

## Weighted Network Evolution Model of Industry Technology Innovation Alliances Knowledge Transfer Based on Node Competitiveness

ZHANG Yujie<sup>[a]</sup>, WU Jie<sup>[a].\*</sup>, LIU Tingting<sup>[a]</sup>

<sup>[a]</sup> School of Economy and Management, Jiangsu University of Science and Technology, Zhenjiang, Jiangsu, China.

\* Corresponding author.

E-mail: 0511wujie@163.com.

**Supported by** National Social Science Fund (No.11BGL039), College Graduate Research and Innovation Projects in Jiangsu Province (No. CXZZ12\_0729), National Natural Science Fund (No. 70773080), College Philosophy and Social Sciences Key Projects in Jiangsu Province (No. 2011ZDIXM036), 2011 Doctoral Fund of Ministry of Education (No. 20113223110007) and the 2011 Annual Project Jiangsu Province Education Science "12th Five-Year Plan" (No. B-b/2011/03/034).

Received 10 January 2013; accepted 16 March 2013

### Abstract

On the basis of the dynamic evolution and competition of the complex network of industry alliances together with the limitations of the BBV network model, a competitive merit-based dynamic evolution model is constructed. It not only considers the addition of new nodes, but also the deletion of old nodes, the rewiring of old nodes and the deletion of old links appear in the networks. By using continuum theory and mean field theory, the corresponding evolution equation is established. The strength and degree distribution of the model still has the power-law characteristics of scale-free networks and BBV scale-free network is a special case. The correctness of the theoretical analysis is proved by the simulation. The results show that by adjusting the parameters, it can coincide with the power-law exponent of many complex networks. Therefore, the improved model is more adaptive and authenticity.

**Key words:** Industry Technology Innovation Coalition; BBV Model; Competitiveness; Degree Distribution; Power-law Exponent

ZHANG Yujie, WU Jie, LIU Tingting (2013). Weighted Network Evolution Model of Industry Technology Innovation Alliances Knowledge Transfer Based on Node Competitiveness. *Management Science and Engineering*, 7(1), 35-44. Available from: <http://www.cscanada.net/index.php/mse/article/view/j.mse.1913035X20130701.2560>  
DOI: <http://dx.doi.org/10.3968/j.mse.1913035X20130701.2560>

### INTRODUCTION

In recent years, the rise of complex networks makes the study of various disciplines substantial breakthroughs. Through the research on the Internet, the World Wide Web, the global aviation network, research cooperation network, social networks, biological metabolic networks etc., it can be found that many systems in the reality can be seen as complex networks. The network nodes represent system elements and the edges represent the link between elements. People have proposed a variety of complex network model from different perspectives, in which the most famous are the ER random graph model proposed by Erdős and Rényi (Erdős, 1960), the WS small-world network model proposed by Watts and Strogatz (Watts, 1998) and the BA scale-free network model proposed by Barabási and Albert (Barabási, 1999). The BA model studied the origin of the macroscopic properties of the network from the perspective of evolution for the first time, and laid the foundation of network evolution model. The BA model indicated that growth and preferential attachment mechanism were reasons for the formation of the complex network scale-free property. This allowed people to recognize the macroscopic properties of complex networks are determined by its microscopic mechanism, thus began to study the macroscopic properties of the real network and its evolution problems.

The BA model explains the scale-free characteristics of the network better, but it is still oversimplified compared to the real network. Researchers of related areas proposed BA modified models from two perspectives based on the actual network: the growth mechanism and merit-based mechanism of the BA model. On the aspect of the growth mechanism improvement issue, Newman M E J (Newman, 2003) considered the increase of node and new connection inside the network on the basis of the BA model, and obtained model of the power law index  $\lambda = 3$ . Tang and other scholars (Tang et al., 2005) extended

the dynamic processes of the BA model and established the Embedded-Delete-Compensation model, including randomly deleting existing nodes or links in the network and link compensation. Chen and Shi (Chen, 2006) studied the important role of the merit-based edge plus and the anti-merit edge deletion on the network scale-free characteristics. They draw the power-law index of network degree distribution between 2 and 3, which was consistent with the reality of many networks; Jia and other scholars (Jia et al., 2009) studied the addition and deletion of nodes and edges more comprehensively from a dynamic evolution perspective, getting the power-law index in the range of 1 to 3. There are also some common growth mechanism improved model such as the Index Network Model (Jia et al., 2005), the Poisson Model of Undirected Complex Networks (Li and Qian, 2006), the AB model (Guo, 2006), the DM model (Albert and Barabási, 2000) and so on. On the aspect of the merit-based mechanism improvement issue, Bianconi and Barabási (Bianconi, 2001) considered competitive factors in the BA scale-free network evolution process and constructed the Fitness Model, pointing out that the degree of the node and its growth rate is related to the inherent nature of the node. Research on the merit-based mechanism also includes the nonlinear preferential attachment (Krapivsky et al., 2000), the node attraction (Zhou et al., 2012) etc.

The above-mentioned correction models are presented based on the real life network features and phenomena. They are built through the amendment and improvement of the growth and merit-based selection mechanism of the BA model. Each model has a focus, revealing the inherent nature of the corresponding network from the microscopic mechanisms to explain the macroscopic phenomena appeared in the corresponding network, which are more realistic, practical and complete than the BA model. However, these amendments models all have inadequacies: they just conceive and analyze certain types of networks from a certain point of view. They can just explain some characteristics of the corresponding network phenomenon and can't reflect the essential attribute of all real networks reality, that is, they are not comprehensive and unified. For example, these models are not related to the actual knowledge transfer problems of the industry alliance, and can only explain part of the network they studied. This shows that these networks all have design deficiencies.

In addition, the above studies are for the unweighted network inquiry, which are only the approximate description of the real network. However, various real networks are weighted network. For example, in research cooperation network, edge weight represents cooperation between researchers; in aviation, railway and highway network, the edge weight reflects the road traffic flow. Obviously, it is more suitable to use the weighted network model with different weights for

each connection to describe these networks. In order to describe the heterogeneity of the edges, Yook, Jeong and Barabási (Yook et al., 2001) firstly investigated the weighted network evolution theory, initially proposed a weighted network theory model. Edges were given the weight values in accordance with the relationship between the nodes' degree. Through the research of the weighted network, Barrat, Barthélemy and Vespignán (Barrat et al., 2004) proposed the most influential weighted network model called BBV model. The model took into account factors such as the network structure and node weights to study the dynamic evolution of the network. With the increase of the scale of the model, the degree, edge weights and node weights of the BBV model network all present scale-free characteristics.

