



Interactive Evolution Model of Industrial Cluster and Regional Innovation Based on LSTM

Le Tong¹ and Fen Wang²(✉)

¹ Wuhan Business University, Wuhan 430050, China

² Wuhan Aiwuyou Technology Co. Ltd., Wuhan 430050, China

Abstract. The current evolution model of the interaction between industrial clusters and regional innovation has not measured the interaction factors between industrial clusters and regional innovation, which leads to inaccurate changes in the industrial chain supply and demand, input-output coefficients, and industrial quantities. To this end, this study designed an LSTM-based interaction evolution model of industrial clusters and regional innovation. First, use LSTM to measure the interaction factors between industrial clusters and regional innovation, and form a network structure; according to the measurement results, analyze the factors that exist in the interaction process, so as to establish the interaction evolution model of industrial clusters and regional innovation. Experimental results show that the model in this paper can better describe the supply-demand relationship and input-output coefficient of the industrial chain in the process of interaction between industrial clusters and regional innovation.

Keywords: LSTM · Industrial clusters · Regional innovation · Interactive evolution model

1 Introduction

Industrial clusters have the characteristics of geographic proximity and spatial agglomeration, which enable industrial clusters to develop more economic activities and present a good economic development trend [1]. And with the vigorous development of economic globalization, industrial clusters, as a new form of industrial organization, can rely on its powerful resource allocation function to promote the development of regional economy [2]. At present, on a global scale, industrial clusters have become accelerators that promote regional economic development and national competitiveness, and have become the business card and symbol of their country or region, and have become a ubiquitous organizational form in developed economies [3]. In addition, industrial clusters also provide entrepreneurs with abundant labor, raw materials, and market orders, which effectively reduces the risks and costs of entrepreneurs entering industrial clusters to start businesses, thereby promoting regional innovation.

However, the above process is a long evolutionary process, and not all regional industrial clusters can form a good interactive evolution trend [4]. Therefore, this study uses the chain form of long-term and short-term memory network (LSTM) to deal with and predict the interactive evolution process of industrial clusters and regional innovation, and designs an interactive evolution model of industrial clusters and regional innovation based on LSTM. Firstly, the interactive factors between industrial clusters and regional innovation are measured by LSTM, and the network structure is formed. According to the measurement results, the factors existing in the interactive process are analyzed, and the interactive evolution model of industrial clusters and regional innovation is established. In addition, the model can well describe the supply-demand relationship and input-output coefficient of industrial chain in the process of interaction between industrial cluster and regional innovation.

2 Design of Interactive Evolution Model of Industrial Clusters and Regional Innovation

2.1 Measurement of Interaction Between Industrial Cluster and Regional Innovation Based on LSTM

Based on the analysis of the current interactive evolution of industrial clusters and regional innovation in the introduction, it can be seen that there is a direct causal relationship between industrial clusters and regional innovation interactive evolution, and it is difficult to describe the causality of the interactive evolution process of industrial clusters and regional innovation only through large-scale theories. relationship. Therefore, the interactive evolution model of industrial clusters and regional innovation established in this study will use LSTM to process and predict the causal relationships that exist in the interactive evolution process of industrial clusters and regional innovations, and discover laws from the macroscopic and external environmental connections, thereby completing the industrial Research on the interactive evolution model of clusters and regional innovation.

2.1.1 Degrees

LSTM emphasizes that each actor has a more or less relationship with other actors. According to the structure describing group relations, it studies the influence between industrial clusters and the evolution of regional innovation interaction.

Therefore, a series of regional innovation subjects are assumed to be N and $N = \{1, 2, \dots, n\}$. If there is a connection between industrial cluster j and regional innovation i , then j is called the “neighbor point” of i ; the number of adjacent points of a regional innovation subject N_i is called the “degree” of the point, which is recorded as d_i .

