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Fuzzy Topsis Decision Method for Configuration Management

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Mass customization refers to an environment in which reducing quantities and increasing varieties of products are being manufactured. A product configuration is defined as an aggregation of parts whose functions and performance parameters must be defined and controlled to achieve the overall performance of a system or product. Since the product configurations would be varied based on consumer needs, selecting effective product configurations from among several alternatives is a challenge during the mass customization design stage. This study developed a structural model which combines a fuzzy quality function deployment with a fuzzy Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) to solve this problem. The configuration alternatives ranked using the proposed method can provide a useful reference for decision makers in implementing configuration management.

Significance: In mass customization environments, configuration management is crucial to product development. Inappropriate PC selection results in poor product quality and increases the development time and cost. The decision model proposed in this study provides a more realistic approach for selecting configuration alternatives in developing design strategies.

Keywords: Mass customization, Configuration management, QFD, Fuzzy set theory, TOPSIS.

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1. INTRODUCTION

Given the highly competitive global market, enterprises frequently select a production strategy capable of achieving a profit on a limited production scale to meet consumer needs. To reduce costs and adapt to small-to-medium batch production scale, flexible design should be an issue in the current environment. Furthermore, to produce added value, systems should be flexible to cope with environmental change (Salvador and Forza, 2004). Such manufacturing systems are defined as mass customization production (Silveira et al., 2001; Salvador and Forza, 2004; Tseng et al. 2005; Tseng and Chen, 2006; Jiao et al., 2007).

In mass customization environments, configuration management (CM) is essential in developing small-to-medium scale products. Configuration identification, one of the main functions of CM, selects a proper set of product configurations to meet consumer needs (ISO-10007, 1995). The product configurations (PCs) describe the multi-composition relationships between parts on the bill of material (BOM). Since the PCs vary with consumer needs, how to select effective PCs from among several configuration alternatives is a challenge during the mass customized design stage. Improper PCs selection will produce poor product quality and increase development time and costs (ISO-10007, 1995). Moreover, selecting too many PCs will increase the cost of management control, while selecting too few PCs or incorrect PCs risks losing markets.

Regarding design problems, Martin and Ishii (2000) and Siddique and Rosen (2001) have researched design problems. This study does not emphasize the design issue but rather decision model construction, including selecting configuration alternatives while developing design strategies. Moreover, an empirical case study dealing with configuration management of CNC lathe machine is provided to demonstrate the computational process and effectiveness of the proposed decision model.

2. PROBLEM DESCRIPTION

The selection of PCs is modeled as a multi-criteria decision making (MCDM) problem (Hwang and Yoon, 1981). The decision makers first establish several strategic criteria from which the configuration alternatives are then ranked and selected. Because considerable incomplete and uncertain information exists in the early design and development stages, it is difficult to choose the PCs based on traditional cost and effectiveness analysis. This study attempts to build a decision model which offers a quantitative reference for selecting configuration alternatives. Furthermore, since most information available during the design stage is imprecise, vague, and uncertain and is generally expressed in natural language by decision makers, fuzzy set theory (FST) was adopted and the decision model, which combines a fuzzy quality function deployment (QFD) with a fuzzy Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) was developed here.

