Study on comprehensive evaluation method of daily transport production quality of railway bureau

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Abstract. According to the definition of daily transport production quality, the evaluation index system of daily transport production quality was constructed. Firstly decision matrix was built with the attribute value of each sample and the decision matrix was standardized. This paper analysed the sample data to obtain each principal component’s values and weight through the principal component analysis and thus to get the optimal value and worst value of each principal component. Then this paper defined four parameters according to the grey relational analysis theory and gave the corresponding calculation method. Finally this paper defined the grey relative closeness coefficient parameter which was used to evaluate transport production quality based on TOPSIS. The method was applied to the Beijing railway bureau. This paper compared the results to those of the principal component analysis and grey correlation analysis, which proved that the method had certain feasibility.

1. Introduction
Under the background of market economy and the reform of state-owned enterprises, the scientific evaluation of daily transport production quality is beneficial to improve the daily transport production management ability of railway transportation enterprises, thus improving the market competitiveness of railway transportation enterprises. For railway transportation, the quality of daily transport production is mainly reflected in the reasonable control of the number of cars, the number of loading and unloading cars and the length of car turnaround time. Daily transport production quality evaluation will be beneficial for railway administrations to master the quality of the specific date of the month. The period of low transport production quality can be obtained through comparative analysis, and this paper can conclude the cause of transport production quality reducing based on the evaluation results. These results can provide the decision-making basis to the transportation management department. At present, there are many researches on the quality evaluation of road transportation production but lack of the researches on production quality evaluation of railway transportation. So an effective and feasible daily transport production quality comprehensive evaluation method for railway transportation will have the very vital significance to study.

2. Construction of daily transportation production quality evaluation index system
The premise of evaluating the quality of daily transport production is to construct a reasonable evaluation index system. This index system should fully reflect car number control quality, loading -
unloading quality and car turnaround quality. Therefore, in line with the principle of easy measurement, strong purpose and reasonable operation, this paper selected 9 typical indicators such as number of loaded cars delivered (NLCD), local loaded cars (NLLC), unloaded cars (NUC), non-serviceable cars (NNC), reserved cars (NRC), car loading (NCL), car unloading (NCU), average detention time of car in transit (ADTCT) and average detention time of car for loading or unloading (ADTCLU) by combining the meaning of daily transport production quality and the existing indicators in literature [15]. Thus the daily transport production quality evaluation index system was constructed. The index system is shown in Table 1.

### Table 1. The index system.

| Target Layer          | Rule layer     | Index layer | Code | Unit | Type  |
|-----------------------|----------------|-------------|------|------|-------|
| Transport Production  | Car Number     | NLCD        | X1   | Car  | Appropriate |
| Quality               | Control Quality| NLLC        | X2   | Car  | Appropriate |
|                       |                | NUC         | X3   | Car  | Appropriate |
|                       |                | NNC         | X4   | Car  | Appropriate |
|                       |                | NRC         | X5   | Car  | Appropriate |
|                       | Loading-unloading| NCL        | X6   | Car  | Efficiency |
| Quality               |                | NCU         | X7   | Car  | Efficiency |
|                       | Car Turnaround | ADTCT       | X8   | Hour | Cost    |
|                       |                | ADTCLU      | X9   | Hour | Cost    |

### 3. Principal component- grey relational TOPSIS((PCGRTOPSIS))

At present, there are many researches on comprehensive evaluation methods at home and abroad. The traditional methods include fuzzy comprehensive evaluation [1-4] and analytic hierarchy process [5-7]. Modern comprehensive evaluation methods include grey relational analysis [8-9], TOPSIS [10], principal component analysis, artificial neural network [11-13] and improvement methods of traditional methods [14]. Artificial neural network needs a large amount of historical data and standard data as training samples, however, the daily transport production quality evaluation index system has not been established and the relevant standards have not been perfected, which leads to the lack of training samples. So artificial neural network will be difficult to achieve. PCA can solve the problem of information overlap and reduce the index dimension, as there are many factors affecting the daily transport production quality and each index inevitably has the correlation and information overlap, less variables can be used to explain and replace most of the variables to achieve the purpose of lowering the index dimension and highlighting the research focus through PCA. Grey relational analysis can process grey systems with incomplete information. The railway bureau transport production quality is affected by many factors and the indicators selected in this paper are only a part of them, the information is not clear enough. Therefore, grey relational analysis can be used to solve the problem of poor information. TOPSIS does not have a strict limit on the sample size. It is suitable for both horizontal (multi-unit) evaluation and vertical (various periods) evaluation. It is flexible and quantitative, but the downside of TOPSIS is that the weight set is usually a subjective value. This paper used PCA to establish weights to overcome this shortcoming. Therefore, this paper combined the advantages of these methods and constructed a comprehensive evaluation method of daily transport production quality based on the principal component- grey relational TOPSIS. The steps are as follows.

