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# DYNAMIC INFORMATION PROPAGATION MODEL OF SOCIAL HYPERNETWORK CONSIDERING POSITIVE AND NEGATIVE INTERFERENCE

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Abstract. *Considering interference of external information in social networks, this paper proposes a SEIR (Susceptible-Exposed-Ignorant-Removal) model of dynamic information transmission in social networks considering positive and negative interference from the perspective of hypernetwork. The model combines hypernetwork theory and propagation dynamics equation, introduces the information interference function, and establishes the dynamic equation of information propagation. First, the influence factors such as hypernetwork structure and external information interference are analyzed theoretically. Furthermore, the dynamic and static comparisons of the model in complex network and hypernetwork are explored in detail. Finally, MATLAB is used to simulate the model. The simulation results show that the dynamic PNSEIR (Positive and Negative Susceptible-Exposed-Ignorant-Removal) model can better reflect the characteristics of ground information transmission in real social networks, which confirms the rationality and effectiveness of the proposed information transmission model.*
**Keywords:** Hypernetwork, Positive and negative interference, Social network, Dissemination of information, The dynamic model

1. **Introduction.** With the rapid development of the Internet, people speak freely through social software, making information spreading faster and wider. At the same time, the spread of rumors is also common, and its emergence has a huge loss to the network order, individuals and society [1,2]. Therefore, establishing a more realistic information dissemination model is of practical significance for revealing the characteristics of information dissemination in social networks and putting forward relevant decisions to deal with the spread of rumors.

Information transmission is similar to epidemic transmission, in that information and the virus can be transmitted to the neighboring individuals of the spreader or infected person, respectively, and then spread. Consequently, the common infectious disease models such as SIS [3], SIR [4] and SEIR [5] are widely used in information dissemination models. Other studies have shown that information dissemination in social networks and human behavior are related to some extent. Lv and Huang [6] established a new ACI-IESR rumor propagation model by introducing authority effect, conformity effect and close friend degree into the rumor propagation model. Tang et al. [7] built the SEIRD model by adding diehard rumor believers and potential rumor believers, considering the lag of the process of rumor spreading, believing and refuting. Nian et al. [8] explored the

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relationship between rumor propagation, user characteristics and subject interest differences based on the SEIR model. Although the above studies have been conducted, there are still some factors affecting information spreading that need to be considered, such as the influence of external information on individuals. Guo et al. [9] studied the influence of external information on individual behaviors, and obtained that the influence of external information on communication behaviors changes with time. Liu et al. [10] confirmed that the information propagation model considering the interference of negative information on information transmission is closer to the real network, which took Sina Weibo platform as an example. Hence, in order to establish a more realistic information dissemination model to reveal the relevant transmission characteristics, it is necessary to be consideration about the external information interference including positive and negative.

In addition, the researches on information dissemination are mainly based on the related characteristics of complex networks in recent years, but the traditional complex networks containing only a single type of nodes and edges to represent the individual and the single relationship. What is more, there are many communication channels and complex social relations in realistic network, the ability of using complex network to describe the system is limited. On the contrary, the hypernetwork [11] can contain multiple subnets, nodes and hyperedges with any number and different types, which better match the relationship complexity of social networks and more correctly reflects the transmission of information in the Internet. Therefore, the development of dynamic information communication model under hypernetwork is more realistic. Although some studies have explored the information propagation model considering external interference based on complex networks, there are few studies on the interference of external information on information propagation in dynamic hypernetworks.

To solve the above problems, we propose a dynamic information propagation model considering the interference of positive and negative external information. Here, dynamic refers to the network structure based on the hypernetwork. That is, the information transmission model is dynamic evolution, in which nodes represent network users, and hyperedges represent friends between users. The whole model includes three dynamic evolution parts: adding hyperedge, reconnecting hyperedge and adding node. In addition, we combine the hypergraph theory to establish the spreading dynamics equation of the information dissemination model. By using numerical simulation, the new model under hypernetwork is compared with the traditional SEIR model, and the results show that the proposed PNSEIR model can better reflect the information transmission characteristics of the real network. This paper aims to consider the influence of the evolution of network structure and the influence of external information interference for the information transmission mechanism, so as to improve the relevant research on the transmission dynamics, and try to provide a new scheme for effectively controlling the spread of rumors.

The rest of this paper is organized as follows. Section 2 introduces the information propagation model based on positive and negative information interference and the theoretical analysis based on the model under the hypernetwork. Section 3 gives the MATLAB simulation results, tests the influence of each parameter on the model, and compares PNSEIR in complex network and super network environment. And Section 4 discusses the research results.

