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A new MCDM method combining QFD with TOPSIS for knowledge management system selection from the user's perspective in intuitionistic fuzzy environment

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ABSTRACT

Knowledge management system (KMS) is crucial for organization knowledge management. In order to help the evaluation and selection of KMS from the user's perspective, a new multiple criteria decision making (MCDM) method combining quality function deployment (QFD) with technique for order preference by similarity to an ideal solution (TOPSIS) in intuitionistic fuzzy environment is proposed. In the method, the customer criteria and system criteria for KMS selection are required. These two kinds of criteria are established from the user's perspective and the designer's perspective respectively. Customers give their linguistic opinions about the importance of the customer criteria and the rating of alternatives with respect to the customer criterion. Analysts give their linguistic opinions about the relationship between the customer criteria and the system criteria, and the correlation between the system criteria. After the aggregation of linguistic opinions in intuitionistic fuzzy environment, the customers' opinions are transformed into the rating of the weight of system criteria and rating of the alternatives concerning the system criteria by the QFD. Afterwards the alternatives are ranked according to system criteria by TOPSIS method in intuitionistic fuzzy environment and the best alternative is determined. In the end an example is provided to illustrate the applicability of the proposed method.

1. Introduction

Knowledge management system (KMS) refers to the computer information system employed to better retain and utilize organizational knowledge, as well as support knowledge utilization within and between organizations [1,2]. Organizations are devoting considerable resources to implement KMS to assist knowledge management. However, customer requirements for the KMS are various in organizations [1,3–7], many of such investments end in less than desirable outcomes possibly due to a mismatch between the KMS and the customer requirements [5]. Therefore, the selection of the best KMS for knowledge management is the crucial task [1,8,9]. Since the evaluation of KMS from various aspects is the complex task, many approaches have been proposed to assist the decision makers in the evaluation and selection of KMS. For example, Wang [10] and Wang and Jiang [11] proposed the integrated evaluation method for the KMS based on linguistic symbol operators. In the methods, the criteria are constructed from the performance, function, cost, environment and humanity aspects. Liu and Peng [12] and Ngai and Chan [13] use the fuzzy AHP method to evaluate KMS. In the former research the KMS are evaluated from function, value, benefit, operation and performance aspects. In the latter research the KMS are evaluated from the cost, functionality and vendor aspects. Yu [14] evaluated the KMS from the performance, function, application and value perspectives. In the method, matter element model is extended to compare the alternatives.

These researches facilitate the evaluation and selection of KMS. Most criteria such as full text search, version control [10–14] and agent [12] are constructed from the designer's perspectives. Designers consider how to fulfill the functions with information technology (IT). Their perspectives focus more on IT and IT related parameters. The criteria well reflect the inherent characteristics of KMS and are fit for the decision makers skilled at IT. However, most decision makers especially the customers are not familiar with IT. They only concern their requirements. Their perspective focuses more on what extent their requirements are fulfilled by the KMS. For example, customers pay more attention to whether the knowledge can be found easily but does not care how to achieve it. Analysts concern more on the rationality of the knowledge map and

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the accuracy of search engine, which are the tools for knowledge finding. Therefore, when evaluating the KMS, knowledge finding, which is the criterion constructed from the user's perspective, fitter for the users. Knowledge map and search engine, which are the criteria constructed from the designer's perspective, fitter for designers.

QFD (quality function deployment) is the tool originally used by manufacturing [15–18]. House of quality (HOQ) is the core of QFD and characterizes the technology [19,20]. It shows the relationship between the voice of customers and the engineering characteristics. HOQ demonstrates how the engineering characteristics satisfy the customer requirements. With QFD, the customer requirements can be transformed into engineering characteristics and then the gap between customers and designers is bridged [20]. Therefore, in KMS selection, it is potential to transform the evaluation information given according to the customer requirements into the opinions with respect to the engineering characteristics by QFD.

The core problem of KMS evaluation and selection is the construction of the criteria and the methods which are used to deal with the evaluation information. In order to evaluate the KMS comprehensively and objectively, multiple aspects need to be considered and a group of experts are invited to give their opinions. Then there arises a question that how to deal with the evaluation information efficiently.

The multiple criteria decision making (MCDM) method is a methodology that is able to consider multiple criteria at the same time and deal with the evaluation information given by decision makers [38]. It just fit for the KMS evaluation and selection. With MCDM method, the KMS candidates can be evaluated and selected comprehensively and objectively.

In this paper, a new MCDM method combining QFD with TOPSIS for KMS evaluation and selection from the user's perspective in intuitionistic fuzzy environment is proposed. Since the importance of the criteria and the rating of alternatives on the criteria are difficult to be precisely expressed by crisp data in the evaluation of KMS [13], decision makers are required to use linguistic variables to express their preference. In the new MCDM method, intuitionistic fuzzy sets introduced by Atanassov [21] are used to deal with the linguistic opinions. Intuitionistic fuzzy sets are the extension of the theory of fuzzy sets [22]. With intuitionistic fuzzy sets, the preferences are expressed more comprehensively because the fuzziness and uncertainties are characterized by not only the membership degree in fuzzy sets [22] but also the non-membership degree. Moreover, TOPSIS method [23,37], which is a practical and useful technique for ranking and selection of a number of externally determined alternatives through distance measures, is employed to compare the alternatives.

The rest of this paper is organized as follows. The next section reviews the basic concepts of intuitionistic fuzzy sets, QFD and TOPSIS. Section 3 develops the new MCDM method. In Section 4, an example is given to illustrate the applicability of the proposed method. The final section makes conclusions.

2. Preliminaries

2.1. Intuitionistic fuzzy sets

Definition 1. Intuitionistic fuzzy sets (IFS) A in a finite set X can be written as [21]:

$$\hat{A} = \{\{x, \mu_A(x), \nu_A(x)\} | x \in X\} \quad (1)$$

which is characterized by a membership function $\mu_A(\chi)$ and a non-membership function $\nu_A(x)$ where $\mu_A(x), \nu_A(x) : X \to [0, 1]$ with the condition $0 \le \mu_A(x) + \nu_A(x) \le 1$. A third parameter of A is $\pi_A(x)$, known as the intuitionistic fuzzy index or hesitation degree of whether x belongs to A or not

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \quad (2)$$

It is obviously seen that for each $x \in X$:
$0 \le \pi_A(x) \le 1$.

