Received August 8, 2016, accepted August 21, 2016, date of publication February 6, 2017, date of current version February 25, 2017.

Digital Object Identifier 10.1109/ACCESS.2016.2605009

Modeling for Information Diffusion in Online Social Networks via Hydrodynamics

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ABSTRACT In recent years, online social networks have gained tremendous popularity because of the massive number of online users, the fast spread of information, and strong inter-personal influence. However, due to the high complexity of the user interaction and the real-time changing of the online social networks, it is still a big challenge to model the spreading process of the information delicately and, then, to predict the information diffusion precisely. In this paper, we exploit a hydrodynamic model to describe the spreading process of the information in online social networks. By using the proposed hydrodynamic information diffusion prediction model (hydro-IDP), we can describe the spreading process of the information on both temporal and spatial perspectives. It is also helpful in extracting the characteristics of information diffusion (e.g., the information popularity, the user influence, and the diffusivity of social platform). We also consider the superimposed effect of the information diffusion resulted from influential users in the model. The high accuracy of the model results has illustrated that our proposed Hydro-IDP model is competent to describe and predict the spreading process of information in online social networks.

INDEX TERMS Online social networks, information diffusion, hydrodynamics, influential users, superimposed effect.

I. INTRODUCTION

The online social networks (OSNs) (e.g., YouTube, Sina-Wibo and Twitter) have stupendously grown up since 2010, and the various of information with forms of SMS, photo and video are spreading easily and effectively through those online social networks. The information which exchange through OSNs platform have become more and more popular and affect our communication with friends and family, and even changed our daily life.

The extremely large amounts of information with various contents have accelerated lots of researches in the field of information spreading in online social networks. The results of these research can help people understand the spreading process of the information better, and then help in better optimizing business performance (e.g. optimizing marketing campaigns), following events (e.g. analyzing revolutionary waves) and solving issues (e.g. preventing terrorist attacks, anticipating natural hazards), etc. [1]. But it is still a greatly challenging to analyze the specific mechanism of the spreading process of information because of the real-time changes of the networks and complexity of the social interactions.

In the present researches, there are two major categories of models for information diffusion modeling, i.e., explanatory models and predictive models [1]. The explanatory models strive to retrace the spreading path of the information in OSNs. Most of them have focused on the measurement and analysis of the network structures [2]–[7], the user interactions [8]–[10], and the spreading characteristics of the social media, such as empirical approaches [11], [12] which utilize data mining [13], [14] and statistical modeling schemes [15]–[17].

The objective of predictive models is to predict how a specific diffusion process would unfold in a given social network, based on the research results of the past process of the information spreading. For example the independent cascades model [17]–[20] and the linear threshold model which is established based on static graph structure [21], [22]. Several studies for information diffusion on temporal pattern are based on the epidemic model [23], [24] and the linear influence model [4]. A few recent attempts use a partial differential equation model to predict the information diffusion on both temporal and spatial dimensions [25]–[27].

As shown in Table 1, we give a summary of popular predictive models in the related works with respect to dimension focus, parameter setting mode and mathematical modeling mode. The proposed hydrodynamic information diffusion prediction model (hydro-IDP) in this paper has been listed in the last row, it is the only attempting for modeling

TABLE 1. Summary of prediction models for information diffusion.

	Dimension focus		Parameter setting		Math modeling	
Model	Time	Space	Fixed	Dynamic	Parametric	non-para.
IC [1]		√	√		√	
LIM [3]	√			√		√
LT [19]		√	√		√	
T-BaSIC [22]	√	√		√	√	
PDE [25], [26]	√	√		√	√	
SIS-SIR [28]	√		√		√	
Hydro-IDP [29]	√	√	√			√

the information diffusion in space-time dimension without parametrization method.

