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USING AN ENTROPY-GRA, TOPSIS, AND PCA METHOD TO EVALUATE THE COMPETITIVENESS OF AFVs – THE CHINA CASE

ABSTRACT

With the increase in severe environmental problems associated with fossil fuel vehicles, the development of Alternative Fuel Vehicles (AFVs) has led to their promotion and use in Chinese provinces and cities. The comprehensive evaluation of competitiveness of the AFV industry in Chinese cities is beneficial to analyse the effects and relationships of different factors to promote the sustainable development of the AFV industry and guide the growth paths of the cities. An industrial competitiveness evaluation index system is established based on the characteristics of AFVs, and the development of the AFV industry in ten typical cities in China is comprehensively evaluated based on the Grey Relative Analysis (GRA) Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) and Principal Component Analysis (PCA) methods. To evaluate the results, the entropy weighting method is used for the weight distribution, and the industrial competitiveness rankings of ten cities are obtained by the entropy-GRA, TOPSIS, PCA (EGTP) method. The results show that Beijing is ranked first, followed by Shanghai, and Qingdao is ranked last. By analysing the correlation between the evaluation methods and indicators, it is found that EGTP has a high correlation with the other three evaluation methods, which proves the rationality of the weighted linear combination of GRA and the other three methods. Indices C_5 (pure electric car proportion) and C_{13} (average concentration of $PM_{2.5}$) were outliers due to the small number of samples.

KEY WORDS

alternative fuel vehicle industry; comprehensive evaluation of competitiveness; entropy weighting method; correlation analysis;

1. INTRODUCTION

With socio-economic development and increases in consumer material consumption, the global car ownership is increasing, and the resulting environmental problems have attracted worldwide attention. Because emissions from the transport sector are growing faster than those from other sectors and are expected to double by 2050, the transport sector is of critical importance in mitigating the climate change [1]. Therefore, clean-energy vehicles must be promoted to reduce these environmental problems. Alternative fuel vehicles (AFVs) have attracted extensive attention since their emergence, due to their reliability, environmental friendliness and pollution-free characteristics.

In China, a survey found that 42% of air pollution comes from the transportation sector, and only 99 of China's 338 cities at or above the prefectural level meet the environmental air quality standards [2]. Because exhaust emissions from traditional automobiles are the primary source of these pollutants, clean AFVs are able to mitigate these environmental problems. In recent years, many cities in China have actively promoted AFVs, hoping to alleviate the environmental and energy problems through the popularization of AFVs. Therefore, studying the development scale, level and industrial competitiveness of AFVs in Chinese urban cities will be conducive to promoting China's economic growth and the essential strategic adjustment of the automobile industry for a country with a population of nearly 1.4 billion and more than 200 million passenger cars.

Many experts and scholars have conducted extensive studies of AFVs, which has helped drive a rapid development of AFVs in recent years. However, most existing studies focus on the environment, policy, consumer behaviour and infrastructure of AFVs but seldom make a comprehensive evaluation of the development within some countries' cities [3-6]. The competitiveness of the AFV industry reflects the development of urban AFVs. In this research area, Ruan and Shi [7] constructed an AFV industry competitiveness evaluation system and used the grey correlation model to conduct empirical research on the three provinces of Guangdong, Fujian, and Hubei. Xie et al. [8] used the new diamond model to evaluate the data related to the development of the AFV industry in typical provinces and cities, concluding that Guangdong's AFV industry has formed a large relevant industry support and technological innovation competitive advantage nationwide. Based on the analytic hierarchy process – fuzzy comprehensive evaluation method, Yan [9] evaluated the competitiveness of Beijing's AFV industry and proposed countermeasures and suggestions accordingly.

The main problems in the above literature are as follows: (1) The research on AFVs mainly focuses on the environment, policy, consumer behaviour and other aspects, lacking relevant research on the development of AFVs in different cities. This paper makes up for this research vacancy. (2) The evaluation methods are relatively singular, and there are no multiple evaluation methods for correlation analysis to make up for the errors between different models. (3) The evaluation method has a significant degree of subjectivity, and there is little research on the weight between evaluation methods.

In summary, there are few studies on the competitiveness of the AFV industry, and most are macro qualitative analyses, while some quantitative evaluation studies are deficient in terms of methods and index selection. Therefore, the aim of this paper is to establish a competitiveness evaluation system of the AFV industry based on relevant guidance documents and use the improved GRA, TOPSIS and PCA methods - EGTP - to comprehensively evaluate the competitiveness of the Chinese urban AFV industry, which can reveal the overall development level of a country at the micro-level and provide policy enlightenment and rules for the development of AFVs in the future.

The rest of the paper is organized as follows. Section 2 establishes an evaluation index system for the competitiveness of the AFV industry with six first-level and 14 second-level indicators and completes the data collection from China. Section 3 introduces three evaluation methods and constructs the EGTP method according to the entropy weighting method. In Section 4, the results of various evaluation methods are analysed, and correlation analysis is carried out to illustrate the application of the proposed approach. Section 5 provides the conclusions.

2. EVALUATION SYSTEM AND DATA ANALYSIS

2.1 Research object

This paper is a comprehensive evaluation of the industrial competitiveness of AFVs in Chinese urban cities. In total, 88 cities in China have been selected for AFV pilot work, and excellent results have been achieved. This paper selects ten typical cities for the exploration and analysis because they cover most of China's provinces and cities with AFV promotion policies, and they are also the most mature cities with the most comprehensive collection of relevant data. Since the economic development in each city is not the same, the popularity of AFVs has varied considerably. Only the development situations in ten cities with relatively mature development histories are comprehensively evaluated in this paper. The ten typical cities and their corresponding identification numbers are shown in *Table 1*.