## 2. Hypernetwork Information Propagation Model Based on Positive and Negative Information Interference.

**2.1. PNSEIR information transmission model with positive and negative information interference.** In general, the information transmission behavior of users in online social networks observes the following rules: When a user posts a message on the sharing platform, his/her friends will receive the message with a specific probability. If someone is interested in it, they will forward it with a certain probability [12]; otherwise they will ignore it.

According to the structure of the social network, users in the social network are defined as nodes, the friend relationships between users are defined as the edge between nodes, and the published information is spread along the edge between nodes. Combined with SEIR infectious disease model, all nodes are divided in the network into four states, namely, the ignorant, the exposed, the spreader and the removal [13].

In addition, the propagation behavior of each node is not only discussed by its neighbors, but also that in the process of spreading initial information, nodes are always affected by the external information flowing in the network more or less. Here, we introduce positive information and negative information (collectively referred to as external information) that interfere with information transmission. Besides, we assume that their influence on the dissemination of original information is as follows: A positive message of official clarification issued by official institutions or someone with great influence will make the original information more accurate and clear, but it will lose the significance of further dissemination, so that it has a certain inhibitory effect on the original information. The negative information can promote the original information to some extent, because the exaggerated false information has specified ambiguity and attraction to the original information, which makes it have a greater transmission power.

In order to describe the interference of external information accurately, combined with the information decay function, the influence function about nodes $f_i$ ($i = 1, 2$) [14] is introduced:

$$f_i = \left|(T - r) \times e^{-\omega \cdot t} - T\right| = \begin{cases} r \times e^{-\omega \cdot t}, & T = 0 \\ 1 - (1 - r) \times e^{-\omega \cdot t}, & T = 1 \end{cases} \tag{1}$$

where $t$ is the information transmission time, $T = 0$ or $T = 1$. When $T = 0$, there is a negative information interference rate $f_0$, and when $T = 1$, the positive information interference rate $f_1$ is obtained. For $r$ ($r \in [0, 1]$), it is the information inflow rate, which refers to the information transmission in the network is always disturbed by external information, such as relevant information with the symbol @ or #. And for $\omega$, the influence of shared media, there is no doubt that $\omega > 0$ is constant.

The propagation rules are defined as follows.

1) When an ignoramus contacts an exposed person, it will turn into an exposed person with probability $p_1$.

2) When an ignoramus contacts with a spreader, it will turn into a spreader with the probability of $p_2$. We assume that $p_2 > p_1$ is constant.

3) When an exposed person contacts a spreader, it will turn into a spreader with probability $\alpha$.

4) When a spreader contacts a remover, he or she will turn into a remover with probability $\beta$.

5) The exposed person will be disturbed by negative information and become a spreader, and the exposed person will be disturbed by positive information and become a removal.

6) A spreader will be disturbed by positive information and turn into a removal.

Based on the above propagation rules, $I(t)$, $E(t)$, $S(t)$ and $R(t)$ refer to the proportion of each state node in the network at time $t$. Assuming that the nodes in the social network are uniformly distributed, the dynamic equation of the corresponding information propagation model can be obtained by means of the mean field equation:

$$\begin{cases} \dfrac{dI(t)}{dt} = -p_1E(t)I(t) - p_2S(t)I(t) \\ \dfrac{dE(t)}{dt} = p_1E(t)I(t) + p_2S(t)I(t) - \alpha S(t)E(t) - f_0E(t) - f_1E(t) \\ \dfrac{dS(t)}{dt} = \alpha S(t)E(t) + f_0E(t) - \beta R(t)S(t) - f_1S(t) \\ \dfrac{dR(t)}{dt} = \beta R(t)S(t) + f_1E(t) + f_1S(t) \end{cases} \tag{2}$$

According to the above equation, we can get that $I(t)+E(t)+S(t)+R(t) = N$, in which $N$ is the total number of network nodes, that is, the total number of nodes contained in the network is constant. The whole information propagation model based on positive and negative information interference is shown in Figure 1.

