Network Opinion Evolution Model Incorporating the Influence of Media Heterogeneity

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ABSTRACT Opinion dynamics is the basic research content of social network research. Traditional opinion dynamics models focus on the heterogeneity of regular users, but ignore the heterogeneity of media users in social networks. Compared to regular users, media users have the characteristics of releasing more information and having greater influence, and their opinions are not easily affected by regular users. Aiming at the characteristics of information transmission with the participation of media users, we propose an opinion dynamics model to reproduce a realistic process of opinion interaction between regular users and media users and between regular users, respectively. The time variable is also incorporated into the probability of opinion adoption to make sure the opinion interaction model has timeliness. The simulation experiments on models of four typical complex network structures have shown that the characteristic of large average path length in a regular network will lead to the media opinion spreading slowly with a small scope, and a low individual opinion interaction frequency. On the other hand, the characteristics of strong heterogeneity and many center users in a scale-free network lead to media opinion spreading fast with a big scope. Moreover, the opinion adoption probability has a great influence on the average opinion value of the final state in four networks, while the bounded trust threshold has a great influence on opinion evolution in regular networks and scale-free networks. Furthermore, the media location selection approach based on the node betweenness results in opinion influence transmission with high speed and large range compared with the approaches based on node degree and clustering coefficient.

INDEX TERMS Opinion dynamics, media heterogeneity, information evolution.

I. INTRODUCTION There are two types of users on the web: regular users and media users. Media users [1] include: traditional news media (CCTV, some sports media, etc) in microblog networks, public accounts (news accounts, sports accounts, food accounts, etc) in the WeChat network, etc. Regular users connect with media users by following and subscribing and so on. For the purpose of news push, advertising marketing or sharing funny stories, the media constantly release news and update their opinions. In this process, communication between regular users and media users continues to increase, and the opinions of regular users are constantly affected. However, unlike in the traditional opinion interaction model, media opinion is not affected by regular users; there is only one-way influence between regular users and media users.

As we discussed before, only regular users are affected by media users. In the process of one-way influence, there are mainly two stages: the information receiving stage and the opinion adopting stage. The information receiving stage is the stage when the media user publishes a new message and regular users have a certain probability of receiving the message. The probability of receiving a message is related to its publish time, its content and the behavioral characteristics of users [2], [3]. The opinion adopting stage refers to the stage when the user receives a new message and adopts the opinion...
of the message, with a certain probability. The adoption probability is related to the reliability of the message, the user’s preferences, and so on [4].

The Receipt-Accept-Sample [5] (RAS) model is used to investigate the change and development of an individual’s opinion when it is affected by external information. When user $i$ receives a new message, the receipt probability $Pr$ can be defined as:

$$Pr(W_i; m, n) = \frac{1}{1 + f + \exp(m + n \times W_i)} \quad (1)$$

where the parameter $W_i$ represents the opinion consciousness of user $i$, and it is related to the behavior or habits of the user. The higher the value of $W_i$, the higher the probability that the user will receive that new message. Parameter $m$ represents the strength of the new message. The higher the value of $m$, the higher the probability that the user will receive that new message. Parameter $f$ refers to the user’s minimum receiving ability, and $n$ is the adjustment coefficient between the viewpoint consciousness and the receiving message. For more details, please see reference [5].

If a user has received a new message according to the mentioned receipt probability $Pr$, then he will decide whether or not to adopt the opinions of the received new message according to adoption probability $Pa$. $Pa$ is defined as:

$$Pa(W_i, L_i; x, y, z) = \frac{1}{1 + \exp(-x - y \times W_i - z \times L_i)} \quad (2)$$

Parameter $L_i$ represents the tendency of user $i$ to adopt the message’s opinion, which is determined by the degree of preference of user $i$ for the message content. Parameter $x$ represents the credibility of the message, parameter $y$ represents the persuasion degree of user consciousness (and the value of $y$ is negative), and parameter $z$ represents the persuasion degree of the adoption tendency of user opinions. By analyzing the formula, we can get the conclusion that the higher the value of $x$ and $z$, the higher the probability that the user will adopt the opinion of the new message.

In conclusion, only when user $i$ receives a new message and adopts its opinion, will the initial opinion of the user change, and the change probability $Pc$ is defined as:

$$Pc = Pr(W_i; m, n)Pa(W_i, L_i; x, y, z)$$
$$= \left(1 - \frac{1}{1 + f + \exp(m + n \times W_i)}\right)$$
$$\times \left(1 + \exp(-x - y \times W_i - z \times L_i)\right) \quad (3)$$

$Pc$ is the result of the combination of acceptance and adoption. $Pc$ is the key index to define whether a user will adopt the opinion (for example, whether a user will repost a new message in her newsfeed).

