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An integrated QFD and FMEA approach to identify risky components of products

Wei Chen [a,b], Bai Yang [a,b], Ying Liu [c,*]

[a] Research Center for Enterprise Management, Chongqing Technology and Business University, Chongqing, China
[b] School of Business Administration, Chongqing Technology and Business University, Chongqing, China
[c] Department of Mechanical Engineering, School of Engineering, Cardiff University, Cardiff CF24 3AA, UK

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ABSTRACT

Identifying risk components is crucial to improve product quality. Failure mode and effects analysis as a useful risk assessment method has become a prevalent application in product design. However, the critical data, which contain failure causality relationships (*FCRs*) between failure modes, importance correlations among risk factors, and customer requirements of the product component, are not considered. This study develops an integrated approach for identifying risky components considering customer requirements and *FCRs*. First, a quality function deployment is established to characterize the customer requirements under fuzzy assessment semantics. Second, the *FCRs* between and within the product components are characterized by a directed network model. In this network, the failure modes are modelled as vertices, and the causality relationships between the failure modes are modelled as directed edges. The values of the directed edges are characterized by weighted risk priority numbers, and the weight of risk factors is optimized by a nonlinear programming model. Then, the interactive relationships among failure modes between and within product components are characterized by the internal failure effect and external failure effect. Finally, a real-world case application of wheel loader is conducted to demonstrate the validity and feasibility of the proposed approach. The results have shown that the proposed method is more effective in identifying risk components.

1. Introduction

Product reliability (*PR*) is one of the key dimensions of the quality of products. New products are usually developed by improving existing products to meet customer requirements (*CRs*), for example, functional rationality, transportation convenience, and quality satisfaction, which is particularly true for mechanical products during their redesign processes [1,2]. To improve *PR*, product design has become an important method in product research and development [3]. Hence, the key issue of product quality is to identify risky components of existing products [4].

Conventionally, *CRs* are extracted as the input of quality function deployment (*QFD*) through those methods of customer surveys, questionnaires, and interviews [5], which are used by designers to select product components (*PCs*) to be improved [6,7]. *QFD* is generally utilized to extract design characteristics from *CRs* with subjective qualitative evaluation [8,9]. Failure mode and effects analysis (*FMEA*) is used to determine the failure risk of *PCs* to enhance the *PR* [10]. Failure modes (*FMs*) are prioritized based on a risk priority number (*RPN*), which is an arithmetic product of three risk factors (*RFs*), namely, severity (*S*), occurrence (*O*), and detection (*D*). Risk factor takes a discrete value from designers, an *FM* with a large *RPN* value has a higher failure risk and greater priority to be improved. However, the conventional *QFD* and *FMEA* have been largely criticized for their limitation in subjectivity and stochastic nature [11,12]. Considerable efforts have been made to improve the QFD and *FMEA* to accommodate various engineering and design problems. For example, to improve the *PR*, a design framework was presented to support the conceptual design of complex products and systems based on *QFD* and *FMEA* [5]. In addition, similar approaches have been presented to solve different problems, such as performance improvement of service demand selection [13], risk assessment with fuzzy information [14], and customer needs analysis [15]. In these studies, *CRs* and failure risk were incorporated into the *QFD* process by *FMEA* and were treated as a constraint in the risk evaluation model. The studies discussed above show that the failure information of a product is accessible and usable for the improvement of

* Corresponding author.
E-mail address: LiuY81@Cardiff.ac.uk (Y. Liu).

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product quality. However, the evaluation value of *CRs* and *PCs* were subjective and uncertain, and the causality relationships among the *FMs* of *PCs* were not considered. The design and manufacturing processes are closely related to each other in the product lifecycle, where failure information obtained by enterprises and customers, can be utilized to identify the risky components in the stage of product design.

To identify risky components for improving product quality, an improved *QFD* and *FMEA* approach is proposed in this article. The main advantages of the proposed method are concluded as follows: (1) an importance index of *PCs* is determined by *QFD*, and the *RPN* of *FM* between or within *PCs* is computed using causal relationship networks considering the reliability data; (2) the interactive relationships among FMs between and within *PCs* are characterized by the direct network.

In summary, an integrated *QFD* and *FMEA* approach is developed to identify risky components in this study. The remainder of this paper is organized as follows. In Section 2, a brief review of related literature is presented. Then, in Section 3, a new methodology for identifying the risky components is introduced. Section 4 presents a real-world case of the mechanical product to demonstrate the effectiveness of the proposed approach. Section 5 gives the comparative analysis. Section 6 concludes.

2. Literature review

To ensure and improve product quality, an organization must follow specific practices during the product design process. For example, acquiring *CRs* and identifying risky components in existing products. Customers tend to evaluate the functions of products and describe their defects from users' perspectives [16,17]. Moreover, designers tend to acquire the *CRs* and failure information of products from product operation data. These evaluations, descriptions, and acquisitions of *CRs* and failure risk information are more reliable than interviews and brainstorming.

2.1. Acquiring and mapping of CRs

The typical methods for acquiring *CRs* include brainstorming, interviews, market surveys, and online reviews [5,17]. As a fundamental step for identifying risky components in product design, mapping the *CRs* has been studied for many years [15–17]. Zhou et al. (2013) proposed an affective and cognitive design perspective to satisfy the latent needs of customers [18]. Wu and Liao (2021) introduced a modified *QFD* framework to solve complex customer-oriented design problems regarding uncertain information on *CRs*, design requirements (*DRs*), and alternative performances [19]. Gangurde and Akarte (2013) proposed a multi-criteria decision making approach to evaluate product design alternatives in respect to the *CRs* [20]. Li et al. (2006) developed a redesign approach to resolve the conflicts between *CRs* and component capability [21]. Bovea and Wang (2007) introduced a redesign approach to incorporate environmental requirements into the product development process [22]. Du and Liu (2021) introduced a novel approach to relative importance ratings of customer requirements in *QFD* based on probabilistic linguistic preferences [23]. Wu and Liao (2021) presented a novel *QFD* framework with complex linguistic evaluations for customer-oriented product and service design [19]. Dong et al. (2022) proposed a complex network-based response method for changes in *CRs* for design processes of complex mechanical products [24]. Wang et al. (2022) presented a novel fuzzy *QFD* considering both the correlations of *CRs* and the ranking uncertainty of technical attributes [25].

In their study, *QFD* was employed to map the *CRs* to *PCs*. The shortcomings of their studies are summarized as follows: 1) Most of the research cases focus on product design and service design, which are analysis the personalization needs of customers through *QFD*. 2) The input data is mostly a qualitative semantic evaluation, which has a direct impact on the outcome of the decision based on the extremes values. 3) The universality of those methods needs to be improved, for example, for complex construction machinery products, simple *QFD* mapping cannot translate *CRs* to *PCs*.

According to the methods discussed above, the application of traditional *QFD* is limited by qualitative evaluation from designers, and the results are somewhat subjective. The proposed method in this paper mainly focuses on *CRs* to translate risky components in the design process that is critical for improving product quality.

2.2. Identifying and analysis of failure risk information

When failure information is mapped to design knowledge, the risky components are identified and product design is implemented by *FMEA* [10].

In this research area, Zhang and Chu (2010) proposed an approach for supporting the product conceptual design by combining FMEA [26]. Liu et al. (2016) introduced a new FMEA model based on a fuzzy digraph and matrix approach [27]. In the meantime, Liu et al. (2016) presented the critical *RFs* of product design through mutual assessments and investigations using a novel *FMEA* [28]. Aguirre et al. (2021) revealed an integrated *FMEA* method to identify key risks [29]. Zheng et al. (2021) proposed a novel approach named product defect identification and analysis model with the *FMEA* [30]. Yucesan et al. (2021) presented a holistic *FMEA* approach by fuzzy-based Bayesian network and best-worst method to deal with uncertain failure data including subjective evaluations of experts [31]. Yener et al. (2021) proposed a *FMEA* based novel intuitionistic fuzzy approach proposal to integrate the intuitionistic fuzzy advance decision-making and mathematical model [32]. Ouyang et al. (2021) proposed an information fusion *FMEA* method to assess the risk of healthcare waste [33]. Lian et al. (2022) proposed an integrated approach for *FMEA* based on weight of risk factors and fuzzy PROMETHEE II to identify the *FMs* [34] Lian et al. presented an integrating method to deal with the reliability analysis and *FMEA* information in the design parameter evaluation process based on TOPSIS and PROMETHEE II [35]. Wu et al. (2021) introduced the literature review and prospect of the development and application of *FMEA* in manufacturing industry [36].

