Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 1568449, 14 pages
https://doi.org/10.1155/2022/1568449

Research Article

Factors Affecting Evaluation of Railway Bulk Freight Rate: A Novel Cloud Theory-Based Approach

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Received 29 June 2022; Accepted 30 August 2022; Published 26 September 2022

Academic Editor: Alessandro Severino

Railway freight rates are seen as a key driving factor of global trade activities, influenced by numerous factors. Given the limitations of fuzziness and randomness of variable quantification in the previous studies, this paper proposes a cognitive cloud model of factors influencing railway bulk goods freight rates. In the cognitive cloud model, randomness and fuzziness are described by three parameters. Furthermore, a cloud generator including forwarding and backward cloud generators is designed to solve the bidirectional conversion between qualitative indicators and quantitative values. In addition, we propose a floating cloud gathering algorithm to determine the weight of the index system to solve the uncertainty problem in the transformation process of qualitative indicators. Finally, the cognitive cloud model and the adapted algorithm are used to perform an in-depth analysis of the affecting factors of Z Railway Bureau freight transport pricing.

1. Introduction

To engender effective influencing factors evaluation, various state-of-the-art methods have been developed, including fuzzy evidential reasoning algorithm [1], fuzzy best-worst method [2], SCOR model [3, 4], and measurement by KPIs [5]. Among these methods, fuzzy mathematics-based models have been proved to be useful for screening important factors, calculating factor influence value and establishing a performance evaluation index system [6, 7]. However, these methods are challenging to deal with qualitative factors effectively [8]. In addition, a simple fuzzy mathematics-based approach cannot accommodate the complex interaction effects between qualitative and quantitative factors in many applications. Therefore, the basic attributes of qualitative and quantitative factors should be fully considered in practice. Recently, a unified approach consisting of fuzzy group decision-making, fuzzy evidential reasoning approach, and the expected utility concept has been utilized to analyze qualitative and quantitative factors [9]. However, the study shows that the randomness and fuzziness of qualitative and quantitative factors limit the effectiveness of importance-performance evaluation.

To deal with the problem, several approaches have been proposed for multifactor assessment based on fuzzy mathematics-based theory, such as grey clustering model [10], multifactor association model [11], and multiunit probabilistic model [12]. By reviewing these literatures, it is easy to find that quantitative factors are easy to analyze, while qualitative factor analysis still limits importance-performance evaluation due to subjectivity scoring. Therefore, some scholars try to quantify qualitative factors to improve evaluation quality. The mainstream method is to build a map from qualitative to quantitative [[13]]. Especially, a combinatorially equivalent matrix is designed to relabel the levels of the qualitative factors as quantitative factors by row and column permutations [14]. However, the quantitative and qualitative factors will interact with each other, which is challenging to realize in matrix operations. At the same time, the randomness and fuzziness of qualitative and quantitative factors are also challenging to reflect in the equivalent matrix. Therefore, considering the context of fuzziness and randomness, the following questions need to be discussed:

(1) How can we determine the conversion scale between qualitative and quantitative factors?

(2) How to deal with qualitative-quantitative bidirectional uncertain transformation

(3) How to consider the fuzziness and randomness of factors in the quantification process of qualitative factors?

Following this research direction, we propose a cognitive cloud model to analyze the factors affecting the freight rate of railway bulk cargo. In the cognitive cloud model, for each factor, the randomness and fuzziness are described by three parameters. Furthermore, a cloud generator including forward and backward cloud generators is designed to solve the bidirectional conversion between qualitative indicators and quantitative values. Moreover, we adopted a floating cloud gathering algorithm to determine the weight of the index system to solve the uncertainty problem in the transformation process of qualitative indicators.

The proposed cloud model is dedicated to dealing with complex fuzzy relationships, i.e., the randomness and uncertainty among the factors affecting railroad bulk cargo tariffs. In fact, it can effectively deal with the bidirectional transformation of the qualitative and quantitative, thus improving the performance of freight rate influencing factors assessment and helping railway enterprises gain insight into freight influencing factors. The study can provide auxiliary decision-making for the railway enteprises to reasonably formulate and adjust the freight rate of railway bulk goods. The main contributions of this paper are threefold.

(1) Considering the great superiority of the cloud model in capturing and explaining the inherent uncertainty (including fuzziness and randomness) of information, a cloud theory-based freight rate factor evaluation of railway bulk goods is first developed to analyze the uncertainty between qualitative indicators and quantitative values of affecting factors in railway bulk freight rates

(2) A cloud generator, including forwarding and backward cloud generators, is designed to solve the bidirectional conversion between qualitative indicators and quantitative values. In addition, this paper establishes an evaluation standard cloud to end the lack of a standard scale in the quantitative process of qualitative indicators and the improper randomness treatment of the transformational mode

(3) A floating cloud gathering algorithm is proposed to determine the weight of the index system to solve the uncertainty problem in the transformation process of qualitative indicators

The remainder of this paper is organized as follows. A literature review is discussed in Section 2. In Section 3, we first present the basic theory of cloud model theory. Then, we introduce the qualitative-quantitative bidirectional transformation method of the cloud model. The proposed cloud theory-based freight rate factor evaluation model is presented in Section 4. Section 5 takes the Z Railway Bureau as a case to verify the method through experiments. Finally, some conclusions and future research directions are summarized in Section 6.

2. Literature Review

Based on the probability theory and fuzzy set theory, Li was the first person to propose the cognitive model of the cloud model [15]. The model not only allows a stochastic disturbance of the membership encircling a determined central value rather than a fixed number (a random number replaces, i.e., the precise membership with a stable tendency) but also formally depicts the inherent relationship between randomness and fuzziness [16, 17]. Furthermore, some scholars showed that it could provide an excellent cognitive framework in various aspects, such as evaluation and decision-making [18], reliability analysis [19, 20], recommendation analysis [21], prediction [22] and optimization [23].

At present, some mature methods have been widely used in the research on the influencing factors of railway freight rates, such as bilevel programming model [24], fuzzy comprehensive evaluation [25], BP neural network [26], and grey relational analysis [27]. However, the ambiguity of indicators are challenges that these methods cannot avoid. The unified processing of these methods is to analyze the indicator attributes with the help of the membership function. But should not be ignored is that existing membership transforming algorithms have some fundamental problems. For example, they cannot show how the indicator feature is converted to the membership degree of fuzzy sets, and which parts in the index membership are useful by using closeness degree and the closest principle of fuzzy sets. It can be seen that the existing evaluation methods are not perfect in the determination of index weights, fuzzy and uncertain factors Compared to the traditional evaluation method (as shown in Table 1), the cloud model can effectively reveal the connection between randomness and fuzziness derived from probability theory and fuzzy set theory. Thus, cloud model theory has proved to be an effective way to simultaneously deal with the fuzziness and randomness of factual information. However, to date, the cloud model is rarely applied in freight rates factor assessment in the railway industry. As a result, factors evaluation with the context of the cloud model is still uncharted territory. In fact, with the uncertainty of the freight transport plan and fierce competition in transportation markets, uncertainty has increased in the railway traffic organization, leading to more significant fuzziness and randomness in factors evaluation. Considering many successful applications, the cloud model provides a feasible way to evaluate freight rates.

Table 1: Comparison of advantages and disadvantages of various evaluation metods.

