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Energy Supply Chain Risk Evaluation based on a Two-Stage Decision Making Approach

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Abstract. Energy has always been an important issue related to people's livelihood and economy. With the energy crisis continues to escalate, the problems exposed in the energy supply chain are becoming increasingly severe. Due to the uncertainty of the external environment and internal structure, the energy supply chain is vulnerable to various risks. This article takes three representative energy companies in China as examples and adopts a two-stage method to evaluate the risks of the energy supply chain. The first stage uses the best-worst method (BWM) to determine the weight of each risk factor, and the second stage uses the linguistic value soft set to evaluate the risk performance of energy companies, and finally obtains the ranking results of the energy supply chain of each company. The results show that none of the three companies have outstanding performance in environmental-related risks, and energy companies should pay more attention to the control of environmental risks. This research supplements the related research on energy supply chain risk in theory, and has guiding significance for practitioners in related industries.

Keywords: energy supply chain, risk evaluation, two-stage method, BWM, linguistic value soft set

1. Introduction

Energy can provide the security of economic development, and an important competitive factor for sustainable global economic development is energy efficiency [1]. As the prices of natural gas, coal and oil soar, the energy crisis has become a problem we cannot ignore. The close relationship between energy and the economy makes energy shortages will further intensify competition and conflicts among stakeholders, and the energy supply chain will also face more challenges. In this scenario, energy companies have adopted more supply chain management strategies, such as lean production and global procurement, to improve their ability to respond to environmental changes. The adoption of these strategies makes the structure of the energy supply chain more complex and more vulnerable to risks. Therefore, how to do a good job in the risk management of the energy supply chain and reduce the risk of the energy supply chain is of vital importance to managers.

Unlike traditional supply chains, energy supply chains are more susceptible to regional and period effects leading to risks. For the energy supply chain management, risk management is one of its key elements. For example, as technology upgrades, petroleum resources will reduce the cost of extraction, but the disturbance of political and economic factors will change the price curve, thereby increasing the risk of oil price fluctuations. With the arrival of the peak demand in the winter, the Eurozone energy consumer price index has risen to the highest level on record. Soaring energy prices may push up the inflation rate in the entire region, harm consumers' interests, and threaten the region's economic recovery after the epidemic. Reducing the risk level of the energy supply chain requires fully revealing the various risk factors it may face. Through the establishment of a set of feasible evaluation indicators and practical evaluation methods, targeted risk improvement measures are proposed.

Through reviewing the existing literature, it is found that there are few studies on energy supply chain risks and the method of risk assessment is relatively simple. Therefore, this article considers the use of a two-stage decision-making model method, through this decision-making model to evaluate the uncertain energy supply chain multi-criteria decision-making (MCDM) problem. The first stage uses the best-worst method (BWM) to determine the standard weights for each energy supply chain risk factor. As a robust MCDM

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method, the BWM can directly reflect complex fuzzy language information. Compared with other subjective evaluation methods for determining weights, it can enhance the consistency of the comparison matrix and reduce the computational complexity. Then we consider that in the process of evaluation, decision makers may have different degrees of familiarity with the evaluation object. Therefore, we decided to use the linguistic value soft set for the second stage of evaluation to solve the problem of different evaluation attributes of decision makers. Being one of the mathematical tools to deal with uncertainty, the linguistic value soft set can effectively express the evaluation of inaccurate and uncertain information. This paper selects three representative energy companies in China to conduct energy supply chain risk assessment and finds the best practitioners. The main energy of these three companies includes oil, natural gas and electricity, and they cover the process from energy exploration, development to utilization, so they are highly representative.

The rest of this article includes: Section 2 derives the theoretical significance of this article by combing through relevant literature, Section 3 introduces the BWM and the linguistic value soft set method, and verifies the feasibility and practical significance of the method through specific cases in Section 4. Then we discuss the evaluation results. The conclusion in Section 5 summarizes the deficiencies of this research and the prospects for future research directions.

