AOM: Adaptive Mobile Data Traffic Offloading for M2M Networks

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***Abstract*—With the emergence of a large number of businesses and applications based cellular Machine-to-Machine (M2M) communication such as telematics, smart metering, point-of-sale terminals, and home security, a heavy data traffic which need through the cellular network has been produced. Although many schemes have been proposed to reduce data traffic, they are inefficient in practical application due to poor adaption. In this paper, we focus on how to adaptively offload data traffic for cellular M2M networks. To this end, we propose an adaptive mobile data traffic offloading model (AOM). This model can decide whether to adopt opportunistic communications or communicate via cellular networks adaptively. In the AOM, we introduce traffic offloading rate (called TOR) and local resource consumption rate (called LRCR), and analyze them based on continue time Markov chain (CTMC). Theory proof and extensive simulations demonstrate that our model is accurate and effective, and can adaptively offload data traffic of cellular M2M networks.**

Keywords—cellular M2M networks; opportunistic communication; continue time Markov chain

1. INTRODUCTION

Machine-to-machine (M2M) networks are composed of large numbers of nodes, since the main subject participating in M2M communication is a machine or object, or indeed it can be everything around us. Because of machine can sense itself or its surrounding physical environment, the traffic per machine is very small. However, a large number of objects generate a large quantity of data with different format. These various data traffics from a large number of sensors are gathered through cellular network, an unpredictable pattern is created at the cellular M2M networks. The accumulated traffic in the cellular networks may cause network congestion and outage of network resources [1]. Although M2M devices have different traffic patterns from smartphones, they are generally competing with smartphones for shared network resources [2].

There are several solutions to offload mobile data traffic. The easiest way to solve this problem is to add more infrastructures (e.g. picocell, femtocell) [3], but imposed a serious challenge as the increase in infrastructure capacity does not scale accordingly. As we known, building a WiFi hotspot is significantly cheaper than network upgrades and build-out, that's why many users install their own WiFi access points (APs) at home and in their cars. Therefore, the most popular research issue is how to offload the mobile data traffic via WiFi. But, in fact, most of the mobile users obtain services from Internet when they are moving, which is hard to set WiFi. Then, some research used the opportunistic communication into mobile networks to reduce the pressure of the huge mobile data [4-12]. A solution [4] has been proposed to offload the amount of mobile data, which exploits opportunistic communications to facilitate information dissemination in the emerging Mobile Social Networks (MoSoNets). This study only focuses on offloading mobile data on MoSoNets, which cannot be applied cellular M2M networks. Then, in order to improve practical application, an integrated architecture has been proposed by Dimatteo et al. [5], which migrates data traffic from cellular M2M networks to metropolitan WiFi Access Points by exploiting the opportunistic networking paradigm. Bulk file transfer and video streaming have been quantified the benefits of their architecture. Their research shows that it is very significantly to improve the delivery performance even with a sparse WiFi network. Meanwhile, iCAR [6] has been proposed as an alternative scheme, which is an integrated cellular and ad hoc relaying scheme, to divert traffic from one (possibly congested) cell to another (non-congested) cell. And the basic idea is to lay up some Ad hoc Relaying Stations (ARSs) at the key locations. ARSs can be used to forward signals between Mobile Hosts and Base Transceiver Stations. And they proved that using ARS can efficiently balance traffic loads between cells. However, the iCAR cannot offload the mobile traffic. Instead, it diverts traffic from one (possibly congested) cell to another (non-congested) cell.

More recently, several schemes have been designed to offload mobile data traffic [7, 11, 12]. For example, HAN et al. [7] proposed a scheme to reduce cellular data traffic, and they intentionally delay the delivery of information and use the opportunistic communications to offload the cellular data traffic. Soon, Whitbeck et al.[12] proposed a content dissemination framework, push-and-track, which minimized the load on the wireless infrastructure by exploiting ad hoc communication opportunities while guaranteeing tight delivery delays. If new copies need to be re-injected into the network through the 3G interface, Push-and-track will use a control loop to collect user-sent acknowledgements to determine it. The scenarios of Periodic message flooding and floating data can use the Push-and-track. Xiaofeng Lu et al. [11] proposed a Subscribe-and-Send architecture and an opportunistic forwarding protocol. In this approach, users can receive subscribed contents from other users who have the contents through WiFi, instead of downloading from the Content Service Provider. This scheme can offload mobile data traffic, but it has poor adaption in the process of mobile data forwarding since it cannot obtain offloaded mobile data traffic and fails in deciding when to use opportunistic communications.

Although the above-mentioned schemes [7, 11, 12] perform well in their respective application domains of offloading the mobile data traffic, they are inefficient in practical application due to poor adaption (Such as a few nodes need the mobile data in sparse surrounding, those schemes may fail to forward mobile data.). In this paper, we propose an adaptive data traffic offloading model for cellular M2M networks. In our model, we put our emphasis on how cellular M2M networks to decide data transfer mechanism adaptively. Compared with the previous data traffic offloading model, we have made three contributions:

1) We propose an adaptive data traffic offloading model in this paper. And this model can adaptive select different data transfer mechanisms, such as opportunistic communications or through cellular M2M networks, to offload data traffic of cellular networks.

2) We define and analyze data traffic offloading rate (called TOR) based on continue time Markov chain in cellular M2M networks, and local resource consumption rate (called LRCR).