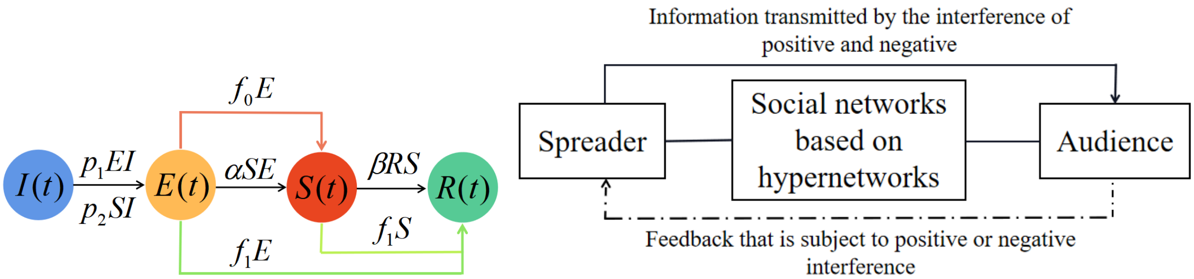



FIGURE 1. (color online) Information transmission model under external information interference and network information transmission framework: In this system, the network contains four node states: ignorance (blue), exposure (orange), propagation (red), and removal (green). In each time step, the network structure will evolve dynamically as shown in Figure 2, in which the state of nodes in the network is affected by propagation rules and changes with the state of connected nodes.

## 2.2. **Social network based on hypernetwork.**

2.2.1. *Super network.* The concept of "hypernetwork" was first clearly defined by Nagumey, an American scholar. Compared with ordinary graph, hypergraph contains any number of nodes [15], which can better fit the real social network than complex network. The mathematical definition of a hypergraph is as follows: let $V = \{v_1, v_2, \dots, v_n\}$ be a finite set, and if $E = \{e_1, e_2, \dots, e_m\}$, writing the binary relation $H = \langle V, E\rangle$ as a hypergraph, where $V$ is the node set elements, $v_1, v_2, \dots, v_n$ are the nodes of the hypergraph, $E_i = \{v_{i_1}, v_{i_2}, \dots, v_{i_j}\}$ ($v_{i_k} \in V$, $k \in N^+$) is the hyperedge of the hypergraph. Hypernetwork [16] is a complex system based on hypergraph.

2.2.2. *Social networks.* Unlike the fixed transmission rate of information in complex networks, the infection rate in hypernetworks varies from person to person, largely due to the differences in social skills and influence of each individual. For example, when a user has great social skills or great influence, he is more likely to get more information, spread and ask his many friends to forward the information, and control the spread of malicious information with his powerful traffic. Here, we express the connection probability between node $i$ and node $j$ as

$$W = \frac{h_j(t, t_i) + \xi_i}{\sum_{i,j=1}(h_j(t, t_i) + \xi_i)} \cdot Y_i \tag{3}$$

where $h_j(t, t_i)$ is the excess degree of the $j$th node of batch $i$ node at time $t$, $Y_i$ is the influence generated after the connection between nodes, and $\xi_i$ is the social skills of nodes themselves. In this paper, $Y_i$ and $\xi_i$ are assumed to follow normal distribution [17], namely $Y \sim N\left(\mu_1, \sigma_1^2\right)$ and $\xi \sim N\left(\mu_2, \sigma_2^2\right)$.

On the basis of non-uniformly distributed network nodes, the dynamic information dissemination model is constructed as follows (as shown in Figure 2).

1) Add $m$ hyperedges in the original network with probability $p$: select a node at random, and select old nodes in the original system to form a new hyperedge with them by probability, where $u$ is a random variable.

2) Reconnect $m$ hyperedges with probability $q$: randomly select a node $v_i$ and its hyperedge $e_i$, delete hyperedge $e_i$ and select $u$ old nodes in the original system to form a new hyperedge $e_i'$ with probability $W$ with this node.

3) $m_1$ new nodes are added to the existing network with probability $1 - p - q$: $m_1$ new nodes are randomly selected to form a hyperedge with $m_2$ old nodes selected with probability $W$.

The above process is repeated $m$ times, and it is required that no repeated hyperedges are formed.

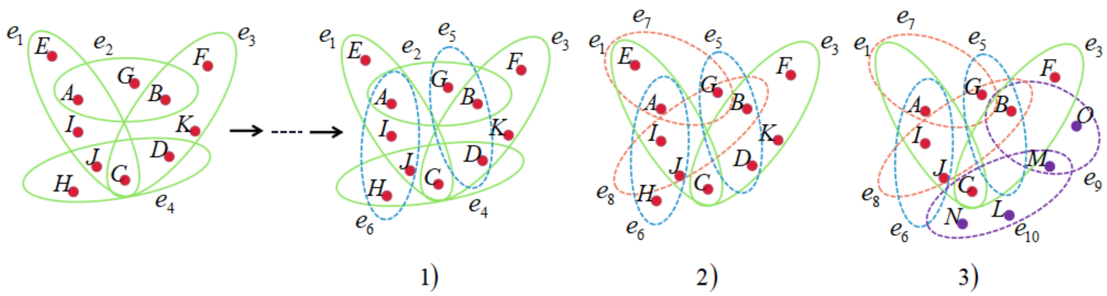



FIGURE 2. Schematic diagram of dynamic network information transmission model

2.2.3. *Model construction.* This paper puts forward the information propagation model under the hypernetwork. According to the dynamic evolution model in Section 2.2.2, we can obtain the following dynamic equation.

