FUZZY TAGUCHI DEDUCTION OPTIMIZATION ON MULTI-ATTRIBUTE CNC TURNING

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ABSTRACT

In this paper, four parameters with three levels are considered to optimize the multi-attribute finish CNC (computer numerical control) turning based on $L_9(3^4)$ orthogonal array. Additionally, nine fuzzy control rules with respective to five linguistic grades for each attribute are constructed. The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is moreover utilized to integrate and evaluate the multiple machining attributes for Taguchi experiment to receive the optimum general deduction parameters. It is shown that the attributes from the fuzzy Taguchi deduction optimization parameters are all significantly advanced comparing to those from benchmark.

Keywords: computer numerical control; orthogonal array; fuzzy deduction; Technique for Order Preference by Similarity to Ideal Solution.

OPTIMISATION DE LA DÉDUCTION PAR LA MÉTHODE DE LOGIQUE FLOUE TAGUCHI SUR UN TOUR CNC MULTI-ATTRIBUT

RÉSUMÉ

Cet article examine quatre paramètres à trois niveaux, employés pour l'optimisation d'un tour CNC(commande numérique par calculateur) multi-attribut basé sur la table orthogonale $L_9(3^4)$ De plus, neuf règles de contrôle de logique floue relatif aux quatre grades linguistiques pour chaque attribut sont élaborées. La méthode TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) est utilisée pour intégrer et évaluer les multiples attributs de l'usinage pour que le schéma d'expérimentation Taguchi reçoive les paramètres de déduction optimale. Il est démontré que les attributs des paramètres d'optimisation de déduction de par la logique floue Taguchi sont en avance si on les compare à ceux des bancs d'essai.

Mots-clés : commande numérique par calculateur; table orthogonale; déduction floue; Technique for Order Preference by Similarity to Ideal Solution.

1. INTRODUCTION

Machining operations have been the core of the manufacturing industry since the industrial revolution [1]. The existing multi-attribute 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 necessarily developed.

Surface roughness, tool life, and cutting force are commonly considered as manufacturing goals [2] for turning operations in many of the existing researches. It is also recognized that lighter cutting force often results to better surface roughness and tool life. This is why smaller cutting conditions conclude toward to be optimum [3] in many of the researches. As the flexibility and adaptability needs increased, the stability of modern CNC machines is now designed robust. Since the productivity concern becomes more critical than the cutting force in the industry, this paper proposes material removal rate (MRR) instead of the cutting force. 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 for attribute 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, tool nose runoff) with three levels (low, medium, high) to optimize the multi-attribute CNC finish turning. The fuzzy control rules using triangle membership function with respective to five linguistic grades for each attribute are additionally constructed. The defuzzification is then quantified using center of gravity. For multiple machining attributes, the preference value from TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) [16] is moreover introduced to Taguchi experiment, and thus 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 multiple machining attributes in CNC turning with profound insight.

2. METHODOLOGY

In this paper, the linguistic variable quantification, multi-attribute integration, and parameter optimization for general deduction CNC turning operations are proposed using fuzzy set theory, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), and Taguchi method respectively. They are described as below.

2.1. Fuzzy Set Theory [13,14]

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) (Fig. 1) [17]. The membership function is defined [17] as

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

In this paper, the two most important parameters for each attribute are primarily concluded through literature review. Additionally, nine fuzzy control rules for each attribute 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 (attribute) intervals are considered to prepare the defuzzification. Through Cartesian product, the degree of membership for both input and output can thus be attained [15] as

$$\mathrm{R} = \mathrm{Input} * \mathrm{Output} \tag{2}$$

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

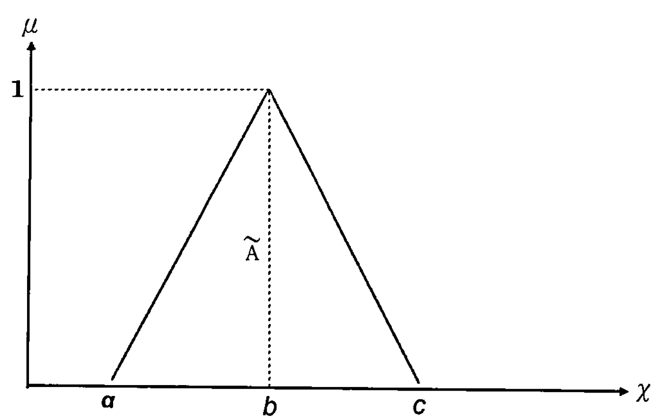

Fig. 1. A triangle fuzzy numbers.