In their study, *FMEA* was employed to evaluate the *FMs* of products. The shortcomings of their studies are summarized as follows: 1) Most of the studies focus on risk evaluation of product, which are derived by *FMEA* under fuzzy semantic environment. 2) The importance and coupling relationship of risk factors are not considered. At the same time, the causal relationship of *FMs* has not been studied in-depth.

According to the methods discussed above, the studies of traditional *FMEA* emphasize the subjective human intervention during risk factors assessment. The proposed method in this paper mainly focuses on integrating risk factors and identifying causal relationship of *FMs* in the product design process, which consider the failure information that is critical for improving product quality.

2.3. A brief summary

The data of *CRs* are applied in design through *QFD*, while the data of product quality are applied in design through *FMEA*. However, the conventional acquiring methods of *CRs* and identification of risky components for product design are result-dependent, leading to difficulties in determining hidden *CRs* and in implementing and identifying risky components of the design procedure. The manufacturing data can provide reliable results for product design. Hence, an integrated approach with objectivity and subjectivity data source from designers, customers, and the manufacturing process needs to be explored for product quality. The main contributions of this study are as follows:

(1) Based on the theory of triangular fuzzy number (*TFN*), a two-stage fuzzy *QFD* (*FQFD*) for converting the *CRs* to *DRs* and *PCs* is applied to reduce the ambiguity and uncertainty of the mapping procedure to calculate the importance index of *PCs*.

(2) A nonlinear programming model is constructed to calculate the weight of *RFs* of *FMs* to calculate the weighted *RPN*. By considering the

FCRs between and within *PCs*, a directed network model is constructed to obtain the failure index of product components.

(3) An index of design risk component (*DRC*) is proposed to model the risk degree of the product component considering the importance index and the failure index. And the *DRC* is used to identify risky components for quality improvement of an existing product.

3. The proposed approach

In this study, the *DRC* is proposed to represent the risk degree of components of an existing product considering the *DRs* and failure risk. The DRC is defined:

$$DRC = C^{W_c} + FI^{W_f} \tag{1}$$

where *C* represents the importance index of the *PC* determined by an improved *QFD* [5] based on *CRs*; FI denotes the failure index determined by failure risk information based on a direct network. The W_c and W_f are the weighting factors of *C* and *FI*, respectively ($W_c + W_f = 1$). The weighting factors of *C* and *FI* represent the importance of the components and they are used to decide whether a component needs design. They can be assigned by designers according to the design characteristics. For example, mechanical products, which are usually characterized by long operation life and good product quality, W_f is assigned a high value. Once the *DRC* of one component exceeds that of another, this component is identified for improvement.

The procedures for calculating *C* and *FI* are described in Sections 3.1 and 3.2, respectively. And the procedures for calculating FCR and identifying risky components are introduced in Section 3.3. The procedures framework of the proposed approach is depicted in Fig. 1, and the subsections can be described as follows:

Section 3.1: Analyze the importance indices to map the *CRs* to *DRs* and *PCs* determined by *QFD* and *TFN*. Section 3.2: Define the failure risk index determined by the *FMEA*, and calculate the weighted *RPN* with the interaction of factors *O*, *S*, and *D* under a nonlinear programming model. Section 3.3: Define the *FCRs* of FMs within or between *PCs* using the directed network, and calculate the values of the *IFE* and *EFE* of *PCs*. Section 4: A real-world case study of wheel loader based on *CRs* and *FCRs*. Different risky components of *PCs* can be identified by *DRC*. Section 5: Method comparison and sensitivity analysis of the proposed approach. Finally, the validity and feasibility of the proposed approach are verified by method comparison and sensitivity analysis.

3.1. Analyze C by QFD

(1) A two-stage *FQFD* is applied to calculate the importance index of *CRs* to *PCs*, as shown in Fig. 2. In this process, the *CRs* are mapped to calculate the *DRs*, which are then mapped to calculate the *C* measure of the *PCs*. In Fig. 2 (on the left side), e_i represents the importance score of *CRi*, where $\sum_{i=1}^{I} e_i = 1$ ($i = 1, 2, \ldots, I$). Generally, e_i is predetermined by designers based on engineering practice. w_h ($h = 1, 2, \ldots, H$) is the importance weight of the *h*th *DR*, which is calculated using Eq. (2).

$$\begin{cases} R'_{ih} = \dfrac{\sum_{t=1}^{H} (R'_{it} \bullet r'_{hH})}{\sum_{h=1}^{H} \sum_{t=1}^{H} (R'_{it} \bullet r'_{hH})} \\ w_h = \sum_{i=1}^{I} e_i \bullet R'_{ih} \end{cases} \tag{2}$$

In Eq. (2), R'_{ih} is the normalized relationship value of R_{ih} between the *i*th *CR* and the *h*th *DR* and is quantified using fuzzy linguistic terms. In Fig. 2 (on the right side), $\ddot{w}_h$ is the normalized importance weight of DR_h. C_j is the importance weight of the *j*th *PC* ($j = 1, 2, \ldots, J$), which is calculated using Eq. (3). In Eq. (3), R_{jh} represents the normalized relationship value between the *h*th *DR* and *j*th *PC*.

$$C_j = \frac{\sum_{j=1}^{J} (R_{jh} \bullet \ddot{w}_h)}{\sum_{j=1}^{J} \sum_{h=1}^{H} (R_{jh} \bullet \ddot{w}_h)} \tag{3}$$

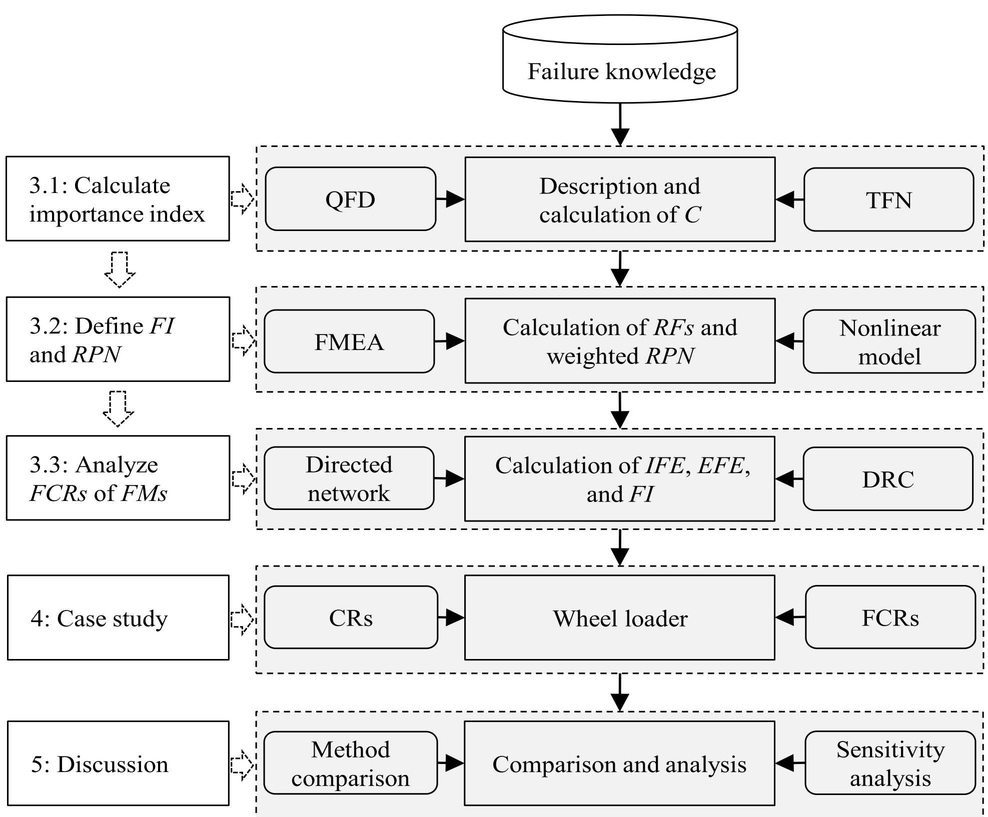

Fig. 1. Procedure framework of the proposed approach.

