Engineering, 2025, 17(9), 425-450
https://www.scirp.org/journal/eng
ISSN Online: 1947-394X
ISSN Print: 1947-3931

Research on Complex Product Engineering Change Configuration Updates Based on Dynamic Intuitionistic Fuzzy Numbers

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How to cite this paper: Yang, W.M. and Yu, Y.Y. (2025) Research on Complex Product Engineering Change Configuration Updates Based on Dynamic Intuitionistic Fuzzy Numbers. *Engineering*, **17**, 425-450.
https://doi.org/10.4236/eng.2025.179026

Received: February 6, 2025
Accepted: September 16, 2025
Published: September 19, 2025

Abstract

After a component change occurs, the enterprise needs to promptly update the configuration along the determined change path and quickly provide feedback on the configuration update plan for the complex product. Based on the design experience of designers, this paper analyzes the component configuration update and provides research ideas on complex product configuration updates driven by change. Firstly, a new modular division method is applied to modularize the complex product. Then, designers' experience is analyzed based on intuitionistic fuzzy numbers, and the weights of alternative indicators for each component are dynamically calculated. The most suitable configuration update plan for production factor-related indicators is determined based on the integrated grey relational method. Finally, the feasibility and effectiveness of the research method proposed are verified by taking the component configuration update of a large capacity full DC high-speed permanent magnet synchronous variable frequency centrifugal unit as an example.

Keywords

Intuitionistic Fuzzy Number, Complex Product, Grey Relational Analysis, Decision Analysis

1. Introduction

Updates to complex product configurations play a pivotal role in improving performance and reliability. The replacement or upgrade of key components can enhance the overall performance and stability of the product. High-quality components not only extend the product's service life but also reduce maintenance and replacement costs associated with failures. The latest safety technologies and adhering to industry standards can further elevate the product's overall safety. However, for complex products, the presence of numerous components and their intricate relationships significantly increases the difficulty of updating product configurations. Consequently, this paper examines the issue of updating complex product configurations.

Research on product configuration updates has been extensively conducted by scholars [1]-[7]. These studies primarily focus on reconfiguration designs based on the generic aspects of product components or modules. However, the involvement of multiple departments and the numerous production factors associated with individual components make existing reconfiguration methods inefficient in addressing configuration changes for complex products. Therefore, it is essential to investigate more suitable methods for dynamic updates in complex product engineering changes. Although many scholars have conducted in-depth research on various aspects of complex product configurations, there remains a lack of focus on quality characteristics and design personnel evaluations. Quality characteristics are critical factors that both professional production personnel and customers value highly. Additionally, owing to the vast number and intricate nature of components in complex products, modularizing these components is crucial when selecting specialized design professionals for dynamic weighting and scoring. The method in this paper enables the selection of domain experts from different modules to perform evaluations and assign scores. The modular division not only streamlines the assessment process but also ensures that each component is evaluated by the most qualified professionals.

In the area of modularity, numerous scholars have conducted extensive research. Li *et al.* [8] proposed a new modularization method for complex products to reduce the impact of design change propagation. Modularization and the Scope of Design Change Propagation (SDCP) were integrated, and a weighted directed network model based on the functional and physical relationships between components was constructed in the paper. Modularization and SDCP metrics were defined through a pre-determined network model and associated matrices. Then, a bi-objective optimization model for complex product modularization was established, which was solved by the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). Dordevic *et al.* [9] developed a model for the MSR-type MODULPRIM automatic configuration system, which integrates various processes including product variant generation, optimal configuration selection, detailed product design, and process flow design. Beck [10] focused on the optimization of modular systems, proposing a mixed-integer model aimed at minimizing total costs. To address the issue of variable dependencies, a solution approach was proposed that transforms the problem into a deterministic mixed-integer optimization problem using binary variables. Osman [11] examined the performance of matrix-based configuration software and its applications in configuration and change management within cooling station designs.

The above research focuses on methods of modularization and the evaluation of division results for complex products. It is crucial for reducing the difficulty of engineering changes and enabling rapid responses to changes. However, modularization schemes must be tailored to specific cases. In the modularity of complex products, due to the complexity of their components, the internal structure needs to be thoroughly considered. Therefore, this paper quantifies the internal structural relationships among components to develop reasonable modularization strategies for complex products. Specifically, this study aims to establish association rules between design components by considering the internal structure. This approach further refines the methodology for achieving effective modularization of complex products.

From previous research, it is evident that numerous scholars have studied design personnel. However, in the manufacturing process of complex products, the characteristics of these products involve multiple forms of knowledge ambiguity, difficulty in obtaining data, and the dynamic nature of design personnel's knowledge. The experience and data provided by some design personnel play a crucial role in the production process. Therefore, this paper attempts to study the decision-making process of design personnel based on dynamic fuzzy numbers.

Existing research has explored the roles of production process subjects or design personnel. But current product configuration designs primarily focus on deterministic products and their functional realization. For complex products with fuzzy and intricate component knowledge, a different configuration solution is required. As an important standard in manufacturing, quality characteristics are crucial for decision-making in complex product configurations. To address these issues, this paper proposes a complex product configuration update method based on comprehensive design personnel evaluation. Firstly, a new modularization method is applied to divide complex products into modules. The representative language of design personnel for each module during different periods is converted into dynamic weight indicators by intuitionistic fuzzy numbers. Finally, the integrated grey relational analysis method is used to update the configuration changes. The research framework for complex product configuration updates driven by engineering changes is illustrated in **Figure 1**.

The rest of this paper is as follows: Section 2 primarily introduces the modular division method proposed in this paper. Section 3 introduces a dynamic analysis method for quality characteristics based on intuitionistic fuzzy numbers and designer ratings. Section 4 describes the methodology for using the grey relational model to determine the configuration scheme. Section 5 is a case study of the configuration update of complex product engineering change. Section 6 summarizes the research work of this paper.

2. A New Modularization Method

The modularization of complex products in this paper can be understood as the division of a complex product into a series of closely related modules based on

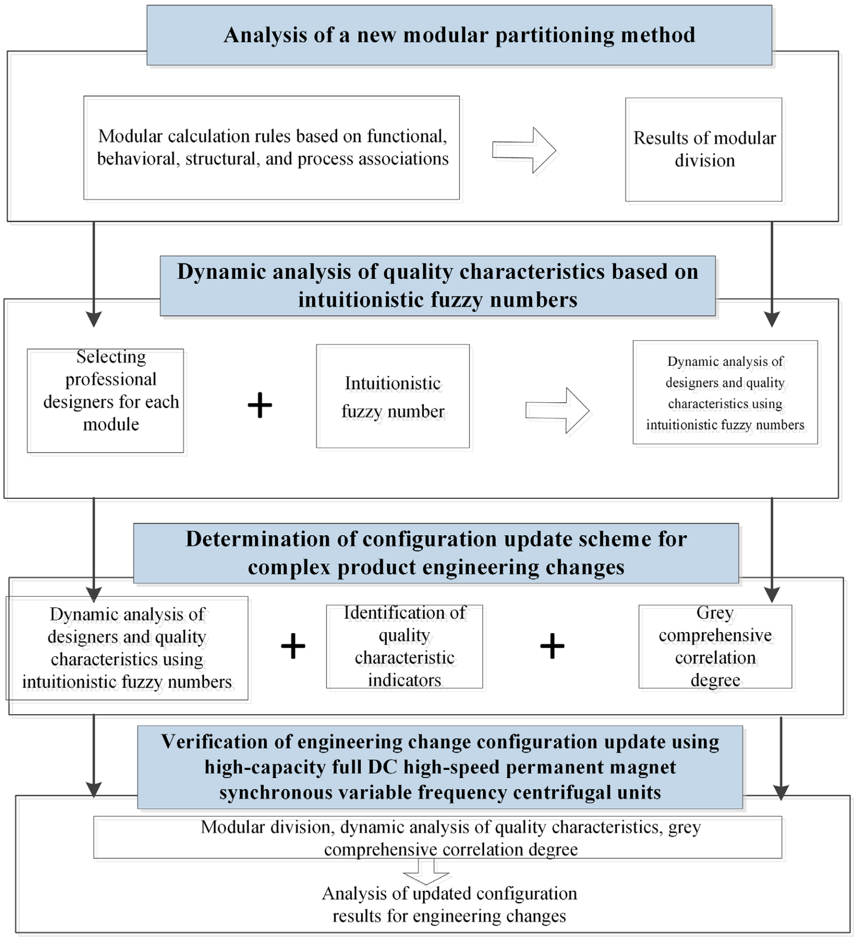

Figure 1. Research framework for configuration update in complex product engineering changes.

certain rules. This division provides a basis for management activities such as production, evaluation, and decision-making. Due to the intricate nature of complex products, modularization is a critical step in the process of configuration updates. In this paper, a modularization method based on the characteristics of components in complex products is proposed. Internal structural relationships are considered and used to quantify the association rules between design components. This approach aims to establish a reasonable modularization strategy for complex products, providing a foundation for professional design personnel to evaluate quality characteristics. This modularization approach can significantly improve the efficiency and accuracy of configuration updates driven by engineering changes in complex products. This structured method provides a solid foundation for professional designers to evaluate and score quality characteristics.