2. Literature Review

2.1. Energy Supply Chain Management

As a hot topic today, the combination of energy and supply chain has attracted the attention of many scholars. Some scholars have focused on improving energy efficiency through supply chain management [2]. Kalenoja, et al. [1] started with energy efficiency measurements and demonstrated that decisions on the supply chain will significantly affect energy consumption. Farahani, et al. [3] argued that energy costs can be reduced by reorganizing the logistics network of industrial supply chains, improving the combustion efficiency of transport assets, and reducing transport distances. Hafezalkotob [4] pointed out that among government regulatory policies, cooperative energy efficiency policies can produce the highest level of social utility and energy savings in green supply chain competition. Iqbal, et al. [5] proposed a supply chain model that eliminates waste in the system and consumes the least energy. Turner and Katris [6] considered the indirect effects of energy use and carbon emissions in supply chains by adopting a carbon saving multiplier indicator. Based on the characteristics and demands of traditional supply chains, the above research explained how to reduce energy consumption and energy costs in the supply chain from different perspectives.

For the study of energy supply chain, scholars seem to be more interested in renewable energy supply chain [7-8]. We speculate that this is because some of the renewable energy sources have been introduced as alternatives to traditional energy sources, thus being able to protect environmental resources and improve the quality of life. Wee, et al. [9] evaluated renewable energy from a supply chain perspective, while Cucchiella and D'Adamo pointed out that the supply chain related to renewable energy also includes physical, information and financial flows [10]. Gold and Seuring [11] believed that sustainability assessments must consider the "triple bottom line" including economic, ecological, and social aspects of sustainability. Ricardo Saavedra, et al. [12] argued that sustainability is essential to improve the supply chain management of renewable energy sources. Mafakheri and Nasiri [13] considered the variability of biomass supply and source, and proposed the important role of the supply chain in providing biomass resources. Mirkouei, et al. [14] proposed a hybrid biomass-based energy supply chain and a MCDM framework to cope with supply-side uncertainties. Al-Nory [15] reduced the variability of renewable energy supply through optimal planning of supply chain operations. Keivanpour, et al. [16] proposed a strategic complexity management approach to analyze and control the complexity of offshore wind energy supply chains. Compared with the traditional supply chain, the renewable energy supply chain pays more attention to the consideration of green and environmental protection.

However, in addition to renewable energy, other energy supply chains should also be taken into account, as traditional energy sources are still an integral part of our lives. Rafique, et al. [17] applied the location optimization model to design the coal-fired energy supply chain to solve the "resource-rich and energy-deficient" dilemma of the energy sector in developing countries. Emenike and Falcone [18] believed that it is possible to increase uptime by reducing shortages and optimizing utilization, balance the increasing energy security needs, and reduce the impact of the epidemic on the supply chain of the energy sector. Xiang [19] put forward an intelligent optimization model of energy emergency supply chain collaboration from the perspective of emergency. Leung, et al. [20] studied the Chinese energy system and found that China is more concerned about the vulnerability of the oil supply chain, rooted in its historical events, and the characteristics of its energy system.

Although there have been many studies on energy supply chain management, few scholars have focused their perspectives on the risk assessment of energy supply chain. Bustamante and Gaustad [21] believed that increasing by-product yields, end-use recycling rates, and end-use material strength could reduce risk in the tellurium supply chain. Shao and Jin [22] evaluated the supply chain resilience of the lithium supply chain under the impact of new energy vehicle demand, and found that promoting recycling design can best improve the risk response capability of the lithium supply chain. Ezequiel Santibanez-Aguilar, et al. [23] proposed a mathematical planning model for optimizing the distributed system of a biorefinery plant, taking into account the uncertainties and related risks associated with supply chain operations. Yan, et al. [24] combined variable weight, cloud model and fuzzy analytic hierarchy process (AHP) to assess the risks faced by China's new energy vehicle supply chain in the period of technological change. Based on the above analysis, this paper focuses on the risk assessment of the energy supply chain.

2.2. Best-worst Method

The methods for energy supply chain risk assessment mainly focus on the AHP [24, 25] and DEA model [26]. However, it is not easy for the AHP method to evaluate the scale of factors, and the DEA method can give less information on the effective unit, so we consider using the BWM. This method has significant advantages in terms of simplicity, lower requirements for comparative data, reliability and consistency.