3) We extend the ONE by adding infection probability and multi-destination nodes setting, and make it to simulate data transfer in the opportunistic networks. Extensive simulations demonstrate that our derivations is accurate and effective.

The rest of this paper is organized as follows. In Section 2, we define TOR, LRCR and minimum completion time, and propose our model. We study the mobile data forward mechanism for TOR and LRCR of our model in Section 3. In Section 4, we give the theory derivation and proof of TOR and LRCR. Extensive simulations are given in Section 5. Finally, we conclude in Section 6.

2. Proposed Model

In order to differentiate nodes with different function better in this paper, we define four types of mobile nodes, i.e., subscription nodes, un-subscription nodes, services nodes and seeds. Subscription nodes denote the mobile nodes which need obtain the data from cellular M2M networks. In contrast, the un-subscription nodes need not obtain the data. And services nodes denote the intermediate nodes to transfer data. Seeds denote the nodes which have the data initially. In other word, the subscription nodes need seeds transfer the data to them. To better understand our model, we define the notions of this paper as shown in Tab. 1.

2.1 Wi-Fi Offloading Model

TABLE I. NOTIONS

Symbol	Meaning
t	Time
M	The number of mobile nodes
N	The number of subscription nodes, $N \le M$
s	The number of seeds
j	The number of subscription nodes which have received mobile data, $j \in [0, N]$
K	The number of groups, $K \le s$
k	The *k*-th group, $k \in [1, K]$
ψ	Infection probability
T_d	The deadline
T_{d_k}	The deadline in *k*-th group
M_k	The number of mobile nodes in *k*-th group
N_k	The number of subscription nodes in *k*-th group
s_k	The number of seeds in *k*-th group
$C(t)$	The number of services nodes at time *t*
$D(t)$	The number of subscription nodes in services nodes at time *t*
$\Omega(t)$	The number of un-subscription nodes in services nodes at time *t*
$C_k(t)$	The number of services nodes in *k*-th group at time *t*
$D_k(t)$	The number of subscription nodes in services nodes in *k*-th group at time *t*
$\Omega_k(t)$	The un-number of subscription nodes in services nodes in *k*-th group at time *t*
T_{d_k}	minimum interval time of $C(t)$ from *i (i=1,2…,M-s)* nodes to *(i+1)* nodes
t_i	$t_i = \sum_{h=0}^{i} T_h$, *i (i=1,2…,M-s)*

Different from previous work that cellular M2M networks use opportunistic communication to forward mobile data directly, our model could calculate how much the mobile data traffic offloading before used the opportunistic communication. To measure how much mobile data traffic can be offloaded, we define *mobile traffic offloading rate* (called TOR) as a performance metric of our model as follows:

Definition 1 (TOR). *At time t, mobile traffic offloading rate ($\gamma(t)$) is the ratio of $D(t)$ and N, denoted by $\gamma(t) \in [0,1]$, is given by the following*:

$$\gamma(t) \triangleq \frac{D(t)}{N} . \tag{1}$$

According to $\gamma(t)$, cellular M2M networks can calculate how much mobile data traffic could be offloaded by the opportunistic communication. Therefore, $\gamma(T_d)$ (T_d indicates deadline) is the maximum value of TOR in our model. However, if we only pay attention on TOR, the effectiveness of the model may be low. For example, one subscription node may need amount of un-subscription nodes to forward the mobile data, which not only cause communication mechanism inefficient, but also consume much of local resource of un-subscription nodes. Therefore, we define *local resources consumption rate* (called LRCR) as another performance metric of our model to measure the resource consume of un-subscription nodes by the following:

Definition 2 (LRCR). *At time t, local resource consumption rate ($\chi(t)$) is a radio of the local resource consumption of un-subscription nodes and the mobile data traffic offloading as follows:*

$$\chi(t) \triangleq f(\Omega(t), D(t)) . \quad (2)$$

Where $f()$ indicates the resource consumption function.

In addition, the minimum time of all subscription nodes receive mobile data is one of key time to in our model. Thus, we introduce a new metric of *minimum completion time*, as defined next:

Definition 3 (*minimum completion time*). *In the process of mobile data forwarding, the time required for forwarding to all subscription nodes at first time, denoted by $T_{\min}$, is defined by the following*:

$$T_{\min} \triangleq \inf\{t : D(t) = N\} . \quad (3)$$

We call $T_{\min}$ the minimum completion time throughout this paper.

Because of T_d is determined by subscription nodes when they send the mobile data request to cellular M2M networks. If $T_{\min} \le T_d$, $\gamma(T_d) = 1$, this means all subscription nodes could obtain mobile data before deadline. Therefore, $T_{\min}$ is a critical metric for TOR in our adaptive offloading mobile data traffic model.

2.2 Our model

Generally, the cellular M2M networks transfer data to subscription nodes via cellular networks directly. The advantage of this communication mechanism is that all subscription nodes can obtain the data immediately, but it could increase the communication cost of the cellular networks at the same time. To solve this problem, a novel communication mechanism has been proposed [7,11,12]. In this communication mechanism, the cellular networks only transfer the data to some nodes. Then these nodes transfer the data to other nodes through opportunistic communication. The advantage of this communication mechanism is that it can offload data traffic through opportunistic communication. However, this mechanism may be inefficient when the subscription nodes distribution is sparse.

