

Parameter Optimization for Computer Numerical Controlled Machining Using Fuzzy and Game Theory

Kai-Chi Chuang ¹, Tian-Syung Lan ^{1,2}, Lie-Ping Zhang ^{1,*}, Yee-Ming Chen ³ and Xuan-Jun Dai ¹

¹ College of Mechanical and Control Engineering, Guilin University of Technology, Guilin Guangxi 541004, China; s1038901@gmail.com (K.-C.C.); 88233255@qq.com (X.-J.D.)

² Department of Information Management, Yu Da University, Miaoli County 36143, Taiwan; tslan888@yahoo.com.tw

³ Department of Industrial Engineering and Management, Yuan Ze University, Taoyuan City 32003, Taiwan; chenyeeming@gmail.com

* Correspondence: zlp_gx_gl@163.com

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Abstract: Under the strict restrictions of international environmental regulations, how to reduce environmental hazards at the production stage has become an important issue in the practice of automated production. The precision computerized numerical-controlled (CNC) cutting process was chosen as an example of this, while tool wear and cutting noise were chosen as the research objectives of CNC cutting quality. The effects of quality optimizing were verified using the depth of cut, cutting speed, feed rate, and tool nose runoff as control parameters and actual cutting on a CNC lathe was performed. Further, the relationships between Fuzzy theory and control parameters as well as quality objectives were used to define semantic rules to perform fuzzy quantification. The quantified output value was introduced into game theory to carry out the multi-quality bargaining game. Through the statistics of strategic probability, the strategy with the highest total probability was selected to obtain the optimum plan of multi-quality and multi-strategy. Under the multi-quality optimum parameter combination, the tool wear and cutting noise, compared to the parameter combination recommended by the cutting manual, was reduced by 23% and 1%, respectively. This research can indeed ameliorate the multi-quality cutting problem. The results of the research provided the technicians with a set of all-purpose economic prospective parameter analysis methods in the manufacturing process to enhance the international competitiveness of the automated CNC industry.

Keywords: CNC machining; semantic rules; fuzzy quantification; fuzzy inference; Game theory

1. Introduction

Under strict international environmental regulations, although there are various cutting conditions related to environmental protection quality, tool wear and cutting noise are always considered preferentially as because of their green environmental protection quality in the practice of machining of cutting. There are often sophisticated nonlinear relationships in the problem of parameter optimization in multi-quality precision CNC production. The industry often selects appropriate machining parameters that rely on the program of the numerically controlled machine tool or the technicians' experience, but the results are not necessarily optimal and are not guaranteed to be optimal under multi-quality (more than two target qualities). Most of the cutting parameter optimization literature obviously does not meet the needs of the industry as it either considers only a single quality (only one target quality) or has overly costly research.

According to the research on cutting parameters, using Analytic Hierarchy Process (AHP) to combine the innovative thinking model of Teoriya Resheniya Izobretatelskikh Zadatch (TRIZ) and

the concept of green production reduces the impact on the environment [1]. The optimal turning parameters obtained by using fuzzy semantic quantification can indeed be used as a method of analyzing parameters for practical cutting operations under environmental and cost considerations [2]. Considering the problem of cutting noise, Lan, Chuang, and Chen analyzed the combination of the optimal factor level with the Taguchi method [3]. However, the research only explored the noise target and thus was research of a single quality. Zhang et al. analyzed the influence of cutting parameters on noise with the variance. The cutting cost model was proposed after the analysis results showed that the cutting depth was the main factor affecting the cutting noise. However, the results of the study also applied only to a single quality material [4]. Hossein and Kops's research showed that the cutting temperature increases under larger cutting depth and higher cutting speed, which in turn shortens the tool life. However, the research took time to carry out the cutting work and belonged solely to the research of a single quality and not a multi-quality research [5]. The research of Schultheiss et al., which pointed out that reducing the tool wear can shorten the time of the production cycle and reduce energy consumption, was also a single quality research and not a multi-quality research [6]. Weng obtained the optimal cutting parameters by using fuzzy quantification. The parameters can reach 10% of the level prior the whole experiment under the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) arrangement. This proved that the experiment is unnecessary in reaching this level and can result in cost and labor savings. While this research obtained optimized combinations of multi-quality parameters, it did not take into account the conflict of quality objectives [7]. Li et al. established a multi-quality optimization model scheme by applying game theory to machining cutting parameters. The research showed that game theory was suitable for multi-quality optimization design, but failed to obtain the best combination [8]. Zhou et al. reduced and optimized the carbon footprint of the cutting process through game theory, but multi-quality was not taken into account [9]. Tian et al. considered the tool wear conditions and optimized the cutting parameters through game theory. The research discussed the conditions of tool wear, which was also a single-quality optimization research [10]. The above-mentioned local or abroad researches on cutting parameters are either discussions of only a single quality or optimization plans with specific conditions. Not only is there no further explanation and analysis of the conflict between the production qualities, but there is a need to be achieved through the actual operation of the cutting equipment, which is a waste of material resources, time, and labor and has an influence on the surrounding environment. Different control parameters are required when the processing conditions (materials, equipment, and tools) are different, which troubles the CNC industry. Therefore, developing a set of general production optimal mechanisms with green innovation by analyzing the inference method of green product design without equipment operation will be positive for the competitiveness and development of the precision CNC turning industry.