Model	Complexity	Fuzzy processing	Random processing	Scientific	Method type	Disadvantage
Bilevel programming model [24]	Complex	×	×	Strong	Combining qualitative and quantitative analysis	Require a high level of data accuracy and complex calculations
Fuzzy comprehension Evaluation method [25]	Simple	√	×	General	Combining qualitative and quantitative analysis	Difficult to determine the membership function
Neural network method [26]	Complex	×	×	Strong	Quantitative analysis	Slow to learn and tends to fall into local minima
Grey relational analysis [27]	Simple	√	×	General	Quantitative analysis	The selection of resolution coefficient needs to be determined by ourselves
Delphi Method [28]	Simple	×	×	Poor	Qualitative analysis	The process is complex and takes a long time.
Analytic hierarchy process [29]	Complex	×	×	Poor	Combining qualitative and quantitative analysis	There are subjectivity and fuzziness in the weight assignment of experts.
This paper	Simple	√	√	Strong	Combining qualitative and quantitative analysis	——

In addition, in terms of economics and technology, freight rates factor assessment is a multicriteria decision-making problem with multiple indicators. Like other fields, the indicators include qualitative indicators and quantitative indicators. In particular, qualitative indicators often face a variety of uncertainty derived from imprecise and uncertain information and subjective decision uncertainty associated with rail freight management [30]. Consequently, many scholars try to quantify qualitative criteria in a multicriteria system [31–33]. Among these methods, the grey system theory has attracted the scholars' attention. In this view, a qualitative indicator can be treated as grey information used to describe situations between "black" where information is unknown and "white" where information is deterministic. After that, determine the qualitative-quantitative comparison criteria based on the grey relational coefficient [34]. However, the essence of this method is still to use descriptive language and ordinal rankings to create an original decision matrix qualitatively. Additionally, the ordinal rankings are difficult to quantify precisely, making grey system theory models difficult to handle. Even though set pair analysis utilized connectedness to deal with uncertainty [35], the extension evaluation method transformed the contradictory problem into the proximal principle problem of multiple characteristics from a qualitative and quantitative standpoint [36], and unascertained measure theory has been used to deal with system uncertainty and data incompleteness [37]. It cannot continue to overlook the unresolved issues of qualitative-quantitative transformation. Hence, it is critical to find an effective measure to determine the conversion scale between qualitative and quantitative factors.

In summary, the cloud model can successfully manage information loss and distortion and has a strong ability to deal with the ambiguity and randomness of information simultaneously. It presents an emerging opportunity for factors evaluation. Therefore, this study proposes the cloud theory of factors affecting the freight rates of railway bulk goods. In addition, following the logic of mutual mapping between qualitative indicators and quantitative values, the paper constructs a qualitative-quantitative bidirectional transformation system. As a result, the conversion between qualitative indicators and quantitative values become clear, specific and controllable. The proposed method can optimize the uncertainty between the qualitative indicators and quantitative values in the influence factor analysis of railway bulk freight rates.

3. Preliminaries

In this section, we first introduce the cloud model. Then, we explain the numerical characteristics of the cloud model in detail. Finally, we present the qualitative-quantitative bidirectional transformation method of the cloud model.

3.1. Cloud Model Theory. The cloud model theory is a novel cognition method for dealing with human thought and behavior uncertainties based on the fuzzy set and probability statistic. Its remarkable feature can effectively and flexibly reflect the fuzziness and randomness of quantitative data and qualitative concepts. In the traditional fuzzy method, the fuzziness and randomness of a given element are still a challenge in qualitative-quantitative transformation. In contrast, the cloud model can effectively handle the uncertainty of random variables by three quantitative numerical parameters (expectation Ex, entropy En, and hyper entropy He).

Suppose T is a qualitative concept that is defined over a universe of discourse U, $x \in U$ be a random instantiation of the concept T. Then, the basic theoretical formula can be

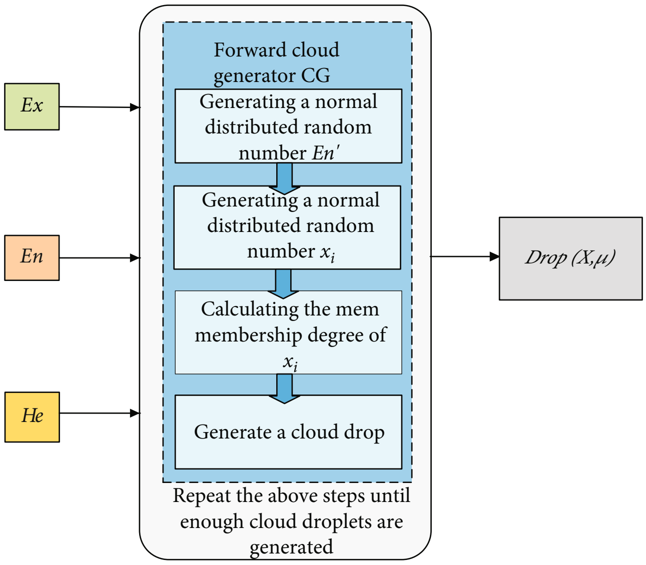

Figure 1: Forward cloud generator.

presented as the following form:

$$\mu:\ U \longrightarrow [0,1]\ \forall x \in U\ x \longrightarrow \mu(x), \tag{1}$$

where the distribution of x over U is defined as a cloud and x is a cloud droplet of U. $\mu(x)$ represents the belongingness degree of x on U, which is not a fixed value, but a probability distribution with slight variations. If $x \in U$ U is a random instantiation of the concept T with $x \sim N(\mathrm{Ex}, \mathrm{En}'^2)$ and $\mathrm{En}' \sim N(\mathrm{Ex}, \mathrm{He}^2)$, the membership degree $\mu(x)$ satisfies the following equation:

$$\mu(x) = e^{-(x-\mathrm{Ex})^2/2\mathrm{En}'2}. \tag{2}$$

3.2. The Numerical Characteristics of Cloud Model. Considering the cloud droplets are random values with a certain tendency, a membership degree $\mu(x)$ is also a random number of stable tendencies located between domain U and internal [0,1]. Although $\mu(x)$ is a random number, it also has its characteristics that can be applied in model property description:

(1) There is no order among the cloud droplets generated by the cloud model. One cloud droplet is a random quantitive realization in the qualitative concept. The more the cloud droplets are, the more overall features of this qualitative concept the droplets will reflect

(2) The probability of a cloud droplet can be known as the degree of this qualitative concept represented by the cloud droplet. The higher the probability of the cloud droplet, the higher the degree of certainty, which is consistent with subjective understanding

Generally speaking, by merging the two characteristics into data processing, the cloud model can vastly decrease the distortion and loss of the risk information of failure modes [16].

In addition, the concepts of randomness and fuzziness in the cloud model are described by three parameters, that is, expectation (hereinafter referred to as Ex for short), entropy (hereinafter referred to as En for short), and hyper entropy (hereinafter referred to as He for short), respectively. The connotation of three parameters can be explained as follows:

(1) Ex is a mathematical expectation that reflects the center-of-gravity of cloud drops. Ex reflects the cloud center of gravity of cloud drops of the concept and is the point which can best represent the quality concept

(2) En is the uncertain measurement of the qualitative concept, which reveals the relevance between fuzziness and randomness. En represents not only the fuzziness of the concept but also randomness and their relations and is an uncertainty measurement of the qualitative concept

(3) He is the uncertainty measurement of the entropy, which reflects the condensation degree of cloud drops. That means, a lower degree of cognitive consensus has a lower He, and a higher degree of cognitive consensus has a higher He

3.3. Qualitative-Quantitative Bidirectional Transformation. In the improved cloud model theory, a cloud generator, including forward and backward cloud generators, is designed to solve the bidirectional transformation between qualitative indicators and quantitative values. More specifically, the process of generating cloud droplets according to three parameters $(\mathrm{Ex}, \mathrm{En}, \mathrm{He})$ is defined as a forward cloud generator, which is used to describe the conversion process of qualitative indicators to quantitative values.

As shown in Figure 1, the steps of generating cloud droplets based on forwarding cloud generator can be summarized as follows:

Step 1. Generating a normal distributed random number En'_i with En as the expected value and He as the standard deviation

Step 2. Generating a normal distributed random number x_i with Ex as expected value and En'_i as standard deviation

Step 3. Calculating the membership degree of x_i according to the following formula.

$$u_i = e^{-(x_i-Ex)^2/\left(2En'^{2}_{i}\right)}. \tag{3}$$

Step 4. Considering x as a cloud drop with the qualitative concept of u_i, the cloud drop (x, u) is generated

Step 5. Repeat the above steps until enough cloud droplets are generated

On the other hand, the backward cloud generator can convert the sample data $(x_1, x_2, \cdots, x_n)$ with the membership degree $(u_1, u_2, \cdots, u_n)$ to the qualitative concept expressed by quantitative characteristics $(\mathrm{Ex}, \mathrm{En}, \mathrm{He})$. Moreover, it can verify the conversion process from quantitative value to qualitative variable.