Beijing, Shanghai, Guangzhou and Shenzhen, which are the four cities with the most influential traditional economies among the selected cities, are also at the forefront of the industrial competitiveness of AFVs in China. Chongqing and Tianjin, which are municipalities directly under the central government, have played an exemplary role in promoting AFVs nationwide. Hangzhou, Changsha and Hefei, which are the famous provincial capitals, and Qingdao, a

Table 1 – The ten studied cities

Number	City
1	Beijing
2	Shanghai
3	Guangzhou
4	Shenzhen
5	Hangzhou
6	Qingdao
7	Changsha
8	Chongqing
9	Tianjin
10	Hefei

city representative of the entire country, have all employed AFVs models. Because the development of AFVs in the above ten cities is relatively mature, by studying the industrial competitiveness in each area, it is possible to better understand and learn from the overall development situation in China.

2.2 Industrial competitiveness indicator system of urban AFVs

In 2014, the China State Council enacted the Guiding Opinions on Accelerating the Promotion and Application of New Energy Vehicles by the State Council of the People's Republic of China (2014, Number 35) [10]. Based on the AFVs industrial development plans of all provinces and cities in China, this guidance puts forward the requirements for accelerating the application of AFVs. It involves the scale, economy, policy and environment indicators of urban AFVs development, which can provide a reference for the construction of the index system in this paper. Additionally, the literature [11] pointed out that the factors restricting the development of urban AFVs include the status of local AFVs, the proportion of allocation, and the policy of purchasing restrictions. In summary, by referencing the literature [10, 11] and based on the scientific, representative and developmental principles of indicator selection, we have constructed a rigorous industrial competitiveness evaluation index system for urban AFVs development, which is divided into six first-level indices (B_1~B_6) and 14 second-level indices (C_1~C_{14}). The above indicators are representative and simultaneously take into account the convenience of data collection, which can comprehensively and systematically reflect the development trends of AFVs in various cities. The specific meaning of the first-level indicators is as follows. Generally, the more significant the benefit-type index, the better the evaluation result. Besides, the smaller the cost-type index, the better the evaluation result.

The scale development (B_1) mainly measures the sales volume, growth rate, ownership and number of significant brand dealers of AFVs in a city, directly reflecting the scale development status and promotion development degree of AFVs in a city. C_1, C_2, C_3 and C_4 are benefit-type indices.

The allocation proportion (B_2) mainly includes the pure electric car proportion and individual proportion. The former is the most significant and most representative proportion of AFVs in the local market, and the latter is the difference in the promotion of AFVs between individuals and units. The index can reflect the different allocation proportions of AFVs among cities and different development levels. The literature [10] proposes that pure electric driving is the primary strategic orientation for the development of new energy vehicles. Therefore, this paper considers that pure electric vehicles are the mainstream for AFVs, with better energy-saving effects and lower costs. A more significant proportion of pure electric cars reflects a higher degree of urban AFV development. At the same time, the greater the individual proportion, the higher the AFV penetration rate of urban residents, so C_5 and C_6 are benefit-type indices.

The popularization of AFVs is generally associated with the development level of local cities, including the total car ownership, economic strength and total urban population. Thus, a city's development strength (B_3) reflects the level of automobile development, along with the economic index and population size of a city. C_7, C_8 and C_9 are benefit-type indices.

The development of AFVs in various cities is closely related to the infrastructure construction (B_4), such as charging piles and public charging facilities, which are required for the growth of AFVs. C_{10} is a benefit-type index.

The local government's policy support (B_5) is essential for AFVs, including subsidies for AFVs and license limits. The earlier the start time of the license limit, the larger will be the scale of urban car ownership. Additionally, the higher the demand for AFVs, the more rapid will be the development of AFVs. C_{11} is a benefit-type index, while C_{12} is a cost-type index.

Table 2 – Industrial competitiveness evaluation system for urban AFVs in China

The first-level index		The second-level index		Index type	Remarks
B_1	Scale development	C_1	Sales volume of AFVs	Benefit	
		C_2	Sales growth rate [%]	Benefit	
		C_3	Ownership of AFVs (10^4 vehicles)	Benefit	
		C_4	Number of significant brand dealers	Benefit	The number of local dealers of BAIC BJEV, BYD, SAIC Motor and other brands with the highest sales volumes in the Chinese AFVs market
B_2	Allocation proportion	C_5	Pure electric cars proportion [%]	Benefit	Refers to the percentage of sales of pure electric vehicles relative to the total sales of AFVs
		C_6	Individual proportion [%]	Benefit	Refers to the percentage of sales in which AFVs are used by individuals
B_3	City development strength	C_7	Total car ownership (10^4 vehicles)	Benefit	
		C_8	City's GDP (One hundred million yuan)	Benefit	
		C_9	Urban population (10^4 people)	Benefit	
B_4	Infrastructure construction	C_{10}	Number of public charging facilities	Benefit	Such as charging piles, charging stations, etc.
B_5	Policy support	C_{11}	Average subsidy index [yuan/km]	Benefit	
		C_{12}	The starting year for a restricted city [year]	Cost	If not available, mark as "2019"
B_6	Environmental impact	C_{13}	The average concentration of $PM_{2.5}$ [MCG/m^3]	Cost	The annual average concentration of $PM_{2.5}$
		C_{14}	Concentration change [%]	Cost	A decrease is negative, and an increase is positive

The environmental impact (B_6) is the environmental quality level of local cities, and the average concentration of $PM_{2.5}$ is taken as the corresponding evaluation index. Moreover, changes in pollutant concentrations can be regarded as effects of AFV promotion on the environment. C_{13} and C_{14} are cost-type indices.