Based on the shortcomings of the above-mentioned researches, this research integrates fuzzy theory and game theory. Through the method of semantic quantification, a set of all-purpose prediction models provides the fuzzy value of each goal for the selection of cutting parameters without actual cutting by the machine. The research also resolves the conflict problem between production qualities and control parameters by using game theory. The best quality strategy was obtained through statistics to help improve the understanding of engineering science by technicians as a consideration in the design or manufacture of future products. Through the result of this research, a set of optimal, all-purpose economic prospective parameter analysis methods could be provided to the technicians to enhance the overall competitiveness of the automated CNC cutting industry.

2. Research Background

2.1. Tool Wear

From Taylor's tool life formula, the wear of high-speed steel tools refers to the use time in the upper limit of the low wear rate area, which was used to record the characteristics of High Speed

Steel (HSS) tools and to obtain Formula 1 after rearrangement [11]. The relationship between feed rate and cutting speed must be properly matched during cutting. For instance, friction phenomenon instead of cutting might occur with overly slow speed. However, unexpected high-speed might break the cutting edge or roughen the transient surface.

$$TV^{1/n} f^{1/m} d^{1/l} = C' \quad (1)$$

T : tool function

V : cutting speed

f : feed rate

D : diameter of milling cutter

n, m : constant of tool material properties (acquired by experiment or experience)

l : cutting length

C' : cutting speed of tool life in 1 minute (supplied by tool manufacturer)

(1) According to the formula, a larger depth of cut and higher cutting speed lead to less tool wear.

(2) From expert experience, higher cutting speed and feed rate lead to less tool wear.

(3) According to the formula, lower cutting speed and feed rate lead to less tool wear.

2.2. Cutting Noise

All the noise values produced by the measurement experiment, including the noise values produced by motor idling and cutting experiments, were substituted in the formula, since their differences are lower than three Decibels, as shown in Formula 2 [12].

$$LPC = 10 \log \left[10^{\frac{LPB}{10}} - 10^{\frac{LPA}{10}} \right] \quad (2)$$

LPB : the measured value of motor running with no cutting.

LPA : the measured value of motor running with cutting.

(1) Smaller depth of cut, less noise.

(2) Slower cutting speed, less noise.

(3) Improving the pressure of the tool, less noise.

2.3. Fuzzy Theory

In 1965, Professor Zadeh of the University of California, Berkeley proposed fuzzy theory, which is a kind of fuzzy concept quantification based on fuzzy sets. It is mainly focused on making a correct judgment without going through complicated calculation processes of the fuzzy message of the human brain or incomplete information [13]. The language 'IF...THEN...' is used in fuzzy theory to represent the fuzzy relationship. A language represents a qualitative conditional sentence and an uncertain rule, which is quantified by fuzzy mathematical tools. Fuzzy logic control was used to convert the input language to a fuzzy set. The fuzzy logic control architecture included the fuzzification interface, interface engine, defuzzification interface, and the fuzzy rule-based system, as shown in Figure 1 [14].

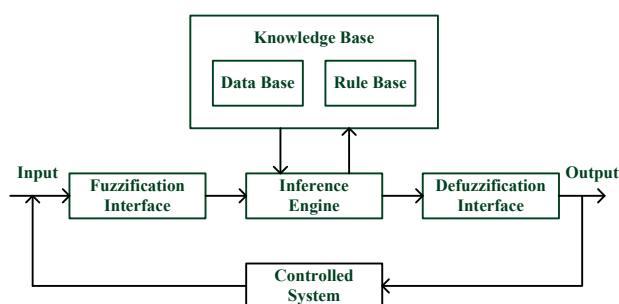


Figure 1. Architecture of fuzzy logic control.

2.4. Game Theory

Game theory was proposed in 1928 [15,16] before being promoted by the economist John Nash. Von Neumann and Oskar Morgenstern co-authored *The Theory of Games and Economic Behavior* in 1944, which analyzed game theory and economic behavior in detail and explained zero-sum games, the league, and the cooperative game, which further laid the theoretical foundation of game theory. Shapley contributed significantly to the development of core theory in game theory through the development of a prisoner's dilemma game [17]. Nash proved the Nash equilibrium existence theorem in 1953, which set a milestone for the current non-cooperative game theory.

Game theory is a state of confrontation for two or more contestants in a rational situation, with the pursuit of their own interests as the greatest goal. The conflict and cooperative relationship between rational contestants, using mathematical model simulation, has been widely used in various types of study.

