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Expert Systems with Applications 31 (2006) 826–834

Expert Systems with Applications

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A fuzzy group-preferences analysis method for new-product development

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Abstract

This paper reports a new idea-screening method for new product development (NPD) with a group of decision makers having imprecise, inconsistent and uncertain preferences. The traditional NPD analysis method determines the solution using the membership function of fuzzy sets which cannot treat negative evidence. The advantage of vague sets, with the capability of representing negative evidence, is that they support the decision makers with the ability of modeling uncertain opinions. In this paper, we present a new method for new-product screening in the NPD process by relaxing a number of assumptions so that imprecise, inconsistent and uncertain ratings can be considered. In addition, a new similarity measure for vague sets is introduced to produce a ratings aggregation for a group of decision makers. Numerical illustrations show that the proposed model can outperform conventional fuzzy methods. It is able to provide decision makers (DMs) with consistent information and to model situations where vague and ill-defined information exist in the decision process.

Keywords: New product development; Idea screening; Vague sets; Similarity measure; Group decision making

1. Introduction

New-product development is one of the most critical tasks in the business process. Every company develops new products to increase sales, profits, and competitiveness; however NPD is a complex process and is linked to substantial risks. The objective of NPD is to search for possible products for the target markets. In Copper (1998), the process for NPD is divided into eight phases as follows: (1) idea generation phase; (2) idea screening phase; (3) concept development and testing phase; (4) marketing strategy development phase (5) business analysis phase (6) product development phase; (7) market testing phase; (8) commercialization phase. In the NPD process, decision makers have to screen new-product ideas according to a number of criteria. Subsequently, they recommend the ideas to R&D engineers, marketers, and sales managers in every stage of development. Idea screening is a concept-level evaluation process that begins when the collection of new product ideas is complete. It uses technical, commercial, and financial information to weed out impractical ideas, so that only appropriate ideas can be selected into development and testing (Hart & Hultink, 2002). Idea screening can avoid both the 'drop-error' and the 'go-error'. The former occurs when the company dismisses a viable idea; the latter takes place when the company permits an inferior idea to move into product development and market testing. A wrong decision in idea screening will lose resources, time to market, business opportunity etc. Hence idea screening is perhaps the most critical phase in NPD process. During the idea screening process, the decision makers' preferences have a significant impact on the selection of new products and the result of the decision making. The method of obtaining the group preference of the decision makers on each new-product in a committee is an important issue which causes many difficulties. In most cases, NPD is risky

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doi:10.1016/j.eswa.2006.01.005

due to the lack of sufficient information about imprecise, inconsistent and uncertain customer preferences. Recent studies (Kim & Kim, 1991; Kotler, 2003) report the failure rate of new consumer products at 95% in the United States and 90% in Europe. The failures lead to substantial monetary and non-monetary losses. For example, Ford lost $250 million on its Edsel; RCA lost $500 million on its videodisk player etc. There are many reasons for the failure of a new product. Some of the important factors in high technology NPD can be summarized as follows:

(1) In an idea-screening phase, it is impossible to acquire precise and consistent information regarding customers' preferences, but it is possible to obtain imprecise, inconsistent and uncertain information.
(2) In a concept development and testing phase, the criteria for new-product screening are not always quantifiable or comparable.
(3) In a product development phase, the choice of enabling technologies for developing new products is a challenging issue as the technologies evolve rapidly. In addition, it is often the case that development costs are higher than expected.
(4) In a commercialization phase, participating competitors will use a variety of means to contend.

This research sets out to provide more human-consistency by including the assumptions (i.e., "I am not sure") often prohibited by other existing approaches (Kao & Liu, 1999; Kessler & Chakrabarti, 1997; Lin & Chen, 2004). In this paper, we propose a new method, which extends the traditional NPD methods to the early product development and evaluation, uses the similarity measures of vague sets (Gau & Buehrer, 1993; Hong & Kim, 1999; Li & Cheng, 2002) to aggregate the ratings of all decision makers including the negative evidence. It supports decisions on the priority among alternatives through the use of a fuzzy synthetic evaluation method (Chen & Hwang, 1992) for phase.

The rest of the paper is structured as follows. Section 2 reviews important NPD literature. Section 3 introduces basic concepts and definitions in vague sets and their operations. Section 4 formulates the problem of new-product screening and describes the proposed algorithms and associated methods. Proofs for four resulting properties from the proposed algorithms are also included. In Section 5, an example of evaluating new ideas is shown, to illustrate the proposed method. Section 6 compares the outcomes with other approaches. Section 7 offers the conclusion on this work.

2. Literature review

Many methods (Calantone, Benedetto, & Schmidt, 1999; Copper, 1981, 1993, 1998; Copper & Kleinschmidit, 1986; Kessler & Chakrabarti, 1997; Lin & Chen, 2004) and tools (Henriksen & Traynor, 1999; Rangaswamy & Lilien, 1997) are used to control NPD process in an attempt to assist product managers in making better screening decisions. For example, 3M, Hewlett-Packard, Lego, and other companies use the stage-gate system to manage the innovation process (Kotler, 2003). Rangaswamy and Lilien (1997) comprehensively classified these methods into three main classes: (1) factor-weighting techniques (Kao & Liu, 1999); (2) eigenvector method, e.g., analytic hierarchy process (AHP) for NPD (Calantone et al., 1999); (3) screening regression methods. The factor-weighting method decides the importance of critical successful factors (CSF) of NPD using the weighted distance function (Kao & Liu, 1999). The AHP method (Satty, 1980) determines the weights of CSF of NPD by solving for the eigenvalues of a rating matrix (Liberatore, 1987; Calantone et al., 1999; Zimmermann & Zysno, 1983). Screening regression methods use a set of variables to analyze the importance weight of factors and to predict the success or failure of a NPD project using regression and statistics techniques (Copper, 1993). Other well-known techniques for NPD include beta-testing, conjoint analysis, quality function deployment (QFD), break-even analysis (Hart & Hultink, 2002).

