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Optimization of CNC Turning for Aluminum Alloy Using Simulated Annealing Method

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Abstract

Surface roughness is a main parameter in Computer Numerical Control (CNC) turning technology. The aim of the present paper is to obtain 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 (46×150mm) in a CNC turning machine type StarChip 450 by using a carbide cutting tool type DNMG 332; surface roughness was measured using the POCKET SURF EMD-1500 tester. 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 forhigh precision modeling and estimation of turning parameters.

Keywords: *: CNC Turning, Regression Analysis, Optimization, Simulated Annealing Method*.

1. Introduction

Machining operation has been the core of the manufacturing industry since the industrial revolution [1]. A surface manufactured by cutting processes is one of the most important criteria for quality. Surface roughness is a significant factor which is not only important for wear, friction and lubrication, which became traditional for tribology, but it is also important for sealing, hydrodynamic, electric, heat transfer. Surface roughness depends on many variables, such as material couple, manufacturing type, cutting conditions, etc. Surface roughness is one of the most important characteristic variables to be monitored in the cutting processes owing to the direct relation between the change of surface roughness and the cutting conditions [2]. For many years, it has been recognized that the conditions during machining, such as Cutting Speed, Feed and Depth of Cut (DOC), should be selected to optimize the economics of the 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 experiences and skills of the machine tool operators for the optimal selection of cutting conditions. In machining industries, the practice of using hand book-based conservative cutting conditions are in progress at the process of the planning level. The disadvantage of this unscientific practice is the decrease of productivity due to the sub optimal use of machining capability [3]. The existing optimization research for CNC turning is simulated within particular manufacturing circumstances [4].

In machining operation, the quality of the surface finish is an important requirement for the work-pieces and parameters 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 work-piece, 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 work-piece or chip. In the metal-cutting process, during which chips are formed, the work-piece material is compressed and subjected to a 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 [5].

Surface roughness is commonly considered as a major manufacturing goal for turning operations in many of the existing research works. The machining process on a CNC

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lathe is programmed by speed, feed rate and cutting depth, which are frequently determined based on the machine performance; the product characteristics are not guaranteed to be acceptable. Therefore, the optimum turning conditions have to be accomplished. It is mentioned that the tool nose run-off will be the performance of the machining process [6].

Parameter optimization for surface roughness is a hard-solving issue because of the interactions between the parameters. Problems related to the enhancement of the product quality and production efficiency can always be related to the optimization procedures [7].

The convergence speed of evolutionary optimization techniques to the optimal results is better than that of the conventional approaches. Therefore, evolutionary algorithms, such as immune algorithm, differential evolution algorithm and artificial bee colony algorithm, have been used in many applications instead of the conventional techniques [8-12].

The use of the traditional optimization methods, such as differential measures and enumeration of all possible solutions, is not very efficient and accurate. The use of met heuristic algorithms in such incidents can improve the speed and the accuracy of the computations [13].

Simulated annealing method is one of the efficient innovative optimization algorithms for solving the optimization problems. This method was introduced in 1982 by “Kirkpatrik”, “Gelatt”and “Vecchi” [14, 15]. Adaptability and ease of programming over the optimization problems and tolerability of feasible non-improving solutions are the most important features of this method.

The related literature review revealed that several researchers have attempted to calculate the optimal cutting conditions in turning operations.

Basim A. Khidhir and Bashir Mohamed *et al.* [16] investigate the effect of cutting speed feed and the depth of cut on surface roughness. It was found that the good surface roughness is obtained with a higher cutting speed, a minimum feed rate, and a lower depth of cut.

Ali R. Yildiz [17] developed a hybrid artificial immune algorithm (AIHC) based on immune algorithm and hill climbing local search algorithm to solve optimization problems. The AIHC was effectively applied to a multi-objective I-beam design problem and machine tool spindle design problem as well as to manufacturing optimization problems.

