

# Tool Wear Optimization for General CNC Turning Using Fuzzy Deduction

Tian-Syung Lan

Department of Information Management, Yu Da University, Miaoli County, Taiwan, China

E-mail: [tslan@ydu.edu.tw](mailto:tslan@ydu.edu.tw)

Received October 12, 2010; revised November 9, 2010; accepted November 6, 2010

## Abstract

Tool wear is frequently considered in the modern CNC (computer numerical control) 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 proposed is deemed to be necessary for the industry. In this paper, four parameters (cutting depth, feed rate, speed, tool nose runoff) with three levels (low, medium, high) are considered to optimize the tool wear 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 tool wear are constructed. Considering four input and twenty output intervals, the defuzzification using center of gravity is then completed and introduced as the S/N (signal-to-noise) ratio. Thus, the optimum general deduction parameters can then be received. The confirmation experiment for optimum general deduction parameters is furthermore performed on an ECOCA-3807 CNC lathe. It is shown that the tool wear ratio from the fuzzy deduction optimization parameters is significantly advanced comparing to those from benchmark. This paper not only proposes a general deduction optimization scheme using orthogonal array, but also contributes the satisfactory fuzzy linguistic approach to tool wear in CNC turning with profound insight.

**Keywords:** CNC, General Optimization, Fuzzy Deduction, Tool Wear Ratio

## 1. Introduction

Machining operations have been the core of the manufacturing industry since the industrial revolution [1]. The existing optimization researches for CNC (computer numerical controlled) 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 run-off will affect the performance of the machining process [8].

Therefore, the tool nose run-off 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 sys-

tems that may influence the decision maker’s decision, fuzzy set theory is the most suitable solution [13-18]. Fuzzy linguistic models permit the translation of verbal expressions into numerical ones [19]. 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, tool nose runoff) with three levels (low, medium, high) to optimize the tool wear in CNC finish turning. The fuzzy control rules using triangle membership function with respective to five linguistic grades for tool wear are additionally constructed. The defuzzification is then quantified using center of gravity and moreover introduced to Taguchi experiment as the S/N (signal-to-noise) ratio; therefore, the optimum general deduction parameters can then be received. This paper definitely proposes a fuzzy deduction general optimization approach and satisfactory fuzzy linguistic technique for improving tool wear in CNC turning with profound insight.

## 2. Methodology

In this paper, the linguistic variable quantification and parameter optimization for general deduction 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 an 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 trip-let  $(a, b, c)$  (Figure 1) [20]. The membership function is defined as

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

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

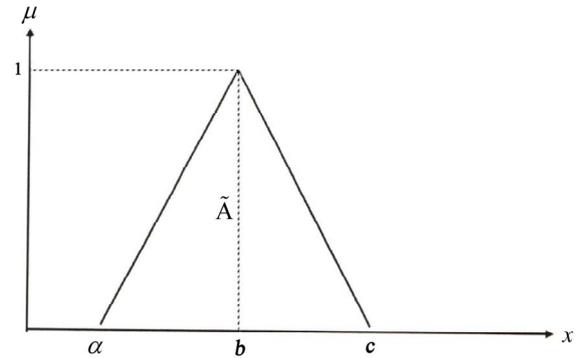


Figure 1. Triangle fuzzy numbers.

To eliminate the computation, four input (parameter) and twenty output (tool wear) 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” 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

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

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

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

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

### 2.2. Taguchi Method

The Taguchi method is a robust design method technique [21,22], 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 [23,24] 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) [25] 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

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

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  $t$  when considering the larger-the-best quality, therefore, by taking the inverse of quality characteristic into Equation (5), the related S/N ratio can also be deduced and shown in Equation (6).

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

In this study, the defuzzification result for tool wear in CNC machining 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) [26] 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

The tool wear is considered as the quality in this paper. Four parameters with three levels are selected to optimize the finish turning based on the  $L_9(3^4)$  orthogonal array. Additionally, nine fuzzy control rules with respective to five linguistic grades for tool wear are constructed. Considering four input and twenty output intervals, the defuzzification using center of gravity is thus completed. Thus, the optimum general deduction 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 D) [27] 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.

