Influence of Risk Group Assessment and Decision-Making for Power Supply Companies Based on Catastrophe Theory and Two-Tuple Linguistic

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Abstract — Risk assessment has been playing an increasingly important role in the development of power supply companies with the deepening of electricity market reform. Thus, for the expert group assessment and decision-making problems of these companies, a risk group assessment and decision-making model based on catastrophe theory and two-tuple linguistic is proposed. In this method, linguistic assessments of experts are transformed into two-tuple linguistic first. Catastrophe theory is expanded from real numbers to two-tuple linguistics based on its definition. Then, combined with the experts' linguistic subjected weights, an eclectic weighting method is presented based on the similarity and deviation, and the order of schemes can be listed by comparing all of the total catastrophe two-tuple values of schemes. Finally, the rationality and effectiveness of this approach are illustrated.

Keywords - power supply company; risk assessment; group decision-making; catastrophe theory; two-tuple linguistic

I. INTRODUCTION

With the constant promotion of the reform in industrial system of power market, the power grid in China has developed from a vertical monopoly model with the integration of power generation, transmission, supply and distribution, to the separation of power plants and power grids with the restructuring of power generation and grids. Thus, the power supply departments have turned to be the enterprises, which have to independently face the fierce market competition, rather than the seller's market with the supply failing to meet the demand. And the risk they have to face has also become complicated and changeable. However, the effective evaluation and measurement can help to identify the existing key risk elements in the company operations, and provide a foundation for the targeted control measures and the risk decision emergency plan.

At present, the risk assessment on power system has become an increasing concern among the professional scholars, but the studies aiming at the risk of power supply companies are still not many. Zhang built a multi-level risk evaluation index system for power supply companies and used analytic hierarchy process(AHP) to further study [1]. Cheng considered the uncertainty in the assessment so that fuzzy comprehensive evaluation model was used to evaluate the power supply safety risk for nuclear power plants [2]. Liu analyzed the relationship of risk factors and used AHP and fuzzy evaluation method, combined with grey correlation method to study the investment risk of power plants [3]. These studies make some certain achievements but still have limitations and deficiencies. The weights of risk indicators are all determined by subjectivity, which are baseless and have poor reproducibility. And using the exact real numbers or certain fuzzy membership functions to describe the risks reduces the fuzziness and uncertainty of the risks needed in the analysis.

Based on the above content, this paper identifies and analyzes the risk sources of the power supply enterprises, and describes the fuzziness and randomness of risk by quantitative linguistic variables to get rid of the limit of designing the index weight. Besides, it combines catastrophe theory with two-tuple linguistic and presents a risk assessment and decision-making method. In order to improve the reliability, group decision-making is introduced to integrate into the method and then an eclectic weighting method is proposed based on the similarity degree and the deviation of the subjective weight from the experts in linguistic form. Finally, this method is tested by an example.

II. FUNDAMENTAL THEORIES

A. Catastrophe Theory

According to catastrophe theory, the critical points of each state in system are classified by the potential function $V(x)$, and every potential function determines a catastrophe. The set of the points, making the first derivative of $V(x)$ zero, is called equilibrium surface $M$, which can integrally describe the whole process of the system catastrophe. Based on the difference of the control variables of $V(x)$, generally, there are 7 basic catastrophe models: fold, cusp, swallowtail, butterfly, elliptic umbilical, hyperbolic umbilical and parabolic umbilical catastrophe.
The features of the first 4 commonly used models are shown in Table I [4-6].

**TABLE I. THE PRIMARY CATASTROPHE MODEL WITH ONE STATE VARIABLE**

<table>
<thead>
<tr>
<th>Type</th>
<th>Control dimension</th>
<th>Potential function ( F(x) )</th>
<th>Equilibrium surface ( M )</th>
<th>Normalized formulas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fold</td>
<td>1</td>
<td>( x^3 + ax )</td>
<td>( 3x^3 + a = 0 )</td>
<td>( x_i = \sqrt{a} )</td>
</tr>
<tr>
<td>Cusp</td>
<td>2</td>
<td>( x^3 + ax^2 + bx )</td>
<td>( 4x^3 + 2ax + b = 0 )</td>
<td>( x_i = \sqrt{a} ), ( x_i = \sqrt{b} )</td>
</tr>
<tr>
<td>Swallowtail</td>
<td>3</td>
<td>( x^3 + ax^2 + bx^2 + cx )</td>
<td>( 6x^4 + 2ax^2 + c = 0 )</td>
<td>( x_i = \sqrt{a} ), ( x_i = \sqrt{b} ), ( x_i = \sqrt{c} )</td>
</tr>
<tr>
<td>Butterfly</td>
<td>4</td>
<td>( x^3 + ax^2 + bx^2 + cx^2 )</td>
<td>( 6x^4 + 4ax^3 + 2bx^2 + d = 0 )</td>
<td>( x_i = \sqrt{a} ), ( x_i = \sqrt{b} ), ( x_i = \sqrt{c} ), ( x_i = \sqrt{d} )</td>
</tr>
</tbody>
</table>

