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ORIGINAL PAPER

Analysis of layered information dissemination model and caching strategy in Social Internet of Things

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Abstract In recent years, the social Internet of Things (SIoT) and its applications have developed rapidly and introduced convenience to people's lives. In view of the massive amount of information generated by the SIoT, it is necessary to model and analyze the communication among smart devices and study the impact of social attributes of smart devices on information dissemination. Therefore, in this study, we propose a layered information dissemination model for SIoT that abstracts the communication process in SIoT as the information dissemination process among nodes, describes the process of wireless communication in SIoT using the microscopic Markov chain method, and derives the information dissemination threshold based on theoretical analyses. In addition, this study proposes a dynamic cache strategy considering the influence of social attributes, such as user interestingness, information popularity, and the interaction between messages on communication. Finally, the correctness of the model and propagation threshold and the effectiveness of the caching strategy are verified by simulation experiments in artificial networks and real networks.

Keywords Social Internet of Things · Complex network · Information dissemination model · Propagation threshold · Dynamic cache strategy

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1 Introduction

Following the rapid development of the Internet of Things (IoT), IoT technologies are extensively used in smart cities, smart manufacturing, and other related fields. IoT devices have been integrated into people's daily lives, thus promoting the intelligent interaction between people and devices and improving people's life experience [1, 2]. Social IoT (SIoT) introduces social attributes into the IoT and establishes a social network among smart IoT devices, thus promoting the collaboration among these devices and improving people's quality of life [3–5]. However, the current research on

SIoT and its applications is still limited by the limited computational resources, and most algorithms used are too complex and require long computation times. Therefore, it is important to conduct research on SIoT.

Complex networks have high-complexity characteristics and can be used to represent various complex systems in the real world [6, 7]. By abstracting individuals in complex systems as nodes, complex networks effectively reduce the complexity of analysis and calculation and provide a new research approach for SIoT. The complex network method can be used to model the information transmission process of the SIoT, and the study of the impact of the social attributes of smart devices on information dissemination will help formulate reasonable communication strategies, thus improving communication efficiency and reducing communication delays. Therefore, an increasing number of scholars have been using complex networks in the study of SIoT in many fields [8–10].

Extensive research has been conducted on SIoT and provided several solutions. Son et al. [11] proposed a trust-aware recommendation system using the decision support system based on SIoT; this system used social interaction information to improve the opinion garbage problem in the recommendation system and improved the prediction accuracy of user preferences. Zhu et al. [12] considered the social relationship between devices in IoT and proposed a cache strategy based on social perception incentives. According to this strategy, if the cost of caching is less than the cost of obtaining the content, the node is listed as a cache node; this effectively reduces the system delay. Zhang et al. [13] considered factors such as interest, geographical location, and individual social class, modeled dynamic social relations in the process of device-to-device (D2D) collaborative communication using random methods, and proposed an improved content caching strategy that combined the similarity between users and user mobility that improved the stability and efficiency of communication. Yi et al. [14] proposed postquantum ring signatures to solve the privacy and security problems induced by the current centralized SIoT system and proposed a blockchain system based on ring signatures. This system can ensure security against both conventional and quantum computers, thus indicating that the blockchain system is suitable for the SIoT. Marche et al. [15] analyzed and discussed various types of attacks that may affect the trust of the IoT and finally proposed a trust management model that can overcome all analytical attacks. Simulation results showed that the model can isolate almost all malicious nodes in the network effectively; however, it requires a large amount of data to achieve convergence. Xiao et al. [16] considered the influences of contextual information fusion based on correlation coefficient and memory network with branch structure on sentiment analysis, proposing a hierarchical self-attention fusion model that can capture contextual information between utterances efficiently and a contextual self-attention temporal convolution network that can perform sentiment recognition in SIoT. Simulation results showed that the hybrid model proposed by them outperformed the current models. Khelloufi et al. [17] proposed a service recommendation system based on the social relationship between device owners in which the recommendation was based on different relationships between service requesters and service providers. The experimental results showed that in the SIoT environment, incorporating users' social relationships into service recommendations can improve the accuracy and diversity of provided services. Zhang et al. [18] developed a secure edge-assisted computing scheme based on the SIoT, defined the security requirements that the algorithm should meet in the scheme, and provided two security algorithm examples. Theoretical analysis and experimental results verified the effectiveness and security of the algorithm. However, the existence of an abstract modeling method for the communication process in the SIoT is still lacking, and the analysis and research of SIoT communication need to be improved further.

In recent years, an increasing number of scholars have studied information transmission models in complex networks. Xiao et al. [19] proposed multi-information and multiway network models by considering the interaction between different information and the diversity of transmission paths and introduced influence factors to describe the complex interactions among different types of information. The dynamic equation of the model was established based on the microscopic Markov chain method, and the influences of the network structure on information transmission were studied. Liu et al. [20] proposed an information dissemination model based on the Weibo social network according to complex network theory and topological characteristics of scale-free networks and studied the information interaction mechanism and diffusion mode in social networks. Wang et al. [21] proposed an information dissemination prediction method based on the dynamic analysis of user roles and topic influences, introduced the topic popularity value, combined the dynamic analysis of user roles and topic influence with the weighted probability model, and accurately predicted the information dissemination in social networks from the perspectives of users and topics. Jia et al. [22] divided information transmission into two communication channels, that is, point-to-point and group transmissions, and optimized the traditional susceptible-infected-recovered (SIR) model. According to the mean field theory, they established the corresponding dynamic equation and theoretically analyzed the model's stability and bifurcation phenomenon. The simulation results verified the correctness of the theory and analyzed the influences of the information dissemination mechanism on the dissemination results. Li et al. [23] regarded the information transmission process caused by emergencies as the competition process of actual and false information, discussed the characteristics of information transmission in different stages, proposed an emergency information transmission model based on competition relations, and studied the control strategy of information transmission. Dang et al. [24] quantified the information energy according to the edge weight and the length of the reachable path between nodes in the network, which determined the probability of information transmission and competition behavior, and constructed the behavior transmission and adversarial competition model based on information energy. Experimental results on artificial networks show that open and tightly connected networks are more conducive to information dissemination. In addition, people's interest in information dissemination is the key to the success of competitive behavior when it appears in the network. Wan et al. [25] constructed a game choice information dissemination model based on the three social factors of opportunity, trust, and game selection in social networks and calculated the social trust threshold by considering comprehensively user influences and content contribution; on this basis, they then studied the game of user information dissemination. The experimental results showed that users' social trust can accelerate the spread of information in the Weibo social network. In the referred research, the number of research on modeling wireless communications in SIoT using complex network information propagation models was relatively small, and the social attributes, such as the communication relationship between information promotion, information popularity, and user interest in SIoT, had not been fully utilized.