The score function S and accuracy function H of an intuitionistic fuzzy number can be represented as follows [24]:

$$S = \mu_A(x) - \nu_A(x), \quad S \in [-1, 1] \quad (3)$$

$$H = \mu_A(x) + \nu_A(x), \quad H \in [0, 1] \quad (4)$$

Definition 2. Arithmetic operations on intuitionistic fuzzy numbers

For two intuitionistic fuzzy numbers (IFNs) $\hat{A} = (x; \mu_A; \nu_A)$ and $\hat{B} = (x; \mu_B; \nu_B)$ with $\mu_A \neq \mu_B$, $\nu_A \neq \nu_B$, for $A > 0$, $B > 0$ and $\lambda > 0$, the arithmetic operation are defined as follows [25,26]:

$$\hat{A} + \hat{B} = (x; \mu_A + \mu_B - \mu_A\mu_B, \nu_A\nu_B) \quad (5)$$

$$\hat{A} \times \hat{B} = (x; \mu_A\mu_B; \nu_A + \nu_B - \nu_A\nu_B) \quad (6)$$

$$\frac{\hat{A}}{\hat{B}} = (x; \min(\mu_A, \mu_B); \max(\nu_A, \nu_B)) \quad (7)$$

$$\lambda\hat{A} = (x; 1 - (1 - \mu_A)^\lambda; \nu_A^\lambda) \quad (8)$$

$$\hat{A}^\lambda = (x; \mu_A^\lambda; 1 - (1 - \nu_A)^\lambda) \quad (9)$$

Definition 3. Normalized Hamming distance on intuitionistic fuzzy numbers

The normalized Hamming distance between intuitionistic fuzzy numbers $\hat{A}$ and $\hat{B}$ is calculated as [27]

$$d_{\text{Hamming}}(\hat{A}, \hat{B}) = \frac{1}{2n}(|\mu_A - \mu_B| + |\nu_A - \nu_B| + |\pi_A - \pi_B|) \quad (10)$$

Definition 4. Normalized Euclidean distance on intuitionistic fuzzy numbers

The normalized Euclidean distance between intuitionistic fuzzy numbers $\hat{A}$ and $\hat{B}$ is calculated as [27]

$$d_{\text{Euclidean}}(\hat{A}, \hat{B}) = \sqrt{\frac{1}{2n}[(\mu_A - \mu_B)^2 + (\nu_A - \nu_B)^2 + (\pi_A - \pi_B)^2]} \quad (11)$$

Definition 5. The order relations on intuitionistic fuzzy numbers.

The order relations between two intuitionistic fuzzy numbers based on the score function S and the accuracy function H are defined as follows [25,26]:

- If $S_A > S_B$, then A is better than B.
- If $S_A = S_B$, then

(1) If $H_A = H_B$, then A and B are equal;
(2) If $H_A > H_B$, then A is better than B.

Definition 6. Intuitionistic fuzzy weighted averaging (IFWA) operator [25].

Let $\widehat{A_j} = (x; \mu_{A_j}; \nu_{A_j})(j = 1, 2, \ldots, n)$ be a collection of intuitionistic fuzzy values and $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ be the weight vector, with $\omega_j \in [0, 1]$ and $\sum_{j=1}^{n} \omega_j = 1$, then the IFWA is defined as follows:

$$\begin{aligned} IFWA_\omega(\widehat{A_1}, \widehat{A_2}, \ldots, \widehat{A_n}) &= \omega_1\widehat{A_1} + \omega_2\widehat{A_2} + \cdots \omega_n\widehat{A_n} \\ &= \left[1 - \prod_{j=1}^{n}(1 - \mu_{A_j})^{\omega_j}, \prod_{j=1}^{n}\nu_{A_j}^{\omega_j}\right] \end{aligned} \quad (12)$$

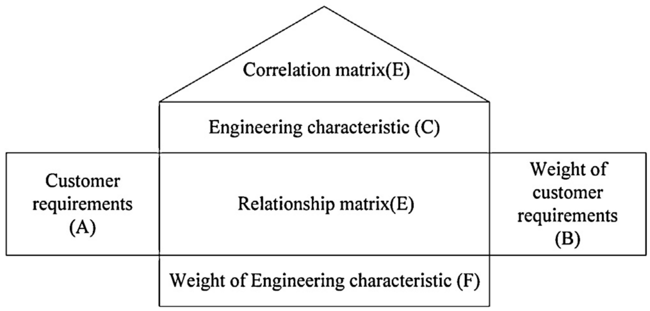

Fig. 1. House of quality.

2.2. QFD

QFD is a tool that supports the planning and realization of products for customer requirements-oriented product development [28]. It deploys the voice of customer into searching for best solutions for the design and development of products. In the application of the QFD model, a typical four-phase QFD model is commonly used [29–31]. These phases consist of customer requirement planning, product characteristics deployment, process and quality control and the operative instruction.

In the study, we focus on the customer requirement planning phase, which transforms the customer's requirements into engineering characteristics [32]. The phase is characterized by the customer requirement planning matrix [19,20]. The customer requirement planning matrix, also known as "house of quality" (HOQ), is the first step in investigating customer requirements [33]. The HOQ is composed of six parts, as is shown in Fig. 1. Part A represents customer requirements (CRs), which is the base of the HOQ as it has influence on all the other parts. The customer requirement is considered as the customer criteria in the study. Part B represents the weight of CRs. Part C represents engineering characteristics (ECs), which shows how the system fulfills the CRs. The engineering characteristic is considered as the system criteria in the study. Part D represents the relationship between CRs and ECs. Part E represents correlation among the ECs, which is how ECs affect each other. Part F shows the weights of ECs.

2.3. TOPSIS

TOPSIS method is originally proposed by Hwang and Yoon [23] to identify solutions from a finite set of alternatives. It has been extended in intuitionistic fuzzy environment [37].

The basic principle is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The procedure of TOPSIS can be expressed in the following steps [23,34,35]:

Step 1 Calculate the normalized decision matrix. The normalized value n_{ij} is calculated as

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{m}^{i=1} x_{ij}^2}} \quad i = 1, \ldots, m, \; j = 1, \ldots, n. \tag{13}$$

Step 2 Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as

$$v_{ij} = w_j n_{ij}, \quad i = 1, \ldots, m, \quad j = 1, \ldots, n, \tag{14}$$

where w_j is the weight of the ith criterion, and $\sum_{j=1}^{n} w_j = 1$.

