Hindawi
Discrete Dynamics in Nature and Society
Volume 2020, Article ID 1915840, 7 pages
https://doi.org/10.1155/2020/1915840

*Research Article*

# Modeling and Analysis of Dynamic Social Ties in D2D Collaborative Video Transmission

**Qi Zhang,[1,2,3] Zufan Zhang,[1,2,3] Tian Zeng,[1,2,3] and Xiaoke Li[1,2,3]**

[1]*School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing 400065, China*
[2]*Chongqing Key Laboratory of Mobile Communications Technology, Chongqing 400065, China*
[3]*Engineering Research Center of Mobile Communications, Ministry of Education, Chongqing 400065, China*

Correspondence should be addressed to Zufan Zhang; zhangzf@cqupt.edu.cn

Received 11 May 2020; Accepted 8 June 2020; Published 23 June 2020

Guest Editor: Wei Wang



Social networks are one of the main carriers of information diffusion. Changes in social ties will affect the quality of Device-to-Device (D2D) communications especially the video transmission. For further improving the communication utility of users, it is of great significance to effectively integrate D2D communications and social networks. To this end, this paper utilizes a stochastic approach to modeling and analysis of dynamic social ties in D2D collaborative video transmission. Specifically, a stochastic mathematical model is established and analyzed, in which the combined effect of many factors such as interest, geographical position, career, social class, value system, and interaction is considered. Based on the Brownian motion theory, the strength of social ties among social individuals with time is studied. Next, the reliability function and adaptive parameter estimation are performed. Finally, some examples are conducted to illustrate the main results of this paper, from which one can see that the proposed model has a good predictive ability of the changing trend of social ties.

## 1. Introduction

With the development of mobile Internet and wireless communication technology, Device-to-Device (D2D) communications have become one of the key technologies of the future wireless communication and social networks have become one of the main carriers of information diffusion [1]. Through D2D communications and social networks, people can not only communicate with friends but also share pictures and videos faster and more conveniently. Since the communication equipment are usually carried by people, the dynamic social environment and a wide range of social applications require D2D communications, especially the D2D collaborative video transmission, to be more self-adapting and to meet more general communication needs. When users share videos locally through the wireless short-distance D2D communications, if users successfully establish a D2D link, the video streams will spread rapidly over social networks. However, there are users' mobility and the occurrence of random events in social networks, and changes in users behavior will lead to dynamic interactions between users, which will affect the success rate of users to establish D2D links, thereby affecting the information diffusion [2]. Therefore, it is essential to study the D2D collaborative video transmission in conjunction with social networks.

In [3], a D2D communication-assisted caching framework for video multicast was proposed, which considers the social trust and social reciprocity to encourage effective collaboration between users. Wang et al. [4] studied an Expected Available Duration (EAD) indicator to measure the chance of D2D users' downloading video packets from neighbors. Zhang et al. [5] considered the D2D pairing for cooperative video transmission. The social tie in previous work was usually calculated according to the personal information of users and the interaction information among different users. However, the social communication is affected by many factors, including social topology, user

behavior, and inherent content characteristics, and the social ties are a dynamic process that changes with time.

The study of social ties is conducive to understanding human behavior, which can be applied in viral spread [6], information recommendation [7], traffic planning, and complex socioeconomic phenomena [8]. Granovetter [9] first defined the social ties that are a combination of time, emotional intensity, intimacy, and reciprocity, which provides a theoretical basis for many researchers to analyze the linear combination of the four elements of social ties.

With the development of social network, the research of modeling the structure of social ties has been paid attention increasingly. In [10], the authors pointed out that strangers established social ties based on shared interests, career, or activities. Xiang et al. [11] proposed an unsupervised model, in which the social ties between users were regarded as a latent variable that caused interactive behaviors. Based on this idea, Zhao et al. [12] presented a probabilistic generative model, which considers life activities and moving patterns. However, Xiang et al. and Zhao et al. [11, 12] neglect the assignment of activity topics. Meanwhile, Xiong et al. [13] proposed a general framework to measure social ties by similarities, interaction activities, and the co-occurrence of users' names. In [14], the authors calculated social ties based on users' profile information and interaction activities in different activity fields. In [15], a language model based on sentiment classification, similarity, and interactivity was applied to compute social ties before adopting K-means clustering method to cluster the users. It is noteworthy that Zhao et al. and Ju and Tao [14, 15] both assume that social ties are a static constant, resulting that the dynamic behavior of social network cannot be analyzed.

In addition to the above theoretical studies on social ties, there are also some application scenarios that describe social ties [16–19]. In traditional social networking websites, modeling the social ties has a wide spectrum of applications [16, 17]. In [18], a graphical probabilistic model and Topical Affinity Propagation (TAP) approach were applied to study social ties and social influence, respectively. In [19], the spatiotemporal patterns of social ties were represented by the factors of the tensors. Yi et al. [20] proposed a dynamic model with social ties and self-confirmation mechanism, and verified the key role of social connections in information diffusion.