However, the traditional technique (Calantone et al., 1999; Copper, 1981; Hart & Hultink, 2002; Kao & Liu, 1999; Kessler & Chakrabarti, 1997; Liberatore, 1987; Satty, 1980) is likely to use quantitative methods, such as optimal techniques, mathematical programming, AHP, and multiple regression models etc., which can only be applied to the case of performance evaluation of the product development phase when the required data are in numeric format.

Since the early phase of new-product screening most often operates in an uncertain situation with incomplete information, it must involve the judgements of decision makers. The expression of human judgment often lacks precision and the confidence levels on the judgment contribute to various degrees of uncertainty. A human-consistent approach is likely to adopt imprecise linguistic terms instead of numerical values in the expression of preference. The issue is compounded when a decision-making process involves a group of decision-makers who have inconsistent preferences.

In the next section, we use vague sets to represent the imprecise linguistic ratings of the group, and define three similarity measures based on mean value of vague sets. These allow the accumulation of the ratings of all the decision makers in order to make an appropriate decision on the priority among alternatives.

3. Preliminary description of vague set theory

The vague set (VS), which is a generalization of the concept of a fuzzy set, has been introduced by Gau and Buehrer (1993) as follows:

A vague set $A'(x)$ in X, $X = \{x_1, x_2, \ldots, x_n\}$, is characterized by a truth-membership function, t_A, and a false-membership function, f_A, for the elements $x_k \in X$ to $A'(x) \in X$, $(k = 1, 2, \ldots, n)$; $t_A : X \to [0,1]$ and $f_A : X \to [0,1]$, where the functions $t_A(x_k)$ and $f_A(x_k)$ are constrained by the condition $0 \leqslant t_A(x_k) + f_A(x_k) \leqslant 1$. $t_A(x_k)$ is a lower bound on the grade of membership of the evidence for x_k, $f_A(x_k)$ is a lower bound on the negation of x_k derived from the evidence against x_k. The grade of membership of x_k in the vague set A' is bounded to a subinterval $[t_A(x_k), 1 - f_A(x_k)]$ of $[0, 1]$. In other words, the exact grade of membership of x_k may be unknown, but it is bounded by $t_A(x_k) \leqslant u_A(x_k) \leqslant 1 - f_A(x_k)$.

Fig. 1 shows a vague set in the universe of discourse X.

Let X be the universe of discourse, $X = \{x_1, \ldots, x_n\}$, $x_k \in X$, a vague set A' of the universe of discourse X can be represented by Chen (1997)

$$A'(x) = \frac{[t_A(x_1), 1 - f_A(x_1)]}{x_1} + \cdots + \frac{[t_A(x_n), 1 - f_A(x_n)]}{x_n}. \quad (1)$$

(1) can be represented as the following formula:

$$A'(x) = \sum_{k=1}^{n} \frac{[t_A(x_k), 1 - f_A(x_k)]}{x_k}, \quad x_k \in X. \quad (2)$$

The vague value is simply defined as a unique element of a vague set. For example, $X = \{\text{Number of friends}\}$ the vague set Likeable could then have vague values associated with each number [0.1, 0.0]/0, [0.2, 0.1]/2,...

In the sequel, we will refer to $A'(x)$ as a vague set, A' as a vague value, and omit the argument x_k of $t_A(x_k)$ and $f_A(x_k)$ throughout unless they are needed for clarity.

Definition 1. The *intersection* of two vague sets $A'(x)$ and $B'(x)$ is a vague set $C'(x)$, written as $C'(x) = A'(x) \wedge B'(x)$, truth-membership and false-membership functions are t_C and f_C, respectively, where $t_C = \min(t_A, t_B)$, and $1 - f_C = \min(1 - f_A, 1 - f_B)$. That is,

$$\begin{aligned}[t_C, 1 - f_C] &= [t_A, 1 - f_A] \wedge [t_B, 1 - f_B] \\ &= [\min(t_A, t_B), \min(1 - f_A, 1 - f_B)]. \quad (3)\end{aligned}$$

Definition 2. The *union* of vague set $A'(x)$ and $B'(x)$ is a vague set $C'(x)$, written as $C'(x) = A'(x) \vee B'(x)$, where truth-membership function and false-membership function are t_C and f_C, respectively, where $t_C = \max(t_A, t_B)$, and $1 - f_C = \max(1 - f_A, 1 - f_B)$. That is,

$$\begin{aligned}[t_C, 1 - f_C] &= [t_A, 1 - f_A] \vee [t_B, 1 - f_B] \\ &= [\max(t_A, t_B), \max(1 - f_A, 1 - f_B)]. \quad (4)\end{aligned}$$

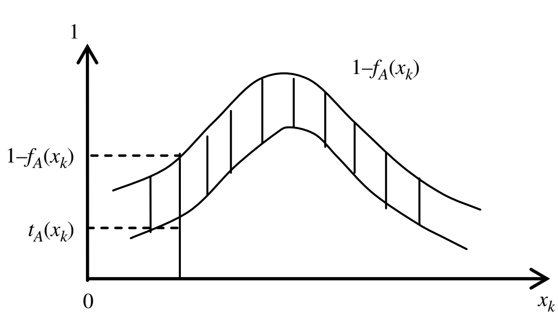

Fig. 1. A vague set.

Further, let us define the similarity measures between two vague values in order to represent the preference agreement between experts' ratings as follows:

Let $A' = [t_A(x_k), 1 - f_A(x_k)]$ be a vague value, where $t_A(x_k) \in [0, 1]$, $f_A(x_k) \in [0, 1]$, and $0 \leqslant t_A(x_k) + f_A(x_k) \leqslant 1$ ($x_k \in \mathrm{X}$).

