Study on Enterprise Competitive Intelligence Evaluation Based on Mixed Uncertain Attribute Group Decision-making

Jiekun Song*, Zhihao Zhao and Yemeng Zhang
China University of Petroleum, School of Economics and Management, Qingdao, Peoples R China

*Corresponding author

Abstract. Enterprise competitive intelligence evaluation has the characteristics of uncertainty and group decision. It is significant to construct the evaluation model based on the mixed uncertain attribute group decision-making. In this paper, we reviewed the algorithms, order relations and distance measures of the main uncertain parameters. Based on mixed uncertain attribute group decision-making, prospect theory and VIKOR theory, we constructed the evaluation model. We put forward the processes including standardization, group integration, value measurement and ranking. An example analysis shows that the evaluation model can integrate a variety of uncertain indicators, comprehensively reflect the evaluation opinions of each expert, and reflect the decision-maker's risk psychology and preferences. The proposed model can provide more scientific and consistent conclusions for the evaluation and selection of competitive intelligence of enterprises.

Keywords: Mixed uncertain attribute; Group decision-making; Competitive intelligence evaluation; VIKOR; Prospect theory.

1. Introduction

Competitive intelligence refers to the information about competitive strategy, competitors and competitive environment of enterprises. The quantity and quality of competitive intelligence possessed by an enterprise affect its judgment of the competitive environment, and the formulation and implementation of competitive strategy. Many scholars researched the evaluation on enterprise competitive intelligence. They have established a relatively consistent evaluation index system. Combined with the indicators’ uncertainty, they established fuzzy comprehensive evaluation [1], interval number ranking [2], fuzzy VIKOR [3] and other evaluation models. In fact, in addition to the above uncertain forms, the indicator can also be expressed as intuitionistic fuzzy number, interval intuitionistic fuzzy number and hesitant fuzzy linguistic terms, etc., and these uncertain forms are also relatively close to the reality. In addition, the importance of competitive intelligence requires the participation of many experts, which means the evaluation is essentially a group decision-making. Therefore, in this paper, we attempt to construct an evaluation model based on mixed uncertain attribute group decision-making, in order to perfect the competitive intelligence evaluation system and provide a practical guidance for enterprises.
2. Calculation Rules, Order Relations and Distance of Uncertain Attribute Values

2.1. Interval Number

For the interval number \( \bar{x}_i = [x^L_i, x^R_i] \), the calculation rules include: ① \( \lambda \bar{x}_i = [\lambda x^L_i, \lambda x^R_i] \), \( \lambda > 0 \); ② \( \bar{x}_i \oplus \bar{x}_2 = [x^L_i + x^L_2, x^R_i + x^R_2] \). The median \( m_i = 0.5(x^L_i + x^R_i) \) and the width \( \Delta_i = 0.5(x^R_i - x^L_i) \). The order relations of two interval numbers \( \bar{x}_i \) and \( \bar{x}_2 \) are: ① If \( m_1 = m_2 \) and \( \Delta_1 = \Delta_2 \), \( \bar{x}_1 = \bar{x}_2 \). ② If \( m_1 < m_2 \), or \( m_1 = m_2 \) and \( \Delta_1 > \Delta_2 \), \( \bar{x}_1 < \bar{x}_2 \). The commonly used distances of interval number is the normalized Euclidean distance as follows [4]:

\[
d_e(\bar{x}_1, \bar{x}_2) = \sqrt{\frac{1}{2} \left( \sum (x^L_i - x^L_j)^2 + \sum (x^R_i - x^R_j)^2 \right)}.
\]

2.2. Hesitant Fuzzy Number

Let \( h(x) = [\gamma_1, \gamma_2, ..., \gamma_m] \) be a hesitant fuzzy number, and each membership degree is arranged from small to large. Without extending boundaries, the hesitant fuzzy number can be extended to an interval fuzzy number \( H(x) = [a, b] \) denoted as \( H(x) = [a, b] \). The calculation rules include: ① \( \lambda H = [1-(1-a)^\lambda, 1-(1-b)^\lambda] \), \( \lambda > 0 \); ② \( H1 \oplus H2 = [a1+\lambda a_2, a_1+\lambda a_2, b_1+\lambda b_2, b_1+\lambda b_2] \); ③ \( H1 - H2 = [1, 1-a_2] \). Interval fuzzy numbers have the order relations similar to interval numbers, i.e., the larger the median and the smaller the width, the larger the interval fuzzy number. The normalized Euclidean distance is the same as formula (1).