In summary, a comprehensive evaluation system is established, as shown in *Table 2*.

2.3 Raw data collection and analysis

With the help of the Economic and Information Commission (EIC), we have collected the specific data in 2018 from the indicator system constructed in this paper as the input for the AFV industrial competitiveness evaluation. The raw data are listed in *Table 3*.

In summary, the development levels of AFVs in No. 1 (Beijing), No. 2 (Shanghai), No. 4 (Shenzhen) and No. 9 (Tianjin) were among the highest in China. Most cities are in the growth stage, with an average sales growth rate of 33.71%. Qingdao, which is the only city with a negative growth rate, may be influenced by the government subsidy policy change in 2018. Beijing and Shanghai, which are the two cities with the largest numbers of AFVs, observed a decrease in the average $PM_{2.5}$ concentration compared to those in previous years, partly due to the extensive promotion of AFVs.

3. METHODS

Through investigation and data collection, the industrial competitiveness of AFVs in typical Chinese urban cities was comprehensively evaluated. The original evaluation matrix collected was analysed using the GRA, TOPSIS and PCA methods, and the final sequencing result was obtained using the EGTP method.

Table 3 – Raw data

Number	1	2	3	4	5	6	7	8	9	10
City	Beijing	Shanghai	Guangzhou	Shenzhen	Hangzhou	Qingdao	Changsha	Chongqing	Tianjin	Hefei
C_1	66,756	61,354	22,133	40,029	26,303	15,537	15,418	18,285	42,112	22,396
C_2	0.57	35	26.52	37.88	42.17	-69.07	52.1	76.79	71	64.14
C_3	17.1	16.5	4.0	11.1	2.0	5.4	5.0	2.7	8.9	2.4
C_4	54	64	26	40	21	22	12	21	34	13
C_5	98.6	23.8	82	46.6	68.6	97.4	95.7	95.8	82.4	99.3
C_6	88.4	73.1	30.8	80.2	48.7	23.4	26.8	66.9	62.4	79.1
C_7	564	359	240	322	244	246	217	371	287	169
C_8	28,000	30,133	21,500	22,286	12,556	11,258	10,200	19,530	18,595	7,191
C_9	2,171	2,418	1,404	1,090	919	871	765	3,372	1,547	937
C_{10}	30,363	25,707	10,000	19,686	4,014	12,000	8,472	4,949	9,788	17,000
C_{11}	700	685	685	700	700	467	560	687	700	467
C_{12}	2,010	1,994	2,012	2,014	2,014	2,019	2,019	2,019	2,013	2,019
C_{13}	57.1	39.3	35.4	28.5	43.9	38.4	53.1	44.4	63.8	56.5
C_{14}	-20.8	-13.7	1.0	5.5	-6.5	-14.3	-0.4	-16.3	-9.5	-0.9

Note: Some of the data are from the China Automobile Industry Development Report [16] and China Traffic Yearbook [17].

3.1 GRA method

The GRA model is used as an evaluation tool to measure the degree of similarity or dissimilarity among the development trends of different factors [12]. This approach comprehensively evaluates a multi-index problem. The specific steps are as follows:

Step 1: Determine the evaluation objects and evaluation criteria. Let there be m evaluation objects and n evaluation indices. The original data are standardized. The sequence of the best index values in each index is called the reference sequence, and the remaining values form the comparison sequence. The reference number column is $x_0=\{x_0(k)|k=1,2,...n\}$, and that of the comparison sequence is $x_i=\{x_i(k)|k=1,2,...n\}$, $i=1,2,...,m$.

Step 2: Determine the corresponding weight of each index value. The corresponding weights $w=[w_1,w_2,...,w_n]$ are given by the method of expert analysis.

Step 3: Calculate the grey correlation coefficient:

$$\lambda_i(k)=\frac{\min_s \min_t\{x_0(t)-x_s(t)\}+\rho\max_s \max_t\{x_0(t)-x_s(t)\}}{[x_0(k)-x_i(k)]+\rho\max_s \max_t\{x_0(t)-x_s(t)\}} \quad (1)$$

where $\lambda_i(k)$ is a correlation coefficient between x_i and x_0 for index k; $t=1, 2,\dots, n$; $s=1, 2,\dots, m$; and ρ ($0<\rho<1$) is a coefficient that is generally set to 0.5.

Step 4: Calculate the grey-weighted relational degree:

$$r_i=\sum_{k=1}^{n} w_i\lambda_i(k) \quad (2)$$

where r_i is the grey-weighted correlation degree of the i-th evaluation object.

Step 5: According to the evaluation analysis of the grey-weighted correlation degree, the evaluation result is denoted by $y_1=[y_{11}, y_{12},..., y_{1n}]$.