#### 3.1 Standardize the initial decision matrix

Firstly this paper created the original data matrix $X'_{m \times n}$, where $m$ is the number of indicators and $n$ is the number of samples. $x'_{ij}$ denotes the original attribute value of the index $i$ of sample $j$. Table 1 shows that each indicator has different types. In order to eliminate the influence of different types and different dimensions on the evaluation results, it is necessary to standardize the indexes and establish
the standard initialization decision matrix $X_{m \times n}$. The normalized matrix is implemented according to the following equations.

For efficiency type (bigger is better):

$$x_{ij} = \frac{x_{ij}' - \min_{i} x_{ij}'}{\max_{i} x_{ij}' - \min_{i} x_{ij}'}$$  \hspace{1cm} (1)

For cost type (smaller is better):

$$x_{ij} = \frac{\max_{i} x_{ij}' - x_{ij}'}{\max_{i} x_{ij}' - \min_{i} x_{ij}'}$$  \hspace{1cm} (2)

For appropriate type (the closer to a standard value, the better, and generally take the average value):

$$x_{ij} = 1 - \frac{|x_{ij}' - \gamma_{i}|}{\max_{i} |x_{ij}' - \gamma_{i}|}$$  \hspace{1cm} (3)

3.2 Obtain the principal component and its weight by PCA

The principle of principal component analysis is as follows:

$$z_1 = \frac{a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p}{\sqrt{D(z_1)}}$$
$$z_2 = \frac{a_{21}x_1 + a_{22}x_2 + \cdots + a_{2p}x_p}{\sqrt{D(z_2)}}$$
$$\vdots$$
$$z_m = \frac{a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mp}x_p}{\sqrt{D(z_m)}}$$  \hspace{1cm} (4)

Where, $z_1, z_2, \cdots, z_m$ is the $x_1, x_2, \cdots, x_p$ corresponding m principal components and $D(z_i)$ denotes the variance. Each principal component score of each sample can be obtained through the above equation, and the normalized variance contribution rate is taken as the weight of each principal component.

3.3 Grey correlation analysis based on principal components

**Definition1 (OCC).** Optimal correlation coefficient $(OCC(j,i))$ denotes the degree of the $i$th principal component score of the $j$th sample tends to the best principal component, which is the real numbers between 0 and 1.

$$OCC(j,i) = \frac{\min_{i} \min_{j} |z_{ij} - g_i| + \rho \max_{i} \max_{j} |z_{ij} - g_i|}{\max_{i} \max_{j} |z_{ij} - g_i|}$$  \hspace{1cm} (5)

**Definition2 (ICC).** Inferior correlation coefficient $(ICC(j,i))$ denotes the degree of the $i$th principal component score of the $j$th sample tends to the worst principal component, which is the real numbers between 0 and 1.

$$ICC(j,i) = \frac{\min_{i} \min_{j} |z_{ij} - h_i| + \rho \max_{i} \max_{j} |z_{ij} - h_i|}{\max_{i} \max_{j} |z_{ij} - h_i|}$$  \hspace{1cm} (6)

**Definition3 (OC).** Optimal correlation $(OC(j))$ denotes the degree of the $j$th sample tends to the best sample, which is the real numbers between 0 and 1.

$$OC(j) = \sum_{i=1}^{n} w_i OCC(i,j)$$  \hspace{1cm} (7)
Definition4(IC). Inferior correlation ($IC(j)$) denotes the degree of the $j$th sample tends to the worst sample, which is the real numbers between 0 and 1.

$$IC(j) = \sum_{i=1}^{n} w_i ICC(i, j)$$  

(8)

The equations are as above. Where, $\rho$ is the resolution coefficient, $\rho \in [0,1]$, in general set as 0.5. $z_i$ is the score value of the $i$th principal component of the $j$th sample. $g_i$ is the maximum value of all samples of the $i$th principal component. $b_i$ is the minimum value of all samples of the $i$th principal component. $w_i$ denotes the weight of the principal component.

3.4 Calculate grey relative closeness degree

TOPSIS is to sort the evaluation object by detecting the distance between the optimal solution and the worst solution. If the evaluation object is closest to the optimal solution and further away from the worst solution, it is the best. Otherwise it's not optimal.

Definition5(GRCD). Grey relative closeness degree of the sample is calculated based on OC and IC obtained earlier, as shown in the following equation.

$$GRCD(j) = OC(j) \cdot (OC(j) + IC(j))^{-1}$$  

(9)

The GRCD is divided into four interval, according to the transport production quality by superior to inferior, in turn, are represented as superior (0.75 1), good (0.5 0.75), middle (0.25 0.5), inferior (0-0.25) four levels. For the railway bureau daily transport production quality evaluation, daily data is as a sample. when GRCD is greater than 0.5, denotes that transport production quality is satisfactory.