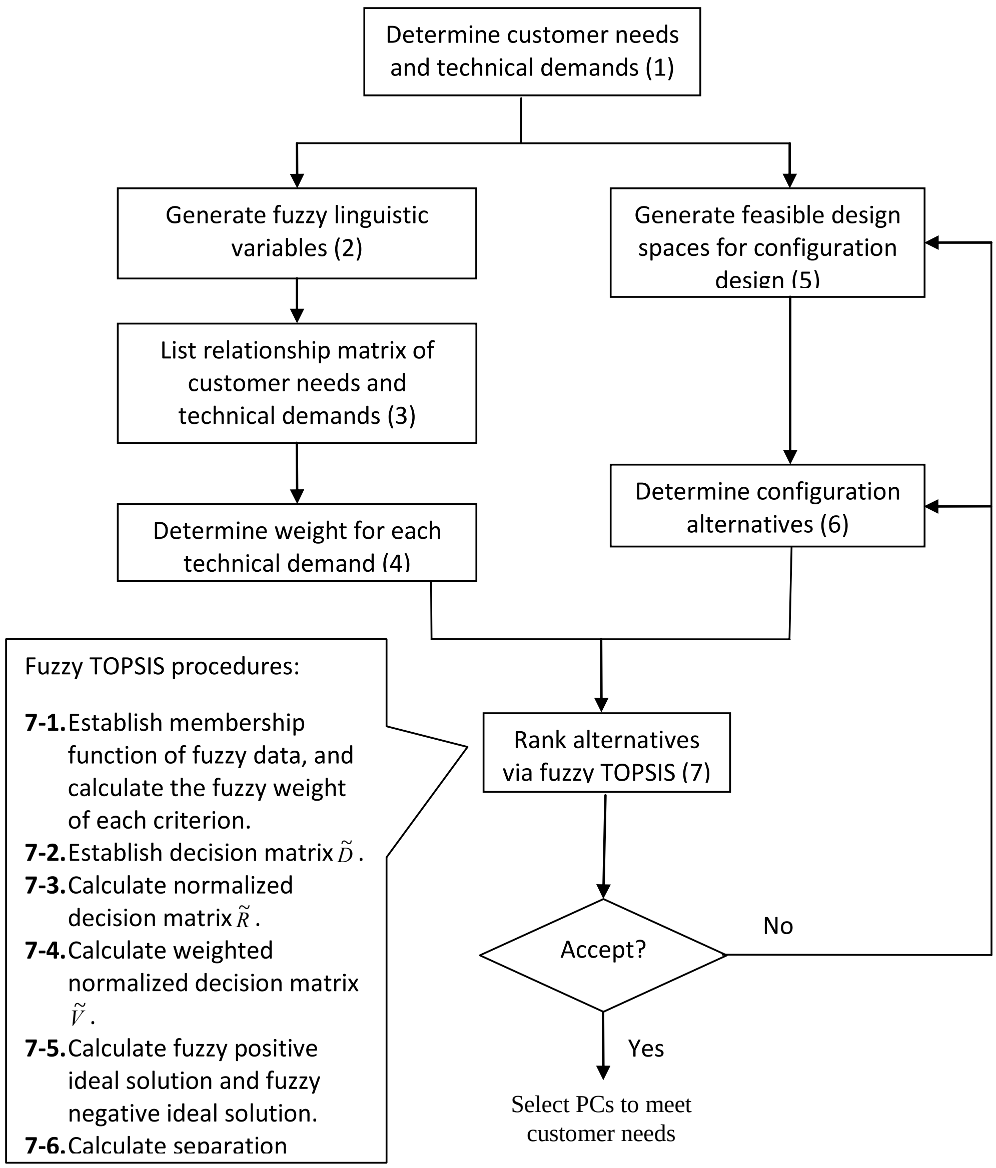

Figure 1: Decision making algorithm for selecting product configurations

The TOPSIS developed by Hwang and Yoon (1981) was applied to solve the MCDM problem because of its numerous advantages: (1) the processing of TOPSIS fits the human decision selection process; (2) the best and the worst solutions are compared quantitatively; (3) it is easy to calculate and implement the algorithm. For the sake of transforming customer needs into product specifications/technical demands, a fuzzy QFD developed by Shen et al. (2000) is adopted. Since numerous factors influence the ranking of technical demands, sensitivity analysis of QFD approach was developed to make it more rigorous and operational (Shen et al., 2000; Chan and Wu, 2002; 2005). Shen et al. (2000) studied the sensitivity of the ranking of technical demands to the defuzzification strategy, as well as the degree of fuzziness of fuzzy numbers. Two common defuzzification methods, namely, the Mean of Maxima (MOM) and the Centroid method, and the degree of fuzziness of fuzzy numbers by the linear index of fuzziness proposed by Kaufmann (1975) were used by Shen et al. (2000). The analytical results indicated that the degree of fuzziness slightly influenced the ranking of technical demands when the Centroid method was used, but did not affect the technical demands when using the MOM method. For convenience of implementation, the Centroid method was adopted in this study.

Figure 1 shows the fuzzy decision making algorithm for selecting PCs. The algorithm comprises seven steps.

Step 1: Determine customer needs and technical demands. Two steps are generally adopted for deciding customer needs and technical demands. First, an in-depth exploration of consumer needs should be performed to understand the values which customers really care about. Customer utility can be achieved via a questionnaire survey. Second, the QFD method can be applied to transform customer needs into precise product specifications/technical demands (Otto and Wood, 2001).

Steps 2-4: Generate the fuzzy linguistic variables, list the relationship matrix of customer needs and technical demands, and determine the weight for each technical demand. The fuzzy linguistic variables will be built to handle the subjective and imprecise opinions expressed in natural language by decision makers. In this study, two important input data are treated as linguistic variables: the importance to customer needs attributes, and the strength of relationship between the customer needs and the technical demands. The fuzzy evaluation score for each technical demand can be calculated by fuzzy QFD method.

