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Impact of Industrial Agglomeration on Regional Economy in a Simulated Intelligent Environment Based on Machine Learning

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ABSTRACT The Internet of Things is based on a communication network to automatically receive various information from the natural world. It uses intelligent objects with perception, communication and computers to automatically receive various information from nature. All independently managed physical objects are connected to each other to achieve integrated perception, reliable transmission and intelligent processing, and to establish intelligent information between people and objects, and objects and object service systems. This article mainly introduces the impact of industrial agglomeration on the regional economy in a simulated intelligent environment based on machine learning. This paper proposes a method to detect industrial agglomeration index to analyze industrial agglomeration. Through the establishment of the industrial agglomeration index system, the level of integration of the manufacturing industry in our city was objectively analyzed, and the impact of the integration of manufacturing industry on our city was tested empirically. Finally, the relationship between industrial integration and regional economic development was tested. The experimental results in this paper show that industrial integration in a smart environment based on simulation learning has a significant positive impact on regional economic development. Among them, the level of cooperation between the manufacturing service industry and the manufacturing industry increased by 1%, and the level of regional economic development increased by 0.025%.

INDEX TERMS Internet of Things, machine learning, smart environment, industry agglomeration, regional economy.

I. INTRODUCTION

The development of the times and the improvement of the level of science and technology have promoted economic development [1], which has also made the country's economic ties increasingly closer, and the production industry is constantly changing. Among them, the changes in the industry have also led to changes in economic internships. On the one hand, due to the continuous progress of transportation and information technology, transportation costs continue to drop, communication costs are close to zero, and distance is no longer an obstacle to trade. The international circulation of commodities and technologies has become simple and convenient, and the global market has become integrated. On the other hand, in the context of increasing economic globalization, the trend of regionalization has not weakened, but has become stronger than before.

In the process of regionalization, the industrial system, a new form of industrial organization formed by the spatial agglomeration of many enterprises, appeared in connection with economic relations. The extent to which the agglomeration of the logistics industry affects economic growth and how the logistics industry affects the regional economy has not yet become a consensus. Therefore, exploratory research on the relationship between logistics industry agglomeration and economic growth is of considerable significance both in theory and in practice. In addition, the study of the relationship between logistics industry agglomeration and regional

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economic growth has important practical significance and has an important guiding role in planning the future development direction of the logistics industry.

The Internet of Things (IoT) is a dynamic global information network composed of objects connected to the Internet, which have become an integral part of the Internet in the future [2]. Perera C surveyed more than one hundred IoT smart solutions on the market and carefully checked them to identify the technologies, functions and applications used. His survey is intended to serve as a guide and conceptual framework for future research on the Internet of Things to inspire and inspire further development. However, due to the ambiguity in the understanding of the Internet of Things, the results obtained will not be so accurate [3]. A survey report by Buczak A describes a key literature survey of computer analysis (ML) and data mining (DM) methods used in network analysis to support intrusion detection. He provides a short tutorial description of each ML/DM method. Based on the number of citations or the relevance of an emerging method, papers representing each method can be identified, read, and summarized. Since data is very important in ML/DM methods, some well-known network data sets used in ML/DM are introduced. However, due to the large amount of data, the investigation process took too much time [4]. In order to cope with large fluctuations in commodity demand, manufacturing systems must have rapid response capabilities. This requirement can be guaranteed through performance metrics. Although manufacturing companies already use information systems to manage performance, it is still difficult to capture real-time data to portray the actual situation [5]. The latest developments and applications of the Internet of Things (IoT) have solved this problem. In order to demonstrate the functions of IoT, Hwang G developed a performance model based on IoT, which is consistent with ISA-95 and ISO-22400 standards, which define the manufacturing process and performance index formulas. However, due to the unstable factors in the demand of goods, the efficiency of the manufacturing part will be very low [6].

The innovations of this article are: (1) Use the threshold regression model to test, and use the endogenous data partition mechanism to find structural change points to achieve more scientific grouping. (2) Urban heterogeneity is included in the analysis, and the manufacturing service industry is subdivided into core manufacturing service industry and pillar industry manufacturing service industry. In addition, the impact of different types of producer services and manufacturing in cities of different sizes on the regional economy was discussed.