On the basis of the BBV model, referencing the improvement of the growth mechanism and merit-based mechanism mentioned in the BA correction models and considering the dynamic evolution and characteristics of the industry alliance knowledge transfer network, this paper proposed the industry alliance knowledge transfer weighted network evolution model based on node competitiveness. The theoretical analysis found that the intensity distribution and degree distribution of the nodes are in line with a power-law distribution. As long as a reasonable adjustment parameters, you can make the power-law index falls [2, 3], consistent with the actual network, which shows that this study is reasonable and practical.

The paper is organized as follows. Section 2 discusses the BBV model and its limitations on the research of the industry alliance knowledge transfer problems. Section 3 contains the description of the industry alliance knowledge transfer weighted network evolution model. Section 4 is devoted to the numerical simulation. Adaptive analysis of the model is analyzed in Section 5. Finally, Section 6 concludes.

## 1. THE BBV MODEL AND ITS LIMITATIONS

Suppose  $w_{ij}$  as the edge weight between nodes  $i$  and  $j$ . A weighted network can be provided with the network connection weight matrix  $(w_{ij})$ , where  $i, j=1, 2, \dots, N$ , is the total number of nodes. Since the paper considers undirected network, the weight matrix is symmetric, i.e.  $w_{ij}=w_{ji}$ . Introducing the concept of node degree in unweighted network into weighted network, it is the node strength  $S_i$ . It contains information about the node degree and the weight of all edges connected, which is defined as:

$$S_i = \sum_{j \in \tau(i)} w_{ij}$$

Where  $\tau(i)$  represents a collection of all nodes connected with node  $i$ .

The construction algorithm of the BBV model is as follows:

- Initial setting. Set a globally coupled network with  $m_0$  nodes as the initial network, where each connected edges are assigned with weights  $w_0$ ;
- Growth. Add a new node  $n$  to the network at each time interval, and is connected to the  $m$  nodes already exist. The probability of node  $i$  being selected to be connected with node  $m$  lines with its strength, which can be illustrated by the formula:

$$P_{n \rightarrow i} = \frac{s_i}{\sum s_i}$$

- Dynamic evolution of the edge weights. Each newly introduced side  $(n, i)$  is assigned with weight  $w_0$ . For simplicity, it is assumed that the newly joined edges  $(n, i)$  can only partially cause the dynamic adjustment of the edge weight of the node  $i$  and its neighbors  $j$ . Adjustment rules can be written as:

$$w_{ij} \rightarrow w_{ij} + \square w_{ij}$$

$$\square w_{ij} = \delta_i \frac{w_{ij}}{s_i}$$

Where  $\delta_i$  is the additional flow burden to node  $i$  brought by each new introduction of an edge  $(n, i)$ . The edges connected with  $i$  will share a certain flow in accordance with the size of their own weights  $w$

$w_{ij}$ , therefore, the strength of the node  $i$  can be expressed as:

$$w_{ij} \rightarrow w_{ij} + w_0 + \delta_i$$

The study indicates that with the increasing of network size, node degrees, node strength (point weights) and edge weights of the BBV model show the scale-free characteristics:

$$P(s) \propto s^{-\gamma}, P(k) \propto k^{-\gamma} : \gamma = \frac{4\delta + 3}{2\delta + 1}$$

$$P(w) \propto w^{-\gamma} : \gamma = 2 + \frac{1}{\delta}$$

Therefore, the BBV model can generate scale-free network with power-law index between 2 and 3 according to different  $\delta$ . If  $\delta=0$  then the model degenerates to the BA model of  $\gamma = 3$ ; If  $\delta \rightarrow \infty$  then  $\gamma = 2$ .

The BBV model, considering factors such as the network structure and node weights, has laid a good foundation for the weighted network's research, but there are still certain gaps between the BBV model and the real network. Considering the actual situation of the industry alliance, it has the following inadequacies:

Firstly, the growth mechanism of the BBV model is inadequate. BBV model is a growth network model, only considering the addition of nodes and the connection with

existing nodes. In the actual evolution of the industry alliance network, there exists a series of changes such as point plus, edge plus, point delete, edge delete and edge reconnect. For instance, in the process of continuous change of market economy, knowledge transfer relationship between the members of the Industry Alliance is not static. Constantly added to the network, there will be new members and old members leaving the network for some reason. It continues to have new members join the Industry Alliance Knowledge Transfer Network and old members leave the network for some reason. Moreover, the knowledge transfer connection between the old members is unstable. Individual members may create a new knowledge transfer between both or stop the knowledge transfer with partners at any time, that is, the network presents dynamic evolution with the increase of nodes. Secondly, the merit-based mechanism of the BBV model is deficient. In the BBV model, the node is preferred selected to connect edges in accordance with its strength. However, in the real network, the number of node connections and the growth rate of nodes strength are related to not only the strength of the link between nodes, but also its own "competitiveness". For example, a new member of the industry alliance has only a few connections, that is, its node strength is lower. But if its knowledge innovation ability is strong or it owns some sort of knowledge resources advantage, lots of other members are willing to expand the exchange of knowledge and technical cooperation with it. The new member will be at a higher rate to get connected and its node strength will grow rapidly. Here we call the competitive ability of nodes as "competitive factor" (Zhou et al., 2012). Therefore, the weighted network, consider node competitiveness is essential. Thus, it is essential to consider nodes' competitiveness in a weighted network.