To sum up, there are two main problems in the current research on SIoT. First of all, the traditional research methods of the SIoT are highly complex and difficult to model. The communication process between devices in the social Internet of things has not been well modeled and studied. Second, the current research on social attributes in the SIoT is still insufficient, and these attributes need to be taken into account in the modeling process of the SIoT.

To solve the problems listed above from the perspective of information dissemination, this study proposes a layered information dissemination model (L-SICR) for SIoT that abstracts the communication in SIoT as the process of information dissemination between nodes. The propagation dynamics equation of the model is established by using the microscopic Markov chain method, and the information propagation threshold is analyzed theoretically. Aiming at the problem of long delay caused by waiting cache in wireless communication of social Internet of things caused by not making full use of social attributes, we formulate a dynamic cache strategy (DCS) that combines the user's social attributes and information popularity to optimize the caching and deletion of information in SIoT communication. Finally, simulation experiments are conducted on actual and artificial networks. The main contributions of this study are as follows:

1. The communication between devices in the SIoT is abstracted as an information dissemination process, and a hierarchical information dissemination model for the SIoT is proposed. The propagation dynamics equation of the model is established based on the microscopic Markov chain method, and the information dissemination threshold of the coupling network is analyzed theoretically.
2. Considering the social attributes of users, the popularity of information, and the interaction between related information, a dynamic cache strategy is formulated to improve the communication efficiency between devices. According to the social attributes of users and the popularity of information, the strategy mines users' potential

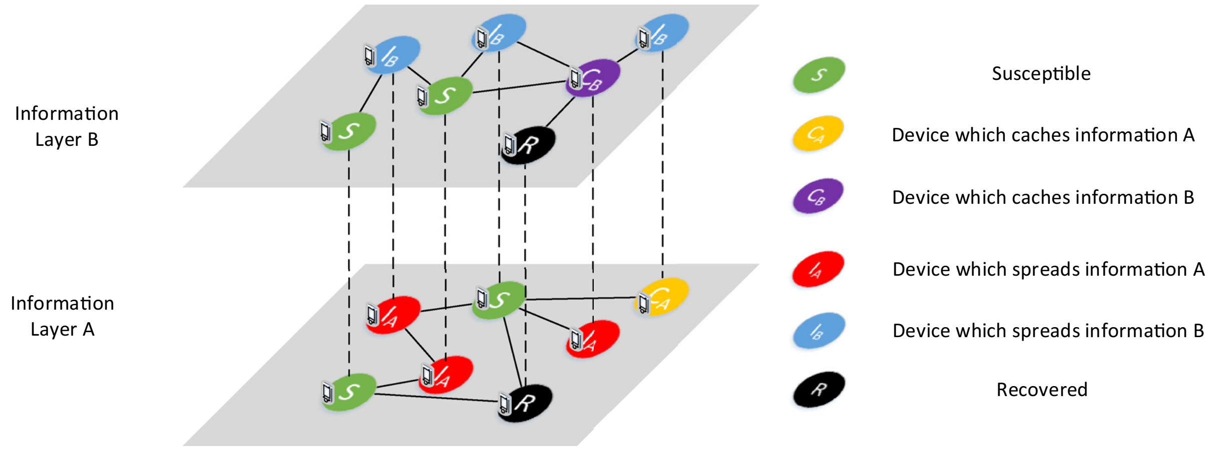

Fig. 1 Social Internet of Things (SIoT) with dual information dissemination

demands for cached information, realizes more reasonable caching and deletion of information, and reduces the delay caused by users' waiting for cached information.

The organization of this study is as follows: Sect. 2 introduces the L-SICR information propagation model. Section 3 uses the microscopic Markov chain method to construct the dynamic equation of the information propagation model and analyzes the propagation threshold of the model. Section 4 introduces the dynamic cache strategy. Section 5 introduces the real network and artificial network L-SICR model simulation experiments. Finally, conclusions are presented in Sect. 6.

2 L-SICR model

This study considers a SIoT communication scenario subject to the environment of massive smart devices. In this scenario, smart devices will share information via direct terminal connection. When an event occurs, multiple related information may be generated. That is, information A and (related) B is transmitted simultaneously on the network. For the scenario in which the two different information types A and B are generated by the same event, we define an L-SICR layered information dissemination model to describe information dissemination in the SIoT, as shown in Fig. 1. We abstracted smart devices as nodes in the network and divided the network into two information layers, wherein information layer A describes the propagation of information A, and information layer B describes the propagation of information B. We assumed that the solid black line in the middle layer of the figure describes the communication connections between different devices in the same information layer, and the dashed black line between layers describes different states that the same device may be in in different information layers [26, 27].

For the propagation of information A, the device may be in one of four states: not getting information (Susceptible, S), spreading information A (Infected A, I_A), cache information A (Cache A, C_A), or not spreading information (Recovered, R). For the propagation of information B, the device may be in one of four states: S, spreading information B (Infected B, I_B), cache information B (Cache B, C_B), or R.

The SIoT can be modeled according to the complex network theory according to which all types of communication devices can be represented by the node set $\text{Node} = (N_1, N_2, \ldots, N_N)$, and communication links established between nodes of different devices can be represented by the adjacency matrix, where A_{adj} represents the connection of information dissemination layer A, and B_{adj} represents the connection of the information dissemination layer B [28, 29]:

$$A_{adj} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1j} \\ a_{21} & a_{22} & \cdots & a_{2j} \\ \vdots & \cdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} \end{bmatrix}, \quad (1)$$

$$B_{adj} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1j} \\ b_{21} & b_{22} & \cdots & b_{2j} \\ \vdots & \cdots & \ddots & \vdots \\ b_{i1} & b_{i2} & \cdots & b_{ij} \end{bmatrix}. \tag{2}$$

By considering comprehensively the node states in the two-layer SIoT network, the nodes in the L-SICR model can be divided into seven categories, as shown in Fig. 2. Node S is the device that has not been exposed to information A and B in SIoT. Susceptible–Infected A (SI_A) indicates that the device in SIoT is spreading information A, and cache requests for information B have not been initiated. Susceptible–Infected B (SI_B) indicates that the device in SIoT is spreading information B, and requests for information A have not been initiated cache. The Infected A–Infected B (I_AI_B) state refers to the device that transmits both information A and B in SIoT. Infected B–Cache A (I_BC_A) represents the state in which the device spreads information B in SIoT and the initiation of the cache request for information A. Infected A–Cache B (I_AC_B) represents the state in which the device transmits information A and initiates the cache request for information B in SIoT. R, which does not spread information, represents the user in SIoT who is not interested in the current event, and neither spreads information A nor B.

The node state transition mode in the SIoT is shown in Fig. 2 and adheres to the following rules:

(1) All users are in a relatively closed environment, that is, in the process of information transmission, the number of devices will not increase or decrease [30].

