Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 4006967, 10 pages
https://doi.org/10.1155/2022/4006967

Research Article

Optimization of Regional Industrial Structure Based on Multiobjective Optimization and Fuzzy Set

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Received 13 April 2022; Revised 2 June 2022; Accepted 4 June 2022; Published 24 June 2022

Academic Editor: Zaoli Yang

With the development of China's economy, it is required to change the mode of economic growth, from extensive growth mode to intensive growth mode. Therefore, the research on industrial structure is of great significance. This study proposes a regional industrial structure optimization method based on multiobjective optimization and fuzzy set. Firstly, the multiobjective industrial structure evaluation model is constructed, then the evaluation model based on improved fuzzy industrial structure is proposed, and finally the application effect of improved fuzzy industrial structure evaluation model is analyzed. The results show that the first generation iteration speed of the improved fuzzy industrial structure evaluation model is fast, but it is slow in the second to eighth iterations. Compared with the traditional square method, the convergence of the fuzzy structure is improved to a certain extent. The improved evaluation model has also been improved. This is better than other algorithms. Using *K*-means and Manhattan distance to initialize the clustering method, the results are relatively stable. In terms of running time, Manhattan distance initialization method and *K*-means clustering method have less iterations and short time-consuming. Therefore, when the data sample is large, the application of K-means clustering algorithm will be more effective.

1. Introduction

With the 30 years of reform and opening up in China, great changes have taken place in the economic outlook and the people's living standards have been continuously improved (Tian et al. 2022) [1]. Although some regions took the lead in getting rich, some underdeveloped regions still have relatively backward economic development (Rezaei et al. 2020) [2]. Therefore, optimizing the industrial structure of such underdeveloped areas plays an important role in promoting their economic development [3]. In this study, taking HZ city as an example, its economic development is relatively backward in the whole region, and its GDP ranks the second from the bottom in the province all the year round, becoming the weakness of economic development in the region (Yang et al. 2020) [4]. Therefore, optimizing the industrial structure of Hz has become an important factor affecting the overall coordinated development of the region. However, there are many enterprises with high pollution and energy consumption in Hz city, so that the ecological environment of the city has been seriously damaged. Many problems force the city to adjust its industrial structure [5]. Therefore, this study aims to put forward countermeasures and suggestions for the optimization and upgrading of relevant industrial structure in HZ city.

The establishment of economic model needs certain economic theory as the basis and based on specific research purposes. The establishment of industrial structure optimization model should also be based on the limitation of optimization objectives. With different objectives, the establishment of optimization model and optimization results must be different. Theoretically, there are many optimization objectives or standards that can be used as industrial structure, but from the perspective of the operability of the optimization model, the objectives should be simplified as much as possible. It is generally believed that the ultimate goal of industrial structure optimization is to realize the rapid, sustainable, and healthy operation of macroeconomy.

Therefore, the goal of industrial structure optimization should be consistent with the goal of macroeconomic regulation.

This study innovatively applies the multiobjective optimization and fuzzy set method to the optimization of regional industrial structure, which provides a reference for the selection of industrial optimization direction. In addition, the fuzzy set method is integrated into the analytic hierarchy process, the Gaussian mixture model (GMM) of the maximum expected value (EM) algorithm is introduced, and the EM-GMM algorithm is used to optimize the fuzzy industrial structure evaluation model.

The research content mainly includes four parts. The second part summarizes the research status of multiobjective optimization and fuzzy set methods at home and abroad. The third part puts forward the optimization method of regional industrial structure based on multiobjective optimization and fuzzy set. The first section establishes the multiobjective industrial structure evaluation model, and the second section constructs the evaluation model of regional industrial structure based on improved fuzzy set. The fourth part verifies the application effect of the improved fuzzy industrial structure evaluation model. The results show that the regional industrial structure optimization method and fuzzy set have good application effect.

2. Related Work

In recent years, the research based on multiobjective optimization and fuzzy set has been highly valued by many relevant professionals, and researchers at home and abroad have also conducted in-depth research on this technology. Saborido et al. proposed a mutation, crossover, and repair operator for multiobjective optimization. This method is mainly to solve the problem of generating cardinality constrained MDRS, combined the operator with evolutionary algorithms NSGA-II, MOEA/D, and GWASF-GA, and analyzed the performance of the algorithm on the data set of Spanish stock market [6]. Sleepongsom and Bureerat proposed a reliability based multiobjective structural topology optimization method. The results show that the proposed technology is effective and simple compared with previous technologies (Sleepongsom and Bureerat 2020) [7]. Ebenuwa et al. proposed a fuzzy based uncertainty modeling method, which uses the optimality energy of hybrid GA-GAM to analyze buried pipelines. An example is given to illustrate the applicability and characteristics of the method. The results provide an acceptable analysis tool for design engineers and can be applied to the analysis of other engineering structures (Ebenuwa et al. 2021) [8]. Li et al. proposed a multiobjective unit commitment model based on value at risk. The model achieves a sufficient balance between performance optimality and robustness and has good convergence ability [9]. Charles et al. carried out linear programming for the sample problem in sampling design, solved the allocation problem in function, and developed the geometric allocation problem based on the mathematical algorithm (Charles et al. 2019) [10].