#### 3.2. Fuzzy Control Rules

Since less tool wear results better tool life, the tool life is used to describe the tool wear in this study. The modified

**Table 1. Orthogonal array.**

Parameter Experiment	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

Taylor equation  $TV^{1/n} f^{1/m} d^{1/l} = C'$  [4] is often utilized to express the tool life, where only the machining speed ( $V$ ) and feed rate ( $f$ ) can be identified and found as the two major parameters to the tool wear. Additionally, for less computation, five linguistic grades for tool wear are determined as excellent (least), good (light), fair, poor (large), and worst (heavy). The nine fuzzy control rules with respective to five linguistic grades for tool wear in this paper are constructed under the following considerations. The fuzzy rules can be described as

RULE 1: If low machining speed and low feed rate, then the tool wear is excellent.

RULE 2: If low machining speed and medium feed rate, then the tool wear is poor.

RULE 3: If low machining speed and high feed rate, then the tool wear is fair.

RULE 4: If medium machining speed and medium feed rate, then the tool wear is good.

RULE 5: If medium machining speed and high feed rate, then the tool wear is fair.

RULE 6: If medium machining speed and low feed rate, then the tool wear is poor.

RULE 7: If high machining speed and high feed rate, then the tool wear is fair.

RULE 8: If high machining speed and low feed rate, then the tool wear is poor.

RULE 9: If high machining speed and medium feed rate, then the tool wear is worst.

#### 3.3. Defuzzification

In this paper, 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 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 tool wear, the membership functions are regard as the intersection of two fuzzy sets, and the height of fuzzy set is considered as  $\mu = 1$  (**Figure 2**). The degree of member

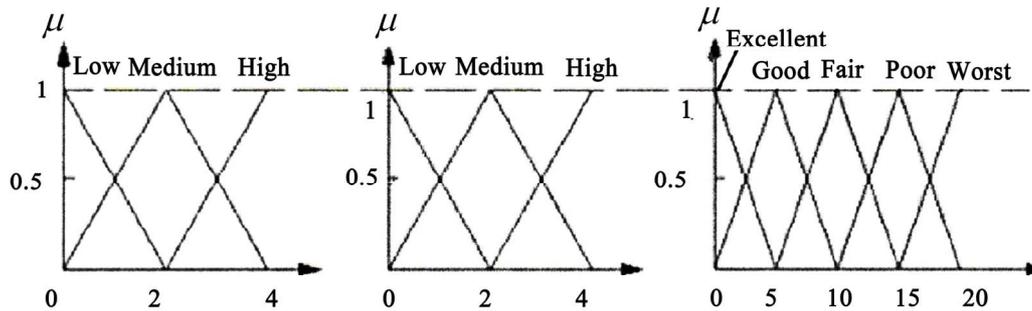


Figure 2. Fuzzy Relationship of two major parameters to the tool wear.

ship for input (parameter) and output (tool wear) can be described as shown in **Table 2** and **Table 3** respectively. Utilizing the average value of the fuzzy set to represent the entire set,

$$\text{Average value} = \frac{\sum \text{Maching Value} \times \mu(s)}{\sum \mu(s)} \quad (7)$$

We then have the quantified result for the fuzzy item of five linguistic grades as shown in **Table 4**.

**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 tool wear are determined and shown as **Table 5**.

Introducing the quantified result as the signal to noise ratio (S/N) for tool wear of smaller-the-best expectation, 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 as **Figure 3**. Therefore, the optimum fuzzy deduction turning parameters for toll wear are found to be A(High), B(High, Medium, Low), C(High), and D(Low).

