A Content Freshness Enhancement with Infrastructures in Mobile Opportunistic Networks

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Abstract—**In mobile opportunistic networks, we investigate the effect of infrastructures on content update process. In the network, an information provider continuously generates a time-sensitive content (e.g., news, twits or military commands) whose freshness decreases with time. This information is propagated to users throughout opportunistic contacts. Users prefer to have the more recently generated (i.e., up-to-date) content. In that, they utilize a content age to compare their freshness and share only the smaller age content when an opportunistic contact occurs.**

Based on this update process, here we analyze the freshness enhancement of users by adding an infrastructure to the contact-based network. This scenario is available when new communication technologies such as satellite or AWACS are used in the network. We propose several content update rules which reflect network environments and users access the infrastructure to update content by following the rules. It is reasonably expected that users receive a freshness improvement under the use of infrastructures. However, to quantify the enhancement degree is not well-defined until now and remains challenging.

By using an ODE model, we show the degree of freshness improvement which users receive. We explain the reasoning of how our model can capture the user freshness and derive an analytical solution for each suggested rule. To validate our approach, we test our update rules on real traces and compare the results between our analytical solutions and ones from traces.

I. Introduction

Constructing a communication infrastructure and defining its feasible use are important in several networks, as it directly relates to the network performance such as reliability, delay and energy consumption. When a local infrastructure is not allowed due to constraints, an ad-hoc network has been widely considered as an alternative. This approach has many applications for military purposes and sensor devices are frequently used to construct a temporary network [1], [2], [3], [4]. Sensors can build a mesh network by static installations and they also support a Delay Tolerant Network (DTN) as mobile relays [5].

For the purpose of *content updates*, we consider a network where sensors are utilized as mobile relays. In there, an information provider keeps renewing a *time-sensitive* content, while mobile users update the content by depending on opportunistic contacts. A time-sensitive content means that its information freshness (i.e., worth) decreases with time (e.g., news, traffic information or commands in military operation). Mobile users preserve the more recently generated content between encounters in that they prefer up-to-date information for the content. This contact-based update may not be suitable for the delivery of time-sensitive contents, as users suffer a large delay for an update when the contact rate is low.

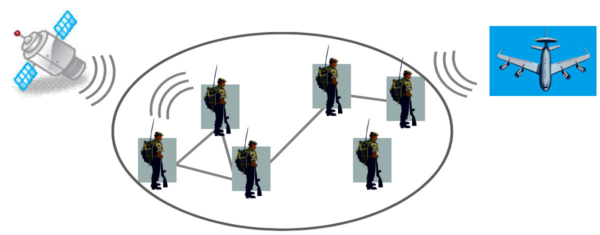

Fig. 1. When new technologies are added to mobile opportunistic networks, it can intuitively provide the better content freshness for users. However, to quantify the degree of improvement is not well-measured and challenging.

The emergence of new communication technologies can relax this problem. For example, in a military operation, a satellite or an Airborne Warning and Control System (AWACS) is deployed in operation areas. They can provide a temporary communication infrastructure in a short time as shown in Fig.1. In this paper, we are interested in the enhancement of content update process when the infrastructures are added to a contact-based network.

It is crucial to *quantify* the effectiveness of new technologies. In mobile opportunistic networks, [6] analyzes the reduction degree of packet transmission delay by installing base-stations and relays. Also, for databases, [7], [8] show the improvement of data consistency under the use of several cache update schemes.

In a similar manner, we measure the enhancement of content freshness when an infrastructure is additionally used in mobile opportunistic networks (i.e., a hybrid-structure). Under the consideration of device limitations (e.g., portability, energy-limitation or cost), we define several update rules. Users utilize opportunistic contacts and they also access the infrastructure as occasion demands by the rules for updates. Due to the content dependency of our update process, we clarify that our work has a fundamental difference from [6] which also analyzes the effect of infrastructures in mobile opportunistic networks. To distinguish this dependency, we utilize the concept of *content-age* which is used in [9], [10], [11]. We model the freshness changes according to the use of different update rules and quantify the freshness improvement that users receive.

The remainder of this paper is as follows: In section 2, we explain the difference between our update process and

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the approach in [6]. Then, we formulate an update problem under the existence of an infrastructure. Section 3 provides the reasoning for our modeling and shows the freshness variation under each update rule. We also provide numerical comparisons among suggested rules. In section 4, our update rules are tested on real-traces and we compare the result to our analytical expectations. After that, we conclude this paper.

II. Background and Problem Formulation

By using the example of epidemic content propagation, we clarify the difference of our update process from [6]. After that, we define "content freshness" and "update process" and formulate our content update problem with an infrastructure in mobile opportunistic networks.