2.1. Division Method of Modules

Module division needs to follow certain rules, which are described as follows:

Rule 1: This refers to the representation of components. The expression of components is $CIR = \{F, B, S, P\}$ where F is the function, including the main function and optional function, and B is the behavior, referring to the objective description of function realization. It includes mechanical and thermal properties and thermal effects. S is the structure. It includes the structural features, connection mode, and overall shape. P is the process. It includes the processing method, process requirements, surface treatment method, and dimensional accuracy.

2.2. Relevance of Parts and Components

$$CIM\_R_{ij} = \left[F_{ij}, B_{ij}, S_{ij}, P_{ij}\right] \times \begin{bmatrix} \omega_f \\ \omega_b \\ \omega_s \\ \omega_p \end{bmatrix} \tag{1}$$

$$\left[F_{ij}, B_{ij}, S_{ij}, P_{ij}\right] \times \begin{bmatrix} \omega_f \\ \omega_b \\ \omega_s \\ \omega_p \end{bmatrix} = F_{ij}\omega_f + B_{ij}\omega_b + S_{ij}\omega_s + P_{ij}\omega_p \tag{2}$$

Rule 2: The component association degree refers to the constraint relationships that exist between any two parts within a product family in terms of assembly, geometric space, and material processes. Assuming the weights of the behavioral, functional, structural, and process associations of a part within the entire module $\omega_f, \omega_b, \omega_s, \omega_p$, $\omega_f + \omega_b + \omega_s + \omega_p = 1$, the specific analysis is presented in Table 1. The association degree between part i and part j is denoted as CIM_R_{ij} ($0 \le CIR \le 1$), where the higher the values of CIM_R_{ij}, the stronger the association between parts.

Table 1. Component functional association rules.

	Index	Weighting	Weighting	Relationship
Functional correlation degree	Primary function	1	0.8	Essential for completion
		0.8		Jointly complete sub-functions
		0.6		Auxiliary in completing sub-functions
		0.4		Complete overall related functions
		0.2		Very weak functional relevance
		0		No functional relevance
	Support function	1	0.2	Identical
		0.5		Similar
		0		Unrelated

1) The functional associations are essential for the modularization of complex products. The interconnectivity and optimization of components are crucial. If a particular component is missing from the overall system, certain functions may disappear entirely, leading to the failure of the final product to meet customer

needs and resulting in production waste. Therefore, analyzing and dividing the functional associations of components is a critical factor. Functional associations are primarily manifested in the following ways:

Number of modules: the number of modules in a complex product determines the ease of assembling the final product.

Coupling degree: the coupling degree between modules plays a decisive role in determining the manufacturing workload in subsequent design and production tasks.

Standardization of Interfaces: standardization of interfaces between modules is fundamental for internal installation norms.

Thus, the functional associations fully reflect the performance differences among modules. To address these aspects, this paper establishes the functional association rules for parts as shown in **Table 1**,

$$F_{ij} = \left(F_{\_V1_{ij}}\right)\omega_{f1} + \left(F_{\_V2_{ij}}\right)\omega_{f2} \tag{3}$$

where F_{ij} represents the combined functional association value between components i and j, $F_{\_V1_{ij}}$ represents the value of the main functional aspect association, ω_{f1} represents the weight of the main functional aspect association, $F_{\_V2_{ij}}$ represents the value of the auxiliary functional aspect association, and ω_{f2} represents the weight of the auxiliary functional aspect association.

2) In complex products, the association degree between components is primarily reflected in the overall shape and connection methods. The overall shape and size determine the installation requirements and positioning, which have a significant impact on the product's layout. The connection methods mainly affect the stability and ease of disassembly of internal components. This paper establishes the structural association rules for parts as shown in **Table 2**. The combined structural association degree can be expressed as follows:

Table 2. Component structural association rules.

	Index	Weighting	Weighting	Relationship
Structural correlation degree	Connection type (primary)	1	0.9	Permanent connection, non-separable
		0.8		Fixed connection, difficult to separate
		0.6		Fixed connection, easy to separate
		0.4		Movable connection, non-separable
		0.2		Movable connection, separable
		0		No connection
	Overall shape	1	0.1	Overall shape is identical
		0.5		Overall shape is basically similar
		0		Overall shape is different

$$S_{ij} = \left(S_{\_V1_{ij}}\right)\omega_{S1} + \left(F_{\_V2_{ij}}\right)\omega_{S2} \tag{4}$$

where S_{ij} is the combined structural association value between components i and j, $S_{\_V1_{ij}}$ is the value of the connection type association, ω_{S1} is the weight of the connection type association, $F_{\_V2_{ij}}$ is the value of the overall shape association, and ω_{S2} is the weight of the overall shape association.

3) The behavioral information of components in complex products is regarded as a bridge between function and structure, providing an objective description of how functionalities are realized. Behavior includes three hidden independent attributes: mechanical properties (strength, inertia, elasticity, etc.), electrical characteristics (conductivity, resistance, charging, etc.), and thermal effects (heat conduction, temperature change, absorption, etc.)

Due to the requirements of complex products, components with the same attribute can form combinations of behavioral attributes. This paper establishes the behavioral association rules for parts as shown in Table 3. The combined behavioral association degree can be expressed as follows:

Table 3. Component behavioral association rules.

	Index	Weighting	Weighting	Relationship
Behavioral correlation degree	Mechanical strength	1	0.4	Identical
		0.5		Similar
		0		Different
	Heat treatment process	1	0.3	Identical
		0.5		Similar
		0		Different
	Electrical conductivity	1	0.3	Identical
		0.5		Similar
		0		Different

$$B_{ij} = \left(B_{\_V1_{ij}}\right)\omega_{b1} + \left(B_{\_V2_{ij}}\right)\omega_{b2} + \left(B_{\_V3_{ij}}\right)\omega_{b3} \tag{5}$$

where B_{ij} is the combined behavioral association value between components i and j, $B_{\_V1_{ij}}$ is the value of the mechanical strength association, ω_{f1} is the weight of the mechanical strength association, $B_{\_V2_{ij}}$ is the value of the heat treatment method association, ω_{b2} is the weight of the heat treatment method association, $B_{\_V3_{ij}}$ is the value of the electrical conductivity characteristic association, and ω_{b3} is the weight of the electrical conductivity characteristic association.

4) Process association refers to the processing technologies involved in transforming raw blanks into finished products. The process plays a crucial role in the manufacturing and production process. It is more convenient to simultaneously

process the parts within the same module if several components share similar or identical processing techniques. The rationality of the process is essential for controlling costs and performance. Therefore, process associations in modularization are also necessary. Based on internal process associations, this paper establishes process association rules for parts as shown in **Table 4**. The combined process association degree can be expressed as follows:

Table 4. Component process association rules.

	Index	Weighting	Weighting	Relationship
Process correlation degree	Processing method	1	0.5	Identical
		0.5		Similar
		0		Different
	Process requirements	1	0.2	Identical
		0.5		Similar
		0		Different
	Surface treatment	1	0.2	Identical
		0.5		Similar
		0		Different
	Dimensional accuracy	1	0.1	Identical
		0.5		Similar
		0		Different

$$P_{ij} = \left(P_{\_V1_{ij}}\right)\omega_{p1} + \left(P_{\_V2_{ij}}\right)\omega_{p2} + \left(P_{\_V3_{ij}}\right)\omega_{p3} + \left(P_{\_V4_{ij}}\right)\omega_{p4} \tag{6}$$

where P_{ij} is the combined process association value between components i and j, $P_{\_V1_{ij}}$ is the value of the processing method association, ω_{p1} is the weight of the processing method association, $P_{\_V2_{ij}}$ is the value of the process requirement association, ω_{p2} is the weight of the process requirement association, $P_{\_V3_{ij}}$ is the value of the surface treatment association, ω_{p3} is the weight of the surface treatment association, $P_{\_V4_{ij}}$ is the value of the dimensional precision association, and ω_{p4} is the weight of the dimensional precision association.