In 2015, Rezaei first proposed the multi-criteria decision-making method BWM, which obtained the criterion weight through fewer pairwise comparisons [27]. In response to the original BWM, scholars have proposed improvements. Guo and Zhao [28] extended BWM to a fuzzy environment to obtain a reasonable preference ranking of alternatives. Aboutorab, et al. [29] provided the Z number for BWM, namely ZBWM, to reduce the inconsistency of the BWM. Omrani, et al. [30] incorporated DEA into the BWM, introduced a multi-objective DEA-BWM model, Pamucar, et al. [31] considered the preferences of decision makers and used a set of common weights. considered the situation where there are more than one best and worst criteria in BWM. Liu, et al. [32] proposed the D-number BWM (D-BWM) weighting model, which is simple and sensitive to subjective information, and is more suitable for realistic decision-making. Majumder, et al. [33] presented intuitionistic fuzzy BWM and its combination with AHP, intuitionistic fuzzy best-worst analysis hierarchical process (BWAHP).

The BWM has also been applied by scholars to solve decision problems in supply chain management. Liu, et al. [34] used a modified BWM to prioritize and weigh suppliers. Haseli, et al. [35] developed a new method G-BWM based on BWM group decision problem, and applied it to green supplier selection and supplier development. The existing research of BWM is becoming mature, but it has not been widely implemented in the field of energy supply chain.

The linguistic value soft set effectively expresses the evaluation of inaccurate and uncertain information, and can be combined with the BWM to provide a new non-parametric theoretical method and tool. Sun, et al. [36] first introduced the concept of linguistic value soft sets. Zhang, et al. [37] combined linguistic value soft sets with the BWM to determine the risk weights of sustainable supply chains and to find the best practitioners of risk management. Chen, et al. [38] provided a new granular computing model by fusing soft set and rough set theories with language value information. The above researches provide ideas for this article. The first stage uses the BWM to determine the standard weight of each energy supply chain risk factor, and the second stage uses the linguistic value soft set for evaluation to solve the problem of different evaluation attributes of decision makers.

3. Methodology

3.1. Research framework

The first stage uses the BWM to determine the standard weights for each energy supply chain risk factor. In the second stage, we use the linguistic value soft set for evaluation. The framework is proposed in Fig. 1.