Step 3 Define the positive ideal solution (PIS) and negative ideal solution (NIS) as

$$\begin{aligned} A^{+} &= \left\{ v_1^{+}, \ldots, v_n^{+} \right\} \\ A^{-} &= \left\{ v_1^{-}, \ldots, v_n^{-} \right\} \end{aligned} \tag{15}$$

where, for benefit criterion,

$$v_j^{+} = \max_i \{v_{ij}\}, \quad j = 1, 2, \ldots, n, \quad v_j^{-} = \min_i \{v_{ij}\}, \quad j = 1, 2, \ldots, n$$

for cost criterion,

$$v_j^{-} = \max_i \{v_{ij}\}, \quad j = 1, 2, \ldots, n, \quad v_j^{+} = \min_i \{v_{ij}\}, \quad j = 1, 2, \ldots, n$$

Step 4 Calculate the distances of each alternative from PIS and NIS using the following equation, respectively:

$$\begin{aligned} d_i^{+} &= \sum_{j=1}^{n} \mathrm{dis}(v_{ij} - v_j^{+}), \quad i = 1, \ldots, m \\ d_i^{-} &= \sum_{j=1}^{n} \mathrm{dis}(v_{ij} - v_j^{-}), \quad i = 1, \ldots, m \end{aligned} \tag{16}$$

where, $\mathrm{dis}(v_{ij} - v_j^{+})$ is the distance between rating of alternative i and PIS on the jth criterion, $\mathrm{dis}(v_{ij} - v_j^{-})$ is the distance between rating of alternative i and NIS on the jth criterion.

Step 5 Calculate the relative closeness to the ideal solution. The relative closeness of the alternative A_i with respect to A^{+} is defined as

$$R_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}}, \quad i = 1, \ldots, m. \tag{17}$$

According to the relative closeness degree R_i, the ranking order of all alternatives can be determined. If any alternative has the highest R_i, then, it is the most desirable alternative.

3. The new MCDM method combining QFD with TOPSIS in intuitionistic fuzzy environment

Let $A = \{A_1, A_2, \ldots, A_m\}$ be a discrete set of alternatives, $CR = \{CR_1, CR_2, \ldots, CR_p\}$ be the set of customer criteria, which is established from the user's perspective, $EC = \{EC_1, EC_2, \ldots, EC_q\}$ be the set of system criteria, which is established from the designer's perspective, $D = \{D_1, D_2, \ldots, D_t\}$ be the set of decision makers which are composed of customers and analysts.

Suppose $\widehat{RL}^{k} = (\widehat{rl}_{ij}^{(k)})_{p\times q} = (\mu_{rl,ij}^{(k)}, v_{rl,ij}^{(k)})_{p\times q}$ be the linguistic decision making matrix of relationship between customer criterion CR_i and system criterion EC_j, $\widehat{CL}^{k} = (\widehat{cl}_{ij}^{(k)})_{q\times q} = (\mu_{\mathrm{cl},ij}^{(k)}, v_{\mathrm{cl},ij}^{(k)})_{q\times q}$ be the linguistic decision making matrix of the correlation between system criteria EC_i and EC_j, $\widehat{CV}^{k} = (\widehat{cv}_{ij}^{(k)})_{m\times p} = (\mu_{cv,ij}^{(k)}, v_{cv,ij}^{(k)})_{m\times q}$ be the linguistic decision making matrix of the rating of alternative A_i with respect to the customer criterion CR_j, $\hat{W}^{k} = (\hat{w}_j^{(k)})_{1\times p} = (\mu_{w,ij}^{(k)}, v_{w,ij}^{(k)})_{1\times p}$ be the linguistic decision making matrix of the weight of the customer criterion CR_j, which are provided by D_k.

Combining the concepts of conventional QFD with TOPSIS in intuitionistic fuzzy environment, the steps of the proposed method can be presented in Fig. 2.

The method is divided into three parts.

The first part is the aggregation of decision makers' opinions. In the part, the approach presented by Chen [36] is extended in intuitionistic fuzzy environment to aggregate the decision makers' opinions.

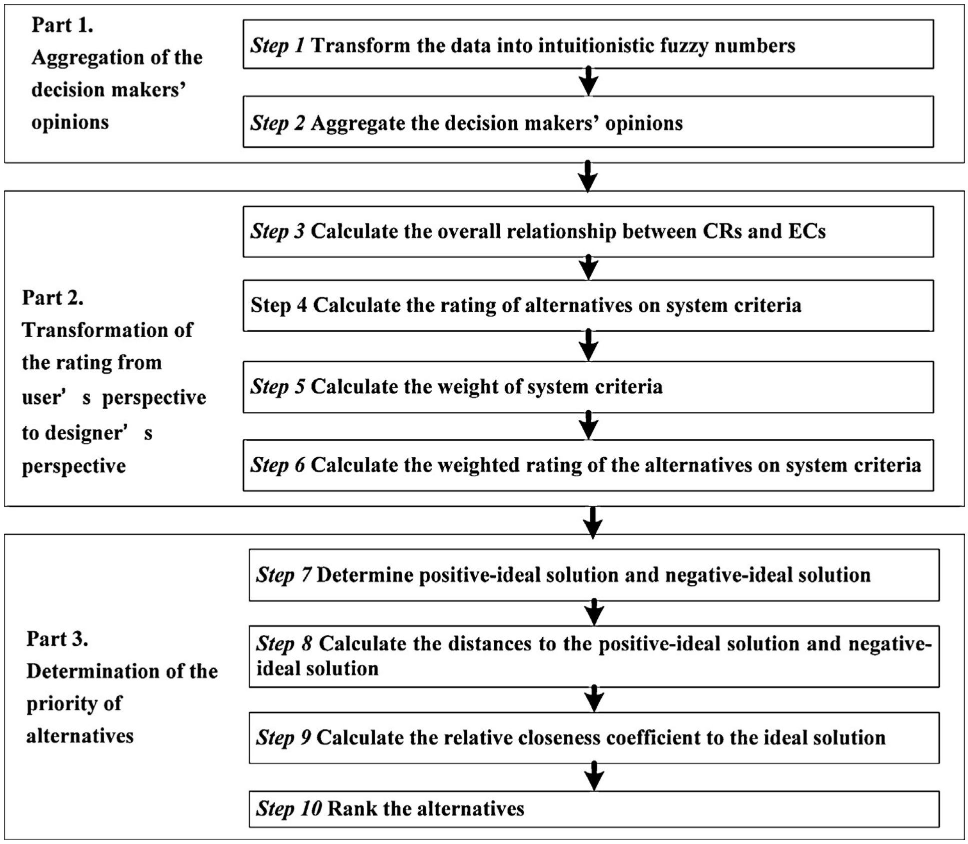

Fig. 2. the steps of the method.