One of the most challenge of modeling the information diffusion in spacial dimension is the superimposed effect due to the influential users. How to calculate the user influence and their sum effect to the information diffusion is concern to the prediction accuracy. On the other hand, because of a large amount of the participant users, the change of the information spreading with time due to the interaction of the users is also a huge challenge in temporal dimension.

In this work, we have greatly improved the initial version of hydrodynamic model [29] to describe the information spreading process in online social networks. In our proposed model of hydro-IDP, we correlate the characters between the information diffusion in the cyber space-time and the fluid-density flow evolution in the physical space-time. Using the density of influenced users, one can describe the spreading of the information fluid in apace-time dimensions with a few initial parameters extracted on the basis of status of information and publisher. It also provides a way to examine the contribution for accelerating information spreading by the social platform diffusivity, the user influence and the information popularity, etc.

The remainder of this paper is organized as follows. We have introduced the framework of our proposed Hydro-IDP model and the numerical solution of the hydrodynamical equations in Sec.II. In the part A of Sec.III, we have present the space-time patterns of a real data set which were collected from the site of Sina-weibo. In the part B and part C of this section, we have validated the hydro-IDP model for predicting the information spreading process. We have also analyzed the model characteristics such as the web-site diffusivity, the information popularity and the user influence of the information publisher, etc. Finally, we have given the conclusion of this paper and the discussion of our future works in Sec.IV.

II. FRAMEWORK FOR HYDRO-IDP MODEL

A. THE FRAMEWORK OF HYDRO-IDP MODEL

There are the following major functional components in the proposed Hydro-IDP model: data acquisition and previous analysis, parameter setting for specified information, hydrodynamic modeling and information diffusion prediction as a goal. In Fig.1, we provide a flow diagram to illustrate the concept of our proposed Hydro-IDP model.

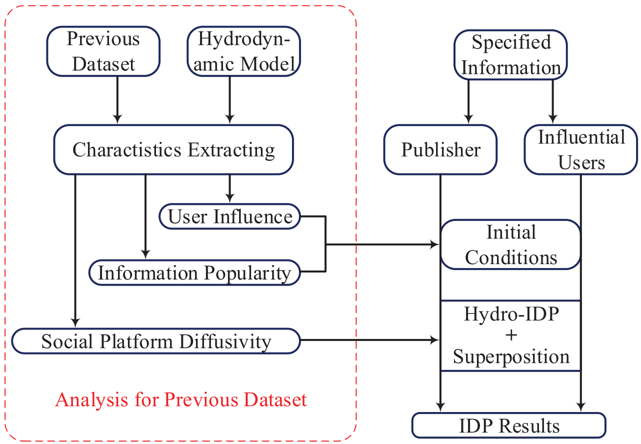

FIGURE 1. The framework of Hydro-IDP.

Specifically, it includes the following three main steps:

1) Data acquisition and analysis: Collect the previous data set for analysing the characteristics of the information diffusion on the social platform.
2) Parameter setting: Determine the model parameters of initial energy density distribution, initial source radius for a specified information, and flow velocity for the social platform.
3) Hydrodynamic modeling: Modeling the information diffusion via Hydro-IDP with optimized parameters.

We will provide more detailed discussions of these three key components later.

B. THE HYDRODYNAMICS

The hydrodynamics which we used in this paper is a solution for modeling the evolution of the various kinds of fluid based on a set of partial differential equations. The hydrodynamic model was been widely used in the fields of meteorology, engineering, chemistry and physics, etc [30]. Once we decide the initial condition and an equation of state, we can describe the spatio-temporal spreading of any fluid through hydrodynamic model. In this work, we attempt to utilize hydrodynamic model on modeling the spreading of the information fluid in OSNs. The formulation of the conservation law of the information fluid in OSNs is similar to that for spatial biology [27], [31]. We extend the discrete space-time points of the information fluid into a continuous interval and then describe the diffusion of the information fluid with Hydro-IDP model.