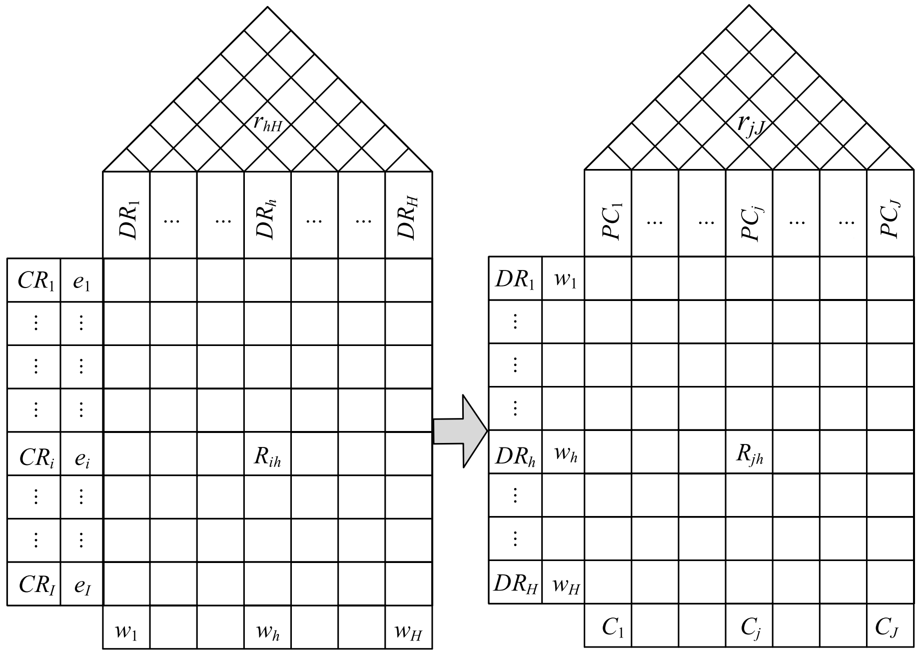

Fig. 2. Two-stage *FQFD* for *CRs* to *PCs*.

So far, the mapping relationships between *CRs* and *DRs*, as well as *DRs* and *PCs*, are determined. To reflect the imprecise nature semantics of the mapping relationships in Fig. 2, the interrelationship value of R_{ih} between the *i*th *CR* and the *h*th *DR* is quantified using a *TFN* [4], as presented in Table 1. The interrelationship value of R_{jh} between the *j*th *DR* and the *h*th *PC* is also quantified by linguistic terms.

The following is a detailed explanation of the *TFN*. A quadruple $\widetilde{\mathrm{m}} = (\mathrm{m}_1, \mathrm{m}_2, \mathrm{m}_3)$ is called a *TFN* and its membership function is:

$$u_{\widetilde{m}}(x) = \begin{cases} \dfrac{x - m_1}{m_2 - m_1}(m_1 \le x < m_2) \\ \dfrac{m_3 - x}{m_3 - m_2}(m_2 < x \le m_3) \\ 0(x < m_1 or x > m_3) \end{cases} \tag{4}$$

where $m_1 \le m_2 \le m_3$ are real numbers and reflect the fuzziness of the evaluation data. The closed interval $[m_2, m_3]$ is the mode of $\widetilde{m}$, while $m_1 and m_3$ are the lower and upper limits of $\widetilde{m}$, respectively. The distance [37] between two TFNs $\widetilde{m} = (m_1, m_2, m_3)$ and $\widetilde{n} = (n_1, n_2, n_3)$ is defined as follows

$$d(\widetilde{m},\widetilde{n}) = \sqrt{\frac{1}{3}\left[(m_1 - n_1)^2 + 2(m_2 - n_2)^2 + 2(m_3 - n_3)^2\right]} \tag{5}$$

Here, the mean value method of the TFN defuzzification process is given by

$$X = \frac{m_1 + m_2 + m_3}{3} \tag{6}$$

Table 1
Semantic terms and their *TFNs*.

Linguistic terms	TFNs
Very low (VL)	(0,1,2)
Low (L)	(1,2,3)
Medium (M)	(3,4,5)
High (H)	(5,6,7)
Very high (VH)	(7,8,9)

3.2. Calculate RPN by FMEA and nonlinear programming model

(1) Suppose a product has *J PCs*, in which each *PC* has various design parameter levels and is accompanied by different *FMs* (i.e., j_1, …, j_2, …, j_v). In the conventional methods for calculating the *DRC* of *PCs*, the *FCRs* between or within the *FMs* of *PCs* are usually ignored. In this study, the *DRC* is considered an important index determined by the *FMEA* considering the *FCRs*. The *FCRs* can be divided into *FMs* of the same *PC* and different *PCs*. Therefore, the *FI* is defined as follows [4]:

$$FI = IFE + EFE \tag{7}$$

where the *IFE* is the index of the internal failure effect corresponding to the *FCRs* within *FMs* of the same *PC*, and *EFE* is the index of the external failure effect corresponding to the *FCRs* among *FMs* of different *PCs*.

To model the *FCRs* within/among *FMs*, a directed network can be described using the graph theory as $G = (V, E)$. For a graph $G = (V, E)$ with two sets, *V* and *E* are the vertex and edge of *G*, respectively. Here, a vertex represents an *FM*, and a directed edge represents the *FCRs* between *FMs*. For example, if FM_A may cause FM_B, a directed edge between the two vertices of FM_A and FM_B needs to be drawn. The two *FMs* can also act as both causes and effects. In this process, the bill of materials and design records of *FMs* in the failure knowledge repository is also used to build the directed network. The topology of the directed network [4] is shown in Fig. 3, where the rectangle represents a product, and the squares represent the *PCs*.

The dotted lines indicate that a *PC* may have many *FMs* with different design parameter levels (failure relationship). In Fig. 3 (the upper *FMs* are not included), the *FCRs* among *FMs* are divided into two types, that is, *IFE* and *EFE*, which are described using the directed solid curves with solid arrows and the directed solid curves with hollow arrows, respectively. The directed edge represents the causality relationship between *FMs*, and the weight of the edge denotes the strength of this relationship. Usually, the assessment of the weight of the causality relationship is subjective and qualitatively described in natural language. Therefore, *TFNs* are used to describe the *FCRs* to reflect this imprecise nature.

(2) For the topology of the directed network, the *RPN* is determined to calculate the result of each FM_{jv}, as shown in Eq. (19). With the help of a failure knowledge repository, the *RFs* of severity (*S*), occurrence (*O*), and detection (*D*) in the FMEA can be obtained from Tables 2 to 4.

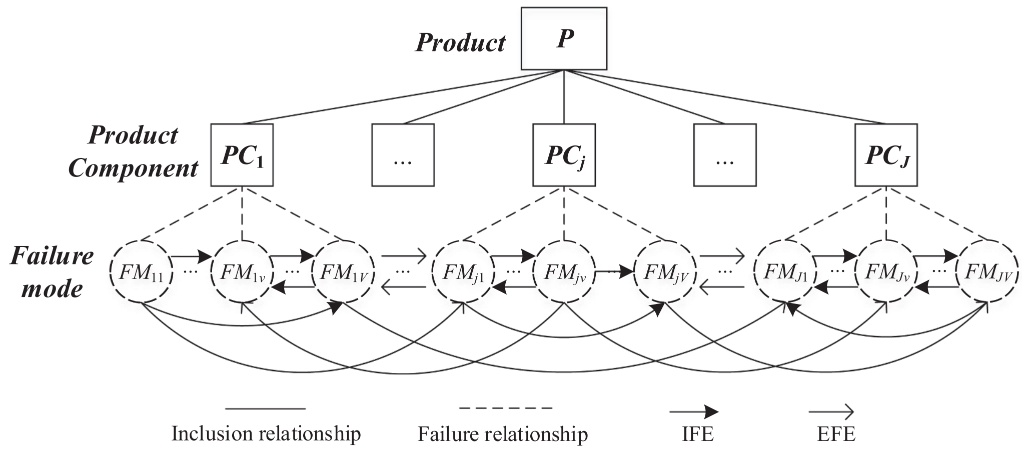

Fig. 3. Topology of the directed network for *PCs* with *FMs.*

Table 2
Description of severity (*S*).

Rating	Description
VH	Weakening of secondary functions.
H	Appearance, noise, etc. do not meet requirements and are perceived by customers (>75%).
M	Appearance, noise, etc., do not meet the requirements and are perceived by many customers (50%).
L	Appearance, noise, etc. do not meet the requirements and are perceived by discerning customers (<25%).
VL	There is no discernible effect.

Table 3
Description of occurrence (O).

Rating	The frequency of occurrence of causes within the reliability and life of the product.
VH	Similar designs (with reference objects), or occasional failures in design simulations and tests (≥1/500).
H	Similar designs (with reference objects), or individual failures in design simulations and tests (≥1/1000).
M	Nearly identical designs or only isolated failures during design simulations and tests (≧1/2000).
L	Almost identical designs or no failures observed during design simulations and tests (≤1/10000).
VL	Failures can be eliminated through preventive control (≦1/100000).

Table 4
Description of detection (*D*).