**5. Confirmation Experiment**

The finishing diameter turning operation of S45C ( $\phi 45\text{mm} \times 250\text{mm}$ ) work piece on an ECOCA-3807 CNC lathe is arranged for the experiment. The TOSHI-BA 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 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  $\pm 0.03$  mm, it is considered as “Medium”.

The tool wearing length  $V_{B2}$  (mm) in **Figure 4** is selected and scaled on the 3D SONY COLOR VIDEO electronic camera. To reduce the costly and timeconsuming experiments, this study employs the tool wear ratio (tool wear length per unit material removal volume) instead of the tool life to demonstrate the tool wear status of turning under specific parameter combination. The tool wearing length is then divided by the volume of material removed as the tool wear ration ( $\text{mm}^{-2}$ ), which is utilized as the indicator of tool wear in this study.

Table 2. Degree of membership for parameter.

Interval Fuzzy item	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 tool wear.

Interval Fuzzy item	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

**Table 5. Fuzzy Deduction Results.**

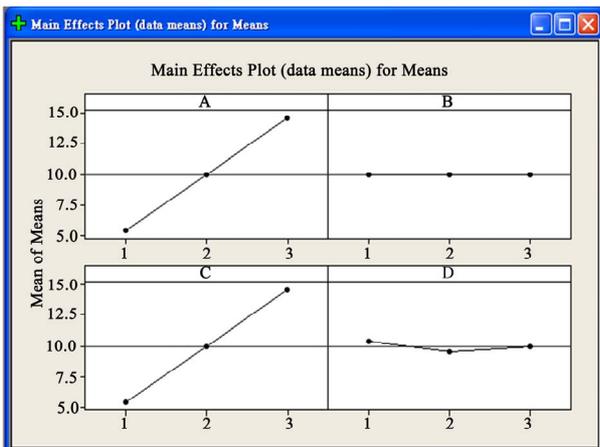
Experiment	Tool Wear
1	1.33
2	5
3	10
4	10
5	15
6	5
7	18.67
8	10
9	15

**Table 6. Result of factor responses.**

Parameter Level	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

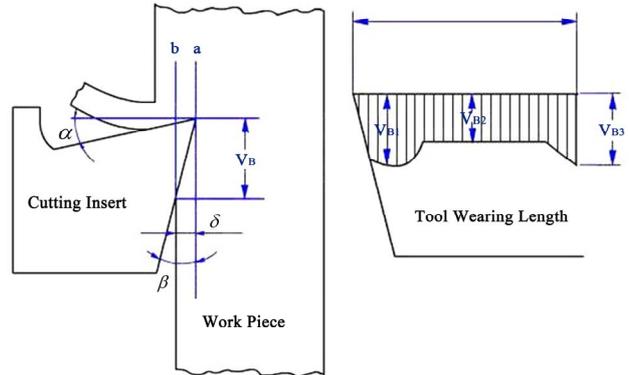
**Table 7. Parameters and levels.**

Parameter	Level	Low (Level 1)	Medium (Level 2)	High (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



**Figure 3. Plot of main effects.**

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), B (Medium), C (Medium), D (Me-



**Figure 4. Tool wear length.**

**Table 8. Confirmation resultse.**

	Tool Wear Ratio
Fuzzy Deduction Optimization Parameters (A3B3C3D1)	3.67 E-07 mm <sup>-2</sup>
Fuzzy Deduction Optimization Parameters (A3B2C3D1)	3.03 E-07 mm <sup>-2</sup>
Fuzzy Deduction Optimization Parameters (A3B1C3D1)	3.99 E-07 mm <sup>-2</sup>
Benchmark Parameters (A2B2C2D2)	4.38 E-07 mm <sup>-2</sup>

dium), which are often introduced into the confirmation experiment in many of the studies [7,28] 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 tool wear ratio under fuzzy deduction parameters are significantly improved by 16.21%, 30.02% and 8.9% respectively, and the average result is also improved by 18.38% from the benchmark parameters. It is shown that our proposed general deduction optimization technique can really advance the tool wear without compromise.