2.4.1. Elements of a Game

The setting of contestants is rational in a game; however, the result could be quite the contrary or could have a Pareto principle, which is just in line with the current economic development trend since the smart contestant sits first in the best strategy of others to greater their own payoff function. Therefore, the result of the game is not necessarily rational or efficient but is closer to the economic situation. The main elements of the game are:

1. Player: The actor who makes decisions with the greatest goal of pursuing his own interest.
2. Nature: If not a contestant, the action taken is determined by a well-known probability.
3. Action set: A collection of all possible actions taken by a contestant.
4. Payoff Function: The remuneration that a contestant receives when the results of a game are shown, which is generally affected by all participants.

2.4.2. Information Structure

The information structure was divided into four types by Rasmusen, which are perfect information, complete information, certain information, and symmetric information [18]. Within a game with perfect information, each information set is a single node, which means that the players are clear about at which decision point the decision is made. If not, the game is called an imperfect information game. A game in which the players sit aware of the following three situations is called a complete information game. If not, the game is called an incomplete information game.

1. The identities of the players.
2. The moves could be taken by all players.
3. The utility function of all players.

Within a game with certain information, players will not act naturally after acting. If not, the game is called an uncertain information game. In a game with symmetric information, the

information a player gets at the move node or at the end is the same with other players. If not, the game is called an asymmetric information game. Based on the player's simultaneous move (static game) or sequential move (dynamic game), and prior information (strategy and payoff) a player has or does not have, the game is divided into four types, as shown in Table 1.

2.4.3. Bargaining Games

The largest difference between bargaining game theory and decision theory is that the problems faced by a group of decision makers in a given situation can solve many economic problems. Therefore, game theory, which is widely used by economic, political, and financial experts, not only has the rigor of a mathematical model, but also simplifies the complex interaction phenomena in a real environment, and provides the strategic behavior analysis method for decision makers. In 1950, Nash assumed that a group of axioms would only get a solution to a set of bargaining models based on a non-cooperative game, which was divided into four parts [19,20].

1. Pareto efficiency

The outcome of the contestants' bargaining is beneficial to both parties; in other words, there is no other bargaining outcome that can increase the interests of all participants at the same time.

2. Independence of the irrelevant alternatives

Add things that do not matter in the game, and the outcome of the bargain is not affected.

3. Symmetry

If there is symmetry in the contestants' negotiation questions, the two contestants will receive an equal result.

4. Invariance under strategically equivalent representations

The utility function after the monotonic transformation still indicates that the participants have the same preference, and the monotonic transformed utility function does not affect the bargaining result.

Nash's suggestion, as shown in Formula 3, proved that the bargaining solution exists and is unique if these four axioms are satisfied.

$$\max_{s_1, s_2} (S_1 - d_1)(S_2 - d_2) \quad (3)$$

d_1, d_2 : the payoff that both players can get when there is no agreement of the bargain.

S_1, S_2 : the payoff that both players can get when there is a agreement of the bargain.

Only if the result of the bargain is better than the one before the bargain can the players be motivated to bargain, so that $(d_1, d_2) \leq (s_1, s_2)$.

Bargaining game theory has been used universally in economics, international relationships, calculator science, military strategy, and other disciplines. Some general topics that had used bargaining game theory are about the efficiency and rationality of solving supplier selection problems [21], the demand-response resource allocation between distribution networks [22], the reduction of environmental risks to enterprises in production processes [23], the solutions to the upload transmission power optimization problems in the multilateral bargaining model [24], and more.

Table 1. Four main types of game.

	Perfect Information	Imperfect Information
Static	Nash Equilibrium	Bayesian Nash Equilibrium
Dynamic	Sub-game Perfect Nash Equilibrium	Perfect Bayesian Nash Equilibrium

3. Research Design

Precision CNC cutting was taken as an example in this research, while tool wear and cutting noise were selected as the green production quality of CNC cutting. The depth of cut, cutting speed, feed rate, and tool nose runoff were taken as control parameters. Fuzzy theory was used to define the semantic rules of the relationship of control parameters and production quality to carry out the fuzzy quantification. The quantified output values were introduced into game theory to resolve the conflict among the two production qualities and four control parameters. The strategy probability statistics of the game result and the strategy option with the highest sum of probability as the best strategy of that production quality were taken.

3.1. Fuzzy Rules Establishment

In the selection of the fuzzy membership function, different membership functions, based on each rule, were compared by entering the three factors: Cutting speed, cutting depth, and feed rate. The minimum membership function was calculated by the intersection, and the maximum value of the union was selected as the output part of the set to calculate the value of the center of gravity of the largest area in order to obtain the fuzzy value. The triangular membership function was used as the fuzzy pattern and the defuzzification was calculated by the center of gravity. Tool wear and cutting noise were chosen as the production qualities in this research. According to the literature, relevant cutting experience level range, and the suggestion of cutting parameters from tool manuals, was determined as low, medium, or high. The cutting characteristics of the target were obtained by using semantic quantification and were divided into five levels: Greatest, large, moderate, small, and minimal.

3.1.1. Tool Wear

Tool wear is a vital factor affecting cutting quality in precision machining. Changing the cutting tool before the end of the tool's life may result in higher production cost, lower production efficiency, and many disposals of tool inserts, which cause environmental pollution. Therefore, this study established fuzzy rules using cutting speed, cutting depth, and feed rate to minimize the tool wear, as shown in Table 2.

