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Evolution of node impact based on secondary propagation

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In real life, the propagation ability of the information disseminator is one of the important factors which is determined to propagate information. The influence of the node, which is altered with time, is proposed to reflect the propagation ability of the information disseminator for the significance of the information propagation in the actual situation in this paper. Therefore, the influence of the node is divided into the high-impact node and the low-impact node. Furthermore, the SSIR information propagation model is proposed and the dynamic BA scale-free network is constructed to carry out evolution of node impact based on secondary propagation experiments. The experiment results indicate three stages, including the initial stage, the rapidly rising stage and the stable stage. The propagation details of the different messages are distinct. However, the trend of propagation is similar.

Keywords: Information dissemination; influence; spread; SSIR; networks.

1. Introduction

In the dynamics of information transmission, the mainstream theories mostly adopt the epidemic model and its variants, which are proposed by Kermack and McKendrick.[1] Different theoretical methods are proposed for various transmission processes, such as Average field method,[2] Point-to-point Approximation method[3] and Generation Function Method based on Edge Percolation theory.[4] In addition, there are two kinds of message dissemination models proposed by researchers. First, the threshold model,[5,6] which is applied to solve the global cascade trigger time problem,[7] the propagation threshold problem of various complex networks,[8] certain special problems of multiplexity networks[9] and random multiplex networks,[10] plays an important role in the dissemination process. Second, the cascade model is constructed based on the interacting particle systems,[11] which include independent cascade model,[12] continuous independent cascade model[13] and T-BASIC model.[14]

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When simulating information dissemination in BA scale-free network,[15] the process of information dissemination[16–19] is studied without considering whether the nodes in the network are changed because of information dissemination. The influence of network structure on information dissemination is important owing to the complexity of information dissemination mechanism while the influence of community structure has been researched[20–24] in the network structure. It is not difficult to understand that the dissemination of information[25–27] is affected by the change of nodes in the network. We should also consider some pdes and exact solutions.[28–34] Thus, a dynamic BA scale-free network is designed to apply in the network. In dynamic BA scale-free network, the large degree node returns a parameter to the small degree node during the information propagation from a small degree node to a large degree node and the edge connected with the small degree node is increased by the parameter, namely, the degree of the small degree node is improved. The degree of nodes in the entire network are in a state of constant change until the end of information dissemination by analogy.

In real life, there are various situations that conform to dynamic BA scale-free network, such as social software Sina Weibo. In Sina Weibo, people publish and forward messages, which is a social reinforcement phenomenon. Namely, when an individual node receives information, if it is strongly recommended by its neighbor numerous times, the willingness of the individual node to receive will be strengthened.[35,36] The users of Sina Weibo are divided into ordinary users and authenticated users. The ordinary users have fewer fans and less influence. The authenticated users are recognized by Sina Weibo and have high credibility so that the authenticated users have numerous fans and great influence. Now, supposing that an ordinary user posts a microblog. In most instances, publishing an ordinary microblog is soon forgotten by the public. However, if the ordinary microblog is forwarded by authenticated users, the situation is different. First, the microblog which is forwarded by the authenticated user will accelerate the dissemination of information and expand the scope of information dissemination. Second, the fans and influence of the ordinary users are increased and further accelerate the dissemination of information. This process is named secondary propagation. The reason the secondary propagation differes from the traditional information transmission is that the status of nodes and the interaction of nodes are considered in the secondary propagation. The speed and range of information transmission are affected by the size of node influence and the influence of the high-impact node on the low-impact node.