Then, the comprehensive association degree of the module can be expressed as follows: if a module contains n effectively connected parts, the association degree of the n parts can be summed, resulting in the comprehensive association degree of the module:

$$R = \frac{1}{n} \cdot \sum_{i,j}^{n} CIM\_R_{ij} = \frac{1}{n} \cdot \sum_{i,j}^{n} F_{ij}\omega_f + B_{ij}\omega_b + S_{ij}\omega_s + P_{ij}\omega_p \tag{7}$$

Therefore, the modularization results for complex products can be determined based on the part association degree CIM_R_{ij}. The calculation of correlation weights is obtained by the Delphi method. The associations between parts are established through these constraint conditions. When the given relationship $CIM\_R_{ij} \geq R$ is satisfied, parts i and j can be grouped into the same module.

3. Dynamic Analysis of Quality Characteristics Based on Intuitionistic Fuzzy Numbers—Design Personnel Scoring

Intuitionistic fuzzy numbers not only encompass membership degrees but also non-membership degrees, enabling a more comprehensive description of the uncertainties that exist when design personnel assign scores. Most evaluation indicators in complex product configuration research are qualitative and difficult to quantify precisely. This paper adopts interval-valued intuitionistic fuzzy numbers to represent evaluation information. Design and manufacturing personnel can more flexibly express their judgments regarding quality characteristics while scoring by intuitionistic fuzzy numbers. Furthermore, in group decision-making processes involving multiple design personnel, intuitionistic fuzzy numbers can effectively integrate scoring opinions from different individuals.

3.1. Intuitionistic Fuzzy Set

Definition 1. Let X be a non-empty classical set, with elements $X = \{x_y \mid y = 1, 2, 3, \cdots, z\}$. *A triplet* $\{[x, \mu_A(x), \gamma_A(x)] \mid x \in X\}$ *on the set* X *is called an intuitionistic fuzzy set* A, *where* $\mu_A(x): X \to [0,1]$, *and it satisfies* $0 \leq \mu_A(x) + \gamma_A(x) \leq 1$. $\mu_A(x)$ *and* $\gamma_A(x)$ *are the membership degree and non-membership degree of element* x *in the domain* X, *respectively. The corresponding intuitionistic fuzzy number is denoted as* $a = (\mu_A(x), \gamma_A(x))$.

Definition 2. *Let* $a = (\mu_\alpha, v_\alpha)$, $b = (\mu_\beta, v_\beta)$ *be two intuitionistic fuzzy numbers,* $0 < \lambda < 1$, *with their operational rules are defined as follows:*

1) $a + b = \mu_\alpha + \mu_\beta - \mu_\alpha \cdot \mu_\beta$

2) $\lambda a = \left(1 - (1 - \mu_\alpha)^\lambda, v_\alpha^\lambda\right)$

Definition 3. *Let* $a = (\mu_\alpha, v_\alpha)$, $b = (\mu_\beta, v_\beta)$ *be two intuitionistic fuzzy numbers. Then,* $D_{a,b} = 1/2\left(|\mu_\alpha - \mu_\beta| + |v_\alpha - v_\beta|\right) - \mu_\alpha \cdot \mu_\beta$ *is defined as the deviation between the intuitionistic fuzzy numbers α and β.*

Definition 4. *Let* $a = (\mu_\alpha, v_\alpha)$, $b = (\mu_\beta, v_\beta)$ *be two intuitionistic fuzzy numbers. Then,* $S(a) = \mu_\alpha - v_\alpha$ *and* $H(a) = \mu_\alpha + v_\alpha$ *are defined as the value function and precision function of the intuitionistic fuzzy number* a. *Similarly,* $S(b) = \mu_\alpha - v_\alpha$ *and* $H(b) = \mu_\alpha + v_\alpha$ *are defined as the value function and precision function of the intuitionistic fuzzy number* b, *respectively.*

1) *If* $S(a) > S(b)$, *then* $a > b$.

2) *When* $S(a) = S(b)$, *if* $H(a) > H(b)$, *then* $a > b$; *if* $H(a) = H(b)$ *then* $a = b$.

3.2. Intuitionistic Fuzzy Ordered Weighted Averaging Operator

Definition 5. *Let* $A = \{a_k = \mu_k, \gamma_k \mid k = 1, 2, 3, \cdots, t\}$ *be a set of intuitionistic fuzzy numbers, IFOWA:* $x^n \to X$; *if*

$IFOWA_{\omega}(a_1, a_2, \cdots, a_t) = \sum_{k=1}^{t} \omega_k b_k = \left(1 - \prod_{k=1}^{t}\left(1 - \mu_{k(b)}\right)^{\omega_k}, 1 - \prod_{k=1}^{t} v_{k(b)}^{\omega_k}\right)$, *then the function IFOWA is defined as the ordered weighted average operator for intuitionistic fuzzy numbers.*

Where $\omega = (\omega_1, \omega_2, \cdots, \omega_t)$ is the weight vector associated with the intuitionistic fuzzy operator IFOWA and $0 \le \omega_k \le 1$ is the element at the *k*-th position in the sorted set of intuitionistic fuzzy numbers $A = \{a_k = (\mu_k, v_k), k = 1, 2, 3, \cdots, t\}$. Specifically, if $b_k = \left(\mu_{k(b)}, v_{k(b)}\right)$, the function IFOWA is defined as the ordered weighted average operator for intuitionistic fuzzy numbers.

3.3. Ordered Weighted Average Operator Derived from Intuitionistic Fuzzy Numbers

Intuitionistic fuzzy numbers are combined with the derived ordered weighted average operator (IOWA) in an integrated manner, based on the intuitionistic fuzzy number-derived ordered weighted average operator (IF-IOWA) proposed in document [12].

$$
\begin{aligned}
&IFIOWA_{\omega}\left[(\alpha_1, \hat{a}_1), (\alpha_2, \hat{a}_2), \cdots, (\alpha_t, \hat{a}_t)\right] \\
&= \sum_{k=1}^{t} \omega_k \hat{b}_k = \left(1 - \prod_{k=1}^{t}\left(1 - \mu_{k(b)}\right)^{\omega_k}, 1 - \prod_{k=1}^{t} v_{k(b)}^{\omega_k}\right).
\end{aligned}
$$

In the formula, $\omega = (\omega_1, \omega_2, \cdots, \omega_t)$ is the weight vector corresponding to the IF-IOWA operator, $0 \le \omega_k \le 1$, $\sum_{k=1}^{t} \omega_k = 1$, $(\alpha_k, \hat{a}_k)$ is the IF-OWA data pair, and $\hat{b}_k = \left(\mu_{k(b)}, v_{k(b)}\right)$ is the second component of the IFOWA data pair corresponding to the k-th largest element in $\alpha_k (k = 1, 2, \cdots, t)$. In the data pair, α_k is the inducing variable, and $\hat{a}_k$ is the intuitionistic fuzzy number variable.

Intuitionistic fuzzy data are not directly related to the weight coefficients. They are only related to the elements in the information aggregation process. Typically, these represent attributes of the information, which in this paper, refer to quality characteristic evaluation periods or decision-makers.

3.4. Designer Experience Dynamic Analysis Based on Intuitionistic Fuzzy Numbers

In the early stages of product development, the project leader organized some market surveys. Through on-site inquiries and observations during design and manufacturing, filling out consultation questionnaires, and in-depth discussions with designers, the key quality characteristics of the components during the production process are identified and denoted as $DI = \{DI_i, i = 1, 2, \cdots, m\}$. From the modularized production departments defined earlier, a consistent group of personnel is selected to evaluate the key quality characteristics of the components, denoted as $DU = \{DU_j, j = 1, 2, \cdots, n\}$. To differentiate the impact of designers from different modules, the company's management personnel conduct pairwise comparisons to determine the weight vector $\omega = (\omega_1, \omega_2, \cdots, \omega_n)$. To adequately reflect the diversity and dynamism of customer needs, the surveys are conducted in representative production phases, denoted as time periods

$PT = \{PT_h, h = 1, 2, \cdots, l\}$.