Rating	Evaluation criteria: the possibility of discovery by design control.
VH	Validation of products using passed/failed tests (reliability tests, development/validation tests) before design finalization.
H	Verify product through trial-to-failure test before final design (e.g., continue to test until leakage, bending, cracking, etc.).
M	Before the design is finalized, the product is verified and confirmed by instrument measurement and aging test.
L	The detection capability of design analysis/detection control is very strong, and virtual analysis (e.g., computer aided engineering, optical simulation.) is highly relevant to the desired actual operating conditions.
VL	Failure causes or failure modes will not occur through adequate prevention by design solutions, such as proven design standards, best practices, or common materials.

The rating scales of *S*, *O*, and *D* are converted into *TFNs* to reflect the imprecise nature of the subjective value, as indicated in Table 1. Meanwhile, the important weights of *S*, *O*, and *D* need to be obtained. According to the principle of similarity measure [38,39], the following steps are presented.

Step 1. The importance of the qualitative evaluation matrix *RF* is obtained using the linguistic variables listed in Table 1. Then, each factor RF_{jv}^{P} is translated into a *TFN* decision matrix as follows:

$$\left(\widetilde{RF}_j\right)_v^P = \begin{bmatrix} \widetilde{r}_1^P \\ \widetilde{r}_2^P \\ \vdots \\ \widetilde{r}_V^P \end{bmatrix} \tag{8}$$

where $\widetilde{r}_v^P = (m_1, m_2, m_3)$ is a normalized *TFN*, which denotes the FM_j for each factor $\left(\widetilde{RF}_j\right)_v^P$ ($j = 1, 2, \ldots, J$; $v = 1, 2, \ldots, V$; P=*S*, *O*, *D*).

Step 2. Based on the principle of ideal solutions [40], the fuzzy reference preferences of the best and worst *RFs* are defined as follows:

$$\left\{\left(\widetilde{\boldsymbol{B}}_j\right)_v = (\widetilde{b}_1, \widetilde{b}_2, \cdots, \widetilde{b}_V), \left(\widetilde{\boldsymbol{W}}_j\right)_v = (\widetilde{w}_1, \widetilde{w}_2, \cdots, \widetilde{w}_V)\right\} \tag{9}$$

where $b_v = (7, 8, 9, 10)$ denotes the fuzzy preference of the best *RFs* of *O*, *S*, and *D*. And $w_v = (0, 0, 1, 2)$ represents the fuzzy preference of the worst *RFs* of *O*, *S*, and *D*.

Step 3. Based on the principles of similarity measure [38,39], a nonlinear programming model is constructed to derive the weight of the *RFs*

$$\begin{cases} F = \left(Minf(\omega_v^{P+}), Maxf(\omega_v^{P-})\right) \\ s.t. \begin{cases} 0 < \omega_v^{P+}, \omega_v^{P-} < 1 \\ \sum_{P=1}^{3} \omega_v^{P+}, \omega_v^{P-} = 1 \\ 0 \leq d(\widetilde{r}_v^p, \widetilde{b}_v) \leq d(\widetilde{r}_v^p, \widetilde{w}_v) \leq 1 \end{cases} \end{cases} \tag{10}$$

Where $Minf(\omega_v^{P+}) = \sum_{v=1}^{V}\sum_{p=1}^{3}(\omega_v^{P+} d(\widetilde{r}_v^P, \widetilde{b}_v))^2$, $Maxf(\omega_v^{P-}) = \sum_{v=1}^{V}\sum_{p=1}^{3}(\omega_v^{P-} d(\widetilde{r}_v^P, \widetilde{w}_v))^2$, ω_v^{P+} and ω_v^{P-} represent the weights of the RF_{jv}^P with the best and worst *RFs* $\widetilde{B}_v$ and $\widetilde{W}_v$, respectively, while $d(\widetilde{r}_v^P, \widetilde{b}_v)$ and $d(\widetilde{r}_v^P, \widetilde{w}_v)$ are the Euclidean distances between $\left(\widetilde{RF}_j\right)_v^P$ and $\widetilde{B}_v$ as well as $\widetilde{W}_v$, respectively. Then, the comprehensive weights ω_j of factors

S, O, and D can be obtained:

$$\omega_v^P = 0.5^*(\omega_v^{P+} + \omega_v^{P-}) \tag{11}$$

According to $\omega_v^P = (\omega_v^1, \omega_v^2, \omega_v^3)$ of the S, O, and D factors, the RPN_v of each FM_{jv} for each PC_j is presented as follows:

$$RPN_v = S^{\omega_v^1} \bullet O^{\omega_v^2} \bullet D^{\omega_v^3} \tag{12}$$

3.3. Calculate FCR by directed network

(1) Based on the results of RPN, the RPN_v of FM_{jv} is regarded as the vertex of the directed network model. The IFE of one PC (as shown in Fig. 4) within the directed network model can be calculated using the following steps.

Step 1. Determine the preference function of FMs within the PC as follows

$$\boldsymbol{F}(\boldsymbol{PC}_j) = \begin{bmatrix} R_j^1 & \cdots & r_j^{1v} & \cdots & r_j^{1V} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_j^{v1} & \cdots & R_j^v & \cdots & r_j^{vV} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_j^{V1} & \cdots & r_j^{Vv} & \cdots & R_j^V \end{bmatrix} \tag{13}$$

According to $\boldsymbol{F}(\boldsymbol{PC}_j)$, modes F_i and F_t (i, t = 1, 2, …, v, …, V) are compared in pairs under different RPN_v. R_j^v represents the RPN of the vth FM of the jth PC, and r_j^{1v}, …, r_j^{1V} denote the fuzzy causality relationship strengths among FMs. The result is a preference function of one over the other and is given as the accuracy value of an RPN_v.

The comprehensive IFE for PC_j can then be calculated as follows:

$$IFE_j = \sum_{j=1}^{J} \sum_{v=1}^{vV} \sum_{v=1}^{V} r_j^{vV} \bullet R_j^V \tag{14}$$

where R_j^V is the $RPNs$ of the jth FM of PC_j.

(2) Similarly, the FMs among different PCs interact with each other. Conventionally, existing methods for DRC analysis do not consider the interactions of FMs between different PCs. To interpret the EFE of the FMs among PCs, a directed network model comprising any two PCs, that is, PC_j with F_j FMs and PC_h with F_h FMs, is illustrated in Fig. 5.

If the jth FM of PC_j leads to the hth FM of PC_h, directed solid curves with hollow arrows are drawn from FM node F_{jv} to FM node F_{hV} (denoted as r_{jh}^{vV}). To incorporate the $FCRs$ content among PCs into the design process, the information matrix of the EFE between PCs is built as follows:

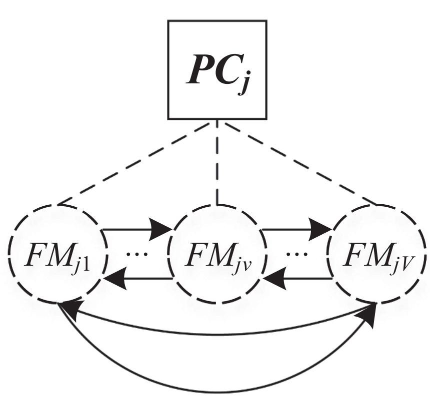

Fig. 4. Directed network for one PC with FMs.

$$\boldsymbol{F}(\boldsymbol{PC}_{jh}) = \begin{bmatrix} R_{jh}^1 & \cdots & r_{jh}^{1v} & \cdots & r_{jh}^{1V} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{jh}^{v1} & \cdots & R_{jh}^v & \cdots & r_{jh}^{vV} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{jh}^{V1} & \cdots & r_{jh}^{Vv} & \cdots & R_{jh}^V \end{bmatrix} \tag{15}$$

Then, the EFE_j of PC_j is defined as

$$EFE_j = \sum_{j=1, j\neq h}^{J} \sum_{j=1}^{jV} \sum_{h=1}^{hV} \sum_{v=1}^{V} r_{jh}^{vV} \bullet R_{jh}^v \tag{16}$$

where R_{jh}^v and R_{hj}^v are the $RPNs$ of the jth FM of PC_j and the hth FM of PC_h, respectively.

After defining and calculating the IFE and EFE of all PCs, the FI of each PC_j can be calculated. The normalized FI_j of each PC_j is calculated as follows:

$$FI_j = IFE_j + EFE_j \tag{17}$$

Now, we can calculate the normalized DRC_j of each PC_j, which is used to identify risky components of a product.