1) Add $m$ hyperedges with probability $p$

$$\frac{\partial h_j(t, t_i)}{\partial t} = p(\lambda_1 - \lambda_2)m \left[\frac{1}{N(t)} + u\frac{h_j(t, t_i) + \xi_i}{\sum_{i,j=1} (h_j(t, t_i) + \xi_i)} \cdot Y_i\right] \tag{4}$$

where the first term on the right side of the equation represents the random selection of the existing nodes to join the new hyperedge, and the second term represents the selection of the remaining $u$ old nodes to join the new hyperedge according to the node priority connection mechanism. The arrival rate and exit rate of new nodes follow Poisson distribution, whose parameters are $\lambda_1$ and $\lambda_2$, respectively.

2) Recombine $m$ hyperedges with probability $q$

$$\frac{\partial h_j(t, t_i)}{\partial t} = q(\lambda_1 - \lambda_2)m \left[-\frac{1}{N(t)} + u\frac{h_j(t, t_i) + \xi_i}{\sum_{i,j=1} (h_j(t, t_i) + \xi_i)} \cdot Y_i\right] \tag{5}$$

where the first term on the right side of the equation represents the random selection of the existing nodes to delete the hyperedge, and the second term represents the nodes to be added to the reconstituted hyperedge according to the preferential connection mechanism when the hyperedge is reconnected.

3) Add $m_1$ new nodes with probability $1-p-q$, and form new hyperedges with $m_2$ original nodes

$$\frac{\partial h_j(t,t_i)}{\partial t} = (1-p-q)(\lambda_1-\lambda_2)mm_2\frac{h_j(t,t_1)+\xi_i}{\sum_{i,j=1}(h_j(t,t_1)+\xi_i)}\cdot Y_i \tag{6}$$

where the right side of the equation indicates that the original node that combines with the newly added node to form the new hyperedge is selected with a certain probability.

When (4)-(6) are connected, $h_j(t,t_i)$ can be obtained as follows:

$$\begin{aligned}\frac{\partial h_j(t,t_i)}{\partial t} &= (\lambda_1-\lambda_2)m(p-q)\frac{1}{N(t)} \\ &\quad + (\lambda_1-\lambda_2)m\left[(p+q)u+(1-p-q)m_2\right]\frac{h_j(t,t_i)+\xi_i}{\sum_{i,j=1}(h_j(t,t_i)+\xi_i)}\cdot Y_i \end{aligned}\tag{7}$$

Moreover, we are assuming that $N(t)\approx(\lambda_1-\lambda_2)t$, $A=\lim_{t\to\infty}\frac{1}{(\lambda_1-\lambda_2)t}\sum_{i,j=1}(h_j(t,t_i)$ $+\,\xi_i)$. Let $B=\frac{A}{m}$, and Equation (7) can be simplified as

$$\frac{\partial h_j(t,t_i)}{\partial t} = (C+Dh_j(t,t_i)+D\xi_i)\cdot\frac{1}{t} \tag{8}$$

where $C=m(p-q)$, $D=\frac{(p+q)u+(1-p-q)m_2}{B}\cdot Y_i$.

For Equation (8), integrating both sides at the same time, and letting $E=h_j(t_i,t_i)=m(1-p-q)$, it can be obtained

$$h_j(t,t_i)=\left(\frac{C}{D}+\xi_i+E\right)\left(\frac{t}{t_i}\right)^D-\frac{C}{D}-\xi_i.$$

## 3. **Numerical Simulation.**

In order to verify the feasibility of the proposed dynamic model, this paper uses MATLAB to conduct numerical simulation of the model, studies the rationality of the dynamic PNSEIR model compared with the static PNSEIR model, and discusses the influence parameters of the parameters in the hypernetwork structure and the parameters of the propagation rules related to external information interference on the propagation scale.

### 3.1. **Network construction.**

In this paper, the scale-free hypernetwork is selected for numerical simulation. The initial settings of relevant parameters [14,17] of specific network are shown in Table 1.