Chang et al. proposed a new multiobjective leading continuous FLS, in addition to defining the objective function for evaluating the control performance of FLS. Finally, the optimization performance of MO-FCACO is verified by comparing with various optimization algorithms based on multiobjective population [11]. He and Xiong solved the problem of large-scale power system with lion ant colony algorithm. The multiobjective ORPD problem is solved by optimizing the high-efficiency model of power operation. At the same time, compared with the traditional multiobjective algorithm, its effectiveness is improved (He and Xiong 2019) [12]. He and Xiong designed a set of optimization theory for urban rail transit. The theory designs a multiobjective control model based on the change of urban rail environment. It ensures the accuracy of the control strategy and the robustness of the control system and meets the target requirements of multiobjective train operation (He and Xiong 2018) [13]. Li et al. discussed the multiobjective dynamic portfolio optimization model of investment. The model designs the multicomponent optimal solution for investors through evolutionary algorithm. The experimental results show that, through this algorithm, the inconsistent model time between investors is optimized, and the algorithm can solve complex nonlinear problems (Li et al. 2020) [14]. Zhao et al. proposed a multiobjective evolutionary intuitionistic fuzzy clustering algorithm (MOEIFC-MSI) with multi-image spatial information for image segmentation. The results show that this method is superior to other methods in noise robustness and segmentation performance (Zhao et al. 2018) [15].

Through the research on multiobjective optimization and fuzzy set method by scholars at home and abroad, this study mainly discusses the optimization of regional industrial structure for the optimization of multiobjective optimization and fuzzy set method.

3. Optimization Method of Regional Industrial Structure

3.1. Multiobjective Industrial Structure Evaluation Model. As far as its application in the national economy is concerned, the main content of the input-output method is to compile the checkerboard input-output table and establish the corresponding linear algebraic equation system. Because this type of industrial structure optimization model is based on the combination of input-output and linear programming, it is also called linear programming model based on input-output method. The research on the modeling of industrial structure optimization by using game theory mainly focuses on the following two aspects: the first is the research on the structure optimization among enterprises in a single industry. For key participants, i.e., those with higher competitiveness index in the alliance, they have stronger voice and decision-making power, so they have the right to obtain more benefit distribution. When constructing the evaluation model of industrial structure, we should evaluate and compare and analyze the similarity and benefit ratio mainly analyzes the coordination ability among industries through grey correlation method and then evaluates the rationalization of industrial structure [16]. If the gross national product and gross industrial output value of a region are

$$X(i) = \{X(i)(1), X(i)(2), \ldots, X(i)(k)\}, \tag{1}$$

where $i = 0,1, \ldots, m$. k indicates the year, then average the data, calculate the average value $X(i)$ of the initial sequence, and divide the original data by the new data $y(i)$. Calculate the grey correlation coefficient through equation (2), $\xi(Xi)$, the resolution coefficient is expressed as ρ. The value is 0.5; △min and △max represent the minimum difference and maximum difference of the second stage, respectively, as shown in formula

$$\xi_{\mathrm{oi}} = \frac{\Delta(\min) + \rho\Delta(\max)}{\Delta_{\mathrm{oi}}(k) + \rho\Delta(\max)}. \tag{2}$$

Among them, ρ's main function of is to improve the significance of the difference between$\xi(Xi)$, which is usually taken as 0.5. Then calculate the grey correlation degree, as shown in formula

$$r_i = \frac{1}{N}\sum_{k=1}^{N}\zeta_i(k), \tag{3}$$

where r_i represents the grey correlation degree of parent and subsequences, and n represents the number of data.

The elevation of industrial structure is evaluated by the street volume index function D, which is mainly to transform the secondary and tertiary industries into a proportional relationship, as shown in formula

$$D = \frac{X_3}{\left[(5 - X_2)^{\wedge}2 + 0.5\right]}, \tag{4}$$

where X_2 and X_3, respectively, represent the proportion of the output value of the secondary industry, the tertiary industry, and the primary industry. The industrial structure upgrading level standard is shown in Table 1.

The industrial structure similarity coefficient S_{ij} is calculated as follows:

$$S_{ij} = \frac{\sum x_{\mathrm{in}}x_{ij}}{\sqrt{\sum x_{\mathrm{in}}^2 \sum x_{ij}^2}}, \tag{5}$$

where x_{in} represents the proportion of employment or output value of industry n in region i; x_{ij} represents the proportion of employment or output value of industry n in region j. The greater the S_{ij} value, the greater the similarity of industrial structure between regions. If $S_{ij} > 0.99$, the industrial structure of the two regions tends to be the same.

The benefit comparison of industrial structure mainly analyzes the deviation degree of industrial structure, so as to analyze the asymmetric state between industrial structure and labor structure. The higher the degree of deviation, the more serious the asymmetry between the two, so the efficiency of the industrial structure will be lower and vice versa. The deviation degree P of industrial structure is calculated as follows:

Table 1: High level of industrial structure.

D value range	Grade	High level of industrial structure
0-0.1	1	Very low
0.1–1	2	Low
1–10	3	Lower
10–35	4	Commonly
35–55	5	Higher
55–75	6	High
75–100	7	Extremely high

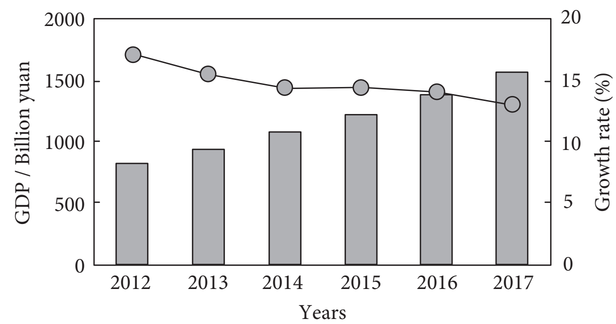

Figure 1: GDP and growth rate from 2012 to 2017.

$$P = \sum\left|I_i - g_i\right|. \tag{6}$$

In the above formula, I_i represents the proportion of the labor force of the i-th industry in the total labor force, and gi represents the proportion of the output value of the i-th industry.