The RAS model divides the process of updating opinion into two stages, and considers that the change of opinion is a complete process. This setting is very consistent with the interaction process between media users and regular users. Firstly, a regular user will receive the new message posted from media users. Secondly, if the message is useful to the regular user, he will adopt it and change his opinion under the influence of the adopted new message. The RAS model has 8 parameter variables in total, which is convenient to establish a connection with the real situation, but reduces the generality of the model. Therefore, we will modify some parameters in the model according to the interaction characteristics between media users and regular users.

II. MODEL

A. OPINION UPDATE RULES WITH THE PARTICIPATION OF MEDIA USERS

In the process of interaction between media users and regular users, regular users are affected by media users in a one-way direction. According to the mentioned RAS model, let the opinion value of the media be $m$, and the probability $Pr$ of ordinary user $i$ receiving new messages from the media can be defined as:

$$Pr(W_i; m) = \frac{1}{1 + \exp(m + W_i)} \quad (4)$$

where $W_i$ refers to the opinion consciousness of user $i$. Considering the individual differences among regular users, $W_i$ can be determined according to the behavioral habits of different users. In the original equation (1), the parameter $f$ represents the minimum receiving capacity. However, in the particular scenario of interaction between regular users and media users, any user may receive media information. Therefore, the setting of $f$ is unreasonable. We will remove $f$ from the model in this section. The variable $m$ represents the strength of the message in Eq. (1). In the model of this article, $m$ is directly defined as the media opinion value. The physical significances of $m$ in Eq. (1) and $m$ in Eq. (2) are interlinked, and the probability of a user’s information acceptance increases as the $m$ value increases.

When regular users receive new messages from media users, they will compare their own opinions with those opinions in the messages. If the difference between regular opinions and media opinions is small, regular users will be more likely to adopt media opinions. On the contrary, regular users will be less likely to adopt media opinions. In Eq. (2), we define the user $i$‘s tendency to adopt the new message’s opinion as $L_i$:

$$L_i = \frac{1}{1 + |m - X_i|} \quad (5)$$

where $X_i$ is the opinion value of regular user $i$. The difference between media opinion and individual opinion is inversely proportional to the adoption tendency of individual opinion. It is difficult for regular users to judge the credibility of the message. Therefore, in order to make the model more general, the influence of parameter $X$ on the model is considered in this section. Then, the probability of adoption $Pa$ can be rewritten as:

$$Pa(W_i, X_i; y, z) = \frac{1}{1 + \exp(yW_i - \frac{1}{1 + |m - X_i|})} \quad (6)$$
The meaning of the parameters y and z remains the same as Eq. (2).

In social networks, information dissemination has the character of timeliness. As time goes by, the freshness of information decreases, which leads to the attenuation of information transmission efficiency. Therefore, the time attenuation factor is taken into account in this model, and the time variable t will be introduced into computing the adoption probability  

\[ P_a(W_i, X_i; y, z) = \frac{1}{1 + \exp(t + yW_i - \frac{z}{1 + |m - X_i|})} \]  

(7)

Finally, when regular user \( i \) receives messages from media users, and meanwhile adopts the media opinions, the change probability \( P_c \) is

\[ P_c(W_i, X_i; m, y, z) = P_r(W_i; m)P_a(W_i, X_i; y, z) \]

\[ = (1 - \frac{1}{1 + \exp(m + W_i)}) \times \frac{1}{1 + \exp(t + yW_i - \frac{z}{1 + |m - X_i|})} \]  

(8)

To sum up, with the participation of media users, the updating rules of regular users \( i \)’s opinions in the next time point can be computed as:

\[ X_i(t + 1) = X_i(t) + (m - X_i(t)) \times P_c(t) \]

\[ = X_i(t) + (m - X_i(t)) \times (1 - \frac{1}{1 + \exp(m + W_i)}) \times \frac{1}{1 + \exp(t + yW_i - \frac{z}{1 + |m - X_i(t)|})} \]

\[ = X_i(t) + \frac{(m - X_i(t)) \times \exp(m + W_i)}{(1 + \exp(m + W_i)) \times (1 + \exp(t + yW_i - \frac{z}{1 + |m - X_i(t)|}))} \]  

(9)

B. OPINION UPDATE RULES AMONG REGULAR USERS

In recent years, the discrete opinion model has been widely studied and applied due to its simple structure, clear mapping relation and convenience for theoretical analysis. However, the discrete opinion model has limitations. The discrete opinion model has difficulty dealing with users’ opinions, which are not binary, but multiple or continuously changing. Therefore, at this point, the continuous opinion model has better adaptability. In this section, we assume that regular users’ initial opinion value is zero before they are affected by media users. After receiving media messages and then adopting their opinions, their individual opinions will change. According to the opinion update rule in the last section, the opinion changes of regular users are continuous, and the opinion values are random numbers within the interval [0,1].