## 6. Concluding Remarks

In this paper, the fuzzy Taguchi deduction was proposed and applied to achieve the optimum CNC finish turning parameters under the considerations of tool wear. A confirmation experiment of the optimum general deduction parameters was conducted to indicate the effectiveness of the proposed fuzzy Taguchi deduction optimization method. Through the confirmation test for the proposed method, the experimental results validate the potency that tool wear ratios can be greatly advanced from our fuzzy Taguchi deduction optimization technique. The considered qualities in the general deduction optimization are found valuable to be possibly extended for the real-world machining industry.

Parameter optimization is a hard-solving issue because of the interactions between parameters. This paper not only proposes a fuzzy deduction general optimization

approach using orthogonal array, but also contributes the satisfactory fuzzy linguistic technique for improving tool wear performance in CNC turning with profound insight. The competition of manufacturing industry will then be economically excited through the proposed development in this study.

## 7. Acknowledgements

Financial support for this work was provided by the National Science Council Taiwan, under the contract of NSC98-2221-E-412-002. The author would like to thank the anonymous referees who kindly provided the suggestions and comments to improve this work.

## 8. References

- [1] R. R. Venkata, "Machinability Evaluation of Work Materials Using a Combined Multiple Attribute Decision-making Method," *International Journal of Advanced Manufacturing Technology*, Vol. 28, No. 3-4, 2006, pp. 221-227.
- [2] J. P. Davim and A. Conceicao, "Optimization of Cutting Conditions in Machining of Aluminium Matrix Composites Using a Numerical and Experimental Model," *Journal Materials Processing Technology*, Vol. 112, No. 1, 2001, pp. 78-82.
- [3] W. S. Lin, B. Y. Lee and C. L. Wu, "Modeling the Surface Roughness and Cutting Force for Turning," *Journal Materials Processing Technology*, Vol. 108, No. 3, 2001, pp. 286-293.
- [4] W. S. Lin, "The Study of Machining Accuracy and Tool Wear Reliability," Ph.D. Thesis, National Central University, Taoyuan, 1998.
- [5] Q., Meng, J. A. Arsecularatne and P. Mathew, (2000) "Calculation of Optimum Cutting Conditions for Turning Operations Using a Machining Theory," *International Journal of Advanced Manufacturing Technology*, Vol. 40, No. 4, 2000, pp. 1709-1733.
- [6] J. Kopac, "Optimal Machining for Achieving the Desired Surface Roughness in Fine Turning of Cold Preformed Steel Work Piece," *International Journal of Machine Tools and Manufacture*, Vol. 42, No. 10, 2002, pp. 707-716.
- [7] N. Tosun and L. Ozler, "Optimisation for Hot Turning Operations with Multiple Performance Characteristics," *International Journal of Advanced Manufacturing Technology*, Vol. 23, No. 11-12, 2004, pp. 777-782.
- [8] L. J. Yeh, "A Study on the Monitoring and Suppression System for Turning Slender Workpieces," Ph. D. Thesis, Tatung University, Taibei, 1994.
- [9] H. Huh, J. H. Heo and H. W. Lee, "Optimization of a Roller Leveling Process for Al7001T9 Pipes with Finite Element Analysis and Taguchi Method," *International Journal of Machine Tools and Manufacture*, Vol. 43, No. 4, 2003, pp. 345-350.
- [10] K. S. Anastasiou, "Optimization of the Aluminium Die Casting Process Based on the Taguchi Method," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Vol. 216, No. 7, 2002, pp. 969-977.
