A Fuzzy 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 the fuzzy set which cannot treat the negative evidence. The advantage of vague sets with the capability of representing negative evidences supports the decision makers with ability of modeling uncertain objects. 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 of vague sets is introduced to proceed with the ratings aggregation for a group of decision makers. From numerical illustrations, the proposed model can outperform conventional fuzzy methods. It is able to provide decision makers (DMs) with consistent information and to model the situation where vague and ill-defined information exist in the decision process.

Keywords: New Product Development, Idea Screening, Vague Sets, Similarity, MPDM

1. Introduction

New-product development is one of the most critical tasks in 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 NPD process, decision makers have to screen new-product ideas according to a number of criteria. Consequently, they recommend the ideas to R&D engineers, marketers, and sales managers in every stage of development. The decision makers' preferences have a significant impact on the selection of new products and the outcome of decision-making. How to reach the consistent group preference on each new-product is an important issue and is notoriously difficult to achieve. In most cases, NPD is risky due to lacking of sufficient information with consumers' preferences for making decisions. The information is often imprecise, inconsistent and uncertain. Recent studies [10] 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 loses. For example, Ford lost $250 million on its Edsel; RCA lost $500 million on its videodisk player etc. Many reasons result in the failure of new products. Some of important factors in high technology NPD can be summarized as follows [2, 6,10]:

1) In 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 concept development and testing phase, the criteria for new-product screening are not always quantifiable or comparable;
3) In 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 commercialization phase, participating competitors will use tactics or other means to contend.

Many methods [2,5,6]and tools [1] 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 [5]. However, the traditional technique [5,6] is likely to use quantitative methods, such as optimal techniques, mathematical programming, and utility models etc, which neglect the human behavior and only can be applied to the case if the required data are sufficient. Since new–product screening process must involve the judgments of decision makers and the expression of human judgments often lacks precision. In addition, the confidence levels on the judgments 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 over the ratings on new products.

This research sets out to tackle more human-consistent by adding the assumptions (i.e., "I am not sure") often prohibited by other existing approaches [2,4,8,9]. In this paper, we propose a new method, which extends the traditional NPD methods to a fuzzy environment, uses the similarity measures of vague sets [3,13] to aggregate the ratings of all decision makers including the negative evidence, and supports the decision on the priority among alternatives through the use of fuzzy synthetic evaluation method [12].

2. 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 [13] as follows:

A vague set $A^{'}(x)$ in X, $X=\{x_1,x_2,\ldots,x_n\}$, is characterized by the truth-membership t_A and a false-membership function f_A of the element $x_k \in X$ to $A^{'}(x) \in X$, (k=1,2,...,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 $0 \le t_A(x_k) + f_A(x_k) \le 1$, (1)

where $t_A(x_k)$ 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 $[t_A(x_k), 1-f_A(x_k)]$ of x_k may be unknown, but it is bounded by $t_A(x_k) \le u_A(x_k) \le 1-f_A(x_k)$.

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

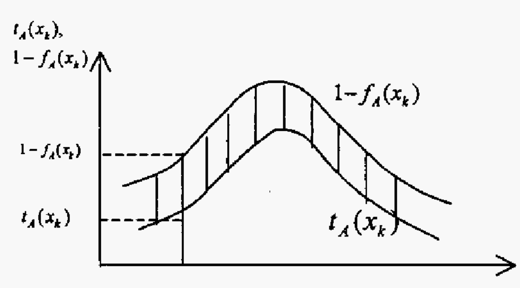

Fig. 1. A vague set

When X is continuous, a vague set $A^{'}(x)$ can be written as

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

When X is discrete, a vague set $A^{'}(x)$ can be written as

$$A^{'}(x) = \sum_{k=1}^{n} [t_A(x_k), 1-f_A(x_k)] / x_k, \quad x_k \in X. \quad (3)$$

The vague value is simply defined as unique element of a vague set. For example, we assume that $X=\{1,2,\ldots,10\}$, a vague value "*Beauty*" of X may be defined by $Beauty = [0.5, 0.4]/5$. It implies the positive preference is 0.5 and the negative preference is 0.6 (i.e., 1-0.4).

In the sequel, we will redefine $A^{'}(x)$ is a vague set, $A^{'}$ is 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 function and false-membership function 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,

$$[t_C, 1-f_C] = [t_A, 1-f_A] \wedge [t_B, 1-f_B] = [Min(t_A, t_B), Min(1-f_A, 1-f_B)]. \quad (4)$$

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,

$$[t_C, 1-f_C] = [t_A, 1-f_A] \vee [t_B, 1-f_B] = [Max(t_A, t_B), Max(1-f_A, 1-f_B)]. \quad (5)$$

Further, let us define the similarity measures between two vague values in order to represent the preference agreement between experts' ratings as follows: [3]

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 $0 \le t_A(x_k) + f_A(x_k) \le 1$.

