

## Research Article

# Athlete Social Support Network Modeling Based on Modern Valence Bond Theory

Ningshe Zhao 

*School of Information Engineering, Xi'an University, Xi'an 710065, China*

Correspondence should be addressed to Ningshe Zhao; [zhaoningshe@foxmail.com](mailto:zhaoningshe@foxmail.com)

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Based on the Valence Bond theory, an attempt is proposed to the complex network. The principle of chemical bonding of the basic particles that make up the substance creates a metaphor between the formation of social networks. By analyzing the integration of atoms by relying on the chemical bonds between particles, then the social basis for the connection between social network nodes should depend on the tangible or intangible attribute resources that characterize social capital around the main node. Based on the above analysis, the social node is divided into active nodes and passive nodes, and a dynamic model of social network formation is proposed, the Valence Bond model of social network. Through this model, the actual athlete group nodes are depicted, and the representation of the model and the evolution of network structure are given with the actual data.

## 1. Introduction

Big data and social network have become a powerful tool to study social phenomena, and the research on social network is still very popular [1–6]. The research of network dynamics is that, under the impetus of “external stimulus” or the trigger of “internal message,” the state of node itself or the information contained in the network changes (the propagation of message), or the change of connection relationship between nodes [7–10]. This process is similar to the formation and decomposition of matter. How do the molecules that make up matter come together into stable states? Atoms are combined with a common electric charge. Because of the simultaneous existence of positive and negative charge, it is inevitable that the effects of both gravity and repulsion between molecules and molecules exist at the same time, and the distance shows different forces at different times. From a different point of view, each matter is a network of particles, connected by gravity and repulsion. The formation of the network should also have a mechanism, that is, there are two kinds of links at the same time, and the social network of the widespread competition and cooperative relations are similar. The connection between nodes is just a superficial phenomenon, and the real connection is the

attraction of node negative resources to other nodes. From the point of view of social networks, it is similar to social capital [11–15]. From the macropoint of view, it may affect the decision of the main node to establish the connection, or the recommendation of the link tendency [10, 12, 16–18]. On the microlevel, from a node point of view, the capital itself has the source of gravity. In fact, there are two kinds of nodes in the network, one is the principal node, which is the active node and is the demand, and the other is the resource node, which is the passive node and is to meet the demand. The nature and number of resource nodes owned by each principal node are different, resulting in different sizes of their influence. The connection of active nodes to each other is essentially driven by the demand for resources. The more the active node's perception is stronger, the greater the probability of establishing a connection with other principal nodes, such as the principal node in the position of the structure hole. If the network is depicted in this way, it is more clearly described and more predictable, for example, to know whether there may be a connection between node  $i$  and node  $j$  in the future, as long as the analysis the resources of node  $i$  and node  $j$ . If they share resource nodes, there is already a connection, if they do not have a similar resource, they have a higher probability of a connection to each other,

and if they have the same resource, the probability of a connection to each other is very small. Considering network evolution, a portion of the principal node will multiply the required resources through the adjacent principal node, thus disconnecting the connection swayed through the resource. The reality is that, after the main node demand changes, it will eliminate old resources with a high probability and create new connections to meet new demands. In this way, the network has become a new pattern. Then, there is a theoretical basis.

Any network consists of two nodes, the principal node and the resource node on the dependency. The principal node provides the demand and generates the power of evolution, and the resource node realizes the transfer or function and completes the evolution. There is a demand (whether subjective or objective) between the principal node and the node with related resources to produce a force, resulting in a connection. The different states of the resource cause the network to have different states. Resource state has parasitic state, and free state and free state resources will be adsorbed by the main node, if the parasitic resources are discarded by the main node, it becomes a free state or undefined state. The two states are different, free state is not bound by the principal node, and undefined resources are parasitic to the principal node.

