Hindawi
Mathematical Problems in Engineering
Volume 2023, Article ID 9853261, 1 page
https://doi.org/10.1155/2023/9853261

Retraction

Retracted: Construction of an Industrial Structure Analysis and Evaluation Model for Oil and Gas Resource-Based Cities Based on Deep Learning Model and Cluster Analysis

Mathematical Problems in Engineering

Received 13 September 2023; Accepted 13 September 2023; Published 14 September 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. Deng, "Construction of an Industrial Structure Analysis and Evaluation Model for Oil and Gas Resource-Based Cities Based on Deep Learning Model and Cluster Analysis," *Mathematical Problems in Engineering*, vol. 2022, Article ID 2179494, 8 pages, 2022.

Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 2179494, 8 pages
https://doi.org/10.1155/2022/2179494

Research Article

Construction of an Industrial Structure Analysis and Evaluation Model for Oil and Gas Resource-Based Cities Based on Deep Learning Model and Cluster Analysis

Shuran Deng

School of Economics and Management, Northeast Petroleum University, Daqing, Heilongjiang 163318, China

Correspondence should be addressed to Shuran Deng; bb19850726@nepu.edu.cn

Received 16 February 2022; Revised 7 March 2022; Accepted 9 March 2022; Published 7 April 2022

Academic Editor: Gengxin Sun

In the present time of resource integration, the industrial transformation of oil and gas resource-based cities has become inevitable. Through the qualitative and quantitative analysis of the current situation of industrial structure, the overweight of industrial structure is pointed out and reasonable suggestions are put forward for the existing problems. This paper constructs an industrial structure analysis and evaluation model for oil and gas resource-based cities based on deep learning model and cluster analysis. The transformation of traditional industries is a long process, and at present the oil and petrochemical industry should still be an important support for Daqing's economic development, so more efforts should be made to extend the service life of oil fields and to get more funds and time for successive industries. Fine exploration is being carried out, relying on continuous innovation in exploration theory, methods, technology and management, and re-measuring old exploratory wells in fields that have already been explored.

1. Introduction

For historical and national industrial policy reasons, the focus of the petrochemical industry in Daqing has been on the production of fuel oil alone, with a short industrial chain and shallow processing levels, which has led Daqing into a strange circle of a single industrial structure [1]. There are generally two routes of oil processing, one is to process crude oil directly into refined oil products, and the other is to process crude oil into cracking materials [2]. Daqing should accelerate the development of supporting industries, extend the industrial chain, take the route of fine chemicals and strengthen the petrochemical industry [3].

Increase investment in scientific research to improve the recovery rate of oil fields. Accelerate the development and application of high technology through cooperation with universities and research institutes to gain time for the development of successive industries [4]. Pay attention to the protection of oil resources, improve the efficiency of resource development and utilization, and strive to create a "century-old oilfield", so as to provide the necessary accumulation and more time for the transformation of the city's economy [5].

Natural resources such as solar and wind energy have always been recognised worldwide as nonpolluting and cost-free renewable resources [6]. The use of solar energy was proposed as early as 1968. Daqing has an abundance of light, with 2,726 hours of sunshine per year, a total annual solar radiation of 491.4 KJ/cm^2 and a high monsoon in spring and autumn, influenced by the cold inland Mongolian air and the warm ocean monsoon [7]. Under the dual pressure of the conventional energy shortage and the deterioration of the global ecological environment, Daqing should increase its independent research and development efforts, accelerate the use of solar and wind energy, continuously optimise the energy structure, improve the efficiency of energy use, and drive the development of related industries to ensure that energy does not become an obstacle to Daqing's low-carbon transformation [8].

On the basis of the oil and petrochemical industry, cultivate new succession industries, gradually invest the large amount of capital accumulated from the development of oil and gas resources and the petrochemical industry into succession industries, cultivate new leading industries, and thus complete the establishment of a diversified economic model as a whole [9]. On the one hand, the development of deep processing industries for agricultural and livestock products. Daqing is rich in arable land and grassland resources, therefore, according to the needs of the market, we can implement the strategy of "conversion of agriculture to animal husbandry" and vigorously develop the farming industry, at the same time, we can support the deep processing of agricultural products enterprises and develop green agriculture. On the other hand, the tertiary industry should be vigorously developed. The tertiary sector is a complex and mixed industry group, and it is important to scientifically determine the priorities and development of the tertiary sector, and to continue to exploit its advantages in order to build Daqing into a distribution and service centre in western Heilongjiang [10, 11].