Definition 3. Let A' be a vague value in X, $X = \{x_1, \ldots, x_n\}$, $A' = [t_A(x_k), 1 - f_A(x_k)]$. The *mean value* of A' (Li & Cheng, 2002) is

$$\varphi_A(x_k) = \frac{t_A(x_k) + 1 - f_A(x_k)}{2}. \quad (5)$$

Definition 4. If a vague set A' is a subset of a vague set B', we denote as $A' \subseteq B'$.

Proposition 1. *For two vague sets A', B', $\varphi_A(x_k) \leqslant \varphi_B(x_k)$ holds, if $A' \subseteq B'$.*

If $A' \subseteq B'$, then each subinterval $[t_A(x_k), 1 - f_A(x_k)]$ is contained inside $[t_B(x_k), 1 - f_B(x_k)]$. According to Definition 3, it implies that the mean values of A' are smaller than those of B', which can be expressed as $\varphi_A(x_k) \leqslant \varphi_B(x_k)$ for all x_k.

Definition 5. For two vague values A' and B' in X, $X = \{x_1, \ldots, x_n\}$, $S(A', B')$ (Li & Cheng, 2002) is a *degree of similarity* between vague values if it preserves the properties (P1)–(P4). Let Δ be the set of vague values in $X = \{x_1, x_2, \ldots, x_n\}$ then $S(\alpha, \beta)$ is a *degree of similarity* for Δ if it preserves the properties (P1)–(P4).

(P1) For all $A', B' \in \Delta$ $0 \leqslant S(A', B') \leqslant 1$;
(P2) $S(A', B') = 1$ if $A' = B'$;
(P3) For all $A', B' \in \Delta$ $S(A', B') = S(B', A')$;
(P4) For all $A', B', C' \in \Delta$ such that $A' \subseteq B' \subseteq C'$, $S(A', C') \leqslant S(A', B')$ and $S(A', C') \leqslant S(B', C')$. (6)

4. The proposed method

In a NPD process, decision makers including marketers, customers, managers, and R&D members, have to form a new-product committee. Each decision maker has to evaluate and screen new-products according to some well-defined criteria, and then assign performance ratings to the alternatives for each criterion individually. The decision makers allocate ratings based on their own preferences and subjective judgments. The explicit representation of their preference and judgment with precise numerical values may not be simple, whereas the use of linguistic terms is more natural to human decision makers. This formulation is imprecise, ambiguous and often leads to an increase in the complexity of the decision making process. To simplify the evaluation process of group decision making, the evaluation criteria are pre-defined here. Hence the new-product screening activity of NPD can be regarded as a fuzzy

MPDM problem. A fuzzy MPDM problem (Chen & Hwang, 1992; Hwang & Lin, 1987), however, can be formulated as a generic decision making matrix.

4.1. Problem formulation

Suppose that a decision group contains m decision makers who have to give linguistic ratings on n alternatives according to q evaluation criteria, then a fuzzy MPDM problem can be expressed concisely in preference-agreement matrix (Chen & Hwang, 1992) as follows:

$$D(t_j) = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}, \tag{7}$$

$$W = [w_1 w_2 \cdots w_m], \quad \text{and} \quad \sum_{i=1}^{m} w_i = 1,$$

where D is a decision matrix of the group, $d_i \in \{d_1, d_2, \ldots, d_m\}$ are a set of decision makers. $t_j \in \{t_1, t_2, \ldots, t_n\}$ are a finite set of possible targets (i.e., new-products) from which decision makers have to select, $\tilde{x}_{ij}$ $(i = 1, \ldots, m,$ $j = 1, \ldots, n)$ is the linguistic rating on target t_j by d_i, and w_i is the importance weight of d_i. These linguistic terms can be transformed into a vague value A' according to Table 1,

$$A' = [t_A(x_k), 1 - f_A(x_k)]/x_k, \quad x_k \in X. \tag{8}$$

In the following, we use the similarity measure of vague sets to aggregate linguistic ratings of a group's preferences in order to obtain their preferences on each new-product.

4.2. Similarity measure

We present a new similarity measure between two vague sets with discrete form. We give corresponding proofs of these similarity measures as follows.

The preference agreement between two experts can be represented by the proportion of the interception to the union. Based on this idea, we use the Definition 6 to represent the similarity between two vague values.

Definition 6. Using mean of vague value, $S^m(A', B')$ is defined as the similarity measure between two vague values according to Zwick, Carlstein, and Budescu (1987)

$$S^m(A', B') = \frac{\sum_{i=1}^{n} (\varphi_A(x_i) \wedge \varphi_B(x_i))}{\sum_{i=1}^{n} (\varphi_A(x_i) \vee \varphi_B(x_i))} = \frac{\sum_{i=1}^{n} \min(\varphi_A(x_i), \varphi_B(x_i))}{\sum_{i=1}^{n} \max(\varphi_A(x_i), \varphi_B(x_i))}. \tag{9}$$

According to Definition 3, we use the mean value of A' and B' to represent the mean of truth-membership and false-membership function.

Theorem 1. *$S^m(A', B')$ preserves the four important properties (P1)–(P4) of the similarity measure of vague value.*

Proof. It is obvious that Theorem 1 satisfies the properties (P1)–(P3) of Definition 6. In the following, $S^m(A', B')$ will be proved to satisfy (P4) as follows.

