Content-Update Process Performance under Energy Saving Schemes in Mobile Opportunistic Networks

Daehyun Ban and Michael Devetsikiotis
Department of Electrical and Computer Engineering
North Carolina State University, Raleigh, NC 27695-7911, U.S.A.
{dban, mdevets}@ncsu.edu

***Abstract*—Mobile hand-held devices such as smart-phones and tablets have gained in popularity over recent years. However, this induces cellular networks to suffer severe traffic demands that are hard to accommodate. In this respect, utilizing the ad-hoc communication of devices (e.g., bluetooth) can be an alternative way to obtain information while reducing the network overhead. Until now, the application possibility has been studied in Mobile Ad-hoc NETworks (MANETs). In the research, 'contacts' are important in the sense of supporting content delivery chances.**

For energy-saving, mobile devices can utilize a sleep/awake control in that their energy is constrained due to battery operations. This reminds us that the contact-based MANET research is not enough because the information delivery opportunities are limited to contacts among awake devices. In a network modeling procedure, we consider the sleep/awake rules of devices and investigate their effects on performance measures.

Specifically, we estimate the performance of a content update process under the device sleep/awake. This process is adequate to the dissemination of 'age-sensitive' contents such as news, tweets or traffic information. In there, one information provider continuously generates content and mobile users keep updating the more recently generated content through opportunistic contacts. Depending on the sleep/awake rule of devices, we analyze the degree of content freshness that users achieve and propose a normalization method to compare the performance of different rules. Also, we validate our analysis from real-trace tests.

I. Introduction

The popularity of mobile hand-held devices over recent years allows users to obtain various information almost without time and space limitations. However, in the perspective of network operation, this trend gives rise to severe traffic demands on cellular networks. The degree of demands already reaches a network capacity limit. The suspension of unlimited data plan services (e.g., Verizon and AT&T) shows the seriousness of this problem.

Mobile devices such as smart-phones and tablets generally support ad-hoc communication methods (e.g., bluetooth). However, the methods have been rarely used because devices are operated under a centralized infrastructure such as 3G networks. At this point, utilizing the ad-hoc communication of devices can be a way to gain information while reducing the traffic overhead of centralized networks. This application possibility has been investigated by Mobile Ad-hoc NETwork (MANET) researches [1], [2], [3]. In the network, it assumes that connectivity among devices is not guaranteed all the time. This makes *contact patterns* important in the sense of providing information delivery opportunities.

While using mobile devices, *energy limitation* is another important issue as their operations depend on a battery [4], [5], [6]. In general, the improving processing capability requires greater energy consumption of devices and this gives more highlights on the energy issue. In this respect, controlling the sleep/awake of devices allows to extend their life-time by reducing the energy consumption. However, by utilizing this method, information delivery opportunities are limited to contacts among awake devices. Thus, the performance of networks can be severely affected by the sleep/awake control of devices. In network modeling procedures, we consider the energy-saving schemes of devices and analyze their effects.

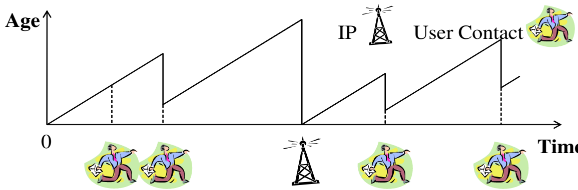
Depending on content categories, they have different properties. For contents such as news, tweets and traffic information, we categorize such content as *time-sensitive* in that the importance of content decreases with time. Under the energy-saving schemes in MANETs, we consider the propagation of time-sensitive contents by investigating *content update process*.

The content update process has a benefit on measuring the efficiency of time-sensitive content propagation. In the process, there exists one *Information-Provider* (IP), which continuously updates content, and *mobile users* share the more recently generated one when opportunistic contacts occur. Throughout this process, we analyze the degree of content freshness that mobile users achieve. This process can be observed from recent MANET studies in [7], [8], [9], [10] and they have a common consideration that every contact gives a chance to deliver information. In contrast, we consider the limitation of content delivery opportunities which comes from the device sleep/awake control and investigate the corresponding performance changes. In short, this can be regarded as the trade-off between energy consumption and content update.

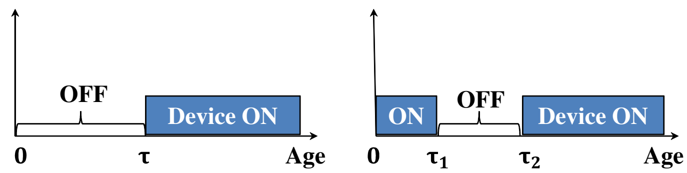
For saving the energy consumption, we consider two simple sleep/awake rules, where each device selects its sleep/awake independently based on the freshness of its own content. We use a term 'content age' to distinguish the freshness degree of content and the age defines the elapsed time of content from the first IP departure. Not only for the sleep/awake decision of devices, this metric also provides a convenience to select the fresher content under opportunistic contacts.

