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Research on the Optimization Method of Japanese Text Information Dissemination Path Based on Graph Theory

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ABSTRACT
Text is the carrier of language, and language is the carrier of cultural soft power, if you want a country's soft power to be enhanced, it will certainly start from the dissemination of the native language. This paper constructs a complex social network J-SEVIR model for the dissemination of Japanese text information with the help of complex network theory combined with the information dissemination model using graph theory as the technical support. The data about Japanese text information on Sina Weibo is used as the research object, and the data analysis is carried out through the dimensions of model simulation, real data comparison, and information dissemination enhancement strategies. The study shows that the peak number of Japanese text message dissemination nodes is 1.987*107, which is 41.32% and 28.94% higher than the peak number of dissemination nodes in the traditional SEIR model and BCIR model, respectively, and the peak number of disseminators of the Japanese text message dissemination enhancement strategy designed by the J-SEVIR model can be up to 0.62, whereas the number of Japanese text message dissemination counterattackers is only 0.12. Therefore, the number of Japanese text message dissemination counterattackers is only 0.12. Therefore, the establishment of Japanese text information dissemination paths with the help of complex networks based on graph theory can be used to provide new research perspectives for optimizing the effect of Japanese text information dissemination.

Keywords: graph theory, complex network, information dissemination model, J-SEVIR model, Japanese text message

1. Introduction

In recent years, people's access to information has become more and more diverse, from newspapers in the past, all the way to television and the Internet in today's society, with richness and diversity, and allowing the globalization of information into people's lives, mainly affected by the dissemination of news and information on the Internet [1-3]. While in the past, the creation and dissemination of

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textual content required the involvement of professional publishers or media organizations, today, anyone can become a content creator and share it with others through various platforms [4-6]. Personal blogs, social media accounts, and online forums have become places for ordinary people to share their opinions and knowledge. Through the Internet, people can easily share and disseminate all types of textual content, from text to images, audio, and video, all over the world in an instant [7-10]. This change has undoubtedly brought a lot of convenience to people's lives, but it has also brought some challenges and problems, and similarly, the dissemination of Japanese texts is also facing these opportunities and challenges.

Due to the rapidity of Japanese text information dissemination, false text information and rumors can easily spread and proliferate on the Internet. And in order to ensure the authenticity of information, users need to have the ability to identify rumors and false information and take appropriate measures to verify them [11-14]. At the same time, the dissemination of Japanese texts also brings some problems to personal privacy and intellectual property rights. In the Internet age, the contents of Japanese texts can be easily copied, edited, and distributed. This poses challenges to the protection of individual privacy and independent creation [15-18]. Relevant laws and policies should be strengthened to protect individual privacy and intellectual property rights in order to maintain a fair and reasonable distribution environment [19].

Literature [20] proposes a strategy to solve the network analysis problem, and identifies the “critical path” of information dissemination by analyzing messages and news in telegraph messengers to identify information dissemination patterns. Literature [21] emphasizes the change in communication methods by social platforms such as Facebook and Twitter, pointing out the negative impact of errors and false information on public trust, etc., and analyzes the potential of deep and integrated learning techniques in content development to improve the accuracy of information categorization. Literature [22] takes implicit links as the driving factor of user participation in information dissemination, constructs the network topology of implicit links, and emphasizes that implicit links play an important role in driving user behavior, which can well explain the information dissemination process and explore the dynamic factors of information dissemination. Literature [23] outlines the research status, methods and theories of data news dissemination path, and adopts Lasswell's 5W model to analyze the aspects of disseminators, channels and contents, based on the results to find out the problems that exist in the combination of news and new media platforms, and to provide reference for the dissemination strategy of data news. Literature [24] constructed a virtual reality book publication communication industry ecosystem with IP operation as the core, discussed the relationship between the stakeholders in the system, and explored the communication path of virtual reality book publications from the aspects of IP operation and organizational integration. The above studies have explored the dissemination paths of textual information through textual contents such as news and book publications, including social network platforms such as Twitter, however, the information dissemination paths of Japanese texts, also as a form of information expression, have not received much attention from academics.

Language and text, as the carrier of spreading culture, gradually form close language contact and communication between different countries with cultural exchange. This paper combines graph theory, complex networks and classical information dissemination models, and constructs a complex social network J-SEVIR model for Japanese textual information dissemination based on analyzing the influence of textual information dissemination and network structure. The data about Japanese text information in Sina Weibo is chosen as the data source, and the simulation analysis of Japanese text information dissemination path and dissemination effect is carried out, and the simulation results provide new development ideas for optimizing the Japanese text information dissemination path.

2. Graph theory and complex network analysis techniques

In the context of globalization, language is not only a bridge of communication between people, but also the degree of internationalization of language has become an important manifestation of a country's comprehensive strength. The promotion of national languages to the world has become an important strategic means to enhance national soft power. Language promotion is not only the promotion and dissemination of the language itself, but also the dissemination of one's own culture and values through the use of one's own language as a carrier and its implementation in texts, so that one's own culture can occupy an important position in the world's multicultural pattern.

2.1. *Basic Theory of Graph Theory*

2.1.1. Simple classification of diagrams. Graph theory is an important tool for studying the structure of complex network systems, as well as a common method for solving structured network problems. For a complex network system, graphs can be used to concisely portray the basic information inside it and to analyze the various properties of the network system by the nature of the reaction on the graph [25].

Graph theory uses graphs as the object of study, where a graph is a figure consisting of a number of points and line segments (also called edges) connecting the points. In practice, if the points represent some specific things, the line segments (edges) represent the relationships between the connected things, and the interactions between the things and between the things form a topological graph.

Figure g is a combination of node set v and edge ε, denoted as $g=(\gamma,\varepsilon)$, where $V=\{v_1,\dots,v_n\},\varepsilon=\{(v_j,v_i)\in V\times V\}$ denotes the connectivity between the nodes. $|V|$ and $|\varepsilon|$ denote the total number of elements in node set v and edge set ε, respectively, and $|V|$ also denotes the order of graph g.

For a graph $g'=(V',E')$, a graph G' is said to be a subgraph of a graph g if $V'\subset V,E'\subset\varepsilon$.

A graph g can be represented by a set of nodes v and a set of edges ε. Alternatively, a graph g can be represented by an adjacency matrix, and a topological graph g has a unique corresponding one.

An adjacency matrix A is a matrix that represents the adjacency between nodes in the corresponding topological graph.

For an nth order directed graph $G=(V,E)$, its corresponding n-dimensional adjacency matrix $A=(a_{ij})_n\times n\in\square^{n\times n}$. Is defined as follows:

$$a_{ij}=\begin{cases} w_{ij}, & e_{ij}\neq 0 \\ 0, & \text{other} \end{cases} \tag{1}$$

where w_{ij} denotes the weight of edge $e_{ij}=(v_j,v_i)$.