Steps 5-6: Generate the feasible design spaces for the configuration design and determine the configuration alternatives. In step 5, the feasible design spaces for the configuration design of product families are generated after filtering the functional specifications based on technical difficulty, cost and effectiveness, and customer satisfaction. Then, the specifications of components, subassembly, or major design variables can be determined. Furthermore, several PCs will be generated based on the environment, company strategy and related factors.

Step 7: Rank alternatives and select the optimum solution via the seven steps of the TOPSIS algorithm. The selection procedure is described in the following section.

3. ALGORITHM FOR COMBINING QFD AND TOPSIS METHOD

This study translates customer needs into technical demands by the QFD method to determine the respective weight for each technical demand. Alternatives are then evaluated by combining it with the TOPSIS method to include the opinions from decision makers during the evaluation of configuration alternatives. In the meantime, it is necessary to adopt the FST to implement the entire evaluation process to solve the decision problems in which descriptions of activities and observations are imprecise, vague, and uncertain.

FST provides a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously studied. It indicates the elements of a set that belong to the degree of that set. Using fractional numbers between 0 and 1 to indicate the degree of membership, FST uses the fuzzy logic concept to compensate for the weaknesses in traditional sets, which use description based on just two values – 0 and 1. The triangular fuzzy number is used throughout this study, and all membership functions for linguistic input data are normalized in the interval [0, 1]. The definitions used in this study are stated below.

3.1 Definition 1. Positive triangular fuzzy number

A positive triangular fuzzy number $\tilde{A}$, a fuzzy set, can be defined by a triplet (*l, m, u*). The membership function $U_{\tilde{A}}(x)$ is defined as (Klir and Yuan, 1995):

$$U_{\tilde{A}}(x) = \begin{cases} (x-l)/(m-l), & l \le x \le m \\ (x-u)/(m-u), & m \le x \le u \\ 0, & \text{otherwise} \end{cases} \qquad \ldots \qquad (1)$$

3.2 Definition 2. Operations of positive triangular fuzzy numbers

When given two positive triangular fuzzy numbers $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$, according to the interval of confidence (Klir and Yuan, 1995), the algebraic operations of these two positive triangular fuzzy numbers $\tilde{A}_1$ and $\tilde{A}_2$ can be expressed as follows:

$$\tilde{A}_1 \oplus \tilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \qquad \ldots \qquad (2)$$

$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1 \cdot l_2, m_1 \cdot m_2, u_1 \cdot u_2) \qquad \dots \qquad (3)$$

The procedures for fuzzy TOPSIS analysis in this study are explained below.

Step 7-1 : Establish the membership function of fuzzy data, and calculate the fuzzy weight of each criterion. Establishing the membership function of the fuzzy evaluation value is done by setting up an interval value between 0 and 1 and expressed by a triangular fuzzy number. Furthermore, the fuzzy weight for each criterion in TOPSIS is calculated by applying the QFD method. The fuzzy weight for criterion j is defined as $\tilde{W}_j = (w_{j1}, \quad w_{j2}, \quad w_{j3})$.

Step 7-2 : Establish the decision matrix $\tilde{D}$. There are two types of values in decision matrix $\tilde{D}$, i.e., a crisp value and a fuzzy number. If the value is a fuzzy number, then use a triangular fuzzy number defined by formula (1).

Step 7-3 : Calculate the normalized decision matrix $\tilde{R}$ based on the type of value in decision matrix $\tilde{D}$.

(A) If the value of x_{ij} representing the evaluation value of alternative i and criterion j is a crisp value, then the transformed evaluation value r_{ij} can be defined as follows:

(a) $$r_{ij} = x_{ij} / x_j^*, \ \forall j, \qquad \dots \qquad (4)$$

where x_j^* is the ideal solution for the benefit criteria;

(b) $$r_{ij} = x_j^- / x_{ij}, \ \forall j, \qquad \dots \qquad (5)$$

where x_j^- is the ideal solution for the cost criteria.