The "OR" rules are then utilized for combining rules for maximum degree of membership [15] as

$$\mu R1 + \mu R2 = \max\{\mu R1, \mu R2\} \tag{3}$$

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 [15] as

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

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. Multiple Attribute Integration [16,18]

Hwang and Yoon developed TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) [16] to assess the alternatives before multiple-attribute decision making. TOPSIS considers simultaneously the distance to the ideal solution and negative ideal solution regarding each alternative, and also selects the most relative closeness to the ideal solution as the best alternative.

When the alternative set for multi-attribute decision and evaluation attribute set are described [18] as $A = \{a_i \| i = 1,2 \ldots\ldots\ldots, m\}$ and $\{g = g_i \| j = 1,2 \ldots\ldots\ldots, n\}$ respectively; the computational steps of TOPSIS can be expressed [18] as

Step 1: This step involves a matrix based on all the information available that describes a material's attributes, and is called a "decision matrix". Each row of this matrix is allocated to one alternative, and each column to one attribute. The decision matrix can be stated as

$$D = \begin{array}{c c} & \begin{array}{ccccc} X_1 & X_2 & . & X_j & X_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdot & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \end{array} \tag{5}$$

where A_i represents the possible alternatives, $i = 1,2 \ldots\ldots, m$; X_j denotes the attributes relating to alternative performance, $j = 1,2 \ldots\ldots, n$; and x_{ij} is the performance of A_i with respect to attribute X_j.

Step 2: Obtain the normalized decision matrix r_{ij}. This can be represented as:

$$r_{uj} = \frac{x_{ij}}{\sqrt{\sum\limits_{i=1}^{m} x_{ij}{}^2}} \tag{6}$$

where r_{ij} represents the normalized performance of A_i with respect to attribute X_j.

Step 3: Assume that the weight of each attribute is $\{w_j \| j=1,2\ldots\ldots\ldots,n\}$, the weighted normalized decision matrix
$V=[v_{ij}]$ can be found as

$$V = w_j \bullet r_{ij} \tag{7}$$

here, $\sum_{j=1}^{n} w_j = 1$

Step 4: Develop the "ideal" (best) and "negative ideal" (worst) solutions in this step. The ideal and negative ideal solution can be expressed as:

$$\begin{aligned} A^+ &= \left\{ \left(\max_i \ v_{ij} | j \in J \right), \left(\min_i \ v_{ij} | j \in J' | i=1,2,\ldots\ldots,m \right) \right\} \\ &= \left\{ v_1{}^+, v_2{}^+, \ldots, v_j{}^+, \ldots, v_n{}^+ \right\} \end{aligned} \tag{8}$$

$$\begin{aligned} A^- &= \left\{ \left(\min_i \ v_{ij} | j \in J \right), \left(\max_i \ v_{ij} | j \in J' | i=1,2,\ldots\ldots,m \right) \right\} \\ &= \left\{ v_1{}^-, v_2{}^-, \ldots, v_j{}^-, \ldots, v_n{}^- \right\} \end{aligned} \tag{9}$$

where, $J=\{j=1,2\ldots\ldots\ldots,n|j\}$ is associated with the beneficial attributes
$J'=\{j=1,2\ldots\ldots\ldots,n|j\}$ is associated with non-beneficial attributes.

Step 5: Determine the distance measures. The separation of each alternative from the ideal one is given by n-dimensional Euclidean distance from the following equations:

$$S_i{}^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j{}^+ \right)^2}, \ i=1,2,\ldots\ldots,m \tag{10}$$

$$S_i{}^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j{}^- \right)^2}, \ i=1,2,\ldots\ldots,m \tag{11}$$

Step 6: The proximity of a particular alternative to the ideal solution is expressed in this step as follows:

$$C_i{}^+ = \frac{S_i{}^-}{S_i{}^+ + S_i{}^-}, \ i=1,2,\ldots\ldots,m; \ 0 \le C_i{}^+ \le 1 \tag{12}$$

Step 7: A set of alternatives is made in descending order according to the preference value indicating the most preferred and least preferred feasible solutions.