A. Multi-Packet Delivery in Epidemic Routing

In DTNs, connectivity among network users is not always guaranteed. To overcome this shortcoming, each user utilizes a *store* and *forward* scheme with the role of *relay* and *sink* at a same time. Epidemic routing guarantees a minimum transmission delay in the network. In paper [6] which analyzes the improvement of content propagation by infrastructures, mobile users still follow the epidemic routing when a contact occurs. Specifically, the delay measure of it is based on an Ordinary Differential Equation (ODE) model of epidemic routing [12]. Before this, Markov Chain (MC) models have been used to estimate a packet delay in epidemic routing [13]. The ODE model comes from the fluid-limit of the MC. Under a feasible scaling, the ODE solution can substitute to solve the MC with less complexity [12], [14].

To emphasize the difference between our update process and [6], we briefly show an ODE model for a packet delay in epidemic routing. Suppose a network with N users whose pair-wise meeting rate is β and set $I(t)$ and $P(t)$ as the number of content holders (i.e., infected) and the delay CDF (i.e., $P(t) = \Pr(T_d < t)$), respectively. Then, an ODE model for epidemic routing is:

$$I'(t) = \beta I(t)(N - I(t)), \quad P'(t) = \beta I(t)(1 - P(t)) \qquad (1)$$

With initial conditions $I(0)=1$ and $P(0)=0$, the closed-form solutions is:

$$P(t) = 1 - \frac{N}{N - 1 + e^{\beta N t}}, \quad \mathrm{E}[T_d] = \frac{\ln N}{\beta(N-1)} \qquad (2)$$

This is an analysis for a single packet transmission delay and can be extended to multi-packet cases with ease when users do not have a buffer-limit. For each packet, its propagation is *independent* from others so that the induced packet delay is identical under this approach.

B. Content Update Process

With restrictions, a content update process is a multi-packet transmission in epidemic routing. A source continuously generates a *time-sensitive* content (i.e., multi-packets). The information is propagated to users through contacts while users only preserve an up-to-date (i.e., fresh) content. We assume that a content is *fresher* if the elapsed time from a source

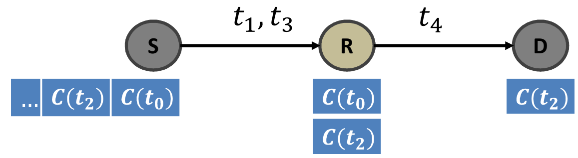


Fig. 2. A content propagation example: Set $t_0 < t_1 < \ldots < t_4$. S, D and R are a source, a destination and the first relay node which meets D, respectively. In contrast to epidemic propagation, the content $C(t_0)$ is never transmitted to D (i.e., dropped) in our update process.

departure is smaller and define the elapsed time as *content-age*, $A(t)$. This is useful to distinguish the freshness. A source is considered to have a fresh information (i.e., $A(t) = 0$) all the time [9], [10], [11]. By using the content-age, a content update process to share a fresh content is described as follows:

- **Content update process**: When a contact occurs between users, they compare their content-age and share the lesser of the two (i.e., $\min\{A_i(t), A_j(t)\}$).

In this process, contents have a *dependency* and users have a buffer-size limitation, as only holding an up-to-date content. During content propagation, there exists a fundamental difference as shown in Fig. 2. Under an ascending time order t_n, we set S, D and R as source, destination and the first relay which delivers the content of S to D, respectively. S updates its content at t_0 and t_2. R meets S at t_1, t_3 and D at t_4. Then, D only receives the content $C(t_2)$ at t_4. In contrast to [6], $C(t_0)$ is never propagated to D in the update process.

Hence, the approach to measure the effect of infrastructure in [6] has different propagation dynamics from our update process. Moreover, the focus of our update process is on the change of content freshness through user interactions.

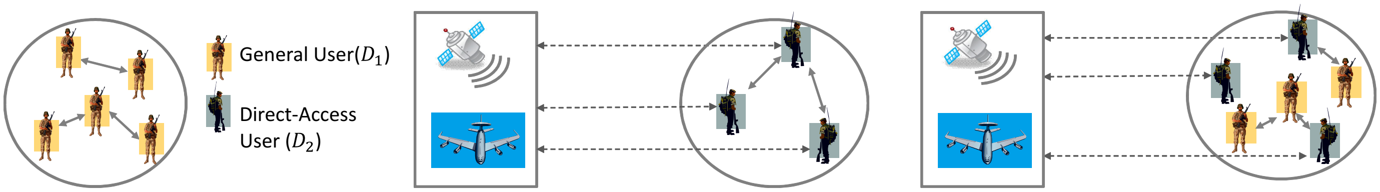
C. Content Update Problem with Infrastructures

We start from considering a military operation in a region without infrastructures. There is a *network user set* $\mathcal{V}$, where $|\mathcal{V}| = n$, and one user in $\mathcal{V}$ is an *Information Provider* (IP). Users listen to the operation commands of IP. In the sense that the more recent command has higher importance during an operation (e.g., the commander may order a sudden mission termination after the initial), we assume the content is time-sensitive. Users utilize the content update process during an operation. Contacts among users occur with an inter-any-contact rate λ and uniformly.