4. Case study

In this case study, the key techniques of the proposed method are implemented by engineering design data, and the proposed approach is used to identify risky components of the existing product to improve product quality. Large amounts of CRs and failure risk information were collected from the process of manufacturing and R&D to assist in the decision-making of product design.

A real-world case of a wheel loader is presented to demonstrate the effectiveness of the proposed approach. The data for this case study were collected from a mechanical manufacturing company located in the city of Xiamen, China. The company was planning to launch a series of quality renovations for the wheel loader to identify risky components for the next-generation wheel loader with high product quality to improve customer satisfaction. At the early design stage, the risky components must be identified because the given design tasks do not require changing all the components. Because the wheel loader is composed of system components, only the main PCs of the wheel loader were selected for identification of the risky components.

The essential PCs of the wheel loader are illustrated in Fig. 6, and the descriptions of the FMs of PCs summarized in Table 5 were collected mostly from the failure knowledge repository of the company.

4.1. Calculation of C and U

First, the subjective semantic terms were quantified to determine the importance of PC_j. By browsing the design repository of the wheel loader, the CRs include appearance and size, vibration noise, maintenance cost, mechanical power, environmental suitability, and life cycle, denoted as six CR_i (CR_1, CR_2, CR_3, CR_4, CR_5, and CR_6). The DRs include the degree of modularity, warning performance, power consumption, product reliability, three new technologies, and assembly time, symbolized as six DR_i (DR_1, DR_2, DR_3, DR_4, DR_5, and DR_6). According to the historical statistical data of the total customer orders, we calculate the weights of six CR_i using the weighted average method ($e_i = \frac{C_i}{\sum_{i=1}^{I} C_i} (i = 1, 2, \cdots, I)$), then the weights CR_i were presented as e_i = (0.1623, 0.1765, 0.2122, 0.1478, 0.1798, 0.1214). The mapping relationships between CR_i and DR_i, as well as DR_i and PC_j, based on a QFD are displayed in Fig. 7.

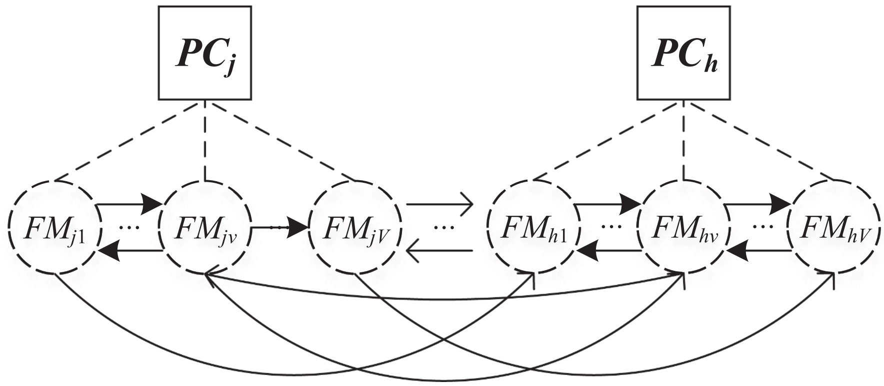

Fig. 5. Directed network for any two *PCs* with *FMs*.

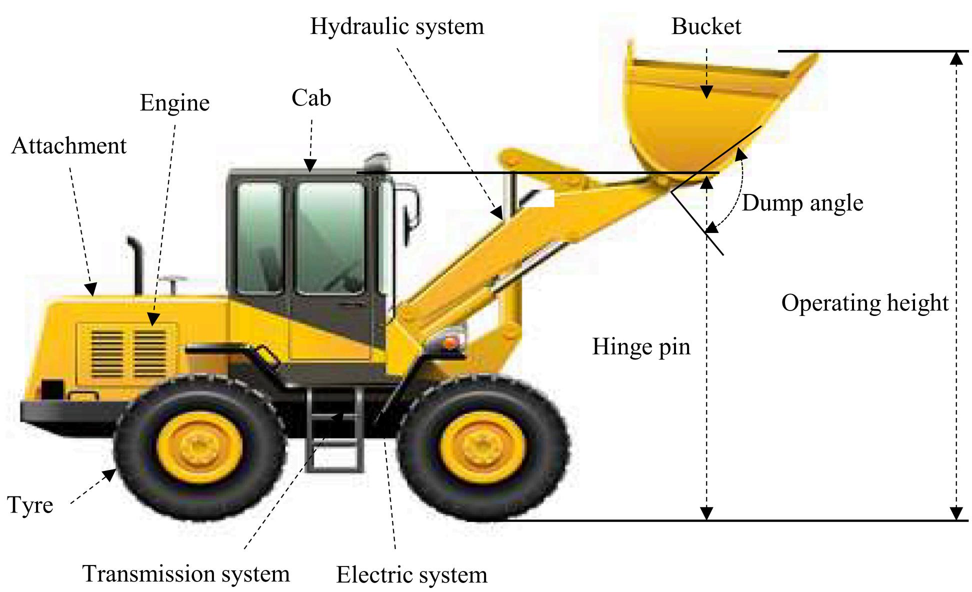

Fig. 6. The overall structure of the wheel loader.

Table 5
Description of *FMs* of risky *PCs*.

Risky *PCs*	Description of *FMs*
Attachment: PC_1	Attachment sound
Cab: PC_2	Cab deformation
Engine: PC_3	Engine noise
Electric system: PC_4	Abnormal Electric system
Hydraulic system: PC_5	Abnormal Electric system
Bucket: PC_6	Bucket tooth fracture
Transmission system: PC_7	Rotational bearing vibration
Hinge pin: PC_8	Hinge pin sound
Operating height: PC_9	Rising slowly
Dump angle: PC_{10}	Dump Angle is too large

The designers' semantic evaluation was quantified according to Table 1. According to Eqs. (1) and (2), the weights of the DR_i were set as $w_h = 0.1832$, 0.1711, 0.1528, 0.1756, 0.1925, and 0.1248, respectively. According to Eq. (3), the subjective importance values of PC_j were $C_j =$ 0.0825, 0.0821, 0.0926, 0.1183, 0.1178, 0.09631, 0.0972, 0.1125, 0.1001, and 0.1013, respectively. Thus, the importance index of the semantic evaluation was determined.

4.2. Calculation of weighted RPN of FMs

Using the failure information repository from the manufacturing process, the factors *S*, *O*, and *D* were obtained from Tables 2 to 4, and their historical evaluation data are provided in Table 7.

The rating scale of *S*, *O*, and *D* was converted to *TFN* to reflect the imprecise nature of the subjective value according to Table 1. Then, the importance weights of *S*, *O*, and *D*, as well as the *RPN* of each *FM* were calculated based on Eqs. (8)–(12). Where the $Lingo^R$ 11 *Software* was used to calculated the weights ω_j of factors *S*, *O*, and *D*. The weights of factors *S*, *O*, and *D*, as well as the normalized *RPN* (*n-RPN*) were shown in Table 8.

4.3. Identification of FI and DRC

According to Eq. (7), the *FCRs* among the *FMs* of *PCs* were constructed, where the *FCRs* was divided into *IFE* and *EFE*. To save space, only PC_7 is shown in the calculation processes, tables, and figures.

(1) In the directed network model of *PCs*, the *IFE* of PC_7 is illustrated in Fig. 8. Based on the *RPN* of *FMs* in one *PC*, the comprehensive *IFE* of PC_7 was obtained based on Eqs. (13) and (14), as listed in Table 9.

(2) In the directed network model of *PCs*, the related *EFE* of PC_7 is displayed in Fig. 9. Based on the *RPNs* of the *FMs* of *PCs*, the *EFE* of PC_7 was obtained based on Eqs. (15) and (16), as presented in Table 9.

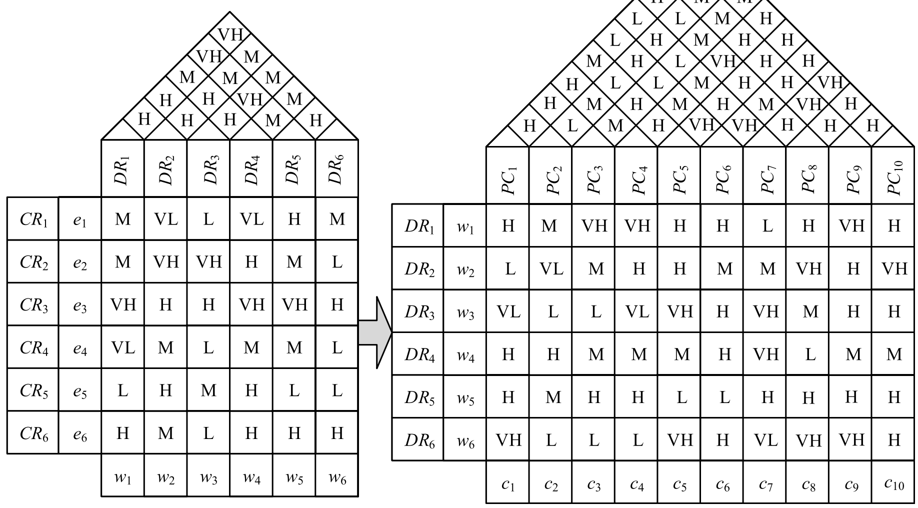

Fig. 7. Mapping relationships of *CR* to *PC*.

