Comprehensive quality-loss Measurement for the outsourcing components of complex product concerning static appraisal and trend evolutionary

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Abstract: A novel calculation method was proposed for evaluating the quality loss level of outsourcing components in complex product supply chain, which were ordered in small batches crossing multi-stages. Specially, Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) was used for appraising static quality loss in an independent stage, which concerned the optimal quality objective and tolerances according to purchaser's quality requirements. Grey Relational Analysis was employed for reflecting the dynamic quality loss covering several order procedures by comparing theoretical learning effect and realistic quality improvements. The comprehensive quality loss indicator was designed combining static and dynamic quality losses, which can describe the quality assurance in a stage and quality improvement effect in trend. The numerical study was conducted for showing the above calculation process and the effectiveness of the new method.

1. Introduction

Complex product can be described as a large-size product or system with complicated structure, high integration, and huge R&D cost, which mostly be manufactured in single and small batches according to customized requirements. Currently, "main manufacture and suppliers" cooperation is always employed to produce the complex product, in which the main manufacture orders high-quality components from worldwide suppliers and assembles the outsourcing parts manufactured in several similar indents with small batches into the final product. The main manufacture should strictly monitor the quality conditions of outsourcing components and appraise on comprehensive quality loss for guaranteeing occupying advantageous position in global serious competition. According to the learning theory, the suppliers' working experience and manufacturing proficiency can be gradually improved, which are highly expected by the main manufacture. Consequently, the comprehensive quality loss of outsourcing components should be concerned in a dynamic continuously optimized process, other than an independent and static stage only.

Referring to the relevant literature in recent years, many related research domains become hotspots, such as quality loss calculation, TOPSIS method (static appraisal) and grey relational analysis (trend evolutionary).

(1) The Quality Loss Calculation

In order to appraise the outsourcing quality level, several quality loss functions are widely used from the perspectives of not only function failure but also deviation from target value. Abdolshah

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explored the Improved Taguchi Loss Function (ITLF) with boundary and asymmetric analysis, which can describe the loss associated with a product characteristic[1]. Li introduced the cubic quality loss function for calculating the hidden quality cost, which can improve the calculation precision of the quality loss[2]. Zhang improved quality loss function from the perspective of Taguchi's quadratic quality loss, which contributed to calculate quality loss for describing the optimal tolerance design of hierarchical product[3].

(2) TOPSIS Method for static evaluation

The TOPSIS is a comprehensive multi-criteria decision analysis (MCDA) method for appraising the performance of alternatives by calculating geometric distance from the positive and negative ideal solutions in a specific stage. Wang and Chen introduced a novel Multiple Attribute Decision Making (MADM) method for Interval-Valued Intuitionistic Fuzzy Sets (IVIFSs), in which TOPSIS was employed for ordering the preference of alternative techniques[4]. Yoon and Kim improved adaptability of TOPSIS methodology by incorporating the decision maker's behavioral tendency[5]. Khan combined TOPSIS with maximizing deviation method, which can assist to make a suitable appraisal results containing Pythagorean hesitant fuzzy information[6].

(3) The Grey Relational Analysis for trend appraise

The grey relational analysis can judge the relational grade between the actual sequences and the ideal sequence, which is used to describe the development trends of quality loss. Gu and Song proposed the effectiveness evaluation model for weapon systems by combining grey relational analysis and TOPSIS, which can comprehensively appraise the effectiveness of weapon systems[7]. Sun established the hesitant fuzzy grey relational recognition model by considering both the closeness and the linear fashion of Hesitant Fuzzy Sets (HFSs), which can overcome the restriction of the previous HFSs fuzzy measures[8].

The existing quality loss function almost calculate the quality loss in a certain stage from a general perspective, which are short of long-term calculation for quality loss. According to the learning curve, the accumulation of experience will enhance the ability of quality assurance, which can reduce the quality loss in the production process. Therefore, the calculation method can be established to measure the static and dynamic quality loss.

2. Comprehensive quality-loss Measurement

2.1. Single-stage quality loss measurement of complex products based on the TOPSIS method

Definition 1 Single-stage quality loss refers to the comprehensive loss, which is the deviation of multiple quality quotas from the optimal target prescribed in the contract for each batch of products provided by the supplier. This is the optimal result of the supplier providing the corresponding variable of the product. The supplier should try to ensure that every quality characteristic approaches the ideal target value specified in the contract to minimize the multiple quality loss.

The evaluation index value of the evaluation object is presented as:

$$X' = X'_{ij}, i = 1, 2, \cdots, m, \ j = 1, 2, \cdots, \mathrm{n} \tag{1}$$

Where m is the evaluation object in chronological order and n is the evaluation index value of the product provided by the supplier S.