Further, we provide a normalization method which induces fair performance comparisons between different energy-saving rules. Using another sleep/awake rule raises variations not only on the degree of content freshness for mobile users, but also on the energy consumption amount of devices. From mean ergodicity, we normalize the energy consumption of sleep/awake rules. This allows us to decide the rule which

978-1-4673-0279-1/11/$26.00 © 2011 IEEE



(a) Content Update Process



(b) Device ON/OFF Control Rules

Fig. 1. We study the performance of (a) content update process, which measures the efficiency of time-sensitive content propagations in MANETs. Especially, we measure the process efficiency when mobile devices utilize (b) the sleep/awake rules for energy-saving.

has the better performance under given network parameters.

The remainder of this paper is as follows: In section 2, with network conditions, we define a content update process and explain two device sleep/awake rules which utilize content age information. For each sleep/awake rule, we derive the content age distribution of mobile users in section 3. We propose an energy normalization method to compare different rules and discuss analytical results under the normalization. Section 4 shows test results by using real-traces. By extracting the trace information, we compare the measurement results with our analytical solutions. After that, we conclude this paper with a summary and discussion section.

II. Problem Formulation

In our mobile opportunistic network, there exist one Information Provider (IP) and a mobile user set $\mathcal{V}$, where $|\mathcal{V}| = n$. The IP continuously generates time-sensitive content and mobile users want to subscribe the content. Each user is aware of its content age and $A_i(t)$ defines the age of user i at time t, where $i \in \mathcal{V}$ or IP.

Due to the continuous content generation, we assume that the content age of IP is 0 (i.e., new) regardless of time. Mobile users want to obtain the lesser age (i.e., fresher) content in that its importance decreases with time. In this respect, they proceed the following content update process:

- **Content update process**: When a contact occurs between users or with IP, they compare their content-age and share the lesser of the two (i.e., $\min\{A_i(t), A_j(t)\}$), where $i, j \in \mathcal{V}$ or IP. Fig. 1(a) shows an example for this process.

This content update process regards that opportunistic contacts are the only factor which affects to content deliveries [7]. We refer that this is different from a content delivery process such as epidemic routing [11], [12]. In contrast to the delivery process where the process is terminated once when all users have information, this content update process is continuous. In this reason, we observe the freshness degree (i.e., content age) that mobile users have, instead of delivery time.

There are opportunistic contacts either between mobile users or between a mobile user and IP. We assume that a contact between one user and IP occurs with rate γ. Also, mobile users have an inter-any-contact rate λ with another user and the contact pair occurrences follow a uniform-random distribution.

A. Content Update Process with Sleep/Awake Rules

We combine the content update process with general device sleep/awake rules. For this, at time t, we consider the content age dynamics of user i, where $i \in \mathcal{V}$. We assume that users always update contents from IP contacts and this allows users to have a totally fresh content (i.e., $A_i(t) = 0$). In contrast, when the contact is with other mobile users, an update process occurs only when the status of both devices is awake. We define a general condition *ON* which implies the device awake. Also, we assume that the time consumption for content exchange is negligible. Under these, we consider the user content age variation of short duration. When the duration is a small ϵ, the variation for user i is described by:

$$A_i(t+\epsilon) = \begin{cases} \epsilon & \text{with prob. } \epsilon\gamma \\ \min\{A_i(t), A_j(t)\} + \epsilon & \text{with prob. } \epsilon\lambda \text{ \& } ON \\ A_i(t) + \epsilon & \text{otherwise} \end{cases} \tag{1}$$

where $i, j \in \mathcal{V}$. The principle of this dynamics applies correctly to any sleep/awake rule.

B. Device Sleep/Awake Rules for Energy-Saving

In the sense of sharing an age-sensitive content, each user can utilize its own content age in designing a sleep/awake rule. We assume that the energy consumption of devices is proportional to their awake period and those devices try to minimize their awake period for energy-saving. However, this is at variance with the content sharing purpose through opportunistic contacts by letting sensors sleep when a contact occurs. We provide two simple sleep/awake rules for devices by differentiating the behavior of users and these rules appear in Fig. 1(b). According to rules, we note that there appear differences on the device age dynamics (1):

1. **Single-Threshold Sleep/Awake (S1)**: For a user, one simple energy-saving method is setting its status awake only when the user needs a content. If a user percepts that its content is up-to-date, keeping an awake status is regarded as an energy waste and we reflects the *selfishness* of users. For this reason, we set a threshold τ (constant) and a content is regarded as same as a fresh IP content until the age τ. Each user turns on its power if its own content age $A_i(t)$ is more than the threshold. By using an indicator function, this rule is described by:
$$\mathbf{S1}_i(t) = \mathbf{1}_{\{A_i(t)>\tau\}}, \quad i = \{1, 2, \ldots, n\} \tag{2}$$
where $\mathbf{S1}_i(t) = 1$ means that the device i is awake at t.
2. **Double-Threshold Sleep/Awake (S2)**: The single-threshold sleep/awake raises difficulties in sharing a fresh content among mobile users. If all users decide to sleep when their content age is less than τ, the effect of sharing process among mobile users only appears once after the