2.1.2. Principles of directed graphs. A directed graph is a directional graph consisting of a number of nodes and directed connected edges, while a directed graph model is a functional model based on graph theory that visually describes the interaction of information in a system. The nodes in the graph represent the elements that make up the system, and the directed edges connecting the nodes represent the interrelationships between the connected nodes. The directed graph model describes the system from the perspective of information flow based on the information interactions between the constituent elements of the system, and is able to visually and clearly represent the information interactions between the constituent elements of the system and their units [26].

If a directed graph is used to analyze the propagation path of Japanese text information, it needs to be carried out based on the following assumptions:

1) Transmissibility of communication relationships

In the propagation directed graph, if a node generates information, this information can be propagated to other nodes directly connected to the node, and can continue to propagate to other nodes based on the newly propagated nodes. And the actual complex network system, often will produce a signal that affects its contact with the normal nodes, is the propagation of information.

2) The type Ⅰ and Ⅱ observation points of the system can be obtained

Type Ⅰ observation point represents the input of the system, and type Ⅱ observation point represents the output of the system. System input is the basis of all system behaviors and also the basis of system behavior against. The system output is the prerequisite for system propagation analysis, and both types of observation points should be measurable.

3) Accepting the assumption of limited independence

There is no other relationship between the two related nodes except the information dissemination relationship, and the information of each node is only related to itself, not related to other nodes. That is, the intermediate nodes only propagate information and do not generate state signals themselves.

2.2. *Complex network technologies*

Graphs are another way of describing a network, complex network system adjacency matrix A, whose nodes and connected edges relations have the mapping of the graph $G=(V,E)$, where $V=\{v_1,v_2,\ldots,v_N\}$ is the set of nodes in the network and $E=\{e_1,e_2,\ldots,e_z\}$, is the number of connected edges between z nodes [27]. If there is a directed edge in the system pointing from node v_i to node v_j it is denoted by $\langle v_i,v_j\rangle$ and if there is an undirected edge in the system pointing from node v_i to node v_j it is denoted by (v_i,v_j). The adjacency matrix $A_{ij}=(a_{ij})$ denotes the elements of the i th row and j th column in the structure matrix, and for the complex network structure matrix A studied in this paper, in its adjacency matrix:

$$\begin{cases} a_{ij}\neq 0, & \text{Node } v_j \text{ has connected edges that point to node } v_i \\ a_{ij}=0, & \text{Node } v_j \text{ does not have a connected edge to node } v_i \end{cases} \tag{2}$$

2.2.1. Principles of Complex Networks. A complex network can be represented as a graph, where the nodes in the graph represent the data objects in the network, and the edges in the graph represent the connections between the network objects [28]. A network can be represented as $G=(V,E,A)$, where V is a set containing n nodes, E is a set containing m edges, A is a nX_n -dimensional adjacency matrix, and A_{ij} represents the weights of the edges between node i and node j. $A_{ij}=1$ if node i is connected to node j and $A_{ij}=0$ otherwise. The graph is called undirected if any pair of points (i,j) and (j,i) corresponds to the same edge, otherwise it is called directed graph. If different weights are assigned to each edge, then the graph is called weighted graph, otherwise it is called unweighted graph. If each node does not contain an edge from itself to itself and there is at most one edge between two different nodes, then the graph is a simple graph. In this paper, we deal with networks that are all directionless without weights, A as a symmetric matrix $(A_{ij}=A_{ji}=1)$.

A graph G is said to be connected if any two nodes in it have pathways to each other, otherwise it is a disconnected graph. If G is a disjoint graph, then each of its connected subgraphs becomes a connected branch. A graph is said to be complete if there are connected edges between any two nodes in G. A complete graph with n nodes has $n(n-1)/2$ edges. A graph in Figure G is a complete subgraph of it. In an undirected graph G, the number of edges connected to a node i is called the degree of the node i and is denoted as k_i. Whereas in a directed graph, the degree of a node is categorized into in-degree and out-degree. The in-degree of a node is the number of edges pointing to that node from other nodes, and the out-degree of a node is the number of edges pointing to other nodes from that node. For two graphs $G=(V,E,A)$ and $G'=(V',E',A')$, if $V'\subset V$ and $E'\subset E$, then into G' is a subgraph of G.

2.2.2. Complex network properties. Degree is the most basic concept for describing the properties of nodes in complex networks. In an undirected network, the degree of node v_i is the number of nodes directly connected to node v_i in the network, denoted as k_i. The more neighbors a node has, the greater the degree of the node [29]. In a directed network, the degree of node v_i is the sum of the outgoing and incoming degrees of the node, where the outgoing degree refers to the number of connected outgoing edges of the node, denoted as k_i^{go}, and the incoming degree refers to the number of connected incoming edges of the node, denoted as k_i^{en}. The average of the degrees of all the nodes in an undirected network is called the average degree of the network, denoted as $\langle k \rangle$, i.e:

$$\langle k \rangle = \frac{1}{n}\sum_{i=1}^{n} k_i \tag{3}$$

The clustering coefficient is a measure of how tightly nodes are clustered in a complex network and is used to evaluate the effectiveness of clustering. The clustering coefficient can help identify more compact clusters, as well as differences between clusters. In a network, the clustering coefficient C_i of node v_i is defined as follows:

$$C_i = \frac{E_i}{F_i} = \frac{2E_i}{k_i(k_i - 1)} \tag{4}$$

Where, E_i is the number of connected edges that node v_i actually exists with k_i neighboring nodes in the network, and F_i is the number of connected edges that node v_i may exist with at most k_i neighboring nodes in the network.

The clustering coefficient of a network C is the average of the clustering coefficients of all the nodes in the network, i.e.:

$$C = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{5}$$

The value of the clustering coefficient C is between 0 and 1. The larger the value, the closer the nodes are within the clustered network, and conversely, the more dispersed they are. It is easy to see from Eq. When $C = 0$, the nodes in the network are isolated nodes and there are no connecting edges between the nodes. When $C = 1$, the network is a complete graph, i.e., there are edges between any two nodes in the network.

Shortest path, network diameter and average path length are commonly used metric information in complex networks. In an undirected unweighted network, the shortest path between node v_i and node v_j is the one that connects these two nodes with the least number of edges, and its length is the shortest path length, denoted as d_{ij}. The maximum of the shortest path lengths in the network is known as the diameter of the network, denoted as D, that is:

$$D = \max_{1 \le i < j \le n}(d_{ij}) \tag{6}$$

The average path length L is the average of the shortest path lengths between all the nodes in the network, i.e:

$$L = \frac{2}{n(n-1)}\sum_{i \ge j} d_{ij} \tag{7}$$

3. Network for the dissemination of information on Japanese-language texts

National culture is the core component of national soft power, and emphasizing cultural communication is an important path to enhance national soft power. Japanese culture relies on textual information combined with the process of informationization to realize the construction of social networks, which in turn provides a new development direction for expanding the path of Japanese textual information dissemination, and lays a solid foundation for further enhancing the dissemination of Japanese culture.