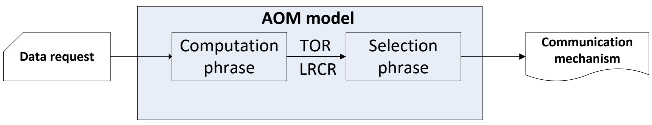


Figure 1. Adaptive offloading data traffic model

Different from traditional offloading data traffic models, we consider the two communication mechanisms above, and propose adaptive offloading data traffic (AOM) model for cellular M2M networks. As shown in Fig.1, AOM model contains two phrases, computation phrase and selection phrase. The TOR and LRCR are calculated in the computation phrase. And different communication mechanisms could be adopted in accordance with TOR and LRCR in the selection phrase.

In computation phrase, when subscription nodes need data from others, the seeds could transfer the data to the cellular networks or other nodes. And the cellular M2M networks calculate TOR and LRCR instead of transfer data to subscription nodes immediately. Firstly, according to the distribution of subscription nodes, the cellular M2M networks should determine whether transfer data to some nodes so that they become seeds. Then, the deadline of the data transfer should be determined in accordance with the subscription nodes. Finally, cellular M2M networks calculate the TOR and LRCR based on the CTMC with the seeds and deadline under the opportunistic communication mechanism.

In selection phrase, the cellular M2M networks first initialize the thresholds of TOR and LRCR. Then, compared the values of TOR and LRCR with the thresholds. Finally, determined the communication mechanism depending on the results of the comparison. If the TOR and LRCR greater than the thresholds, the cellular M2M networks could adopt opportunistic communication to transfer data before deadline, otherwise transfer the data to the subscription nodes directly.

3. Opportunistic Communication for TOR and LRCR

In this section, we first introduce the basic of opportunistic communication mechanism. We then derivation the expectations of the number of services nodes and the number of subscription nodes in services nodes, respectively.

3.1 The Basic of Opportunistic Communication

In classic information dissemination scheme, researchers always use the epidemiology to simulate information forwarding between mobile nodes [13]. Without loss of generality, we also use the epidemiology in our model. In the epidemiology, an individual is often classified into susceptible, infected, or removed, which can be denoted by S, I, R. And three epidemic models, SIS, SIR, and SI, are reduced, respectively. Generally, information forwarding model is more similar with SI model, so we focus on the SI model, which indicates a susceptible node will stay infected for the remainder of the epidemic process once it is infected. Hence, the infection probability is a critical basic to study mobile data forwarding, and we give its description as follows.

In the mobile data forward mechanism, a services node (say node α), meets a mobile node not having the data yet (say node β), it should deliver mobile data to node β with probability $\psi_\alpha \in (0,1]$. Similarly, node β receive mobile data successfully with probability $\psi_\beta \in (0,1]$. In our opportunistic communication mechanism, a mobile node becomes a service node once it receives mobile data successfully. Therefore, node β becomes a service node with the infection probability $\psi_\alpha \psi_\beta$, we use ψ indicates the infection probability $\psi_\alpha \psi_\beta$.

In the pairwise meeting process of mobile networks, the temporal behavior of the mobile data forwarding process is determined by its stochastic characteristic which is a critical factor for the mobile forwarding process. Recently studies show that the time duration between two consecutive contacts of a pair of nodes, called *pairwise inter-contact time*, can be modeled by an exponential random variable [14-16]. When nodes movement follow the Lévy flight mobility, which is known to closely mimic human mobility patterns [16], the *pairwise inter-contact time* distribution is an exponential distribution. In [17], the author assumed that the *pairwise inter-contact time* of node α and node β, denoted by $M_{\alpha,\beta}$, follows an exponential distribution with rate $\lambda_{\alpha,\beta}(>0)$, i.e.,

$$P\{M_{\alpha,\ \beta} > t\} = \exp(-\lambda_{\alpha,\beta} t),\ \ t \ge 0\ . \tag{4}$$

Suppose that node α is a service node and node β is an un-service node. According to the meeting process between them, we can obtain the interval of mobile data forwarding successful. Then assuming $\lambda_{\alpha,\beta}^{suc} = \lambda_{\alpha,\beta}\psi$, from (1), we have:

$$P\{M_{\alpha,\beta}^{suc} > t\} = \exp(-\lambda_{\alpha,\beta}^{suc} t),\ \ t \ge 0\ . \tag{5}$$

Where $M_{\alpha,\beta}^{suc}$ denotes the interval of mobile data forwarding successful from α to β. And the detailed proof of (5) is given in [17].

3.2 Derivation for TOR and LRCR

In this section, we develop an analytical framework for deriving the performance metrics defined in (1), (2), and (3). Firstly, we identify the temporal behavior of the total number in service nodes and subscription nodes (See Lemma 1 and Corollary 1). Then, using the results of Lemma 1 and Corollary 1, we are able to obtain the probability distribution of the subscription nodes (See Lemma 2). Finally, we discuss the fluctuation of LRCR according to the former lemmas (See Lemma 3), and give formulas of $C(t)$ and $D(t)$.

To derive TOR, we need know the temporal distribution of total number in services nodes $C(t)$ according to Definition 1. However, it is very intractable to solve this problem directly. To solve this problem, we prove that the joint temporal distribution of $C(t)$ can be derived from the theory of CTMC. Hence, we divide *M* mobile nodes into *K (K=1, 2,…, s)* mutual independence groups. Then, at time *t*, we have $C(t) = \sum_K C_k(t)$ and $s = \sum_K s_k$. Finally, we use the multi-dimensional CTMC to identify the distribution of $C(t)$ as shown in Lemma 1.