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 median value of $A^{'}$ is [6]

$$\varphi_A(x_k) = \frac{t_A(x_k) + 1 - f_A(x_k)}{2}. \quad (6)$$

Definition 4. For two vague values A' and B' in X, $X = \{x_1,...,x_n\}$, $S(A',B')$ is the degree of similarity between A' and B' which preserves the properties (P1)-(P4).

(P1) $0 \le S(A',B') \le 1$;

(P2) $S(A',B')=1$ if $A'=B'$; (7)

(P3) $S(A',B')=S(B',A')$.

(P4) $S(A',C') \le S(A',B')$ and $S(A',C') \le S(B',C')$ if $A' \subseteq B' \subseteq C'$, C' is a vague set in X.

3. The Proposed Method

In 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 the 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 [4,8], however, can be formulated as a generic decision making matrix.

3.1 Problem Formulation

Suppose that a decision group contains q decision makers who have to give linguistic ratings on m alternatives according to n evaluation criteria, then a fuzzy MPDM problem can be expressed concisely in preference-agreement matrix [12] as follows: Suppose that a decision group has m decision makers who have to give linguistic ratings on n evaluated targets,

$$D(t_j) = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}, \quad (8)$$

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

where D is a decision matrix of the group, $d_i \in \{d_1, d_2,..., d_m\}$ are a set of decision makers, and $t_j \in \{t_1, t_2,..., t_n\}$ are a finite set of possible targets(i.e., new-products) from which decision makers have to select, $\tilde{x}_{ij}$ (i,j=1,...,m) is the linguistic rating on target t_j by d_i, and w_i is the importance weights of d_i.

These linguistic terms can be transformed into a vague value A', $A' = [t_A(x_k), 1-f_A(x_k)]/x_k, x_k \in X$. (9)

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.

3.2. Similarity Measure

We present a new similarity measure between two vague sets which may be continuous or discrete form. We give corresponding proofs of these similarity measures as follows.

According to Def. 3, we use the median value of A' and B' to represent the mean of truth-membership and false-membership function. The preference agreement between two experts can be represented by the proportion of the consistent area to the total area, as shown in Figure 2 [11].

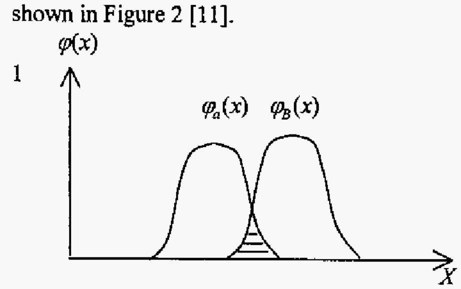

Fig. 2. Preference agreement between two DMs' linguistic ratings expressed by median of vague sets

Definition 5. Using median of vague value, $S^m(A',B')$ is defined as the similarity measure between two vague values

$$S^m(A',B') = \frac{\int(\varphi_A(x) \wedge \varphi_B(x))dx}{\int(\varphi_A(x) \vee \varphi_B(x))dx} = \frac{\int \min\{\varphi_A(x), \varphi_B(x)\}dx}{\int \max\{\varphi_A(x), \varphi_B(x)\}dx}. \quad (10)$$

3.3 Preferences Aggregation

We calculate the preference-agreement degree of two experts' ratings expressed by Eq.(9) and denote $S^m(I,I')$ as $a_{ii'}$, $i,i'=1,...,m$, where two vague sets I, and I' represents the linguistic rating of decision maker $d_i, d_{i'}$. The preference-agreement matrix A for evaluated targets $t_1..t_n$ is

$$A(t_1) = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1m} \\ a_{21} & 1 & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & 1 \end{bmatrix}, \cdots A(t_n) = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1m} \\ a_{21} & 1 & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & 1 \end{bmatrix}. (11)$$

Remark. For $a_{ii'} = S^m(I, I')$ if $I \neq I'$, and $a_{ii'} = 1$ if $I = I'$; It means that if two decision makers fully agree to an evaluated target, and they have $\tilde{a}_{ii'} = 1$; 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 are 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 of all the decision makers on an evaluated target as

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

3.4 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 [7]. This index synthesizes confidence level of preference of 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

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

As the compensation parameter γ varied from 0 to 1, the operator describes the aggregation properties of "AND" and "OR", that is,

$$\max_{j=1,\ldots,n} (t_j) \geq F(t_1, \ldots, t_n) \geq \min_{j=1,\ldots,n} (t_j). \tag{14}$$

where F is an aggregation function of Eq.(15).