Table 7
Description of *RFs* of *FMs*.

PCs	FM_{jv}	*S*	*O*	*D*
PC_1	FM_{11}	H	V	H
PC_2	FM_{21}	VH	M	M
PC_3	FM_{31}	M	L	H
PC_4	FM_{41}	M	H	L
	FM_{42}	H	M	L
…	…	…	…	…
PC_{10}	FM_{101}	VH	H	VL
	FM_{102}	H	L	VL
	FM_{103}	M	H	H
	FM_{104}	H	L	M
	FM_{105}	H	H	VL
	FM_{106}	VH	L	M

Table 8
Weights of *RFs* and normalized *RPNs* of *FMs*.

FM_{jv}	w^S	w^O	w^D	*n-RPN*
FM_{11}	0.5799	0.2104	0.5799	0.0605
FM_{21}	0.7165	0.3269	0.3269	0.0591
FM_{31}	0.3747	0.3747	0.6209	0.0445
FM_{41}	0.3747	0.4978	0.4978	0.0426
FM_{42}	0.3747	0.4978	0.4978	0.0431
…	…	…	…	…
FM_{101}	0.5956	0.3506	0.4241	0.043
FM_{102}	0.5956	0.3506	0.4241	0.0409
FM_{103}	0.5956	0.3506	0.4241	0.0389
FM_{104}	0.5956	0.3506	0.4241	0.0419
FM_{105}	0.5956	0.3506	0.4241	0.043
FM_{106}	0.5956	0.3506	0.4241	0.0417

Finally, the normalized FI_j of PC_7 was obtained based on Eq. (17), as listed in Table 9.

Similarly, the FI_j values of the other *PCs* are presented in Table 9. Here, the weights of *C* and *FI* are specified as $(W_c, W_f) = (0.5, 0.5)$. Finally, the *DRCs* of all *PCs* were calculated based on Eq. (1), as listed in Table 10. The rank of *PCs* according to the *DRCs* is presented in Table 10. These different results with different weights and methods are discussed further in Sections 5.1 to 5.3.

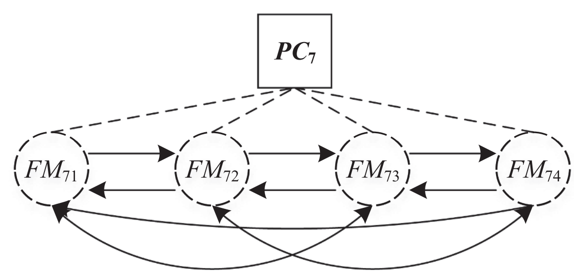

Fig. 8. *FCRs* for the *IFE* of PC7 with *FMs* in one *PC*.

5. Comparison study and sensitivity analysis

To verify the shortcomings of the traditional method, the robustness of the proposed method, and the accuracy of the proposed method, an in-depth discussion is carried out. So, the comparison study and sensitivity analysis were conducted to demonstrate the superiority of the proposed approach.

5.1. Comparison indices between DRC, C, and FI

The ranking results of risky components of the three design indices [4] among *C*, *FI*, and *DRC* are presented in Fig. 10. Some observations on the ranking results are summarized:

(1) PC_9 has the highest ranking among all *PCs* based on design indices *DRC*, *FI*, *U*, and *C*. The rankings with respect to *DRC*, *FI*, and *C* are $PC_9 > PC_{10} > PC_5 > PC_7 > PC_6 > PC_8 > PC_4 > PC_2 > PC_1 > PC_3$; $PC_9 > PC_{10} > PC_7 > PC_5 > PC_6 > PC_8 > PC_4 > PC_2 > PC_3 > PC_1$; and $PC_9 > PC_{10} > PC_4 > PC_5 > PC_7 > PC_8 > PC_6 > PC_1 > PC_3 > PC_2$, respectively. Based on the three design indices, except for PC_9 and PC_{10}, the rankings of the other *PCs* are different. The main reason for this is that different methods have different computational emphases with evaluation preferences in terms of extremum data and weights of attributes.

(2) The variation tendency of the ranking results of the three design indices is clear: the fluctuations of the design indices *C* among *PCs* are not obvious; therefore, it is difficult for decision makers to prioritize the risky *PCs*. In contrast, *DRC* and *FI* can satisfactorily depict the priorities of risky *PCs*.

Table 9
Values of the *FI*, *EFE*, and *IFE* for each *PC*.

Index	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7	PC_8	PC_9	PC_{10}
IFE_j	0.0255	0.0273	0.0257	0.0302	0.0302	0.0337	0.0354	0.0326	0.0355	0.0418
EFE_j	0.0447	0.0615	0.0466	0.0883	0.1527	0.1203	0.1532	0.1101	0.2442	0.2093
FI_j	0.0702	0.0888	0.0723	0.1185	0.1829	0.154	0.1886	0.1427	0.2797	0.2511

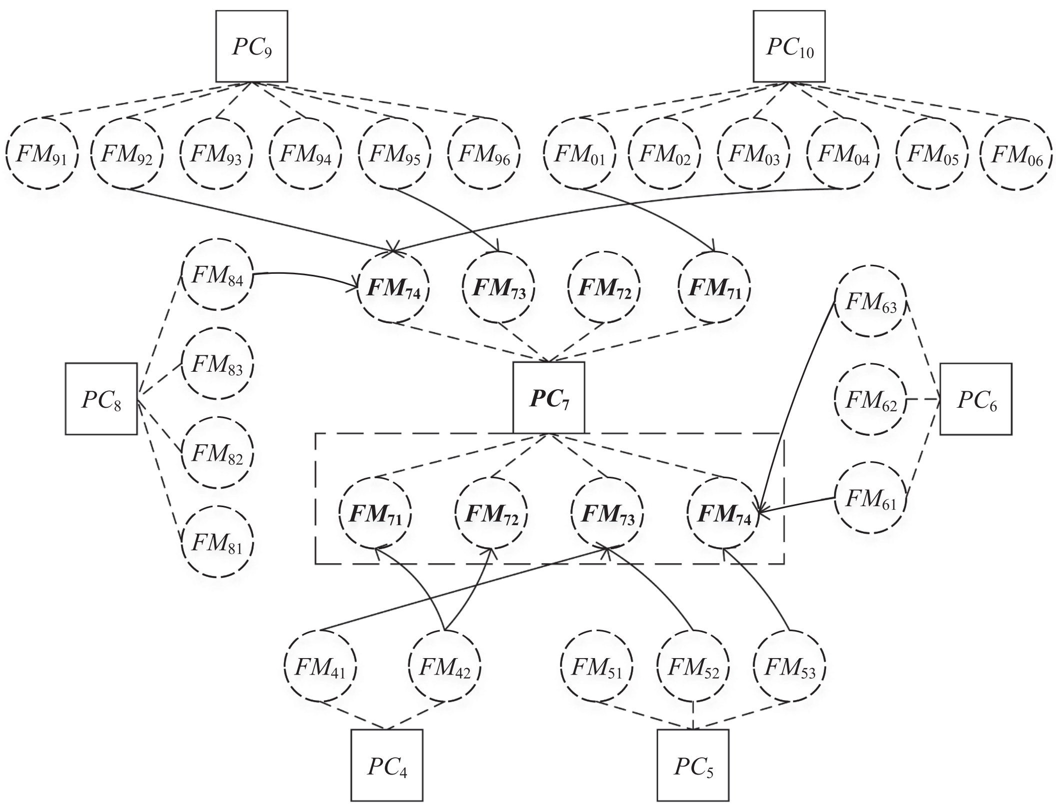

Fig. 9. *FCRs* for the *EFE* of *PC7* with the *FMs* among *PCs*.

Table 10
Values of *DRCs* and rank of *PCs*.