Table 2. Tool wear fuzzy rule table.

Parameter Rule	Cutting Speed	Cutting Depth	Feed Rate	Tool Wear Rate
1	low	low	low	high
2	low	low	moderate	maximum
3	low	low	high	high
4	low	moderate	low	moderate
5	low	moderate	moderate	high
6	low	moderate	high	high
7	low	high	low	minimum

8	low	high	moderate	minimum
9	low	high	high	low
10	moderate	low	low	maximum
11	moderate	low	moderate	maximum
12	moderate	low	high	maximum
13	moderate	moderate	low	moderate
14	moderate	moderate	moderate	moderate
15	moderate	moderate	high	high
16	moderate	high	low	low
17	moderate	high	moderate	minimum
18	moderate	high	high	low
19	high	low	low	high
20	high	low	moderate	maximum
21	high	low	high	maximum
22	high	moderate	low	moderate
23	high	moderate	moderate	low
24	high	moderate	high	low
25	high	high	low	low
26	high	high	moderate	minimum
27	high	high	high	low

3.1.2. Cutting Noise

The noise during the cutting process is mainly caused by the vibration phenomenon, which not only interferes with the entire cutting process, but also seriously influences the quality of the work piece. The noise might even influence the mood of the technicians during work, which has a certain negative impact on production quality. In order to reduce the vibration frequency, it is necessary to reduce the cutting speed, depth of cutting, and feed rate of the tool, which in turn reduces productivity. Therefore, the fuzzy rules were established with cutting speed, depth of cutting, and feed rate as the factors based on the semantic considerations, as shown in Table 3.

Table 3. Cutting noise fuzzy rule table.

Parameter Rule	Cutting Speed	Cutting Depth	Feed Rate	Cutting Noise
1	low	low	low	minimum
2	low	low	moderate	minimum
3	low	low	high	low
4	low	moderate	low	minimum
5	low	moderate	moderate	low
6	low	moderate	high	moderate
7	low	high	low	low
8	low	high	moderate	low
9	low	high	high	low
10	moderate	low	low	moderate
11	moderate	low	moderate	moderate
12	moderate	low	high	moderate
13	moderate	moderate	low	low
14	moderate	moderate	moderate	high
15	moderate	moderate	high	high
16	moderate	high	low	moderate
17	moderate	high	moderate	moderate
18	moderate	high	high	moderate
19	high	low	low	maximum
20	high	low	moderate	maximum
21	high	low	high	maximum
22	high	moderate	low	maximum

23	high	moderate	moderate	maximum
24	high	moderate	high	maximum
25	high	high	low	maximum
26	high	high	moderate	maximum
27	high	high	high	maximum

3.2. Variability of the Input and Output Domains

The operation had three inputs and one output. The input target was the control factor, and the output target was the default result. The input domain of the variables was in the interval [0,5] and was divided into five equal parts. The output domain of the variables was in the interval [0,40] and was divided into 40 equal parts.

1. Input target (1): The degree of membership of cutting speed as the control factor (Figure 2).

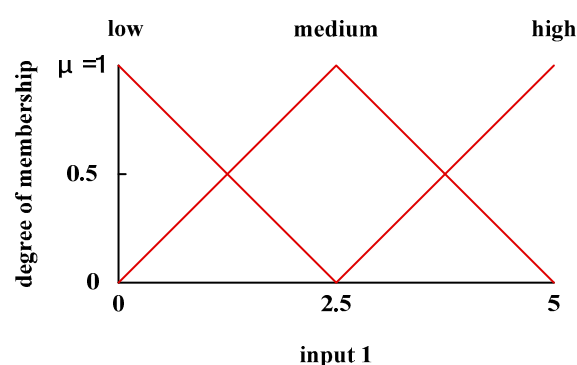


Figure 2. Degree of membership of the cutting speed.

Fuzzy terms: The degree of membership presented in Figure 2 is listed in Table 4.

Table 4. Input membership values of cutting speed.

Fuzzy Term	0	1.25	2.5	3.75	5
Low	1	0.5	0	0	0
Medium	0	0.5	1	0.5	0
High	0	0	0	0.5	1

2. Input target (2): The degree of membership of cutting depth as the control factor (Figure 3).

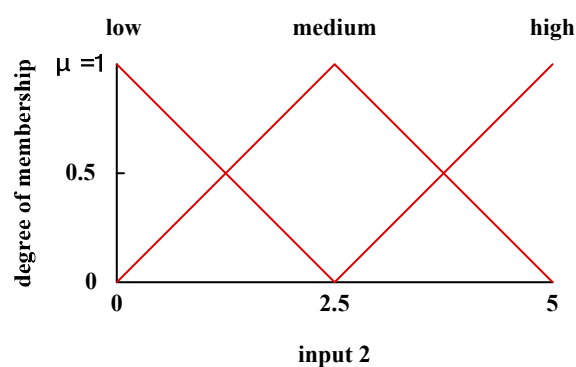


Figure 3. Degree of membership of the cutting depth.