(2) $S \to SI_A$, $S \to SI_B$, $SI_B \to I_AI_B$, $SI_A \to I_AI_B$
When S node's neighbors are nodes that spread information A (SI_A and I_AI_B), its neighbors will spread information A to that S node with probability β_A. When S node's neighbors are nodes that spread information B (SI_B and I_AI_B), its neighbors will spread information B to that S node with a probability of β_B. Assuming that the neighbors of node i have independent influence on it, the probability $f_i^{A'}$ of this node receiving information A is

$$f_i^{A'} = 1 - \prod_j \left[1 - a_{ij}\beta_A\left(P_j^{SI_A}(t) + P_j^{I_AC_B}(t) + P_j^{I_AI_B}(t)\right)\right]. \tag{3}$$

Similarly, the probability $f_i^{B'}$ of this node receiving information B is

$$f_i^{B'} = 1 - \prod_j \left[1 - b_{ij}\beta_B\left(P_j^{SI_B}(t) + P_j^{I_BC_A}(t) + P_j^{I_AI_B}(t)\right)\right]. \tag{4}$$

This process is represented by the solid red line in Fig. 2.

(3) $SI_A \to I_AC_B$, $SI_B \to I_BC_A$
After receiving information A (becomes SI_A), the node will initiate a cache request for related information B with a probability equal to η_B, thus becoming the cache request node I_AC_B. After receiving information B (becomes SI_B), the node initiates A cache request for related information A with a probability equal to η_B, thus becoming cache request node I_BC_A. The cache requesting node causes the cumulative waiting delay while waiting for the cache. This process is represented by the solid yellow line in Fig. 2.

(4) $I_AC_B \to I_AI_B$, $I_BC_A \to I_AI_B$
When cache request node I_BC_A sends a request for cache information A, its neighboring nodes (in the state of spreading information A) (SI_A, I_AC_B, and I_AI_B) will spread information A to it with a probability equal to β_A. When the cache request node I_AC_B sends a request to cache information B, its neighboring nodes in the state of spreading information B (SI_B, I_BC_A, and I_AI_B) will spread information B to it with a probability equal to β_B. In this case, the probability that the I_BC_A node caches

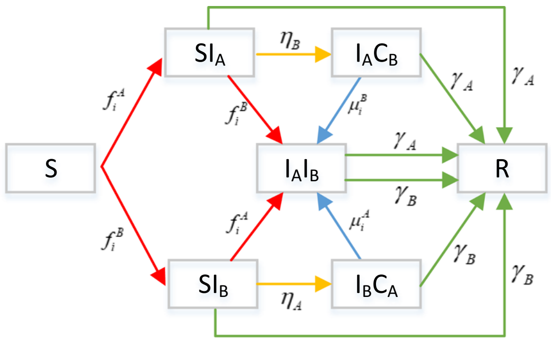

Fig. 2 Node state transition process in the SIoT

information A is $\mu_i^{A'} = f_i^{A'}$, and the probability that the I_AC_B node caches information B is $\mu_i^{B'} = f_i^{B'}$. This process is represented by the solid blue line in Fig. 2.

(5) $SI_A \to R$, $SI_B \to R$, $I_AC_B \to R$, $I_BC_A \to R$, $I_AI_B \to R$
When nodes spreading information A (SI_A, I_AC_B, and I_AI_B) lose interest in one of the two types of information, they will delete the cache of information A with probability γ_A, will become an immune state R, and will no longer pay attention to the event. When the nodes spreading information B (SI_B, I_BC_A, and I_AI_B) lose interest in one of the two types of information, they will delete the cache containing information B with probability γ_B, will become an immune state R, and will no longer pay attention to the event. When the node no longer pays attention to the event, it no longer receives and spreads information A and B. This process is represented by the solid green line in Fig. 2.

3 Model analysis

We constructed the dynamic equation of L-SICR model based on the microscopic Markov chain method to describe the information dissemination process in SIoT, as follows:

$$\begin{cases} P_i^{SI_A}(t+1) = P_i^S(t) f_i^{A'}\left(1-f_i^{B'}\right) + P_i^{SI_A}(t)(1-\eta_B)(1-\gamma_A)\left(1-f_i^{B'}\right) \\ P_i^{SI_B}(t+1) = P_i^S(t) f_i^{B'}\left(1-f_i^{A'}\right) + P_i^{SI_B}(t)(1-\eta_A)(1-\gamma_B)\left(1-f_i^{A'}\right) \\ P_i^{I_AC_B}(t+1) = P_i^{SI_A}(t)\eta_B(1-\gamma_A)\left(1-f_i^{B'}\right) + P_i^{I_AC_B}(t)\left(1-\mu_i^{B'}\right)(1-\gamma_A) \\ P_i^{I_BC_A}(t+1) = P_i^{SI_B}(t)\eta_A(1-\gamma_B)\left(1-f_i^{A'}\right) + P_i^{I_BC_A}(t)\left(1-\mu_i^{A'}\right)(1-\gamma_B) \\ P_i^{I_AI_B}(t+1) = P_i^{SI_A}(t) f_i^{B'}(1-\gamma_A)(1-\eta_B) + P_i^{SI_B}(t) f_i^{A'}(1-\gamma_B)(1-\eta_A) \\ \quad + P_i^{I_AC_B}(t)\mu_i^{B'}(1-\gamma_A) + P_i^{I_BC_A}(t)\mu_i^{A'}(1-\gamma_B) \\ \quad + P_i^{I_AI_B}(t)(1-\gamma_A)(1-\gamma_B) \\ P_i^R(t+1) = P_i^{SI_A}(t)\gamma_A(1-\eta_B)\left(1-f_i^{B'}\right) + P_i^{SI_B}(t)\gamma_A(1-\eta_A)\left(1-f_i^{A'}\right) \\ \quad + P_i^{I_AC_B}(t)\gamma_A\left(1-\mu_i^{B'}\right) + P_i^{I_BC_A}(t)\gamma_B\left(1-\mu_i^{A'}\right) \\ \quad + P_i^{I_AI_B}(t)(\gamma_A+\gamma_B) \end{cases} \tag{5}$$

As there are only seven states of nodes in the network, and the total number of nodes in the network is fixed, it is easy to obtain the following:

$$\begin{aligned} P_i^S(t+1) = 1 &- P_i^{SI_A}(t+1) - P_i^{SI_B}(t+1) \\ &- P_i^{I_AI_B}(t+1) \\ &- P_i^{I_AC_B}(t+1) - P_i^{I_BC_A}(t+1) \\ &- P_i^R(t+1) \end{aligned} \tag{6}$$

The propagation threshold is an important parameter which can be used to analyze the information dissemination in the network. It describes the conditions and influencing factors indicating whether information can be transmitted in the network. The propagation threshold of the model will be theoretically deduced and analyzed next.