The continuous opinion model mainly includes the Deffuant model [6]–[8] and the Hegselmann-Krause [9]–[11] (HK) model. What the Deffuant model and the HK model have in common is a bounded trust mechanism. They all assume that users interact with each other’s opinions within the scope of trust, but users’ opinions do not influence each other beyond the scope of trust. The difference between the Deffuant model and the HK model is the scope of interaction. In the Deffuant model, individuals interact with all neighbors, whereas in the HK model, individuals interact with all neighboring individuals within the bounded trust range. Therefore, the HK model is more suitable for scenarios where opinions are exchanged on the same topic or influenced by the same topic within a certain range. We will choose the HK model to model opinion interaction between regular users.

Assume in time series \( t \), the regular users set is defined as \( S = \{1, 2, 3, \ldots, N\} \). The adjacency matrix \( A^t \) represents the social relations of users in the set \( S \) at time \( t \). For all the \( i, j \), we have \( i, j \in S \), \( A^t_{ij} \in \{0, 1\} \), which indicates that there is a connection between ordinary user \( i \) and \( j \) at time \( t \). The \( N \times N \) Adjacency matrix \( A^t \) can be defined as:

\[ A^t_{ij} = \begin{cases} 1, & \text{there exists connection between } i \text{ and } j \\ 0, & \text{there doesn’t exist connection between } i \text{ and } j \end{cases} \]  

(10)

Unlike the one-way influence of media users on regular users, influence among regular users is two-way. For \( i, j \in S \), at any time, we have \( A^t_{ij} = A^t_{ji} \). Let \( X_i(t) \) represents user \( i \)'s opinion at time point \( t \), \( D^t_{ij} \) represents the opinion difference between user \( i \) and user \( j \) at the time point \( t \),

\[ D^t_{ij} = |X_i(t) - X_j(t)| \]  

(11)

Obviously, for regular users \( i \) and \( j \), at any time point \( t \), we have \( D^t_{ij} = 0 \) and \( D^t_{ji} = D^t_{ij} \). According to the principle of bounded trust, when \( D^t_{ij} < d \), opinion will be exchanged between user \( i \) and \( j \). On the contrary, when \( D^t_{ij} > d \), there is no influence between user \( i \) and user \( j \). We consider the influence between users in this article. The influence weight of user \( i \) on user \( j \) is expressed as

\[ w^t_{ij} = \begin{cases} 1, & D^t_{ij} < d \text{ and } A^t_{ij} = 1 \\ 0, & \text{others} \end{cases} \]  

(12)

Therefore, the opinion update rule between ordinary users is obtained:

\[ X_i(t + 1) = \frac{\sum_{j=1}^{N} w^t_{ij} X_j(t)}{\sum_{j=1}^{N} w^t_{ij}} \]  

(13)

C. MEDIA USER BASED OPINION EVOLUTION MODEL

In the section of the model, (1), the characteristics of media opinions and the traditional RAS model are analyzed. (2), the improved RAS-based interaction mechanism between media opinions and individual opinions is proposed, in which the influence of the difference between media opinions and individual opinions on adoption probability is fully taken
into account, and time variables are introduced to describe the attenuation process of the influence of media opinions. (3), the HK model is introduced to describe the process of opinion update among regular users under the influence of media. Combined with the above research, this section will establish an interactive evolution model of users' opinions based on media heterogeneity. In order to clarify the boundary conditions, we propose the following explanations:

1) in order to intuitively describe the interaction of opinions, we will take a grid network as an example to illustrate the flow direction of information. It is shown in Figure 1.

Information from the media user is unidirectionally propagated to the regular user (as shown in the red one-way connection). Information is propagated bidirectionally between regular users, and users’ opinions influence each other, as shown in the blue bidirectional connection.

2) individual opinions are updated only when they are influenced by media opinions or users; the influence of the spontaneous attenuation of individual opinions is ignored in this article.

3) isolated users’ opinions are unaffected in the network.