For any $C' = [t_C(x), 1 - f_C(x)]/x$ and $A' \subseteq B' \subseteq C'$, we have $A' \subseteq B'$, as $A' \subseteq B'$ implies $\varphi_{A'}(x) \leqslant \varphi_{B'}(x)$.

$$\begin{aligned} S^m(A', C') &= \frac{\sum_{i=1}^{n} \min(\varphi_A(x_i), \varphi_C(x_i))}{\sum_{i=1}^{n} \max(\varphi_A(x_i), \varphi_C(x_i))} = \frac{\sum_{i=1}^{n} \varphi_A(x_i)}{\sum_{i=1}^{n} \varphi_C(x_i)} \\ &\leqslant \frac{\sum_{i=1}^{n} \varphi_B(x_i)}{\sum_{i=1}^{n} \varphi_C(x_i)} = \frac{\sum_{i=1}^{n} \min(\varphi_B(x_i), \varphi_C(x_i))}{\sum_{i=1}^{n} \max(\varphi_B(x_i), \varphi_C(x_i))} \\ &= S^m(B', C'). \end{aligned}$$

Since $A' \subseteq B'$, we have $S^m(A', C') \leqslant S^m(B', C')$. Similarly, we can prove that $S^m(A', C') \leqslant S^m(A', B')$ if $A' \subseteq B' \subseteq C'$. □

In the following, we introduce the explicit form of $S^m(A', B')$, called Mean Similarity.

In some cases, the weight of the element $x \in X$ might be considered. Then, we present the following weighted measure between vague sets.

Assume that the weight of $x \in X = \{x_1, \ldots, x_n\}$ is $w_k (k = 1, 2, \ldots, n)$, where $0 \leqslant w_k \leqslant 1$, and $\sum_{k=1}^{n} w_k = 1$.

We denote

$$S^w(A', B') = \frac{\sum_{i=1}^{n} w(x_i).\min\{\varphi_A(x_i), \varphi_B(x_i)\}}{\sum_{i=1}^{n} w(x_i).\max\{\varphi_A(x_i), \varphi_B(x_i)\}}. \tag{10}$$

Theorem 2. *$S^w(A', B')$ is a degree of similarity between the two vague sets A' and B' in X.*

Proof. This proof is similar to that of Theorem 1 (omitted). □

Obviously, if $w_k = 1/(b - a)$ $(k = 1, 2, \ldots, n)$, Eq. (12) becomes Eq. (11). So Eq. (12) is a general form of Eq. (11).

Definition 7. $S^w(A', B')$ is the *weighted similarity* between vague sets A' and B'.

Table 1
Linguistic variables for the rating of new product

Very low/very poor	$[t_A(1), 1 - f_A(1)]/1$
Low/poor	$[t_A(2), 1 - f_A(2)]/2$
Medium	$[t_A(3), 1 - f_A(3)]/3$
High/good	$[t_A(4), 1 - f_A(4)]/4$
Very high/very good	$[t_A(5), 1 - f_A(5)]/5$

4.3. Preferences aggregation

We calculate the preference-agreement degree of two experts' ratings expressed by Eq. (9) and denote $S^m(i, i')$ as $a_{ii'}$, $i, i' = 1, \ldots, m$, where two vague sets i, and i'

represents the linguistic rating of decision maker $d_i, d_{i'}$. The preference-agreement matrix $A(t)$ for evaluated targets $t = t_1 \ldots, t_n$ is (need to show dependence on t in the matrix.)

$$A(t) = \begin{bmatrix} 1 & a_{12}(t) & \cdots & a_{1m}(t) \\ a_{21}(t) & 1 & \cdots & a_{2m}(t) \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1}(t) & a_{m2}(t) & \cdots & 1 \end{bmatrix} \tag{11}$$

Remark. For $a_{ii'} = S^m(i, i')$ if $i \neq i'$, and $a_{ii'} = 1$ if $i = i'$. Two decision makers fully agree to an evaluated target, if they have $a_{ii'} = 1$; it implies: $t_A(x) = t_B(x)$, $1 - f_A(x) = 1 - f_B(x)$. By contrast, if they have completely different estimates, then we get $a_{ii'} = 0$.

After all the preference-agreement degrees between two decision makers have been measured, we then aggregate those pairs of vectors using the average aggregation rule to obtain the preference of the group on each new-product.

By applying simple additive aggregation rule, we have the group preference (not sure that this is what it is, you are adding up similarities.) of all the decision makers on an evaluated target as

$$C(t_j) = \frac{2}{m(m-1)} \sum_{i=1}^{m-1} \sum_{i'=i+1}^{m} a_{ii'}(t_j). \tag{12}$$

(There should be a definition here. The quantity appears to be an agreement average on a given target. It might be useful to call it that.)

4.4. Group preference on new-product

In order to synthesize the preference degree of group, a general compensation operator proposed by Zimmermann and Zysno (1983) is adopted as the group-preference operator in this paper (Kacprzyk & Fedrizzi, 1989; Zimmermann & Zysno, 1983). This index synthesizes a confidence level of preference for all experts on an evaluated target t_j. A global measure of preference on each evaluated targets $(t_1, \ldots, t_n)$ is obtained as

$$C(t) = \left(\prod_{j=1}^{n} C(t_j)\right)^{1-r} \left(1 - \prod_{j=1}^{n}(1 - C(t_j))\right)^{r}. \tag{13}$$

(The above formula needs correcting, there is no definition of C_s and product is over values of 'j' which is not mentioned). As the compensation parameter γ varied from 0 to 1, the operator describes the aggregation properties of "AND" and "OR", that is,

$$\max_{j=1,\ldots,n} C(t_j) \geqslant C(t) \geqslant \min_{j=1,\ldots,n} C(t_j), \tag{14}$$

where F (so is F the same thing as C?) is an aggregation function of Eq. (15) (This does not make sense, the t_i have not yet been defined numerically so how can we have a max and min).