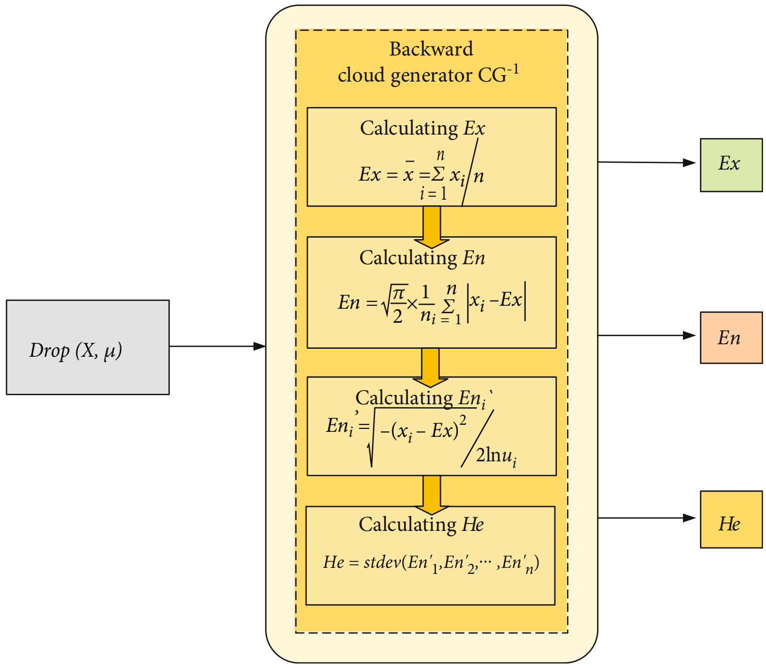

Figure 2: Forward cloud generator.

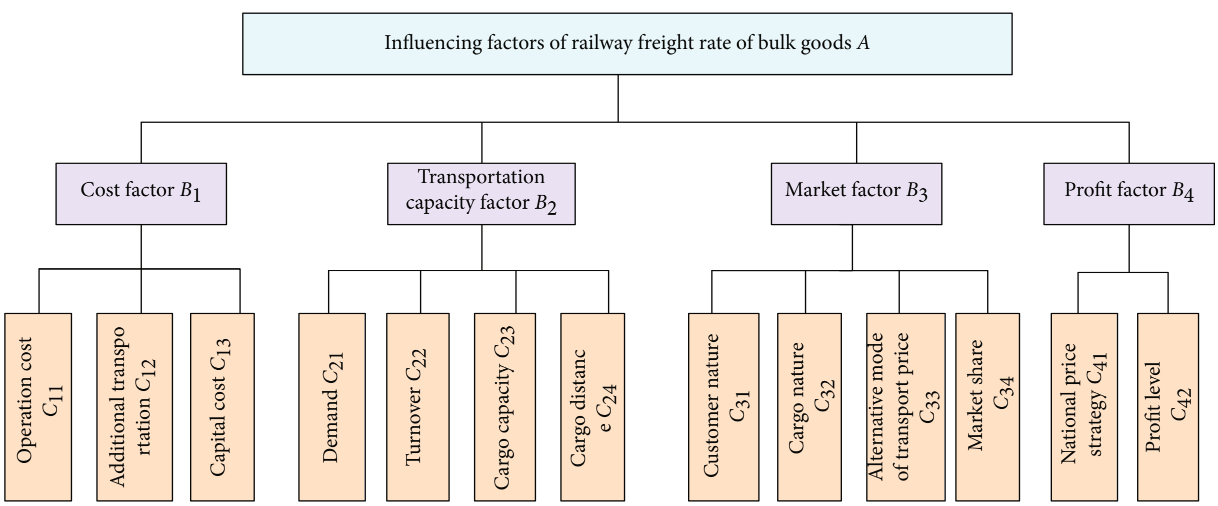

Figure 3: Index system of factors affecting the freight rate of railway bulk goods.

Table 2: Comment on cloud quantitative characteristics of railway bulk freight tariff factors.

Reviews the cloud		Ex	En	He
Very unimportant	[0,30)	15	5	0.5
Unimportant	[30,50)	40	10/3	0.5
Generally	[50,70)	60	10/3	0.5
Important	[70,90)	80	10/3	0.5
Very important	[90,100]	95	5/3	0.5

As shown in Figure 2, the steps of generating cloud droplets based on backward cloud generator can be summarized as follows:

Step 1. Calculate Ex according to the samples by the following formula:

$$\mathrm{Ex} = \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \tag{4}$$

Where N is the amount of the sample data and x_i is the observed value of the i -th sample.

Step 2. Calculating En by the following formula:

$$\mathrm{En} = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n} |x_i - \mathrm{Ex}|. \tag{5}$$

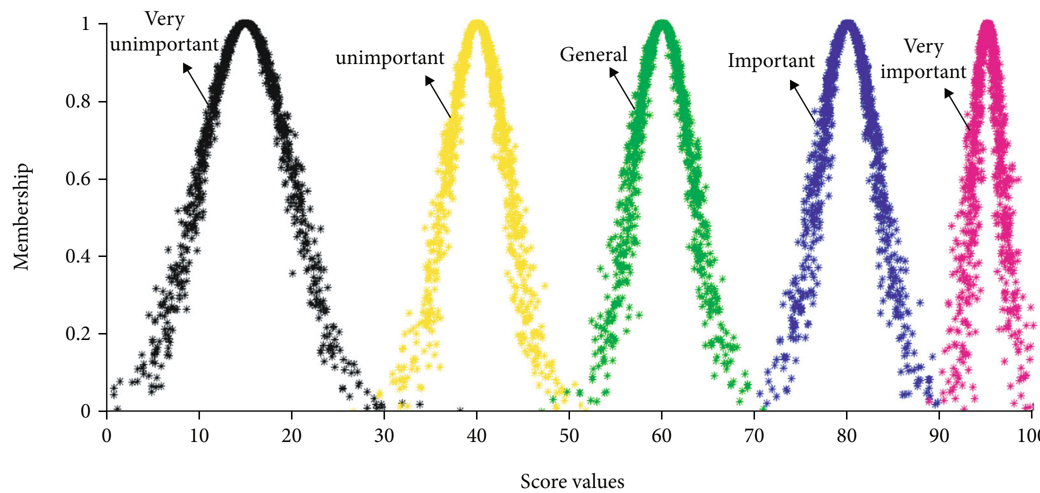

Figure 4: The significance evaluation standard cloud.

Table 3: Important scale table.

Important degree D_α	Importance cloud parameter Ex	En	He
D_1	1	0.437	0.073
D_2	2	0.707	0.118
D_3	3	0.437	0.073
D_4	4	0.707	0.118
D_5	5	0.437	0.073
D_6	6	0.707	0.118
D_7	7	0.437	0.073
D_8	8	0.707	0.118
D_9	9	0.437	0.073

Step 3. Calculating En_i' by the following formula:

$$\mathrm{En}_i' = \sqrt{\frac{-(x_i - \mathrm{Ex})^2}{2\ln u_i}}. \tag{6}$$

Step 4. Computing the hyper entropy by the following formula:

$$\mathrm{He} = \mathrm{stdev}\left(\mathrm{En}_1', \mathrm{En}_2', \cdots, \mathrm{En}_n'\right). \tag{7}$$

where stdev represents standard deviation function.

In general, backward and forward cloud generators are the core of cloud estimation. The cloud model generates a specific algorithm first used to estimate three quantitative characteristics by a backward cloud generator. Then, according to three quantitative characteristics, the next population is produced by a forward cloud generator.

4. The Proposed Cloud Theory-Based Freight Rate Factor Evaluation Model

4.1. The Establishment of Index System. Under the background of the marketization of railway freight rates, the quality of the evaluation index system has a direct bearing on results. The establishment of the evaluation index system must follow systematization, science, comparability, and the comparative independence of indicators. Freight rates influencing indicators must follow two principles: One is the subjective conditions that should go as far as possible to find all the affecting factors from the historical operational data, all kinds of literature, expert questionnaire surveys, and other comprehensive analysis. The other is the objective basis that selected freight rate influencing indicators must be able to accurately evaluate all types of possible influences that may exist in bulk freight transportation on railway networks. Therefore, combined with the previous literatures [38–40], this paper summarizes the fundamental indicators based on scientificity, feasibility, hierarchy, representativeness, systematical, and reality. Furthermore, the sociological in-depth interview method is used to screen the representative, reliable, and hierarchical evaluation index set. Consequently, a preliminary index system of factors affecting the freight rate of railway bulk goods has been established, as shown in Figure 3.

