A BITM based Operation Performance Evaluation Approach for Regional Electric Power Material Supply Chain

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Abstract. The traditional subjective weighting method used in the comprehensive evaluation of electric power material supply chain usually requires experts to carry out multiple evaluations. The evaluation standard is vague and subjective. Aiming at the above problems, taking 14 cities in Hubei Province as the research object, we firstly constructed an evaluation framework including five major capabilities, and then calculated the weights by using entropy weight method and ordering relation method respectively. Then we evaluated the operational performance of the power material supply chain based on the Business Information TOPSIS Model (BITM) with 20 dynamic indicators and proved the feasibility and validity of the method through empirical evidence and comparative analysis. Finally, based on the results of the study, we proposed that the operational performance of the electric power material supply chain can be improved by improving the supply chain basic capability and risk prevention & control capability.

Keywords: TOPSIS, Power Material Supply Chain, Entropy Weight, Performance Evaluation.

1 INTRODUCTION

In recent years, with the continuous development of the electric power material supply chain, new requirements have been put forward for the level of material supply chain management. The supply chain performance evaluation, as an important of supply chain management, is closely related to the security and reliability of the electric power grid. The regional electric power material supply chain performance evaluation in various cities has a significant impact on the long-term and stable development of electric power enterprises. The evaluation indicators of each regional electric power material supply chain have the characteristics of complicated types and numerous quantities. The traditional crude evaluation mode can no longer meet the demand for integration and intelligence of supply chain. It is necessary to optimize the traditional supply chain management methods by means of new information technology.

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At present, the electric power industry has gradually integrated information technology and intelligent means into the supply chain management. It also exposes some problems in the management practice. For example, low integration between different information systems, data sharing and interoperability, resulting in the emergence of "information islands". The operation and performance evaluation of supply chain and other business processes rely too much on the subjective evaluation of expert's knowledge, lack of standardized and reliable evaluation standards and scientific and efficient quantitative evaluation methods. In the face of complex business scenarios and a variety of evaluation indicators, the information system is lack of intelligence. There are still a lot of business scenarios relying on human resources.

These problems show that the current power industry in the material supply chain operation evaluation still exists problem like: insufficient degree of informatization, insufficient application of data, and module function redundancy et al. It requires enterprises to strengthen the data governance capacity and improve the information management mode of data collection, processing, and application. The level of regional supply chain performance not only affects the operation and development of itself, but also affects the operation of the upstream suppliers and the satisfaction of the downstream customers. It will even affect the stability of the industry development. Therefore, the study of supply chain performance evaluation has essential value. In this paper, we apply the method based on BITM to the supply chain performance evaluation, which can analyze the operation performance of electric power material supply chain more objectively.

2 RELATED WORK

Existing research on supply chain performance evaluation mainly focuses on evaluation indicators and methods. Ali et al. argued that disruptions faced by companies can come from any part of the supply chain and that evaluation metrics need to be constructed to assess the resilience of the supply chain[1]. Gualandris et al. divided two dimensions of procurement into supply exploration and supply utilization. The former refers to the activities required to experiment and discover new ideas, capabilities, and solutions in the supply network. The latter refers to the activities required to implement and improve ideas, capabilities, and solutions in the supply network[2]. They believed that balancing the utilization activities of procurement with the exploration activities is conducive to performance improvement. Ardito et al. argued that one factor that enables supply chains to generate extraordinary profitability is the fact that important resources are embedded in the processes, practices, and inter-organizational relationships of supply chain companies[3][4]. Partanen et al. investigated the relationships among supply chain ambidexterity, network capabilities, strategic information flow, and company performance[5]. Modak et al. studied the impact of price and delivery time sensitivity on customer demand, conducted an analysis of the omnichannel supply chain, and believed that price, inventory decision-making, and delivery preparation time are key factors affecting the stability and development of the supply chain[6]. Modak and Kelle analyzed the prices, order quantities, and delivery times of physical dual channel supply chains, namely retail and online channels. They found that delivery time and customer channel preferences affect the optimal decision-making of enterprise operations[7].