According to the information transmission mechanism and opinion updating rules in the above social networks, the model is established as follows:

i. Suppose there are $M$ media users and regular users in the model, and the proportion of the number of media users in the total number is $p$.

ii. Opinions of each regular user in the initial state are $X_i(0) = 0$. According to the characteristics of media, the opinion value of each media user in the initial state is $m$ and remains unchanged.

iii. The update of opinions of regular users is synchronous. In each time step, regular users update their opinions under the influence of media messages, and then they interact with each other and update their opinions.

iv. When there is participation of media users, regular users first receive new messages from media users with probability $Pr$, and then adopt opinions from media message with probability $Pr$. Therefore, we use Eq.(9) to compute the final change probability of opinions of regular users. $X_i(t)$ is user i’s opinion in the time point $t$, and we use the proposed Eq.(10) to update the user’s opinion.

v. After being influenced by media opinions, we adopt the proposed bounded trust HK model to update regular users opinions.

vi. All users update their opinions according to the above rules, and then the model moves on to the next time step. Repeat step iii to step v until the opinion stabilizes, it can be defined as:

$$\sum_{i=1}^{M(1-p)} (X_i(t + 1) - X_i(t))^2 < \eta, \quad (14)$$

where $\eta$ is a minimum value.

III. SIMULATION ANALYSIS

In order to further study the process of regular users’ opinion evolution after media users are added into social networks and the key factors influencing the final state of the opinion evolution system, the Monte Carlo method [12], [13] was used to conduct numerical simulation on the interaction model of the opinions proposed in the last section. In the process of simulation, on the one hand, we need to explore the influence of media opinions and parameters of the improved model on the evolution of regular users’ opinions, and on the other hand, we need to consider the influence of social network topology on the model. Therefore, in the simulation of this section, four different complex network structures [14], namely, regular network [15], [16], random network [17], scale-free network [18], [19] and small-world network [20], [21], are used to evaluate the model. There are 1000 network users of different types of network structures, and each experiment runs 100 times independently, and then the arithmetic mean value is taken to draw simulation results.

A. EVALUATION OF OPINION EVOLUTION PROCESS

At the beginning of the simulation, the opinion value of each regular user is 0, and that of each media user is 1. In the network, 10% nodes are randomly selected as media users, and the rest are set as regular users. The average degree of all nodes in the network is 10. In order to reflect the difference of information received by individuals, $W_i$ is a random number between 0 and 1.

Figure 2 shows the evolution process of regular users’ opinion values in the regular network, small world network, random network and scale-free network, respectively. According to the simulation results, regardless of the time taken to reach the stable state or the distribution of the final opinion,
the regular network is quite different from the other three networks. More specifically, the reason is that the average path length of the regular network is large, the information transmission path is long, and the speed at which users receive media information decreases, resulting in a decrease in the probability that regular users’ opinions are affected by media opinions, and at the same time, it leads to a decrease in the chance of opinion interaction between regular users, and finally leads to a split state of opinion evolution. In the other three networks, opinion evolution basically reaches a unified state. The opinion values in small-world networks are basically distributed between 0.2 and 0.3, the opinion values in random networks are basically distributed between 0.3 and 0.4, and the opinion values in scale-free networks are basically distributed between 0.3 and 0.5. The common characteristic of the three networks is that the average path length is small. However, there are still slight differences among the three networks. In the random networks, the final state of opinion consistency is the strongest and the speed system stability is reached is the fastest. The characteristics of the small world networks and scale-free networks are basically the same.

B. EVALUATION OF THE AVERAGE OPINION EVOLUTION PROCESS

In order to further explore the influence of different network structures and model parameters on the evolution process of group opinion, the average view value of each step in the simulation process was calculated and drawn as shown in Figure 3. It can be concluded from Figure 3 that when the parameter \(z\) is small, the attenuation effect of time \(t\) is very obvious. In the four different network structures, the average opinions of regular users are always maintained at a very low level. When the parameter \(z\) is large, the effect of time attenuation is no longer obvious in small-world networks, random networks and scale-free networks. The average opinion of regular users rises rapidly and reaches a stable state, and the average opinion value is close to 1, indicating that all users are affected by media users and the system reaches a unified state. However, in the regular networks, the evolution characteristics are different. The average opinion does not reach a stable state after a rapid rise, but begins to decline after reaching a peak, and shows a trend of continuous decline with time. The reason is that the large average path length leads to slower information transmission speed and less timely media influence diffusion, and the probability of opinion adoption decreases with the passage of time, and ultimately leads to the decline of the influence of media opinion. When the parameter \(z\) is at the middle value, both of them play an important role. In the four network structures, the evolution laws of opinions are basically the same. After the simulation starts, the average opinion values start to rise, and after reaching a high point, they slowly decline and finally plateau.

