Energy-efficient Joint Control of Epidemic Routing in Delay Tolerant Networks

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Abstract

Due to the uncertain of connections in Delay Tolerant Networks (DTNs), most routing algorithms in DTNs need nodes to forward the message to others based on the opportunistic contact. The contact is related with the *beaconing rate*. In particular, nodes have more chances to encounter with each other with bigger *beaconing rate*, but more energy will be used. On the other hand, if the nodes forward the message to every node all the time, the efficiency of the routing algorithm is better, but it needs more energy, too. This paper tries to exploit the optimal *beaconing rate* and *forwarding rate* when the total energy is constraint. First, a theoretical framework is proposed, which can be used to evaluate the performance with different *forwarding rate* and *beaconing rate*. Then, this paper formulates a joint optimization problem based on the framework. Through Pontryagin's Maximal Principle, this paper obtains the optimal policy and proves that both the optimal *forwarding* and *beaconing* rates conform to *threshold* form. Simulation results show the accuracy of the theoretical framework. Extensive numerical results show that the optimal policy obtained in this paper is the best.

Keywords: Delay tolerant networks, joint control, epidemic routing, Pontryagin's Maximal Principle

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1. Introduction

The Delay Tolerant Networks (DTNs) are sparce mobile networks, where the connectivity among mobile nodes is not always guaranteed [1]. Examples of such networks include deep-space exploration networks [2], mobile social networks [3], and vehicular networks [4], etc. Routing protocols in traditional ad hoc networks, which relay on the end-to-end paths, cannot work in DTNs efficiently.

In order to overcome the network partitions, nodes in DTNs communicate through a *store-carry-forward* way. When the next hop is not immediately available for the current node, some relay nodes will *store* the message in their buffer, *carry* the message along their movements, and *forward* the message to other nodes when a new communication opportunity is occurring [1]. It is easy to see that such communication mode is related with the opportunistic contact between nodes. In particular, if nodes have more chances to meet each other, the message can be transmitted much faster between nodes. Furthermore, the opportunistic contacts between nodes are closely related with the *beaconing rate* of nodes. If we increase the *beaconing rate*, we can obtain more communication contacts, and consequently higher message delivery ratio, at the cost of higher energy consumption [5]. However, if we decrease the *beaconing rate*, nodes may not detect each other timely, and many forwarding opportunities will lose. Therefore, the delivery ratio will decrease. For this reason, how to decide the optimal *beaconing rate* is an important problem. On the other hand, the efficiency of routing algorithms is also related with the cooperative level of the relay nodes. If these nodes forward the message to any node all the time, the efficiency is better, but more energy will be used [6], too. If nodes carrying a message forward the message to any node that they encounter with based on the opportunistic contact, the message will be propagated according to the pure Epidemic Routing (ER) algorithm [7]. In the ER algorithm, the destination can get message much faster at the cost of more energy consumption. If nodes do not forward the message to others at all, the destination may get message slower, but certain energy will be saved. In summary, both the *beaconing* and *forwarding* processes need certain energy, and a higher energy consumption may bring a bigger delivery ratio. In the real world, the energy is very precious for the wireless devices (e.g., smart phones, wireless sensors, etc), so the network manager may not want to use too much energy. Therefore, how to get the optimal *beaconing* and *forwarding* policies with energy constraint is a very important problem in DTNs. As shown in [8], the energy consumption in the wireless communication process mainly includes the transmitting and receiving consumption in the communication state as well as the beaconing consumption in the idle state, so we only consider the energy in above processes and ignore other energy consumption (e.g., energy consumption for computation or mobility) similar to the works in [9]-[10].

At present, there are many works, which explore the optimal energy-efficient routing problem in DTNs through a theoretical manner. The work in [9] studies the joint optimization problem underlying activation of mobiles and forwarding control in the context of DTN, but the algorithm used is Two-hop routing algorithm, which is a variation of the ER algorithm and very simple. The work in [10] studies the optimal control problem for ER algorithm, but it only considers the optimal *beaconing* control and ignores the optimal *forwarding* control. The work in [11] studies the optimal *forwarding* policies for ER algorithm through discrete Markov process, and proves that the optimal *forwarding* policy conforms to the *threshold* form. Li, etc. consider the optimal *forwarding* policy for ER algorithm in [12] through continuous Markov process. The work in [13] explores the optimal *forwarding* problem when the energy in nodes is heterogeneous. In addition, the work in [14] considers the optimal *forwarding* control and the social behaviors of nodes in DTNs. However, the works in [11]-[14] ignore the optimal *beaconing* control problem. To our best knowledge, we are the first to explore the joint optimization problem for ER algorithm.

In this paper, we first propose a unifying framework based on the mean-field limit, which can be used to evaluate the performance under different *beaconing* and *forwarding* policies with energy constraint. Then based on the framework, we formulate a joint optimization problem. Through Pontryagin's Maximum Principle, we explore the stochastic control problem, and prove that the optimal policy conforms to the *threshold* form. By comparing the simulation results with the theoretical results, we show that our theoretical framework is very accurate. In addition, we compare the performance of the optimal policy with other policies through extensive numerical results, and find that the optimal policy obtained by Pontryagin's Maximum Principle is the best.

In Section 2, we briefly review the previous work. Section 3 first presents the theoretical framework, and then formulates the joint optimization problem. In Section 4, we introduce the simulation and numerical results. At last, we conclude our main work.

2. Related Work

There are many research problems in DTNs, such as the clock synchronization problem [15], caching problem [16], etc. For simplicity, we just introduce the works related with the optimal control of routing algorithms in DTNs, which is very hot now. However, before exploiting the optimal control problem, a theoretical framework, which can be used to evaulate the performance of the corresponding routing algorithms is necessary. In the past few years, many routing protocols have been proposed in DTNs. For example, the *deterministic* policy proposed by Jain et al. introduces a modified Dijkstra algorithm based on the determistic information about the schedulded contacts [17]. Another example is the *enforced* policy, and the basic idea is to deploy certain special purpose mobile devices, which move over predefined paths in order to provide connectivity [18]. In addition, the *utility* based policy tries to evaluate the utility of nodes and use the high utility nodes to improve the perfornance, such as [19]-[20], etc. These routing algorithms have certain advantages, but most of them are very complex, and it is hard to present an accurate theoretical framework to model the routing process for these algorithms. Therefore, the studies using the theoretical manner often focus on the ER algorithm or its variations. On the other hand, ER algorithm and its variations are easy to carry out, for example, the only constraint imposed on the hop-based policies is the message hop count [21]. Therefore, they are very hot recently, too . For example, the work in [22] studies the performance of ER based on the sparsely exponential graph. In particular, it proposes a rigorous, unified framework to explore the performance of ER algorithm and its variations based on the ordinary differential equations (ODEs), which is a mean-field limit. The concept of mean-field is first introduced in statistical mechanics [23]. On the other hand, this convergence result often provides an approximation for networks consisting of large numbers of interacting nodes. In addition, the method can model the system on an abstract level as the distribution of nodes in the set of possible states, and it allows one to observe the evolution of this distribution over time. At present, the mean-field method has been commonly used to analyze the performance of communication networks. For examples, the work in [24] explores the gossip protocol in dynamic networks by the mean-field method. The work in [25] presents a generic result for the convergence of a discrete time model of interacting objects to the solution of an ordinary differential equation. There are also many works which use the mean-field method to evaluate the performance of various routing protocols in DTNs, and [22] is a classic example. Later, the work in [26] proposes a model to explore the performance of ER algorithm in DTN with heterogeneous nodes based on mean-field limit. Performance of ER with coding policy is studied in [27]. Then, the work in [28] studies the performance of hop-limited ER algorithm based on the mean-field limit.

