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# The fluctuation analysis of public opinion energy: Modeling social group opinion base on the event of social networks

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## ABSTRACT

In the period of Corona Virus Disease 2019 (COVID-19), millions of people participate in the discussion of COVID-19 on the Internet, which can easily trigger public opinion and threaten social stability. To find out the relationship between the intergroup variability in numbers and perspectives and the dynamic change of the number of infected people, this paper defines the public focus level to quantify the level of attention of people to the information related to an epidemic situation, and the POF model based on the level of epidemic focus is proposed. In this paper, we have carried out simulation experiments in small-world networks and scale-free networks, respectively, to explore the relationship between the model parameters and the spreading range and speed of each population. Furthermore, the paper also analyzed all the original microblog posts published by the People's Daily from January 14, 2020, to February 12, 2020, and compared the data simulated by the POF model with the real data from the People's Daily, the simulation data and the real data can be well fitted to prove the reliability of the model.

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## 1. Introduction

With the widespread use of social networking platforms such as WeChat, Weibo, Facebook and Twitter around the world, social networking has become a tool and platform for people to share their experiences and opinions with each other (Doshi, Nadkarni, Ajmera & TweerAnalyzer, 2017; Li & Lin, 2015; Li & Xu, 2016; Stai, Milaiou, Karyotis & Papavassiliou, 2018; Xu, Yapeng & Wenxin, 2016; Yuan, Ong, Gupta & Xu, 2018). When a public event happens in society, relevant information would spread quickly on social network, and the wide spread of irrational or negative news can easily cause panic among the public and cause serious consequences. Since the discovery of COVID-19 in Wuhan on December 12, 2019, Globally, the COVID-19 pandemic infected more than 197 million individuals up to the end of July 2021, and among these more than 4 million individuals have died (Kifle & Obsu, 2022). Understanding how information about infectious diseases spreads through social networks can help guide public opinion and defuse crises, thus helping the authorities to spread science and control the COVID-19. This is an unsolved and urgent problem, and has at-

tracted the attention of many scholars from the fields of physics, sociology, computer, and so on.

The information spreading model evolved from the COVID-19 spreading model (SI, SIR, SIRS, SIS) (Boguñá & Castellano, 2013; Daley & Kendall, 1965; Ren & Wang, 2014; Song, Castillo-Chavez & Aparicio, 2002; van den & Watmough, 2000; Wen-jie & Xing-Yuan, 2013). Through extensive research on the spreading dynamics of complex networks, it is found that the structural characteristics and propagation mechanism of networks have great influence on the threshold of information burst (Chao, Yuanping, Chengyuan, Zhihong & Jianfeng, 2014; Guo, 2012; Nian & Diao, 2019; Pastor-Satorras & Vespignani, 2001; Shi, Nian, Liu, Cao, 2020; Tunc & Shaw, 2014; Xu, Xu & Su, 2015; Zhang, Boccaletti, Guan & Liu, 2015). On the one hand, there is evidence that the heterogeneity of level distribution reduces the prevalence threshold (Boguñá & Castellano, 2013), but the Heterogeneity of the edge weight suppresses the outbreak of popularity (Wang et al., 2014). On the other hand, there is a growing body of actual data showing that the underlying mechanisms of transmission are unique and different in different dynamical system. Many scholars begin to study the information propagation model which combines the propagation mechanism with the topological characteristics of various networks Zanette (2002), Huang and Jin (2011), Ping and Zhao (2011) studied the propagation modes of rumors on small-world networks and

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scale-free networks Zan, Wu, Li & Yu (2014), Kostka, Oswald and Wattenhofer (2008), Xia, Jiang, Song and Song (2015), Zhao, Wu, Feng, Xiong and Xu (2012) add the mechanism of counter-attack and self-resistance, hesitation, trust and information push to the classic rumor spreading model. In the process of information dissemination, we should not only consider the network structure and dissemination mechanism, but also consider the characteristics of information. Among them, the dynamics of the number of infectious diseases is a very important factor. The effect of message characteristics on the speed and scope of information spreading has not been taken into account in any of these studies. As the COVID-19 situation becomes more serious, understanding how information about infectious diseases spreads through social networks and its characteristics would help guide public opinion and help the government to better control and spread the COVID-19. In this paper, the public focus level related to the number of infected people is proposed to quantify public focus level about the COVID-19 information.