The index weight w_{ij} can be determined by analytic hierarchy process, which can be used to calculate the weighted index value.

$$\mathrm{Y}_{ij} = X_{ij} \times w_{ij}, i = 1, 2, \cdots, m, \ j = 1, 2, \cdots, \mathrm{n} \tag{2}$$

Where X_{ij} is the dimensionless index value of the evaluation object.

The distance between the evaluated object and the ideal solution can be calculated as follows:

$$\begin{cases} d_i^+ = \sqrt{\sum_{j=1}^{n}\left(Y_{ij} - Y_j^+\right)^2} \\ d_i^- = \sqrt{\sum_{j=1}^{n}\left(Y_{ij} - Y_j^-\right)^2} \end{cases}, i = 1, 2, \cdots, m, \ j = 1, 2, \cdots, \mathrm{n} \tag{3}$$

Where Y_j^+ is the target value specified in the contract, named the positive ideal solution. Y_j^- is the minimum tolerance value, called the negative ideal solution.

The Euclidean distance between the product provided by the supplier S and the ideal solution can be shown as follows:

$$\begin{cases} d^+ = \frac{1}{m}\sqrt{\sum_{i=1}^{m} d_i^+} \\ d^- = \frac{1}{m}\sqrt{\sum_{i=1}^{m} d_i^-} \end{cases}, i = 1, 2, \cdots, m \tag{4}$$

The relative closeness of the product provided by the supplier S can be presented as follows:

$$c = \frac{d^-}{d^+ + d^-}, i = 1, 2, \cdots, m \tag{5}$$

2.2. Multi-stage quality loss assessment model based on the learning curve

Definition 2 Multi-stage quality loss refers to the deviation degree between the quality of each batch provided by different suppliers and the theoretical quality loss of the learning curve. Because the evaluated object is the products provided by the supplier in chronological order, which can be described by t. The steps of the dynamic evaluation method based on the grey relative analysis of the learning curve are as follows:

The quality loss value of the evaluated object can be calculated as follows:

$$\Delta \mathrm{Y}_{ij} = Y_j^+ - Y_j, t = 1, 2, \cdots, m, \ j = 1, 2, \cdots, n \tag{6}$$

The theoretical evaluation index of learning curve can be written as follows:

$$\mathrm{F}_j = \Delta Y_{1j} \times \left(j\right)^{\log b \div \log 2}, \ \mathrm{j} = 1, 2, \cdots, n \tag{7}$$

The grey correlation coefficient can be calculated between the evaluation index and the theoretical evaluation index of the learning curve, which can be used to form the matrix ξ_S.

$$\xi_{\mathrm{tj}} = \frac{\min_t \min_j F_j + \rho \times \max_t \max_j F_j}{F_j + \rho \times \max_t \max_j F_j}, t = 1, 2, \cdots, m, \ j = 1, 2, \cdots, n, \ \rho \in (0, 1) \tag{8}$$

Where ρ is the resolution coefficient, whose general value is 0.5.

The grey relational order of the evaluated object can be calculated as follows:

$$r_j = \frac{1}{m}\sum_{t=1}^{m} \xi_{tj}, t = 1, 2, \cdots, m, \ j = 1, 2, \cdots, n \tag{9}$$

The grey correlation degree between the product provided by the supplier S and the ideal value of learning curve can be expressed as follows:

$$r = \frac{1}{n}\sum_{j=1}^{n} r_j,\ j = 1, 2, \cdots, n \tag{10}$$

2.3. The calculation method of the quality loss coefficient

Definition 3 The quality loss coefficient is weighted by the Euclidean distance and the grey correlation degree, which reflects the positional relationship between the quality loss and the ideal value as well as the similarity of the developed data curve. The formula can be determined as follows:

$$h = \alpha \times c + (1-\alpha) \times r,\ \alpha \in (0,1) \tag{11}$$

Where α is the preference of the main manufacturer for location and shape. When α>1-α, the main manufacture pays more attention to the distance calculated by TOPSIS. When α<1-α, the situation is contrary. When α=1-α, the distance and the trend is equally important. The main manufacturer can determine the values according to their preference.

The production cost of the supplier is C, and the comprehensive quality loss of the products provided by the supplier is W.

$$W = C \times h \tag{12}$$

3. Case Study

A large aircraft (Main Manufacture M) orders outsourcing components of the five systems, include the system of airframe, system of cargo compartment, dynamical system, electronic system and environmental system. The case selects three suppliers from the supply chain to show the comprehensive quality-loss measurement, which can calculate the quality loss coefficient for different quality characteristics. The product quality of supplierⅠ which has different evaluation indexes can be shown in Table 1. As above, the product quality of supplierⅡ and supplierⅢ can be obtained.