The problem of finding optimal *forwarding* or *beaconing* policies in DTNs has been investigated in many works [9]-[14]. Most of these works consider a cost for overall energy usage, and they try to maximize the average probability that the destination gets a message before the deadline of the message when the total energy usage is constraint. For example, the work in [10] studies the optimal *forwarding* problem of probabilistic ER algorithm, and they prove that the optimal forwarding policy conforms to the *threshold* form. Then the work in [11] explores the problem again with continuous time Markov process. However, none of the existing works considers the joint optimization problem for ER algorithm in DTNs.

3. Theoretical Framework and Optimal Control

3.1 Network Model

In this paper, we assume that there are N relay nodes and one destination D. Among the relay nodes, there is one source S. At time 0, only the source is carrying a message and it tires to make the destination D obtain the message before the deadline T. In this paper, we also assume that nodes that have a message do not receive the same message any more. Here, we mainly consider the ER algorithm, which floods the message over the whole network, and attempts to send the message over all possible paths in the network. To decrease the energy consumption, we adopt the probabilistic ER algorithm [10]-[14]. That is, nodes send the message to others with probability $p(t)$ at time t. If we have $p(t)=1, t\in[0,T]$, it is the original ER algorithm. On the other hand, message can be transmitted between nodes only when they encounter with each other, so the mobility rule of nodes can have important impact on the performance.

In this paper, we assume that the occurrence of contacts between two nodes follows a Poisson distribution, so the inter-meeting time between two contacts follows the exponential distribution. This assumption has been used in wireless communications many years. At present, some works show that this assumption is only an approximation to the message propagation process, and they reveal that nodes encounter with each other according to the Power law distribution [29]. However, they also find that if you consider long traces, the tail of the distribution is exponential. In addition, the work in [30] shows that the individual inter-meeting time can be shaped to be exponential by choosing an approximate domain size with respect to given time scale. Moreover, there are also some works, which describe the inter-meeting time of human or vehicles by exponential distribution and validate their model experimentally on real motion traces [31]-[32]. According to the description above, the exponential inter-meeting time is rational in some applications. However, the distribution is closely related with the *beaconing rate* of nodes. If the *beaconing rate* is bigger, nodes can find each other timely, but this will bring higher energy consumption. In this paper, we assume that if nodes use the biggest *beaconing rate*, the inter-meeting time between two nodes follows an exponential distribution with the parameter denoted by λ. To reduce the energy consumption in the *beaconing* process, we define $\mu(t)$ as the *beaconing rate* at time t, and we have $\mu_{min}\leq\mu(t)\leq 1$, where μ_{min} is the minimum *beaconing rate*, which satisfies $\mu_{min}\geq 0$. If $\mu(t)=1$, all nodes have the biggest *beaconing rate*, so nodes encounter with each other with parameter λ. In summary, we mainly have two control parameters:

a. *Beaconing rate* $\mu(t)$, $\mu_{\min} \le \mu(t) \le 1$: the beaconing power is controlled in order to mitigate the battery discharge of relay nodes. In particular, at time t, the *beaconing rate* is $\mu(t)$. Furthermore, under the policy $\mu(t)$, the contact rate between nodes is $\lambda\mu(t)$ at time t. In this paper, we assume that the destination always beacons at the biggest *beaconing rate* similar to the work in [9]-[10].

b. *Forwarding rate* (*Forwarding* probability) $p(t)$, $0 \le p(t) \le 1$: the energy in the forwarding process can be controlled by adjusting the value of $p(t)$. At time t, the *forwarding rate* is $p(t)$. However, nodes are always willing to forward the message to D. That is, relay nodes make the value of $p(t)$ always be 1 for the destination.

In addition, we assume that once a node obtains the message, it will stop beaconing to save energy. In other words, only those nodes that do not have the message keep beaconing to find other nodes, and similar assumption has been used in [9]-[10].

The list of commonly used notations can be found in **Table 1**.

TABLE 1. THE LIST OF COMMONLY USED VARIABLES

N	Number of relay nodes
λ	Exponential parameter of the inter-meeting time (biggest value)
T	The maximal lifetime of the message
$p(t)$	The *forwarding rate* at time t
$\mu(t)$	The *beaconing rate* at time t
$X(t)$	The number of relay nodes carrying message at time t
$F(t)$	The delivery ratio at time t
C	The maximal energy

3.2 Theoretical Framework

Let $X(t)$ denote the number of relay nodes (including the source S) that have message at time t. Because only S has message at time 0, we have $X(0)=1$. Given a minor interval Δt, we have:

$$X(t+\Delta t) = X(t) + \sum\nolimits_{m\in\{Y(t)\}} \varphi_m(t, t+\Delta t) \tag{1}$$

$\{Y(t)\}$ denotes the set of nodes that do not have message at time t, so it has N-$X(t)$ elements. Symbol $\varphi_m(t, t+\Delta t)$ denotes the event that node m successfully gets message in time interval $[t, t+\Delta t]$. If $\varphi_m(t, t+\Delta t)=1$, we say that this event happens. Otherwise, if $\varphi_m(t, t+\Delta t)=0$, this event does not happen. In addition, if this event happens, node m must encounter with a node (e.g., n), and node n is willing to forward the message to m. As described in above section, the *beaconing rate* is $\mu(t)$ at time t, so the inter-meeting rate between node m and n is $\lambda\mu(t)$. On the other hand, node n forward a message to m with probability $p(t)$ at time t. Therefore, we have,

$$p(\varphi_m(t, t+\Delta t)=1) = 1-(1-(1-e^{-\lambda\mu(t)\Delta t})p(t))^{X(t)} \tag{2}$$

Similar to [12], we can get the following equation based on Eq.(1) and Eq.(3),

$$\begin{aligned} & E(X(t+\Delta t)) - E(X(t)) = E(N - X(t))E(\varphi_m(t, t+\Delta t)) \\ & \Rightarrow E(\dot{X}(t)) = (N - E(X(t)))\lim_{\Delta t\to 0}\frac{E(\varphi_m(t, t+\Delta t))}{\Delta t} \\ & \quad = \lambda\mu(t)(N - E(X(t)))E(X(t))p(t) \end{aligned} \tag{3}$$

We can easily see that Eq.(3) is a mean-field limit of the original Markov process, which is a close-form expression. We check the accuracy of the model by simulation and the result shows that it is very accurate. By the way, $E(*)$ denotes the expection of *.