Index	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7	PC_8	PC_9	PC_{10}
C_j	0.0825	0.0821	0.0926	0.1183	0.1178	0.09631	0.0972	0.1125	0.1001	0.1013
FI_j	0.0702	0.0888	0.0723	0.1185	0.1829	0.154	0.1886	0.1427	0.2797	0.2511
DRC_j	0.5639	0.5962	0.5637	0.6831	0.7919	0.7242	0.7794	0.7233	0.9350	0.8759
Ranking	9	8	10	7	3	5	4	6	1	2

5.2. Comparison between different methods

The conventional *QFD* method [4,13] was employed to identify the risky components *PCs* for the comparative study. The results based on *QFD*, *C*, and *DRC* are listed in Table 11. The rankings with respect to *QFD*, *C*, and *DRC* are $PC_9 > PC_{10} > PC_4 > PC_5 > PC_7 > PC_8 > PC_6 > PC_1 > PC_3 > PC_2$, $PC_9 > PC_{10} > PC_5 > PC_7 > PC_6 > PC_8 > PC_4 > PC_2 > PC_3 > PC_1$; and $PC_9 > PC_{10} > PC_5 > PC_7 > PC_6 > PC_8 > PC_4 > PC_2 > PC_1 > PC_3$, respectively. According to the actual project, PC_9 and PC_{10} are the main risk components. Some differences exist between the results achieved based on *QFD*, *C*, and *DRC*: (1) the rank of PC_4 dropped from the third for *QFD* to the seventh for *DRC* and *C*; (2) the rank of PC_5 jumped from the fourth for *QFD* to the third for *DRC* and *C*; (3) the rank of PC_7 jumped from the fifth for *QFD* to the fourth for *DRC* and *C*.

There are two reasons for the above ranking differences. The first is that the *QFD* considers the preferences of designers and customers without the *FCRs* of the *FMs* of *PCs*. The second is the subjective semantic term from designers without the objective attention data from quality tests. It is noteworthy that the proposed approach can degenerate into one of the above methods or more general indices when the data are insufficient or unavailable. For instance, if the test data are unavailable, the *FCRs* data among *FMs* and interaction data among *RFs* are insufficient.

5.3. Sensitivity analysis for Wc and Wf

In determining the *DRCs* of *PCs*, the weights of *C* and *FI* are predetermined by the designer based on experience. Different designers may have different preferences for the weights of the three indices, which may affect the final ranking result.

To verify the robustness of the proposed approach, a sensitivity analysis was performed by changing the values of W_c and W_f, where $W_c + W_f = 1$. The influence of W_c and W_f on the *DRC* calculation is depicted in Fig. 11. With the changes in W_f, the rank of the *DRCs* of *PCs* fluctuates

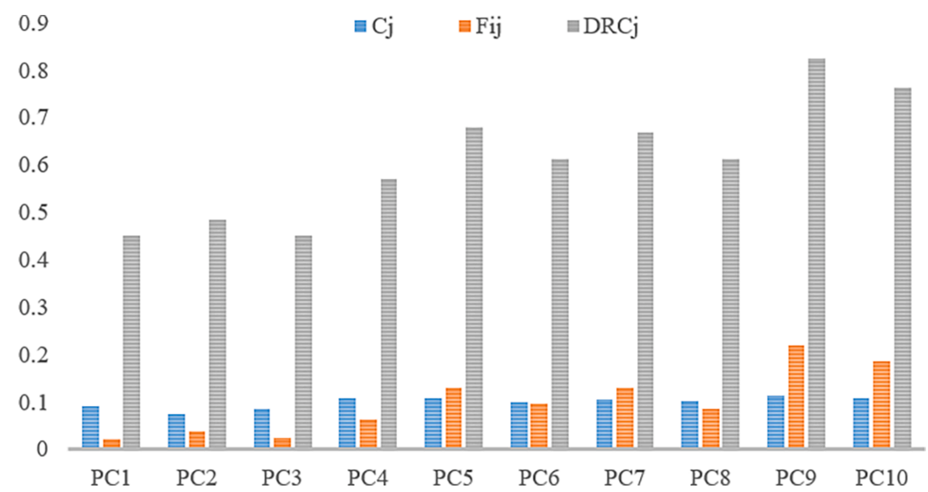

Fig. 10. Comparisons among the ranking results of the four design indices.

Table 11
Comparison between QFD, C•U, and DRC.

Index	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7	PC_8	PC_9	PC_{10}
QFD	0.1017	0.0862	0.0959	0.1194	0.1189	0.1108	0.1181	0.1151	**0.1253**	0.1198
C	0.4696	0.5174	0.4726	0.5834	0.6902	0.6321	0.6842	0.6233	**0.8048**	0.7756
DRC	0.5639	0.5962	0.5637	0.6831	0.7919	0.7242	0.7794	0.7233	**0.9350**	0.8759

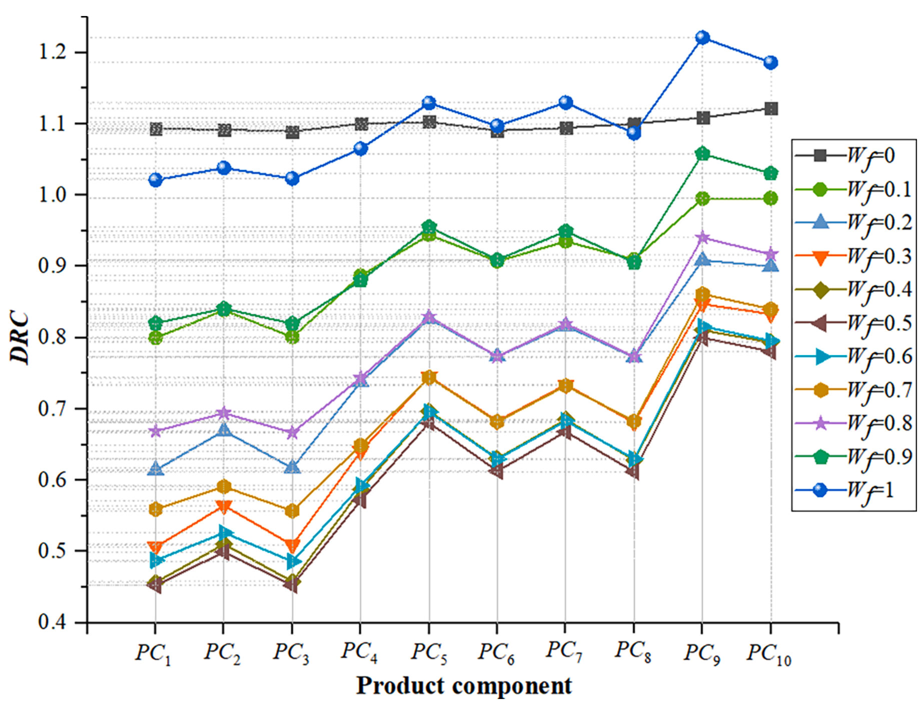

Fig. 11. Ranking of risky *PCs* with changes in weights.

stably. When $W_f = 0.5$, the rank is the same as that of the *DRC* in Fig. 10. When $W_f = 0$, the rank of the *DRC* is indistinguishable. Overall, the influence of the weights on the rank is insignificant. However, the *DRCs* for all *PCs* gradually increase with changes in W_f (compared to $W_f = 0.5$). Furthermore, a larger W_f means that the designers pay more attention to the *DRC* to improve the reliability of product quality.

In the collaborative project, PC_9 and PC_{10} as the risk components for improving product quality, are selected to support the redesign (conceptual design and parameter design) effectively, trial manufacturing, operating conditions configuration and transportation of a new product with operating height and dump angle. It confirms the rationality of the identification result from the viewpoint of engineering perspective. Quickly and accurately identify risky components, which provides decision support for the company's research and development direction, saving product development time cycle and potential costs.

6. Conclusions

The failure risk information collected *FCRs* between or among failure models should be considered as inputs to the product design. In this paper, the failure data and *CR* information were integrated to identify risky components based on an integrated *QFD* and *FMEA* approach. The main highlights of this study are as follows:

(1) A systematic approach for identifying risky components is proposed by integrating the *QFD* and FMEA considering the subjective and objective data. Based on the *TFN*, a *QFD* for converting the *CRs* to *PCs* is applied to reduce the uncertainty of decision-making.

(2) A nonlinear programming model is constructed to calculate the weights of *RFs* of *FMs*, and then to calculate the weighted *RPN* based on historical failure risk data. By considering the *FCRs* between or within *PCs*, a directed network model is constructed to obtain the *FI* of *PCs*, which is divided into *IFE* and *EFE*. The values of *IFE* and *EFE* are obtained.