3.1. Textual information and dissemination networks

3.1.1. Dissemination of information in Japanese texts. Japanese language and literature is an important carrier that can fully reflect Japanese culture, development history, customs and ideology. Through analyzing and studying Japanese texts, we can clearly find that Japanese texts are a great way to understand Japanese culture, which contains many values and behaviors of the Japanese people, and is an important carrier and foundation for carrying Japanese folklore and customs. Through the analysis of the characteristics of Japanese text information, it is found that Japanese writers are good at using beautiful, elegant and peaceful language expression, highlighting the personality of the characters, focusing on the fate of the characters and the final end of the arrangement and the close connection with the real society, which enables readers to understand the Japanese text of the period, to recognize the social background and development, and to bring the spiritual enjoyment, and the overall structure of the approach is very creative. Modern Japanese texts uphold the literary concepts of beauty, introspection, and calmness, and portray a sense of uneasiness and confusion among contemporary Japanese in the face of increasingly competitive social environments and serious life pressures in today's era, outlining a variety of flavors of the human world.

In the process of disseminating Japanese text information to foreign countries, the Japanese government has continuously introduced measures to strengthen the characteristics and advantages of local culture and to improve the competitiveness of foreign communication. Utilizing all available resources within the existing system, the Japanese government has continuously improved the foreign dissemination of related cultural industries. Relying on new media and information technology to expand colorful Japanese textual information dissemination channels to the outside world, and combining social networks to deepen international communication and understanding of Japanese textual information in various fields, the Japanese government has laid a solid foundation for further expanding the channels of Japanese cultural dissemination and shaping the international image of Japan.

3.1.2. Classical information dissemination models. In the process of information dissemination, relying on complex networks can maximize the effect of information dissemination, and the basic model of classical information dissemination mainly includes independent cascade model and linear threshold model.

The independent cascade model is a probabilistic model, centered on the sender, in which the information propagation process is carried out on Fig. $G=(V,E)$. where V represents the users in the network, E represents the relationship between users, and each edge of $G=(V,E)$ corresponds to the propagation probability $P[v,w]$, where v and w are two neighboring nodes in Fig. $G=(V,E)$, respectively. In information propagation, nodes are categorized into two states: active and inactive, where an active point indicates that a message has been received and an inactive point indicates that a message has not been received, and a node can only transition from an inactive point to an active point, and this transition cannot be reversed. When at moment t node v is activated, it gets a chance to have an impact on neighboring node w with a success rate of $P[v,w]$. If the activation is successful, then at moment $t+1$, node w transitions to active state.

The linear threshold model is receiver-centric and nodes in the model listen to messages in the social network and receive messages from neighboring nodes. In this model, the edges of node v and its neighbor node w have a weight b_w that indicates the influence of node v on node w and $b_{vw} \neq b_{vw}$, the sum of the weights of all neighboring points of node v is less than or equal to 1. Node v is activated when the sum of all neighboring weights of inactive node v is greater than node v randomly given a threshold $\theta_v (0 \leq \theta_v \leq 1)$, i.e., $\sum_{u \in N(v)} b_w \geq \theta_v$.

3.2. Modeling of Text Information Dissemination Networks

3.2.1. Impact with network structure. In the real Japanese text information dissemination path, there is an inevitable correlation between the evolution of its real network structure combined with graph theory and the evolution of Japanese text information dissemination on the network, and the evolution between the two dynamics is mutually influential. The mutual influence of information dissemination and network structure evolution is categorized into two types depending on the time scale. One is immediate influence, when a user receives a certain message and forwards it, it is possible that the characteristics of this message cause this user to gain a new relationship of following and being followed in a short period of time. The other is long-term influence, which means that repeated information dissemination shapes the network structure among users, and these changed network structures in turn influence the next information dissemination. The mechanism of interaction between Japanese textual information dissemination and network structure evolution is shown in Figure 1. Almost all real network systems are to some extent the result of co-evolution of 2 aspects, i.e., the dynamics on the network and the network topology feed back and influence each other.

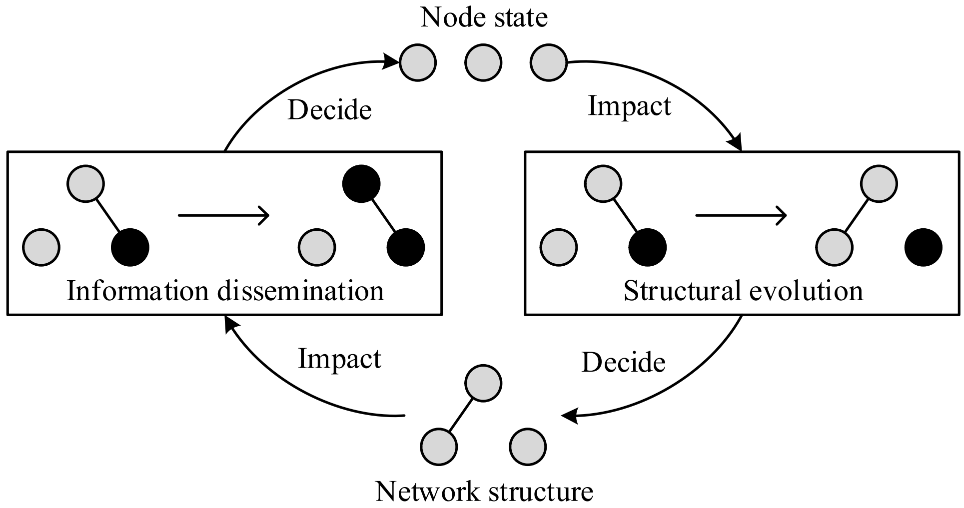


Fig. 1. Coevolutionary mechanism

3.2.2. Information dissemination network model:

1) Japanese Text Information Dissemination Model. Based on the previous analysis, it is known that there is a mutual influence between Japanese text information dissemination and network structure evolution, based on which, this paper constructs a Japanese text information dissemination model supported by complex social networks by combining graph theory and complex networks. The heat effect of information describes the popularity and propagation speed of information in a period of time, and as time goes by, fewer people will pay attention to a certain information or the information will be replaced by some new information, which leads to the decrease of heat. The node localization factors affecting information propagation include various factors such as node influence, intimacy between nodes, the number of times a message is received and the status of neighboring nodes.

The contact incentive effect is when an individual in the network receives the same message in the network multiple times, the messages act as an incentive for it. When a node receives a message, it does not always choose to believe it at the first opportunity, but remains in a state of questioning and wait and see.

The contact incentive effect ($H_i^R(t)$) of Japanese text messages on nodes in the network is defined as follows:

$$H_i^R(t) = a - be^{-c\frac{RUM_i(t)}{RUM_i(t)+RIR_i(t)}} \tag{8}$$

Where, $RUM_i(t)$ is the number of times node i receives Japanese language text messages in the network at t moments, $RTR_i(t)$ is the number of times node i receives rumor debunking messages in the network at t moments, c is the contact incentive strength, and a,b is the coefficient.

In complex social network information dissemination, nodes in the network will be influenced by their neighboring nodes, which is defined as neighbor node attraction in this paper. Specifically, the more the number of nodes in the infected state in the neighboring nodes of a node in the network, the easier the node will be influenced by its neighboring nodes, and thus also become a Japanese text disseminator. Neighbor node attraction ($N_i(t)$) is defined as follows:

$$N_i(t) = 1-(1-\beta_0)^{P_i(t)} \tag{9}$$

where β_0 is the initial dissemination capacity of Japanese text message, which indicates the attractiveness of the Japanese text message itself. $P_i(t)$ is the proportion of Japanese text disseminators in t moment nodes i neighbor nodes.