**FIGURE 2.** Evolution of opinion values over time (a) regular network (b) small world network (c) random network (d) scale-free network \( y = 0.1, z = 0.1, d = 0.8 \).
C. EVALUATION OF THE RELATIONSHIP BETWEEN AVERAGE OPINION OF THE FINAL STATE AND THE MODEL PARAMETERS

In the simulation in this section, we will focus on discussing the relationship between the main parameters in the model and opinion of the final state. At the end of each simulation, the average opinion value of users in the network is counted, the average opinion value will be called the average opinion of the final state in this article. Figure 4 shows the relationship between the parameter $y$ and the average opinion value of the final state. As can be seen from the figure, in general, as $y$ increases, the average opinion value of the final state in the four networks decreases. When $y$ is between 0.1 and 10, parameter $y$ has little influence on the final state of opinions in the regular network, random network and small-world network, while it has a great influence on the scale-free network. That is because in the scale-free network, the influence of the center node decreases as $y$ increases. When $y$ is greater than 10, the average value of the final state of all networks decreases rapidly. As can be seen from Eq. (9), the parameter $y$ is the adjustment coefficient of opinion consciousness $W_i$, which is inversely proportional to the adoption probability. If $y$ is large enough, the adoption probability is extremely low, so that regular users are not affected by media opinions. When $y$ value is 100, the opinions of all network users are 0.

In this part, we explore the influence of parameter $z$ on the final state of opinion evolution when the parameters $y$ and $d$ remain unchanged. According to the numerical analysis of Eq.(9), it can be seen that the parameter $z$ is directly proportional to the probability of opinion adoption. It can be seen from Figure 5 that in the random network, small-world network and scale-free network, parameter $z$ has a polarizing effect on the average opinion of the final state. When the parameter $z$ is less than 10, the average opinion value of the final state grows slowly with the parameter $z$ in the interval $[0.5, 2.6]$, while when the parameter $z$ is greater than 10, the average opinion value of the final state jumps, and the
value range reaches $[0.95, 1]$. The main reason for this jump is that when the parameter $z$ is small, although the average path length in the network is small, the aggregation degree is high, and the information propagation range is wide, and the time variable has a significant exponential attenuation effect on the probability of opinion adoption. Regular users can receive media information, but the probability of opinion change is very low, so the average opinion value of users is always maintained in a low range. When the parameter $z$ is large, the attenuation of the time variable can be overcome. In addition, the strong aggregation of the network makes the media influence spread rapidly, and the opinion value of regular users rises rapidly. As a result, the opinion of regular users in the final state reaches a unified state. Regular users’ opinions are almost completely affected by the opinion of media. However, in the regular network, the average opinion value of the final state increases steadily with the parameter $z$. When $z$ is greater than 30, the rise speed obviously increases but no jump occurs. The reason is that the average distance in the regular network is long and the diffusion speed of media information is slow. Even though the probability of opinion change of regular users is high, it cannot change because no media information has been received. As a result, the average opinion value in the final state of the regular network fails to reach a unified state like the other three network structures.

Bounded trust threshold $\varepsilon$ is a key parameter in the HK model. Therefore, in the model in this part, the threshold of bounded trust mainly affects the opinion interaction behavior between regular users. Increasing the threshold of bounded information can make the range of opinion communication between regular users wider and the frequency of opinion interaction higher. In random networks and small world networks, the threshold of bounded trust has little effect on the average opinion of the final state. It can be seen from Figure 6 that in scale-free networks, when the threshold value is less than 0.6, the mean opinion value of the final state grows slowly, and when the threshold value is greater than 0.6, the mean opinion value of the final state grows rapidly. The reason for this result is that in scale-free networks, there exist common central users with large node degrees, whose opinions are easily affected by media opinions. Therefore, central users with high degree values usually have high opinion values. With the increase of the threshold of bounded trust, the interaction range of opinions of such a central user is increased, and the probability of other users being affected is increased. Finally, the average opinion value of the final state is increased. In regular networks, there are no central users with high degree values, which leads to a low opinion value of regular users, and even leads to the existence of a large number of users with zero opinion change. Increasing the threshold of bounded trust increases the interaction frequency of users and ultimately leads to a decrease in the average opinion value of users.