2.3. Taguchi Method [9–12]

The Taguchi method is a robust design method technique [19,20], 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 [21,22] 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) [23] 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 [9,10] as

$$S/N = -10\left(\log \sum_{i=1}^{n} \frac{y_i^2}{n}\right)\ (\text{dB}) \tag{13}$$

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 Eq. (13), the related S/N ratio can also be deduced [9,10] and shown in Eq. (14).

$$S/N = -10\left(\log \sum_{i=1}^{n} \frac{1/y_i^2}{n}\right)\ (\text{dB}) \tag{14}$$

In this study, the preference value using TOPSIS for multiple CNC machining attributes is introduced to the Taguchi experiment as the S/N ratio. Therefore, it is judged as the quality of larger-the-best. In addition to the S/N ratio, a statistical analysis of variance (ANOVA) [24] 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, tool wear, and material removal rate (MRR) are considered major attributes in this paper. Four parameters with three levels are selected to optimize the multi-attribute finish turning based on the $L_9(3^4)$ orthogonal array. Additionally, nine fuzzy control rules with respective to five linguistic grades for each attribute are constructed. Considering four input and twenty output intervals, the defuzzification using center of gravity is thus completed. The TOPSIS is moreover utilized to integrate multiple machining attributes for the Taguchi experiment, and 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) [25] 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

The nine fuzzy control rules with respective to five linguistic grades for each attribute in this paper are constructed under the following considerations.

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

3.2.1. Surface roughness

The five linguistic grades for surface roughness are determined as excellent, good, fair, poor, and worst. From the existing literature [26], 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 major parameters to surface roughness. Therefore, the fuzzy rules can be described as

RULE 1: If medium machining speed and low feed rate, then the surface roughness is excellent.

RULE 2: If low machining speed and medium feed rate, then the surface roughness is good.

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

RULE 4: If medium machining speed and medium feed rate, then the surface roughness is fair.

RULE 5: If medium machining speed and high feed rate, then the surface roughness is poor.

RULE 6: If medium machining speed and low feed rate, then the surface roughness is good.

RULE 7: If high machining speed and high feed rate, then the surface roughness is worst.

RULE 8: If high machining speed and low feed rate, then the surface roughness is fair.

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

3.2.2. Tool wear

Since less tool wear results better tool life, the tool life is used to describe the tool wear in this study. The modified Taylor equation $TV^{1/n}f^{1/m}d^{1/l}=C'$ [4] is often utilized to express the tool life, where the machining speed (V) and feed rate (f) are found as major parameters to the tool wear. The five linguistic grades for tool wear are determined as excellent (least), good (light), fair, poor (large), and worst (heavy). Therefore, 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.

3.2.3. Material removal rate

The material removal rate can be expressed as $MRR = 1000fdV$. As the experimental results [2], the surface speed (V) has the least effect to the MRR. Therefore, the depth of cut (d) and feed rate (f) are considered major parameters for MRR. The five linguistic grades for tool wear are determined as excellent (huge), good (large), fair, poor (light), and worse (least). The fuzzy rules can be described as

RULE 1: If low depth of cut and low feed rate, then the MRR is worst.
RULE 2: If medium depth of cut and medium feed rate, then the MRR is fair.
RULE 3: If high depth of cut and high feed rate, then the MRR is excellent.
RULE 4: If low depth of cut and medium feed rate, then the MRR is poor.
RULE 5: If medium depth of cut and high feed rate, then the MRR is good.
RULE 6: If high depth of cut and low feed rate, then the MRR is fair.
RULE 7: If low depth of cut and high feed rate, then the MRR is fair.
RULE 8: If medium depth of cut and low feed rate, then the MRR is poor.
RULE 9: If high depth of cut and medium feed rate, then the MRR is good.

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 each machining attribute, the input (parameter) membership functions are regard as the intersection of two fuzzy sets, and the height of fuzzy set is considered as $\mu = 1$ (Fig. 2). The degree of membership for input (parameter) and output (attribute) can be described as shown in Table 2 and Table 3

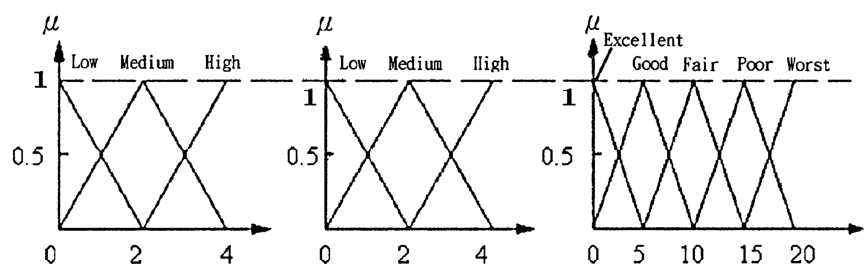

Fig. 2. Relationship of membership functions.

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

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.

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 attributes are determined and shown as Table 5.

With the fuzzy deduction results, the original decision matrix can then be formulated as

$$D = \begin{bmatrix} 1.33 & 1.33 & 1.33 \\ 5 & 5 & 10 \\ 10 & 10 & 18.67 \\ 10 & 10 & 5 \\ 15 & 15 & 15 \\ 5 & 5 & 10 \\ 18.67 & 18.67 & 10 \\ 10 & 10 & 5 \\ 15 & 15 & 15 \end{bmatrix}$$

Table 3. Degree of membership for attribute.