In Table I, the state variable stands for the behavior state of the system. The coefficients are the control variables of each state variable with decreasing importance, which stand for the interactional factors in the system. The potential function denotes the relationship between state variable and control variables. And the normalized formula is used to obtain the catastrophe value of each control variable, which is also called catastrophe progression.

**B. Two-Tuple Linguistic**

Two-tuple linguistic is a representation model presented by a Spanish scholar, Herrera, in 2000, for the decision problem of linguistic assessment information. It uses tuple to represent linguistic assessment information and carry out computation by the translation of symbols, which can effectively avoid information loss and distortion in the integration and operation process, and lead to the improvement in the accuracy of expression and computation result. Its definition and the introduction of computation operators are as follows [7-8].

**III. RISK GROUP ASSESSMENT MODEL**

In general, due to the differences of subjective cognition and experience among experts, obtaining the score of each scheme according to all experts' subjective weights can’t ensure the consistency between individual opinion and group minds. Thus, to improve the reliability, this paper uses the similarity degree with the average of group information and the deviation of the subjective weight aggregation result to determine weights.

**A. A Weight Determining Method Based on Similarity**

Determine weights by the similarity degree between individual opinion and the average level of group. That is to say, the smaller the difference is, the more similar the opinion of this expert with group minds, and the bigger the weight of him [9]. Combining the above principle and gray relation coefficient, this paper defines the similarity degree and presents a corresponding weight determining method.

**Definition 5:** Let \( x_{ij}^e \) be the linguistic assessment information of the scheme \( f_i \) for the risk \( r_j \) from the expert \( e_k \), and \( \bar{x}_j \) be the average information of \( f_i \) for \( r_j \) from the group \( \bar{e} \). The similarity degree between \( x_{ij}^e \) and \( \bar{x}_j \) can be

\[
S_e(x_{ij}^e, \bar{x}_j) = \frac{\min \min D(x_{ij}^e, \bar{x}_j) + \rho \max \max D(x_{ij}^e, \bar{x}_j)}{D(x_{ij}^e, \bar{x}_j) + \rho \max \max D(x_{ij}^e, \bar{x}_j)}
\]

In it, \( 1 \leq k \leq l \), \( 1 \leq i \leq m \), and \( 1 \leq j \leq n \) (\( l, m, n \) respectively are the numbers of experts, schemes and risks indexex). \( \xi(x_{ij}^e, \bar{x}_j) \) is the gray relation coefficient, and its formula is

The parameter \( \rho \) is a distinguishing coefficient and usually has the value 0.5. Then, obviously, the larger \( S_e(x_{ij}^e, \bar{x}_j) \) is, the more consistent between the expert \( e_k \) and the group minds in the scheme \( f_i \) under the risk \( r_j \).

**Definition 6:** With \( S_e(x_{ij}^e, \bar{x}_j) \), the similarity degree between the expert \( e_k \) and the group \( \bar{e} \) is

\[
S_e(e_k, \bar{e}) = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} S_e(x_{ij}^e, \bar{x}_j)}{\sum_{i=1}^{m} \sum_{j=1}^{n} S_e(x_{ij}^e, \bar{x}_j)}
\]

In this formula, \( 0 \leq S_e(e_k, \bar{e}) \leq 1 \), and \( \sum_{k=1}^{n} S_e(e_k, \bar{e}) = 1 \).

Based on the principle mentioned above, the similarity degree between \( e_k \) and \( \bar{e} \) can be regarded as the weight \( w_{ek} \) of the expert \( e_k \), i.e. \( w_{ek}^i = S_e(e_k, \bar{e}) \). Likewise, there are two constraints: (1) \( 0 \leq w_{ek} \leq 1 \), \( 1 \leq k \leq l \); (2) \( \sum_{k=1}^{n} w_{ek} = 1 \).