Fuzzy terms: The degree of membership presented in Figure 3 is listed in Table 5.

Table 5. Input membership values of cutting depth.

Fuzzy Term	0	1.25	2.5	3.75	5
Low	1	0.5	0	0	0
Medium	0	0.5	1	0.5	0
High	0	0	0	0.5	1

3. Input target (3): The degree of membership of feed rate as the control factor (Figure 4).

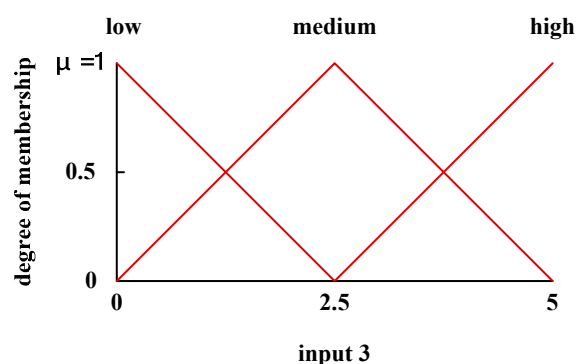


Figure 4. Degree of membership of the feed rate.

Fuzzy terms: The degree of membership presented in Figure 4 is listed in Table 6.

Table 6. Input membership values of feed rate.

Fuzzy Term	0	1.25	2.5	3.75	5
Low	1	0.5	0	0	0
Medium	0	0.5	1	0.5	0
High	0	0	0	0.5	1

4. Output target: Membership functions of the output variable (Figure 5).

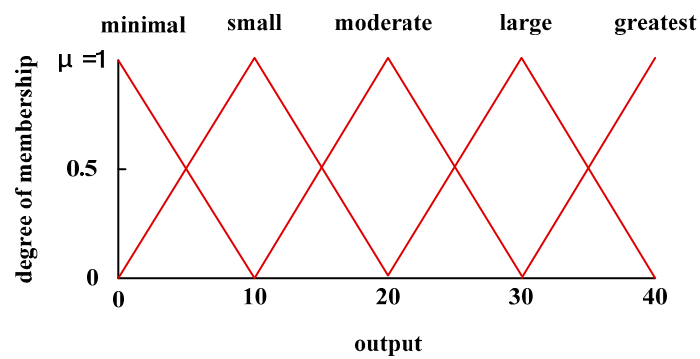


Figure 5. Degree of membership of output variables.

Fuzzy terms: The degree of membership presented in Figure 5 is detailed in Table 7.

Table 7. Output membership values.

No.	Minimal	Small	Moderate	Large	Greatest
0	1	0	0	0	0
1	0.84	0	0	0	0
2	0.68	0	0	0	0
3	0.52	0	0	0	0
4	0.36	0	0	0	0
5	0.2	0.04	0	0	0
6	0.04	0.2	0	0	0
7	0	0.36	0	0	0
8	0	0.52	0	0	0
9	0	0.84	0	0	0
10	0	1	0	0	0
11	0	0.68	0	0	0
12	0	0.52	0	0	0
13	0	0.36	0	0	0
14	0	0.2	0.04	0	0
15	0	0.04	0.2	0	0
16	0	0	0.36	0	0
17	0	0	0.52	0	0
18	0	0	0.68	0	0
19	0	0	0.84	0	0
20	0	0	1	0	0
21	0	0	0.84	0	0
22	0	0	0.68	0	0
23	0	0	0.52	0	0
24	0	0	0.36	0	0
25	0	0	0.2	0	0

26	0	0	0.04	0.04	0
27	0	0	0	0.2	0
28	0	0	0	0.36	0
29	0	0	0	0.52	0
30	0	0	0	0.68	0
31	0	0	0	0.84	0
32	0	0	0	1	0
33	0	0	0	0.84	0
34	0	0	0	0.68	0.04
35	0	0	0	0.52	0.2
36	0	0	0	0.36	0.36
37	0	0	0	0.2	0.52
38	0	0	0	0.04	0.68
39	0	0	0	0	0.84
40	0	0	0	0	1

3.3. Combination of Rules and Fuzzy Operation

According to the level range (low, medium, and high), the corresponding membership functions were the highest point of each fuzzy area, and the membership functions of input targets were determined by way of the intersection. The fuzzy operations of each target-preset result are shown below.

1. When the fuzzy region denotes “minimal” tool wear:

$$\text{Average value} = \frac{1 \times 0.84 + 2 \times 0.68 + 3 \times 0.52 + 4 \times 0.36 + 5 \times 0.2 + 6 \times 0.04}{1 + 0.84 + 0.68 + 0.52 + 0.36 + 0.2 + 0.04} = 1.1769$$

2. When the fuzzy region denotes “small” tool wear:

$$\begin{aligned} \text{Average value} &= \frac{5 \times 0.04 + 6 \times 0.2 + 7 \times 0.36 + 8 \times 0.52 + 9 \times 0.84 + 10 \times 1 + 11 \times 0.68 + 12 \times 0.52 + 13 \times 0.36 + 14 \times 0.2 + 15 \times 0.04}{0.04 + 0.2 + 0.36 + 0.52 + 0.84 + 1 + 0.68 + 0.52 + 0.36 + 0.2 + 0.04} \\ &= 9.966 \end{aligned}$$