In summary, a simple dynamic BA scale-free network evolution process, which is shown in Fig. 1, is established. In this network, there are two nodes, A and B. The influence of node A is 3 and the influence of node B is 8. When node A successfully propagates the information to node B, node B will propagate the information second. As the influence of node B is bigger than the influence of node A, the transmission ability of B is stronger than A. The information of node B is received by numerous nodes. If other nodes are interested in the information of node B, the

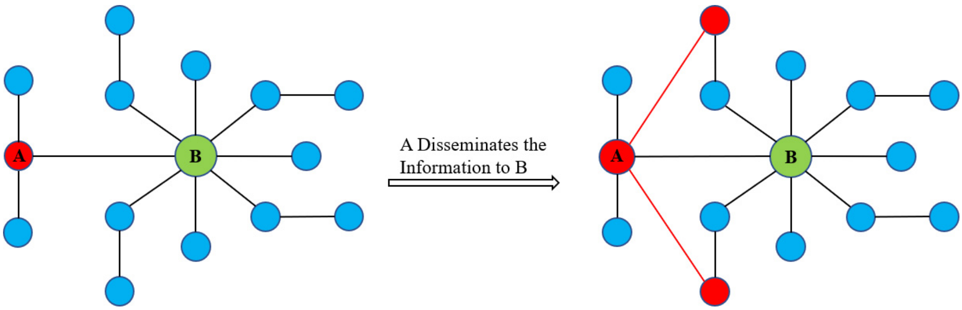


Fig. 1. (Color online) The evolution of a simple dynamic BA scale-free network.

nodes are directly connected with node A, which will increase the influence of a node B and node A, and accelerate the dissemination of information. In Fig. 1, the influence of node A is 5 in the end. This is the evolution of information secondary propagation of node A affected by node B.

2. SSIR Information Dissemination Model

There are three states in the susceptible-infected-removal (SIR) virus infection model. S is the susceptible, which indicates a healthy node with a certain possibility of being infected. I is the infected, which means an infected node and other healthy nodes are infected by the infected node. R is the removal, which illustrates an infected node has been vaccinated and cured. The state transfer graph of SIR is shown in Fig. 2.

$$\boxed{S} \xrightarrow{\varepsilon} \boxed{I} \xrightarrow{\eta} \boxed{R}$$

Fig. 2. The state transfer graph of SIR.

In Fig. 2, S is converted to I with a certain infection probability ε and I is converted to R with a certain recovery probability η. The dynamic equation of SIR model is obtained as follows:

$$\begin{cases} \dfrac{dS(t)}{dt} = -\varepsilon * S(t) * I(t)\,, \\[2ex] \dfrac{dI(t)}{dt} = \varepsilon * S(t) * I(t) - \eta * I(t)\,, \\[2ex] \dfrac{dR(t)}{dt} = \eta * I(t)\,. \end{cases} \tag{1}$$

Based on the SIR virus infection model, let the S be directly transformed into R with a certain probability and a virus infection model, named SIR_{S-R}, is formed. The state transfer graph of SIR_{S-R} is shown in Fig. 3.

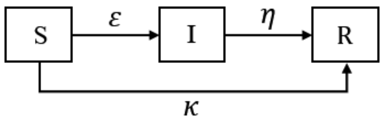


Fig. 3. The state transfer graph of SIR_{S-R}.

In Fig. 3, S is converted to I with a certain infection probability ε. Meanwhile, S is also converted to R with a certain direct immune probability κ. I is converted to R with a certain recovery probability η. Therefore, the dynamic equation of SIR_{S-R} model is obtained as follows:

$$\begin{cases} \dfrac{dS(t)}{dt} = -\varepsilon * S(t) * I(t) - \kappa * S(t) * R(t)\,, \\ \dfrac{dI(t)}{dt} = \varepsilon * S(t) * I(t) - \eta * I(t)\,, \\ \dfrac{dR(t)}{dt} = \eta * I(t) + \kappa * S(t) * R(t)\,. \end{cases} \tag{2}$$

Equation (2) is different from Eq. (1). In the first formula and third formula of Eq. (2), the transition variable $\kappa * S(t) * R(t)$ of S and R is added. Similarly, based on Eq. (2), S is divided into two parts to construct a new messages dissemination model. There are four states of the network nodes in the new model. S_L means the information to be received and the ability to transmit information is weak. The nodes in S_L are named low-impact nodes. S_H means the information to be received and the ability to transmit information is relatively strong. The nodes in S_H are called high-impact nodes. I means the information has been received and disseminated. The nodes in I are called information dissemination nodes. R means the information has been received and not transmitted. The nodes in R are called information immune nodes. An information dissemination model, named "SSIR", is constructed. When information is transmitted in the network, the node state is switched between the four states. The detailed description is shown in Fig. 4. In the process of information dissemination, the states of nodes are changed with a certain probability. α denotes the probability of high transmission, namely, the probability of receiving and transmitting information by nodes with strong ability to transmit