The second part is the transformation of the rating from user's perspective to designer's perspective. With the HoQ, which is the core of the QFD, the customers' opinions are transferred to the analysts' opinions, as is shown in Fig. 3. In Fig. 3, the input data, which is derived from the first two steps of the proposed method, fills in the part A to part D. Part A is the aggregated ratings of alternative A_f with respect to the customer criterion CR, part B is the aggregated relationships $\widehat{RL}$ between customer criterion CR and system criterion EC, part C is the aggregated correlations $\widehat{CL}$ between system criteria EC, part D is the aggregated weights of the customer criteria CR.

The output of the sixth step is the rating $\widehat{ec}$ of alternatives on system criteria and the weight $\hat{u}$ of system criteria, which are in the part F and part E respectively.

The last part is the determination of the priority of alternatives. In this part, based on the idea of the TOPSIS method in intuitionistic fuzzy environment [37], the ranking of the alternatives are derived.

The detailed explanations of the methods are as follows.

Step 1 Transform the data into intuitionistic fuzzy numbers

Preference values take the form of linguistic terms. Since linguistic terms are not mathematically operable, firstly, they must be transformed into intuitionistic fuzzy numbers.

Step 2 Aggregate the decision makers' opinions

In the step, the approach presented by Chen [36] is extended in intuitionistic fuzzy environment to aggregate the decision makers' opinions. The steps are as follows:

Step 2.1 Calculate the collective ratings of each alternative with respect to CRs

Step 2.1.1 Calculate the degree of agreement. Eq. (18) is used to calculate the degree of agreement $S(\widehat{CV}^i, \widehat{CV}^j)$ of the ratings of alternatives with respect to CRs between the pair of decision makers D_i

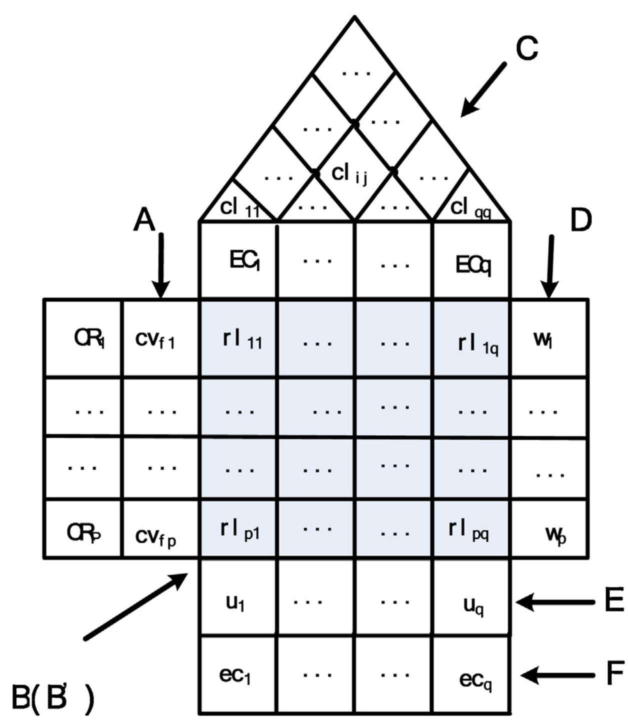

Fig. 3. The HoQ of alternative A_f.

and D_j, where $S(\widehat{CV}^i, \widehat{CV}^j) \in [0, 1]$, $1 \le i \le t, 1 \le j \le t, i \ne j$.

$$S(\widehat{CV}^i, \widehat{CV}^j) = d_{\text{Hamming}}(\widehat{CV}^i, \widehat{CV}^j) = \frac{1}{2 \times m \times p} \times \sum_{x=1}^{m}\sum_{y=1}^{p}(|\mu_{cv,xy}^{(i)} - \mu_{cv,xy}^{(j)}| + |\nu_{cv,xy}^{(i)} - \nu_{cv,xy}^{(j)}| + |\pi_{cv,xy}^{(i)} - \pi_{cv,xy}^{(j)}|) \quad (18)$$

Step 2.1.2 Calculate the average degree of agreement $A(D_i)$ of decision maker D_i, where

$$A(D_i) = \frac{1}{t-1}\sum_{\substack{j=1\\ j\ne i}}^{t} S(\widehat{CV}^i, \widehat{CV}^j) \quad (19)$$

Step 2.1.3 Calculate the relative degree of agreement $RA(D_i)$ of decision maker D_i, where

$$RA(D_i) = \frac{A(D_i)}{\sum_{i=1}^{t} A(D_i)} \quad (20)$$

Step 2.1.4 Suppose that the importance weight of the weight w_i of decision maker D_i and the agreement weight of the decision maker are y_1 and y_2, where $y_1 \in [0,1]$, $y_2 \in [0,1]$ and $\sum_{i=1}^{t} w_i = 1$. The consensus degree coefficient $CY(D_i)$ of decision maker D_i are calculated by

$$CY(D_i) = \frac{y_1}{y_1+y_2} * w_i + \frac{y_2}{y_1+y_2} * RA(D_i) \quad (21)$$

Step 2.1.5 By Eq. (12), the intuitionistic fuzzy opinion about the rating of alternative A_i on CR_j is aggregated as follows:

$$\widehat{cv}_{ij} = (\mu_{cv,ij}, \nu_{cv,ij}) = CY(D_1) \times \widehat{cv}_{ij}^{(1)} + CY(D_2) \times \widehat{cv}_{ij}^{(2)} + \cdots + CY(D_t) \times \widehat{cv}_{ij}^{(t)} = \left[1 - \prod_{z=1}^{t}(1-\mu_{cv,ij}^{(z)})^{CY(D_z)}, \prod_{j=1}^{n} \nu_{cv,ij}^{(z)\,CY(D_z)}\right] \quad (22)$$

where, $CY(D_z)$ is the consensus degree coefficient of decision maker D_z in the ratings of alternatives with respect to CRs.

Step 2.2 Calculate the collective weights of CRs

In the step, similar to step 2.1, we also use the method presented by Chen [36] to aggregate the opinions. By Eq. (12), the aggregated result of the weight of CR_j is derived as follows:

$$\hat{w}_j = (\mu_{w,j}, \nu_{w,j}) = CW(D_1) \times \hat{w}_j^{(1)} + CW(D_2) \times \hat{w}_j^{(2)} + \cdots + CW(D_t) \times \hat{w}_j^{(t)} = \left[1 - \prod_{z=1}^{t}(1-\mu_{w,j}^{(z)})^{CW(D_z)}, \prod_{j=1}^{n} \nu_{w,j}^{(z)\,CW(D_z)}\right] \quad (23)$$

where, $CW(D_z)$ is the consensus degree coefficient of decision maker D_z in the rating of weights of CRs.

