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Change impact analysis of complex product using an improved three-parameter interval grey relation model

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A B S T R A C T

Change impact evaluation of complex product plays an important role in controlling change cost and improving change efficiency of engineering change enterprises. In order to improve the accuracy of engineering change impact evaluation, this paper introduces three-parameter interval grey number to evaluate complex products according to the data characteristics. The linear combination of BWM and Gini coefficient method is used to improve the three-parameter interval grey number correlation model. It is applied to the impact evaluation of complex product engineering change. This paper firstly constructs a multi-stage complex network for complex product engineering change. Then the engineering change impact evaluation index system is determined. Finally, a case analysis was carried out with the permanent magnet synchronous centrifugal compressor in a large permanent magnet synchronous centrifugal unit to verify the effectiveness of the proposed method.

A R T I C L E I N F O

Keywords:
Manufacturing;
Engineering;
Complex product;
Change impact analysis;
Three-parameter interval grey number;
Grey relational model;
BWM method (best-worst model);
Gini weighting method

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1. Introduction

There are increasingly fierce competition among complex product manufacturing enterprises in the rapidly changing market environment. In order to improve competitiveness and meet the changing needs of customers for engineering change, companies inevitably face more and more complex engineering changes. When engineering changes occur, many structures of complex products will be affected. The management of engineering change is roughly divided into four stages: engineering change application, engineering change process impact analysis and evaluation, engineering change decision and approval, and engineering change implementation. In these four stages, the analysis of the engineering change impact can not only be used to determine the necessity of change implementation, but also provide guidance for the formulation of change decision and strategies [1-4]. It is of great significance to control the cost of change and improve the efficiency of change, especially to consider the multi-stage impact when evaluating the impact of engineering change.

Many studies have done some research on the production of complex products [5-9]. However, due to the complexity of parts, the complexity of disciplines and the heterogeneity of knowledge, as well as the difficulty of data acquisition, there is great opacity in the process of change impact evaluation. Therefore, this article improved three-parameter interval grey relational and applied to the evaluation of the impact of engineering changes.

Many scholars have studied the impact evaluation of engineering change. It mainly includes the evaluation of change impact scope and the change impact degree. Based on the weighted network theory, (Cheng and Chu, 2012) proposed three variable indexes (degree variable, reachable variable and interval variable) [9]. The degree variability is used to calculate the impact of direct change by Ahmad *et al*. (2013) studied a cross domain approach to decompose design and identify possible change propagation links, supplemented by an interactive tool to functions, components and detailed design process [10]. Chen *et al*. (2015) proposed an assess the impact of changes. This method considered the information domain of requirements, object-oriented method, and described its components and related requirements by attributes and links, so as to model the integrated content of products and perform CIA tasks in variant product design [11]. Maazoun *et al.* (2016) proposed an automatic method to analyze the evolution of feature change model, tracked their impact on SPL design, and provided a set of suggestions to ensure the consistency of the two models [12]. Gong *et al.* (2021) analyzed the problems existing in modern product packaging and its impact on the ecological environment, and summarized the design methods of modern green packaging [13]. Zheng *et al.* (2020) put forward the evaluation method of change propagation probability based on grey comprehensive relational analysis and the evaluation method of change propagation impact probability based on configuration change value analysis [14]. (Li and Zhao, 2014) proposed an engineering change scheduling method which combined change propagation simulation with optimization algorithm in complex product development process [15]. Ma *et al.* (2016) established an engineering change analysis model based on the design attribute network and defined the influence of change propagation on the intensity of change propagation through the quantification of change propagation influence factors[16]. Maldini *et al.* (2019) proposed methods to assess the impact of such approaches and applied them to the specific case of "product personalisation" [17]. (Zhang and Yang, 2019) constructed a complex product design structure-task network evolution model under the influence of engineering changes, and analyzed the impact of changes on design tasks[18]. Maurya *et al.* (2017)targeted such dependencies and non-creative hindrances at concept generation stage through a mixed reality implementation. They established requirements for creating a suitable design-tool and presents a proof-of-concept use-case [19]. Palumbo *et al*. (2018) presented a method of achieving accurate Life cycle assessment results, which helps with decision-making and provides support in the selection of building products and materials. [20]. Li *et al.* (2020) established an engineering change risk propagation model based on load capacity [21].

Some of the existing studies have studied the change risk of change evaluation, and the change propagation. Then based on the multi-stage complex network model, this paper analyzes the multifaceted change propagation impact from the aspect of change propagation path. In addition, there are many parts in complex products and their relationship is complex. The relationship of each stage and parts is dynamic under the influence of engineering changes. Engineering change involves a series of activities such as product design or process, related documents, components or assembly, self-made or purchased parts, production process and even suppliers. The acquisition of engineering change data for complex products is more difficult and the data is poor, with greater ambiguity. Therefore, this paper adopts the three-parameter grey relational model based on BWM and Gini coefficient method to evaluate and analyze the impact of engineering change propagation.

Many scholars have studied three-parameter interval grey number decision model [22-27]. There are also some researches on the index weight of grey relational model. (Yin and Ren, 2018) and Liu *et al.* (2020) respectively introduced entropy weight method into grey relation analysis to study the risk evaluation of tunnel, the representative volume evaluation of concrete and the comprehensive analysis of the influencing factors of gas outburst [28, 29]. Based on entropy TOPSIS grey relational method, Gu *et al.* (2020) studied the path selection of the evaluation of the opening level of coastal cities in China and the evaluation of the implementation effect of TCM standards [30]. (Li and Zhu, 2019) studied the grey relational decision model based on AHP and DEA [31]. Based on the sensitivity and grey relational degree, Zhou *et al.* (2017) proposed a model based on combining weights and gray correlation analysis [32]. So the index weights of different schemes should be different. Therefore, this article combines the advantages of subjective and objective to comprehensively empower it and apply it to the evaluation of complex product engineering changes.