## 2. THE WEIGHTED NETWORK DYNAMIC EVOLUTION MODEL

In view of problems mentioned in the BBV model above and the actual characteristics of the industry alliance knowledge transfer, the paper proposes a weighted network model taking into account the network dynamic evolution and node competitiveness. The new model made the following improvements on the basis of the BBV: On the one hand, with the evolution of the industry alliance knowledge transfer network, as new nodes constantly join the network, there exists deletion of nodes and disconnection of old edges. And in order to ensure the connectivity of the network and effectiveness of information transfer, the network will continue to produce new connection. The article fully takes into account the dynamic evolution of the industry alliance network and compensate for inadequacies of the BBV network growth mechanism; On the other hand, each node in the network

has certain competitiveness, that is, the competitive factor  $\eta$ , which is defined as the number of edges connected in the unit time:  $\eta_i = n_i / \Delta t$  (Tao et al., 2009), where  $\Delta t$  is the unit time,  $n_i$  is the number of edges connected in  $\Delta t$  time by node  $i$ .

New nodes select old ones depending on their strength, which contains node weight and competitiveness factor. The probability of the node being selected gives:

$$\Pi_i = \frac{\eta_i + k_i}{\sum \eta_j + k_j}$$

The paper considers the existence of competition in the industry alliance to make up for inadequacies of the merit-based mechanism of the BBV model.

### 2.1 Evolution Algorithm of the Model

On the basis of the BBV model, the weighted network dynamic evolution model construction algorithm is as follows:

- Initial setting: set a given  $m_0$  nodes and  $e_0$  full coupling network edge, given the initial weights  $w_0$  to each edge.
- Dynamic evolution: On the basis of the initial network, it starts to perform the following procedures at each time step cyclically:

i) Addition of nodes: Add a new node to the network with the probability of  $p_1$ , and is connected to  $m$  ( $m \leq m_0$ ) nodes already exists to produce  $m$  new edges. The probability of the node  $i$  being connected lines with the node weight  $s_i$  and the competitiveness factor  $\eta_i$ , which satisfies the following equation:

$$\Pi_{n \rightarrow i} = \frac{\eta_i + s_i}{\sum \eta_j + s_j} \quad (1)$$

The dynamic evolution of the new model's edge weights is the same with the BBV model. Each node does not allow self-connected and re-connected. The weight of each new edge is given  $w_0$ .

ii) Deletion of nodes: delete one node in the network randomly with probability  $p_2$ , and all edges connected to the node are deleted.

iii) Addition of edges: Add new edge to the network with probability  $p_3$ , wherein one end of the new edge is selected randomly, and the other end shall be chosen in accordance with the equation(1). Reconnection is allowed here. If the edge is reconnected, then its edge weights  $w_{ij}$  will be increased by 1; If not, the new edge weights  $w_{ij}$  is given 1.

iv) Deletion of edges: select one node randomly with probability  $p_4$ , and determine another one from the nodes connected to it according to below equation(2), then disconnect the connection between the two.

$$\Pi'_i = \frac{1 - \Pi_{n \rightarrow i}}{N_t - 1} \quad (2)$$

where  $p_1, p_2, p_3, p_4$  satisfy the equation  $p_1 + p_2 + p_3 + p_4 = 1$ .

$N_t$  represents the total number of nodes in the network through  $t$  time interval.  $\sum s_j$  represents the sum of strength of all nodes. The average strength of the nodes in the network is  $\langle s_t \rangle = \sum s_j / N_t$ .

### 2.2 Derivation of the Node Strength Distribution

Using continuum theory and the mean-field theory (Barabasi et al., 1999), we can be obtain the strength distribution of node  $s_i$  within the network. Suppose  $s_i$  is continuously changed, then the rate of change of  $s_i$  is derived as follows:

i) Add a new node to the network with probability  $p_1$ , and connected to  $m$  other nodes, causing the change rate of  $s_i$ :

$$\frac{\partial s_i}{\partial t} = m p_1 (1 + \delta) \Pi_{n \rightarrow i} + \sum_{j \in V(i)} m p_1 \Pi_{n \rightarrow i} \delta \frac{w_{ij}}{s_i}$$

where  $V(i)$  represents the collection of all nodes connected with node  $i$ .  $\delta$  is the additional flow burden brought by adding a new node mentioned in the BBV model.

ii) Remove the old node in the network with probability  $p_2$ , causing the change rate of  $s_i$ :

$$\frac{\partial s_i}{\partial t} = -p_2 \frac{s_i}{N_t}$$

Usually, the deleted nodes are usually the peripheral one, which are often marginalized in the network. Therefore, we will not consider its neighbor nodes' additional weight reduction  $\delta$  caused by the withdrawal of the nodes.

iii) Add new edges within the network with the probability  $p_3$ , causing the change rate of  $s_i$ :

$$\frac{\partial s_i}{\partial t} = p_3 \left[ \frac{1}{N_t} + \left( 1 - \frac{1}{N_t} \right) \Pi_{n \rightarrow i} \right]$$

The above equation shows that there exists two ways to increase the strength of node  $i$ . The first term on the right side indicates the rate of change caused by the randomly selection of one end of the additional edge. The second term represents the rate of change of the merit-based selection.

iv) Disconnect edge with the probability  $p_4$ , causing the rate of change of  $s_i$ :

$$\frac{\partial s_i}{\partial t} = -p_4 \left[ \frac{1}{N_t} + \left( 1 - \frac{1}{N_t} \right) \frac{1 - \Pi_{n \rightarrow i}}{N_t - 1} \right]$$

It is shown that connections of node  $i$  can be reduced from two aspects. The first term on the right side indicates the rate of change caused by the randomly selection of one end of the deletion edge. The second term represents the rate of change of the merit-based selection.