In practice, some physical connections in the social network may be very low, and physical connections with relatives between two relatives exist, but there is little interaction, and that connection can actually be ignored. What is the reason? If the principal node has no requirements, the role of the fact will not be produced. According to the above phenomenon, the network can be simplified, some weak contacts removed, making the network more sparse, and the advantage is more convenient for storage and relationship delivery. The key is to record the needs of the main node, and there is a demand of the main node may have a role to occur, such as competitive resources, attract talent, request assistance. To study this network dynamics, the demand of the principal node is the driving force of the whole network. Social nodes and life nodes have certain independent intentions, which belong to the main nodes.

From the point of view of social capital theory, Pierre Bourdieu pointed out that social capital is a collection of all kinds of social resources, which is formed by the accumulation of the quantity and quality of capital owned by individuals as actors in various social network relations [10, 12, 17]. This accumulation mainly depends on the size and initiative of the network relationship in which the individual is located [18–20]. The above theory provides microsupport for this view.

## 2. Social Network Representation Based on Valence Bond Theory

In modern Valence Bond theory [21–23], there are two basic points of view. (1) When two atoms are close, unpaired valence electrons in the opposite direction of spin can be paired to form a covalent bond. (2) The more the atomic orbits of the bonded atoms overlap with each other, the more

stable the covalent bonds are formed. Therefore, the covalent key should be formed as far as possible along the direction of the largest overlap of the atomic orbit, which is the principle of maximum overlap of atomic orbits. When the composition is stable, it is in the lowest energy state. Communities and even social networks can be compared to the formation of compounds. The formation of covalent compounds reflects the sharing of resources, while the ion key reflects the transfer of resources, such as trade relations and exchange relations.

The principal node is not an isolated existence, but has a certain companionship. From the phenomenon point of view, this accompaniment is determined by the performance of the principal nodes interacting with each other, but from the microanalysis, it is determined by the attributes. For a long time, we do not pay enough attention to the analysis of node properties [23–28]. However, the behavior of the principal node depends on its properties. The principal node is active and operates within the network at a certain probability. For social nodes, the principal nodes have a certain degree of free, while the properties are parasitic.

*2.1. Model Thought Description.* For the principal node in the network, the principal node  $i$  is expressed in the vector  $\eta_i = (p_{i1}, p_{i2}, \dots, p_{in})$ , where  $p_{in}$  is an integer, and  $p_{ij}$  ( $i, j$  as integer) is an integer. When  $p_{ij} > 0$ , it indicates the strength of the attribute  $k$  professional support capability. When  $p_{ik} < 0$ , it indicates the strength of the professional demand for the attribute  $k$ . Vectors  $\lambda_i = (h_{i1}, h_{i2}, \dots, h_{in})$ , and  $h_{ij} \in [0, 1]$  is the attribute weights.

NA (node activity): within the network  $W$ , for any principal node  $i$ , let

$$S_i = [\eta_i, \lambda_i]. \quad (1)$$

It indicates the activity of the node, represents the measurement of the activity capacity of the node, and the two nodes with the same NA have the same activity ability.

NSA (network system activity): for network  $W$ , the system activity is weighted by the activity of all nodes, namely,

$$A_w = \sum_{i=1}^N k_i S_i, \quad (2)$$

where  $k_i$  denotes the influence weight of the main node; obviously, the more influential main nodes, the more stable the network performance.

Network activity characterizes the stability of the network; it is an integer, and the activity is positive network. The greater the activity is, the more the network tends to diverge, with a greater probability of node free. For networks with negative activity, the smaller the activity is, the more the network tends to converge and the less likely the nodes to escape.  $W$  is usually a small world network that can grow by node aggregation connecting to form a larger network or by connections break which split into multiple small world networks.

When the node is aggregated, the key value of the passive node is consumed by the active node, the attribute value of

the active node is partially satisfied with the key bit, and the attribute value of the node changes in real time. When the internode bond breaks, the free node recovers the original activity. Network system activity also changes.

**2.2. Node Aggregation.** The social principal node activity has a certain suddenness, where the probability obeys the power law distribution, that is,  $P(r) \sim r^{-\alpha}$ , where  $r$  is arranged in the descending order of activity.