threshold age. In this aspect, we allow devices to have a little bit *altruistic* behavior. Each user utilizes two-thresholds τ_1 and τ_2 to control its sleep/awake status, where $\tau_1 < \tau_2$, and the rule is given by:

$$\mathbf{S2}_i(t) = \mathbf{1}_{\{A_i(t) \leq \tau_1 \text{ or } A_i(t) > \tau_2\}}, \; i = \{1, 2, \ldots, n\} \quad (3)$$

where $\mathbf{S2}_i(t) = 1$ means that the device i is awake at time t. By letting the short awake phase while the device has a fresh content (i.e., $A_i(t) \leq \tau_1$), mobile users still have opportunities to obtain a fresh content through opportunistic contacts under the rule **S2**.

For each sleep/awake rule, we investigate the performance changes in content update process. Further, we compare the efficiency of two rules. The comparison is challenging because using a different rule raises changes not only on the energy-consumption of devices, but also on the achievable content freshness. In steady-state, we provide a method for their fair comparison by normalizing the energy consumption of devices.

III. Model and Analysis

During our analysis, we suppose that the number of mobile users (n) is large enough due to the popular use of smart-phones and tablets. Also, those mobile users utilize an energy-saving rule either **S1** or **S2**. Under the condition, [8] shows that the modeling of content update process based on mean-field regime has a validity. In this respect, we show steps to build Ordinary Differential Equations (ODEs) to describe the content update process when those energy-saving rules are additionally deployed (The literature of ODE modeling based on mean-field regime can be found in [8], [13]).

When sleep/awake rules are used, out interest is on measuring the degree of content freshness that mobile users achieve and this has a certain difference from the delay estimation in epidemic propagation. The content freshness of users is expressed by using an age metric $A(t)$. Simply, the smaller age means the fresher content. In the followings, we show procedures to obtain the age distribution of mobile users under energy-saving rules. Then, an energy-normalization method is suggested to compare their performance fairly.

A. User Age Distribution under Sleep/Awake Rules

We select one mobile user i, where $i \in \mathcal{V}$, and define a state $\mathbf{F}_i(t, a)$ as a probability, where the content age of user i is larger than a at time t (i.e., $\mathbf{F}_i(t, a) \equiv \mathbf{P}(A_i(t) > a)$). For a small time duration ϵ, we consider the dynamics of $\mathbf{F}_i(t, a)$. The following conditional expectation describes the dynamics:

$$\mathbf{F}_i(t+\epsilon, a) = \mathbf{E}[\mathbf{F}_i(t+\epsilon, a) | A_i(t)] \quad (4)$$

The state $\mathbf{F}$ in (4) includes two variables *time* and *age*. When ϵ is small enough, we consider their variation sum:

$$\frac{d\mathbf{F}(t,a)}{dt} + \frac{d\mathbf{F}(t,a)}{da} = \lim_{\epsilon \to 0} \frac{\mathbf{F}(t+\epsilon, a) - \mathbf{F}(t, a-\epsilon)}{\epsilon} \quad (5)$$

where $\mp\mathbf{F}(t, a)$ are canceling each other. In steady-state (i.e., $t \to \infty$), the time-dynamics of (5) is ignored (i.e., $\frac{dF}{dt} = 0$) and the state abbreviation becomes available from $\mathbf{F}(t, a)$ to $\mathbf{F}(a)$. From the state definition, this abbreviated state represents a Complementary Cumulative Distribution Function (CCDF).

In steady-state, we note that the left side of (5) becomes the CCDF variation of content age for user i (i.e., $\mathbf{F}'_i(a)$). Additionally, its right side terms can be computed by using the conditional expectation (4). For content update process with sleep/awake rules, these give a full feature for an ODE construction.

The computation of (4) needs two considerations. One is $A_i(t)$ (i.e., the content age of user i at t) and the other is its dynamics described by (1), which raises differences depending on sleep/awake rules.

First, we note that the value $\mathbf{F}_i(t+\epsilon, a)$ is affected only when $A_i(t) > a - \epsilon$ in that *time* and *age* have a same scale. Additionally, during a small time interval ϵ, the following conditions affect the value of (4):

1. User i does not meet IP or any user.
2. User i has a contact with user j, where $j \in \mathcal{V}$. But, no update occurs due to the device sleep (either i or j).
3. User i has a contact with user j, where $j \in \mathcal{V}$, and an update occurs. But, the updated content age of user i is still larger than the age a.

For each sleep/awake rule, we model an ODE for its content update process and find its solution which describes the achievable content freshness of mobile users.

