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Evaluation of the Security of Coal Enterprises in China Based on a New Fuzzy Linguistic Decision Making Method

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Abstract: Coal industry, as a type of basic energy is a significant foundation of the development of economy in China. The risk problem of coal enterprises has been attracting the attentions of our society and business. So, how to assess the security or risk of coal enterprises is a hot topic in academic and practical fields. In this paper, we propose a new multiple attribute group decision making method to assess the security of coal enterprises. Firstly, based on the existing studies, the factors that may influence this problem are selected. Secondly, a new fuzzy linguistic method is developed based on fuzzy linguistic representation model related to distribution assessments. Finally, an illustrative example is introduced to verify the applicability of this proposed method in solving the problem of evaluation of the security of coal enterprises.

Keywords: *assessment, security, coal enterprises, fuzzy linguistic method*

1. Introduction

Coal industry plays an important role in the structure of energy consumption in China. Compared with other industries, there are more dangerous and uncertain in coal industry. In particular, the coal resources in our country are widely distributed and their geological conditions are very complex. Coal industry is regarded as a complicated system including many factors but not a single factor. Therefore, these situations may bring much uncertain risk in coal enterprises. In 2003, an accident related to gas explosion happened in a coal mine in Sichuan province. Here, this accident killed 28 people. The main reason why this accident could happen is the lack of sufficient recognition about risk. How to scientifically and rationally assess the risk is still a hot topic in the research of coal enterprises [1, 5].

Zhu proposed fuzzy comprehensive evaluation method to evaluate the safety of coal mine from some attributes such the mortality of million tons, the cultural level of staff, the technical measures and gas level. Qiao and Li analyzed the factors which may influence the safety of coal mine. Then, from the perspective of these factors, they constructed the model to measure the risk of coal enterprises. Lin, Kang, Zhou and Wang analyzed the existing conditions of the security management of coal enterprises so as to find the main reasons that may impact on the safety of coal enterprise [2]. Based risk matrix, Guo developed a new method to assess the risk of coal enterprises in our country [4]. Here, the risk matrix is used to rank the factors that may impact on the risk of coal enterprises, and then the key factors are selected. According to these key factors, security risk management can be conducted.

Although the mentioned research has required some effects on the evaluation of security of coal enterprises, most focus on qualitative analysis and lack of quantitative measure especially quantitative evaluation with uncertain information [3]. In general, evaluation can be considered a type of decision making which has found to be widely applied in economics, management, healthcare, military and so on. Therefore, from the perspective of decision making, we will deal with the evaluation problem related the security of coal enterprises.

Because the security of coal enterprises are influenced by many factors, this assessment problem can be considered a multiple attribute decision making problem. Owing to the importance of this assessment problem, we often need to invite many experts. So, this problem can be further considered a multiple attribute group decision making problem in this paper. It should be noted that this real problem need to handle with uncertain information, so the conduct of such uncertain information is still a big challenge. Hereinto, the first challenge is to portray the preferences or opinions provided by the decision makers. In general, these decision makers have different background, knowledge systems, risk attitudes and so on. It is always a problems that how to select an appropriate way to express the opinions of the decision makers. In order to deal with this problem, many researchers have been proposed many methods [9]. Here, fuzzy linguistic method has attracted much attention [11, 12].

Meng and Pei proposed weighted unbalanced linguistic aggregation operators to handle group decision making problems, which extends the linguistic weighted averaging operator and the linguistic ordered weighted averaging operator. This operator has obtained good results in a case study on the evaluation of human resource performance [6]. Wang and Hao defined a new version of 2-tuple fuzzy linguistic representation model for decision making. Here, canonical characteristic values were developed to help the decision maker aggregate information denoted by proportional 2-tuple linguistic term sets [7]. Herrera, Herrera-Viedma and Martinez proposed a fusion method to manage multi-granularity linguistic term set for decision making. Hereinto, choice degree is defined to be used to rank alternatives [8]. Recently, Zhang, Dong and Xu developed a new linguistic term set based on distribution assessments for group decision making. This new fuzzy linguistic term set overcomes some existing drawbacks such as the loss of original information [10]. But this new fuzzy linguistic term set is only used in decision problem related to preference relations of the decision makers.