In summary, the strength change rate of node  $i$  at time  $t$  can be expressed as:

$$\begin{aligned} \frac{\partial s_i}{\partial t} &= mp_1(1+2\delta)\Pi_{n \rightarrow i} - p_2 \frac{s_i}{N_t} + p_3 \left[ \frac{1}{N_t} + \left(1 - \frac{1}{N_t}\right) \Pi_{n \rightarrow i} \right] - \\ & p_4 \left[ \frac{1}{N_t} + \left(1 - \frac{1}{N_t}\right) \frac{1 - \Pi_{n \rightarrow i}}{N_t - 1} \right] \\ &= [mp_1(1+2\delta) + p_3] \Pi_{n \rightarrow i} - p_2 \frac{s_i}{N_t} + (p_4 - p_3) \frac{\Pi_{n \rightarrow i}}{N_t} - \frac{p_3 - 2p_4}{N_t} \\ &= [mp_1(1+2\delta) + p_3] \frac{\eta_i + s_i}{\sum \eta_j + s_i} - p_2 \frac{s_i}{N_t} + (p_4 - p_3) \frac{1}{\sum \eta_j + s_i} \\ & \quad - \frac{p_3 - 2p_4}{N_t} \end{aligned} \quad (3)$$

After  $t$  time steps, the sum of nodes' strength are equal to:

$$\sum s_j = 2e_0 + 2[mp_1(1+\delta) - p_2 \langle s_t \rangle + p_3 - p_4]t$$

The total number of nodes in the network is calculated as:

$$N_t = m_0 + (1 - p_2)t$$

When  $t \rightarrow \infty$ , we get

$$\sum s_j \approx 2[mp_1(1+\delta) - p_2 \langle s_t \rangle + p_3 - p_4]t \quad (4)$$

$$N_t \approx (1 - p_2)t \quad (5)$$

Then the average strength of all nodes at time  $t$  is:

$$\langle s_t \rangle = \frac{\sum s_j}{N_t} = \frac{2[mp_1(1+\delta) - p_2 \langle s_t \rangle + p_3 - p_4]}{(1 - p_2)}$$

$$\langle s_t \rangle = \frac{2(mp_1(1+\delta) + p_3 - p_4)}{1 + p_2}$$

Substitute the above equation into equation (4), we can obtain formula:

$$\sum s_j = \frac{2[mp_1(1+\delta) + p_3 - p_4](1 - p_2)}{1 + p_2} t \quad (6)$$

In order to facilitate research, we define the network's node competitiveness as  $\bar{\eta}$ , which reflects the average competitiveness of all the nodes in the network.

$$\bar{\eta} = \frac{\sum \eta_j}{n} = \eta_0$$

The greater the average node competitiveness is, the more important the competition factor is in the network. Each node's competitiveness can play greater role in the connecting edges. Under ideal conditions, each node's competitiveness is not reduced. It is supposed that only one node is added to the network at every time step and the competitiveness of each additional node is  $k$ . Then the competitiveness of the total nodes of the network is in linear relationship with time  $t$ , that is,

$$\sum \eta_j \approx kt$$

Where  $k$  is more appropriate to be the average node

competitiveness  $\eta_0$ , so

$$\sum \eta_j \approx \eta_0 t$$

$$\sum \eta_j + s_j = \left\{ \frac{2[mp_1(1+\delta) + p_3 - p_4](1 - p_2)}{1 + p_2} + \eta_0 \right\} t \quad (8)$$

$$\text{Let } A = \frac{2[mp_1(1+2\delta) + p_3](1 + p_2)}{2[mp_1(1+\delta) + p_3 - p_4](1 - p_2) + \eta_0(1 + p_2)} \quad (9)$$

Substitute equations (5)—(8) into equation (4), we can obtain the following expression:

$$\begin{aligned} \frac{\partial s_i}{\partial t} &= \left\{ \beta' = \frac{(mp_1 + p_3)(1 + p_2)}{2[mp_1(1+\delta) + p_3 - p_4](1 - p_2) + \eta_0(1 + p_2)} \right\} \eta_i \\ & \quad - \frac{p_3 - 2p_4}{1 - p_2} \left\{ \frac{s_i}{t} + \left( A \eta_i - \frac{p_3 - 2p_4}{1 - p_2} \right) \right\} \end{aligned} \quad (10)$$

$$\text{Let } \alpha = \frac{[mp_1(1+2\delta) + p_3](1 + p_2)}{2[mp_1(1+\delta) + p_3 - p_4](1 - p_2) + \eta_0(1 + p_2)},$$

$$\beta = A \eta_i - \frac{p_3 - 2p_4}{1 - p_2} \quad (11)$$

So equation (8) can be changed to

$$\frac{\partial s_i}{\partial t} = \alpha \frac{s_i}{t} + \beta \frac{1}{t}$$

Set the initial condition  $s_i(t_i) = m$ , we can obtain the following expression:

$$s_i = \left( m + \frac{\alpha}{\beta} \right) \left( \frac{t}{t_i} \right)^\alpha - \frac{\alpha}{\beta} \quad (12)$$

Using equation (10), the probability of the node  $P(s_i(t) < s)$  can be written as:

$$\begin{aligned} P(s_i(t) < k) &= P\left( t_i > t \left( \frac{m + \beta/\alpha}{k + \beta/\alpha} \right)^{1/\alpha} \right) = \\ & 1 - P\left( t_i < t \left( \frac{m + \beta/\alpha}{k + \beta/\alpha} \right)^{1/\alpha} \right) \end{aligned}$$

The generation rules of the network shows that, the time of node  $i$  adding to the system obeys uniform distributed, so the probability density of  $t_i$  is:

$$P(t_i) = \frac{1}{m_0 + t}$$

Therefore, we get the degree distribution of the nodes

$$P(s) = \frac{\partial P(s_i(t) < s)}{\partial s} = \frac{1}{\alpha} \frac{t}{m_0 + t} \frac{(m + \beta/\alpha)^{1/\alpha}}{(s + \beta/\alpha)^{1/\alpha + 1}} \quad (13)$$

When  $t \rightarrow \infty$

$$P(s) = \frac{1}{\alpha} \left( m + \frac{\beta}{\alpha} \right)^{1/\alpha} \left( s + \frac{\beta}{\alpha} \right)^{-\gamma}$$

$$\gamma = \frac{1}{\alpha} + 1 = \frac{1}{2 \left[ \frac{mp_1(1+2\delta) + p_3}{mp_1(1+\delta) + p_3 - p_4} (1-p_2) + \eta_0(1+p_2) \right] - \frac{p_2}{1-p_2}} + 1 \quad (14)$$