Firstly, Eq. (5) can be rewritten as follows:

$$\vec{P}(t+1) = f\left(\vec{P}(t)\right), \tag{7}$$

where

$$\begin{aligned} \vec{P}(t) = \Big(&\vec{P}^{SI_A}(t), \vec{P}^{SI_B}(t), \vec{P}^{I_AC_B}(t), \\ &\vec{P}^{I_BC_A}(t), \vec{P}^{I_AI_B}(t)\Big) \end{aligned} . \tag{8}$$

$\vec{P}^{SI_A}(t) = \left(P_1^{SI_A}, P_2^{SI_A}, \ldots, P_N^{SI_A}\right)$
In addition, $\vec{P}^{SI_B}(t)$, $\vec{P}^{I_AC_B}(t)$, $\vec{P}^{I_BC_A}(t)$ and $\vec{P}^{I_AI_B}(t)$ are calculated in the same way.

Lemma 1 *When the system satisfies Eq. (7), if the absolute values of the eigenvalues of $\nabla g(P*)$ are all less than one, then the system is asymptotically stable at $P* = \vec{0}$ points [31–34], and its Jacobian matrix can be expressed by the following equation*:

$$J = [\nabla g(P*)]_{m,n} = \frac{\partial f_{m,t+1}}{\partial P_{n,t}}\bigg|_{P_n = P*}. \tag{9}$$

To analyze the propagation threshold, it is necessary to solve the Jacobian matrix when the system satisfies $\nabla g(P*)$. In this case, the Jacobian matrix of the system at $P* = \vec{P}(t) = \left(\vec{0}, \vec{0}, \vec{0}, \vec{0}\vec{0}\right)$ is as follows:

$$J\left(\vec{0},\vec{0},\vec{0},\vec{0}\vec{0}\right)=\begin{bmatrix} Q_1 & Z & Z & Z & Z \\ Z & Q_2 & Z & Z & Z \\ Q_6 & Z & Q_3 & Z & Z \\ Z & Q_7 & Z & Q_4 & Z \\ Q_8 & Q_9 & Q_{10} & Q_{11} & Q_5 \end{bmatrix}. \tag{9}$$

Z is an all-zero matrix. Given that the Jacobian matrix is a lower triangular matrix, the calculation of its eigenvalues is determined only by submatrix $Q_1 \sim Q_5$; thus, submatrix $Q_6 \sim Q_{11}$ is not discussed. The value of submatrix $Q_1 \sim Q_5$ is shown below:

$$\begin{cases} Q_1 = (1-\eta_B)\left(1-\gamma^A\right)E + \beta^A A_{adj} \\ Q_2 = (1-\eta_A)\left(1-\gamma^B\right)E + \beta^B B_{adj} \\ Q_3 = \left(1-\gamma^A\right)E \\ Q_4 = \left(1-\gamma^B\right)E \\ Q_5 = \left(1-\gamma^A\right)\left(1-\gamma^B\right)E \end{cases} \tag{10}$$

where E is the identity matrix. According to Lemma 1, when the system is stable at $P* = \vec{0}$, the absolute value of the eigenvalue of the Jacobian matrix is less than one. Thus, the following conditions can be obtained:

$$\mathrm{Max}\begin{Bmatrix} \left|(1-\eta_B)\left(1-\gamma^A\right)E + \beta^A \lambda_A\right|, \\ \left|(1-\eta_A)\left(1-\gamma^B\right)E + \beta^B \lambda_B\right|, \\ \left|\left(1-\gamma^A\right)E\right|, \\ \left|\left(1-\gamma^A\right)\left(1-\gamma^B\right)E\right|. \end{Bmatrix} < 1. \tag{11}$$

where $\lambda_x, x \in (A,B)$ is the largest eigenvalue of the adjacency matrix. The adjacency matrices A_{adj} and B_{adj} are non-negative and irreducible symmetric. According to the Perron–Frobenius theorem, $\lambda_x, x \in (A,B)$ are positive real numbers. Because $1 \geq \gamma_i^A \geq 0$ and $1 \geq \gamma_i^B \geq 0$, the conditions satisfying Eq. (12) can be rewritten as follows:

$$\begin{cases} (1-\eta_B)(1-\gamma_A) + \beta^A \lambda_A < 1 \\ (1-\eta_A)(1-\gamma_B) + \beta^B \lambda_B < 1 \end{cases} \Rightarrow \begin{cases} \dfrac{\beta^A}{\eta_B + \gamma_A - \eta_B\gamma_A} < \dfrac{1}{\lambda_A} \\ \dfrac{\beta^B}{\eta_A + \gamma_B - \eta_A\gamma_B} < \dfrac{1}{\lambda_B} \end{cases} \tag{12}$$

Therefore, when the conditions in Eq. (13) are met at the same time, there will be no information dissemination in the network. It can be observed that network structure, information transmission, cache request, and cache clearance rates all affect the information propagation threshold.

4 Dynamic cache strategy

The cache strategy with fixed cache probability cannot be dynamically adjusted according to the demand of changing communications, and it will cause a large delay when many cache requests are received in the L-SICR model scenario. To solve these problems, this study proposes a DCS scheme based on the prediction results of user social attributes and information popularity.

This strategy takes into account three characteristics that are not considered in traditional strategies and exist in the information dissemination of SIoT: (1) the popularity of different information is different, and the information spread by nodes is affected by the popularity of information, (2) different nodes pay different attentions to the same information, and the information transmission process will be affected by the node's interest in the information. (3) When most of the neighbors of a node are states in which they do not receive the information, the local information popularity is low, and the neighbor of the node may potentially demand the information; thus, the device needs to consider the local popularity when deleting the cache. Therefore, this study proposes a DCS for the process of information caching and cache deletion in SIoT communications. The strategy consists of three mechanisms: caching mechanism based on interest degree and global information popularity, increasing the interest degree, and cache deletion mechanism based on the number of neighbors.

The working flow of DCS is shown in Fig. 3: at time t, check which state the node is in. If the state is in R, this means that the device is not interested in the current event and will no longer participate in information dissemination. If the device is in the S state, this indicates that the device does not contact any information and uses the cache mechanism. If the device is neither in the R nor in the S states, this indicates that the device has received the information and needs to consider whether to delete the cache. If the device deletes the cache, it changes into the R state and ends. If the device does not delete the cache, the device is still involved in information dissemination and determines the information obtained by the node. If the node has obtained all the information (information A and information B), it does not consider obtaining information from other nodes. If the node only obtains part of the information, then the interest degree raising mechanism is used to increase the probability of obtaining the information that has not been obtained. Finally, the cache mechanism is used to cache the information that has not been obtained. Thus, the DCS ends at time t. The pseudocode of DCS is shown as Algorithm 1.