In this paper, we propose a new model, namely, the public opinion fluctuation model (POF Model), which is unique to online social networks. In Section 2, the model is described in detail, and the dynamic process of information spreading is described by means of the mean-field equation. In Section 3, the theoretical analysis is given, including the steady-state analysis of the model and the effect of the parameters on the density of five groups. In Section 4, the effects of different initial parameters and public focus level on information transmission are verified and compared with the real data. Finally, the conclusion is given in Section 5.

## 2. POF model based on public focus level

In the POF model, individuals in the population are divided into three different states: unknown (no message was received), participant (receive information and participate in the discussion), ignorant (receive information but do not participate in the discussion). participant is divided into three different states: give a like, comment, and retweet. The relationships between individuals in different states are shown in Fig. 1.

The model in which outbreak information is spreading over a network is called the POF model, and the rules for spreading of outbreak information are summarized below.

- (1) When an unknown user(U) sees a user, he follows posting information related to the COVID-19, the probability of him becoming a participant user is participation probability  $\alpha$ , while the probability of choosing not to participate to become an ignorant user (I) is  $\gamma$ .

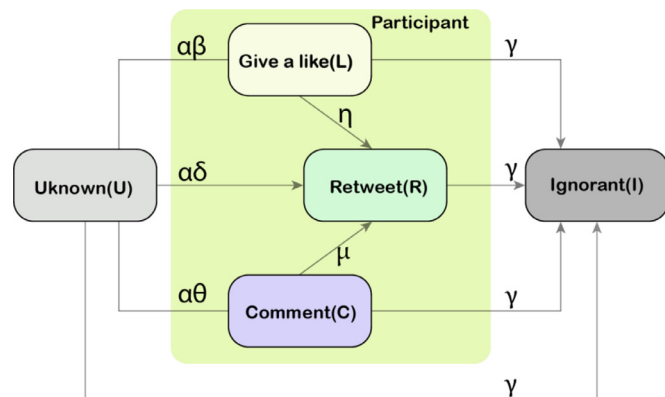


Fig 1. Relationships between individual states.

- (2) Participants have three engagement statuses for the COVID-19 information: like user (L), retweet user (R) and comment user (C).
- (3) The probability of a participant gives this COVID-19 information a like as a like user is  $\beta$ , The probability that a participant will become a retweet user of outbreak information is  $\delta$ , The probability of a participant commenting on COVID-19 information to become a comment user is  $\theta$ .
- (4) Like user and comment user are also likely to retweet the message after give a like and comment and become retweet user with probabilities  $\eta$  and  $\mu$ , respectively.

Based on the equilibrium and stability analysis of the COVID-19 basic regeneration number (Kifle & Obsu, 2022; Yue et al., 2021)  $R_0$ , we refer to papers on the relevance of the COVID-19 infection number prediction model to the population's opinion to construct the following definitions (Liu, Liu, Tu, Li & Li, 2022; Pasetto, Lemaire, Bertuzzo, Gatto & Rinaldo, 2021; Scabini et al., 2021; Wu, Deng & Liu, 2022; Yang, Zhang, Zhang, Cao & Zhang, 2022; Yousefinaghani, Dara, Mubareka, Papadopoulos & Sharif, 2021), followed by a detailed description of the meaning of each factor.

**Definition 1.** Public focus level  $\chi$  is the level to which people are focused about information about the COVID-19.

$$\chi = \tau \frac{t\xi_h}{h\xi_m} + (1-\tau) \frac{tv_h}{hv_m}. \quad (1)$$

In (1),  $h$  is the median incubation period of the COVID-19,  $h=3$ .  $\xi_h$  is the number of new diagnoses in Hubei province in the  $h$ -day before moment  $t$ ,  $\xi_m$  is the cumulative number of diagnoses in Hubei at time  $t$ ,  $v_h$  is the number of new diagnoses in the non-Hubei region in the  $h$ -day before moment  $t$ ,  $v_m$  refers to the cumulative number of diagnoses in non-Hubei at time  $t$ . Among them,

$$\tau = \begin{cases} \frac{\xi_h}{\xi_h+v_h} \\ \frac{v_h}{\xi_h+v_h} \end{cases}. \quad (2)$$

**Definition 2.** The participation probability  $\alpha$  is the probability that an unknown user will discuss the information after receiving the COVID-19 information.

$$\alpha = \omega\chi. \quad (3)$$

Among them,  $\omega$  is the base spreading probability (Jardón-Kojakhmetov, Kuehn, Pugliese & Sensi, 2021; Kermack, McKendrick & Walker, 1927; Rojas, 2020; te Vrugt, Bickmann & Wittkowski, 2020; Zhou, Zhang & Yuan, 2014) of COVID-19 information.