1) Direct-Update: We additionally consider the deployment of satellite or AWACS in the network. For users, these facilities allow the following *direct-update*:

- **Direct-update**: An IP uploads its commands continuously into a satellite or an AWACS used as an information storage. Each user is allowed to access the storage for updates, limited by user update rules. We assume that an IP and a storage is synchronized so that users receive the effect of an IP contact from direct-updates.

There can exist several reasons for limiting the direct-update (e.g., energy-consumption of devices, portability and device cost issues). We consider two device categories D_1 and D_2.



(a) Opportunistic Contact Only ($\mathbf{S}_1$) (b) Direct-Update by All Users ($\mathbf{S}_2$ and $\mathbf{S}_3$) (c) Direct-Update by Partial Number of Users ($\mathbf{S}_4$ and $\mathbf{S}_5$)

Fig. 3. User update rules: For content updates, all users utilize opportunistic contacts. D_2 users access an infrastructure and proceed a direct-update which provides a fresh IP content (i.e., $A(t) = 0$), limited by update rules. We show the improvement of content freshness for users by using each rule.

For updates, D_1 only utilizes opportunistic contacts, whereas D_2 can use both contacts and direct-updates. In the following, we define the operation rules of the devices.

2) Content Update Rules for Users: For all update rules, users utilize opportunistic contacts for updates.

- **Opportunistic Contact Only** (S_1): Users utilize only mobile contacts for the update of IP contents. This is for the performance comparison with other rules.
- **Probabilistic Direct-Update** (S_2): All users have D_2 devices. To extend device life-time, each user chooses a direct-update with rate γ.
- **Age-Based Direct-update** (S_3): Under probabilistic direct access, users can decide a direct-update even if they have a fresh content (i.e., young age). To prevent this, users control the rate of direct-access based on their content age, $A(t)$. There exists a *threshold-age* τ and the direct-access rate is set to γ_1 (low rate) and γ_2 (high rate) when $A(t)$ is lower and higher than τ, respectively.
- **Base-Station Update** (S_4): Users utilize only opportunistic contacts for updates. Instead, to improve a freshness, L_1 number of Base-Stations (BSs) which are synchronized with the IP are installed in a network. With an inter-contact rate χ, each user visits one of BSs and updates an up-to-date (i.e., $A(t) = 0$) content.
- **Sub-Leader Update** (S_5): With high frequency, a partial number (L_2) of users chooses a direct-update. The remaining users receive the effect of direct-updates from the contacts with those partial users.

In the following section, we show the changes of user content freshness (i.e., age) from the interaction of users and the update rule selection.

III. Model and Analysis

As mentioned, we utilize a content age $A(t)$, specifically a *mean content age*, as a metric to compare the content freshness of users. For one user, we first observe the age dynamic of content update process. Then, we explain the reasoning of how to compute the content-age distribution of users and derive the close-form solutions from ODE modeling. They allow us to see the variation of freshness under each rule. We show numerical results and analyze the quantity of freshness improvement.

A. The Age-Dynamics of Users

We select user i at time t and describe its age variation for a small ϵ time duration, where $i \in \mathcal{V}$. When the time consumption to exchange contents is negligible, the age at $t+\epsilon$ is given by:

$$A_i(t+\epsilon) = \begin{cases} \epsilon & \text{under condition } 1 \\ \min\{A_i(t), A_j(t)\} + \epsilon & \text{under condition } 2 \\ A_i(t) + \epsilon & \text{otherwise} \end{cases} \tag{3}$$

Eq. (3) allows us to express the dynamics of update process under several update rules by changing conditions. Condition 1 occurs when a user either selects a direct-update or meets an IP at t. Also, a contact with a BS or a sub-leader has an equivalent effect. According to the update rules, the probability of condition 1 varies (e.g., an IP contact probability is $\frac{\epsilon\lambda}{N}$). Condition 2 describes a contact between users. From the rate of inter-any-contact, the probability becomes $\frac{N-1}{N}\epsilon\lambda$. We utilize this age-dynamics to construct an ODE model for the content age distribution of users.