Inspired by the abovementioned work and based on the fact that the real world is a dynamic environment and it is difficult to gather accurate real-time date to track the changes of social ties, this paper attempts to utilize stochastic processes to study social ties. A stochastic mathematical model, which incorporates the combined effect of many factors such as interest, geographical position, career, social class, value system, and interaction, is proposed and analyzed. Specifically, the reliability function and adaptive parameter estimation are conducted. To illustrate the main results, some numerical examples are given at the end of this paper.

The subsequent materials of this paper are organized as follows. Section 2 formulates the stochastic model. Section 3 makes a mathematical analysis of this model. Some numerical examples are given in Section 4. Finally, Section 5 outlines this work.

## 2. Model Formulation

*2.1. Scenario Description.* Social tie is a key factor for the successful spread of video streaming among users in D2D communications. Since there are many influencing factors in social networks that affect the social tie between users, the social tie between users is dynamic, which will affect the success rate of D2D link establishment between users, thereby affecting communication performance. Based on the above description, the purpose of this paper is to build a dynamic model of social ties among social individuals for better understanding the D2D collaborative video transmission. As shown in Figure 1, considering a single-cell cellular network, there are $D$ D2D users $D = \{D_1, D_2, \ldots, D_D\}$ and $M$ cellular users $C = \{C_1, C_2, \ldots, C_M\}$ in the coverage area of the base station. At time $t = t_k$, users $D_1$ and $D_2$ establish a D2D communication link and reuse the spectrum resources of cellular user $C_2$. Between time $t = t_k$ and $t = t_{k+1}$, if $D_1$ and $D_2$ have a negative interaction, resulting that the strength of the social ties decreases and is below the trust threshold of user $D_1$. Then, at time $t = t_{k+1}$, users $D_1$ and $D_2$ cannot successfully communicate. Similarly, at time $t = t_k$, user $D_4$ needs to obtain the required video resources from $D_3$, and user $D_3$ is willing to share the data packet with $D_4$ if the physical conditions are met, then a trust relationship is established between $D_4$ and $D_3$ at time $t = t_{k+1}$. Based on this background, starting from the social level of users, a model of dynamic social ties between users is established. The strength of the social ties between any two users $i$ and $j$ can be regarded as a set of random variables $\{S_{ij}(t), t \geq 0\}$ that related to the time $t$.

*2.2. Model Assumption.* At any time $t$, $S_{ij}(t)$ can be defined as a random representation of the strength of social ties between individuals, then $\{S_{ij}(t), t > 0\}$ can be understood as a random process of social ties strength between individuals. To modeling and analysis of dynamic social ties $\{S_{ij}(t), t \geq 0\}$ between users $i$ and $j$ at any given time $t$, the following assumptions are imposed:

(A1) As the social ties between users $i$ and $j$ can be regarded as a random variable $S_{ij}(t)$, then for $\tau > 0$, let $\Delta S_{ij}(t) = S_{ij}(t+\tau) - S_{ij}(t)$ represent the change of $S_{ij}(t)$ during the interval $(t, t+\tau]$ and $S_{ij}(t) = \sum_{l=1}^{t} \Delta S_{ij}(l)$.

(A2) The social ties are influenced by many random factors, such as interest, geographical position, career, social class, value system, and interaction. Let a set of random variables $\{\xi_m(t), m \in N^+\}$ represent these random factors.

(A3) The random variables $\xi_1(t), \xi_2(t), \ldots, \xi_m(t), m \in N^+$ are independent of each other. Let $\Delta\xi_m(t)$ represent the change of $\xi_m(t)$.

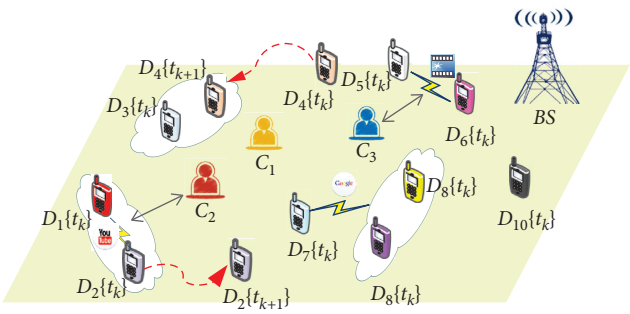


Figure 1: D2D collaborative video transmission scenario.

(A4) $\Delta\xi_1(t), \Delta\xi_2(t), \ldots, \Delta\xi_m(t), m \in N^+$ obey the same distribution. Let $E[\Delta\xi_m(t)] = \mu, D[\Delta\xi_m(t)] = \sigma^2 > 0$ and $\Delta S_{ij}(t) = \sum_{k=1}^{m} \Delta\xi_k(t)$.