Fuzzy item \ Interval	0	1	2	3	4	5	6	7	8	9	10
Excellent	1	0.8	0.6	0.4	0.2	0	0	0	0	0	0
Good	0	0.2	0.4	0.8	1	0.6	0.4	0.2	0	0	0
Fair	0	0	0	0	0	0	0.2	0.4	0.6	0.8	1
Poor	0	0	0	0	0	0	0	0	0	0	0
Worst	0	0	0	0	0	0	0	0	0	0	0

Fuzzy item \ Interval	11	12	13	14	15	16	17	18	19	20
Excellent	0	0	0	0	0	0	0	0	0	0
Good	0	0	0	0	0	0	0	0	0	0
Fair	0.8	0.6	0.4	0.2	0	0	0	0	0	0
Poor	0.2	0.4	0.6	0.8	1	0.8	0.6	0.4	0.2	0
Worst	0	0	0	0	0	0.2	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.

Attributes / Experiment	Surface Roughness	Tool Wear	MRR
1	1.33	1.33	1.33
2	5	5	10
3	10	10	18.67
4	10	10	5
5	15	15	15
6	5	5	10
7	18.67	18.67	10
8	10	10	5
9	15	15	15

With the transformation by Eq. (6), the normalized decision matrix is found as

$$R = \begin{bmatrix} 0.0392 & 0.0392 & 0.0392 \\ 0.1472 & 0.1472 & 0.2948 \\ 0.2948 & 0.2948 & 0.5504 \\ 0.2948 & 0.2948 & 0.1474 \\ 0.4423 & 0.4423 & 0.4423 \\ 0.1472 & 0.1472 & 0.2948 \\ 0.5504 & 0.5504 & 0.2948 \\ 0.2948 & 0.2948 & 0.1472 \\ 0.4422 & 0.4422 & 0.2948 \end{bmatrix}$$

After determining the ideal and negative ideal solution, the separation of each alternative from the ideal and negative ideal solution can then be achieved. Therefore, the closeness to the ideal solution and the preference value (Table 6) are derived for each experiment in the orthogonal array.

Introducing the preference value as the signal to noise ratio (S/N) for multiple machining attributes for larger-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. 3. Therefore, the optimum fuzzy deduction multi-attribute turning parameters are found to be A(Medium), B(High), C(Medium), and D(Medium).

5. CONFIRMATION EXPERIMENT

In this study, a Fuzzy Taguchi Deduction Optimization on Multi-Attribute CNC Turning is developed. This is considered a general linguistic optimization. The advanced approach to the multiple attributes can be found on a specific CNC lathe. It is hardly possible to locate other authors' result with the same machining equipment and conditions. Thus, 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

Table 6. Preference value.

Experiment	Preference value
1	0.461853
2	0.856326
3	0.717185
4	0.653124
5	0.595853
6	0.856326
7	0.520259
8	0.653124
9	0.595853

Table 7. Result of factor responses.

Level \ Parameter	A	B	C	D
Low	0.6785	0.5451	0.6571	0.5512
Medium	0.7018	0.7018	0.7018	0.7443
High	0.5897	0.7231	0.6111	0.6745
Delta	0.1120	0.1780	0.0907	0.1931
Rank	3	2	4	1

