

Research Article

Fuzzy Linguistic Optimization on Surface Roughness for CNC Turning

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Received 16 January 2010; Accepted 21 June 2010

Academic Editor: Miguel Cerrolaza

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Surface roughness is often considered the main purpose in contemporary computer numerical controlled (CNC) machining industry. Most existing optimization researches for CNC finish turning were either accomplished within certain manufacturing circumstances or achieved through numerous equipment operations. Therefore, a general deduction optimization scheme is deemed to be necessary for the industry. In this paper, the cutting depth, feed rate, speed, and tool nose runoff with low, medium, and high level are considered to optimize the surface roughness for finish turning based on $L_9(3^4)$ orthogonal array. Additionally, nine fuzzy control rules using triangle membership function with respect to five linguistic grades for surface roughness are constructed. Considering four input and twenty output intervals, the defuzzification using center of gravity is then completed. Thus, the optimum general fuzzy linguistic parameters can then be received. The confirmation experiment result showed that the surface roughness from the fuzzy linguistic optimization parameters is significantly advanced compared to that from the benchmark. This paper certainly proposes a general optimization scheme using orthogonal array fuzzy linguistic approach to the surface roughness for CNC turning with profound insight.

1. Introduction

Machining operations have been the core of the manufacturing industry since the industrial revolution [1]. The existing optimization researches for computer numerical controlled (CNC) turning were either simulated within particular manufacturing circumstances [2–5] or achieved through numerous frequent equipment operations [6, 7]. Nevertheless, these are regarded as computing simulations, and the applicability to real-world industry is still uncertain. Therefore, a general deduction optimization scheme without equipment operations is deemed to be necessarily developed.

The machining process on a CNC lathe is programmed by speed, feed rate, and cutting depth, which are frequently determined based on the job shop experiences. However, the machine performance and 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 runoff will affect the performance of the machining process [8]. Therefore, the tool nose runoff is also selected as one of the control factors in this study.

Parameter optimization is a hard-solving issue because of the interactions between parameters. Problems related to the enhancement of product quality and production efficiency can always be related to the optimization procedures. Taguchi method, an experimental design method, has been widely applied to many industries. It can not only optimize quality characteristics through the setting of design parameters but also reduce the sensitivity of the system performance to sources of variation [9–12]. The Taguchi method adopts a set of orthogonal arrays to investigate the effect of parameters on specific quality characteristics to decide the optimum parameter combination. These kinds of arrays use a small number of experimental runs to analyze the quality effects of parameters as well as the optimum combination of parameters.

To achieve the general optimization, it is necessary to first describe the dynamic behavior of the system to be controlled. Because of the number, complexity, and unclear, vague nature of the variables of the dynamic systems that may influence the decision maker's decision, fuzzy set theory is the most suitable solution [13, 14]. Fuzzy linguistic models permit the translation of verbal expressions into numerical ones [15]. Therefore, the input-output relationship of the process can be described by the collection of fuzzy control rules involving linguistic variables rather than a complicated dynamic mathematical model.

With all the viewpoints above, this paper considers four parameters (cutting depth, feed rate, speed, and tool nose runoff) with three levels (low, medium, and high) to optimize surface roughness in CNC finish turning. The fuzzy control rules using triangle membership function with respective to five linguistic grades for surface roughness are additionally constructed. The defuzzification is then quantified using center of gravity and introduced to Taguchi experiment. Thus, the optimum fuzzy linguistic parameters can then be received. This paper definitely proposes a general deduction optimization approach and satisfactory fuzzy linguistic technique for improving surface roughness in CNC turning with profound insight.

2. Methodology

In this paper, the linguistic variable quantification and parameter optimization for CNC turning operations are proposed using fuzzy set theory and Taguchi method, respectively. They are described as below.