Lemma 1 (Joint temporal distribution of $C(t)$). *For K=1,2,…,s, let*

$$\mathbb{C}(t) \triangleq (C_1(t), C_2(t), \dots, C_K(t))\ .$$

Then, the process $\{\mathbb{C}(t): t \ge 0\}$ *is a K-dimensional CTMC. And the state space is given by:*

$$\varepsilon \triangleq \prod_{k=1}^{K} \{s, s+1, \dots, M-s\} \setminus 0\ . \qquad \square$$

Proof: See Appendix A.

According to the literature [17], we know Lemma 1 has some properties as follows:

(P1) The state space ε *can be decomposed into transient state space* $\varepsilon_{\mathbb{C}}^{*}$ *and absorbing state space* $\varepsilon_{\mathbb{C}}^{o}$*, denoted as following:*

$$\varepsilon_{\mathbb{C}}^{*} \triangleq \{e \in \varepsilon_{\mathbb{C}} : |e| < M - s\},$$

$$\varepsilon_{\mathbb{C}}^{o} \triangleq \{M_1 - s_1, M_2 - s_2, \dots, M_K - s_K\}.$$

Without loss of generality, we assume that the states in $\varepsilon_{\mathbb{C}}^{*} = \{e_1, e_2, \dots, e_K\}$ *are arranged as* $|e_1| \le |e_2| \le \dots \le |e_K|$.

(P2) According to the (P1), we can obtain the infinitesimal generator Q of the Markov chain as following:

$$Q = \begin{bmatrix} F & F^o \\ 0 & 0 \end{bmatrix}.$$

Where $F = (F_{i,j})$ *is a matrix representing transition rate from* $\varepsilon_{\mathbb{C}}^{*}$ *to* $\varepsilon_{\mathbb{C}}^{*}$*, and* F^o *is a column vector representing transition rate from* $\varepsilon_{\mathbb{C}}^{*}$ *to* $\varepsilon_{\mathbb{C}}^{o}$.

(P3) For a given time t(>0), we assume $\pi(t) \triangleq P\{\mathbb{C}(t) = e\}_{e \in \varepsilon_{\mathbb{C}}^{*}}$ *which indicates the distribution of* $\mathbb{C}(t)$ *on* $\varepsilon_{\mathbb{C}}^{*}$*. Obviously, at the stage of initialization, we have* $P\{\mathbb{C}(0) \in \varepsilon_{\mathbb{C}}^{*}\} = 1$*. From the (P2), we have:*

$$\pi(t) = \pi(0)\exp(Ft)\ . \tag{6}$$

Thus, we can obtain the distribution of $\mathbb{C}(t)$ *on* $\varepsilon_{\mathbb{C}}^{o}$ *through* $P\{\mathbb{C}(t) = M\} = 1 - \pi(t)$.

The detail proof of properties is given in literature [17].

From the Lemma 1, the number of services nodes increase as time *t* is a CTMC. And we know $D(t)$ is a part of $C(t)$ in this paper. Hence, with a similar with Lemma 1, we have follow corollary:

Corollary 1. (Joint temporal distribution of $D(t)$). *For K=1,2,…,s, assume the k-th group have* N_k *subscription nodes, i.e.,* $N = \sum_K N_k$*, let*

$$\mathbb{N}(t) \triangleq (D_1(t), D_2(t), \dots, D_K(t))\ .$$

Then, the process $\{\mathbb{N}(t): t \ge 0\}$ *is a K-dimensional CTMC.* $\square$

Proof: In this paper, the process $\{\mathbb{N}(t): t \ge 0\}$ is a sub-process of $\{\mathbb{C}(t): t \ge 0\}$, since $\{\mathbb{C}(t): t \ge 0\}$ is a *K*-dimensional CTMC, and according to the inference of theorems of Markov chain, thus the process $\{\mathbb{N}(t): t \ge 0\}$ is proved to be a K-dimensional CTMC. ■

In opportunistic communication mechanism, mobile data is forwarded from services nodes to other nodes through the opportunistic communication. This means more and more mobile nodes become services nodes gradually, as well as $D(t)$. According to Definition 1, $D(t)$ determines TOR. Therefore, it is very important to obtain $D(t)$. However, it is very hard to get the $D(t)$ because of the uncertainty of transition probability. Fortunately, we can derive the probability distribution of $D(t)$ by finding the relationship between $D(t)$ and $C(t)$, and we have the follow lemma:

Lemma 2 (the probability of $D(t)$): *Assuming that the minimum interval time of $C(t)$ from i (i=1,2…,M-s) nodes to (i+1) nodes is T_i, and $t_i = \sum_{h=0}^{i} T_h$, we have $C(t_i) = s + i$. At time t_i, assuming $D(t_i) = j$ (j=0,1,…,N-1), then we give the probability of $D(t) = j+1$ at time $t(> t_i)$ as follows:*

$$P\{D(t) = j+1\} = (N-j)\sum_{i=j}^{M-s-N+j} \frac{P\{C(t) = s+i+1\}}{M-s-i}. \tag{7}$$

Where, i denotes the services nodes number, j denotes the number of subscription of services nodes. □

Proof: Refer to Appendix B.