Taseen and Nair applied multivariate analysis methods to study the impact of supplier integration, customer integration, and internal integration on the operational performance of enterprise supply chains[8]. They established basic dimensions of cost, quality, delivery, and sensitivity, analyzed the breadth and depth of performance measurement indicators. HUO et al. studied the impact of supply chain information integration on company performance from a resource perspective[9]. They analyzed the impact of supply chain cooperation and technological level on operational and financial performance. Chang et al. introduced strategic performance, operational performance, and relational performance when studying the performance of supply chain integration, demonstrating that supply chain integration can improve enterprise profits[10]. Kamble et al. divided supply chain performance indicators into two categories: big data analysis capability and supply chain process performance[11]. Narimissa et al. focused on analyzing the performance evaluation system of sustainable development supply chain, starting from the three dimensions of economy, society, environment, and evaluating their link of the supply chain[12].

3 THE BITM BASED PERFORMANCE EVALUATION

In economic and management activities, it is usually necessary to carry out a comprehensive evaluation of multiple objects, that is, to categorize, compare and rank the operating conditions of m evaluated objects when n evaluation indicators $x_1, x_2, \ldots, x_n$ are selected. One of the most critical aspects of comprehensive evaluation is to determine the weights. In this paper, we first standardize the data. And then we calculate the objective weights and subjective weights using entropy and ordering relation methods respectively. Finally, we use the objective weights and subjective weights in the TOPSIS model respectively.

3.1 Organize the Data

(1) Data initialization. Construct the initial matrix X=(xij)m×n, where n is the number of objects to be evaluated and m is the number of indicators.

(2) Data standardization. It is necessary to standardize all the data in a uniform way, so that all indicator values are between 0 and 1. We can use Equation (1) for positive indicators and Equation (2) for the negative indicators.

$$y_{ij} = \frac{x_{ij} - Min(x_{ij})}{Max(x_{ij}) - Min(x_{ij})} \tag{1}$$

$$y_{ij} = \frac{Min(x_{ij}) - x_{ij}}{Max(x_{ij}) - Min(x_{ij})} \tag{2}$$

(3) Dimensionless processing. In constructing the weighted norm matrix, the attributes are vector-normalized, i.e., each column element is divided by the norm of the current column vector (using the cosine distance metric).

$$p_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} y_{ij}^2}} (i = 1,2,\dots,m; j = 1,2,\dots,n) \tag{3}$$

3.2 Calculate the Objective Weight

We use the entropy weight method to calculate the objective weights of each indicator without relying on the subjective judgment of experts.

(1) Calculate the entropy value using equation (4).

$$e_i = -k \sum_{i=1}^{n} p_{ij} ln p_{ij} \tag{4}$$

where k is related to the number of samples and is often taken the value as k=1/*ln n.*

(2) Calculate the objective weight based on traditional entropy weight method using equation (5).

$$w_{oi} = \frac{1 - e_i}{\sum_{k=1}^{m}(1 - e_k)} \ (i = 1, 2, \dots, m) \tag{5}$$

(3) Calculate the objective weight based on improved entropy weight method. If the values of the indicators are close, we use Equation (6) to calculate the entropy value.

$$w_{oi} = \frac{\exp(\sum_{t=1}^{m} e_t + 1 - e_i) - \exp(e_i)}{\sum_{l=1}^{m}(\exp(\sum_{t=1}^{m} e_t + 1 - e_l) - \exp(e_l))} \ (i = 1, 2, \dots, m) \tag{6}$$

3.3 Assign the Subjective Weight

We use objective and subjective weights separately in this paper. As an experimental comparison, we use the following method to get the subjective weights. Let wsi be the subjective weight of the ith indicator assigned by experts.

Definition 1: Suppose in one evaluation criterion, the importance of indicator x_i is higher than indicator x_j, it is recorded as $x_i \succ x_j$, and there is a ordering relation "≻" between xi and x_j.

Definition 2: If the importance degree of the indicators in the set of evaluation indicators X={x_1, x_2, …, x_n} has the relationship as shown Equation (7).

$$x_1^* \succ x_2^* \succ \cdots \succ x_m^* \tag{7}$$

It can be defined that there is ordering relation among X={x_1, x_2, …, x_n} according to "≻", where x_i^* represents the i[th] indicator (i=1, 2, …, m) after X is arranged according to ordering relation "≻".

For some problems, it is not enough only providing an ordering relation. It is necessary to determine the weight w_{si} of an evaluation indicator relative to a certain evaluation criterion (or goal).

The rational judgments of experts regarding the importance ratio w_{k-1}/w_k of evaluation indicators x_{k-1} and x_k is shown as Equation(8)

$$\frac{w_{k-1}}{w_k} = r_k \ (k = m, m - 1, m - 2, \dots, 3, 2) \tag{8}$$

When m is large enough, r_m=1 according the ordering relation (7).