In fact, the “degree” of a regional innovation subject is the number of lines connected to it. If there is a connection between industrial clusters and regional innovation subjects, that is, they are connected by a line, they are called “adjacent.” If the degree of an innovative subject is 0, it is called an “isolated point” [5]. At this time, the average

value of LSTM points measures the average degree \bar{d} of industrial clusters and regional innovation in a region, and its expression is:

$$\bar{d} = \frac{\sum_{i=1}^g d(n_i)}{g} = \frac{2l}{g} \quad (1)$$

In formula (1), g represents the scale of LSTM, that is, the number of interactive evolution between industrial clusters and regional innovation subjects in a region; l is the number of LSTM lines formed between industrial clusters and regional innovation entities.

2.1.2 LSTM Network Density

In addition to the degree parameters obtained by formula (1), we also need to calculate the LSTM density and centrality, so as to obtain the interaction measure between industrial clusters and regional innovation, and infer the causal relationship between industrial clusters and regional innovation.

Taking LSTM density as an index to measure the interaction between industrial clusters and regional innovation can reflect the degree of closeness between industrial clusters and regional innovation subjects in a region. In short, the more connections between fixed scale industrial clusters and regional innovation entities, the greater the LSTM density of industrial clusters and regional innovation.

Therefore, assuming that the LSTM density of industrial clusters and regional innovation in a certain area is 1, then in the LSTM of the region, the industrial clusters and regional innovation entities are connected with industrial clusters and regional innovation entities in other regions; when the LSTM density is 0, It means that the industrial clusters in any region of the network are not connected with the regional innovation subjects. The expression of LSTM network density m is:

$$m = \frac{g * \bar{d}}{g(g-1)} = \frac{2l}{g(g-1)}, m \in [0, 1] \quad (2)$$

According to formula (2), the LSTM density index in the measurement of interaction between industrial clusters and regional innovation can be obtained. At this time, we only need to calculate the LSTM centrality, then we can get the measurement of the interaction between industrial clusters and regional innovation, and analyze the formation and causes of the interactive evolution between industrial clusters and regional innovation.

2.1.3 Centrality

The interactive evolution process of industrial cluster and regional innovation is also the result of artificial promotion [6]. Therefore, there will be power elements, which need to be analyzed from the perspective of network. Therefore, it is divided into local and global dimensions. There are two indexes of local center degree and global center degree.

Calculate the degree index in the measurement of the interaction between industrial clusters and regional innovation based on formula (1), and convert it to obtain a certain regional innovation subject. The expression of the degree centrality index $C_1(i)$ is:

$$C_1(i) = \frac{d_i}{g - 1} \quad (3)$$

When the point degree centrality $C(i) = 0$ in formula (3), the actor is an isolated point; when $C(i) = 1$, it is one of the core points of LSTM and the center point of the evolution of the interaction between industrial clusters and regional innovation, according to formula (3) It can be seen that there is a direct relationship between industrial clusters and regional innovation interaction and evolution.

The intermediate centrality index can express the degree of control over the regional resources during the interaction and evolution of industrial clusters and regional innovation. The intermediate centrality measure expression is:

$$C_{2i} = \sum_j^n \sum_k^n b_{jk}(i), j \neq k \neq i, \text{ and } j < k \quad (4)$$

In formula (4), b_{jk} represents the probability that regional innovation subject i is on the geodesic between industrial cluster j and k .

No matter what level (individual, group or organization) the actors in LSTM are at, it is an important goal of network analysis to obtain information about the whole LSTM network through the analysis of actors. At this point, we need to use the concept of near centrality. Therefore, the concept of proximity centrality is: the proximity centrality of a point is the sum of geodesic distances between the point and all other points in the network [7]. Then the expression close to centrality C_{3i}^{-1} is as follows:

$$C_{3i}^{-1} = \sum_{j=1}^g d_{ij} \quad (5)$$

In formula (5), d_{ij} represents the geodesic distance between the regional innovation subject i and the industrial cluster j (that is, the number of lines included in the geodesic).

The centrality of LSTM measures the ability of a regional industrial cluster to develop the relationship with regional innovation subjects, and the close to centrality is the regional industrial cluster and regional innovation subject. It depends on the LSTM relationship between the industrial cluster and the regional innovation subject, rather than the direct relationship between the industrial cluster and the regional innovation subject in the neighborhood.