2.1. Fuzzy Set Theory

Let X be a universe of discourse; \tilde{A} is a fuzzy subset of X if for all $x \in X$, there is a number $\mu_{\tilde{A}}(x) \in [0, 1]$ assigned to represent the membership of x to \tilde{A} , and $\mu_{\tilde{A}}(x)$ is called the membership function of \tilde{A} . A triangular fuzzy number \tilde{A} can be defined by a triplet (a, b, c) (Figure 1) [16]. The membership function is defined as

$$\mu_{\tilde{A}}(x : a, b, c) = \begin{cases} \frac{x - a}{b - a}, & a < x \leq b, \\ \frac{x - b}{c - b}, & b < x \leq c, \\ 0, & \text{otherwise.} \end{cases} \quad (2.1)$$

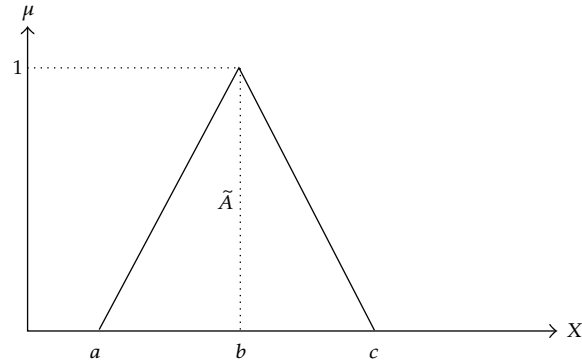


Figure 1: A triangle fuzzy numbers.

In this paper, the two most important parameters for surface roughness are primarily concluded through literature review. Additionally, nine fuzzy control rules for surface roughness using triangle membership function with respective to five linguistic grades will be constructed following IF-THEN rules.

To eliminate the computation, four input (parameter) and twenty output (quality) intervals are considered to prepare the defuzzification. Through Cartesian product, the degree of membership for both input and output can thus be attained as

$$R = \text{Input} * \text{Output}. \quad (2.2)$$

Here, "Input" describes the parameter, "Output" represents the quality, and R denotes the fuzzy relation between the parameter and quality.

The "OR" rules are then utilized for combining rules for maximum degree of membership as

$$\mu R1 + \mu R2 = \max\{\mu R1, \mu R2\}, \quad (2.3)$$

where $R1$ and $R2$ symbolize for the two rules.

In this study, the average value using center of gravity is determined to represent the fuzzy set as

$$F(x_i) = \frac{\sum_i x_i * \mu_{\tilde{A}}(x_i)}{\sum_i \mu_{\tilde{A}}(x_i)}, \quad (2.4)$$

where $F(x_i)$ is the final rating of activity, and $\mu_{\tilde{A}}(x_i)$ describes the membership function of fuzzy set \tilde{A} .

2.2. Taguchi Method

The Taguchi method is a robust design method technique [17, 18], which provides a simple way to design an efficient and cost-effective experiment. In order to efficiently reduce the

numbers of conventional experimental tasks, the orthogonal array [10, 19] by using design parameters (control factors) in column and standard quantities (levels) in row is proposed and further adopted. The performance measure, signal-to-noise ratio (S/N) [20] proposed by Taguchi is used to obtain the optimal parameter combinations. The larger S/N means that the relation to the quality will become better. The lower quality characteristic will be regarded as a better result when considering the smaller-the-best quality. The related S/N ratio is defined as

$$S/N = -10 \left(\log \sum_{i=1}^n \frac{y_i^2}{n} \right) \quad (\text{dB}), \quad (2.5)$$

where n is the number of experiments for each experimental set, and y_i expresses the quality characteristic at the i th experiment. On the contrary, the larger quality characteristic will have better result when considering the larger-the-best quality, therefore, by taking the inverse of quality characteristic into (2.5), the related S/N ratio can also be deduced and shown in

$$S/N = -10 \left(\log \sum_{i=1}^n \frac{1/y_i^2}{n} \right) \quad (\text{dB}). \quad (2.6)$$

In this study, the defuzzification result for CNC machined surface roughness is introduced to the Taguchi experiment as the S/N ratio. In addition to the S/N ratio, a statistical analysis of variance (ANOVA) [21] can be employed to indicate the impact of process parameters. In this way, the optimal levels of process parameters can be estimated.

3. Research Design

Surface roughness is considered the quality in this paper. Four parameters with three levels are selected to optimize the surface roughness in finish turning based on the $L_9(3^4)$ orthogonal array. Additionally, nine fuzzy control rules with respective to five linguistic grades for surface roughness are constructed. Considering four input and twenty output intervals, the defuzzification using center of gravity is thus completed and introduced into the Taguchi experiment. Therefore, the optimum fuzzy linguistic parameters can then be received.