From the case study of identifying risky components, the proposed approach demonstrated its validity and feasibility in dealing with the design process of the wheel loader. By comparison with other methods, the most serious risk component (PC_9) obtained are consistent, indicating the effectiveness of the proposed method. Through sensitivity analysis, the proposed method can stably identify the risk components (PC_9 and PC_{10}), which indicate that the robustness of the proposed method is better. Several research directions need to be explored in the future: *CRs* can be integrated into the *FMEA* by constructing a selection model. The proposed framework can be further improved by considering more data on the wheel loader based on new technologies, for example, the multiple-view algorithm can be used to implement the product design.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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References

[1] J. Wang, R. Li, G. Ding, et al., Product-service system engineering characteristics design for life cycle cost based on constraint satisfaction problem and Bayesian network, Adv. Eng. Inf. 52 (2022), 101573.
[2] L. Zhang, X. Chu, D. Xue, Identification of the to-be-improved product features based on online reviews for product redesign, Int. J. Prod. Res. 57 (2019) 2464–2479.
[3] S. Smith, G. Smith, Y.T. Shen, Redesign for product innovation, Des. Stud. 33 (2012) 160–184.
[4] H. Ma, X. Chu, D. Xue, D. Chen, Identification of to-be-improved components for redesign of complex products and systems based on fuzzy QFD and FMEA, J. Intell. Manuf. 30 (2019) 623–639.
[5] J. Zhou, Y. Liu, T. Xiahou, T. Huang, A novel fmea-based approach to risk analysis of product design using extended Choquet integral, IEEE Trans. Reliab. 2017 (2021) 1–5.
[6] J.H. Shin, D. Kiritsis, P. Xirouchakis, Design modification supporting method based on product usage data in closed-loop PLM, Int. J. Comput. Integr. Manuf. 28 (2015) 551–568.
[7] F. Geyer, J. Lehnen, C. Herstatt, Customer need identification methods in new product development: What works "best"? Int. J. Innov. Technol. Manage. 15 (1) (2018) 1850008.
[8] S. Li, D. Tang, J. Yang, et al., A novel approach for capturing and evaluating dynamic consumer requirements in open design, Adv. Eng. Inf. 39 (2019) 95–111.
[9] H.R. Fazeli, Q. Peng, Integrated approaches of BWM-QFD and FUCOM-QFD for improving weighting solution of design matrix, J. Intell. Manuf. (2021) 1–18.
[10] M. Yucesan, M. Gul, Failure modes and effects analysis based on neutrosophic analytic hierarchy process: method and application, Soft. Comput. 25 (2021) 11035–11052.
[11] L. Jing, J. Yao, F. Gao, et al., A rough set-based interval-valued intuitionistic fuzzy conceptual design decision approach with considering diverse customer preference distribution, Adv. Eng. Inf. 48 (2021), 101284.
[12] G.N. Zhu, J. Ma, J. Hu, A fuzzy rough number extended AHP and VIKOR for failure mode and effects analysis under uncertainty, Adv. Eng. Inf. 51 (2022), 101454.
[13] S.H. Chen, Determining the service demands of an aging population by integrating QFD and FMEA method, Qual. Quant. 50 (2016) 283–298.
[14] D. Liang, F. Li, Risk assessment in failure mode and effect analysis: improved oreste method with hesitant Pythagorean fuzzy information, IEEE Trans. Eng. Manage. (2021), https://doi.org/10.1109/TEM.2021.3073373.
[15] Q. Xu, R.J. Jiao, X. Yang, M. Helander, H.M. Khalid, A. Opperud, An analytical Kano model for customer need analysis, Des. Stud. 30 (2009) 87–110.
[16] S. Smith, G.C. Smith, Y.R. Chen, A KE-LSA approach for user-centered design, J. Intell. Manuf. 24 (2013) 919–933.
[17] R. Mu, Y. Zheng, K. Zhang, Y. Zhang, Research on customer satisfaction based on multidimensional analysis, Int. J. Comput. Intell. Syst. 14 (2021) 605–616.
[18] F. Zhou, Y. Ji, R.J. Jiao, Affective and cognitive design for mass personalization: status and prospect, J. Intell. Manuf. 24 (2013) 1047–1069.
[19] X. Wu, H. Liao, Customer-oriented product and service design by a novel quality function deployment framework with complex linguistic evaluations, Inf. Process. Manage. 58 (2) (2021), 102469.
[20] S.R. Gangurde, M.M. Akarte, Customer preference oriented product design using AHP-modified TOPSIS approach. Benchmarking: Int. J., (2013) 10.1108/BIJ-08-2011-0058.
[21] Z.S. Li, F.H. Kou, X.C. Cheng, T. Wang, Model-based product redesign, Ijcsns 6 (2006) 100–108.
[22] M.D. Bovea, B. Wang, Redesign methodology for developing environmentally conscious products, Int. J. Prod. Res. 45 (2007) 4057–4072.
[23] Y. Du, D. Liu, A novel approach to relative importance ratings of customer requirements in QFD based on probabilistic linguistic preferences, Fuzzy Optim. Decis. Making 20 (3) (2021) 365–395.
[24] C. Dong, Y. Yang, Q. Chen, Z. Wu, A complex network-based response method for changes in customer requirements for design processes of complex mechanical products, Expert Syst. Appl. 199 (2022), 117124.
[25] L. Wang, Y.u. Liying, Z. Ni, A novel IVIF QFD considering both the correlations of customer requirements and the ranking uncertainty of technical attributes, Soft. Comput. 26 (9) (2022) 4199–4213.
[26] Z. Zhang, X. Chu, Risk prioritization in failure mode and effects analysis under uncertainty, Expert Syst. Appl. 38 (2011) 206–214.
[27] H.C. Liu, Y.Z. Chen, J.X. You, H. Li, Risk evaluation in failure mode and effects analysis using fuzzy digraph and matrix approach, J. Intell. Manuf. 27 (2016) 805–816.
[28] S.F. Liu, J.H. Cheng, Y.L. Lee, F.R. Gau, A case study on FMEA-based quality improvement of packaging designs in the TFT-LCD industry, Total Quality Manage. Busin. Excellence 27 (2016) 413–431.
[29] P.A. Aguirre García, L. Perez-Dominguez, D. Luviano-Cruz, J.J. Solano Noriega, E. Martinez Gomez, M. Callejas-Cuervo, PFDA-FMEA, an integrated method improving FMEA assessment in product design, Appl. Sci. 11 (4) (2021) 1406.
[30] L. Zheng, Z. He, S. He, An integrated probabilistic graphic model and FMEA approach to identify product defects from social media data, Expert Syst. Appl. 178 (2021), 115030.
[31] M. Yucesan, M. Gul, E. Celik, A holistic FMEA approach by fuzzy-based Bayesian network and best–worst method, Complex Intell. Syst. 7 (3) (2021) 1547–1564.
[32] Y. Yener, G.F. Can, A FMEA based novel intuitionistic fuzzy approach proposal: Intuitionistic fuzzy advance MCDM and mathematical modeling integration, Expert Syst. Appl. 183 (2021), 115413.
[33] L. Ouyang, et al., An information fusion FMEA method to assess the risk of healthcare waste, J. Manage. Sci. Eng. 6 (1) (2021) 111–124.
[34] X. Lian, et al., An Integrated Approach for Failure Mode and Effects Analysis Based on Weight of Risk Factors and Fuzzy PROMETHEE II, Symmetry 14 (6) (2022) 1196.
[35] X.Z. Lian, L. Hou, et al., Selection method of design scheme for LCD products based on RA and DFMEA, Comput. Integr. Manuf. Syst. (2022) 1–22. http://kns.cnki.net/kcms/detail/11.5946.TP.20220725.1912.006.html.
[36] Z. Wu, W. Liu, W. Nie, Literature review and prospect of the development and application of FMEA in manufacturing industry, Int. J. Adv. Manuf. Technol. 112 (5) (2021) 1409–1436.
[37] S.P. Wan, J.Y. Dong, Interval-valued intuitionistic fuzzy mathematical programming method for hybrid multi-criteria group decision making with interval-valued intuitionistic fuzzy truth degrees, Inform. Fusion 26 (2015) 49–65.
[38] G. Selvachandran, H. Garg, M.H.S. Alaroud, A.R. Salleh, Similarity measure of complex vague soft sets and its application to pattern recognition, Int. J. Fuzzy Syst. 20 (2018) 1901–1914.
[39] R. Chutia, M.K. Gogoi, Fuzzy risk analysis in poultry farming based on a novel similarity measure of fuzzy numbers, Appl. Soft Comput. 66 (2018) 60–76.
[40] Z.p. Tian, J.q. Wang, H.y. Zhang, An integrated approach for failure mode and effects analysis based on fuzzy best-worst, relative entropy, and VIKOR methods, Appl. Soft Comput., 72 (2018) 636–646.