Step 2.3 Calculate the collective relationships between CRs and ECs

In the same way, similar to step 2.1, based on the method presented by Chen [36] and Eq. (12), the aggregated result of the relationship between customer criterion CR_j and system criterion EC_k is derived by

$$\widehat{rl}_{jk} = (\mu_{rl,jk}, \nu_{rl,jk}) = CD(D_1) \times \widehat{rl}_{jk}^{(1)} + CD(D_2) \times \widehat{rl}_{jk}^{(2)} + \cdots + CD(D_t) \times \widehat{rl}_{jk}^{(t)} = \left[1 - \prod_{z=1}^{t}(1-\mu_{rl,jk}^{(z)})^{CD(D_z)}, \prod_{j=1}^{n} \nu_{rl,jk}^{(z)\,CD(D_z)}\right] \quad (24)$$

where, $CD(D_z)$ is the consensus degree coefficient of decision maker D_z in the rating of relationship between CRs and ECs.

Step 2.4 Calculate the collective correlation between ECs

Based on the method presented by Chen [36] and Eq. (12), similar to step 2.1, the aggregated result of the correlation between system criteria EC_k and EC_l is derived by

$$\widehat{cl}_{kl} = (\mu_{cl,kl}, \nu_{cl,kl}) = CL(D_1) \times \widehat{cl}_{kl}^{(1)} + CL(D_2) \times_{kl}^{(2)} + \cdots + CL(D_t) \times \widehat{cl}_{kl}^{(t)} = \left[1 - \prod_{z=1}^{t}(1-\mu_{cl,kl}^{(z)})^{CL(D_z)}, \prod_{j=1}^{n} \nu_{cl,kl}^{(z)\,CL(D_z)}\right] \quad (25)$$

where, $CL(D_z)$ is the consensus degree coefficient of decision maker D_z in the rating of correlation between ECs.

Step 3 Calculate the overall relationship between CRs and ECs

Both the relationship between CRs and ECs and the correlation between ECs can be given by the analysts directly. Since ECs are possibly correlated to each other. The overall relationship between CRs and ECs is determined by the relationship between CRs and ECs, and the correlation between ECs. As shown in Fig. 3, part B' is determined by part C and part B.

The overall relationship $\widehat{rl'}_{jk}$ between the customer criterion CR_j and the system criterion EC_k is determined by the relationship between CR_j and $EC_f (f = 1, 2 \ldots q)$ integrated with the correlation between EC_k and $EC_f (f = 1, 2 \ldots q)$.

By Eq. (7), the overall relationship $\widehat{rl'}_{jk}$ between the customer criterion CR_j and the system criterion EC_k can be got as follows:

$$\widehat{rl'}_{jk} = (\mu_{rl',jk}, \nu_{rl',jk}) = \sum_{z=1}^{q} \widehat{rl}_{jz} \times \widehat{cl}_{zk} = \sum_{z=1}^{q}(\mu_{rl,jz}\mu_{cl,zk}, \nu_{rl,jz} + \nu_{cl,zk} - \nu_{rl,jz}\nu_{cl,zk}) \quad (26)$$

Step 4 Calculate the rating of alternatives on system criteria

In the step, the opinions given by the users are transformed into the opinions with respective the system criteria. Since the overall relationships derived in Step 3 represents the relationship between customer criteria and system criteria, the transformation is made by the overall relationships matrix. As shown in Fig. 3, the part A is transformed to part F via part B′.

The rating $\widehat{ec}_{ik}$ of alternative A_i on system criterion EC_k is determined by the overall relationship $\widehat{rl'}_{jk}$ and the rating of the alternative on customer criteria. By Eq. (7), it is derived as follows:

$$\widehat{ec}_{ik} = (\mu_{ec,ik}, \nu_{ec,ik}) = \sum_{l=1}^{p} \widehat{rl'}_{lk} \times \widehat{cv}_{il} = \sum_{l=1}^{p}(\mu_{rl',lk}\mu_{cv,il}, \nu_{rl',lk} + \nu_{cv,il} - \nu_{rl',lk}\nu_{cv,il}) \quad (27)$$

By using Eqs. (3) and (4), the value of score and accuracy functions of alternative A_i on system criterion EC_k can be derived as follows:

$$S_{ik} = \mu_{ec,ik} - \nu_{ec,ik} \quad (28)$$

$$H_{ik} = \mu_{ec,ik} + \nu_{ec,ik} \quad (29)$$

Step 5 Calculate the weight of system criteria

In the step, the weight given by the customers are transformed into the weights with respective the system criteria. Since the overall relationships derived in Step 3 represents the relationship between customer criteria and system criteria, the transformation is also made by the overall relationships matrix. As shown in Fig. 3, the part D is transformed to part E via part B′.

Accordingly, By Eq. (7), the weight $\hat{u}_k$ of system criterion EC_k is determined by the overall relationship $\widehat{rl'}_{ij}$ and the weights of customer criteria, which is got as follows:

$$\hat{u}_k = (\mu_{u,k}, \nu_{u,k}) = \sum_{l=1}^{p} \widehat{rl'}_{lk} \times \hat{w}_l$$

$$= \sum_{l=1}^{p} (\mu_{rl',lk}\mu_{w,l}, \nu_{rl',lk} + \nu_{w,l} - \nu_{rl',lk}\nu_{w,l}) \tag{30}$$

By using Eqs. (3) and (4), the value of score and accuracy functions of system criterion EC_k can be derived as follows:

$$S_k = \mu_{u,k} - \nu_{u,k} \tag{31}$$

$$H_k = \mu_{u,k} + \nu_{u,k} \tag{32}$$

Step 6 Calculate the weighted rating of the alternatives on system criteria

After the weights of the system criteria and rating of alternatives on the system criteria are determined, the weighted rating $\widehat{ec'}_{ik}$ of alternative A_i on system criterion EC_k is got by

$$\widehat{ec'}_{ik} = (\mu_{ec',ik}, \nu_{ec',ik}) = \widehat{ec}_{ik} \times \hat{u}_k$$

$$= (\mu_{ec,ik}\mu_{u,k}, \nu_{ec,lk} + \nu_{u,k} - \nu_{ec,lk}\nu_{u,k}) \tag{33}$$

Step 7 Determine positive-ideal solution and negative-ideal solution

The fuzzy positive $A^+ = \{A_1^+, A_2^+, \ldots, A_q^+\}$ and fuzzy negative $A^- = \{A_1^-, A_2^-, \ldots, A_q^-\}$ ideal solutions of the alternatives on system criteria are defied as follows.