3.2 TOPSIS method

TOPSIS is an effective multi-index evaluation method that involves the construction of positive and negative ideal solutions to an evaluation problem. These solutions represent the optimal solution and the worst solution for each index. The relative closeness of each scheme to the ideal scheme is calculated to sort the schemes and select the optimal one [13]. The specific steps in this approach are as follows:

Step 1: Obtain the canonical decision matrix by vector programming. We establish the index matrix $\boldsymbol{A}=(a_{ij})_{m\times n}$ of the original problem and the normalized matrix $\boldsymbol{B}=(b_{ij})_{m\times n}$, where

$$b_{ij} = \frac{a_{ij}}{\sqrt{\sum_{p=1}^{m} a_{pj}^2}} \tag{3}$$

Step 2: Establish the weighted norm matrix $\mathbf{C}=(c_{ij})_{m\times n}$. The weight vector $w=[w_1,w_2,...,w_n]$ is given by the decision maker to obtain the following equation.

$$c_{ij} = w_j \cdot b_{ij} \tag{4}$$

Step 3: Calculate the positive ideal solution C^* and negative ideal solution C^0.

$$c_j^* = \begin{cases} \max\limits_i c_{ij}, \ j \text{ is an efficiency indicator} \\ \min\limits_i c_{ij}, \ j \text{ is a cost - type indicator} \end{cases} \quad j = 1,2,\dots,n \tag{5}$$

$$c_j^0 = \begin{cases} \max\limits_i c_{ij}, \ j \text{ is a cost - type indicator} \\ \min\limits_i c_{ij}, \ j \text{ is an efficiency indicator} \end{cases} \quad j = 1,2,\dots,n \tag{6}$$

Step 4: Calculate the distances s_i^* and s_i^0 of each scheme from the positive and negative ideal solutions.

$$s_i^* = \sqrt{\sum_{j=1}^{n} (c_{ij} - c_j^*)^2}, \ i = 1,2,\dots,m \tag{7}$$

$$s_i^0 = \sqrt{\sum_{j=1}^{n} (c_{ij} - c_j^0)^2}, \ i = 1,2,\dots,m \tag{8}$$

Step 5: Calculate the comprehensive evaluation index of each scheme as follows.

$$f_i^* = \frac{s_i^0}{s_i^0 + s_i^*} \tag{9}$$

Step 6: Arrange the values of f_i^* from the largest to the smallest, and determine the order of the solution. The evaluation result is denoted by $y_2=[y_{21},y_{22},...,y_{2n}]$.

3.3 PCA method

PCA uses the concept of dimensionality reduction to convert multiple indices into a few comprehensive indices, and each principal component reflects a large portion of the information associated with the original variable [14]. This method not only eliminates many variables but also reduces various complex factors into several principal components to effectively obtain relevant information in a simplified manner. The specific steps in this process are as follows:

Step 1: Standardize the original data and record them as $\boldsymbol{X}_{(1)}=(x_{ij})_{m\times n}$;

Step 2: Calculate the correlation coefficient matrix $\boldsymbol{R}=(r_{ij})_{m\times n}$.

$$r_{ij} = Cov(x_i,x_j) = \frac{\sum_{p=1}^{n} (x_{ip} - \bar{x}_i)(x_{jp} - \bar{x}_j)}{n - 1} \tag{10}$$

Step 3: Compute the eigenvalues λ_i (i=1, 2,…, n) and feature vectors $\xi_i=[\varphi_1,\varphi_2,...\varphi_m]$;

Step 4: Select k ($k\leq5$) principal components. Calculate the overall evaluation value, and the evaluation result is denoted by $y_3=[y_{31},y_{32},...,y_{3n}]$.

3.4 EGTP method

Based on the GRA, TOPSIS and PCA methods, the EGTP method uses the entropy method to weight the above three evaluation methods and obtain the final evaluation results. This approach reduces the errors among different evaluation models. The entropy method is an objective weighting method that uses the real relationships among data to determine the relevant weights, thereby avoiding the subjectivity and arbitrariness of subjective weighting [15]. The steps in this process are as follows:

Step 1: The results obtained by the three evaluation methods form the set $\boldsymbol{Y}=[y_1, y_2, y_3]$, and $\boldsymbol{X}_{(2)}=(x_{ij})_{\mathrm{m}\times\mathrm{n}}$ is the input vector of the entropy weighting method after standardization;

Step 2: Index translation processing is conducted. There are some negative numbers in the standardized data, and data translation processing sets the maximum negative number to a value greater than 0 after the standardization process (for ease of calculation, we set the minimum precision to 0.001). The smaller the translation value, the smaller will be the effect on the result. We let the data after translation processing be y_{ij}, and if A_j is the absolute value of the minimum of x_{ij}, then the calculation formula of y_{ij} is as follows:

$$y_{ij} = A_j + x_{ij} + 0.001 \tag{11}$$

Step 3: Ratio p_{ij} associated with x_{ij} in this index is calculated using the translated data.

$$p_{ij} = \frac{y_{ij}}{\sum_{p=1}^{m} y_{pj}} \tag{12}$$

Step 4: The entropy value of index j is calculated as follows:

$$E_j = -k\sum_{i=1}^{m} p_{ij} \cdot (\ln p_{ij}) \tag{13}$$

At this time, this index does not provide any information. When p_{ij}=0, let $p_{ij} \cdot (\ln p_{ij})$=0 to ensure that $E_j\in[0,1]$.

Step 5: The weight of index j is calculated.

$$w_j = \frac{1 - E_j}{\sum_{k=1}^{n} (1 - E_k)} \tag{14}$$

To more intuitively reflect the differences among methods, the results are obtained by combining the GRA, TOPSIS and PCA models, and their weights are determined by the entropy weighting method. Then, the final evaluation results are obtained by EGTP as a linear combination of the GRA, TOPSIS and PCA methods.

4. RESULTS AND DISCUSSION

4.1 Solutions based on various evaluation methods

By using MATLAB programming calculations, the evaluation values of the various methods were calculated in *Table 4*.

The EGTP method uses the entropy weighting method to distribute the weights of the results of the first three evaluation methods. After the three sets of results were standardized and combined, the weights were determined. The results are listed in *Table 5*.

The weights of the three evaluation methods, as determined by the entropy weighting method, were 0.335, 0.29, and 0.375. In summary, the industrial competitiveness rankings of AFVs in the Chinese cities are shown in *Table 6*. Moreover, the variation trends of the results of the four evaluation methods are shown in *Figure 1*. It can be seen that the four evaluation results are highly consistent.