One of the main metrics for routing algorithms in DTNs is the delivery ratio, which denotes the probability that the destination D obtains the message within given time. In this paper, we let $F(t)$ denote the delivery ratio when the given time is t. Our objective is to maximize the value of $F(T)$. Then, we define another symbol $H(t)=1-F(t)$, which denotes the probability that the destination does not obtain the message before time t. In addition, let $H(t, t+\Delta t)$ denote the probability that D does not get the message in time interval $[t, t+\Delta t]$. Therefore, we have,

$$H(t+\Delta t)=H(t)H(t,t+\Delta t) \tag{4}$$

As described in above section, we assume that the destination beacons at the biggest rate, so the inter-meeting rate between the destination and other nodes is λ. In addition, we also assume that the relay nodes always forward the message to D with probability 1. In fact, our result can be easily extended to the case that the destination beaconing with different rates or the relay nodes forward the message to D with other probability. Then, we can easily obtain,

$$H(t,t+\Delta t)=e^{-\lambda \Delta t X(t)} \tag{5}$$

Furthermore, we have,

$$\begin{cases} E(\dot{H}(t)) = -\lambda E(H(t))E(X(t)) \\ E(\dot{F}(t)) = \lambda(1-E(F(t)))E(X(t)) \end{cases} \tag{6}$$

Now, we begin to explore the model of the energy consumption. Because there is only one destination, we ignore the energy consumption for the destination. Note that we only consider the energy consumption in the *forwarding* and *beaconing* processes. As shown in [10]-[13], the first part of energy consumption is proportional to the expected number of transmission times, where the energy of one transmission includes both the reception energy at the receiving node and the transmission energy at the forwarding node. Therefore, the average energy consumption in the *forwarding* process can be expressed as $\alpha(E(X(t))-1)$ at time t, where α is the system specified positive constant that weights the energy consumption of each transmission. The *beaconing* energy consumption is proportional to the *beaconing rate* and the number of relay nodes that do not have message, whose *beaconing rate* is $\mu(t)$ at time t. Thereofore, the total *beaconing* energy consumption up to time T is,

$$\beta\int_0^T \mu(t)(N-E(X(t))dt \tag{7}$$

That is, the energy used to beacon at time t is $\beta\mu(t)(N-E(Y(t))$, where β is the system specified positive constant that weights the energy consumption of each beaconing.

Furthermore, the total energy consumption for the *forwarding* and *beaconing* processes is,

$$E(U(T))=\alpha(E(X(T))-1)+\beta\int_0^T \mu(t)(N-E(X(t))dt \tag{8}$$

3.3 Optimal Control

Now, our main objective is to solve the following joint optimization problem,

$$\begin{cases} Max\, E(F(T)) \\ E(U(T)) \le C \end{cases} \tag{9}$$

T is the maximal lifetime of the message, and C is the maximal energy that nodes can be used. Obviously, above equation is an optimal control problem with control parameters $p(t)$

and $\mu(t)$. Let $((F, X, U), p, \mu)$ be an optimal solution. In particular, at time t, X denotes the value of $E(X(t))$, F denotes the value of $E(F(t))$, and U denotes the value of $E(U(t))$. Similarly, p denotes the value of $p(t)$ and μ denotes the value of $\mu(t)$, respectively. Consider the *Hamiltonian H* as follows:

$$
\begin{aligned}
H &= \dot{F} + \lambda_X \dot{X} + \lambda_F \dot{F} + \lambda_U \dot{U} \\
&= \lambda(1-F)(1+\lambda_F)X + \lambda\lambda_X X(N-X)\mu p + \lambda_U(\alpha \dot{X} + \beta(N-X)\mu) \\
&= \lambda(1-F)(1+\lambda_F)X + \lambda(\lambda_X + \alpha\lambda_U)X(N-X)\mu p + \lambda_U \beta(N-X)\mu
\end{aligned}
\tag{10}
$$

Then, the *co-state* or *adjoint* functions λ_F, λ_X and λ_U are defined as:

$$
\begin{cases}
\dot{\lambda}_F = -\dfrac{\partial H}{\partial F} = \lambda(1+\lambda_F)X \\
\dot{\lambda}_X = -\dfrac{\partial H}{\partial X} = -\lambda(1+\lambda_F)(1-F) - \lambda(\lambda_X + \alpha\lambda_U)(N-2X)\mu p + \beta\lambda_U \mu \\
\dot{\lambda}_U = -\dfrac{\partial H}{\partial U} = 0
\end{cases}
\tag{11}
$$

The *transversality* conditions are shown as follow:

$$
\lambda_F(T) = \lambda_X(T) = \lambda_U(T)(E(U(T) - C) = 0, \lambda_U(t) \le 0 \tag{12}
$$

Then according to the Pontryagin's Maximum Principle [33, P.109, Theorem 3.14], there exist continuous or piece-wise continuously differentiable state and *co-state* functions, which satisfy:

$$
(p, \mu) \in \arg \max_{0 \le p^* \le 1, \mu_{\min} \le \mu^* \le 1} H(\lambda_F, \lambda_X, \lambda_U, (F, X, U), (p^*, \mu^*)) \tag{13}
$$

This equation between the optimal control parameter (p, μ) and the *Hamiltonian H* allows us to express (p, μ) as a function of the state (F, X, U) and *co-state* $(\lambda_F, \lambda_X, \lambda_U)$, resulting in a system of differential equations involving only the state and *co-state* functions, and not the control function. We know the initial values of the states (F, X, U), and we have $(F(0)=0, X(0)=1, U(0)=0)$. In addition, we know the final values of the state $(\lambda_F, \lambda_X, \lambda_U)$ (see Eq.12). Therefore, numerical methods for solving the *boundary value* nonlinear differential equation problems may now be used to solve for the state and adjoint funtions. On the other hand, this equation means that maximizing the value of $E(U(T))$ equals to maximizing the corresponding *Hamiltonian H*. In particular, at given time t, the state (F, X, U) and *co-state* $(\lambda_F, \lambda_X, \lambda_U)$ can be seen as constants, and (p, μ) can maximize H at this time. Based on Eq.(10), we have,

$$
\begin{cases}
\dfrac{\partial H}{\partial p} = \lambda(\lambda_X + \alpha\lambda_U)X(N-X)\mu \\
\dfrac{\partial H}{\partial \mu} = \lambda(\lambda_X + \alpha\lambda_U)X(N-X)p + \lambda_U \beta(N-X)
\end{cases}
\tag{14}
$$