The principal node with negative activity is due to the inertia, forming the adsorption effect, when there are multiple active positive body nodes will expand competition and when there are multiple negative nodes at the same time, and the number of positive nodes is small. There are also negative nodes in order to compete with the negative node swell, which can be called the key position competition. The smaller the negative node activity, the greater the adsorption force, the greater the positive node NA, and the stronger the overall competitiveness. The competitively successful positive node produces a new connection, and the node state that does not compete to the key bit remains unchanged.

For any principal node, the smaller the  $S_i$ , the smaller the probability of movement; when there is negative infinity, the probability of movement tends to be 0. Starting with probability  $p_i$ , if node  $i$  meets  $j$ , check the attribute, check whether the attribute meets the conditions of integration (one of which is negative), and form a composite node (node group) at the meeting point to form a temporary steady state. If multiple nodes meet at the same time, then the active sort, the active high node mobility is strong, the first integration, the integration from the most inert nodes. As shown in Figure 1, when there are  $a$ ,  $b$ , and  $c$  three positive nodes, node activity in turn decreases, and they are combined with negative nodes, and finally form a node group, as shown in the right part of Figure 1, and the node group external performance is like that of a large node.

**2.3. Node Group Fission.** The properties of the principal node are dynamic indicators, and each attribute has a continuous change process according to a certain rate.

There are two aspects of change. On the one hand, the adsorption of the inert node is attenuated, and when the gravitational force between the active node is insufficient, the active node will escape and create a new movement. On the other hand, a node activity is enhanced, and the current key position and its activity no longer match with the activity overflow and natural escape. Typically, of course, both aspects of the situation exist at the same time over a historical period of time. The probability of escape is related to the amount of active spillage,  $P(e) = k\Delta S^\beta$ . The resulting escape causes the connection to be disconnected, as shown in Figure 2.

**2.4. Connection Prediction Algorithm for the Evolution of Network Structure.** For a complex network  $W$  with a certain scale,  $W = (W_c, W_s)$ , where  $W_c$  is network composition, while  $W_{S0}$  is initial network structure. The trend of network

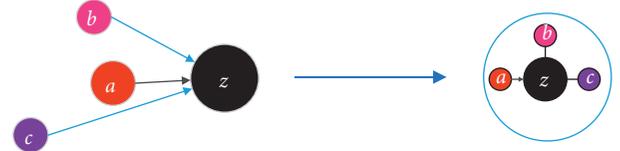


FIGURE 1: Node aggregation.



FIGURE 2: Node group fission.

evolution is spending system activity; the smaller the system activity, the more stable the network.

For all nodes, a power-based law produces a period of random evolution.

- (1) For all nodes, compute node activity, the production of network activity descending sequence  $S$ .

Connection establishment prediction: (2) to (5) steps.

- (2) To sequence  $S$ , take a node  $i$  with probability  $p_i$  to start a random walk, and in a unit time, it is only allowed to walk once.
- (3) If the node wanders away, start with the least probability of negative node  $j$  and execute (5), otherwise, remove one node and execute (2).
- (4) If the current node is the last positive node, the algorithm ends.
- (5) If node  $i$  and  $j$  combination conditions are true, the probability  $p_j$  is the competition key; if the competition is successful, then turn to (2), otherwise  $j$  removes the position of a negative node until the competition is successful or the negative node traversal ends and then turns to (2).

Connection fracture prediction: (6) to (7).

- (6) Check the connection that has been formed (node group), take one of its edges, and if the bonding activity overflow  $\Delta S = 0$ , then it remains unchanged. If the bonding activity overflow  $\Delta S > 0$ , the probability of escape is  $p$ . If the bonding activity overflow  $\Delta S < 0$ , there is a probability  $p$  for disconnection (passive node rejection).
- (7) If this is the last edge, continue, else get the next edge, execute (6).
- (8) If this is the last node, the algorithm ends, else get the next node.

**2.5. Probability Function Construct.** The constructed probability function is  $p_i = (a \tan(S/A)/\pi) + 0.5$ , where the value of the shape adjustment parameter  $A$  is related to the value field of  $S_i$ . The function image is shown in Figure 3.