The presented results indicate that the industrial competitiveness levels of AFVs in Beijing and Shanghai are the highest in the country. The sales volume, vehicle ownership level, policies, economy and other factors considered in the index system

Table 4 – Calculation results of each evaluation method

Number	City	GRA	TOPSIS	PCA
1	Beijing	0.861	0.819	2.434
2	Shanghai	0.770	0.771	2.137
3	Guangzhou	0.493	0.314	-0.776
4	Shenzhen	0.582	0.434	0.478
5	Hangzhou	0.478	0.341	-0.827
6	Qingdao	0.437	0.39	-1.675
7	Changsha	0.42	0.296	-1.46
8	Chongqing	0.583	0.497	0.184
9	Tianjin	0.552	0.515	0.472
10	Hefei	0.445	0.346	-0.968

Table 5 – Weight calculation table

Number	City	GRA	TOPSIS	PCA
1	Beijing	1.000	1.000	1.000
2	Shanghai	0.794	0.908	0.928
3	Guangzhou	0.166	0.034	0.219
4	Shenzhen	0.367	0.264	0.524
5	Hangzhou	0.132	0.086	0.206
6	Qingdao	0.039	0.180	0.001
7	Changsha	0.001	0.001	0.052
8	Chongqing	0.370	0.384	0.452
9	Tianjin	0.299	0.419	0.523
10	Hefei	0.057	0.096	0.172
Sum		3.22	3.37	4.08
Entropy		1.544	1.470	1.608
Discrimination		-0.544	-0.470	-0.608
Weight		0.335	0.290	0.375

Table 6 – The final ranking of each city

Number	City	EGTP	Ranking
1	Beijing	1.439	1
2	Shanghai	1.283	2
9	Tianjin	0.511	3
4	Shenzhen	0.5	4
8	Chongqing	0.408	5
3	Guangzhou	-0.035	6
5	Hangzhou	-0.051	7
10	Hefei	-0.114	8
7	Changsha	-0.321	9
6	Qingdao	-0.369	10

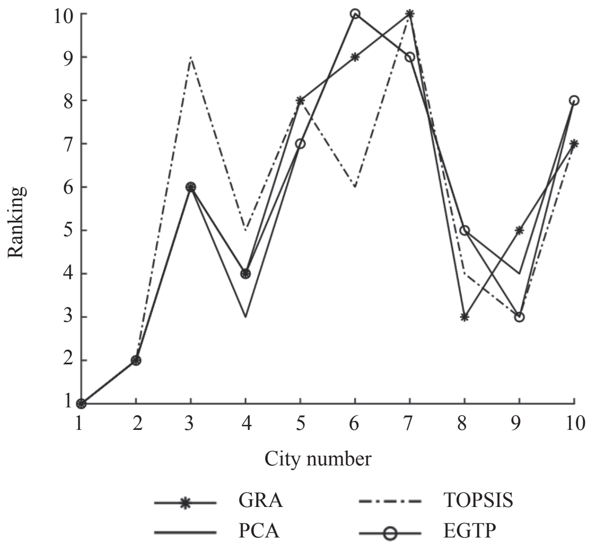

Figure 1 – Results of the four the methods

provide favourable conditions for the industrial competitiveness of AFVs. The evaluation results indicate that the license plate and driving restriction policies, i.e. new energy license plates and car purchase subsidies, were the main reasons for the differences in AFVs industrial competitiveness among cities. In contrast, the industrial competitiveness degree of AFVs in Changsha and Qingdao was relatively low, especially in Qingdao, where the sales volume in the first two years was high due to supportive policies, after which a reduction in the subsidy policy led to a stagnant development.

4.2 Correlation between different evaluation methods

The scatter distributions of the sorting results of the four evaluation methods obtained by MATLAB are shown in *Figure 2*.

It can be seen that the four evaluation results have a strong correlation. The last row is the scatter distribution between the EGTP method proposed in this paper and the results of the traditional GRA, TOPSIS and PCA methods. The strong linear correlation shows that the entropy method is reliable. At the same time, the correlation between the other three methods is also high, which indicates the rationality of the combination of multiple evaluation methods. The correlation coefficients between the methods were calculated, as shown in *Table 7*.

Most methods are highly correlated with each other, and only the correlation coefficient between TOPSIS and PCA is less than 0.8. Most correlation coefficients are above 0.8, which shows that most combinations are reasonable and that each evaluation result is highly correlated. The entropy weight method can be used for linear combination. At the same time, it should be noted that the ranking results obtained by TOPSIS are somewhat different from the other three results, which also explains the significance of the entropy weighting method in the weighting of the methods, as TOPSIS is given the lowest weight (0.29). Although the GRA, TOPSIS, and PCA methods are similar in overall ranking, it is impossible to achieve the same evaluation results. Due to the difference in calculation formulas, a certain degree of deviation is generated. Therefore, the entropy weight method is used to combine them, and lower weight is given to the method with larger bias.

4.3 Correlation between indices and ranking results

The original values of the 14 indicators in ten cities were correlated with the sorted result values obtained by the EGTP evaluation method, and the scatter plot distributions are shown in *Figure 3*.