In the table 2, we list the corresponding physical meaning of the parameters of Hydro-IDP model and their counterpart definitions for information fluid in OSNs. Corresponding with the characteristic parameters of the hydrodynamics, we treat the information publisher as a centre space-time point of the fluid source. And then the model parameters of initial source energy, the initial source radius, the initial flow velocity are correspond to the information popularity, publisher influence and the diffusivity of the social platform, respectively.

TABLE 2. Model parameters and counterpart definitions in OSNs.

Symbol	Model parameters	Definitions in OSNs
S	space-time centre	information publisher
R	initial source radius	publisher influence
E	initial source energy	information popularity
v	initial flow velocity	diffusivity of social platform
r	space distance	friendship hops between users
ϵ	energy density of fluid	density of the influenced users

In this work, we use the "friendship hops" to describe the user's cyber-distance in the spatial dimension [27]. One can use friendship hops to refer to the number of user's links. And then, the distance of any two users is defined as the length (the number of friendship hops) of the shorted path between them in the social network graph. Clearly, the direct link of two users have a distance of 1, while one's direct followers have a distance of 2 from the other user, and so on. Finally, we use the density of the influenced users to measure the diffusion of the information flow.

With the model parameters and the counterpart definitions in OSNs, the ideal hydrodynamic description for the system of a information diffusion could be defined with local energy density conservations

$$\partial_\mu T^{\mu\nu} = 0, \tag{1}$$

where $T^{\mu\nu}$ is the so called energy-momentum tensor for the ideal fluid, $T^{\mu\nu} = (E + p)u^\mu u^\nu - pg^{\mu\nu}$ with the energy density E and the pressure p for the fluid element in the local rest frame which moving with flow velocity u^μ. In the Hydro-IDP model, we use the invariant-time coordinate as $X^\mu = (t, r)$, and the space-time metric tensor as $g^{\mu\nu} = \mathrm{diag}(1, -1, -1, -1)$ [30].

Considering the cyber-distance of friendship hops in online social networks and the isotropic diffusion, the hydrodynamic equation (1) can be written as below in the spherical symmetry frame

$$\begin{aligned} \partial_t E + \partial_r[(E+p)v] &= -\frac{2v}{r}(E+p), \\ \partial_t M + \partial_r(Mv+p) &= -\frac{2v}{r}M, \end{aligned} \tag{2}$$

where M is the momentum density which corresponds to the energy density E.

In this work, we use a so-called Godunov method to solve the hydrodynamic equations numerically (2) [32]. It allows to solve the equations with type of

$$\partial_t U + \partial_r F(U) = -G(U) \tag{3}$$

(which U being E or M in equations (2)) by first solving the partial differential equation

$$\partial_t U + \partial_r F(U) = 0 \tag{4}$$

with Harten-Lax-van Leer-Einfeldt (HLLE) algorithm [33], which yields a prediction $\tilde{U}$ for the true solution U. And then one corrects this prediction by solving the ordinary differential equation

$$\frac{dU}{dt} = -G(U), \tag{5}$$

which is numerically realized as

$$U = \tilde{U} - \Delta t G(\tilde{U}). \tag{6}$$

In our calculation, we simply use a equation of states of ideal fluid, $p = 2/3\, E$, to close the hydrodynamic equations (2).

III. MODEL RESULTS FOR INFORMATION DIFFUSION

A. CHARACTERISTIC OF INFORMATION DIFFUSION IN REAL DATA SET

We collected the data set of 6500 video tweets during May 2012 to February 2013 from the most popular online social network in China of Sina-weibo [34]. The data set include all repost/comment actions of user property for each video tweet, for example, action timestamp, the action-user's identity document (ID), user's follower-counts, friendships relationship for every user, etc. The reposted or commented to the tweets were labeled as an action by the influenced users. In totally, there are more than 200 million action records have been labeled on these video tweets. These data set of the friendship hops and timestamps for the tweets provide the opportunity to analyse the density of the influenced users in both temporal and spatial dimensions. It is necessary and important work to study the impact of the friendship relationship on the information spreading and then to predict the information diffusion through online social networks which are especially built on the friendship pattern. In this work we have analysed all of these 6500 video tweets and in the next we demonstrate the results of three representative tweets of different following-user scales in fig.2. The video tweet 1 is the most popular tweet which have been followed by 92992 users, video tweet 2 and 3 have been followed by 65660 and 35401 times, respectively.