B. Age-distribution and Mean-Content Age

To investigate the age distribution of users, we provide an ODE model based on a mean-field regime [9], [14]. We define $\mathbf{F}(t,a)$ as the state of ODE, where $\mathbf{F}(t,a) \equiv \mathbf{P}(A(t) > a)$. The state includes two dynamic variables (*time* and *age*). Hence, its ODE form has the following expression:

$$\frac{d\mathbf{F}(t,a)}{dt} + \frac{d\mathbf{F}(t,a)}{da} = \lim_{\epsilon \to 0} \frac{\mathbf{F}(t+\epsilon, a) - \mathbf{F}(t, a-\epsilon)}{\epsilon} \tag{4}$$

where $\mp\mathbf{F}(t,a)$ canceled out each other on the right-hand side. Suppose that it reaches a steady-state (i.e., $t \to \infty$). Then, the time dynamics can be ignored so that $\frac{dF(t,a)}{dt} = 0$ and the $\mathbf{F}(t,a)$ is abbreviated to $\mathbf{F}(a)$ which is the Complementary Cumulative Distribution Function (CCDF). Under this case, eq. (4) provides an ODE for the content age-distribution of a user in steady-state.

By choosing one user i and using the age dynamics (3), we compute $\mathbf{F}_i(t+\epsilon, a)$ to solve (4). This is expressed by the following conditional expectation:

$$\mathbf{F}_i(t+\epsilon, a) = \mathbf{E}[\mathbf{F}_i(t+\epsilon, a) | A_i(t)] \tag{5}$$

As probability conditions in the update process (3) change according to update rules, eq. (5) also has different expectation values, respectively. In spite of that, we can find common conditions to satisfy the expectation. First, *time* and *age* have the same scale. Therefore, the content age can be larger than a at $t+\epsilon$ only when the age of user i is larger than $a-\epsilon$ (i.e., $A_i(t) > a - \epsilon$). Second, an update can occur during ϵ and user i obtains different content freshness according to the kind of updates defined by condition 1 and condition 2. As an IP contact and a direct-update at t set $A_i(t) = 0$, they do not affect (5). In contrast, a contact with user j affects the expectation when $A_j(t) > a - \epsilon$, where $j \in \mathcal{V}, i \neq j$. We summarize the above conditions to compute (5):

I The age of user i is larger than $a - \epsilon$.
II No opportunistic contact or update occurs during ϵ.
III During ϵ, an opportunistic contact occurs with user j, where $i \neq j$ and $j \in \mathcal{V}$. However, the content age of user j is larger than $a - \epsilon$ at time t.

Then, (5) is satisfied under $I \cap (II \cup III)$. From now on, we derive the ODE of content age distribution (4) and its closed-form solution for each update rule.

1) Opportunistic Contacts Only (S_1): In S_1, the probability of condition 1 and 2 on (3) become $\frac{\epsilon\lambda}{N}$ (an IP contact) and $\frac{\epsilon(N-1)\lambda}{N}$ (a user contact). Then, (5) is modeled by:

$$\mathbf{F}_i(t+\epsilon, a) = \{\underbrace{(1 - \epsilon\lambda)}_{\text{No Contact}} + \underbrace{\epsilon\lambda\frac{N-1}{N}\mathbf{P}(A_j(t) > a - \epsilon)}_{\text{A Contact without Update}}\} \cdot \mathbf{P}(A_i(t) > a - \epsilon) \tag{6}$$

The probability notations on (6) have the form of $\mathbf{F}(\cdot)$ and they can be simplified (e.g., $\mathbf{P}(A_j(t) > a - \epsilon) = \mathbf{F}_j(t, a - \epsilon)$ by definition). We put (6) in (4) while setting $t \to \infty$ and have the following ODE:

$$\mathbf{F}'_i(a) = \{-\lambda + \frac{N-1}{N}\lambda\mathbf{F}_j(a)\}\mathbf{F}_i(a), \quad a \in (0, \infty] \tag{7}$$

The solution of this ODE is the content age distribution of user i (i.e., CCDF) in steady-state. However, eq. (7) includes the dynamics of two different users i and j. Usually, we cannot solve this ODE without the distribution of user j.