The data required by the model is the input-output table data of HZ city in 2017, and the basic research data are obtained in the statistical yearbook of HZ city in 2017. From 2012 to 2017, the GDP of HZ city continued to rise, and its proportion in the province also increased year by year, as shown in Figure 1.

As can be seen from Figure 1, the total GDP of HZ city continued to increase from 2012 to 2017. However, the growth rate continues to decline, from 17.06% in 2012 to 13% in 2017, and the downward trend is more obvious in 2017. Therefore, it can be seen that the economy of HZ still needs further development. The industrial structure adjustment of economic zone is a complex systematic project, including politics, economy, culture, environment, resources, and other aspects. According to the basic principles of the construction of the evaluation index system, this study designs the evaluation index system for the industrial structure adjustment of HZ Economic Zone, as shown in Table 2.

3.2. Based on Improved Fuzzy Industrial Structure Evaluation Model

In the process of applying mathematics to transform actual semantics into a value that can be quantitatively analyzed, it is difficult for many factors to carry out accurate quantitative analysis [17]. Therefore, generally speaking, in the research process, professionals of relevant disciplines are required to conduct target quantitative analysis and detection, so as to reduce the loss in the evaluation process. More accurate target detection results can be obtained through

Table 2: Industrial evaluation index system of economic zone.

Target layer	Criterion layer	Scheme layer
Economics	Economic aggregate	Total GDP per capita (10000 yuan) C1
		Per capita fiscal income (yuan)
	Industrial structure	Proportion of tertiary industry in GDP (%) C3
	Growth rate	GDP growth (%) C4
		Fiscal revenue growth (%) C5
		Growth rate of fixed investment (%) C6
Environment	Environmental pollution	10000 yuan GDP industrial smoke emission intensity (kg) C7
		RMB 10000 GDP solid waste emission intensity (kg) C8
		10000 yuan GDP wastewater discharge intensity (kg) C9
	Environmental governance	Standard rate of industrial wastewater discharge (%) C10
		Harmless treatment rate of municipal solid waste (%) C11
		Comprehensive utilization rate of industrial solid waste (%) C12
		Proportion of environmental protection investment in GDP (%) C13
		Days with excellent air quality (days) C14
Resources	Resource utilization	10000 yuan GDP energy consumption (ton/standard coal) C15
		10000 yuan GDP power consumption C16
		Industrial water recycling rate (%) C17
	Resource potential	Population density index (person/km^2) C18
		Per capita available water resources (thousand cubic meters) C19
		Proportion of land structure occupied by commercial land (%) C20
Sociology	Resident life	Urban registered unemployment rate (%) C21
		Engel coefficient of urban residents (%) C22
		Per capita living area of urban residents (M2) C23
		Urban per capita disposable income (10000 yuan) C24
	Population quality	Proportion of population with higher education (%) C25

subjective evaluation. If any fuzzy subset is within the measured triangular fuzzy number and the evaluation semantics of experts are transformed into quantitative values, the calculation can proceed to the next step. The membership function in trigonometric function definition analysis is expressed as

$$\mu_A(x) = \begin{cases} \dfrac{x-m}{n-m}, & m < x < n, \\ \dfrac{x-r}{n-r}, & n < x < r, \\ 0, & \text{other}. \end{cases} \tag{7}$$

In equation (7), the range of $\mu_A(x)$ is between $[0, 1]$, m, n, r are real numbers, m is the upper limit of A, n is the most likely value of A, and r is the lower limit of A. Arbitrary triangular fuzzy numbers $A_1(m_1, n_1, r_1)$ and $A_2(m_2, n_2, r_2)$ need to satisfy the following equation:

$$\begin{cases} A_1 + A_2 = (m_1 + m_2, n_1 + n_2, r_1 + r_2), \\ A_1 - A_2 = (m_1 - m_2, n_1 - n_2, r_1 - r_2), \\ \lambda A_1 = (\lambda m_1, \lambda n_1, \lambda r_1), \\ A_1 \otimes A_2 = (m_1 m_2, n_1 n_2, r_1 r_2), \end{cases} \tag{8}$$

$$f = \frac{(r-m)+(n-m)}{3} + m. \tag{9}$$

In equation (9), f represents the clear value obtained by the center of gravity method. Therefore, this study will apply the center of gravity method to solve the ambiguity and A converts it into clear numerical value.

In order to improve the accuracy of fuzzy calculation, this study introduces the Gaussian mixture model (GMM) of maximum expected value (EM) algorithm, that is, EM-GMM algorithm is used to optimize the fuzzy industrial structure evaluation model. E-M can solve the parameter estimation problem of missing data. The missing parameters are the so-called hidden variables. In the approximate realization of the maximum likelihood estimation of the observed data, GMM can do cluster analysis. When a new sample comes, it will make a calculation according to the parameters. Calculate the probability that the sample belongs to each Gaussian distribution, select the maximum probability, and the corresponding distribution is the class to which the sample belongs. If there is one-dimensional Gaussian distribution $p(x|\theta)$ and $\theta = (u, \sigma^2)$, set $\log L(\theta|X) = 0$ to obtain u and σ^2. The standard equation is as follows:

$$\overline{u} = \frac{1}{n}\sum_{i=1}^{n} x_i, \sigma 2 = \frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{u}\right)^2. \tag{10}$$