In addition, the arrival rate and exit rate of nodes are set to follow Poisson distribution $\lambda_1\sim P(5)$ and $\lambda_2\sim P(10)$, respectively, and the influence of nodes and the attention of

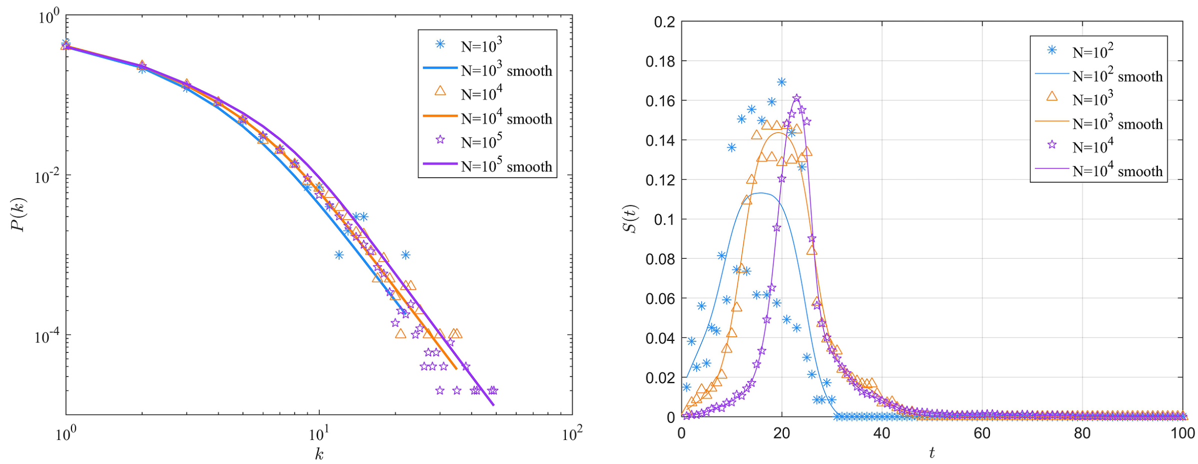
Table 1. Network parameters for initial settings

| Network parameters | Parametrization | Value |
|---|---|---|
| Total number of nodes in the network | $N$ | 10,000 |
| Number of nodes per hyperedge | $u$ | 10 |
| The probability of adding a hyperedge | $p$ | 0.1 |
| The probability of recombining hyperedges | $q$ | 0.05 |
| The probability of an exposed infecting an ignorant | $p_1$ | 0.5 |
| The probability of a spreader infecting an ignorant | $p_2$ | 0.6 |
| The probability of a spreader infecting an exposed | $\alpha$ | 0.2 |
| The probability of a removal affects a spreader | $\beta$ | 0.3 |
| Information inflow rate | $r$ | 0.2 |
| Share influence on social platforms | $\omega$ | 0.6 |

nodes themselves are set to follow normal distribution $Y \sim N(1,1)$ and $\xi \sim N(10,10)$, respectively.

## 3.2. Parameters in the hypernetwork structure.

3.2.1. *Total number of network nodes $N$.* In social networks, the spread of information is affected by the number of users on the platform. In order to analyze the influence of the total number of network nodes on information transmission, we select the total number of network nodes of $N = 10^3$, $N = 10^4$, $N = 10^5$, and obtain the simulation results of the total number of nodes in hypernetwork and information transmission as shown in Figure 3. As can be seen from Figure 3(a), when the node degree $k$ reaches a certain value, the distribution of degree increases with the increase of $N$, which indicates that the number of users associated with each user on the platform is positively correlated with the total number of operating users on the platform. Meanwhile, it can be seen from Figure 3(b) that the proportion of information disseminators in the network increases with the increase of the total number of network nodes. In general, the total number of network nodes is positively correlated with the number of disseminators.




(a) (b)

FIGURE 3. Influence of the total number of network nodes on hypernetwork and information dissemination

3.2.2. *Number of old nodes $u$ that generate new hyperedges on the network.* The hypernetwork changes $u$ to be 5, 10 and 15, respectively, and the influence of the number of old nodes generating new hyperedges on the hypernetwork and information dissemination is shown in Figure 4. It can be seen from Figure 4(a) that when the node degree $k$ is fixed, the image as a whole moves upward with the increase of $u$, that is, the node has a greater chance to be selected in the hyperedge. In the real social network, each person will gain more social connections with the increase of potential social opportunities. At the same time, it can be seen from Figure 4(b) that when the number of old nodes generating hyperedges increases, the speed of information transmission in the network will be accelerated, and the proportion of the corresponding disseminators will also increase. In other words, $u$ means potential social opportunities, which will promote the establishment of social relations and thus accelerate the dissemination of information. Therefore, the strong social chain formed by good social communication will make more people receive the correct information, so as to control the spread of malicious information effectively.