II. DETECTION METHODS FOR INDUSTRIAL CLUSTERS IN THE INTERNET OF THINGS AND SMART ENVIRONMENTS

A. INTERNET OF THINGS TECHNOLOGY

1) RFID TECHNOLOGY

RFID is abbreviated as radio frequency identification technology, which mainly uses the unique identification number corresponding to the tag to identify the indicator light. RFID is a simple radio system with only two basic elements [7]. The system is used to control, detect and monitor objects. The POS machines we use to swipe bus cards and go to the supermarket to shop are all applications of radio frequency technology [8].

2) SENSOR TECHNOLOGY

For the collection of basic data, according to specific rules, it is converted into electrical signals or other forms of output information to meet the needs of data transmission, processing, storage, projection, recording, and control requirements [9], [10].

3) ARTIFICIAL INTELLIGENCE TECHNOLOGY

Used for network communication. In the Internet of Things, communication between objects and people is bound to be inseparable from high-speed wireless networks, which can transmit large amounts of data [11].

4) WIRELESS NETWORK TECHNOLOGY

Artificial intelligence is the study of how to use computers to simulate certain processes of human thinking and intelligent behavior (such as learning, thinking, thinking, design, etc.) [12]. In the Internet of Things, artificial intelligence technology is mainly responsible for analyzing the content of ‘‘voice’’ objects and starting automatic processing by computers.

5) CLOUD COMPUTING TECHNOLOGY

The cloud in cloud computing technology actually represents the Internet [13]. Computer capabilities through the network, instead of using the software originally installed on the computer or replacing the original data storage energy on your own hard disk, using the network to perform various operations, these operations will lead to The realization structure exceeds the maximum operating range, resulting in a large excess of ore, and even large fluctuations, which is not allowed in production [14].

B. INDUSTRIAL CLUSTER MEASUREMENT INDEX METHOD

According to the basic meaning of industrial agglomeration, this article selects the classic indicators of industrial agglomeration as a basis, and constructs a measurement indicator suitable for this article to study the level of manufacturing industry agglomeration in our city from the three perspectives of location quotient, industry concentration, and industrial spatial concentration [15].

1) LOCATION QUOTIENT

Location quotient was first proposed by Hargate and used in location analysis to measure the degree of concentration of a certain aspect of a specific industry in a certain area. It is a relatively common method to judge the degree of agglomeration [16]. The location quotient index indirectly reflects the way of inter-regional economic relations by calculating the ratio of the specific index of a certain industry in a certain area to the specific index of all industries in the region and the ratio of the specific index of the industry in the country to the index of all industries in the country And structure. Commonly used measurement indicators include output value, sales income, number of employees, etc. [17]. The calculation formula is:

$$LQ_x = (c_x / \sum_{x=1}^{n} c_x)/(C_x / \sum_{x=1}^{n} C_x) \quad (1)$$

Among them, c_x represents the output value population of industrial x in a certain area, and C_x usually represents the output value population of the entire country's industrial x [18].

Generally speaking, when LQ is greater than 1, it indicates that the degree of specialization of the industry in the region is higher than the national level. Indirectly, it can also indicate that the degree of agglomeration is higher and belongs to an industry with comparative advantages. The industry or its products can be expanded or exported., The larger the LQ value, the higher the degree of aggregation [19]. When LQ is equal to 1, it indicates that the degree of agglomeration of industries in the region is the same as that of the whole country. When LQ is less than 1, it means that the degree of agglomeration of industries in the region is relatively low, and it is necessary to import industrial products or industries from outside the region to meet the needs [20].

2) INDUSTRY CONCENTRATION

Among the various methods for measuring the level of industrial agglomeration, it is more convenient to obtain industrial concentration index data, the data is very real, and the measurement is also very convenient [21].Therefore, it is an important indicator to measure the degree of market aggregation [22]. Manufacturing concentration refers to the market share of the original main business in the manufacturing industry. Total output, sales, number of employees, total assets, etc. represent the share of the entire manufacturing industry [23]. Calculated as follows:

$$IC_n = \sum_{x=1}^{n} X_x / \sum_{x=1}^{N} X_x \quad (2)$$

In the above formula, IC_n represents the market concentration of the top n industries with the largest scale in the industry, X_x represents the relevant values of the x industry, such as production, sales, number of employees, total assets, etc. The total number of industries in the manufacturing industry is represented by N [24].