Thus, in this paper, we introduce the new fuzzy linguistic term set based on distribution assessments to help the decision makers express their preferences or opinions of alternatives on each attribute. By combining the ordered weighted averaging operator and the weighted averaging operator, we define a new aggregation operator called hybrid weighted averaging operator to aggregate the assessments provided by each decision maker on each attribute. Then, expectation values are introduced to rank all alternatives denoted by collective assessments. Finally, an illustrative example is addressed by the proposed method to verify the applicability of the proposed method.

The rest of this paper is organized as follows. In Section 2, the assessment framework is constructed by analyzing the existing research. Section 3 proposes the new fuzzy linguistic method. Section 4 demonstrates an illustrative example to verify the validity of the proposed model. Section 5 concludes this paper.

2. Main Text

In this section, an assessment framework is constructed to assess the security risk of coal enterprises and further to help the decision maker conduct the process of this assessment.

2.1. Descriptions of Assessment Problems

Over the past two decades, coal industry is a significant foundation of the development of economy in our country. It is commonly accepted that the security of coal mine is closely related to the sustainable development of coal industry. From a broader perspective, the security of coal mine could also determine the degree of the security of national energy. As mentioned in Introduction, evaluation of security risk of coal enterprises is very important and meaningful for our country. However, the actual situation of coal mining in China is complicated and volatile. The level of information in coal enterprises is relative low. The capability of security management for coal enterprise is not yet sound and perfect. These reasons may lead to the appearance of accidents in coal mine. That is, these reasons are why there are many accidents in coal enterprises of our country each year. The results of these accidents are always dangerous and may result in serious influence on an enterprise even or a family. Many lives are vanished owing to these accidents.

In order to build the assessment framework of security risk of coal enterprises, four experts from China Coal Economic Research Association and local coal bureau of industry are invited as the decision makers in this paper. Meanwhile, an expert from Ministry of Land and Resources of the People's Republic of China is invited as a manger to facilitate the process of this evaluation.

2.2. The Selection of Attributes

In general, many factors may impact on the result of evaluation, which are always called attributes in evaluation. The attributes could be organized into several hierarchies, which constitute attribute system related to the evaluation. Each upper layer is comprised by several attributes in the lower layer. Based on the existing studies [4], four attributes are selected as shown in Table 1. Hereinto, Risk of staff mainly refers to the responsibility of staff and violation of rules and regulations caused by staff. Risk of device is related to the failure rate of equipment or the maintenance and operation of equipment or its mechanization level. Risk of environment includes atmospheric conditions, gas drainage, dust concentration or the security of the environment. Risk of management is reflected from the construction of management system and rule, the training of safety education, the quality of managers, the improvement of emergency system or supervision and inspection of safety. Risk of Information involves in the collection of information, the management of information or the forecast of information. Obviously, they are composed by internal and external factors [3].

Table 1: *Description of the four attributes*

Attributes	Explanation
C_1	Risk of staff
C_2	Risk of device
C_3	Risk of environment
C_4	Risk of management
C_5	Risk of Information

2.3. The modeling of multiple attribute group decision making

After the attributes are selected, the next step is to model the decision making problem based on a common form of multiple attribute group decision making.

Suppose a multiple attribute group decision making problem includes t expert E_j (j = 1, 2, …, T) and a manager. The relative weights of the t experts on attribute C_i for alternative A_l are denoted by $\varphi(C_i) = (\varphi^1(C_i), \varphi^2(C_i), \ldots, \varphi^T(C_i))$ such that

$$0 \le \varphi^T(C_i) \le 1 \text{ and } \sum_{j=1}^{T} \varphi^j(C_i) = 1. \quad (1)$$