In addition, the POF model is applied to a homogeneous network consisting of  $N$  nodes.  $U(t), L(t), C(t), R(t), I(t)$  represents the node density of the unknown, the like, the comment, the comment and the ignore in the network at time  $t$ , respectively.  $U(t)+L(t)+C(t)+R(t)+I(t)=1$ .

Considering the above information spreading rules, the mean-field equation of the POF model can be described as follows.

$$\begin{cases} \frac{dU(t)}{dt} = -(\alpha+\gamma)U(t)R(t) \\ \frac{dL(t)}{dt} = \alpha\beta U(t)R(t) - \eta L(t) \\ \frac{dC(t)}{dt} = \alpha\theta U(t)R(t) - \mu C(t) \\ \frac{dR(t)}{dt} = \alpha\delta U(t)R(t) + \mu C(t) + \eta L(t) \\ \frac{dI(t)}{dt} = \gamma U(t)R(t) \end{cases} \quad (4)$$

Assume that there is only one source of information at the initial stage. In the initial phase of the outbreak information dissemination, the initial state of each group is

$$U(t) = \frac{N-1}{N}, L(t) = 0, C(t) = 0, R(t) = \frac{1}{N}, I(t) = 0. \quad (5)$$

### 3. Theoretical analysis

When the node state of each node(individual) is no longer changing, the density of the unknown user, the ignorant user, the comment user, the like user, and the retweet user in the network is denoted as  $U_e, I_e, C_e, L_e, R_e$ . In other words,  $\lim_{t \rightarrow \infty} U(t) = U_e$ ,  $\lim_{t \rightarrow \infty} L(t) = L_e$ ,  $\lim_{t \rightarrow \infty} C(t) = C_e$ ,  $\lim_{t \rightarrow \infty} R(t) = R_e$ ,  $\lim_{t \rightarrow \infty} I(t) = I_e$ . Thus,  $U_e + L_e + C_e + R_e + I_e = 1$ . The unknown user would choose to participate or ignore the COVID-19 information from the retweet user they follow, so  $\alpha + \gamma = 1$ . There are three different forms of participation for participants. In order to study the spread thresholds of individuals in four different states, we first assume that  $\eta = \mu = 0$ , and when  $\eta = \mu = 0$  and  $\gamma \neq 0, L_e, C_e, R_e, I_e$  is not equal to 0. The mean-field equation of the POF model can be adapted to the following form.

$$\begin{cases} \frac{dU(t)}{dt} = -(\alpha + \gamma)U(t)R(t) \\ \frac{dL(t)}{dt} = \alpha\beta U(t)R(t) \\ \frac{dC(t)}{dt} = \alpha\theta U(t)R(t) \\ \frac{dR(t)}{dt} = \alpha\delta U(t)R(t) \\ \frac{dI(t)}{dt} = \gamma U(t)R(t) \end{cases} \quad (6)$$

**Theorem 1.** Make  $\alpha + \gamma = 1, \beta + \delta + \theta = 1$ , then for a fixed value  $\alpha, \beta, \gamma, \xi, \theta$ , and the peak of the like user  $L_{\max} = L(t)_{\max}$  and comment user  $C_{\max} = C(t)_{\max}$  decreases as  $\eta$  and  $\mu$  increases.