(B) If the evaluation value $\tilde{x}_{ij} = (n_{1ij}, \quad n_{2ij}, \quad n_{3ij})$ is a fuzzy number, then the evaluation value $\tilde{r}_{ij}$ after normalization can be defined as follows:

(a) $$\tilde{r}_{ij} = (\frac{n_{1ij}}{n_{3j}^*}, \frac{n_{2ij}}{n_{3j}^*}, \frac{n_{3ij}}{n_{3j}^*}), \ n_{3j}^* = \max_i \ n_{3ij}, \qquad \dots \qquad (6)$$

where j is the benefit criterion, n_{3j}^* is the largest ending value of the fuzzy number in all alternatives;

(b) $$\tilde{r}_{ij} = (\frac{n_{1j}^-}{n_{1ij}}, \quad \frac{n_{1j}^-}{n_{2ij}}, \quad \frac{n_{1j}^-}{n_{3ij}}), \ n_{1j}^- = \min_i \ n_{1ij}, \qquad \dots \qquad (7)$$

where j is the cost criterion, n_{1j}^- is the smallest ending value of the fuzzy number in all alternatives.

Step 7-4 : Calculate the weighted normalized decision matrix $\tilde{V}$. In formula (8) $\tilde{v}_{ij}$ is the element evaluation value after normalizing the decision matrix by including the weight value. This evaluation can be calculated by formula (3).

$$\tilde{v}_{ij} = \tilde{r}_{ij} \ (\cdot) \ \tilde{W}_j \quad , \quad \forall i, j. \qquad \dots \qquad (8)$$

The value of $\tilde{W}_j$, which is determined by the QFD method, is the weight value of the criteria.

$$\tilde{v}_{ij} = (\frac{n_{1ij}}{n_{3j}^*} w_{j1}, \ \frac{n_{2ij}}{n_{3j}^*} w_{j2}, \ \frac{n_{3ij}}{n_{3j}^*} w_{j3}), \qquad \dots \qquad (9)$$

where j is the benefit criterion;

$$\tilde{v}_{ij} = (\frac{n_{1j}^-}{n_{1ij}} w_{j1}, \ \frac{n_{1j}^-}{n_{2ij}} w_{j2}, \ \frac{n_{1j}^-}{n_{3ij}} w_{j3}), \qquad \dots \qquad (10)$$

where j is the cost criterion.

Step 7-5 : Calculate the fuzzy positive ideal solution $\tilde{A}^*$ and the fuzzy negative ideal solution $\tilde{A}^-$.

$$\tilde{A}^* = (\tilde{v}_1^*, \quad \tilde{v}_2^*, \quad \cdots \quad \cdots \quad \tilde{v}_n^*), \ \tilde{v}_j^* = \max_i \ \tilde{v}_{ij}, \ \forall j \qquad \dots \qquad (11)$$

$$\tilde{A}^- = (\tilde{v}_1^-, \quad \tilde{v}_2^-, \quad \cdots \quad \cdots \quad \tilde{v}_n^-), \ \tilde{v}_j^- = \min_i \ \tilde{v}_{ij}, \ \forall j \qquad \dots \qquad (12)$$

In this step, it is necessary to transform a fuzzy number into a non-fuzzy number (i.e., defuzzification) in order to rank the alternatives. This study adopts the Centroid method for defuzzification. The formula for defuzzifying the number $\tilde{V}_{ij}$ is:

$$V_{ij} = \frac{(n_{1ij} + n_{2ij} + n_{3ij})}{3}. \quad \cdots \quad (13)$$

When there is an equal value among the fuzzy-number values of each alternative, one can choose randomly. The value of the cost criteria after normalization will be the same as that of the benefit criteria. The larger the attribute value, the better. Therefore, the selection of the fuzzy positive ideal solution V_j^* and the fuzzy negative ideal solution V_j^- is the same as that of the benefit criterion.

Step 7-6 : Calculate the distance between each alternative and the fuzzy positive ideal solution $\tilde{A}^*$ and the distance between each alternative and the fuzzy negative ideal solution $\tilde{A}^-$.

When given two triangular fuzzy numbers $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$, the distance between the two can be calculated by the vertex method, which is defined as follows (Chen, 2000):

$$d(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]} \quad \cdots \quad (14)$$

Thus, the distance between $\tilde{v}_{ij}$ and the positive ideal solution is:

$$D_{ij}^* = d(\tilde{v}_{ij}, \tilde{v}_j^*), \quad \forall i, \quad j \quad \cdots \quad (15)$$

and, the distance between $\tilde{v}_{ij}$ and the negative ideal solution is:

$$D_{ij}^- = d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad \forall i, \quad j. \quad \cdots \quad (16)$$

On the other hand, the distance between the alternative i and $\tilde{A}^*$ is:

$$S_i^* = \sum_{j=1}^{n} D_{ij}^* \quad \cdots \quad (17)$$

and, the distance between the alternative i and $\tilde{A}^-$ is:

$$S_i^- = \sum_{j=1}^{n} D_{ij}^- . \quad \cdots \quad (18)$$

The reason for adopting the vertex method in this study is that it is an effective and easy method among many distance-measuring methods. As long as there is a different vertex value between the two triangular fuzzy numbers, a distance exists which can be calculated by the vertex method.