3.1. Construction of Orthogonal Array

In this study, the four turning parameters ((A) speed, (B) cutting depth, (C) feed rate, and (D) tool nose runoff) [22] with three different levels (low, medium, and high) (see Table 1) are constructed for the deduction optimization of machining operation. In Table 1, the three levels of speed, cutting depth, and feed rate are considered according to the machining handbook suggested by the tool manufacturer. The tool nose runoff is positioned by using different shims located under the tool holder. The orthogonal array is then selected to perform the nine sets of deduction experiments.

Table 1: Orthogonal array.

Experiment	Parameter			
	A (speed)	B (cutting depth)	C (feed rate)	D (tool nose runoff)
1	Low	Low	Low	Low
2	Low	Medium	Medium	Medium
3	Low	High	High	High
4	Medium	Low	Medium	High
5	Medium	Medium	High	Low
6	Medium	High	Low	Medium
7	High	Low	High	Medium
8	High	Medium	Low	High
9	High	High	Medium	Low

3.2. Fuzzy Control Rules

The nine fuzzy control rules with respect to five linguistic grades for the surface roughness in this paper are constructed. The five linguistic grades for surface roughness are determined as excellent, good, fair, poor, and worst. From the existing literature [23], it is found that the surface roughness can be expressed as $R_i (i = a, zD, t, p, q, 3z) = C_i V^{m_i} f^{n_i}$, where the machining speed (V) and feed rate (f) are concluded as major parameters to surface roughness. Therefore, the fuzzy rules can be described as follows.

Rule 3.1. If the fuzzy rules are medium machining speed and low feed rate, then the surface roughness is excellent.

Rule 3.2. If the fuzzy rules are low machining speed and medium feed rate, then the surface roughness is good.

Rule 3.3. If the fuzzy rules are low machining speed and high feed rate, then the surface roughness is fair.

Rule 3.4. If the fuzzy rules are medium machining speed and medium feed rate, then the surface roughness is fair.

Rule 3.5. If the fuzzy rules are medium machining speed and high feed rate, then the surface roughness is poor.

Rule 3.6. If the fuzzy rules are medium machining speed and low feed rate, then the surface roughness is good.

Rule 3.7. If the fuzzy rules are high machining speed and high feed rate, then the surface roughness is worst.

Rule 3.8. If the fuzzy rules are high machining speed and low feed rate, then the surface roughness is fair.

Rule 3.9. If the fuzzy rules are high machining speed and medium feed rate, then the surface roughness is worst.

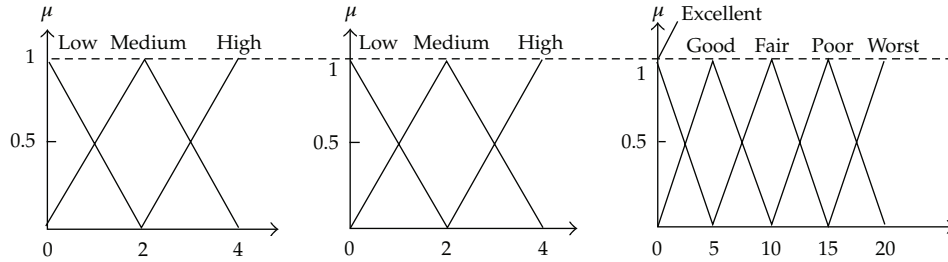


Figure 2: Relationship of membership functions.

Table 2: Degree of membership for parameter.

Fuzzy item	Interval				
	0	1	2	3	4
Low	1	0.5	0	0	0
Medium	0	0.5	1	0.5	0
High	0	0	0	0.5	1

Table 3: Degree of membership for surface roughness.

Fuzzy item	Interval																				
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Excellent	1	0.8	0.6	0.4	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Good	0	0.2	0.4	0.8	1	0.6	0.4	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0
Fair	0	0	0	0	0	0	0.2	0.4	0.6	0.8	1	0.8	0.6	0.4	0.2	0	0	0	0	0	0
Poor	0	0	0	0	0	0	0	0	0	0	0	0.2	0.4	0.6	0.8	1	0.8	0.6	0.4	0.2	0
Worst	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.4	0.6	0.8	1

Table 4: Quantified results for linguistic results.

Scale	Excellent	Good	Fair	Poor	Worse
Defuzzification	1.33	5	10	15	18.67

3.3. Defuzzification

In this paper, the three parameter levels are selected based on the Taguchi experimental method, therefore, the triangle membership function is related to the peak point of its fuzzy area. Considering four input and twenty output intervals, the defuzzification of five linguistic grades using center of gravity can then be completed.