**Lemma 1.** *$\{S_{ij}(t), t > 0\}$ is a Markov process.*

*Proof.* Assume that $S_{ij}(t_k) = S_{t_k}$, for any time $t = t_k, k \in N^+$. Then,

$$\begin{aligned} &P\left\{S_{ij}(t_k) \le S_{t_k} \,\middle|\, S_{ij}(t_1) = S_{t_1}, \ldots, S_{ij}(t_{k-1}) = S_{t_{k-1}}\right\} \\ &= P\left\{S_{ij}(t_k) - S_{ij}(t_{k-1}) \le S_{t_k} - S_{t_{k-1}} \,\middle|\, \Delta S_{ij}(t_1), \ldots, \Delta S_{ij}(t_{k-1})\right\} \\ &= P\left\{S_{ij}(t_k) \le S_{t_k} \,\middle|\, S_{ij}(t_{k-1}) = S_{t_{k-1}}\right\}. \end{aligned} \tag{1}$$

According to the above formula, one can get that, given the present state of the process, the future state is independent of the past. From the definition of Markov process in [21], the random variable $S_{ij}(t)$ satisfies the Markov property, and $\{S_{ij}(t), t > 0\}$ is called the Markov process. Thus, the proof is complete. □

**Lemma 2.** *The random variable $\Delta S_{ij}(t)$ obeys the normal distribution.*

*Proof.* From assumptions (A3) and (A4), the claimed result follows from the central limit theorem [22].

Collecting the foregoing assumptions and Lemmas 1 and 2, at time $t = t_k, k \in N^+$, the social ties $S_{ij}(t)$ can be modeled by the Wiener process with an adaptive drift, which can be expressed by the following stochastic system [23]:

$$\begin{aligned} &\{u(t_k) = u(t_{k-1}) + \eta W(t_k), \\ &S_{ij}(t_k) = S_{ij}(t_{k-1}) + u(t_{k-1})\Delta t_k + \alpha B(\Delta t_k), \end{aligned} \tag{2}$$

where $\Delta t_k = t_k - t_{k-1}$, $W(t_k)$ is a Brownian motion independent of $B(t_k)$ ($B(t_k)$ is the standard Brownian motion) and $W \sim N(0, Q)$, $Q$ is a constant, $u(t_k)$ is the drift parameter at $t_k$, and $\eta$ and $\alpha$ are diffusion coefficients of the adaptive drift and social ties, respectively. □

## 3. Model Analysis

*3.1. Reliability Function.* This section considers a liner model of system (2) based on a Wiener process as follows:

$$S_{ij}(t) = S_{t_0} + ut + \alpha B_t, \tag{3}$$

where $S_{t_0}$ is the observed social tie at $t = t_0$, $u$ is the drift parameter and $u_{t_k} \sim N(u_k, \sigma_k)$ at $t = t_k, k \in N^+$, and $B_t$ is the standard Brownian motion.

During the interaction, any two users $i$ and $j$ trust each other whether their relationship reaches to a given threshold $S_{ij}^T$ or not, $T = \{t \mid S_{ij}(t) \ge S_{ij}^T\}$ is the time that users trust each other for the first time. It is well known that the Probability Density Function (PDF) of $T$ follows inverse Gaussian distribution [24]. Then, it can be expressed as follows [25]:

$$F^T(t \mid u) = \frac{S_{ij}^T}{\sqrt{2\pi\alpha^2 t^3}} \exp\left(-\frac{\left(S_{ij}^T - ut\right)^2}{2\alpha^2 t}\right). \tag{4}$$

According to statistic characteristics and conditional distribution of the Wiener process, the cumulative distribution function (CDF) can be expressed as the following reliability function [24, 25]:

$$\begin{aligned} R^T(t \mid u) &= 1 - P\left(S_{ij}(t) \le S_{ij}^T\right) \\ &= 1 - \Phi\left(\frac{S_{ij}^T - ut}{\alpha\sqrt{t}}\right) + \Phi\left(-\frac{S_{ij}^T + ut}{\alpha\sqrt{t}}\right)\exp\left(-\frac{2uS_{ij}^T}{\alpha^2}\right), \end{aligned} \tag{5}$$

where $\Phi(\cdot)$ expresses the CDF of the standard normal random variable.

Combined the foregoing analysis, one of main results of this paper can be obtained as follows.

**Theorem 1.** *For the social tie process $\{S_{ij}(t), t > 0\}$ given by system (3), the PDF and CDF can be expressed as equations (4) and (5), respectively.*

*3.2. Adaptive Parameter Estimation.* In this section, the Kalman filtering [26] is applied to estimate the mean and variance of drift parameter $u$. On this basis, parameters $\alpha$ and $Q$ are estimated by the expectation-maximization (EM) algorithm [27].