Step 7-7 : Calculate the relative closeness to the fuzzy positive ideal solution for each alternative.

In formula (19), C_i^* is the relative closeness for alternative A_i to the fuzzy positive ideal solution $\tilde{A}^*$.

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*} \quad \cdots \quad (19)$$

Obviously, $0 \le C_i^* \le 1, \; i = 1, 2, \cdots, m$. The closer C_i^* is to 1, the closer the alternative i is to the positive ideal solution. Thus, the alternative has a higher/superior ranking.

4. CASE STUDY

This study used a CNC lathe from one company as a case study of PCs selection (http://www.llcnclathe.com/index.asp). The lathe comprises six important modules: (1) headstock, (2) bed, (3) tailstock, (4) carriage, (5) controller and (6) other important parts, as illustrated in Fig. 2.

- Headstock: the key part of the lathe structure; it includes the head shaft, motor and speed-changer set.
- Bed: the main part of the lathe, which supports the tailstock, carriage, head shaft box and motor system.
- Tailstock: also called the tailshelf, cartail, or bottomstock; it supports long pointing tools and is used to store drill bits, saws and other tools.

- Carriage: transferring tools with reciprocating motion on the bed stage of the lathe bed. The tools can be moved via manual horizontal or vertical movements, or by a rod.
- Controller: the main module controlling working parts in the CNC lathe. The different modules have different functional parameters.

The designer can plan the complete configuration alternative on the entire lathe based on the functional parameters, as shown in Fig. 2. The designer must consider every design parameter which influences the lathe during the designing process. Among these parameters, customers must provide at least two types of data, namely, the diameter and length of the processing parts. The diameter of the parts determines the center height, while their length determines the length of the lathe bed. Furthermore, the length of the lathe bed limits its width. From the analytical results, some parameters do not affect the design structure, namely, center height, bed length, bed width, turret, tailstock body movement, tailstock quill movement, and controller. These parameters are termed unchangeable parametric sets, and are represented by B. However, B does not make design changes based on customer choices. Instead, B accompanies other changeable parameters which have a configuration variant, as shown in Table 1. Basically, the possible choices for B remain unchanged. The only changes which occur in cross slide do so owing to the choices of either the dove tail or the box, and each choice differs between the fixed and rotary types. Thus, this study develops the different configuration alternatives by focusing on the functional parameters affecting the entire body design. Sixteen sets of alternative solutions are obtained, with each set of parametric alternative assemblies representing a possible solution to extending product configuration.

