Parametric Deduction Optimization for Surface Roughness

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Abstract: Problem statement: Surface roughness is a major consideration in modern Computer Numerical Control (CNC) turning 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. **Approach:** In this study, four parameters (cutting depth, feed rate, speed, tool nose runoff) with three levels (low, medium, high) were considered to optimize the surface roughness for Computer Numerical Control (CNC) finish turning. Additionally, twenty-seven fuzzy control rules using trapezoid membership function with respective to seventeen linguistic grades for the surface roughness were constructed. Considering thirty input and eighty output intervals, the defuzzification using center of gravity was moreover completed. Through the Taguchi experiment, the optimum general deduction parameters can then be received. **Results:** The confirmation experiment for optimum deduction parameters was furthermore performed on an ECOCA-3807 CNC lathe. It was shown that the surface roughness from the fuzzy deduction optimization parameters are significantly advanced comparing to those from benchmark. **Conclusion:** This study not only proposed a parametric deduction optimization scheme using orthogonal array, but also contributed the satisfactory fuzzy approach to the surface roughness for CNC turning with profound insight.

Key words: Computer numerical control, orthogonal array, fuzzy deduction, surface roughness

INTRODUCTION

Machining operations have been the core of the manufacturing industry since the industrial revolution (Rao, 2006). The existing optimization researches for Computer Numerical Controlled (CNC) turning were either simulated within particular manufacturing circumstances (Sivarao *et al.*, 2009; Lin *et al.*, 2001; Lin, 1998; Meng *et al.*, 2000), or achieved through numerous frequent equipment operations (Kopac *et al.*, 2002; Tosun and Ozler, 2004). Nevertheless, these are regarded as computing simulations and the applicability to real world industry is still uncertain. Therefore, a general optimization scheme without equipment operations is deemed to be necessarily developed.

Surface roughness is commonly considered as a major manufacturing goal (Tosun and Ozler, 2004) for turning operations in many of the existing researches. 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 run-off will affect the performance of the machining process (Yeh and Lai, 1995). Therefore, the tool nose run-off is also selected as one of the control factors in this study.

Parameter optimization for surface roughness 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 (Huh *et al.*, 2003; Suhail *et al.*, 2010; Kim *et al.*, 2003; Benhamid and Othman, 2009). 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 deduction 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 (Zadeh, 1965; Zimmerman, 2001). Fuzzy linguistic models permit the translation of verbal expressions into numerical ones (Gungor and Arikan, 2007). 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 study considers four parameters (cutting depth, feed rate, speed, tool nose runoff) with three levels (low, medium, high) to optimize the surface roughness in CNC finish turning. The fuzzy control rules using triangle membership function with respective to seventeen linguistic grades for surface roughness are additionally constructed. The defuzzification is then quantified using center of gravity and introduced as the Signal-to-Noise (S/N) ratio to Taguchi experiment and thus the optimum deduction parameters can then be received. This study definitely proposes a fuzzy deduction general optimization approach and satisfactory fuzzy linguistic technique for improving surface roughness in CNC turning with profound insight.

MATERIALS AND METHODS

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

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 trapezoid fuzzy number $\tilde{A}$ can be defined by a trip-let (a, b, c, d) (Fig. 1) (Kaufmann *et al.*, 1991). The membership function is defined as:

$$\mu_{\tilde{A}}(x:a,b,c,d) = \begin{cases} \dfrac{x-a}{b-a} & a < x \le b \\ 1 & b < x \le c \\ \dfrac{x-d}{c-d} & c < x \le d \\ 0 & \text{otherwise} \end{cases} \quad (1)$$
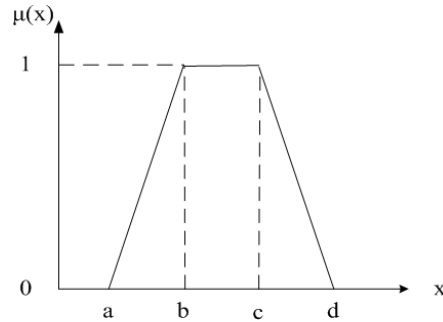

Fig. 1: Trapezoid fuzzy numbers

In this study, the three most important parameters for the surface roughness are primarily concluded through literature review. Additionally, twenty-seven fuzzy control rules using trapezoid membership function with respective to seventeen linguistic grades will be constructed following IF-THEN rules.