IC_n can vividly reflect the level of manufacturing concentration, calculate the concentration of major manufacturing industries in the market, and research on the impact of industrial agglomeration on regional economic growth-taking the manufacturing industry in our city as an example to indirectly understand the degree of manufacturing agglomeration, but this indicator It can only indicate the situation in the top industries, and the manufacturing concentration is also related to the total number and distribution of manufacturers, so this indicator does not reflect the overall situation of the market, and has certain limitations [25].

3) REGIONAL SPATIAL CONCENTRATION

The regional industrial spatial agglomeration index is developed on the basis of the industrial concentration index, and is used to calculate the production volume of many major industries in the region as the percentages of the national industries [26]. The highest percentage indicates that the largest local industry has a competitive advantage in the country. It also reflects the strong overall strength of the industry in this region. Relatively small means that the competitiveness of the most advantageous industries in the region has not been cultivated in the country, and the region has to increase support for key industries [27], [28]. The specific formula of regional industrial spatial concentration is:

$$RSC_n = \sum_{x=1}^{n} DX_x / \sum_{x=1}^{n} X_x \quad (3)$$

Among them, the numerator represents the sum of the output values of the n industries that account for the largest share in the region, and the denominator represents the sum of the output values of the corresponding industries in the country [29].

Of course, there are many indicators to measure industrial agglomeration, such as H index and regional Gini coefficient. In recent years, foreign scholars have developed many new methods for calculating industrial agglomeration, such as the agglomeration index of industrial clusters and dynamic agglomeration index methods. However, some statistical indicators are not used in China's statistical standards, and the calculations are too complicated, and data collection is very difficult. This article mainly uses the indicators introduced above to simply analyze the level of manufacturing agglomeration in our city [30].

C. CALCULATION OF INDUSTRIAL AGGLOMERATION

To find a suitable indicator to measure the degree of industrial agglomeration, some statistical knowledge is needed [31]. The indicators describing the geographic concentration or agglomeration of industries should meet some basic conditions based on statistics:

(1) Comparable among different industries. It can be seen from the results which industries are more concentrated;

(2) Comparable between different spatial scales. For example, the calculation results in a region and a country require Be comparable;

(3) The estimated value of the index is constant or unique; Here are a few more commonly used indicators [32].

1) HERFINDAHL COEFFICIENT

The Herfindahl coefficient is a comprehensive index to measure the degree of industrial concentration, and it is a commonly used indicator in economics and government regulatory agencies [33], [34]. The specific formula is as follows:

$$H = \sum_{i=1}^{N} (\frac{A_i}{B_i})^2 \tag{4}$$

Among them, A_i represents the relevant value (output value or number of employees) of a certain industry in the i region, B_i represents the relevant value (output value or number of employees) of a certain industry in all regions, and N is the total number of enterprises in the industry in all regions [35].

It measures the absolute concentration of the industry. If economic activity is only concentrated in a certain area, then $H = 1$; if economic activity is evenly distributed in each area, then $H = 1/N$.

2) SPACE GINI COEFFICIENT

Krugman borrowed the concepts of Lorentz curve and Gini coefficient and put forward the concept of spatial Gini coefficient, which is used to measure the degree of industrial distribution in space. The specific formula is as follows:

$$G = \sum (a_i - x_i)^2 \tag{5}$$

Among them, G is the spatial Gini coefficient, a_i is the proportion of a certain industry in the i area to the number of employees in the industry in the country, and x_i is the proportion of the number of employees in the region to the total number of employees in the country.

Compared with the Herfindale coefficient, the spatial Gini coefficient measures relative concentration. The value range of G is [0, 1]. The closer G is to 0, the more even the industry is distributed in space; if $G = 0$, then the industry is evenly distributed in space. The higher the value of G, the more obvious the concentration of the industry in the region.