4.2. Evaluation Grade and Standard Formulation. This paper establishes a standard cloud for evaluation to end the lack of a standard scale in qualitative-quantitative transformation and improper randomness treatment of the transformational model. First, a percentile system of expert scoring is used to initially collect the importance evaluation information of the factors affecting the freight rates of railway bulk goods. Then, the bilateral restriction is introduced to define the cloud classification of significant assessments. Finally, the quantitative characteristics of the established standard

Table 4: Determination of the random index.

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.51

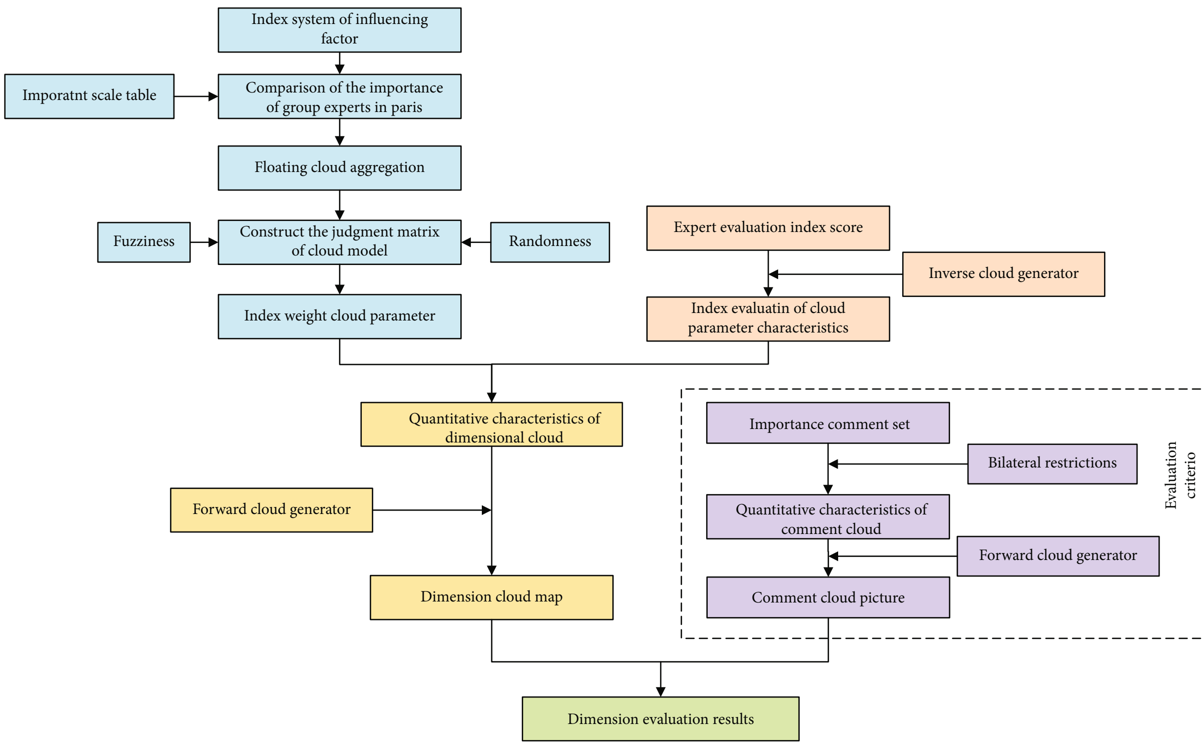

Figure 5: The evaluation flow.

evaluation cloud are as follows:

$$\begin{cases} \mathrm{Ex} = \dfrac{(l_{\min} + l_{\max})}{2} \\ \mathrm{En} = \dfrac{(l_{\max} - l_{\min})}{6} \\ \mathrm{He} = k \end{cases} \qquad (8)$$

According to the reference, k is a constant with a value of 0.5 [41]. Generally speaking, the evaluation values of the indicators are all within [0,100]. The scoring standard should be divided into different grades: very unimportant, unimportant, general, important, and very important. The corresponding scores for each level are [0,30), [30,50), [50,70), [70,90), and [90,100], respectively. The quantitative characteristics of the standard cloud model are obtained by Equation (8), as shown in Table 2.

Based on the results in Table 2, the significance evaluation standard cloud is obtained as shown in Figure 4.

Table 2 and Figure 4 allow us to visually determine the evaluation level of the evaluation subject. The similarity calculation technique compares each indicator evaluation cloud to the evaluation criteria cloud for similarity values in order to identify the evaluation criteria subcloud that is most similar to the evaluation criteria cloud.

4.3. Index Weight Cloud Parameters Determination. The subjective empowerment approach and the objective empowerment method are the two commonly utilized weight determination methods. The subjective empowerment approach is easily influenced by specialists. Several procedures in the objective empowerment approach, such as the entropy weight method and the principal component analysis method, are complex to calculate and have low generality. Furthermore, there are uncertainties in the transformation of qualitative indicators using these methods. This paper proposes a floating cloud gathering algorithm to determine the weight of the index system to solve the uncertainty problem in the transformation process of qualitative indicators. The method of determining weight indicators can be explained as follows:

Step 1: Calculating the comparative importance matrix.

Using the traditional 1-9 scale method to compare the indexes quantitatively for initial collection, the larger the scale value is, the more important the comparison index is relative to the compared index [42]. Then, output the comparative importance matrix.

Table 5: The judgment matrix of $B_1 - C$.

B_1	Operation cost C_{11}	Additional transportation cost C_{12}	Capital cost C_{13}
Operation cost C_{11}	1,0,0	7.333,0.535,0.157	3.667,0.633,0.182
Additional transportation cost C_{12}	0.136,0.010,0.003	1,0,0	0.250,0.044,0.013
Capital cost C_{13}	0.273,0.047,0.014	4,0.707,0.204	1,0,0

Table 6: The judgment matrix of $B_2 - C$.

B_2	Demand C_{21}	Turnover C_{22}	Cargo capacity C_{23}	Cargo distance C_{24}
Demand C_{21}	1,0,0	7,0.617,0.182	2.333,0.591,0.182	8.333,0.610,0.182
Turnover C_{22}	0.143,0.013,0.004	1,0,0	0.231,0.032,0.010	2,0.707,0.204
Cargo capacity C_{23}	0.429,0.109,0.033	4.333,0.603,0.182	1,0,0	5,0.617,0.182
Cargo distance C_{24}	0.120,0.009,0.003	0.5,0.177,0.051	0.2,0.025,0.007	1,0,0

Table 7: The judgment matrix of $B_3 - C$.

B_3	Customer nature C_{31}	Cargo nature C_{32}	Alternative mode of transport price C_{33}	Market share C_{34}
Customer nature C_{31}	1,0,0	0.2,0.017,0.005	0.120,0.009,0.003	0.143,0.013,0.004
Cargo nature C_{32}	5,0.437,0.126	1,0,0	0.333,0.049,0.014	0.5,0.177,0.051
Alternative mode of transport price C_{33}	8.333,0.610,0.182	3,0.437,0.126	1,0,0	3,0.617,0.182
Market share C_{34}	7,0.617,0.182	2,0.707,0.204	0.333,0.069,0.020	1,0,0

In practical application, when it is difficult and unstable to obtain data, the golden section method is used to determine the entropy En and hyper entropy He in the adjacent important degree cloud parameters. That is, the smaller one is 0.618 times that of the larger one [43]. The importance scale is shown in Table 3.

Step 2: Calculating the quantitative characteristics values.

Expert groups use cloud parameter language sets to judge the importance of pairwise indicators after a comparative importance matrix is established. And the three quantitative characteristics values are obtained by

$$\mathrm{Ex} = \lambda(\mathrm{Ex}_1 + \mathrm{Ex}_2 + \cdots + \mathrm{Ex}_m), \tag{9}$$

$$\mathrm{En} = \frac{\lambda_1 \mathrm{Ex}_1 \mathrm{En}_1 + \lambda_2 \mathrm{Ex}_2 \mathrm{En}_2 + \cdots + \lambda_m \mathrm{Ex}_m \mathrm{En}_m}{\lambda_1 \mathrm{Ex}_1 + \lambda_2 \mathrm{Ex}_2 + \cdots + \lambda_m \mathrm{Ex}_m}, \tag{10}$$

$$\mathrm{He} = \sqrt{\mathrm{He}_1^2 + \mathrm{He}_2^2 + \cdots + \mathrm{He}_m^2}, \tag{11}$$

where $\lambda = 1/m$ denotes the equal rights of M experts, Ex_m represents the importance cloud expectation for expert M, En_m is the degree of importance cloud entropy for expert M, and He_m represents the hyper entropy for expert M.