For a given observation sample $\mathbf{S} = \{S_{t_1}, S_{t_2}, \ldots, S_{t_k}\}$, the observation equation of drift parameter $u$ forms a Kalman filtering framework. Let $u_{t_k}$ and $\sigma_{t_k}$ stand for the updated drift parameter and variance, respectively. Let $u_{t_k|t_{k-1}}$ and $\sigma_{t_k|t_{k-1}}$ represent the estimated mean and variance based on the previous moment, respectively. Therefore, the mean and variance of drift parameter $u$ can be derived from the following Kalman filtering equations for $k \in N^+$:

$$\begin{aligned} u_{t_k|t_{k-1}} &= u_{t_{k-1}}, \\ \sigma_{t_k|t_{k-1}} &= \sigma_{t_{k-1}} + \eta^2 Q, \\ K_k &= \sigma_{t_k|t_{k-1}} + \left(\sigma_{t_k|t_{k-1}} + \alpha^2\right)^{-1}, \\ u_{t_k} &= u_{t_{k-1}} + \sigma_{t_k|t_{k-1}} K_k \left(S_{t_k} - u_{t_k|t_{k-1}}\right), \\ \sigma_{t_k} &= (1 - K_k)\sigma_{t_k|t_{k-1}}. \end{aligned} \tag{6}$$

With initial conditions $u_{t_0} = u_0$ and $\sigma_{t_0} = \sigma_0$, $K_k$ is the Kalman gain.

The EM algorithm includes E-step and M-step, and it is necessary to take the expectation of the complete log-likelihood function in the first step, and then maximize the expectation to obtain estimated parameters until a convergence is achieved.

Let $\Theta = (u_0, \sigma_0, \alpha, Q)$ and $\mathbf{u} = \{u_{t_0}, u_{t_1}, \ldots, u_{t_{k-1}}\}$. Then, the complete log-likelihood function for $n$ points can be expressed as follows [28]:

$$L(\Theta, \mathbf{S}; \mathbf{u}) = \log\left[P\left(u_{t_0}; \Theta\right)\prod_{k=1}^{n-1} P\left(u_{t_k} \middle| u_{t_{k-1}}; \Theta\right)\prod_{k=1}^{n} P\left(S_{t_k} \middle| u_{t_{k-1}}; \Theta\right)\right], \tag{7}$$

where

$$\begin{aligned} u_{t_0} &\sim N(u_0, \sigma_0), \\ u_{t_k}\Big|u_{t_{k-1}} &\sim N\left(u_{t_{k-1}}, Q\right), \\ S_{t_k}\Big|u_{t_{k-1}} &\sim N\left(S_{t_{k-1}} + u_{t_{k-1}}(t_k - t_{k-1}), \sigma^2(t_k - t_{k-1})\right). \end{aligned} \tag{8}$$

By ignoring constant terms, the function $L(\Theta, \mathbf{S}; \mathbf{u})$ can be rewritten as follows:

$$\begin{aligned} 2L(\Theta, \mathbf{S}; \mathbf{u}) = &-\log\sigma_0 - \frac{\left(u_{t_0} - u_0\right)^2}{\sigma_0} - \sum_{k=1}^{n-1}\left(\log Q - \frac{\left(u_{t_k} - u_{t_{k-1}}\right)^2}{\sigma_0}\right) \\ &- \sum_{k=1}^{n}\left(2\log\alpha - \frac{\left(S_{t_k} - S_{t_{k-1}} - u_{t_{k-1}}\Delta t_k\right)^2}{\sigma^2\Delta t_k}\right). \end{aligned} \tag{9}$$

Next, $E(u_{t_k}^2 \mid \mathbf{S}, \Theta)$ and $E(u_{t_k}u_{t_{k-1}} \mid \mathbf{S}, \Theta)$ are calculated by the Rauch–Tung–Striebel (RTS) smoothing algorithm [29]. The backward iteration rules are as follows:

$$\begin{aligned} D_{t_{k-1}} &= \sigma_{t_{k-1}}\sigma_{t_k|t_{k-1}}^{-1}, \\ u_{t_{k|n}} &= u_{t_k} + D_{t_k}\left(u_{t_{k+1|n}} - u_{t_k}\right), \\ \sigma_{t_{k|n}} &= \sigma_{t_k|t_k} + D_{t_k}^2\left(\sigma_{t_{k+1|n}} - u_{t_{k+1}|t_k}\right), \end{aligned} \tag{10}$$

where $u_{t_{k|n}}$, $\sigma_{t_{k|n}}$, and $D_{t_{k-1}}$ are the RTS smoothing state estimation, variance, and gain function on the basis of the current estimated parameters, respectively. Then,

$$\begin{aligned} E\left(u_{t_k} \mid \mathbf{S}, \Theta\right) &= u_{t_{k|n}}, \\ E\left(u_{t_k}^2 \mid \mathbf{S}, \Theta\right) &= \sigma_{t_{k|n}} + u_{t_{k|n}}^2, \\ E\left(u_{t_k}u_{t_{k-1}} \mid \mathbf{S}, \Theta\right) &= D_{t_{k-1}}\sigma_{t_{k|n}} + u_{t_{k|n}}u_{t_{k-1|n}}. \end{aligned} \tag{11}$$