According to Lemma 1 and Lemma 2, we can derive $D(t)$ and $\Omega(t)$, which are variables of resource consumption function. And opportunistic communication usually relies on free shortwave transmission (such as Bluetooth), therefore we mainly consider the number of un-subscription nodes to participate mobile data forwarding. To derive LRCR, we define the resource consumption function $f(\Omega(t), D(t))$ is the ratio of the $D(t)$ and $(\Omega(t)+\mathrm{s})$ according to Definition 2, and LRCR ($\chi(t)$) is denoted as follows:

$$\chi(t) = f(\Omega(t), D(t)) \triangleq \frac{D(t)}{C(t)-D(t)} = \frac{D(t)}{\Omega(t)+s} \ . \tag{8}$$

And according to Lemma 1 and Corollary 1, $D(t)$ and $\Omega(t)$ could increase or un-increase as $C(t)$ increase before deadline. Therefore we have the following lemma:

Let $\boldsymbol{\pi(t) = (\pi_1(t), \pi_2(t), ..., \pi_{M-s}(t))}$ denote the probability distribution of $C(t)$ at time *t*. And from the (P3) of Lemma 1, we can obtain the probability of $C(t)$. Then, the expectation of $C(t)$ as follows:

$$E[C(t)] = \sum_{i=0}^{i=M-s} (i+s)\pi_i(t) \ . \tag{10}$$

Where $\pi_j(t) = P\{C(t) = s+j\},\ j = 0,1,...,M-s$.

The value of $D(t)$ is the major factor to determine TOR. According to Lemma 2, the probability distribution of $D(t)$ relies on the probability distribution of $C(t)$, and we derive $E[D(t)]$ as follows:

$$E[D(t)] = \sum_{j=0}^{N}\sum_{i=j}^{M-s-N+j} \frac{\mathbf{j}\bullet(N-j)}{M-s-i}\pi_i(t) \ . \tag{11}$$

4. Analysis TOR and LRCR

In this section, we first study the parameters of TOR and LRCR such as population sizes, infection probability and multiple groups. Then we derive the formulas of TOR and LRCR.

4.1 The parameters of population size

In our opportunistic communication mechanism, each non-seed node is considered as a workload to finish. However, once the node becomes a services node, it works in a similar manner as the seed and is involves in forwarding the mobile data. Hence, it is not straightforward whether the population sizes (*M*, *N*, *s*) accelerates or slows down the speed of mobile data forward. We give the answer based on $T_{\min}$, and we have the following theorem:

Theorem 1 (Impact of different population sizes). *In mobile networks, the relationship between different population sizes (M, N and s) and the expectation of $T_{\min}$ as shown in (12):*

$$E[T_{\min}] = \sum_{N}^{M-s} \varphi(t_i)\bullet\frac{1}{M\psi}\ln\left(\frac{M-s-1}{M-s-i}\bullet\frac{s+i}{s+1}\right) \ , \tag{12}$$

And the relationship between population sizes and the expectation of t_i as follows:

$$E[t_i] \ = \frac{1}{\psi M}\ln\left(\frac{M-s-1}{M-s-i}\bullet\frac{s+i}{s+1}\right) \ , \tag{13}$$

Where $\varphi(t_i) = \dfrac{P\{C(t) = s+i \mid C(t_{N-1}) = s+i-1\}}{M-s-i+1}$ *, and* ψ *indicates the infection probability.* □

Proof: See Appendix C.

4.2 The parameters of infection probability

As shown in the (12), the infection probability can impact the $T_{\min}$. And according to the (5), the infection probability is one of factor to decide the mobile data forwarding time. In this section, we present a theorem to describe how infection probability impacts on $T_{\min}$, and denotes by the following:

Theorem 2 (Impact of the infection probability). *Suppose that the infection probability ψ is scaled by ω (>0) times for all α, β, denote by $\hat{\psi}$, i.e. $\hat{\psi} = \omega\psi$. Let $\hat{T}_{\min}$ be the correspondences of $T_{\min}$, the relationship of them as follows:*

$$\hat{T}_{\min} \overset{d}{=} \omega^{-1} T_{\min} \ . \tag{14}$$

Where $\overset{d}{=}$ denotes "equal in distribution." □

Proof: Refer to Appendix D.

Theorem 2 indicates that the mobile data forward becomes faster proportionally to the level of infection probability in distribution sense. And this means the higher infection probability the more subscription nodes can receive mobile data before the deadline.

4.3 The parameters of multiple groups

Exception the impacts of population sizes and infection probability, TOR and LRCR are also impacted by the number of groups. As we known, the distribution of mobile nodes is not uniform, and changing over time in real mobile networks. K. Yooar et al. [17] has proved we can use the multi-dimensional CTMC to study information forward in heterogeneity network. In this section, we study multiple groups in our mobile data opportunistic communication mechanism.