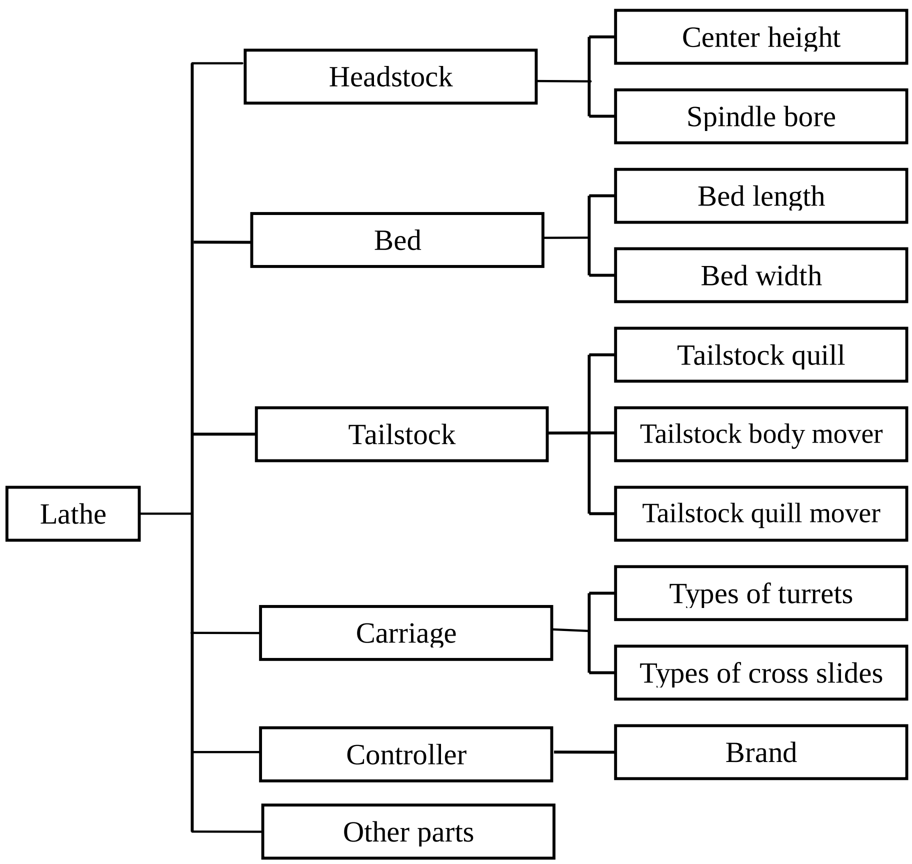

Figure 2: Important modules of CNC lathe

Four main considerations must be made regarding customer needs for CNC lathe: (1) the speed in completing the processing of the parts, (2) the degree of accuracy in cutting, (3) the rate of damage to the machine bench, and (4) the price. Consequently, it is possible to identify the technical demands which need to be considered to fulfill customer needs. The decision makers can then identify the relationship between the technical demands and customer needs. The relative importance of each technical demand can be determined by calculating the normalized total fuzzy evaluation score by applying fuzzy QFD method. Table 2 shows the investigation result of the present case study which lists the strength of relationship between the customer needs and the technical demands. This study also uses the fuzzy linguistic variables (defined in Table 3) combined with fuzzy calculation to determine the fuzzy weight value of the technical demands. Table 4 listed the result obtained from calculating the normalized total fuzzy evaluation score.

Table 1. Design parameters of configuration alternatives

Alternative assemblies	Conditions	Alternative assemblies	Conditions
A_1	B+ bore 4+ dove tail+ fixed	A_9	B+ bore 4+box + fixed
A_2	B +bore 6+dove tail+ fixed	A_{10}	B+ bore 6+box+ fixed
A_3	B +bore 9+ dove tail + fixed	A_{11}	B+ bore 9+box+ fixed
A_4	B + bore 12+ dove tail + fixed	A_{12}	B+ bore 12+box+ fixed
A_5	B +bore 4+ dove tail + Rotary	A_{13}	B+ bore 4+box+ Rotary
A_6	B +bore 6+ dove tail + Rotary	A_{14}	B+ bore 6+box+ Rotary
A_7	B +bore 9+ dove tail + Rotary	A_{15}	B+ bore 9+box+ Rotary
A_8	B +bore 12+ dove tail + Rotary	A_{16}	B+ bore 12+box+Rotary

Table 2. Relationship matrix between customer needs and technical demands

Technical demands / Customer Needs	Cost	Speed	Strength	Lubrication system	Coolant pump system
Speedily finishing processing parts	Medium	Very strong	Weak	Very weak	Very weak
High degree of accurate cutting	Strong	Medium	Strong	Strong	Strong
Low damaged rate	Medium	Strong	Weak	Very strong	Medium
Low price	Very strong	Weak	Very weak	Medium	Weak

Table 3. Fuzzy numbers for linguistic variables.

Linguistic variables in relationship matrix	Fuzzy numbers
Very weak relationship	(0, 0, 0.25)
Weak relationship	(0, 0.25, 0.5)
Regular relationship	(0.25, 0.5, 0.75)
Strong relationship	(0.5, 0.75, 1.0)
Very strong relationship	(0.75, 1.0, 1.0)

Table 4. Result obtained from calculating the normalized total fuzzy evaluation score.

Technical demands / Customer needs	Cost X_1	Speed X_2	Strength X_3	Lubrication system X_4	Coolant pump system X_5
Speedily finishing processing parts	(0.25, 0.5, 0.75)	(0.75, 1.0, 1.0)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0, 0, 0.25)
High degree of cutting accuracy	(0.5, 0.75, 1.0)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1.0)	(0.5, 0.75, 1.0)	(0.5, 0.75, 1.0)
Low damage rate	(0.25, 0.5, 0.75)	(0.5, 0.75, 1.0)	(0, 0.25, 0.5)	(0.75, 1.0, 1.0)	(0.25, 0.5, 0.75)
Low price	(0.75, 1.0, 1.0)	(0, 0.25, 0.5)	(0, 0, 0.25)	(0.25, 0.5, 0.75)	(0, 0.25, 0.5)
Total score of fuzzy evaluation of technical demands	(1.75, 2.75, 3.5)	(1.5, 2.5, 3.25)	(0.5, 1.25, 2.25)	(1.5, 2.25, 3.0)	(0.75, 1.5, 2.5)
Normalized total score of fuzzy evaluation of technical demands	(0.5, 0.79, 1)	(0.43, 0.71, 0.93)	(0.14, 0.36, 0.64)	(0.43, 0.64, 0.86)	(0.21, 0.43, 0.71)