To relax this problem, we utilize a symmetric interaction property. Although the CCDF of each user is unknown, all users come to have an identical distribution in steady-state under the homogenous interactions (i.e., same λ and uniform-random contact pairs). Also, an asymptotic independent property holds among users in a mean-field regime, when N is large enough [9], [14]. For this reason, we omit the subscripts for user differentiations on (7). From the CCDF property, we use an initial condition $\mathbf{F}(0) = 1$. Then, the ODE is the form of a bernoulli-differential equation which has a closed-form solution. We set $\mathbf{F}_{S1}(a)$ as the CCDF under $\mathbf{S}_1$ and the distribution is shown in Table. I.

2) Probabilistic Direct-Update (S_2): The only difference from $\mathbf{S}_1$ is that users proceed a direct-update with rate γ so that the probability of condition 1 on (3) becomes $\epsilon(\gamma + \frac{\lambda}{N})$. For user i, the conditional expectation (5) is expressed as:

$$\mathbf{F}_i(t+\epsilon, a) = \{\underbrace{1 - \epsilon(\lambda + \gamma)}_{\text{No Update}} + \underbrace{\epsilon\lambda\frac{N-1}{N}\mathbf{P}(A_j(t) > a - \epsilon)}_{\text{A Contact without Update}}\} \cdot \mathbf{P}(A_i(t) > a - \epsilon) \tag{8}$$

Similarly, its ODE form is induced by using (4) with setting $t \to \infty$. Also, we omit the user subscripts from symmetric interactions and asymptotic independence. Then, the ODE for the content-age distribution of users under $\mathbf{S}_2$ is derived as:

$$\mathbf{F}'_{S2}(a) = \{-(\lambda + \gamma) + \frac{N-1}{N}\lambda\mathbf{F}_{S2}(a)\}\mathbf{F}_{S2}(a), \ a \in (0, \infty] \tag{9}$$

The closed-form solution of this ODE is shown in Table. I.

3) Age-based Direct-Update (S_3): In contrast to $\mathbf{S}_2$, users control their direct-update rate based on their content age. Thus, the condition 1 on (3) becomes $\epsilon(\frac{\lambda}{N} + \gamma_1\mathbf{1}_{\{A(t) \leq \tau\}} + \gamma_2\mathbf{1}_{\{A(t) > \tau\}})$ and (5) is following:

$$\mathbf{F}_i(t+\epsilon, a) = \{\underbrace{1 - \epsilon(\lambda + \gamma_1\mathbf{P}(A_i(t) \leq \tau) + \gamma_2\mathbf{P}(A_i(t) > \tau))}_{\text{No Update}} + \underbrace{\epsilon\lambda\frac{N-1}{N}\mathbf{P}(A_j(t) > a - \epsilon)}_{\text{A Contact without Update}}\} \cdot \mathbf{P}(A_i(t) > a - \epsilon) \tag{10}$$

Using (10) in (4) with $t \to \infty$ gives an ODE under $\mathbf{S}_3$. For a simpler notation, we divide the range of content age at τ because $\mathbf{P}(A > \tau) = 0$ when $a \in (0, \tau]$ and vice versa. Also, we remove user subscripts under same assumptions.

$$\mathbf{F}'_{S3}(a) = \begin{cases} (-(\gamma_1 + \lambda) + \lambda\frac{N-1}{N}\mathbf{F}_{S3}(a))\mathbf{F}_{S3}(a) & , a \in (0, \tau] \\ (-(\gamma_2 + \lambda) + \lambda\frac{N-1}{N}\mathbf{F}_{S3}(a))\mathbf{F}_{S3}(a) & , a \in (\tau, \infty] \end{cases} \tag{11}$$

In the ODE form, the only difference from $\mathbf{S}_2$ appears as the different direct-update rate on each age range. We assume that the CCDF $\mathbf{F}_{S3}(a)$ is smooth enough so that continuity holds at $\mathbf{F}_{S3}(\tau)$. By using $\mathbf{F}_{S3}(0) = 1$ and the continuity at $a = \tau$, we compute the closed-form solution $\mathbf{F}_{S3}(a)$, shown in Table. I.

4) Base-Station (BS) Access (S_4): As users update a totally fresh content (i.e., $A(t) = 0$) when they meet an IP or any BSs, condition 1 on (3) is $\epsilon(\frac{\lambda}{N} + L_1\chi)$ and (5) is modeled by:

$$\mathbf{F}_i(t+\epsilon, a) = \{(1 - \epsilon(\lambda + L_1\chi)) + \epsilon\frac{N-1}{N}\lambda\mathbf{F}_j(t, a - \epsilon)\} \cdot \mathbf{F}_i(t, a - \epsilon) \tag{12}$$

This has the same form with (8) except that γ is changed to $L_1\chi$. The closed-form solution $\mathbf{F}_{S4}$ is in Table. I.