In addition to the above factors, the degree of interest in Japanese text messages is also an important factor. Generally a message has a higher interest level when it first appears and people tend to share the message with others. As time passes, the heat of the message cools down, and people's interest in this message decreases. Define people's interest level in a message as $\Omega(t)$, i.e:

$$\Omega(t) = re^{-\eta t} \tag{10}$$

where η is the intensity of interest decay, r is the decay coefficient, and t is the time of information propagation.

On the basis of existing studies, combining the contact incentive effect of nodes in the network, the attractiveness of neighboring nodes, and the degree of interest in the information, the dynamic infection rate $\beta(i,t)$ of nodes in the social network infected by Japanese text dissemination nodes is denoted as:

$$\beta(i,t) = \beta_0 H_i^R(t)\Omega(t) + N_i(t) \tag{11}$$

When a node in the Japanese text dissemination state realizes that this message is a Japanese text message, it will turn into a Japanese text message counter-attacker with a certain probability and disseminate the message to its neighboring nodes with a certain probability. The probability of a node to turn from the propagation state to the opposition state is also affected by a variety of factors, and here in this paper, we mainly consider the message contact incentive effect $H_i^{\tau}(t)$ as well as the node authority $A(i)$. Combining with Eq. (8) defines the contact incentive effect of the Japanese-language text message to the nodes in the network, that is:

$$H_i^T(t) = a - be^{-\grave{o}\frac{RTR_i(t)}{RTR_i(t)+RUM_i(t)}} \tag{12}$$

Node authority is the degree of importance and influence of a node in a network, which can be measured in the field of complex networks using several metrics such as degree of a node, median centrality, and proximity centrality. In this paper, we use $A(i)$ to denote the authority of a node in the network. Namely:

$$A(i) = \frac{k_i}{2(\log(N-1)+k_i)} \tag{13}$$

Combining the definitions of Japanese text message contact incentive effect and node authority in Eqs. (12) and (13), the probability $\gamma_{(i,t)}$ that a node in the Japanese text dissemination state turns into a Japanese text counterattacker can be expressed as:

$$\gamma(i,t) = \gamma_0 H_i^T(t) + A(i) \tag{14}$$

The dynamic infection rate $\beta(i,t)$ as well as the dynamic recovery rate $\gamma_{(i,t)}$ are brought into the classical SIR propagation model, and an improved J-SEVIR model for Japanese text propagation based on the SIR model is obtained, with the propagation dynamics equation:

$$\begin{cases} \dfrac{ds(t)}{dt} = -(\beta_0(a-be^{-c\frac{RUM_i(t)}{RUM_i(t)+RTR_i(t)}})re^{-\eta t} + 1-(1-\beta_0)^{P_i(t)})s(t)i(t) \\ \dfrac{di(t)}{dt} = (\beta_0(a-be^{-f\frac{RUM_i(t)}{RUM_i(t)+RTR_i(t)}})re^{-\eta t} + 1-(1-\beta_0)^{P_i(t)})s(t)i(t) \\ \qquad -(\gamma_0(a-be^{-f\frac{RTR_i(t)}{RUM_i(t)+RTR_i(t)}}) + \dfrac{k_i}{2(\log(N-1)+k_i)})i(t)r(t) \\ \dfrac{di(t)}{dt} = (\gamma\ \_\{\_0\}(a-be^{-c\frac{RTR_i(t)}{RUM_i(t)+RTR_i(t)}}) + \dfrac{k_i}{2(\log(N-1)+k_i)})i(t)r(t) \end{cases} \tag{15}$$

2) Evolution of information dissemination in complex social networks. The stochastic game of information dissemination in complex social networks can be described as:

$$(N,W,D,Q,\pi,V,\beta) \tag{16}$$

where $N=1,2,\ldots,n$ is the set of all users in the network population, W is the set of user state attributes representing their private information, $D=D_1\times D_2\times\cdots\times D_n$, D_i is the set of user i behaviors, $Q:W\times D\times W\to[0,1]$ is the transfer function, and $\pi:T\to[0,1]$ is the user's strategy representing the probability of choosing a particular strategy. $V=\{V_1,V_2,\cdots,V_n\}$ is the payoff function after a user i chooses a behavior, where, for $i\in N$, there $V_i\in(-\infty,\infty);\beta(0<\beta<1)$ is a discount factor that describes the relationship between the payoff of the next state and the payoff of the current state.

Suppose that user i and user j are neighboring nodes in a social relationship network and the game between them is as follows:

At moment t, in state w_i, user i chooses a behavior d_i^i from D_i and user j chooses a behavior d_i^i from D_j. User i receives a payoff $r_i^i=V^i(w_i,d_i^i,d_i^j)$ and user j receives a payoff $r_t^j=V^j(w_t,d_t^i,d_t^j)$, and then the game proceeds to the next state with conditional probability $P(w_{t+1}\mid w_t,a_i^i,a_i^j,w_{t+1})=Q(w_i,a_i^i,a_i^j,w_{i+1})$. w_{i+1} The expected payoffs are denoted by column vectors, viz:

$$U_{x^i,x^j}^k=\left[U_{x^i,x^j}^k(w_1)\cdots U_{x^i,x^j}^k(w_N)\right]^{\mathrm{T}},K=\{i,j\} \tag{17}$$

Among them:

$$\begin{aligned} U_{x^i,x^j}^k(w)&=E_{x^i,x^j}\left\{r_l^k+\beta r_{l+1}^k+\cdots+(\beta)^N r_{l+N}^k\right\} \\ &=E_{x^i,x^j}\left\{\sum_{n=0}^{N}\beta^N r_{i+N}^k\right\} \end{aligned} \tag{18}$$

Expectation $E_{x^i,x^j}\{\cdot\}$ denotes that user k adopts probability π^k, i.e., user k adopts the probability distribution of $\pi^k(w_{t+n})$ to choose a behavior at state w_{t+n}, at which time, an associated payoff $r_{i+n}^k=\pi^i(w_{i+n})^T V^k(w_{t+n})\pi^j(w_{t+n}),n\ge 0.V^k(w)=[V^k(w,d^i,d^j)]$ is obtained, and $K=\langle i,j\rangle$ is the payoff matrix of user k at state w.