4. case study

This paper took the data of Beijing railway bureau on June 1, 2018 solstice on June 30, 2018 as the sample set, and there were 30 samples in total. The application process was as follows:

Step1. The data were normalized and the initial decision matrix was established.

Step2. The original samples data were analysed by SPSS.

Before extracting principal components, applicability test is required. The test results was shown in table 2. As can be seen from table 2, the KMO measurement value was 0.773, greater than 0.5, indicating that the applicability test of PCA passed.

| KMO Measure of Sampling Adequacy | 0.773 |
|----------------------------------|------|
| Bartlett Test of Spheres | The Approximate Chi-square | 239.544 |
| df | 36 |
| Sig | 0.000 |

The characteristic value, variance contribution rate and accumulative contribution rate of the principal component can be obtained by the total variance decomposition of the original variable. The results were shown in table 3. In this case, the feature value greater than 1 was used as the basis for screening principal components. The cumulative contribution rate of the first three principal components has reached 83.096%, indicating that these three principal components were sufficient to represent the influencing factors of daily transportation and production quality. Therefore, three principal components were extracted to replace the original 9 indicators. According to the variance contribution rate in the table, it can be normalized to obtain the weight vector of the principal component (0.67, 0.19, 0.14). According to the characteristic vector of the principal component, the principal component scoring equations of daily transport production quality were obtained as follows. According to the principal component scoring equation, the daily value of the principal component score of transport production quality of Beijing railway bureau can be obtained. As shown in table 4,
the optimal solution of the three principal components was \((0.32, 0.88, 0.41)\), and the worst solution was \((-0.34, 0.06, -0.60)\).

\[
z_1 = 0.032X_1 + 0.407X_2 + 0.021X_3 - 0.286X_4 - 0.221X_5 + 0.047X_6 + 0.251X_7 + 0.007X_8 - 0.281X_9 \\
z_2 = 0.084X_1 - 0.344X_2 + 0.265X_3 + 0.054X_4 - 0.052X_5 + 0.223X_6 - 0.099X_7 + 0.273X_8 + 0.616X_9 \\
z_3 = -0.634X_1 + 0.045X_2 + 107X_3 + 0.161X_4 + 0.135X_5 + 0.370X_6 + 0.165X_7 - 0.249X_8 - 0.011X_9 \\
\] (10)

### Table 3. The total variance of the interpretation.

| Component | Initial Eigenvalues | Extract Sum of Squares and Loads | Rotation sum of squares and loads |
|-----------|---------------------|----------------------------------|----------------------------------|
|           | Total Variance %    | sum %                            | Total Variance %                | sum %                            |
| 1         | 4.985               | 55.384                           | 4.985                           | 55.384                           |
| 2         | 1.438               | 15.980                           | 1.438                           | 15.980                           |
| 3         | 1.056               | 11.732                           | 1.056                           | 11.732                           |
| 4         | .655                | 7.280                            | .655                            | 7.280                            |
| 5         | .385                | 4.276                            | .385                            | 4.276                            |
| 6         | .209                | 2.321                            | .209                            | 2.321                            |
| 7         | .192                | 2.128                            | .192                            | 2.128                            |
| 8         | .066                | .737                             | .066                            | .737                             |
| 9         | .014                | .161                             | .014                            | .161                             |

### Table 4. Principal component score.

| Date | Z1  | Z2  | Z3  | Date | Z1  | Z2  | Z3  | Date | Z1  | Z2  | Z3  |
|------|-----|-----|-----|------|-----|-----|-----|------|-----|-----|-----|
| 1    | .05 | .77 | .01 | 11   | .22 | .43 | -.39| 21   | -.16| .70 | -.51|
| 2    | .24 | .35 | .15 | 12   | .02 | .15 | .07 | 22   | -.09| .74 | -.36|
| 3    | .30 | .06 | .41 | 13   | -.29| .60 | -.02| 23   | -.13| .72 | -.50|
| 4    | -.01| .36 | .32 | 14   | -.10| .54 | -.10| 24   | .01 | .59 | -.36|
| 5    | .17 | .08 | -.25| 15   | -.34| .83 | -.27| 25   | .11 | .62 | -.49|
| 6    | -.09| .63 | -.15| 16   | -.11| .67 | -.03| 26   | -.04| .66 | .06 |
| 7    | .04 | .61 | -.23| 17   | .04 | .54 | -.34| 27   | -.04| .72 | -.49|
| 8    | .19 | .66 | -.45| 18   | .16 | .43 | -.60| 28   | .11 | .33 | -.41|
| 9    | .32 | .31 | -.38| 19   | -.07| .61 | -.17| 29   | -.07| .45 | -.31|
| 10   | .21 | .52 | -.43| 20   | -.27| .88 | -.32| 30   | -.28| .56 | -.13|