Complex products have the characteristics of many parts, a wide range of technical fields, complex component interfaces, one-off or even small batch production, and many supporting suppliers. It is different from general mass-manufactured parts and technical fields. The engineering change process of complex products need huge human, material and financial resources. If a predictive analysis of the possible impact scope can be made, manufacturing enterprise can avoid the waste of cost, and further accelerate the product development and production cycle. In this paper, the multi-stage complex network topology is firstly established for complex product engineering change, then the engineering change impact evaluation system is established. Finally, the proved three-parameter interval grey relational model is used to evaluate the impact of engineering change. The framework is shown in the Fig. 1.

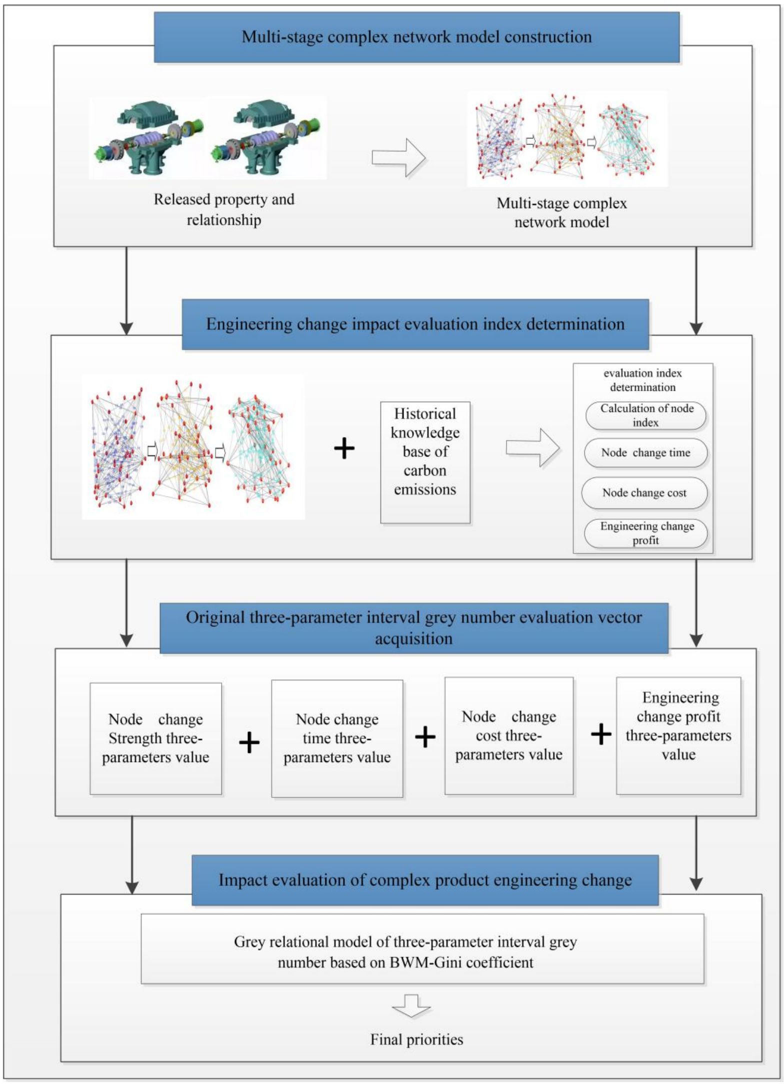

Fig. 1 Framework of the proposed complex product engineering change impact evaluation method

2. Multi-stage complex network

Engineering changes occur in product design, process, manufacturing and other stages. When these changes occur, it is necessary to respond at any time to achieve real-time change design response, rather than follow a fixed process of production. All processes will be affected when the change occurs. It is very vital about how to effectively collect, organize and manage scattered product engineering change knowledge, and use existing domain knowledge to ensure the integrity of product assembly structure. As an important part of the re-generation of product design schemes after product changes, it is critical to timely feed back the engineering change information to the design department. This article builds a multi-stage complex network based on design libraries, knowledge bases, and case libraries.

The propagation characteristic of design change will make the simple parameter change of any part may cause the chain change, and even lead to the avalanche effect of change propagation, which will bring various negative effects to the enterprise. A reasonable and effective communication path of design change can provide decision support for designers to implement design change, help improve product quality, shorten R & D time and reduce design cost. In addition, there are many professional categories of complex products, difficult processing technology, long manufacturing process and complex supporting relationship of parts. Complex products involve multiple processes in the process of engineering change. While continuously shortening the development cycle and improving the product development quality, it tends to the close coordination of design, process and manufacturing process. We integrate the complex network relationship of design, process and manufacturing process in the production process of complex products, so as to comprehensively consider the changes in each stage. The network of each stage is constructed according to its process knowledge and knowledge base. The construction process is shown in Fig. 2.

The single stage network is represented as: $G_k = (V, E_K, W_K)V = (V_i, i = 1,2, \ldots N)$. If there are connecting edges between parts knowledge, the $e_{k,j}^{k} = 1$, else, $e_{k,j}^{k} = 0$. When the multi-stage network is calculated, the connected edges and edge weights of its indexes are added and processed. For the same connected edge, the weight value is $w_{i,j} = \sum_{\alpha}^{3} w_{i,j}^{\alpha}$. The schematic diagram of the multi-stage network is shown in Fig. 3. The high speed permanent magnet synchronous variable frequency centrifugal high power chiller of G enterprise is taken as an example.