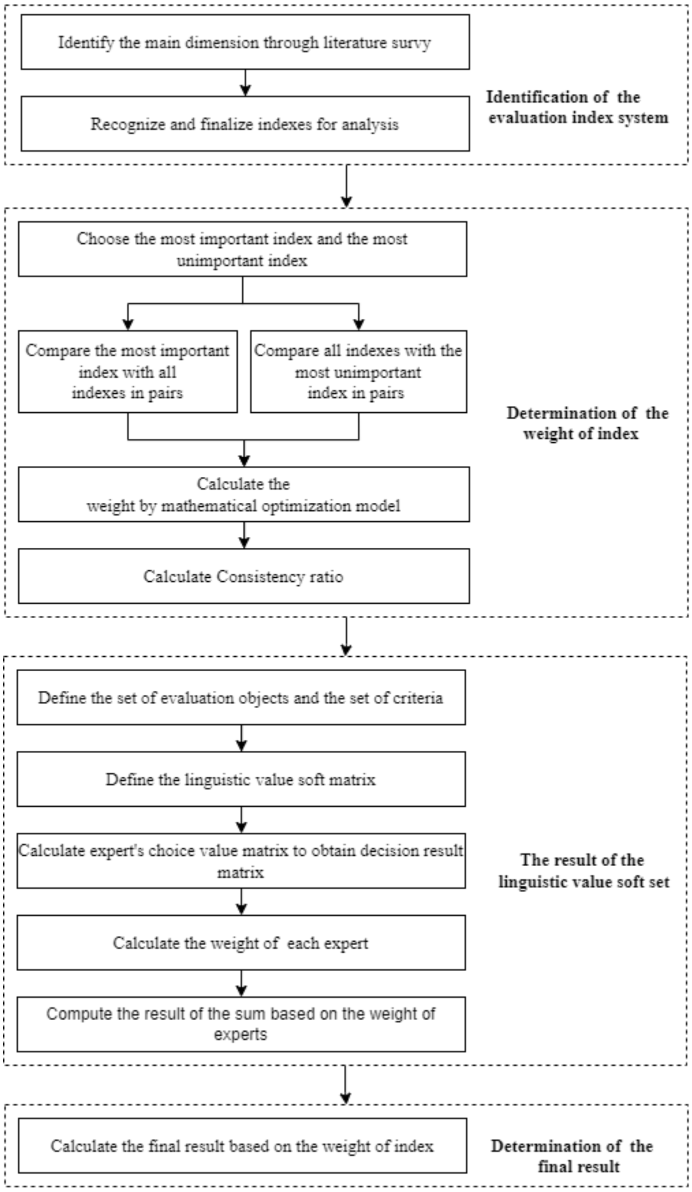

Fig. 1: The evaluation method of BWM and linguistic value soft set.

3.2. Best-worst Method

As a typical method for solving multi-attribute decision making problems, BWM simplifies the calculation process and improves the consistency of results by selecting the best and worst indexes and comparing the rest indexes with the most important index and the most unimportant index. Therefore, the application of this method has become one of the research hotspots. This paper will adopt BWM to get the weight of each index accurately. The specific steps are as follows [39]:

STEP1. Establish an evaluation index system. Define $E=\{E_1,E_2,\ldots,E_j,\ldots,E_n\}$ is a set of evaluation criteria.

STEP2. Experts choose the most important index E_B and the most unimportant index E_W from the indexes determined in Step 1.

STEP3. Compare the index with all indexes in pairs. Define $H_{Bj}^{n}=\{h_{B1},h_{B2},...,h_{Bn}\}$ is a metric that indicates the degree to which the most important index prefers the other index. The preference of E_B over all the other index are determined by every expert using a number 1-7.

STEP4. In the same way, compare the index with all indexes in pairs. Define $H_{jW}^{n}=\{h_{1W},h_{2W},...,h_{nW}\}$ is a metric that indicates the degree to which the other index prefers the most unimportant index. The preference of all the other index over E_W are determined by every expert using a number 1-7.

STEP5. The weight is obtained by mathematical optimization model. When the mathematical model is used to solve the weight, the maximum error η of $|w_B-h_{Bj}w_j|$ and $|w_j-h_{jW}w_W|$ should be minimized, thus the optimization model (1) can be established:

$$\begin{aligned}&\min\ \eta\\&s.t.\\&|w_B-h_{Bj}w_j|\le\eta,\ for\ \text{all j}\\&|w_j-h_{jW}w_W|\le\eta,\ for\ \text{all j}\\&\sum_{j=1}w_j=1\\&w_j\ge 0,\ for\ \text{all j}\end{aligned}\tag{1}$$

The weight vector of each index $W=\{w_1,w_2,...,w_n\}^T$ and η can be obtained by solving (1).

STEP6. Calculate Consistency ratio. Based on the Table 1 and (2), we can conclude that the consistency ratio. In addition, $a_{BW}=w_B/w_w$. The closer the consistency ratio is to zero, the stronger the consistency is

$$Consistency\ \text{ratio}=\frac{\eta}{Consistency\ \text{index}}\tag{2}$$

Table 1: Consistency index table

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency Index	0.00	0.44	1.00	1.63	2.30	3.00	3.75	4.47	5.23

3.3. Linguistic Value Soft Set Method

STEP1. Define a set of linguistic variables, and are the lower and upper limits, where is a positive integer [40].

STEP2. Define $U=\{U_1,U_2,...,U_m\}$ is a set of evaluation objects and $E=\{E_1,E_2,\dots,E_j,\dots,E_n\}$ be the set of criteria about the alternatives in U [36].