Therefore, we can obtain the optimal value for p as follows,

$$
p = \begin{cases}
0, (\lambda_X + \alpha\lambda_U)X(N-X)\mu < 0 \\
1, (\lambda_X + \alpha\lambda_U)X(N-X)\mu > 0
\end{cases}
\tag{15}
$$

In fact, if $(\lambda_X+\alpha\lambda_U)>0$, we can let the optimal value of p be 1. This is because if $X(N-X)\mu=0$, we have $(\lambda_X+\alpha\lambda_U)X(N-X)\mu=0$, and p can be any value, so 1 is a feasible one. Otherwise, if $X(N-X)\mu>0$, we have $(\lambda_X+\alpha\lambda_U)X(N-X)\mu>0$, so the optimal value is 1. Similarly, if $(\lambda_X+\alpha\lambda_U)\le 0$, the optimal value can be 0. That is, Eq.(15) can be described as,

$$p = \begin{cases} 0, (\lambda_X + \alpha\lambda_U) \le 0 \\ 1, (\lambda_X + \alpha\lambda_U) > 0 \end{cases} \tag{16}$$

From Eq.(14), we can get the optimal value for μ as follows,

$$\mu = \begin{cases} \mu_{\min}, \lambda(\lambda_X + \alpha\lambda_U)X(N-X)p + \lambda_U\beta(N-X) < 0 \\ 1, \lambda(\lambda_X + \alpha\lambda_U)X(N-X)p + \lambda_U\beta(N-X) > 0 \end{cases} \tag{17}$$

If 1-F=0, the destination has got the message, and there is no need to explore the optimal policy at all, so we only consider the case 1-F<0. Under the assumption, we have the following theorem.

Theorem 1: The optimal policy of p has at most one jump and it satisfies: $p(t)=1$, $t<h$, and $p(t)=0$, $t>h$, $0 \le h \le T$. Time h can be seen as the *stopping time*.

Proof: First, from Eq.(11) and Eq.(12), we can see that $1+\lambda_F>0$. Otherwise, if $1+\lambda_F \le 0$ at certain time (e.g., s), we have,

$$\begin{cases} \lambda_F(s) \le -1 < 0 \\ \dot{\lambda}_F(s) = \lambda(1+\lambda_F(s))X(s) \le 0 \end{cases}$$

Therefore, λ_F is non-increasing at time s, that is, it cannot increase at time s. On the other hand, λ_F is negative at time s. This means that if $1+\lambda_F \le 0$ at certain time s, λ_F does not have the chance to increase in the future and will remain negative. Furthermore, we can have $\lambda_F(T)<0$, and this is contradiction with Eq.(12). Therefore, we have $1+\lambda_F>0$.

Now, we define a new function as follows,

$$L_p(t) = \lambda_X(t) + \alpha\lambda_U(t) \tag{18}$$

Furthermore, we have,

$$\dot{L}_p(t) = \dot{\lambda}_X(t) + \alpha\dot{\lambda}_U(t) = \dot{\lambda}_X(t) \tag{19}$$

We will prove that if $L_p(s) \le 0$, we have $L_p(t) \le 0$, $t>s$. From Eq.(19), we have,

$$\begin{aligned} \dot{L}_p = \dot{\lambda}_X &= -\lambda(1+\lambda_F)(1-F) - \lambda(\lambda_X + \alpha\lambda_U)(N-2X)\mu p + \beta\lambda_U\mu \\ &= -\lambda(1+\lambda_F)(1-F) - \lambda L_p(N-2X)\mu p + \beta\lambda_U\mu \end{aligned} \tag{20}$$

Combining with Eq.(16), when $L_p(s) \le 0$, we have,

$$\begin{cases} L_p(s)p(s) = 0 \\ \dot{L}_p(s) = -\lambda(1+\lambda_F(s))(1-F(s)) - \beta\lambda_U\mu(s) \end{cases}$$

Because we have proved $1+\lambda_F>0$ and $\lambda_U \le 0$, we can see that $\dot{L}_p(s) < 0$. This means L_p is decreasing at time s. Furthermore, we can see that if $L_p(s) \le 0$, we have $L_p(t) < 0$, $t>s$.

Therefore, L_p has at most one jump, if the jump is at time h, we have $L_p(t) > 0$, $t<h$, $L_p(t) < 0$, $t>h$. Combining with Eq.(16), we know that the optimal policy of p has at most one jump and it satisfies: $p(t)=1$, $t<h$, and $p(t)=0$, $t>h$, $0 \le h \le T$. ■

Similar to Eq.(16), Eq.(17) can be converted to the following case,

$$\mu = \begin{cases} \mu_{\min}, \lambda(\lambda_X + \alpha\lambda_U)Xp + \lambda_U\beta \le 0 \\ 1, \lambda(\lambda_X + \alpha\lambda_U)Xp + \lambda_U\beta > 0 \end{cases} \tag{21}$$

When $\lambda(\lambda_X+\alpha\lambda_U)Xp+\lambda_U\beta>0$, if N-X=0, μ can be any value, so 1 is feasible. If Y>0, the optimal value of μ is 1. Similarly, when $\lambda(\lambda_X+\alpha\lambda_U)Xp+\lambda_U\beta<0$, if N-X=0, μ can be any value, so $\mu_{\min}$ is feasible. If N-X >0, the optimal value of μ is $\mu_{\min}$. In addition, if $\lambda(\lambda_X+\alpha\lambda_U)X(N-X)p+\lambda_U\beta(N-X)=0$, $\mu_{\min}$ is feasible, too. Therefore, we can obtain Eq.(21).

Furthermore, we can obtain Theorem 2.

Theorem 2: if $\lambda_X+\alpha\lambda_U \leq 0$, we can have $\mu=\mu_{\min}$.

Proof: First, if $\lambda_X+\alpha\lambda_U<0$, we have $\lambda(\lambda_X+\alpha\lambda_U)Xp+\lambda_U\beta<0$ ($\lambda_U\leq 0$). Then, if $\lambda_X+\alpha\lambda_U=0$, we can obtain $\lambda(\lambda_X+\alpha\lambda_U)Xp+\lambda_U\beta=\lambda_U\beta\leq 0$. Therefore, from Eq.(21), we have $\mu=\mu_{\min}$. ■

Now, we consider the case that $\lambda_X+\alpha\lambda_U>0$, and we have Theorem 3.

Theorem 3: When $\lambda_X+\alpha\lambda_U>0$, the optimal policy of μ has at most one jump and it satisfies: $\mu(t)=1$, $t<h$, and $\mu(t)=\mu_{\min}$, $t>h$, $0\leq h\leq T$.