All experts addresses a common multiple attribute decision making problem which has m alternatives A_l (l = 1, 2, …,m) and L attributes C_i (i = 1, 2, …, n). The relative weights of the n attributes are signified by $w_i = (w_1, w_2, \ldots, w_L)$ such that

$$0 \le w_i \le 1 \text{ and } \sum_{i=1}^{n} w_i = 1 \quad (2)$$

On the basis of Eqs. (1) – (2), we construct a decision matrix denoted by $D = [A_{li}^j]_{m\times n}$, where all the assessments are denoted by A_{li}^j (l = 1, 2, ..., m; i = 1, 2, ..., n; j = 1, 2, ..., T) given by the decision makers from different background. For each alternative denoted by A_l, the decision makers are invited to express preferences in term of each attribute denoted by C_i. Then, According to the mentioned analysis, a normal decision making matrix $D = [A_{li}^j]_{m\times n}$ can be generated in the following:

$$D_{m\times n} = \begin{pmatrix} A_{11}^j & A_{12}^j & \cdots & A_{1n}^j \\ A_{21}^j & A_{22}^j & \cdots & A_{2n}^j \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1}^j & A_{m2}^j & \cdots & A_{mn}^j \end{pmatrix} \quad (3)$$

It should be noted this common decision making matrix will help the next research in the remaining paper.

3. The Proposed Method

In order to deal with this assessment problem, a new multiple attribute group decision making method based on fuzzy linguistic computational model is proposed in this section. First of all, the basic concepts about fuzzy linguistic method especially fuzzy linguistic computational model based on distribution assessments are introduced below.

3.1 Basic Concepts

Fuzzy linguistic method is considered a useful tool to handle the uncertainty in many real world problems as analyzed in Introduction. Here, the concept of linguistic variable is used to model the linguistic information provided by the decision makers. These linguistic variables are not numbers, but words or sentences in the form of natural or artificial language. Many researchers have proposed different fuzzy linguistic computational models such as a fundamental fuzzy linguistic computational model, 2-tuple fuzzy linguistic computational model, proportional 2-tuple fuzzy linguistic computational model and others [13-17]. Their detailed concepts will be respectively demonstrated in the following.

Let $S = \{s_\alpha \mid \alpha = -t, ..., -1, 0, 1, ..., t\}$ be a linguistic term set with odd cardinality. The term s_α represents a possible value for a linguistic variable and t is a positive integer. It is usually acquired that the linguistic term set should satisfy the characteristics as follows:

(1) The set is ordered: $s_\alpha > s_\beta$ if and only if $\alpha > \beta$. Therefore, there exist two linguistic comparison operators, the min and max operators.
(2) There is a negation operator: $Neg(s_\alpha) = s_{-\alpha}$, especially, $Neg(s_0) = s_0$.

This linguistic term set S can be called as the linguistic scale. For example, S may be defined as:
S = {s_{-3} = extremely poor, s_{-2} = very poor, s_{-1} = poor, s_0 = fair, s_1 = good, s_2 = very good, s_3 = extremely good}.

In order to realize all the information provided by the decision makers, Xu [9] extended the discrete linguistic term set S to a continuous linguistic term set $\overline{S} = \{s_\alpha \mid \alpha \in [-q, q]\}$, where $q \ge t$ is a sufficiently large positive integer. If $s_\alpha \in S$, s_α is named the original term, otherwise, it is called the virtual linguistic term which can only appear in operations.
Then, the operational law could be defined.

Considering any two linguistic terms $s_\alpha, s_\beta \in \overline{S}$, and $\mu_1, \mu_2 \in [0, 1]$, some operational laws(Xu et al., 2005) are defined as follows:

(1) $s_\alpha \oplus s_\beta = s_{\alpha+\beta}$;
(2) $s_\alpha \oplus s_\beta = s_\beta \oplus s_\alpha$;
(3) $\mu s_\alpha = s_{\mu\alpha}$;
(4) $(\mu_1 + \mu_2) s_\alpha = \mu_1 s_\alpha \oplus \mu_2 s_\alpha$;
(5) $\mu(s_\alpha \oplus s_\beta) = \mu s_\alpha \oplus \mu s_\beta$.

Here, let $s \in S$, we denote $I(s)$ as the lower index of s, and call it as the gradation of s in S.

However, the mentioned original linguistic term set may lead to the loss of decision information. In response to this problem, the 2 tuple linguistic term set is developed by Herrera and Martinez (2000).

Let $S = \{s_0, s_1, ..., s_g\}$ be a linguistic label set with odd cardinality and β be the aggregation result of the indexes of labels assessed in a set of S of linguistic terms, i.e., the result of a symbolic aggregation operation such that $\beta \in [0, g]$. Let i = round(β) and $\alpha = \beta - i$ satisfy that $i \in [0, g]$ and $\alpha \in [-0.5, 0.5)$. Then α is referred to as a symbolic translation.