The influence vector is $\rho = (\rho_1, \rho_2, \cdots, \rho_n)$ for each production stage. In the early stages of complex product design, design personnel are invited to use intuitionistic fuzzy numbers to provide preference information on the importance of key quality characteristics for various components. Each specialist designer evaluates the specific quality characteristics of existing components for particular production phases, leading to the subjective importance evaluation matrix $R_j = (\hat{r}_{hi}^j)_{l \times m} (j = 1, 2, \cdots, n)$ of the quality characteristic indicators considered by the designers. The selected designer DU_j uses the intuitionistic fuzzy number $r_{hi}^j = (\mu_{hi}^j, v_{hi}^j)$ to represent the quality characteristic indicators, and DI_i is the subjective importance evaluation value for production phase PT_h. The weight vector $\omega = (\omega_1, \omega_2, \cdots, \omega_n)$ of the selected designers and the subjective importance evaluation matrix $R_j = (d\hat{r}_{hi}^j)_{l \times m} (j = 1, 2, \cdots, n)$ of the quality characteristic indicators are aggregated to obtain the comprehensive evaluation matrix $DR = (d\hat{r}_{hi}^j)_{l \times m}$, $\begin{aligned}(d\hat{r}_{hi}) &= IFIOWA_\omega\left[(DU_1, r_{hi}^1), (DU_1, r_{hi}^2), \cdots, (DU_1, r_{hi}^j)\right] \\ &= \sum_{j=1}^n \omega_n \hat{b}_{hi}^j = \left(1 - \prod_{j=1}^n \left(1 - \mu_{hi}^j(b)\right)^{\omega_j}, 1 - \prod_{j=1}^n v_{hi}^j(b)^{\omega_j}\right)\end{aligned}$ of the designers' subjective importance evaluations of the indicators using the IF-IOWA operator. In the equation, ω represents the element at the k-th position in the weight vector $\hat{b}_{hi}^j$ of the selected designers. Let $DDI_i = (DDI_1, DDI_2, \cdots, DDI_m)$ be the subjective importance of the quality characteristic indicator DI_i in production phase PT_h. $\begin{aligned}DDI_i &= IFIOWA_\rho\left[(PT_1, c\hat{r}_{1i}), (PT_1, c\hat{r}_{2i}), \cdots, (PT_l, c\hat{r}_{li})\right] \\ &= \sum_{h=1}^l \rho_h f_{hi} = \left(1 - \prod_{h=1}^l \left(1 - \varphi_{hi(f)}\right)^{\rho_h}, 1 - \prod_{h=1}^l \varphi_{hi(f)}^{\rho_h}\right)\end{aligned}$, where ρ represents the influence degree of different production phases. f_{hi} represents the element at the h-th position in $d\hat{r}_{hi}^j (h = 1, 2, \cdots, l)$.

According to the definition of the value function, the subjective dynamic values of the quality characteristic indicators are calculated. Finally, the normalized dynamic vector $NDDI = (NDDI_1, NDDI_2, \cdots, NDDI_m)$ of the subjective importance of the quality characteristic indicators is obtained. The overall evaluation value is $cr(h_i) = (h_i, \varphi h_i)$. The production phase influence vector $\rho = (\rho_1, \rho_2, \cdots, \rho_l)$ with the comprehensive evaluation matrix $DR = d_r(h_i)_{1 \times m}$ of the subjective importance of the quality characteristic indicators is aggregated using the IF-IOWA operator, resulting in the dynamic vector $DDI = (DDI_1, DDI_2, \cdots, DDI_m)$, $sv_i = 1 - \prod_{h=1}^l \left(1 - \varphi_{hi(f)}\right)^{\rho h}\left(1 - \prod_{h=1}^l \varphi_{hi(f)}^{\rho h}\right)$, $NDDI_i = (sv_i + 0.5) \big/ \sum_{i=1}^m (sv_i + 0.5)$ of subjective importance [13] [14].

4. Determination of Configuration Update Plan by Grey Relational Model

Due to the characteristics of small data and limited information, grey relational analysis is used to determine the final configuration scheme for the changing components in the final step of selecting the updated configuration options. Grey relational analysis is one of the mainstream methods for analyzing relationships in discrete datasets and for multi-attribute decision-making. The method of grey relational analysis is widely applied to solve uncertain problems under conditions of discrete data or limited information. The fundamental task of grey relational analysis is to analyze and determine the degree of influence among factors or the contribution measure of factors to the main behavior based on the micro- or macro-geometric proximity of behaviors. As a geometric analysis method, its advantages and characteristics include the following: 1) It can perform ordered analysis of factors within a grey system. 2) It can meet the requirements for small-sample analysis. 3) It is capable of performing correlation analysis of multiple factors relative to different reference points, offering superior overall analytical capabilities compared to methods such as regression and correlation analysis.

The primary advantage of this method is the low requirement for statistical data, making it highly suitable for analyzing various types of incomplete statistical data. It involves numerous design and manufacturing stages and a multitude of evaluation indicators in the context of complex product configuration updates. It is impractical to fully account for all influencing factors in the change proposals. Therefore, this paper employs grey relational analysis to evaluate the correlation degrees of alternative configuration schemes. Grey relational analysis is a method for quantitatively describing and comparing the development trends of a system. The basic idea is to determine the closeness of association by the similarity of the geometric shapes of the reference sequence and several comparison sequences, reflecting the degree of association between the curves.

The steps in the grey relational analysis method are introduced as follows:

Step 1: Determine the analysis sequences. The selection of the reference sequence is related to the evaluation purpose and the type of evaluation indicator data. Typically, the optimal values of each statistical indicator are chosen as the reference sequence. In this paper, evaluation metrics positively correlated with the suitability of configuration schemes are selected. Therefore, the best (highest) value is extracted from each evaluation metric to form a reference sequence. Meanwhile, the evaluation metric data of each alternative scheme are used as comparative sequences. The dynamic weighting vector derived from the subjective importance of quality characteristics in the earlier sections of this paper is utilized to weigh the data of the alternative schemes. The processed data are then used as the original sequences.

Set the reference sequence as follows:

$$X_0 = \left(x_0(1), x_0(2), \cdots, x_0(n)\right) \tag{8}$$

Set the comparison sequences as follows:

$$X_i = \left(x_i(1), x_i(2), \cdots, x_i(n)\right) \ \left(i = 1, 2, 3, \cdots, m\right) \tag{9}$$

Step 2: Normalize the original data.

The initialized reference sequence is as follows:

$$X_0' = X_0(k) / x_0(1) = \left(x_0(1), x_0(2), \cdots, x_0(n)\right) \tag{10}$$

The initialized comparison sequences are as follows:

$$X_i' = X_i(k)/x_i(1) = \left(x_i'(1), x_i'(2), \cdots, x_i'(n)\right) \ \left(i = 1, 2, 3, \cdots, m\right) \tag{11}$$

Step 3: Calculate the sequence differences.

The formula for calculating the sequence differences is as follows:

$$\Delta_{0i}(k) = \left|x_0(k) - x_i(k)\right| \ \left(i = 1, 2, 3, \cdots, m; k = 1, 2, 3, \cdots, n\right) \tag{12}$$

The maximum and minimum values in the absolute difference matrix obtained from Formula (12) are denoted, for better clarity and coherence, as follows:

Maximum value: $M = \max_i \max_k \Delta_i(k) = \Delta_{\max}$

Minimum value: $m = \min_i \min_k \Delta_i(k) = \Delta_{\min}$

Step 4: Calculate the grey relational coefficients.

The formula for calculating the grey relational coefficients is as follows:

$$\gamma_{0i}(k) = \frac{m + \rho M}{\Delta_{0i}(k) + \rho M} \tag{13}$$

In the formula, $\rho \in (0,1)$, $i = 1, 2, 3, 4, 5$, $k = 1, 2, 3, 4, 5$, ρ is called the discrimination coefficient, typically taken as $\rho = 0.5$.

Step 5: Calculate the grey relational degrees. Due to the dispersed nature of the correlation coefficient data, it is insufficient for deriving an accurate overall evaluation result by analyzing individual indicator correlation coefficients alone. To comprehensively analyze the entire dataset, we combine the dynamically weighted vectors of subjective importance degrees of quality characteristics derived in previous sections. Then, the overall grey relational degree between the comparison sequences and the reference sequence (optimal sequence) is calculated. The integrated relational order is obtained by the integrated relational degrees ranking.

The formula for the grey relational degrees is as follows:

$$\gamma_{0i} = \frac{1}{n}\sum_{k=1}^{n} \gamma_{0i}(k) \tag{14}$$

γ_{0i} is the relational degree of the comparison sequence x_i relative to the reference sequence x_0, revealing their degree of association. The larger γ_{0i} is, the greater their degree of association, and vice versa [15] [16].