To eliminate the computation, thirty input and eighty output intervals are considered to prepare the defuzzification. Through Cartesian product, the degree of membership for both input and output can thus be attained as:

$$R = \text{Input} * \text{Output} \quad (2)$$

Here:
"Input" = The parameter
"Output" = The attribute
R = The fuzzy relation between the parameter and attribute

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

$$\mu R1 + \mu R2 = \max\{\mu R1, \mu R2\} \quad (3)$$

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:

$$F(x_i) = \frac{\sum\limits_i x_i * \mu_{\tilde{A}}(x_i)}{\sum\limits_i \mu_{\tilde{A}}(x_i)} \quad (4)$$

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

Taguchi method: The Taguchi method is a robust design method technique (Palanikumar, 2008; Ross,

1995), 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 (Senapati *et al*., 2007; Wei *et al*., 2002) 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) (Park *et al*., 2005) proposed by Taguchi is used to obtain the optimal parameter combinations. The larger S/N means 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:

$$S/N = -10\left(\log \sum_{i=1}^{n}\frac{y_i^2}{n}\right)(dB) \qquad (5)$$

Where:
n = The number of experiments for each experimental set
y_i = The quality characteristic at the i-th experiment

On the contrary, the larger quality characteristic will have better result t when considering the larger-the-best quality, therefore, by taking the inverse of quality characteristic into Eq. 13, the related S/N ratio can also be deduced and shown in Eq. 14:

$$S/N = -10\left(\log \sum_{i=1}^{n}\frac{1/y_i^2}{n}\right)(dB) \qquad (6)$$

In this study, the defuzification result is introduced to the Taguchi experiment as the S/N ratio. Therefore, it is judged as the quality of smaller-the-best. In addition to the S/N ratio, a statistical Analysis of Variance (ANOVA) (Wu and Chyu, 2002) can be employed to indicate the impact of process parameters. In this way, the optimal levels of process parameters can be estimated.

Research design: Surface roughness is considered the major goal in this study. Four parameters with three levels are selected to optimize the finish turning based on the orthogonal array. Additionally, twenty-seven fuzzy control rules with respective to seventeen linguistic grades for each attribute are constructed. Considering thirty input and eighty output intervals, the defuzzification using center of gravity is thus completed for the Taguchi experiment and the optimum deduction parameters can then be received.

Construction of orthogonal array: In this study, the four turning parameters (A-speed, B-cutting depth, C-feed rate and D-tool nose runoff) (Lan and Wang, 2009) with three different levels (low, medium and high) (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

Table 2: Fuzzy rules for surface roughness

Rules	Speed	Feed rate	Deduction
1	Low	Low	medium
2	Low	Medium	large
3	Low	High	largest
4	Low	Low	medium
5	Low	Medium	large
6	Low	High	largest
7	Low	Low	medium
8	Low	Medium	large
9	Low	High	largest
10	Medium	Low	small
11	Medium	Medium	medium
12	Medium	High	large
13	Medium	Low	small
14	Medium	Medium	medium
15	Medium	High	large
16	Medium	Low	small
17	Medium	Medium	medium
18	Medium	High	large
19	High	Low	smallest
20	High	Medium	small
21	High	High	medium
22	High	Low	smallest
23	High	Medium	small
24	High	High	medium
25	High	Low	smallest
26	High	Medium	small
27	High	High	medium

Table 3: Trapezoid ranges of three linguistic levels for parameters

Linguistic level	Low	Medium	High
Range	[0,12.5,15]	[0,2.5,27.5,30]	[15,17.5,30]

Table 4: Trapezoid ranges of seventeen linguistic levels for attributes

Linguistic level	Smallest	Extreme small	Super small	Small small	Small
Range	[0,2.5,5]	[0,2.5,7.5,10]	[5, 7.5,12.5,15]	[10,12.5,17.5,20]	[15,17.5,22.5,25]
Smaller	Much smaller	A little smaller	Medium	A little larger	Much larger
[20,22.5,27.5,30]	[25,27.5,32.5,35]	[30,32.5,37.5,40]	[35,37.5,42.5,45]	[40,42.5,47.5,50]	[45,47.5,52.5,55]
Larger	Large	Large large	Super large	Extreme large	Largest
[50,52.5,57.5,60]	[55,57.5,62.5,65]	[60,62.5,67.5,70]	[65,67.5,72.5,75]	[70,72.5,77.5,80]	[75,77.5,80]

Table 5: Quantified results for linguistic results

Linguistic level	Smallest	Extreme small	Super small	Small small	Small	Smaller	Much smaller	A little smaller
Defuzzification	1.666667	5	10	15	20	25	30	35
Medium	A little larger	Much larger	Larger	Large	Large large	Super large	Extreme large	Largest
40	45	50	55	60	65	70	75	78.33333

Fuzzy control rules: The twenty-seven fuzzy control rules with respective to seventeen grades for the surface roughness in this study are determined. From the existing literature (Petropoulos *et al*., 2006), it is found that the surface roughness can be expressed as:

$$R_i(i = a, zD, t, p, q, 3z) = C_i V^{mi} f^{ni}$$

where the machining speed (V) and feed rate (f) are concluded as priority parameters to surface roughness. Therefore, the fuzzy rules can be described as shown in Table 2.