2. Basic Information about Daqing City

Daqing is an oil and chemical capital, located in the western part of Heilongjiang Province, with a total area of 22,200 square kilometres, 5 districts, 3 counties, 1 autonomous county and 1 national high-tech industrial development zone, and is the largest oil production base and an important petrochemical industry base in China [12]. The added value of the city's industry reached 305.91 billion yuan, an increase of 3.8% year-on-year, of which the added value of the regulated industry reached 241 billion yuan, an increase of 2.3% year-on-year; 40 million tons of crude oil and 3.51 billion cubic metres of natural gas were produced, with the added value of the oil industry reaching 178.8 billion yuan, a decrease of 0.1% year-on-year; the added value of the petrochemical industry reached 27.19 billion yuan, an increase of 7.1% year-on-year. The ratio of the three industries was 4.5 : 77 : 18.5, with the secondary industry dominating and ranking 11th in terms of comprehensive strength among the prefecture-level cities in China, as shown in Table 1[13].

3. Analysis of the Characteristics of the Industrial Structure in Daqing

3.1. Basic Characteristics of Daqing's Industrial Structure. As a typical city of oil and gas resources, Daqing, while making a great contribution to the country, has also accumulated many problems of its own. As far as its industrial structure is concerned, the main problems in Daqing are [14].

3.1.1. Declining Oil Production, Resulting in a Reduction of the Regional GDP. With the continuous exploitation of oil resources, it is an inevitable and objective fact that oil resources are decreasing. After 27 consecutive years of high and stable production of over 50 million tonnes of crude oil per year, Daqing oilfield has produced steadily for 11 years on the 40 million tonne plateau, with the recovery rate of the main oilfield exceeding 50%. It was estimated that the reduction in crude oil production and oil prices reduced Daqing's GDP by RMB 84.91 billion in current prices. In constant prices, the reduction in crude oil production drove GDP growth down by 1.36 percentage points. According to the plan, the Daqing oilfield will reduce production by 1.5 million tonnes per year. As oil production decreases year after year, the GDP of Daqing will inevitably decline [15].

3.1.2. A Single Industrial Structure, with Serious Implications for the Future Development of the City. Like most resource-based cities in China, Daqing has a single industrial structure, with secondary industries being the mainstay of its industrial structure, and the oil and petrochemical industry having the largest share in terms of industrial structure ratio. Daqing's economic development is overly dependent on the oil industry, which makes it difficult to switch to other industries and has a weak multiplier effect. Oil as the leading industry drives the development of related industries with slow radiation, which is prone to economic deformation or decline [16].

3.1.3. Scattered Industrial Structure and Difficulty in Urbanisation. Due to the constraints of oil and gas resources generation and exploitation, the exploration, development and refining sites are unevenly distributed and the urban agglomeration is poor. Usually, the city is concentrated on the construction of certain areas in good condition and in the right location, making it a relatively concentrated central living area, such as the early mining area of Jean-Houlou, and then connected by certain traffic routes, forming a cluster of districts, counties and towns in a dotted pattern. The overall layout of Daqing is therefore relatively fragmented, which does not facilitate the full use of some facilities and affects the urbanisation of the city [17].

There are many other problems with the industrial structure of Daqing, such as the single structure of scientific and technological talents, the lack of awareness and the management system.

3.2. Empirical Analysis of Industrial Structure in Daqing. In order to make the analysis of the industrial structure of Daqing accurate and specific, this paper further analyses the basic characteristics and problems of the industrial structure of Daqing from a quantitative perspective, in addition to the qualitative description. Taking into account the scope of the indicators and the conditions of application, the following indicators have been selected.

3.2.1. Industry Value Added Share. The value added share of industries in resource-based cities can be expressed by the following formula:

$$\mathrm{WI}_{ij} = \left(\frac{G_{ij}}{G_i}\right) \times 100\%, \tag{1}$$

where G_{ij} is the value added of industry j in region i and G_i is the total value added of industry in region i. Generally

Table 1: Gross regional product of Daqing city, 2014.