Similarly, the degree change rate of node  $i$  can be expressed as:

$$\begin{aligned} \frac{\partial k_i}{\partial t} &= mp_1 \Pi_{n \rightarrow i} - p_2 \frac{s_i}{N_t} + p_3 \left[ \frac{1}{N_t} + \left(1 - \frac{1}{N_t}\right) \Pi_{n \rightarrow i} \right] - \\ & p_4 \left[ \frac{1}{N_t} + \left(1 - \frac{1}{N_t}\right) \frac{1 - \Pi_{n \rightarrow i}}{N_t - 1} \right] \\ &= (mp_1 + p_3) \frac{\eta_i + s_i}{\sum \eta_j + s_j} - p_2 \frac{s_i}{N_t} + (p_4 - p_3) \frac{1}{N_t} \frac{\eta_i + s_i}{\sum \eta_j + s_j} \\ & - \frac{p_3 - 2p_4}{N_t} = \alpha' \frac{s_i}{t} + \beta' \frac{1}{t} \end{aligned} \quad (15)$$

Where

$$\begin{aligned} \alpha' &= \frac{(mp_1 + p_3)(1 + p_2)}{2 \left[ \frac{mp_1(1 + \delta) + p_3 - p_4}{mp_1(1 + \delta) + p_3 - p_4} (1 - p_2) + \eta_0(1 + p_2) \right] - \frac{p_2}{1 - p_2}} \\ \beta' &= \frac{(mp_1 + p_3)(1 + p_2)}{2 \left[ \frac{mp_1(1 + \delta) + p_3 - p_4}{mp_1(1 + \delta) + p_3 - p_4} (1 - p_2) + \eta_0(1 + p_2) \right]} \eta_i \\ & - \frac{p_3 - 2p_4}{1 - p_2} \end{aligned}$$

Combine with the equation  $\frac{\partial s_i}{\partial t} = \alpha \frac{s_i}{t} + \beta \frac{1}{t}$ , we can draw that:

$$k_i = \frac{\alpha'}{\alpha} s_i + B \quad (16)$$

The equation (16) shows that the degree  $k_i$  and strength  $s_i$  has a linear correlation for any node  $i$ , while the value of this coefficient is  $\alpha'/\alpha$ .

### 3 NUMERICAL SIMULATIONS

#### 3.1 Experimental Simulation

In response to the above theoretical analysis, we test the power-law characteristics of the node through simulation. In the simulation experiment, let  $\delta_i = \delta = 1$ ,  $w_0 = 1$ ,  $m_0 = m = 3$ . As can be seen from figure 1, the strength distribution and the degree distribution of the nodes both show significant power-law characteristics, matching with the theoretical analysis of the results. Figure 2 shows that the node strength has a linear correlation with the node degree, which is consistent with the theoretical results and verify the reasonableness and correctness of the model.

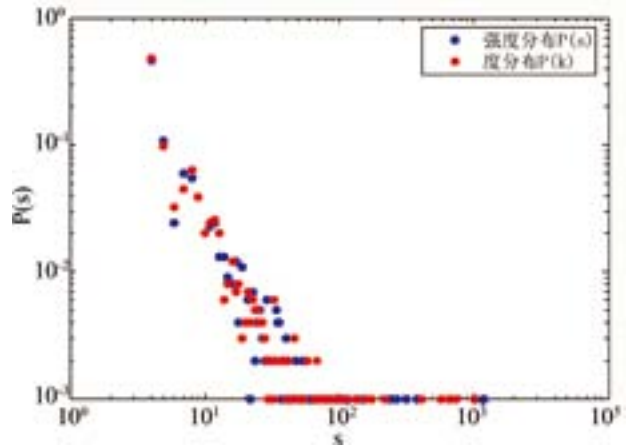


Figure 1 Diagram of Degree and Strength Distribution

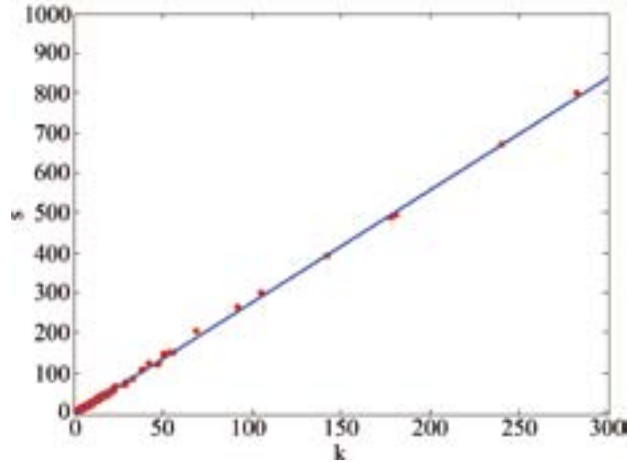


Figure 2 Diagram of Relation Between Degree and Strength

#### 3.2 The Competitiveness Factor

According to the evolution rules of the new model, we simulate the power-law characteristics in different situations through numerical simulation. In the simulation experiment, set the final evolution of the network size  $N=3000$ ,  $m_0=m=3$ , take different value of nodes competitiveness factor  $h$  to examine their impact on network characteristics.

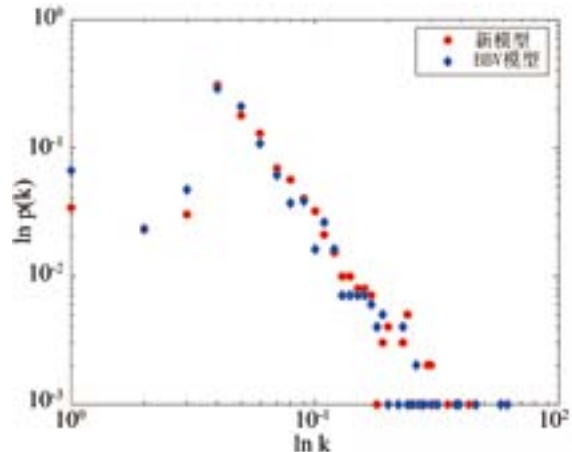
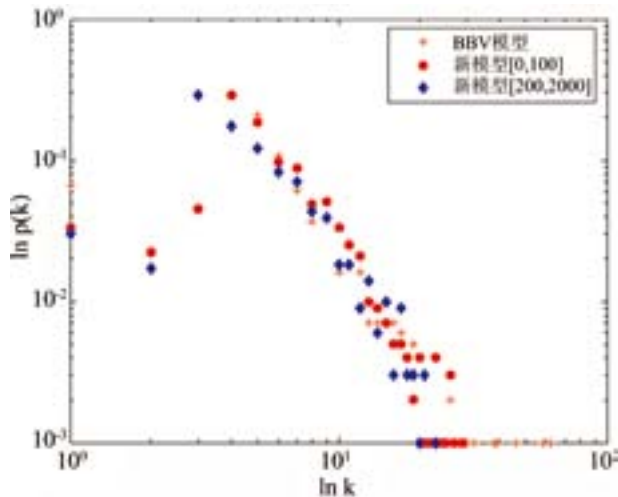