In our model, the cellular M2M networks divides all mobile nodes into *k (k=1,2,…,K)* mutual independence groups. Suppose the correspondence populations sizes are M_k, N_k, and s_k in *k*-th group. For different groups, the minimum completion time may difference. We calculate the minimum completion time of *k*-th group, $T_{\min_k}$, based on (12) where $T_{\min} = \max\{T_{\min_1}, T_{\min_2}, ..., T_{\min_K}\}$. Similarly, we can set the deadline of *k-th* group, T_{d_k}, according to $T_{\min_k}$, without loss of generality to arrange as $T_{d_1} \le T_{d_2} \le ... \le T_{_K}$. Based on those above analysis, we derive the formula of TOR is indicated by (15), and the formula of LRCR is indicated by (16).

$$\gamma(T_d) = \frac{\sum_K D_k(T_{d_k})}{N}, \tag{15}$$

$$\chi(T_d) = \frac{\sum_K D_k(T_{d_k})}{\sum_K (C_K(T_{d_k}) - D_K(T_{d_k}))}. \tag{16}$$

4.4 Formulate of TOR and LRCR

According to Definition 1, TOR is restricted by time *t*. Then according to (12), we can calculate the expectation of $T_{\min}$, and the value of TOR is 1 when the deadline is greater than $T_{\min}$. If we set $T_d = T_{\min}$, then (16) can be rewritten as (17).

$$E[\chi(T_{\min})] = \frac{E[\sum_K D_k(T_{\min_k})]}{E[\sum_K (C_K(T_{\min_k}) - D_K(T_{\min_k}))]}. \tag{17}$$

By combing (10) and (11), we rewrite (17) as follows:

$$E[\chi(T_{\min})] = \frac{\sum_{k=1}^{K}\sum_{i=0}^{M_k-s_k}(i+s_k)\pi_{k_i}(T_{\min_k})}{\sum_{k=1}^{K}\left(\sum_{i=0}^{M_k-s_k}(i+s_k)\pi_{k_i}(T_{\min_k}) - \sum_{j=0}^{N_k}\sum_{i=j}^{M_k-s_k-N_k+j}\frac{N_k-j+1}{M_k-s_k-i}\pi_{k_i}(T_{\min_k})\right)} \tag{18}$$

Where $\pi_{k_i}(t)$ indicates the probability distribution of the *k*-th group.

Similarly, when $T_{\min} > T_d$, the formula of TOR is indicated by (19) and the formula of LRCR is indicated by (20).

$$E[\gamma(T_d)] = \frac{\sum_{j=0}^{N_k}\sum_{i=j}^{M_k-s_k-N_k+j}\frac{j\bullet(N_k-j+1)}{M_k-s_k-i}\pi_{k_i}(T_{d_k})}{N}, \tag{19}$$

$$E[\chi(T_d)] = \frac{\sum_{k=1}^{K}\sum_{i=0}^{i=M_k-s_k}(i+s_k)\pi_{k_i}(T_{d_k})}{\sum_{k=1}^{K}\left(\sum_{i=0}^{i=M_k-s_k}(i+s_k)\pi_{k_i}(T_{d_k}) - \sum_{j=0}^{N_k}\sum_{i=j}^{M_k-s_k-N_k+j}\frac{j\bullet(N_k-j+1)}{M_k-s_k-i}\pi_{k_i}(T_{d_k})\right)} \tag{20}$$

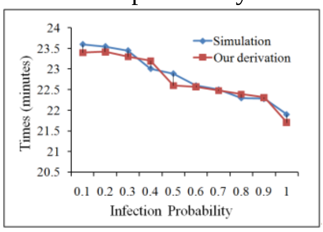
Where, $\pi_{k_i}(t)$ indicates the probability distribution of the *k*-th group.

According to (19) and (20), the cellular M2M networks can obtain TOR and LRCR. On the basis of TOR and LRCR, our model can decide whether to adopt opportunistic communications to transfer data or transfer data from the cellular M2M networks.

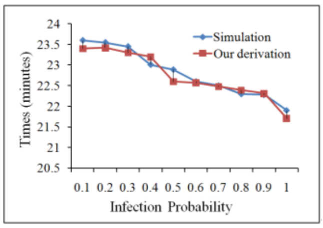
5. Performance Evaluation

In this section, we verify TOR and LRCR through simulations. To simulate our opportunistic communication mechanism better, we extend the ONE [18] by adding multi-destination nodes setting and infection probability in the ONE. Then, we use the extend ONE[1] to simulate mobile data forward in the opportunistic networks.

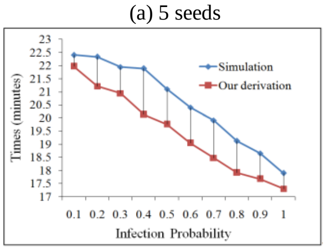
Firstly, we study the impact of minimum completion time on different number of subscription nodes and seeds. We set 3500 mobile nodes including 500 subscription nodes in our extend ONE. We select 5, 10, 15 and 20 seeds to test its impact on infection probability.



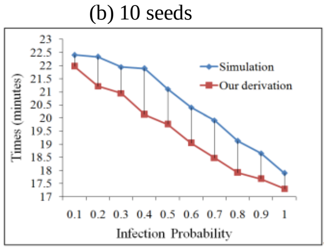
(a) 5 seeds



(b) 10 seeds



(c) 15 seeds



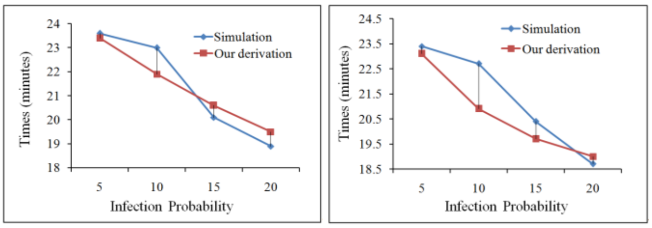
(d) 20 seeds

Figure 2. The minimum completion time with (a) 5 seeds, (b) 10 seeds, (c) 15 seeds, (d) 20 seeds. And simulation results show Theorem 2 is also correct.