D. EVOLUTION OF EVALUATION OF OPINION CLUSTERS

Opinion clusters are formed when individual opinion values are similar. An opinion cluster is an indicator of the degree of individual opinion clustering and a statistical standard to describe the system from disordered state to ordered state. In the simulation in this section, if the difference between two individual users’ opinions is less than 0.01, it is considered that they belong to the same opinion cluster, and the number of opinion clusters is counted. According to the simulation results, the number of opinion clusters decreases with time, and the opinions evolve in an orderly and unified direction, and show different evolution characteristics under different conditions. When the parameter $z$ is 0.1, the probability of opinion adoption is low, the conversion rate of media information is not high, and the probability of opinion adoption is further reduced over time, which further reduces the influence of media users. As a result, only a small number of regular users in the network can be affected by media opinions, and their own opinions will be updated. According to the statistical results in Figure 7 (a), in the scale-free network, due to the large number of central users with large degree value and the easy diffusion of media influence, a certain number of regular users in the network are affected. However, there are great differences between individuals and a large number of opinion clusters in the
However, in the regular network, the opinions of most users are not affected and their values are zero. Only a small number of regular users update their opinions, so the number of opinion clusters in this kind of network is the least. In random networks and small-world networks, the efficiency of information transmission lies between the two networks, so the final number of opinion clusters also lies between the two networks.

When $z$ is 100, the probability of opinion adoption is greatly improved, and the information transmission efficiency of media opinions is significantly improved. In Figure 7 (b), the number of point clusters of random networks, small-world networks and scale-free networks quickly peaked at the beginning of the simulation and then began to decline. Combining with the orange curve in Figure 3, the opinions of regular users in the network quickly affected by media opinions, the average opinion value of them rise to nearly 1. It shows that all users have the same opinion and the system reaches a unified state. And in the regular network, the number of opinion clusters has an obvious rising process and decreasing process; at the beginning of the simulation, regular users are gradually affected by media opinions, and the number of opinions increases. With the increase of the frequency of opinion interaction among regular users, the updating rules of the HK model make the individual opinion draw close to the median value, reduce the differences between individual opinions, and gradually reduce the number of opinion clusters. However, due to its large average path length, high clustering coefficient and low frequency of opinion interaction among individuals, the descending speed of opinion clusters is much lower than that of the other three network structures.

Based on the observation of Figure 7 (c), it can be found that, on one hand, reducing the threshold of bounded trust can significantly reduce the time taken for the system to reach a stable state, because the threshold of bounded trust determines the interaction range of regular users’ opinions. The threshold of trust decreases, which reduces the frequency of opinion interaction among regular users, and the number of opinion clusters quickly reaches a stable level. On the other hand, reducing the threshold of bounded trust increases the number of opinion clusters in the final state, because the scope of opinion interaction decreases, the distance between opinion clusters increases, the communication opportunities decrease, and the opinion clusters fail to further integrate to form larger opinion clusters.

### E. EVOLUTION OF EVALUATION OF OPINION CLUSTERS

In this section, we will discuss the influence of the media users on the evolution and final state of opinion. In the previous evaluation, the proportion of media users on the web is set at a fixed value. We will fix other parameters and increase the proportion of media users in turn to evaluate the influence of media user proportion.

Figure 8 shows that the proportion of media users has an obvious influence on the final state of opinion evolution. With the increase of the proportion of media users in the network, the average opinion value of the final state increases significantly. When $z$ is set at 0.1, the average opinions of the final states in the four networks all grow linearly. The average opinion value in the scale-free network is the highest, the average opinion value in the regular network is the lowest, the average opinion value of the random network and the small world network are in between. We have done a total
the final average opinion (a)

FIGURE 8. The relationship between the proportion of media users and the final average opinion (a) \( y = 0.1, z = 0.1, d = 0.8 \) (b) \( y = 0.1, z = 10, d = 0.8 \).

of 10 simulations, and all the simulations have shown the above results. The fundamental reason is the difference in information transmission efficiency in the network. When \( z \) is set at 10, the average opinions of the final state of random networks, small world networks and scale-free networks are all increasing rapidly, when the proportion of media users is more than 5%, the individual opinions in all networks can reach a unified state. However, in the regular network, when the proportion of media users is 19%, the individual opinions will reach a unified state. Once again, it states that the longer average path leads to the lower efficiency of information transmission. In addition, when the value of \( z \) is small, even if the proportion of media users is as high as 19%, the average opinion value of the final state of the network still remains between 0.4 and 0.55. When the value of \( z \) is large, but only when the proportion of media users is 5%, the average opinion value of the final state of the network is close to 1. It can be seen that the probability of opinion adoption has an extremely important influence on the evolution of individual opinions.