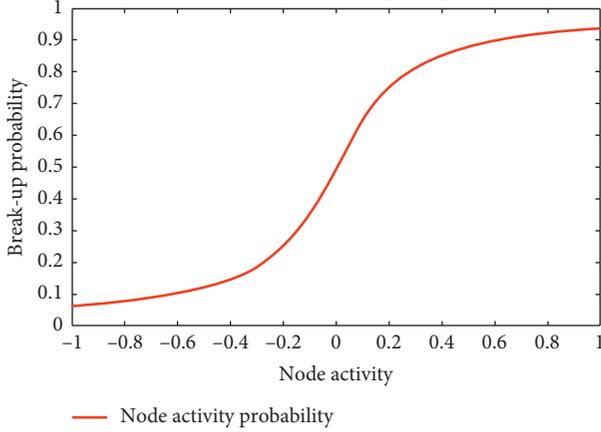


FIGURE 3: Node activity probability function construct.

**2.6. Node Attribute Field Classification.** For different applications, there are different weight configurations. The weight of the properties in this model gives the priority of the probe when the node establishes the connection.

The attribute field of the node can be divided into polar field and nonpolar field, the nonpolar field means that the content of the attribute is only different, there is no comparison on the quantity, and the description field belongs to the nonpolar data, and therefore does not consider.

As for the storage of the network, because the connection of the network in this paper is based on the application of social capital, it is necessary to use more special expressions, such as the element value of the adjacency matrix in two cases. (1) There are links. Storing elements as an attribute subscript indicates that the current connection is linked through that attribute. (2) In the case of no connection, a subscript of 0 is saved as  $-1$ , indicating no connection.

### 3. Modelling Athletes' Social Support Networks

In sports applications, the model is suitable for the description of athletes' networks. In the study of athletes' social support networks, we get a static link between athletes and answers on multiple topics. After the analysis of the answers of the theme questionnaire, we can get a description of some attributes of athletes. From the athlete's social support network questionnaire, the principal node activity usually has a certain motivation, which comes from individual needs, such as daily help, economic help needs and economic ability inversely proportional, emotional help and gender differences, and personality-related, employment support needs, and employment information holding degree, symn. Achievement requirements are related to achievement support capabilities.

**3.1. Attribute Analysis of Athlete Nodes.** The descriptive information about the subject node is gender, age, sports program, and education level. These descriptive attributes are related to certain support attributes, such as education, which may be related to social support skills, income, etc.

The issue of the relevance of research properties is beyond the scope of this article.

Social support attribute, economic help contact can use income as a capacity indicator. When income is less than 0, only expenditure exists. The more the spending is, the greater the degree of economic help needed is. Achievement needs are positive values that are related to achievement support capabilities. A higher value indicates a stronger achievement support ability. If the achievement support ability takes a negative value, the smaller the value is, the stronger the achievement demand is.

**3.2. Athlete Social Support Attributes.** By refining, the social support attribute vector for any athlete can be expressed (actual support ability, emotional support ability, employment support ability, achievement support ability, social interaction ability, marriage topic support ability, and management topic support ability) as depicted in Table 1. The actual support capacity refers to the degree of access and support for daily help. Table 2 is the normalization of Table 1 data to weaken the influence of dimension, where the last column is the calculated node activity.

**3.3. Athlete's Social Support Network Model.** If there are  $n$  athletes in this study and each athlete has  $m$  attributes, then the principal node vector is  $\beta_i = (p_{i1}, p_{i2}, \dots, p_{im})$ ,  $i \in [1, n]$ . Then, athlete network  $W$  is shown as follows:

$$W = (W_c, W_s), \quad (3)$$

where  $W_{c_{n \times m}} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{bmatrix}$  and

$$W_{s_{n \times n}} = \begin{bmatrix} \theta & \alpha_{12} & \cdots & \alpha_{1n} \\ \alpha_{21} & \theta & \cdots & \alpha_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{n1} & \alpha_{n2} & \cdots & \theta \end{bmatrix}. W_c \text{ is an } n \times m \text{ network com-}$$

position matrix, each row represents a node, each column represent node attribute.  $W_s$  is an  $n$ -step network structure matrix, rows and columns represent network nodes, and it is a super-adjacent matrix. In  $W_s$ ,  $\alpha_{ij} = (b_1, b_2, \dots, b_m)$  is a Boolean vector that represents the vector of node  $N_i$  connected to node  $N_j$ , and the component  $b_k = 1$  indicates that node  $i$  and node  $j$  are connected at property  $k$ .