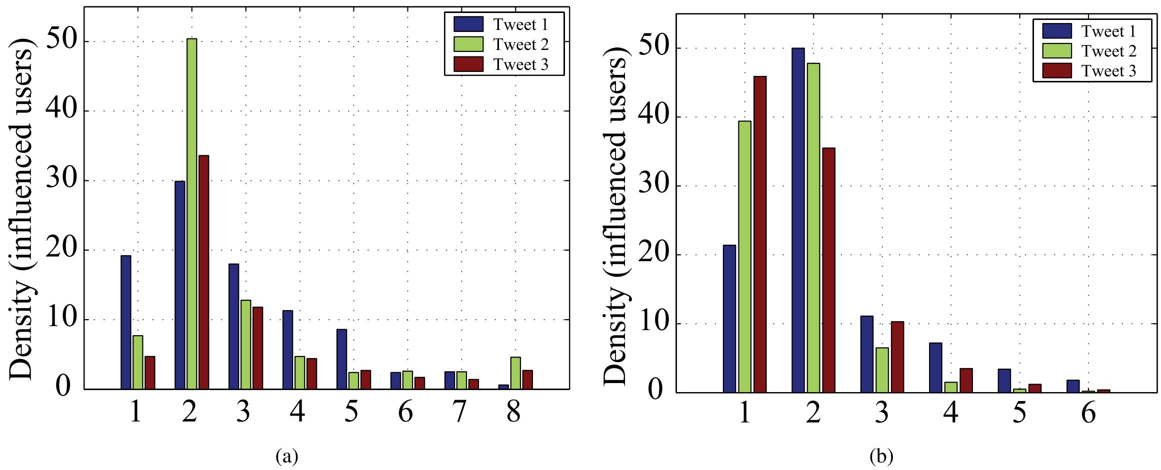

FIGURE 2. (Color online) Density distribution of the influenced users for three representative tweets with (a) days as time and (b) friendship hops as distance.

In the Fig.2 (a), we have shown the density distributions of the influenced user with the time of 8 days for three representative video tweets which have been followed by 92992, 65660 and 35401 times, respectively. We can find that for all of these three tweets, there are above 95 percent influenced users have reposted and commented the video tweets in the first eight days. We also find from Fig.2 (b) that there are above 98 percent influenced users have followed the tweets in the first six friendship hops. So we only present the real data set and the model results from 1 to 8 days and from 1 to 5 friendship hops in this work.

In the Fig.3 (a-c), each line represents the density of influenced users at a certain friendship hops from 1 to 5 for three tweets which have been shown in fig.2. Our analysis results have shown that almost 87.3% of all the video tweets in the real data set fall into this category of picture (a), we label this kind of video tweets with type I. From picture of tweet type I, we can find that the density distribution of the influenced users evolves regularly for every distance with the time and the density value becomes stable at the 5th day. This is because this video tweet is no longer 'popular' and has almost stopped spreading. We also can find that the density distribution of the influenced users at the small hops are obvious higher than that of influenced users at the big hops. This is because that the followers who were closer to the tweet publisher play the more important role in information diffusion.

In the pictures of (b) and (c) in Fig.3, we have also shown the density distribution of the influenced users for the other two video tweets. It's worth noting that the density value at hops $=$ 2 are higher than that of the density value at hops $=$ 1 in Fig.3 (b) which was labeled type II. This is because that there are more influential users who have followed the video tweet than that of type I, and then greatly improve the diffusion of this type of tweets. In this paper, we also improved the Hydro-IDP model to consider the affection for information diffusion resulted by the influential user who has more than one hundred thousand followers. In picture (c), there is a sudden rise of the density value at the 7th day (i.e., New Year's day), which further promotes the information spreading.