3) SPATIAL AGGLOMERATION INDEX

In fact, a large spatial Gini coefficient does not mean that there should be a phenomenon of industrial agglomeration, because if there is a large-scale monopoly in a certain industry in a certain area, the rural Gini coefficient calculated from this will also be very large, but this kind of industry The phenomenon of accumulation does not necessarily occur in space. In order to solve the distortion of the Gini factor, improvements were made on the basis of Herfindahl and Gini factors, and a new cumulative index was proposed to measure the degree of industrial agglomeration, called the European Community Index.

$$y = \frac{G - (1 - \sum x_i^2)H}{(1 - \sum x_i^2)(1 - H)} \tag{6}$$

Among them, y is the spatial agglomeration index, G is the industry's spatial Gini coefficient, H is the industry's Huffendale coefficient, and x_i is the proportion of employment in the region to the total employment in the country. among

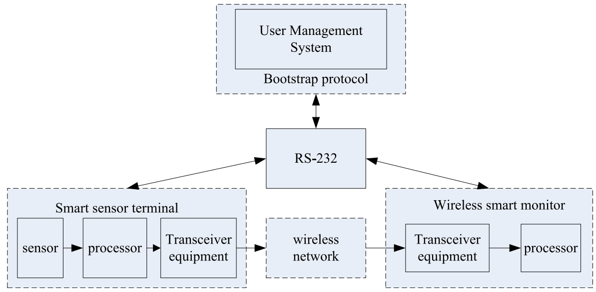

FIGURE 1. Structure diagram of smart sensor system.

them:

$$H = \sum\nolimits_{i=1}^{N} (\frac{A_i}{B_i})^2 \tag{7}$$

The EG index is divided into three ranges. When $y < 0.02$, the industry has a low degree of agglomeration; when $0.02 \leq y \leq 0.05$, the industry shows a moderate degree of agglomeration; when $y > 0.05$, the industry has a higher degree of agglomeration.

III. INDUSTRY CLUSTER EXPERIMENT IN SENSOR ENVIRONMENT

A. ESTABLISHMENT OF INTELLIGENT ENVIRONMENT SYSTEM

The overall structure of the smart sensor system is divided into three parts: smart sensor terminal, wireless smart monitor and user management system based on Bootstrap protocol [36]. These three parts are used for data transmission through a wireless network based on ZigBee technology and an RS-232 port based on Bootstrap protocol. The design idea of this text runs through the whole system, whether it is hardware selection, PCB design, embedded processor internal program, etc., all have been processed with low power consumption. The composition of the intelligent sensor system is shown in Figure 1:

The smart sensor terminal is responsible for collecting sensor data [37], then process the sensor data and save it in the internal memory, and then transmit the data to the wireless smart terminal monitor through the wireless network. The wireless smart monitor is responsible for setting the monitoring threshold of each smart sensor terminal, and regularly collects the data information of the sensor terminal, and saves the information in the data memory. The user management system is mainly responsible for the monitoring data collection and analysis of the wireless smart monitor [38], and is responsible for the software upgrade of the smart sensor terminal and the wireless smart monitor.

According to the functional division of the smart sensor system, the system can be divided into: sensor data collection function, sensor data processing function, smart terminal data collection function, monitor data collection function, smart sensor terminal software update function, and smart monitor software update function. The system function division is shown in Figure 2:

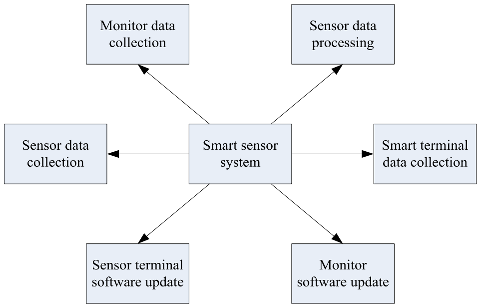

FIGURE 2. Functional diagram of smart sensor system.

B. ESTABLISHMENT OF THE THRESHOLD MODEL OF INDUSTRIAL AGGLOMERATION

Since the single-threshold model is similar to the multiple-threshold model, it can be easily extended to the case of multiple thresholds with a slight change [39]. Therefore, only the setting and testing methods of the single-threshold model are introduced here.