Let $E_u\{L(\Theta, \mathbf{S}; \mathbf{u})\}$ denote the conditional expectation of the complete log-likelihood function given $u_{t_k}$, $C_{t_k t_{k-1}|n} = E(u_{t_k}u_{t_{k-1}} \mid \mathbf{S}, \Theta)$, and $C_{t_k|n} = E(u_{t_k}^2 \mid \mathbf{S}, \Theta)$. Then,

$$\begin{aligned} E_u\{L(\Theta, \mathbf{S}; \mathbf{u})\} = &-\log\sigma_0 - \frac{C_{t_0|n} - 2u_0u_{0|n} + u_0^2}{\sigma_0} \\ &+ \sum_{k=1}^{n-1}\left(\log\frac{1}{Q} - \frac{C_{t_k|n} + C_{t_{k-1}|n} - 2C_{t_k t_{k-1}|n}}{Q}\right) \\ &- \sum_{k=1}^{n}\left(2\log\alpha + \frac{\left(S_{t_k} - S_{t_{k-1}}\right)^2 + (t_k - t_{k-1})^2 C_{t_{k-1}|n}}{\alpha^2(t_k - t_{k-1})}\right) \\ &+ \sum_{k=1}^{n}\frac{2\left(S_{t_k} - S_{t_{k-1}}\right)(t_k - t_{k-1})u_{t_{k-1|n}}}{\alpha^2(t_k - t_{k-1})}. \end{aligned} \tag{12}$$

Finally, the estimation of parameters can be obtained by maximizing the complete log-likelihood function in (12).

## 4. Numerical Examples

Some numerical examples are given to illustrate the main results of this paper in this section.

*Example 1.* Consider system (2) with initial conditions $u_0 = 0.1$, $\sigma_0 = 0.1$, $n = 50$, and $S_{ij}^T = 0.7$. The social tie sample $\mathbf{S}$ is randomly produced by obeying normal distribution. Figure 2 shows the estimated mean and variance of the drift parameter $u$ and the square of diffusion coefficients $\alpha^2$ and $Q$.

*Example 2.* Consider system (2) with initial conditions $u_0 = 0.1$, $\sigma_0 = 0.1$, $n = 3$, and $S_{ij}^T = 0.7$. The social tie sample $\mathbf{S}$ is randomly produced by obeying normal distribution. Figure 3 displays the probability density function of achieving social trust for the first time.

*Example 3.* Consider system (2) with initial conditions $u_0 = 0.1$, $\sigma_0 = 0.1$, $n = 3$, and $S_{ij}^T = 0.7$. The social tie sample $\mathbf{S}$ is randomly produced by obeying normal distribution. Figure 4 shows the reliability of social tie over time. As time increases, the reliability between users gradually increases with time. In addition, at the same time point, the greater the drift coefficient, the greater the reliability.

*Example 4.* Consider system (2) with initial conditions $u_0 = 0.1$, $\sigma_0 = 0.1$, and $n = 50$. The social tie sample $\mathbf{S}$ is randomly produced by obeying normal distribution. Figure 5 reveals the variation curve of the estimated social tie strength under adaptive and fixed drift coefficient, respectively. The changes of social tie over time are not monotonous, and the interaction process is positive or negative. The estimated values obtained from the two methods have the same trend as the observed values, and the model has a good predictive ability. In addition, the predicted value