Index	Index value	Year on year growth (±%)
Regional GDP	4070	4.5
Primary industry	185	8.5
The secondary industry	3133	3.7
Construction	3059.1	3.8
The service sector; the tertiary industry	73.9	−1.3

speaking, it is considered that the industry is likely to become the leading industry when it is $\mathrm{WI}_{ij} > 15\%$. As can be seen from Tables 2 and 3, the secondary industry accounts for 77% of the three industries in Daqing and 55% of the key industrial sectors above the scale, which is absolutely dominant. The petroleum and petrochemical industry accounts for 50.6% of the total regional GDP and 65.7% of the secondary industry. It can be seen that the industrial structure of Daqing is dominated by the secondary industry, especially by the petroleum and petrochemical industry, indicating the overweight and homogeneous nature of Daqing's industrial structure.

3.2.2. Value of Change in Industrial Structure. The value of the change in the industrial structure of a resource-based city can be expressed by the following formula:

$$K = \sum_{i=1}^{n} \left| q_{i1} - q_{i0} \right|, \tag{2}$$

where q_{i1} and q_{i0} are the shares of the output value of industry i in the total output value in the reporting period and the base period respectively. The value of industrial structure change, K, is an indicator of the rate of change of industrial structure, the larger the value, the greater the rate of change of industrial structure; conversely, the smaller the value [18].

Using the data in Table 4 to calculate the value of industrial structure change in Daqing City, we calculated the value of industrial structure change in Daqing City from 2011 to 2014 with the ratio of K2011 = 0.004, K2012 = 0.026, K2013 = 0.056 and K2014 = 0.104, which shows that the industrial structure of Daqing City tends to be constant.

3.2.3. Industrial Structure Entropy Values. The entropy value of the industrial structure of a resource-based city can be expressed by the following formula:

$$e^t = \sum_{i=1}^{n} \left(W_{it} \ln \frac{1}{W_{it}} \right), \tag{3}$$

where e^t is the entropy value of the industrial structure in period t, W_{it} is the proportion of the output value of industry i in period t, and n is the number of industrial sectors. The larger the entropy value of the industrial structure, the more balanced the industrial development is and the more diversified the development structure tends to be.

Table 4 was used to calculate the entropy value of the industrial structure of Daqing, see Table 5. From Table 6, it can be seen that the entropy value of the industrial structure of Daqing is on the rise between 2010 and 2014, but the value is small compared to the national entropy value of the industrial structure, indicating that the overall development of the industrial structure of Daqing tends to be homogeneous and uneven.

4. Cluster Analysis and Deep Learning-Based Industrial Structure Optimisation

The precise and efficient allocation of the hundreds of associated oil manufacturing points is a key factor affecting the structure of the industry. In this paper, machine learning techniques are used to adjust the network configuration of oil manufacturing points in order to achieve uniform distribution of network service load among the capacity layer, coverage layer and wide and deep coverage layer according to the oil carrying capacity [19]. At the same time, oil types are classified according to the characteristics of urban oil production distribution, and personalised optimisation schemes are generated for different types of oil, and the load optimisation schemes can be updated automatically as the network service development changes. The process of industrial structure optimisation based on machine learning is shown in Figure 1.

The data obtained are petroleum-grade data for a certain period of time, including public petroleum manufacturing point data, measurement report (MR) data, configuration data and performance data. The ETL (extract-transform-load) processing of the data is done based on the storage and computing resources of the Big Data platform, providing useable formatted data for subsequent analysis and modelling [20].

The MR data are segmented according to RSRP (reference signal receiving power) strength, and the data are classified according to RSRP strength, reference signal receiving power, reference signal receiving power, reference signal receiving power, and reference signal receiving power. The two-dimensional curves are plotted according to RSRP strength and MR quantity, as shown in Figure 2.

The key features for oil scene classification were extracted from the MR data. The arithmetic mean, variance, kurtosis coefficient and skewness coefficient of each MR data were extracted. Using these four extracted features for scene delineation, the scene is automatically delineated using the K-means clustering algorithm, defining the number of oil as N, and the MR data of each oil has the above four features extracted, the data matrix is as follows:

Table 2: Distribution of Daqing's three industries in 2014 Unit: RMB billion.