**Proof.** Dividing the second, third, fourth, and fifth terms of Eq. (7) with the first term, respectively, then

$$\begin{cases} \frac{dL(t)}{dU(t)} = -\alpha\beta + \eta \frac{L(t)}{U(t)R(t)} \\ \frac{dC(t)}{dU(t)} = -\alpha\beta + \mu \frac{C(t)}{U(t)R(t)} \\ \frac{dR(t)}{dU(t)} = -\alpha\delta - \mu \frac{C(t)}{U(t)R(t)} - \eta \frac{L(t)}{U(t)R(t)} \\ \frac{dI(t)}{dU(t)} = -\gamma \end{cases} \quad (7)$$

Adding up the second, third, and fourth terms in Eq. (7), one can obtain

$$\frac{dC(t)}{dU(t)} + \frac{dR(t)}{dU(t)} + \frac{dI(t)}{dU(t)} = -(1 - \alpha\beta) - \eta \frac{L(t)}{U(t)R(t)}. \quad (8)$$

Because  $\alpha + \gamma = 1, \beta + \delta + \theta = 1, I(0) = C(0) = R(0) = 0, U(0) = 1$ , so

$$C(t) + R(t) + I(t) = (1 - \alpha\beta) - (1 - \alpha\beta)U(t) - \eta \int \frac{L(t)}{R(t)} d \ln U(t) \quad (9)$$

And because  $U(t) + L(t) + C(t) + R(t) + I(t) = 1$ , so

$$L(t) = \alpha\beta(1 - U(t)) + \eta \int \frac{L(t)}{R(t)} d \ln U(t) \quad (10)$$

The derivative of Eq. (10) with respect to  $t$  is obtained as follows

$$\frac{dL(t)}{dt} = -\alpha\beta + \eta \frac{L(t)}{S(t)R(t)} \frac{dS(t)}{dt} \quad (11)$$

Make  $\frac{dL(t)}{dt} = 0$ , and because  $\frac{dU(t)}{dt} < 0$ , so  $-\alpha\beta + \eta \frac{L(t)}{U(t)R(t)} = 0$ , then when  $\frac{dL(t)}{dt} = 0$ ,

$$U(t)R(t) = \frac{\eta}{\alpha\beta} L(t) \quad (12)$$

Combining Eqs. (11) and (12) shows that

$$L_{\max} + \eta L_{\max} - \alpha\beta - \eta \int \frac{L_{\max}}{R(t)} d \ln U(t) = 0 \quad (13)$$

Derivative of Eq. (13) with respect to  $t$ .

$$\frac{dL_{\max}}{d\eta} = \frac{(1 - \eta)L_{\max}}{\eta^3 - \eta - 1} < 0 \quad (14)$$

So, the peak value  $L_{\max}$  will decrease as  $\eta$  increases. For the same reason, the peak value  $C_{\max}$  will decrease as  $\mu$  increase.

### 4. Experimental simulation

#### 4.1. The impact of different experimental parameters on public opinion fluctuation

In order to verify the relationship between  $U_e, L_e, R_e, C_e, I_e$  and  $\alpha, \gamma, \beta, \theta, \delta$ , this paper simulates the process of COVID-19 information spreading in the network based on the POF model on the small-world network  $G_{WS}(N, K, \zeta)$  and scale-free network  $G_{BA}(N, K)$ , respectively. In the experiment,  $N = 20000, K = 5, \zeta = 0.7$ . The basic parameters of the model are  $\chi = 1, \omega = 0.7, \alpha = 0.7, \beta = 0.2, \delta = 0.6, \theta = 0.2, \eta = 0$ , and  $\mu = 0$ . As shown in Fig. 2. When the number of unknowns user ( $U$ ) in the network approaches zero, the act of spreading COVID-19 information no longer occurs, and the node state of each

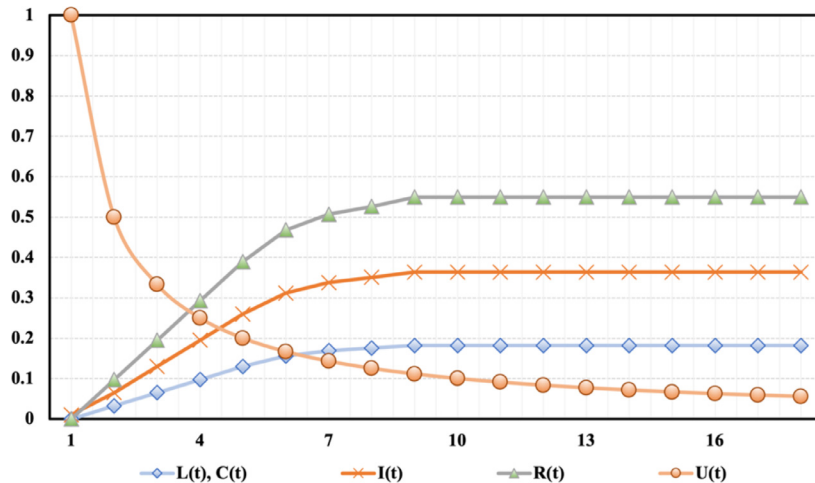


Fig 2. Variation in the density of different individuals in the network.