5. Case Study on Configuration Update of Complex Product Engineering Change

G Enterprise's high-speed permanent magnet synchronous variable-frequency centrifugal large-power water chiller unit has achieved international leading levels in technology, serving as a prime example of a complex product. This complex product is used as a case study for calculations in this paper. The core components of the high-speed permanent magnet synchronous variable-frequency centrifugal large-power water chiller unit include the main shaft, suction chamber, intake pipe, impeller, diffuser, volute casing, fixed ring, locking ring, thrust disk, separator, balance disk, return flow device, seal, bend, baffle for bends, permanent magnet rotor, stator, core, casing, pressure regulating valve, temperature sensor, cooler, pressure sensor, evaporator, reflux evaporator, lubricating oil, refrigerant, oil cooler, electronic expansion valve, drier filter, condenser, and others. Based on the modular division method proposed in the second part of this paper, which is grounded in internal product associations, an in-depth investigation at G Enterprise regarding this product was conducted. Professional process engineers were invited to provide assessment opinions on the behavior, structure, and process interrelationships of core components. Subsequently, the degrees of association were calculated according to the calculation methods provided in the second section of this paper. The results are presented in Table 5 and Table 6.

Table 5. Calculation of functional and behavioral association of components.

Component 1	Component 2	Functional Association 1	Functional Weight 1	Functional Association 2	Functional Weight 2	Functional Integration	Behavioral Association 1	Behavioral Weight 1	Behavioral Association 2	Behavioral Weight 2	Behavioral Association 3	Behavioral Weight 3	Behavioral Integration
inlet chamber	impeller	0.8	0.8	0.5	0.2	0.74	0.5	0.4	0.5	0.3	1	0.3	0.65
inlet chamber	diffuser	1	0.8	0.5	0.2	0.9	0.5	0.4	0	0.3	1	0.3	0.5
inlet chamber	volute	0.8	0.8	0	0.2	0.64	0.5	0.4	0.5	0.3	1	0.3	0.65
inlet chamber	intake pipe	0.8	0.8	1	0.2	0.64	0	0.4	0	0.3	0	0.3	0
intake pipe	thrust disk	1	0.8	1	0.2	1	1	0.4	0.5	0.3	0.5	0.3	0.7
impeller	diffuser	0.8	60.8	0.5	0.2	0.74	0.5	0.4	0.5	0.3	0.5	0.3	0.5
impeller	main shaft	1	0.8	0.5	0.2	0.9	0	0.4	0.5	0.3	0.5	0.3	0.3
impeller	retaining ring	1	0.8	1	0.2	1	1	0.4	1	0.3	1	0.3	1
impeller	intake pipe	1	0.8	1	0.2	1	1	0.4	0.5	0.3	0.5	0.3	0.7
impeller	locking ring	1	0.8	0.5	0.2	0.9	0.5	0.4	0.5	0.3	0.5	0.3	0.5
impeller	separator	0.8	0.8	0.5	0.2	0.74	0.5	0.4	0.5	0.3	0.5	0.3	0.5
impeller	balance disk	1	0.8	0.5	0.2	0.9	0	0.4	0.5	0.3	0.5	0.3	0.3
impeller	refluxer	1	0.8	0.5	0.2	0.9	0.5	0.4	0.5	0.3	0.5	0.3	0.5
impeller	seal	1	0.8	0.5	0.2	0.9	0.5	0.4	0.5	0.3	0.5	0.3	0.5
main shaft	locking ring	0.6	0.8	0	0.2	0.48	0	0.4	0	0.3	0	0.3	0
main shaft	bend baffle	0.6	0.8	0	0.2	0.48	0	0.4	0	0.3	0	0.3	0
main shaft	bend	0.6	0.8	0	0.2	0.48	0.5	0.4	0.5	0.3	0	0.3	0.35
bend	bend baffle	0.6	0.8	0	0.2	0.48	0	0.4	0	0.3	0	0.3	0
bend baffle	recirculator	1	0.8	0.5	0.2	0.9	0	0.4	0	0.3	0	0.3	0
reflux device	seal	0.6	0.8	0.5	0.2	0.58	0	0.4	0	0.3	0	0.3	0
seal	seal	1	0.8	1	0.2	1	0.5	0.4	0	0.3	0.5	0.3	0.35
housing	permanent magnet rotor	1	0.8	1	0.2	1	0.5	0.4	0	0.3	0.5	0.3	0.35

Continued

permanent magnet rotor	stator	1	0.8	1	0.2	1	0.5	0.4	0.5	0.3	0.5	0.3	0.5
stator	iron core	0.6	0.8	0.5	0.2	0.58	0	0.4	0	0.3	0	0.3	0.2
iron core	refrigerant	0.6	0.8	0	0.2	0.48	0	0.4	0	0.3	0	0.3	0.2
refrigerant	condenser	1	0.8	1	0.2	1	0	0.4	0	0.3	0.5	0.3	0.15
condenser	cooler	1	0.8	1	0.2	1	0	0.4	0	0.3	0	0.3	0
cooler	electronic expansion valve	1	0.8	0.5	0.2	0.9	0.5	0.4	0.5	0.3	0.5	0.3	0.5
refrigerant	evaporator	1	0.8	0.5	0.2	0.9	0	0.4	0	0.3	0	0.3	0
evaporator	reflux evaporator	1	0.8	1	0.2	1	0.5	0.4	0.5	0.3	0.5	0.3	0.5
reflux evaporator	lubricant	0.8	0.8	0	0.2	0.64	0	0.4	0	0.3	0	0.3	0
lubricant	reflux evaporator	1	0.8	1	0.2	1	0	0.4	0	0.3	0.5	0.3	0.15
reflux evaporator	dryer filter	1	0.8	0.5	0.2	0.9	0	0.4	0	0.3	0	0.3	0
dryer filter	pressure regulator	1	0.8	1	0.2	1	0	0.4	0	0.3	0	0.3	0
pressure regulator	pressure sensor	0.8	0.8	0.5	0.2	0.74	0	0.4	0	0.3	0	0.3	0
pressure sensor	temperature sensor	0.8	0.8	0.5	0.2	0.74	0.5	0.4	0.5	0.3	0.5	0.3	0.5

Table 6. Calculation of the structure-process association degree of components (Continued from the previous table).

Component 1	Component 2	Structural Association 1	Structural Weight 1	Structural Association 2	Structural Weight 2	Structural Integration	Process Association 1	Process Weight 1	Process Association 2	Process Weight 2	Process Association 3	Process Weight 3	Process Association 4	Process Weight 4	Process Integration	Integrated Value
inlet chamber	impeller	0.2	0.9	0.5	0.1	0.23	0.5	0.5	0.5	0.2	0.5	0.2	0	0.1	0.45	0.54
inlet chamber	diffuser	0.4	0.9	0	0.1	0.36	0.5	0.5	1	0.2	0.5	0.2	1	0.1	0.65	0.633
inlet chamber	volute	1	0.9	1	0.1	1	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.736
inlet chamber	intake pipe	0.2	0.9	0	0.1	0.18	0.5	0.5	0.5	0.2	0.5	0.2	1	0.1	0.55	0.565
intake pipe	thrust disk	1	0.9	0	0.1	0.9	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.86
impeller	diffuser	0.8	0.9	0	0.1	0.72	0	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.25	0.637
impeller	main shaft	1	0.9	0	0.1	0.9	0	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.25	0.715

Continued

impeller	retaining ring	0.4	0.9	1	0.1	0.46	1	0.5	1	0.2	1	0.2	1	0.1	1	0.838
impeller	intake pipe	1	0.9	0	0.1	0.9	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.86
impeller	locking ring	0.4	0.9	0	0.1	0.36	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.618
impeller	separator	0.8	0.9	0	0.1	0.72	0	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.25	0.637
impeller	balance disk	1	0.9	0	0.1	0.9	0	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.25	0.715
impeller	refluxer	0.4	0.9	0	0.1	0.36	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.618
impeller	seal	0.4	0.9	0	0.1	0.36	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.618
main shaft	locking ring	0.8	0.9	0	0.1	0.72	0	0.5	0.5	0.2	0	0.2	0.5	0.1	0.15	0.423
main shaft	bend baffle	1	0.9	0	0.1	0.9	0	0.5	0.5	0.2	0	0.2	0.5	0.1	0.15	0.477
main shaft	bend	1	0.9	0.5	0.1	0.95	0.5	0.5	0.5	0.2	0	0.2	0.5	0.1	0.4	0.587
bend	bend baffle	1	0.9	0.5	0.1	0.95	0.5	0.5	0.5	0.2	0	0.2	0.5	0.1	0.4	0.517
bend baffle	recirculator	0.4	0.9	0	0.1	0.36	0	0.5	0	0.2	0	0.2	0	0.1	0	0.468
reflux device	seal	0.4	0.9	0.5	0.1	0.41	0	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.25	0.38
seal	seal	1	0.9	0	0.1	0.9	0	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.25	0.765
housing	permanent magnet rotor	1	0.9	0	0.1	0.9	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.79
permanent magnet rotor	stator	1	0.9	0	0.1	0.9	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.82
stator	iron core	1	0.9	0	0.1	0.9	0	0.5	0	0.2	0	0.2	0	0.1	0	0.542
iron core	refrigerant	0	0.9	0	0.1	0	0	0.5	0	0.2	0	0.2	0	0.1	0	0.232
refrigerant	condenser	1	0.9	0	0.1	0.9	0	0.5	1	0.2	1	0.2	1	0.1	0.5	0.75
condenser	cooler	0.4	0.9	0.5	0.1	0.41	1	0.5	1	0.2	1	0.2	1	0.1	1	0.623
cooler	electronic expansion valve	0.4	0.9	0	0.1	0.36	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.618
refrigerant	evaporator	0.2	0.9	0	0.1	0.18	0	0.5	0	0.2	0	0.2	0	0.1	0	0.414
evaporator	reflux evaporator	1	0.9	0	0.1	0.9	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.82
reflux evaporator	lubricant	0.2	0.9	0	0.1	0.18	0.5	0.5	0	0.2	0	0.2	0	0.1	0.25	0.335
lubricant	reflux evaporator	0.6	0.9	0	0.1	0.54	0	0.5	0	0.2	0	0.2	0	0.1	0	0.592
reflux evaporator	dryer filter	0.2	0.9	0	0.1	0.18	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.464
dryer filter	pressure regulator	0.4	0.9	0	0.1	0.36	0	0.5	0	0.2	0	0.2	0	0.1	0	0.508
pressure regulator	pressure sensor	0.2	0.9	0	0.1	0.18	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.4
pressure sensor	temperature sensor	0.2	0.9	0	0.1	0.18	0.5	0.5	0.5	0.2	0.5	0.2	0.5	0.1	0.5	0.5