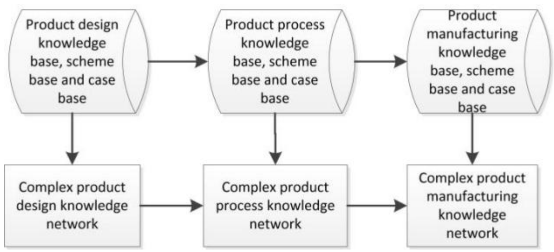

Fig. 2 Multi-stage complex network of complex product

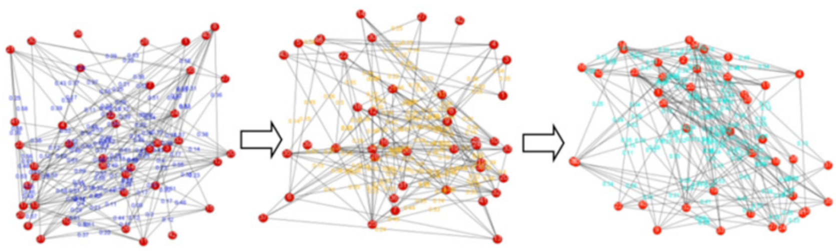

Fig. 3 Multi-stage complex knowledge network

3. Construction of engineering change evaluation index

3.1 Engineering change propagation intensity evaluation

The propagation intensity of engineering change defined in this paper includes node proximity, edge betweenness and propagation probability.

Node proximity: Node proximity is the reciprocal of total distance from the node to all other nodes: $C_i = \frac{1}{\sum_{j=1}^{n} \beta_{ij}}$. Where β_{ij} is the number of edges in the shortest path from the start node$i$to the end node$j$, and$n$is the total number of nodes. Node proximity describes the degree a node is to the center of a network. The larger the value, the more important the node is.

Edge betweenness: Edge betweenness is defined as the ratio of the number of paths passing through the edge to the total number of shortest paths in the network. Edge betweenness test is an important index to measure the role of connected edges in the whole network. The edge betweenness is expressed as:

$$G_{i,j} = \sum_{h}^{N} \sum_{m}^{N} \frac{L_{\hbar,m(e_{i,j}^{u})}}{g_{\hbar,m}} / m = 1,2,\ldots,N, \hbar \neq m(\hbar,m) \neq (i,j)] \tag{1}$$

Propagation probability of connected edges: $p_{i,j}$ is the probability of propagation from node i to node$j$. If node j doesn't belong to the next connected edge, the propagation probability is 0. It is easier to pass through this connecting edge when the propagation probability of the edge is greater. It can be expressed as:

$$P_{ij} = p(v_j|v_i) = \frac{p(v_i \cap v_j)}{p(v_i)} = \frac{p(v_j|v_i)p(v_j)}{p(v_i)} = \frac{p_{ji}p(v_j)}{p(v_i)} \tag{2}$$

Then, the change propagation intensity can be expressed as:

$$I_{ij} = \begin{cases} \omega_1(1 - p_{ij}) + \omega_2 C_i + \omega_3 G_i, & p_{ij} \neq 0 \\ 0, p_{ij} = 0 \end{cases} \tag{3}$$

3.2 Engineering change cost

Engineering changes of different parts will require different change costs. Changes in components can be mapped to changes in nodes in the network model (node addition and deletion). Therefore, we can evaluate the impact of customer demand change on complex product change by calculating the change cost of node change (node addition and deletion) in the network, the cost of node change in a network can be expressed as: $C_A = \sum_{i=1}^{N_A} c_{(v_i)}$, where c_{v_i} is the change cost of node change, N_A is the total number of change nodes.

The cost details involved in the product production process include: (1) Material cost: It refers to the cost of product standard consumption, supporting raw materials, product accessories and various materials used for production or providing services. It mainly includes the purchase price, related taxes, freight, loading and unloading fees, insurance premiums and other costs that can be directly attributable to the acquisition of materials. (2) Labor cost: It refers to the remuneration and other expenses paid to employees which in order to obtain the services provided by employees. It mainly includes the salary, bonus, allowance, welfare, education fund and so on. (3) Manufacturing cost: It refers to energy consumption, manufacturing accessories, labor insurance, office and fixed expenses. (4) Others: Some consumption including fuel cost, power cost, office cost and depreciation consumed by each production unit.

3.3 Engineering change time

In the process of engineering, change of different parts needs different change time. The node change time in a network can be expressed as:

$$T_A = \sum_{i=1}^{N_A} t_{(v_i)} + t_{(e_{i,j})} \tag{4}$$

Where $t_{v_i}$is the change time of node change. $N_A$is the total number of change nodes.

3.4 Engineering change profit

It refers to the positive impact obtained in the change process, such as customer satisfaction, product performance improvement and so on. The engineering change profit can be expressed as: $I_A = \sum_{i=1}^{N_A} i_{(v_i)}$. Where t_{v_i} is the engineering change profit of node change. N_A is the total number of change nodes.

The impact evaluation indexes are as shown in Table 1.

Table 1 Evaluation indexes of engineering change impact

Primary index	Secondary index	Tertiary indicators
Engineering change impact evaluation	Change propagation intensity	Node betweenness
		Node degree
		Node proximity
		Edge betweenness
		Propagation probability of connected edges
	Engineering change cost	Material cost
		Labor cost
		Manufacturing cost
		Manufacturing cost
	Engineering change time	Node change time
		Edge propagation time
	Engineering change profit	improvement of customer satisfaction
		improvement of product quality

4. Grey relational evaluation model based on three-parameter interval grey number

4.1 Three-parameter interval grey number

From the definition of three-parameter interval grey number, it can be known that it refers to the interval grey number where the center of gravity point with the greatest possible value is known. It can be marked as $A(\otimes) = [\underline{a}, \tilde{a}, \bar{a}]$, where $\underline{a} \leq \tilde{a} \leq \bar{a}$, $\underline{a}$、 $\bar{a}$ are the upper and lower limits of the interval respectively. $\tilde{a}$ is called the "center of gravity" point (Li and Zhang, 2020) [37].