Step 3: Calculating the importance of cloud judgment matrix.

The cloud parameters of importance judgment given by different experts are aggregated to obtain the importance of cloud judgment matrix is expressed as

Table 8: The judgment matrix of $B_4 - C$.

B_4	National price strategy C_{41}	Profit level C_{42}
National price strategy C_{41}	1,0,0	0.333,0.049,0.014
Profit level C_{42}	3,0.437,0.126	1,0,0

$$M_{s\times s} = \begin{bmatrix} M_{11} & M_{12} & \cdots & M_{1s} \\ M_{21} & M_{22} & \cdots & M_{2s} \\ \cdots & \cdots & \cdots & \cdots \\ M_{s1} & M_{s2} & \cdots & M_{ss} \end{bmatrix}. \tag{12}$$

In which, entropy and hyper entropy are zero on the diagonal, namely, $M_{\mathrm{pp}}(\mathrm{Ex}_{\mathrm{pp}}, \mathrm{En}_{\mathrm{pp}}, \mathrm{He}_{\mathrm{pp}}) = M(1,0,0)$. If we compare two indexes, the importance of the latter compared to the former is expressed as a reciprocal. The calculation process can be expressed as

$$M_{\mathrm{qp}} = \frac{1}{M_{\mathrm{pq}}} = M\left(\frac{1}{\mathrm{Ex}_{\mathrm{pq}}}, \frac{\mathrm{En}_{\mathrm{pq}}}{\mathrm{Ex}_{\mathrm{pq}}^2}, \frac{\mathrm{He}_{\mathrm{pq}}}{\mathrm{Ex}_{\mathrm{pq}}^2}\right), \tag{13}$$

Table 9: Importance evaluation results of cloud quantitative characteristics.

Indicator	Indicator cloud quantitative characteristics Ex	En	He	Dimension	Dimensional cloud quantitative characteristics Ex	En	He
Operation cost	89.667	2.228	0.5	Cost factor	84.857	2.250	0.5
Additional transportation cost	57	2.507	0.5				
Capital cost	79.333	2.228	0.5				
Demand	87.333	1.950	0.5	Transportation capacity factor	77.978	1.823	0.5
Turnover	52.667	2.228	0.5				
Cargo capacity	70.667	1.950	0.5				
Cargo distance	59	2.507	0.5				
Customer nature	37.667	2.228	0.5	Market factor	64.626	2.510	0.5
Cargo nature	68.667	3.621	0.5				
Alternative mode of transport price	68	3.342	0.5				
Market share	59.667	3.064	0.5				
National price strategy	70.333	1.950	0.5	Profit factor	78.833	1.726	0.5
Profit level	81.667	3.899	0.5				

where M_{pq} represents the importance evaluation cloud of the p index relative to the q index in each dimension.

Step 4: Calculating the weighted index set.

Based on the cloud judgment matrix, calculate the weight wtj(Extj, Entj, Hetj)$(t = 1, 2, 3, 4)$ of each indicator C_{tj}. Furthermore, the index weight set $w_t = (w_{t1}, w_{t2}, \cdots, w_{tj})^T$ under the dimension can be obtained. The specific calculation process can be expressed as

$$\mathrm{Ex}_{tj} = \frac{\left(\prod_{q=1}^{s} \mathrm{Ex}_{pq}\right)^{1/s}}{\sum_{p=1}^{s}\left[\left(\prod_{q=1}^{s} \mathrm{Ex}_{pq}\right)^{1/s}\right]}, \tag{14}$$

$$\mathrm{En}_{tj} = \frac{\left[\left(\prod_{p=1}^{s} \mathrm{Ex}_{pq}\right)\sqrt{\sum_{q=1}^{s}\left(\mathrm{En}_{pq}/\mathrm{Ex}_{pq}\right)^2}\right]^{1/s}}{\sum_{p=1}^{s}\left[\left(\left(\prod_{q=1}^{s} \mathrm{Ex}_{pq}\right)\sqrt{\sum_{q=1}^{s}\left(\mathrm{En}_{pq}/\mathrm{Ex}_{pq}\right)^2}\right)^{1/s}\right]}, \tag{15}$$

$$\mathrm{He}_{tj} = \frac{\left[\left(\prod_{q=1}^{s} \mathrm{Ex}_{pq}\right)\sqrt{\sum_{q=1}^{s}\left(\mathrm{He}_{pq}/\mathrm{Ex}_{pq}\right)^2}\right]^{1/s}}{\sum_{p=1}^{s}\left[\left(\left(\prod_{q=1}^{s} \mathrm{Ex}_{pq}\right)\sqrt{\sum_{q=1}^{s}\left(\mathrm{He}_{pq}/\mathrm{Ex}_{pq}\right)^2}\right)^{1/s}\right]}. \tag{16}$$

Step 5: Consistency check.

In order to evaluate the expected significant difference level in the cloud parameters of the desired index weight, calculating the inconsistency index is required. The inconsistency index is defined by $C.I. = \lambda_{\mathrm{t\ max}} - s/s - 1$. where $\lambda_{\mathrm{t\ max}} \approx 1/s\sum_{p=1}^{s}(\sum_{q=1}^{s}\sum_{j=q}(\mathrm{Ex}_{pq}w_{tj})/\sum_{j=p}w_{tj})$ represents the maximum value of t dimension in the judgment matrix and s is the number of alternatives in the problem.

Furthermore, the inconsistency ratio is computed by $C.R. = C.I./R.I.$ Finally, the random index values are provided in Table 4.

If this ratio is less than or equal to 0.1, the consistency is accepted in judgments; otherwise, it should be reconsidered [44].

4.4. Evaluate Cloud Output. Based on the percentage of expert evaluation index, the quantitative characteristic matrix V of each index evaluation cloud is computed as follows:

$$V = \begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \end{bmatrix} = \begin{bmatrix} v_{11} \\ v_{12} \\ \vdots \\ v_{42} \end{bmatrix} = \begin{bmatrix} \mathrm{Ex}(v_{11}), \mathrm{En}(v_{11}), \mathrm{He}(v_{11}) \\ \mathrm{Ex}(v_{12}), \mathrm{En}(v_{12}), \mathrm{He}(v_{12}) \\ \vdots \\ \mathrm{Ex}(v_{42}), \mathrm{En}(v_{42}), \mathrm{He}(v_{42}) \end{bmatrix}. \tag{17}$$

Next, by multiplying the index weight cloud parameter set w_t and the index evaluation cloud quantitative characteristic matrix V_t under the obtained dimension, the evaluation cloud quantitative characteristic $R_t$of each dimension can be obtained as follows:

$$R_t = w_t \times V_t = (\mathrm{Ex}_t, \mathrm{En}_t, \mathrm{He}_t), \tag{18}$$

$$\begin{cases} \mathrm{Ex}_t = \sum \mathrm{Ex}(v_{tj})\mathrm{Ex}(w_{tj}) \\ \mathrm{En}_t = \sqrt{\sum\left(\mathrm{En}^2(v_{tj})\mathrm{En}(w_{tj})\right)}, \\ \mathrm{He}_t = \sum \mathrm{He}(v_{tj})\mathrm{He}(w_{tj}) \end{cases} \tag{19}$$

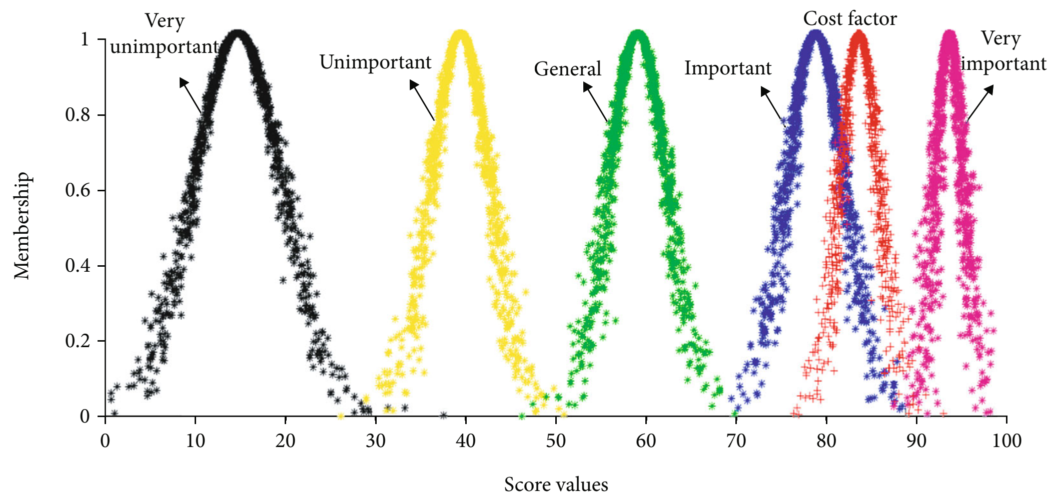

FIGURE 6: The comprehensive evaluation of cost factor.