If there is a complete data set $Y = (X, Z)$ and $X = (x_1, x_2, \ldots, x_n)$ is an incomplete data set, Z_i represents the implicit variables introduced into the data set. Then $Z_i = (1, 2, \ldots, M)$, where M represents the specified finite integer and there is $Y = \{(x_1, z_1), \ldots, (x_n, z_n)\}$. Therefore, the likelihood function and expected representation are shown in the following equations:

$$L(\theta|X,Z) = p(X,Z|\theta) = \prod_{i=1}^{n} p(x_i, z_i|\theta), \tag{11}$$

$$E(L(\theta|X,Z)) = \int_z p(X,Z|\theta) f(Z) d_z. \tag{12}$$

Em's algorithm is mainly aimed at the complete data set Y. If all data are independently distributed in Gaussian distribution, it is Gaussian mixture model. When the parameters of GMM are known, the probability of each component data point can be deduced through the model, and the values of each component can be modified and iterated repeatedly until the conditions are met (Dai et al. 2018) [18]. Make the initial value of the parameter θ^0 and carry out multistep iteration. After each iteration, a new parameter θ can be obtained, and each iteration is shown in the following equation:

$$\begin{aligned} Q\left(\theta, \theta^{(i-1)}\right) &= E(\log L(\theta|X,Z)) \\ &= \int_z \log L(\theta|X,Z) f\left(Z|\theta^{(i-1)}\right) d_z, \end{aligned} \tag{13}$$

where $Q(\theta, \theta^{(i-1)})$ is a function of θ and the expected value of $\log L(\theta|X,Z)$. $\theta^{(i-1)}$ represents the parameters obtained in the last iteration. The second step is the maximization step, which mainly solves the θ^*, and the maximum $Q(\theta^*, \theta^{(i-1)})$ is obtained. See the following equation:

$$\theta^* = \theta^i = \arg\max Q\left(\theta, \theta^{(i-1)}\right). \tag{14}$$

It can be seen from equation (14) that X and $\theta^{(i-1)}$ jointly determine the random vector Z. Let the maximum likelihood function value of iteration i be θ^* and the maximum likelihood function value of iteration $i-1$ be Q_{i-1}^*, so the EM algorithm can ensure $Q_i^* \geq Q_{i-1}^*$ and the algorithm converges at the same time.

In GMM, if x_i represents the observed variable, z_i represents the implied variable, and the complete data can be expressed as $y_i = (x_i, z_i)$, where $z_i = (z_{i1}, z_{i2}, \ldots, z_{ik})$, when x_i is the m-th class, $Z_{im} = 1$, and others are $Z_{im} = 0$.

When z_i is independent and identically distributed in class k, the density of probability $\pi_1, \pi_2, \ldots, \pi_k$, Z_i is determined by x_i, i.e., $\prod_{k=1}^{k} f_k(x_i|\theta_k)^{z_{ik}}$. The complete likelihood function is shown as follows:

$$L(\theta_k, \pi_k, z_{ik}|x) = \sum_{i=1}^{n}\sum_{k=1}^{K} z_{ik} \log \pi_k f_k(x_i|\theta_k). \tag{15}$$

Therefore, the logical flow of EM algorithm in GMM model is shown in Figure 2.

EM algorithm will determine and set the initial parameters of the model before starting the iteration, take the calculated new model parameters as the initial parameters of the model for the next iteration, and stop the iteration after meeting the convergence conditions. In the GMM-EM algorithm, the clustering results of the algorithm will be greatly affected by the initial value (Sattar et al. 2019) [19]. The initialization of EM algorithm is to obtain the initial value of EM iteration through specific other algorithms. In the cluster analysis of GMM-EM algorithm, covariance $\sum 0$, mean μ_0, and weight π_0 are the initial values to be determined.

This study uses random initialization method and K-means clustering to calculate the initial value to be determined. The random initialization method replaces all kinds of initial mean μ_0 with k points, the weight is $\pi_0 = (1)/(k)$, and the covariance is expressed as

$$\sum_0 = \begin{pmatrix} \dfrac{\max(0)-\min(0)}{2} & 0 & \cdots & 0 \\ 0 & \dfrac{\max(1)-\min(1)}{2} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \dfrac{\max(m)-\min(m)}{2} \end{pmatrix}, \tag{16}$$

where m is the dimension of x. Through the above initialization process, we can obtain an initial class mark, calculate the probability density function of the class for each data point (except k points), put these points into a class in class k, and give the points of the same class the same class mark. The operation of random initialization method is more convenient, but there is a certain deviation in the selection of random clustering center, and the main body of clustering is EM. Therefore, this study further selects the K-means clustering method to select the initial parameters of the algorithm model.

K-means clustering method belongs to a partition algorithm, which is mainly to find K (number of clusters) mean vectors. Through each iterative update, it is close to the optimal value of the objective function and finally achieves the minimum value of the objective function. K-means clustering method first randomly selects K points as the clustering center, then calculates the distance from the data object to each clustering center, classifies it in the class closest to the data object, and calculates the new clustering center. If there is no change in the previous and subsequent clustering centers, it means that the adjustment of the data object is over, and the clustering function meets the conditional convergence, so the covariance, mean value, and weight of each class can be obtained. K-means clustering method is a widely used partition method. This method is mainly to find K (number of clusters) mean vectors in the target. This study mainly refers to the K-means initialization clustering method in [20] to better realize the division of original data.