When two of the three parameters $\underline{a}$, $\tilde{a}$, $\bar{a}$ are the same, the three-parameter interval grey number degenerates to the interval grey number. When $\underline{a} = \tilde{a} = \bar{a}$,the three parameter interval grey number degenerates to the real number. In fact, the interval grey number and the real number are special cases of the three-parameter interval grey number.

Its algorithm is similar to interval grey number. Let three-parameter interval grey number $A(\otimes) = [\underline{a}, \tilde{a}, \bar{a}]$, $B(\otimes) = [\underline{b}, \tilde{b}, \bar{b}]$, then

$$A(\otimes) + B(\otimes) = [\underline{a} + \underline{b}, \tilde{a} + b, \bar{a} + \bar{a}] \quad (5)$$

$$\frac{A(\otimes)}{B(\otimes)} \in \left[min\left\{\frac{\underline{a}}{\underline{b}}, \frac{\underline{a}}{\bar{b}}, \frac{\bar{a}}{\underline{b}}, \frac{\bar{a}}{\bar{b}}\right\}, \frac{\tilde{a}}{\tilde{b}}, man\left\{\frac{\underline{a}}{\underline{b}}, \frac{\underline{a}}{\bar{b}}, \frac{\bar{a}}{\underline{b}}, \frac{\bar{a}}{\bar{b}}\right\}\right] \quad (6)$$

$$\lambda A \otimes = [\lambda \underline{a}, \lambda \tilde{a}, \lambda \bar{a}] \quad (7)$$

4.2 Three-parameter interval grey number grey relational model

Suppose that there are n alternative engineering change schemes. They constituted by evaluation schemes set $A = \{a_1, a_2, \cdots, a_n\}$. The index set $S = \{s_1, s_2, \cdots, s_m\}$is composed of m attributes. The index value of scheme$a_i$under the evaluation index$s_j$can be expressed as $u_{ij}(\otimes) = [\underline{u}_{ij}, \tilde{u}_{ij}, \bar{u}_{ij}](\underline{u}_{ij} \leq \tilde{u}_{ij} \leq \bar{u}_{ij}, i = 1,2, \cdots, n; j = 1,2, \cdots, m)$. The effect evaluation vector of each scheme is $u_i(\otimes) = (u_{i1}(\otimes), u_{i2}(\otimes), \cdots, u_{im}(\otimes)), i = 1,2, \cdots, n$. The weight of index under each scheme is $w_{i1}, w_{i2}, \cdots, w_{im}$, and $\sum_{j=1}^{m} w_{ij} = 1 (i = 1,2, \ldots, n)$. There are different attribute indexes with different dimensions and measurement standards. In order to increase the comparability of alternatives, it is necessary to normalize the effect evaluation vector of decision alternatives. In this paper, we use the range transformation method to normalize the decision matrix.

For profitable attribute values:

$$\underline{x}_{ij}=\frac{\underline{u}_{ij}-\underline{u}_j^{\nabla}}{\bar{u}_j^{*}-\underline{u}_j^{\nabla}},\tilde{x}_{ij}=\frac{\tilde{u}_{ij}-\underline{u}_j^{\nabla}}{\bar{u}_j^{*}-\underline{u}_j^{\nabla}},\bar{x}_{ij}=\frac{\bar{u}_{ij}-\underline{u}_j^{\nabla}}{\bar{u}_j^{*}-\underline{u}_j^{\nabla}} \tag{8}$$

For cost attribute values:

$$\underline{x}_{ij}=\frac{\bar{u}_j^{*}-\bar{u}_{ij}}{\bar{u}_j^{*}-\underline{u}_j^{\nabla}},\tilde{x}_{ij}=\frac{\bar{u}_j^{*}-\tilde{u}_{ij}}{\bar{u}_j^{*}-\underline{u}_j^{\nabla}},\bar{x}_{ij}=\frac{\bar{u}_j^{*}-\underline{u}_{ij}}{\bar{u}_j^{*}-\underline{u}_j^{\nabla}} \tag{9}$$

Where $\bar{u}_j^{*}=\max_{1\le i\le n}\{\bar{\mu}_{ij}\},\bar{u}_j^{\nabla}=\min_{1\le i\le n}\{\underline{\mu}_{ij}\},j=1,2,\dots m$

Let the normalized effect evaluation vector be:

$$x_i(\otimes)=\left(x_{i1}(\otimes),x_{i2}(\otimes),\cdots,x_{im}(\otimes)\right),i=1,2,\cdots,n \tag{10}$$

Where $x_{ij}(\otimes)\in\left[\underline{x}_{ij},\tilde{x}_{ij},\bar{x}_{ij}\right]$ is a three-parameter interval grey number in [0,1].

Recorded that $\underline{x}_j^{+}=\max_{1\le i\le n}\{\underline{x}_{ij}\}$, $\tilde{x}_j^{+}=\max_{1\le i\le n}\{\tilde{x}_{ij}\}$, $\bar{x}_j^{+}=\max_{1\le i\le n}\{\bar{x}_{ij}\}$, $\underline{x}_j^{-}=\min_{1\le i\le n}\{\underline{x}_{ij}\}$, $\tilde{x}_j^{-}=\min_{1\le i\le n}\{\tilde{x}_{ij}\}$, $\bar{x}_j^{-}=\min_{1\le i\le n}\{\bar{x}_{ij}\}(j=1,2,\cdots,m)$. Then the m-dimensional three-parameter non negative interval grey number vectors

$$x^{+}(\otimes)=\{x_1^{+}(\otimes),x_2^{+}(\otimes),\cdots,x_m^{+}(\otimes)\},x^{-}(\otimes)=\{x_1^{-}(\otimes),x_2^{-}(\otimes),\cdots,x_m^{-}(\otimes)\} \tag{11}$$

are called ideal optimal scheme effect evaluation vectors and critical scheme effect evaluation vectors respectively.