### 4. Representation and Prediction of Athlete Support Network

A social network observation model can be represented by a simple formula:

$$R = UV^T + e, \quad (4)$$

where  $U$  and  $V$  are  $m \times d$  and  $n \times d$  matrices, respectively.  $e$  is error matrix, and target matrix  $R$  can be obtained by  $U$  and  $V$  approximation. As the same is true of the athlete network, when the evolution simulation is carried out, the  $e$  is taken as a disturbance term to continuously inject subtle

TABLE 1: Athlete social support attribute stake table.

Serial number	Actual support	Emotional support	Employment support	Achievement support	Income	Social interaction	Marriage support	Management support
1	72	-42	-29	52	1676	-97	31	57
2	70	2	-86	94	1078	-54	49	54
3	-69	54	27	-4	5013	85	-45	-12
4	-11	-59	-95	25	-6525	-26	-3	20
5	36	7	-15	33	3989	89	11	-64
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
91	-68	87	20	30	3236	-78	-23	-21

TABLE 2: Normalization of social support attributes of athletes.

Serial number	Actual support	Emotional support	Employment support	Achievement support	Income	Social interaction	Marriage support	Management support	Activity
1	1.25	-0.80	-0.37	0.68	0.29	-1.75	0.98	1.03	0.00
2	1.21	-0.05	-1.36	1.36	0.18	-1.00	1.56	0.98	0.22
3	-1.40	0.84	0.61	-0.21	0.89	1.42	-1.45	-0.26	0.24
4	-0.31	-1.09	-1.52	0.25	-1.21	-0.51	-0.11	0.34	-0.47
5	0.57	0.03	-0.12	0.38	0.71	1.49	0.34	-1.23	0.17
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
91	-1.38	1.40	0.49	0.33	0.57	-1.42	-0.75	-0.43	-0.21