Index	Industrial added value	WI_{ij}
Primary industry	185	4.5%
The secondary industry	3133	77%
The service sector; the tertiary industry	752	18.5%

Table 3: Distribution of key industries in Daqing above-scale industry, 2014.

Index	Industrial added value	WI_{ij}
Oil industry	1788	44%
Petrochemical industry	271.9	7%
Agricultural and sideline products processing industry	98.3	2%
Building materials industry	30.1	1%
Equipment manufacturing industry	39	1%

Table 4: Structure ratio of three industries in Daqing, 2010–2014.

Index	2010	2011	2012	2013	2014
Gross output value of primary industry	95	132.9	153.6	175.6	185
Total output value of secondary industry	2385.1	3070	3235.9	3318.4	3133
Total output value of tertiary industry	420	537.4	611	687.5	752
Proportion of tertiary industrial structure	3.3 : 82.2 : 14.5	3.5 : 82.1 : 14.4	3.8 : 80.9 : 15.3	4.2 : 79.4 : 16.4	4.5 : 77 : 18.5

Table 5: National structure ratio of three industries, 2010–2014.

Index	2010	2011	2012	2013	2014
Gross output value of primary industry	40533.6	47486.2	52373.6	56957	58332
Total output value of secondary industry	187383.2	220412.8	235162	249684.4	271392
Total output value of tertiary industry	173596	205205	231934.5	262203.8	306739
Proportion of tertiary industrial structure	10.1 : 46.7 : 43.2	10 : 46.6 : 43.3	10.1 : 45.3 : 44.6	10 : 43.9 : 46.1	9.2 : 42.6 : 48.2

Table 6: Industry structure entropy index values in Daqing and nationally, 2010–2014.

Particular year	Daqing city	Whole country
2010	0.543	0.9494
2011	0.545	0.9487
2012	0.558	0.9503
2013	0.638	0.9484
2014	0.653	0.9220

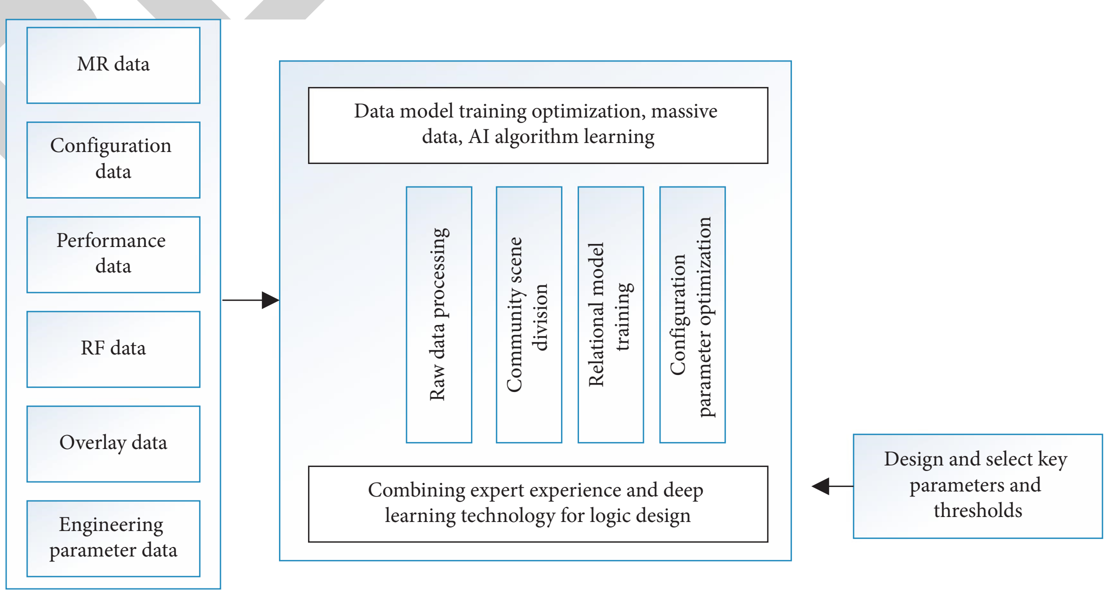

Figure 1: Machine learning-based industrial structure optimisation process.