The compensation parameter γ indicates the confidence level of preference of decision maker. A small γ implies the higher degree of confidence. Finally, the moderator can estimate the degree of confidence and decide whether the group preference has been reached throught the use of $C(t)$ 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.

3.5 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.

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

However, the aggregation results $\tilde{V}$ 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 Def.3, the synthetic evaluation values $\tilde{V}$ can be represented as

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

Finally, the fuzzy ranking method proposed by Yager(1981) is adopted to determine the ranking of results of synthetic evaluation as follows [12]:

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

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

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

4. 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 Figure 3.

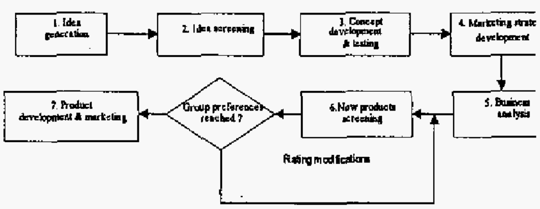

Fig. 3. The evaluation process of LCD-TV products screening.

Suppose that there is a new-product committee consisting of six decision makers, {R&D manager, marketer, sales manager, sales, accounting manager, customer} and a set of four different models with various choices such as colors, shapes, and prices, which must be selected through product-screening process. The resulting selection will be sent to product development 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= {VL, L, M, H, VH} presents linguistic variables of sales price as Table 2. For example, "High" may be represented as

$A' = (0.7, 0.2)/4$,

where $t_A(4) = 0.7$, $f_A(4) = 0.8$.

Table 2. Linguistic variables for the rating of new-product

Very low / Very Poor	$[t_A(x), 1 - f_A(x)]/1$
Low/ Poor	$[t_A(x), 1 - f_A(x)]/2$
Medium	$[t_A(x), 1 - f_A(x)]/3$
High/ Good	$[t_A(x), 1 - f_A(x)]/4$
Very high/ Very Good	$[t_A(x), 1 - f_A(x)]/5$

We use the linguistic variables, shown in Table 2, to assess the ratings of new products using vague value as Table3.

Step 3: For evaluated target t_1, we calculate the preference agreement vectors between d_1, d_2 using Eq.(8) as

$$a_{12} = \frac{\int_0^1 [\min\{t_{11}, t_{21}\}, \min\{1 - f_{11}, 1 - f_{21}\}] dx}{\int_0^1 [\max\{t_{11}, t_{21}\}, \max\{1 - f_{11}, 1 - f_{21}\}] dx} = \frac{\int_0^1 [0.7, 0.8] dx}{\int_0^1 [0.8, 0.9] dx} =$$

$$\frac{\int_0^1 0.75 dx}{\int_0^1 0.85 dx} = \frac{0.75}{0.85} = 0.882.$$

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

$$A(t_1) = \begin{bmatrix} 1.00 & 0.88 & 0.93 & 0.00 & 0.83 & 0.87 \\ 0.88 & 1.00 & 0.82 & 0.00 & 0.94 & 0.77 \\ 0.93 & 0.82 & 1.00 & 0.00 & 0.78 & 0.93 \\ 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 \\ 0.83 & 0.94 & 0.78 & 0.00 & 1.00 & 0.72 \\ 0.87 & 0.77 & 0.93 & 0.00 & 0.72 & 1.00 \end{bmatrix} \quad A(t_2) = \begin{bmatrix} 1.00 & 0.00 & 0.88 & 0.69 & 0.75 & 0.89 \\ 0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.88 & 0.00 & 1.00 & 0.79 & 0.86 & 0.78 \\ 0.69 & 0.00 & 0.79 & 1.00 & 0.92 & 0.61 \\ 0.75 & 0.00 & 0.86 & 0.92 & 1.00 & 0.67 \\ 0.89 & 0.00 & 0.78 & 0.61 & 0.67 & 1.00 \end{bmatrix}$$