The procedures for evaluating configuration alternatives are shown below:

Step 7-1 : Establish the membership function of fuzzy data, and calculate the fuzzy weight of each criterion. Two things must be considered regarding the application of the configuration alternatives evaluation principles of the headstock: (1) the evaluation results for the five attributes, including cost (X_1), speed (X_2), strength (X_3), lubrication system (X_4), coolant pump system (X_5), and (2) the fuzzy weight value for each attribute, the fuzzy weight for each criterion in TOPSIS, listed in Table 4. $\tilde{W} = [(0.5, 0.79, 1) \quad (0.43, 0.71, 0.93) \quad (0.14, 0.36, 0.64) \quad (0.43, 0.64, 0.86) \quad (0.21, 0.43, 0.71)]$. The attributes which cannot be expressed numerically, for example, strength, lubrication system and coolant pump system, can be defined using linguistic variables, as listed in Table 5.

Table 5: Attributes defined using linguistic variables.

Degree	Strength of linguistic variable	Fuzzy numbers	Linguistic variable after lubricating effect	Fuzzy numbers	Linguistic variable after radiating effect	Fuzzy numbers
1	Very weak	(0, 0, 0.3)	Worst	(0, 0, 0.3)	Worst	(0, 0, 0.3)
2	Weak	(0, 0.3, 0.5)	Bad	(0, 0.3, 0.5)	Bad	(0, 0.3, 0.5)
3	Normal	(0.3, 0.5, 0.7)	Normal	(0.3, 0.5, 0.7)	Normal	(0.3, 0.5, 0.7)
4	Strong	(0.5, 0.7, 1.0)	Good	(0.5, 0.7, 1.0)	Good	(0.5, 0.7, 1.0)
5	Very strong	(0.7, 1.0, 1.0)	Best	(0.7, 1.0, 1.0)	Best	(0.7, 1.0, 1.0)

Step 7-2 : Establish the decision matrix $\tilde{D}$ by including the fuzzy number of the linguistic variables to the decision matrix, as listed below.

Step 7-3 : Determine the normalized decision matrix $\tilde{R}$, which can be calculated by using formulas (4), (5), (6), and (7).

Step 7-4 : Determine the weighted normalized decision matrix $\tilde{V}$, which can be calculated by using formula (8).

Step 7-5 : Calculate the fuzzy positive ideal solution $\tilde{A}^*$ and the fuzzy negative ideal solution $\tilde{A}^-$ by using formulas (11), (12), and (13).

Step 7-6 : Calculate separation measures for each alternative by using formulas (14), (15), and (16). The values of S_i^* and S_i^- can be calculated by using formulas (17) and (18).

Step 7-7 : Calculate the relative closeness to the fuzzy positive ideal solution. The relative closeness C_i^* can be calculated by using formula (19). The result is listed in Table 6.

$$\tilde{D} = \begin{array}{c|ccccc} & x_1 & x_2 & x_3 & x_4 & x_5 \\ & \$M & rpm & & & \\ \hline A_1 & 4.25 & 250 & (0.0, 0.3, 0.5) & (0.3, 0.5, 0.7) & (0.5, 0.7, 1.0) \\ A_2 & 5.55 & 550 & (0.3, 0.5, 0.7) & (0.3, 0.5, 0.7) & (0.3, 0.5, 0.7) \\ A_3 & 4.57 & 850 & (0.5, 0.7, 1.0) & (0.5, 0.7, 1.0) & (0.5, 0.7, 1.0) \\ A_4 & 5.78 & 1050 & (0.5, 0.7, 1.0) & (0.7, 1.0, 1.0) & (0.5, 0.7, 1.0) \\ A_5 & 4.46 & 150 & (0.3, 0.5, 0.7) & (0.3, 0.5, 0.7) & (0.7, 1.0, 1.0) \\ A_6 & 5.69 & 300 & (0.5, 0.7, 1.0) & (0.5, 0.7, 1.0) & (0.7, 1.0, 1.0) \\ A_7 & 4.85 & 350 & (0.7, 1.0, 1.0) & (0.5, 0.7, 1.0) & (0.5, 0.7, 1.0) \\ A_8 & 6.15 & 500 & (0.7, 1.0, 1.0) & (0.7, 1.0, 1.0) & (0.0, 0.3, 0.5) \\ A_9 & 4.32 & 700 & (0.3, 0.5, 0.7) & (0.5, 0.7, 1.0) & (0.7, 1.0, 1.0) \\ A_{10} & 5.13 & 650 & (0.5, 0.7, 1.0) & (0.5, 0.7, 1.0) & (0.3, 0.5, 0.7) \\ A_{11} & 4.65 & 450 & (0.5, 0.7, 1.0) & (0.3, 0.5, 0.7) & (0.5, 0.7, 1.0) \\ A_{12} & 6.12 & 1200 & (0.0, 0.3, 0.5) & (0.7, 1.0, 1.0) & (0.5, 0.7, 1.0) \\ A_{13} & 5.87 & 400 & (0.7, 1.0, 1.0) & (0.3, 0.5, 0.7) & (0.7, 1.0, 1.0) \\ A_{14} & 6.07 & 600 & (0.7, 1.0, 1.0) & (0.7, 1.0, 1.0) & (0.5, 0.7, 1.0) \\ A_{15} & 5.74 & 750 & (0.3, 0.5, 0.7) & (0.5, 0.7, 1.0) & (0.7, 1.0, 1.0) \\ A_{16} & 6.33 & 800 & (0.5, 0.7, 1.0) & (0.7, 1.0, 1.0) & (0.5, 0.7, 1.0) \end{array}$$