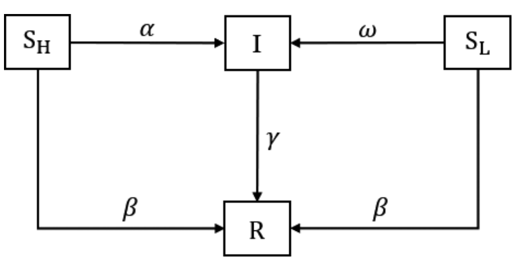


Fig. 4. The state transfer graph of SSIR.

information. ω denotes the probability of low transmission, namely, the probability of receiving and transmitting information by nodes with weak ability to transmit information. β denotes the probability of propagation lost, namely, the probability is that a node has received information and does not propagate. γ denotes the probability of recovery, namely, the probability is that a node is not propagated after transmitting information for a period of time.

A complete process of information dissemination is simulated according to Fig. 4 in real life. First, when a node in the network is in S (whether S_H or S_L), the node receives information with a certain probability and propagates the information. Meanwhile, the node state of the node is changed from S to I. However, the node in S may receive the information and not choose to spread the information. The node state of the node is changed from S to R. The last case is that the node in S refuses to receive information and its node state is not changed. The node state is still in S. Second, when a node in the network is in I, it may stop propagating after transmitting information for a period of time and the node is recovered from I to R.

Based on Eqs. (1) and (2), the information dissemination model in dynamic BA scale-free network is constructed as follows:

$$\begin{cases} \dfrac{dS_H(t)}{dt} = -\alpha * |k| * S_H(t) * I(t) - \beta * |k| * S_H(t) * R(t)\,, \\[2ex] \dfrac{dS_L(t)}{dt} = -\omega * |k| * S_L(t) * I(t) - \beta * |k| * S_L(t) * R(t)\,, \\[2ex] \dfrac{dI(t)}{dt} = \alpha * |k| * S_H(t) * I(t) + \omega * |k| * S_L(t) * I(t) - \gamma * I(t)\,, \\[2ex] \dfrac{dR(t)}{dt} = \beta * |k| * S_H(t) * R(t) + \beta * |k| * S_L(t) * R(t) + \gamma * I(t)\,. \end{cases} \tag{3}$$

In Eq. (3), $S_H(t)$ represents a high-impact group. $S_L(t)$ represents a low-impact group. $I(t)$ represents an information dissemination group. $R(t)$ represents an information immunization group. The four are altered with the information dissemination. $\alpha * |k| * S_H(t) * I(t)$ and $\omega * |k| * S_L(t) * I(t)$ denote the number of groups that have not received information and become information dissemination groups. The difference between $\alpha * |k| * S_H(t) * I(t)$ and $\omega * |k| * S_L(t) * I(t)$ is that the initial state of nodes is different and the probability of state transition is different. The values of $\alpha * |k| * S_H(t) * I(t)$ and $\omega * |k| * S_L(t) * I(t)$ are increased and then decreased as the information is disseminated, and eventually stabilized. $\beta * |k| * S_H(t) * R(t)$ and $\beta * |k| * S_L(t) * R(t)$ denote the number of groups that do not receive information and become information-immune groups. The difference between $\beta * |k| * S_H(t) * R(t)$ and $\beta * |k| * S_L(t) * R(t)$ is that the initial state of nodes is different. The values of $\beta * |k| * S_H(t) * R(t)$ and $\beta * |k| * S_L(t) * R(t)$ are increased as the information is disseminated, and eventually stabilized. $\gamma * I(t)$ denotes the number of information-disseminating groups transformed into information-immune groups. The value of $\gamma * I(t)$ is increased as the information is disseminated, and eventually stabilized.