5) Sub-Leader Access (S_5): In contrast to $\mathbf{S}_4$, L_2 number of users replace the role of BSs. Hence, conditions 1 and 2 are $\frac{\epsilon(L_2+1)}{N}\lambda$ and $\frac{\epsilon(N-L_2-1)}{N}\lambda$, respectively. We model (5) for D_1 users as follows and the solution $\mathbf{F}_{S5}(a)$ is shown in Table. I.

$$\mathbf{F}_i(t+\epsilon, a) = \{(1 - \epsilon\lambda) + \epsilon\frac{N-1-L_2}{N}\lambda\mathbf{F}_j(t, a - \epsilon)\} \cdot \mathbf{F}_i(t, a - \epsilon) \tag{13}$$

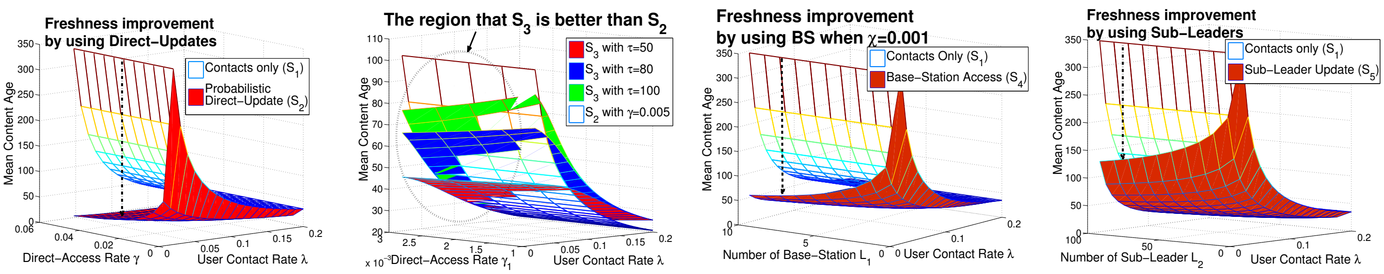
We use the *mean content age of users* as a metric to estimate a content freshness. When CCDF for the content age A is given, its mean value $\mathbf{E}[A]$ is simply computed by using $\mathbf{E}[A] = \int_{a=0}^{\infty}\mathbf{F}_{s_k}(a)da$, where $k = 1, ..., 5$. Table. I includes the mean value for each update rule.

C. Numerical Results and Freshness Enhancements

When infrastructures are additionally used in opportunistic networks, it is intuitively expected that users receive the enhancement of freshness. However, the more intriguing point is

Update Rule	CCDF $\mathbf{F}(a)$	Mean Content Age
$\mathbf{S}_1$	$\mathbf{F}_{S1}(a) = \frac{Ne^{-\lambda a}}{(N-1)e^{-\lambda a}+1}$	$\frac{N}{\lambda(N-1)} \ln N$
$\mathbf{S}_2$	$\mathbf{F}_{S2}(a) = \frac{N(\lambda+\gamma)e^{-(\lambda+\gamma)a}}{(N-1)\lambda e^{-(\lambda+\gamma)a}+(N\gamma+\lambda)}$	$\frac{N}{\lambda(N-1)} \ln(\frac{N\gamma+\lambda N}{N\gamma+\lambda})$
$\mathbf{S}_3$	$\frac{N(\lambda+\gamma_1)e^{-(\lambda+\gamma_1)a}}{(N-1)\lambda e^{-(\lambda+\gamma_1)a}+N\gamma_1+\lambda}\mathbf{1}_{\{a\le\tau\}} + \frac{N(\lambda+\gamma_2)e^{-(\lambda+\gamma_2)a}}{(N-1)\lambda e^{-(\lambda+\gamma_2)a}+C}\mathbf{1}_{\{a>\tau\}}$	$\frac{N}{\lambda(N-1)} \ln(\frac{N(\lambda+\gamma_1)}{(N-1)\lambda e^{-(\lambda+\gamma_1)\tau}+N\gamma_1+\lambda}\frac{(N-1)\lambda e^{-(\lambda+\gamma_2)\tau+C}}{C})$
$\mathbf{S}_4$	$\mathbf{F}_{S4}(a) = \frac{N(\lambda+L_1\chi)e^{-(\lambda+L_1\chi)a}}{(N-1)\lambda e^{-(\lambda+L_1\chi)a}+(NL_1\chi+\lambda)}$	$\frac{N}{\lambda(N-1)} \ln(\frac{NL_1\chi+\lambda N}{NL_1\chi+\lambda})$
$\mathbf{S}_5$	$\mathbf{F}_{S5}(a) = \frac{Ne^{-\lambda a}}{(N-1-L_2)e^{-\lambda a}+1+L_2}$	$\frac{N}{\lambda(N-1-L_2)} \ln \frac{N}{1+L_2}$