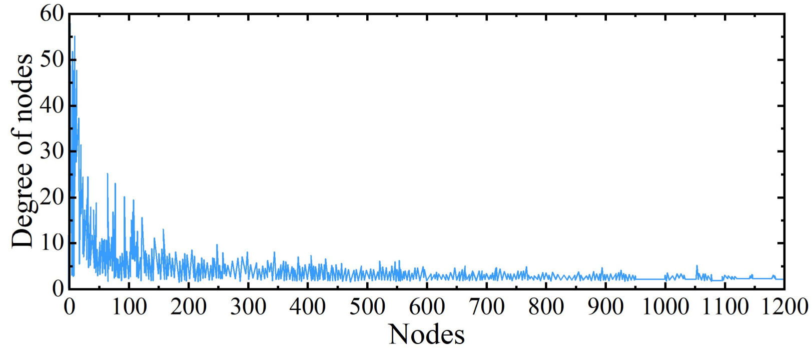
During the dissemination of Japanese text information in the network, there will be new users joining the network group at any time to participate in the dissemination of the information, and at the same time, there will be existing users withdrawing from the network group and no longer participating in the dissemination of Japanese text information. As a result, Japanese text messages have an important impact on the evolution of the network community, and at the same time, the evolution of the network community also plays a key role in the dissemination of Japanese text messages.

4. Simulation of information dissemination paths for Japanese texts

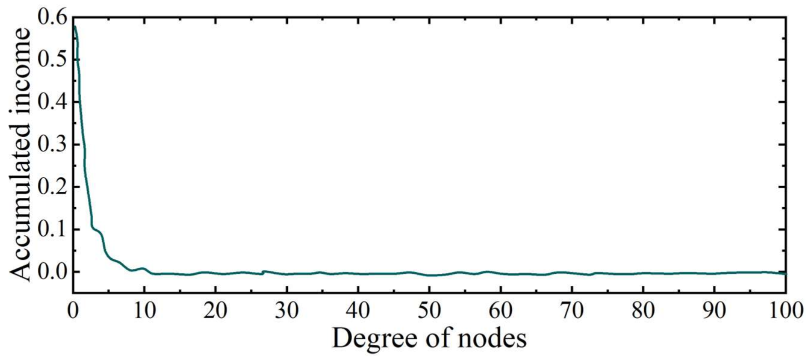
The network as a new media for information dissemination makes the environment for information dissemination somewhat special. The wide application of mobile communication tools and the rise of microblogging and other microblogging tools in the network era have made it possible for everyone in the network to become an instant publisher and disseminator of information. At the same time, there are different preferences of network information disseminators for their own interests in the process of information dissemination. Combining Japanese text information dissemination with complex social networks can effectively realize the interactive game between information publishers and retweeters, and provide a reliable optimization path to promote the effect of Japanese text information dissemination.

4.1. Model Simulation Experiments and Results

4.1.1. Model simulation experiments. Based on the complex social network model of Japanese text information dissemination constructed in the previous paper, a Japanese text information dissemination network with an average degree of 5 and a clustering coefficient of 0.75 is generated using the scale-free network generation algorithm with a total number of nodes of 1,200.The degrees and degree distributions of the nodes in the network are shown in Fig. 2. As can be seen from the figure, the statistical properties of the degree distribution of the complex social network of Japanese text information established in this paper show a power law distribution, which is consistent with the phenomenon that many social networks in the real world obey a power law distribution. It can effectively reflect the specific path of Japanese text information dissemination and provide a reliable complex social network foundation for exploring Japanese text information dissemination.



(a) Degree of nodes



(b) Degree distribution

Fig. 2. The degree and degree distribution of nodes in the network

The updating rule used in the complex social network dissemination model of Japanese text information designed in this paper is Fermi rule, in order to further clarify the influence of the noise factor in the Fermi rule on the evolution of Japanese text information dissemination, this paper selects the values of the noise factor taken by different Fermi rules and explores the evolution of its value on the proportion of Japanese text information of the collaborators. Figure 3 shows the results of the analysis of Japanese text message evolution. As can be seen from the figure, under the condition of the same network parameters and game gains, the fluctuation range of the proportion of cooperators decreases from [0.26,0.37] to [0.01,0.18] when the noise factor of the Fermi rule increases from 0.15 to 0.85. This indicates that the noise factor of Fermi's rule has a greater influence on the complex social network communication evolution model of Japanese text messages, and has an inhibiting effect on the proportion of collaborators in it.

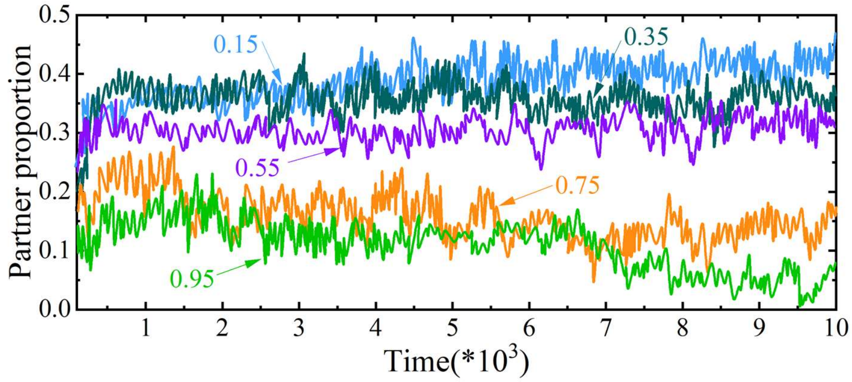


Fig. 3. The effect of noise factor on the proportion of authors

Combining the simulation results of the Evolutionary Game Model of Information Dissemination in Complex Social Networks and the statistical results of real data from Sina Weibo, the Japanese text information dissemination behaviors of users in microblogs are analyzed, and the dataset is the publicly available microblogging dataset of AMiner at Tsinghua University. In this paper, the cooperative behavior of network nodes is quantified as the number of tweets related to Japanese text information posted and retweeted by users over a period of time. 156,147 users' microblogging data were selected, and the average number of tweets posted/retweeted by each user was 1,564.78, and users higher than this average were defined as cooperators, and the proportion of cooperators was obtained to be 0.261. Substituting into the complex social network information propagation evolution game model can find the specific location of the closest collaborator, it can be seen that the network topology formed by the nodes of Sina Weibo users has a high degree of aggregation. At the same time, the high betrayal temptation indicates the selfishness of users' behavior, i.e., most of the microblogging users are only recipients of Japanese text messages, harvesting the information resources of other users without posting or retweeting the information themselves.

4.1.2. Comparative analysis of models. In order to illustrate the advantages of the J-SEVIR model proposed in this paper in controlling the information dissemination of Japanese text, this chapter compares it with the information dissemination model of traditional social networks (SEIR) and the information dissemination model of existing blockchain social networks (BCIR). Among them, the BCIR model mainly considers the impact of blockchain technology on users' dissemination of information, ignoring the latent nodes and other influencing factors in the network. Through simulation experiments and using the maximum number of propagation nodes as the evaluation index, the time is the number of days. The comparison results are shown in Fig. 4 to Fig. 6, and the number of nodes control is generated as shown in Table 1.

First of all, from the data plots of the three models, it can be observed that the peak of the number of nodes disseminating information in the SEIR model, the BCIR model, and the J-SEVIR model proposed in this paper in the Japanese language is 1.406*107, 1.541*107, and 1.987*107 people, respectively. Compared with the traditional social network SEIR model, the blockchain-based social network model and the model constructed in this paper show a significant increase in the number of dissemination nodes. Among them, compared with the traditional SEIR model, the peak value of the number of propagation nodes of this model increased by 41.32%, and compared with the BCIR model, the peak value of the number of propagation nodes of this model increased by 28.94%. It shows that the users of this model can make more rational decisions in the process of Japanese text information dissemination in complex social network evolution, which can effectively enhance the number of Japanese text information dissemination.