For benefit criteria,

$$\begin{aligned} A_z^+ &= (\mu_{A^+,z}, \nu_{A^+,z}) = (\max_i \mu_{ec',iz}, \min_i \nu_{ec',iz}) \\ A_z^- &= (\mu_{A^-,z}, \nu_{A^-,z}) = (\min_i \mu_{ec',iz}, \max_i \nu_{ec',iz}) \end{aligned} \tag{34}$$

For cost criteria,

$$\begin{aligned} A_z^+ &= (\mu_{A^+,z}, \nu_{A^+,z}) = (\min_i \mu_{ec',iz}, \max_i \nu_{ec',iz}) \\ A_z^- &= (\mu_{A^-,z}, \nu_{A^-,z}) = (\max_i \mu_{ec',iz}, \min_i \nu_{ec',iz}) \end{aligned} \tag{35}$$

Step 8 Calculate the distances to the positive-ideal solution and negative-ideal solution

We use normalized Euclidean distance to calculate the distances to the positive-ideal solution and negative-ideal solution of the alternatives. The distances S_{i^+} to positive-ideal solution and S_{i^-} to negative-ideal solution of alternative A_i are derived by

$$S_{i^+} = \sqrt{\frac{1}{2n} \sum_{z=1}^{q} [(\mu_{ec',iz} - \mu_{A^+,z})^2 + (\nu_{ec',iz} - \nu_{A^+,z})^2 + (\pi_{ec',iz} - \pi_{A^+,z})^2]} \tag{36}$$

$$S_{i^-} = \sqrt{\frac{1}{2n} \sum_{z=1}^{q} [(\mu_{ec',iz} - \mu_{A^-,z})^2 + (\nu_{ec',iz} - \nu_{A^-,z})^2 + (\pi_{ec',iz} - \pi_{A^-,z})^2]} \tag{37}$$

Step 9 Calculate the relative closeness coefficient to the ideal solution

The relative closeness coefficient of the alternative A_i with respect to the positive-ideal solution is defined as follows.

$$C_i = \frac{S_{i^-}}{S_{i^+} + S_{i^-}} \tag{38}$$

Step 10 Rank the alternatives

Table 1
Linguistic terms.

Linguistic terms	IFNs
Definitely low (DL)	[0.10, 0.90]
Very low (VL)	[0.25, 0.75]
Low (L)	[0.40, 0.55]
Medium (M)	[0.50, 0.45]
High (H)	[0.60, 0.30]
Very high (VH)	[0.75, 0.10]
Definitely high (DH)	[0.90, 0.10]

Table 2
The linguistic rating of the alternatives with respect to the customer criteria.

	E_1					E_2					E_3				
	A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
CR_1	VL	L	DL	VL	DH	L	VL	H	DL	L	M	H	VL	H	VL
CR_2	L	M	L	H	VL	VL	L	VL	DH	VL	VL	VL	L	VL	L
CR_3	VL	M	VL	M	H	VH	VL	DH	L	M	L	M	VH	DL	L
CR_4	M	M	H	VL	M	DH	M	L	VH	L	VH	VL	VH	M	L

After the relative closeness coefficient of each alternative is obtained, the alternatives are ranked in the descending order of C_i and the best alternative is the one that get the highest relative closeness coefficient.

4. Numerical examples

Let us suppose there is an aviation design institute, which is in urgent needs of KMS to accumulate and reuse the dispersive knowledge. In order to find the best KMS, five KMSs denoted by A_1, A_2, A_3, A_4 and A_5 are to be evaluated. From the analysis of the questionnaire and interview results, four customer criteria and five system criteria are identified. The customer criteria includes 'knowledge finding' (CR_1), 'knowledge storing' (CR_2), 'knowledge sharing' (CR_3) and 'personalized supporting' (CR_4). The system criteria include 'knowledge store' (EC_1), 'knowledge map' (EC_2), 'knowledge recommendation' (EC_3), 'knowledge search' (EC_4) and 'knowledge community' (EC_5).

The decision makers includes three users in the institute denoted by E_1, E_2 and E_3, and three system analysts in the software development company denoted by E_4, E_5 and E_6. They all use the linguistic terms in Table 1to express their preferences. Firstly, the three users are required to give their opinions about the weight of customer criteria and then are invited to use the five alternatives. Afterwards they are required to give their linguistic rating of the alternatives with respect to the customer criteria from the user's perspective. The three system analysts are required to give the linguistic rating of the relationship between customer criteria and system criteria and the linguistic rating of the correlation between the system criteria.

The linguistic rating of the alternatives and the weights of the customer criteria given by the three users are shown in Tables 2 and 3.

The linguistic rating of the relationship between customer criteria and system criteria given by the three analysts are shown in Table 4.

Table 3
The linguistic rating of the weights of the customer criteria.

	CR_1	CR_2	CR_3	CR_4
E_1	VL	L	VL	M
E_2	L	VL	VH	DH
E_3	M	VL	L	VH

Table 4
The linguistic rating of the relationships between the customer criteria and system criteria.

	E_4				E_5				E_6			
	CR_1	CR_2	CR_3	CR_4	CR_1	CR_2	CR_3	CR_4	CR_1	CR_2	CR_3	CR_4
EC_1	M	VH	M	L	L	DH	H	L	M	DH	M	L
EC_2	VH	L	L	M	DH	L	L	M	DH	VL	L	M
EC_3	L	VL	H	VH	M	VL	H	DH	H	VL	H	VH
EC_4	VH	L	M	L	DH	M	M	M	VH	M	M	M
EC_5	L	VL	VH	VL	M	VL	DH	VL	L	VL	DH	VL

Table 5
The linguistic rating of correlation between system criteria.

	E_4					E_5					E_6				
	EC_1	EC_2	EC_3	EC_4	EC_5	EC_1	EC_2	EC_3	EC_4	EC_5	EC_1	EC_2	EC_3	EC_4	EC_5
EC_1	DH	L	VL	VL	VL	DH	M	M	M	L	DH	M	M	M	M
EC_2	L	DH	L	L	M	M	DH	VL	M	L	M	DH	L	H	M
EC_3	VL	L	DH	M	M	M	VL	DH	H	H	M	L	DH	VH	H
EC_4	VL	L	M	DH	L	M	M	H	DH	M	M	H	VH	DH	M
EC_5	VL	M	M	L	DH	L	L	H	M	DH	M	M	H	M	DH

Table 6
The collective rating of the alternatives with respect to the customer criteria.