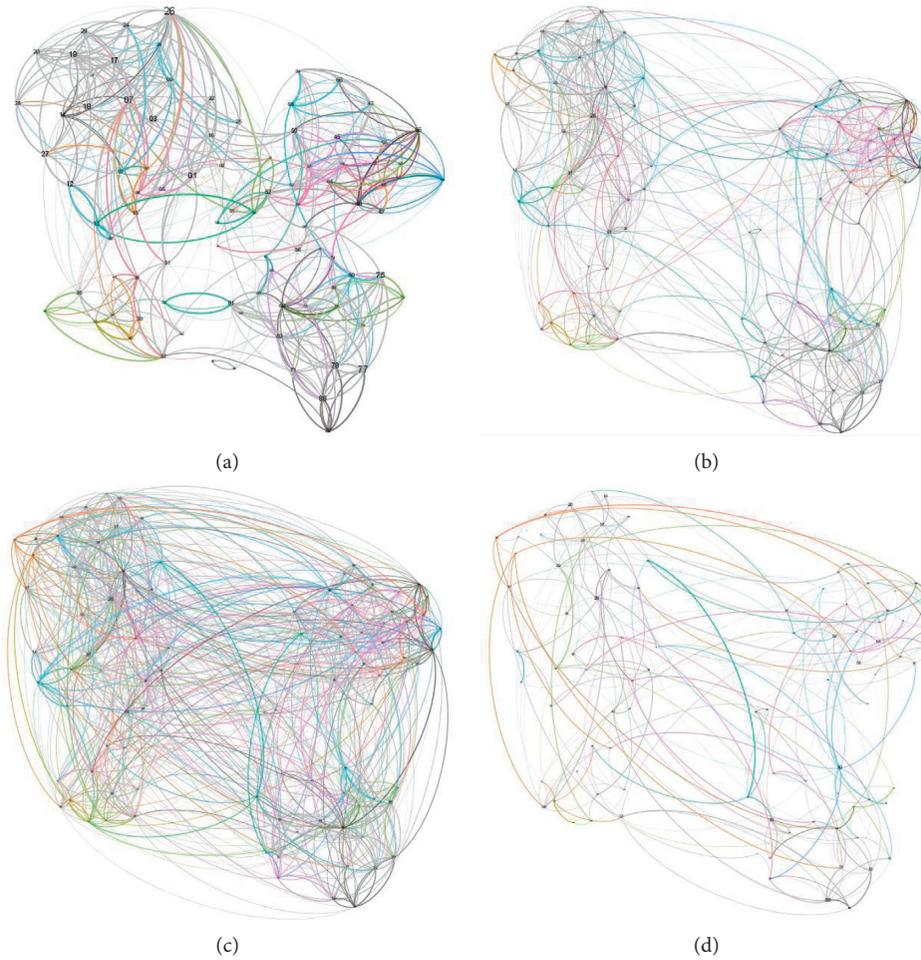


FIGURE 4: The evolution of the network structure of athletes. (a) The original. (b) After 100 iterations. (c) After 500 iterations. (d) After 1000 iterations.

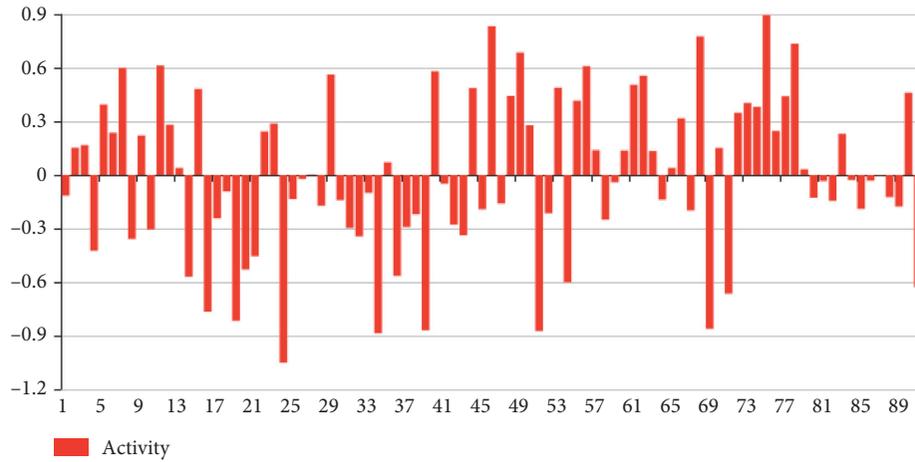


FIGURE 5: Node activity distribution.

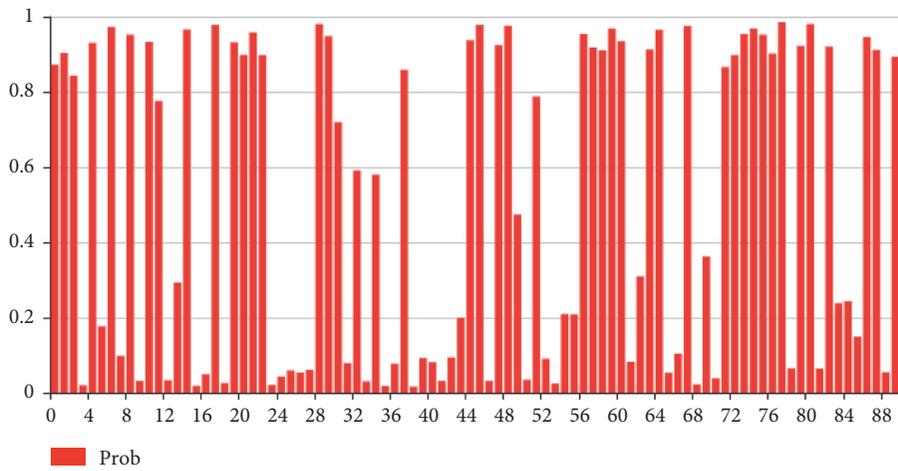


FIGURE 6: Probability distribution of node activity.