Proof: Note that in this case, we have $p=1$ according to Eq.(16). First, we define a new function as follows,

$$\begin{aligned} L_\mu(t) &= \lambda(\lambda_X(t)+\alpha\lambda_U(t))X(t)p(t)+\lambda_U(t)\beta \\ &= \lambda L_p(t)X(t)+\lambda_U(t)\beta \end{aligned} \tag{22}$$

Furthermore, we have,

$$\begin{aligned} \dot{L}_\mu &= \lambda \dot{L}_p X + \lambda L_p \dot{X} + \dot{\lambda}_U \beta \\ &= \lambda \dot{L}_p X + \lambda L_p \dot{X} \end{aligned} \tag{23}$$

In addition, we have (with p=1, see Appendix 1),

$$\dot{L}_p = -\lambda(1+\lambda_F)(1-F) - \lambda L_p(N-X)\mu + \mu L_\mu \tag{24}$$

Then, we have (with p=1, see Appendix 2),

$$\dot{L}_\mu = \lambda(-\lambda(1+\lambda_F)(1-F)+\mu L_\mu)X \tag{25}$$

Suppose that at certain time s, we have $L_\mu(s)\leq 0$. In this case, we can easily obtain $\mu(s)L_\mu(s)\leq 0$. Because we have proved $1+\lambda_F>0$. We have,

$$\dot{L}_\mu(s) = \lambda(-\lambda(1+\lambda_F(s))(1-F(s))+\mu(s)L_\mu(s))X(s) < 0 \tag{26}$$

This means that L_μ is decreasing at time s. In other words, if L_μ is not positive at certain time, it will decrease later. That is, if $L_\mu(s)\leq 0$, we have $L_\mu(t)<0$, $t>s$. Therefore, L_μ has at most one jump, if the jump is at time h, we have $L_\mu(t)>0$, $t<h$, $L_\mu(t)<0$, $t>h$. Combining with Eq.(21), we know that the optimal policy of μ has at most one jump and it satisfies: $\mu(t)=1$, $t<h$, and $\mu(t)=\mu_{\min}$, $t>h$, $0\leq h\leq T$. ■

From Theorem 3, we have,

$$\mu = \begin{cases} \mu_{\min}, L_p>0 \,\&\, \lambda L_p Xp+\lambda_U\beta \leq 0 \\ 1, L_p>0 \,\&\, \lambda L_p Xp+\lambda_U\beta>0 \end{cases}, L_p=(\lambda_X+\alpha\lambda_U) \tag{27}$$

Corollary 1: Combining with Theorem 2 and Theorem 3, we can see that the optimal policy of μ has at most one jump in any case and it satisfies: $\mu(t)=1$, $t<h$, and $\mu(t)=\mu_{\min}$, $t>h$, $0\leq h\leq T$.

Proof: First, we can see that if $\lambda_X+\alpha\lambda_U=0$, we can obtain $\lambda(\lambda_X+\alpha\lambda_U)Xp+\lambda_U\beta=\lambda_U\beta\leq 0$. However, if $\lambda_U\beta=0$, we have $\lambda(\lambda_X+\alpha\lambda_U)Xp+\lambda_U\beta=0$, and μ may be any value, and $\mu_{\min}$ is only one of them. In other words, μ may jump when $\lambda_X+\alpha\lambda_U=0$ and $\lambda_U=0$. On the other hand, if μ jumps when $\lambda_X+\alpha\lambda_U=0$ and $\lambda_U=0$, it cannot jump when $\lambda_X+\alpha\lambda_U>0$. This is because that λ_U is a constant. If $\lambda_U=0$, the function in Eq.(22) will bigger than 0 all the time when $\lambda_X+\alpha\lambda_U>0$, and the optimal value of μ will be 1.Therefore, μ cannot jump when $\lambda_X+\alpha\lambda_U>0$. Furthermore, from the proving process of Theorem 2, we can see when $\lambda_X+\alpha\lambda_U<0$, we have $\mu=\mu_{\min}$. In other words, μ does ot jump when $\lambda_X+\alpha\lambda_U<0$. Therefore, the optimal value of μ has at most one jump in the whole lifetime of the message. ■

In particular, the optimal value of μ can be denoted as follows,

$$\mu=\begin{cases}\mu_{\min}, L_p\le 0\\ \mu_{\min}, L_p>0\ \&\ \lambda L_p Xp+\lambda_U\beta\le 0, L_p=(\lambda_X+\alpha\lambda_U)\\ 1, L_p>0\ \&\ \lambda L_p Xp+\lambda_U\beta>0\end{cases} \tag{28}$$

From Theorem 1 and Corollary 1, we can see that both the optimal policies of p and μ conform to the *threshold* form. Now, we assume that the *stopping time* is h_p and h_μ, respectively. Then, we have Theorem 4.

Theorem 4: For the *stopping time* h_p and h_μ, we have $h_\mu\le h_p$.

Proof: First, we assume that Theorem 4 is not correct, that is, $h_\mu>h_p$. Therefore, for any time t belongs to $(h_p, h_\mu]$, we have $p(t)=0$, $\mu(t)=1$. Note that, we only consider the case that N-X>0, that is, at least one relay node does not have message. Furthermore, according to Eq.(16), we have $L_p=(\lambda_X+\alpha\lambda_U)\le 0$. Then according to Theorem 2, we have $\mu(t)=\mu_{\min}$, which is contradiction, because we have got $\mu(t)=1$.

Therefore, $h_\mu>h_p$ cannot be correct, and Theorem 4 is correct. ■

Remark: When $\mu=\mu_{\min}=0$, the optimal value of p can be any value. That is, the system can have multiple optimal policies for p, and the result in Eq.(16) is one of them. In other words, the optimal value may be not unique in certain cases, but our result can get one of them. In fact, if $\mu=\mu_{\min}=0$, the relay nodes do not beacon at all, and nodes cannot find each other, so nodes do not have a chance to forward the message to others at all. In this case, the value of the *forwarding* ratio cannot have any impact and may be any value.

4. Simulation and Numerical Results

4.1 Simulation Results

In this section, we will check the accuracy of our theoretical framework, and we run several simulations using the Opportunistic Network Environment (ONE) [34]. The first simulation is based on the famous Random Waypoint (RWP) mobility model [35], which is commonly used in many mobile wireless networks. We assume that there are 500 nodes, which move according to the RWP model within a 10000m×10000m terrain according to a scale speed chosen from a uniform distribution from 4m/s to 10m/s. The maximal communication range is 50m. The second simulation is based on the Poisson-contact model, and the parameter of node contact events is $\lambda=3.71\times10^{-6}s^{-1}$. This value is obtained from a real-world based scenario. In particular, it comes from the Shanghai city motion trace collected by GPS [36], which includes 2100 operational taxis. The location information of the taxis is recorded at every 40 seconds within the area of 102 km^2. For this simulation, we also randomly pick 500 nodes, and the source and destination nodes are randomly selected, too. In addition, if the *beaconing rate* is μ, we use the parameter $\mu\lambda$ to generate the node contact events. Finally, we carry out the simulation based on the Infocom 2005 dataset, which includes 41 nodes [37].