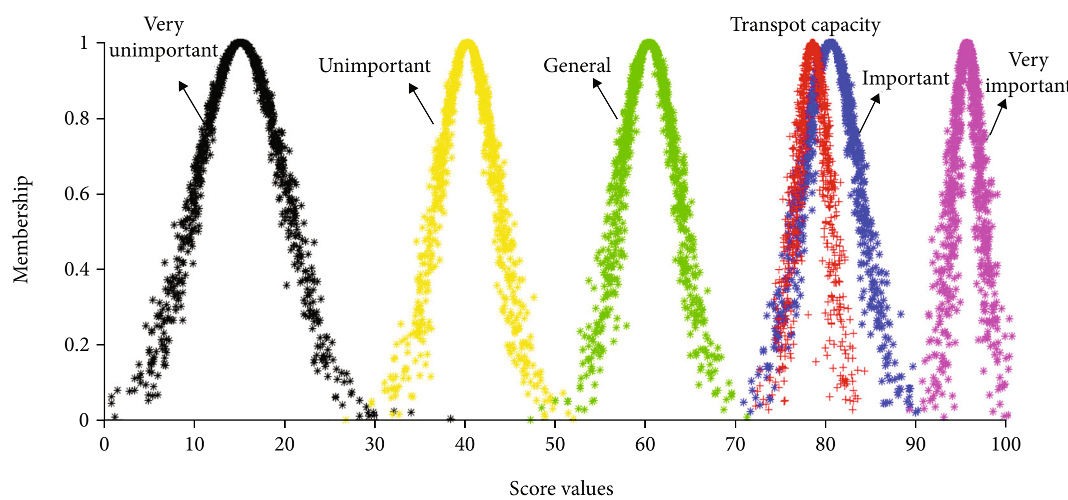

FIGURE 7: The comprehensive evaluation of transportation capacity.

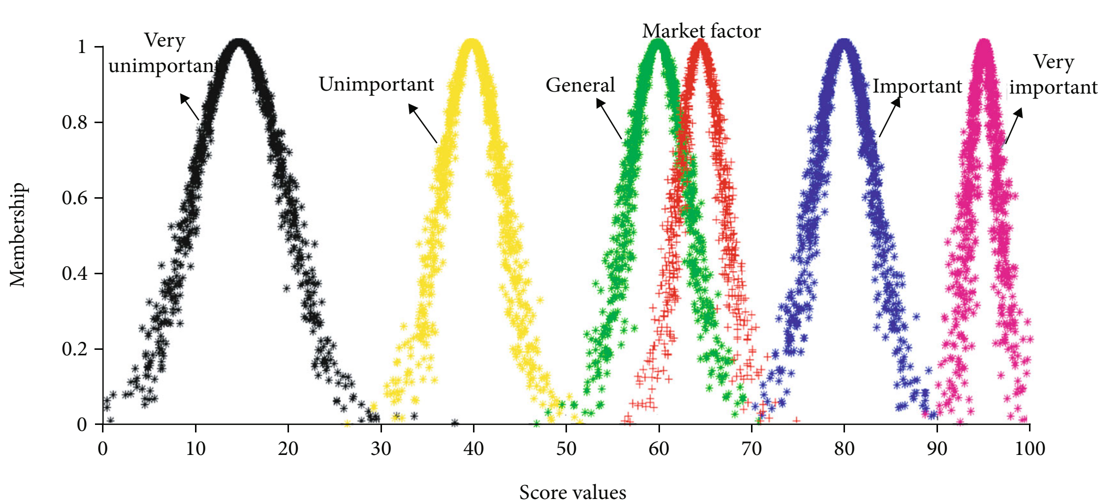

FIGURE 8: The comprehensive evaluation of market factor.

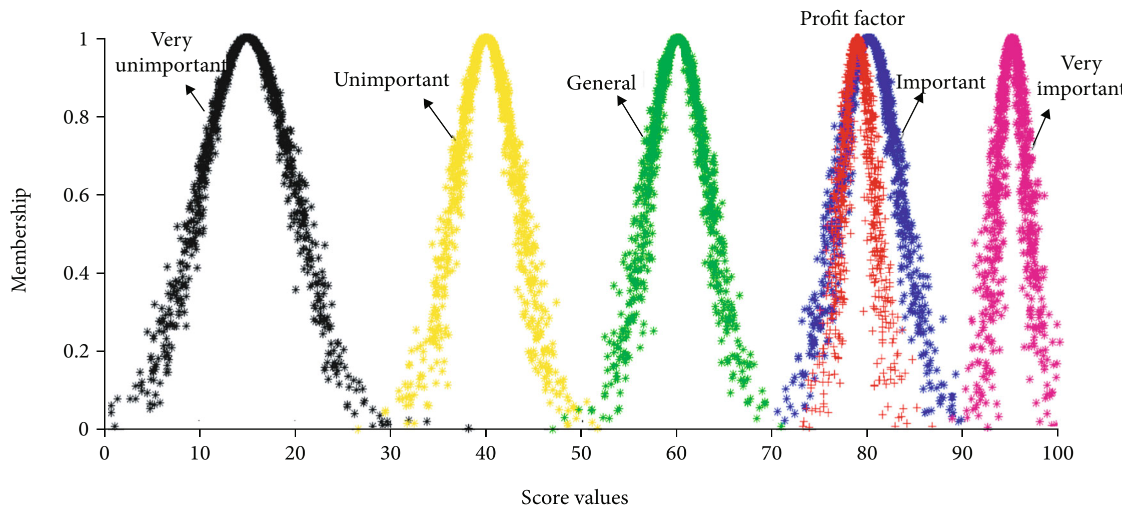

FIGURE 9: The comprehensive evaluation of profit factor.

where $\mathrm{Ex}(w_{tj})$ represents the expectation corresponding to w_{tj}, $\mathrm{En}(w_{tj})$ denotes the entropy corresponding to w_{tj}, and $\mathrm{He}(w_{tj})$ represents the hyper entropy corresponding to w_{tj}.

According to the calculation method and the quantitative cloud feature, simulation can be carried out in the *MATLAB* environment using a forward cloud algorithm. The evaluation cloud map can be combined to identify the importance of each dimension cloud and output the evaluation result. In detail, the cloud theory evaluation process of the factors affecting the freight rates of railway bulk goods can be described in Figure 5.

5. Case Study

In order to verify the feasibility and effectiveness of the designed model, this paper selects three experts from Z Railway Bureau as members of the decision-making group: the director of the freight center, the director of the freight rates management agency, and the director of the freight marketing department. These experts have rich professional knowledge and working experience. Therefore, the results of their consultation have high authenticity and reliability. Then, we calculate and output evaluation results according to the cloud theory evaluation process of the factors affecting the freight rates of railway bulk goods (as shown in Figure 3).

Taking C_{11} and C_{12} in the cost factor B_1 as an example, three experts make the important judg1ments for elements C_{11} and C_{12} based on the language judgment scale of cloud parameters: $D_1 = (7, 0.437, 0.073)$, $D_2 = (8, 0.707, 0.118)$, and $D_3 = (7, 0.437, 0.073)$. First, according to Equations (9)–(11), the importance cloud parameter of the indicator C_{11} to C_{12} can be calculated, and the value is (7.333, 0.535, 0.157). Subsequently, the importance of C_{12} to C_{11} can be obtained through Equation (13), and the cloud parameter is (0.136, 0.010, 0.003). Similarly, the importance of other indicators can be obtained to judge cloud parameters. Furthermore, the judgment matrix is obtained by assembling the importance judgment cloud parameters as shown in Tables 5–8.