The compensation parameter γ indicates the complement level of decision maker. A small γ implies the higher degree of complement. Finally, the moderator can estimate the degree of consensus depending on γ and decide whether group consensus has been reached using $C_{Q_1 \backslash E \backslash Q_2}(t)$ (some explanation of $Q_1 \backslash E \backslash Q_2$ would be helpful) and γ. If the group consensus has not been reached, then the decision makers have to modify their ratings according to the Delphi iterative procedures.

4.5. Fuzzy synthetic evaluation method

Once the group preference for all decision makers on each new-product has reached, the fuzzy synthetic evaluation method is employed to attain the priorities of new products. The fuzzy simple weighting additive rule is adopted to derive the synthetic evaluations of alternatives by multiplying the importance weight of each decision maker (w_i) with fuzzy rating of alternatives ($\tilde{x}_{ij}$). The formulation of synthetic evaluations of new products which is shown as follows:

$$\widetilde{V} = [\tilde{v}_j] = \sum_{j=1}^{n} w_i \otimes \tilde{x}_{ij}, \quad i = 1, 2, \ldots, m, \ \ j = 1, 2, \ldots, n. \tag{15}$$

However, the aggregation results $\widetilde{V}$ are still vague values, which cannot be applied directly to decision making. The use of fuzzy ranking method and α-cuts of fuzzy number is to rank the order of alternatives and to transform them into numerical values, according to the synthetic evaluation results.

Based on Definition 3, the synthetic evaluation values $\widetilde{V}$ can be represented as

$$\widetilde{V} = \sum_{i=1}^{n} \frac{[t_A(x_k), 1 - f_A(x_k)]}{x_k} = \sum_{k=1}^{n} \frac{\varphi_A(x_k)}{x_k}. \tag{16}$$

Finally, the fuzzy ranking method proposed by Yager (1981) is adopted to determine the ranking of results of synthetic evaluation as follows (Chen & Hwang, 1992):

Given a fuzzy number $\widetilde{V}$, Yager's index is defined as

$$F(\widetilde{V}) = \int_0^{\alpha_{\max}} \overline{X}(\widetilde{V}_\alpha) \mathrm{d}\alpha, \tag{17}$$

where $\alpha_{\max} = \sup_x u_{\widetilde{V}}(x)$ and $\overline{X}(\widetilde{V}_\alpha)$ represents the average value of the elements having at least α degree of membership.

In summary, the solution algorithm can be summarized as follows:

Step 1. Form a new-product committee and identify the appropriate criteria and importance weights for each decision maker.

Step 2. Select the appropriate linguistic terms for representing the rating of new products and perform the idea screening process using vague value according to confidence level of decision maker.

Step 3. Calculate the preference-agreement vector between two decision makers using Eq. (9).

Step 4. Construct the preference-agreement matrixes for all decision makers using Eq. (11).

Step 5. Aggregate the preference-agreement vectors to obtain the group preference of each new product using Eq. (12).

Step 6. Calculate the group-preference index on all products using Eq. (13).

Step 7. The new-product manager judges whether group preference on each new-product has been reached according to the index. If it has not reached, then decision maker has to modify his/her rating according to the Delphi iterative procedures.

Step 8. Repeat steps (2)–(6) until group-preference index is reached the accepted level by all decision makers. If group preference has been reached, then go to step 9, else go to step 2.

Step 9. The new-product manager determines the ranking of new products using Eq. (19) and make one of four decisions: *go*, *kill*, *hold*, or *recycle* according to the company's screening policy of NPD.

5. Numerical example: new-products screening

In this section, an example for a LCD TV development is used as a demonstration of the application of the proposed method in a realistic scenario, as well as a validation of the effectiveness of the method. The evaluation process of products screening is specified as Fig. 2.

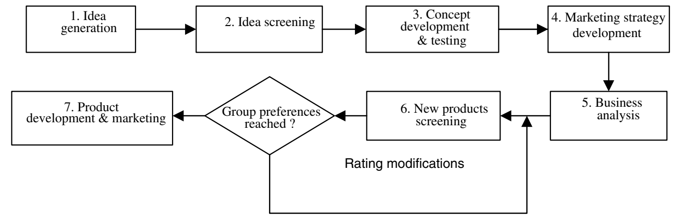

Fig. 2. The evaluation process of LCD-TV new products screening.

Suppose that there is a new-product committee consisting of six decision makers, {R&D manager, quality manager, sales manager, engineering manager, accounting manager, customer} has to screen new-product ideas as Table 1 according to the five criteria: (c1) project resource compatibility (c2) product superiority and unique, (c3) technology complexity and magnitude, (c4) market need, growth and size (c5) maintenance of market share and sunk cost (Balachandra & Friar, 1997; Copper, 1993; Kim & Kim, 1991). A set of four concept models has been built. Four concept models must be selected through idea-screening process and be sent to mass product and market testing. The committee has to perform the screening process and select the best target from the four candidates according to the defined criteria. The proposed method is applied to solve this problem according to the following computational procedure:

Step 1: Form a working group $d = \{d_1, d_2, d_3, d_4, d_5, d_6\}$, and possible targets $t = \{t_1, t_2, t_3, t_4\}$. In the following, we have the priori information to determine the weighting vectors of each decision maker by his/her relative importance, $w_i = w_i / \sum_{i=1}^{n} w_i$, that is,

$$W = [w_i] = \{0.15, 0.2, 0.25, 0.15, 0.15, 0.1\}.$$

Step 2: Let a vague set A' in $X = \{\text{VL}, \text{L}, \text{M}, \text{H}, \text{VH}\}$ presents linguistic variables of sales price as Table 1. For example, "High" may be represented as $A' = (0.7, 0.8)/4$, where $t_A(4) = 0.7$, $f_A(4) = 0.2$. We use the linguistic variables, shown in Table 1, to assess the ratings of new products using vague value as Table 2.