The process shown in formula (1) to (5) above is the measurement of interaction between industrial clusters and regional innovation. According to the measurement index values obtained from formula (1)–formula (5), we can analyze the direct/indirect relationship existing in the interactive evolution process of industrial cluster and regional innovation, and the influence of causality, human factors and asset factors on the interactive evolution process of industrial cluster and regional innovation.

2.2 Establish an Interactive Evolution Model of Industrial Clusters and Regional Innovation

The last section uses LSTM to analyze the influencing factors in the interactive evolution process of industrial cluster and regional innovation by measuring the interaction between industrial cluster and regional innovation. It is found that the interactive evolution process of industrial cluster and regional innovation has certain relationship with the number of people, development space, economy, interactive industrial cluster and regional innovation scale Firstly, the interactive evolution model of industrial cluster and regional innovation is established.

Assuming that the population of this area in year t is $N(t)$, then:

$$N(t) = N_0 e^{r(t-t_0)} \tag{6}$$

In formula (6), N_0 represents the population number under the initial conditions; t_0 represents the initial value of the equation, in this calculation, $t_0 = 0$; r represents the natural growth rate of the population, which is a constant [8].

In the interactive evolution process of industrial cluster and regional innovation, in addition to the influence of population, economic influence is also an important factor in the interactive evolution of industrial cluster and regional innovation

$$\frac{dx}{dt} = R \left(1 - \frac{x}{x_1} \right) x = f(x, R), x(0) = x_0 \tag{7}$$

In formula (7), $x(t)$ represents the amount of economic change produced when the industrial cluster interacts with regional innovation at time t ; R represents the economic growth rate generated when the industrial cluster interacts with regional innovation; $\left(1 - \frac{x}{x_1} \right)$ represents the remaining amount when the industrial cluster interacts with regional innovation. The proportion of interactive evolution resources to the total interactive evolution resources.

$\left(1 - \frac{x}{x_1} \right)$ in formula (7) has the following characteristics: if the number of regional innovation individuals tends to zero, then item $\left(1 - \frac{x}{x_1} \right)$ tends to 1, which means that almost all industrial cluster resources are not used, and regional innovation pole is in the best development trend; if x tends to x_1 , then $\left(1 - \frac{x}{x_1} \right)$ tends to zero, which means that almost all resources of industrial cluster are utilized, and the growth rate of regional innovation pole will tend to zero; with the development of innovation pole, industry will tend to zero. The cluster resource surplus $\left(1 - \frac{x}{x_1} \right)$ is smaller and smaller, and the growth rate of innovation pole is also slower and slower [9].

If there are relative industrial clusters in a region, and these industrial clusters influence each other, it is assumed that the industrial clusters, regardless of their size, can form a symbiosis and develop together from the perspective of competing for resources. Therefore, assuming that there are two innovation poles, A and B, when they only exist in the regional innovation system, the development and evolution of the innovation poles all follow the Logistic law. At this time, under the influence of industrial clusters of different sizes, the scales of the two innovation poles are denoted as $x_1(t)$ and $x_2(t)$

respectively, and the inherent growth rates of the assets of the two industrial clusters are R_1 and R_2 . The maximum increased capacity is denoted as N_1 and N_2 respectively, and for the Innovation Extreme A, there are:

$$\frac{dx}{dt} = R_1 x_1 \left(1 - \frac{x}{N_1} \right) \quad (8)$$

In formula (8), factor $\left(1 - \frac{x}{N_1} \right)$ represents the retarding effect on the growth of its own scale due to the consumption of limited resources of the industrial cluster by the innovation pole A; $\frac{x}{N_1}$ is the percentage of industrial cluster resources consumed by A. In the model of this study, the total resource of the industrial cluster is set to 1.

When the two innovation poles exist in the same region, as mentioned above, there are three symbiotic relationships between a and B: mutual symbiosis, mutual independence symbiosis, and mutual competition symbiosis. If two innovation poles co-exist with each other, the other will develop better due to the existence of one; if the two innovation poles coexist independently, it is considered that the two innovation poles have no innovation connection in the growth process, and their industrial cluster resources are not in conflict, and the two innovation poles develop separately; if the two innovation poles compete and coexist, one of them consumes a limited industrial cluster Resources have an impact on the growth of the other innovation pole, leading to the decrease of the growth rate of the other innovation pole [10].