### Table 5. The value of OC, IC and GRCD.

| Date | OC  | IC  | GRCD | Date | OC  | IC  | GRCD |
|------|-----|-----|------|------|-----|-----|------|
| 1    | .60 | .44 | .58  | 11   | .66 | .45 | .59  |
| 2    | .72 | .41 | .64  | 12   | .51 | .54 | .49  |
| 3    | .83 | .47 | .64  | 13   | .43 | .73 | .37  |
| 4    | .54 | .50 | .52  | 14   | .47 | .55 | .46  |
| 5    | .59 | .52 | .53  | 15   | .45 | .82 | .36  |
| 6    | .49 | .54 | .48  | 16   | .49 | .54 | .48  |
| 7    | .54 | .48 | .53  | 17   | .53 | .49 | .52  |
| 8    | .66 | .45 | .59  | 18   | .60 | .51 | .54  |
| 9    | .81 | .44 | .65  | 19   | .49 | .52 | .49  |
| 10   | .66 | .45 | .59  | 20   | .49 | .70 | .41  |

**Step 3.** The parameters were calculated based on principal component. According to the optimal solution and worst solution as well as equation (5) and equation (6), the
OCC and ICC of the principal components of each sample can be obtained. Based on the equation (7), equation (8) and equation (9), the OC and IC of each sample as well as the GRCD can be obtained. The results were shown in table 5.

5. Results comparison and analysis
We compared the results of PCGRTOPSIS with those of the grey correlation analysis (GCA) and the principal component analysis (PCA) to test the accuracy of PCGRTOPSIS. It can be seen from figure 1 that the comprehensive evaluation value obtained by PCGRTOPSIS was roughly the same as that obtained by grey correlation analysis (GCA) and principal component analysis (PCA). The figure showed that the comprehensive evaluation curve was more smooth with PCGRTOPSIS. It can be concluded from table 6 that the average relative error of PCGRTOPSIS to GCA and PCA was less than 12% and the maximum error was less than 25%, indicating that this method had certain feasibility.

It can be seen from the curve of figure 1 that the daily transport production quality of Beijing railway bureau had a certain volatility in this month. There were four phases of ascent and four phases of descent. The evaluation value of daily transport production quality on 15th was the lowest, which reduced to 0.35, and the quality was medium. The daily transport production quality evaluation values of no.2 and no.3 were the highest, which were 0.64 and good quality. The overall trend was downward. The quality of daily transport production had four stages of decline, which were 3-6, 9-13, 18-20 and 25-30. In order to analyze the main reasons for the decline trend, we made the following analysis on the car number control quality, loading-unloading quality and car turnover quality. The time series diagram of car number control quality, loading-unloading quality and car turnover quality was shown in figure 2. As can be seen from figure 2, the loading-unloading quality of no.3-6 showed a significant downward trend, and the quality evaluation value decreased by 0.16, with the highest reduction range. Therefore, the main reason for the first decline stage was the reduction of loading-unloading quality. The car number control quality of no. 9-13 showed a significant downward trend, and the quality evaluation value decreased by 0.41, with the highest reduction. Therefore, the main reasons for the second decline stage were the reduction of car number control quality and the imbalance of car structure. The reduction trend of car number control quality and car turnover quality of no. 18-20 was obvious, with the quality evaluation values reduced by 0.26 and 0.15 respectively. Therefore, the main reasons for the third decline stage were car number control quality and car turnover quality reduction. The car number control quality of no. 25 to 30 showed a significant downward trend, and the quality evaluation value decreased by 0.29. Therefore, the main reason for the fourth decline stage was the reduction in car number control quality. The overall car turnover quality was low, which was the main reason for the decline of the general trend of daily transport production quality.

| Maximum Relative Error | Average Relative Error |
|------------------------|------------------------|
| PCA 14%                | 11%                    |
| GCA 23%                | 8%                     |

Figure 1. Comparison of results of different evaluation methods.
6. Discussion and conclusions

The proposed PCGRTOPSIS fully integrates the advantages of PCA, GCA and TOPSIS, and overcome the shortcomings of high dimension, poor information and weight subjectivity. The evaluation index system of the daily transport production quality of the railway bureau is established in combination with the actual situation, which is helpful to understand and evaluate the daily transport production quality of the railway bureau. By evaluating and analysing three aspects that affect the quality of daily transport production, we can get the reasons that cause the decline of daily transport production quality, and provide data reference for the railway administration department to take measures.

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