1) Single-Threshold Sleep/Awake: For the single-threshold sleep/awake rule, its conditional expectation (4) is modeled by:

$$\begin{aligned} \mathbf{F}_i(t+\epsilon, a) = \int_{a-\epsilon}^{\infty} \{ & \underbrace{(1-\epsilon(\gamma+\lambda))}_{\textit{no contact}} + \underbrace{\epsilon\lambda\mathbf{P}(A_i(t) \leq \tau)}_{\textit{user i power off}} \\ & + \underbrace{\epsilon\lambda\mathbf{P}(A_i(t) > \tau)\mathbf{P}(A_j(t) \leq \tau)}_{\textit{user j power off}} \\ & + \underbrace{\epsilon\lambda\mathbf{P}(A_i(t) > \tau)\mathbf{P}(A_j(t) > \tau)\mathbf{P}(A_j(t) > a-\epsilon)}_{\textit{updated to an age larger than a}} \} \\ & \cdot \mathbf{P}(A_i(t) = k) dk \end{aligned} \quad (6)$$

where the integration range $(a - \epsilon, \infty]$ corresponds to the condition where $A_i(t) > a - \epsilon$. In there, we observe that all probability notations are either CDF or CCDF. These notations can be simplified by using $\mathbf{F}$ (e.g., $\mathbf{P}(A(t) > \tau) = \mathbf{F}(t, \tau)$ and $\mathbf{P}(A(t) \leq \tau) = 1 - \mathbf{F}(t, \tau)$). Then, we put the simplified form into (5) and set $t \to \infty$ (i.e., steady-state). This provides an ODE form and its solution implies the content age distribution of user i under **S1**. However, the ODE form still has a user differentiation (i.e., $\mathbf{F}'_i(a)$ has $\mathbf{F}_i(a)$ and $\mathbf{F}_j(a)$ together, where $j \in \mathcal{V}$) and this hampers to get the solution $\mathbf{F}_i(a)$.

We consider the symmetric interaction of users (i.e., users have same contact rates γ and λ under **S1**). In [8], [13], it is showed that, in steady-state, all objects reach an *identical distribution* under symmetric interactions and there holds an *asymptotic independence* among system objects. These allow us to remove the subscript of mobile users and the general solution $\mathbf{F}(a)$ represents the content age distribution of all users.

Additionally, the suggested sleep/awake rules are based on threshold decision either τ or (τ_1, τ_2) and this gives an advantage which further simplifies the ODE by dividing its range. For example, $\mathbf{P}(A > \tau) = 0$ in range $a \in (0, \tau]$ and $\mathbf{P}(A \leq \tau) = 0$ in range $a \in (\tau, \infty)$. After the range division, we have the following ODE form for $\mathbf{F}'(a)$:

$$\mathbf{F}'(a) = \begin{cases} -\gamma \mathbf{F}(a) & , a \in (0, \tau] \\ \mathbf{F}(a)\{-(\gamma + \lambda \mathbf{F}(\tau)) + \lambda \mathbf{F}(\tau)\mathbf{F}(a)\} & , a \in (\tau, \infty] \end{cases} \tag{7}$$

In $a \in (\tau, \infty]$, (7) has the form of bernoulli differential equation whose closed-form solution exists (see [11] for the solution of similar ODEs). From CCDF properties, we set an initial condition $\mathbf{F}(0)$ (i.e., $\mathbf{P}(A \geq 0)$) to 1 and assume that the solution $\mathbf{F}(a)$ is smooth enough to hold a continuity at $a = \tau$. Then, the closed-form CCDF ($\mathbf{F}_{S1}(a)$), which is the content age distribution of mobile users under **S1**, is given by:

$$\mathbf{F}_{S1}(a) = \begin{cases} e^{-\gamma a} & , a \in (0, \tau] \\ \frac{e^{-(\gamma + \lambda F(\tau))a}}{\frac{\lambda F(\tau)}{\gamma + \lambda F(\tau)} e^{-(\gamma + \lambda F(\tau))a} + \mathbf{c}} & , a \in (\tau, \infty] \end{cases} \tag{8}$$

where $\mathbf{c} = \frac{1}{F(\tau)}(1 - \frac{\lambda F^2(\tau)}{\gamma + \lambda F(\tau)})e^{-(\gamma + \lambda F(\tau))\tau}$ and $\mathbf{F}(\tau) = e^{-\gamma\tau}$.

2) Double-Threshold Sleep/Awake: By using similar steps, we compute the content age distribution of users under the use of double-threshold sleep/awake rule. The following model describes the conditional expectation (4). In there, we abuse the notation $A_k(t)$ as A_k, where $k = \{i, j\}$:

$$\begin{aligned} \mathbf{F}_i(t + \epsilon, a) = \int_{a-\epsilon}^{\infty} \{ & \underbrace{(1 - \epsilon(\lambda + \gamma))}_{\textit{no contact}} + \underbrace{\epsilon\lambda \mathbf{P}(\tau_1 \leq A_i < \tau_2)}_{\textit{user } i \textit{ power off}} \\ + \; & \underbrace{\epsilon\lambda((\mathbf{P}(A_i \leq \tau_1) + \mathbf{P}(A_i > \tau_2))\mathbf{P}(\tau_1 \leq A_j < \tau_2))}_{\textit{user } j \textit{ power off}} \\ + \; & \epsilon\lambda((\mathbf{P}(A_i > \tau_2) + \mathbf{P}(A_i \leq \tau_1))(\mathbf{P}(A_j > \tau_2) \\ + \; & \underbrace{\mathbf{P}(A_j \leq \tau_1)))\mathbf{P}(A_j > a - \epsilon)}_{\textit{updated age is larger than } a} \} \cdot \mathbf{P}(A_i = k)dk \end{aligned} \tag{9}$$

We simplify (9) by changing all probability terms into state $\mathbf{F}$ expressions and set $t \to \infty$. Then, putting the simplified form into (5) gives an ODE for the content age of users under **S2**. Again, the user subscripts are removed in the sense of symmetric interactions and an asymptotic independence.

