Modeling and optimization of surface quality in turning process on micro-alloy steels using Taguchi method and simulated annealing algorithm

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Abstract

In turning process, determination of the optimal tool geometry and cutting parameters in order to improve the surface quality and reduce the production cost is vital. In this paper, based on experimental results and statistical analysis, one of the most important characteristic (surface quality) in turning process on micro-alloy steels has been modeled and optimized. The process input parameters consist of cutting speed, feed rate, depth of cut, clearance angle and tool radius. The experiments have been carried out on micro-alloy 30SMV6 steel and they have been based on Taguchi experimental design approach. Then regression functions including linear, quadratic and logarithmic models have been fit on the experimental data. Then the best and most fitted model was selected based on the results of statistical analysis. The statistical analysis showed that the linear model for surface quality is the best ones. In the next step of the research, simulated annealing (SA) algorithm has been employed to determine the optimal levels to reach the best surface quality. Finally, for validation test has been performed, and the results showed that the proposed method is quite efficient in modeling and optimization of turning process.

Keywords: regression modeling, micro-alloy steel, design of experiment, Taguchi method, simulated annealing algorithm**.**

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Introduction

Nowadays manufacturers seek to improve the quality and to reduce the cost of their products. Machining is the most important process in manufacturing 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 machining adjust parameters [1]. However, one of the most important criteria for evaluating the quality of the machined pieces is the final surface roughness [2]. It depends on several factors, the most important is tool geometry and cutting parameters (depth of cut, cutting speed and feed rate). Therefore, to achieve desirable finished surface, the optimal levels of parameters and clearance angles must be determined regarding the work piece 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, the 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.

In these studies, the statistical techniques, natural networks and fuzzy theory are applied for modeling the processes [3]. On the other hand, to determine the optimal adjustable parameters, a range of approaches such as Taguchi Method, and meta-heuristic algorithms are applied. Yung and Trang have used Taguchi method and analysis of variance to determine the optimal values of the parameters on S45C steel turning [3]. Kopac et al [4], has achieved the optimal levels of machining parameters (cutting speed, depth of cut, tool material and work piece material) to obtain the desired high quality surface in turning operations for cooled worked steel parts using Taguchi method. Using the natural network, Chien and Tsai have developed a model to predict tool wear, and they have obtained the optimal values of machining parameters on 4PH-17 stainless steel by combination of the model and genetic algorithm (GA) [5].

Another important issue in researches related to machining is tool geometry. For example, Nalbant et al. [6], used Taguchi method and analysis of variance, for determination of the effect 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%). Aslan et al [7], have investigated the effect of cutting parameters on surface roughness in turning on heat treated hardened steel and they have presented their relationship as a mathematical model. The main features of the tool geometry are the tool radius, clearance angle, rake angle and the major and minor tool angles. In most studies, the effect of tool geometry parameters on surface quality has been studied separately. The results of the researches indicate that the overall level of quality can improve by increasing the rake angle, whereas clearance angle doesn't have a significant effect on the surface quality and the material removal rate, it just facilitates the machining conditions [8].

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. To gather the experimental data, 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 measure (surface quality). Finally the proposed model is embedded into the simulated annealing (SA) algorithm to specify the best set of input parameters.

Design of experiments

Design of experiments consists of a series of exact and 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 input and output of the process is shown in Fig. 1. In this study, the Taguchi method is used. Levels considered for the input variables are presented in Table 1.

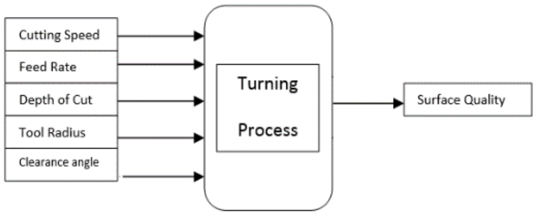

Fig. 1. The process input variables and output response

Table1. Process input variables and their corresponding levels

Parameters	Level 1	Level 2	Level 3	Level 4
Spindle Round (r/min)	250	355	500	710
Feed (mm/rev)	0.08	0.12	0.16	0.2
Depth of Cut (mm)	0.5	1	1.5	2
Tool Radius (mm)	0.8	1.2	-	-
Clearance angle	5	7	-	-

As seen, 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 are subject to change. The proposed matrix, Taguchi Design, L_{16}, is presented in Table 2.