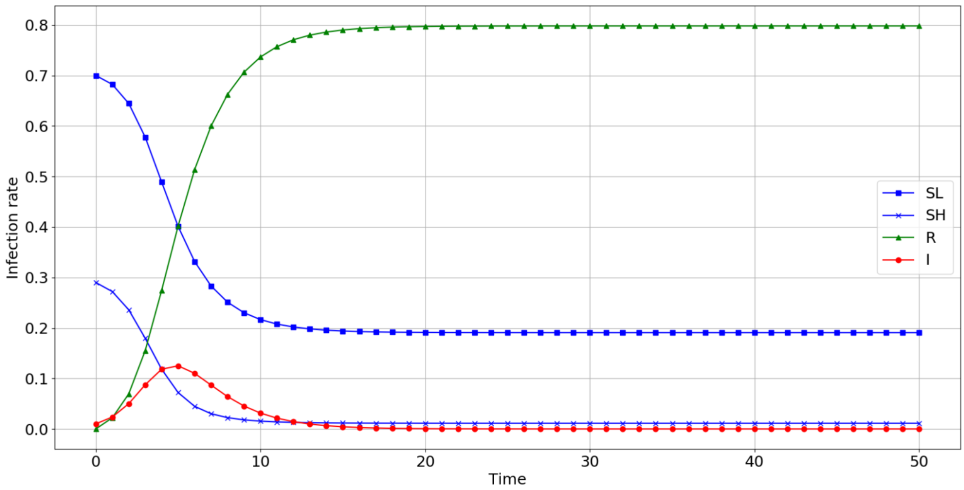
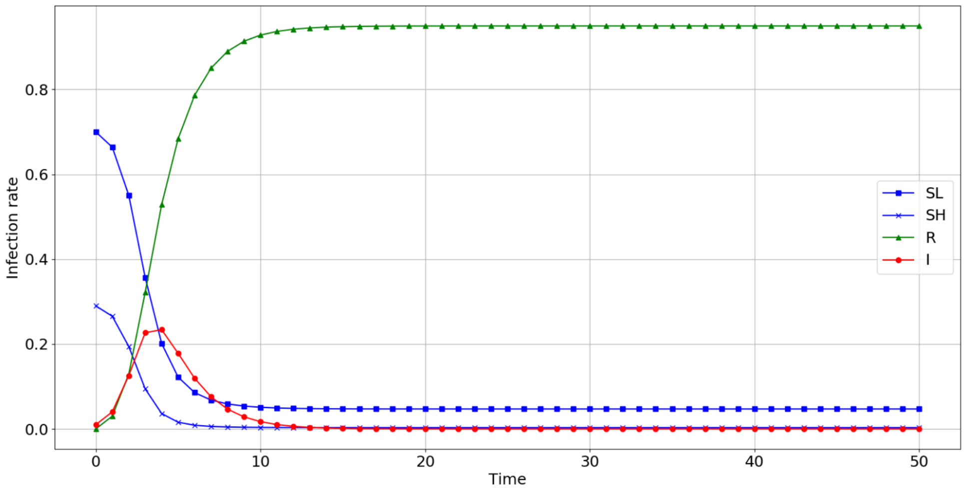