Based on the module division rules in this paper, a module is defined as having a combined association degree greater than 0.4. It can be seen that there are five modules: the pneumatic components module, the motor module, the evaporation module, and the condensation module. According to the results of market research and production surveys, the quality characteristics emphasized during the design process are reliability (DT_1), safety (DT_2), durability (DT_3), adaptability (DT_4), and appearance requirements (DT_5). The collection and scheduling of information and data are arranged as follows: 1) Product Design (PT_1): The unilateral information is provided by the product design personnel. 2) Product Process Design Stage (PT_2): Designers derive updated designs and the weights of various factors based on feedback from the process department. 3) Product Production and Manufacturing (PT_3): Design personnel update the design based on knowledge gained during the production and manufacturing stage. 4) Sales and Maintenance Stage (PT_4): Design personnel update the design based on knowledge from the sales and after-sales stages involving the product components.

The team conducts pairwise comparisons for the survey time periods to determine the influence vectors for different time periods. Updates are made based on the knowledge of product components involved during the sales and after-sales stages. The team conducts pairwise comparisons of the research time periods to derive vectors representing the impact levels of different time intervals. $\rho = (0.261, 0.223, 0.231, 0.285)$. Five designers from the departments are selected to participate in the assessment of requirement importance (Table 7). Subsequently, the weight vector $\omega = (0.192, 0.187, 0.211, 0.223, 0.187)$ of the five designers id determined by the pairwise comparison method.

Table 7. The information of the selected designers.

		DI_1	DI_2	DI_3	D_{I4}	DI_5
DU_1	PT_1	(0.51, 0.31)	(0.54, 0.41)	(0.71, 0.31)	(0.51, 0.32)	(0.44, 0.21)
	PT_2	(0.62, 0.32)	(0.51, 0.33)	(0.71, 0.23)	(0.52, 0.44)	(0.43, 0.52)
	PT_3	(0.71, 0.23)	(0.63, 0.34)	(0.82, 0.11)	(0.53, 0.33)	(0.52, 0.43)
	PT_4	(0.62, 0.24)	(0.64, 0.42)	(0.83, 0.12)	(0.53, 0.44)	(0.61, 0.44)
DU_2	PT_1	(0.42, 0.21)	(0.61, 0.42)	(0.6, 0.31)	(0.53, 0.13)	(0.41, 0.51)
	PT_2	(0.53, 0.33)	(0.62, 0.33)	(0.71, 0.22)	(0.52, 0.34)	(0.21, 0.61)
	PT_3	(0.64, 0.31)	(0.63, 0.41)	(0.62, 0.11)	(0.51, 0.32)	(0.52, 0.41)
	PT_4	(0.64, 0.33)	(0.61, 0.31)	(0.72, 0.21)	(0.63, 0.22)	(0.62, 0.42)
DU_3	PT_1	(0.62, 0.12)	(0.63, 0.21)	(0.42, 0.33)	(0.61, 0.22)	(0.53, 0.21)
	PT_2	(0.61, 0.31)	(0.61, 0.31)	(0.53, 0.23)	(0.52, 0.33)	(0.51, 0.33)
	PT_3	(0.62, 0.22)	(0.51, 0.42)	(0.62, 0.14)	(0.62, 0.23)	(0.51, 0.43)
	PT_4	(0.72, 0.22)	(0.71, 0.22)	(0.61, 0.24)	(0.61, 0.31)	(0.43, 0.43)

Continued

DU_4	PT_1	(0.53, 0.43)	(0.62, 0.33)	(0.62, 0.33)	(0.44, 0.32)	(0.34, 0.53)
	PT_2	(0.62, 0.23)	(0.62, 0.24)	(0.63, 0.23)	(0.52, 0.34)	(0.43, 0.54)
	PT_3	(0.63, 0.13)	(0.62, 0.34)	(0.63, 0.12)	(0.63, 0.34)	(0.53, 0.32)
	PT_4	(0.62, 0.23)	(0.63, 0.34)	(0.72, 0.22)	(0.63, 0.24)	(0.52, 0.43)
DU_5	PT_1	(0.42, 0.33)	(0.43, 0.33)	(0.53, 0.33)	(0.62, 0.22)	(0.41, 0.52)
	PT_2	(0.51, 0.44)	(0.54, 0.43)	(0.63, 0.23)	(0.52, 0.32)	(0.52, 0.32)
	PT_3	(0.62, 0.34)	(0.64, 0.23)	(0.73, 0.13)	(0.62, 0.33)	(0.52, 0.22)
	PT_4	(0.62, 0.23)	(0.64, 0.23)	(0.72, 0.23)	(0.63, 0.34)	(0.62, 0.22)

The comprehensive evaluation matrix $DR = \left(dr\left(hi\right)\right)_{5\times5}$ of the designers' subjective importance of the quality characteristic indicators are obtained with the weight vector $\omega = \left(\omega_1, \omega_2, \cdots, \omega_n\right)$. The selected designers with the subjective importance evaluation matrix $R_j = \left(r_{hi}^j\right)_{4\times5}\left(j = 1, 2, \cdots, 5\right)$ of the quality characteristic indicators are as shown in **Table 8**.

Table 8. Comprehensive evaluation matrix.

	DI_1	**DI_2**	**DI_3**	**D_{I4}**	**DI_5**
PT_1	(0.504, 0.282)	(0.569, 0.337)	(0.575, 0.322)	(0.540, 0.245)	(0.425, 0.395)
PT_2	(0.580, 0.322)	(0.582, 0.324)	(0.639, 0.228)	(0.520, 0.353)	(0.423, 0.464)
PT_3	(0.643, 0.244)	(0.604, 0.349)	(0.681, 0.122)	(0.584, 0.309)	(0.520, 0.362)
PT_4	(0.645, 0.249)	(0.647, 0.304)	(0.720, 0.205)	(0.605, 0.308)	(0.556, 0.391)

The dynamic evaluation values (0.58576025, 0.26728861), (0.59443649, 0.3233682), (0.64581067, 0.21844461), (0.55581413, 0.29768529), and (0.47652309, 0.39724679) of the subjective importance of the quality characteristic indicators are computed by the aggregated influence vectors $\rho = \left(0.285, 0.214, 0.227, 0.274\right)$ for different time periods with the comprehensive evaluation matrix $CR = \left(c\hat{r}_{hi}\right)_{4\times5}$ of the subjective importance of the quality characteristic indicators.

According to the definition of the value function, the subjective dynamic value sv_i of the demand indicators is calculated, and the normalized dynamic vector NDDI = (0.21235225, 0.200053463, 0.240604878, 0.196696326, 0.150293082) of the designers' comprehensive subjective importance of the indicators is further computed. Through multiple company interviews, it was learned that there are three other similar solutions for this type of high-speed permanent magnet synchronous variable frequency centrifugal large-capacity chiller in this company. Through interviews, the importance evaluation matrix for all proposed solutions was obtained from the designers (**Table 9**).

Table 9. Objective importance evaluation matrix of designers for different production stages.