Because the main goal of this section is to check the accuracy of the Ordinary Differential Equations (ODE), we can assume that the total energy C is not limit. In particular, we compare the simulation results with the numerical results based on the metric *average delivery ratio*. In addition, we also show the results for the *energy consumption*. For other theoretical related parameters, there may be infinite settings. First, both α and β are the system specified positive constants that weights the energy consumption of each transmission and the energy consumption of each beaconing, respectively. Their value is related with the system, so they can have different value in different applications. For simplicity, many works just assign a value to them. For example, the works in [11]-[12] let α=1. In this section, we just check the accuracy of our model, so we can assign any value, too. In particular, we let α=1, $\beta=10^{-6}$. Simulations with real value of these parameters will be our future work. On the other hand, we only consider two simple policies: Case 1, $p(t)$=1, $\mu(t)$=1; Case 2, $p(t)$=0.2, $\mu(t)$=0.2. Let the maximal message lifetime T increase from 0s to 5000s, and we can obtain **Fig. 1, Fig. 2** and **Fig. 3**. Through these results in **Fig. 1** and **Fig. 2**, we can see that the average deviation between the theoretical and the simulation results is very small. For example, the average deviation is about 3.26% for the RWP mobility model, and 3.07% for the Poisson-contact motion trace. This demonstrates the accuracy of our theoretical framework. However, the average deviation based on the Infocom 2005 dataset is a little bigger (see **Fig. 3**). In fact, some works have shown that the Infocom 2005 datasets may conform to the power law and exponential decay distribution [29], so if we use the exponential model to fit this dataset, it will bring bigger deviation. However, the deviation is only about 7.016%, and we think that it is not too big. Therefore, our model is useful in certain cases, where the inter-meeting time does not conform to the exponential distribution accurately. For this reason, we can use the numerical results obtained by our theoretical framework to evaluate the performance of different policies.

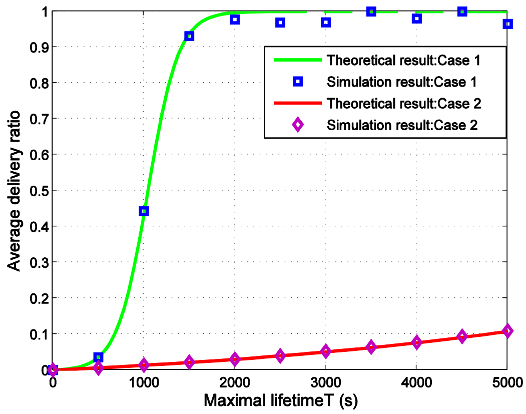

Fig. 1. Simulation and numerical results comparison with RWP mobility model

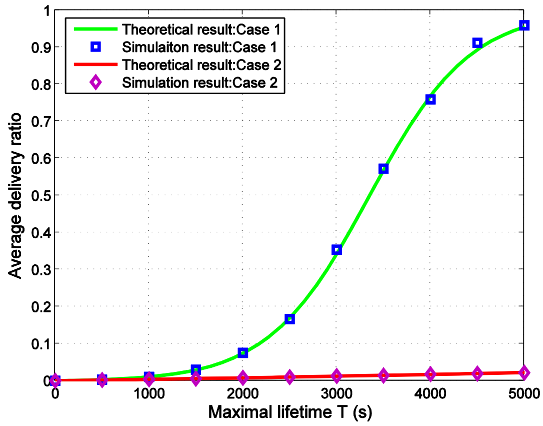

Fig. 2. Simulation and numerical results comparison with Poisson-contact model

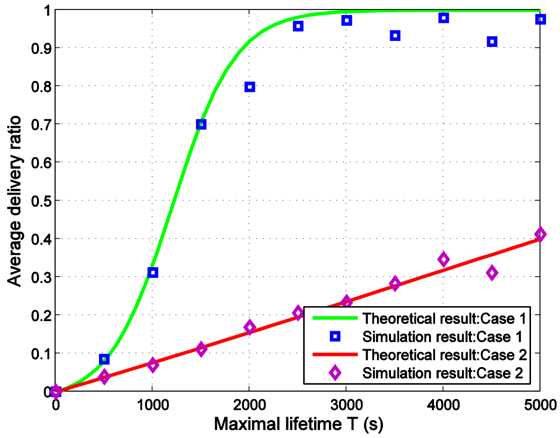

Fig. 3. Simulation and numerical results comparison with Infocom 2005 dataset

The results in above results also show that if the *forwarding* and *beaconing* rates are bigger, the average delivery ratio is better. However, it will use more energy. In other words, we can increase the performance at the cost of more expenditure. We can see that bigger *forwarding* and *beaconing* rates really bring more energy consumption in **Fig.4, Fig.5** and **Fig.6**. In addition, the results further show that our model is very accurate.

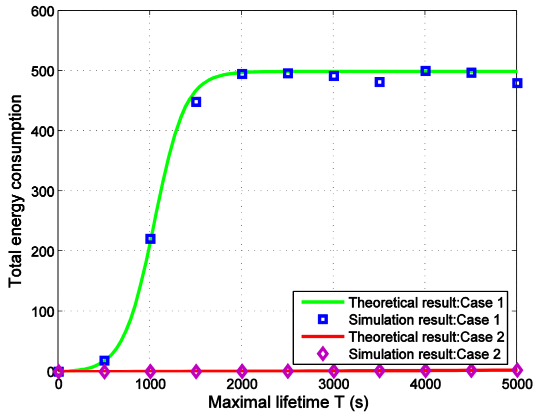

Fig. 4. Energy consumption with RWP mobility model

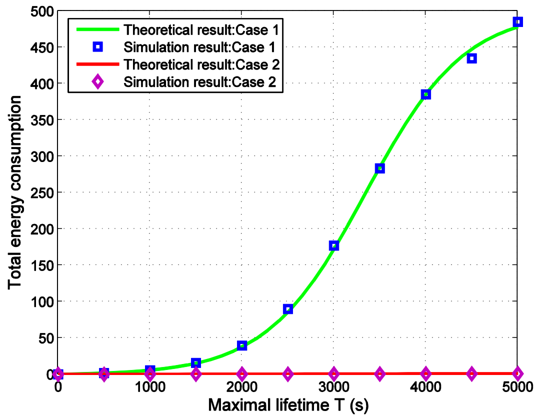

Fig. 5. Energy consumption with Poisson-contact model

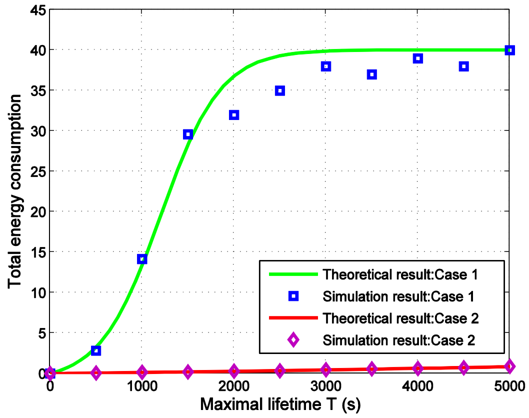

Fig. 6. Energy consumption with Infocom 2005 model

4.2 Performance Analysis with Numerical Results

All of the numerical results are obtained by our theoretical framework based on the best fitting for the Shanghai city motion trace.