Second, by comparing and analyzing the data of the three models, it is found that the information dissemination model based on blockchain social network takes shorter time in reaching the peak of the number of dissemination. Among them, this model is a little later than the BCIR model in reaching the peak number of propagation nodes, which is because this model simultaneously considers factors such as incentive mechanism, node intimacy and information credibility function, and for the propagation of Japanese text information, users will be more rational and cautious, so it results in slower propagation of information. Moreover, the number of voting nodes in this model is higher than the BCIR model. It shows that the model in this paper can not only effectively promote users' participation in the information dissemination process and increase the activity of the social network in the process of Japanese text information dissemination, but also shorten the time needed to reach a stable state, which helps to enhance the existence time of Japanese text information in the network. This in turn enhances the probability of other node users contacting and spreading Japanese text information, further verifying the effectiveness of this paper's model in controlling Japanese text information dissemination.

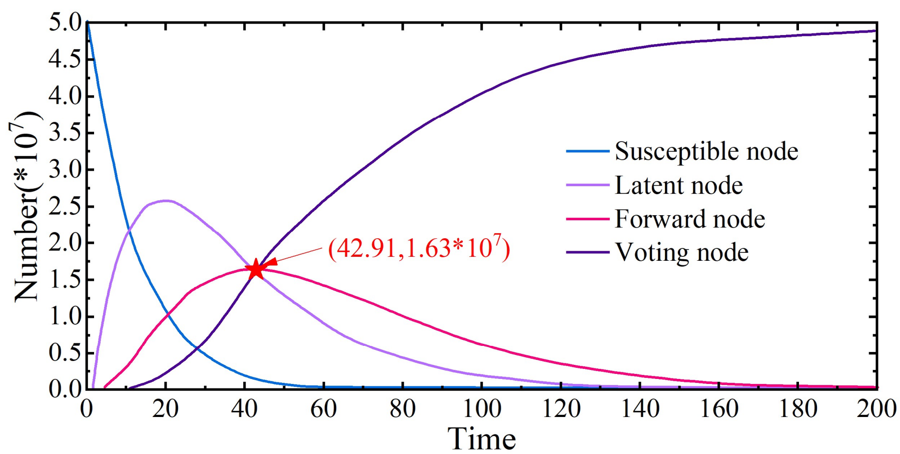


Fig. 4. The transition process diagram of each state node in the SEIR model

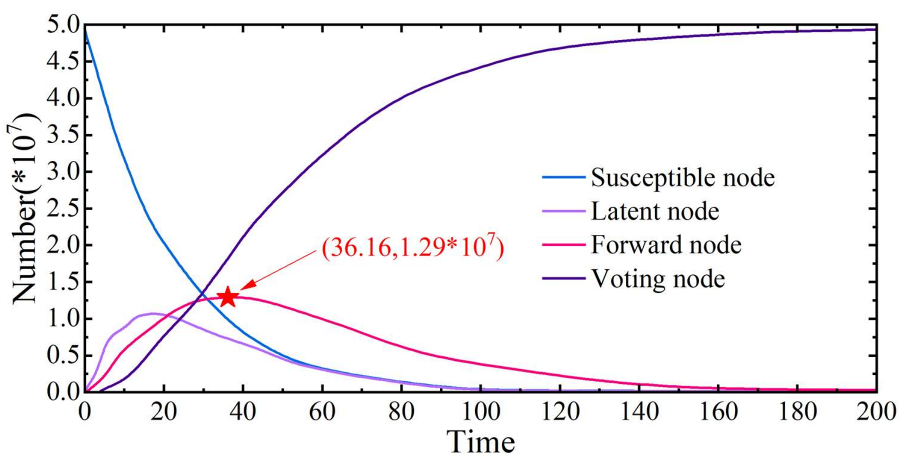


Fig. 5. The transition process diagram of each state node in the BCIR model

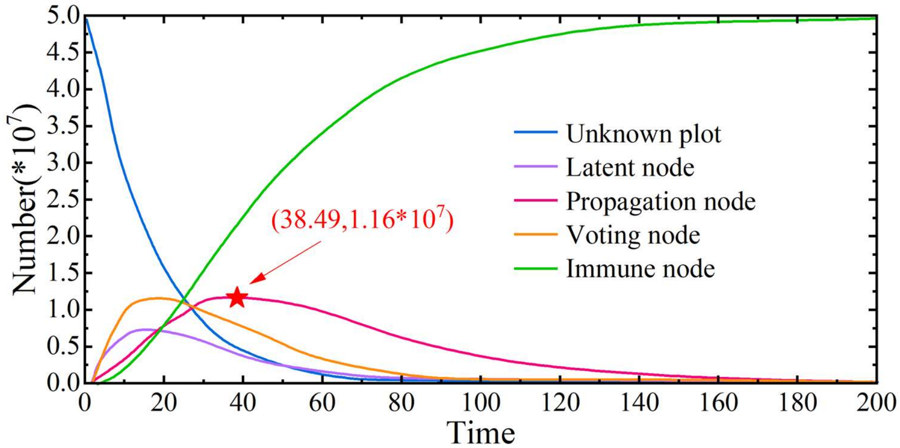


Fig. 6. The transition process diagram of each state node in the J-SEVIR model

Table 1. Comparison table of the number of nodes

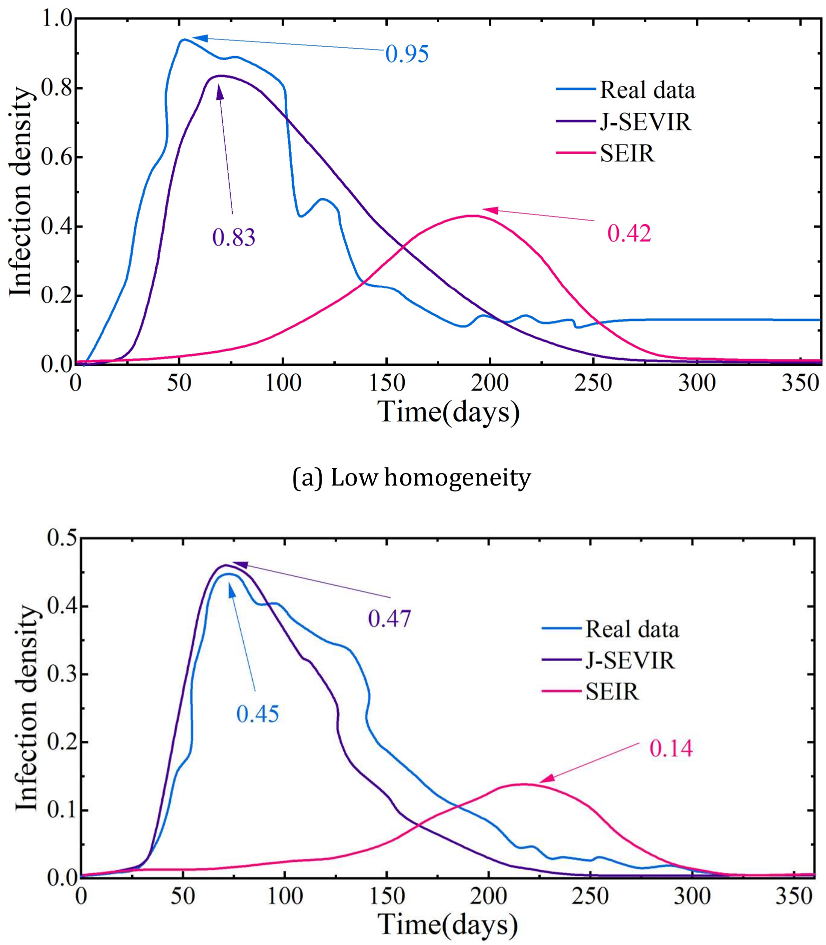
Model	Number of voting nodes (*107)/days	Number of propagation nodes (*107)/days
SEIR	0/0	1.406/26
BCIR	1.263/15	1.541/24
J-SEVIR	1.359/15	1.987/35