Step 3: For evaluated target t_1, we calculate the preference agreement vectors between d_1, d_2 using Eq. (9) as

Table 2
Ratings of evaluated targets using vague sets

DMs	Targets									
	t_1					t_2				
	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5
d_1	(0.7, 0.8)/2	(0.8, 0.8)/3	(0.7, 0.7)/4	(0.6, 0.7)/3	(0.7, 0.9)/4	(0.6, 0.6)/4	(0.7, 0.9)/4	(0.7, 0.9)/3	(0.7, 0.7)/3	(0.7, 0.8)/4
d_2	(0.8, 0.9)/2	(0.6, 0.7)/4	(0.8, 0.8)/4	(0.7, 0.7)/3	(0.8, 0.9)/4	(0.7, 0.7)/3	(0.8, 0.8)/4	(0.6, 0.8)/3	(0.8, 0.9)/3	(0.8, 0.9)/3
d_3	(0.6, 0.8)/2	(0.6, 0.7)/3	(0.5, 0.7)/4	(0.8, 0.9)/3	(0.8, 0.8)/3	(0.6, 0.8)/4	(0.8, 0.9)/4	(0.6, 0.7)/3	(0.9, 0.9)/4	(0.7, 0.8)/4
d_4	(0.5, 0.6)/3	(0.5, 0.8)/3	(0.6, 0.7)/3	(0.6, 0.6)/4	(0.6, 0.7)/4	(0.5, 0.6)/4	(0.7, 0.9)/4	(0.6, 0.9)/3	(0.6, 0.7)/3	(0.8, 0.8)/4
d_5	(0.9, 0.9)/2	(0.9, 0.9)/3	(0.6, 0.7)/4	(0.8, 0.8)/3	(0.7, 0.7)/4	(0.6, 0.6)/4	(0.6, 0.6)/4	(0.8, 0.9)/3	(0.6, 0.8)/3	(0.9, 0.9)/4
d_6	(0.6, 0.7)/2	(0.9, 0.9)/3	(0.9, 0.9)/4	(0.8, 0.9)/3	(0.8, 0.8)/4	(0.6, 0.7)/4	(0.6, 0.7)/4	(0.7, 0.9)/3	(0.6, 0.7)/3	(0.8, 0.8)/4
	t_3					t_4				
d_1	(0.7, 0.7)/5	(0.7, 0.8)/4	(0.7, 0.8)/5	(0.6, 0.8)/2	(0.8, ,0.8)/4	(0.6, 0.6)/3	(0.9, 0.9)/3	(0.6, 0.8)/5	(0.6, 0.8)/3	(0.7, 0.8)/5
d_2	(0.6, 0.6)/4	(0.8, 0.9)/3	(0.8, 0.9)/5	(0.7, 0.7)/3	(0.7, 0.9)/4	(0.6, 0.7)/3	(0.8, 0.9)/3	(0.5, 0.6)/4	(0.7, 0.9)/4	(0.7, 0.7)/4
d_3	(0.6, 0.7)/4	(0.7, 0.7)/4	(0.8, 0.8)/4	(0.8, 0.9)/3	(0.8, 0.9)/5	(0.7, 0.7)/3	(0.8, 0.8)/3	(0.7, 0.8)/4	(0.8, 0.9)/3	(0.8, 0.8)/4
d_4	(0.9,0.9)/4	(0.7, 0.7)/4	(0.9, 0.9)/5	(0.6, 0.6)/3	(0.9, 1.0)/4	(0.6, 0.6)/3	(0.5, 0.8)/3	(0.5, 0.6)/4	(0.5, 0.6)/3	(0.4, 0.6)/4
d_5	(0.7, 0.8)/4	(0.8, 0.9)/4	(0.8, 0.9)/5	(0.8, 0.8)/3	(0.9, 0.9)/4	(0.8, 0.9)/3	(0.8, 0.9)/3	(0.5, 0.6)/4	(0.8, 0.9)/3	(0.6, 0.8)/4
d_6	(0.8, 0.9)/4	(0.7, 0.7)/4	(0.7, 0.7)/5	(0.7, 0.8)/3	(0.8, 0.8)/4	(0.6, 0.8)/3	(0.7, 0.8)/3	(0.6, 0.7)/4	(0.7, 0.8)/3	(0.7, 0.8)/4

$$a_{12} = \frac{\int_2^3 [\min\{t_{11}, t_{21}\}, \min\{1 - f_{11}, 1 - f_{21}\}]\mathrm{d}x}{\int_2^3 [\max\{t_{11}, t_{21}\}, \max\{1 - f_{11}, 1 - f_{21}\}]\mathrm{d}x} = \frac{\int_2^3 [0.7, 0.8]\mathrm{d}x}{\int_2^3 [0.8, 0.9]\mathrm{d}x} = \frac{\int_2^3 0.75\mathrm{d}x}{\int_2^3 0.85\mathrm{d}x} = \frac{0.75}{0.85} = 0.882.$$

Following the same way, we can obtain the others elements $a_{13}, a_{14}, \ldots, a_{65}$ for targets t_1, t_2, t_3 and t_4.