If $X=\{x_1, x_2, \ldots, x_n\}$ has the ordering relation (7), the r_{k-1} and r_k must satisfy Equation (9).

$$r_{k-1} \succ \frac{1}{r_k}, (k = m, m-1, m-2, \ldots, 3, 2) \tag{9}$$

3.4 BITM based Evaluation

In this paper, some business indicators are used in the TOPSIS model to evaluate the material supply chain operational performance.

(1) Assign Weights.

Assign weights $W_i=(w_1, w_2, \ldots, w_n)^T$ to the matrix Y to get a weighted normative matrix A=(a_{ij}), where $a_{ij}=w_i \times y_{ij}$ (i=1, 2, …, m; j=1, 2, …, n).

(2) Calculate positive and negative ideal solutions.

$$A^+ = \{a_1^+, a_2^+, \ldots, a_n^+\} = \{Max\ a_{ij} \mid j = 1,2,\ldots,n\} \tag{10}$$

$$A^- = \{a_1^-, a_2^-, \ldots a_n^-\} = \{Min\ a_{ij} \mid j = 1,2,\ldots,n\} \tag{11}$$

(3) Calculate the proximity of each evaluation object to the optimal solution and the worst solution.

$$D_i^+ = \sqrt{\sum_{j=1}^{m} w_j \left(A_j^+ - (a_{ij})\right)^2}, D_i^- = \sqrt{\sum_{j=1}^{m} w_j \left(A_j^- - a_{ij}\right)^2} \tag{12}$$

Analyze the evaluation object by calculating the proximity degree c_i. As c_i gets closer to 1, it means that it is closer to the positive ideal solution, indicating better performance.

$$c_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{13}$$

4 Empirical Analysis

4.1 Data Collection

We firstly selected 20 indicator items from 5 capabilities such as supply chain basic capability, regulation & management Capability, service quality & effectiveness capability, risk prevention & control capability, and value creation capability, as shown in Table 1.

For the data of these indicators, they are first standardized, as shown in Equations (1) and (2), then processed dimensionless, as shown in Equation (3). Finally, the objective weights are calculated using the traditional entropy weight method and the subjective weights are calculated using the ordering relation analysis method independently.

Then when the indicators changed, we found that the values of some indicators were close, so we recalculated them using the improved entropy weight method (Equation (6)) as shown in Table 2.

Table 1. The Indicators and Weights of Framework (A).

No.	First-Level Indicators	Second-Level Indicators	Subjective Weights	Objective Weights
1	Supply Chain Basic Capability	Staff Adequacy Rate	0.130346232	0.037717999
2		Talent Density	0.032586558	0.091886059
3		Annual Purchase Amount	0.010183299	0.099652558
4		Material Supply Amount	0.010183299	0.09811398
5	Regulation & Management Capability	Timeliness of Contingency Settlement	0.024439919	0.061038553
6		Balance Profit	0.020366599	0.036409754
7		Number of Operation Analysis Reports	0.020366599	0.036409754
8		Number of Supply Chain Operation Monthly Reports	0.073319756	0.036409754
9	Service Quality & Effectiveness Capability	Sampling Inspection Pass Rate	0.071283096	0.040003838
10		Application Rate of Preferred Materials	0.073319756	0.036409754
11		Supervision of Manufacturing Coverage Rate	0.081466395	0.037759327
12		Procurement Standardization Rate	0.032586558	0.036409754
13	Risk Prevention & Control Capability	Incidence Rate of Abnormal Problems in Key Projects	0.142566191	0.048697226
14		Contract Abnormality rate	0.162932790	0.056727239
15		Number of Major Problems	0.032586558	0.037214003
16		Number of Abnormalities in Monitoring	0.032586558	0.051187034
17	Value Creation Capability	Number of QC Achievements	0.001018330	0.036409754
18		Number of Green Chain Innovation Initiatives Procurement	0.001018330	0.036409754
19		Number of Papers	0.032586558	0.036409754
20		Number of Patents	0.014256619	0.048724154

4.2 Results

Firstly, some experts give the weights W_s for indicators system (A) and directly give the ranking order of 14 cities respectively. Then the weights W_s are used to calculate the ranking order of the cities using TOPSIS. Finally, the objective weights W_o are used to calculate the ranking order of the cities using TOPSIS, MOORA[13] and SAW[14] method respectively. The operation performance ranking of 14 cities is shown in Figure 1. We recalculated above steps using the improved entropy weight method as shown in Table 2 and the results is shown in Figure 2. Through the experimental data, we found that (1) the methods using objective weights W_o and TOPSIS are closest to the ranking of cities given directly by experts; (2) supply chain basic capability and risk prevention & control capability have the most influence on the results.