Each alternative is ranked from favorable to unfavorable. The degree of preference of an alternative increases with the value of C_i^*. Thus, the alternative rankings are determined as:

$$A_4 \succ A_3 \succ A_{12} \succ A_9 \succ A_{16} \succ A_{14} \succ A_{15} \succ A_7 \succ A_{10} \succ A_{11} \succ A_6 \succ A_8 \succ A_{13} \succ A_5 \succ A_1 \succ A_2 .$$

The proposed decision model ranks configuration alternatives into complete orders that can assist decision makers in selecting more appropriate sets of configuration alternatives. Alternatives with higher-ranking order have higher priority for consideration as a PC, satisfying both customer needs and technical demands for configuration management. The number of PCs selected depends on the budget available for configuration management. Furthermore, the ranking of the configuration alternatives offered by this study can provide a valuable reference for forecasting market trends and further developing specific products. In this case, A_4 is chosen as the optimum alternative. From the result, based on the unchangeable nature of body structure B, the company can further stabilize and enhance the design of the fixed dove-tail type cross-slide.

Table 6: Relative closeness to the positive ideal solution.

i	C_i^*
1	0.5824 / （1.1472 + 0.5824） = 0.3367
2	0.5322 / （1.1689 + 0.5322） = 0.3128
3	1.2670 / （0.5295 + 1.2670） = 0.7053
4	1.3168 / （0.4419 + 1.3168） = 0.7487
5	0.5925 / （1.1065 + 0.5925） = 0.3487
6	0.8386 / （0.9257 + 0.8386） = 0.4753
7	0.9600 / （0.8047 + 0.9600） = 0.5432
8	0.7516 / （0.9458 + 0.7516） = 0.4428
9	1.1473 / （0.5895 + 1.1473） = 0.6606
10	0.9336 / （0.8327 + 0.9336） = 0.5286
11	0.8409 / （0.9178 + 0.8409） = 0.4781
12	1.1679 / （0.5617 + 1.1679） = 0.6752
13	0.7422 / （0.9552 + 0.7422） = 0.4373
14	1.0544 / （0.6752 + 1.0544） = 0.6696
15	0.9849 / （0.7519 + 0.9849） = 0.5671
16	1.1164 / （0.6424 + 1.1164） = 0.6348

5. CONCLUSIONS AND RECOMMENDATIONS

This study has established a structural and effective model for selecting product configurations. Fuzzy set theory was adopted to solve evaluation problems involving incomplete, uncertain and subjective information. A relationship matrix for QFD has been applied to transform customer needs into technical demands and determine the weights for each criterion in TOPSIS. The TOPSIS method has been implemented to assess product configurations. A case study involving a CNC lathe machine serves as a practical example to demonstrate the effectiveness of the proposed method.
In future, since configuration management is an incremental learning process and it is difficult to develop the ‘best’ design concept in single shop, it should be possible to combine the approaches of case-based reasoning (CBR) with the selected alternatives by the TOPSIS method and process them dynamically. Furthermore, the objectiveness of the evaluation process can be enhanced by group decision approaches. The decision model proposed in this study can undoubtedly be applied to other mass-customized products.

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BIOGRAPHICAL SKETCH

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