STEP3. Define (F^l,E) is the linguistic value soft set about U. Define $F^L=(f_{ij}^L)_{m\times n}$ as the linguistic value soft matrix, where $f_{ij}^L=F^L(U_i)(E_j)$, i=1,2,3,…,m, j=1,2,3,…,n. That is [36]:

$$F^L=\begin{pmatrix}F^L(U_1)(E_1)&F^L(U_1)(E_2)&\cdots&F^L(U_1)(E_n)\\F^L(U_2)(E_1)&F^L(U_2)(E_2)&\cdots&F^L(U_2)(E_n)\\\vdots&\vdots&\ddots&\vdots\\F^L(U_m)(E_1)&F^L(U_m)(E_2)&\cdots&F^L(U_m)(E_n)\end{pmatrix}\tag{3}$$

STEP4. Define $C(A,B)$ is two different experts obtained the choice value matrix, where $A,B\in E$, and further the choice value matrix in relation to experts A and B be expressed as $C(A,B)=(\alpha_{ij})_{n\times n}$, where $\alpha_{ij}(1\le i,j\le n)$ are defined as follows[41]:

$$\alpha_{ij}=\begin{cases}1, & \mathrm{E}_i\in A,\mathrm{E}_i\in B\\0, & \text{others}\end{cases}\tag{4}$$

STEP5. For $A,B\in E$, the choice value matrix given by experts A and B can be $C(A,B)$. We define $F^L\otimes C(A,B)$ as the product [36]. We define

$$P^L=F^L\otimes C(A,B)=(\beta_{jk})_{m\times l}=(\max_{j=1}^{m}\min_{i=1}^{n}\{f_{ji}^L,\alpha_{ik}\})_{m\times n}\tag{5}$$

STEP6. Define the set of experts as $D=\{d_1,d_2,d_3,...,d_l\}$. Similarly, the choice value matrix between

d_e (the expert) and the combination of the other experts of D can be defined as $C(d_e, D \setminus d_e)(1 \le e \le l)$, where $D \setminus d_e$ is the subtraction operation between two sets [36]. Then the weight of expert d_e is defined as w_e .

$$w_e = \frac{\sum_{\alpha_{ij} \in C(d_e, D\setminus d_e), \alpha_{ij}=1} \alpha_{ij}}{\sum_{e=1}^{l} \sum_{\alpha_{ij} \in C(d_e, D\setminus d_e), \alpha_{ij}=1} \alpha_{ij}}$$
$$0 \le w_e \le 1, \ for \text{ all e;} \tag{6}$$
$$\sum_{e=1}^{l} w_e = 1$$

STEP7. Compute the result of the sum for

$$P^L = \sum_{e=1}^{l} w_e P_e^L \tag{7}$$

4. Empirical Analysis

4.1. Case Background

We select three state-owned energy enterprises (referred to as Company A, Company B, Company C) in China as the research samples of energy supply chain risk assessment, two of which are mainly involved in oil and gas, and the other is focused on power supply. The three enterprises are related to the lifeblood of national economy and national energy security, so it is very important to manage the risk of energy supply chain. We make an empirical analysis based on linguistic value soft set method.

4.2. Empirical Analysis

Index system determination: In this paper, based on the relevant literature, combining with the characteristics of energy supply chain of energy enterprises, and following the principles of objectivity, systematization, scientific, comparability and representativeness of the evaluation index system, the comprehensive evaluation index system of energy supply chain risk is formed. It mainly includes four aspects: supplier operation risk, economic risk, environmental risk and social risk. The evaluation index system is shown in Table 2.

TABLE 2: The evaluation index system of energy supply chain risk

1st-Level Criteria	2nd-Level Criteria
E1 Supply Operational Risk	E11 Supply and demand uncertainty
	E12 Machine equipment risk
	E13 Shortage of human resources
	E14 Information leakage
	E15 Supplier dishonesty
	E16 Logistics risk
	E17 Lack of knowledge and technologies
	E18 Lack of planning and time management
E2 Economic risk	E21 Changes in raw material prices and costs
	E22 Energy price fluctuation
	E23 Poor earnings expectations
	E24 Market share reduction
E3 Environmental risk	E31 Natural disaster
	E32 Inefficient use of energy
	E33 Environmental pollution
	E34 Government policy risk
E4	E41 Lack of business ethics

1st-Level Criteria	2nd-Level Criteria
Social risk	E42 Unhealthy and dangerous work environment
	E43 Failure to achieve social commitment

Calculate the weight of each index based on BWM: According to experts' opinions, Environmental risk E3 is the most important index and Social risk E4 is the most unimportant index. Then, the most important index is compared with other index, and other index are compared with the most unimportant index to obtain the evaluation information of preference relationship. The results are as follows:

$$H_{Bj}^{4}=\{3,3.67,6,1\}$$

$$H_{jW}^{4}=\{4.33,3.33,1,6\}$$

Based on (1), the weight of each index we can calculate is $w_j=\{0.2136,0.1746,0.5389,0.0729\}$ .Based on the Table 1 and (2), we can conclude that the consistency ratio is 0.0273.