Step 4: Construct the preference-agreement matrixes for color criterion for all targets as

$$A(t_1) = \begin{bmatrix} 1.00 & 0.88 & 0.93 & 0.00 & 0.83 & 0.87 \\ 0.88 & 1.00 & 0.82 & 0.00 & 0.94 & 0.77 \\ 0.93 & 0.82 & 1.00 & 0.00 & 0.78 & 0.93 \\ 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 \\ 0.83 & 0.94 & 0.78 & 0.00 & 1.00 & 0.72 \\ 0.87 & 0.77 & 0.93 & 0.00 & 0.72 & 1.00 \end{bmatrix},$$

$$A(t_2) = \begin{bmatrix} 1.00 & 0.00 & 0.88 & 0.69 & 0.75 & 0.89 \\ 0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.88 & 0.00 & 1.00 & 0.79 & 0.86 & 0.78 \\ 0.69 & 0.00 & 0.79 & 1.00 & 0.92 & 0.61 \\ 0.75 & 0.00 & 0.86 & 0.92 & 1.00 & 0.67 \\ 0.89 & 0.00 & 0.78 & 0.61 & 0.67 & 1.00 \end{bmatrix},$$

$$A(t_3) = \begin{bmatrix} 1.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.92 & 0.67 & 0.80 & 0.72 \\ 0.00 & 0.92 & 1.00 & 0.72 & 0.87 & 0.77 \\ 0.00 & 0.67 & 0.72 & 1.00 & 0.83 & 0.94 \\ 0.00 & 0.80 & 0.87 & 0.83 & 1.00 & 0.88 \\ 0.00 & 0.72 & 0.77 & 0.94 & 0.88 & 1.00 \end{bmatrix},$$

$$A(t_4) = \begin{bmatrix} 1.00 & 0.92 & 0.86 & 0.67 & 0.71 & 0.86 \\ 0.92 & 1.00 & 0.93 & 0.72 & 0.77 & 0.93 \\ 0.86 & 0.93 & 1.00 & 0.78 & 0.82 & 0.87 \\ 0.67 & 0.72 & 0.78 & 1.00 & 0.94 & 0.78 \\ 0.71 & 0.77 & 0.82 & 0.94 & 1.00 & 0.82 \\ 0.86 & 0.93 & 0.87 & 0.78 & 0.82 & 1.00 \end{bmatrix}.$$

Similarly, c2, c3, c4 and c5 of the preference-agreement matrixes are also constructed.

Step 5: Aggregate the preference-agreement vectors to obtain the group preference of each new product using Eq. (12) as

	t_1	t_2	t_3	t_4
$C(t_j)$	0.564	0.715	0.575	0.676

Step 6: Calculate the group-preference index on all targets for $\gamma = 0$, $\gamma = 0.5$, $\gamma = 1$, respectively

	$\gamma = 0$	$\gamma = 0.5$	$\gamma = 1$
$C(t)$	0.157	0.393	0.983

Step 7: The new-product manager averages new-product with three different levels of confidences: low, moderate, and high, $C(t) = 0.511$ to judge that group preferences have been reached due to the fact $C(t) = 0.511 \geqslant 0.5$.

Step 8: If a group has been reached a consensus over the preferences, then go to step 9. If not, it goes back to step 1.

Step 9:

(9.1) The weighted fuzzy rating is obtained using Eq. (15) as shown in Table 3 and synthetic results for four target is obtained by integrating $\overline{X}(\widetilde{V}_\alpha)$ at $\alpha = 0.05$, 0.10, 0.15–1 through Eqs. (16) and (17).

For example, the mean form of $\widetilde{V}$ for $\widetilde{V}(1,1)$ (i.e., rating on t_1 evaluated by d_1) is $\widetilde{V}(1,1) = 0.11/2 + 012/3 + 011/4$.

The various α level sets are

$\widetilde{V}_\alpha = \{4,3,2\}, \quad 0 < \alpha \leqslant 0.05;$

$\widetilde{V}_\alpha = \{4,3,2\}, \quad 0.05 < \alpha \leqslant 0.1;$

$\widetilde{V}_\alpha = \{0\}, \quad 0.10 < \alpha \leqslant 0.15.$

From this set of $\widetilde{V}_\alpha$, we can compute $\overline{X}(\widetilde{V}_\alpha)$ as

$\overline{X}(\widetilde{V}_\alpha) = (4+3+2)/3 = 3, \quad 0.00 < \alpha \leqslant 0.05;$

$\overline{X}(\widetilde{V}_\alpha) = (4+3+2)/3 = 3, \quad 0.05 < \alpha \leqslant 0.1;$

$\overline{X}(\widetilde{V}_\alpha) = 0, \quad 0.10 < \alpha \leqslant 0.15;$

$\overline{X}(\widetilde{V}_\alpha) = 0, \quad 0.15 < \alpha \leqslant 1.00.$

Since the synthetic evaluation is a discrete form, $F(\widetilde{V})$ index is computed by

$$F(\widetilde{V}) = \int_0^1 \overline{X}(\widetilde{V}_\alpha)\mathrm{d}\alpha = \int_0^{0.05} 3\mathrm{d}\alpha + \int_{0.05}^{0.10} 3\mathrm{d}\alpha = 0.30.$$

Table 3
Weighted ratings of evaluated targets using vague sets

DMs	Targets			
	t_1	t_2	t_3	t_4
d_1	$0.11/2 + 0.22/3 + 0.23/4$	$0.23/3 + 0.32/4$	$0.11/2 + 0.23/4 + 0.22/5$	$0.34/3 + 0.22/5$
d_2	$0.16/2 + 0.14/3 + 0.48/4$	$0.45/3 + 0.33/4$	$0.31/3 + 0.28/4 + 0.17/5$	$0.48/3 + 0.25/4$
d_3	$0.18/2 + 0.37/3 + 0.35/4$	$0.39/3 + 0.59/4$	$0.37/3 + 0.59/4$	$0.59/3 + 0.39/4$
d_4	$0.37/3 + 0.10/4$	$0.24/3 + 0.32/4$	$0.28/3 + 0.25/4 + 0.14/5$	$0.35/3 + 0.17/4$
d_5	$0.14/2 + 0.26/3 + 0.21/4$	$0.24/3 + 0.33/4$	$0.25/3 + 0.25/4 + 0.13/5$	$0.39/3 + 0.19/4$
d_6	$0.07/2 + 0.18/3 + 0.17/4$	$0.15/3 + 0.21/4$	$0.08/3 + 0.24/4 + 0.07/5$	$0.30/3 + 0.08/4$

Similarly, we can obtain the other elements for all decision makers. We, then, average the rating derived from six decision makers with respect to t_1, t_2, t_3 and t_4 are

	t_1	t_2	t_3	t_4
$V(t_i)$	0.455	0.592	0.620	0.524

(9.2) The order of the preferences of the decision makers on four models can be stated as $t_3 \succ t_2 \succ t_4 \succ t_1$.