3. When the fuzzy region denotes “moderate” tool wear:

$$\begin{aligned} \text{Average value} &= \frac{14 \times 0.04 + 15 \times 0.2 + 16 \times 0.36 + 17 \times 0.52 + 18 \times 0.68 + 19 \times 0.84 + 20 \times 1 + 21 \times 0.84 + 22 \times 0.68 + 23 \times 0.52 + 24 \times 0.36 + 25 \times 0.2 + 26 \times 0.04}{0.04 + 0.2 + 0.36 + 0.52 + 0.68 + 0.84 + 1 + 0.84 + 0.68 + 0.52 + 0.36 + 0.2 + 0.04} \\ &= 20 \end{aligned}$$

4. When the fuzzy region denotes “large” tool wear:

$$\begin{aligned} \text{Average value} &= \frac{26 \times 0.04 + 27 \times 0.2 + 28 \times 0.36 + 29 \times 0.52 + 30 \times 0.68 + 31 \times 0.84 + 32 \times 1 + 33 \times 0.84 + 34 \times 0.68 + 35 \times 0.52 + 36 \times 0.36 + 37 \times 0.2 + 38 \times 0.04}{0.04 + 0.2 + 0.36 + 0.52 + 0.68 + 0.84 + 1 + 0.84 + 0.68 + 0.52 + 0.36 + 0.2 + 0.04} \\ &= 32 \end{aligned}$$

5. When the fuzzy region denotes “greatest” tool wear

Average value

$$= \frac{34 \times 0.04 + 35 \times 0.2 + 36 \times 0.36 + 37 \times 0.52 + 38 \times 0.68 + 39 \times 0.84 + 40 \times 1}{0.04 + 0.2 + 0.36 + 0.52 + 0.68 + 0.84 + 1}$$

$$= 38.23$$

3.4. Optimal Strategies of Games

A bargaining game for the two production qualities that are often considered in precision machining of cutting, tool wear, and cutting noise was conducted, and an innovative optimal mechanism was development afterward. The conflict among two production qualities and four control parameters was resolved through the perfect Bayesian equilibrium of game theory with one production quality as one individual player. The main strategy was chosen according to different production qualities. The probability value of strategies generated by the game was calculated to select the one with the highest sum of probability as the optimal strategy of each production quality. The optimal strategy chosen was also used to obtain the optimal plan of multi-quality and multi-strategy.

3.4.1. Establishment of the Game Model

1. Player (target)

Tool wear and cutting noise were set as players. The experimental data of the qualities are shown in Table 8 and Table 9. Player A is referred to as the tool wear (the smaller, the better) and player B as the cutting noise (the smaller, the better) in the following.

Table 8. Test data of tool wear.

Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	Tool Nose Runoff (mm)	Tool Wear (μm^2)
2	2	2	2	4.38
3	2	2	1	4.13
3	2	2	2	3.87
1	2	2	1	4.21
2	3	2	2	2.97
1	2	2	3	4.13
2	2	1	1	4.38
2	2	2	1	4.04
2	1	3	3	4.13
1	2	1	3	4.55
1	3	3	2	3.38

Table 9. Test data of cutting noise.

Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	Tool Nose runoff (mm)	Cutting Noise (dB)
2	2	2	2	82.83
1	2	2	2	81.73
3	2	2	2	85.97
2	1	2	2	82.61
2	3	2	2	82.91

2	2	1	2	82.55
2	2	3	2	82.93
2	2	2	1	82.79
2	2	2	3	82.81
1	1	1	1	81.5
1	3	3	2	81.94

2. Strategic planning (control parameter)

- (1) Cutting speed
- (2) Depth of cut
- (3) Feed rate
- (4) Tool nose runoff

3.4.2. Target of Bargaining Games

The overall optimal improvement strategy was prioritized to obtain important control parameters considered preferentially by each production quality and was used to improve the turning process to obtain the best multi-quality and multi-strategy optimization. In order to take both the production qualities into account to develop a multi-quality and multi-strategy optimization, the numbers of the appearance of each strategy of the production qualities were counted. Four main strategies were selected, and the output values of their corresponding semantic rules after quantification were imported into game theory. The initial payoff matrix (Z1) was constructed under consideration of the strategies of the two production qualities, as shown in Table 10.

Table 10. Initial payoff matrix Z1.

	B			
	B-1	B-2	B-3	B-4
A-1				
A-2				
A-3				
A-4				

3.4.3. Mixed Strategies Game

In the initial payoff matrix initially established, the payoff value of all strategic combinations were filled in the corresponding spaces, resulting in the two-player multi-strategy game payoff matrix Z2, as shown in Table 11. Matrix Z2 was analyzed to establish whether the dominant strategy (one player's strategies are always better than the other player's strategies) existed. If positive, the matrix must first be simplified, as shown in Table 12. Finally, the probability values generated by all the games were statistically analyzed with their strategy probability, and the strategy with the highest probability sum was chosen to be the optimal strategy of that production quality. The optimal strategy of each production quality and its adoption probability are listed in Table 13 to obtain the optimal multi-quality and multi-strategy strategies.