Fig.4 has shown the density distribution of influenced users with spatio-temporal dimension. The dash lines illustrate the model results for video tweet 1, and the solid lines are correspond value for the real data set. The results have shown that the density value of influenced users decreased regularly with distance and time.

B. MODEL RESULTS FOR INFORMATION OF TYPE I

The past empirical studies have shown that the process of the information spreading present different space-time patterns with a variety of factors, for example the different social platform, the network structure, the real-time changes of the network, the interaction of the users, and so on. Such factors make it more challenging to model and predict the information spreading. In this work, we have proposed a Hydro-IDP model for describing the information evolution in temporal and spatial dimensions.

We have given the comparison results of the density distribution of the influenced users between the model value (solid lines) and the real data set (dashed lines) in Fig.4. In the model calculation, the flow velocity which describe the platform diffusivity of Sina-weibo was fixed with $v = 1$. We also extract the initial radius of the spheriform source with $R = 5$ which matching the publisher's influence scale of 1.5 million followers. And then we adjust the initial energy density of the spheriform source which decrease linearly from the maximum value of $E = 300$ to 0. The largest value of $E = 300$ at the first distance on the first day indicates the most active degree of the information and it is the datum point of the parameter tuning.

Takes into account both the efficiency and the accuracy of the model, we have chose 50 time steps and 100 space