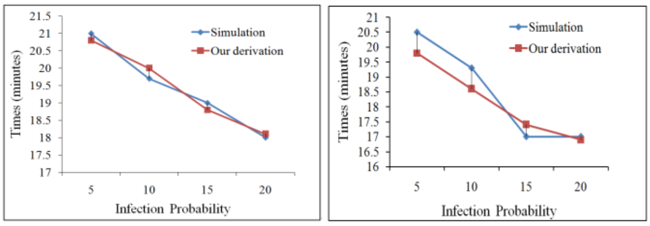
[1] https://www.netlab.tkk.fi/tutkimus/dtn/theone/

As shown in Fig.2 (a, b c, d), the minimum completion time ($T_{\min}$) decrease with the increasing infection probability. According to the Theorem 1, we calculate $T_{\min}$ with different infection probability. And the calculation results are as shown in Fig.2 (a, b, c, d). Although the results of simulation are irregular because of the random of the nodes movement, the tendency of $T_{\min}$ is consistent with our derivation. Hence, simulation results show Theorem 2 is also correct.

We also study the impact of $T_{\min}$ on infection probability. We select 0.2, 0.6, 0.8 and 1.0 to test its impact on the number of seeds. As shown in Fig.3 (a, b c, d), $T_{\min}$ decreases with the increasing seeds. We find $T_{\min}$ is also consistent with our derivation. Hence, simulation results show Theorem 1 is also correct.



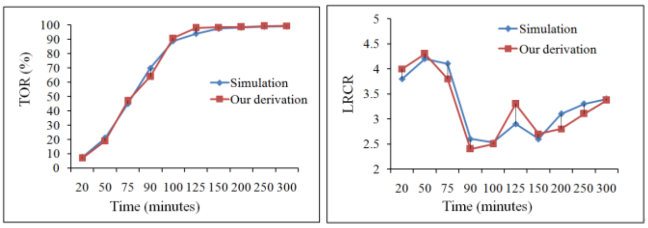
(a) Infection probability with 0.2, (b) Infection probability with 0.6



c) Infection probability with 0.8, (d) Infection probability with 1.0

Figure 3. The minimum completion time with (a) infection probability of 0.2, (b) infection probability of 0.6, (c) infection probability of 0.8, (d) infection probability of 1.0. And the simulation results show Theorem 1 is also correct

Finally, we investigated the formulas for TOR and LRCR. In this simulation, we set 2000 subscription nodes, 5 seeds and the infection probability is 0.8. As shown in Fig. 4(a), the value of TOR increases with increasing time *t*. Further, as shown in Fig. 4(b), the value of LRCR changes irregularly. Thus, the simulation results confirm that our derivation for TOR and LRCR is correct.



(a) The tendency of TOR (b) The tendency of LRCR

Figure 4. The tendency of (a) TOR, and (b) LRC. The simulation results show our derivation of TOR and LRCR is correct.

All the simulations show that, although minor differences exist, the simulations and derivations are consistent. This proves that using TOR and LRCR in our model enables it to adaptively offload data traffic for the cellular M2M networks.

6. Conclusion

In this paper, we first proposed an adaptive offloading mobile data traffic model for cellular M2M networks. This model contains two data transfer mechanisms: transfer the data via the cellular networks and transfer of data through opportunistic communication. Then, we derived TOR and LRCR based on continuous time Markov chain. Finally, the results of extensive simulations conducted demonstrate that the derivation in our model is accurate and effective.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China under Grant No. 61202435 and 61272521 and the Natural Science Foundation of Beijing under Grant No.4132048.

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APPENDIX A

PROOF OF LEMMA 1

We take an arbitrary $C_k(t)$ to prove that it follows the CTMC.

We assume that the minimum time of the number of services node from *i* nodes to *(i+1)* nodes is T_i in group *k (k=1,2,…,K)*, and s_k indict the number of seeds. From (2), we have:

$$P\{C_k(0)=s_k\}=1$$

$$\begin{aligned} &P\{C_k(T_1)=s_k+1 \mid C_k(0)=s_k\} \\ &\quad =\exp(-\lambda_{s,\mathrm{M}-s}^{suc}T_1) \quad , \\ &\quad = P\{C_k(T_1)=s_k+1\} \end{aligned}$$

$$\begin{aligned} &P\{C_k(T_1+T_2)=s_k+2 \mid C_k(T_1)=s_k+1, C_k(0)=s_k\} \\ &\quad = P\{C_k(T_1+T_2)=s_k+2, C_k(T_1)=s_k+1, C_k(0)=s_k\} / \\ &\qquad\qquad P\{C_k(T_1)=s_k+1, C_k(0)=s_k\} \\ &\quad = P\{C_k(T_1+T_2)=s_k+2 \mid C_k(T_1)=s_k+1\} \end{aligned}$$

$$\dots ,$$

$$\begin{aligned} &P\{C_k(T_1+T_2+\dots+T_i+T_{i+1}) \\ &\quad = s_k+i+1 \mid C_k(T_i)=s_k+i, \dots, C_k(0)=s_k\} \\ &\quad = P\{C_k((T_1+T_2+\dots+T_i+T_{i+1})=s_k+i+1 \mid \\ &\qquad\qquad C_k(T_i)=s_k+i\} \end{aligned}$$

Thus, $C_k(t)$ is a CTMC. Because of each group is mutual independence, so each one group is a CTMC. So the process $\{\mathbb{C}(t): t\ge 0\}$ is a K-dimensional CTMC. ■