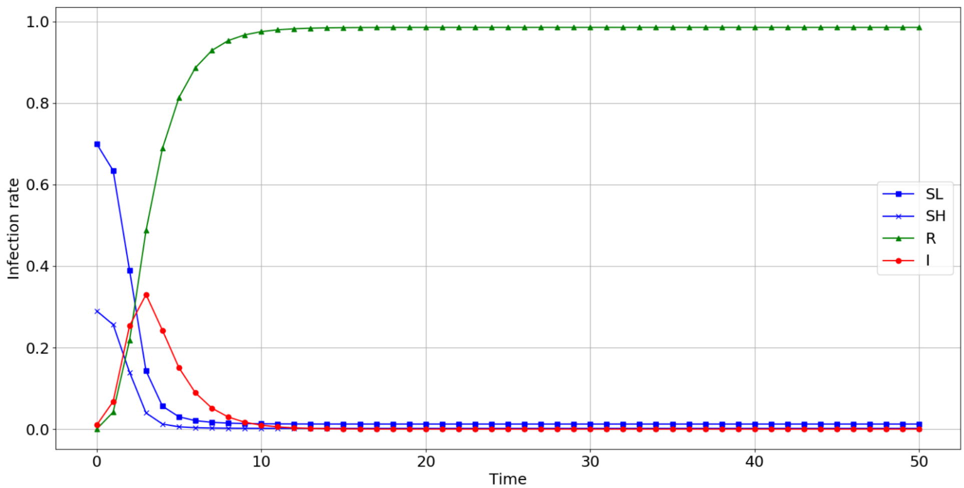
Fig. 5. (Color online) The proportion of the population change in $S_H(t)$, $S_L(t)$, $I(t)$ and $R(t)$ ($\omega = 0.2$).

Therefore, the number of high-impact receiving information nodes in the network is set to S_{H_0} before the beginning of information dissemination. The number of low-impact receiving information nodes is set to S_{L_0}. The number of information dissemination nodes is set to I_0 and the number of information immune nodes is set to R_0. The initial values are shown as follows. $S_{H_0} = S_H(0)$, $S_{L_0} = S_L(0)$, $I_0 = I(0)$, $R_0 = R(0)$. Let $S_H(0) = 0.29$, $S_L(0) = 0.7$, $I(0) = 0.01$, $R(0) = 0$, $\alpha = 0.8$, $\omega = 0.2$, $\beta = 0.2$, $\gamma = 0.6$, $|k| = 4$. The population change scale of $S_H(t)$, $S_L(t)$, $I(t)$, $R(t)$ are shown in Fig. 5. Figure 5 shows that when information begins to spread in the network, the proportion of two groups of information to be received are decreased while the proportion of information dissemination group and information immunity group are increased. After a certain time of dissemination, the proportion of information dissemination group reaches maximum. The information is stopped from being disseminated. Furthermore, the proportion of information dissemination groups is gradually declined to zero. Meanwhile, the proportion of information immunization group has a stable tendency and reach maximum. The proportion of the group of information to be receive has a stable tendency and stopped decreasing. The reason is that a part of the two groups did not receive information and did not disseminate information. The primary state is maintained as steady.

Based on the above description, suppose that ω is increased by the spread of information. ω is increased from 0.2 to 0.4 and from 0.4 to 0.6, respectively. The change ratio map of the group quality of $S_H(t)$, $S_L(t)$, $I(t)$ and $R(t)$ is shown in Fig. 6. The entire trend of the number of the four groups has not changed from Fig. 6. However, the maximum proportion of information dissemination groups is increased with the increase of ω. Namely, the number of information dissemination



(a) $\omega = 0.4$



(b) $\omega = 0.6$

Fig. 6. (Color online) The proportion of the population change in $S_H(t)$, $S_L(t)$, $I(t)$ and $R(t)$

groups is increased naturally with the increase of low probability of transmission. Afterwards, the minimum proportion of low-impact groups to receive information is decreased with the increase of low transmission probability. Finally, the maximum proportion of information immune groups is increased due to the increase of low transmission probability.

To date, the information dissemination model used in this experiment has been constructed different from the traditional SIR model, as S is divided into S_H and S_L in SSIR model. The purpose of SSIR model is to simulate the propagation process of information in dynamic BA scale-free network reasonably.

3. Information Dissemination Experiment

In this section, SSIR information propagation model is applied to dynamic BA scale-free network. First, a dynamic BA scale-free network, which is composed of 20,000 nodes and average degree of 4 nodes, is constructed. Each node in the network is randomly assigned a degree. The largest degree of node M is found before simulating information propagation and M is set to ϑ in the network. Here, suppose that the degree of nodes except M in the network is set to ξ and $\Theta = \xi/\vartheta$. When $\Theta > 0.6$, the node is identified as a high-impact node and $\Theta < 0.6$, the node is identified as a low-impact node.