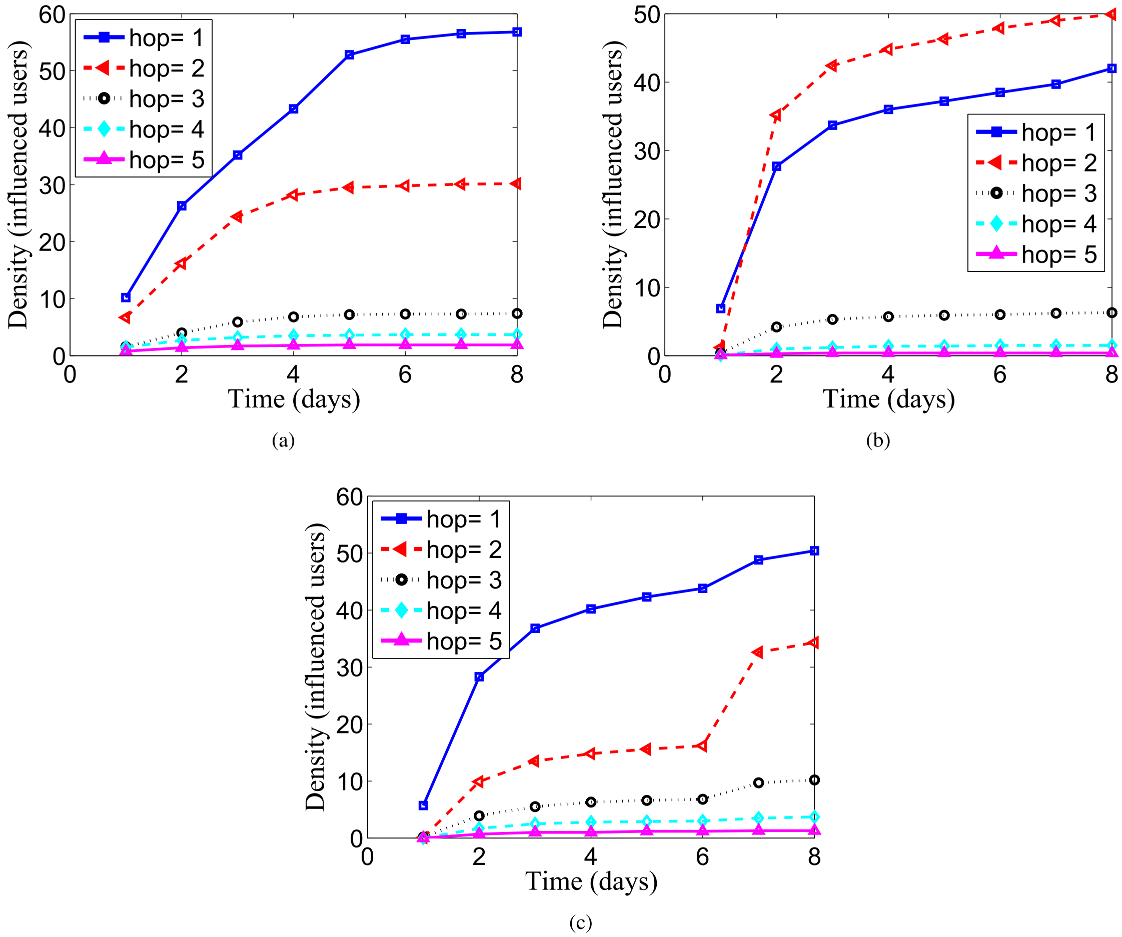

FIGURE 3. (Color online) Density of influenced users over 8 days with 5 friendship hops as distance for three tweets of (a)-(c) corresponding to tweet1-tweet3 which have been shown in Fig.2.

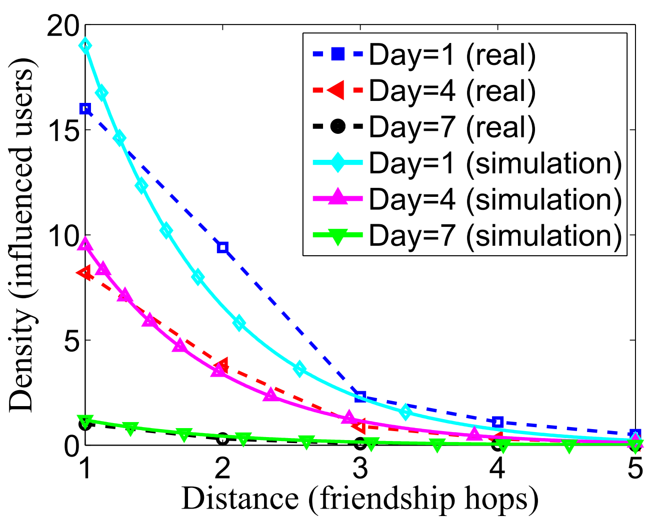

FIGURE 4. (Color online) Comparison for model results (solid lines) and actual data (dashed lines) of influenced user density for a tweet of type I with distance at different times.

steps in the numerical calculation of our Hydro-IDP model to correspond to one day and one hop of the information spreading.

We calculate the accuracy of the model results with A_p which was defined as

$$A_p = 1 - \frac{|D_p(t,d) - D_a(t,d)|}{D_a(t,d)}, \tag{7}$$

where $D_p(t,d)$ is the space-time density value of the influenced users for the model results and $D_a(t,d)$ is the actual value of the real data set. We have also list the accuracy of model results in table 3 with hops form 1 to 5 and days from 1 to 6 for the video tweet 1. One can find the average accuracy of the hydro-IDP results are 81.82% at distance 1 and 75.70% for the first three hops.

C. MODEL RESULTS FOR INFORMATION OF TYPE II

In our analyses of information spreading which were shown in Fig.4, we have find that the model results (solid lines) have shown a slightly concave. It does not conforms with the real data set (dash lines) of slightly up-convex especially at distance 2, and the prediction accuracy of the model results are not very satisfactory. This is because we have ignored the superimposed effect of the influential users in the diffusion of tweet type I in our calculation. But these kind of superimposed effect should not be ignored for the tweets of type II.