4. Application Effect Analysis of Improved Fuzzy Industrial Structure Evaluation Model

The data required by the model is the input-output table data of HZ city in 2017, and the basic research data are obtained in the statistical yearbook of HZ city in 2017. The Gaussian

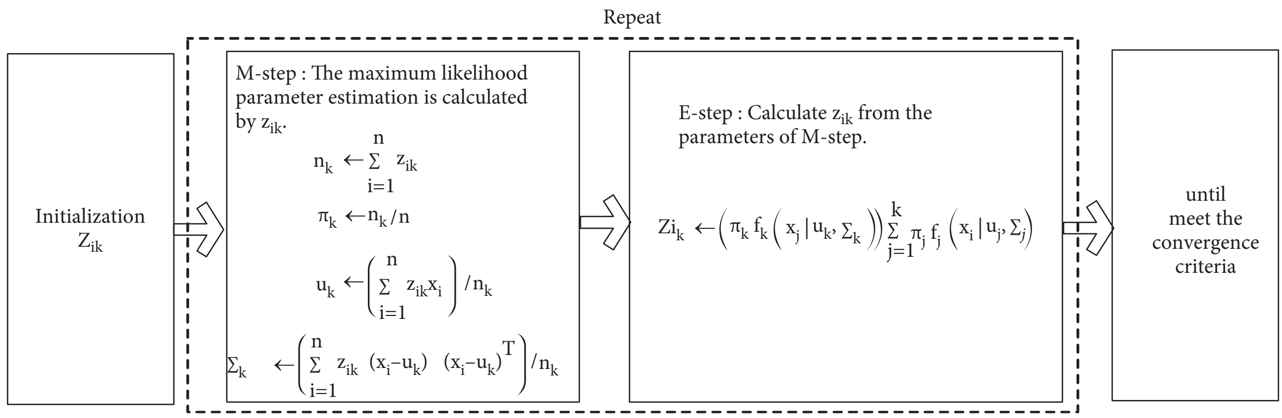

Figure 2: Flowchart of EM algorithm in GMM model.

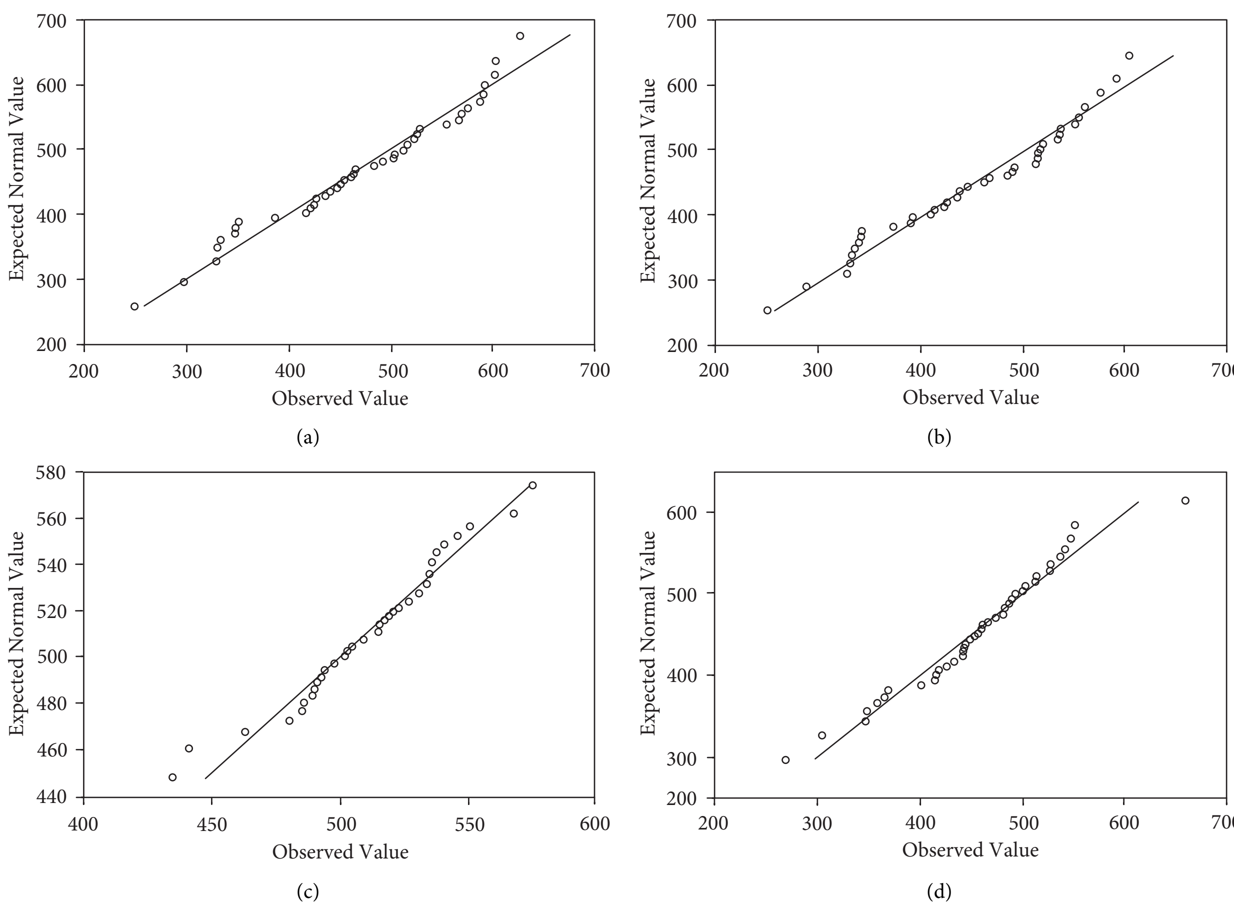

Figure 3: Verification results of normality of indicators in target layer. (a) Normal Q-Q plot of economics, (b) normal Q-Q plot of economics, (c) normal Q-Q plot of economics, and (d) normal Q-Q plot of economics.

method is used to further verify the normality of the target and social indicators, as shown in Figure 3.