Ali R. Yildiz [18] developed a new optimization of immune algorithm based on immune algorithm and hill climbing local search algorithm to solve optimization problems. The hybrid immune algorithm was effectively applied to a single objective test problem, multi-objective I-beam and machine-tool spindle optimization problems. The results obtained by the proposed approach for milling operations indicate that the hybrid approach is more effective in optimizing the cutting parameters for milling operations than the immune algorithm and hybrid immune algorithm.

Anil Gupta *et al.* [19] investigated the effect of cutting speed, feed rate, depth of cut, nose radius and cutting environment on surface roughness, tool life, cutting force and power consumption. It has been found that the cutting speed of 160 m/min, nose radius of 0.8 mm, the feed of 0.1 mm/rev, the depth of cut of 0.2 mm and the cryogenic environment are the most favorable cutting parameters for the high speed CNC turning of AISI P-20 tool steel.

Ilhan Asiltürk *et al.* [20] investigated the effect of cutting speed, feed rate and depth of cut on surface roughness of AISI 1040 steel. It was implemented to full factorial experimental design to increase the confidence limit and reliability of the experimental data, Artificial Neural Networks (ANN) and multiple regression approaches; it was compared with multiple regression and neural network using statistical methods. It has been found that the proposed models are capable of predicting the surface roughness. The ANN model estimates the surface roughness with high accuracy compared to the multiple regression model.

Attanasio *et al.* [21] investigated a series of orthogonal hard turning tests that were conducted to study the effects of tool wear and cutting parameters (cutting speed and feed rate), on white and dark layer formation in hardened AISI 52100 bearing steel. It has been found that the crater wear rate is influenced by both cutting speed and feed rate, while flank wear rate seems to be mainly affected by cutting speed. It was also found that the thickness of the white and dark layers increases with the increase of the tool flank wear. Moreover, a higher cutting speed generates thicker white layers and thinner dark layers. In addition, smaller feed rates moderately influence the white layers thickness, while the latter rises with a higher feed rate. In contrast, the dark layers thickness decreases with the increase of the feed rate, especially when flank wear values of higher than 0.075 mm were observed.

Ali R. Yildiz [22] studied the optimization of cutting parameters in turning operations. The population-based optimization technique, such as differential evolution algorithm, is becoming more popular in the design and manufacturing tasks because of the availability and affordability of high-speed computers.

Ilhan Asiltürk and Süleyman Neseli [23] tried to determine the effect of cutting parameters, namely cutting speed, depth of cut and feed rate on surface roughness during machining of AISI 304 austenitic stainless. Then, the model for the surface roughness, as a function of cutting parameters, is obtained using the Response Surface Methodology (RSM). It was found that the feed rate is the dominant factor affecting the surface roughness, which is minimized when the feed rate and depth of cut are set to the lowest level, while the cutting speed is set to the highest level. The percentages of error all fall within 1%, between the predicted values and the experimental values.

Suleyman Neseli *et al.* [24] investigated the effect of tool geometry parameters on the surface roughness during turning of AISI 1040 steel. They developed a prediction model related to average surface roughness (Ra) using experimental data. It was found that the tool nose radius was the dominant factor on the surface roughness with 51.45% contribution in the total variability of model. Also, the approach angle and the rake angle are significant factors on surface roughness with 18.24% and 17.74% contribution in the total variability of model, respectively. In addition, a good agreement between the predicted and measured surface roughness was observed.

H. K. Dave *et al.* [25] investigated the machining characteristics of different grades of EN materials in CNC turning process using Tin coated cutting tools. The present study focuses on 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. It was found that ANOVA showed that the depth of cut has plays a significant role in producing higher MRR and that insert has a significant role in producing a lower surface roughness. Thus, it is possible to increase the machine utilization and decrease the production cost in an automated manufacturing environment.

M. Kaladhar *et al.* [26] investigated the effects of process parameters on surface finish and Material Removal Rate (MRR) to obtain the optimal setting of these process parameters. The Analysis Of Variance (ANOVA) is also used to analyze the influence of cutting parameters during machining. In the present work, AISI 304 austenitic stainless steel work-pieces 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 was found that the feed and nose radius are the most significant process parameters on the work-piece surface roughness. However, the depth of cut and feed are the significant factors on MRR. Optimal range and optimal level of parameters are also predicted for responses.