Definition 1. Let $S = \{s_0, s_1, ..., s_g\}$ be a linguistic term set with odd cardinality and $\beta \in [0, g]$ a value representing the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following transformation:

$$\Delta: [0, g] \rightarrow S \times [-0.5, 0.5),$$
$$\Delta(\beta) = (s_k, \alpha) \text{ with } i = \text{round}(\beta) \text{ and } \alpha = \beta - i,$$

where round(·) is the usual round operation, s_i has the closet index label to β, and α is the value of the symbolic translation. For convenience, the range of Δ is denoted as $\overline{S}$. Meanwhile, we have

$$\Delta^{-1}: S \times [-0.5, 0.5) \rightarrow [0, g],$$
$$\Delta^{-1}(s_k, \alpha) = \alpha + k = \beta.$$

Obviously, when $\alpha = 0$, a 2-tuple linguistic representation can reduce to a classical linguistic representation.

Then, the operational law of two 2-tuple linguistic term set is defined (Herrera and Martinez (2000)).

Definition 2. Let (s_k, α_1) and (s_l, α_2) be two 2-tuple linguistic term sets, with each one representing a counting of information as follows:

(1) if $k < l$, then (s_k, α_1) is smaller than (s_l, α_2);
(2) if $k = l$, then

1) if $\alpha_1 = \alpha_2$, then(s_k, α_1), (s_l, α_2) represents the same information;
2) if $\alpha_1 < \alpha_2$, then(s_k, α_1) is smaller than (s_l, α_2);
3) if $\alpha_1 > \alpha_2$, then(s_k, α_1) is bigger than (s_l, α_2).

In short, it can be further referred from the mentioned analysis that the 2-tuple linguistic term set can be applied to improve the accuracy of original linguistic term set.

3.2 Fuzzy linguistic information based on distribution assessments

Although 2-tuple linguistic term set can avoid the loss of decision information, it cannot deal with more complex decision problem as shown in Introduction. In order to copy with this problem, Zhang et al., (2014) proposed linguistic preference relations based on distribution assessments. Referred to this fuzzy linguistic term set, a new similar fuzzy linguistic term set is developed to solve classical multiple attribute group decision making problem but not the decision problems related to preference relations of decision makers.

Definition 3. Let $S = \{s_0, s_1, ..., s_t\}$ be a linguistic term set. Let $m = \{(s_k, \beta_k) \mid k = 0, 1, ..., t\}$, where $s_k \in S$, $\beta_k \geq 0$,and $\sum_{k=0}^{t} \beta_k = 1$ and β_k is the symbolic proportion of s_k. Then m is called a distribution assessment of S.

Definition 4. Let $m = \{(s_k, \beta_k) \mid k = 0, 1, ..., t\}$, where $s_k \in S$, $\beta_k \geq 0$,and $\sum_{k=0}^{t} \beta_k = 1$ be a distribution assessment of S. The expectation of m is defined as follows:

$$E(m) = \sum_{k=0}^{t} \beta_k s_k \qquad (4)$$

Here, $\sum$ is used to denote the operation $\oplus$ of fuzzy linguistic term sets.

Then, the operation laws of distribution assessment of linguistic term set S should satisfy the following characteristics:

(1)A comparison operator: Let m_1 and m_2 be two distribution assessments of S,

1) if $E(m_1) < E(m_2)$, then m_1 is smaller than m_2; and
2) if $E(m_1) = E(m_2)$, then m_1 and m_2 have the same expectation.

(2) There is a negation operator: $Neg(s_k, \beta_k) = (s_k, \beta_{g-k})$.

According to Definitions 3 and 4, fuzzy linguistic term set based on distribution assessments could be defined in the next section.

3.3 The New Aggregation Operator

Firstly, the existing aggregation operators such as the weighted averaging operator and the ordered weighted averaging operator of linguistic term sets based on distribution assessments are reviewed in order to develop their new aggregation operator.