Similarly, we can also use this method to determine the weight of the second-level indexes under each first-level index, so as to obtain the global weight of each index. The results are shown in the Table 3.

Table 3: Weight calculation results of index

1st-Level Index	Weight	2nd-Level Index	Weight	Consistency Ratio	Global Weight
E1	0.2136	E11	0.3015	0.0122	0.0644
		E12	0.0970		0.0207
		E13	0.1333		0.0285
		E14	0.0370		0.0080
		E15	0.1186		0.0253
		E16	0.0970		0.0207
		E17	0.1186		0.0253
		E18	0.0970		0.0207
E2	0.1746	E21	0.2040	0.0253	0.0356
		E22	0.5174		0.0903
		E23	0.0746		0.0131
		E24	0.2040		0.0356
E3	0.5389	E31	0.5434	0.0209	0.2928
		E32	0.0711		0.0383
		E33	0.1471		0.0793
		E34	0.2384		0.1285
E4	0.0729	E41	0.2743	0.0269	0.0200
		E42	0.0938		0.0068
		E43	0.6319		0.0460

According to the weight calculation results of indicators at all levels, among the four first-level indicators, environmental risk E3 has the highest weight, followed by supply chain operation risk E1, indicating that environmental risk and supply chain operation risk have a great impact on energy supply chain risk. Social risk E4 had the least impact. Among all the secondary indicators, Natural disaster E31 and Government policy risk E34 have the highest global weight, indicating that they have a great impact on energy supply chain risk. The global weight of Unhealthy and dangerous work environment E42 is the lowest, and its influence on energy supply chain risk is weak.

Develop the linguistic value soft set: There experts $D=\{d_1,d_2,d_3\}$ were selected to comprehensively evaluate the energy supply chain risks of three energy enterprises based on their professional knowledge. The experts selected the indicators to be evaluated as follows:

$$d_1^E = \begin{Bmatrix} E11, E13, E14, E16, E17, E18, E21, E22, E23, \\ E24, E31, E32, E33, E34, E41, E42 \end{Bmatrix}$$

$$d_2^E = \begin{Bmatrix} E11, E12, E13, E15, E16, E17, E21, E22, E23, \\ E24, E31, E32, E33, E34, E41, E42, E43 \end{Bmatrix}$$

$$d_3^E = \begin{Bmatrix} E11, E12, E13, E14, E15, E16, E17, E18, E21, \\ E22, E23, E24, E31, E32, E34, E42, E43 \end{Bmatrix}$$

At the same time, we obtain four corresponding linguistic value soft matric F_1^L, F_2^L, F_3^L

$$F_1^L = \begin{pmatrix} s_{-1} & s_0 & \cdots & s_0 \\ s_{-1} & s_0 & \cdots & s_0 \\ s_3 & s_0 & \cdots & s_0 \end{pmatrix}$$

$$F_2^L = \begin{pmatrix} s_0 & s_2 & \cdots & s_3 \\ s_1 & s_2 & \cdots & s_2 \\ s_3 & s_0 & \cdots & s_1 \end{pmatrix}$$

$$F_3^L = \begin{pmatrix} s_1 & s_3 & \cdots & s_4 \\ s_0 & s_1 & \cdots & s_1 \\ s_2 & s_{-1} & \cdots & s_3 \end{pmatrix}$$

Calculate the product operation result and the weight of expert: Based on (4), the combined choice value matrices $C(d_e^E, \bigcap_{h=1,h\neq e}^{D} d_h^E)(e=1,2,3)$ are calculated as follows:

$$C(d_1^E, \bigcap_{h=2,3}^{D} d_h^E) = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{pmatrix}$$

$$C(d_2^E, \bigcap_{h=1,3}^{D} d_h^E) = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 \end{pmatrix}$$

$$C(d_3^E, \bigcap_{h=1,3}^{D} d_h^E) = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 \end{pmatrix}$$