Anderson P. Paiva *et al.* [27] conducted an experiment on AIAI 52100 with different parameters (cutting speed, feed rate and depth of cut). The outputs considered were (the mixed ceramic tool life, processing cost per piece, cutting time, the total turning cycle time, surface roughness and material removing rate). The results indicated that the multi response optimization was achieved at a cutting speed of 238 m/min, with a feed rate of 0.08 mm/rev and at a depth of cut 0.32 mm.

Tian Syung Lan [28] investigated the effect of cutting speed, feed, cutting depth, tool nose runoff with three levels (low, medium, high) n MRR in finish turning based on L9(34) orthogonal array. It was found that the material removal rates from the fuzzy Taguchi deduction optimization parameters were all significantly advanced compared 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.

2. Experimental Part

In machining operations, the quality of the Surface Roughness (Ra) plays an important role for many turned work-piece. ENAC43400 Aluminum alloy shaft (46×150mm) was machined on CNC lathe (type StarChip 450) by using a carbide cutting tool, as shown in Figure 1.

Figure 1. CNC lathe use in experimental work [29]

The chemical composition of ENAC43400 aluminum alloy is shown in Table 1.

Table 1. Chemical composition of ENAC43400 aluminum alloy

Element	Si	Fe	Mg	Mn	Cr	Cu	Ti	Zn	Other	Al
Wt %	10.40	0.70	0.30	0.20	0.02	0.10	0.05	0.13	0.15	Bal.

Surface roughness was measured using an automatic digital POCKET SURF EMD-1500. Table 2 lists the range of machining parameters use in experimental work.

Table 2. Experimental machining parameters

Cutting parameters	Operational Range
Cutting Speed (m/min)	165-250
Spindle Speed (RPM)	1142-1941
Feed Rate (mm/rev)	0.5-0.7
Depth of cut (mm)	0.5-1

The measured Surface Roughness (Ra) values from experimental data is shown in Table 3.

Table 3. Data obtained from experimental work for Surface Roughness

Experiment No.	Cutting Speed (m/min)	Spindle Speed (RPM)	Feed Rate (mm/rev)	Depth of cut (mm)	Surface Roughness (μm)
1	165	1142	0.05	0.5	1.4
2	165	1447	0.06	0.75	1.18
3	165	1941	0.07	1	1.41
4	200	1142	0.06	1	1.06
5	200	1447	0.07	0.5	1.3
6	200	1941	0.05	0.75	1.26
7	250	1142	0.07	0.75	1.16
8	250	1447	0.05	1	1.13
9	250	1941	0.06	0.5	1.2

All specimens are cylindrical with a diameter equal to 46 mm, and a length equal to 150 mm, Surface Roughness for the specimens before machining are equal to 3.16μm.

3. Multiple Regression Modeling

After the surface roughness is obtained for all experiments, a table needs to be filled in order to obtain several values for the analysis. In order to obtain regression coefficient estimates β_0, β_1, β_2, β_3, and β_4, it is necessary to solve the given simultaneous system of linear equations.

$$n\beta_0 + \beta_1 \Sigma X_{1i} + \beta_2 \Sigma X_{2i} + \beta_3 \Sigma X_{3i} + \beta_4 \Sigma X_{4i} = \Sigma Y_i \quad (1)$$

$$\beta_0 \Sigma X_{1i} + \beta_1 \Sigma X^2_{1i} + \beta_2 \Sigma X_{1i} X_{2i} + \beta_3 \Sigma X_{1i} X_{3i} + \beta_4 \Sigma X_{1i} X_{4i} = \Sigma X_{1i} Y_i \quad (2)$$

$$\beta_0 \Sigma X_{2i} + \beta_1 \Sigma X_{1i} X_{2i} + \beta_2 \Sigma X^2_{2i} + \beta_3 \Sigma X_{2i} X_{3i} + \beta_4 \Sigma X_{2i} X_{4i} = \Sigma X_{2i} Y_i \quad (3)$$