Materials and equipment used in the experiments

As mentioned, the material used in this study is 30SMV6 steel that is frequently used in automotive and part manufacturing industries.

The lathe used in this study is semi-automated TN50BR model manufactured by Tabriz Machine Tool Manufacturing Co.

Inserts are coded and identified according to their geometrical parameters. Inserts used in this study include DNMA150608-MT6110 and DNMA150612-MT6110. These types of inserts are widely used in various turning operations of micro alloys and cast iron parts. They are both made of tungsten carbide coated with AL_2O_3 and TiCN but have different cutting angels. To measure the quality of the machined surfaces, Perth meter M2 roughness gauge, made by the German company Maher (Figure 2) was used.

Fig. 2. The surface roughness tester used

Conducting the experiments based on the Taguchi method

To perform the experiments, at first cutting parameters were set on the lathe machine in accordance to experimental matrix design (Table 2). 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 (Fig. 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).

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 2.

Table 2. DOE design matrix and Experimental results

No	f (mm)	a (mm)	r (mm)	γ (deg)	V_C (m/min)	R_a µm
1	0.08	0.5	0.8	5	30	2.26
2	0.12	1.0	0.8	5	30	2.62
3	0.16	1.5	1.2	7	30	2.69
4	0.20	2.0	1.2	7	30	3.11
5	0.08	1.0	1.2	7	42.3	2.05
6	0.12	0.5	1.2	7	42.3	2.39
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
14	0.12	1.5	1.2	5	84.7	2.29
15	0.16	1.0	0.8	7	84.7	3.02
16	0.20	0.5	0.8	7	84.7	3.46

Fig. 3. The Specimen used in the Experiments

Regression modeling

Regression is a statistical method used to establish the mathematical relationship between input and output parameters of the process. This statistical method has wide usage in different scientific areas such as engineering, physics, economics and other sciences. In this study, regression analysis 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. And eventually, by confidence level of 95%, the equation factors for surface quality and the value of clearance surface wear in MINITAB environment were extracted. (table 3)

One criteria of selecting the appropriate model, is correlation coefficient) R^2 and R^2-adj (that has been calculated for all of the equations [9]. Linear models for surface quality shows the best fitting on the experimental data. Another statistic criterion is f-value which is compared against critical values obtained of the table, and if it is greater, it means that, it is a good model .Obtained values related to linear model of surface quality is 27.8. These values are greater than the critical values (3.33), so it shows fitness of the model.

Another criterion that could be used to determine the proper model is the diagram of probability of data and the histogram of the residuals. Similar to Fig. 4, it is obvious that linear model of surface quality has normal distribution.

Table 3. The proposed models

Process Response	Model	Equation	R^2	R_{adj}^2
Surface Quality	Linear	R_a= 2.06 + 9.41 f + 0.015 a-0.759 r + 0.0144 γ-0.0067 V_C	99.3	98.9
	Second Degree (quadratic)	R_a = 2.35 + 5.79f – 0.072a – 0.763r + 0.0148γ –0.098 V_C +12.9 f^2+ 0.175 a^2+0.054 V_C^2 – 0.09 V_C *f + 0.004 V_C *a + 0.08f*a	99.5	97.2
	Logarithmic	ln R_a =1.83+0.458 ln f –0.006 ln r +0.0348 ln γ–0.0133 ln V_C	98.9	97.9

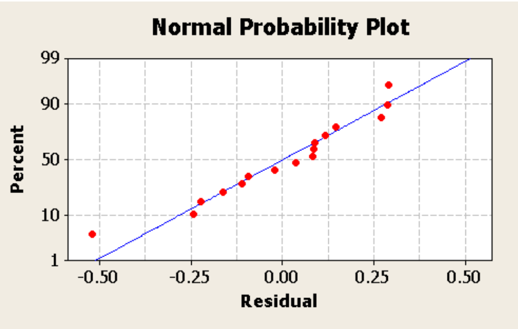

Fig. 4. Normal probability of linear model for surface quality

After finding the appropriate models for studying the influence of the input parameters on surface quality using analysis of variance method.