Definition 5 (Zhang et al. 2014). Let $S = \{s_0, s_1, ..., s_t\}$ be a linguistic term set and $\{m_1, ..., m_n\}$ a set of distribution assessments of S, where $m_i = \{(s_k, \beta_{ki}^j) \mid k = 0, 1, ..., t\}$, $j = 1, 2, ..., T$. Let $w = \{w_1, ..., w_n\}$ be an associated weighting vector that satisfies $0 \leq w_i \leq 1$ and $\sum_{i=1}^{n} w_i = 1$. The weighted averaging operator of linguistic term sets based on distribution assessments is calculated as

$$DAWA_w(m_1, ..., m_n) = \{(s_k, \beta_k^j) \mid k = 0, 1, ..., t\}, \qquad (5)$$

Where $\beta_k^j = \sum_{i=1}^{n} w_i \beta_{ki}^j$.

Definition 6 (Zhang et al. 2014). Let $S = \{s_0, s_1, ..., s_t\}$ be a linguistic term set and $\{m_1, ..., m_n\}$ a set of distribution assessments of S, where $m_i = \{(s_k, \beta_{ki}^j) \mid k = 0, 1, ..., t\}$, $j = 1, 2, ..., T$. Let $\omega = \{\omega_1, ..., \omega_n\}$ be an associated position weighting vector that satisfies $0 \leq \omega_i \leq 1$ and $\sum_{i=1}^{n} \omega_i = 1$. The ordered weighted averaging operator of linguistic term sets based on distribution assessments is computed as

$$DAOWA_w(m_1, ..., m_n) = \{(s_k, \beta_k^j) \mid k = 0, 1, ..., t\}, \quad (6)$$

where $\beta_k^j = \sum_{i=1}^{n} \omega_i \beta_{k\sigma(i)}^j$ and $\{\sigma(1), \sigma(2), ..., \sigma(n)\}$ is a permutation of $\{1, 2, ..., n\}$such that $m_{\sigma(i-1)} \geq m_{\sigma(i)}$ for $i = 2, ..., n$.

Then, by combining the mentioned two operators, the new aggregation operator is developed, which considers not only the attribute weight and position weight.

Definition 7. Let $S = \{s_0, s_1, ..., s_t\}$ be a linguistic term set and $\{m_1, ..., m_n\}$ a set of distribution assessments of S, where $m_i = \{(s_k, \beta_{ki}^j) \mid k = 0, 1, ..., t\}$, $j = 1, 2, ..., T$. Let $w = \{w_1, ..., w_n\}$ be an associated weighting vector and $\omega = \{\omega_1, ..., \omega_n\}$ be an associated position weighting vector that satisfy $0 \le w_i, \omega_i \le 1$ and $\sum_{i=1}^{n} w_i = 1$ and $\sum_{i=1}^{n} \omega_i = 1$. The hybrid weighted averaging operator of linguistic term sets based on distribution assessments is computed as

$$DAHWA_w(m_1, ..., m_n) = \{(s_k, \beta_k^j) \mid k = 0, 1, ..., t\}, \quad (7)$$

where $\beta_k^j = \sum_{i=1}^{n} n w_i \omega_i \beta_{k\sigma(i)}^j$ and $\{\sigma(1), \sigma(2), ..., \sigma(n)\}$ is a permutation of $\{1, 2, ..., n\}$such that $m_{\sigma(i-1)} \ge m_{\sigma(i)}$ for $i = 2, ..., n$, and n is a parameter to balance the weighting vector and the position weighting vector.

3.4 The Procedure of the Proposed Method

After the relative concepts of the proposed method are demonstrated, we will further show the procedure of the proposed fuzzy linguistic method in the following.
Step1. Model the multiple attribute group decision making problems as mentioned in Section 2.3.

Step2. Assume $S = \{s_0, s_1, ..., s_t\}$ as a linguistic term set with odd cardinality. The alternative A_{li}^j is assessed by the expert E_j on the attribute C_i to the linguistic term S_k with a symbolic proportion $\beta_k\left(A_{li}^j\right)$. The distribution assessment $D(A_{li}^j) = \{(s_k, \beta_k\left(A_{li}^j\right)) \mid k = 0, 1, ..., t\}$ where $0 \le \beta_k\left(A_{li}^j\right) \le 1$ and $\sum_{k=1}^{T} \beta_k\left(A_{li}^j\right) \le 1$.