2.3. Intuitionistic Fuzzy Number

Let \( I(x) = <\mu, \nu> \) be an intuitionistic fuzzy number, \( 0 \leq \mu + \nu \leq 1 \). The calculation rules include: ① \( \lambda I = 1-(1-\mu)^\lambda, (1-\nu)^\lambda \), \( \lambda > 0 \); ② \( I_1 \oplus I_2 = I_{\mu_1, \mu_2, \nu_1, \nu_2} \); ③ \( I_1 = <\nu \mu> \). The score function of \( I(x) \) is \( s(I) = \mu - \nu \), and the precise function is \( p(I) = \mu + \nu \). Intuitionistic fuzzy numbers have the same order relations as hesitant fuzzy numbers, and the normalized Euclidean distance is [5]:

\[
d_e(I_1, I_2) = \sqrt{\frac{1}{2} \left( \sum (\mu_1 - \mu_2)^2 + \sum (\nu_1 - \nu_2)^2 \right)}.
\]

2.4. Interval Intuitionistic Fuzzy Number

Let \( U(x) = [a, c, b, d] \) be an interval intuitionistic fuzzy number, \( 0 \leq b + d \leq 1 \). The calculation rules include: ① \( \lambda U = [1-(1-a)^\lambda, 1-(1-b)^\lambda, c^\lambda, d^\lambda] \), \( \lambda > 0 \); ② \( U_1 \oplus U_2 = [a_1 + a_2, a_1 + a_2, b_1 + b_2, b_1 + b_2] \); ③ \( U_1 = [c, d, a, b] \). The score function of \( U(x) \) is \( s(U) = 0.5(a - c + b - d) \), and the precise function is \( p(U) = 0.5(a + b + c + d) \). Interval intuitionistic fuzzy numbers have the order relations similar to hesitant fuzzy numbers, and the normalized Euclidean distance is

\[
d_e(U_1, U_2) = \sqrt{\frac{1}{4} \left( \sum (a_1 - a_2)^2 + \sum (b_1 - b_2)^2 + \sum (c_1 - c_2)^2 + \sum (d_1 - d_2)^2 \right)}.
\]

2.5. Linguistic Terms and Hesitant Fuzzy Linguistic Terms Set

Let \( S = \{s_0, s_1, ..., s_g\} \) be a linguistic terms set, where \( s_t \) denote a specific language term, \( t = 0, 1, ..., g \). The calculation rules include: ① \( \lambda S = s_{t\lambda} \), \( 0 < \lambda \leq 1 \); ② \( S_{t1} \oplus S_{t2} = s_{t1+t2} \); ③ \( S_{t1} - S_{t2} = s_{t1-t2} \). There are two ways to compare language terms. One is to convert them into fuzzy numbers, and the other is to process language subscripts based on symbol transfer. Herrera's binary semantic model is an improved symbol transfer method, which solves the problem of discretization of language subscripts. Xu et al. further extended the discrete language scale to the continuous language numerical scale. According to whether the distribution of linguistic terms is symmetrical and even, there are many forms of numerical scaling.
function. In the symmetrical and even distribution of linguistic terms, the distance measure of \( st \) can be defined as \( f(st) = t \), and the distance between \( si \) and \( sj \) is the absolute value between numerical scales \( |i-j| \).

Let \( L = \{s_0, s_1, \ldots, s_d\} \) be a hesitant fuzzy linguistic terms set defined on the linguistic terms set \( S \), and each language subscript is arranged from small to large. Without considering the endpoint extensions of binary semantics, the hesitant fuzzy linguistic terms set can be extended to a continuous language interval \( L = [s_0, s_d] \). The subscripts can be transformed into interval numbers for operation, order relation judgment and distance measure.

3. The Evaluation model Based on Mixed Uncertain Attribute Group Decision

3.1. Standardization

The dimensions of different indicators are different, so it is necessary to standardize the individual values of each decision maker for all the \( m \) evaluated objects. There are mainly linear transformation, range transformation, vector transformation and other methods. Take the range transformation as an example, the standardization formula of an interval number \( [x^l, x^r] \) is:

\[
\tilde{x}_j = \left[ \frac{x^l_j - \min_{j=1,2,\ldots,m} x^l_j}{\max_{j=1,2,\ldots,m} x^l_j - \min_{j=1,2,\ldots,m} x^l_j}, \frac{x^r_j - \min_{j=1,2,\ldots,m} x^r_j}{\max_{j=1,2,\ldots,m} x^r_j - \min_{j=1,2,\ldots,m} x^r_j} \right],
\]

\( \tilde{x}_j \) is the value of a positive indicator, and \( \tilde{x}_j \) is the value of a reverse indicator.