Since two major parameters are considered for surface roughness, the input (parameter) membership functions are regarded as the intersection of two fuzzy sets, and the height of fuzzy set is considered as $\mu = 1$ (Figure 2). The degree of membership for input (parameter) and output (quality) can be described as shown in Tables 2 and 3, respectively. Utilizing the average value of the fuzzy set to represent the entire set, we then have the quantified result for the fuzzy item of five linguistic grades as shown in Table 4.

Table 5: Fuzzy deduction results.

Experiment	Surface roughness
1	1.33
2	5
3	10
4	10
5	15
6	5
7	18.67
8	10
9	15

Table 6: Result of factor responses.

Level	Parameter			
	A	B	C	D
Low	5.443	10	5.443	10.443
Medium	10	10	10	9.557
High	14.557	10	14.557	10
Delta	9.113	0	9.113	0.887
Rank	1.5	4	1.5	3

4. Results and Discussion

By considering the parameter combinations of the nine sets of experiment based on the $L_9(3^4)$ orthogonal array, the quantified results from fuzzy deduction for the machining surface roughness are determined and shown in Table 5.

Introducing the deduction result as the signal-to-noise ratio (S/N) for surface roughness, the results of factor responses are calculated and listed in Table 6. The mean effects for S/N ratios are then drawn by MINITAB 14 and shown in Figure 4. Therefore, the optimum fuzzy linguistic turning parameters are found to be A (High), B (High, Medium, and Low), C (High), and D (Low).

5. Confirmation Experiment

The finishing diameter turning operation of S45C ($\varphi 45 \text{ mm} \times 250 \text{ mm}$) work pieces on an ECOCA-3807 CNC lathe is arranged for the experiment. The TOSHIBA WTJNR2020K16 tool holder with MITSUBISHI NX2525 insert is utilized as the cutting tool. The four turning parameters (speed, cutting depth, feed rate, and tool nose runoff) with three different levels (low, medium, and high) (Table 7) are experimentally distinguished for the machining operation on the basis of $L_9(3^4)$ orthogonal array. In Table 7, the three levels of speed, cutting depth, and feed rate are identified from the machining handbook suggested by the tool manufacturer. The tool nose runoff is positioned by using different shims located under the tool holder and determined by measuring the tip after the face turned the work piece. When the tool nose is set approximately 0.1 mm higher (lower) than the center of the work piece, it is regarded as "High (Low)". When the tool nose is set within $\pm 0.03 \text{ mm}$, it is considered as "Medium".

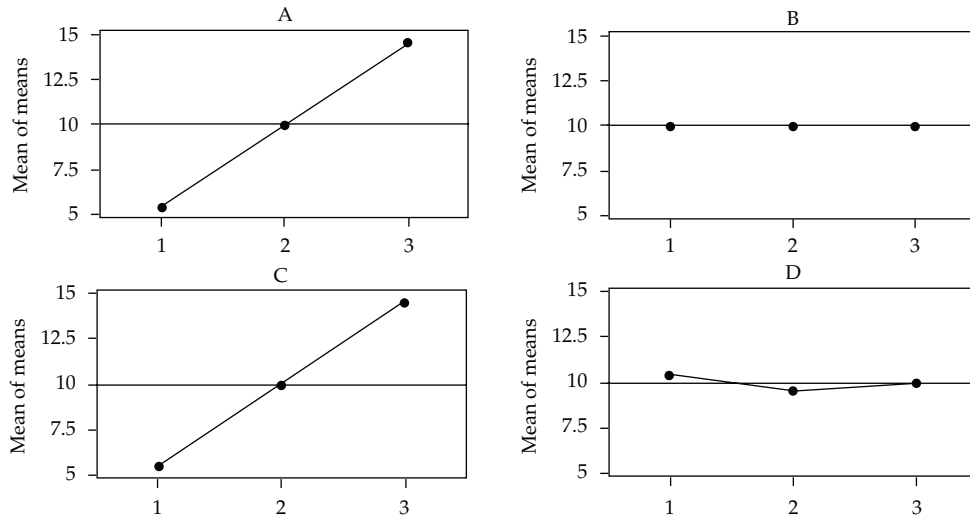


Figure 3: Plot of main effects.