The basic model of the single threshold model is set as follows:

$$y_{it} = a_i + b_1 x_{it} \cdot I(Q_{it} \leq e) + b_2 x_{it} \cdot I(Q_{it} > e) + \lambda_{it} \quad (8)$$

Among them, $i = 1, 2, \ldots, N$ represents different individuals (company, country, region),$t = 1, 2, \ldots, T$ represents time, threshold variable is represented by Q_{it}, threshold value is represented by e, y_{it} and x_{it} are explained variables and explanatory variables respectively, $I(\bullet)$ is an indicator function, It can be regarded as a form of a dummy variable. When the condition in brackets is established, its value is 1, otherwise it is 0. The difference in the intervals separated by the threshold value is reflected in the coefficients of different intervals, such as b_1 and b_2.

Using the piecewise function in mathematics, the following formula will be expressed more clearly.

$$y_{it} = \begin{cases} a_i + b_1 x_{it} + \lambda_{it}, Q_{it} \leq e \\ a_i + b_2 x_{it} + \lambda_{it}, Q_{it} > e \end{cases} \quad (9)$$

Perform ordinary least squares (OLS) regression analysis on formula (9), and obtain the residual sum of squares function as:

$$S_1(e) = d_i'(e) d_i(e) \quad (10)$$

Finding the e corresponding to the smallest residual square sum $S_1(e)$ is the threshold value we are looking for, which is:

$$\hat{e} = \arg\min S_i(e) \quad (11)$$

According to the general form of the threshold model, in order to investigate the relationship between logistics industry agglomeration and economic growth, this paper uses the logistics industry agglomeration level as the threshold variable to establish a threshold regression model. Because the number of existing thresholds is undetermined, a single threshold regression model is first established. If the number of thresholds is greater than one, adjustments will be made based on this model. The empirical model of the single threshold is as follows:

$$\begin{aligned} G_{it} = u_i &+ b_1 G_{it} I(L_{it} \leq e) + b_2 G_{it} I(L_{it} > e) \\ &+ \rho_1 G_{it} + \rho_2 Iab_{it} + \rho_3 L_{it} + \rho_4 O_{it} + n_{it} \quad (12) \end{aligned}$$

Among them, i, t represents the province and year respectively, G represents the level of economic development, u_i represents the individual effect, lq represents the level of logistics industry agglomeration, L represents the degree of government intervention, O represents the degree of economic openness, I represents the level of capital investment, and Lab represents the level of human capital, $I(\bullet)$ is the indicator function.

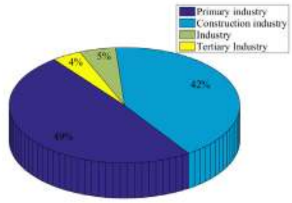

FIGURE 3. The composition of the three industries in our city in 2018.

IV. ANALYSIS OF THE IMPACT OF INDUSTRIAL AGGLOMERATION ON THE REGIONAL ECONOMY UNDER THE INTERNET OF THINGS ENVIRONMENT

A. OVERALL ANALYSIS OF INDUSTRIAL ECONOMY

In 2018, the city achieved a regional GDP of 431.8 billion yuan, an increase of 9% over the previous year at comparable prices. The primary industry increased by 17.9 billion yuan, an increase of 4%; the secondary industry achieved an added value of 241.2 billion yuan, an increase of 8%, the industrial added value was 210 billion yuan, an increase of 8.4%; the tertiary industry's added value was 177.9 billion yuan. Increase by 10%. The proportion of the three industries is 4:55:41, of which industrial added value accounts for 49%. Based on the permanent population, the per capita GDP is 61,000 yuan. The proportions of the three major industries in our city are shown in Figure 3:

Statistics on the changes in the city's industrial GDP from 2014 to 2019, it can be seen that the city's industrial added value accounted for between 48% and 54% of the regional GDP, which shows that industry is in the city's economic development. Has a vital role. The specific results are shown in Figure 4:

According to the data analysis in the figure, it can be seen that the industrial output value of our city will not be lower than the overall 48%, but in 2019 it increased by 1% over the previous year. From this we can see that the development of the industry will continue to grow.