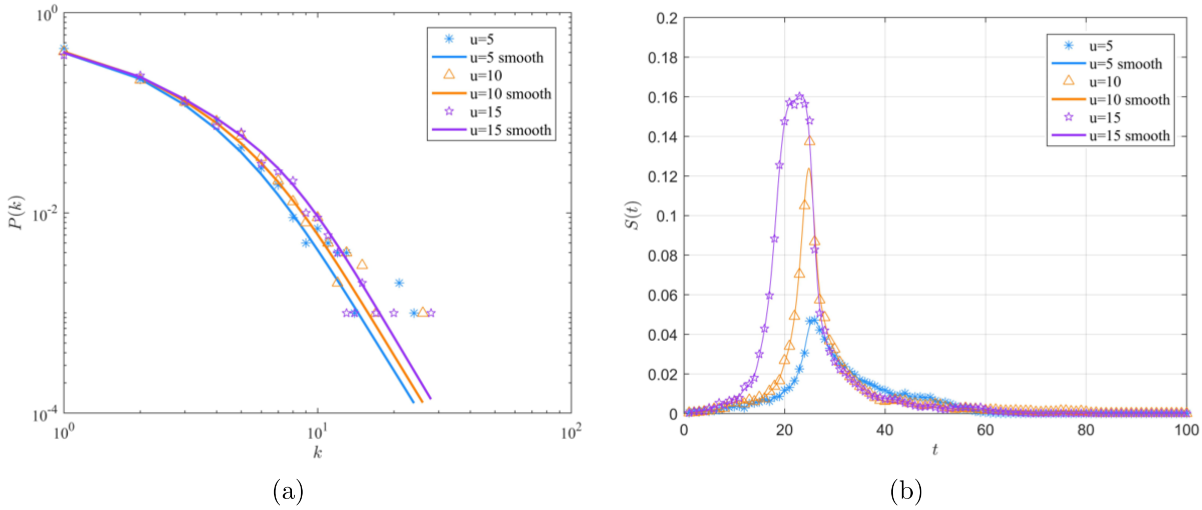



FIGURE 4. The influence of the number of old nodes generating new hyperedges on the hypernetwork and information dissemination

### 3.3. **External information interferes with the parameters of relevant communication rules.**

3.3.1. *Information inflow rate $r$.* According to Equation (1), the information inflow rate $r$ is positively correlated with the external information interference function $f_i$, that is, the greater the information inflow rate, the greater the effect of external interference. To further explore the influence of information inflow rate on information dissemination, $r$ is respectively selected as 0.2, 0.4 and 0.6 in the experiment, and the comparison results are shown in Figure 5. As can be seen from Figure 5, with the increase of the inflow rate of external information, the speed of information transmission is accelerated, and the proportion of communicators in the network also increases. It shows that when the information inflow rate is high, the spread of false information can be controlled quickly to a great extent if people with great influence can timely convey the correct direction and make the correct information spread widely.

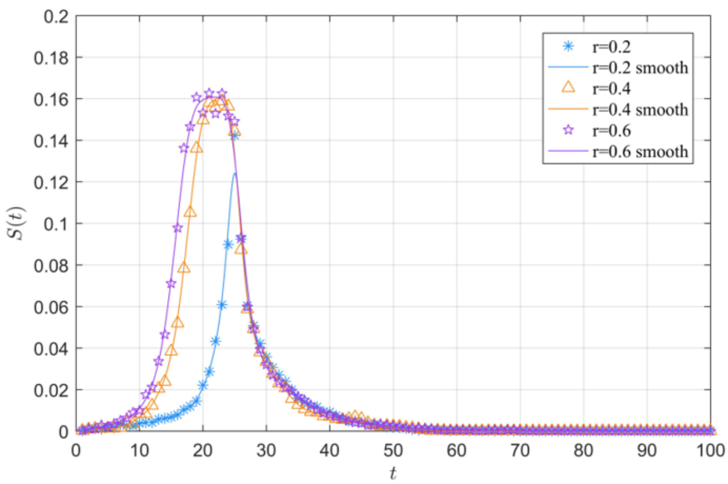



FIGURE 5. Influence of information inflow rate

3.3.2. *Information transmission rate $p_2$.* Information transmission rate refers to the average probability that a piece of information is published or forwarded by users (exposers or spreaders) on social platforms. Obviously, the higher the rate of information transmission, the wider the range of information transmission. In order to further verify the effectiveness of information transmission rate on information transmission, the experimental values of $p_2$ are respectively 0.2, 0.4 and 0.6, and the comparison results are shown in Figure 6. As can be seen from Figure 6, with the increasing of information transmission rate, the more information disseminators, the longer and wider the information transmission time.

