between experimental and ANFIS values; a) Material Removal Rate experimental; b) Material Removal Rate Adaptive Neuro Fuzzy Inference System.**

## 5. CONCLUSION

The main conclusions which can be deduced from this research summarized as follows:

1- ANFIS is used to estimate material removal rate in CNC turning.

2- The average deviation of the training data is 2.255%, and average deviation of the checking data is 3.044%.

3- The ANFIS predicted material removal rate values show a good comparison with those obtained experimentally.

## REFERENCES:

[1] C. Natarajan, S. Muthu and P. Karuppuswamy "Investigation of cutting parameters of surface roughness for a non-ferrous material using artificial neural network in CNC turning", Journal of Mechanical Engineering Research, Vol. 3(1), pp. 1-14, January, 2011.

[2] F. Kolahan, R. Golmezerji, M. A. Moghaddam, "Multi Objective Optimization of Turning Process using Grey Relational Analysis and Simulated Annealing Algorithm" Applied Mechanics and Material, Vol. 110-116 pp. 2926-2932, 2012.

[3] H. M. Somashekara and D. N. Lakshmana," Optimizing Surface

Roughness in Turning Operation using Taguchi Technique and ANOVA ‶, International Journal of Engineering Science and Technology, Vol. 4, No. 05, India, May 2012.
[4] H. K. Dave, I. Asiltürk and M.Çunkas, "Effect of machining conditions on MRR and surface roughness during CNC turning of different Materials Using TiN Coated Cutting Tools-A Taguchi approach", International Journal of Industrial Engineering Computations, Vol. 3 pp. 925-930, 2012.
[5] I. Asiltürk and M. Çunkas, "Modeling and predication of Surface Roughness in truing operations using artificial neural network and multiple regression method", Expert System with Applications 38, 5826-5832, 2011.
[6] M. Kaladhar, K. V. Subbaiah and Ch. S. Rao, "Determination of Optimum Process parameters during turning of AISI 304 Austenitic Stainless Steel using Taguchi method and ANOVA "International Journal of lean thinking, volume 3, issue 1, 2012.
[7] Q. R. Sardinas, R. M. Santana and A. E. Brindis,"Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes", International Journal of Engineering Applications of Artificial Intelligence, Vol. 19, pp. 127-133, 2006.
[8] R. K. Patel and H. R. Prajapati,″ Parametric Analysis of Surface Roughness (SR) and Material Removal Rate (MRR) of Harden Steel on CNC Turning using ANOVA Analysis ″, International Journal of Engineering Science and Technology, Vol. 4, No. 07, India, July 2012.
[9] S. S. Moshat, B. Datta, P. P. Asish and Kumar,″ Optimization of milling process parameters using PCA-based Taguchi method″, International Journal of Engineering Science and Technology, Vol. 2, pp. 92-102, 2010.
[10] Sh. H. Aghdeab, B. A. Ahmed, M. S. Jabbar and A. A. Abbas "Influences and Optimization of CNC Turning Machining Parameters", Al-Qadisiyah Journal for Engineering Sciences, Vol. 9, No. 2, pp. 200-209, 2016.
[11] Sh. H. Aghdeab, L. A. Mohammed and A. M. Ubaid "Optimization of CNC Turning for Aluminum Alloy Using Simulated Annealing Method", Jordan Journal of Mechanical and Industrial Engineering, Vol. 9, No. 1, ISSN 1995-6665, pp. 39-44, 2015.

[12] T. S. Lan "Fuzzy Deduction Material Removal Rate Optimization for Computer Numerical Control Turning", American Journal of Applied Sciences, 1026-1031, 2010.

[13] W.A. Yurdusev, M.A. Firat, M.A. Turan, "Adaptive neuro fuzzy inference system approach for municipal water consumption modeling", Turkey. J. Hydrol., 365(3-4), pp. 225-234, 2009.

# النظام العصبي الضبابي القابل للتكيف الأمثل من ظروف القطع لمعدل المادة المزالة في عمليات الخراطة

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**الخلاصة:-**

في هذا العمل،الهدف هو الحصول على الضبط الأمثل لظروف الخراطة بالمكائن المبرمجة رقميا ( سرعة القطع ،عمق القطع والتغذية) وبالتالي الحصول على القيمة المثلى لمعدل إزالة المادة من سبيكة الألمنيوم. أن من الضروري أيجاد عملية التحسين المناسبة والتي تعطي عوامل القطع الأمثل لأعلى معدل إزالة للمادة. في هذا البحث تم تشغيل سبيكة ألمنيوم باستخدام ماكنة خراطة مبرمجة رقميا وعدة قطع كاربيدية. النموذج لنسبة إزالة المادة كدالة لعوامل القطع تم الحصول عليه باستخدام نظام عصبي ضبابي قابل للتكيف باستخدام برنامج الماتلاب للتحسين الأمثل لمعدل إزالة المادة في الخراطة المبرمجة رقميا.

النتائج التي تم الحصول عليها لمعدل إزالة المادة حوالي 4125-17500ملم$^3$/دقيقة وأعظم قيمة لمعدل إزالة المادة هي 17500ملم$^3$/دقيقة عند ظروف أعلى سرعة قطع 250متر/دقيقة، أعلى معدل تغذية 0.07ملم/دورة وأعلى عمق قطع 1ملم. نموذج تقنية النظام العصبي الضبابي القابل للتكيف يمكن استخدامه عمليا للحصول على القيم المثلى لمعدل إزالة المادة عند محاولة خطا بقيمة 2.255%.