		DI₁	DI₂	DI₃	DI₄	DI₅
PT_1	DA_1	(0.54, 0.21)	(0.64, 0.31)	(0.53, 0.21)	(0.52, 0.31)	(0.42, 0.22)
	DA_2	(0.42, 0.22)	(0.61, 0.34)	(0.41, 0.23)	(0.53, 0.42)	(0.34, 0.51)
	DA_3	(0.51, 0.33)	(0.54, 0.32)	(0.52, 0.11)	(0.55, 0.31)	(0.43, 0.33)
	DA_4	(0.53, 0.24)	(0.62, 0.22)	(0.63, 0.12)	(0.44, 0.13)	(0.41, 0.21)
PT_2	DA_1	(0.32, 0.41)	(0.41, 0.32)	(0.62, 0.21)	(0.44, 0.12)	(0.41, 0.32)
	DA_2	(0.54, 0.63)	(0.52, 0.23)	(0.51, 0.22)	(0.51, 0.23)	(0.11, 0.53)
	DA_3	(0.62, 0.23)	(0.62, 0.42)	(0.64, 0.12)	(0.44, 0.21)	(0.43, 0.31)
	DA_4	(0.63, 0.34)	(0.52, 0.33)	(0.63, 0.23)	(0.54, 0.11)	(0.41, 0.24)
PT_3	DA_1	(0.52, 0.21)	(0.54, 0.22)	(0.52, 0.31)	(0.53, 0.21)	(0.43, 0.24)
	DA_2	(0.51, 0.31)	(0.63, 0.32)	(0.51, 0.24)	(0.44, 0.12)	(0.42, 0.23)
	DA_3	(0.61, 0.24)	(0.41, 0.32)	(0.61, 0.24)	(0.43, 0.24)	(0.34, 0.44)
	DA_4	(0.72, 0.22)	(0.64, 0.23)	(0.54, 0.32)	(0.52, 0.11)	(0.41, 0.21)
PT_4	DA_1	(0.43, 0.52)	(0.41, 0.33)	(0.52, 0.31)	(0.52, 0.21)	(0.24, 0.51)
	DA_2	(0.54, 0.43)	(0.61, 0.22)	(0.61, 0.32)	(0.53, 0.31)	(0.41, 0.51)
	DA_3	(0.61, 0.23)	(0.54, 0.23)	(0.53, 0.13)	(0.51, 0.31)	(0.54, 0.24)
	DA_4	(0.52, 0.33)	(0.61, 0.32)	(0.53, 0.21)	(0.53, 0.13)	(0.54, 0.41)

The weight vector $\omega = \omega_1, \omega_1, \cdots, \omega_5$ of the selected designers with the objective importance evaluation matrix $E^{j(h)} = \left(\hat{e}_{ki}^{j(h)}\right)_{4\times5} \left(j = 1, 2, \cdots, n; h = 1, 2, \cdots, l\right)$ of the quality characteristic indicators for time period PT_h are aggregated. Then, the comprehensive evaluation matrix $DE^{(h)} = \left(d\hat{e}_{ki}^{(h)}\right)_{4\times5}$ of the designers considering the objective importance of the quality characteristic indicators for time period PT_h can be obtained (As shown in Table 10).

Table 10. Comprehensive evaluation matrices for different production stages.

		DI₁	DI₂	DI₃	DI₄	DI₅
PT_1	DA_1	(0.591, 0.208)	(0.587, 0.237)	(0.544, 0.194)	(0.539, 0.237)	(0.579, 0.212)
	DA_2	(0.561, 0.246)	(0.577, 0.224)	(0.519, 0.207)	(0.579, 0.244)	(0.582, 0.29)
	DA_3	(0.552, 0.284)	(0.587, 0.243)	(0.596, 0.181)	(0.556, 0.219)	(0.56, 0.221)
	DA_4	(0.578, 0.202)	(0.585, 0.174)	(0.604, 0.233)	(0.561, 0.193)	(0.551, 0.221)
PT_2	DA_1	(0.536, 0.198)	(0.571, 0.224)	(0.573, 0.21)	(0.549, 0.129)	(0.555, 0.241)
	DA_2	(0.591, 0.26)	(0.584, 0.338)	(0.561, 0.255)	(0.593, 0.241)	(0.468, 0.231)
	DA_3	(0.558, 0.218)	(0.565, 0.28)	(0.59, 0.204)	(0.536, 0.165)	(0.539, 0.29)
	DA_4	(0.584, 0.222)	(0.599, 0.272)	(0.601, 0.257)	(0.572, 0.201)	(0.547, 0.199)

Continued

PT_3	DA_1	(0.539, 0.248)	(0.587, 0.214)	(0.609, 0.262)	(0.548, 0.166)	(0.576, 0.221)
	DA_2	(0.526, 0.287)	(0.612, 0.258)	(0.597, 0.246)	(0.532, 0.205)	(0.563, 0.227)
	DA_3	(0.591, 0.235)	(0.488, 0.251)	(0.636, 0.21)	(0.527, 0.229)	(0.539, 0.218)
	DA_4	(0.566, 0.185)	(0.609, 0.216)	(0.597, 0.223)	(0.581, 0.209)	(0.559, 0.236)
PT_4	DA_1	(0.506, 0.245)	(0.643, 0.263)	(0.573, 0.269)	(0.562, 0.235)	(0.531, 0.241)
	DA_2	(0.544, 0.277)	(0.648, 0.223)	(0.586, 0.234)	(0.561, 0.272)	(0.55, 0.266)
	DA_3	(0.576, 0.224)	(0.509, 0.246)	(0.583, 0.204)	(0.563, 0.256)	(0.577, 0.216)
	DA_4	(0.45, 0.245)	(0.673, 0.239)	(0.59, 0.255)	(0.55, 0.203)	(0.589, 0.225)

The dynamic evaluation matrix $DDE = \left(dd\hat{e}_{ki}^{(h)}\right)_{4\times5}$ of the objective importance of the component quality characteristics is obtained by the aggregated influence vector for different time periods with the comprehensive evaluation matrix $DE^{(h)} = \left(d\hat{e}_{ki}^{(h)}\right)_{4\times5}$ of the subjective importance of the component quality characteristics. (As shown in Table 11).

Table 11. Dynamic evaluation matrix.

	DI_1	DI_2	DI_3	D_{I4}	DI_5
DA_1	(0.551, 0.228)	(0.608, 0.239)	(0.582, 0.238)	(0.557, 0.199)	(0.567, 0.232)
DA_2	(0.562, 0.271)	(0.615, 0.260)	(0.574, 0.237)	(0.575, 0.246)	(0.551, 0.258)
DA_3	(0.577, 0.245)	(0.544, 0.256)	(0.609, 0.203)	(0.555, 0.222)	(0.563, 0.237)
DA_4	(0.548, 0.218)	(0.627, 0.227)	(0.606, 0.246)	(0.573, 0.204)	(0.572, 0.224)

The optimal solutions for the objective importance coefficients ovi of the quality characteristics of each component are calculated as follows: (0.450, 0.581, 0.424, 0.461, 0.260). Finally, the normalized dynamic vector is computed NDDE = (0.207, 0.267, 0.195, 0.212, 0.119) for the objective importance of the quality characteristics of the components. The balance coefficient between subjective opinions and the objective environment is determined as $x = 0.532$ and $y = 0.468$. Through these calculations, the dynamic vector DIDE = (0.209, 0.236, 0.216, 0.205, 0.134) for the composite importance of the quality characteristics of the components is obtained.

Based on historical data from Company G, the configuration alternatives that meet the requirements for changes are listed in Figure 2. The configuration alternatives are weighted for reliability, durability, safety, adaptability, and appearance. The grey relational degree is then calculated with respect to the ideal solution, and the comprehensive grey relational degree for each alternative module is presented in Table 12.

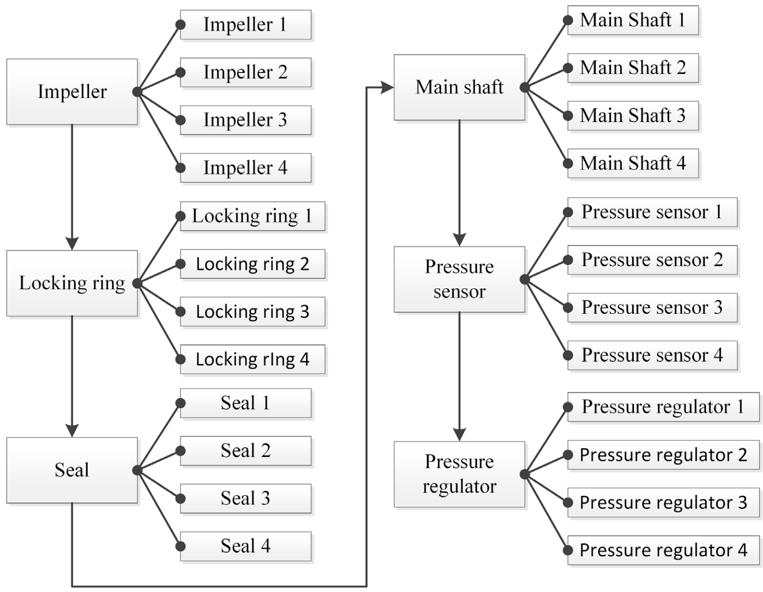

Figure 2. Figure of potential modules for components.

