ICISE 2020
6th International Conference on Industrial and Systems Engineering
• 9 & 10 Sep. 2020 • Ferdowsi University of Mashhad
ششمین کنفرانس بین المللی
مهندسی صنایع و سیستم ها
۱۹ و ۲۰ شهریور ۱۳۹۹ • دانشگاه فردوسی مشهد

Optimization of tool wear rate and surface quality in turning process of 30MV6 steel parts

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ABSTRACT

In this paper, modeling and optimization of tool wear rate and surface quality in turning process have been considered. Cutting speed, feed rate, depth of cut, clearance angle and tool radius have been considered as the process input variables. The experiments have been carried out on micro-alloy 30SMV6 steel parts commonly used in automotive industries. Taguchi approach has been chosen to gather the required data for modeling and optimization purposes. Next, regression functions (linear, quadratic and logarithmic) have been fit on the experimental data. Then, the best and most fitted models were selected based on the results of statistical analysis. The statistical analysis showed that the logarithmic and linear models are the best ones for tool wear rate and surface quality respectively. In the next stage of the research, simulated annealing (SA) algorithm has been developed to determine the optimal levels of input parameters to reach the least tool wear rate and the best surface quality. Finally, a set of validation tests were performed. The results showed that the proposed method is sufficient in modeling and optimization of the process.

Keywords: regression modeling, design of experiment, Taguchi method, simulated annealing algorithm.

1. Introduction

Nowadays manufacturers seek to improve the quality of their products and reduce their expenses. Machining is the most important process amongst manufacturing processes that is widely used in various industries. Quality of the machined pieces and the production costs are directly influenced by the geometry of the tools and cutting parameters. In this regard, studies on machining mainly focus on two groups of parameters 1) the tool geometry, 2) the surface quality of the products [1]. However, one of the most important criteria for evaluating the quality of the machined pieces is the final surface roughness [2, 3]. To achieve desirable surface quality and tool wear rate, the optimal levels of parameters and clearance angles must be determined regarding the workpiece material.

In most practical applications, tool geometry and cutting parameters are usually determined experimentally based on trial and error. However, these methods are often very expensive and prone to errors. In recent years, application of scientific and mathematical approaches in modeling and optimization of manufacturing processes has increased dramatically. In recent years, modeling and optimization of machining parameters have been increasingly studied.

Nalbant et al. [4], used Taguchi method and analysis of variance to determine the effect of the process input parameters and the optimal values of the tool radius, feed rate and depth of cut to obtain a high surface quality in turning on AISI 1030 steel. According to their findings, tool radius and feed rate have the most effect on surface roughness while depth of cut has the least effect (less than 4%). The effect of cutting parameters on surface roughness in turning on heat treated hardened steel have been investigated by Aslan et al. [5]. In this study the relation between process input variables and output measures has been presented using mathematical modeling. Kini and Chincholkar [6] have studied the influence of machining parameters on surface roughness and material removal rate in turning of polymer material reinforced with fiberglass, and as a result they have presented an experimental relationship between surface roughness and material removal rate.

To the best of our knowledge there is no study in which the effect of turning process input variables on tool wear rate and surface quality has been investigated. Therefore, the purpose of this study is modeling and optimization of machining parameters and tool geometry as the effective variables on surface quality and tool life in turning on micro-alloy 30MV6 Steel extensively used in automation industry. Micro-alloy 30SMV6 steel is one of the hard to machine alloys finding an optimized machining condition to reduce the machining Cost and time is required. To gather the experimental data required for modeling and optimization purposes Taguchi Method has been used. The experimental results are then used to develop mathematical models. These models would establish the relations between input parameters (tool geometry specifications and cutting parameters) and the process performance measures (tool life and surface quality). Finally the proposed models have been embedded into Simulated annealing (SA) algorithm to specify the best set of input parameters.

2. Experimental setup and equipment used

Design of experiments consists of a series of systematic operations to characterize one or more from possible experiments, which make systematic changes to the input variables to identify the degree of changes in the output response.

The process input variables and output measures are shown in Figure. 1. In this study, Taguchi method was used to design the experimental matrix required for data gathering. Process input parameters and their corresponding intervals and levels have been determined based on the literature survey and preliminary experiments (Table 1). As can be seen in this Table, tool radius and clearance angle from the geometric parameters are considered as the most important features. The cutting parameters in four levels and geometric parameters in two levels. Based on the number of process input parameters and their levels, Taguchi Design of experiments (L_{16}) has been considered.