Based on (6), wo can obtain that:

$$w_1 = 0.31, w_2 = 0.345, w_3 = 0.345$$

Then, based on (5), we calculate the product operation result of $P_e^L(e=1,2,3)$ as follows:

$$P_1^L = F_1^L \otimes C(d_1^E, \bigcap_{h=2,3}^{D} d_h^E) = \begin{pmatrix} s_3 & s_3 & \cdots & s_3 \\ s_3 & s_3 & \cdots & s_3 \\ s_4 & s_4 & \cdots & s_4 \end{pmatrix}$$

$$P_2^L = \begin{pmatrix} s_4 & s_{-4} & \cdots & s_{-4} \\ s_2 & s_{-4} & \cdots & s_{-4} \\ s_3 & s_{-4} & \cdots & s_{-4} \end{pmatrix}$$

$$P_3^L = \begin{pmatrix} s_4 & s_{-4} & \cdots & s_{-4} \\ s_{-1} & s_{-4} & \cdots & s_{-4} \\ s_3 & s_{-4} & \cdots & s_{-4} \end{pmatrix}$$

Calculate the end result: Then we can obtain the linguistic value soft matrix:

$$P^L = \sum_{e=1}^{3} w_e P_e^L =$$

$$\begin{pmatrix} s_{3.69} & s_{-1.83} & s_{3.69} & s_{-1.24} & s_{-1.83} & \cdots & s_{-1.24} & s_{3.69} & s_{-1.83} \\ s_{1.275} & s_{-1.83} & s_{1.275} & s_{-2.965} & s_{-1.83} & \cdots & s_{-2.965} & s_{1.275} & s_{-1.83} \\ s_{3.31} & s_{-1.52} & s_{3.31} & s_{-1.585} & s_{-1.52} & \cdots & s_{-1.585} & s_{3.31} & s_{-1.52} \end{pmatrix}$$

Based on the weight of each index, we can calculate the final ranking of the three enterprise.

$$R_{P^L}(U1) = s_{2.5507},\ R_{P^L}(U2) = s_{0.4762},\ R_{P^L}(U3) = s_{2.2387}$$

4.3. Analysis and Results

The comprehensive evaluation results show that among the three enterprises, Company A and Company B have better energy supply chain risk management ability, reaching the medium level. However, B's energy supply chain risks are relatively high.

Company A and Company C perform better in terms of financial risk, indicating that the current economic risk of the company is relatively low, while Company B does not perform well in this aspect. On the whole, the supply chain operation risk of Company B is high, and other indicators except economic indicators are not ideal. Among them, environmental risk is considered to be an important factor affecting enterprise energy supply chain risk, but the performance of these three enterprises is not outstanding in this aspect. In the second-level index of environmental risk, the three companies all scored low in environmental pollution, indicating that the three companies should pay more attention to environmental pollution. This indicates that energy enterprises should pay more attention to environmental risks when dealing with supply chain risks.

5. Conclusion

This research aims to analyze the factors that affect the energy supply chain risk. We construct an energy supply chain risk evaluation model based on three representative energy companies in China. By adopting the BWM and the linguistic value soft set, a two-stage method is constructed for energy supply chain risk assessment. We evaluate the energy supply chain risks of enterprises from four aspects, including supply chain operation risks, economic risks, environmental risks, and social risks.

This study theoretically enriches the risk management research of energy supply chain and provides a new research idea for risk evaluation. In the evaluation process, the possibility of incomplete information was considered, and the preferences of decision makers were more truly reflected through the two-stage method. In practice, this research can provide decision-making methods and suggestions for relevant practitioners in the energy industry to better control risks in the energy supply chain.

The limitation of this paper is that the interrelationship between risk factors is not considered, and tacitly assumes that the factors are not related to each other. In future research, decision makers can take the links between risk factors into consideration to obtain more accurate weights of risk factors. At the same time, the method of this research can also be applied to supply chain risk control in other areas.

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