$$\beta_0 \Sigma X_{3i} + \beta_1 \Sigma X_{1i} X_{3i} + \beta_2 \Sigma X_{2i} X_{3i} + \beta_3 \Sigma X^2_{3i} + \beta_4 \Sigma X_{3i} X_{4i} = \Sigma X_{3i} Y_i \quad (4)$$

$$\beta_0 \Sigma X_{4i} + \beta_1 \Sigma X_{1i} X_{4i} + \beta_2 \Sigma X_{2i} X_{4i} + \beta_3 \Sigma X_{3i} X_{4i} + \beta_4 \Sigma X^2_{4i} = \Sigma X_{4i} Y_i \quad (5)$$

The simultaneous system of linear equations above can be simplified into a matrix form. The values of regression coefficients estimated can then be more easily obtained.

$$\begin{bmatrix} n & \sum x_{1i} & \sum x_{2i} & \sum x_{3i} & \sum x_{4i} \\ \sum x_{1i} & \sum x_{1i}^2 & \sum x_{1i}x_{2i} & \sum x_{1i}x_{3i} & \sum x_{1i}x_{4i} \\ \sum x_{2i} & \sum x_{1i}x_{2i} & \sum x_{2i}^2 & \sum x_{2i}x_{3i} & \sum x_{2i}x_{4i} \\ \sum x_{3i} & \sum x_{1i}x_{3i} & \sum x_{2i}x_{3i} & \sum x_{3i}^2 & \sum x_{3i}x_{4i} \\ \sum x_{4i} & \sum x_{1i}x_{4i} & \sum x_{2i}x_{4i} & \sum x_{3i}x_{4i} & \sum x_{4i}^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} = \begin{bmatrix} \sum Y_i \\ \sum X_{1i}Y_i \\ \sum X_{2i}Y_i \\ \sum X_{3i}Y_i \\ \sum X_{4i}Y_i \end{bmatrix} \quad (6)$$

After the simultaneous system of the linear equations above is solved, the regression coefficient estimates will be substituted by the following regression model for surface roughness.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} \quad (7)$$

Where:

Y_i= surface roughness (µm)
X_{1i}= cutting speed (m/min)
X_{2i} = spindle speed (RPM)
X_{3i} = Feed rate (mm/rev)
X_{4i} = depth of cut (mm)

After solving the system of the equations above, the regression equation obtained to predict surface roughness is:

Surface Roughness = 1.52 - 0.00189 Cutting Speed + 0.000111 Spindle Speed + 1.33 Feed Rate - 0.200 Depth of cut

4. Simulated Annealing Method

In the present work, the simulated annealing method has been applied to determine the optimal set of machining parameters required in turning ENAC43400 Aluminum alloy. This method begins with an initial solution and stepwise searches the solution domain for optimal solution.

At each iteration, a new solution in the neighborhood of the current solution is generated and evaluated. A move to new solution is then made under the following conditions [30]: (a) If the objective functions value of the new solution is better than the current one, and (b) If the value or the probability function implemented in simulated annealing has a higher value than a randomly generated number between zero and one.

For the simulated annealing of turning operation, every feasible solution is a combination of cutting speed, spindle speed, feed rate and depth of cut within their specified ranges (constraints lower and upper bounds, shown in Table 2, (cutting speed, spindle speed, feed rate, depth of cut) are: Lower: 165, 1142, 0.05, 0.5. Upper: 250, 1941, 0.07, 1). The optimal solution is a combination of machining parameters that result in minimum surface roughness.