	CR_1	CR_2	CR_3	CR_4
A_1	(0.401, 0.560)	(0.298, 0.683)	(0.517, 0.347)	(0.772, 0.157)
A_2	(0.446, 0.484)	(0.382, 0.582)	(0.430, 0.531)	(0.418, 0.545)
A_3	(0.354, 0.588)	(0.355, 0.608)	(0.742, 0.183)	(0.618, 0.242)
A_4	(0.372, 0.564)	(0.677, 0.296)	(0.338, 0.623)	(0.549, 0.322)
A_5	(0.618, 0.371)	(0.310, 0.668)	(0.499, 0.430)	(0.432, 0.518)

Table 7
The collective weights of the customer criteria.

CR_1	CR_2	CR_3	CR_4
(0.402, 0.559)	(0.297, 0.686)	(0.525, 0.336)	(0.777, 0.154)

The linguistic rating of the correlation between the system criteria given by the three analysts is shown in Table 5.

Step 2 Aggregate the decision makers' opinions

After the transformation of the data in Tables 2–5 into intuitionistic fuzzy numbers, the decision makers' opinions are aggregated and the collective rating of the alternatives, the collective weights of CRs, the collective relationships between CRs and ECs and the collective correlations between ECs are derived, as is in Tables 6–9.

Step 3 Calculate the overall relationship between CRs and ECs

The overall relationship between CRs and ECs derived by Eq. (24) are given in Table 10.

Step 4 Calculate the rating of the alternatives with respect to the system criteria

The rating of the alternatives with respect to the system criteria are derived by Eq. (25), as is shown in Table 11.

The values of the score and accuracy functions of the alternatives with respect to the system criteria are derived by Eqs. (28) and (29), as is shown in Table 12.

Step 5 Calculate the weights of system criteria

The weights of system criteria and the values of score and accuracy functions of the system criteria are derived by Eqs. (31) and (32), which are shown in Table 13.

Step 6 Calculate the weighted rating of the alternatives with respect to system criteria

The weighted rating of the alternatives with respect to system criteria is the rating multiplied by the weight of system criteria. The calculation of the weighted rating $\widehat{ec'}_{11}$ of the alternative A_1 with respect to system criteria EC_1 is provided as an illustration.

$$\begin{aligned}\widehat{ec'}_{11} &= \widehat{ec}_{11} \times \hat{u}_1 = (\mu_{ec,11}\mu_{u,1}, \nu_{ec,11} + \nu_{u,1} - \nu_{ec,11}\nu_{u,1}) \\ &= (0.894 \times 0.896, 0.050 + 0.049 - 0.050 \times 0.049) \\ &= (0.801, 0.097)\end{aligned}$$

The weighted rating is shown in Table 14.

The result in Table 14 represents the weighted rating of the alternatives with respect to system criteria. The evaluation information given according to the four customer criteria has been transformed into the evaluation information with respect to the system criteria. It is the system view of the opinions given by the customers. Since the system analysts are more familiar with system criteria, the result in Table 14 makes them understand the evaluation information more easily and directly.

Step 7 Determine positive-ideal solution and negative-ideal solution

By Eqs. (34) and (35), the positive-ideal solution and negative-ideal solution are determined, which are shown in Table 15.

Step 8 Calculate the distances to the positive-ideal solution and negative-ideal solution

By Eqs. (36) and (37), the distances to the positive-ideal solution and negative-ideal solution are derived, the results of which are shown in Table 16.

Step 9 Calculate the relative closeness coefficient to the ideal solution

Based on the distances to the positive-ideal solution and negative-ideal solution, the relative closeness coefficient to the ideal solution is given in Table 17.

Step 10 Rank the alternatives

The alternatives are ranked in the descending order of the relative closeness coefficient. From Table 16, we get the final priority of alternatives: $A_3 > A_1 > A_4 > A_5 > A_2$. Clearly, we see that A_3 is the best KMS, while A_2 is considered as the worst.

In the case study, both the customer criteria and system criteria are constructed. Firstly, the opinions given by a group of customers and analysts are aggregated in the first three steps. Then the aggregated rating and weights given by customers are transformed into the rating and weights with respect to the system criteria in Step 4 and Step 5. In step 4, analyst can know the advantage and disadvantage of each candidate KMS from the technology

Table 8
The collective relationships between the customer criteria and system criteria.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	(0.464, 0.485)	(0.880, 0.100)	(0.528, 0.395)	(0.823, 0.100)	(0.440, 0.510)
CR_2	(0.880, 0.100)	(0.341, 0.627)	(0.250, 0.750)	(0.481, 0.469)	(0.250, 0.750)
CR_3	(0.540, 0.386)	(0.400, 0.550)	(0.600, 0.300)	(0.500, 0.450)	(0.880, 0.100)
CR_4	(0.400, 0.550)	(0.500, 0.450)	(0.823, 0.100)	(0.481, 0.469)	(0.250, 0.750)

Table 9
The collective correlations between system criteria.

	EC_1	EC_2	EC_3	EC_4	EC_5
EC_1	(0.900, 0.100)	(0.477, 0.473)	(0.447, 0.511)	(0.447, 0.511)	(0.410, 0.548)
EC_2	(0.477, 0.473)	(0.900, 0.100)	(0.352, 0.613)	(0.522, 0.402)	(0.467, 0.483)
EC_3	(0.447, 0.511)	(0.352, 0.613)	(0.900, 0.100)	(0.650, 0.213)	(0.577, 0.332)
EC_4	(0.447, 0.511)	(0.522, 0.402)	(0.650, 0.213)	(0.900, 0.100)	(0.477, 0.473)
EC_5	(0.410, 0.548)	(0.467, 0.483)	(0.577, 0.332)	(0.477, 0.473)	(0.900, 0.100)

Table 10
The overall relationships between CRs and ECs.

	EC_1	EC_2	EC_3	EC_4	EC_5
CR_1	(0.866, 0.087)	(0.940, 0.037)	(0.900, 0.044)	(0.942, 0.026)	(0.878, 0.072)
CR_2	(0.891, 0.088)	(0.757, 0.187)	(0.756, 0.180)	(0.791, 0.158)	(0.725, 0.223)
CR_3	(0.849, 0.097)	(0.837, 0.105)	(0.900, 0.048)	(0.883, 0.061)	(0.934, 0.040)
CR_4	(0.783, 0.155)	(0.791, 0.149)	(0.897, 0.057)	(0.859, 0.069)	(0.799, 0.127)

Table 11
The rating of the alternatives on the system criteria.