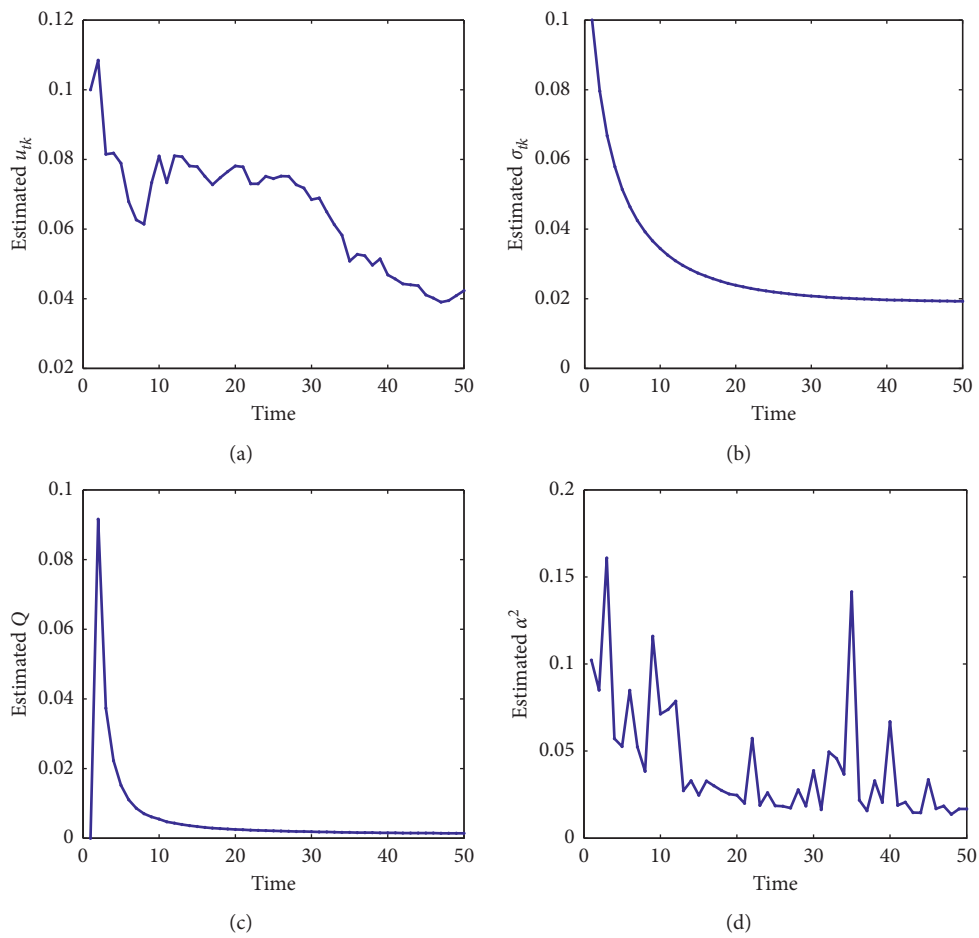


Figure 2: The estimated parameters for system (2) with initial conditions given in Example 1.

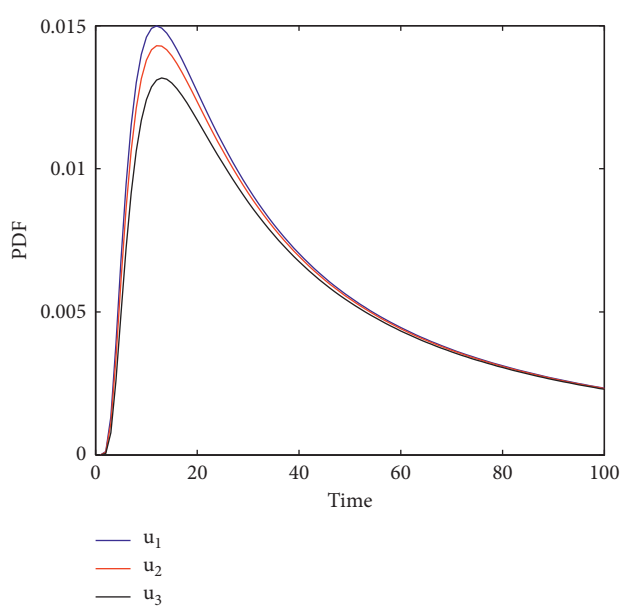


Figure 3: The PDF of achieving social trust for system (2) with initial conditions given in Example 2.

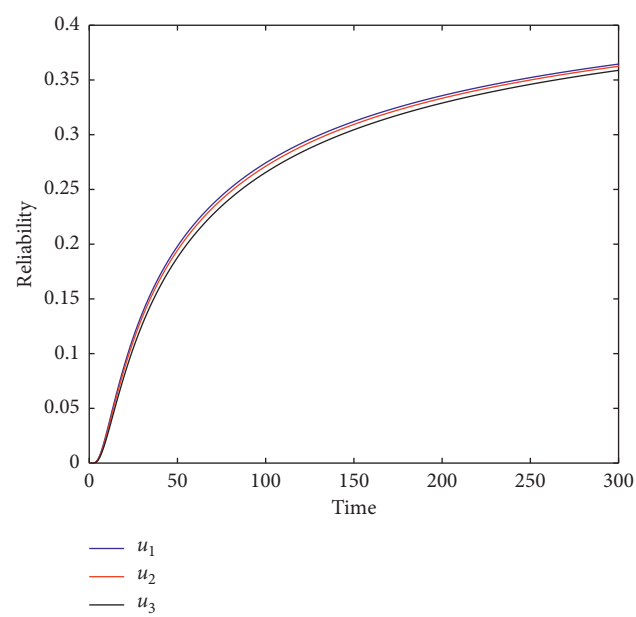


Figure 4: The reliability of social tie for system (2) with initial conditions given in Example 3.