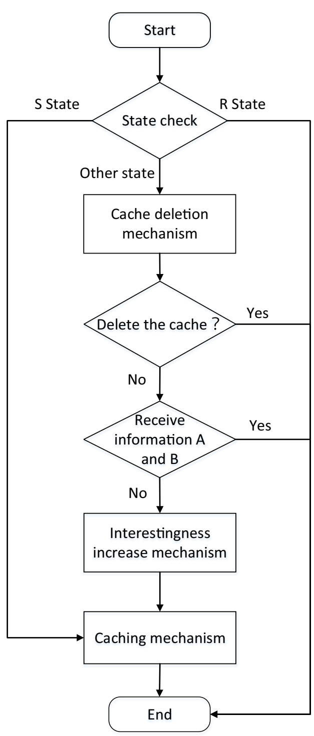

Fig. 3 Flow chart of dynamic cache strategy (DCS)

Algorithm 1: Dynamic Cache Strategy

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Input: A_adj, B_adj, N, N_SI_A(t), N_SI_B(t), N_I_A I_B(t),
       N_I_A C_B(t), N_I_B C_A(t), α, δ, τ
Output: μ_i^A(t), μ_i^B(t), γ_A^i(t), γ_B^i(t)
for each node do
    if this node in R state then
        Continue;
    else if this node in S state then
        Caching mechanism based on interest and
         global information popularity;
    else
        Cache deletion mechanism based on local
         information popularity;
        if this node has deleted the cache or has
         obtained all information then
            continue;
        else
            Mechanism of interest level increase;
             Caching mechanism based on interest and
             global information popularity;
        end
    end
end
```

4.1 Caching mechanism based on interest and global information popularity

The caching mechanism based on interest and information popularity considers the node's interest in information and the information popularity predicted by the information propagation model and calculates comprehensively the caching probability at the current moment. When the information popularity is low, the device cache probability is also low to avoid the waste of storage resources caused by excessive caching. When the information popularity is high, the device cache probability is also high; this speeds up the information transmission and reduces the communication delay. This study defines the node's interest in information A and B. The greater the node's interest is, the stronger the node's acceptance of the information and the greater the probability of receiving and forwarding the information will be [35]. The node's interest in information A and information B is defined as:

$$R_x = \left({r_x}^1, {r_x}^2, \ldots, {r_x}^i\right)^T, i \in (1, N), x \in (A, B). \tag{13}$$

where ${r_x}^i$ represents the interest of node i in the content of information x and N is the total number of nodes in the network. In addition, definition $p_x(t)$ is the popularity of information x, and the popularity is the proportion of nodes that propagate x information and request x information cache in the total nodes at the current moment is expressed as:

$$p_A(t) = \frac{N_{SI_A}(t) + N_{I_AI_B}(t) + N_{I_AC_B}(t) + N_{I_BC_A}(t)}{N}, \tag{14}$$

$$p_B(t) = \frac{N_{SI_B}(t) + N_{I_AI_B}(t) + N_{I_AC_B}(t) + N_{I_BC_A}(t)}{N}. \tag{15}$$

where $N_{SI_A}(t), N_{SI_B}(t), N_{I_AI_B}(t), N_{I_AC_B}(t), N_{I_BC_A}(t)$ represent the numbers of various nodes.

In real life, when the popularity of a certain information increases, the node accepts the information easier; accordingly, the probability of receiving and spreading the information is increased. Considering the factors listed above, the probability of information dissemination is defined as the weighted sum of nodes interest and information popularity according to

$$\beta_x{}^i(t) = \alpha r_x{}^i + \delta p_x(t), i \in (1, N), x \in (A, B). \tag{16}$$

where the information transmission probability $\beta_x{}^i$ is the probability that a neighboring node to node i transmits information x to it, and α and δ are the weights of node interest and information popularity, respectively. Thus, the probability of node i receiving information A and B subject to a DCS can be obtained as follows:

$$\begin{aligned} f_i^A(t) =& 1 - \prod_j \Big[1 - a_{ij}\beta_A^i \Big(P_j^{SI_A}(t) \\ & + P_j^{I_AC_B}(t) + P_j^{I_AI_B}(t) \Big) \Big], \end{aligned} \tag{17}$$

$$\begin{aligned} f_i^B(t) =& 1 - \prod_j \Big[1 - b_{ij}\beta_B^i \Big(P_j^{SI_B}(t) \\ & + P_j^{I_BC_A}(t) + P_j^{I_AI_B}(t) \Big) \Big]. \end{aligned} \tag{18}$$

4.2 Mechanism of interest level increase

When a node receives information A and spreads it, to obtain more event information, it may be interested in the derived information or related information B of information A; thus, it is more likely to receive information B and spread it. In the same way, when a node receives information B, it will also be interested in its related information A. Therefore, this study proposes a mechanism to increase the interest levels of nodes, that is, when a node receives a specific type of information, it will increase the interest level in the relevant information to cache the relevant information with a higher probability to promote the rapid dissemination of information, expand the dissemination range of information, and reduce the communication delay caused by caching. By multiplying the set rate of increase in interest level τ and interest level r_{xi}, the probability of node i neighbors spreading information to node i with the mechanism of interest level increase is $\beta_x{}^{i*}$,

$$\beta_x{}^{i*}(t) = (1 + \tau)\alpha r_x{}^i + \delta p_x(t), i \in (1, N), x \in (A, B) \tag{19}$$