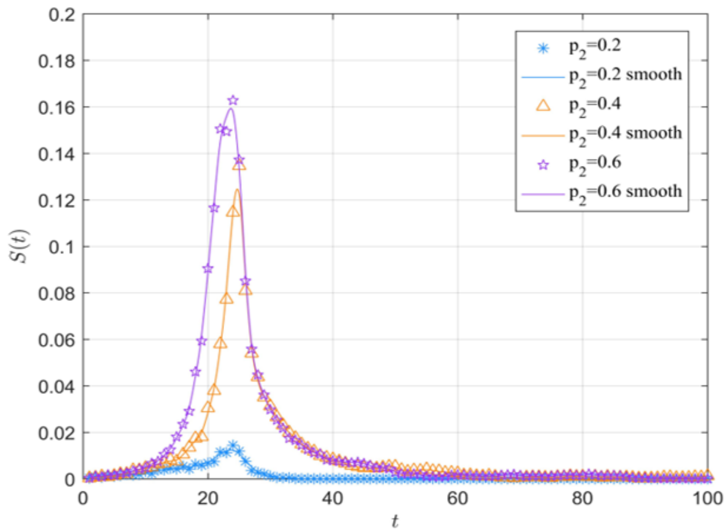



FIGURE 6. Influence of information transmission rate

3.4. **Comparison of PNSEIR model in complex network and hypernetwork.** The PNSEIR model constructed in this paper is compared in complex network environment and hypernetwork environment (static and dynamic). The initial parameters are shown in Table 1. Through repeated experiments, the comparison results are shown in Figure 7. It shows the proportion of $I$, $E$, $S$, $R$ in PNSEIR over time in static and dynamic environments.

It can be seen from Figure 7(a), $I$ decrease rapidly with the increase of time before $t = 25$, and the number of points reaches the lowest proportion of 25% at $t = 25$ and remains stable. At the same time, in the dynamic PNSEIR model, the number of $I$ that have never received original information in the first half of information transmission is higher than that in the static environment. This is because, under the hypernetwork environment, the probability of receiving information is more flexible, which makes the original information after experiencing the external information interference lose the ambiguity quickly, so as to lose the transmission power. As a result, some of the original information has disappeared into the social network before it has been received by the unsuspecting. At the same time, as the proportion of the ignorant increases, the number of the ignorant turning into the exposed is smaller in the dynamic network than in the complex network environment with fixed transmission probability, as shown in Figure 7(b). In the static environment, $E$ reach the maximum value of 23% at around $t = 25$, while in the dynamic environment, it reaches the maximum value of 19% at around $t = 22$, and keeps constant after $t = 25$.

However, the infection rate varies from person to person in the super network. For individuals with strong social skills, as long as they want to spread, they can spread to more people in a shorter time even if they accept it later. This is also the reason for