Step3. The decision makers provide their opinions by using linguistic term sets based on distribution assessments as mentioned in Definition 3.

Step4. The information provided by different decision makers is combined to form assessments on each attribute by using Definition 7.

Step5. The assessments on each attribute are aggregated by using Definition 7 to form collective assessments of each alternative.

Step6. The assessments of each alternative are compared by using Definition 4.

Step7. The final ranking-order is generated.

4. Case Study

In this section, the evaluation problem of the security risk of coal enterprises is conducted according to the constructed attribute framework in section 2 and the proposed method using fuzzy linguistic multiple attribute group decision making method in section 3.

According to Step 1, the manager first provides the relative weights of four experts on each attribute as shown in Table 2. These weights reflect the relative importance of specific expert on specific attribute compared to other experts. In addition, the linguistic term set is defined as $S = \{s_0$ = extremely poor, s_1 = very poor, s_2 = poor, s_3 = fair, s_4 = good, s_5 = very good, s_6 = extremely good$\}$ by the manager.

***Table 2**: The relative weights of the four experts on the five attributes*

Attributes	$\varphi^1(C_i)$,	$\varphi^2(C_i)$	$\varphi^2(C_i)$	$\varphi^2(C_i)$
C_1	0.2	0.4	0.35	0.05
C_2	0.15	0.25	0.25	0.15
C_3	0.2	0.3	0.2	0.3
C_4	0.3	0.2	0.4	0.1
C_5	0.3	0.2	0.3	0.2

Then, the four experts are required to express their opinions by using linguistic terms with distribution assessments of each alternative on each attribute, which form four original decision making matrixes. This results are demonstrated in Table 3-Table6.

***Table 3**: The assessment provided by the expert E_1*

E_1	A_1	A_2	A_3	A_4
C_1	$(s_3,0.2)$, $(s_4,0.8)$	$(s_2,1)$	$(s_4,0.7)$, $(s_5,0.3)$	$(s_3,0.8)$, $(s_4,0.2)$
C_2	$(s_2,0.6)$, $(s_3,0.4)$	$(s_3,0.5)$, $(s_4,0.5)$	$(s_3,1)$	$(s_4,1)$
C_3	$(s_3,0.4)$, $(s_4,0.6)$,	$(s_3,0.2)$, $(s_4,0.8)$	$(s_5,1)$	$(s_2,1)$
C_4	$(s_3,1)$	$(s_2,1)$	$(s_4,0.7)$, $(s_5,0.3)$	$(s_5,1)$
C_5	$(s_4,1)$	$(s_3,1)$	$(s_3,0.2)$, $(s_4,0.4)$, $(s_5,0.4)$	$(s_2,0.1)$, $(s_3,0.9)$

***Table 4**: The assessment provided by the expert E_2*

E_2	A_1	A_2	A_3	A_4
C_1	$(s_4,1)$	$(s_2,1)$	$(s_2,0.6)$, $(s_3,0.4)$	$(s_3,0.8)$, $(s_4,0.2)$
C_2	$(s_2,0.8)$, $(s_4,0.2)$	$(s_1,0.4)$, $(s_2,0.6)$	$(s_4,1)$	$(s_5,1)$
C_3	$(s_3,0.6)$, $(s_4,0.4)$,	$(s_4,0.7)$, $(s_5,0.3)$	$(s_1,0.6)$, $(s_3,0.4)$	$(s_4,0.8)$, $(s_5,0.2)$
C_4	$(s_3,1)$	$(s_3,1)$	$(s_3,0.7)$, $(s_4,0.3)$	$(s_4,1)$
C_5	$(s_2,0.6)$, $(s_3,0.4)$	$(s_2,0.4)$, $(s_4,0.5)$, $(s_5,0.1)$	$(s_3,1)$,	$(s_1,0.8)$, $(s_2,0.2)$