TABLE I
CONTENT AGE-DISTRIBUTION AND ITS MEAN VALUE, WHERE $C = (N-1)\lambda(\frac{\gamma_2-\gamma_1}{\lambda+\gamma_1})e^{-(\gamma_2+\lambda)\tau} + (\frac{\lambda+\gamma_2}{\lambda+\gamma_1})(N\gamma_1+\lambda)e^{(\gamma_1-\gamma_2)\tau}$ (CONSTANT)



(a) Probabilistic Direct-Update ($\mathbf{S}_2$) (b) Age-Based Direct-Update ($\mathbf{S}_3$) (c) Base-Station Update ($\mathbf{S}_4$) (d) Sub-Leader Update ($\mathbf{S}_5$)

Fig. 4. Numerical results: In (a),(c) and (d), the freshness enhancement is compared with rule $\mathbf{S}_1$. (b) shows the comparison between $\mathbf{S}_2$ and $\mathbf{S}_3$.

the degree of freshness improvement according to update rules. We show the enhancement scale of update rules, compared to the opportunistic contact only ($\mathbf{S}_1$). Also, we plot the change of mean-content age with varying a user contact rate (λ) and user control parameters (i.e., $\gamma, (\gamma_1, \gamma_2, \tau), L_1$ and L_2 for update rules S_2 to S_5, respectively) in Fig. 4, when $N = 1,000$.

1) Comparisons with Opportunistic Contacts Only: When a freshness is compared with an opportunistic contact only:

- **Probabilistic direct-update** (S_2): The content freshness is improved as $O(\ln(\frac{N\gamma+\lambda}{\gamma+\lambda}))$. In other words, users receive approximately $\ln(N\gamma)$ fresher contents than $\mathbf{S}_1$ when each user controls the direct-update rate (γ).
- **Base-station access** (S_4): The freshness improvement compared to $\mathbf{S}_1$ is bounded by $O(\ln(\frac{NL_1\chi+\lambda}{L_1\chi+\lambda}))$. This has the same form with the probabilistic direct-update. The difference appears on the user control parameter (i.e., L_1) and the enhancement degree is same when $\gamma = L_1\chi$.
- **Sub-leader access** (S_5): The improvement of freshness is $O(\frac{\ln(L_2)}{L_2})$. In contrast to the above, the freshness improvement is not strictly affected by the number of users, N.

2) Probabilistic Update vs. Age-Based Update: Age-based update ($\mathbf{S}_3$) additionally utilizes content-age information $A(t)$ than probabilistic direct-update ($\mathbf{S}_2$), while users utilize the same opportunistic contacts. When the more network information is given, its efficient use can achieve the better freshness for users all the time. We compare the freshness between $\mathbf{S}_2$ and $\mathbf{S}_3$. However, their fair-comparison is an issue, as their direct-update rates are different according to control parameter selections (i.e., γ and $(\gamma_1, \gamma_2, \tau)$, respectively) and this leads an imbalanced energy consumption between them.

To overcome this issue, we provide a method to normalize their energy-consumption. Suppose that user devices consume the same amount of energy for a direct-update. From mean ergodicity, time-average and space-average are the same in steady-state. Hence, we can compute the mean direct-update rate (γ^*) under age-based update $\mathbf{S}_3$ by using its CCDF:

$$\text{Mean Direct-Access Rate } (\gamma^*) = \mathbf{1}_{\{A_i(t)\le\tau\}}\gamma_1 + \mathbf{1}_{\{A_i(t)>\tau\}}\gamma_2 \quad (14)$$

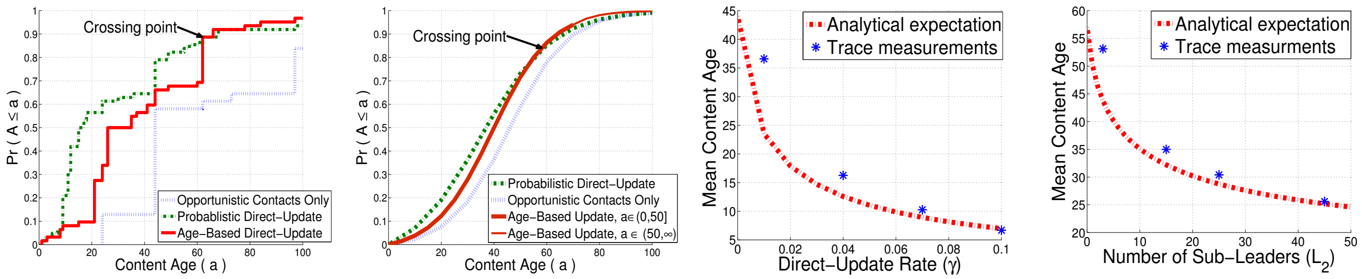
When $\gamma = \gamma^*$, users consume the same amount of energy in steady-state and this allows the fair performance comparison between $\mathbf{S}_2$ and $\mathbf{S}_3$. There exist several such $(\gamma_1, \gamma_2, \tau)$ tuples which satisfies the condition (14) for a fixed γ^*. Under the energy normalization, we plot the freshness comparison result in Fig. 4(b). It shows the existence of feasible regions where $\mathbf{S}_3$ brings the better freshness than $\mathbf{S}_2$ all the time.