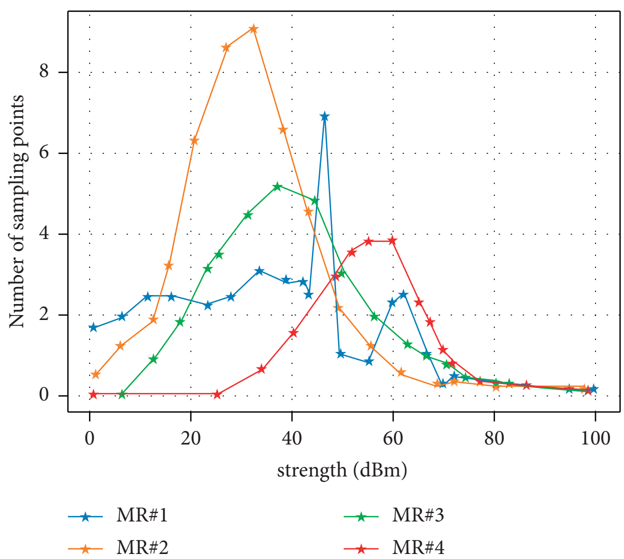

FIGURE 2: Example of the distribution of MR sampling points in the RSRP intensity interval.

$$\begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ \cdots & & & \\ x_{N1} & x_{N2} & x_{N3} & x_{N4} \end{pmatrix}, \tag{4}$$

where x_{ij} denotes the jth attribute of the i-th sector.

First, K points are randomly selected from the data set as the initial cluster centres, then the distance between each sample and the cluster centre is calculated and the sample is assigned to the class in which the nearest cluster centre is located. Euclidean distance is used to calculate the distance between data objects:

$$\operatorname{dist}\left(x_i, x_j\right) = \sqrt{\sum_{d=1}^{4}\left(x_{i,d} - x_{j,d}\right)^2}. \tag{5}$$

Update the class cluster centre: the average value of all data objects in the corresponding class cluster, i.e. the updated class cluster centre of that class cluster. Define the class cluster centre of the kth class cluster as Center_k, then the class cluster centre is updated as follows:

$$\text{Center}_k = \frac{1}{\left|C_k\right|}\sum_{x_i \in C_k} x_i, \tag{6}$$

where C_k is the kth class cluster and $|C_k|$ is the number of data objects in the kth class cluster, the summation here is the sum of all elements in class cluster C_k over each column of attributes, so Center_k is also a vector with 4 attributes, denoted as

$$\text{Center}_k = \left(\text{Center}_{k,1}, \text{Center}_{k,2}, \ldots, \text{Center}_{k,4}\right). \tag{7}$$

Iterations are continuously performed to reclassify the class clusters and update the class cluster centres, and the number of iterations T is set, and the iteration is terminated after the T th iteration, at which point the resulting class clusters are the final clustering results.

Based on the scenarios classified in (2), the impact of configuration oil manufacturing points on performance indicators and the implied relationship between configuration and performance data are explored in each scenario to adjust the wireless oil manufacturing points, improve network performance and enhance the network KPI (key performance indicator). A DNN (deep neural network) model is used to learn the intrinsic relationship between the configured oil manufacturing points and the performance indicator oil manufacturing points to obtain a trained and stable neural network model.

Define the configuration of oil manufacturing points X to include the whole set of oil manufacturing points of the entire oil group, including the resource configuration oil manufacturing points, frequency configuration oil manufacturing points and boundary level configuration oil manufacturing points of each oil it contains, etc. The matrix containing m frequency points and n oil manufacturing points per frequency point can be expressed as

$$X = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \ldots & & & \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix}, \tag{8}$$

where x_{mn} denotes the nth oil manufacturing point for the mth frequency point. If the network structure of F1D1D2FDD 900 MHz contains 4 frequency points and each frequency point has 12 oil manufacturing points configuration data, the size of the X matrix is (4, 12).