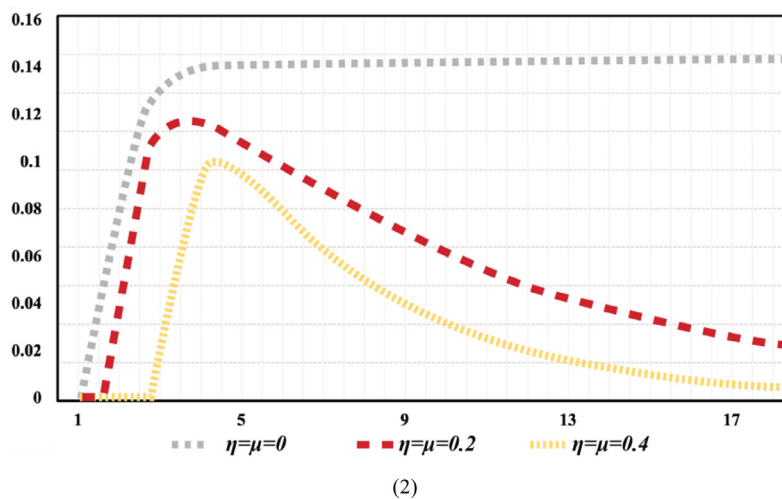
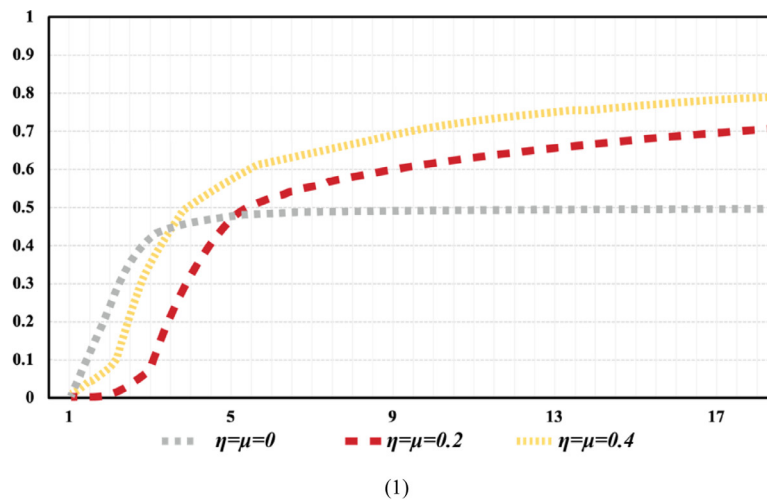


Fig 3. Variation of individual density with parameters in networks. (1) The density of like user(L). (2) The density of retweet user(R) and comment user(C).

node(individual) in the online social network no longer changes, and  $L_e \approx 0.14 = \alpha\beta$ ,  $C_e \approx 0.14 = \alpha\theta$ ,  $R_e \approx 0.42 = \alpha\delta$ ,  $I_e \approx 0.3 = \gamma$ .

In order to investigate the relationship between  $\eta$ ,  $\mu$  and the maximum density of like user, retweet user and comment user in the network, this paper experimentally sets different values of  $\eta$  and  $\mu$  to observe the changes in the density of like user, retweet user and comment user in  $G_{BA}(20000, 5)$  over time.

As we can see from Fig. 3, different  $\eta$  and  $\mu$  have a significant impact on the density of like user, retweet user, and comment user in the network. As  $\eta$  and  $\mu$  continue to increase, the maximum density  $L_{max}$  of like user(L) and the maximum density  $C_{max}$  of comment user(C) in the network will follow decreases, and the value of the maximum density  $R_{max}$  of retweet user(R) in the network increases as a result. This experimental result validates the conclusion of Theorem 1.