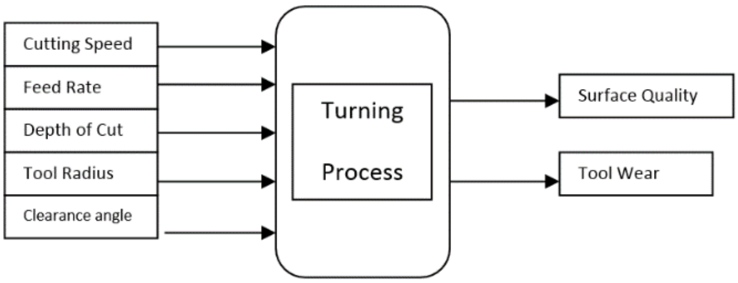

Figure 1. The Process Input Variables and Output Parameter

Table 1. The process parameters and their corresponding levels

Level	Spindle Round	Feed (mm/rev)	Depth of Cut	Tool Radius	Clearance
Level 1	710	0.08	0.5	0.8	5
Level 2	250	0.12	1.0	1.2	7
Level 3	355	0.16	1.5	-	-
Level 4	500	0.20	2.0	-	-

As mentioned, the material used in this study is 30SMV6 steel that is frequently used in automotive and military manufacturing industries. This material is one of the hard to machine alloys, finding the optimal machining condition considering tool wear rate and surface finish draw the attention of most scholars. The chemical composition of this alloy is shown in Table 2. The lathe used in this study is semi-automated TN50BR model manufactured by Tabriz Machine Tool Manufacturing Co.

Table 2. Chemical Composition of 30SMV6 Steel (%)

V	N2	Al	Mo	Ni	Cu	Cr	Ti	S	P	Mn	Si	C
0.08- 0.14	Min 0.012	0.01-0.04	0-0.06	0-0.17	0-0.4	0-0.25	0.015-0.025	0.065-0.09	0-0.025	1.4-1.6	0.5-0.7	0.3-0.33

To measure the quality of the machined surfaces, Perthometer M2 roughness gauge, made by the German company Maher (Figure 2) was used. D-M17 microscope made by Vickers English Company was used to measure wear rates on the clearance surface (Figure3).

To perform the experiments, at first cutting parameters were set on the lathe machine in accordance to experimental matrix design (Table 3). Then piece of work (rod with diameter of 38mm) is set on the machine and it starts working. After 1 minute of machining and before changing the geometric parameters of the tool caused by the wear, the piece is opened and using the machining gauge (Figure 3), surface quality is measured and recorded. (Changing the geometric parameters of the tool leads to changes in machining conditions and on the other hand, since the goal is measuring the surface quality at preliminary condition, after 1 minute machinery, surface quality is measured).

Figure 2. D-M17 microscope used

Figure 3. The Roughness tester

After measurement of surface quality, machining operation continues with the same conditions for 19 minutes, as the result, the total machining spends 20 minutes. At the end of each experiment, using microscope, the wear is measured and recorded on the clearance surface of insert. It is noticeable that the order of performed experiments is completely random. The results are shown in table 3. f (Feeding) , a (Depth of Cut) , r (Tool Radius) , γ (Clearance Angle) , Vc (Cutting Speed) , Ra (Surface roughness) , D (Tool wear).

Table 3. The Results of Experiments

No.	f (mm)	a (mm)	r (mm)	γ	Vc	Ra	D
1	0.08	0.5	0.8	5	30	2.26	0.04
2	0.12	1.0	0.8	5	30	2.62	0.10
3	0.16	1.5	1.2	7	30	2.69	0.42
.	.	.	.	.	.	.	.
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14	0.12	1.5	1.2	5	84.7	2.29	0.28
15	0.16	1.0	0.8	7	84.7	3.02	0.43
16	0.20	0.5	0.8	7	84.7	3.46	0.30

3. Modeling of the process

In this study, regression modeling is used for determining the relationship between input and output variables of the process. In order to model the process under consideration, different mathematical functions such as linear, second order (quadratic) and logarithmic are fitted on the experimental results of experiments the regression equations for surface roughness and tool wear rate has been shown in Table 4.