Table 11. Payoff matrix Z2.

	B			
	B-1	B-2	B-3	B-4
A	A-1	(P_{a1}, P_{b1})	(P_{a2}, P_{b2})	(P_{a3}, P_{b3})
	A-2	(P_{a5}, P_{b5})	(P_{a6}, P_{b6})	(P_{a7}, P_{b7})
	A-3	(P_{a9}, P_{b9})	(P_{a10}, P_{b10})	(P_{a11}, P_{b11})
	A-4	(P_{a13}, P_{b13})	(P_{a14}, P_{b14})	(P_{a15}, P_{b15})

P_a : the payoff value of quality A under different situation; P_b : the payoff value of quality B under different situation.

Table 12. Simplified payoff matrix Z3.

	B	
	B-1	B-2
A	A-1	(P_{a1}, P_{b1})
	A-2	(P_{a3}, P_{b3})

Table 13. Optimal multi-quality and multi-strategy strategies.

Player	Optimal Strategy	Adoption Probability (%)
Tool wear (S)		
Cutting noise (Z)		

4. Experimental Verification

4.1. Experimental Condition

As a precision turning experiment, medium-carbon steel S45C with $\varnothing 45 \text{ mm} \times 250 \text{ mm}$, 100 mm clamping length, and a disposable tool were, respectively, used as the research targets and the cutting tool. The cutting blade was model NX2525, manufactured by Mitsubishi, and the tool holder was model WTJNR2020K16, manufactured by Toshiba. With the control parameter range recommended by the blade manufacturer, the cutting speed was between 150–300 meters per minute, the cutting depth was 1–4.5 millimeter, and the feed rate was 0.17–0.45 millimeter per revolution, the experiment setting was listed in below.

1. Cutting depth: 0.5mm, 1 mm, and 1.5 mm.

2. Cutting speed: The highest CNC lathe rotational speed of the tool was 3000 rpm, the diameter of the medium-carbon steel S45C used in the turning experiment was $\varnothing 45 \text{ mm}$, and its highest cutting speed was 339.292 meters per minute. The cutting speed was set as 250 meters per minute, 200 meters per minute, and 150 meters per minute, according to the recommendations given by the disposable blade.

3. Feed rate: The feed rate of the precision turning experiment was 0.02 millimeters per revolution, 0.06 millimeter per revolution, and 0.1 millimeters per revolution.

The cutting parameters, according to the above, are shown in Table 14.

Table 14. Cutting parameters.

Control Parameter	Level1	Level2	Level3
A: Depth of cut (mm)	0.5	1	1.5
B: Cutting speed (m/min)	150	200	250
C: Feed rate (mm/rev)	0.02	0.06	0.1
D: Tool nose runoff (mm)	− 0.1	± 0.03	0.1

4.2. Result of Single Target Production Quality Verification

The median of the experimental results was used for comparative analysis. The median of the tool wear was $4.38 \mu\text{m}^2$, as shown in Table 15. The median of the cutting noise was 82.83 dB, as shown in Table 16. According to the median and the comparative analysis of the two production qualities, the data obtained in this research was better than the median, which showed that the innovative strategies of both production qualities were optimized, as shown in Table 17.

Table 15. Median values of tool wear.

Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	Tool Nose Runoff (mm)	Tool Wear (μm^2)
200	1	0.06	± 0.03	4.38

Table 16. Median values of cutting noise.

Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	Tool Nose Runoff (mm)	Cutting Noise (dB)
200	1	0.06	± 0.03	82.83

Table 17. Data of single quality optimization.

Tool Wear	Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	Tool Nose Runoff (mm)	(μm^2)
Cutting speed	250	1	0.06	± 0.03	3.87
Depth of cut	200	1.5	0.06	± 0.03	2.97
Feed rate	200	1	0.02	± 0.03	4.55
Median	200	1	0.06	± 0.03	4.38
Cutting noise	Cutting speed (m/min)	Depth of cut (mm)	Feed rate (mm/rev)	Tool nose runoff (mm)	(dB)
Cutting speed	150	1	0.06	± 0.03	81.73

Depth of cut	200	0.5	0.06	± 0.03	82.61
Feed rate	200	1	0.02	± 0.03	82.55
Median	200	1	0.06	± 0.03	82.83

4.3. Multi-quality Optimal Strategy

4.3.1. Establish Initial Payoff Matrix Z2

Four preferred groups of the strategy were chosen through the experimental combination and fuzzy quantified. The output values were input into matrix Z2, as shown in Table 18. The parameters of the matrix were defined as follows.