Table 2. The Indicators and Weights of Framework (B).

No.	First-Level Indicators	Second-Level Indicators	Subjective Weights	Objective Weights
1	Supply Chain Basic Capability	Staff Adequacy Rate	0.134595163	0.038908453
2		Talent Density	0.033648791	0.094786163
3		Material Storage Area	0.010515247	0.042640143
4		Testing Capability Level	0.021030494	0.086727652
5	Regulation & Management Capability	Timeliness of Contingency Settlement	0.025236593	0.045597376
6		Balance Profit	0.021030494	0.037558917
7		Data Quality Standardization Rate	0.021030494	0.037558917
8		Data Problem Rectification Rate	0.075709779	0.037558917
9	Service Quality & Effectiveness Capability	Sampling Inspection Pass Rate	0.073606730	0.041266437
10		Application Rate of Preferred Materials	0.075709779	0.037558917
11		Warehouse Physical Amount Reduction Rate	0.033648791	0.037601549
12		Material Supply Guarantee Rate	0.147213460	0.037558917
13	Risk Prevention & Control Capability	Incidence Rate of Abnormal Problems in Key Projects	0.168243954	0.050234206
14		Contract Abnormality Rate	0.033648791	0.040972363
15		Warehouse Anomaly Rate	0.033648791	0.098732809
16		Abnormal Supply Rate	0.016824395	0.038388549
17	Value Creation Capability	Number of QC Achievements	0.001051525	0.037558917
18		Number of Green Chain Innovation Initiatives Procurement	0.033648791	0.047721370
19		Number of Advanced Recognition	0.014721346	0.050261983
20		Number of Participation in Specialized Work	0.025236593	0.060807445

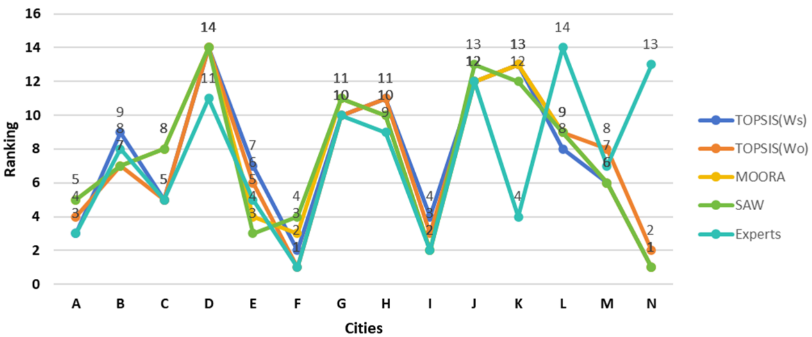

Fig. 1. The Ranking of 14 Cities' Power Materiel Supply Chain Performance based on Indicator System (A).

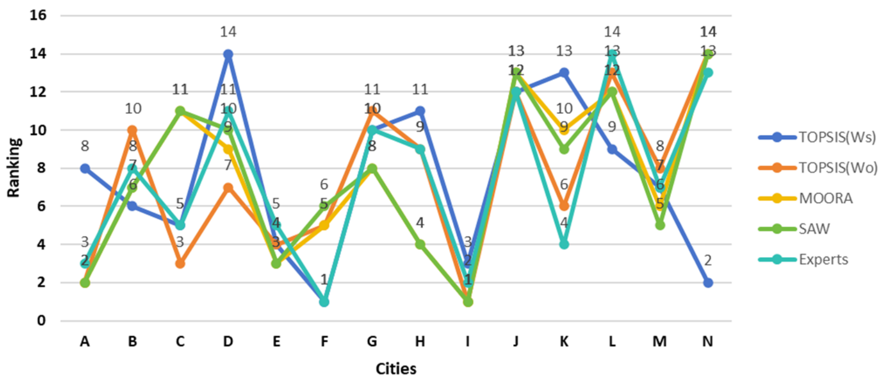

Fig. 2. The Ranking of 14 Cities' Power Materiel Supply Chain Performance based on Indicator System (B).