Therefore, in view of the above relationship, for innovation pole a $x_1(t)$, the symbiosis coefficient b of innovation pole should be introduced into factor $\left(1 - \frac{x}{N_1} \right)$. The size of the symbiosis coefficient b can indicate the size of the symbiosis effect. Obviously, the symbiotic effect of innovation pole a $x_1(t)$ is directly proportional to the number of innovation pole a x_2 and inversely proportional to N_2 . Therefore, under this symbiosis condition, the evolution dynamic equation of innovation polar beetle is as follows:

$$\frac{dx_1}{dt} = R_1 x_1 \left(1 - \frac{x_1}{N_1} - b_1 \frac{x_2}{N_2} \right) = f_1(x_1, x_2) \quad (9)$$

In formula (9), R_1 is the proportional coefficient, b_1 is the symbiosis coefficient of innovation pole B to innovation pole a, and $\frac{x_2}{N_2}$ is the unit number. If the two are symbiotic, then b_1 is negative, and its absolute value indicates the strength of regional innovation and industrial cluster resource symbiosis. If the two innovation poles are symbiotic, then b value is positive, which indicates the degree of competition between them, that is, the consumption intensity of resources of industrial cluster a caused by the existence of b_1 ; if the two innovation poles coexist independently; if the value of b_1 is 0, then the two innovation poles do not affect each other, and both follow the evolutionary dynamic mode of a single innovation pole.

Therefore, the existence of innovation pole A will inevitably affect the scale growth of innovation pole B. The evolutionary dynamics equation of innovation pole B is:

$$\frac{dx_2}{dt} = R_2 x_2 \left(1 - \frac{x_2}{N_2} - b_2 \frac{x_1}{N_1} \right) = f_2(x_1, x_2) \quad (10)$$

The proportion coefficient b_2 in formula (10) represents the symbiosis coefficient between innovation pole a and innovation pole B, and $b_2 \frac{x_1}{N_1}$ is the consumption percentage of industrial cluster resources of innovation pole B by unit quantity a.

To sum up, it is the interaction evolution model of industrial clusters and regional innovation. According to the model established this time, it is possible to analyze the economic growth trend, population change, impact on the region, Change parameters.

3 Experimental Discussion

In order to verify the application performance of the interactive evolution model of industrial cluster and regional innovation based on LSTM, the following experiments are designed.

In the experiment, the effectiveness of the interactive evolution model of industrial cluster and regional innovation based on LSTM is verified by comparison. The model in this paper is recorded as a model, and the two traditional interactive evolution models are recorded as B model and C model respectively, which are used for complete performance comparison and verification with the model in this paper.

3.1 Experimental Preparation

Select a certain industrial cluster area in a certain province as the experimental verification object. The area has a total area of 13,472 square kilometers and a population of 7.145 million. The mountainous region has a mild climate, diverse landforms, and fertile soil. It is a rich production area for a variety of agricultural and sideline products. The coastline of the coastal land area in this area is 196.5 km long, and the development potential of tidal flats and shallow seas is great. There are many types of mineral resources, large reserves, good quality, concentrated distribution, and easy mining and selection,

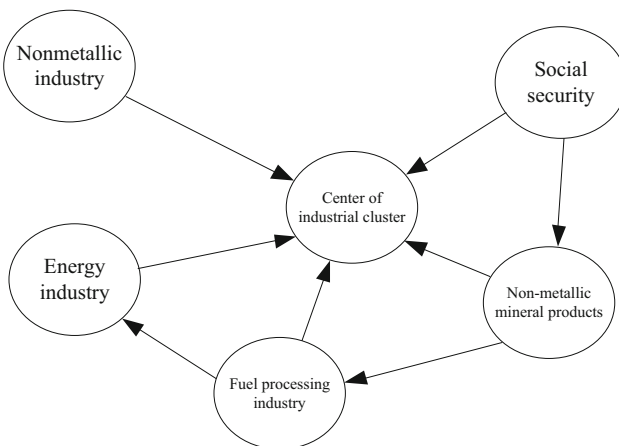


Fig. 1. General structure of industrial clusters

forming major pillar industries such as steel, energy, cement, machinery, chemicals, ceramics, textiles, papermaking, food, and electronics.