We assume that the grey interval relational degree of the normalized effect evaluation vector $x_i(\otimes)$ of scheme A_i with respect to the ideal optimal scheme effect evaluation vector $x^{+}(\otimes)$ is $G\left(x^{+}(\otimes),x_i(\otimes)\right)$. And the grey interval relational degree of critical scheme effect evaluation vector $x^{-}(\otimes)$ is $G\left(x^{-}(\otimes),x_i(\otimes)\right)$. Assume that the weights of two grey relational degrees are α_1, α_2 $(\alpha_1+\alpha_2=1)$. Then,

$$G\left(x_i(\otimes)\right)=\alpha_1 G\left(x^{+}(\otimes),x_i(\otimes)\right)+\alpha_2\left[1-G\left(x^{-}(\otimes),x_i(\otimes)\right)\right],i=1,2,\cdots,n \tag{12}$$

is the three-parameter grey interval linear relational degree of the effect evaluation vector $x_i(\otimes)$.

$$G\left(x_i(\otimes)\right)=\left[G\left(x^{+}(\otimes),x_i(\otimes)\right)\right]^{\alpha_1}+\left[1-G\left(x^{-}(\otimes),x_i(\otimes)\right)\right]^{\alpha_2},i=1,2,\cdots,n \tag{13}$$

is the three-parameter grey interval product relational degree of the effect evaluation vector $x_i(\otimes)$.

The distribution probability of barycenter point with the highest probability of taking the value of three-parameter interval grey number $x_{ij}(\otimes)\in\left[\underline{x}_{ij},\tilde{x}_{ij},\bar{x}_{ij}\right]$ is $f\left(\tilde{x}_{ij}\right)\ge\sigma$. Normally, $\sigma\ge 60$ %. If $\sigma\le 60$ % it indicates that the decision is wrong, and the most likely value needs to be determined again. Based on the center of gravity, we can build a three-parameter interval grey number relational degree evaluation model.

Definition 1: For three-parameter interval grey number $x_{ij}(\otimes)\in\left[\underline{x}_{ij},\tilde{x}_{ij},\bar{x}_{ij}\right]$, then

$$\gamma_{ij}^{+}=\frac{3}{5}\times\frac{\tilde{m}^{+}+\eta\tilde{M}^{+}}{\tilde{\Delta}_{ij}^{+}+\eta\tilde{M}^{+}}+\frac{2}{5}\left[(1-\beta)\frac{\underline{m}^{+}+\eta\underline{M}^{+}}{\underline{\Delta}_{ij}^{+}+\eta\underline{M}^{+}}\beta\frac{\bar{m}^{+}+\eta\bar{M}^{+}}{\bar{\Delta}_{ij}^{+}+\eta\bar{M}^{+}}\right] \tag{14}$$

is called the three-parameter grey interval relational coefficient of sub factor. x_{ij} with respect to ideal factor x_j^{+}. $\eta\in(0,1)$ is the resolution coefficient. $\beta\in(0,1)$ is the decision preference coefficient. Where,

$$\underline{\Delta}_{ij}^{+}=\left|\underline{x}_j^{+}-\underline{x}_{ij}\right|,\tilde{\Delta}_{ij}^{+}=\left|\tilde{x}_j^{+}-\tilde{x}_{ij}\right|,\bar{\Delta}_{ij}^{+}=\left|\bar{x}_j^{+}-\bar{x}_{ij}\right|,i=1,2,\cdots,n;j=1,2,\cdots,m$$

$$\underline{m}^+ = \min_{1\le i\le n}\min_{1\le j\le m} \underline{\Delta}_{ij}^+, \tilde{m}^+ = \min_{1\le i\le n}\min_{1\le j\le m} \tilde{\Delta}_{ij}^+, \bar{m}^+ = \min_{1\le i\le n}\min_{1\le j\le m} \bar{\Delta}_{ij}^+$$

$$\underline{M}^+ = \max_{1\le i\le n}\max_{1\le j\le m} \underline{\Delta}_{ij}^+, \tilde{M}^+ = \max_{1\le i\le n}\max_{1\le j\le m} \tilde{\Delta}_{ij}^+, \bar{M}^+ = \max_{1\le i\le n}\max_{1\le j\le m} \bar{\Delta}_{ij}^+$$

$$G\big(x^+(\otimes), x_i(\otimes)\big) = \sum_{j=1}^{m} w_{ij}\gamma_{ij}^+ , i = 1,2,\cdots,n \tag{15}$$

is called the three-parameter grey interval relational degree of the effect evaluation vector $x_i(\otimes)$ about the ideal optimal scheme effect evaluation vector $x^+(\otimes)$.