	EC_1	EC_2	EC_3	EC_4	EC_5
A_1	(0.894, 0.050)	(0.893, 0.050)	(0.919, 0.033)	(0.913, 0.035)	(0.899, 0.044)
A_2	(0.827, 0.116)	(0.823, 0.118)	(0.837, 0.105)	(0.839, 0.104)	(0.825, 0.117)
A_3	(0.909, 0.038)	(0.905, 0.039)	(0.926, 0.026)	(0.922, 0.027)	(0.921, 0.031)
A_4	(0.891, 0.061)	(0.871, 0.070)	(0.885, 0.057)	(0.888, 0.056)	(0.869, 0.070)
A_5	(0.872, 0.085)	(0.877, 0.083)	(0.886, 0.072)	(0.889, 0.071)	(0.876, 0.081)

Table 12
The values of score and accuracy functions of the alternatives on the system criteria.

	EC_1		EC_2		EC_3		EC_4		EC_5	
	S	H	S	H	S	H	S	H	S	H
A_1	0.843	0.944	0.843	0.944	0.885	0.952	0.878	0.948	0.856	0.943
A_2	0.711	0.943	0.705	0.941	0.731	0.942	0.735	0.943	0.708	0.941
A_3	0.872	0.947	0.866	0.945	0.900	0.952	0.895	0.950	0.889	0.952
A_4	0.830	0.951	0.802	0.941	0.829	0.942	0.832	0.944	0.798	0.939
A_5	0.787	0.957	0.794	0.960	0.813	0.958	0.818	0.961	0.795	0.957

Table 13
The weights of system criteria.

	EC_1	EC_2	EC_3	EC_4	EC_5
Value	(0.896, 0.049)	(0.896, 0.049)	(0.921, 0.032)	(0.915, 0.034)	(0.902, 0.042)
S	0.847	0.847	0.889	0.882	0.860
H	0.945	0.944	0.953	0.949	0.944

perspective. For example, in Table 12, A_1 is better than A_2 with respect to the criterion knowledge map (EC_2). In Step 5, analysts directly get which criteria have more influence on the customers' satisfaction. In Table 13, we see that knowledge recommendation (EC_3) and knowledge search are more important. In order to satisfy the customers, more attention needs to be paid on these important criteria. It makes the evaluation be understood more directly and easily. The remaining steps are used to rank the alternatives based on the TOPSIS. In Table 17 we see that the candidates can be differentiated. A_3 gets the highest score and A_2 gets the lowest

Table 14
The weighted rating of the alternatives with respect to system criteria.

	EC_1	EC_2	EC_3	EC_4	EC_5
A_1	(0.801, 0.097)	(0.800, 0.096)	(0.846, 0.064)	(0.836, 0.067)	(0.811, 0.084)
A_2	(0.741, 0.159)	(0.737, 0.161)	(0.771, 0.134)	(0.768, 0.134)	(0.744, 0.154)
A_3	(0.815, 0.085)	(0.811, 0.086)	(0.853, 0.057)	(0.844, 0.060)	(0.830, 0.072)
A_4	(0.798, 0.107)	(0.781, 0.115)	(0.815, 0.087)	(0.813, 0.088)	(0.783, 0.109)
A_5	(0.781, 0.130)	(0.786, 0.128)	(0.815, 0.102)	(0.814, 0.103)	(0.790, 0.120)

Table 15
The positive-ideal solution and negative-ideal solution.

	EC_1	EC_2	EC_3	EC_4	EC_5
A^+	(0.815, 0.085)	(0.811, 0.086)	(0.853, 0.057)	(0.844, 0.060)	(0.830, 0.072)
A^-	(0.741, 0.159)	(0.737, 0.161)	(0.771, 0.134)	(0.768, 0.134)	(0.744, 0.154)

Table 16
The distances to the positive-ideal solution and negative-ideal solution.

	A_1	A_2	A_3	A_4	A_5
A^+	0.501	0.560	0.500	0.510	0.516
A^-	0.545	0.500	0.560	0.522	0.516

Table 17
The relative closeness coefficient to the ideal solution.

A_1	A_2	A_3	A_4	A_5
0.521	0.472	0.528	0.506	0.500

score. It means that A_3 is the best KMS and A_2 is the worst. The case study shows the feasibility of the proposed method.

The proposed MCDM method is not limited to the KMS selection. It is also fit for the product selection in which the criteria prefer linguistic values, especially when designers want to know what the customer cares more and characteristics of the candidates more directly.

5. Discussions

The main difference between the model proposed in this paper and those models proposed in previous studies is the application of QFD in KMS evaluation and selection. In the previous studies [10–14], the opinions are given directly according to the system criteria or the customer criteria. The system criteria facilitate analysts' understanding of the advantages and disadvantages but it is hard to use for customers. The customers are familiar with customer criteria but the evaluation results cannot be understood directly by analysts. Therefore, connecting the two criteria through QFD in the proposed method resolves the problem. The other difference is the use of linguistic fuzzy sets instead of traditional fuzzy sets [10–14]. The fuzziness and uncertainties in linguistic environment are characterized more comprehensively because not only the membership but also the non-membership degrees are used in intuitionistic fuzzy environment. The utilization of the proposed model is demonstrated with an example. The results show that the proposed model fit the KMS evaluation and selection well.

6. Conclusions

The main object of the paper is to provide a method to help the evaluation and selection of KMS from the user's perspective. In order to do that, the new MCDM method combining QFD with TOPSIS in intuitionistic fuzzy environment is proposed. In the method, the customer criteria and system criteria are required. Customers give their opinions of the alternatives concerning the customer criteria. The correlation between the system criteria and the relationship between the customer criteria and the system criteria are evaluated by analysts. Then the customers' opinions are transformed into the opinion concerning the system criteria by the QFD, in which the QFD and the aggregation method proposed by Chen [36] are extended in intuitionistic fuzzy environment. Afterwards the alternatives are ranked by the TOPSIS method based on system criteria in intuitionistic fuzzy environment and the best KMS is determined. The applicability of the proposed method is validated by a case study. Since the decision information may be provided at the different period [37,39,40] and different granularities linguistic term sets may be used, the dynamic MCDM method for KMS selection in intuitionistic fuzzy environment and the multiple linguistic terms sets with different granularities will be considered in the future research.

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