Table 1 The product quality of the supplier I

	Index A	Index B	Index C	Index D
Product 1.1	15.79	86.50	1.72	56.78
Product 1.2	16.26	86.80	1.79	57.52
Product 1.3	16.98	87.20	1.83	58.23
Product 1.4	17.53	88.30	1.91	59.65
Positive ideal solution	18.00	90.00	2.00	60.00
Negative ideal solution	14.98	85.90	1.46	54.87

3.1. The static evaluation based on TOPSIS

(1) The index weights

According to the AHP, the index weights of supplierⅠare successively 0.16, 0.35, 0.35 and 0.14. The index weights of supplierⅡare 0.28, 0.24, 0.32 and 0.16. The index weights of supplierⅢ are 0.16, 0.26, 0.3, 0.13 and 0.15.

(2) The calculations of TOPSIS

Based on Eq. (2) to Eq. (5), the distance between the evaluated object and the ideal solution can be expressed, which can used to describe the relative closeness.

Table 2 The Euclidean distance and the relative closeness

	Positive ideal solution	Negative ideal solution	The relative closeness
Supplier I	0.039727	0.073378	0.648096
Supplier II	0.078745	0.082093	0.489838
Supplier III	0.061251	0.379736	0.863072

3.2 The Grey relational analysis

(1) The matrix of the grey correlation coefficient

Assume that the learning rate is 80%, the matrix I of the grey correlation coefficient based on Eq.(7) and Eq.(8) can be calculated as follows. The matrix II and III can be expressed by following the same step mentioned above.

$$\xi_I = \begin{bmatrix} 0.475113 & 0.572985 & 0.547619 & 0.405797 \\ 0.553603 & 0.607711 & 0.657143 & 0.479218 \\ 0.741176 & 0.661136 & 0.741935 & 0.579882 \\ 1 & 0.871933 & 1 & 1 \end{bmatrix}$$

(2) The grey correlation coefficient of the supplier

Combined Eq.(9) and Eq.(10), the grey correlation coefficient of suppliers is 0.680953217, 0.735637781 and 0.680953217 in sequence.

3.3. The calculation of comprehensive quality loss

If α=0.5, the purchase cost of suppliers is ￥10000,￥12000 and ￥8000 in order. The quality loss coefficient and the comprehensive quality loss can be shown as follows:

Table 3 The quality loss coefficient and the comprehensive quality loss

	Supplier I	Supplier II	Supplier III
The quality loss coefficient	0.664524388	0.612738111	0.772012688
The comprehensive quality loss	￥3354.756	￥4647.143	￥1823.898

In conclusion, $h_{III}>h_I>h_{II}$, the quality loss coefficient of the supplier III is the minimum, the main manufacture can reward the suppliers III and pay more attention to the supplier II.

3.4. The advantage of the calculation method

Based on generalized quality loss, the quality loss coefficient of suppliers in sequence is 0.514042025, 0.552920433 and 0.735661116. $h'_{\mathrm{III}} < h'_{\mathrm{II}} < h'_{\mathrm{I}}$, the result of generalized quality loss is caused by calculating the quality level in a static state, which is different from the comprehensive quality-loss measurement. At present, almost papers calculate the quality loss in an independent stage only. The comprehensive quality-loss measurement can use grey relative analysis to obtain the comprehensive quality loss crossing multi-stages by considering the quality improvement process.

4. Conclusion and future work

There are many suppliers in the production process of complex products, who provide greatly different types and quantity characteristic values of their products. The relative closeness of the product in a stage can be obtained by the TOPSIS, and grey correlation degree of the overall development can also be calculated by grey relative analysis. The comprehensive quality-loss measurement combining the TOPSIS and grey relative analysis not only can reflect static appraisal but also can show trend evolutionary. According to the ranking result of quality loss coefficient, the main manufacturer can motivate the suppliers to improve the integral quality level of the supply chain. For example, the main manufacture can reward the suppliers which provide the low comprehensive quality loss, pay more attention to even punish the suppliers with the large quality loss.

Referring to the learning theory, when the yield increases twice, the reduced quality loss of the product is the learning rate, which may be different for the products of suppliers. The outsourcing components ordered by the main manufacture have different different learning rates. Therefore, the calculation of learning rate should be focused on in multi-stage quality loss measurement.

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