Simulating the information dissemination is begun after the nodes are divided into high-impact nodes and low-impact nodes. A low-impact information dissemination node 1 and a high-impact node 2 are randomly selected from all nodes. Node 1 propagates information to node 2 with a certain probability of dissemination. Node 2 successfully receives information while continuing to disseminate information, which undoubtedly accelerates the dissemination of information. The other nodes directly connected to node 2 except node 1 are represented as a node set $\Lambda = \{3, 4, \ldots, 500\}$, most nodes in Λ will receive this information. The most nodes are represented as a set $\Lambda' = \{3, 4, \ldots, 400\}$. At this time, some nodes in Λ' will be directly connected with node 1 with a certain probability to increase the influence of node 1 and accelerate the spread of information. Information dissemination of the entire network is to repeat the above process until the end of dissemination.

Furthermore, the experiment is executed according to the above information dissemination rules. In this paper, the information spread is defined ρ, namely, $\rho = N_I/N$, where N denotes the total number of network nodes and N_I denotes the number of information dissemination nodes. ρ is used to measure the degree of information dissemination. In the initial state, 10 high-impact nodes and 10 low-impact nodes in the network are randomly assigned to I state and initial information spread is set to 0.001, high propagation probability $\alpha = 0.8$, low propagation probability $\omega = 0.2$, propagation loss probability $\beta = 0.2$, recovery probability $\gamma = 0.6$. The information transmission is run 120 rounds. The result is shown in Fig. 7.

As is shown in Fig. 7, information propagates slowly in the initial phase (0–4 rounds) in the dynamic BA scale-free network. A wide variety of high-impact and low-impact information dissemination nodes, which account for 0.1–1% of the total nodes, are immensely small in the initial stage so that the information dissemination is relatively low. Afterwards, the information dissemination is in a fast-rising phase (5–50 rounds), which is mainly attributed to the rapid increase of low-impact nodes. In this stage, the number of high-impact nodes and the number of high-impact information dissemination nodes are basically stable, while the rapid increase of low-impact nodes gives information a desirable opportunity to disseminate and makes the information spread grow rapidly. Ultimately, the information spread is basically stable in the stable stage of information dissemination (51–120 rounds). Certain information dissemination nodes, high-impact nodes and low-impact nodes have lost

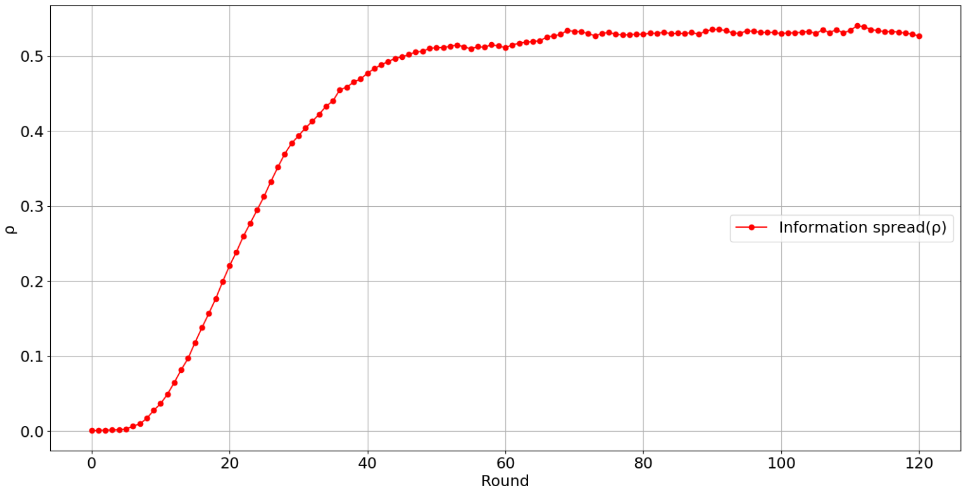


Fig. 7. (Color online) The information spread in the dynamic BA scale-free network.

all interest in dissemination to become information immune nodes and the number of four types of nodes has reached a balance. In real life, the dissemination of information at the beginning has received little attention and the scope of dissemination is small. As more and more people get to know the information, including a wide variety of highly acclaimed people, there is an acceleration of the dissemination of information. After the dissemination of information to a certain extent, people gradually lose interest in the information and stop disseminating. The description is the same as the above simulation process.