Definition 2: For three-parameter interval grey number $x_{ij}(\otimes) \in [\underline{x}_{ij}, \tilde{x}_{ij}, \bar{x}_{ij}]$,

$$\gamma_{ij}^- = \frac{3}{5}\times\frac{\tilde{m}^- + \varepsilon\tilde{M}^-}{\tilde{\Delta}_{ij}^- + \varepsilon\tilde{M}^-} + \frac{2}{5}\times\left[(1-\delta)\frac{\underline{m}^- + \varepsilon\underline{M}^-}{\underline{\Delta}_{ij}^- + \varepsilon\underline{M}^-} + \delta\frac{\bar{m}^- + \varepsilon\bar{M}^-}{\bar{\Delta}_{ij}^- + \varepsilon\bar{M}^-}\right] \tag{16}$$

is called the three-parameter grey interval relational coefficient of sub factor. $x_{ij}$with respect to ideal factor x_j^- .$\eta \in (0,1)$ is the resolution coefficient. $\delta \in (0,1)$is the decision preference coefficient. Where,

$$\underline{\Delta}_{ij}^- = |\underline{x}_{ij} - \underline{x}_j^-|, \tilde{\Delta}_{ij}^- = |\tilde{x}_{ij} - \tilde{x}_j^-|, \bar{\Delta}_{ij}^- = |\bar{x}_{ij} - \bar{x}_j^-|, i = 1,2,\cdots,n; j = 1,2,\cdots,m$$

$$\underline{m}^- = \min_{1\le i\le n}\min_{1\le j\le m} \underline{\Delta}_{ij}^-, \tilde{m}^- = \min_{1\le i\le n}\min_{1\le j\le m} \tilde{\Delta}_{ij}^-, \bar{m}^- = \min_{1\le i\le n}\min_{1\le j\le m} \bar{\Delta}_{ij}^-$$

$$\underline{M}^- = \max_{1\le i\le n}\max_{1\le j\le m} \underline{\Delta}_{ij}^-, \tilde{M}^- = \max_{1\le i\le n}\max_{1\le j\le m} \tilde{\Delta}_{ij}^-, \bar{M}^- = \max_{1\le i\le n}\max_{1\le j\le m} \bar{\Delta}_{ij}^-$$

$$G\big(x^-(\otimes), x_i(\otimes)\big) = \sum_{j=1}^{m} w_{ij}\gamma_{ij}^- , i = 1,2,\cdots,n \tag{17}$$

is called the three-parameter grey interval relational degree of the effect evaluation vector$x_i(\otimes)$ about the critical scheme effect evaluation vector $x^-(\otimes)$.

4.3 Determination of weight

At present, scholars attach great importance to the development and application of subjective and objective empowerment methods in the research of evaluation. The subjective weight reflects the subjective willingness of the evaluation subject, and highlights the degree of distinction between the evaluation objects through index data information. The combination of them will make the result more objective. In this paper, the simplified BWM subjective weighting method and the Gini coefficient weighting method which can better reflect the data difference information are selected for combination weighting.

4.3.1 Determination of weight based on BWM

BWM(best-worst method) is a new method to determine the subjective weight of index proposed by Rezaei in 2014. The most frequently used method in the multiple indexex evaluation is AHP method. In AHP method, any two indexes are usually compared with each other to get the evaluation matrix of indexes, which needs $n(n-1)/2$ times of comparison. The calculation process of it is complicated and will cause certain errors. However, BWM only needs $2n-3$ calculations by selecting the best and the worst indexes and comparing them with other indexes. It simplifies the complicated process of AHP, greatly reduces the amount of data, reduces the mistakes caused by too much data, makes it easier to pass the consistency test, and improves the reliability. The calculation steps are as follows (Behzad *et al.* (2020))[33]:

- The best index $X_B$and the worst index X_W are selected according to experts' opinions in index set$X = \{x_1, x_2, \ldots x_n\}$.
- Experts use 1-9 point scale to score and determine the importance of other indexes relative to the optimal indexes. We construct the comparison vector $C_B = ({C_B}_1, {C_B}_2, \ldots, {C_B}_j)$. ${C_B}_j$rep-

resents the importance of the optimal index compared with index$j$. 1 means C_B and $C_{B\,j}$ are equally important. 9 means C_B is extremely important than $C_{B\,j}$.

- We need to determine the unimportance of other indexes relative to the worst indexes and construct a comparison vector $C_w = (\mathrm{C_{1w}}, \mathrm{C_{B_{2w}}}, \ldots, \mathrm{C_{jw}})^{\mathrm{T}}$. Where C_{jw} represents the least importance of the worst index compared with index j. 1 means C_{jw} and C_w are equally unimportant. 9 means C_{jw} and C_w are extremely unimportant.
- From the goal programming model, a mathematical programming formula is established and solved to obtain the optimal index weight $\omega_j^* = (\omega_1^*, \omega_2^*, \ldots, \omega_n^*)$.

$$minmax_j \left\{ \left| \frac{\omega_j}{\omega_W} - aB_j \right| \right\}$$

$$s.t. \begin{cases} \sum_{j=1}^{n} \omega_j \\ \omega_j \geq 0, j = 1,2, \ldots n \end{cases} = 1 \tag{18}$$

Where ω_B is the weight of C_B, C_j is the criterion vector. ω_j is the weight of C_j. ω_B is the weight of C_W. aB_j represents the importance of C_B to C_j; a_{jW} represents the importance of C_j to C_W. It can be transformed to min^k

$$s.t. \begin{cases} \left| \frac{\omega B}{\omega_j} - aBj \right| \leq k \\ \left| \frac{\omega_j}{\omega W} - ajW \right| \leq k \\ \sum_{j=1}^{n} \omega_j = 1 \\ \omega_j \geq 0 \end{cases}, j = 1,2, \ldots, n \tag{19}$$

- Calculate the consistency ratio. The obtained Kcan be represented by K^*, and the consistency ratio C_R (C_1 is the given value) can be obtained from $C_R = \frac{k^*}{C_1}$.

  The closer of the value is to 0, the better the consistency. When it is 0, it is consistent. If there are P experts participate in the judgment, the final weight will be calculated by weighted average, and the final weight is $\bar{\omega}_j^* = \frac{\sum_{a=1}^{p} \omega_j^a}{p}$.