According to the judgment matrix in Table 5, the weights of relative to is calculated by Equations (14)–(16):

$$w_1 = \begin{bmatrix} w_{11} \\ w_{12} \\ w_{13} \end{bmatrix} = \begin{bmatrix} (0.689, 0.673, 0.672) \\ (0.075, 0.073, 0.074) \\ (0.237, 0.254, 0.254) \end{bmatrix}, \tag{20}$$

where the inconsistency index is 0.026 ($C.I.$) and the random index value is 0.58 (R.$I.$). Hence, consistency is accepted in judgments($C.R. = 0.045 < 0.1$).

Meanwhile, combining Table 6, the weight of $C_{2i} (i = 1, 2, 3, 4)$ relative to B_2 (w_2) is calculated as follows:

$$w_2 = \begin{bmatrix} w_{21} \\ w_{22} \\ w_{23} \\ w_{24} \end{bmatrix} = \begin{bmatrix} (0.569, 0.545, 0.559) \\ (0.085, 0.074, 0.089) \\ (0.291, 0.324, 0.294) \\ (0.055, 0.057, 0.058) \end{bmatrix}, \tag{21}$$

where the inconsistency index is 0.017 and the random index value is 0.9. Hence, consistency is accepted in judgments ($C.R. = 0.019 < 0.1$).

In addition, combining Table 7, the weight of $C_{3i} (i = 1, 2, 3, 4)$ relative to B_3 (w_3) is calculated as follows:

$$w_3 = \begin{bmatrix} w_{31} \\ w_{32} \\ w_{33} \\ w_{34} \end{bmatrix} = \begin{bmatrix} (0.043, 0.034, 0.036) \\ (0.170, 0.174, 0.179) \\ (0.525, 0.519, 0.504) \\ (0.262, 0.272, 0.281) \end{bmatrix}, \tag{22}$$

where the inconsistency index is 0.038 and the random index value is 0.9. Hence, consistency is accepted in judgments ($C.R. = 0.042 < 0.1$).

Additionally, combining Table 8, the weight of $C_{4i}(i=1, 2)$ relative to B_4 (w_4) is calculated as follows:

$$w_4 = \begin{bmatrix} w_{41} \\ w_{42} \end{bmatrix} = \begin{bmatrix} (0.250, 0.350, 0.354) \\ (0.750, 0.650, 0.646) \end{bmatrix}, \tag{23}$$

where both inconsistency index and random index values are 0. Hence, consistency is accepted in judgments $(C.R. = 0 < 0.1)$.

Next, based on the quantitative characteristic matrix V_t obtained by the backward cloud generator, the evaluation cloud quantitative characteristic R_t of each dimension can be obtained by Equation (18) as shown in Table 9.

In order to obtain the significance analysis results of factors affecting the freight rates of railway bulk goods more clearly and intuitively, we substitute the results of Table 8 into the forward cloud generator to simulate in the MATLAB environment. Then, compared with the standard cloud map of the important evaluation in Figure 4, the comprehensive evaluation cloud map of various factors are generated and shown in Figures 6–9.

It is clear from Figure 6 that the comprehensive evaluation of cost factor (84.857, 2.250, 0.5) is between “important” and “very important” and mostly falls within the range of “important.” In detail, the comprehensive evaluation of the cost factor intersects with “important” at a degree of certainty more than 0.7 and with “very important” at a degree of certainty less than 0.2. According to the principle of maximum membership degree, the comprehensive cost factor is consistent with the “important” evaluation.

A main finding of Figure 7 is that the comprehensive evaluation of transportation capacity (77.978, 1.823, 0.5) mostly falls within the range of “important.” Although it intersects with the “general” at a degree of certainty less than 0.1, its distribution range is small, and its importance tends to be “important.”

As is shown in Figure 8, the comprehensive evaluation of profit factor (64.626, 2.510, 0.5) is between “important” and “general” and mostly falls within the range of “important.” In detail, the comprehensive evaluation of cost factor intersects with the “general “at a degree of certainty between 0.6 and 0.8 and with “very important” at a degree of certainty less than 0.2. Hence, the importance of market factors tends to be “general.”

Figure 9 displays that the comprehensive evaluation of profit factor (78.833, 1.726, 0.5) falls within the range of “important”.

In total, the cloud theory of factors affecting the freight rates of railway bulk goods provides a more reasonable and convenient way to optimize the uncertain problems between qualitative indicators and quantitative values. The issue of bidirectional conversion between the qualitative and quantitative values is solved. Meanwhile, through case studies, this paper verifies the effectiveness and availability of the proposed model. The results show that the Z Railway Bureau firstly pays attention to cost factors, followed by profit factors and transportation capacity, and finally considers market factors in freight rates adjustment.

6. Conclusions

In this paper, the cloud theory-based freight rate factor evaluation of railway bulk goods is studied. In detail, a cognitive cloud model of factors affecting the freight rates of railway bulk goods is proposed to describe the transformation of qualitative variables and processing of the model mapping and transformation. In the cognitive cloud model, for each factor, the randomness and fuzziness are described by three parameters: expectation, entropy, and hyper entropy, respectively. Furthermore, a cloud generator including forward and backward cloud generators is designed to solve the bidirectional conversion between qualitative indicators and quantitative values. Moreover, we adopted a floating cloud gathering algorithm to determine the weight of the index system to solve the uncertainty problem in the transformation process of qualitative indicators. Through an in-depth analysis of the factors influencing the pricing of bulk goods transportation in Z Railway Bureau, several valuable and interesting findings were discovered:

(1) Random fuzzy mapping integrates the fuzziness and randomness of linguistic terms to effectively quantify qualitative variables, and a cloud generator can solve the bidirectional conversion between qualitative indicators and quantitative values

(2) Simulation can be carried out in MATLAB using the proposed calculation method and cloud quantitative characteristics. The evaluation cloud map can be combined to identify the importance of each influencing factor of railway bulk freight rates and output the evaluation result

(3) Compared to the standard cloud map of importance evaluation, we can quickly get the significance analysis results of factors that affect railway bulk goods freight rates. For instance, Z Railway Bureau should adjust freight rates in this order: cost > profit > capacity > market

Further extensions can be envisaged as follows. First, considering the competition between railway transportation and other modes of transportation is more realistic. The cloud-based cognitive model for freight influencing factors based on competition would be an important research area. Secondly, this paper only focuses on the bidirectional conversion between qualitative indicators and quantitative values. It is necessary to investigate the perturbation relationship between indicators. Finally, the periodicity characteristic of rail freight fluctuations is worth investigating, particularly if it influences market equilibrium.

Data Availability

All data generated or analysed during this study are included in this published article.

Conflicts of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and publication of this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (No. 61803147 and 72201218), in part by the Science and Technology R&D Program of China State Railway Group Co., Ltd. (P2021X013).

References

[1] D. K. Pathak, R. Shankar, and A. Choudhary, “Performance assessment framework based on competitive priorities for sustainable freight transportation systems,” *Transportation Research Part D, Transport and Environment*, vol. 90, article 102663, 2021.

[2] A. Kumar and R. Anbanandam, “Assessment of environmental and social sustainability performance of the freight transportation industry: an index-based approach,” *Transport Policy*, vol. 124, pp. 43–60, 2022.

[3] K. H. Lai, E. W. T. Ngai, and T. C. E. Cheng, “Measures for evaluating supply chain performance in transport logistics,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 38, no. 6, pp. 439–456, 2002.

[4] E. Gonzalez-Pascual, J. Nosedal-Sanchez, and J. Garcia-Gutierrez, “Performance evaluation of a road freight transportation company through SCOR metrics,” *Case Studies on Transport Policy*, vol. 9, no. 4, pp. 1431–1439, 2021.

[5] M. Grote, B. Waterson, and F. Rudolph, “The impact of strategic transport policies on future urban traffic management systems,” *Transport Policy*, vol. 110, pp. 402–414, 2021.

[6] N. Madrid, M. Ojeda-Aciego, J. Medina, and I. Perfilieva, “_L_ -fuzzy relational mathematical morphology based on adjoint triples,” *Information Sciences*, vol. 474, pp. 75–89, 2019.

[7] H. O. W. Peiris, S. Chakraverty, S. S. N. Perera, and S. M. W. Ranwala, “Novel fuzzy linguistic based mathematical model to assess risk of invasive alien plant species,” *Applied Soft Compting*, vol. 59, pp. 326–339, 2017.