4.2. Performance of the information dissemination model

4.2.1. Comparison of real data. In order to further validate the effectiveness of the J-SEVIR model of complex social networks based on graph theory in the dissemination of Japanese text messages, this paper uses the open-source program "Weibo-Spider" on GitHub to crawl Sina Weibo for data involving the keyword "Japanese text messages" from May 2023 to May 2024 as real data. We use the program "Weibo-Spider", which is open source on GitHub, to crawl Sina Weibo for the period from May 2023 to May 2024 for the keyword "Japanese text messages". The first "Japanese text message" is posted on Weibo at the moment of initial state $t0$. The publisher of the message is regarded as the infected user, and its followers are the susceptible people, i.e., $(t0) = 1$, $S(t0) = X$, and X is the number of followers. Figure 7 shows the comparison results between the model simulation results and the actual Japanese text message dissemination trends, where Figures 7(a)~(b) show the comparisons of lower and higher degrees of homogenization, respectively. The real data curve indicates the evolution of the proportion of people involved in the dissemination of information in this category of Japanese texts over time.

By analyzing the two comparative graphs, we find that the propagation of the J-SEVIR model in the web is closest to the actual trend of Japanese textual information propagation. This result proves that our proposed J-SEVIR dynamic information dissemination model is consistent with the actual homogenized information dissemination process. In the real Japanese text information dissemination social network, there are numerous topics about Japanese text homogenization information, such as the current status of Japanese text development and dissemination, data performance, scientific research inquiry, dissemination measures, and people's deeds. At the same time, people's curiosity has led them to be interested in various aspects of Japanese text information, and they are not too tired of Japanese text information. At this time, Japanese text homogenized information spreads quickly and widely. This also fits with the effect shown in our model considering the case of low homogenization. However, after a long period of dissemination of Japanese text information, people's interest in Japanese text information plummets, fatigue builds up for a long time, and the discussion on the topic of Japanese text homogenization information focuses mainly on dissemination measures and cultural self-confidence, with a large number of related information recurring in a large number of occasions.

At this time, the degree of homogenization of Japanese text homogenized information is high, and therefore, the spread of Japanese text homogenized information is slower and less widespread. This also fits with the effect shown in our model considering the high degree of homogenization. Further, we also find that the model fit is better when the degree of homogenization is high, which is due to the fact that when the degree of homogenization is high, the data is of higher quality and is clearer and more accurate due to the relative concentration of information topics. In contrast, when the degree of homogenization is low, the data is more cluttered and contains more noise and uncertainty due to scattered and thematically inconsistent information, which leads to the model not being able to predict more accurately to some extent.



(b) High homogeneity

Fig. 7. Real data comparison results

4.2.2. Communication enhancement pathways. In order to study the influence path of enhanced Japanese textual information in the dissemination network and to enhance the dissemination ability of the disseminator I-state users on the network, the dissemination strategy of enhanced high-yield disseminator is proposed. The dissemination strategy makes full use of the model features to present the dissemination ability of the online user layer in the form of game gain values. When the return of a user in the I-state of the propagator exceeds a certain threshold, the user will be processed to enhance the propagation capacity, such as “attracting flow”, to expand the online propagation behavior of the user, so as to achieve the greatest propagation effect with the smallest propagation scale.

First of all, we analyze the revenue distribution of each moment of the communicator in the case, and its specific structure is shown in Figure 8. The data show that, using the data distribution characteristics of the box plot, all the moments on the quartile gain value statistics (removing the 2, 3, 5 moments), and calculate its average value, the result is 4.26. that is, when a moment of the propagator I state of the user's gain value reaches 4.26, the user will be taken to the user “diversion” and other treatments to expand the user's online propagation behavior, and at the same time, the user's online propagation behavior, and to achieve the maximum effect of the minimum scale of propagation. At the same time, the user's revenue is adjusted to the initial value of I-state revenue. Then, the next moment of propagation is carried out. We continue to count the propagation thresholds of the I-state users and the processing of propagation strategies, and so on, to arrive at the final results of the experiment.

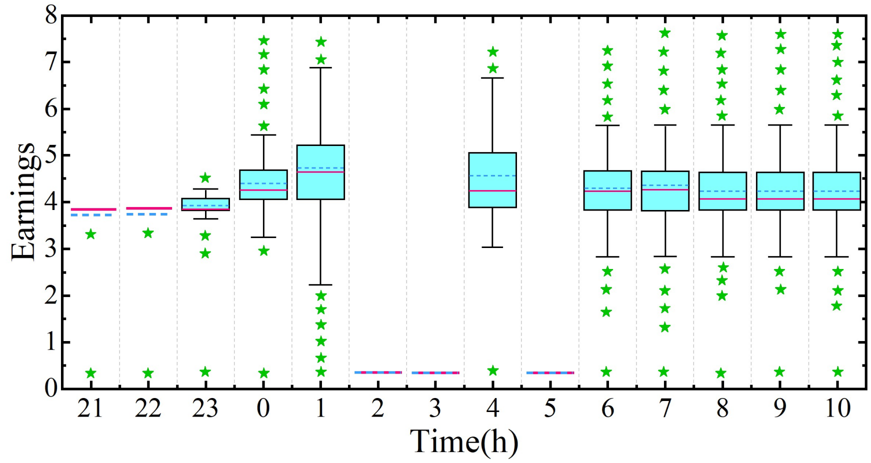


Fig. 8. The distribution of the communicator in different moments

Then the propagation gain threshold is derived by analyzing the gain distribution graph, the propagation gain threshold is applied to the model to derive the simulation results, and finally the results of this propagation strategy are compared with the classical target propagation strategy to verify the effectiveness of this propagation strategy. When the classical target propagation method is used for the experiments, the propagation is carried out to the online users with a high degree of network nodes, and the state of the propagating users is set to be R state. The propagation node size of the propagation strategy with enhanced high-yield propagators is set to be the same as the classical target propagation node size in the experiments to ensure reliability. Figure 9 shows the enhancement effect of different dissemination strategies for the Japanese text message dissemination path, where Figures 9(a)~(c) show the enhancement effect of the unused dissemination strategy, the target dissemination strategy and the strategy of this paper, respectively.