First, we will evaluate the performance of the optimal policy obtained by Eq.(16) and Eq.(28), and we let the maximal energy C be 200. In addition, we let μ_{min}=0. For comparison, we also consider other two policies, that is: Case 1, $p(t)$=1, $\mu(t)$= μ; Case 2, $p(t)$=p, $\mu(t)$=1, t belongs to [0, T]. It is easy to see that the average delivery ratio is increasing with μ and p, so we should make them as big as possible. However, above policies must conform to the constraint condition in Eq.(9). Other settings are the same as that in simulation, and we can obtain **Fig.7**.

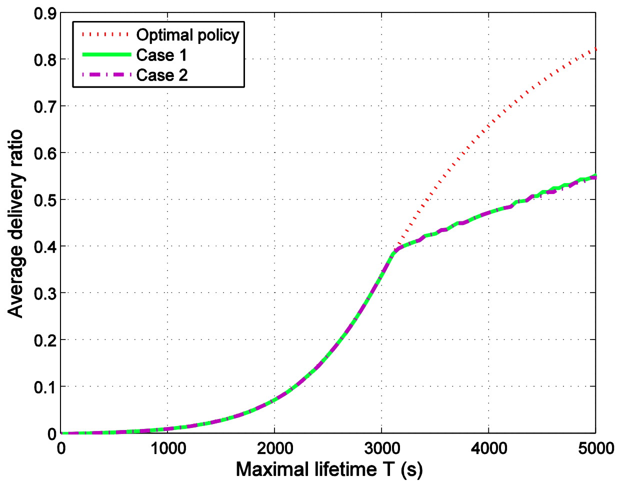

Fig. 7. Performance comparison with different policies

The result in **Fig.7** shows that the policy obtained by Eq.(16) and Eq.(28) is the best. In addition, when the value of T is smaller, the performance of the optimal policy is nearly the same as that of other policies. This is because that when T is smaller, the energy is enough even though nodes *forwarding* and *beaconing* by the biggest rate. On the other hand, the performance of Case 1 and Case 2 is nearly the same. In fact, from Eq.(9), we can see that one part of the energy consumption bringing by the beaconing process is proportional to β. In above numerical result, the value of β is very small, so the energy consumption of this part can be ignored. Now, we change the value of β to 0.0001, and obtain **Fig.8**

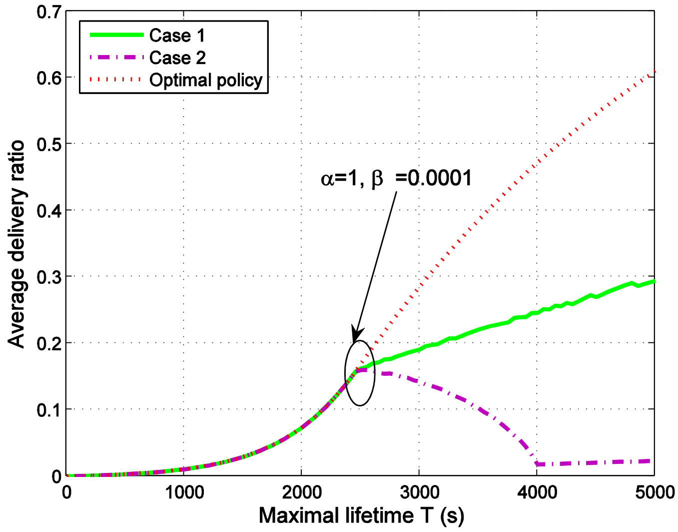

Fig. 8. Performance comparison with different policies when α=1, β=10^{-4}

Obviously, when β equals to 0.0001, the performance of Case 1 and Case 2 is bigger. In particular, the average delivery ratio in Case 2 will decrease when T is big enough. This is because that the value of p is decrease with T when T is big enough. We can see the result more clearly in **Fig.9**. For example, when T reaches to about 2500s, the value of p begins to decrease and it nearly equals to 0 when T is bigger than 4000s. When the policy is fixed, we can increase the average delivery ratio by increasing the value of T. However, when the *forwarding rate* decreases too much, the performance will decrease. On the other hand, from **Fig.9**, we also can see that the value of μ in Case 1 decrease when T is big enough. However, the decreasing ratio is smaller comparing with that of p. Though the decreasing of μ will make the average delivery ratio be smaller when T is fixed, it may not decrease when T increases. Therefore, the average delivery ratio can increase in Case 1.

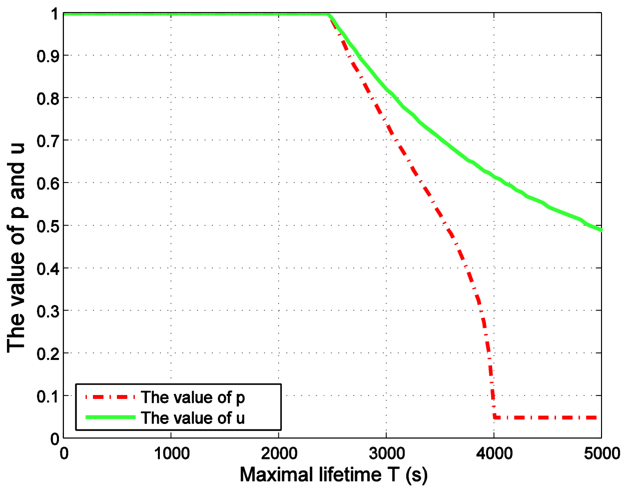

Fig. 9. The value of p and μ in Case 2 when α=1, β=10^{-4}

Now, we further compare the performance of different policies when the number of nodes is different. In this case, we assume that the maximal message lifetime equals to 4000s, and let the number of relay nodes increase from 50 to 500. Other settings are the same as that for **Fig.8**. Based on these settings we obtain **Fig.10**.