In the whole year, the production and sales of industrial enterprises above designated size in Ningbo increased by 35% and 34% respectively, reaching the highest annual

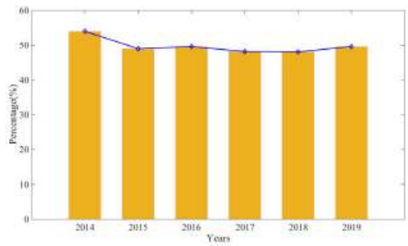

FIGURE 4. The city's industrial growth as a percentage of GDP from 2014 to 2019.

TABLE 1. The total cost of the logistics industry and the proportion of GDP from 2013 to 2019.

Years	Total logistics cost	Percentage of GDP
2013	61000	18.20%
2014	71000	17.90%
2015	84000	17.70%
2016	93700	18.10%
2017	102400	18.10%
2018	106800	16.70%
2019	109000	16.10%

growth rate in the past eight years. The overall industrial economy showed a good development trend of high growth and steady progress. In terms of different industries, among the 30 major industries in the city, except for the negative growth of the output value of the non-metallic mining and dressing industry, the other 29 industries have different growth rates, of which the production growth rate of 10 industries exceeds the city's average level; among the top 5 industries, The growth rates of four industries, including electrical machinery, petroleum processing, general equipment manufacturing, chemical raw materials and chemical products, were all above 40%. The growth rate of heavy industry is 12% faster than that of light industry, but the growth of light industry is more stable. The total industrial output value of all young industries was 340 billion yuan, a year-on-year increase of 27%, and the cumulative growth rate was 3 percentage points higher than that in the first quarter. The cumulative growth rate of heavy industry was affected by energy conservation and power restrictions, and the cumulative growth rate was 15 percentage points lower than the first quarter.

B. ANALYSIS OF THE AGGREGATION OF THE LOGISTICS INDUSTRY UNDER THE INTERNET OF THINGS ENVIRONMENT

As the country's statistics do not separate the logistics industry as an industry, it is difficult to find relevant statistics. According to incomplete statistics, the output value of transportation, warehousing and postal industry accounts for more than 80% of the output value of the logistics industry. The three of them can represent the logistics industry to a certain extent. Therefore, in actual operation, generally use transportation, storage and postal services. Industry to represent the logistics industry. Table 1 shows the changing trend of my country's total social logistics costs and its proportion of GDP in recent years. From the data in the table below, we can see that in 2019, the total cost of social logistics in the country reached 1.1 trillion yuan, which was not much higher than that of the previous year. The increase was only 2.01%, and its proportion of GDP fell by 0.7%. Logistics costs have decreased. Observing the trend of changes in the proportion of total social logistics costs in GDP across the country over the years, we can find that the value remained at about 19% from 2013 to 2017, and the proportion has declined slightly year by year, but after 2017 there has been a large decline, and it has dropped to 15 in 2018 and 2019. %, indicating that my country's logistics development level is improving; but compared with developed countries, such as the United States, the value is 8%, indicating that my country's logistics development level still has a certain gap with developed countries.

Figure 5 records the total fixed assets of the logistics industry in the eastern, central and western regions of my country over the years. It can be seen from the figure that during 2013-2019, except for the small decline in fixed asset investment in the eastern and central regions in 2013, 2014, and 2015, the fixed asset investment in the logistics industry in the eastern, central and western regions The amount has been steadily increasing year by year. Due to its early development, the eastern region has always maintained a leading position in total volume. At the end of 2019, the fixed asset investment in the logistics industry in the eastern, central, and western regions reached 1.782.9 billion, 1.1 trillion and 1.5 trillion yuan, which was 2013 7 times, 8 times, 11 times of the year, the overall investment volume has been greatly improved. Although the total amount in the central and western regions is relatively small, in 2014, 2015, 2018, and 2019 respectively, their annual growth rates exceeded those in the eastern region. The largest increase was in 2015. The increases were 31%, 59%, and 53% respectively. In summary, the eastern region maintains its economic advantages in the more developed regions, and investment in fixed assets in the logistics industry is still large. Compared with the central and western regions, its logistics network system is relatively complete; however, there are several The annual growth rate of fixed investment in the logistics industry exceeded that of the eastern region, forming a catching-up trend.