***Table 5**: The assessment provided by the expert E_3*

E_3	A_1	A_2	A_3	A_4
C_1	$(s_4,1)$	$(s_3,1)$	$(s_5,1)$	$(s_4,1)$
C_2	$(s_3,0.6)$, $(s_4,0.4)$	$(s_2,0.3)$, $(s_4,0.7)$	$(s_1,0.2)$, $(s_3,0.8)$	$(s_3,0.4)$, $(s_4,0.6)$
C_3	$(s_4,0.6)$, $(s_5,0.4)$,	$(s_3,0.5)$, $(s_4,0.5)$	$(s_2,0.5)$, $(s_3,0.5)$	$(s_2,0.5)$, $(s_4,0.5)$
C_4	$(s_1,0.4)$, $(s_2,0.6)$	$(s_2,0.5)$, $(s_3,0.5)$	$(s_4,1)$	$(s_3,1)$
C_5	$(s_2,0.5)$,	$(s_4,0.7)$,	$(s_3,1)$	$(s_4,1)$

(s_3,0.5),	(s_5,0.3)

***Table 6**: The assessment provided by the expert E_4*

E_4	A_1	A_2	A_3	A_4
C_1	(s_2,1)	(s_3,1)	(s_4,1)	(s_3,1)
C_2	(s_3,1)	(s_5,1)	(s_3,1)	(s_4,1)
C_3	(s_4,1)	(s_2,1)	(s_4,1)	(s_3,1)
C_4	(s_4,1)	(s_1,1)	(s_2,1)	(s_5,1)
C_5	(s_1,1)	(s_5,1)	(s_4,1)	(s_2,1)

By using Definition 7, the hybrid weighted averaging operator of linguistic term sets based on distribution assessments is introduced to aggregate the information in Tables 3-6. Firstly, the assessments by different experts are combined into the assessments on each attribute. Secondly, the assessments on each attribute are combined into the collective assessments of each alternative. The final collective assessments are demonstrated in Table 7.

***Table 7**: The collective assessments*

Alternative	*Linguistic assessments*
A_1	(s_1,0.009),(s_2,0.16) ,(s_3,0.3275), (s_4,0.4025), (s_5,0.02)
A_2	(s_1,0.005),(s_2,0.35175) ,(s_3,0.32875), (s_4,0.2575), (s_5,0.012)
A_3	(s_1,0.0425),(s_2,0.11) ,(s_3,0.35), (s_4,0.2925), (s_5,0.205)
A_4	(s_1,0.04),(s_2,0.1425) ,(s_3,0.2), (s_4,0.44), (s_5,0.1775)

In general, it is difficult to directly compare the collective assessments. So, the expectation value defined in Definition 4 is introduced to calculate the collective assessments denoted by linguistic terms with distribution assessments. The results are demonstrated in Table 8.

***Table 8**: The ranking order*

Alternative	*ranking*
A_1	3
A_2	4
A_3	2
A_4	1

Therefore, the ranking order of all alternative is generated and the optimal alternative can be selected by considering opinions of all experts. This result could help the decision maker compete the next research of the analysis of the security of coal enterprises.

From this case study, the main contributions of the proposed multiple attribute group decision making method can be further discussed and summarized as follows:

(1) The linguistic term set based on distribution assessment is introduced to construct decision matrix with absolute assessments.
(2) The new information aggregation operator named the hybrid weighted averaging operator is proposed and applied to combine the assessments of each alternative provided all experts on all attributes.
(3) Uncertain information related to the evaluation of risk or security of coal enterprises is considered and analyzed.
(4) The new method to assess security of coal enterprises is proposed with uncertainty.
(5) In short, the applicability of this method is verified and demonstrated in this case study and is worth to be further applied in many coal enterprises.

5. Conclusions

In general, the security of coal enterprises is closely related to the sustainable development of coal industry, which is a basic industry in our country. In this paper, considering uncertain information in evaluation problem, a new method to assess security of coal enterprises is proposed. This method is not based on a decision maker or an expert but depending on several experts who have different backgrounds and knowledge. In addition, many factors that may influence this evaluation problem are proposed and considered as multiple attributes. On the basis of these, a multiple attribute group decision making method is developed. Here, q new information aggregation operator is proposed to combine the assessments of all experts on all attributes. The ranking order is obtained by expectation values. An illustrative example is introduced to verify the applicability of this proposed method in solving the problem of evaluation of the security of coal enterprises.

In the future study, this result will be further analyzed to help the manager improve security. More other methods may be applied in this evaluation problem in the different contexts.

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