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

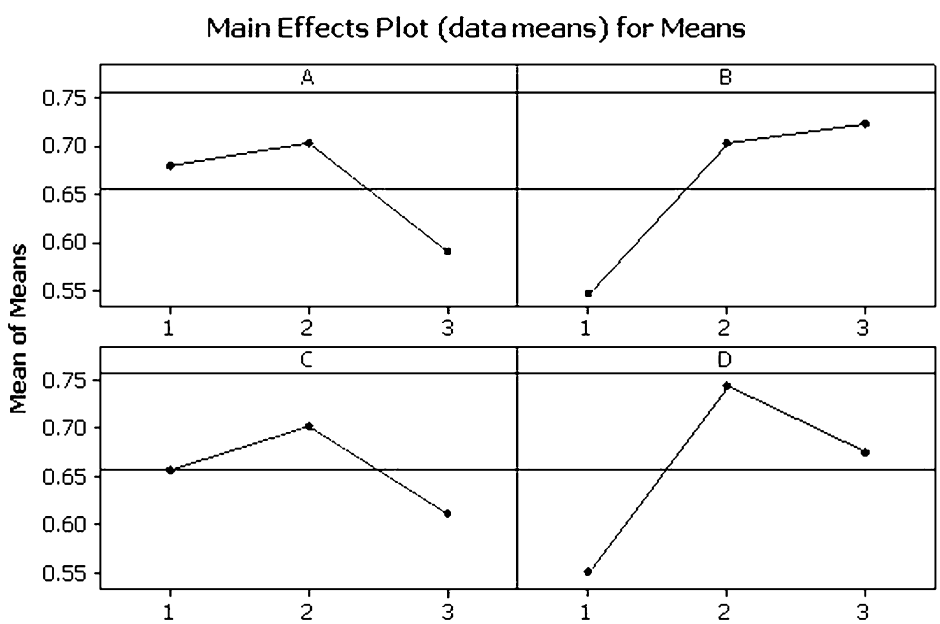

Fig. 3. Plot of main effects.

Table 8. Parameters and levels.

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

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 sections of 40 mm, 80 mm, and 120 mm from the face, therefore, the average data are received as the attribute of surface roughness. The tool wearing length V_{B2}(mm)in Fig. 4 is selected and scaled on the 3D SONY COLOR VIDEO electronic camera. To reduce the costly and time-consuming 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 (mm^{-2}), which is utilized as the indicator of tool wear in this study. And, the MRR(mm^3/min) is calculated using $MRR = 1000fdV$. Here; f (mmper revolution) denotes the feed rate, d (mm) describes the cutting depth, and V (m/min)presents the surface speed of the turning operation.

To verify the applicability of the optimum result achieved by our proposed general multi-attribute optimization technique, the machining operations under both fuzzy Taguchi

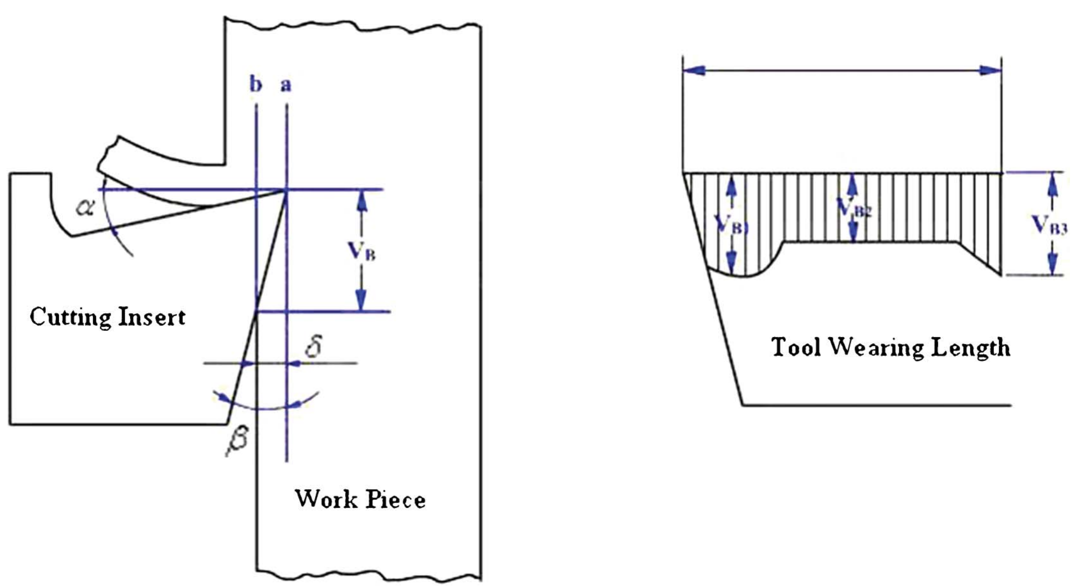

Fig. 4. Tool wear length.

Table 9. Confirmation results.

	Surface roughness	Tool wear ratio	MRR	Preference order
Fuzzy Deduction	0.7951 μm	4.29 E-07 mm^{-2}	0.015 mm^3/min	0.735664
Benchmark	0.9233 μm	4.38 E-07 mm^{-2}	0.012 mm^3/min	0.640723

deduction 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 [7, 27] 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, tool wear ratio, and MRR under fuzzy deduction parameters are significantly improved by 13.88%, 2.05% and 25% respectively, and the overall multi-attribute preference value is also improved by 14.82% from the benchmark parameters. It is shown that our proposed general deduction optimization technique can really advance the multiple machining attributes 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 multiple attributes. 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 all the attributes can be greatly advanced from our fuzzy Taguchi deduction optimization technique. The considered attributes 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 multiple machining performances 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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