$$A(t_3) = \begin{bmatrix} 1.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 1.00 & 0.92 & 0.67 & 0.80 & 0.72 \\ 0.00 & 0.92 & 1.00 & 0.72 & 0.87 & 0.77 \\ 0.00 & 0.67 & 0.72 & 1.00 & 0.83 & 0.94 \\ 0.00 & 0.80 & 0.87 & 0.83 & 1.00 & 0.88 \\ 0.00 & 0.72 & 0.77 & 0.94 & 0.88 & 1.00 \end{bmatrix} \quad A(t_4) = \begin{bmatrix} 1.00 & 0.92 & 0.86 & 0.67 & 0.71 & 0.86 \\ 0.92 & 1.00 & 0.93 & 0.72 & 0.77 & 0.93 \\ 0.86 & 0.93 & 1.00 & 0.78 & 0.82 & 0.87 \\ 0.67 & 0.72 & 0.78 & 1.00 & 0.94 & 0.78 \\ 0.71 & 0.77 & 0.82 & 0.94 & 1.00 & 0.82 \\ 0.86 & 0.93 & 0.87 & 0.78 & 0.82 & 1.00 \end{bmatrix}$$

Similarly, shape and price 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 γ =0, γ =0.5, γ =1, respectively

	γ=0	γ=0.5	γ=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 $C(t) = 0.511 \geq 0.5$.

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:

1.The weighted fuzzy rating is obtained using Eq.(15) and synthetic results for four target is obtained by integrating $\bar{X}(\tilde{V}_\alpha)$ at α =0.05,0.10,0.15~1 through Eqs.(16)~(17)

For example, the median form of $\tilde{V}$ for $\tilde{V}(1,1)$ (i.e., rating on t_1 evaluated by d_1) is

$\tilde{V}(1,1) = 0.11/2 + 012/3 + 011/4$. The various α level sets are

$\tilde{V}_\alpha = \{4,3,2\}$, $0 < \alpha \leq 0.05$; $\tilde{V}_\alpha = \{4,3,2\}$, $0.05 < \alpha \leq 0.1$;

$\tilde{V}_\alpha = \{0\}$, $0.10 < \alpha \leq 0.15$;

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

$\bar{X}(\tilde{V}_\alpha) = (4+3+2)/3 = 3$, $0.00 < \alpha \leq 0.05$;

$\bar{X}(\tilde{V}_\alpha) = (4+3+2)/3 = 3$, $0.05 < \alpha \leq 0.1$;

$\bar{X}(\tilde{V}_\alpha) = 0$, $0.10 < \alpha \leq 0.15$; $\bar{X}(\tilde{V}_\alpha) = 0$, $0.15 < \alpha \leq 1.00$;

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

$$F(\tilde{V}) = \int_0^1 \bar{X}(\tilde{V}_\alpha) d\alpha = \int_0^{0.05} 3 d\alpha + \int_{.05}^{0.10} 3 d\alpha = 0.30.$$

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

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

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.

5. 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 [2], to treat the same problem.

From Eq.(18), 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 3.

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

$$\bar{v}_j = \frac{1}{n}\sum_{i=1}^{n}[\tilde{v}_{ij}^{1} \oplus \tilde{v}_{ij}^{2} \oplus \ldots \oplus \tilde{v}_{ij}^{n}] \quad (19)$$

	t_1	t_2	t_3	t_4
$\tilde{V}(t_i)$	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

Table 3. Rating of evaluated targets using fuzzy sets

Targets / DMs	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	06/2+0.6/3+0.5/4	0.6/4+0.8/4+0.6/3	0.6/3+ .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+ .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+ .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+ .7/4+0.7/5	0.6/3+0.7/3+0.6/3

In the following, the left-and-right fuzzy ranking method is applied to synthesize the fuzzy ratings [12]

$$V_R = \sup_x [u_{\bar{v}_j}(x) \wedge u_{\max}(x)], \quad (20)$$

$$V_L = \sup_x [u_{\bar{v}_j}(x) \wedge u_{\min}(x)], \quad (21)$$

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

The synthetic evaluation on each target is given by

$$V = \frac{|V_R + (1-V_L)|}{2}. \quad (22)$$

The synthetic value on each target is calculated using Eqs.(19)~(22) or geometric graphics described as [13]

	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 3 and Eq. (22), the traditional fuzzy method on NFD process is not able to dynamically analyze the group preferences of decision makers and does not specify whether the group consensus on targets have attained. In addition, the synthetic evaluation is neither flexible nor can it illustrate the degree of confidence level of the decision makers. We can conclude that the proposed method is more effective than the traditional fuzzy method on NPD process.

6. Conclusion

This paper presents a new fuzzy approach to solve NPD screening problems. 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. The experimental results indicate that our approach can not only effectively reveal the uncertainty of decision makers' subjective judgments, but also is applicable to NPD screening problems. From a numerical illustration, the usefulness and effectiveness of the proposed model has been demonstrated.

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