Table 7 – Correlation coefficients between different evaluation methods

	GRA	TOPSIS	PCA	EGTP
GRA	1	0.855	0.939	0.927
TOPSIS	0.855	1	0.794	0.818
PCA	0.939	0.794	1	0.988
EGTP	0.927	0.818	0.988	1

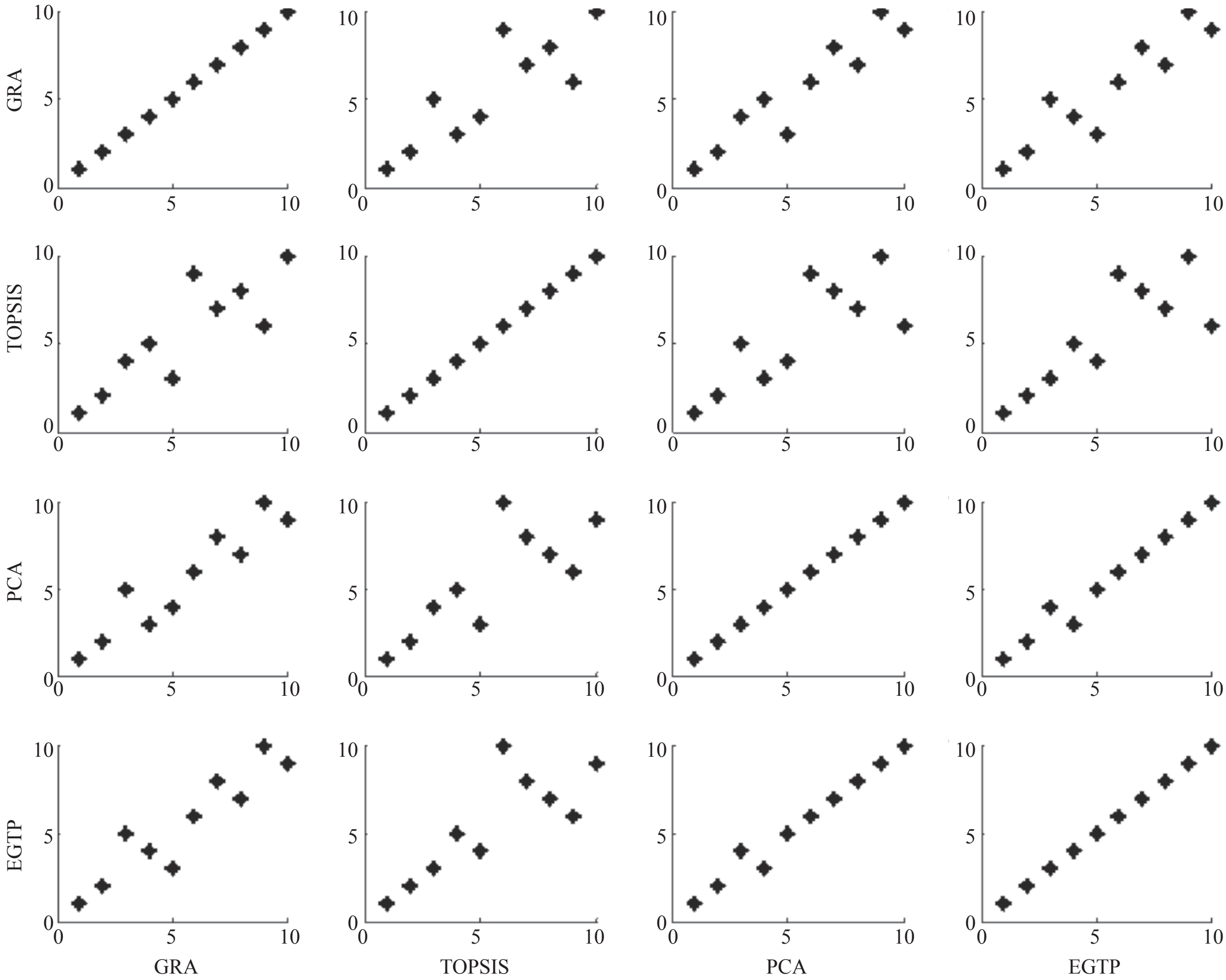

Figure 2 – The scatter distributions among the four evaluation results

Some indices had little impact on the final results, such as C_2, C_{13} and C_{14}, indicating a low degree of correlation between these indicators. Most of the other indicators have a good linear relationship with the final EGTP results, demonstrating that these indicators had a significant impact on the evaluation results, and the rationality of evaluating these indicators with the EGTP method has thus been verified. The correlation coefficients of the EGTP sequencing results were calculated as shown in *Table 8*.

We have observed an interesting phenomenon in that the correlation coefficients of some indicators for the ranking results are contrary to the index types shown. In general, the larger the value of a benefit-type index, the more favourable will be the evaluation result, and the ranking result should be smaller. Therefore, a benefit-type index shows a negative correlation with the ranking results, while a cost-type index shows a positive correlation. However, according to the correlation calculation, index C_5 (pure electric car proportion) is different from

Table 8 – Correlation coefficients of 14 indices for the EGTP sequencing results

Index	Correlation coefficient	Index type
C_1	-0.896	Benefit
C_2	-0.249	Benefit
C_3	-0.789	Benefit
C_4	-0.857	Benefit
C_5	0.45	Benefit
C_6	-0.731	Benefit
C_7	-0.789	Benefit
C_8	-0.893	Benefit
C_9	-0.62	Benefit
C_{10}	-0.609	Benefit
C_{11}	-0.774	Benefit
C_{12}	0.676	Cost
C_{13}	-0.116	Cost
C_{14}	0.372	Cost