The performance indicator oil manufacturing point Y is the determination indicator data of the industrial structure of the oil group, which may include: the maximum number of connected users of RRC (radio resource control), the utilization rate of uplink PRB (physical resource block) and downlink PRB utilization rate of each frequency point included in the oil group, including m frequency points, each frequency point has k oil manufacturing points, and the matrix size is (m, k), which can be expressed as

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1k} \\ y_{21} & y_{22} & \cdots & y_{2k} \\ \cdots & & & \\ y_{m1} & y_{m2} & \cdots & y_{mk} \end{bmatrix}, \tag{9}$$

where y_{mk} is the kth load indicator data for the mth frequency point. If the network structure of F1D1D2FDD 900 MHz contains 4 frequency points, each with 3 indicator data, the size of the Y matrix is (4, 3).

The relationship between performance metrics and configured oil manufacturing points is investigated and the problem is modelled as a multivariate regression problem. The intrinsic relationship of the regression problem is learnt using a fully connected neural network algorithm model, using training data to train the neural network model. The input is X. The data in X is read in and converted to a column

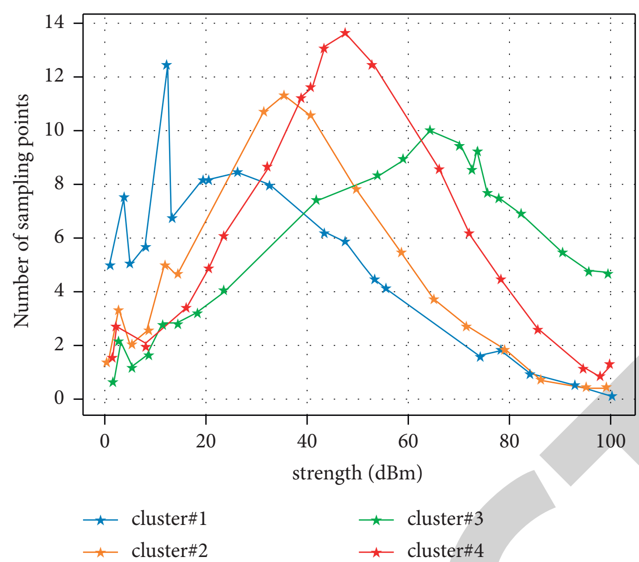

FIGURE 3: Mean distribution of MR statistics by scenario category.

matrix as the input to the neural network, and similarly the Y matrix is converted to a column matrix as the output of the neural network.

The output of the regression problem, Y, contains multiple variables, so the cost function is designed based on this problem as

$$\mathrm{MSE}(y, y') = \frac{\sum_{i=1}^{l}(y_i - y_i')^2}{l}, \tag{10}$$

where y_i is the sample data and y_i' is the predicted value calculated by the neural network.

The average of MSE (mean squared error) of each variable is used as the loss function, and the cost function of the network is minimized by training the model, adjusting the weights and bias, thus obtaining a stable neural network model [21].

5. Model Training and Results Analysis

According to the oil scene classification method proposed above, the oil scene is classified using MR data. The scene is automatically classified using the K-means clustering algorithm, and the time complexity of the algorithm is $O(t \times k \times m \times n)$ and the space complexity is $O(m \times (n + k))$, where t is the number of iterations, k is the number of clusters, m is the number of features and n is the number of samples [22, 23]. Generally t, k and m can be considered as constants, so the time and space complexity can be simplified to $O(n)$. The mean value of MR statistics for each category is found, and the distribution of the mean value of MR statistics for each scene category is shown in Figure 3.

The model of the relationship between configuration oil manufacturing points and performance oil manufacturing points was trained for each of the four types of oil scenarios, and the deep learning algorithm model was used to learn the intrinsic relationship between configuration oil manufacturing points and performance index oil manufacturing points. The complexity of the DNN algorithm is mainly determined by the number of hidden layers, hidden units and samples. The evaluation indexes of the DNN model are shown in Table 7, and the evaluation results show that the deep learning algorithm has a good fit to the data and the error between the predicted data and the real data is small.

The optimisation search is performed based on the trained DNN model, and the optimized configuration recommendations and tuning effect prediction results are output. The problem is transformed into a hill-climbing algorithm to solve the multi-dimensional constrained optimisation problem, and the optimized configuration recommendations and tuning prediction results are shown in Table 8. The oil scenario selected in this paper is F1D1D2FDD 900 MHz, where F1, D1 and D2 are all 20 MHz bandwidth in the existing network, and FDD 900 MHz is 5 MHz bandwidth. Therefore, the closer the amount of services carried by the four frequency points is to the bandwidth ratio, the better the service balance is.