The results (Figure 3) show that the indexes of the target layer obey Gaussian distribution.

Questionnaire reliability analysis is an important analysis method for the reliability of questionnaire results. Since this study is a questionnaire survey aimed at the optimization of regional industrial structure, it is considered to adopt internal consistency reliability analysis. This method is mainly to convince the consistency between the questionnaires, that is, whether the relationship between various topics in the questionnaire points to the same characteristics. Alpha reliability coefficient method can be used to judge whether the internal consistency between

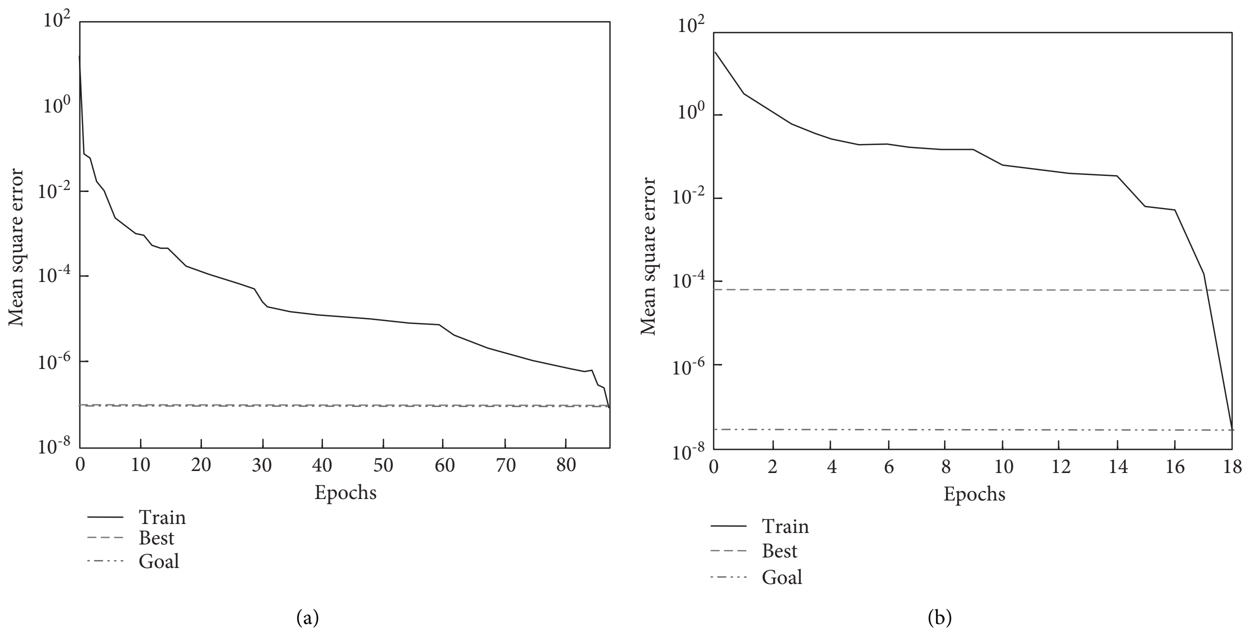

Figure 4: Mean square error of improved fuzzy algorithm. (a) Traditional fuzzy algorithm model. (b) Improved fuzzy algorithm model.