F. EVALUATION OF THE POSITION OF MEDIA USERS IN THE SOCIAL NETWORK

In social networks, node position (position of each user in the network) is an important indicator to measure the influence of users. The position of media users in the network also plays an important role in spreading the influence of their opinions. In this section, we will evaluate the influence of the position of media users by introducing degree, betweenness, and clustering coefficient. And degree, betweenness, and clustering coefficient will be used to describe the network position of media users.

In the simulation, we use four kinds of selection methods to simulate media users position. They are random selection, priority selection based on high degree of nodes, priority selection based on high value of betweenness of nodes and priority selection based on high clustering coefficient of nodes. In the regular network, the degree, the betweenness and the clustering coefficient are all equal, and there is no difference with the method of random selection, so the difference of media position in regular network is not discussed in the simulation in this section. The higher the node degree value is, the more neighbors it has and the more direct influence it has. The higher the node betweenness value is, the more information flows through the node, indicating the greater importance of the node. The higher the clustering coefficient of nodes, the denser the surrounding network. At the beginning of the simulation, the opinion values of regular users in the network are zero. Under the influence of the opinions of media users, the opinion values of regular users increase gradually. Therefore, the increase of the average opinion value in the network can be regarded as a reflection of the influence of media opinions.

From the analysis of Figure 9, we can see that in random networks, small world networks and scale-free networks, the media position selection method based on betweenness makes the speed of average opinion of users in the network rise fastest, and the value of the average opinion of the final state of users is the largest. We can reach the conclusion that media users with high betweenness not only accelerate the spread of their opinions’ influence, but also make the range of their opinions wider. In scale-free networks, the average final state opinion value is about 0.95, while in small world and random networks, the average final state opinion value is about 0.2. It states that the heterogeneity of scale-free network promotes the interaction of users’ opinions and expands the influence of media opinions. In random networks and small-world networks, the mean opinion value of the final state of the media position selection method based on degree value is lower than that based on betweenness. This indicates that the influence of nodes with a high betweenness value is greater than that of nodes with a high degree value.

In scale-free networks, the opinion evolution curve of the media position selection method based on degree value and betweenness is basically the same, and states that the nodes with high betweenness values in the scale-free network overlap with the nodes with high degree value. In these three networks, the media position selection method based on clustering coefficient and random selection has smaller average opinion values. In the random network, the opinion change curves when the mentioned two kinds of media position
selection method basically coincide, while in the small-world network and scale-free network, the average opinion value of the media position selection method based on the clustering coefficient is lower than the average opinion value of the random selection method, indicating that the node with high clustering coefficient usually has a low value of degree and betweenness. From the above simulation results, it can be seen that the nodes with high betweenness and high degree value have greater influence; among them, nodes with high betweenness are more important than those of high degree values, while the nodes with a high clustering coefficient have less influence. It means that media users’ position, with its high betweenness, has the highest influence.

IV. CONCLUSION

The research focus of this article is to add a new role—social media users—into the opinion interaction evolution model, and study the influence of its heterogeneity on the opinion evolution process and final state. Compared with regular users, media users have the distinct characteristics of releasing more messages and having more influence. In the process of interacting with regular users, their opinions are not easily influenced. In view of the heterogeneity of media, this article proposes a new opinion dynamic model, which mainly includes two parts: one is to model the interaction process between media users and regular users, and the other is to model the interaction process between regular users.

In this article, four typical network structures, regular networks, random networks, small world networks and scale-free networks are used for simulation analysis. Through simulation analysis, we draw the following four conclusions. First, media opinions have different characteristics under different network structures. Especially in the scale-free network, there are many central nodes with high degree value, which makes the opinion of media users spread quickly, and information dissemination efficiency is high. Secondly, the important parameters $y$ and $z$ in the model mainly affect the adoption probability of individual opinions. Parameter $y$ is inversely proportional to the adoption probability and has little influence on the probability of opinion adoption. Parameter $z$ has a large influence on the average opinion of the final state, and polarization occurs. Thirdly, the threshold of bounded trust mainly determines the interaction behavior of regular users’ opinions. A high trust threshold means wide range and high frequency of regular users’ opinions interaction. Finally, the position of media users in the network has an important influence on the spread of their opinion influence. We found that the media users’ position, with its high value of betweenness, has a fast propagation speed and a wide range of influence.

In brief, compared with regular users, media users in the network have distinctive characteristics and have a special influence on the dissemination of users’ opinions, which is worthy of further study.