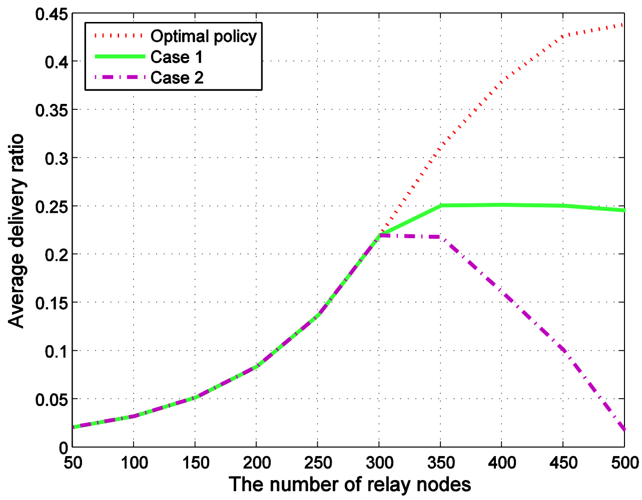

Fig. 10. Performance comparison with different policies when the different number of relay nodes

The result further shows that the optimal policy obtained by Eq.(16) and Eq.(28) is the best. As shown in Theorem 1 and Corollary 1, both the optimal *forwarding rate* and *beaconing rate* conform to the *threshold* form. For example, when N=350 and N=400, the numerical result conforms to Theorem 1 and Corollary 1 (see **Fig.11**, when T=4000s).

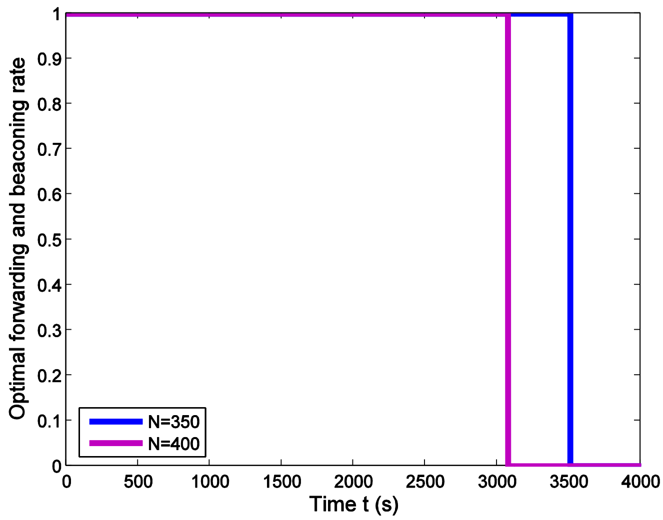

Fig. 11. Optimal *forwarding rate* and *beaconing rate*

First, **Fig.11** shows that the optimal policy really conforms to the *threshold* form. Second, it shows that the *stopping time* h_p and h_μ are the same, this is because $\mu_{\min}$=0. Now, we want to explore the optimal policy when $\mu_{\min}$>0. In particular, we let $\mu_{\min}$ be 0.05. In addition, we have T=4000s and N=500. Other settings remain unchanged, and we have **Fig.12**. This result shows that if $\mu_{\min}$>0, h_p and h_μ may be different, and we have h_p>h_μ in **Fig.12**, which conforms to Theorem 4. This means that when the relay nodes that do not have message beacon at the smallest rate, the nodes that have message will still forwarding the message to others within certain time.

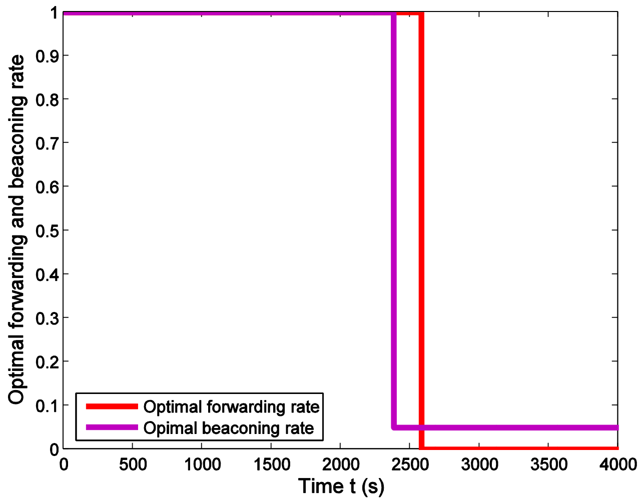

Fig.12. Optimal *forwarding* and *beaconing* policy when $\mu_{\min}$=0.05

5. Conclusion

This paper presents a continuous-time Markov and fluid model to analysis the performance of ER algorithm. In particular, it can evaluate the performance under different *forwarding* and *beaconing* rates for ER algorithm. Simulations based on both synthetic and Poisson-contact model show the accuracy of our theoretical model. Based on the model, we formulate a joint optimization problem. We solve the problem through Pontryagin's Maximal Principle, and prove that both the optimal *forwarding rate* and *beaconing rate* conform to the *threshold* form. Extensive numerical results further show that the optimal policy is really better.

In this paper, we assume that inter-meeting time is exponential. At present, many works show that it may conform to the Power-law distribution in certain applications. Therefore, we want to extend our work in the future, and explore the optimal control problem with the Power-law distribution.

Appendix

Appendix 1: The derivation for Eq.(24):

Proof: According to Eq.(20), when p=1, we have,

$$\begin{aligned}\dot{L}_p &= -\lambda(1+\lambda_F)(1-F) - \lambda L_p(N-2X)\mu p + \beta\lambda_U\mu \\ &= -\lambda(1+\lambda_F)(1-F) - \lambda L_p(N-X)\mu + \lambda L_p X\mu + \beta\lambda_U\mu \\ &= -\lambda(1+\lambda_F)(1-F) - \lambda L_p(N-X)\mu + \mu L_\mu\end{aligned}$$

Appendix 2: The derivation for Eq.(25):

Proof: Combining with Eq.(23) and Eq.(24), when p=1, we have,

$$\dot{L}_{\mu} = \lambda(-\lambda(1+\lambda_F)(1-F) - \lambda L_p(N-X)\mu + \mu L_{\mu})X + \lambda L_p \dot{X}$$
$$= \lambda(-\lambda(1+\lambda_F)(1-F) + \mu L_{\mu})X - \lambda\lambda L_p(N-X)X\mu + \lambda L_p \dot{X}$$
$$= \lambda(-\lambda(1+\lambda_F)(1-F) + \mu L_{\mu})X - \lambda\lambda L_p(N-X)X\mu p + \lambda L_p \dot{X}$$
$$= \lambda(-\lambda(1+\lambda_F)(1-F) + \mu L_{\mu})X - \lambda L_p \dot{X} + \lambda L_p \dot{X}$$
$$= \lambda(-\lambda(1+\lambda_F)(1-F) + \mu L_{\mu})X$$

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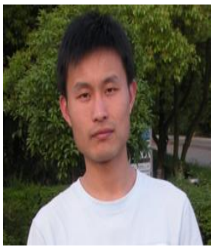

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