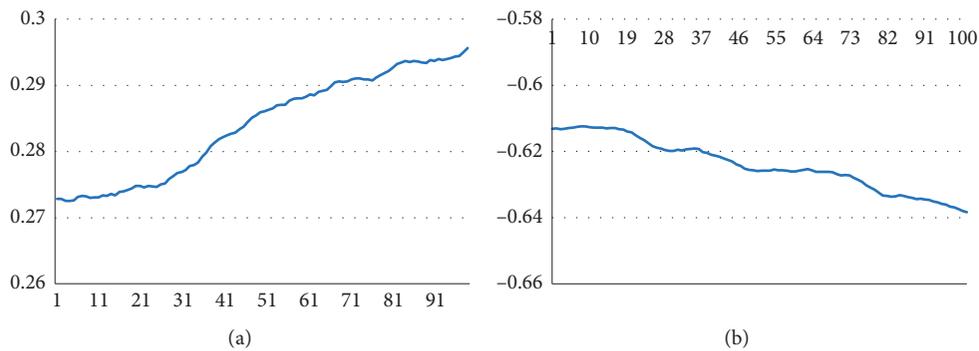


FIGURE 7: Time series of node activity evolution. (a) Active node ( $x$ ). (b) Passive node ( $y$ ).

disturbances into the network, which can stimulate the variation evolution of the original network.

The social support network of 91 athlete nodes is represented and predicted [26, 29–32], and the effect is shown in Figure 4. The different subnets of each athlete are represented by the edges of different colors, the network is simulated according to the evolution process of the network structure described in the article, and the subplot 1 shows the structure

of the original social support network of the athlete group. Subgraphs 1, 3, and 4 represent the overall structure of the network after 100, 500, and 1000 iterations according to the prediction algorithm, respectively.

By defining the activity of all nodes, the node set is divided into two subsets according to the positive and negative attributes of node activity, that is, passive node set and active node set. Passive nodes have low probability of

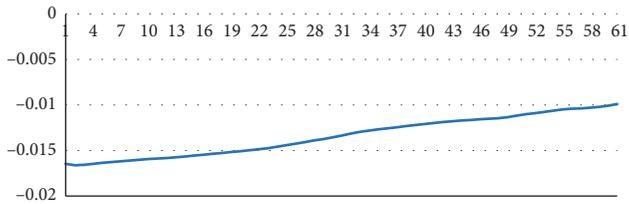


FIGURE 8: Time series of network system activity evolution.

walking and strong inertia, but play the role of resource adsorption, while active nodes play the nature of active nodes moving closer to passive nodes, as shown in Figure 5; this is the initial activity distribution for all nodes. Figure 6 shows the activity probability distribution calculated according to the activity of each node.

As shown in Figure 7, the left is the active sequence of an active node, whose activity is increasing under disturbance, and the right is the active sequence of a passive node, which is more and more inert under disturbance injection.

As shown in Figure 8, it is a network system activity sequence. In this example, although the network system activity is less than 0, the system has adsorption effect, but the trend is gradually approaching to 0, indicating that the whole network evolves towards stability.

## 5. Conclusion

A presentation model of complex network is put forward, which is expounded experimentally from the aspects of representation and structural evolution.

**5.1. Advantages and Disadvantages.** The model has the following advantages. (1) Incorporating node attributes into the modeling process and making node analysis more specific. (2) Explaining the connection mechanism between the principal nodes and giving the connection reasons. (3) The model is not only suitable for static network ingress but also more suitable for the prediction and evolution of network structure analysis. (4) Can guide the design questionnaire from the establishment of network links from two aspects of the design problem. (5) Suitable for the representation of multiple networks.

The model also has some shortcomings; the network represented by the model cannot be well supported by the current network mainstream visualization software, so according to the model, to draw a network map requires researchers to write their own programs.

**5.2. Future Research.** In the following research, the model will be improved through verification feedback in practice. The focus of the work will be on two aspects; on the one hand, it continues to improve the theory, combined with the existing node influence algorithm [33–37], node activity, and change probability index optimization; on the other hand, it hopes to write appropriate multinetwork visualization software to better model presentation.

## Data Availability

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

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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