- [11] M. N. Dhavlikar, M. S. Kulkarni and V. Mariappan, "Combined Taguchi and Dual Response Method for Optimization of a Centerless Grinding Operation," *Journal Materials Processing Technology*, Vol. 132, No. 1-3, 2003, pp. 90-94.
- [12] S. J. Kim, K. S. Kim and H. Jang, "Optimization of Manufacturing Parameters for a Brake Lining Using Taguchi Method," *Journal Materials Processing Technology*, Vol. 136, No. 1-3, 2003, pp. 202-208.
- [13] L. A. Zadeh, "Fuzzy sets," *Information and Control*, Vol. 8, No. 3, 1965, pp. 338-353.
- [14] H. J. Zimmerman, "Fuzzy Sets Theory and Its Applications," Kluwer Academic Publisher, Boston, 1992.
- [15] J. Wanga, C. Yao and Z. Zhang, "A Fuzzy-AHP Comprehensive Evaluation Method for Optimization Design of Machine Tool," *Mechanic Automation and Control Engineering*, Wuhan, 26-28 June 2010, pp. 2652-2656.
- [16] G. Chai, C. Lu and D. Wen, "Study on the Multiple Objective Parameter Optimization Method for NC Turning," *Advanced Materials Research*, Vol. 102-104, 2010, pp. 705-709.
- [17] J. Mao, Y. Cao, H. Ching and R. Du, "Fuzzy Tolerancing Based on Available Manufacturing Resources," *Computer-Aided Design and Applications*, Vol. 6, No. 2, 2009, pp. 253-261.
- [18] H. Gao, M. Xu, Y. Su, P. Fu and Q. Liu, "Experimental Study of Tool Wear Monitoring Based on Neural Networks," *Intelligent Control and Automation*, Chongqing, 25-27 June, pp. 6906-6910.
- [19] Z. Güngör and F. Arkan, "Using Fuzzy Decision Making System to Improve Quality-based Investment," *Journal of Intelligent Manufacturing*, Vol. 18, No. 2, 2007, pp. 197-207.
- [20] A. Kaufmann and M. M. Gupta, "Introduction to Fuzzy Arithmetic Theory and Applications," Van Nostrand Reinhold, New York, 1991.
- [21] K. Palanikumar, "Application of Taguchi and Response Surface Methodologies for Surface Roughness in Machining Glass Fiber Reinforced Plastics by PCD Tooling," *International Journal of Advanced Manufacturing Technology*, Vol. 36, No. 1-2, 2008, pp. 19-27.
- [22] P. J. Ross, "Taguchi Techniques for Quality Engineering," McGraw-Hill Publication, New York, 1998.
- [23] J. C. Chang, "The Application of Taguchi Method in the Finite Element Analysis for the Optimal Structural Design of Compressed Sheet in Huge Extended Plate," Master's Thesis, National Chung Hsing University, Taichung, 2000.
- [24] H. S. Wei, S. C. Hwang and S. J. Liu, "Analysis for the Optimum Conditions in Derrick Hook by Using Taguchi Method," Master's Thesis, Nation Pingtung University of Science and Technology, Pingtung, 2002.
- [25] J. H. Park, K. M. Yang and K. S. Kang, "A Quality Function Deployment Methodology with Signal and Noise Ratio for Improvement of Wasserman's Weights," *International Journal of Advanced Manufacturing Technology*,

Vol. 26, No. 5-6, 2005, pp. 631-637.

- [26] F. C. Wu and C. C. Chyu, "A Comparative Study on Taguchi's SN Ratio, Minimising MSD and Variance for Nominal-the-best Characteristic Experiment," *International Journal of Advanced Manufacturing Technology*, Vol. 20, No. 9, 2002, pp. 655-659.
- [27] T. S. Lan and M. Y. Wang, "Competitive parameter optimization of multi-quality CNC turning," *International Journal of Advanced Manufacturing Technology*, Vol. 41, No. 7-8, 2009, pp. 820-826.
- [28] J. L. Lin and J. F. Lin, "Grey Theory Applied to Evaluate the Tribological Performances of The a-CH(N) Coating Films Prepared by Differing the Nitrogen Content and The Film Thickness," *International Journal of Advanced Manufacturing Technology*, Vol. 27, No. 9-10, 2006, pp. 845-853.