Table 12. Comprehensive scoring results of alternative impeller parts by design personnel.

	Reliability	Durability	Safety	Adaptability	Form Requirements
P_1	80	85	78	78	81
P_2	82	81	78	79	82
P_3	74	76	80	69	72
P_4	72	74	78	67	72

To illustrate this process, the impeller of a candidate core component is used as an example. There are four alternative parts under consideration. Design personnel were invited to evaluate these alternatives, and the comprehensive scores obtained from their evaluations are as follows.

The scoring results are weighted by the dynamically calculated vectors of the comprehensive importance degrees of the components' quality characteristics, as determined in previous sections. Grey relational analysis and the TOPSIS method are applied to calculate the grey relational degrees and TOPSIS closeness for each component. The results are shown in **Table 13**.

Table 13. Comparative analysis of results.

	Alternative Parts	TOPSIS	Ranking of Alternative Parts		Ranking of Alternative Parts by Grey Relational Degrees
Impeller	Alternative parts 1	0.2212	$d_1 \succ d_2 \succ d_3 \succ d_4$	0.8191	$\gamma_1 \succ \gamma_2 \succ \gamma_3 \succ \gamma_4$
	Alternative parts 2	0.2300		0.7374	

Continued

	Alternative parts 3	0.3262		0.7262	
	Alternative parts 4	0.4260		0.6727	
locking ring	Alternative parts 1	0.2780	$d_3 \succ d_2 \succ d_1 \succ d_4$	0.6569	$\gamma_3 \succ \gamma_2 \succ \gamma_1 \succ \gamma_4$
	Alternative parts 2	0.2601		0.7465	
	Alternative parts 3	0.0895		0.9672	
	Alternative parts 4	0.3731		0.6468	
Sealing component	Alternative parts 1	0.2879	$d_3 \succ d_2 \succ d_4 \succ d_1$	0.8054	$\gamma_3 \succ \gamma_4 \succ \gamma_1 \succ \gamma_2$
	Alternative parts 2	0.2469		0.764	
	Alternative parts 3	0.1564		0.9002	
	Alternative parts 4	0.2545		0.7726	
Main shaft	Alternative parts 1	0.3237	$d_4 \succ d_3 \succ d_1 \succ d_2$	0.6422	$\gamma_4 \succ \gamma_3 \succ \gamma_1 \succ \gamma_2$
	Alternative parts 2	0.4348		0.5765	
	Alternative parts 3	0.0774		0.8172	
	Alternative parts 4	0.0337		0.8968	
Pressure sensor	Alternative parts 1	0.1898	$d_3 \succ d_4 \succ d_1 \succ d_2$	0.6857	$\gamma_3 \succ \gamma_4 \succ \gamma_1 \succ \gamma_2$
	Alternative parts 2	0.4538		0.6495	
	Alternative parts 3	0.1567		0.9667	
	Alternative parts 4	0.1568		0.8864	
Pressure regulating valve	Alternative parts 1	0.3562	$d_3 \succ d_4 \succ d_1 \succ d_2$	0.77	$\gamma_3 \succ \gamma_4 \succ \gamma_1 \succ \gamma_2$
	Alternative parts 2	0.4277		0.7672	
	Alternative parts 3	0.0787		0.8592	
	Alternative parts 4	0.3215		0.8086	

From the results, it can be observed that, for the impeller, the ranking of candidate components by grey relational degrees is as follows: $\gamma_1 \succ \gamma_2 \succ \gamma_3 \succ \gamma_4$, and the TOPSIS calculation result is $d_1 \succ d_2 \succ d_3 \succ d_4$. We can see that the results obtained from both methods are consistent, indicating that Scheme 1 is the optimal solution for the impeller. For the tight ring, the ranking of candidate components by grey relational degrees is as follows: $\gamma_{P3} > \gamma_{P2} > \gamma_{P1} > \gamma_{P4}$, and the TOPSIS calculation result is $d_3 \succ d_2 \succ d_1 \succ d_4$. The optimal alternative part for the tight ring is alternative part 3. For the sealing module, the ranking of candidate components by grey relational degrees is as follows: $\gamma_3 \succ \gamma_4 \succ \gamma_1 \succ \gamma_2$, and the TOPSIS calculation result is $d_3 \succ d_2 \succ d_4 \succ d_1$. The optimal alternative part for the sealing module is alternative part 3. For the main shaft module, the ranking of candidate components by grey relational degrees is as follows: $\gamma_4 \succ \gamma_3 \succ \gamma_1 \succ \gamma_2$, and the TOPSIS calculation result is $d_4 \succ d_3 \succ d_1 \succ d_2$. The optimal alternative part for the main shaft module is alternative part 4. For the pressure sensor, the ranking of candidate components by grey relational degrees is as follows: $\gamma_3 \succ \gamma_4 \succ \gamma_1 \succ \gamma_2$, and the TOPSIS calculation result is $d_3 \succ d_4 \succ d_1 \succ d_2$. The optimal alternative part for the pressure sensor is alternative part 3. For the pressure regulating valve, the ranking of candidate components by grey relational degrees is as follows: $\gamma_3 \succ \gamma_4 \succ \gamma_1 \succ \gamma_2$, and the TOPSIS calculation result is $d_3 \succ d_4 \succ d_1 \succ d_2$. The optimal alternative part for the pressure regulating valve is alternative part 3.

From the above comparison of results, it can be seen that the rankings of components obtained from both methods are generally similar. However, due to the characteristic features of the grey relational method, such as its applicability to small datasets with incomplete information (grey information), the results exhibit greater variability and better highlight the differences in rankings. This makes the grey relational method more suitable for operational purposes and for clearly identifying ranking disparities, making it more appropriate for this research. Therefore, this paper chooses the grey relational analysis for evaluating the configuration selection.

6. Conclusions

This paper addresses the configuration update problem for complex product engineering changes. Building on previous research, a component configuration update method that considers dynamic ratings from design engineers is proposed in this paper. Firstly, a novel modular division approach is employed to segment the complex product into different modules. Then, representative design personnel are selected for each module to score the quality characteristics of components, and dynamic weights are calculated by intuitionistic fuzzy numbers. Finally, an integrated grey relational analysis method is used to determine the configuration update scheme, which is then compared with the results obtained using the TOPSIS method to validate the effectiveness of this paper. Through a case study involving the configuration update of components in a large-capacity fully DC high-speed permanent magnet synchronous variable-frequency centrifugal unit, it is demonstrated that this method can quickly determine the final decision-making scheme for complex product engineering changes with the help of professionals.

The advantages of the proposed method are summarized below: 1) The modular division approach introduced in this paper takes into account the functional, structural, and behavioral characteristics of the designed product. This allows for more accurate and precise descriptions of the production and design features of complex products. 2) The fuzziness of knowledge, the ease of data acquisition, and the dynamic nature of designers' expertise in the complex product design and manufacturing process are fully considered based on the intuitionistic fuzzy number-based scoring method proposed in this paper. This enables a more accurate depiction of the preferences and changes throughout the various stages of configuration updates for complex products. 3) The study employs grey relational analysis to evaluate configuration schemes, addressing the challenges of limited knowledge and sparse data in the design process of complex products.

There are several aspects of this research that warrant further exploration. For instance, the proposed method is suitable for complex products in the engineering field. These features are more suitable for complex products in the engineering field. Further research into its applicability to other domains can be valuable for future investigations.

Funding

This research was financially supported by Guangdong Provincial Philosophy and Social Science Youth Foundation Project, Guangdong Planning Office of Philosophy and Social Science (GD23YGL40), General Fund Project of the Guangdong Provincial Party School, Party School of the Guangdong Provincial Committee of CPC (XYYB202314) and Chongqing Social Science Foundation Project, Chongqing Planning Office of Social Science (2023BS037).

Data Availability

All data generated or analysed during this study are included in this published article. The datasets used and analysed during the current study available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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