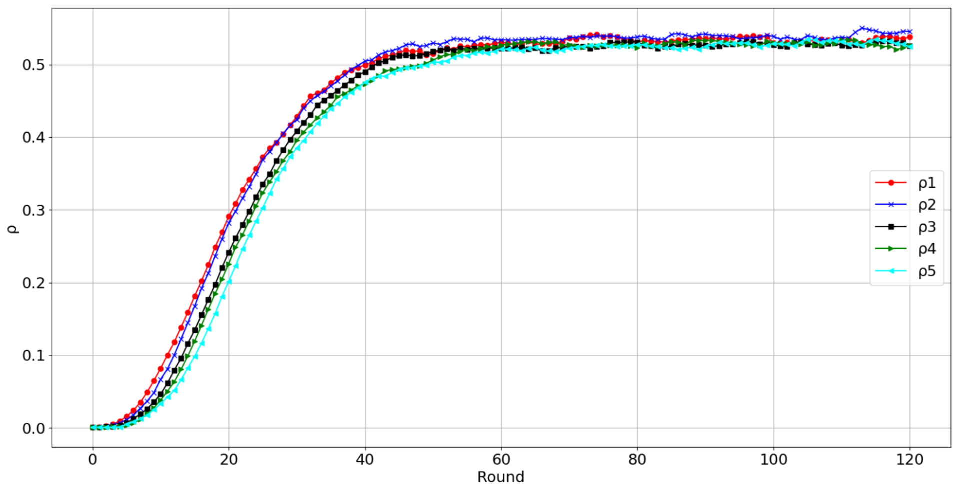


Fig. 8. (Color online) The information spread of five different messages in the dynamic BA scale-free network.

Table 1. The information spread amount of five different messages in round N.

Round \ Message	Message_1	Message_2	Message_3	Message_4	Message_5
0	0.001	0.001	0.001	0.001	0.001
4	0.013	0.008	0.013	0.008	0.016
20	0.289	0.296	0.293	0.275	0.305
50	0.516	0.518	0.528	0.523	0.515
80	0.530	0.542	0.541	0.538	0.539
120	0.534	0.542	0.536	0.546	0.536

When five different message dissemination experiments are executed in dynamic BA scale-free network, will the information spread amount ρ be different? First, five messages are set as follows, Message_1, Message_2, Message_3, Message_4 and Message_5. The information spread of the five messages are ρ_1, ρ_2, ρ_3, ρ_4 and ρ_5, respectively. And then, the five messages are simulated in the dynamic BA scale-free network. The results are shown in Fig. 8.

It is seen that although the five different messages are transmitted in the network, the trend of information spread is immensely similar, which illustrates the universality of the experiment. Different messages have unique information dissemination processes and it is proving that SSIR information dissemination model applied in the dynamic BA scale-free network is practical. The value of information spread of five different messages are given in Table 1 during the N-rounds, which clearly shows the above.

4. Conclusion

Compared with SIR epidemic model, S is divided into S_H and S_l by SSIR information dissemination model. A realistic situation is that the node to receive information may not choose to disseminate information after receiving information and the node is directly transformed into information immune nodes. Compared with BA scale-free network, the nodes in dynamic BA scale-free network are divided into high-impact nodes and low-impact nodes according to certain rules. The nodes influence each other and the influence plays an important role in the process of information dissemination. In real life, the identity of the disseminator of information also has a great impact on the dissemination of information.

In this paper, SSIR information dissemination model is applied to dynamic BA scale-free network. First, by simulating the dissemination of an information in the network, it is found that the three stages of the dissemination process are highly consistent with the information dissemination in real life. Second, five different messages are simulated to disseminate in the network. Although the dissemination process of their information is different, the dissemination trend is identical. All phenomena show that the simulation information dissemination in the dynamic BA scale-free network is close to the reality.

Acknowledgments

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