**B. A weight Determining Method Based on Deviation**

In order to avoid blindly pursuing the consistency and ignore the impact of some experts on the results, this paper borrows the idea from the reference [10] that using deviation determines the weights. The smaller the deviation between
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the expert’s decision result and the group minds is, the smaller the amount of information for schemes ranking from this expert is, so that his weight should be small. Following this principle, the definition of the deviation and the corresponding weight determining method are as follows.

Definition 7: Let \( y^i_k \) be the assessment result of the expert \( e_k \) for the scheme \( f_i \), and \( z_i \) be the final result of the whole group for \( f_i \) by subjective weights aggregation, then the deviation between the expert \( e_k \) and the group \( e \) can be

\[
H(e_k, e) = \sum_{i=1}^{m} (y^i_k - z_i)^2
\]  

(4)

Definition 8: Let \( H(e_k, e) \) be the deviation between the expert \( e_k \) and the group \( e \), then the weight of \( e_k \) can be

\[
w_{e_k} = \frac{w_{e_k}}{\sum_{i=1}^{m} H(e_k, e)}
\]  

(5)

Obviously, \( 0 \leq w_{e_k} \leq 1 \), \( 1 \leq k \leq l \) and \( \sum_{i=1}^{k=1} w_{e_k} = 1 \).

Thus, with these two different weight determining methods, an eclectic method is presented to consider both the consistency and the individual contribution:

\[
w_{e_k} = \alpha w_{e_k} + (1 - \alpha) w_{e_0}
\]  

(6)

In it, \( k = 1, \ldots, l \), and \( \alpha, 1 - \alpha \) respectively are the eclectic preference coefficients for these two methods with a constraint \( 0 \leq \alpha \leq 1 \). When \( \alpha > 0.5 \), it means the decision maker prefers the mean opinion of the group. When \( \alpha < 0.5 \), the individual opinions are more preferred. And \( \alpha = 0.5 \) means the same preference to these two.

C. Risk Evaluation and Decision-Making Method

To describe clearly, some symbols and parameters are prescribed at first. The scheme set is represented by \( F = \{f_1, \ldots, f_m\} \), and \( R = \{r_1, \ldots, r_n\} \) denotes the risk set to be assessed. The expert group is \( E = \{e_1, \ldots, e_k\} \) with their respective weights \( \lambda_k \) \((k = 1, \ldots, l)\) determined by their knowledge and experience. The linguistic assessment value of the expert \( e_k \) to the scheme \( f_i \) under the risk \( r_j \) is represented by \( x^i_j(k = 1, \ldots, l; i = 1, \ldots, m; j = 1, \ldots, n) \), so that the risk evaluation and decision matrix is \( D = (x^i_j)_{m \times n} \).

Then, the steps of this method are as follows:

Step 1: According to definition 1, convert the risk information matrix \( D = (x^i_j)_{m \times n} \) described qualitatively into two-tuple linguistic decision matrix \( D_{2-T} = (x^i_j, 0)_{m \times n} \).

Step 2: Determine the weights of experts.

1) According to definitions 2 and 3, for every scheme under each risk indicator, use the following formulas to calculate the assessment result of the expert \( e_k \) and the group \( e \) based on definition 3 and formula (5):

\[
S_k\left((x^i_j, 0), (\bar{x}^i_j, a_{e_k})\right) = \frac{\xi((x^i_j, 0), (\bar{x}^i_j, a_{e_k}))}{\sum_{k=1}^{l} \xi((x^i_j, 0), (\bar{x}^i_j, a_{e_k}))}
\]  

(8)

And the distance value of the grey correlation coefficient \( \xi() \) is

\[
D\left((x^i_j, 0), (\bar{x}^i_j, a_{e_0})\right) = \left|\Delta^{-1}(x^i_j, 0) - \Delta^{-1}(\bar{x}^i_j, a_{e_0})\right|
\]  

(5):

\[
(x^i_j, b) = \Delta^{-1}\left(\sum_{i=1}^{n} \Delta(x^i_j, 0) / l\right)
\]  

(7)

In it, \( a_{e_0} \in [-0.5, 0.5) \). Then, calculate the similarity degree \( S_k\left((x^i_j, 0), (\bar{x}^i_j, a_{e_k})\right) \) of each scheme between the expert \( e_k \) and the group \( e \) based on definition 3 and formula (5):

\[
S_k\left((x^i_j, 0), (\bar{x}^i_j, a_{e_k})\right) = \frac{\xi((x^i_j, 0), (\bar{x}^i_j, a_{e_k}))}{\sum_{k=1}^{l} \xi((x^i_j, 0), (\bar{x}^i_j, a_{e_k}))}
\]  