The standardization values of the positive hesitant fuzzy number, intuitionistic fuzzy number and interval intuitionistic fuzzy number are still equal to themselves, and those of the reverse uncertain numbers are equal to the values of their complement sets respectively. The value of a positive linguistic terms set \( st \in S = \{s_0, s_1, \ldots, s_g\} \) can be standardized as \( st^\prime \in S^* = \{s_0, s_{1/g}, \ldots, s_1\} \), while a reverse one can be standardized as \( s_1 - st^\prime \in S^* \).

3.2. Group Integration

Suppose the standardization value of the \( k \)th expert evaluating the \( j \)th indicator of the \( i \)th object is \( z_{ijk} \), and the decision weight is \( \lambda_k, i=1,2,\ldots,m; j=1,2,\ldots,n; k=1,2,\ldots,q \). The group integration value of the \( j \)th indicator of the \( i \)th object is:

\[
f_{ij} = \sum_{k=1}^{q} \lambda_k z_{ijk}. 
\]

3.3. Value Measurement

The prospect theory takes the risk decision-making psychology into account, and it is widely used in multi-attribute decision-making. In this paper, we use the value function of prospect theory to describe the value of each indicator [6]:

\[
v(x) = \begin{cases} 
  x^\alpha & x \geq 0, \\
  -\Theta(-x)^\beta & x < 0.
\end{cases}
\]

where \( x \) represents the profit or loss between the evaluated object and the reference point; \( \alpha \) and \( \beta \) represent the risk attitude coefficient of the decision-maker, \( 0 \leq \alpha, \beta \leq 1 \); \( \Theta \) represents the loss avoidance coefficient, \( \Theta = 1 \). Usually \( \alpha = \beta = 0.88 \) and \( \Theta = 2.25 \).

For each indicator, we take the median of all evaluated intelligence as the reference point, and compare the indicator’s value of each intelligence with the median. If the former is greater than or equal to the latter, it means profit; otherwise, it means loss. Take the Euclidean distance between them as the absolute value of profit or loss, and substitute the formula (5) to calculate the value of each indicator, so we can obtain the value matrix \( V = [v_{ij}]_{m \times n} \).
3.4. VIKOR Value Calculation

VIKOR takes full account of the maximum utility of the population and the minimum regret of the individual, and can make a comprehensive evaluation and reflect the preference of the decision maker [7]. According to the value matrix, the positive and negative ideal points are:

\[ v^+ = [v^+_1, v^+_2, \ldots, v^+_m], \]
\[ v^- = [v^-_1, v^-_2, \ldots, v^-_m], \]

The population utility value \( P_i \), the individual regret value \( N_i \), and the VIKOR value \( Q_i \) of the evaluated object from the positive ideal point are calculated as follows:

\[ P_i = \sum_{j=1}^{n} w_j (v^+_j - v^-_j), \quad N_i = \max_{j=1,2,\ldots,m} \frac{w_j (v^+_j - v^-_j)}{v^+_j - v^-_j}, \]
\[ Q_i = \sigma^* \frac{P_i - \min_{k=1,2,\ldots,m} P_k}{\max_{k=1,2,\ldots,m} P_k} + (1 - \sigma^*) \frac{N_i - \min_{k=1,2,\ldots,m} N_k}{\max_{k=1,2,\ldots,m} N_k}. \]

where \( w_j \) is the weight of the \( j \)th indicator, and \( \sigma \) is the compromise coefficient, \( \leq \sigma \leq 1 \).

3.5. Ranking

By sorting \( Q_i, P_i \) and \( N_i \) from small to large, we get three sequences and the sequence of \( Q_i \) is \( Q_{(1)} \leq Q_{(2)} \leq \ldots \leq Q_{(m)} \). If both of the following conditions are met, then the evaluated intelligence corresponding to \( \sigma(1) \) ranks the first:

Condition 1: \( Q_{(2)} - Q_{(1)} \geq 1/(m-1) \);
Condition 2: In the ranking of \( P_i \) or \( N_i \), \( \sigma(1) \) ranks the first, that is, the compromise solution is stable.