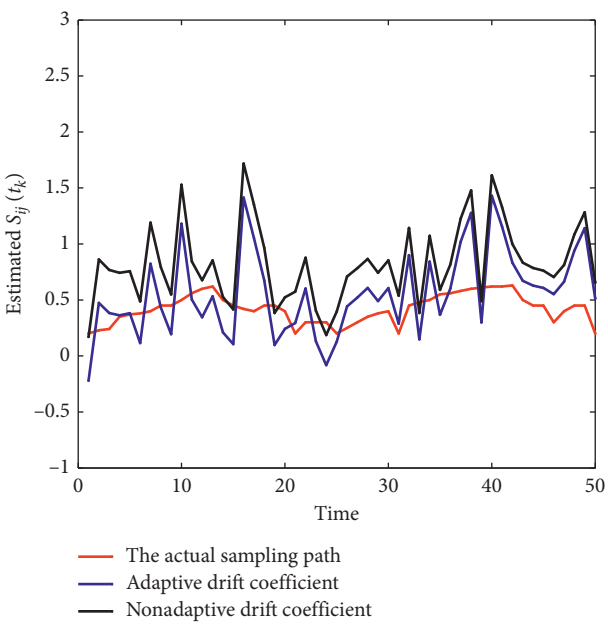


Figure 5: The estimated social tie for different drift parameters with initial conditions given in Example 4.

obtained by updating the drift parameter is closer to the real value than that of the fixed drift parameter.

## 5. Conclusions and Future Work

In this paper, a stochastic mathematical model describing the social ties, which incorporates the combined effect of many factors, such as interest, geographical position, career, social class, value system, and interaction, has been proposed and analyzed. The reliability function and adaptive parameter estimation have both been determined. To illustrate the main results, some numerical examples have been given at the end of this paper. This work contributes to the understanding of social phenomena.

As research based on the background of big data and artificial intelligence gradually enters people's vision [30, 31], our proposed model can also open up new research directions under this background. For example, using artificial intelligence methods to abstract and analyze multidimensional features such as network behavior, content attributes, positional relationships, structural features, and privacy protection policies. In addition, the data in the social network is dynamic and transmitted in the form of data streams. The linking and generation of relationships are constantly changing, and the popularity of the video will also change over time. For large-scale dynamic networks, it is of great significance to further study efficient dynamic models and algorithms for video transmission.

## Data Availability

Data sharing is not applicable to this article as no datasets were generated.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Authors' Contributions

The authors claim that the research was realized in collaboration with the same responsibility. All authors read and approved the last version of the manuscript.

## Acknowledgments

This work was supported by the Natural Science Foundation of China (Grant nos. 61702066 and 11747125), Major Project of Science and Technology Research Program of Chongqing Education Commission of China (Grant no. KJZD-M201900601), Chongqing Research Program of Basic Research and Frontier Technology (Grant nos. cstc2017jcyjAX0256 and cstc2018jcyjAX0154), Project Supported by Chongqing Municipal Key Laboratory of Institutions of Higher Education (Grant no. cqupt-mct-201901), Technology Foundation of Guizhou Province (QianKeHeJiChu [2020]1Y269), and New Academic Seedling Cultivation and Exploration Innovation Project (QianKeHe Platform Talents [2017]5789-21).

## References

[1] Y. Yi, Z. Zhang, L. Yang, C. Gan, X. Deng, and L. Yi, "Reemergence modeling of intelligent information diffusion in heterogeneous social networks: the dynamics perspective," *IEEE Transactions on Network Science and Engineering*, 2020.

[2] C. Gan, X. Li, L. Wang, and Z. Zhang, "The impact of user behavior on information diffusion in D2D communications: a discrete dynamical model," *Discrete Dynamics in Nature and Society*, vol. 2018, Article ID 3745769, 9 pages, 2018.

[3] Y. Cao, T. Jiang, X. Chen, and J. Zhang, "Social-aware video multicast based on device-to-device communications," *IEEE Transactions on Mobile Computing*, vol. 15, no. 6, pp. 1528–1539, 2016.

[4] Z. Wang, H. Shah-Mansouri, and V. W. S. Wong, "How to download more data from neighbors? A metric for D2D data offloading opportunity," *IEEE Transactions on Mobile Computing*, vol. 16, no. 6, pp. 1658–1675, 2017.

[5] Z. Zhang, T. Zeng, X. Yu, and S. Sun, "Social-aware D2D pairing for cooperative video transmission using matching theory," *Mobile Networks and Applications*, vol. 23, no. 3, pp. 639–649, 2018.

[6] C. Gan, Q. Feng, Q. Zhu, Z. Zhang, Y. Zhang, and Y. Xiang, "Analysis of computer virus propagation behaviors over complex networks: a case study of Oregon routing network," *Nonlinear Dynamics*, vol. 100, no. 2, pp. 1725–1740, 2020.

[7] Z. Zhao, H. Lu, D. Cai, X. He, and Y. Zhuang, "User preference learning for online social recommendation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 28, no. 9, pp. 2522–2534, 2016.

[8] X. Hu, T. H. S. Chu, V. C. M. Leung, E. C.-H. Ngai, P. Kruchten, and H. C. B. Chan, "A survey on mobile social networks: applications, platforms, system architectures, and future research directions," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 3, pp. 1557–1581, 2015.