4.3.2 Weight determination method based on Gini coefficient

Principle of Gini coefficient weighting method

Gini coefficient weighting method is an objective weighting method by calculating Gini coefficient of evaluation index and normalizing Gini coefficient of each index. First of all, the different data of$n$evaluation objects of a specific evaluation index can be regarded as the income of different levels people. Then the Gini coefficient of a certain index can be calculated. The value of Gini coefficient can reflect the data difference between different evaluation objects. Then, In order to ensure that weight of all indexes are in the range of 0 to 1 and the sum is 1, the Gini coefficient value of each index will be normalized to get the Gini coefficient weight of the evaluation index. Zahng *et al.* (2020) [34].

Gini coefficient weight' calculation of evaluation index

We assume that $G_k$is the Gini coefficient of the kth index, Y_{ki} is the ith data of the kth index, and μ K. μK is the expected value of all data of the kth index. Then the Gini coefficient $G_k$of the k-th index is shown as follows:

$$G_k = \sum_{i=1}^{n} \sum_{j=1}^{n} \left| Y_{ki} - Y_{kj} \right| / \, 2n^2 \mu_k \tag{20}$$

$$G_k = \sum_{i=1}^{n} \sum_{j=1}^{n} \left| Y_{ki} - Y_{kj} \right| / \, (n^2 - n) \tag{21}$$

Especially, when the mean value of index data is not 0, the Gini coefficient is calculated by the improved formula (13). When the mean value of the index data is 0, the Gini coefficient of the index is calculated by the original formula (14). Gini coefficient of the index truly reflects the data changes of different evaluation objects of the index.

Gini coefficient weight $g_k$of the k-th index can be obtained by normalizing the Gini coefficient value of each index:

$$g_k = G_k/(\sum_{i=1}^{m} G_i) \tag{22}$$

Where $g_k$is Gini coefficient weight of the kth index, G_k is Gini coefficient value of the k-th index, and m is the number of indexes.

The advantages of Gini coefficient weighting method are as follows: first, the weight calculation is not affected by the unit dimension of the index, the definition of Gini coefficient itself eliminates the dimensional influence. Second, Gini coefficient value of the evaluation index reflects the difference between any two evaluation objects. Gini coefficient weight reflects the difference between the data of different evaluation objects of an index. And the weight reflects the data information of the index, which meets the requirements of the objective weighting method.

4.3.3 Combination weighting method based on BWM-Gini coefficient

The BWM method determines the index weight according to the subjective preference of the evaluator, and the method of Gini coefficient determines the objective index weight. In order to fully combine the advantages of the two methods, from the subjective and objective point of view, this paper combines BWM method and Gini coefficient method to determine the comprehensive weight of the evaluation index by linear weighting:

$$W_i^* = \xi W + (1-\xi)W_i = [w_1^*, w_2^*, \cdots, w_n^*]^T \tag{23}$$

Where W_i^* is the comprehensive weight of the decision unit$i$, ξ is the subjective preference coefficient, $1-\xi$ is the objective preference coefficient ($\xi \in [0,1]$), and the specific value of ξ is given by the decision maker according to personal preference.

5. Case study

The high-speed permanent magnet synchronous centrifugal unit of G enterprise is a high-tech, high value-added and complex mechanical product involving multi-disciplinary and multi domain knowledge. It has high requirements for continuous innovation ability. Centrifugal compressor is an important part of it, which determines many functions. The product organization diagram and component composition are shown in Fig. 4 and Table 2. The continuous innovation knowledge of full capacity DC high-speed permanent magnet synchronous frequency conversion centrifugal unit involves many aspects within the enterprise, within the industry and across fields. It has the characteristics of multi domain, high frequency, massive, heterogeneous and complex. Combined with the historical case of common engineering change innovation mode of large capacity full DC high-speed permanent magnet synchronous variable frequency centrifugal unit and its design process manufacturing process knowledge base, its multi process network is analyzed to determine the evaluation index value of change impact.

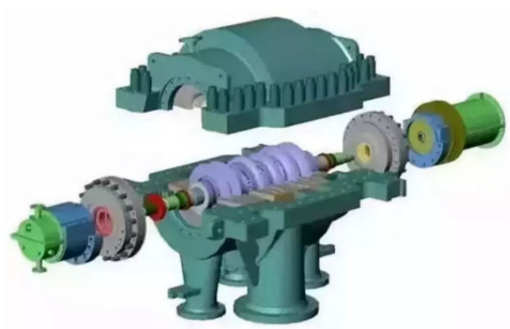

Fig. 4 Large permanent magnet synchronous centrifugal unit and permanent magnet synchronous centrifugal compressor

Table 2 Main parts and node name of permanent magnet synchronous centrifugal compressor

Node	Parts	Node	Parts
V1	mainshaft	V13	bend casing
V2	impeller rim 1	V14	curved separator
V3	roulette 1	V15	refluxer separator
V4	blade 1	V16	refluxer flow channels
V5	shrink-ring	V17	volute
V6	fixed collar	V18	impeller rim 2
V7	balance disc	V19	roulette 2
V8	reinforcement on the back of impeller	V20	blade 2
V9	thrust disc	V21	stator winding
V10	axle sleeve	V22	stator core
V11	suction chamber	V23	foundation
V12	diffuser	V24	p-m rotor

It is known that part 4 needs to be improved due to increased customer demand. There are 4 changed routes, and the impact evaluation of the changed routes is carried out. The four routes are as follows: Engineering change node route 1:4-3-2-6-5-7-9; Engineering change node route 2:4-3-2-5-8-1; Engineering change node route 3:4-3-15-16-17-24; Engineering change node route 4:1-2-3-4-14-22.

The physical schematic diagram of the change routes are shown in Fig. 5.

Fig. 5 Physical schematic diagram of the change routes

First of all, we analyze the relationship between process, design and manufacturing network of the direct drive variable frequency centrifugal compressor. The multi-stage complex network diagram can be referred to Fig. 3.