Relying on the provincial big data platform and the resource capacity of the cloud resource pool, the above for the oil scenario segmentation, DNN model training and optimal configuration of oil manufacturing point solution are all done on the offline side, which is a light-weight operation. The efficiency of the online deployment part depends mainly on the number of samples, which is much less complex compared to the offline side, and is more beneficial for real-time and efficient oil manufacturing point optimisation. The current manual configuration solution is labour- and time-consuming and has a low percentage of improvement for load-unbalanced oil. Test results show that the machine learning-based load optimisation solution can achieve fine-grained load sharing according to the bandwidth capacity of the oil, and the improvement ratio of oil with unbalanced load reaches over 90%, saving a lot of manpower while improving the accuracy of load optimisation.

Table 7: DNN model evaluation metrics.

Evaluating indicator	Performance parameter	Class A scenario	Class B scenario	Class C scenario	Class D scenario
MAE	F1	0.0503051	0.085069	0.08326	0.072
	D1	0.07581453	0.081356	0.0903	0.0974
	D2	0.04953281	0.062331	0.05916	0.0634
	FDD900 MHz	0.0662423	0.056063	0.07729	0.082
MSE	F1	0.00471382	0.012049	0.01459	0.0086
	D1	0.00946774	0.0104574	0.01183	0.0152
	D2	0.00405008	0.007063	0.00561	0.0069
	FDD900 MHz	0.0069552	0.004995	0.00956	0.0116
R-squared	F1	0.04108796	0.072958	0.11181	0.1228
	D1	0.28745744	0.287098	0.23328	0.1461
	D2	0.2960221	0.197456	0.29042	0.1505
	FDD900 MHz	0.16222446	0.226527	0.25251	0.0653

Table 8: Optimisation proposals and predicted results of adjustment effects.

Result	Class A scenario	Class B scenario	Class C scenario	Class D scenario
Optimize configuration parameters	−103	−109	−107	−110
	−101	−103	−99	−92
	−87	−93	−86	−101
	−98	−101	−98	−88
	−88	−85	−84	−96
Business forecast proportion	F1	0.305	0.311	0.306
	D1	0.305	0.311	0.306
	D2	0.310	0.311	0.298
	FDD 900 MHz	0.077	0.071	0.068

6. Conclusion

This paper presents a cluster analysis and deep learning-based solution for the industrial structure of oil cities. At the same time, the development of the load optimisation system and the validation of the existing network have been carried out jointly with the manufacturer. In the selected test grid for the poor load optimisation of the existing network, the oil is tested and validated in the existing network, and the test improvement ratio can reach 90%. The system truly combines machine learning with industrial economic optimisation, forming a technical solution for network oil manufacturing point tuning based on machine learning, and exploring a dynamic urban industrial adaptive load optimisation solution with more refined oil granularity and time granularity.

Data Availability

The dataset used in this paper are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest regarding this work.

References

[1] S. Jiang, C. Lu, S. Zhang et al., "Prediction of ecological pressure on resource-based cities based on an RBF neural network optimized by an improved ABC algorithm," *IEEE Access*, vol. 7, pp. 47423–47436, 2019.

[2] W. Chen, W. Chen, S. Ning et al., "Exploring the industrial land use efficiency of China's resource-based cities," *Cities*, vol. 93, pp. 215–223, 2019.

[3] D. Wang, Y. Shi, and K. Wan, "Integrated evaluation of the carrying capacities of mineral resource-based cities considering synergy between subsystems," *Ecological Indicators*, vol. 108, Article ID 105701, 2020.

[4] M. Xing, F. Luo, and Y. Fang, "Research on the sustainability promotion mechanisms of industries in China's resource-based cities -- from an ecological perspective." *Journal of Cleaner Production*, vol. 315, Article ID 128114, 2021.

[5] Y. Meng, L. Liu, J. Wang, Q. Ran, X. Yang, and J. Shen, "Assessing the impact of the national sustainable development planning of resource-based cities policy on pollution emission intensity: evidence from 270 prefecture-level cities in China," *Sustainability*, vol. 13, no. 13, p. 7293, 2021.