The asymptotic independence allows us to divide the ODE range by $(0, \tau_1]$, $(\tau_1, \tau_2]$ and $(\tau_2, \infty]$ and we have the following ODE form:

$$\mathbf{F}'(a) = \begin{cases} \{-(\gamma + \lambda) + \lambda \mathbf{F}(a)\}\mathbf{F}(a) & , a \in (0, \tau_1] \\ -\gamma \mathbf{F}(a) & , a \in (\tau_1, \tau_2] \\ g(\mathbf{F}(a), \lambda, \gamma) & , a \in (\tau_2, \infty] \end{cases} \tag{10}$$

where the function $g = \{-(\lambda + \gamma) + \lambda(\mathbf{F}(\tau_1) - \mathbf{F}(\tau_2)) + \lambda(1 - \mathbf{F}(\tau_1) + \mathbf{F}(\tau_2))\mathbf{F}(a)\}\mathbf{F}(a)$.

We use an initial condition $\mathbf{F}(0) = 1$. Under the assumption that $\mathbf{F}$ is continuous, (10) can be fully solved even if $\mathbf{F}(\tau_1)$ and $\mathbf{F}(\tau_2)$ are unknown constants. We set the first and second order coefficients of g as M_1 and M_2. Then, the content age distribution of mobile users under using **S2** ($\mathbf{F}_{S2}(a)$) becomes:

$$\mathbf{F}_{S2}(a) = \begin{cases} \frac{(\gamma + \lambda)e^{-(\gamma + \lambda)a}}{\lambda e^{-(\gamma + \lambda)a} + \gamma} & , a \in (0, \tau_1] \\ e^{-\gamma a} + \mathbf{c}_1 & , a \in (\tau_1, \tau_2] \\ \frac{e^{M_1 a}}{-\frac{M_2}{M_1} e^{M_1 a} + \mathbf{c}_2} & , a \in (\tau_2, \infty) \end{cases} \tag{11}$$

where $\mathbf{c}_1$ and $\mathbf{c}_2$ are constant values which guarantee the continuity of $\mathbf{F}_{S2}(a)$.

In these ODE analysis, we note that the sleep/awake rule **S2** includes the rule **S1** by setting $\tau_1 = 0$ and $\tau_2 = \tau$. This provides a simple modeling check. We observe that putting them into (10) induces the same ODE for **S1** shown in (7).

B. Performance Comparison via Energy Normalization

Previous ODE analysis allows us to know the achievable content freshness of mobile users when sleep/awake rules are used. However, it only defines the performance variation under each rule and we do not have a method to compare their efficiency. This is because the difference appears not only on the age distribution, but also on their energy consumption. For this reason, we suggest a method to compare the performance of sleep/awake rules by normalizing the energy consumption of devices.

For a given threshold τ^* under **S1**, we consider that there exist corresponding (τ_1, τ_2) tuples for **S2** which consume the same amounts of energy in steady-state. When the consumed power for awaking a device is identical, the power consumption of device i at time t is expressed by an indicator function $p_i(t)$, where $p_i(t) = \mathbf{1}_{\{\text{Device } i \text{ is awake at time } t\}}$.

We know the closed-form CCDF solution which represents the content age of users under the use of **S1** and **S2**. From mean ergodicity, there holds a steady-state equality between time and space averages for the content age dynamics. For this reason, we compute the space-average of close-form CCDF solutions for the region which satisfies the sleep/awake rules. Set measurements E_{S1} and E_{S2} as the mean consumed energy under the rules **S1** and **S2**, respectively:

$$E_{S1} = \mathbf{P}(A > \tau) = \mathbf{F}_{S1}(\tau) \tag{12}$$

$$E_{S2} = \mathbf{P}(A \leq \tau_1) + \mathbf{P}(A > \tau_2) = 1 - \mathbf{F}_{S2}(\tau_1) + \mathbf{F}_{S2}(\tau_2) \tag{13}$$

When there holds an equality between E_{S1} and E_{S2}, this implies the same mean energy consumption between rules **S1** and **S2**. By using closed-form solutions in (8) and (11), we find the condition. From the value $\mathbf{F}_{S2}(\tau_1), \mathbf{F}_{S2}(\tau_2)$ and $\mathbf{F}_{S1}(\tau)$, the equality condition is following:

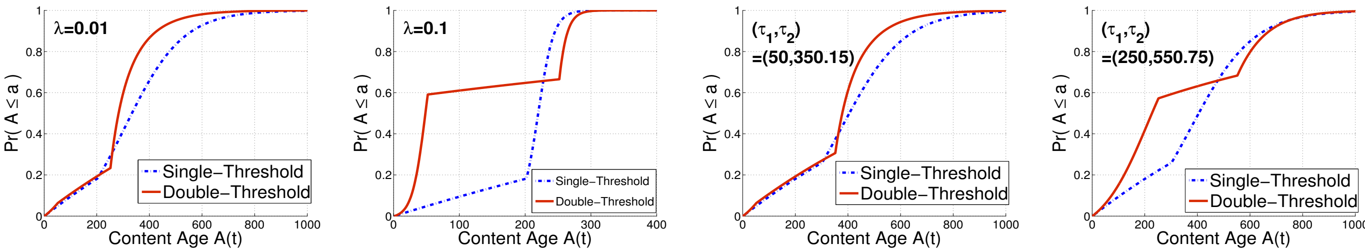
$$e^{-\gamma\tau} = 1 - e^{-\gamma\tau_1} + e^{-\gamma\tau_2} \tag{14}$$

For a given τ^* under **S1**, we can find several (τ_1^*, τ_2^*) tuples by using (14). Measuring the content age of mobile users under this normalization allows us to have fair comparisons between different sleep/awake rules.

C. Analytical Results and Discussions

For several network scenarios, we plot the closed-form solutions (8) and (11) in Fig. 2 and discuss their properties. We note that all results are plotted under energy-normalization by using (14).

1) The Effect of User Contact Rate λ: The difference between rules **S1** and **S2** is whether there exists an early awake phase or not. Users can obtain the better content freshness by contacting the early awake users under **S2**. According to the increase of user contact rate λ, this allows us to expect that the achieved content age distribution under **S2** will become more fresher than the one under **S1**. With setting all other network parameters are identical except λ (detailed parameters



(a) Low User Contact Rate (b) High User Contact Rate (c) $(\tau_1, \tau_2) = (50, 350.15)$ (d) $(\tau_1, \tau_2) = (250, 550.75)$

Fig. 2. Analytical CDFs for content age distribution: (a) and (b) plot the performance difference of **S1** and **S2** depending on mobile contact rate λ variations. (c) and (d) show differences on age distribution for different energy normalization tuples. Network parameters are set as $(\gamma, \tau^*, \tau_1^*, \tau_2^*) = (0.001, 200, 50, 250.1)$.

are in the figure), Fig. 2(a) and (b) plot the content age CDF of mobile users when the user contact rate λ is low and high, respectively. We observe clear differences on those distributions under energy-normalization. The increasing λ brings the higher performance improvement on **S2**.

2) Energy Normalization Tuple (τ_1, τ_2) Selection and Age Distribution: From (14), setting τ^* for **S1** makes several energy normalized (τ_1, τ_2) tuples for **S2**. Even under the same energy consumption tuples, we show that the achieved content age distribution under **S2** can have huge differences. For $\tau^* = 300$, we find two normalized tuples $(50, 350.15)$ and $(250, 550.75)$ for rule **S2**. In the network setting, the user contact rate λ is set to 0.01. This implies that a user contact occurs on every 100 s in average. Under the condition, setting $(\tau_1, \tau_2) = (50, 350.15)$ (i.e., devices are awake until their age reaches 50) will rarely have an advantage than using **S1**. In contrast, devices almost utilize the early phase for updates under $(250, 550.75)$ tuple. In Fig. 2(c) and (d), we plot the age distribution for different (τ_1, τ_2) tuples. Under energy normalization, we observe that the setting $(250, 550.75)$ brings much better freshness for users than using $(50, 350.15)$.

IV. Trace-Based Test Results and Discussions

We utilize the symmetric interactions and asymptotic independence to induce closed-form solutions. This means the homogeneity of network users (i.e., contact rates (λ, γ) are same for all users). However, the contact pattern of users has a certain heterogeneity in reality. For this reason, we test the content update process with sleep/awake rules on real-traces. We provide the measurements of content age distribution and the energy consumption of mobile users.

A. Trace Analysis

1) Roller-Net Trace: We select roller-net trace shown in [14]. This includes the traces of 62 i-Mote contacts in Paris roller-blade tour during 3 hours $(9,976$ s). Participants tend to gather within a small area as a moving group. The contact rates among users (λ) is relatively high and dynamic (i.e., $\lambda_i \neq \lambda_j$, where $i, j \in \mathcal{V}$ and $i \neq j$). Hence, we assume the content update process after 9976 s almost reaches steady-state and the trace has enough heterogeneity (see [14] for trace details).