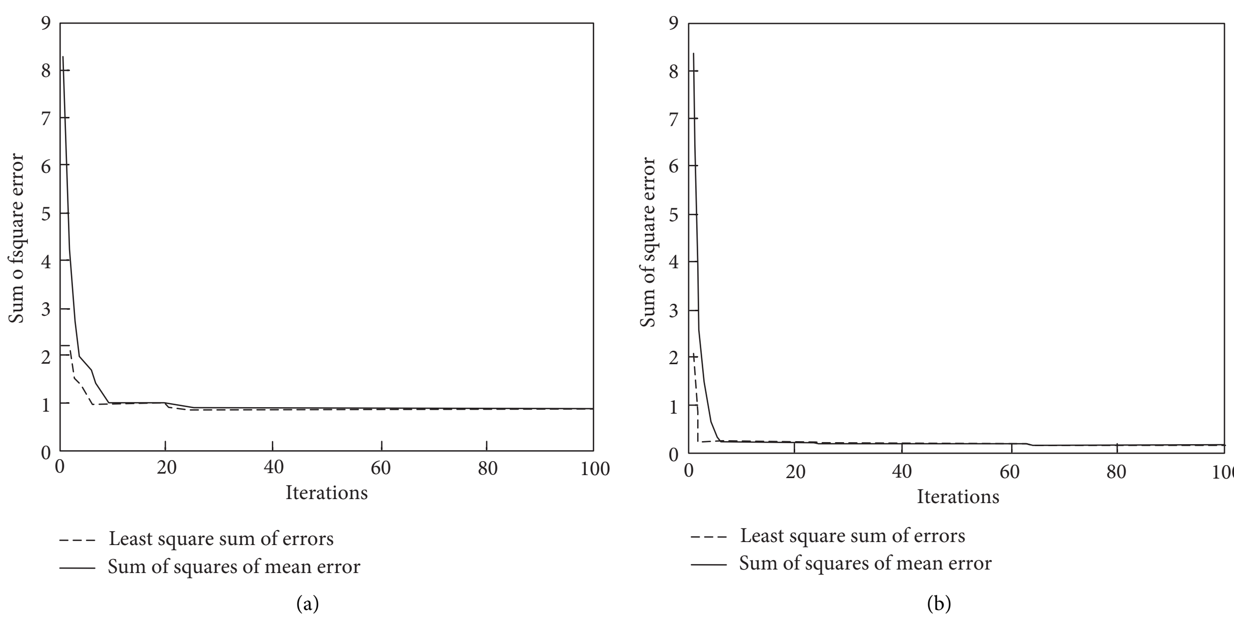

Figure 5: Compare the change of error square sum of the improved fuzzy industrial structure evaluation model with the error square sum of the traditional fuzzy clustering algorithm. (a) Traditional fuzzy algorithm model. (b) Improved fuzzy algorithm model.

various items is high. The reliability analysis coefficient of the questionnaire is 0.964, which reflects the good reliability of the questionnaire.

Through the simulation experiment of the evaluation model, the experimental results are shown in Figure 4. Through different replacement times, the improved fuzzy industrial structure evaluation is continuously improved, reflecting that the improved fuzzy industrial structure evaluation model has better practicability.

Compare the change of error square sum of the improved fuzzy industrial structure evaluation model with the error square sum of the traditional fuzzy clustering algorithm, as shown in Figure 5. Therefore, the improved fuzzy industrial structure evaluation model can quickly realize global optimization.

The comparison results of model evaluation accuracy are shown in Figure 6. Four different algorithm models are used to test the average accuracy of 100 groups of sample data.

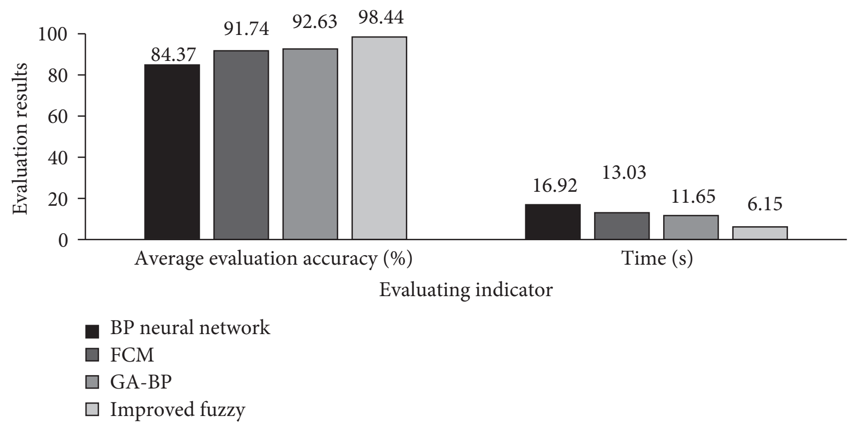

Figure 6: Model performance comparison.

Table 3: Results of random initialization clustering method (part).

Scheme layer	Random 1	Random 2	Random 3
Total GDP per capita (10000 yuan) C1	2	2	2
Per capita fiscal income (yuan)	1	1	1
Proportion of tertiary industry in GDP (%) C3	1	1	3
GDP growth (%) C4	1	2	1
Fiscal revenue growth (%) C5	2	2	2
Growth rate of fixed investment (%) C6	2	2	2
...	...	...	...
Urban registered unemployment rate (%) C21	2	2	2
Engel coefficient of urban residents (%) C22	2	3	2
Per capita living area of urban residents (M2) C23	1	1	3
Urban per capita disposable income (10000 yuan) C24	1	2	2
Proportion of population with higher education (%) C25	1	2	1
Running time	7 s	8 s	9 s

The results of improved fuzzy industrial structure evaluation model are 84.37%, 91.74%, 92.63%, and 98.44%, respectively, and the improved fuzzy industrial structure evaluation model is improved by 14.07%, 6.70%, and 5.18%, respectively, while the improved fuzzy industrial structure evaluation model increases, so the evaluation result of the model proposed in this study is better.

The improved fuzzy industrial structure evaluation model proposed in this study is used to cluster the evaluation indexes. The experimental data adopts the scores of each index in the above research, and the evaluation units are divided into three categories to compare the performance and clustering effect of the evaluation model after different initialization operations. Firstly, the random initialization method is used for three times of cluster analysis, and the results are shown in Table 3.

It can be seen from Table 3 that the three times random initialization method is close in time, but the results of random 1 and random 2 are relatively close, and there is a certain difference from the results of random 3, indicating that the initial value is very sensitive to the clustering results of the improved fuzzy industrial structure evaluation model and has a great impact on the clustering results. In order to enhance the accuracy of the results, Manhattan distance initialization method and K-means clustering are further used for initialization. After the initial values of the algorithm model are grouped into three categories by Manhattan distance initialization method, the results are shown in Figure 7.

After 9 iterations, the model starts to converge and three kinds of initial values are obtained, with a running time of 5 s. Then *K*-means clustering is used for initialization. When the number of clusters is 3, the final cluster center is shown in Figure 8.

The model converges after three iterations to obtain three kinds of initial values, and the running time is 2 s. The results of three types of initialization clustering are counted, as shown in Table 4.