If these two conditions cannot be met at the same time, the compromise solution scan be reached in the following two cases:

1) If condition 2 is not satisfied, the corresponding objects of \( \sigma(1) \) and \( \sigma(2) \) are both compromise solutions;
2) If condition 1 is not satisfied and the largest positive integer \( r \) is obtained by \( Q_{(r)} - Q_{(1)} < 1/(m-1) \), the evaluated objects corresponding to \( \sigma(1), \sigma(2), \ldots, \sigma(r) \) are all compromise solutions.

4. An Example Analysis

Company A is a professional enterprise engaged in UAV training. In order to develop H market, the company has collected five aspects of competitive intelligences: A1 is macro and industry environment analysis report, A2 is UAV training demand forecast report of H market, A3 is competitor analysis report of H market, A4 is UAV training technology progress report, and A5 is the development report of UAV training benchmark enterprise. The company invited three experts to evaluate five kinds of competitive intelligence. First, the company built a consistent evaluation index system, as shown in Table 1, where the indicators C1 and C2 are positive hesitant fuzzy variables; C3 is a reverse interval intuitionistic fuzzy variable; C4 is a positive intuitionistic fuzzy variable; C5 is a reverse hesitant fuzzy variable; C6, C7 and C8 are positive hesitant fuzzy language term sets; C9 and C10 are positive linguistic terms; C11 and C12 are reverse and positive interval variables.
Table 1. Evaluation index system of competitive intelligence.

| First level indicators | Second level indicators |
|------------------------|-------------------------|
| Intelligence sources (B1) | Channel reliability (C1), Acquisition timeliness (C2), Information distortion (C3), Environmental relevance (C4), Industry knowledge (C5) |
| Intelligence value (B2) | Content completeness (C6), Analysis depth (C7), Conclusion rationality (C8), Expression comprehensibility (C9), Novelty of intelligence (C10) |
| Input and output (B3) | Acquisition cost (C11), Expected return (C12) |

Three experts jointly determine the weight of the indicators by using the analytic hierarchy process, and the composite weights of the 12 secondary indicators C1 ~ C12 are 0.0296, 0.0685, 0.0953, 0.0156, 0.0685, 0.1907, 0.0526, 0.1987, 0.0296, 0.0371, 0.0156 and 0.1987, respectively. The evaluation matrixes of each expert is provided. For instance, the evaluation matrix of the first expert is as follows:

{0.8, 0.9} {0.6, 0.7} {0.6, 0.7, 0.8} {0.7, 0.8} {0.5, 0.6}
{0.4, 0.5} {0.5, 0.6, 0.7} {0.6, 0.7} {0.7, 0.8} {0.3, 0.4, 0.5}

Standardize the evaluation matrix of the three experts respectively. Suppose the weights of three experts are the same with 1/3, and the integrated evaluation matrix is as follows:

\[
\begin{bmatrix}
0.7711, 0.8413 & 0.6366, 0.7711 & 0.6366, 0.7711 & 0.7116, 0.8183 & 0.4687, 0.5691 \\
0.5068, 0.6443 & 0.5, 0.6366 & 0.6366, 0.7379 & 0.6085, 0.7116 & 0.4407, 0.5358 \\
0.6698, 0.8183 & 0.7711, 0.874 & 0.4354, 0.5068 & 0.5691, 0.7116 & 0.5691, 0.7116 \\
0.7711, 0.2 & 0.8183, 0.126 & 0.7116, 0.2621 & 0.8183, 0.3684 & 0.5691, 0.2884 \\
0.1347, 0.2348 & 0.2348, 0.3684 & 0.6085, 0.7116 & 0.2042, 0.3048 & 0.6085, 0.7379 \\
\end{bmatrix}
\]

We calculate the distances between the integrated evaluation values of five competitive intelligences and the corresponding medians, and calculate the value of each indicator according to the order relation and the formula (5). The results of P_i, N_i and Q_i are shown in Table 2. It can be seen that the VIKOR value corresponding to competitive intelligence A_2 is the smallest, and the VIKOR value corresponding to A_3 is greater than it by only 0.0318, which is less than 1/4. Both A_2 and A_3 are compromise solutions, that is to say, company A can consider A_2 and A_3 meanwhile.
Table 2. The values of parameters of five competitive intelligence.

|   | $P_i$ | $N_i$ | $Q_i$ |
|---|---|---|---|
| $A_1$ | 0.4852 | 0.1987 | 1.2604 |
| $A_2$ | 0.2511 | 0.0946 | 0 |
| $A_3$ | 0.274 | 0.0953 | 0.0318 |
| $A_4$ | 0.3325 | 0.1907 | 1.0137 |
| $A_5$ | 0.7007 | 0.1987 | 1.5 |

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