TABLE 3. Model accuracy of tweet type I.

Time / Distance	day = 1	day = 2	day = 3	day = 4	day = 5	day = 6	Mean value
Hop = 1	81.33	86.56	77.58	84.22	86.27	74.93	81.82
Hop = 2	70.31	64.63	65.71	89.63	62.47	58.66	68.57
Hop = 3	98.03	94.19	93.72	71.94	50.18	52.14	76.70
Hop = 4	67.82	98.48	67.33	75.24	68.72	90.10	77.95
Hop = 5	45.66	61.94	50.57	78.14	67.82	65.94	61.51

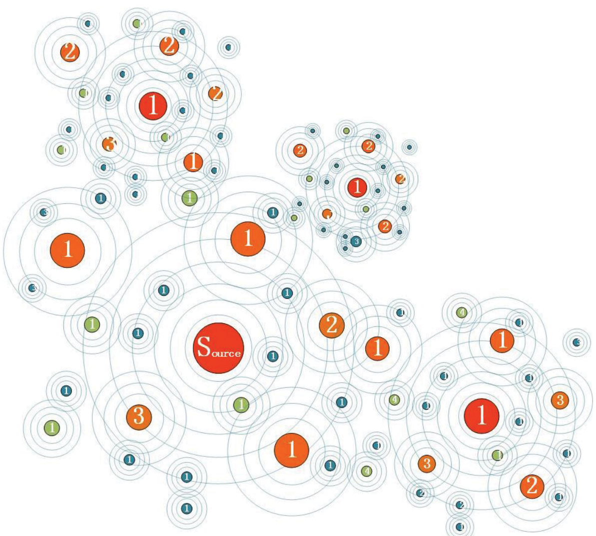

FIGURE 5. **(Color online) Superimposition effect of the tweet diffusion resulted by influential users.**

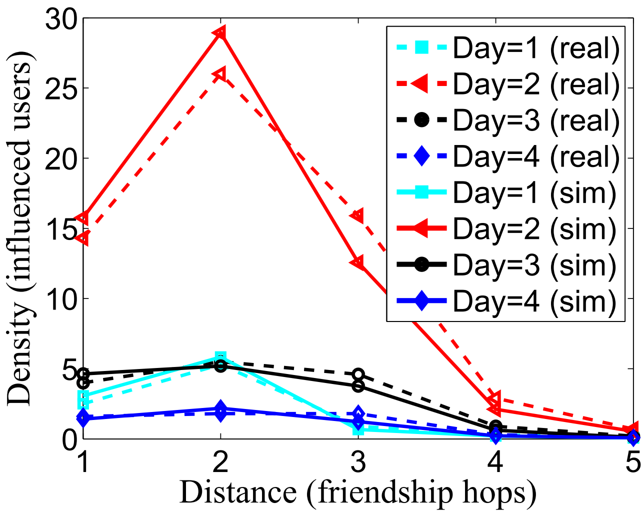

FIGURE 6. **(Color online) Comparison for model results (solid lines) and actual data (dashed lines) of influenced user density for a tweet of type II with distance at different times.**

In Fig.6, we give the density value of a video tweet of type II with the friendship hops at the different days. We can see that there are two differences with the video tweet of type I which have been shown in Fig.4. The density value of the influenced users on the second distance are much bigger than the value on the first distance, as well as the density value with the time. This is because that there are more influential users of 15 than the most case of tweets type I which less than 3, and then greatly improve the spreading of this tweet at distance 2. So we must consider the superimposition effect (see Fig.5 for a schematic diagram) in our hydrodynamic model to describe the spreading of tweet type II. In Fig.5, the circle with the text of "Source" is the tweet publisher and the circle with the number of 1, 2, 3 or 4 describe the publisher's follower with distance of 1, 2, 3 or 4, respectively. The radius of the concentric circles describe the scope of the user's influence.