APPENDIX B

PROOF OF LEMMA 2

According to the define of t_i, the conditional probability of $D(t)=j+1$ *is :*

$$P\{D(t)=j+1 \mid C(t)=s+i+1\}=\frac{N-j}{M-s-i} \ .$$

And

$$\begin{aligned} &P\{D(t)=j+1 \mid C(t)=s+i+1\} \\ &\quad = P\{D(t)=j+1, C(t)=s+i+1\} \\ &\qquad\qquad / P\{C(t)=s+i+1\} \end{aligned}$$

According to the formula total probability, we have:

$$\begin{aligned} &P\{D(t_{i+1})=j+1\} \\ &\quad =\sum_i P\{D(t)=j+1, C(t)=s+i+1\} \quad , \end{aligned}$$

And (7) has been proved in Lemma 2. ■

■ APPENDIX C

PROOF OF THEOREM 1

Assume that the minimum time of $C(t)$ from *i (i=1,2…,M-s)*, nodes to *(i+1)* nodes is T_i. Let $t_i=\sum_{h=0}^{i}T_h$, then according to Lemma 2, the probability of $T_{\min}$ as follows:

$$P\{T_{\min}<t_N\}=0 \ ,$$

$$P\{T_{\min}=t_N\}=\frac{P\{C(t)=s+N \mid C(t_{N-1})=s+N-1\}}{M-s-N+1} \ ,$$

$$P\{T_{\min}=t_{N+1}\}=\frac{P\{C(t)=s+N+1 \mid C(t_N)=s+N\}}{M-s-N} \ ,$$

$$\dots ,$$

$$P\{T_{\min}=t_{M-s-1}\}=\frac{P\{C(t)=M-s-1 \mid C(t_{M-s-2})=M-s-2\}}{2}$$

$$P\{T_{\min}=t_{M-s}\}=P\{C(t)=M-s \mid C(t_{M-s-1})=M-s-1\} \ .$$

According to the probability distribution of $T_{\min}$, we can obtain the expectation of $T_{\min}$:

$$\begin{aligned} E[T_{\min}] &= \sum_{1}^{M-s} t_i P\{T_{\min}=t_i\} = \sum_{N}^{M-s} t_i P\{T_{\min}=t_i\} \\ &= \sum_{i=N}^{M-s} \frac{P\{C(t)=s+i \mid C(t_{N-1})=s+i-1\}}{M-s-i+1} \bullet \frac{1}{M\psi} t_i \end{aligned} .$$

Let $\varphi(t_i)=\dfrac{P\{C(t)=s+i \mid C(t_{N-1})=s+i-1\}}{M-s-i+1}$, then we have:

$$E[T_{\min}]=\sum_{i=N}^{M-s}\varphi(t_i)\bullet\frac{1}{M\psi}t_i$$

Similarly, we calculate the expectation of t_i:

$$E[t_i]=\sum\nolimits_i E[T_i] \ ,$$

Because of T_i follows exponential distribution, according to (2), we have:

$$E[t_i] = \sum_i E[T_i] = \frac{1}{\psi}\sum_1^i \frac{1}{(s+i)(M-s-i)}$$
$$\approx \frac{1}{\psi M}\int_1^i \left(\frac{1}{s+t} + \frac{1}{M-s-t}\right)\mathrm{dt} \quad .$$
$$= \frac{1}{\psi M}\ln\left(\frac{M-s-1}{M-s-i}\bullet\frac{s+i}{s+1}\right)$$

Summary, the Theorem 1 has been proved. ■

APPENDIX D

PROOF OF THEOREM 2

According to Theorem 1 at time *t*, we can obtain the probability distribution of $\hat{T}_{\min}$ and $T_{\min}$:

$$P\{T_{\min} = t_{N+i}\} = \frac{P\{C(t) = s+i-N \mid C(t_{N-1}) = s+i-N-1\}}{M-s-N-i+1} \ ,$$

$$P\{\hat{T}_{\min} = t_{N+i}\} = \frac{P\{C(t) = s+i+N \mid C(t_{N-1}) = s+i+N-1\}}{M-s-N-i+1} \, ,$$

i.e., $P\{T_{\min} = t_{N+i}\} = P\{\hat{T}_{\min} = t_{N+i}\}$. From (13), we have,

$$Et_i = \frac{1}{\psi M}\ln\left(\frac{M-s-1}{M-s-i}\bullet\frac{s+i}{s+1}\right) .$$

And because $\hat{\lambda}_{\alpha,\beta}^{suc} = \omega\lambda_{\alpha,\beta}^{suc}$, i.e., $\hat{\psi} = \omega\psi$, the expectation of $\hat{t}_i$ denotes as follows:

$$E\hat{t}_i = \frac{1}{\hat{\psi} M}\ln\left(\frac{M-s-1}{M-s-i}\bullet\frac{s+i}{s+1}\right)$$
$$= \frac{1}{\omega\psi M}\ln\left(\frac{M-s-1}{M-s-i}\bullet\frac{s+i}{s+1}\right) .$$
$$= \omega^{-1}Et_i$$

In other words, $P\{\hat{T}_{\min} < t\} = P\{\omega^{-1}T_{\min} < t\}$, then:

$$\hat{T}_{\min} \overset{d}{=} \omega^{-1}T_{\min} \, .$$ ■