Figure 3 Strength Distribution of  $N=3000$ ,  $h \in [0,10]$



**Figure 4**  
**Strength Distribution of Different  $\delta$**

When node competitive factor ranges very small, as can be seen from figure 3 that  $\eta \in [0, 10]$ , representing almost not considering the impact of competitive factors. We can see that the new model is consistent with the BBV model. However, when the competitive factor's range is large, as shown in figure 4 that  $\eta \in [200, 2000]$ , the node is also subject to the power distribution. But the distribution interval of the node strength changes significantly. Nodes of high degree decrease significantly, suggesting that competitive factor has a certain influence on the strength distribution of the network node. Moreover, with the increase of  $\eta$  such as  $\eta \in [0, 100]$  and  $[200, 2000]$  shown in figure 4, nodes of large strength reduced in the latter interval. The strength distribution of nodes in the network is more uniform, that is, "overload" nodes don't appear in the network, so do the "useless" nodes. This has certain reference significance value for the study of real networks. For example, in the industry alliance knowledge transfer network, as for a specific research project, we can not only select leader members of certain influence, but can also consider new members with innovation and competitiveness capacity to participate in. So in the course of the project, new members can promote the process of the project by virtue of its unique advantages in resources and innovation ability, which can improve the development and application efficiency of scientific research. At the same time, since the advantages of the members are complementary, there will not appear that some members undertake too much task while others doing nothing, so as to conserve resources and manpower.

### 3.3 The Impact of Parameters $p_1-p_4$ on Network Characteristics

From the above analysis, we know that  $\gamma=1/a+1$ , where

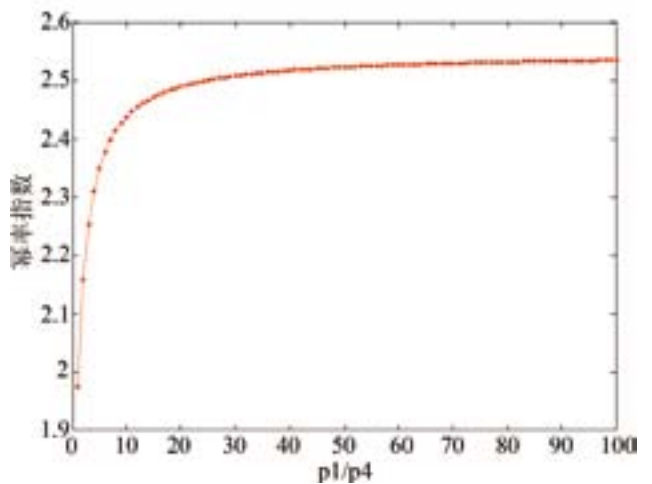
$$\alpha = \frac{[mp_1(1+2\delta)+p_3](1+p_2)}{2[mp_1(1+\delta)+p_3-p_4](1-p_2)+\eta_0(1+p_2)} - \frac{p_2}{1-p_2}$$

In order to simplify the description of the influence on network characteristics with the introduction of parameters  $p_1-p_4$ , we just not consider the competitive factor  $\eta$  and set  $m=3, \delta=1$ , so the above equation can be deformed into:

$$\alpha = \frac{3(3\frac{p_1}{p_4} + \frac{p_3}{p_4})(1+p_2)}{2\left(6\frac{p_1}{p_4} + \frac{p_3}{p_4} - 1\right)(1-p_2)} - \frac{p_2}{1-p_2} a$$

i) Fix  $p_2$  and  $p_2/p_4$  (let  $p_2=0.1, p_3/p_4=3$ ), and parameter  $p_1-p_4$  satisfy equation  $p_1+p_2+p_3+p_4=1$ . Change the value of  $p_1/p_4$ , and we find that the power-law index  $i$  increases with  $p_1/p_4$  as seen in figure 5. This is because  $p_1$  represents the increase of edges in the network,  $p_4$  represents the deletion of edges. The increase of  $p_1/p_4$  reflects the deletion trend of edge is greater than the increase trend, so the network strength value will increase accordingly. In other words, the trend of edges' relative increments will make the strength distribution of the original network becomes more uneven, making the rich richer and the poor poorer.

ii) Fix  $p_2$  and  $p_1/p_4$  (let  $p_2=0.1, p_1/p_4=3$ ), and makes parameter  $p_1-p_4$  satisfy equation  $p_1+p_2+p_3+p_4=1$ . Change  $p_1/p_4$ , and we reach conclusion that the power-law index  $\gamma$  decreases with the increase of  $p_1/p_4$  as seen in figure 6. This phenomenon shows that the increase of edges within the network can narrow the gap of strength between each node, making the strength distribution of the network becomes uniform.