IV. TRACE TESTS

We utilized the symmetric interaction and asymptotic independence of users while inducing closed-form solutions. This assumes the homogeneity of users (i.e., contact rate λ is same for all users). In reality, the mobility pattern of users has a heterogeneity (i.e., λ_i is different, where $i \in \mathcal{V}$). Hence, it is necessarily required to test our approach under a heterogeneous condition. We test our rules on the roller-net trace [15] and compare them with our analytical expectations.

A. Network Conditions in the Roller-Net Trace

This trace includes the contacts of 62 motes on Paris rollerblade tour during 10140 s. Participants tend to gather within a small area as a moving group and the contact rate among users is relatively high and dynamic. The detailed information



(a) Age-Distribution from Traces (b) Analytical Age-Distribution (c) Freshness Comparison under $\mathbf{S}_2$ (d) Freshness Comparison under $\mathbf{S}_5$

Fig. 5. Trace results: (a)-(b) show the CDF of content-age distribution under $\mathbf{S}_1 \sim \mathbf{S}_3$ with parameters $\gamma = 0.005$, $(\gamma_1, \gamma_2, \tau) = (0.003, 0.0077, 50)$, $\lambda = 0.0957$ and $N = 62$. (c)-(d) are freshness comparison results under $\mathbf{S}_2$ and $\mathbf{S}_5$, respectively, with $\lambda = 0.0957$ and $N = 62$.

of this heterogeneity can be found in [15]. From the trace, the estimated mean user contact rate ($\overline{\lambda}$) is 0.0957.

B. Test Results

As the same mean content age (i.e., freshness) can appear under several age distributions, we first show the distribution similarities to validate our approach. After that, we compare the freshness variation under update rules.

1) Comparisons of Content-Age Distribution: Each user utilizes its update rule from $t=0$. We assume the extracted content age of users at $t=10,140$ already reaches steady-state, as enough interactions occur due to the high contact rate of trace. Fig. 4(a) shows the CDF of user content age under $\mathbf{S}_1 \sim \mathbf{S}_3$ with control parameters and Fig. 4(b) plots our analytical solution in steady-state. Between them, we see the probability order conservation and the shape similarity of distributions in $a \in (0, \infty]$. Moreover, the crossing point between $\mathbf{S}_2$ and $\mathbf{S}_3$ which shows their trade-off appears around $a=60$ and both CDF values reach almost 1 at $a=100$.

2) Comparisons of Freshness: We measure the change of freshness under $\mathbf{S}_2$ and $\mathbf{S}_5$ with varying γ and L_2, respectively. Fig. 4(c)-(d) show those measurements along with our analytical expectations. Although there exist a small value difference between trace measurements and analytical results due to user heterogeneity, the freshness improvement trend shows a high closeness for both cases.

These comparison results imply that our analytical approach which estimates the freshness enhancement is still effective even under the heterogeneous network conditions.

V. Conclusion

Recent advances in communication technologies are giving us more ways to propagate information. Therefore, it is rarely expected that users adhere to one content acquisition method only. For that reason, in this paper, we considered a hybrid network structure for content updates where an infrastructure and a DTN are combined. We clarified the property of the update process and proposed various update rules. Those rules defined the infrastructure usage of users based on device constraints.

We were especially interested in measuring the degree of freshness enhancement by user update rules. Although the performance improvement by using an infrastructure is well-expected, it is challenging to quantify the degree of increase. Based on symmetric interactions and asymptotic independence between users, we suggested an ODE model to compute a content age distribution under update rules. The solution of these ODEs allowed us to measure the changes in freshness. After that, we showed the freshness improvement scale according to the use of update rules. Additionally, we tested our rules on real roller-net traces to overcome the homogeneity assumption of our model and verified our analytical expectations by comparisons.

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