In the development process of the region, the above industries belong to industrial clusters with different products. The general structure of the industrial clusters is shown in Fig. 1.

The running environment of the experiment is shown in Table 1.

Table 1. Operating environment of the three groups of models on the computer

Experimental environment	Configuration	Configuration description
Configuration	Hardware framework	RACK
	CPU model	315-2DP
Software environment	Model writing	Matlab
	Operating environment	Windows XP SP3

3.2 The First Group of Experiments

Three sets of models are used to calculate the supply and demand industries and input-output coefficients of the industrial chain in the experimental area, and are compared with the actual calculated coefficients to judge the similarity between the calculated results of the three sets of models and the actual coefficients, so as to compare the analysis effects of different models. The experimental results are shown in Table 2.

Table 2. Supply and demand industries and input-output coefficients of industrial chain

Model	Coefficient of complete consumption	Innovation industry	Coefficient of complete consumption
A model	0.252003	5	0.263984
B model	0.110864	5	0.154844
C model	0.32439	5	0.37132
Actual value	0.253013	5	0.264104

It can be seen from Table 1 that the supply and demand industries and input-output coefficients of the industrial chain evolved from model C are significantly higher than the actual value; the supply and demand industries and input-output coefficients of the industrial chain evolved from model B are significantly lower than the actual value; only the supply and demand industries and input-output coefficients of the industrial chain evolved from model a are very close to the actual value. Therefore, this model can accurately evolve the supply and demand industries and input-output coefficient of the industrial chain.

3.3 The Second Group of Experiments

Perform the second set of experiments on the basis of the first set of experiments. Three sets of models are used to respectively evolve the changes in the number of industries in the process of interaction between industrial clusters and regional innovation, and compare them with actual changes. The comparison results are shown in Fig. 2.

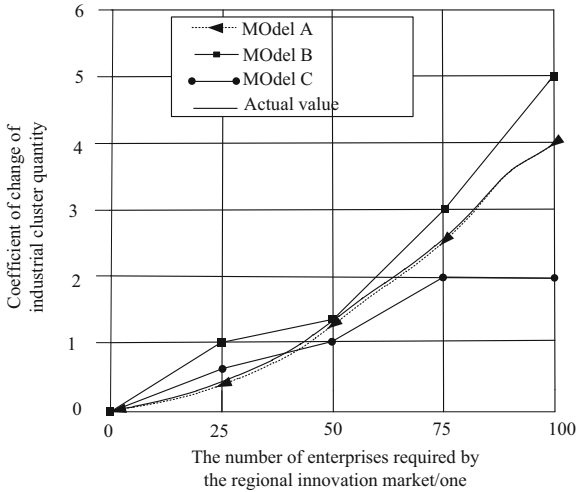


Fig. 2. Comparison of changes in the number of industries

It can be seen from Fig. 2 that the similarity between the quantity change of evolutionary industries obtained by model C and the actual change is the lowest; although the quantity change of evolutionary industries obtained by model B is close to the actual value, there are still large changes; the similarity between the quantity change of evolutionary industries obtained by model a and the actual change is the highest. Therefore, this model can accurately evolve the change of industrial quantity in the process of interaction between industrial clusters and regional innovation.

4 Concluding

This paper designs an interactive evolution model of industrial cluster and regional innovation based on LSTM, which makes full use of the advantages of LSTM to analyze the factors existing in the interactive evolution process of industrial cluster and regional innovation, and effectively reflects the interactive evolution characteristics of industrial cluster and regional innovation. In addition, the model can well describe the supply-demand relationship and input-output coefficient of industrial chain in the process of interaction between industrial cluster and regional innovation. However, this model does not consider the interactive evolution structure and coupling between industrial cluster and regional innovation, which is not comprehensive enough for the interactive evolution

process of industrial cluster and regional innovation. Therefore, in the future research, it is necessary to study the interactive evolution model of industrial cluster and regional innovation, and integrate the interactive evolution structure and coupling characteristics of industrial cluster and regional innovation into the evolution model.

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