REFERENCES

[1] J. H. Heinrichs, J.-S. Lim, and K.-S. Lim, “Influence of social networking site and user access method on social media evaluation,” J. Consum. Behav., vol. 10, no. 6, pp. 347–355, Nov. 2011.
[2] M. Magnani, D. Montesi, and L. Rossi, “Information propagation analysis in a social network site,” in Proc. Int. Conf. Adv. Social Netw. Anal. Mining, 2010, pp. 296–300.
[3] J. Tang, J. Sun, C. Wang, and Z. Yang, “Social influence analysis in large-scale networks,” in Proc. 15th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2009, pp. 807–815.
[4] H. Wang and L. Shang, “Opinion dynamics in networks with common-neighbors-based connections,” Phys. A, Stat. Mech. Appl., vol. 421, pp. 180–186, Mar. 2015.
[5] J. R. Zaller, The Nature and Origins of Mass Opinion. Cambridge, U.K.: Cambridge Univ. Press, 1992.
[6] Y. Shang, “Defquant model with general opinion distributions: First impression and critical confidence bound,” Complexity, vol. 19, no. 2, pp. 38–49, Nov. 2013.
[7] D. Stauffer, A. Sousa, and C. Schulze, “Discretized opinion dynamics of the defquant model on scale-free networks,” Jasss–J. Artif. Soc. Social Simul., vol. 7, Jun. 2004. [Online]. Available: http://jasss.soc.surrey.ac.uk/7/3/7.html
[8] G. Chen, H. Cheng, C. Huang, W. Han, Q. Dai, H. Li, and J. Yang, “Defquant model on a ring with repelling mechanism and circular opinions,” Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top., vol. 95, no. 4, Apr. 2017, Art. no. 042118.
[9] J. Lorenz, “Consensus strikes back in the Hegselmann–Krause model of continuous opinion dynamics under bounded confidence,” Jasss–J. Artif. Soc. Social Simul., vol. 9, Jan. 2006. [Online]. Available: http://jasss.soc.surrey.ac.uk/9/1/8.html
[10] J. Lorenz, “Consensus strikes back in the Hegselmann–Krause model of continuous opinion dynamics under bounded confidence,” Jasss–J. Artif. Soc. Social Simul., vol. 9, Jan. 2006. [Online]. Available: http://jasss.soc.surrey.ac.uk/9/1/8.html
[11] S. Kurz and J. Rambau, “On the Hegselmann–Krause conjecture in opinion dynamics,” J. Difference Equ. Appl., vol. 17, no. 6, pp. 859–876, Jun. 2011.
[12] R. Parasnis, M. Franceschetti, and B. Touri, “Hegselmann-krause dynamics with limited connectivity,” in Proc. IEEE Conf. Decision Control (CDC), Dec. 2018, pp. 5364–5369.
[13] H. Niederreiter, “Random number generation and quasi-Monte Carlo methods,” J. Amer. Stat. Assoc., vol. 89, pp. 147–153, 1992.
[14] E. Estrada, “Introduction to complex networks: Structure and dynamics,” Evol. Ecol. Res. with Appl., vol. 2126, pp. 93–131, Oct. 2015.
[15] F. Xiong, Y. Liu, Z.-J. Zhang, X.-M. Si, and F. Ding, “An opinion formation model with dissipative structure,” Phys. A, Stat. Mech. Appl., vol. 390, no. 13, pp. 2504–2510, Jul. 2011.
[16] C. Altafini, “Dynamics of opinion forming in structurally balanced social networks,” PLoS ONE, vol. 7, no. 6, Jun. 2012, Art. no. e38135.
[17] G.-X. Luo, Y. Liu, Q.-A. Zeng, S.-M. Diao, and F. Xiong, “A dynamic evolution model of human opinion as affected by advertising,” Phys. A, Stat. Mech. Appl., vol. 414, pp. 254–262, Nov. 2014.
[18] F. Xiong and Y. Liu, “Opinion formation on social media: An empirical approach,” Chaos, Interdiscipl. J. Nonlinear Sci., vol. 24, no. 1, Mar. 2014, Art. no. 013130.
[19] A.-L. Barabási and R. Albert, “Emergence of scaling in random networks,” Science, vol. 286, no. 5439, pp. 509–512, Oct. 1999.
[20] R. Amato, N. E. Kouvaris, M. S. Miguel, and A. Díaz-Guilera, “Opinion competition dynamics on multiplex networks,” New J. Phys., vol. 19, no. 12, Dec. 2017, Art. no. 123019.
[21] V. Kiermer, “Six degrees of separation,” Nature Methods, vol. 3, no. 12, p. 964, Dec. 2006.

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