**Figure 5**  
**Diagram of Relation Between  $\gamma$  and  $p_1/p_4$**

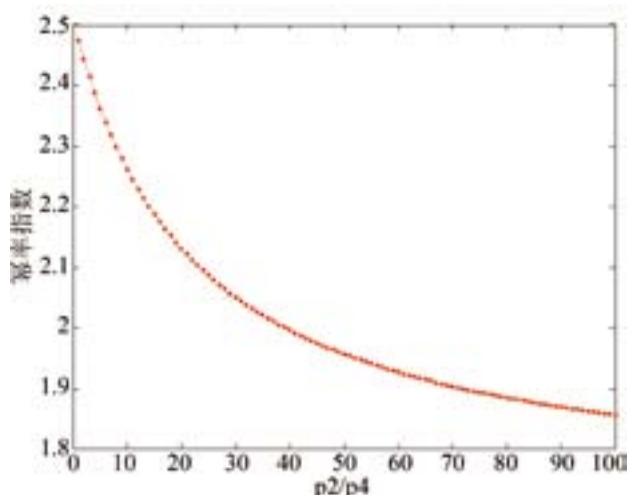


Figure 6  
 Diagram of Relation Between  $\gamma$  and  $p_2/p_4$

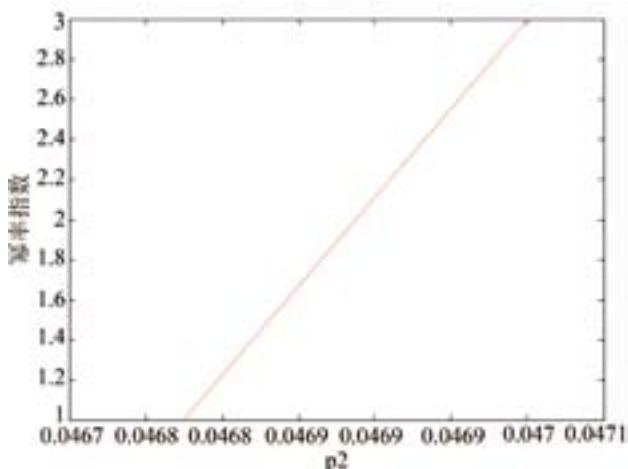


Figure 7  
 Diagram of Relation Between  $\gamma$  and  $p_2$

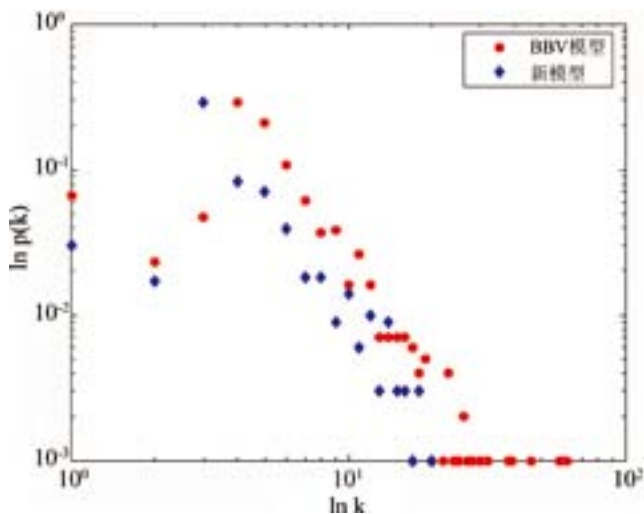


Figure 8  
 Strength Distribution of BBV Model and the New Model

iii) Fix  $p_1/p_4$  and  $p_3/p_4$  and change  $p_2$ , making parameter  $p_1-p_4$  satisfy equation  $p_1+p_2+p_3+p_4=1$ .

We get the diagram 7 of the power-law exponent  $\gamma$  and  $p_2$ , which shows that  $\gamma$  is linear increment relationship with  $p_2$ . As  $p_2$  represents deletion of the nodes, the increase of  $p_2$  means the number of nodes in the network is reduced corresponding. Thus, connection edges assigned to the remaining nodes would increase, so that the strength of the network can be increased.

#### 4. ADAPTIVE ANALYSIS

Now, we use the competitive merit-based weighted network evolution model to explain the knowledge transfer problem of the industry alliance. Consider each industry alliance member as a network node, knowledge transfer relationship as an edge, and the number of cooperation between two members is seen as the edge weight. In the early stage of development of the industry alliance, there are only a small number of members (nodes) and knowledge transfer relations (edges). With the increasingly fierce market competition, more and more companies are beginning to realize that integration of resources is the key to maintaining their competitive advantage, so companies would continuously chose to join the industry alliance. When the new enterprise start to set up knowledge exchange relationship, it will not only give priority to the core enterprises that have already established knowledge transfer and cooperative relations with many other ones, but also want to build relationships with some young companies that owning competitive advantage in the market. For instance, a young enterprise have only found knowledge transfer relationship with a small amount of enterprises temporarily just because its added time is shorter or its product is relatively new for other members. But if it has a strong knowledge innovation capability or owns some technical advantages in resources or other aspects, others members will try to cooperate with it unceasingly. As a result, the young enterprise will be booming gradually. Therefore, new enterprises will comprehensively consider the popularity (length of established time) and competitiveness of the other members in choice of partners. In the development process of Industry Alliance, two members who have had fine cooperation experience with each other will be likely to interact more frequently in order to promote the development of both; while members with no cooperation experience can also build knowledge transfer relationships if new cooperation projects or other opportunities appear. At the same time, after experiencing cooperation, some members would no longer be willing to proceed with knowledge exchanging due to differences in corporate culture or exchange barriers or other reasons. Cooperation between the two is less, or there would no cooperation eventually. Each member of the Industrial Alliance may exit due to various reasons, such as the Industry Alliance is no longer conducive to their own development or the



enhancement of their competitiveness, then the originally established partnership will be disconnect. The dynamic

evolution mode of the Industry Alliance knowledge transfer network is as follows (see Li and Zhao, 2012):

**Table 1**  
**Industry Alliance Knowledge Transfer Network Evolution Model**

Evolution behavior	Representation	Illustration
New members join	Node addition	Enterprises choose to join the alliance in order to obtain the resources and enhance their own competitiveness Some enterprises can not meet the Union's needs (technical standards, knowledge level, etc.), and are required to withdraw;
Old members quit	Node deletion	Companies can not obtain knowledge or resources that favoring their own development, so they take the initiative to withdraw from the Union. Members who have had fine collaboration experience will continue to cooperate with each other; New research projects or activities may make many of the non-cooperation enterprises to participate in;
Establish new cooperative relationship	Edge addition	Each member will continue to look for new partners to expand their business knowledge and technology resources for their own development.
Cancel existing cooperative relationship	Edge deletion	As partners are unable to carry out effective knowledge exchange or meet each other's capacity requirements, they will not continue their cooperation