#### 4.2. The impact of public focus level on the information propagation processes

The relationship between the numbers of participants added over time at different public focus level is shown in Fig. 4. In the early stages of an COVID-19, the number of new participants (like user, retweet user, and comment user) increases rapidly, peaks after a period of time, and then begins a rapid decline eventually producing no more new participants. At this point the spread of information across the network is at its maximum. In Fig. 4, the

different colored lines represent different public focus level and the Fig. 4 shows that public focus level can have a significant effect on the number of participants added each round. The greater the public focus level, the greater the number of new participants per round. This provides constructive suggestions for outbreak information detection. In the event of an COVID-19, we can effectively predict the scale and scope of information dissemination by observing the number of new participants in the early stages of the COVID-19, so that we can guide public opinion and resolve the crisis.

#### 4.3. The impact of COVID-19 focuses on the process of POF

To validate the reliability of the model, this study collected all the original tweets posted by People’s Daily through the Weibo platform from January 14, 2020 to February 12, 2020. People’s Daily has more than 112 million followers on Weibo, and is the first to report the representative real news happening in the world. People’s Daily posted a total of 2260 tweets on various topics during this period, which received 3899,2209 retweets, 12,480,623 comments and 23,298,9454 likes. In order to study the characteristics of the spread of COVID-19 information on the Internet, this experiment incorporates real COVID-19 trends by means of an COVID-19 attention-based POF model to simulate the process by which the development of an COVID-19 affects the extent of the spreading of daily released COVID-19 information, and the model

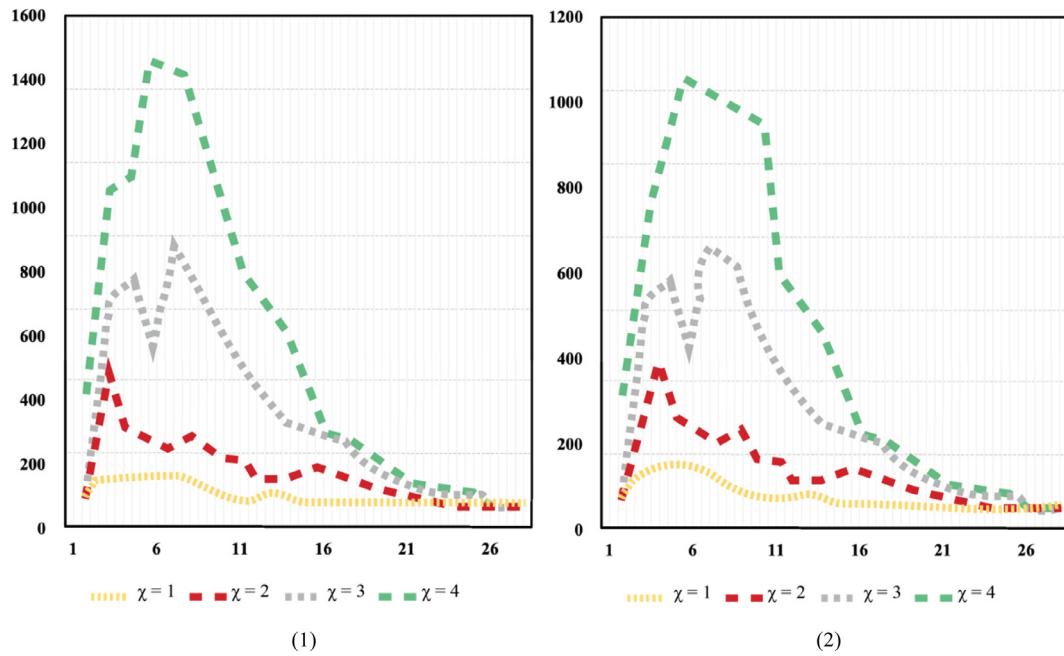


Fig 4. The relationship between new participant individual density and the public focus level about COVID-19. (1) Retweet users, (2) Like users and comment users.