Through the calculation of index system，we can get the three parameter interval grey number of the evaluation index as follows:

$$X(\otimes)=\begin{bmatrix}[3.38,3.41,3.46][11.21,11.32,11.35][5421,5423,5425][5.98,6.05,6.11]\\ [2.97,3.21,3.04][10.71,11.24,11.46][5275,5279,5283][5.76,6.14,6.17]\\ [3.23,3.34,4.47][11.05,11.10,11.16][5865,5868,5871][6.03,6.17,6.21]\\ [3.18,3.41,3.57][11.28,11.31,11.36][5903,5932,5952][6.11,6.15,6.46]\end{bmatrix}$$

The normalized three-parameter interval grey number evaluation matrix is:

$$X(\otimes)=\begin{bmatrix}[0.59,0.63,0.65][0.61,0.63,0.65][0.80,0.82,0.83][0.60,0.65,0.70]\\ [0.67,0.85,1.00][0.67,0.70,1.00][0.73,0.81,1.00][0.00,0.73,0.75]\\ [0.00,0.73,0.74][0.72,0.76,0.79][0.00,0.62,0.63][0.64,0.76,0.79]\\ [0.53,0.55,0.59][0.00,0.63,0.69][0.57,0.58,0.60][0.70,0.74,1.00]\end{bmatrix}$$

According to formula (4), the effect evaluation vectors of ideal optimal scheme and critical scheme are obtained:

$x^+(\otimes) = ([0.67, 0.85, 1.00], [0.72, 0.76, 1.00], [0.80, 0.82, 1.00], [0.70, 0.76, 1.00])$
$x^-(\otimes) = ([0.00, 0.55, 0.59], [0.00, 0.62, 0.65], [0.00, 0.57, 0.60], [0.00, 0.65, 0.70])$

The weight matrix obtained by expert BWM method is as follows: $W = (w_1, w_2, w_3, w_4) = (0.37, 0.16, 0.32, 0.14)$

The weight obtained from Gini coefficient is as follows:

$W = (w_1, w_2, w_3, w_4) = (0.33, 0.11, 0.31, 0.25)$

Then we can calculate the comprehensive weight. this paper takes the preference coefficient 0.4. $W_i^* = 0.6W_B + 0.4W_J$ can be obtained from formula (17). Then we can get the comprehensive weight: $W = (w_1, w_2, w_3, w_4) = (0.35, 0.14, 0.31, 0.18)$

According to Eq. 8 and Eq. 10, the grey interval relational degree of each scheme with ideal optimal scheme and critical scheme is obtained as follows:

$$G\left(x^+(\otimes), x_1(\otimes)\right) = 0$$
$$G\left(x^-(\otimes), x_1(\otimes)\right) = 0.88$$
$$G\left(x^+(\otimes), x_2(\otimes)\right) = 0.72$$
$$G\left(x^-(\otimes), x_2(\otimes)\right) = 0.67$$
$$G\left(x^+(\otimes), x_3(\otimes)\right) = 0.80$$
$$G\left(x^-(\otimes), x_3(\otimes)\right) = 0.54$$
$$G\left(x^+(\otimes), x_4(\otimes)\right) = 0.74$$
$$G\left(x^-(\otimes), x_4(\otimes)\right) = 0.80$$

The three-parameter grey interval linear relational degree of each scheme is calculated by Eq. 5: $G\left(x_1(\otimes)\right) = 0.53$, $G\left(x_2(\otimes)\right) = 0.67$, $G\left(x_3(\otimes)\right) = 0.48$, $G\left(x_4(\otimes)\right) = 0.43$. These relational degree can be expressed as shown in the Fig. 6.

According to the linear relational degree of three-parameter interval grey number, we can find that the most relevant to the ideal optimal scheme is scheme 2. Change node route2 is 4-3-2-5-8-1:blade1-roulette1-impeller rim1-shrink-ring-reinforcement on the back of impeller-mainshaft. The physical schematic diagram of the change route 2 is shown in Fig. 7. We can find that the choice of engineering change route is in line with the reality.

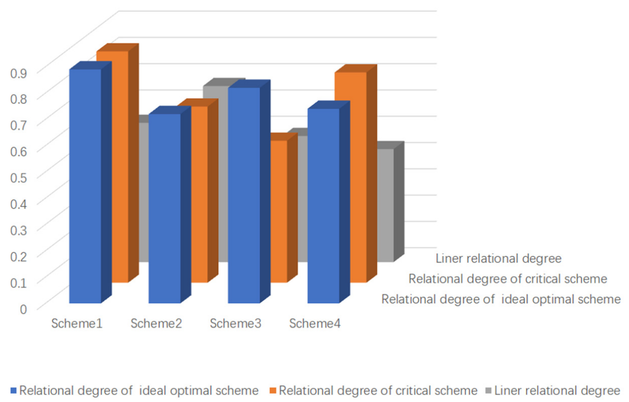

Fig. 6 Relational degree results

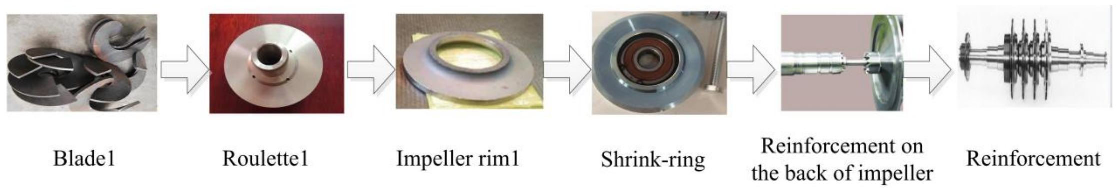

Fig. 7 Physical schematic diagram of change route 2