2) Extracted Features from Traces: We select one IP user and consider other 61 motes as mobile users. As the performance of content update process can vary depending on IP selection, we test all 62 possible IP cases and Fig. 3 plots their averaged results. From the trace, we extract the following information:

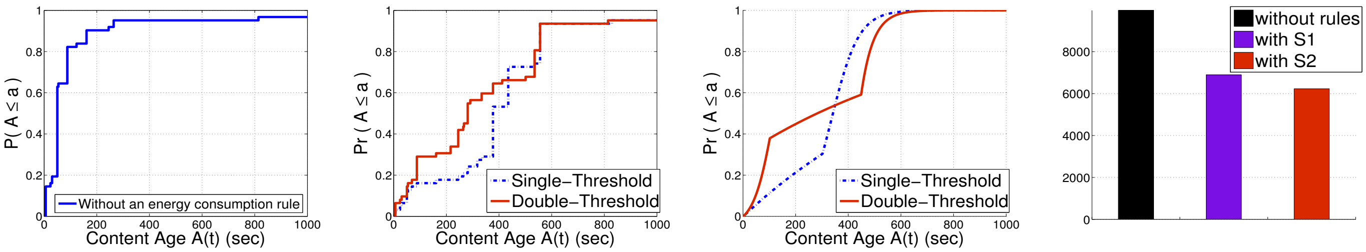
- *Age Distribution without Sleep/Awake Rule*: We test content update process without a device sleep/awake and this is the general update process in [7]. Fig. 3(a) shows the averaged content age distribution of mobile users.
- *Age Distribution with Sleep/Awake Rules*: From Fig.3(a), we select an adequate threshold $\tau = 300$ for the single-threshold sleep/awake. We measure the averaged network parameters λ and γ from the trace. Then, by using (14) with those values, we compute an energy normalized tuple $(\tau_1^*, \tau_2^*) = (100, 447.36)$. When devices use those settings, Fig. 3(b) plots the age distribution of mobile users from traces.
- *Measuring the Energy Consumption of Devices*: The roller-net trace provides measurements per second and includes information for $9,976$ s. We measure the device awake period and regard it as the energy consumption amount. Fig. 3(d) plots the measured average energy consumption of devices with/without sleep/awake rules.

From the measurement results shown in Fig. 3(a) and (b), we observe the trade-off between content update process and sleep/awake rules. In Fig. 3(c), we plot the analytical CDF solutions by using the average λ and γ of traces (Those values are 0.0256 and 0.0012 for λ and γ, respectively). We compare the analytical solution with the trace CDF plot shown in Fig. 3(b). For the content age distribution, we observe similarities on their CDF trends. Also, the crossing point which represents the performance trade-off between rules **S1** and **S2** similarly appears around the age 400 s.

For energy-consumption, we utilize an energy-normalization for both **S1** and **S2** by using (14). This lets us expect that the measured energy consumption of devices should be close. In Fig. 3(d), we observe the effect of energy normalization. In there, the appeared energy consumption difference is 5.42%. Eq. (14) means that there can exist several energy normalized tuples for a given τ^*. For this reason, we compute several (τ_1, τ_2) tuples and measure the energy consumption of devices for each case. In Fig. 4(a), we plot the energy consumption ratio of devices and the ratio 1 implies that the consumed energy is equal between **S1** and **S2**. For all tuples, we observe that the differences are less than 15% and these validate the effectiveness of our normalization method.

B. Discussion: Modeling Applications

The solution of our approach gives the content age distribution of mobile users. When we measure the performance of



(a) Age CDF without a device sleep/awake (b) Age CDF with sleep/awake rules (c) Age CDF from analytical solutions (d) Device energy consumption

Fig. 3. Roller-net trace results: (a) shows the age distribution of users without a device sleep/awake. (b) and (c) plot age distributions with sleep/awake rules, where $\tau^* = 300$ and $(\tau_1^*, \tau_2^*) = (100, 447.36)$, and analytical CDFs, respectively. (d) plots the device energy consumption in $t \in (0, 9976]$.

different energy-saving rules, this raises a difficulty because it requires the comparison between *distributions*. For this reason, we propose simple metrics which allow us to compare the performance of different rules with *values*.

1) Mean Content Age: For different sleep/awake rules, we can compute their content age distribution (8) and (11). Further we can normalize their energy consumption by using (14). Under the *energy* normalization, a mean achievable content age ($E[A]$) is a simple metric to compare their performance and our CCDF solution form provides an efficient way to compute the mean. In Lebesgue measure, the mean content age is computed by $E[A] = \int_0^\infty \mathbf{F}(a)da$. Fig. 4(b) plots the mean content age under the use of **S1** and **S2**. We observe that this supports a simple value comparison, instead of distributions.