(8)

2) According to definitions 2 and 3, for every scheme, use the following formulas to calculate the assessment result of each expert \( (x^i_j, b) \) and the result of the group \( (z_i, c_i) \):

\[
\left(x^i_j, b\right) = \Delta\left(\sum_{i=1}^{n} \Delta^{-1}(x^i_j, 0)\right)
\]  

(10)

\[
(z_i, c) = \Delta\left(\sum_{i=1}^{l} w_i \sum_{j=1}^{n} \Delta^{-1}(x^i_j, 0)\right)
\]  

(11)

In these formulas, \( 1 \leq k \leq l \), \( b, c \in [-0.5, 0.5] \), and \( w_k \) is the weight converted from the linguistic expert weight \( \lambda_k \) with the formula \( w_k = \Delta^{-1}(\lambda_k, 0) / \sum_{i=1}^{l} \Delta^{-1}(\lambda_k, 0) \). Then, calculate the deviation between each expert and the group by

\[
H(e_k, e) = \sum_{i=1}^{n} \left|\Delta^{-1}(x^i_j, 0) - \Delta^{-1}(z_i, c_i)\right|
\]  

(12)

And get the final weight \( w_{e_k} \), based on formula (9):

\[
w_{e_k} = \frac{H(e_k, e)}{\sum_{k=1}^{l} H(e_k, e)}
\]  

(13)

3) Calculate the final weight \( w_{e_k} \) to consider both the similarity degree and the deviation.

Step 3: Aggregate the assessment information of each expert. For every scheme under each risk indicator, aggregate the assessment information by the formula

\[
\left(x^i_j, a_{e_k}\right) = \Delta\left(\sum_{k=1}^{l} w_{e_k} \times \Delta^{-1}(x^i_j, 0)\right)
\]  

(14)
Step 4: According to above equations to calculate the schemes’ total catastrophe values.
Step 5: Sort the schemes by the principle “the larger the two-tuple linguistic total catastrophe value is, the higher the risk is, and the worse the scheme is” to obtain the best one.

IV. CASE STUDY

This paper studies risk assessment and decision-making of power companies based on the actual science and technology project of State Grid Corp of China, and refers to the index system in references [1], which built is shown in Table II.

<table>
<thead>
<tr>
<th>1st level</th>
<th>2nd level</th>
<th>3rd level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic risks (R₁)</td>
<td>Regional power demand risk (R₁₁)</td>
<td>Classified power price risk (R₁₂)</td>
</tr>
<tr>
<td>Policy risks (R₂)</td>
<td>Peak and valley time-of-use power price policy risk (R₂₁)</td>
<td>Interruptible power price policy risk (R₂₂)</td>
</tr>
<tr>
<td></td>
<td>Local investment attraction policy risk (R₂₃)</td>
<td>Large consumers direct-supplying policy risk (R₂₄)</td>
</tr>
<tr>
<td>Trading risks (R₃)</td>
<td>Purchase power price risk (R₃₁)</td>
<td>Power charges collection risk (R₃₂)</td>
</tr>
<tr>
<td>Internal management risks (R₄)</td>
<td>Grid construction risk (R₄₁)</td>
<td>Power supply cost control risk (R₄₂)</td>
</tr>
<tr>
<td>External competition risks (R₅)</td>
<td>Technology and equipment selection risk (R₅₃)</td>
<td>Captive power plant risk (R₅₄)</td>
</tr>
<tr>
<td>Substitute risk (R₆)</td>
<td>Distribution and retail separation risk (R₆₁)</td>
<td></td>
</tr>
</tbody>
</table>

A = \{A₁, A₂, A₃, A₄\} contains 4 power supply companies, and 3 senior experts are invited to assess these risks by reading documentation and communicating with staff. The risk assessment set using qualitative linguistic variables is:

\[ S = \{s₀ = VL(Very Low), s₁ = L(Low), s₂ = ML(Medium Low), s₃ = M(Medium), s₄ = MH(Medium High), s₅ = H(High), s₆ = VH(Very High)\} \]

The assessment result is shown in Table III. According to the knowledge accumulation and experience of experts, use qualitative linguistic to determine the experts weights:

\[ W₅ = \{w₁ = VH(s₁), w₂ = H(s₂), w₃ = M(s₃)\} \]

And based on the proposed method, these companies can be ranked.