(9.3) The new-product manager makes the decision according to new-product screening rule of company as

	t_1	t_2	t_3	t_4
Decision	kill	go	go	kill.

6. Discussion

Without any comparison of the proposed method with other well-established methods, the resulting decision may be questionable. In this section, we will compare the new-product ranking procedures, developed by Lin and Chen's approach (Lin & Chen, 2004), to treat the same problem.

From Eq. (17), the synthetic evaluation of traditional fuzzy approach can be obtained when it is true that $t(x) = 1 - f(x)$ for vague sets (i.e., ignore uncertainty) as Table 4.

Then, the average value of rating all decision makers is given by

$$\tilde{v}_j = \frac{1}{n}\sum_{i=1}^{n}\left[\widetilde{v_{ij}^{1}} \oplus \widetilde{v_{ij}^{2}} \oplus \ldots \oplus \widetilde{v_{ij}^{n}}\right], \tag{18}$$

	t_1	t_2	t_3	t_4
$\widetilde{V}(t_i)$	$0.72/2 + 0.67/3 + 0.68/4$	$0.686/3 + 0.634/4$	$0.78/3 + 0.7/4 + 0.78/5$	$0.74/3 + 0.55/4 + 0.6/5$.

In the following, the left-and-right fuzzy ranking method is applied to synthesize the fuzzy ratings

$$V_{\mathrm{R}} = \sup_x[u_{\tilde{v}_j}(x) \wedge u_{\max}(x)], \tag{19}$$

$$V_{\mathrm{L}} = \sup_x[u_{\tilde{v}_j}(x) \wedge u_{\min}(x)], \tag{20}$$

where $u_{\max}(x) = \begin{cases} x, & 0 \leqslant x \leqslant 1, \\ 0, & \text{otherwise,} \end{cases}$ $u_{\min}(x) = \begin{cases} 1-x, & 0 \leqslant x \leqslant 1, \\ 0, & \text{otherwise.} \end{cases}$

The synthetic evaluation on each target is given by

$$V = \frac{|V_{\mathrm{R}} + (1 - V_{\mathrm{L}})|}{2}. \tag{21}$$

The synthetic value on each target is calculated using Eqs. (18)–(21) or geometric graphics described as (Chen & Hwang, 1992)

	t_1	t_2	t_3	t_4
$V(t_i)$	0.47	0.51	0.55	0.49.

Obviously, the target 3 is the best choice and the ranking order is $t_3 \succ t_2 \succ t_4 \succ t_1$. The solution of Lin and Chen's method concludes the same result as our proposed model.

From Table 4 and Eq. (21), the rational outcomes can be obtained using either our method or Lin and Chen's method. Furthermore, our method is capable of revealing the positive and negative preference degree associated with DM's subject judgements and assisting the DM to make a normal decision based on group consensus. We believed that this method is complimentary to Lin and Chen (2004) as it introduces another dimension to new product development based on group preference.

7. Conclusion

This paper presents a new fuzzy approach to solve NPD screening problems considering the group consensus. The proposed method allows the decision makers to express their preferences in linguistic terms and explicitly represent their uncertainty of their judgments using vague sets during the conceptual design phase. From a numerical illustration for early evaluation of LCD-TV new products screening, it can assist the manager to make the screening decision based on the proposed model. The experimental results

Table 4
Rating of evaluated targets using fuzzy sets

DMs	Targets			
	t_1	t_2	t_3	t_4
d_1	$0.7/2 + 0.8/3 + 0.7/4$	$0.6/4 + 0.7/4 + 0.7/3$	$0.7/5 + 0.7/4 + 0.7/4$	$0.6/3 + 0.9/3 + 0.6/5$
d_2	$0.8/2 + 0.6/4 + 0.8/4$	$0.7/3 + 0.8/4 + 0.6/3$	$0.6/4 + 0.8/3 + 0.8/5$	$0.6/3 + 0.8/3 + 0.5/4$
d_3	$0.6/2 + 0.6/3 + 0.5/4$	$0.6/4 + 0.8/4 + 0.6/3$	$0.6/3 + 0.7/4 + 0.8/4$	$0.7/3 + 0.8/3 + 0.7/4$
d_4	$0.5/3 + 0.5/3 + 0.6/3$	$0.5/4 + 0.7/4 + 0.6/3$	$0.9/3 + 0.7/4 + 0.9/5$	$0.9/3 + 0.8/3 + 0.5/4$
d_5	$0.9/2 + 0.9/3 + 0.6/4$	$0.6/4 + 0.6/4 + 0.8/3$	$0.7/4 + 0.8/3 + 0.8/5$	$0.8/3 + 0.8/3 + 0.5/4$
d_6	$0.6/2 + 0.6/3 + 0.9/4$	$0.6/4 + 0.7/4 + 0.8/3$	$0.8/4 + 0.7/4 + 0.7/5$	$0.6/3 + 0.7/3 + 0.6/3$

indicate that our approach not only effectively reveals the uncertainty of decision makers' subjective judgments, but also is applicable to analyze the consensus degree of group during the NPD screening process.

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