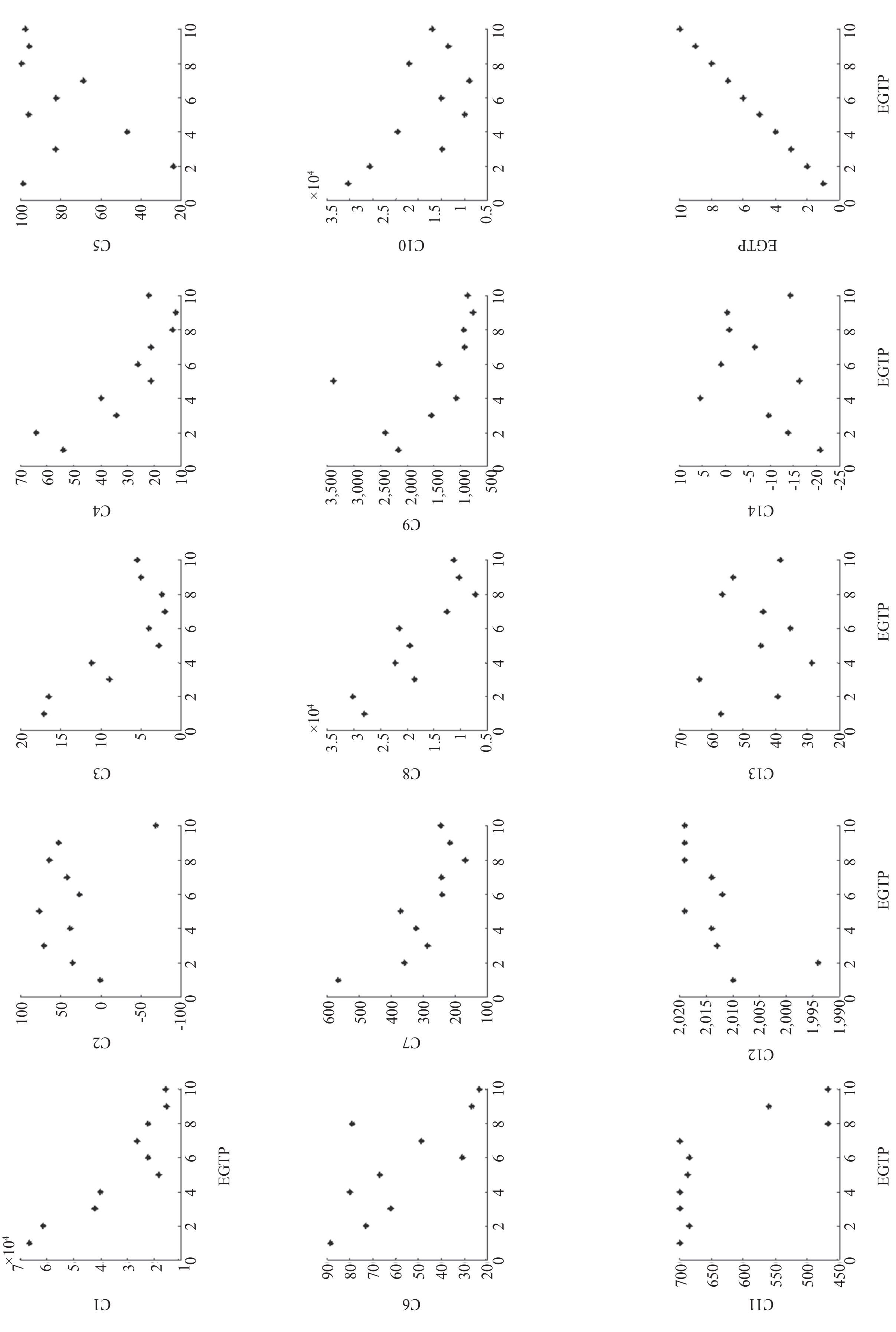

Figure 3 – Scatter distributions of different indices and EGTP results

the other efficiency models, showing a positive correlation with the ranking. Index C_{13} (average concentration of $PM_{2.5}$) is also different from other cost indicators, but its impact on the final evaluation value is negatively correlated. This result goes against common sense.

This result was due to the data sample being too few (there are only ten sets of indices, and the evaluation matrix is 10×14). Some cities have an outlier bias, such as Changsha, Qingdao, Hefei and other cities ranked lower in terms of the overall industrial competitiveness level, but their pure electric car proportion indices are ranked first. The overall industrial competitiveness levels of Beijing and Tianjin are at the top, but their average concentrations of $PM_{2.5}$ are at the bottom, which has a misleading influence on the final result. In the correlation analysis of the indices and results, these outliers lead to deviation of the results, producing irregular phenomena.

This provides a direction for our future improvement, including screening outliers or expanding the sample size to evaluate better and show the actual industrial competitiveness level of each city AFVs. As the sample size increases, the outliers will decrease.

5. CONCLUSION

This paper proposes an evaluation method for the industrial competitiveness of urban AFVs based on the entropy-GRA, TOPSIS, and PCA methods. The following conclusions were drawn from the study:

1) For this case, the weights of the three evaluation methods (GRA, TOPSIS and PCA) obtained by the entropy weight method were 0.335, 0.29 and 0.375, respectively, among which the reference value of TOPSIS was the lowest;
2) The EGTP evaluation results indicate that the industrial competitiveness levels of AFVs in various cities in China are currently unbalanced and uncoordinated. Beijing, Shanghai, Tianjin and other cities have experienced rapid AFV development due to favourable political and economic conditions. However, the development in Changsha, Qingdao and other cities is relatively slow, especially in Qingdao, where changes to beneficial policies have hindered the production and sale of AFVs;
3) The correlation analysis of the evaluation results shows that GRA, TOPSIS, PCA and EGTP are highly correlated, which confirms the rationality of using EGTP for the weighted linear combination of the three methods. At the same time, the correlation coefficients of the ranking results of indices C_5 and C_{13} are opposite of their intuitive natures. This result was due to the data sample being too small, and some outliers led to biasing of the results; however, this problem can be mitigated by expanding the sample size of the evaluation cities.