Defuzzification: In this study, the three parameter levels are selected based on the Taguchi experimental method, therefore, each triangle membership function is related to the peak point of its fuzzy area. Considering thirty input and eighty output intervals, the defuzzification of seventeen linguistic grades using center of gravity can then be completed. The degree of membership for input (parameter) and output (attribute) can be described as shown in Table 3 and 4 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 seventeen linguistic grades as shown in Table 5.

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 surface roughness are determined and shown as Table 6. Introducing the deduction results as the Signal to Noise ratio (S/N) for surface roughness under smaller-the-best expectation, the results of factor responses are calculated and listed in Table 7. The mean effects for S/N ratios are then drawn by MINITAB 14 and shown as Fig. 2. Therefore, the optimum fuzzy deduction multi-attribute turning parameters are found to be A (Low), B (High), C (High) and D (Low or High).

Table 6: Fuzzy deduction results

Attributes experiment	Surface roughness
1	40.0000
2	60.0000
3	70.8854
4	60.0000
5	40.0000
6	20.0000
7	40.0000
8	9.1146
9	60.0000

Table 7: Result of factor responses

	Parameter			
Level	A	B	C	D
Low	56.96	46.67	23.04	46.67
Medium	40.00	36.37	60.00	40.00
High	36.37	50.30	50.30	46.67
Delta	20.59	13.92	36.96	6.67
Rank	2.00	3.00	1.00	4.00

Table 8: Parameters and levels

	Level		
Parameter	Low (level 1)	Medium (level 2)	High (level 3)
A: Speed (m/min)	150.0	200.00	250.0
B: Cutting depth (mm)	1.0	2.00	3.0
C: Feed rate (mm/rev)	0.2	0.30	0.4
D: Tool nose runoff (mm)	-0.1	±0.03	0.1

The finishing diameter turning operation of S45C (φ45 mm×250 mm) work piece 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 8) are experimentally distinguished for the machining operation on the basis of $L_9(3^4)$ orthogonal array. In Table 8, 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 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 regard as "High (Low)". When the tool nose is set within ±0.03 mm, it is considered as "Medium".

The surface Roughness (R_a) of machined work pieces are measured on the MITSUTOYO SURFTEST at three different segments of 40mm, 80mm and 120 mm from the face, therefore, the average data are received as the attribute of surface roughness. To verify the applicability of the optimum result achieved by our proposed deduction optimization technique, the machining operations under both fuzzy linguistic optimization parameters and benchmark parameters; A (medium), B (medium), C (medium), D (medium), which are often introduced into the confirmation experiment in many of the studies (Tosun and Ozler, 2004; Lin and Lin, 2006) for comparison to the optimum parameters, are performed on the CNC lathe. The machined results are concluded and listed in Table 9. From Table 9, it is observed that the surface roughness under fuzzy deduction parameters are significantly improved by 14.4 and 23.1% respectively and the average result is also improved by 18.75% from the benchmark parameters. It is shown that our proposed general deduction optimization technique can really advance the surface roughness for CNC turning.
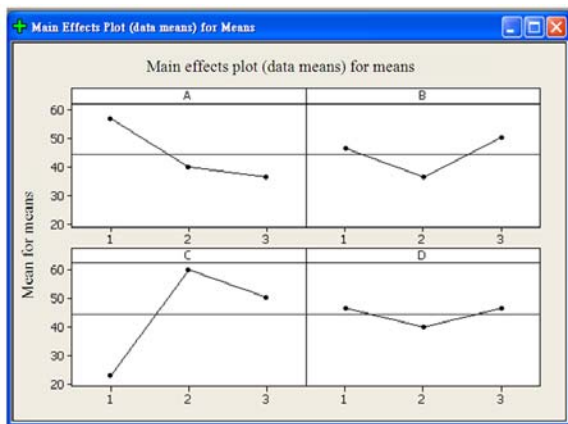

Fig. 2: Plot of main effects

Table 9: Confirmation results

	Surface roughness
Fuzzy deduction optimization parameters (A1B3C3D1)	0.7900 μm
Fuzzy deduction optimization parameters (A1B3C3D3)	0.7100 μm
Benchmark parameters (A2B2C2D2)	0.9233 μm

CONCLUSION

In this study, the parametric deduction scheme was proposed and applied to achieve the optimum CNC finish turning parameters under the considerations of surface roughness. A confirmation experiment of the optimum deduction parameters was conducted to indicate the effectiveness of the proposed fuzzy optimization method. Through the confirmation test, the experimental results validate the potency that the surface roughness can be advanced from our parametric deduction optimization technique.

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

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