[8] M. H. Kao and H. Khogeer, “Optimal designs for mixed continuous and binary responses with quantitative and qualitative factors,” *Journal of Multivariate Analysis*, vol. 182, article 104712, 2021.

[9] A. H. Liu, S. P. Wan, and J. Y. Dong, “An axiomatic design-based mathematical programming method for heterogeneous multi-criteria group decision making with linguistic fuzzy truth degrees,” *Information Sciences*, vol. 571, pp. 649–675, 2021.

[10] R. Rajesh, “Measuring the barriers to resilience in manufacturing supply chains using grey clustering and VIKOR approaches,” *Measurement*, vol. 126, pp. 259–273, 2018.

[11] B. C. Kim, “Multi-factor dependence modelling with specified marginals and structured association in large-scale project risk assessment,” *European Journal of Operational Research*, vol. 296, no. 2, pp. 679–695, 2022.

[12] T. Zhou, M. Modarres, and E. L. Droguett, “Multi-unit nuclear power plant probabilistic risk assessment: a comprehensive survey,” *Reliability Engineering & System Safety*, vol. 213, p. 107782, 2021.

[13] E. K. Burke, M. Dror, S. Petrovic, and R. Qu, “Hybrid graph heuristics in hyper-heuristics applied to exam timetabling problems,” in *The next wave in computing, optimization, and decision technologies*, pp. 79–91, 2005.

[14] T. I. Katsaounis, “Equivalence of factorial designs with qualitative and quantitative factors,” *Journal of Statistical Planning and Inference*, vol. 142, no. 1, pp. 79–85, 2012.

[15] D. Y. Li, H. J. Meng, and X. M. Shi, “Membership clouds and membership cloud generators,” *Journal of Computer Research and Development*, vol. 32, no. 6, pp. 15–20, 1995.

[16] G. Wang, C. Xu, and D. Li, “Generic normal cloud model,” *Information Sciences*, vol. 280, pp. 1–15, 2014.

[17] J. Q. Wang, J. J. Peng, H. Y. Zhang, T. Liu, and X. H. Chen, “An uncertain linguistic multi-criteria group decision-making method based on a cloud model,” *Group Decision and Negotiation*, vol. 24, no. 1, pp. 171–192, 2015.

[18] W. Song and J. Zhu, “A multistage risk decision making method for normal cloud model considering behavior characteristics,” *Applied Soft Computing*, vol. 78, pp. 393–406, 2019.

[19] A. Kavousi-Fard, T. Niknam, and M. Fotuhi-Firuzabad, “A novel stochastic framework based on cloud theory and θ-modified bat algorithm to solve the distribution feeder reconfiguration,” *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 740–750, 2016.

[20] H. Yang, G. Xu, and X. Fan, “A reliability analysis method of cloud theory–Monte Carlo based on performance degradation data,” *Eksploatacja i Niezawodnosc-Maintenance and Reliability*, vol. 17, no. 3, pp. 435–442, 2015.

[21] F. Khedim, N. Labraoui, and A. A. Ari, “A cognitive chronometry strategy associated with a revised cloud model to deal with the dishonest recommendations attacks in wireless sensor networks,” *Journal of Network and Computer Applications*, vol. 123, pp. 42–56, 2018.

[22] Z. Zhou, G. Si, K. Zheng, X. Xu, K. Qu, and Y. Zhang, “CMBCF: a cloud model based hybrid method for combining forecast,” *Applied Soft Computing*, vol. 85, p. 105766, 2019.

[23] W. Zang, L. Ren, W. Zhang, and X. Liu, “A cloud model based DNA genetic algorithm for numerical optimization problems,” *Future Generation Computer Systems*, vol. 81, pp. 465–477, 2018.

[24] X. Zhang and L. Li, “An integrated planning/pricing decision model for rail container transportation,” *International Journal of Civil Engineering*, vol. 17, no. 10, pp. 1537–1546, 2019.

[25] W. X. Li, “Research on China’s railway freight rate evaluation system,” *Research on Quantitative Economy and Technical Economy*, vol. 7, pp. 67–71, 2003.

[26] J. Zeng, S. Y. Guo, F. R. Qi, H. Q. Pan, and B. T. Dong, “A railway bulk cargo freight rate risk early warning judgment method based on BP neural network,” *Railway Computer Application*, vol. 29, no. 7, pp. 25–29, 2020.

[27] J. Zeng, F. R. Qi, S. Y. Guo, H. Q. Pan, and B. T. Dong, “Research on freight rate risk assessment of railway bulk freight transportation based on improved grey correlation degree,” *Railway Freight*, vol. 38, no. 6, pp. 48–54, 2020.

[28] D. Li, M. Koopialipoor, and D. J. Armaghani, “A combination of fuzzy Delphi method and ANN-based models to investigate factors of flyrock induced by mine blasting,” *Natural Resources Research*, vol. 30, no. 2, pp. 1905–1924, 2021.

[29] W. Ho and X. Ma, “The state-of-the-art integrations and applications of the analytic hierarchy process,” *European Journal of Operational Research*, vol. 267, no. 2, pp. 399–414, 2018.

[30] J. W. Guo, W. Wang, Y. Y. Tang, Y. X. Zhang, and H. Y. Zhuge, "A CNN-Bi_LSTM parallel network approach for train travel time prediction," *Knowledge-Based Systems*, p. 109796, 2022.

[31] B. Y. Tahmasebi and F. Yazdandoost, "An integrated framework to evaluate resilient-sustainable urban drainage management plans using a combined-adaptive MCDM technique," *Water Resources Management*, vol. 32, no. 8, pp. 2817–2835, 2018.

[32] M. S. Tsai and F. Y. Hsu, "Application of grey correlation analysis in evolutionary programming for distribution system feeder reconfiguration," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 1126–1133, 2010.

[33] H. C. Wang, *Study on Peak-Shaving Heating Modes of Combined District Heating System and the Comprehensive Optimization*, Dissertation Harbin Institute of Technology, Harbin, China, 2013.

[34] Z. Yang, K. Yang, Y. Wang, L. Su, and H. Hu, "Multi-objective short-term hydropower generation operation for cascade reservoirs and stochastic decision making under multiple uncertainties," *Journal of Cleaner Production*, vol. 276, p. 122995, 2020.

[35] F. Yan and K. Xu, "A set pair analysis based layer of protection analysis and its application in quantitative risk assessment," *Journal of Loss Prevention in the Process Industries*, vol. 55, pp. 313–319, 2018.

[36] H. Wong and B. Q. Hu, "Application of improved extension evaluation method to water quality evaluation," *Journal of Hydrology*, vol. 509, pp. 539–548, 2014.

[37] J. Zhou, C. Chen, M. Wang, and M. Khandelwal, "Proposing a novel comprehensive evaluation model for the coal burst liability in underground coal mines considering uncertainty factors," *International Journal of Mining Science and Technology*, vol. 31, no. 5, pp. 799–812, 2021.

[38] X. J. Wang, *Impact factors of transportation pricing on railway bulk cargo and its countermeasure for pricing*, no. 2pp. 5–8, Prices Monthly, 2017.

[39] W. Q. Huang, T. Bureau, and C. R. Corporation, "Study on the market-oriented reform of railway freight rates for bulk goods," *Railway Freight Transport*, vol. 35, no. 10, pp. 5–9, 2017.

[40] P. K. Li, "Research on the pricing of bulk cargo rail transportation in China," *Reformation & Strategy*, vol. 33, no. 6, pp. 82–84, 2017.

[41] L. Y. Wang, Y. K. Wu, H. M. Li, and Y. C. Cao, "Contract water-saving management risk assessment based on cloud model," *Water Saving Irrigation*, vol. 44, no. 5, pp. 104–108, 2019.

[42] P. Biswas, S. Pramanik, and B. C. Giri, "TOPSIS method for multi-attribute group decision-making under single-valued neutrosophic environment," *Neural Computing & Applications*, vol. 27, no. 3, pp. 727–737, 2016.

[43] Y. X. Jiang, "Study On Risk Analysis and Disaster Loss Assessment of Dam Break Based on Cloud Model and GIS/RS," Huazhong University of Science and Technology, Wuhan, 2012.

[44] E. W. Stein and N. Ahmad, "Using the analytical hierarchy process (AHP) to construct a measure of the magnitude of consequences component of moral intensity," *Journal of Business Ethics*, vol. 89, no. 3, pp. 391–407, 2009.