It can be seen from the clustering results in Table 4 that the results obtained by *K*-means and Manhattan distance initialization clustering method are relatively more stable. In terms of running time, Manhattan distance initialization method and *K*-means clustering method have fewer iterations and shorter time-consuming. In particular, the running time of *K*-means clustering algorithm is only 2 s. Therefore, when the data sample is large, the application of *K*-means clustering algorithm will be more efficient.

To sum up, the improved fuzzy industrial structure evaluation model has increased by 14.07%, 6.70%, and 5.18%, respectively. The improved fuzzy industrial structure

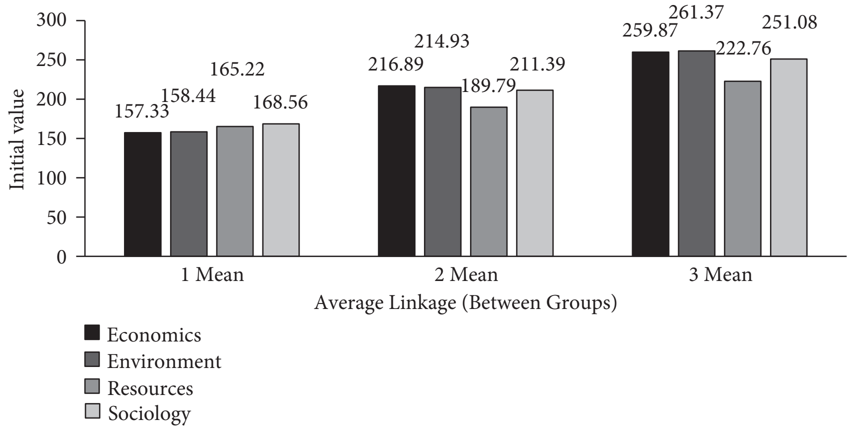

Figure 7: Manhattan distance initialization clustering method results.

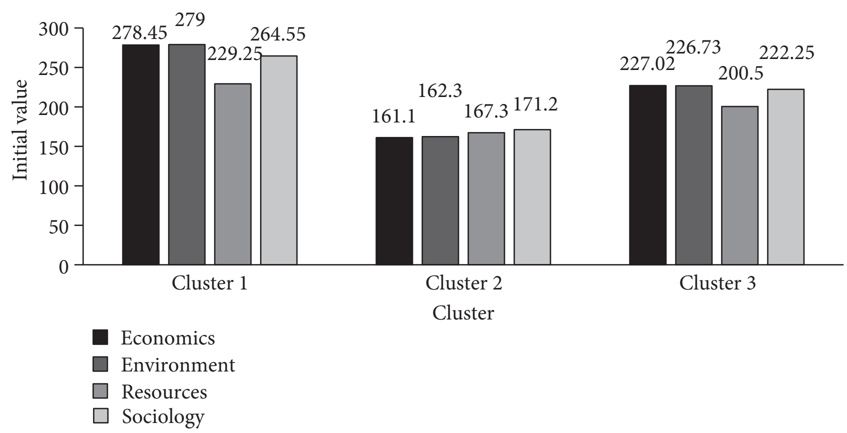

Figure 8: Results of K-means clustering initialization method.

Table 4: Comparison of results of three types of initialization clustering methods (part).

Scheme layer	Random 1	Random 2	Random 3	K-means	Manhattan distance
Total GDP per capita (10000 yuan) C1	2	2	2	2	2
Per capita fiscal income (yuan)	1	1	1	1	1
Proportion of tertiary industry in GDP (%) C3	1	1	3	1	1
GDP growth (%) C4	1	2	1	2	1
Fiscal revenue growth (%) C5	2	2	2	2	2
Growth rate of fixed investment (%) C6	2	2	2	2	2
...	...	...	...	...	...
Urban registered unemployment rate (%) C21	2	2	2	2	2
Engel coefficient of urban residents (%) C22	2	3	2	3	2
Per capita living area of urban residents (M2) C23	1	1	3	1	1
Urban per capita disposable income (10000 yuan) C24	1	2	2	2	1
Proportion of population with higher education (%) C25	1	2	1	2	1
Running time	7 s	8 s	9 s	5 s	2 s

evaluation model has increased, so the evaluation result of the model proposed in this paper is better. The initial value of the improved fuzzy industrial structure evaluation model is very sensitive to the clustering results and has a great impact on the clustering results. In order to improve the accuracy of the results, Manhattan distance initialization method and K-means clustering method are used for initialization. Compared with the traditional square method, the convergence of the fuzzy structure is improved to a certain extent. The improved evaluation model has also been improved. This is better than other algorithms.

5. Conclusion

This study mainly aims at the optimization of regional industrial structure, applies the evaluation model based on improved fuzzy industrial structure, and verifies the accuracy of the index system model. The results show that the first generation iteration speed of the improved fuzzy industrial structure evaluation model is fast, but it is slow in the second to eighth iterations. After the 9th iteration, the accuracy of the model has been greatly improved. Compared with the traditional fuzzy convergence method, the improved industrial structure converges for many times, and the error square is reduced to a certain extent, in which the relative convergence is improved. The improved evaluation model has also been improved, which is better than other algorithms. The results obtained by K-means and Manhattan distance initialization clustering method are relatively more stable. In terms of running time, Manhattan distance initialization method and K-means clustering method have fewer iterations and shorter time-consuming. In particular, the running time of K-means clustering algorithm is only 2 s. Therefore, when the data sample is large, the application of K-means clustering algorithm will be more efficient. However, these models studied in this paper are established from the micro or static point of view. Therefore, further modification and discussion are needed on the general applicability.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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