The parameters of applying simulated annealing method are:

- Start point: 165, 1142, 0.05, 0.5
- Annealing Function: fast annealing
- No. of iteration: 2346

The final objective function value found by the simulated annealing method for surface roughness is (1.049 µm) which corresponds to the following machining parameters, shown as the best point in Figure 2:

- Cutting speed: 249.43 m/min,
- Spindle speed: 1210.077 rev/min,
- Feed rate: 0.05 mm/rev,
- Depth of cut: 0.999 mm

Conclusions

CNC turning process modeling of ENAC43400 aluminum alloy, based on multiple regression models, is a successfully implemented and developed model and it is optimized with simulated annealing algorithm. The surface roughnesses (Ra) in the present work are about (1.06-1.41µm).

Selecting Cutting speed in 249.43 (m/min), Spindle speed in 1210.077 (rev/min), Feed rate in 0.05 (mm/rev) and Depth of cut value in 0.999 (mm) conclude an optimum machining condition in multi performance characteristics. This work shows that the multiple performance characteristics, such as surface roughness, can be improved by using this method. Also, the simulated annealing due to adaptability and ease of programming are a powerful tool for optimum condition determination. Analysis of variance suggests that the insert is the most significant factor for Ra.

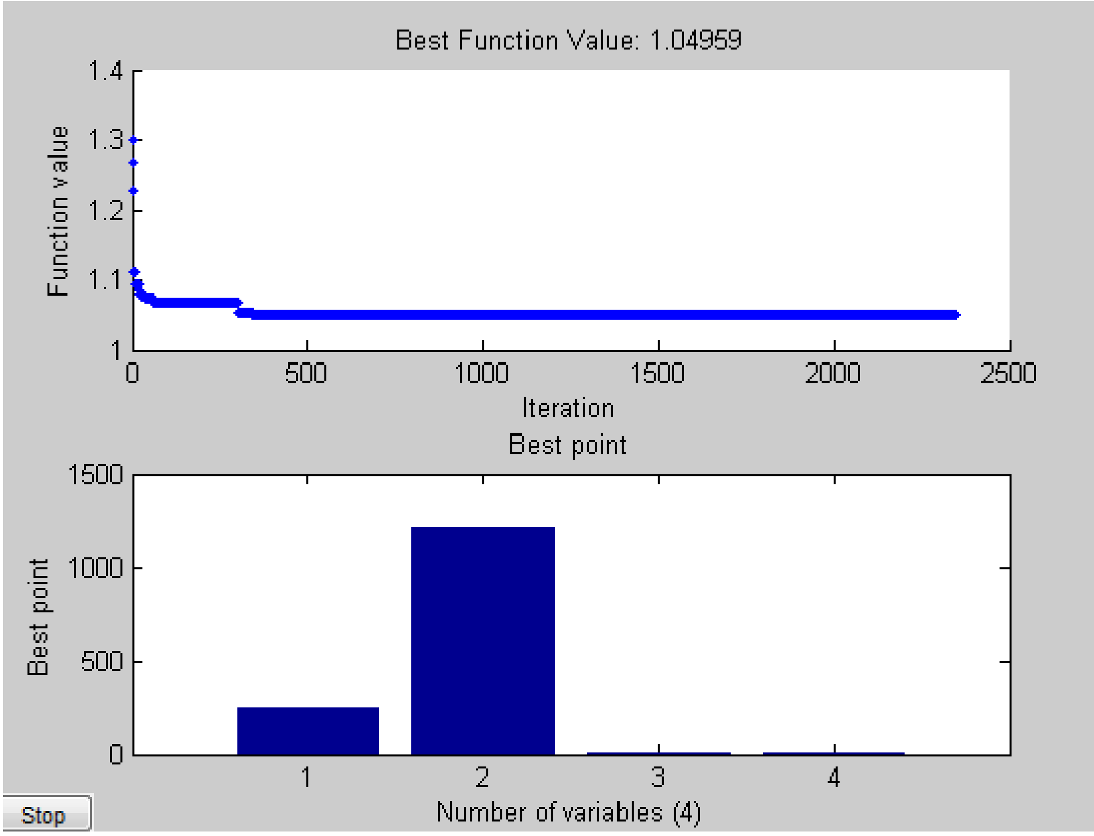

Figure 2. Results of Simulated Annealing Method.

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