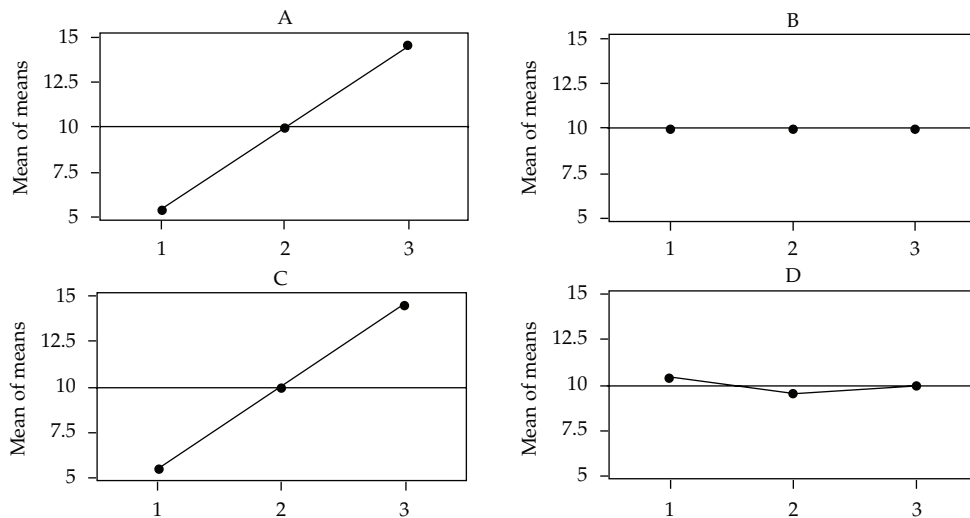


Figure 4: Plot of main effects.

The surface roughness (R_a) of machined work pieces is measured on the MITSUTOYO SURFTEST at three different sections of 40 mm, 80 mm, and 120 mm from the face, therefore, the average data are received as the surface roughness. To verify the applicability of the optimum result achieved by our proposed general optimization technique, the machining operations under both fuzzy Taguchi deduction optimization parameters and benchmark parameters (A (medium: 200 m/min), B (medium: 2 mm), C (medium: 0.3 mm/rev), and D (medium: ± 0.03 mm)), which are often introduced into the confirmation experiment in many of the studies [7, 24] for comparison to the optimum parameters, are performed on the CNC lathe. The machined results are concluded and listed in Table 8. From Table 8, it is observed that the surface roughness under fuzzy linguistic parameters is significantly improved by

Table 7: Parameters and levels.

Parameter	Level		
	Level 1	Level 2	Level 3
A: speed (m/ min)	150	200	250
B: cutting depth (mm)	1	2	3
C: feed rate (mm/rev)	0.2	0.3	0.4
D: tool nose runoff (mm)	-0.1	± 0.03	0.1

Table 8: Confirmation results.

	Surface roughness (R_a)
Fuzzy linguistic (A3B3C3D1)	0.6666 μm
Fuzzy linguistic (A3B2C3D1)	0.8033 μm
Fuzzy linguistic (A3B1C3D1)	0.7830 μm
Benchmark (A2B2C2D2)	0.9233 μm

27.80%, 12.99%, and 15.20%, respectively, and the average result is found to be improved by 18.66% from the benchmark parameters. It is shown that our proposed fuzzy linguistic optimization technique can really advance the surface roughness.

6. Concluding Remarks

In this paper, the fuzzy linguistic optimization was proposed and applied to achieve the optimum CNC finish turning parameters under the considerations of surface roughness. A confirmation experiment of the optimum fuzzy linguistic parameters was conducted to indicate the effectiveness of the proposed optimization method. Through the confirmation test for the proposed method, the experimental results validate the potency that the surface roughness can be significantly advanced from our fuzzy linguistic optimization technique. The considered qualities in the fuzzy linguistic optimization are found valuable for future study to be possibly extended in the real-world machining industry. Future studies are also encouraged to verify the proposed fuzzy linguistic optimization scheme on hard-to-machine metals like stainless steels and titanium alloys.

Parameter optimization is a hard-solving issue because of the interactions between parameters. This paper not only proposes a fuzzy linguistic optimization approach using orthogonal array but also contributes the satisfactory technique for improving machining performance in CNC turning with profound insight. The competition of manufacturing industry will then be economically excited through the development proposed in this study.

Acknowledgments

The author would like to thank the anonymous referees who kindly provided suggestions and comments to improve this work. Financial support for this work was provided by the National Science Council Taiwan, under the contract of NSC97-2221-E-412-003.

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