The video tweets of type II make up only about 6.7% of the overall total. But the publishers with more influential followers have a lot of social influence and can promote the information diffusion tremendously. So, it is very interesting and necessary to model and predict the diffusion of this kind of information. In this section, we improve the hydro-IDP and use the superposition method to describe the effects of multi-influential-users and then model the information diffusion for tweets of type II.

Firstly, we extract the influential follower of the publisher with the tweet 2 has been shown in Fig.3 (b). There are 15 influential followers who have been followed by more than a half million users. We have list the number of the influential followers (NOIF) with the magnitude of the followers (MOF) and their hydrodynamic contrast of the initial source radius (ISR) for this tweet in table 4.

TABLE 4. Model parameters of influential users for tweet 2.

MOF/million	1.5	1.0	0.5
NOIF/person	2	5	8
ISR	5	3.4	1.7

Secondly, we use the Hydro-IDP model to calculate the spreading process of the tweet for nth influential user, $D_n(t, d)$, with the initial energy density $D_{publisher}(t, 2)$ of the tweet at distance 2 with tth day.

Finally we use the superimposed method to calculate the total effect of the tweet diffusion as

$$D_{Total}(t, d) = D_{publisher}(t, d) + \sum_{1}^{n} D_n(t, d). \tag{8}$$

The model results have been shown in Fig.6 with solid lines and the prediction accuracy are listed in table 5. We can

TABLE 5. Model accuracy of tweet type II.

Distance \ Time	day = 1	day = 2	day = 3	day = 4	Mean value
Hop = 1	77.6	89.8	84.25	88.13	84.95
Hop = 2	90.00	88.75	94.37	78.89	88.00
Hop = 3	74.50	78.99	82.96	68.34	76.20
Hop = 4	84.22	72.76	68.89	90.10	78.99
Hop = 5	70.00	77.15	60.00	80.00	71.79

find that the model results present the characteristic of the diffusion of the tweet type II which have large number of the influential followers in distance 2. The average accuracy of the hydro-IDP prediction are 84.95, 88.00 and 76.20 percent in the first three steps. It's necessary to note that we only consider the effect of the influential users at the distance (friendship hops) 2. So the density value of the model results at distance 3 are all slightly smaller than that of the data set.

Our studies have shown that one can use the proposed Hydro-IDP to model the information spreading in a specific online social networks, once we decided the information popularity, the scale of the user influence and the platform diffusivity. The parameters of the model, in turn, offer a opportunity to extract the affect of the information popularity, user influence, the diffusivity of the specific social platform, etc. These results may help people better understand the spreading mechanism of the information in online social networks.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we have extended a prediction model for describing the spreading process of the information in the online social networks. Because the model was based on the hydrodynamics, one can use it to model the information diffusion in both temporal and spatial perspectives. In the model calculation, we have connected the physical space-time of the hydrodynamics with the cyberspace space-time for the information diffusion. By modeling the information spreading process for the video tweets collected from the most popular social platform, Sina-weibo, we have studied the contribution for promoting the information spreading by the publisher's influence, the platform diffusivity for the social networks, the influential users and the information popularity, etc. The model results achieved an averaged accuracy of 76.70% in the first three hops for the video tweet of type I in the real data set.

For considering the influence for the information diffusion resulted from the influential users like the tweet of type II shown in Fig.3 (b), we have improved the Hydro-IDP model to added the superimposed effect. Based on the improved model, we describe the spreading process of video tweet type II with the averaged accuracy of 83.05% for the first three hops.

In the further work, we plan to improve the Hydro-IDP to model the cross-platform diffusion of the information in online social networks. In addition, the infection rate of the influential users is worthy to be studied deeply to refine the model.

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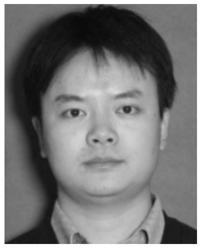

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