Comparison of Fig. 9(a) and (b) yields:

1) At moment 0, the percentage of users in the propagator I state peaks in both figures. In particular, the percentage of communicator I-state in Fig. 9(a) is 0.42, while that in Fig. 9(b) is 0.62. It is clear from the comparison that the percentage of communicator I-state users can be effectively enhanced by using the communication strategy that enhances high-yield communicators.

2) At moment 0, the percentage of counterpuncher C-state users peaks in both figures. Among them, the percentage of counterattacker C-state in Fig. 9(a) is 0.19, while that in Fig. 9(b) is 0.12. In comparison, it can be seen that the percentage of counterattacker C-state users using the propagation strategy of enhancing high-yield propagators decreases by 0.07.

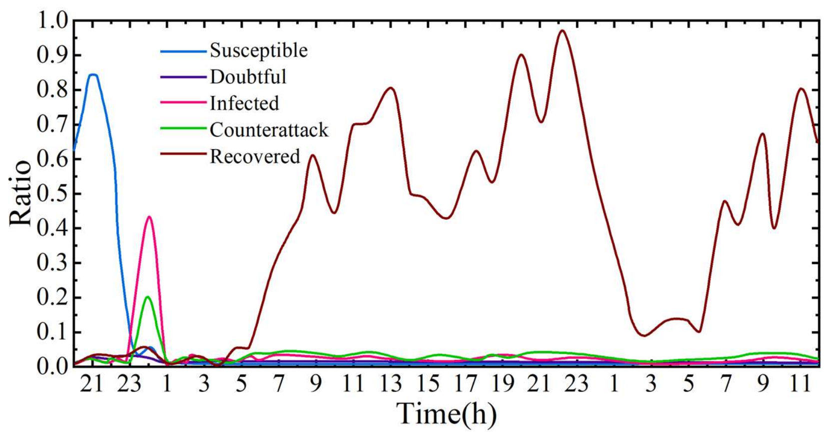
It is analyzed that this is due to the fact that when this strategy is used, the propagation ability of the propagator I state in the network is enhanced, which can better realize the wide spread of Japanese text messages, resulting in better reception of the information from the users of the propagator I state by other users, which weakens the users' behavior of attacking the Japanese text messages, and contributes to the decrease in the proportion of users of the C state of the counterattacker, which effectively enhances the propagation of the Japanese text messages.

Comparison of Fig. 9 (b) and (c) shows that:

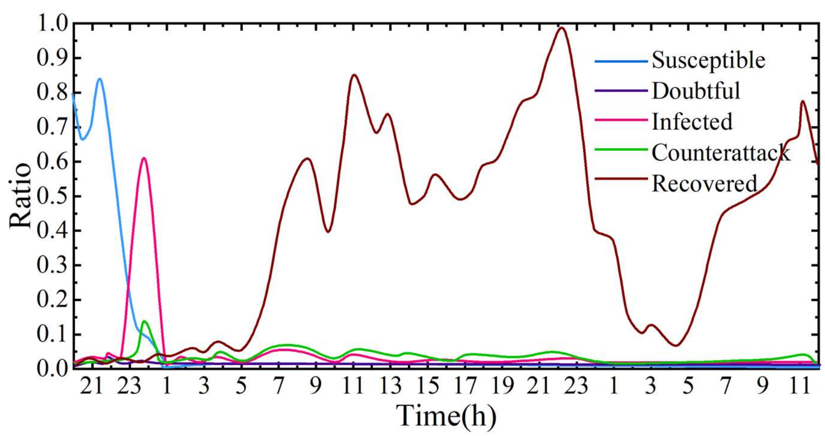
1) At moment 0, the proportion of communicator I-state users peaks in both figures. In Fig. 9(b), the percentage of propagator I state is 0.62, while that in Fig. 9(c) is 0.49, so the propagation strategy of enhancing high-yield propagators is more effective.

2) At moment 0, the percentage of users in the C-state of the counterattacker peaks in both figures. Among them, the percentage of the C-state of the counterattacker in Fig. 9(b) is 0.12, while that in Fig. 9(c) is 0.18, so the dissemination strategy using the enhanced high-yield disseminator is more effective.

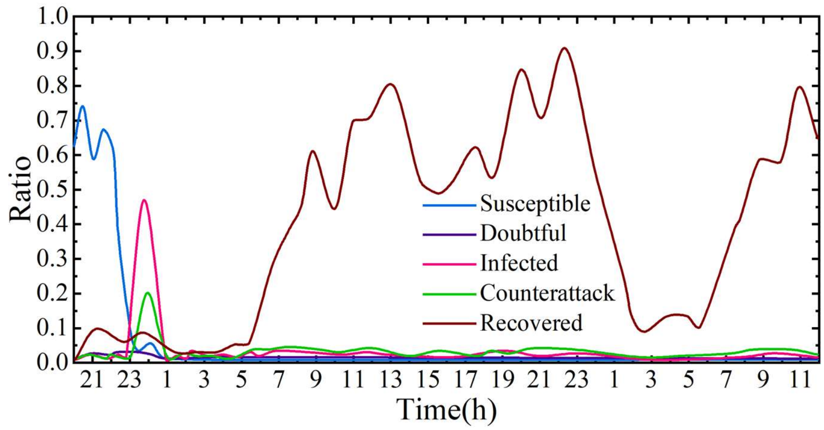
In summary, the Japanese text information dissemination path enhancement strategy method proposed in this paper can effectively enhance the dissemination of Japanese text information on the network, and the dissemination effect is better than the classical target dissemination strategy to avoid the waste of dissemination resources. Therefore, the enhancement of the dissemination ability of fixed-point users can achieve the best effect of Japanese text information dissemination control, which not only focuses on the structural characteristics of user nodes, but also needs to consider the user's own dissemination ability.



(a) Unused communication strategy



(b) Target communication strategy



(c) This strategy

Fig. 9. Propagation path enhancement effect

5. Conclusion

The article proposes a complex social network information dissemination J-SEVIR model based on graph theory and applies it to Japanese text information dissemination through simulation analysis, aiming to explore the enhancement path of Japanese text information dissemination effect. In the simulation results, the peak number of nodes of Japanese text information dissemination is $1.987*10^7$ people, which is 41.32% and 28.94% higher than that of the traditional SEIR model and BCIR model, respectively. This shows that the J-SEVIR model designed in this paper can make more rational decisions when applied to the dissemination of Japanese text information, and can effectively enhance the number of Japanese text information dissemination. The high yield communication strategy constructed based on the model in this paper has a peak ratio of 0.62, while the peak ratio of the number of counterattackers under this strategy is only 0.12. Therefore, the communication of Japanese text information in combination with graph theory can be enhanced by relying on the social network to provide a more effective communication strategy to improve the scope of Japanese text information dissemination.

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