The practical significance of the new model is as follows:

i) The four kinds of assumptions mentioned in the new model have all emerged in the real industry alliance knowledge transfer network, which is in line with the actual situation. Actual networks are not like the BBV model which simply adds nodes and edges. When the network size increases, it will present a dynamic evolution with a series of changes, such as deletion of nodes, construction of new edges and deletion of old edges. Due to the existence of competition, the industry alliance members will not only consider the length of time other member staying in the alliance but also each other's potential competitiveness. This is why we introduce parameter  $p_1, p_2, p_3, p_4$  and  $\eta$  to the model. By appropriately adjusting the parameters, we enable the network tend towards equilibrium. As shown in figure 8, due to the introduction of the parameters, the new model's power curve downward trend has slowed and nodes of great strength has also significantly reduced, thereby enhancing the robustness of the network. Therefore, we can change the value of the power law index  $\gamma$  by adjusting  $p_1, p_2, p_3, p_4$  and  $\eta$  according to the impact of different parameters on  $\gamma$ . Then use it as a reference to control the industry alliance network artificially according to the actual needs to balance the network load and enhance its performance.

ii) Competitive differences and merit-based chosen always appear in the movie networks, the World Wide Web, social cooperation networks, biological networks and many other real networks. Using the new model can explain these phenomena occur in the network. For example, the power law index of the movie cooperation network is 2.3, the www network is 2.4, and the metabolic network is 2.1, which is in the range of the new model. Therefore, we can change get the same power law index and the actual network, by adjusting various parameters can change the value of  $\gamma$ . to get the same power law index with the actual network. We can guide the construction of the actual network and adjust the characteristics of

the network as a whole on the basis to the simulation results. The model has universal usability and practical significance.

## CONCLUSION

Based on the improvement of the BBV weighted network model, the paper also considers the addition of new edges, the deletion of old nodes and connections and the competitiveness factor by introducing parameters  $p_1, p_2, p_3, p_4$  and  $\eta$ . Through using continuum theory and the mean field theory, we got the asymptotic solution of the strength and degree distribution of the power-law index. Results showed that it still had the general nature of the scale-free network, and the BBV network model was just a special case. The correctness of the theoretical analysis is proved by the simulation. Such a competitive merit-based dynamic evolution model has a wider range of practical and applicable use than the BBV model. We can utilize the new model to regulate the entire network by add or delete edges and nodes randomly, making the actual network develop toward an ideal and favorable direction. At the same time, we can analog and characterize the evolution and characteristics of many real networks by adjusting parameters to change the scope of the power-law index, therefore, the model is more universal and authenticity.

The present work could be extended in at least three directions. First, one could investigate the inherent mechanism and evolution of the industry alliance knowledge transfer more in-depth. The new model construction is based on the industry alliance knowledge transfer, which is the simplification of the real network. So its evolution algorithm should be further improved. Analyzing the actual situation of the industry alliance can provide a realistic basis for the theoretical model building. Second, enhance the applicability of the model in the industry alliance complex networks. At present, the use of complex network theory into the industry alliance is still in the trial stage, especially the weighted network research. How to make the complex network theory more

effectively guide the industry alliance knowledge transfer activities is worthy of further study. Finally, increase empirical research and analysis. One could extend our model by conducting empirical research combined with case studies. Through analysis of a typical case, one could get a combination of qualitative analysis and quantitative analysis, which will become further research objectives of this study.

---

## ACKNOWLEDGEMENT

---

We would like to thank PING Qian for offering the helps on computer program.

---

## REFERENCES

---

- [1] Erosds, P. & Ren, Y. (1960). On the evolution of random graphs. *Publ Math Inst Hung Acad Sci*, (5), 17-61.
- [2] Watts, D. F. & Strogatz, S. H. (1998). Collective dynamics of small-world network. *Nature (London)*, 393, 440-442.
- [3] Barabasi, A. L. & Albert, R. (1999). Emergence of scaling in random networks. *Science*, 9(286), 509-512.
- [4] Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM Review*, 45, 167- 256.
- [5] Tang, F. R., Cai, S. H. & Li, Z. H. (2005). The establishment and analysis of the embedded-deletion- compensation scale-free networks model. *Journal of China University of Mining and Technology*, 34(3), 3-4.
- [6] Chen, Q. H. & Shi, D. H. (2004). The modeling of scale-free networks. *Phys. A*, 335, 240 -248.
- [7] Jia, X. L., Cai, S. H. & Zhang, F. R. (2009). A dynamic scale-free network model. *Journal of Sichuan Normal University*, 32(6), 839-842.
- [8] Jia, X. L., Cai, S. H. & Zhang, F. R. (2008). A scale-free network model of points and edges changing at the same time. *Journal of Northeast Normal University*, 40(4), 58-62.
- [9] Li, S. W. & Qian, S. S. (2005). Exponential growth of the scale-free networks and dynamic local world. *Complex Systems and Complexity Science*, (1), 45-48.
- [10] Guo, J. L. (2006). Poisson model of the directed complex networks. *Shanghai University of Technology*, (3), 712-718.
- [11] Albert, R. & Barabasi, A. L. (2000). Topology of evolving networks: local events and universality. *Phys. Rev. Lett.*, 85, 5234- 5237.
- [12] Bianconi, G., & Barabási, A. L. (2001). Bose Einstein condensation in complex networks. *Phys. Rev. Lett.*, 86, 5632- 5635.
- [13] Krapivsky, P. L., Redner, S. & Leyvraz, F. (2000). Connectivity of growing random networks. *Physica Review Lett.*, 85, 4629-4632.
- [14] Zhou, J., Zhang, Z. & Cheng, K. Q. (2012). Research on the point weight limited BBV model based on node attraction. *System Simulation*, 24(6), 1293-1297.
- [15] Yook, S. H., Jeong, H. & Barabasi, A. L. (2001). Weighted evolving networks. *Phys Rev Lett.*, 86, 5835-5838.
- [16] Barrat, A., Barthélemy, M. & Vespignani, A. (2004). Modeling the evolution of weighted networks. *Phys Rev E (S1539-3755)*, 70(066149), 1-13.
- [17] Tao, S. H., Yang, C., Li, H. N. & Zhang, Y. (2009). Research on complex networks evolution model based on nodes attractive. *Computer Engineering*, 35(1), 111-113.
- [18] Barabasi, A. L., Albert, R. & Jeong, H. (1999). Mean-field theory for scale-free random networks. *Phys A*, 272, 173-187.
- [19] Li, G. & Zhao, D. Z. (2012). Scale-free characteristics of the supply chain network research. *Industrial Engineering*, 15(1), 28-32.