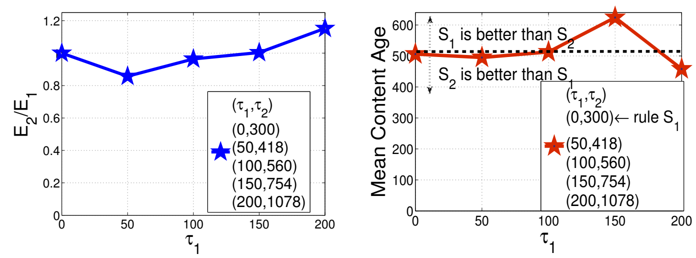
2) Efficiency measure by Using a Utility Function: Depending on contents, users can define its utility function $U(a)$ which matches the content importance with a content age (a). For instance, any decreasing function can be a candidate in case of time-sensitive contents. Under the energy normalization, the following utility measure (Ψ) supports comparisons with values between different energy saving rules:

$$\Psi(\mathbf{S}_k, \mathbf{U}) = \int_0^\infty \mathbf{P}(A_{S_k} = a) \cdot \mathbf{U}(a) da, \text{ where } k = 1, 2 \quad (15)$$

V. Conclusion

For the purpose of reducing traffic demands in cellular networks, utilizing the ad-hoc communication of mobile devices has been studied in MANETs. Until now, the research focus is mainly on the device contact patterns in that they provide content delivery opportunities. However, the energy constraint is another important issue while using mobile devices and it should be considered in the MANET analysis because the content delivery can be severely affected by the sleep/awake control of mobile devices.

In this paper, we investigated the content update process, which allows us to measure the efficiency of time-sensitive content propagations, when mobile devices utilize a sleep/awake control for energy-saving. Based on user behaviors, we considered two simple sleep/awake control rules and analyzed the trade-offs between the content update process and the energy-saving of devices. Additionally, we provided an energy normalization method which allows fair performance comparisons between different sleep/awake rules. We verified our analysis through real-trace tests. Further, the application



(a) Energy Consumption Ratio $\mathbf{E}_2/\mathbf{E}_1$ (b) Mean Content Age

Fig. 4. (a) plots the energy consumption ratio for several energy normalized (τ_1, τ_2) tuples when $\tau^* = 300$. (b) Mean content age supports simple performance comparisons between different energy-saving rules with values.

possibility of our model was discussed by suggesting metrics which capacitate the performance comparison of energy-saving rules with ease.

References

[1] I. Chlamtac, M. Conti, and J. Liu, "Mobile ad hoc networking: imperatives and challenges," *Ad Hoc Networks*, vol. 1, no. 1, pp. 13–64, 2003.

[2] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer networks*, vol. 38, no. 4, pp. 393–422, 2002.

[3] M. Kuorilehto, M. Hannikainen, and T. Hamalainen, "A survey of application distribution in wireless sensor networks," *EURASIP Journal on Wireless Communications and Networking*, no. 5, pp. 774–788, 2005.

[4] J. Kim, X. Lin, and N. Shroff, "Optimal anycast technique for delay-sensitive energy-constrained asynchronous sensor networks," *Networking, IEEE/ACM Transactions on*, no. 99, pp. 1–1, 2009.

[5] J. Elson and K. Romer, "Wireless sensor networks: A new regime for time synchronization," *ACM SIGCOMM Computer Communication Review*, vol. 33, no. 1, pp. 149–154, 2003.

[6] M. Bin Tariq, M. Ammar, and E. Zegura, "Message ferry route design for sparse ad hoc networks with mobile nodes," in *Proceedings of the 7th ACM international symposium on Mobile ad hoc networking and computing*. ACM, 2006, pp. 37–48.

[7] S. Ioannidis, A. Chaintreau, and L. Massoulie, "Optimal and scalable distribution of content updates over a mobile social network," in *INFOCOM 2009, IEEE*. IEEE, 2009, pp. 1422–1430.

[8] A. Chaintreau, J. Le Boudec, and N. Ristanovic, "The age of gossip: spatial mean field regime," in *Proceedings of the eleventh international joint conference on Measurement and modeling of computer systems*. ACM, 2009, pp. 109–120.

[9] E. Altman, P. Nain, and J. Bermond, "Distributed storage management of evolving files in delay tolerant ad hoc networks," in *INFOCOM 2009, IEEE*. IEEE, 2009, pp. 1431–1439.

[10] E. Altman, R. El-Azouzi, D. Menasche, and Y. Xu, "Forever young: Aging control in dtns," *Arxiv preprint arXiv:1009.4733*, 2010.

[11] X. Zhang, G. Neglia, J. Kurose, and D. Towsley, "Performance modeling of epidemic routing," *Computer Networks*, vol. 51, no. 10, pp. 2867–2891, 2007.

[12] N. Banerjee, M. Corner, D. Towsley, and B. Levine, "Relays, base stations, and meshes: enhancing mobile networks with infrastructure," in *Proceedings of the 14th ACM international conference on Mobile computing and networking*. ACM, 2008, pp. 81–91.

[13] J. Le Boudec, D. McDonald, and J. Mundinger, "A generic mean field convergence result for systems of interacting objects," in *Quantitative Evaluation of Systems, 2007. QEST 2007*. IEEE, 2007, pp. 3–18.

[14] P. Tournoux, J. Leguay, F. Benbadis, V. Conan, M. De Amorim, and J. Whitbeck, "The accordion phenomenon: Analysis, characterization, and impact on dtn routing," in *INFOCOM*. IEEE, 2009.