Thus, in the case of DCS, the probability of caching information A and B of the cache requesting node i after the interest level is increased and can be obtained as follows:

$$\begin{aligned} \mu_i^A(t) =& 1 - \prod_j \Big[1 - a_{ij}\beta_A^{i*} \Big(P_j^{SI_A}(t) \\ & + P_j^{I_AC_B}(t) + P_j^{I_AI_B}(t) \Big) \Big], \end{aligned} \tag{20}$$

$$\begin{aligned} \mu_i^B(t) =& 1 - \prod_j \Big[1 - b_{ij}\beta_B^{i*} \Big(P_j^{SI_B}(t) \\ & + P_j^{I_BC_A}(t) + P_j^{I_AI_B}(t) \Big) \Big]. \end{aligned} \tag{21}$$

4.3 Cache deletion mechanism based on local information popularity

After receiving the information, the node will delete the information with a certain probability and will no longer pay attention to the event. The traditional equal probability deletion method does not consider the local information popularity and ignores the potential cache requirements. Therefore, this study proposes a cache deletion mechanism based on local information popularity, which is defined as the ratio of the number of neighbors who have received the information to the total number of neighbors. When many neighbor devices have not received the information, the local information popularity is low. Therefore, the node reduces the probability of deleting the cache information so that the neighboring node can provide the content required by the neighbor as soon as possible when the caching demand is imposed. When most neighboring devices have received the information, the local information popularity is high. Therefore, the node increases the probability of deleting the cache information and reduces the unnecessary waste of cache resources. The cache deletion probability after adding the cache deletion mechanism based on local information popularity is shown as follows:

$$\gamma_i^A(t) = \gamma_A\left[1 - a_{ij}\left(P_j^S(t) + P_j^{SI_B}(t) + P_j^{I_B C_A}(t)\right)\right], \tag{22}$$

$$\gamma_i^B(t) = \gamma_B\left[1 - b_{ij}\left(P_j^S(t) + P_j^{SI_A}(t) + P_j^{I_A C_B}(t)\right)\right]. \tag{23}$$

where ${\gamma_A}^i(t)$ is the probability that node i deletes the cache of information A at time t, and ${\gamma_B}^i(t)$ is the probability that node i deletes the cache of information B at time t.

5 Simulation results and analysis

In this section, we conduct simulation experiments on actual network and manually generated network datasets. The software used in the simulation experiment was MATLAB R2018b. Firstly, we verify the correctness of the propagation threshold of the model. Then, through comparison and simulation, it is proved that the proposed DCS can effectively reduce the delay caused by waiting for cache. Finally, the influence of interest degree and network structure on the communication of SIoT under DCS is studied.

5.1 Network structure

Considering the characteristics that most devices have according to which only a few connections and a few devices involve many connections in SIoT communications, we used a scale-free network to simulate device links in SIoT. The network is characterized by serious heterogeneity, and the connections among its nodes are unevenly distributed. A few core nodes have more connections, while most nodes have few connections, which is consistent with the distribution of device links in the SIoT communication scenario. In addition, considering the social nature of the device connection, we also used for the experiment an employee relationship network from an actual enterprise.

Artificial network: Information layers A and B are both scale-free network structures; however, the nodal connections of the network are different. We use the Barabási–Albert (BA) scale-free network model with $N = 2000$ and $M = 3$, where M represents the number of connected edges of a new node after its addition. In this scale-free network, layer A and layer B both show obvious uneven connections. It can be seen from the maximum and average degree values that many nodes in this network have only a few connections, and very few nodes have close to 100 connections.

Actual network[1]: We used a social network dataset of enterprise employees, which included networks composed of (a) employee device connections, (b) employee colleague relations, and (c) employee friend relations, which contained 71 nodes and 2223 connected edges. We used the colleague relationship network as information layer A, and the friend relationship network as information layer B. In this actual network, the average degree of nodes in layer A and layer B is very large, the nodes are very closely connected, and the average path length is small, which reflects the characteristics of small-world network, and also makes the information propagation speed in this network faster than that in scale-free network.

The relevant statistical outcomes of the network datasets are listed in Table 1.