C. ANALYSIS OF THE IMPACT OF INDUSTRIAL CO-AGGREGATION ON REGIONAL ECONOMY

In order to further study the impact of collective integration on the regional economy under the background of urban heterogeneity, this module adopts a threshold regression model and selects the city size as a threshold variable for experimental testing. In order to ensure the scientificity and rationality of the regression results, we must first check whether there is a limit. The threshold effect test can effectively determine whether there is a threshold effect and the number of

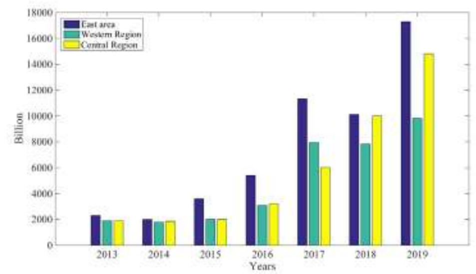

FIGURE 5. Logistics industry investment in different regions.

TABLE 2. Test results of threshold effect of industrial collaborative aggregation.

Threshold variable	model	F statistics	P value	Sampling times	1% threshold	5% threshold	10% threshold
gm	The first threshold	31	0.005	600	25	10	6.7
	The second threshold	27	0.003	600	18	5	0.3
	The third threshold	18	0.03	600	19	11	7.2

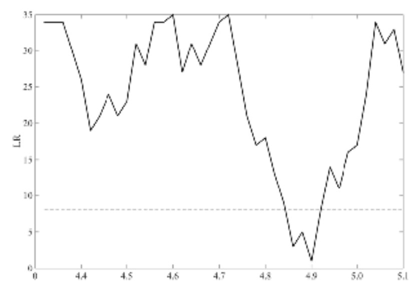

FIGURE 6. Schematic diagram of threshold parameters.

thresholds. If the test fails, there is no threshold result. In the absence of a threshold, we use the "self-sampling" method to calculate one threshold and two thresholds. The specific results are shown in Table 2:

We use city scale as a threshold variable to control the threshold phenomenon of cooperation and integration between the production service industry and the manufacturing industry. The results show that there is a threshold phenomenon and a triple limit. In order to ensure the rationality and sensitivity of the test results, the probability ratio test chart is further used to select the threshold.

In order to have a clearer understanding of the process of establishing the levy point price and the confidence interval, we are designing a threshold probability program for regional economic development under different urban conditions. The criterion for selecting the estimated value of the threshold phenomenon is the value when the probability ratio test is zero. See Figure 6 for details:

Through the self-sampling threshold test and the probability ratio test, and the thorough test of the confidence interval of the threshold, we believe that in cities of different sizes, cooperative clusters have a double threshold for regional economic development. The threshold price of city size is relatively close, 4 and 5. The actual values are 550,000 and 1.46 million respectively.

V. CONCLUSION

This article analyzes the level of industrial agglomeration in our city using indicators such as location scale, industrial concentration and regional industrial spatial concentration. The results show that the accumulation level of production in our city is relatively high. There is a two-digit average production location greater than the aggregation location. It is higher than the national average and has a competitive advantage. At the same time, the use of the Cobb production function verifies the positive impact of industrial integration on regional economic development.

Based on China's logistics technology and logistics requirements, combined with the basic theories and technologies of the Internet of Things, this article proposes to build an intelligent logistics service system under the Internet of Things environment, implement a large logistics alliance strategy, focus on intelligent logistics information processing platforms, and integrate intelligent needs The management and operation system provides integrated solutions for the upgrading of China's logistics industry, and analyzes the logistics industry clusters and regional economies.

In this paper, the indicators for measuring the regional economy are relatively simple, and only the GDP index is selected as the indicator for measuring the economic development of various provinces. It is hoped that more indicators can be discussed in future research, such as total factor productivity (TFP) and local industrial structure indicators. In addition, the analysis of the impact mechanism of the logistics industry agglomeration on the regional economy is slightly weak, and more theoretical basis and actual data are needed as support. The future research direction may be based on related theoretical models, combined with the characteristics of the logistics industry and my country's actual conditions to demonstrate its influence mechanism.

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