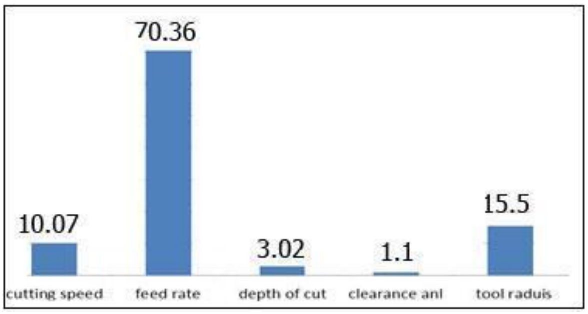

Fig. 5. The percentage contribution of input variables on surface quality

In order to approve and to confirm models ability in predicting the processes, eight experiments were performed for linear model of surface quality to show the accuracy of the proposed models. The comparisons of the predicted values and experimental values are presented in Table 4.

Table 4. The average error percentage in linear model

No	The Experiment Results	The Predicted Value by the Model	Error (%)
1	2.36	2.399	-0.039
2	2.17	2.101	-3.2
3	2.64	2.618	0.84
4	2.32	2.383	-2.64
5	2.37	2.401	-1.29
6	2.12	2.104	-0.75
7	2.70	2.684	0.59
8	2.34	2.386	-1.93
The Average Error Percentage (Absolute Value)			1.4

Simulated annealing algorithm

Simulated annealing algorithm is neighborhood searcher that was introduced for solving non-linear and complexity of optimizing problems in early 1980s [10]. 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. The value of probability function of move is calculated using Equation 1.

$$P_r = \exp(-\Delta z / C_k) \quad (1)$$

In this formula Δz is the difference value of target function between current and new answer. Index of k shows number of repetition and CK shows the controlling parameter which is called temperature .Usually at the beginning of research, a high degree of early temperature (C_0) is selected, as if algorithm will find more chance to move toward non optimizing answers. But with increasing in repetition number, this temperature accordance with the following formula with certain coolness rate, slowly decreases.

$$C = \quad C_{k+1} = \alpha \times C_k \quad (2)$$

Coolness rate (α) is usually selected between 95% to99%. In accordance with the above discussion, the probability of selection of worse answers decreases by increasing the move numbers. But as the research progresses, moves are carried out based on improvement in target function and as a result, the role of random nature of algorithm in acceptance of new answer decreases. More details of this algorithm and some of its usages are presented in the literature.

In this research, the early temperature degree (C_0), stop condition, and coefficient of change of control parameters is considered as presented in table 5.

Table 5. Basic parameters of algorithm

Coefficient of change in control parameter (α)	Primary control function (C_0)	Stop criteria
0.95	1	Final amount of control parameter C_{K+1}=0.001

Table 6. The optimal condition

Machining Parameters	
Cutting Speed (V_c)	300 (4.3)
Feeding (f)	0.05
Cutting Depth (a)	2
Tool Radius (r)	1.6
clearance Angle (γ)	15
The Predicted Surface Quality (R_a)	1.48

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 are presented in table 7. The error is calculated using Equation 3.

$$\%E = \frac{A-P}{P} \times 100 \tag{3}$$

Where, E, A, and P are error percentage, experimental value, and predicted value respectively.

Table 7. The results of confirming experiment

Process Characteristics	Ra
Predicted Value	1.48
Experimental Value	1.59
Error	7 %

As observed, the error is 7% which shows efficiency of the proposed method.

Conclusion

Due to the high number of effective parameters in turning process, achieving desired outputs demands a complete understanding of parameters and their influence, as well creating new models. Therefore, by studying, examining the turning principles and regarding facilities important parameters were provided to perform practical experiments and to gather demanded data.

Because of direct relationship surface quality and machining cost, among various outputs, surface roughness is considered as the evaluation principles of turning quality. In the first stage the mathematical models are obtained based on finding mean approach which presents the relationship between output and inputs of turning process. In order to process modeling, different kinds of regressions functions are fitted on experimental data. Statistical tests showed that linear model has the most agreement on actual process of turning on micro-alloy steels for surface roughness. In the second part of study, simulating annealing algorithm was used in order to predict and to determine the optimal levels of regulated parameters to reach ideal output response. The results of confirming experiment showed the appropriate performance and the high accuracy of the proposed method for solving such problem.

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