[6] X. Ge, J. Xu, Y. Xie, X. Guo, and D. Yang, "Evaluation and dynamic evolution of eco-efficiency of resource-based cities-A case study of typical resource-based cities in China," *Sustainability*, vol. 13, no. 12, p. 6802, 2021.

[7] M. Xing and F. Luo, "Comparative study on the optimization path of industrial value chain in China's resource-based cities," *Sustainability*, vol. 10, no. 5, p. 1338, 2018.

[8] E. Tok, "The incentives and efforts for innovation and Entrepreneurship in a resource-based economy: a survey on perspective of qatari residents," *Sustainability*, vol. 12, no. 2, p. 626, 2020.

[9] P. An, Z. Wang, and C. Zhang, "Ensemble unsupervised autoencoders and Gaussian mixture model for cyberattack detection," *Information Processing & Management*, vol. 59, no. 2, Article ID 102844, 2022.

[10] M. Xue, X. Zhang, X. Sun, T. Sun, and Y. Yang, "Expansion and evolution of a typical resource-based mining city in

transition using the google earth engine: a case study of datong, China," *Remote Sensing*, vol. 13, no. 20, p. 4045, 2021.

[11] P. An, Z. Wang, and C. Zhang, "Ensemble unsupervised autoencoders and Gaussian mixture model for cyberattack detection," *Information Processing & Management*, vol. 59, no. 2, Article ID 102844, 2022.

[12] J. Tan, K. Lo, F. Qiu, W. Liu, J. Li, and P. Zhang, "Regional economic resilience: resistance and recoverability of resource-based cities during economic crises in Northeast China," *Sustainability*, vol. 9, no. 12, Article ID 2136, 2017.

[13] J. Yao, H. Li, D. Shang, and L. Ding, "Evolution of the industrial innovation ecosystem of resource-based cities (RBCs): a case study of Shanxi Province, China," *Sustainability*, vol. 13, no. 20, Article ID 11350, 2021.

[14] M. Yang, "A review of regional innovation system studies in resource-based city," *Advanced Materials Research*, vol. 524, pp. 2751–2756, 2012.

[15] L. Liu, X. Yang, Y. Meng, Q. Ran, and Z. Liu, "Does the construction of national eco-industrial demonstration parks improve green total factor productivity? Evidence from prefecture-level cities in China," *Sustainability*, vol. 14, no. 1, p. 26, 2022.

[16] H. Zhou, W. Ping, Y. Wang, Y. Wang, and K. Liu, "China's initial allocation of interprovincial carbon emission rights considering historical carbon transfers: p," *Ecological Indicators*, vol. 121, Article ID 106918, 2021.

[17] M. Cristina De Stefano, M. J. Montes-Sancho, and T. Busch, "A natural resource-based view of climate change: innovation challenges in the automobile industry," *Journal of Cleaner Production*, vol. 139, pp. 1436–1448, 2016.

[18] Y. Zhao, Y. Yang, S. Leszek, and X. Wang, "Experience in the transformation process of "coal city" to "beautiful city": taking Jiaozuo City as an example," *Energy Policy*, vol. 150, Article ID 112164, 2021.

[19] J. Larty, S. Jack, and N. Lockett, "Building regions: a resource-based view of a policy-led knowledge exchange network," *Regional Studies*, vol. 51, no. 7, pp. 994–1007, 2017.

[20] D. Chen, P. Wawrzynski, and Z. Lv, "Cyber security in smart cities: a review of deep learning-based applications and case studies," *Sustainable Cities and Society*, vol. 66, Article ID 102655, 2021.

[21] O. O. Adejuwon, "An examination of linkages in the sawn wood sector of the Nigerian forest industry: policy implications for natural resource-based development," *Technological Forecasting and Social Change*, vol. 128, pp. 74–83, 2018.

[22] Y. Shi, C. Shao, and Z. Zhang, "Efficiency and driving factors of green development of tourist cities based on ecological footprint," *Sustainability*, vol. 12, no. 20, Article ID 8589, 2020.

[23] J. Li and S. Geng, "Industrial clusters, shared resources and firm performance," *Entrepreneurship & Regional Development*, vol. 24, no. 5-6, pp. 357–381, 2012.