5.2 Propagation threshold analysis

According to the conclusion of the theoretical analysis in Sect. 3, the conditions subject to which information can spread in the SIoT is $\frac{\beta^A}{\eta_B+\gamma_A-\eta_B\gamma_A} < \frac{1}{\lambda_A}$ and $\frac{\beta^B}{\eta_A+\gamma_B-\eta_A\gamma_B} < \frac{1}{\lambda_B}$, which will be verified by numerical simulation analysis in the BA scale-free network. In Fig. 4, the abscissa represents the propagation time in milliseconds, and the ordinate represents the proportion of nodes in percentage.

Scenario 1: $\frac{\beta^A}{\eta_B+\gamma_A-\eta_B\gamma_A} < \frac{1}{\lambda_A}$, $\frac{\beta^B}{\eta_A+\gamma_B-\eta_A\gamma_B} < \frac{1}{\lambda_B}$
According to Fig. 4a, in scenario 1, the numbers of SI_A, SI_B, and $I_A I_B$ rapidly decrease to zero, and the

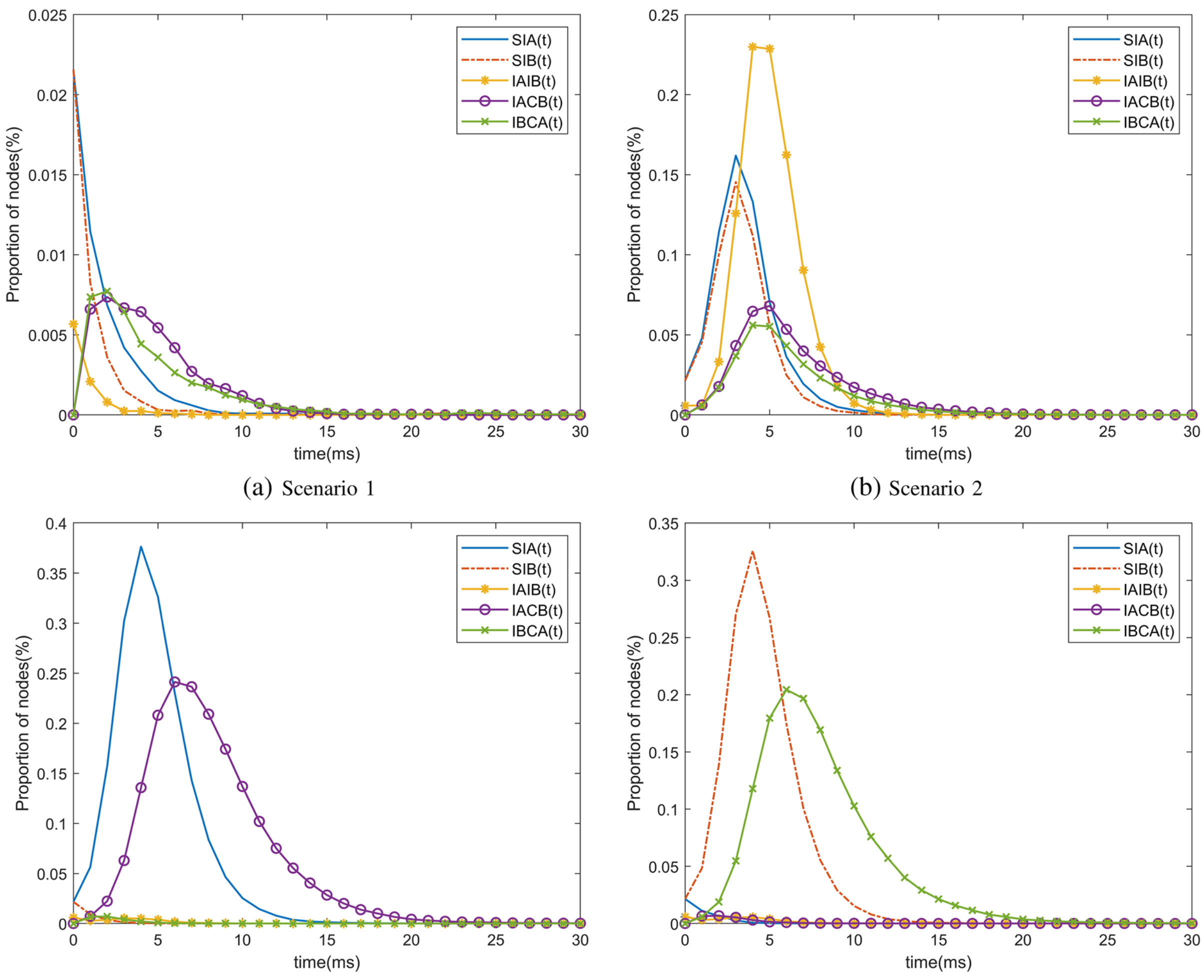
[1] Dataset: https://manliodedomenico.com/data.php.

Table 1 Statistics of network datasets

Network datasets	Information layer	Number of nodes	Number of edges	Maximum degree	Average degree
BA scale-free network	A	2000	5991	96	5.991
	B	2000	5956	105	5.956
Actual network	A	71	726	45	20.4507
	B	71	399	28	11.2394

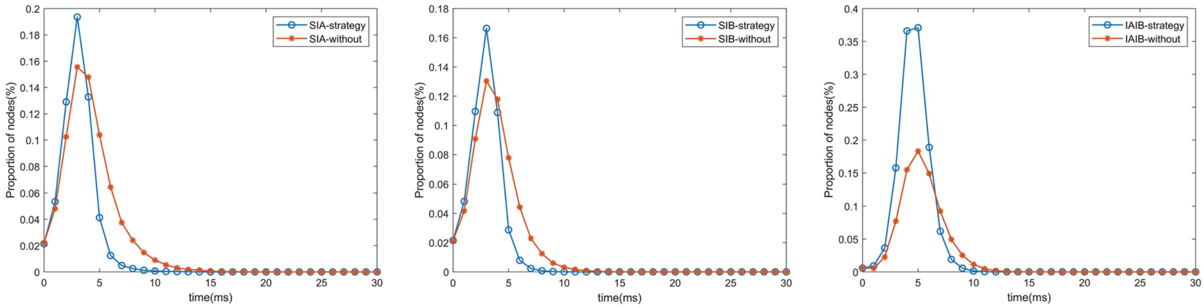
numbers of I_AC_B and I_BC_A increase in the initial stage because some initial nodes are interested in the information and initiate cache requests. However, when the cache requirements are met, the number of nodes soon drop to zero. Thus, subject to the threshold condition of scenario 1, neither information A nor information B can propagate in the network.

Scenario 2: $\frac{\beta^A}{\eta_B+\gamma_A-\eta_B\gamma_A} > \frac{1}{\lambda_A}$, $\frac{\beta^B}{\eta_A+\gamma_B-\eta_A\gamma_B} > \frac{1}{\lambda_B}$ According to Fig. 4b, subject to the condition of scenario 2, each nodal number increases rapidly and



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3 (d) Scenario 4

Fig. 4 Information propagation with or without the DCS in an actual network



(a) Changes in the proportion of SI_A **(b)** Changes in the proportion of SI_B **(c)** Changes in the proportion of I_AI_B

Fig. 5 Information propagation with or without the DCS in a BA scale-free network

soon reaches the peak, information flow is achieved by mass communication in SIoT, and the information of A and B undergoes heat fading, irrespective of whether the number of nodes SI_A, SI_B, and I_AI_B, or I_AC_B and I_BC_A cache request nodal numbers began to decline. After a period of time, the dissemination process ends and the number of nodes decreases to zero. Thus, subject to the threshold condition of scenario 2, both information A and B can be propagated in the network.

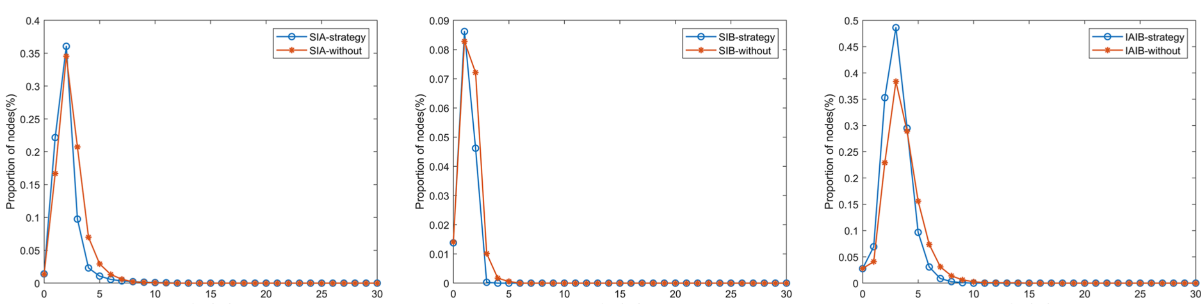
Scenario 3: $\frac{\beta^A}{\eta_B+\gamma_A-\eta_B\gamma_A} > \frac{1}{\lambda_A}, \frac{\beta^B}{\eta_A+\gamma_B-\eta_A\gamma_B} < \frac{1}{\lambda_B}$

According to Fig. 4c, subject to scenario 3, the numbers of SI_A and I_AC_B increase rapidly, and information A is propagated in the network; however, the number of SI_B and I_BC_A keeps decreasing and soon decreases to zero. Thus, subject to the threshold condition of scenario 3, information A can propagate in the network; however, information B will not propagate and will disappear quickly.

Scenario 4: $\frac{\beta^A}{\eta_B+\gamma_A-\eta_B\gamma_A} < \frac{1}{\lambda_A}, \frac{\beta^B}{\eta_A+\gamma_B-\eta_A\gamma_B} > \frac{1}{\lambda_B}$

According to Fig. 4d, subject to scenario 4, the numbers of SI_B and I_BC_A increase rapidly, and information B is propagated extensively in the network; however, the numbers of SI_A and I_AC_B keeps decreasing and soon reduces to zero. Thus, in the case of the threshold condition of scenario 4, information B can propagate in the network; however, information A will not propagate and will disappear quickly.

Combination of Fig. fig.4c, d, yields an interesting inference: although individual information A or B propagates extensively in SIoT, the number of I_AI_B does not surge but drops to zero quickly after a short and small increase, thus indicating that the broad propagation of one piece of information cannot drive the propagation of relevant information. If two pieces of relevant information will be propagated in the network at the same time, their propagation threshold conditions need to be met at the same time.



(a) Changes in the proportion of SI_A (b) Changes in the proportion of SI_B (c) Changes in the proportion of I_AI_B

Fig. 6 Information propagation with or without the DCS in an actual network

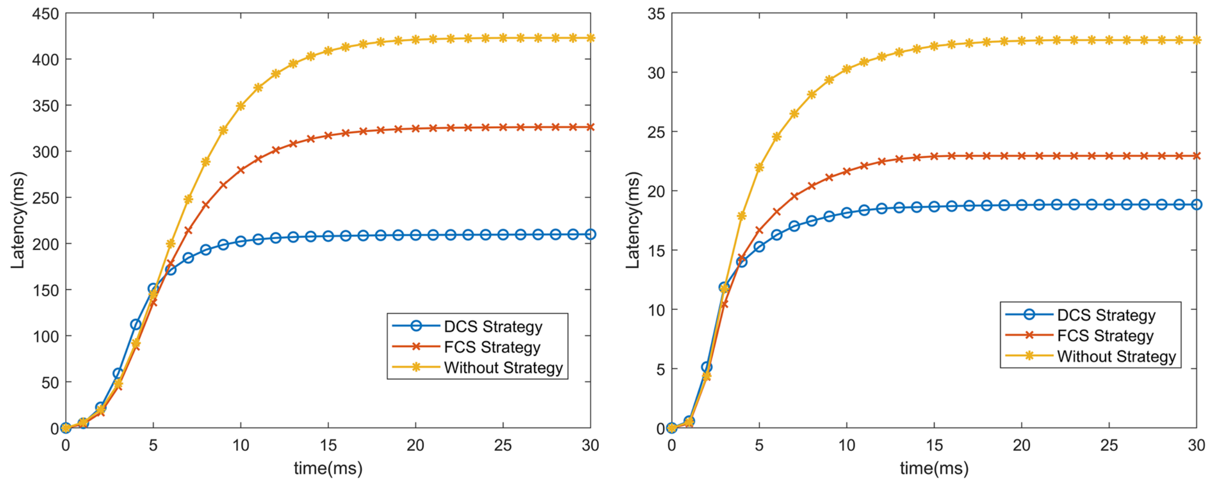
5.3 Analysis of information propagation subject to the DCS