According to the above steps, convert the linguistic assessment matrix in Table III into two-tuple linguistic decision matrix at first, and then calculate the similarity degree and the deviation with the corresponding weights, as shown in Table IV. Convert the weights of experts \[ W₅ = \{s₀, s₁, s₂, s₃\} \] into real numbers \[ W₅ = \{0.428, 0.357, 0.215\} \] by the inverse function of two-tuple linguistic. And when the eclectic preference coefficient \( \alpha = \{0, 0.25, 0.5, 0.75, 1\} \), the final experts weights are shown in Table V.

<table>
<thead>
<tr>
<th>3rd level</th>
<th>Expert E₁</th>
<th>Expert E₂</th>
<th>Expert E₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>R₁₁</td>
<td>s₁</td>
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<tr>
<td>R₁₂</td>
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It can be seen from Table IV and Table V that the assessment information of the expert $E_1$ is most similar to the group minds with the value 37.447. So when $\alpha = 1$, his weight $w_{e_1} = 0.3504$ is the largest. And the largest deviation with the group belongs to the expert $E_3$ with the value 86.663. So when $\alpha = 0$, his weight $w_{e_3} = 0.5796$ is the largest. In order to give consideration to both methods, this paper chooses $\alpha = 0.5$, i.e. $w_{e_1} = \{0.266, 0.2876, 0.4464\}$.

According to Step 3, the aggregation result of experts’ assessment information is shown in Table VI. Then, follow Step 4 to determine the catastrophe type of the 2nd level index. Economic risks and trading risks with 2 sub-indexes belong to cusp catastrophe model, while internal management risks and external competition risks are swallowtail catastrophe models, and the ascription of policy risks is butterfly catastrophe model. Normalize these risk indexes, and attention must be paid to the importance ranking of their control variables. In the index system mentioned above, the 3rd level risk indexes are all sorted by importance except indexes of policy risks. So, taking it as an example, its two-tuple linguistic catastrophe values after normalization are shown in Table VII.
In the process of recursive operation for these two-tuple linguistic values of the 3rd level indexes, economic risks follow the complementation principle, while others follow the non-complementation one. Then the catastrophe values of the 2nd level indexes of each scheme and their normalized values can be obtained. And the importance ranking of them is 4235, as shown in Table VIII.

Let the 2nd level indexes follow the complementation principle and obtain the two-tuple linguistic total catastrophe values of all schemes:

\[ A_1 = (s_1, 0.166), \quad A_2 = (s_1, 0.158), \quad A_3 = (s_1, 0.144), \quad A_4 = (s_1, 0.158) \]

According to the principle in Step 5, the ranking result of these 4 companies is \( A_1 < A_2 = A_3 < A_4 \), and the risk of \( A_4 \) is minimal.

In addition, the corresponding results under other 4 eclectic preference coefficients are displayed in Table IX to show the impact of the coefficient and verify the reliability of the ranking above.

| Index | Normalization formula | \( x_1 = \sqrt{a} \) | \( x_2 = \sqrt{b} \) | \( x_3 = \sqrt{c} \) | \( x_4 = \sqrt{d} \) | \( x_5 = \sqrt{e} \) |
|-------|-----------------------|-----------------|-----------------|-----------------|-----------------|
| \( A_1 \) | \((s_1, 0.046)\) | \((s_1, 0.219)\) | \(-0.376\) | \(0.144\) | \(-0.243\) |
| \( A_2 \) | \((-0.024)\) | \((s_1, 0.196)\) | \(-0.285\) | \(0.065\) | \(-0.291\) |
| \( A_3 \) | \((-0.001)\) | \((s_1, 0.246)\) | \(-0.471\) | \(0.021\) | \(-0.474\) |
| \( A_4 \) | \((s_1, 0.003)\) | \((s_1, 0.252)\) | \(-0.413\) | \(0.212\) | \(-0.359\) |

Table IX shows the ranking result changes with the coefficient \( \alpha \). A mean opinion oriented risk aversion decision maker prefers \( \alpha \) close to 1, while a risk appetite decision maker is opposite. Thus, \( \alpha \) should be determined by actual situation. Besides, the risk of the company \( A_4 \) is always minimal, which confirms the reliability of the result.

V. CONCLUSIONS

This paper studied by the combination of catastrophe theory and two-tuple linguistic to get rid of the limitation of proper weight determination. It expands the application of catastrophe theory from real numbers to uncertain and fuzzy linguistic variables, which provides a new way for the theory.

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