[9] M. Granovetter, "The strength of weak ties: a network theory revisited," *Sociological Theory*, vol. 1, no. 6, pp. 201–233, 1983.

[10] D. M. Boyd and N. Ellison, "Social network sites: definition, history, and scholarship," *IEEE Engineering Management Review*, vol. 38, no. 3, pp. 210–230, 2010.

[11] R. Xiang, J. Neville, and M. Rogati, "Modeling relationship strength in online social networks," in *Proceedings of the ACM International Conference on World Wide Web*, pp. 981–990, ACM, Raleigh, NC, USA, April 2010.

[12] W. X. Zhao, N. Zhou, W. Zhang, J.-R. Wen, S. Wang, and E. Y. Chang, "A probabilistic lifestyle-based trajectory model for social strength inference from human trajectory data," *ACM Transactions on Information Systems*, vol. 35, no. 1, pp. 1–28, 2016.

[13] L. Xiong, Y. Lei, W. Huang, X. Huang, and M. Zhong, "An estimation model for social relationship strength based on users' profiles, co-occurrence and interaction activities," *Neurocomputing*, vol. 214, pp. 927–934, 2016.

[14] X. Zhao, J. Yuan, G. Li, X. Chen, and Z. Li, "Relationship strength estimation for online social networks with the study on Facebook," *Neurocomputing*, vol. 95, pp. 89–97, 2012.

[15] C. Ju and W. Tao, "A novel relationship strength model for online social networks," *Multimedia Tools and Applications*, vol. 76, no. 16, pp. 17577–17594, 2017.

[16] J. Sang and C. Xu, "Right buddy makes the difference: an early exploration of social relation analysis in multimedia applications," in *Proceedings of the 20th ACM international conference on Multimedia-MM'12*, ACM, Nara Japan, pp. 19–28, 2012.

[17] C. Huang, D. Wang, J. Tao, and B. Mann, "On physical-social-aware localness inference by exploring big data from location-based services," *IEEE Transactions on Big Data*, 2017.

[18] J. Tang, J. Sun, C. Wang, and Z. Yang, "Social influence analysis in large-scale networks," in *Proceedings of the ACM Sigkdd International Conference on Knowledge Discovery and Data Mining*, ACM, Paris, France, pp. 807–816, 2009.

[19] B. Yang, H. Pei, H. Chen, J. Liu, and S. Xia, "Characterizing and discovering spatiotemporal social contact patterns for healthcare," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 8, pp. 1532–1546, 2017.

[20] Y. Yi, Z. Zhang, and C. Gan, "The effect of social tie on information diffusion in complex networks," *Physica A: Statistical Mechanics and Its Applications*, vol. 509, pp. 783–794, 2018.

[21] O. Ibe, *Fundamentals of Applied Probability and Random Processes*, Academic Press, Cambridge, MA, USA, Second edition, 2014.

[22] B. W. Gnedenko, "Limit distributions for sums of independent random variables," *Mathematical Gazette*, vol. 39, no. 330, pp. 264–343, 1953.

[23] X.-S. Si, Z. X. Zhang, and C. H. Hu, "An adaptive prognostic approach via nonlinear degradation modeling: application to battery data," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 8, pp. 5082–5096, 2015.

[24] G. Jin, D. Matthews, Y. Fan, and Q. Liu, "Physics of failure-based degradation modeling and lifetime prediction of the momentum wheel in a dynamic covariate environment," *Engineering Failure Analysis*, vol. 28, pp. 222–240, 2013.

[25] Y. S. Sherif and M. L. Smith, "First-passage time distribution of Brownian motion as a reliability model," *IEEE Transactions on Reliability*, vol. 29, no. 5, pp. 425-426, 1980.

[26] A. Harvey, *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, Cambridge, MA, USA, 1989.

[27] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via theEMAlgorithm," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 39, no. 1, pp. 1–22, 1977.

[28] H. Li, D. Pan, and C. L. P. Chen, "Reliability modeling and life estimation using an expectation maximization based wiener degradation model for momentum wheels," *IEEE Transactions on Cybernetics*, vol. 45, no. 5, pp. 969–977, 2015.

[29] L. L. Cam, "Maximum likelihood: an introduction," *International Statistical Review/Revue Internationale de Statistique*, vol. 58, no. 2, pp. 153–171, 1990.

[30] Z. Zhang, C. Wang, C. Gan, S. Sun, and M. Wang, "Automatic modulation classification using convolutional neural network with features fusion of SPWVD and BJD," *IEEE Transactions on Signal and Information Processing Over Networks*, vol. 5, no. 3, pp. 469–478, 2019.

[31] C. Gan, L. Wang, Z. Zhang, and Z. Wang, "Sparse attention based separable dilated convolutional neural network for targeted sentiment analysis," *Knowledge-Based Systems*, vol. 188, pp. 1–10, 2020.