Player (target)

A: Tool wear

B: Cutting noise

Strategy planning

A-1: Cutting speed is “low”, cutting depth is “high”, and feed rate is “high”. (Rule9)

A-2: Cutting speed is “medium”, cutting depth is “medium”, and feed rate is “low”. (Rule13)

A-3: Cutting speed is “medium”, cutting depth is “high”, and feed rate is “low”. (Rule16)

A-4: Cutting speed is “medium”, cutting depth is “high”, and feed rate is “high”. (Rule18)

B-1: Cutting speed is “low”, cutting depth is “high”, and feed rate is “high”. (Rule9)

B-2: Cutting speed is “medium”, cutting depth is “medium”, and feed rate is “low”. (Rule13)

B-3: Cutting speed is “medium”, cutting depth is “high”, and feed rate is “low”. (Rule16)

B-4: Cutting speed is “medium”, cutting depth is “high”, and feed rate is “high”. (Rule18)

Table 18. Multi-quality payoff matrix Z2.

		B			
		B-1	B-2	B-3	B-4
A	A-1	(9.966,9.966)	(9.966,9.966)	(9.966,20)	(9.966,20)
	A-2	(20,9.966)	(20,9.966)	(20,20)	(20,20)
	A-3	(9.966,9.966)	(9.966,9.966)	(9.966,20)	(9.966,20)
	A-4	(1.769,9.966)	(1.769,9.966)	(1.769,20)	(1.769,20)

4.3.2. Mixed Strategy as the Problem Solver

Since the initial payoff matrix Z2 cannot obtain the equilibrium solution or the approximate equilibrium solution, the cycle repeated continuously in some strategy combinations and a mixed strategy was needed for problem solving. As shown in the simplified payoff matrix Z3 (Table 19), two strategies remained, respectively, in both production quality A and B. However, the values of the strategies were output after fuzzy quantification, the differences of the values couldn't be distinguished clearly. To solve the problem, the strategy values were restored to the corresponding experimental values, as shown in Table 20. The optimal strategy combination was A1 and B1, as shown in Table 20. The optimal strategy of the two production qualities and its adoption probability are shown in Table 21.

Table 19. Simplified multi-quality payoff matrix Z3.

		B	
		B-1	B-2
A	A-1	(9.966,9.966)	(9.966,9.966)
	A-3	(9.966,9.966)	(9.966,9.966)

Table 20. Restored data of simplified payoff matrix Z3.

		B	
		B-1	B-2
A	A-1	(3.38,81.94)	(3.38,82.55)
	A-3	(4.38,81.94)	(4.38,82.55)

Table 21. Multi-quality optimization.

Player	Optimal Strategy	Adoption Probability (%)
Tool wear (S)	Increasing the cutting depth	100
Cutting noise (Z)	Reducing the cutting speed	100

4.3.3. Analysis of the Results of Multi-Quality Optimization

The conflict between production qualities and control parameters was aimed to be solved through the game matrix with the green production issue, which was internationally concerned and was selected as the research target. Multi-quality optimization was obtained through game theory. The optimal strategies of tool wear and cutting noise were, respectively, increasing the cutting depth and decreasing the cutting speed. The optimization obtained was further compared to the median commonly used in the industry, as shown in Table 22. The results of the comparison show that the improvement of the multi-quality cutting problem can indeed be achieved even without the operation of the equipment, and further develop a set of universal green innovative production optimization mechanism, which can provide technical personnel with a set of all-purpose economic prospective parameter analysis methods to stimulate alternative, innovative considerations of the industry.

Table 22. Comparison of multi-quality optimization and median data.

	Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	Tool Nose Runoff (mm)	Comparison
Multi-Quality Optimization	150	1.5	0.1	± 0.03	Tool wear 3.38(μm^{-2})
					Cutting noise 81.94(dB)
Median	200	1	0.06	± 0.03	Tool wear 4.38(μm^{-2})
					Cutting noise 82.83(dB)

5. Conclusion

Nowadays, the industrial production design is getting more and more complicated, and with the increasingly demanding machining requirements, the setting of cutting parameters must be extremely strict to prevent changes to some parameters that could influence other production qualities. The most difficult breakthrough of CNC turning was the difficulty in setting the turning parameter. Due to the considerations of cost and time, the quality characteristics were judged by expert experience with a trial and error method, which might cause the doubts of improper use of quality measurement indicators.

Coupled with the environmental awareness and international regulation in recent years, reducing environmental harm in the product design stage avoids being labeled as a high pollution industry and prevents being forced to move or even close down factories. It is necessary for the automated CNC turning industry to use an easy-to-use quality-improving analysis program. In view of the inability of the operators to optimize the turning quality, fuzzy theory was used in the research to define the semantic rule of the relationship between control parameters and production qualities for fuzzy quantification. The output value after quantification was input into game theory to resolve the conflict between control parameters and production qualities for carrying out the game of multi-quality. With the statistic of the strategy probability, the strategy with the highest sum of probability was selected to obtain the multi-quality and multi-strategy optimization.

The results show that, within the parameter combination of multi-quality optimization, compared with the parameter combination recommended in the cutting manual, the tool wear reduced by 23% and the cutting noise reduced by 1%. The cutting problem of multi-quality is indeed improved by the research. In order to enhance the international competitiveness of the automated CNC cutting industry, the method used in the research can further be promoted and applied to the process or other industries.

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