5 CONCLUSION

It is necessary to find a simple and effective objective weighting method that can be applied to multiple evaluation indicators. We constructed an evaluation framework including five major capabilities, and then calculated the weights by using entropy weight method and ordering relation method respectively. We evaluated the operation performance of the power material supply chain based on the BITM with 5 capabilities. Through the experimental data, we found that the methods using objective weights W_o and TOPSIS are closest to the ranking of cities given directly by experts. Finally, based on the results of the study, we proposed that the operational performance of the electric power material supply chain can be improved by improving the supply chain basic capability and risk prevention & control capability. We plans to extend the BITM-based evaluation method to more regions and areas in our future work.

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REFERENCES

1. Ali, A., Mahfouz, A., Arisha, A.: Analysing supply chain resilience: integrating the constructs in a concept mapping framework via a systematic literature review. Supply Chain Manag. An Int. J. 22, 16–39 (2017). https://doi.org/10.1108/SCM-06-2016-0197.
2. Gualandris, J., Legenvre, H., Kalchschmidt, M.: Exploration and exploitation within supply networks. Int. J. Oper. Prod. Manag. 38, 667–689 (2018). https://doi.org/10.1108/IJOPM-03-2017-0162.

3. Ardito, L., Messeni Petruzzelli, A., Dezi, L., Castellano, S.: The influence of inbound open innovation on ambidexterity performance: Does it pay to source knowledge from supply chain stakeholders? J. Bus. Res. 119, 321–329 (2020). https://doi.org/10.1016/j.jbusres.2018.12.043.
4. Im, G., Rai, A., Lambert, L.S.: Governance and Resource-Sharing Ambidexterity for Generating Relationship Benefits in Supply Chain Collaborations*. Decis. Sci. 50, 656–693 (2019). https://doi.org/10.1111/deci.12353.
5. Partanen, J., Kohtamäki, M., Patel, P.C., Parida, V.: Supply chain ambidexterity and manufacturing SME performance: The moderating roles of network capability and strategic information flow. Int. J. Prod. Econ. 221, 107470 (2020). https://doi.org/10.1016/j.ijpe.2019.08.005.
6. Modak, N.M.: Exploring Omni-channel supply chain under price and delivery time sensitive stochastic demand. Supply Chain Forum An Int. J. 18, 218–230 (2017). https://doi.org/10.1080/16258312.2017.1380499.
7. Modak, N.M., Kelle, P.: Managing a dual-channel supply chain under price and delivery-time dependent stochastic demand. Eur. J. Oper. Res. 272, 147–161 (2019). https://doi.org/10.1016/j.ejor.2018.05.067.
8. Ataseven, C., Nair, A.: Assessment of supply chain integration and performance relationships: A meta-analytic investigation of the literature. Int. J. Prod. Econ. 185, 252–265 (2017). https://doi.org/10.1016/j.ijpe.2017.01.007.
9. Huo, B., Han, Z., Prajogo, D.: Antecedents and consequences of supply chain information integration: a resource-based view. Supply Chain Manag. An Int. J. 21, 661–677 (2016). https://doi.org/10.1108/SCM-08-2015-0336.
10. Chang, W., Ellinger, A.E., Kim, K. (Kate), Franke, G.R.: Supply chain integration and firm financial performance: A meta-analysis of positional advantage mediation and moderating factors. Eur. Manag. J. 34, 282–295 (2016). https://doi.org/10.1016/j.emj.2015.11.008.
11. Kamble, S.S., Gunasekaran, A.: Big data-driven supply chain performance measurement system: a review and framework for implementation. Int. J. Prod. Res. 58, 65–86 (2020). https://doi.org/10.1080/00207543.2019.1630770.
12. Narimissa, O., Kangarani-Farahani, A., Molla-Alizadeh-Zavardehi, S.: Evaluation of sustainable supply chain management performance: Dimensions and aspects. Sustain. Dev. 28, 1–12 (2020). https://doi.org/10.1002/sd.1959.
13. Tuyls, K., Hoen, P.J. 'T, Vanschoenwinkel, B.: An Evolutionary Dynamical Analysis of Multi-Agent Learning in Iterated Games. Auton. Agent. Multi. Agent. Syst. 12, 115–153 (2006). https://doi.org/10.1007/s10458-005-3783-9.
14. R, M.K.: Decisionmaking among Multiple-Attribute Alternatives: A Survey and Consolidated Approach. rand. (1968).