Table 4. The proposed models

Response Variable	Model	The fitted Model	R^2	R^2_{adj}
Surface Quality	Linear	$Ra = 2.06 + 9.41\,f + 0.0115\,a - 0.759\,r + 0.0144\,\gamma - 0.00067\,vc$	99.3	98.9
	Second Degree (quadratic)	$Ra = 2.35 + 5.79\,f - 0.072\,a - 0.763\,r + 0.0148\,\gamma - 0.098\,vc + 12.9\,f^2 + 0.175\,a^2 + 0.054\,vc^2 - 0.09\,vc \cdot f + 0.004\,vc \cdot a + 0.08\,f \cdot a$	99.3	97.2
	Logarithmic	$Ln\,(Ra) = 1.83 + 0.458 \ln f - 0.006 \ln r + 0.0348 \ln \gamma - 0.0133 \ln vc$	98.9	97.9
Tool Wear	Linear	$D = -0.634 + 1.13\,f + 0.191\,a + 0.0469\,r + 0.0581\,\gamma + 0.136\,vc$	84.8	77.2
	Second Dgree (quadratic)	$D = -0.392 + 1.86\,f + 0.023\,a - 0.011\,r + 0.0733\,\gamma - 0.454\,vc + 5.1\,f^2 + 0.023\,a^2 + 0.274\,vc^2 - 1.18\,vc \cdot f + 0.162\,vc \cdot a - 0.43\,f$	89	78.8
	Logarithmic	$\ln(D) = -2.03 + 0.887 \ln f + 0.96 \ln a + 2.18 \ln r + 1.34 \ln \gamma + 0.777 \ln vc$	97.3	96.4

One criteria of selecting the appropriate model, is correlation coefficient) R^2 and R_{adj}^2 that has been calculated for all of the equations [3]. Linear models for surface quality and logarithmic model for surface wear on the clearance surface of the tool have correlation coefficients of 98.9% and 96.4%, respectively, which shows the perfect fitting of these models on experimental data (Tables 5 and 6). Another statistic criterion is f-value which is compared against critical values, and if it is greater, it means that, it is a good model .Obtained values related to linear model of surface quality and logarithmic model of tool wear are 27.8 and 21.44, respectively. These values are greater than the critical values (3.33). The importance of process input parameters on the process measures have been illustrated in Figure 4.

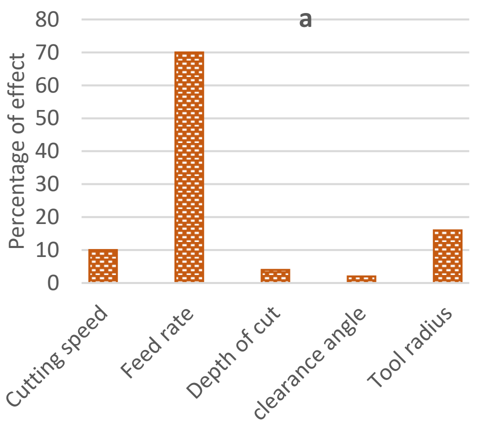
Table 5. The Average Error Percentage for Surface Quality

Column	The Experiment Results	The Predicted Value by the Model	The Estimated Error (%)
1	2.36	2.399	-1.65
2	2.17	2.101	3.17
3	2.64	2.618	0.83
4	2.32	2.383	-2.715
5	2.37	2.401	-1.3
6	2.12	2.104	0.75

7	2.70	2.684	0.59
8	2.34	2.386	-1.92
The Average Error Percentage (Absolute Value)			-0.28

Table 6. The Average Error Percentage for Tool Wear Rate

Column	The Experiment Results	The Predicted Value by the Model	The Estimated Error (%)
1	0.16	0.18	-12.5
2	0.36	0.33	8.33
The Average Error Percentage (Absolute Value)			-2.08



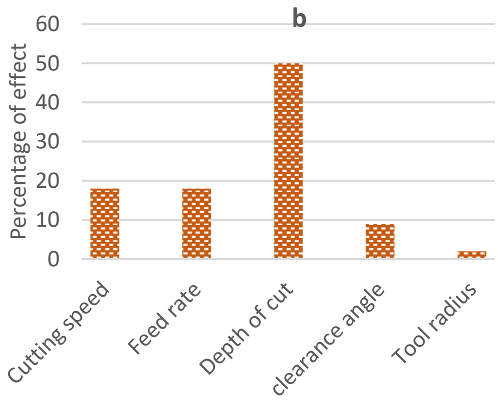


Figure 4. The Percentage of Input Parameters Effects on:

a) the Surface Quality in Linear Model **b) the Tool Wear in Logarithmic Model**

4. Simulated Annealing algorithm

Simulated annealing algorithm is neighborhood searcher that was introduced for solving non-linear and complexity of optimizing problems in early 1980s [7]. This algorithm is a random searching technique that is obtained from metallurgic process of annealing of metals. In Annealing, a melted metal is slowly cooled. Gradual decrease of temperature makes ordered crystal construction and without deficiency in material and minimizes its energy level. Therefore, gradual decrease of temperature is as an obligation. In the technique of optimizing by simulated annealing algorithm, this criterion has been used for minimizing value of target function.

The nature of this algorithm performance is as if for each move, a new random neighbor is produced and analyzed. Moving to the response is done in 2 settings; 1) The new answer is better than current answer and 2) The value of probability function is greater than a random number from the range of (0, 1). Otherwise, the searcher produces and analyses a new answer. This move will continue step by step (the number of repetitions, the calculating time…) to satisfy stop of algorithm condition.

In this paper, by the use of simulating annealing algorithm as an optimizing method, input parameters levels of the process are determined as if they have the best surface quality and the lowest degree of tool wear. Machining processes are usually performed in 2 or 3 steps of rough turning, semi finishing and finishing. Rough turning is carried out with the aim of increasing machining speed in which surface quality isn't important. In contrast, in the semi-finishing and finishing steps, the goal is to increase surface quality and dimensional accuracy. Therefore, optimizing is designed to satisfy every steps needed. To satisfy it, by the means of weighting schema target function could be determined for 2 outputs with regard to approximate importance of each one.

The results of simultaneous optimization of 2 outputs for different machining condition, are presented in table 7 (α_1 and α_2 determine surface roughness and tool ware rate significance respectively). The first column of Table 7, represent the machining parameters

Table 7. The optimal levels for weighted outputs

Machining parameters	**Weighting Conditions**		
	$\alpha_1 = 0\ ,\alpha_2 = 1$	$\alpha_1 = 0.5\ ,\alpha_2 = 0.5$	$\alpha_1 = 1\ ,\alpha_2 = 0$
Cutting Speed (Vc)	25	90	300
Feeding (f)	0.05	0.05	0.05
Cutting Depth (a)	0.1	1.7	2
Tool Radius (r)	0.4	1.6	1.6
Clearance Angle ((γ)	0	13	15
The Predicted Surface Quality	27.2	1.6	1.48
The Predicted Tool Wear	0.02	0.3	2.22

After determining the optimal conditions, the results and effectiveness of optimizing methods were confirmed again by repeating the experiments under the optimal conditions. The results of confirmation tests have been presented in table 8.

Table 8. The results of Confirming Experiments

	Optimal Machining Conditions		
	$\alpha_1 = 0\ ,\alpha_2 = 1$	$\alpha_1 = 0.5\ ,\alpha_2 = 0.5$	$\alpha_1 = 0\ ,\alpha_2 = 1$
The Quality Surface (Ra)	26	1.56	1.59
The Tool Wear (Wear)	0.03	0.38	2.8
The Highest Error	5%		

As observed, the highest error is 5% which shows the adequacy of the proposed method. Due to the resistant cover on the surface of insert which is applied against wear, the exact place of starting the wear on the tool free surface isn't clear and this leads to error in measuring and as a result, it causes error in tool wear value. Therefore, errors in approval experiments in logarithmic model of tool wear in modeling and optimizing is higher than linear model of surface quality.

5.Conclusion

Because of direct relationship between tools wear rate and machining cost, and on the other hand, the effect of surface roughness in final quality and products performance, among various outputs, two parameters of tool wear and surface roughness are considered as the evaluation principles of turning quality. Based on the process input parameters and their corresponding levels, experimental design matrix has been chosen using Taguchi method. To establish the relations between process input and output parameters regression modeling has been employed. Based on the results, the most effective parameters affect the surface quality and tool wear rate are feed rate and depth of cut respectively. In the second part of the study, simulated Annealing algorithm was used in order to optimize the process input parameters to reach ideal output variables as a single and multi-criteria optimization. The results of confirmation experiments (with about 5% error) showed that the proposed regression based modeling and SA based optimization procedure is quite efficient in modeling and optimization purposes of turning process of micro alloy.

5. References

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