We apply herein the DCS to the proposed L-SICR information propagation model and study the information propagation process subject to it. We set $\alpha = \delta = 0.5$, $\eta_A = 0.3$, $\eta_B = 0.2$, $\gamma_A = 0.3$, $\gamma_B = 0.2$, and the initial proportion of each node is $S = 93\%$, $SI_A = SI_B = 2.25\%$, $I_A I_B = 0.5\%$, $I_A C_B = I_B C_A = 0\%$, and $R = 2\%$. The abscissas in Figs. 5 and 6 represent the propagation time in milliseconds, and the ordinates represent the proportions of nodes in percentage.

Maximum infection peak (MIP) refers to the ratio between the maximum number of devices in the state of transmitter and the total number of nodes [36]. This index is used to represent the speed of information diffusion. The larger the MIP, the larger the scale of information dissemination in unit time, leading to a wider coverage of information. Figures 5 and 6 show that the DCS effectively improves MIP, expands the information transmission range per unit time, reduces the information transmission time, and improves the communication efficiency of SIoT. By comparing each figure in Figs. 5 and 6, it can be seen that the DCS is more effective in BA scale-free network than in enterprise employee relationship network. This is because in the enterprise employee network, the network connection is closer than the BA scale-free network, the average node degree in the network is higher, and the device has a very high probability of receiving information. As a result, the effect of dynamic caching strategy is not obvious.

Figure 7 shows the cumulative delay caused by the device waiting for caching with DCS, freshness-aware cache strategy (FCS) [37], and without strategy. As the number of nodes in the BA scale-free network is higher than that in the enterprise employee relationship network, the cumulative delay is also higher. In Fig. 7, the abscissa represents the propagation time in milliseconds, and the ordinate represents the cumulative delay in milliseconds. Figure 7 shows that the DCS reduces the communication delay in SIoT in both networks, and the communication delay generated is smaller than that generated by FCS. This is because the DCS considers the caching requirements of cache devices and provides more devices to disseminate information when information is spread on a large scale. In addition, the effect of dynamic caching policy is more obvious in the BA scale-free network. This is because the employee relationship network is closely connected. Correspondingly, the device that sends the cache request will soon receive the information transmitted by other devices; thus, the effects of DCS are not obvious.

Figure 8 shows the variation in communication delay caused by different interest increase rates in a BA scale-free network. We set $\alpha = \delta = 0.5$, $\eta_A = 0.25$, $\eta_B = 0.15$, $\gamma_A = 0.35$, $\gamma_B = 0.25$, and the initial proportion of each node is $S = 93\%$,



(a) BA scale-free network (b) Actual network

Fig. 7 Device waits for the cache delay with or without DCS

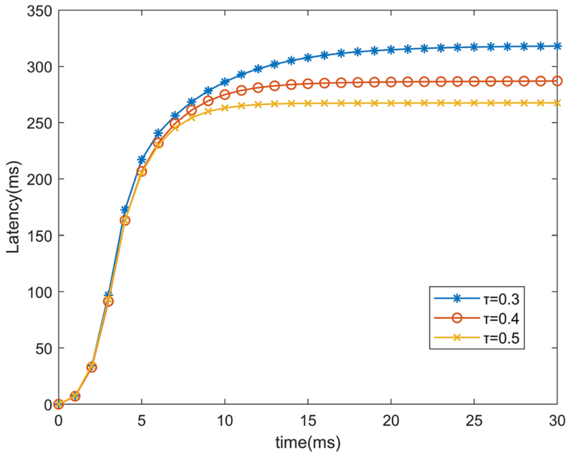


Fig. 8 Effect of interest rate increase on time delay

$SI_A = SI_B = 2.25\%$, $I_AI_B = 0.5\%$, $I_AC_B = I_BC_A = 0\%$, and $R = 2\%$. In Fig. 8, the abscissa represents the propagation time in milliseconds, and the ordinate represents the cumulative delay in milliseconds. As shown in Fig. 8, with the increase in interest rate, the time delay caused by devices waiting for cache in the whole network keeps decreasing, effectively reducing the communication delay in the SIoT. This is because the interest rate improvement mechanism improves interest in relevant information being transmitted, thus caching relevant information with a higher probability. In this way, the waiting time for information cache is shortened and the information spread in the network is accelerated.

6 Conclusion

In this study, the communication process of SIoT was regarded as an information dissemination process, and the L-SICR information dissemination model was proposed. Based on the microscopic Markov chain method, the dynamic equation was established and the information dissemination threshold was derived; accordingly, a DCS was formulated based on the node's social attributes and information popularity. The simulation results based on artificial and actual networks proved the correctness of the model threshold and the effectiveness of DCS and showed that DCS is more effective in the sparsely connected network.

In future work, we will model the information dissemination process in the cloud edge collaborative scenario in the SIoT. The information dissemination model can also be applied to other scenarios, and the influence of dynamic network, user mobility, and the strengths of the social attributes among users on information dissemination can be considered.

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Data availability Data available on request from the authors.

Declarations

Conflict of 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.

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