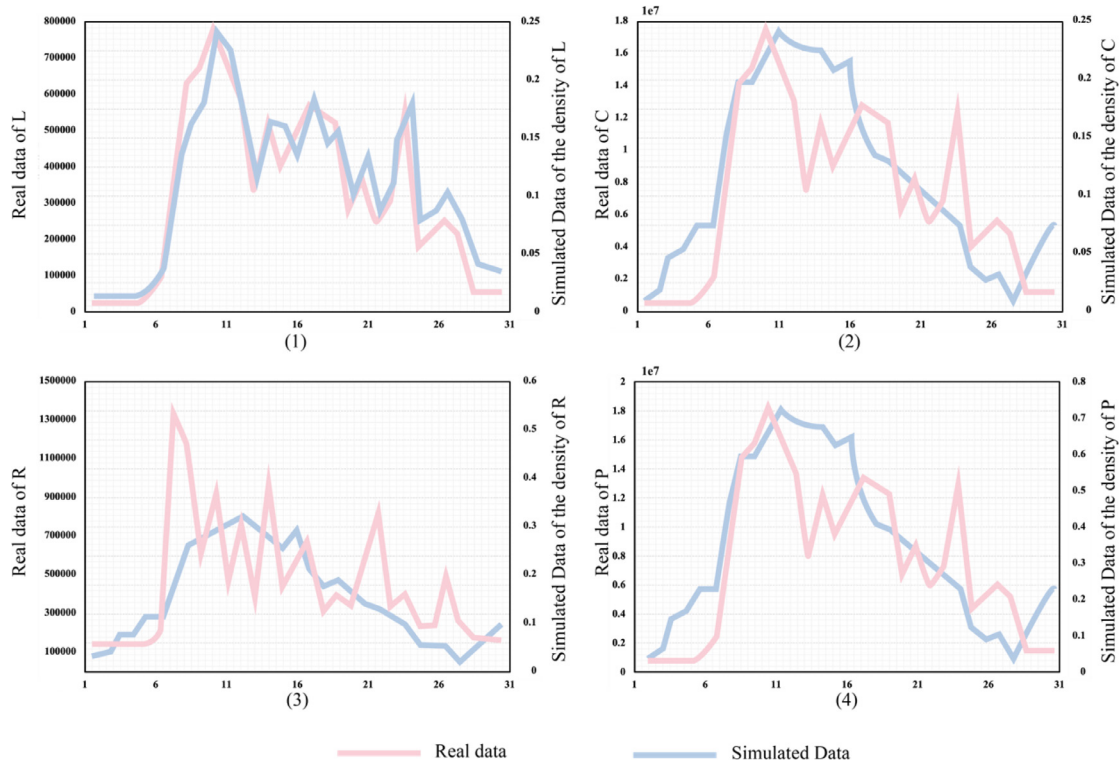


Fig. 5. Compare real data with simulation data by model. a. Like users, b. Comment users, c. Retweet users, d. Participants.

simulation of the results were compared to real data from the People's Daily.

Whether users participate in discussions about the information they receive depends not only on the information itself, but also on the trend of the COVID-19. Influenced by the daily changes in the number of infected people, the level of focus about the COVID-19 changes every day. Thus, the maximum spread of information in the network is constantly changing. In order to observe the effect of COVID-19 attention level on the participation probability  $\alpha$ , this paper sets the probability of base message spreading  $\omega=0.2$

in a simulation experiment, and records the maximum density of infections reached by like user, comment user, and retweet user in the network after the source node posts daily COVID-19 information under different COVID-19 attention level.

From Fig. 5, it can be seen that in the early stages of the COVID-19, the spread of COVID-19 information in the network increased rapidly, and at this time the COVID-19 information attracted widespread attention from the community. At this time, people are in a stage of both unknown and panic about the COVID-19 and are maintaining a high level of interest in information re-

lated to the COVID-19. However, as awareness of the COVID-19 grew and the COVID-19 was brought under control, attention to information about the COVID-19 began to slowly decrease. While whether people engage in the discussion about the outbreak is influenced by the information itself, overall, the number of like users, retweet user, and comment user on news about the COVID-19 is slowly declining. The experiments also demonstrated the reliability of the model by comparing the data simulated by the POF model based on COVID-19 focus with real data.

## 5. Conclusion

In this paper, a new POF model, is proposed. The POF model includes five individual states: unknown (U), ignorant user (I), like user (L), retweet user (R), and comment user (C), and defines the transition relationship between the individual states. One theorem is presented in this paper, which reveals the relationship between peaks and parameters for both like user and comment user. In this paper, the Theorem 1 are validated by performing numerical simulations of different networks. This paper also compares the data simulated by the model with the real data from the People's Daily, and the reliability of the model is proven by the fact that the simulated data and the real data can be better fitted.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## CRedit authorship contribution statement

**Yayong Shi:** Writing – original draft, Visualization, Investigation. **Jianpeng Qi:** Writing – original draft. **Rui Wang:** Software.

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