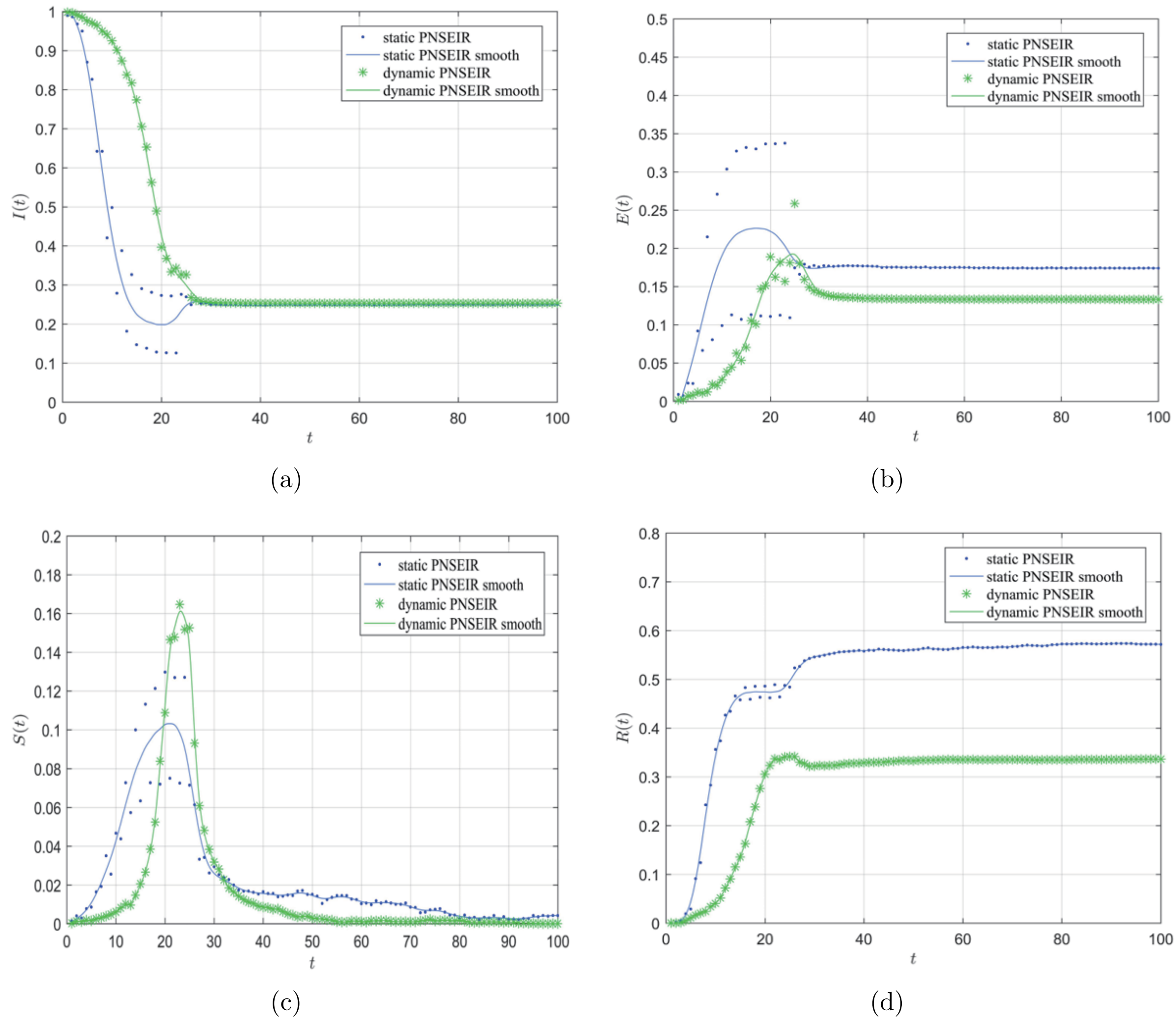



FIGURE 7. Comparison of PNSEIR model in complex network and hypernetwork

the higher proportion of spreaders in the super network in Figure 7(c), although the transmission duration is shorter. It can be seen that under the hypernetwork, $S$ reach the highest value of 17% at $t = 25$, while under the complex network, it reaches the highest value of about 10% at $t = 22$.

Figure 7(d) shows that $R$ increase rapidly with time before $t = 25$, and tend to be stable at $t = 30$. That is to say, it shows that the node removal rate is very high under the interference of external information. This is because, for the spreaders, when the original information is clearer, their motivation to spread it will be greatly reduced, and then they will become removers. Moreover, the number of $R$ in the dynamic network accounts for 33%, which is much less than the highest proportion of 57% in the static network. That is because, due to the efficiency of the network, some information disappears when new users enter the network, leaving them as ignorants rather than removers in the dynamic network environment. Or the personal influence of the communicators is strong, and they maintain the original state without being interfered by other information, which makes the proportion of removed nodes lower than that in static networks.

4. **Conclusion.** According to the PNSEIR model, the propagation of information in social networks is not only affected by the network topology, but also influenced by the interference of external information related to the original information and the dynamic

evolution of network structure. In this model, the users in the network are the nodes of the hypernetwork, and the relationships between users are the edges of the hypernetwork. For information transmission, it is defined as the transmission and forwarding of information between nodes. As the external factor to describe the interference of the original information transmission, the external information interference function was introduced to obtain the response mechanics equation. Meanwhile, combined with hypergraph theory, the network structure of the model is kept dynamically evolving, and the combination of the two ensures that the model can reflect the information transmission of the social network more truly.

Future research directions include the following. 1) Although this paper considers the influence of positive and negative information interference on information dissemination, information spreading is also impacted by many other factors, such as the timeliness of information and relevant policies of network platforms. Therefore, other factors affecting information dissemination can be further studied. 2) Comparison with actual network data will make the model more persuasive, so it is necessary to further validate the rationality and accuracy of the model with real data.

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