The limitation of this paper is that there are some deficiencies in the established indicator system. For example, the indicator system lacks resident satisfaction indicators. The citizens' degree of support for AFVs should be collected, and a questionnaire survey should be conducted appropriately. We believe that the satisfaction of the public will also promote the vigorous development of the AFV industry. Future research can further expand the evaluation system, and some indices that are not easy to be inductively calculated should also be taken into account, such as indicators of resident satisfaction, AFVs pulling index to the economy, and indicators for the upstream and downstream services of the AFV industry. The evaluation system should be applied to assess AFV industrial competitiveness in different countries and regions with the continuous advancement of global integration. The evaluation results are used to guide the countries around the world to promote the development of the AFV industry in order to achieve the purpose of saving natural resources.

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使用熵权—*GRA*，*TOPSIS*，*PC*A方法评估可替代燃料汽车的竞争力—以中国为例

摘要

随着可替代燃料汽车技术的迅速发展和环保问题的日渐严峻，中国各省市越来越重视对新能源汽车的推广和应用。对中国各城市可替代燃料汽车产业发展进行竞争力评价，有利于分析不同因素产生的效果及它们之间的关系，从而推动产业可持续发展，指导各城市的发展路径。首先根据新能源汽车的特征，建立产业竞争力评价指标体系，依次采用灰色关联分析法（*GRA*）、理想解法（*TOPSIS*）、主成分分析法（*PCA*）等多种评价方法对中国*10*个典型城市的新能源汽车产业发展进行综合评价，对于评价结果运用熵权法进行权重分配，最终得到*10*个城市的产业竞争排名：北京第一，上海次之，发展状况最差的是青岛。对评价方法间和指标间的相关性进行分析，得到*EGTP*法对于其他三种评价方法具有较高的相关性，证明了对*GRA*等三种方法加权线性组合的合理性。同时指标C_5（纯电动汽车比例）和指标C_{13}（$PM_{2.5}$平均浓度）由于样本数过少出现了离群现象。

关键词

可替代燃料汽车产业；竞争力综合评价；熵权法；相关性分析

REFERENCES

[1] Creutzig F, Jochem P, Edelenbosch OY, Mattauch L, van Vuuren DP, McCollum D, Minx J. Transport: A roadblock to climate change mitigation? *Science.* 2015;350: 911-912.

[2] Ministry of Ecology and Environment of the People's Republic of China. *2017 China Ecological Environment Status Bulletin Background Material*; 2018. Available from: http://www.mee.gov.cn/gkml/sthjbgw/qt/201805/t20180531_442212.htm

[3] Sengupta S, Cohan DS . Fuel cycle emissions and life cycle costs of alternative fuel vehicle policy options for the City of Houston municipal fleet. *Transportation Research Part D: Transport and Environment.* 2017;54: 160-171.

[4] Hackbarth A, Madlener R. Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment*. 2013;25: 5-17.

[5] Jenn A, Azevedo I, Michalek J. Alternative-fuel-vehicle policy interactions increase U.S. greenhouse gas emissions. *Transportation Research Part A: Policy and Practice*. 2019;124: 396-407.

[6] Zhang Y, Qi D, Jiang W, et al. Optimal allocation of changing station for electric vehicle based on queuing theory. *Promet – Traffic&Transportation*. 2016;28(5): 497-505.

[7] Ruan X-J, Shi R-L. Study on the evaluation of competitiveness of new energy automobile industry based on grey correlation model. *Mathematics in Practice and Theory*. 2016; 46(21):72-79.

[8] Xie W-H, Zeng D-C. Empirical study on competitiveness evaluation of new energy automobile industry in Guangdong province based on the new diamond model. *Science and Technology Management Research.* 2019;9: 56-61.

[9] Yan S-G. Assessment of Beijing's new energy industry based on AHP-FCE comprehensive evaluation. *Science and Technology Management Research*. 2017;7: 93-97.

[10] The State Council of the People's Republic of China. *Guiding Opinions on Accelerating the Promotion and Application of New Energy Vehicles by the State Council of the People's Republic of China*; 2014. Available from: http://www.gov.cn/zhengce/content/2014-07/21/content_8936.htm

[11] Tang B-J, Wang X-Y, Wei Y-M et al. *Analysis and Prospect of China's New Energy Automobile Industry Development Level.* Beijing Institute of Technology Energy and Environmental Policy Research Center; 2019. Available from: http://ceep.bit.edu.cn/docs/2019-01/20190114103247617774.pdf

[12] Chan J, Tong T. Multi-criteria material selections and end-of-life product strategy: Grey relational analysis approach. *Materials & Design*. 2007;28(5): 1539-1546.

[13] Kuo T. A modified TOPSIS with a different ranking index. *European Journal of Operational Research.* 2016;260(1): 152-160.

[14] Abdi H, Williams LJ, Valentin D. Multiple factor analysis: principal component analysis for multitable and multiblock data sets. *Wiley Interdisciplinary Reviews: Computational Statistics*. 2013;5(2): 149-179.

[15] Wang Q, Wu C, Sun Y. Evaluating corporate social responsibility of airlines using entropy weight and grey relation analysis. *Journal of Air Transport Management*. 2015;42: 55-62.

[16] Industrial Economy Research Department of Development Research Center of the State Council. *China automobile industry development report*. Beijing: Social Sciences Academic Press; 2018.

[17] China Traffic Yearbook Editorial Committee. *China traffic yearbook*. Beijing: Yearbook of China Transportation & Communication; 2018.